Nutrient Pollution and U.S. Agriculture: Causal Effects, Integrated Assessment, and Implications of Climate Change

Konstantinos Metaxoglou and Aaron Smith*

This version: July 2022

Abstract

We study the relationship between water nutrient pollution and U.S. agriculture using data between the early 1970s and late 2010s. We estimate a positive causal effect of corn acreage on nitrogen concentration in the country's surface water quality. We find that a 10% increase in corn acreage causes an increase in nitrogen concentration in water by at least 1% and show that the magnitude of the acreage effect increases with precipitation but not with extreme-heat degree days. Based on the average streamflow of the Mississippi River at the Gulf of Mexico during this period and damages of about \$16 per kilogram of nitrogen, this 1% increase in average nitrogen concentration implies an annual external cost of \$800 million. Using recent climate models to project the implications of climate change for the magnitude of the estimated effects, we conclude that climate change will not materially change the estimated relationship between corn acreage and nitrogen concentration.

Keywords: crops, environmental externalities, hypoxia, integrated assessment, nutrient pollution.

JEL codes: Q15, Q48, Q51, Q53, Q58

*Corresponding address: Metaxoglou: Department of Economics, Carleton University, 1125 Colonel By Drive, Ottawa, ON K1S 5B6. Email: konstantinos.metaxoglou@carleton.ca. Smith: Department of Agricultural and Resource Economics, University of California, Davis, One Shields Avenue, Davis, CA 95616. Email: adsmith@ucdavis.edu. We thank Joe Shapiro for helping us navigate through the USGS data in the very early stages of the paper, Sergey Robotyagov and Cathy Kling for sharing results of previous work, Jeremy Proville of the Environmental Defense Fund for sharing the results of an in-progress report, and seminar participants at Oregon State and UC Berkeley for comments. We received feedback from Ariel Dinar, Gary Libecap, and Lynne Lewis that helped us to significantly improve the original draft. Any remaining errors are ours.

1 Introduction

Nutrient pollution is one of the country's most widespread, costly, and challenging environmental problems. It is caused by excess nitrogen and phosphorus in the air and water. Although nutrients such as nitrogen and phosphorous are chemical elements that plants and animals need to grow, when too much nitrogen and phosphorus enter the environment, usually from a wide range of human activities, the air and water can become severely polluted.

Some of the largest sources of nutrient pollution include commercial fertilizers, animal manure, sewage treatment plant discharge, storm water runoff, cars, and power plants. In the Mississippi River Basin (MRB), which spans 31 states and drains 40% of the contiguous U.S. (CONUS) into the Gulf of Mexico (GoM), nutrients from row crops, large farms, and concentrated animal feeding operations account for most of the nutrient pollution. Fertilizer runoff from agricultural crops has been estimated to contribute somewhere between 50% (CENR (2000)) and 76% (David et al. (2010)) of the annual and spring nitrogen riverine export from the MRB to the GoM fueling a hypoxic ("dead") zone, with oxygen levels that are too low for fish and other marine life to survive. The GoM hypoxic zone is the second largest in the world behind the dead zone in the Arabian Sea with a peak areal extent equal to that of New Jersey (8,776 square miles) recorded in the summer of 2017.

According to the EPA (2016), 46% (about 546,000 miles) of U.S. streams and rivers are in poor condition in terms of their phosphorous levels and 41% (about 495,000 miles) are in poor condition in terms of their nitrogen levels based on sampling results from almost 2,000 sites benchmarked against conditions represented by a set of least-disturbed sites. Excessive nitrogen and phosphorus in water and the air can cause health problems, damage land and water, and take a heavy toll on the economy.[1] Reducing the areal extent of the hypoxic zone to a 5-year running average of 5,000 square kilometers, a target set in the Action Plan of the GoM Hypoxia Task Force, comes at an estimated price tag of $2.7 billion per year (Rabotyagov et al. (2014b)).

In this chapter, we focus on water pollution and its relationship to U.S. agriculture. We use regression analysis to establish a causal link between farmers' decisions about crop acreage and nutrient pollution that is detrimental to surface water quality. In particular, we estimate the causal effects of corn acreage on nitrogen concentration in water bodies using panel fixed-effect (FE) regressions and what we call "(c)ounty-centric" analysis. We make few and transparent assumptions

[1] See CENR (2000), EPA (2007), and, more recently, Olmstead (2010), GOMNTF (2013) and Rabotyagov et al. (2014a). Several papers assess the the cost of nitrogen pollution employing a variety of methodologies; see Dodds et al. (2009), Compton et al. (2011), Birch et al. (2011), Rabotyagov et al. (2014b), and Sobota et al. (2015), among others.

that allows us to the assess the robustness of our findings to various factors. In contrast, most prior estimates of effects similar to the ones estimated in this chapter are based on agronomic and hydrologic models.

To perform our c-centric analysis, we combine annual county-level data on acres planted and nitrogen pollution. Data on acres planted are readily available from the U.S. Department of Agriculture (USDA). We compile data on nitrogen pollution using U.S. Geological Survey (USGS) monitoring sites within a 50-mile radius from the county centroids. Based on our preferred estimate of the elasticity of nitrogen concentration (mg/L) with respect to corn acreage of about 0.1, an increase in corn acres planted equal to 1 within-county standard deviation implies a 3.3% increase in the level of nitrogen concentration. At the average nitrogen concentration of about 2.5 mg/L and the average streamflow of the Mississippi River in the GoM in our sample, this effect entails close to 50,800 additional metric tons of nitrogen in the GoM. Using the median potential damages of nitrogen due to declines in fisheries and estuarine/marine life of $15.84 per kilogram ($2008) from Sobota et al. (2015), the implied annual external cost is about $800 million. The magnitude of the estimated effects depends on the amount of annual precipitation but not on extreme heat despite its well-documented negative impact on crop growth and, hence, nutrient uptake.

We also explore the implications of climate change for nitrogen pollution using the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) dataset to obtain out-of-sample projections for precipitation and temperature, which we translate into projections of corn acreage marginal effects on nitrogen pollution. The NEX-GDDP-CMIP6 dataset is comprised of global downscaled climate scenarios derived from the General Circulation Model runs conducted under the Coupled Model Intercomparison Project Phase 6 and across two of the four "Tier 1" greenhouse gas emissions scenarios known as shared socioeconomic pathways (SSPs), namely, SSP2-4.5 and SSP5-8.5. Abstracting from the impact that climate change may have an acreage, yields, nitrogen fertilizer use, legacy nitrogen, runoff, and streamflow, all of which may contribute to nitrogen pollution, the out-of-sample precipitation and temperature projections imply similar effects of corn acreage on nitrogen concentration as in our estimation sample. This finding arises because the climate models project relatively small changes in precipitation and because our estimated effects of corn acreage on nitrogen concentration do not vary a lot with temperature.

The focus of this chapter is different from the chapter by Elbakidze et al. (2022) in this volume. Elbakidze et al. study the effects of changes in nitrogen fertilizer use by U.S. farmers on surface water quality due to climate change. Investigating the effect of climate-driven productivity changes on water quality in the GoM using an integrated hydro-economic agricultural land use model (IHEAL), they find that land and nitrogen use adaptation in agricultural production to climate change increases nitrogen loads to the GoM by 0.4%–1.58%. As we discuss later in the chapter, our findings are consistent with a new research in environmental science arguing that there is a large amount of nitrogen stored in subsurface soil and groundwater and contributes to the so-called legacy nitrogen, which may increase loadings in rivers and streams with a long delay. The work by Elbakidze et al. does not address legacy nitrogen. Elbakidze et al. account for farmers' adaptation to climate change in their analysis while our reduced-form econometric analysis does not.

The remainder of the paper is organized as follows. Section 2 provides a background on nutrient pollution emphasizing the role of agriculture and shedding light on the impacts of climate change. Section 3 is a simple theoretical backdrop for Section 4, where we describe the empirical approach for estimating the causal effects of interest. Subsequently, having discussed the data and provided some descriptive analysis in Section 5, we present the results from our regressions in Section 6. We next explore the implications of climate change for nitrogen pollution in Section 7. We finally conclude.

2 Background on Nutrient Pollution

Preamble. Nitrogen inputs to the ecosystem from both anthropogenic and natural sources, are transported via atmospheric, surface flow, drain flow, and groundwater pathways. Nitrate-nitrogen concentrations in the Mississippi River, which drains most U.S. cropland, increased dramatically in the second half of the last century, especially between the early 1960s and the mid 1980s, largely coinciding with the surge in commercial-fertilizer use for row crops in the MRB states (e.g., see Capel et al. (2018)). The corn-and-soybeans cropping system that dominates the Corn Belt is an inherently "leaky" system—some nitrogen loss to subsurface drainage water is inevitable (McLellan et al. (2015)). In fact, the majority of agricultural nitrogen loss occurs via subsurface drainage water, either as seepage through soils and shallow geologic units or in engineered drainage structures such as drainage tiles and ditches.

Aside from oscillations in streamflow, artificial drainage and other changes to the hydrology of the Midwest (e.g., dams and reservoirs), atmospheric deposition of nitrates within the MRB, non-point discharges from urban and suburban areas, and point discharges, particularly from domestic wastewater treatment systems and feedlots, all contribute to the nutrients that reach the GoM (Goolsby et al. 1999). Between 1980 and 2016, close to 1.5 million metric tons of nitrogen (about 63% in the form of nitrate) per year were discharged, on average, to the GoM. From 1968–2016, the average annual Mississippi streamflow was close to 21,500 cubic meters per second.[2] During

[2] We refer to the average flow and total Mississippi-Atchafalya nitrogen flux (sum of NO_3+NO_2, TKN, and NH_3)

this time, there was a strong positive relationship between the streamflow of the Mississippi and nitrogen flux in the GoM.

Dairy, beef, hog, poultry, and aquaculture systems can also cause significant discharges of nutrients to streams and rivers. Untreated wastewater from these systems generally has very high concentrations of nitrogen, most often as ammonia–nitrogen, although high concentrations of nitrate–nitrogen are also possible. Urban and suburban areas have significant runoff from lawns, parking lots, rooftops, roads, highways, and other impervious sources. The major point sources of direct discharges of nutrients, particularly nitrogen-nitrogen, appear to be domestic wastewater treatment plants. Fossil-fuel combustion in car engines and electric generating plants also contributes to airborne nitrates that return to the earth's surface with rain, snow, and fog (wet deposition) or as gases and particulate (dry deposition). This nitrogen then enters streams and rivers and/or is retained in terrestrial systems in the same pathways as nitrate–nitrogen fertilizer.

Damages and abatement costs of nitrogen pollution. In Table 1, we summarize studies related to damages and abatement costs associated with nitrogen pollution noting that the estimation of the economic value of the damages associated with nutrient pollution can be particularly challenging.[3] The social cost of pollution in the context of water quality has received less attention than the social cost of carbon in the context of climate change. Quantifying the social cost of nitrogen is challenging due to multiple loss pathways associated with damages to water quality, air quality, and climate change that occur over heterogeneous spatial and temporal scales (Gourevitch et al. (2018)). The diversity of nitrogen loss pathways and endpoints at which damages occur makes it challenging to construct a single cost metric. The impacts are largely driven by the location where the nitrogen is emitted and applied, the transport and transformation of nitrogen into different forms, and the expected damages along the flow path (Keeler et al. (2018)).

Nitrogen pollution and agriculture. Using too little nitrogen for a highly responsive crop such as corn entails lower yields, poorer grain quality, and reduced profits. When too much nitrogen is applied, crop yields and quality are not affected, but profit can be reduced somewhat and negative environmental consequences are very likely. Thus, many farmers choose to err on the liberal side in terms of nitrogen application rates. This extra nitrogen is often called "insurance" nitrogen; see Mitsch et al. (1999) and CENR (2000), among others. Overall, nitrogen use efficiency (uptake) and the "4Rs" in nutrient management—right source, rate, time, and place for plant nutrient application based on local agronomic recommendations—in order to minimize nitrogen losses to the environment are of paramount importance for addressing nitrogen pollution.

AMLE estimates using data in this link.

[3] EPA (2015) provides estimates of external costs associated with nutrient pollution impacts on tourism and recreation, commercial fishing, property values, human health, as well as drinking water treatment costs, mitigation costs, and restoration costs.

The prevention of nutrient pollution, particularly in the form of nitrate–nitrogen, is possible through a number of general approaches and specific techniques, ranging from modification of agricultural practices to the construction and restoration of riparian zones and wetlands as buffer systems between agricultural lands and waterways.[4] To provide some examples, on-site control of agricultural drainage is possible via adoption of one or a combination of the following: nitrogen fertilizer application rates, management of manure spreading, timing of nitrogen application, the use of nitrification inhibitors, the change of plowing (tillage) methods, and increasing drainage tile spacing. Wetlands and riparian buffers can be effective means of off-site control.

Policy responses to nutrient pollution. As of this writing, the major federal response to nutrient pollution from agriculture continues to be through research, education, outreach, and voluntary technical and financial incentives. A number of USDA agencies provide support through education, outreach, and research, while federal funds are provided through conservation programs to help agricultural producers, who participate voluntarily, to adopt best management practices in crop production to achieve nutrient pollution reduction. At a very high level, the USDA programs are distinguished between land-retirement and working-land programs with the spending on conservation programs having increased substantially since the 2002 Farm Security and Rural Investment Act.[5] In the case of the land-retirement programs, landowners receive payments in exchange for taking land out of active agricultural production and putting the land into perennial grasses, trees, or wetland restoration. Landowners or producers participating in working-land programs receive payments to cover part or all of the costs of making changes in conservation practices and management decisions on their land that remains in agricultural production.

In one of the most comprehensive assessments of conservation practices by U.S. farmers, the USDA Conservation Effects Assessment Project (CEAP) national nitrogen loss report (NRCS (2017b)) found that 29% of nitrogen applied as commercial fertilizer or manure was lost from the fields through various pathways based on survey data for 2003–2006. The mean of the average annual estimates of total nitrogen loss was 34 lb per cultivated cropland acre per year. The amount varied considerably, however, among cultivated cropland acres. Total nitrogen losses were highest for acres receiving manure (56 lb per acre per year). Based on simulations performed using the APEX model in the report, the use of conservation practices during 2003–2006 reduced total nitrogen loss (all loss pathways) by 14.9 lb per acre per year, on average, representing a 30% reduction.

[4] EPA (2007), Ribaudo et al. (2011), NRCS (2017b), and Capel et al. (2018), among others, offer a very informative discussion on controlling nitrogen pollution from agricultural sources.

[5] We refer to this link and Capel et al. (2018) for a succinct and very informative discussion of the various USDA conservation programs.

3 A Simple Theoretical Framework

We estimate the *reduced-form* effect of an increase in corn acreage on nitrogen pollution via OLS regressions. We focus on this relationship in part because corn acreage is the driving force behind the amount of nitrogen fertilizer used. In addition, acreage is much better measured than fertilizer use. We observe nitrogen fertilizer sales by county, but we do not know in which county or year that fertilizer was applied to a field. In contrast, we observe annual acreage by county.[6]

Our empirical analysis, which focuses on the relationship between corn acreage and nitrogen pollution and it is motivated by the following. Farmers decide how to allocate acreage to various crops including corn, which is the most fertilizer intensive and is the crop we focus on. Soybeans, the other commonly planted crop in the U.S. Corn belt, require little nitrogen fertilizer. Farmers apply about 150 lb of nitrogen fertilizer per planted acre of corn and 5 lb per planted acre of soybeans. About 70% of soybean acres receive no nitrogen fertilizer.[7] Crop production requires various inputs such as labor, capital, fuel, seeds, fertilizers, and chemicals. Farmers' planting decisions are based on the expected post-harvest crop price and expected costs. Weather conditions, especially precipitation and temperature, during the growing season determine plant growth and eventually yields. Pre-planting weather conditions may also affect planting decisions.

As farmers plant more corn acres, they use more nitrogen fertilizer, generally following agronomic recommendations. The shape of the crop production function implies that fertilizer application in excess of agronomic recommendations does not reduce yields, which provides an insurance motivation to use extra fertilizer, as we discussed earlier. A combination of factors in and out of the farmers' control, including weather, determine the crop nitrogen uptake, and, hence, the amount of surplus (excess) nitrogen that will not be used by the plants and will remain in the soil. This surplus nitrogen will eventually find its way to lakes, rivers, and streams, contributing to nutrient pollution. The amount of surplus nitrogen that enters waterways is determined in part by the weather. Wetter conditions affect acreage, nutrient runoff, and streamflow, all of which can contribute to nutrient pollution. All else equal, more rainfall means more nutrients carried

[6] Paudel and Crago (2020) use the nitrogen fertilizer sales data to estimate the effect of fertilizer on nitrogen pollution. They obtain an elasticity of nitrogen pollution with respect to nitrogen fertilizer of about 0.15 for the U.S. We find an elasticity of nitrogen pollution with respect to corn acres of a very similar magnitude. Adding the assumption of no substitution between nitrogen fertilizer and other inputs to the assumption of a fixed amount of nitrogen fertilizer per corn acre allows us to link the price elasticity of the demand for fertilizer (η_{fert}) to the price elasticity demand for corn (η_{corn}) via $\eta_{fert} = (p_{fert}/p_{corn}) \times \eta_{corn}$. In terms of notation, p_{fert} and p_{corn} are the prices of nitrogen fertilizer and corn, respectively. As we discuss later in the paper, fertilizer costs account for about 20% of the value of corn production during the period we study, which coupled with a reasonable value of η_{corn} of about -0.3, also supported empirically in subsequent section, imply $\eta_{fert} = -0.3 \times 0.2 = -0.06$. Hence, the demand for nitrogen fertilizer is highly inelastic.

[7] Based on the USDA ERS Fertilizer Use and Price data for 2018 (U.S. average).

through the soil and along the surface into waterways. Thus, we expect increases in corn acreage to increase nitrogen concentration, especially in wet years. Similarly, extreme heat, which has a well-documented negative impact on crop growth (e.g., Jägermeyr et al. (2021), among others) may limit nutrient uptake and contribute to runoff. On the one hand, it is plausible that farmers may compensate for the loss in yields by fertilizing more. On the other hand, as discussed in the chapter by Elbakidze et al. (2022), lower yields may reduce the profitability of crop production and may result in decreased crop acreage, which could reduce nitrogen runoff.

In general, more rainfall due to a warmer and wetter atmosphere is increasing nitrogen pollution exacerbating algae growth and expanding dead zones in coastal areas.[8] Evidence suggests that several projected outcomes of global climate change will act to increase the prevalence and negative impacts of dead zones.[9] Warmer waters hold less oxygen than cooler water, thus making it easier for dead zones to form. Warmer waters also increase metabolism of marine creatures, thereby increasing their need for oxygen. Additionally, warmer temperatures and increased runoff of freshwater will increase stratification of the water column, thus further promoting the formation of dead zones. Increased runoff will also increase nutrient inputs into coastal water bodies. On the other hand, projections of more intense tropical storms and lower runoff would act to decrease stratification and thus make dead zones less likely to form or less pronounced if they do form.[10]

Diaz and Rosenberg (2008) assembled a database of over 400 dead zones worldwide showing that their number is increasing exponentially over time. To characterize the severity of climate change that these ecosystems are likely to experience over the coming century, Diaz and Rosenberg also explored the future annual temperature anomalies predicted to occur for each of these systems. The majority of dead zones are in regions predicted to experience over 2°C warming by the end of this century. Sinha et al. (2017) show that precipitation changes due to climate changes alone will increase by 19% the riverine total nitrogen loading within the CONUS by the end of the century for their business-as-usual scenario. The impacts are particularly large in the Northeast (28%), the upper MRB (24%), and the Great Lakes Basin (21%). According to the authors, precipitation changes alone will lead to a 18% increase in nitrogen loads in the MRB, which would require a 30% reduction in nitrogen inputs. The target of a 20% load reduction set by the GoM Hypoxia Task Force in 2015, would require a 62% reduction in nitrogen inputs taking into account the

[8] In the U.S. Gulf coast, the frequency and severity of hurricanes, which have been linked to climate change, can also play an important role in the areal extent the hypoxic zone formed every summer.

[9] Our discussion borrows heavily from the discussion on "Dead Zones and Climate Change" available in the VIMS website here.

[10] According to Diaz and Rosenberg (2008), tropical storms and hurricanes influence the duration, distribution, and size of the GoM dead zone in a complex way. In 2005, four hurricanes (Cindy, Dennis, Katrina, and Rita) disrupted stratification and aerated bottom waters. After the first two storms, stratification was reestablished and hypoxia reoccurred, but the total area was a fourth less than predicted from spring nitrogen flux. The other two hurricanes occurred later in the season and dissipated hypoxia for the year.

confounding effect of precipitation.[11]

4 Empirical Approach

We estimate panel fixed-effect (FE) OLS regressions of the form:

$$y_{it} = \delta_i + \beta_1 a_{it} + \beta_2 a_{it} p_{it} + \mathbf{z}'_{it}\gamma + g_i(t) + \varepsilon_{it}, \tag{1}$$

where i denotes the cross-sectional unit (county) and t denotes the time (year) in what we call the (c)ounty-centric (henceforth, *c-centric*) analysis. The dependent variable y_{it} is nitrogen concentration in milligrams per liter (mg/L), a_{it} denotes corn acres planted, p_{it} denotes precipitation, and $\mathbf{z}_{it}$ is a vector of weather-related control variables. The weather-related controls include precipitation, squared precipitation, moderate-heat, and extreme-heat degree days. We use $g_i(t)$ to denote alternative functions of time (e.g., time trend, year FE, etc.). Finally, ε_{it} is the error term.

For our c-centric analysis, y_{it} is the average nitrogen concentration recorded at USGS monitoring sites within a 50 mile-radius from the county centroids, and a_{it} are corn acres planted in county i at time t. As part of a series of robustness checks to our results, we estimate (1) using average nitrogen concentration recorded at sites within larger (100- and 200-mile) radii, as well as accounting for streamflow using only sites downstream of the county centroids).

Our specifications aim to capture the most salient factors that are both in the control and out of the control of U.S. farmers and that influence the nitrogen concentration of waters draining cropland some of which we have already discussed. Aside from weather, factors outside farmers' control include hydrologic conditions, terrain properties of the cropland (e.g., slope and elevation), and soil properties (e.g., depth, texture, mineralogy, capacity to support crop growth, and susceptibility to erosion). Factors in farmers' control include agricultural management practices used to boost profits, such as cropping systems, rate of and timing of nitrogen application, use and type of drainage and tillage systems, deployment of programs aiming to combat nutrient pollution by the U.S. Environmental Protection Agency (EPA) and conservation programs administered by the USDA, among others.

Precipitation and temperature generally affect the farmers' decision making during the spring

[11] In February 2015, the states and federal agencies that comprise the Mississippi River/GoM Watershed Nutrient Task Force (Hypoxia Task Force or HTF) announced that the HTF would retain its goal of reducing the areal extent of the GoM hypoxic zone to less than 5,000 km^2, but that it will take until 2035 to do so. The HTF agreed on an interim target of a 20% nutrient load reduction in the Gulf of Mexico by the year 2025 as a milestone toward achieving the final goal in 2035.

planting season (e.g., when and what to plant, and how much to fertilize). Miao et al. (2015) include monthly precipitation in March to May to control for the effect of pre-planting weather conditions on corn acreage in the U.S. They argue that a wet spring can make it difficult for corn to be planted on time, and, hence, corn acreage may be switched to soybean acreage. During the growing season, which is somewhere between March and September for most of the U.S., both temperature and precipitation have an effect on crop growth and, hence, on the plants' nutrient uptake. In the absence of robust crop growth rates, nutrients that are not absorbed by the plants can be carried over to streams, rivers, and lakes, depending on soil characteristics and precipitation.

Nitrogen concentrations in a basin like the MRB, which drains most of the cropland where corn is grown and is characterized by an abundant supply of nitrogen in the soil, tend to peak in the late winter and spring when streamflow is highest, and lowest in the late summer and fall when streamflow is low. This strong positive relationship between concentration and streamflow has been well documented in the Midwest; see Goolsby et al. (1999) and the references cited. Importantly, the same strong positive relationship implies that nitrogen pollution is predominantly due to non-point sources. Nitrogen concentrations generally decrease in the summer and fall as streamflow and agricultural drainage decrease. Assimilation of nitrate by agricultural crops on the land and aquatic plants in streams also helps decrease nitrogen concentrations in streams during the summer. Moreover, in-stream denitrification rates also increase during the summer due to increased temperatures and longer residence times of water in the streams. Hence, temperature and precipitation are correlated with both acres planted and nitrogen concentration.

The fixed effects δ_i aim to capture time invariant spatial attributes such as soil properties and texture, and water infiltration rates that affect both the farmers' planting decisions and levels of nitrogen in the water due to, say, transport and attenuation. For example, soil texture—the proportions of sand, clay, and silt— influences the ease with which the soil can be worked, the amount of water and air the soil holds, and the rate at which the water can enter and move through the soil. Fine-grained (clayey) solid can hold more water than coarse-grained (sandy) soils.

Finally, $g_i(t)$ allows us to model in a flexible way trends in fertilization rates, and land management practices, such as tillage, and subsurface tile drainage, for which data with good spatial and time coverage are not available. They also allow us to account for farmers' participation in conservation programs administered by the USDA and other unobservables that may exhibit spatially differentiated trends and affect both the corn acreage and nitrogen concentration.

In the robustness checks discussed later in the chapter, we consider a long list of additional controls to capture factors that may be correlated with both corn acres planted and nitrogen concentration as discussed above to alleviate concerns for potentially biased estimates. We also explore alternative ways to measure nitrogen concentration including distance, streamflow, and time of the year, as well as spatial and temporal variation in the effects of corn acreage on nitrogen concentration.

5 Data

5.1 Data Sources

Water quality. The data on nitrogen concentration are from the Water Quality Portal (WQP). The WQP is a cooperative service sponsored by the USGS, the EPA, and the National Water Quality Monitoring Council. It serves data collected by over 400 state, federal, tribal, and local agencies with more than more than 297 million water quality records.

We accessed WQP data on sites and sample results (physical/chemical metadata) associated with the parameter code 00600, which is described as "total nitrogen [nitrate + nitrite + ammonia + organic-N], water, unfiltered, milligrams per liter" without imposing any other of the additional filters available in the portal in December 2019. At the time we accessed the WQP data, there were close to 754,000 observations in the sample results data and 41,800 observations in the site data.[12]

The site data contain information regarding the site's location such as longitude and latitude, county, and the 8-digit hydrologic unit (HUC8). The site data also contain information on the agency operating the site (e.g., "USGS-IL") and the site type (e.g., "stream," "facility," "lake," "well," etc.) The sample results data contain a long list of variables related to water quality measures, such as the date, time, and method, of the water sample collection. Linking the site to the sample results data is straightforward using the site location identifier field, which is present in both datasets.

We measure nitrogen pollution using concentration in milligrams per liter (mg/L). We limit the data to those for sites in the CONUS and for which we track "surface water" and "ground water" concentration in the sample results data. For the interested reader, some additional information regarding the WQP data used in the paper is available in Sections A.2–A.4.

Crops. Annual county-level data on corn acres planted are available from the National Agricultural Statistics Service (NASS) of the USDA.[13] Following Schlenker and Roberts (2009) and Annan and Schlenker (2015), among others, in a long stream of literature in agricultural economics, and to focus on rain-fed agriculture, we limit our sample to counties east of the 100th meridian and

[12]The WQP data can be accessed in this link using web service calls. A parameter code is a 5-digit number used in the National Water Information System (NWIS) to uniquely identify a water quality characteristic.

[13]Table A1 shows corn production by state for 1970–2017.

exclude Florida. This is the part of the country that accounts for more than 95% of the corn produced during the time relevant for our analysis; as part of our robustness checks, we expand the geographic scope of our analysis to the CONUS.

Weather. We use updated temperature and precipitation data from Schlenker and Roberts (2009), which are available for each county during the growing season for 1970–2017 and are based on PRISM gridded weather data. The data from Schlenker and Roberts have been used extensively in the literature on the effects of climate change on U.S. agriculture and are discussed in great detail elsewhere (Roberts et al. 2012). Following this stream of the literature, we use precipitation, the square of precipitation, cumulative degree days (DDs) between 10°C and 29°C (moderate heat), and cumulative degree days above 29°C (extreme heat). In what follows, the precipitation is measured in meters, the moderate heat is measured in 1,000 DDs, and the extreme heat is measured in 100 DDs.

Hydrologic Units. We use the USDA Natural Resources Conservation Service (NRCS) watershed boundary dataset (WBD) to identify hydrologic units of different size.[14] We use 2-digit hydrologic unit codes (HUC2s) to explore spatial variation in our estimated acreage effects in the panel FE regressions and to construct spatial FEs in robustness checks that pertain to cross-section regressions. We use 4-digit hydrologic unit codes (HUC4s) to cluster the standard errors in our regressions. We use HUC8s in an analysis based on an alternative data aggregation scheme, as part of our robustness checks.

National hydrography dataset plus V21. As in Keiser and Shapiro (2018), we use the NHD Plus flowline network to follow water pollution upstream and downstream. In particular, we use the National Seamless Geodatabase built on NHD Plus to identify monitoring sites downstream of counties of interest.

5.2 Data Overview and Descriptive Statistics

For our baseline estimates, we use data for counties east of the 100th meridian (EAST-100) excluding Florida for 1970–2017. We use the latitude and longitude of the county centroids to identify the

[14]The GBD files for hydrologic units of different size are available in the following link. The U.S. is divided into successively smaller hydrologic units which are classified into four levels: regions, subregions, accounting units, and cataloging units. The hydrologic units are arranged or nested within each other from the largest geographic areas (regions) to the smallest geographic areas (cataloging units). Each hydrologic unit is identified by a unique hydrologic unit code (HUC) consisting of 2–8 digits based on the four levels of classification in the hydrologic unit system. It is common to refer to hydrologic units as watersheds and what we describe here as hydrologic accounting is also described as watershed delineation. The word watershed is sometimes used interchangeably with drainage basin or catchment.

relevant EAST-100 counties which we obtain from the CENSUS TIGER shape files. As we discussed earlier, we calculate nitrogen concentration using USGS monitoring sites within a 50-mile radius from the county centroids.

Table 2 shows basic summary statistics for nitrogen concentration, our measure of pollution, and corn acres planted. These are the dependent and main explanatory variable of interest in our regression models. The table also shows summary statistics for precipitation (total annual and total by month), as well as for moderate and extreme heat by month. Precipitation plays an important role in our assessment of the effects of agriculture on nutrient pollution based on our earlier discussion regarding the tight connection between nitrogen pollution and rainfall.

We have about 64,000 observations and 2,200 counties. On average, we track a county for 29 years during the 48-year period 1970–2017. The mean nitrogen concentration is about 2.5 mg/L and both the between-counties and within-county standard deviation are around 1.65 mg/L. Hence, pollution exhibits similar variation across counties and within a county over time. On average, 38,000 acres of corn are planted per year in a county. Contrary to nitrogen pollution, the variation in acres is much larger across counties (48,000 acres) than within a county over time (11,000 acres). As a benchmark for the acres planted, the mean (median) county land area is 603 (556) square miles or 386,187 (355,969) acres. The total annual precipitation is, on average, close to 1.1 meters and varies more across counties than within a county over time. On average, February and May are the months with the smallest (0.067 meters) and largest (0.111 meters) total precipitation, respectively. July is the month with the largest number of moderate-heat (430) and extreme-heat (21.6) DDs. While monthly precipitation varies more within a county over time than across counties with the exception of January, extreme and moderate heat DDs vary more across counties than within a county over time for most months.

5.3 Nitrogen Concentration Across Space and Over Time

The choropleth maps in Figure 1 offer visualizations of the spatial variation for the variables used in our analyses and provide some descriptive evidence on the spatial correlation between nitrogen concentration and corn acreage. In general, we see higher concentration in watersheds in southern Minnesota, Iowa, Illinois, Indiana, and Ohio that drain large areas of agricultural land. We explore this spatial correlation in more depth using cross-section regressions.

In panel A of Figure 2, based on monitoring-site level data on average daily nitrogen concentrations (mg/L), we show trends in nitrogen concentration. We also show flow-normalized annual nitrogen concentration in the GoM using data from the USGS National Water Quality Network in panel B.

Panels C and D provide information related to fertilizer use and acreage, which are important in understanding the relationship between agriculture and nitrogen concentration.

The use of nitrogen fertilizer increased from about 2.5 million metric tons (mmts) in 1964 to 11.8 mmts in 2015; it reached its peak of about 12 mmts in 2013. Most of the almost 5-fold increase took place before the early 1980s (panel C). By 1981, nitrogen use had steadily increased to 10.8 mmts.[15] The expansion of nitrogen use during this time was due to expanded acreage (panel D), increase in application rates, and a higher share of acres receiving fertilizer (from 85% to 97%); the percent of U.S. corn acreage receiving nitrogen fertilizer has been 95%, on average, in the last 50 years or so. Since then fertilizer use has fluctuated over time following changes in cropping system implementation and fertilizer crop prices, but has shown no persistent trend (Hellerstein et al. (2019)). The application rates in the major corn producing states follow similar trends with a notable increase between the mid-1960s and early 1980s. The fertilizer costs have oscillated between 14% and 27% of the corn gross value of production averaging close to 20%.

Overall, there is an increase in nitrogen concentration between the early 1970s and early 1980s from about 2 mg/L to a peak of about 3 mg/L. This pattern is consistent with the increase in corn acreage and nitrogen fertilizer use. Following a downward trend between the mid 1980s and the mid 1990s, nitrogen concentration has plateaued at about 2.3 mg/L in the last 20 years or so. These are roughly the concentration levels in the early 1970s. The flow-normalized annual nitrogen concentration in the GoM exhibits a very similar behavior over time.[16]

6 Econometric Estimates

Preamble. Table 3 shows detailed results of the panel FE regressions for our (c)ounty-centric analysis. In panel A, we report results from regressing nitrogen pollution on corn acres planted without controlling for weather. In panel B, we control for weather. In particular, we use 12 control variables (one for each month) for precipitation, squared precipitation, moderate-heat DDs, and extreme-heat DDs, for a total of 48 variables. In panel C, we add the interaction of acres with total annual (January–December) precipitation to the set of explanatory variables. The standard errors are clustered at the HUC4 level (124 clusters) accommodating arbitrary correlation of the

[15] See Table 9 (percent of corn acreage receiving nitrogen fertilizer) in this link.

[16] Sprague et al. (2011) estimate changes in nitrate concentration and flux during 1980–2008 at 8 sites in the MRB using the WRTDS model, which produces flow-normalized (FN) estimates of nitrate concentration and flux. Their results show that little consistent progress had been made in reducing riverine nitrate since 1980, and that FN concentration and flux had increased in some areas. Murphy et al. (2013), who extended the analysis in Sprague et al., show that trends in FN nitrate concentration and flux were increasing or near-level at all sites for 1980–2018. They note, however, that trends at some sites began to exhibit decreases or greater increases during 2000–2008.

unobservables across time and space.[17] To explore the implications of climate change for our estimated effects, we also interact corn acreage with moderate- and extreme-heat DDs in a subsequent section.

Baseline estimates. For the models without weather-related controls, the adjusted R-squared ($\overline{R}^2$) is 0.26–0.53 depending on the specification with most of the fit improvement attributed to the county FEs. Apart from the specifications with county-specific linear trends in columns A7 and A8, the acres coefficient is statistically significant at 5% level with values between 3.862 (column A5) and 23.581 (column A1). According to these estimates, the implied elasticities are 0.060–0.364 and they are significant at 5% level. For the specifications with county-specific linear trends, the elasticities are not significant at conventional levels.[18]

In the presence of weather-related controls, there is a notable change in the acres coefficient from 23.581 (column A1) to 18.458 (column B1) for the specification without county FEs. The model fit improvements, however, are relatively minor. As it was the case for the models without weather-related controls, the acres coefficients fail to be statistically significant at conventional levels for the specifications with county-specific trends (columns B7 and B8). Apart from the specification without county FEs (column B1), the elasticity of nitrogen concentration with respect to corn acreage is between 0.061 (column B5) and 0.093 (column B6).

The interaction of acres with precipitation implies effects that are significant at 5% level even in the presence of county-specific trends. Indeed, all but two of the 24 elasticities are significant at 5% level. Once again, apart from the specification without county FEs that implies elasticities of 0.278 (first precipitation quartile) to 0.395 (third quartile), we see elasticities of up to 0.086, 0.130, and 0.178, depending on the precipitation quartile, all of which are significant at 1% level. For the richest specification (column C8) that includes county FEs, county-specific trends, and year FEs, the elasticities are significant at 1% level and equal to 0.076 and 0.118 for the second and third precipitation quartiles, respectively; their counterpart for the first quartile is not significant at conventional levels.

Figure 3 shows point estimates along with 95% CIs for the 48 weather-related controls. Among the 48 coefficients, only the ones associated with January precipitation and its square are statistically

[17] In Section A.5, we discuss results from cross-section regressions. In Section A.6, we discuss results from *(h)ydrologic unit-centric* and *(m)onitoring site-centric* analyses. For the h-centric analysis, i denotes an 8-digit hydrologic unit (HUC8), y_{it} is the average nitrogen concentration using sites located in the same HUC8, and a_{it} are acres planted planted in counties that lie in the same HUC8 weighted by their area. For the m-centric analysis, y_{it} is the concentration for monitor i and a_{it} are the acres planted in counties within a 50-mile radius from the site. Regarding the weather-related variables, in the case of the m-centric analysis, p_{it} and $\mathbf{z}_{it}$ are averages across counties within the assumed radius of site i. For the h-centric analysis, we use averages of the same variables weighted by the area of the counties that lie within the HUC8 polygons.

[18] Throughout the paper, we we refer to statistical significance at $\leq 10\%$ as significance at conventional levels.

significant. Based on multiple-hypotheses testing performed separately for each of the three sets of weather-related controls, the 24 precipitation controls, as well as the 12 extreme-heat controls, are jointly significant at 5%. The 12 moderate-heat controls are not jointly significant at conventional levels.[19]

Statistical significance. In all, we see positive and statistically significant effects of corn acreage on nitrogen pollution. The specifications that control for weather and contain an interaction of corn acreage with precipitation generally imply larger effects than their counterparts that do not contain such interactions. Spatial FEs matter more than time-related controls for the magnitude of the effects. According to our preferred specification (column C8), the elasticity of nitrogen concentration with respect to corn acreage is 0.076 for the second precipitation quartile and increases to 0.118 for the third quartile. In both instances, the elasticity is significant at 1% level.

Economic significance. The statistically significant effects reported above are also economically meaningful according to a back-of-the-envelope calculation that utilizes the (median) potential damage costs of nitrogen due to declines in fisheries and estuarine/marine life of \$15.84 per kg (\$2008) from Table 1 in Sobota et al. (2015). At the third precipitation quartile, a 1 within-county standard deviation increase in corn acres planted implies a 3.3% increase in the level of nitrogen concentration. At the average nitrogen concentration of about 2.5 mg/L and the average streamflow of the Mississippi River in the GoM in our sample ($\approx$ 21,500 cubic meters per second), this effect entails close to 50,800 additional metric tons of nitrogen in the GoM. Hence, our estimated increase in nitrogen concentration of 3% implies an external cost of \$805.5 million per year in \$2008, or approximately $\$805.5 \times 1.14 = \$918.3$ in \$2017 (the last year in our sample) using the GDP deflator (FRED GDPDEF series).[20]

Reconciling our baseline estimates. Table 4 in Hendricks et al. (2014) gives the average nitrogen loss from the edge-of-field (EoF) as predicted by the SWAT model—coupled with an econometric model—for different land uses in Iowa, Illinois, and Indiana for 2000–2010. Nitrogen losses are the sum of nitrate and organic nitrogen loss. Corn after corn generates the largest nitrogen losses (34.7 lb per acre per year (lb/a/y), on average) because more fertilizer is applied to corn after corn since there is no nitrogen carry-over from a previous soybean crop. The mean loss of 34.7 lb/a/y reported by the authors is similar to the average estimate of total nitrogen loss of 34 lb/a/y in the USDA CEAP national nitrogen loss report (NRCS (2017b)) we discussed earlier.

[19] We discuss additional estimates for the panel FE regressions summarized in Table 4–Table 6 and Figure 4 in Section A.6. A detailed discussion of the motivation behind our additional estimates and any related data sources for the panel FE regressions is available in Section A.6.1 and Section A.6.2. A similar discussion for the cross-section regressions is available in Section A.6.3.

[20] We use the average flow for years 1970–2016 from column F (Total Mississippi-Atchafalaya River) available in the following link.

Assuming the mean annual EoF loss of about 35 lb/a/y from Hendricks et al. and 79,384,857 corn acres per year (average of national corn acres planted during the same period according to USDA data), we have 1,260,294 metric tons of total nitrogen per year. This calculation assumes that the EoF losses translate to an equivalent nitrogen loading in the GoM— admittedly a strong assumption, because some nitrogen that leaves the field does not reach the GoM. Note that the average annual total nitrogen flux of the Mississippi and the Atchafalaya rivers to the GoM between is 1,460,419 metric tons for 1968–2016.[21]

In our case, the average nitrogen concentration is 2.5 mg/L. According to the USGS, the mean annual flow of the Mississippi plus Atchafalaya to the GoM (Ibid) is about 21,376 cubic meters per second for 1968–2016. This mean annual flow implies 1,685,245 metric tons of total nitrogen per year, which translates to 46.8 lb/a/y using the average annual corn acreage for 1968–2016. However, a comparison of 46.8 lb/a/y with 35 lb/a/y from Hendricks et al. hinges on the assumption that all nitrogen pollution recorded at the USGS monitoring sites is due to fertilizer loss from corn fields but it is not. A better, albeit imperfect comparison, is to assume that 70% of the 1,685,245 metric tons are attributed to agriculture (David et al. (2010)) in which case we have 32.8 lb/a/y (see Wu and Tanaka (2005) for a similar approach). This loss of 32.8 lb/a/y calculated using our estimates is similar to the average loss of 34.7 lb/a/y in Hendricks et al.

According to our baseline panel FE estimates in column C8 of Table 3, a 28% increase in corn acres planted—assuming an increase equal 1 within-county standard deviation (11,000 acres) and using the mean acreage (38,000 acres) from Table 2 to calculate the percent increase—implies a a 3.3% increase in nitrogen concentration when evaluated at the mean concentration of 2.5 mg/L. A 3.3% increase in mean concentration of 2.5 mg/L implies an increase in flux equal to 55,613 metric tons. Assuming that this 3.3% increase in concentration is associated with a 28% increase in 79,384,857 corn acres, the implied increase is 5.52 lb/a/y.

The effect of additional corn acres on measured nitrogen in waterways is an order of magnitude smaller than agronomic estimates of excess nitrogen applied to those acres assuming EoF losses translate to an equivalent nitrogen loading to streams and rivers. However, we do not interpret our results as evidence that the amount of surplus nitrogen used on crops is much smaller than previously believed. Instead, our findings are consistent with a new research in environmental science arguing that there is a large amount of nitrogen stored in subsurface soil and groundwater (e.g., Van Meter et al. (2017), Van Meter et al. (2018), Ilampooranan et al. (2019)) and contributes to the so-called legacy nitrogen, which may increase loadings in rivers and streams with a long delay.[22] The presence of large quantities of legacy nitrogen has substantive policy implications

[21] See the USGS link here.

[22] Van Meter et al. (2016) study soil data from cropland in the Mississippi River Basin and find nitrogen accumula-

because it increases the relative efficacy of downstream policies such as fluvial wetlands (i.e., those connected to waterways) and it is a topic we explore in more detail in Metaxoglou and Smith (2022).

Using the elasticity estimate of 0.076 from column C8 of Table 3, an additional corn acre generates an average of 3.5 lb/a/y of nitrogen in small (level 4) streams within a 50-mile radius from the country centroids for median precipitation and average streamflow of 362 cubic feet per second (cfs).[23] This estimate is close to 10% of the USDA CEAP estimate of 34 lb/a/y of EoF losses. If we instead use 5.52 lb/a/y, per our discussion in the previous paragraph, and a streamflow of 1,997 cfs, which is the average across all streams, an additional corn acre generates an average of 30 lb/a/y in streams and rivers, which is almost 80% of the NRCS estimate of surplus nitrogen.

Additional estimates. Panel A of Figure 4 shows that a more flexible specification for the interaction of corn acreage with precipitation does not have a material effect on our estimated corn acreage elasticities. Similar flexible specifications based on total precipitation for different time windows during the year (March–August and April-September) produced very similar elasticities to the ones shown here. In panels B and C of Figure 4, we explore the role of crop nutrient uptake. Holding extreme-heat DDs and precipitation constant, additional moderate-heat DDs imply lower elasticities. Holding moderate-heat DDs and precipitation constant, an increase in extreme-heat DDs has no material impact on the magnitude of the acreage elasticities despite the well-documented negative effect of extreme heat on yields. Holding moderate- and extreme-heat DDs constant, an increase in precipitation implies larger elasticities. In all, the elasticity estimates when we interact corn acreage with moderate- and extreme-heat DDs in addition to precipitation, are very similar to their baseline counterparts obtained by interacting the corn acreage with precipitation alone. The pattern in the magnitude of the elasticities just described also holds for panel FE regressions estimated using counties in the MRB, and counties in the most northern (coldest) states east of the 100th meridian from Schlenker and Roberts (2009). The elasticity estimates for the most southern (warmest) states from Schlenker and Roberts are generally noisy and indistinguishable from zero at conventional levels. Their counterparts for the middle states exhibit very little variation across the quartiles of precipitation and heat we considered. Yield shocks, calculated as deviations from county-specific yield trends, do not matter for the magnitude of the acreage elasticities either.

The implied corn acreage elasticities for a number of models we estimated performing a series of robustness checks discussed in detail in Section A.6 are summarized by precipitation quartile using the kernel density plots in panel D of Figure 4. Similar to the baseline results, the coefficient of the

tion of 25–70 kg per hectare per year (22–62 lb per acre per year).

[23] This is the average streamflow based on the Enhanced Unit Runoff Method (EROM) Flow Estimation in the USGS NHD Plus data for years 1971–2000 and is readily available by river segment (COMID).

interaction of corn acreage and precipitation (coefficient β_2 in equation (1)) is positive and highly significant in the vast majority of the models we explored. Hence, the amount of precipitation matters for the magnitude of the estimated acreage elasticities. With very few exceptions, the corn acreage elasticities based on the second and third precipitation quartiles are highly significant. Their counterparts based on the first precipitation quartile are not. For the second precipitation quartile, the elasticities that are significant at conventional levels are 0.043–0.331. Their counterparts for the third precipitation quartile are 0.059–0.438. As a reminder, for our preferred baseline specification in column C8 of Table 3, the acreage elasticities are 0.076 and 0.118 for the second and third precipitation quartiles.

7 Climate Change and Nitrogen Pollution

According to our econometric analysis, corn acreage drives nitrogen concentration and the magnitude of the acreage effect depends on precipitation with more precipitation implying larger effects for our baseline estimates that pertain to the part of the country east of the 100th meridian. An additional specification in which we also interact corn acreage with moderate and extreme-heat DDs, shows that, all else equal, an increase in moderate-heat DDs implies smaller effects, while an increase in extreme-heat DDs has no material impact on the magnitude of the effects.

We now explore the implications of climate change for our findings regarding the relationship between corn acreage and nitrogen concentration. In particular, we use the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) dataset to obtain projections for precipitation, moderate-, and extreme-heat DDs, and, in turn, projections of the marginal effects (MEs) of corn acreage on nitrogen concentration. The NEX-GDDP-CMIP6 dataset is comprised of global downscaled climate scenarios derived from the General Circulation Model runs conducted under the Coupled Model Intercomparison Project Phase 6 (Eyring et al. (2016)) and across two of the four "Tier 1" greenhouse gas emissions scenarios known as shared socioeconomic pathways (SSPs), namely, SSP2-4.5 and SSP5-8.5.[24]

We use out-of-sample projections from 3 climate models (CanESM5, UKESM1-0-LL, and GFDL-ESM4) and SSP2-4.5 and SSP5-8.5 for 3 weather-related variables available at a latitude/longitude resolution of 0.25°, namely, the mean of the daily precipitation rate (pr), the daily minimum near surface air temperature (tasmin), and the daily maximum near surface air temperature (tasmax). Projections of these variables from the climate models based on alternative SSPs allow us to obtain projections of total annual precipitation, moderate-heat, and extreme-heat DDs, which in their turn

[24]The data are available here. Additional information including variable descriptions is available here.

translate to projections of corn acreage ME on nitrogen concentration. These MEs do not take into account the impacts of climate change on other factors affecting nitrogen concentration and loads (e.g., streamflow, change in farmers' behavior as in Elbakidze et al. (2022), etc.).

Although projections for the three weather-related variables are available until 2100, we obtain ME projections for 2018–2050, as we are skeptical about the use of a model that has been estimated using data for 1970–2017 to project MEs more than 20–30 years out of sample. We opt for projections of MEs as opposed to elasticities because the former do not require an assumption about future values of nitrogen concentration and corn acreage while the later do. To the best of our knowledge, projections of both acreage and nitrogen concentration with the spatial and temporal coverage required to obtain projections of elasticities are not available. The MEs discussed are estimated assuming an increase in corn acreage equal to the historical (in-sample) within-county standard deviation and estimating different regressions for five sets of counties. The specification of these regression equations is identical to specification C8 of Table 3. The sets of counties for which we obtained projections of MEs are as follows: counties east of the 100th meridian excluding Florida (baseline), counties in the MRB, as well all counties in the northern, middle, and southern states east of the 100th meridian as in Schlenker and Roberts (2009).

The precipitation projections are generally smaller than their historical counterparts across all climate models, SSPs, and quartiles of the precipitation distribution. A notable exception is the median precipitation for the middle counties for which the projections exceed their historical counterpart for all climate models and SSPs. The projected quartiles for moderate-heat DDs are larger than their historical counterparts for all climate models and SSPs for all sets of counties and all three quartiles of precipitation considered. The projected quartiles for extreme-heat DDs, on the other hand, are generally smaller than their historical counterparts, especially for the lower quartiles of the extreme-heat distribution. It is also the case that the differences between projected and historical quartiles are generally larger for the moderate- and extreme-heat DDs than for precipitation.

For the discussion that follows, it important to keep in mind that for the panel FE regressions in which we interact acreage only with precipitation, the coefficient on the interaction is significant at conventional levels for the MRB and northern counties, in addition to the baseline counties. For the regressions in which we interact corn acreage with precipitation and DDs, in addition to the baseline counties, the coefficient on the interaction of corn acreage with precipitation is significant at conventional levels in the MRB and northern counties. The coefficients on the interaction of the corn acreage with moderate-heat DDs, as well those on the interaction of the corn acreage with extreme-heat DDs are indistinguishable from zero at conventional levels.

For the baseline counties—depending on the climate model and SSP—the projected median precipitation is 1.047–1.078 meters (panel A, Table 7). Its third-quartile counterpart is 1.242–1.289 meters. The implied MEs based on the projected median precipitation are 0.048–0.053 mg/L, which are similar in magnitude to the ME of 0.051 mg/L based on the historical median precipitation. For the MRB counties, an area of particular interest for policies aiming to address the GoM HZ areal extent, the median precipitation projections are 0.945–0.980 meters implying MEs of 0.045–0.051 mg/L, the lower end of which is slightly smaller than their historical counterpart of 0.056 mg/L but similar to their baseline counterparts. For the northern counties, the median precipitation projections are 0.875–0.937 meters implying MEs of 0.017–0.031 mg/L, respectively. Their historical ME counterpart is 0.032 mg/L. For the middle counties, the median precipitation projections are 1.057–1.079 meters implying MEs of 0.133–0.134 mg/L, which are essentially identical to their historical counterpart, noting that the coefficient of the interaction of corn acreage with precipitation is statistically indistinguishable from zero. Finally, for the southern counties, the median precipitation projections are 1.233–1.298 meters implying MEs of -0.025 to -0.023 mg/L, which are also essentially identical to their historical counterpart. Similar to the middle counties, the coefficient of the interaction of corn acreage with precipitation is statistically indistinguishable from zero for the southern counties.

Figure 5 shows the spatial variation of the MEs when we interact corn acres with precipitation projections for the two SSPs of the GFDL-ESM4 climate model. For comparison, we also show MEs based on historical precipitation. For each county, we calculate MEs using the average precipitation for either 1970–2017 (historical) or 2018–2050 (projected) and the appropriate coefficients of the estimated panel FE regression. For the baseline counties, we see some of the largest MEs in counties in the South (e.g., Louisiana, Mississippi, Alabama, Arkansas) and some of the smallest effects in the Plains (e.g., northern Texas, Oklahoma) and in the upper Midwest (e.g., Michigan, Wisconsin). We see a very similar spatial pattern in the MEs for the MRB counties. The lack of variation across the middle and southern counties is because of the coefficients on the interaction of corn acreage with precipitation being indistinguishable from zero. For the northern counties, we see negative MEs in North and South Dakota, and some of the larger positive MEs in Pennsylvania and New Jersey. The negative MEs are due to a combination of a large negative coefficient on corn acreage and very low precipitation.

Figure 6 shows the spatial variation of MEs when we interact corn acres with precipitation, moderate-heat DDs, and extreme-heat DDs for the two SSPs of the GFDL-ESM4 climate model. For each county, we calculate MEs using the average precipitation, extreme-heat, and moderate heat DDs for either 1970–2017 (historical) or 2018–2050 (projected) and different panel FE regressions for each of the 5 sets of counties. Across the baseline set of counties, the median ME based on the historical data is 0.049. Its projections-based counterparts are 0.030 for SSP 245 and 0.027 SSP 585. All three median MEs are smaller than their counterparts based on the panel FE regression in which we interact corn acreage with precipitation only. This is especially true for the projected MEs. In terms of the spatial pattern of the MEs, we see some of the largest effects in Tennessee, and in the northern parts of Alabama and Mississippi. Some of the smallest MEs are those for counties along the 100th meridian, as well as in Georgia and South Carolina. Across the MRB counties, we also see smaller median MEs when we interact corn acres with precipitation and the DDs and more so when we use the 2018–2050 projections. The same is true for the middle and northern counties. For the southern counties, the median historical and projected MEs are negative and larger in magnitude than their counterparts based on the interaction of corn acreage with precipitation alone.

8 Conclusion and Policy Implications in an Era of Climate Change

We study the relationship between water nutrient pollution and U.S. agriculture using data from 1970–2017 documenting a causal positive effect of corn acreage on nitrogen concentration in the country's water bodies east of the 100th meridian using alternative empirical approaches. According to our baseline estimates, a 10% increase in corn acreage increases nitrogen concentration in water by up to 1%. Annual precipitation plays an important role in the magnitude of the estimated effects with higher precipitation exacerbating the acreage effect on nitrogen concentration. Temperature also matters for the magnitude of the acreage effect. An increase in moderate-heat degree leads to smaller effects due to its beneficial effect on the crop nutrient uptake. Extreme-heat degree days do not seem to matter for the magnitude of the effect. The 1% increase in the average level of nitrogen concentration in the Midwest coupled with the average streamflow of the Mississippi River at the Gulf of Mexico during this period and damages of about $16 per ton of nitrogen, implies an annual external cost of $800 million.

Our estimated effect of additional corn acres on measured nitrogen in waterways is an order of magnitude smaller than agronomic estimates of excess nitrogen applied to those acres assuming edge-of-field losses translate to an equivalent nitrogen loading to streams and rivers. Our findings regarding the magnitude of the effect are consistent with a new line of research showing that large amounts of nitrogen stored in subsurface soil and groundwater give rise to the so-called legacy nitrogen, which may contribute to loadings in rivers and streams with a long delay, a topic we explore in more detail in Metaxoglou and Smith (2022).

Given the role of precipitation and temperature on the magnitude of the estimated effect of corn acreage on nitrogen concentration, we explore the implications of climate change for our findings. We use the NASA Earth Exchange Global Daily Downscaled Projections dataset to obtain precipitation and temperature projections for 2018–2050, which we translate to projections of marginal effects of corn acreage on nitrogen concentration. The marginal effects based on precipitation projections from the NASA GFDL-ESM4 climate model and two shared socioeconomic pathways are very similar in magnitude to their counterparts calculated using historical data. The marginal effects based on temperature projections are slightly smaller than those using historical data. These estimated effects do not account for the impacts of climate change on acreage, nitrogen fertilizer use, legacy nitrogen, runoff, and streamflow, all of which contribute to nutrient pollution.

Based on recent work identifying wetlands as a powerful weapon in the war against nutrient pollution, especially due to their efficacy in also removing legacy nitrogen, we ought to emphasize their vulnerability to changes in landscapes and weather patterns impacted by climate change. Increased flooding, drought spells, extreme heat, and frequency of severe storms due to climate change all can negatively affect wetlands (Salimi et al. (2021)). Taking into consideration other ecosystem services that wetlands also provide, such as absorbing floodwaters, providing habitat for wildlife, and acting as net carbon sinks, increased attention by policymakers seems to be warranted, especially in the light of recent developments in redefining the *Waters of the United States* that are protected by the Clean Water Act.

References

ALEXANDER, R. AND R. SMITH (1990): "County-Level Estimates of Nitrogen and Phosphorus Fertilizer Use in United States, 1945-1985," *U.S. Geological Survey Open File Report 90-130*.

ALEXANDER, R., R. SMITH, G. SCHWARZ, E. BOYER, J. NOLAN, AND J. BRAKEBILL (2008): "Differences in Phosphorous and Nitrogen Delivery to the Gulf of Mexico from the Mississippi River Basin," *Environmental Science and Technology*, 42, 822–830.

ANDERSON, D., P. HOAGLAND, Y. KAORU, AND A. WHITE (2000): "Estimated Annual Economic Impacts from Harmful Algal Blooms (HABs) in the United States," *Woods Hole Oceanographic Institution Technical Report*.

ANNAN, F. AND W. SCHLENKER (2015): "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat," *American Economic Review Papers and Proceedings*, 105, 262–266.

BIRCH, M. B. L., B. M. GRAMIG, W. R. MOOMAW, O. C. DOERING, III, AND C. J. REELING (2011): "Why Metrics Matter: Evaluating Policy Choices for Reactive Nitrogen in the Chesapeake Bay Watershed," *Environmental Science & Technology*, 45, 168–174.

BLOTTNITZ, H. V., A. RABL, D. BOIADJIEV, T. TAYLOR, AND S. ARNOLD (2006): "Damage costs of nitrogen fertilizer in Europe and their internalization," *Journal of Environmental Planning and Management*, 49, 413–433.

BRAKEBALL, J. AND J. GRONBERG (2017): "County-Level Estimates of Nitrogen and Phosphorus from Commercial Fertilizer for the Conterminous United States, 1987-2012," *U.S. Geological Survey data release, https://doi.org/10.5066/F7H41PKX*.

BYRNES, D., K. VAN METER, AND N. BASU (2020): "Long-term shifts in US nitrogen sources and sinks revealed by the new TREND-nitrogen data set (1930–2017)," *Global Biogeochemical Cycles*, 34, e2020GB006626.

CAPEL, P., K. MCCARTHY, R. H. COUPE, K. GREY, S. AMENUMEY, N. T. BAKER, AND R. JOHNSON (2018): "Agriculture–A River Runs Through It–The Connections Between Agriculture and Water Quality," *U.S. Geological Survey Circular 1433*.

CENR (2000): "Integrated Assessment of Hypoxia in the Northern Gulf of Mexico," *National Science and Technology Council Committee on Environment and Natural Resources*.

CLAASSEN, R., M. BOWMAN, J. MCFADDEN, D. SMITH, AND S. WALLANDER (2018): "Tillage Intensity and Conservation Cropping in the United States," *U.S. Department of Agriculture Economic Information Bulletin Number 197*.

COMPTON, J. E., J. A. HARRISON, R. L. DENNIS, T. L. GREAVER, B. H. HILL, S. J. JORDAN, H. WALKER, AND H. V. CAMPBELL (2011): "Ecosystem services altered by human changes in the nitrogen cycle: a new perspective for US decision making," *Ecology Letters*, 14, 804–815.

DAVID, M. B., L. E. DRINKWATER, AND G. F. MCISAAC (2010): "Sources of Nitrate Yields in the Mississippi River Basin," *Journal of Environmental Quality*, 39, 1657–1667.

DESCHENES, O. AND M. GREENSTONE (2007): "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 97, 354–385.

DIAZ, R. J. AND R. ROSENBERG (2008): "Spreading dead zones and consequences for marine ecosystems," *science*, 321, 926–929.

DODDS, W. K., W. W. BOUSKA, J. L. EITZMANN, T. J. PILGER, K. L. PITTS, A. J. RILEY, J. T. SCHLOESSER, AND D. J. THORNBRUGH (2009): "Eutrophication of U.S. Freshwaters: Analysis of Potential Economic Damages," *Environmental Science and Technology*, 43, 12–19.

DOERING, O., F. DIAZ-HERMELO, C. HOWARD, R. HEIMLICH, F. HITZHUSEN, R. KAZMIERCZAK, J. LEE, L. LIBBY, W. MILON, T. PRATO, AND M. RIBAUDO (1999): "Evaluation of the Economic Costs and Benefits of Methods for Reducing Nutrient Loads to the Gulf of Mexico: Topic 5 Report for the Integrated Assessment on Hypoxia in the Gulf of Mexico," *National Oceanic and Atmospheric Administration*.

DUBROVSKY, N., K. BUROW, G. CLARK, J. GRONBERG, P. HAMILTON, K. HITT, D. MUELLER, M. MUNN, B. NOLAN, L. PUCKETT, M. RUPERT, T. SHORT, N. SPAHR, L. SPRAGUE, AND W. WILBER (2018): "The Quality of Our Nation's Water: Nutrients in the Nation's Streams and Groundwater, 1992–2004," *U.S. Geological Survey Circular 1350*.

ELBAKIDZE, L., Y. XU, J. ARNOLD, AND H. YEN (2022): "Climate Change and Downstream Water Quality in Agricultural Production: The Case of Nutrient Runoff to the Gulf of Mexico," in *Economic Perspectives on Water Resources, Climate Change, and Agricultural Sustainability*, ed. by G. Libecap and A. Dinar, University of Chicago Press.

EPA (2007): "Hypoxia in the Northern Gulf of Mexico: An Update by the EPA Science Advisory Board," *U.S. Environmental Protection Agency*.

——— (2015): "A Compilation of Cost Data Associated with the Impacts and Control of Nutrient Pollution," *U.S. EPA Office of Water EPA 820-F-15-096*.

——— (2016): "National Rivers and Streams Assessment 2008–2009: A Collborative Survey," *U.S. Environmental Protetcion Agency Office of Research and Development*.

EYRING, V., S. BONY, G. A. MEEHL, C. A. SENIOR, B. STEVENS, R. J. STOUFFER, AND K. E. TAYLOR (2016): "Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization," *Geoscientific Model Development*, 9, 1937–1958.

FALCONE, J. (2018): "Changes in anthropogenic influences on streams and rivers in the conterminous U.S. over the last 40 years, derived for 16 data themes: U.S. Geological Survey data release," https://doi.org/10.5066/F7XW4J1J.

GARCIA, A. M., R. B. ALEXANDER, J. G. ARNOLD, L. NORFLEET, M. J. WHITE, D. M. ROBERTSON, AND G. SCHWARZ (2016): "Regional Effects of Agricultural Conservation Practices on Nutrient Transport in the Upper Mississippi River Basin," *Environmental Science & Technology*, 50, 6991–7000.

GOMNTF (2013): "Reassessment 2013: Assessing Progress Made Since 2008," *Mississippi River Gulf of Mexico Watershed Nutrient Task Force*.

——— (2015): "Mississippi River Gulf of Mexico Watershed Nutrient Task Force: 2015 Report to the Congress," *U.S. Environmental Protection Agency*.

GOOLSBY, D., W. BATTAGLIN, G. LAWRENCE, R. ARTZ, B. AULENBACH, R. HOOPER, D. KEENEY, AND G. STENSLAND (1999): "Flux and Sources of Nutrients in the Mississippi–Atchafalaya River Basin: Topic 3 Report for the Integrated Assessment on Hypoxia in the Gulf of Mexico," *National Oceanic and Atmospheric Administration*.

GOUREVITCH, J., B. KEELER, AND T. RICKETTS (2018): "Determining socially optimal rates of nitrogen fertilizer application," *Agriculture Ecosystems and Environment*, 254, 292–299.

HELLERSTEIN, D., D. VILORIO, AND M. RIBAUDO (2019): "Agricultural Resources and Environmental Indicators 2019," *U.S. Department of Agriculture Economic Information Bulletin Number 208*.

HENDRICKS, N., A. SMITH, AND D. SUMNER (2014): "Crop Supply Dynamics and the Illusion of Partial Adjustment," *American Journal of Agricultural Economics*, 96, 1469–1491.

HO, J. C., A. M. MICHALAK, AND N. PAHLEVAN (2019): "Widespread global increase in intense lake phytoplankton blooms since the 1980s," *Nature*, 574, 667–670.

ILAMPOORANAN, I., K. J. VAN METER, AND N. B. BASU (2019): "A Race Against Time: Modeling Time Lags in Watershed Response," *Water Resources Research*, 55, 3941–3959.

JÄGERMEYR, J., C. MÜLLER, A. C. RUANE, J. ELLIOTT, J. BALKOVIC, O. CASTILLO, B. FAYE, I. FOSTER, C. FOLBERTH, J. A. FRANKE, ET AL. (2021): "Climate impacts on global agriculture emerge earlier in new generation of climate and crop models," *Nature Food*, 2, 873–885.

KEELER, B. L., J. D. GOUREVITCH, S. POLASKY, F. ISBELL, C. W. TESSUM, J. D. HILL, AND J. D. MARSHALL (2018): "The social costs of nitrogen," *Science Advances*, 2.

KEISER, D. AND J. SHAPIRO (2018): "CONSEQUENCES OF THE CLEAN WATER ACT AND THE DEMAND FOR WATER QUALITY," *Quarterly Journal of Economics*, 134, 349–396.

KLING, C. (2011): "ECONOMIC INCENTIVES TO IMPROVE WATER QUALITY IN AGRICULTURAL LANDSCAPES: SOME NEW VARIATIONS ON OLD IDEAS," *American Journal of Agricultural Economics*, 93, 297–309.

KLING, C. L., Y. PANAGOPOULOS, S. S. RABOTYAGOV, A. M. VALCU, P. W. GASSMAN, T. CAMPBELL, M. J. WHITE, J. G. ARNOLD, R. SRINIVASAN, M. K. JHA, J. J. RICHARDSON, L. M. MOSKAL, R. E. TURNER, AND N. N. RABALAIS (2014): "LUMINATE: linking agricultural land use, local water quality and Gulf of Mexico hypoxia," *European Review of Agricultural Economics*, 41, 431–459.

KUDELA, R., E. BERDALET, S. BERNARD, M. BURFORD, L. FERNAND, S. LU, S. ROY, P. TESTER, G. USUP, R. MAGNIEN, ET AL. (2015): "Harmful algal blooms. A scientific summary for policy makers. IOC," *UNESCO, IOC/INF-1320, 20pp*.

MARSHALL, E., M. AILLERY, M. RIBAUDO, N. KEY, S. SNEERINGER, L. HANSEN, S. MALCOLM, AND A. RIDDLE (2018): "Reducing Nutrient Losses From Cropland in the Mississippi/Atchafalaya River Basin: Cost Efficiency and Regional Distribution," *U.S. Department of Agriculture Economic Research Report Number 258*.

MCCABE, G. J. AND D. M. WOLOCK (2011): "Independent effects of temperature and precipitation on modeled runoff in the conterminous United States," *Water Resources Research*, 47, W11522.

MCLELLAN, E., J. PROVILLE, AND M. MONAST (2016): "RESTORING THE HEARTLAND: COSTS AND BENEFITS OF AGRICULTURAL CONSERVATION IN THE U.S. CORN BELT," Environmental Defense Fund Draft Report.

MCLELLAN, E., D. ROBERTSON, K. SCHILLING, M. TOMER, J. KOSTEL, D. SMITH, AND K. KING (2015): "Reducing Nitrogen Export from the Corn Belt to the Gulf of Mexico: Agricultural Strategies for Remediating Hypoxia," *JAWRA Journal of the American Water Resources Association*, 51, 263–289.

MENDELSOHN, R., W. NORDHAUS, AND D. SHAW (1994): "The Impact of Gloabl Warming on Agriculture: A Ricardian Analysis," *American Economic Review*, 84, 753–771.

METAXOGLOU, K. AND A. SMITH (2022): "Agriculture's Nitrogen Legacy," Working Paper.

MIAO, R., M. KHANNA, AND H. HUANG (2015): "Responsiveness of Crop Yield and Acreage to Prices and Climate," *American Journal of Agricultural Economics*, 98, 191–211.

MITSCH, W., J.W.DAY, J. GILLIAM, P. GROFFMAN, D. HEY, G. RANDALL, AND N. WANG (1999): "Reducing Nutrient Loads, Especially Nitrate–Nitrogen, to Surface Water, Ground Water, and the Gulf of Mexico: Topic 5 Report for the Integrated Assessment on Hypoxia in the Gulf of Mexico," *National Oceanic and Atmospheric Administration*.

MURPHY, J., R. HIRSCH, AND L. SPRAGUE (2013): "Nitrate in the Mississippi River and Its Tributaries, 1980–2010: An Update," *U.S. Geological Survey Scientific Investigations Report 2013–5169*.

NAKAGAKI, N. AND M. WIECZOREK (2016): "Estimates of subsurface tile drainage extent for 12 Midwest states, 2012: U.S. Geological Survey data release," http://dx.doi.org/10.5066/F7W37TDP.

NAKAGAKI, N., M. WIECZOREK, AND S. QI (2016): "Estimates of subsurface tile drainage extent for the conterminous United States, early 1990s: U.S. Geological Survey data release," http://dx.doi.org/10.5066/F7RB72QS.

NRCS (2017a): "Assessment of the Effects of Conservation Practices on Cultivated Cropland in the Upper Mississippi River Basin," *U.S. Department of Agriculture National Resources Conservation Services Conservation Effects Assessment Project*.

——— (2017b): "Effects of Conservation Practices on Nitrogen Loss from Farm Fields," *U.S. Department of Agriculture National Resources Conservation Services Conservation Effects Assessment Project*.

OLMSTEAD, S. (2010): "The Economcis of Water Quality," *Review of Environmental Economics and Policy*, 4, 44–62.

OLMSTEAD, S. M., L. A. MUEHLENBACHS, J.-S. SHIH, Z. CHU, AND A. J. KRUPNICK (2013): "Shale gas development impacts on surface water quality in Pennsylvania," *Proceedings of the National Academy of Sciences*, 110, 4962–4967.

PAUDEL, J. AND C. L. CRAGO (2020): "Environmental Externalities from Agriculture: Evidence from Water Quality in the United States," *American Journal of Agricultural Economics*, n/a.

RABOTYAGOV, S., C. KLING, P. GASSMAN, N. RABALAIS, AND R. TURNER (2014a): "The Economics of Dead Zones: Causes, Impacts, Policy Challenges, and a Model of the Gulf of Mexico Hypoxic Zone," *Review of Environmental Economics and Policy*, 8, 58–79.

RABOTYAGOV, S. S., T. D. CAMPBELL, M. WHITE, J. G. ARNOLD, J. ATWOOD, M. L. NORFLEET, C. L. KLING, P. W. GASSMAN, A. VALCU, J. RICHARDSON, R. E. TURNER, AND N. N. RABALAIS (2014b): "Cost-effective targeting of conservation investments to reduce the northern Gulf of Mexico hypoxic zone," *Proceedings of the National Academy of Sciences*, 111, 18530–18535.

READ, E. K., L. CARR, L. DE CICCO, H. A. DUGAN, P. C. HANSON, J. A. HART, J. KREFT, J. S. READ, AND L. A. WINSLOW (2017): "Water quality data for national-scale aquatic research: The Water Quality Portal," *Water Resources Research*, 53, 1735–1745.

RIBAUDO, M., J. DELGADO, L. HANSEN, M. LIVINGSTON, R. MOSHEIM, AND J. WILLIAMSON (2011): "Nitrogen in Agricultural Systems: Implications for Conservation Policy," *U.S. Department of Agriculture Economic Research Report Number 127*.

RIBAUDO, M. O., R. HEIMLICH, R. CLAASSEN, AND M. PETERS (2001): "Least-cost management of nonpoint source pollution: source reduction versus interception strategies for controlling nitrogen loss in the Mississippi Basin," *Ecological Economics*, 37, 183–197.

ROBERTS, M., W. SCHLENKER, AND J. EYER (2012): "Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change," *American Journal of Agricultural Economics*, 95, 236–243.

ROBERTSON, D. AND D. SAAD (2006): "Spatially Referenced Models of Streamflow and Nitrogen, Phosphorus, and Suspended-Sediment Loads in Streams of the Midwestern United States," *U.S. Geological Survey Scientific Investigations Report 2019–5114*.

SALIMI, S., S. A. ALMUKTAR, AND M. SCHOLZ (2021): "Impact of climate change on wetland ecosystems: A critical review of experimental wetlands," *Journal of Environmental Management*, 286, 112160.

SCHLENKER, W. AND M. ROBERTS (2009): "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 106, 15594–15598.

SINHA, E., A. M. MICHALAK, AND V. BALAJI (2017): "Eutrophication will increase during the 21st century as a result of precipitation changes," *Science*, 357, 405–408.

SOBOTA, D. J., J. E. COMPTON, M. L. MCCRACKIN, AND S. SINGH (2015): "Cost of reactive nitrogen release from human activities to the environment in the United States," *Environmental Research Letters*, 10, 025006.

SPRAGUE, L., R. HIRSCH, AND B. AULENBACH (2011): "Nitrate in the Mississippi River and Its Tributaries, 1980 to 2008: Are We Making Progress?" *Environmental Science & Technology*, 45, 7209–7216.

SPRAGUE, L., G. OELSNER, AND D. ARGUE (2017): "Challenges with secondary use of multi-source water quality data in the United States," *Water Research*, 110, 252–261.

SUGG, Z. (2007): "Assessing U.S. Farm Drainage: Can GIS Lead to Better Estimates of Subsurface Drainage Extent?" *Water Resources Institute*.

TALLIS, H., S. POLASKY, J. HELLMANN, N. P. SPRINGER, R. BISKE, D. DEGEUS, R. DELL, M. DOANE, L. DOWNES, J. GOLDSTEIN, T. HODGMAN, K. JOHNSON, I. LUBY, D. PENNINGTON, M. REUTER, K. SEGERSON, I. STARK, J. STARK, C. VOLLMER-SANDERS, AND S. K. WEAVER (2019): "Five financial incentives to revive the Gulf of Mexico dead zone and Mississippi basin soils," *Journal of Environmental Management*, 233, 30–38.

TAYLOR, C. AND G. HEAL (2021): "Algal Blooms and the Social Cost of Fertilizer," Working Paper.

UCS (2020): "Reviving the Dead Zone: Solutions to Benefit Both Gulf Coast Fishers and Midwest Farmers," *Union of Concerned Scientists*.

USEPA (2001): "The national costs of the total maximum daily load program," .

VALAYAMKUNNATH, P., M. BARLAGE, F. CHEN, D. J. GOCHIS, AND K. J. FRANZ (2020): "Mapping of 30-meter resolution tile-drained croplands using a geospatial modeling approach," *Scientific data*, 7, 1–10.

VAN GRINSVEN, H. J. M., M. HOLLAND, B. H. JACOBSEN, Z. KLIMONT, M. A. SUTTON, AND W. JAAP WILLEMS (2013a): "Costs and Benefits of Nitrogen for Europe and Implications for Mitigation," *Environmental Science & Technology*, 47, 3571–3579.

——— (2013b): "Costs and Benefits of Nitrogen for Europe and Implications for Mitigation," *Environmental Science & Technology*, 47, 3571–3579.

VAN METER, K., P. VAN CAPPELLEN, AND N. BASU (2018): "Legacy nitrogen may prevent achievement of water quality goals in the Gulf of Mexico," *Science*, 360, 427–430.

VAN METER, K. J., N. B. BASU, AND P. VAN CAPPELLEN (2017): "Two centuries of nitrogen dynamics: Legacy sources and sinks in the Mississippi and Susquehanna River Basins," *Global Biogeochemical Cycles*, 31, 2–23.

VAN METER, K. J., N. B. BASU, J. J. VEENSTRA, AND C. L. BURRAS (2016): "The nitrogen legacy: emerging evidence of nitrogen accumulation in anthropogenic landscapes," *Environmental Research Letters*, 11, 035014.

WHITE, M. J., C. SANTHI, N. KANNAN, J. G. ARNOLD, D. HARMEL, L. NORFLEET, P. ALLEN, M. DILUZIO, X. WANG, J. ATWOOD, ET AL. (2014): "Nutrient delivery from the Mississippi River to the Gulf of Mexico and effects of cropland conservation," *Journal of Soil and Water Conservation*, 69, 26–40.

WHITTAKER, G., B. L. BARNHART, R. SRINIVASAN, AND J. G. ARNOLD (2015): "Cost of areal reduction of gulf hypoxia through agricultural practice," *Science of The Total Environment*, 505, 149–153.

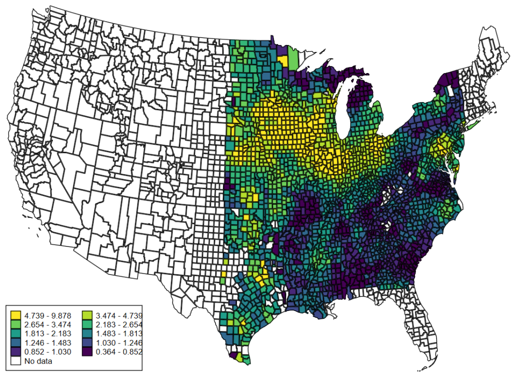
WOLOCK, D. AND G. MCCABE (2018): "Water Balance Model Inputs and Outputs for the Conterminous United States, 1900-2015," https://doi.org/10.5066/F71V5CWN.

WU, J. AND K. TANAKA (2005): "Reducing Nitrogen Runoff from the Upper Mississippi River Basin to Control Hypoxia in the Gulf of Mexico: Easements or Taxes," *Marine Resource Economics*, 20, 121–144.

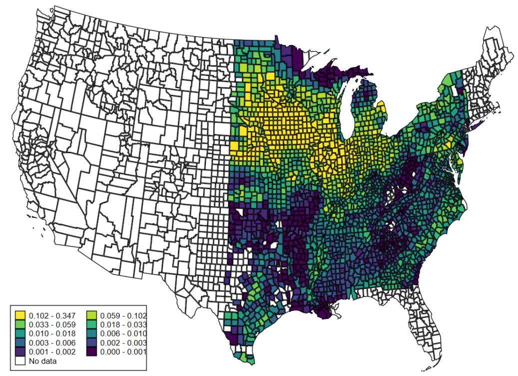
XU, Y., L. ELBAKIDZE, H. YEN, J. ARNOLD, P. GASSMAN, J. HUBBART, AND M. STRAGER (2021): "Integrated assessment of N runoff in the Gulf of Mexico," *Working Paper*.

9 Figures

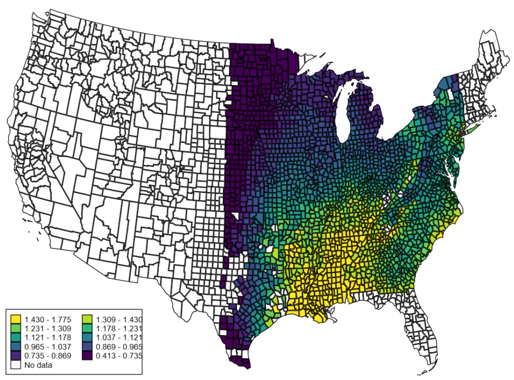
Figure 1. Nitrogen concentration, corn acreage, and weather-related variables



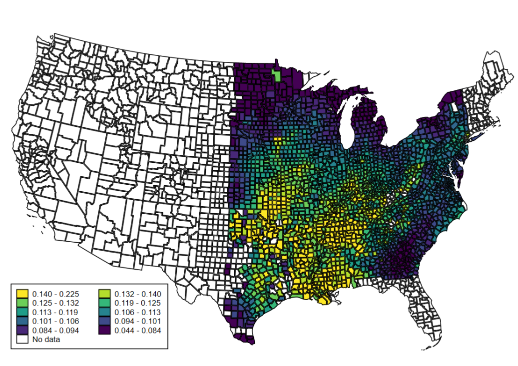
A. nitrogen concentration



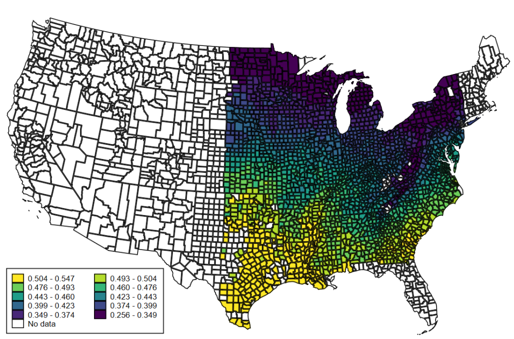
B. corn acres planted



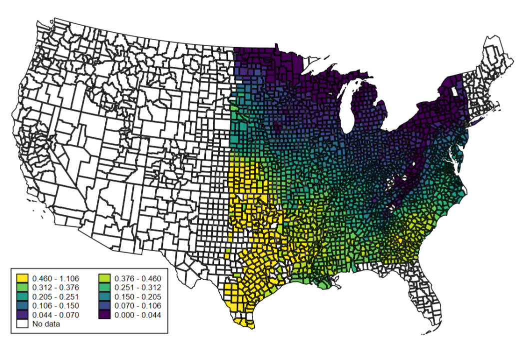
C. total annual precipitation



D. May precipitation



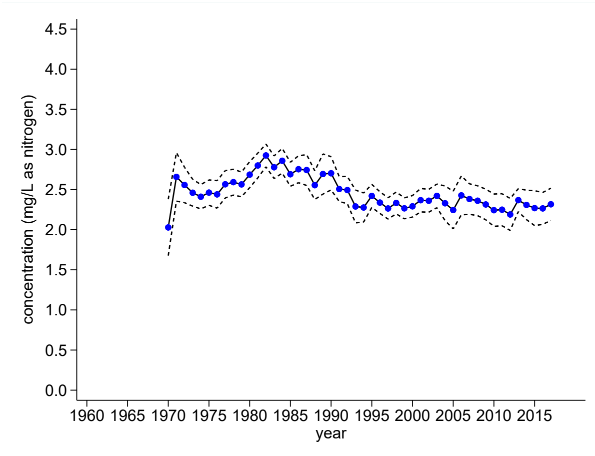
E. July moderate-heat degree days



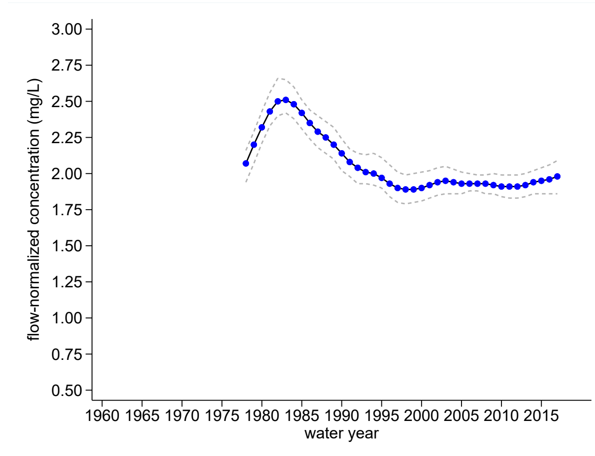
F. July extreme-heat degree days

Note: In all panels, we show averages for 1970–2017. The shading of the choropleth maps is based on the deciles of the empirical distribution. In panels D, E, and F, we show the months with the highest average values. The acres are in millions and the nitrogen concentration is in mg/L. The precipitation is in meters. The moderate heat is in 1,000 degree days between 10°C and 29°C. The extreme heat is in 100 degree days above 29°C. For additional details, see Section 5.2.

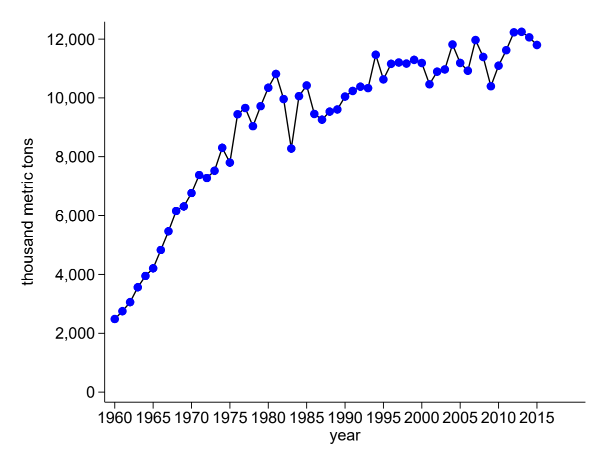
Figure 2. Nitrogen pollution and related factors



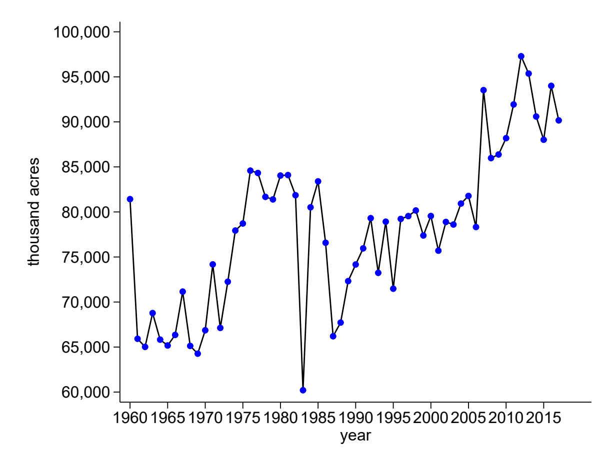
A. nitrogen concentration



B. flow-normalized nitrogen concentration



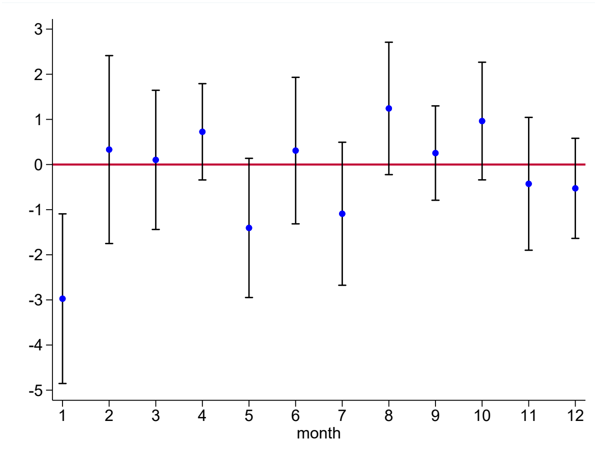
C. nitrogen fertilizer use



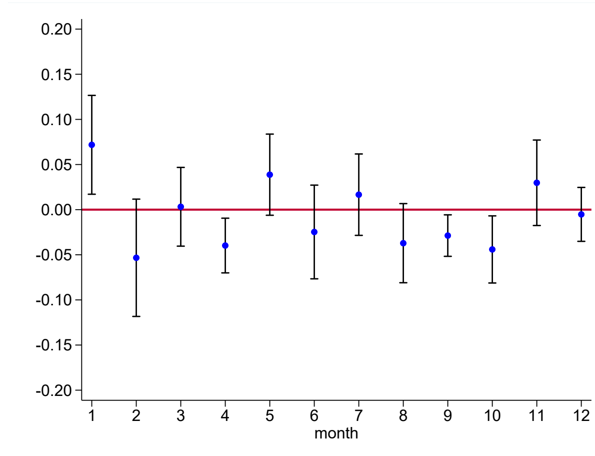
D. corn acres planted

Note: In panel A, we regress the average daily nitrogen concentration at the USGS monitoring-site level for the CONUS on site fixed effects (FEs), year FEs, day, day squared, day cubed, month, month squared, month cubed, and report the estimated year FEs. The 95% confidence intervals shown are constructed using standard errors clustered by HUC8. Additional details regarding the flow-normalized total nitrogen concentration in the Gulf in panel B are available in the following USGS link. In panel C, we show U.S. consumption of nitrogen fertilizer from Table 1 in the USDA ERS report on fertilizer use and price. In panel D, we show corn acres planted from the USDA Historical Track Records. For additional details, see Section 5.3.

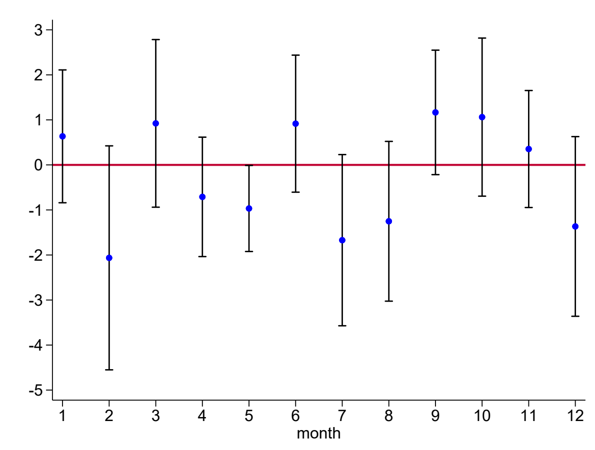
Figure 3. Panel FE regressions, weather related controls



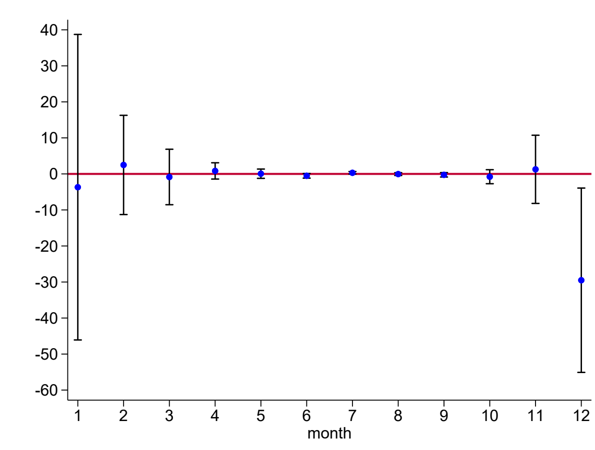
A. precipitation



B. precipitation squared



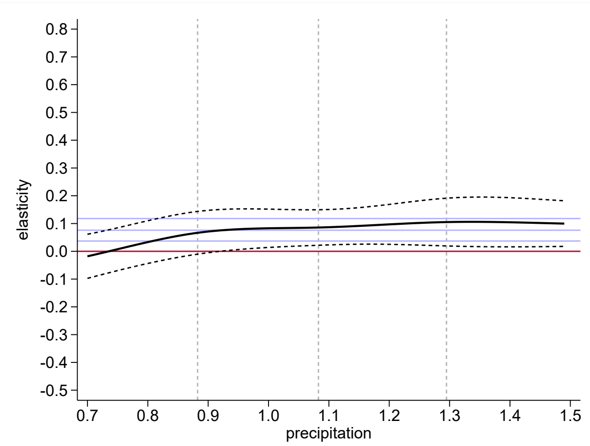
C. moderate heat



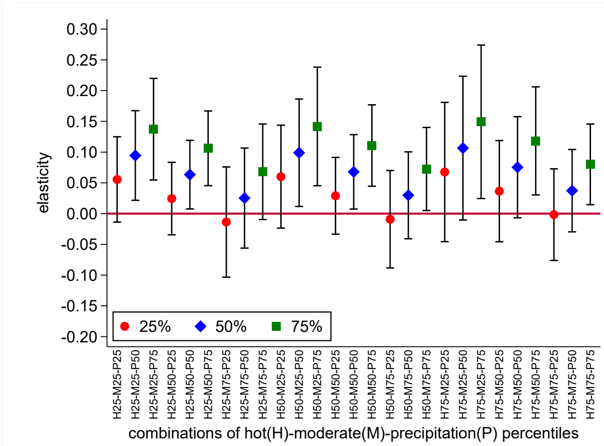
D. extreme heat

Note: The figure shows point estimates and 95% confidence intervals (CIs) for the 48 weather related controls in specification C8 of the panel FE regressions in Table 3. The CIs are constructed using standard errors clustered by HUC4. The F statistics and the p-values in squared brackets for the joint significance of the coefficients shown in the 4 panels are as follows: 2.06 [0.024] for panel A, 2.94 [0.001] for panel B, 1.39 [0.178] for panel C, and 2.02 [0.027] for panel D. For additional details, see Section 6.

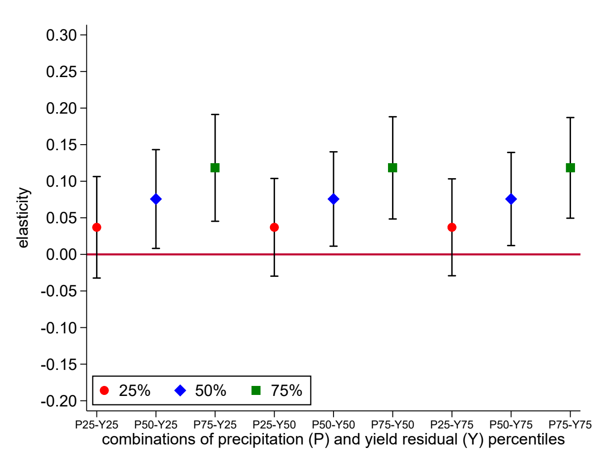
Figure 4. Additional elasticity estimates based on panel fixed-effect regressions



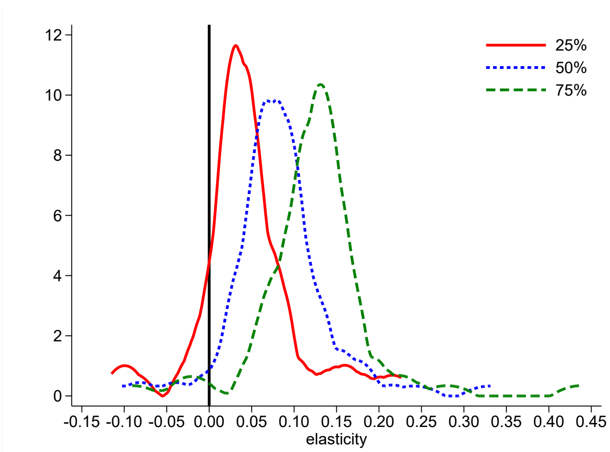
A. Flexible specification



B. Interaction with heat and precipitation



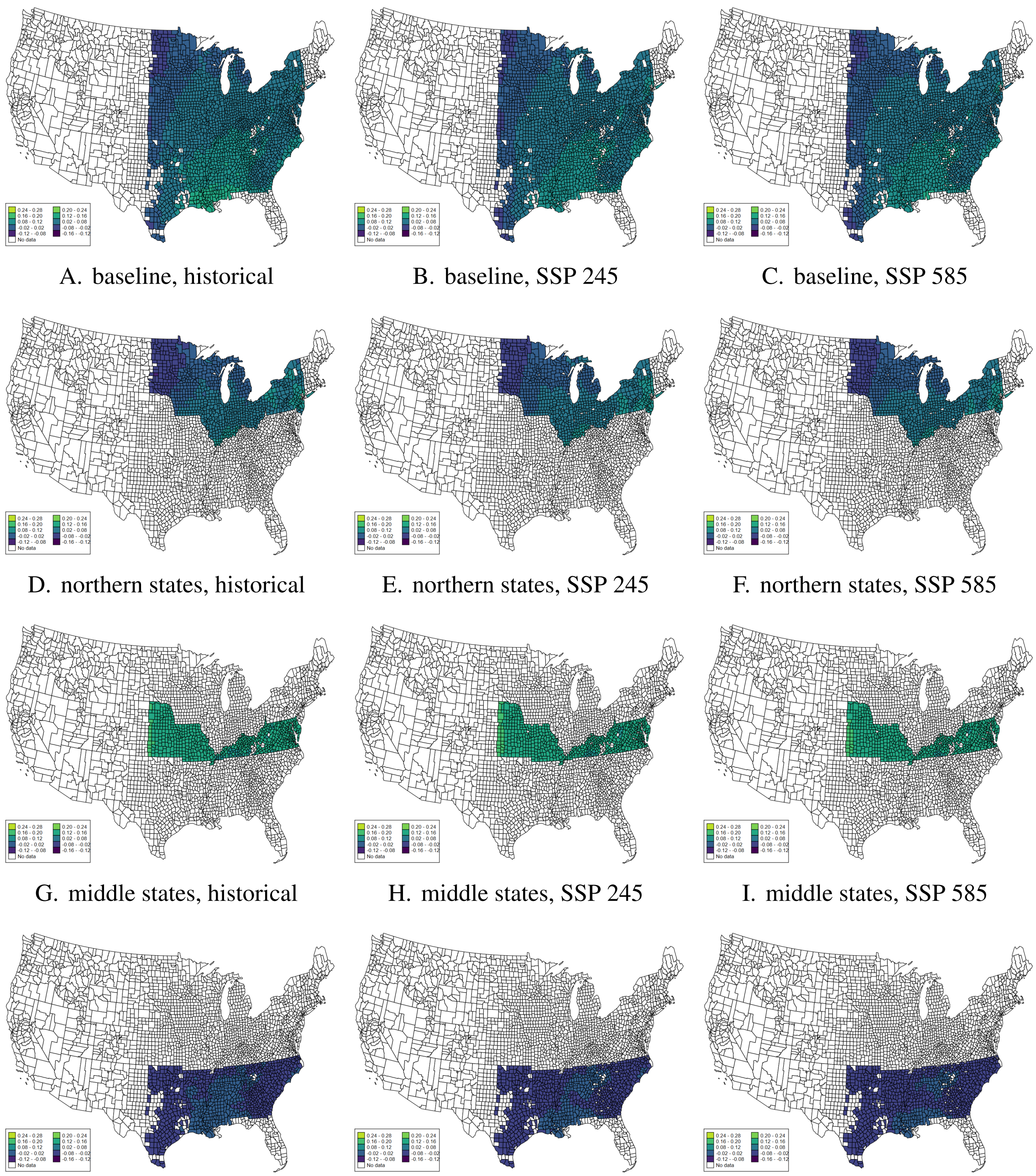
C. Interaction with yield residuals



D. Other estimates

Note: In panels A–C, we report elasticity estimates along with 95% confidence intervals using standard errors clustered by HUC4. In panels B and C, the legend pertains to the quartiles of total annual precipitation. We use the set of weather-related controls, county fixed effects (FEs), year FEs, and county-specific trends as in column C8 in Table 3. In panel A, we use a flexible specification (cubic spline) to model the interaction of corn acreage and precipitation. We use the gray vertical dashed lines to indicate the precipitation quartiles and the horizontal light blue lines to indicate the elasticities from specification C8 in Table 3. In panel B, we interact corn acreage with total annual precipitation, annual moderate-, and extreme-heat degree days. In panel C, we interact corn acreage with total annual precipitation and corn yield residuals. We obtain the yield residuals by regressing yields on county-specific trends. In panel D, we summarize the elasticity estimates in Table 4–Table 6 by precipitation quartile using kernel density plots. For additional details, see Section A.6.

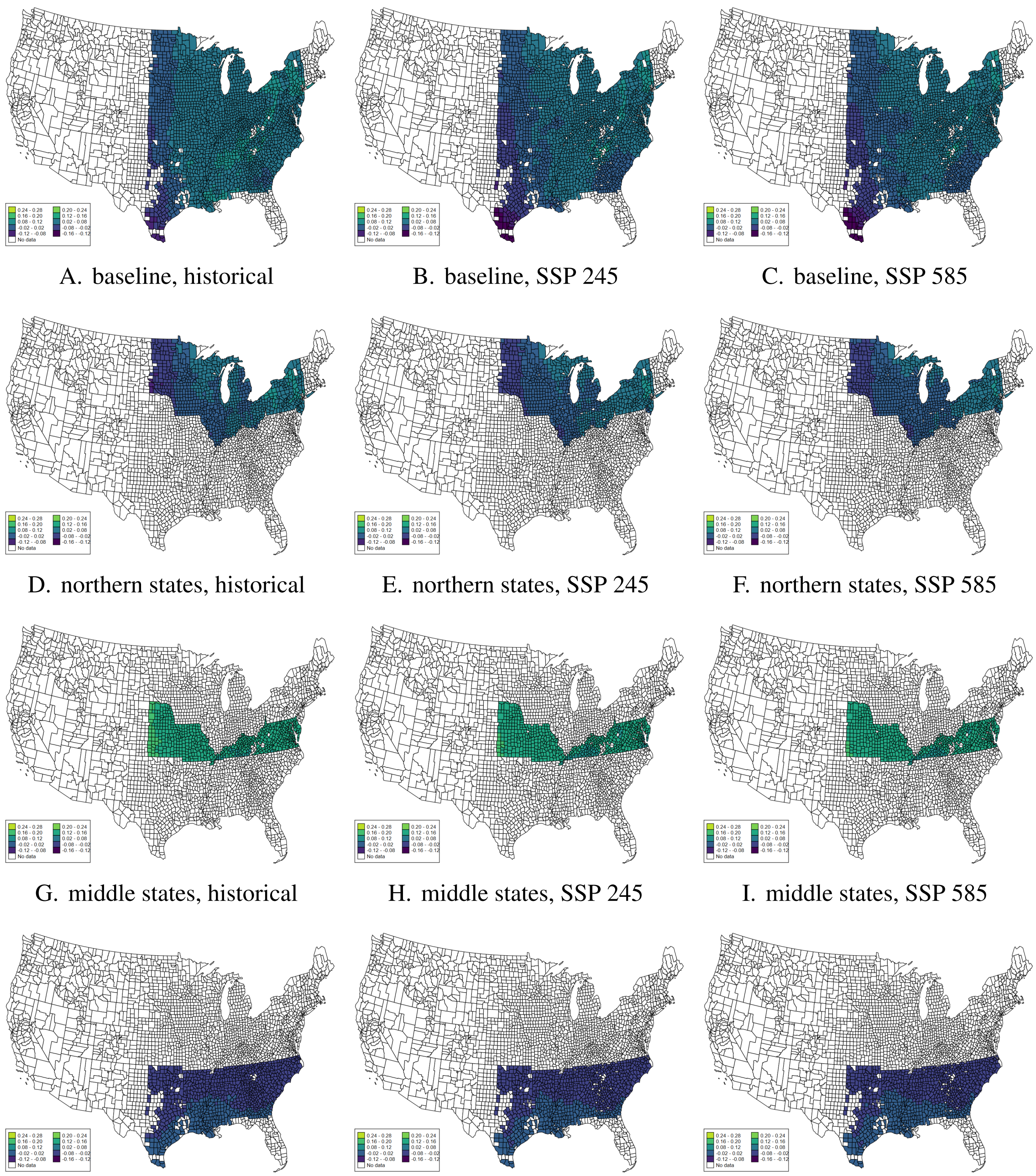
Figure 5. Corn acreage marginal effects with GFDL-ESM4 precipitation projections



A. baseline, historical
B. baseline, SSP 245
C. baseline, SSP 585
D. northern states, historical
E. northern states, SSP 245
F. northern states, SSP 585
G. middle states, historical
H. middle states, SSP 245
I. middle states, SSP 585
J. southern states, historical
K. southern states, SSP 245
L. southern states, SSP 585

Note: We show corn acreage marginal effects (MEs) in mg/L for specification C8 of the panel fixed-effect (FE) regressions in Table 3. We use baseline to refer to counties east of the 100th meridian excluding Florida. We define the northern, middle, and southern states following Schlenker and Roberts (2009). For the MEs based on the historical data, we use precipitation averages for 1970–2017. For the MEs based on the projections from two SSPs of the GFDL-ESM4 climate model, we use precipitation averages for 2018–2050. The shading of the choropleth maps is based on deciles of the ME empirical distribution. For additional details, see Section 7.

Figure 6. Corn acreage marginal effects with GFDL-ESM4 precipitation and heat projections



A. baseline, historical
B. baseline, SSP 245
C. baseline, SSP 585
D. northern states, historical
E. northern states, SSP 245
F. northern states, SSP 585
G. middle states, historical
H. middle states, SSP 245
I. middle states, SSP 585
J. southern states, historical
K. southern states, SSP 245
L. southern states, SSP 585

Note: We show corn acreage marginal effects (MEs) in mg/L for the panel fixed-effect (FE) regressions in which we interact corn acreage with precipitation, moderate-heat DDs, and extreme-heat DDs. In the regressions, we use the same set of weather-related controls, county fixed effects (FEs), year FEs, and county-specific trends as in column C8 in Table 3. We use baseline to refer to counties east of the 100th meridian excluding Florida. We define the northern, middle, and southern states following Schlenker and Roberts (2009). For the MEs based on the historical data, we use precipitation, moderate-, and extreme-heat DD averages for 1970–2017. For the MEs based on the projections from two SSPs of the GFDL-ESM4 climate model, we use averages for 2018–2050. The shading of the choropleth maps is based on deciles of the ME empirical distribution. For additional details, see Section 7.

10 Tables

Table 1. Nitrogen pollution damages and abatement costs

A. Damages		
Source	Damages	Details
Taylor and Heal (2021)	\$583	U.S., per ton of nitrogen
Sobota et al. (2015)	\$15,840	U.S., per ton of nitrogen
Van Grinsven et al. (2013a)	\$13,338–\$53,351	E.U., per ton of nitrogen
Compton et al. (2011)	\$56,000	GoM fisheries decline, per ton of nitrogen
Compton et al. (2011)	\$6,380	CB recreational use, per ton of nitrogen
Blottnitz et al. (2006)	\$300	E.U., per ton of nitrogen
Dodds et al. (2009)	\$2.2 billion	U.S., freshwater eutrophication, annually
Kudela et al. (2015)	\$4 billion	U.S., algal blooms, annually
UCS (2020)	\$0.552–\$2.4 billion	GoM fisheries & marine habitat, annually
Anderson et al. (2000)	\$449 million	U.S., algal blooms, annually
B. Abatement costs		
Source	Abatement costs	Geographic scope
Xu et al. (2021)	\$6 billion	Mississippi River Basin
Tallis et al. (2019)	\$2.6 billion	Mississippi River Basin
Marshall et al. (2018)	\$1.9–\$3.3 billion	Mississippi River Basin
McLellan et al. (2016)	\$1.48 billion	Mississippi River Basin
Whittaker et al. (2015)	\$9.25 billion	Mississippi River Basin
Rabotyagov et al. (2014a)	\$2.6 billion	Mississippi River Basin
USEPA (2001)	$<$ \$1–\$4.3 billion	US, national
Ribaudo et al. (2001)	\$0.1–\$7.91 billion	Mississippi River Basin
Doering et al. (1999)	$-$\$0.1–\$17.95 billion	Mississippi River Basin

Note: In Van Grinsven et al. (2013a), the reported cost of €25–100 billion per year implies a cost of €4.11–16.43 per lb of nitrogen using $0.6 \times 4.6 = 2.6$ million tons of nitrogen attributed to agricultural sources. At an exchange rate of \$1.5/€in 2008, we have a cost of 6.05–24.20 per lb of nitrogen in \$2008. We report the cost per ton of nitrogen. In the case of USEPA (2001), the costs are per year for the development of TMDLs. Table IV-1 in USEPA (2001) shows the leading causes of water impairment (nutrients account for 11.5%) and leading sources (agriculture accounts for 24.6%). See Table 6.1 in Doering et al. (1999), where the numbers are reported as net social benefits. See Table 2 in Ribaudo et al. (2001), where the numbers are reported as net social benefits too. We use "CB" to refer to the Chesapeake Bay, "GoM" to refer to the Gulf of Mexico. For additional details, see Section 2 in the main text and Section A.1 of the online appendix.

Table 2. Summary statistics

variable	panel	obs	years	mean	s.d. B	s.d. W	median
nitrogen	2,232	64,121	28.7	2.451	1.645	1.663	1.683
acres planted	2,232	64,121	28.7	0.038	0.048	0.011	0.015
precipitation annual	2,232	64,121	28.7	1.088	0.259	0.174	1.070
precipitation jan	2,232	64,121	28.7	0.073	0.041	0.039	0.060
precipitation feb	2,232	64,121	28.7	0.067	0.036	0.036	0.055
precipitation mar	2,232	64,121	28.7	0.092	0.038	0.046	0.081
precipitation apr	2,232	64,121	28.7	0.095	0.024	0.048	0.086
precipitation may	2,232	64,121	28.7	0.111	0.022	0.050	0.104
precipitation jun	2,232	64,121	28.7	0.109	0.017	0.050	0.101
precipitation jul	2,232	64,121	28.7	0.106	0.023	0.049	0.098
precipitation aug	2,232	64,121	28.7	0.099	0.021	0.047	0.091
precipitation sep	2,232	64,121	28.7	0.094	0.021	0.056	0.082
precipitation oct	2,232	64,121	28.7	0.082	0.019	0.049	0.072
precipitation nov	2,232	64,121	28.7	0.082	0.031	0.044	0.073
precipitation dec	2,232	64,121	28.7	0.078	0.038	0.043	0.067
moderate heat jan	2,232	64,121	28.7	0.018	0.027	0.017	0.004
moderate heat feb	2,232	64,121	28.7	0.027	0.035	0.017	0.011
moderate heat mar	2,232	64,121	28.7	0.070	0.062	0.027	0.051
moderate heat apr	2,232	64,121	28.7	0.138	0.076	0.030	0.125
moderate heat may	2,232	64,121	28.7	0.253	0.082	0.040	0.245
moderate heat jun	2,232	64,121	28.7	0.361	0.071	0.029	0.365
moderate heat jul	2,232	64,121	28.7	0.430	0.061	0.027	0.439
moderate heat aug	2,232	64,121	28.7	0.408	0.068	0.031	0.415
moderate heat sep	2,232	64,121	28.7	0.295	0.082	0.033	0.291
moderate heat oct	2,232	64,121	28.7	0.157	0.079	0.031	0.144
moderate heat nov	2,232	64,121	28.7	0.064	0.055	0.024	0.047
moderate heat dec	2,232	64,121	28.7	0.025	0.033	0.017	0.008
extreme heat jan	2,232	64,121	28.7	0.000	0.000	0.000	0.000
extreme heat feb	2,232	64,121	28.7	0.000	0.001	0.001	0.000
extreme heat mar	2,232	64,121	28.7	0.000	0.003	0.002	0.000
extreme heat apr	2,232	64,121	28.7	0.004	0.010	0.009	0.000
extreme heat may	2,232	64,121	28.7	0.022	0.034	0.026	0.006
extreme heat jun	2,232	64,121	28.7	0.106	0.100	0.071	0.066
extreme heat jul	2,232	64,121	28.7	0.216	0.172	0.119	0.167
extreme heat aug	2,232	64,121	28.7	0.174	0.165	0.108	0.108
extreme heat sep	2,232	64,121	28.7	0.061	0.074	0.054	0.024
extreme heat oct	2,232	64,121	28.7	0.006	0.016	0.011	0.000
extreme heat nov	2,232	64,121	28.7	0.000	0.001	0.001	0.000
extreme heat dec	2,232	64,121	28.7	0.000	0.000	0.000	0.000

Note: An observation is a county-year combination. The panel column indicates the number of counties. The years column gives the average number of observations per county. We also report the between-counties (s.d. B) and within-county (s.d. W) standard deviation. The acres are measured in millions and the nitrogen concentration is measured in mg/L. The precipitation is measured in meters. The moderate heat is measured in 1,000 degree days between 10°C and 29°C. The extreme heat is measured in 100 degree days above 29°C. For additional details, see Section 5.2.

Table 3. Panel fixed effect regressions and corn acreage elasticities

	A. Acres only							
	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)	(A7)	(A8)
acres	23.581***	5.146***	4.202**	5.845***	3.862**	6.117***	-0.523	2.741
	(2.032)	(1.714)	(1.659)	(1.902)	(1.596)	(1.941)	(1.987)	(1.955)
$\overline{R}^2$	0.26	0.46	0.47	0.47	0.48	0.48	0.52	0.53
Obs.	64,121	64,121	64,121	64,121	64,121	64,121	64,121	64,121
Clusters	124	124	124	124	124	124	124	124
elast est.	0.364***	0.079***	0.065**	0.090***	0.060**	0.094***	-0.008	0.042
elast s.e.	(0.031)	(0.026)	(0.026)	(0.029)	(0.025)	(0.030)	(0.031)	(0.030)
elast pval	0.000	0.003	0.013	0.003	0.017	0.002	0.793	0.163
	B. Acres plus weather							
	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)	(B7)	(B8)
acres	18.458***	5.212***	4.317***	5.490***	3.941**	6.058***	-0.678	2.477
	(1.872)	(1.669)	(1.640)	(1.864)	(1.525)	(1.970)	(1.941)	(1.942)
$\overline{R}^2$	0.30	0.47	0.47	0.48	0.48	0.49	0.52	0.53
Obs.	64,121	64,121	64,121	64,121	64,121	64,121	64,121	64,121
Clusters	124	124	124	124	124	124	124	124
elast est.	0.285***	0.080***	0.067***	0.085***	0.061**	0.093***	-0.010	0.038
elast s.e.	(0.029)	(0.026)	(0.025)	(0.029)	(0.024)	(0.030)	(0.030)	(0.030)
elast pval	0.000	0.002	0.010	0.004	0.011	0.003	0.727	0.205
	C. Acres plus weather and interaction with precipitation							
	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)	(C7)	(C8)
acres	0.765	-9.793**	-10.379***	-8.444**	-10.699***	-7.947**	-13.730***	-9.566**
	(3.315)	(3.968)	(3.916)	(3.602)	(3.804)	(3.542)	(4.887)	(4.495)
acres × prec	19.486***	16.342***	16.043***	15.355***	15.870***	15.277***	14.409***	13.517***
	(3.381)	(3.899)	(3.877)	(3.667)	(3.845)	(3.715)	(3.927)	(3.805)
$\overline{R}^2$	0.31	0.47	0.47	0.48	0.48	0.49	0.52	0.53
Obs.	64,121	64,121	64,121	64,121	64,121	64,121	64,121	64,121
Clusters	124	124	124	124	124	124	124	124
elast 25 est.	0.278***	0.072**	0.059**	0.079***	0.052**	0.086***	-0.015	0.037
elast 25 s.e.	(0.029)	(0.029)	(0.027)	(0.028)	(0.025)	(0.030)	(0.035)	(0.034)
elast 25 pval	0.000	0.013	0.031	0.006	0.042	0.005	0.666	0.275
elast 50 est.	0.333***	0.119***	0.105***	0.123***	0.097***	0.130***	0.026**	0.076***
elast 50 s.e.	(0.032)	(0.030)	(0.029)	(0.031)	(0.027)	(0.033)	(0.032)	(0.032)
elast 50 pval	0.000	0.000	0.000	0.000	0.000	0.000	0.032	0.001
elast 75 est.	0.395***	0.170***	0.155***	0.171***	0.147***	0.178***	0.071**	0.118***
elast 75 s.e.	(0.037)	(0.036)	(0.035)	(0.037)	(0.034)	(0.040)	(0.033)	(0.035)
elast 75 pval	0.000	0.000	0.000	0.000	0.000	0.000	0.032	0.001
precip 25	0.885	0.885	0.885	0.885	0.885	0.885	0.885	0.885
precip 50	1.070	1.070	1.070	1.070	1.070	1.070	1.070	1.070
precip 75	1.274	1.274	1.274	1.274	1.274	1.274	1.274	1.274
mean acres	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038
mean N	2.451	2.451	2.451	2.451	2.451	2.451	2.451	2.451
county FE		✓	✓	✓	✓	✓	✓	✓
trend			✓					
year FE				✓		✓		✓
state × trend					✓	✓		
county × trend							✓	✓

Note: We control for weather (precipitation, squared precipitation, moderate-heat degree days, and extreme-heat degree days) in all 8 models of panels B and C. The standard errors reported in parentheses are clustered by HUC4. The elasticities in the bottom of each panel are calculated using the means of corn acreage (mean acres) and nitrogen concentration (mean N), and 3 precipitation quartiles (precip25, precip50, precip75) in panel C. The acreage is in millions, the concentration is in mg/L, and the precipitation is total annual (January–December) in meters. The asterisks denote statistical significance as follows: 1% (***), 5% (**), 10% (*). For additional details, see Section 6.

Table 4. Additional estimates of corn acreage elasticities based on panel fixed-effect regressions

			sample					coefficients		mean	mean	precipitation			elasticities		
no.	model	obs	starts	ends	counties	years	Clusters	β_1	β_2	nitrogen	acres	25%	50%	75%	25%	50%	75%
M1	BEA SAEMP25	64,121	1970	2017	2,232	48	124	-9.561**	13.527**	2.451	0.038	0.885	1.070	1.274	0.037	0.076**	0.118***
M2	BEA SAGDP2	64,121	1970	2017	2,232	48	124	-9.598**	13.502**	2.451	0.038	0.885	1.070	1.274	0.036	0.075**	0.117***
M3	BEA REA CAINC	63,477	1970	2017	2,209	48	124	-7.123	13.477**	2.462	0.038	0.884	1.070	1.274	0.074*	0.113***	0.156***
M4	M1 plus EIA-SEDS	64,121	1970	2017	2,232	48	124	-9.518**	13.619**	2.451	0.038	0.885	1.070	1.274	0.039	0.078**	0.121***
M5	M2 plus EIA-SEDS	64,121	1970	2017	2,232	48	124	-9.547**	13.589**	2.451	0.038	0.885	1.070	1.274	0.038	0.077**	0.120***
M6	M3 plus EIA-SEDS	63,477	1970	2017	2,209	48	124	-7.325	13.564**	2.462	0.038	0.884	1.070	1.274	0.072*	0.111***	0.154***
M7	M4 plus EPA NO_x	23,735	1996	2017	1,749	22	117	-12.560*	16.716**	2.710	0.044	0.886	1.063	1.254	0.037	0.085	0.137
M8	M5 plus EPA NO_x	23,735	1996	2017	1,749	22	117	-12.428*	16.634**	2.710	0.044	0.886	1.063	1.254	0.038	0.086	0.137
M9	M6 plus EPA NO_x	23,488	1996	2017	1,731	22	117	-7.555	16.884**	2.725	0.045	0.884	1.062	1.254	0.121	0.170	0.223**
M10	BLS LAUS	33,496	1990	2017	1,983	28	121	-8.207	10.625**	2.637	0.042	0.894	1.076	1.272	0.020	0.051	0.084
M11	M10 plus EIA-SEDS	33,496	1990	2017	1,983	28	121	-8.112	10.675**	2.637	0.042	0.894	1.076	1.272	0.023	0.053	0.086
M12	M11 plus EPA NO_x	23,735	1996	2017	1,749	22	117	-12.664*	16.407**	2.710	0.044	0.886	1.063	1.254	0.030	0.078	0.129
M13	M6 plus WWTPs	11,475	1978	2012	559	35	46	5.738	6.035	2.845	0.042	0.718	0.912	1.124	0.147*	0.164**	0.183***
M14	M6 plus TREND livestock	63,406	1970	2017	2,207	48	124	-7.306*	13.568**	2.459	0.038	0.884	1.070	1.275	0.073*	0.112***	0.155***
M15	M6 plus TREND human	63,406	1970	2017	2,207	48	124	-7.335*	13.581**	2.459	0.038	0.884	1.070	1.275	0.072*	0.111***	0.154***
M16	M6 plus TREND ATMDEP	63,406	1970	2017	2,207	48	124	-7.321*	13.481**	2.459	0.038	0.884	1.070	1.275	0.071*	0.110***	0.153***
M17	M6 plus TREND fertilizer	63,406	1970	2017	2,207	48	124	-7.444*	13.431**	2.459	0.038	0.884	1.070	1.275	0.069*	0.107***	0.150***
M18	M6 plus TREND fixing	63,406	1970	2017	2,207	48	124	-7.561*	13.512**	2.459	0.038	0.884	1.070	1.275	0.068*	0.107**	0.149***
M19	M6 plus TREND uptake	63,406	1970	2017	2,207	48	124	-7.320*	13.649**	2.459	0.038	0.884	1.070	1.275	0.073*	0.113***	0.156***

Note: The coefficients β_1 and β_2 are the ones for corn acres and their interaction with precipitation in equation (1). All regressions are estimated using the 48 weather-related controls, the fixed effects, and the time-related controls, in specification C8 in Table 3. The corn acres (acres) are in millions and the nitrogen concentration (N) is in mg/L. The precipitation (measured in meters) and runoff (measured in millimeters) are both total annual. The elasticities in the three rightmost columns are calculated using the precipitation (or runoff, when appropriate) quartiles and the mean acreage and nitrogen concentration reported in the table. The standards errors are clustered by HUC4 except for the robustness checks in which we explore alternative clustering schemes. The asterisks denote statistical significance as follows: 1% (***), 5% (**), 10% (*). For additional details, see Section A.6.

Table 5. Additional estimates of corn acreage elasticities based on panel fixed-effect regressions (continued)

		sample					coefficients		mean	mean	precipitation/runoff			elasticities		
model	obs	starts	ends	counties	years	Clusters	β_1	β_2	nitrogen	acres	25%	50%	75%	25%	50%	75%
A. Baseline																
Baseline	64,121	1970	2017	2,232	48	124	-9.566**	13.517**	2.451	0.038	0.885	1.070	1.274	0.037	0.076**	0.118***
B. Control for conservation programs, acres of other major crops, and fertilizer sales																
Other acres	64,121	1970	2017	2,232	48	124	-10.440**	14.320**	2.451	0.038	0.885	1.070	1.274	0.034	0.075*	0.120***
CRP acres	64,121	1970	2017	2,232	48	124	-10.135**	13.655**	2.451	0.038	0.885	1.070	1.274	0.030	0.069**	0.112***
Fertilizer sales	58,047	1970	2012	2,230	42	124	-7.842	11.932**	2.408	0.037	0.877	1.071	1.279	0.041	0.076**	0.115***
Other and CRP acres	64,121	1970	2017	2,232	48	124	-11.018**	14.517**	2.451	0.038	0.885	1.070	1.274	0.028	0.070	0.115**
Other and Fertilizer	58,047	1970	2012	2,230	42	124	-7.542	12.540**	2.408	0.037	0.877	1.071	1.279	0.054	0.091**	0.132***
Other, CRP, Fertilizer	58,047	1970	2012	2,230	42	124	-8.049	12.743**	2.408	0.037	0.877	1.071	1.279	0.048	0.087**	0.128***
C. Temporal variation in corn acreage effects																
1970s	12,765	1970	1979	2,079	10	122	-9.481	3.085	2.020	0.034	0.873	1.109	1.341	-0.115	-0.103	-0.091
1980s	17,657	1980	1989	2,058	10	123	-5.666	14.718**	2.416	0.033	0.875	1.040	1.230	0.100*	0.133**	0.172**
1990s	14,878	1990	1999	1,920	10	121	2.534	12.690*	2.568	0.038	0.905	1.095	1.307	0.205	0.241	0.280
2000s	11,204	2000	2009	1,561	10	117	0.568	10.340*	2.630	0.043	0.875	1.064	1.252	0.159*	0.191**	0.223***
2010s	7,095	2010	2017	1,225	8	110	-9.319	15.012	2.785	0.047	0.906	1.056	1.232	0.072	0.109	0.154
D. Spatial variation in corn acreage effects																
MRB	40,906	1970	2017	1,534	48	87	-10.456**	15.178**	2.866	0.048	0.789	1.008	1.230	0.026	0.082*	0.138***
North	26,799	1970	2017	826	48	58	-14.556**	18.324**	3.302	0.065	0.801	0.940	1.087	0.003	0.053	0.106
Middle	15,974	1970	2017	546	48	38	17.912**	-5.230	2.345	0.031	0.881	1.055	1.222	0.174***	0.162***	0.151***
South	21,348	1970	2017	860	48	51	-8.309	4.253	1.462	0.009	1.111	1.279	1.475	-0.022	-0.018	-0.012
E. Alternative time windows for measuring nitrogen concentration, precipitation, and degree days																
January-June	60,177	1970	2017	2,227	48	124	-3.271	11.310**	2.604	0.037	0.417	0.526	0.655	0.021	0.038	0.059**
March-August	61,308	1970	2017	2,227	48	124	-3.487	10.127**	2.528	0.038	0.503	0.600	0.705	0.024	0.038	0.054*
April-September	61,654	1970	2017	2,228	48	124	-5.550*	13.773**	2.461	0.038	0.509	0.599	0.701	0.022	0.042	0.063**
May-October	61,890	1970	2017	2,230	48	124	-9.066**	20.689**	2.435	0.038	0.501	0.588	0.688	0.020	0.048	0.080**
F. Interacting corn acres with runoff instead of precipitation																
Runoff	62,420	1970	2015	2,232	46	124	-0.521	0.002**	2.435	0.038	1752.310	2824.000	4112.086	0.048	0.083**	0.124***
G. Nitrogen concentration accounting for streamflow																
Downstream main	33,335	1970	2017	1,913	48	123	-15.821**	17.665**	2.305	0.038	0.878	1.059	1.261	-0.005	0.047	0.105***
Downstream all	40,145	1970	2017	2,037	48	124	-15.974**	17.006**	2.322	0.038	0.878	1.058	1.262	-0.017	0.033	0.090***

Note: The coefficients β_1 and β_2 are the ones for corn acres and their interaction with precipitation in equation (1). All regressions are estimated using the 48 weather-related controls, the fixed effects, and the time-related controls, in specification C8 in Table 3. The corn acres (acres) are in millions and the nitrogen concentration (N) is in mg/L. The precipitation measured in meters is total annual unless it is indicated otherwise (panel E). The runoff (measured in millimeters) is total annual. The models with fertilizer sales in panel B exclude 1986 due to data availability. The elasticities in the three rightmost columns are calculated using the quartiles of precipitation or runoff and the mean acreage and nitrogen concentration reported in the table. The standards errors are clustered by HUC4 except for the robustness checks in which we explore alternative clustering schemes. The asterisks denote statistical significance as follows: 1% (***), 5% (**), 10% (*). For additional details, see Section A.6.

Table 6. Additional estimates of corn acreage elasticities based on panel fixed-effect regressions (continued)

model	obs	sample starts	sample ends	counties	years	Clusters	coefficients β_1	coefficients β_2	mean nitrogen	mean acres	precipitation/runoff 25%	precipitation/runoff 50%	precipitation/runoff 75%	elasticities 25%	elasticities 50%	elasticities 75%
A. Baseline																
Baseline	64,121	1970	2017	2,232	48	124	-9.566**	13.517**	2.451	0.038	0.885	1.070	1.274	0.037	0.076**	0.118***
B. Nitrogen concentration accounting for streamflow and stream levels																
Downstream all L1	13,922	1971	2017	753	47	86	-16.085**	10.893**	1.803	0.026	0.916	1.091	1.290	-0.088	-0.060	-0.029
Downstream all L2	16,581	1970	2017	1,155	48	107	-10.587**	10.669**	1.873	0.038	0.920	1.084	1.277	-0.016	0.020	0.061
Downstream all L3	15,789	1971	2017	1,289	47	117	-26.341**	25.282**	1.813	0.043	0.882	1.061	1.257	-0.096	0.011	0.129**
Downstream all L4	8,667	1970	2017	977	48	112	-8.760	20.881**	1.755	0.045	0.838	1.033	1.231	0.226***	0.331***	0.438***
C. Include lagged acres																
1 lag	58,258	1970	2017	2,232	48	124	-8.307	13.331**	2.451	0.040	0.885	1.070	1.274	0.057**	0.097**	0.142**
2 lags	58,258	1970	2017	2,232	48	124	-6.713	13.516**	2.451	0.040	0.885	1.070	1.274	0.086*	0.126**	0.171**
3 lags	58,258	1970	2017	2,232	48	124	-6.451	13.774**	2.451	0.040	0.885	1.070	1.274	0.093*	0.135*	0.181*
D. Reporting limits in nitrogen concentration																
Reporting limit	64,670	1970	2017	2,232	48	128	-11.043**	15.602**	2.346	0.035	0.884	1.070	1.274	0.041	0.085***	0.133***
Zero	64,676	1970	2017	2,232	48	128	-11.276**	15.128**	2.157	0.035	0.884	1.070	1.274	0.034	0.081***	0.131***
E. Nitrogen concentration using alternative radii																
100 miles	80,612	1970	2017	2,242	48	124	-6.409**	9.943**	2.615	0.040	0.869	1.061	1.271	0.034	0.063***	0.094***
200 miles	85,359	1970	2017	2,243	48	124	-3.426**	6.379**	2.642	0.040	0.863	1.059	1.272	0.031*	0.050***	0.070***
F. Data filtering																
KS filter	64,096	1970	2017	2,232	48	124	-9.533**	13.651**	2.442	0.038	0.885	1.070	1.274	0.039	0.079**	0.122***
G. Alternative datasets and geographic scope (CONUS)																
USGS-NWIS	72,751	1970	2017	2,688	48	188	-10.446**	13.608**	2.418	0.035	0.814	1.038	1.256	0.009	0.053*	0.096***
USGS-NWQN	107,994	1970	2017	2,998	48	205	-10.862**	13.897**	2.200	0.026	0.798	1.049	1.278	0.003	0.043***	0.080***
USGS+EPA	113,372	1970	2017	3,027	48	205	-7.528**	14.386**	2.044	0.025	0.767	1.037	1.270	0.043**	0.091***	0.133***
H. Alternative data aggregation																
Hydrologic unit	17,943	1970	2017	986	48	128	-18.535**	21.895**	2.100	0.030	0.888	1.077	1.280	0.013	0.071*	0.134***
Monitoring site	56,466	1970	2017	9,596	48	129	-1.359**	1.566**	2.356	0.292	0.939	1.108	1.286	0.014	0.046*	0.081***
I. Statistical inference with alternative clustering schemes																
HUC2 x year	64,121	1970	2017	2,232	48	528	-9.566**	13.517**	2.451	0.038	0.885	1.070	1.274	0.037	0.076**	0.118***
HUC4 x year	64,121	1970	2017	2,232	48	5132	-9.566**	13.517**	2.451	0.038	0.885	1.070	1.274	0.037	0.076**	0.118***
year	64,121	1970	2017	2,232	48	48	-9.566**	13.517**	2.451	0.038	0.885	1.070	1.274	0.037	0.076*	0.118***

Note: The coefficients β_1 and β_2 are the ones for corn acres and their interaction with precipitation in equation (1). All regressions are estimated using the 48 weather-related controls, the fixed effects, and the time-related controls, in specification C8 in Table 3. The corn acres (acres) are in millions and the nitrogen concentration (N) is in mg/L. The precipitation (measured in meters) is total annual. The elasticities in the three rightmost columns are calculated using the quartiles of precipitation or runoff and the mean acreage and nitrogen concentration reported in the table. The standards errors are clustered by HUC4 except for the robustness checks in which we explore alternative clustering schemes. The asterisks denote statistical significance as follows: 1% (***), 5% (**), 10% (*). For additional details, see Section A.6.

Table 7. Projections of precipitation, moderate, and extreme heat degree days

source	year	precipitation 25%	precipitation 50%	precipitation 75%	moderate heat 25%	moderate heat 50%	moderate heat 75%	extreme heat 25%	extreme heat 50%	extreme heat 75%
A. Baseline										
Historical	1970-2017	0.885	1.070	1.274	1.700	2.149	2.695	0.150	0.415	0.854
CANESM5 SSP245	2018-2050	0.848	1.070	1.269	2.309	2.877	3.496	0.061	0.244	0.739
CANESM5 SSP585	2018-2050	0.852	1.078	1.289	2.395	2.960	3.593	0.071	0.301	0.812
GFDL-ESM4 SSP245	2018-2050	0.870	1.073	1.275	1.985	2.557	3.232	0.048	0.198	0.559
GFDL-ESM4 SSP585	2018-2050	0.866	1.062	1.251	2.016	2.590	3.265	0.052	0.213	0.615
UKESM1-0-LL SSP245	2018-2050	0.834	1.073	1.282	2.360	2.923	3.568	0.070	0.362	0.968
UKESM1-0-LL SSP585	2018-2050	0.838	1.047	1.242	2.411	2.989	3.633	0.116	0.488	1.342
B. Mississippi River Basin										
Historical	1970-2017	0.789	1.008	1.230	1.699	2.043	2.402	0.177	0.401	0.756
CANESM5 SSP245	2018-2050	0.695	0.963	1.203	2.278	2.705	3.151	0.055	0.234	0.716
CANESM5 SSP585	2018-2050	0.691	0.967	1.218	2.356	2.798	3.263	0.072	0.292	0.834
GFDL-ESM4 SSP245	2018-2050	0.720	0.980	1.208	1.928	2.369	2.818	0.033	0.146	0.452
GFDL-ESM4 SSP585	2018-2050	0.726	0.975	1.191	1.965	2.408	2.880	0.034	0.160	0.523
UKESM1-0-LL SSP245	2018-2050	0.673	0.960	1.199	2.308	2.725	3.170	0.058	0.296	0.813
UKESM1-0-LL SSP585	2018-2050	0.686	0.945	1.163	2.343	2.789	3.258	0.098	0.395	1.092
C. Northern states east of the 100th meridian										
Historical	1970-2017	0.801	0.940	1.087	1.421	1.642	1.887	0.061	0.142	0.286
CANESM5 SSP245	2018-2050	0.761	0.905	1.068	1.936	2.206	2.478	0.015	0.070	0.207
CANESM5 SSP585	2018-2050	0.767	0.907	1.074	1.979	2.281	2.590	0.018	0.084	0.243
GFDL-ESM4 SSP245	2018-2050	0.797	0.937	1.089	1.621	1.876	2.139	0.008	0.048	0.140
GFDL-ESM4 SSP585	2018-2050	0.793	0.927	1.069	1.649	1.911	2.176	0.008	0.050	0.137
UKESM1-0-LL SSP245	2018-2050	0.725	0.875	1.031	1.967	2.256	2.535	0.008	0.068	0.218
UKESM1-0-LL SSP585	2018-2050	0.731	0.883	1.019	1.992	2.305	2.612	0.021	0.109	0.296
D. Middle states east of the 100th meridian										
Historical	1970-2017	0.881	1.055	1.222	2.005	2.196	2.379	0.302	0.494	0.730
CANESM5 SSP245	2018-2050	0.848	1.066	1.215	2.622	2.856	3.058	0.106	0.307	0.711
CANESM5 SSP585	2018-2050	0.845	1.072	1.225	2.681	2.935	3.187	0.150	0.401	0.830
GFDL-ESM4 SSP245	2018-2050	0.868	1.076	1.244	2.305	2.542	2.752	0.089	0.249	0.536
GFDL-ESM4 SSP585	2018-2050	0.878	1.064	1.204	2.329	2.572	2.786	0.105	0.283	0.565
UKESM1-0-LL SSP245	2018-2050	0.866	1.079	1.216	2.650	2.894	3.107	0.156	0.445	0.817
UKESM1-0-LL SSP585	2018-2050	0.857	1.057	1.189	2.682	2.960	3.197	0.249	0.617	1.160
E. Southern states east of the 100th meridian										
Historical	1970-2017	1.111	1.279	1.475	2.673	3.000	3.368	0.636	0.991	1.414
CANESM5 SSP245	2018-2050	1.072	1.253	1.438	3.354	3.693	4.058	0.232	0.628	1.377
CANESM5 SSP585	2018-2050	1.082	1.275	1.468	3.427	3.788	4.177	0.270	0.676	1.372
GFDL-ESM4 SSP245	2018-2050	1.047	1.243	1.433	3.090	3.435	3.813	0.235	0.535	1.139
GFDL-ESM4 SSP585	2018-2050	1.047	1.233	1.401	3.110	3.471	3.853	0.256	0.604	1.370
UKESM1-0-LL SSP245	2018-2050	1.123	1.298	1.460	3.435	3.758	4.120	0.503	1.024	1.675
UKESM1-0-LL SSP585	2018-2050	1.074	1.253	1.436	3.480	3.808	4.184	0.601	1.382	2.227

Note: We report quartiles of total annual precipitation, moderate-heat, and extreme-heat degree days based on projections from 3 climate models (UKESM1-0-LL, CANESM5, and GFDL-ESM4) and two shared socioeconomic pathways (SSPs), namely 245, 585, for 2018–2050. We also report quartiles based on historical data for 1970–2017. The precipitation is total annual and it is measured in meters. The moderate heat is measured in 1,000 degree days between 10°C and 29°C. The extreme heat is measured in 100 degree days above 29°C. We use baseline to refer to counties east of the 100th meridian excluding Florida. We classify states as northern, middle, and southern following Schlenker and Roberts (2009). For additional details, see Section 7.

Table 8. Marginal effects of corn acreage on nitrogen concentration
alternative climate models & SSPs

model & SSP	year	P25%	P50%	P75%	ME25%	ME50%	ME75%
A. Baseline							
Historical	1970-2017	0.885	1.070	1.274	0.025	0.051	0.080
CANESM5 SSP245	2018-2050	0.848	1.070	1.269	0.020	0.051	0.080
CANESM5 SSP585	2018-2050	0.852	1.078	1.289	0.020	0.053	0.083
GFDL-ESM4 SSP245	2018-2050	0.870	1.073	1.275	0.023	0.052	0.081
GFDL-ESM4 SSP585	2018-2050	0.866	1.062	1.251	0.023	0.050	0.077
UKESM1-0-LL SSP245	2018-2050	0.834	1.073	1.282	0.018	0.052	0.082
UKESM1-0-LL SSP585	2018-2050	0.838	1.047	1.242	0.018	0.048	0.076
B. Mississippi River Basin							
model & SSP	year	P25%	P50%	P75%	ME25%	ME50%	ME75%
Historical	1970-2017	0.789	1.008	1.230	0.018	0.056	0.095
CANESM5 SSP245	2018-2050	0.695	0.963	1.203	0.001	0.048	0.090
CANESM5 SSP585	2018-2050	0.691	0.967	1.218	0.000	0.048	0.092
GFDL-ESM4 SSP245	2018-2050	0.720	0.980	1.208	0.005	0.051	0.091
GFDL-ESM4 SSP585	2018-2050	0.726	0.975	1.191	0.006	0.050	0.088
UKESM1-0-LL SSP245	2018-2050	0.673	0.960	1.199	-0.003	0.047	0.089
UKESM1-0-LL SSP585	2018-2050	0.686	0.945	1.163	-0.001	0.045	0.083
C. Northern states east of the 100th meridian							
model & SSP	year	P25%	P50%	P75%	ME25%	ME50%	ME75%
Historical	1970-2017	0.801	0.940	1.087	0.002	0.032	0.063
CANESM5 SSP245	2018-2050	0.761	0.905	1.068	-0.007	0.024	0.059
CANESM5 SSP585	2018-2050	0.767	0.907	1.074	-0.006	0.024	0.060
GFDL-ESM4 SSP245	2018-2050	0.797	0.937	1.089	0.001	0.031	0.064
GFDL-ESM4 SSP585	2018-2050	0.793	0.927	1.069	-0.000	0.029	0.059
UKESM1-0-LL SSP245	2018-2050	0.725	0.875	1.031	-0.015	0.017	0.051
UKESM1-0-LL SSP585	2018-2050	0.731	0.883	1.019	-0.014	0.019	0.049
D. Middle states east of the 100th meridian							
model & SSP	year	P25%	P50%	P75%	ME25%	ME50%	ME75%
Historical	1970-2017	0.881	1.055	1.222	0.144	0.134	0.125
CANESM5 SSP245	2018-2050	0.848	1.066	1.215	0.146	0.133	0.125
CANESM5 SSP585	2018-2050	0.845	1.072	1.225	0.146	0.133	0.124
GFDL-ESM4 SSP245	2018-2050	0.868	1.076	1.244	0.145	0.133	0.123
GFDL-ESM4 SSP585	2018-2050	0.878	1.064	1.204	0.144	0.133	0.126
UKESM1-0-LL SSP245	2018-2050	0.866	1.079	1.216	0.145	0.133	0.125
UKESM1-0-LL SSP585	2018-2050	0.857	1.057	1.189	0.145	0.134	0.126
E. Southern states east of the 100th meridian							
model & SSP	year	P25%	P50%	P75%	ME25%	ME50%	ME75%
Historical	1970-2017	1.111	1.279	1.475	-0.030	-0.024	-0.017
CANESM5 SSP245	2018-2050	1.072	1.253	1.438	-0.031	-0.025	-0.018
CANESM5 SSP585	2018-2050	1.082	1.275	1.468	-0.031	-0.024	-0.017
GFDL-ESM4 SSP245	2018-2050	1.047	1.243	1.433	-0.032	-0.025	-0.018
GFDL-ESM4 SSP585	2018-2050	1.047	1.233	1.401	-0.032	-0.025	-0.020
UKESM1-0-LL SSP245	2018-2050	1.123	1.298	1.460	-0.029	-0.023	-0.017
UKESM1-0-LL SSP585	2018-2050	1.074	1.253	1.436	-0.031	-0.025	-0.018

Note: For each climate model and SSP combination, we report precipitation (P) quartiles and marginal effects (MEs) calculated assuming an increase in corn acreage equal to 1 within-county standard deviation using the appropriate set of counties in each panel. For comparison, we show MEs calculated using data for 1970–2017. The precipitation is total annual and it is measured in meters. In panel A, the MEs are in mg/L and they are calculated using specification C8 in of the panel fixed-effect (FE) regressions in Table 3. In panels B–E, the MEs are also in mg/L and they are calculated for the same specification of the panel FE regressions estimated using counties in the Mississippi River Basin, and the northern, middle, and southern states following the classification in Schlenker and Roberts (2009). For additional details, see Section 7.

A Appendix

A.1 Nitrogen pollution damages and abatement costs

In this section, we discuss in more detail studies related to nitrogen pollution damages and abatement costs that are summarized in Table 1 of the main text. We also discuss some additional studies.

Taylor and Heal (2021) estimate the economic effects of U.S. algal blooms generated by nitrogen fertilizers excluding health effects, which, according to the authors, can be viewed as lower bounds for the external costs of the fertilizers. Based on their estimates, 1 ton of nitrogen entails an external (damage) cost of \$583 (they also report the range \$370–\$1,400) to downstream coastal counties. Blottnitz et al. (2006) estimate damage costs of nitrogen fertilizer equal to €0.3 per kg (see their Table 2) that is about 60% of the market price of fertilizer (farmers' private cost) at the time. Damages pertain to global warming due to the production of fertilizer, damages due to air pollutants emitted during the production of fertilizer, global warming due to the application of fertilizer, eutrophication due to leaching of fertilizer, and damages due to to the release of volatile substances from fertilizer.

Sobota et al. (2015) compile damages from specific nitrogen inputs from Compton et al. (2011) and Van Grinsven et al. (2013b) per kg of nitrogen input (see their Table 1). They provide damages for air/climate, land, freshwater, drinking water, and coastal zones. The damages from coastal nitrogen loadings (\$2008), which are relevant for some analysis in this paper, are due to recreational use (\$6.38), and declines in fisheries and estuarine/marine habitat (\$15.84). The damages from recreational use are for the Chesapeake Bay and are from Figure 2 in Birch et al. (2011). Van Grinsven et al. (2013a) provide a range of damages from nitrogen pollution that account for human health, ecosystems, and climate from nitrogen for E.U. 27 in 2008 (see their Table 2). The range of the total damages attributed to nitrogen loss to rivers and seas from agricultural sources is €25–100 billion per year. The damages of €25–100 billion per year implies damages of €4.11–16.43 per lb of nitrogen using $0.6 \times 4.6 = 2.6$ million tons of nitrogen attributed to agricultural sources. At an exchange rate of about \$1.5/€in 2008, we have damages of 6.05–24.20 per lb of nitrogen in \$2008.

UCS (2020) found that, on average, 87,000 tons of excess nitrogen (per year) have washed off Midwest cropland into the Mississippi and Atchafalaya rivers, and ultimately into the Gulf of Mexico (GoM). This nitrogen has contributed between \$552 million and \$2.4 billion (\$2018) of damages to ecosystem services generated by fisheries and marine habitat every year during 1980–2017. Ho et al. (2019) argue that freshwater algal blooms result in damages of more than \$4 billion annually in the U.S. alone (citing Kudela et al. (2015)), primarily due to harm to aquatic food production, recreation and tourism, and drinking water supplies. Dodds et al. (2009) calculate potential annual value losses in recreational water usage, waterfront real estate, spending on recovery of threatened and endangered species, and drinking water, due to nutrient pollution and the resulting eutrophication in U.S. freshwaters. The combined damages are approximately \$2.2 billion annually. In an early paper, Anderson et al. (2000) discuss annual economic impacts from harmful U.S. algal blooms. The estimates (\$2000) are for 1987–1992 and pertain to public health, commercial fishery, recreation & tourism, and monitoring management. Their low, average, and high estimates of the 15-year capitalized impacts are: \$309 million, \$449 million, and \$743 million, respectively (see also GOMNTF (2015)).

Averted damages and abatement costs. Xu et al. (2021) use an integrated assessment model (IAM) to evaluate the effects of energy and nitrogen fertilizer prices on nitrogen runoff to the GoM and to assess abatement costs. They find that changes in energy costs have a modest impact on land-use change and nitrogen runoff, while the price of nitrogen fertilizer has a more notable effect on acreage and nitrogen delivery to the GoM. The cost of achieving the GoM Hypoxia Task Force goal of nitrogen reduction is \$6 billion, which corresponds to the average cost of \$29.3 per kg of nitrogen runoff abatement.

UCS (2020) show how improved agricultural practices in the Midwest can offer economic benefits to the GoM fishing industry. Their findings are based on nitrogen-loss reduction scenarios achieved through changes in agricultural practices, derived from four previously published studies (NRCS (2017a), Kling et al. (2014), Rabotyagov et al. (2014a), and Tallis et al. (2019)). Their calculations show that 98 million to 2.8 billion (\$2018) in damages to Gulf fisheries and marine habitat could have been averted every year from 1980–2017 through shifts in agricultural practices (see their Figure 5 and Appendix 3 for details). Moreover, reductions in the May GoM nitrogen loading of the Mississippi and Atchafalaya rivers due to shifts in agricultural practices upstream ranged from just over 5% to 45%.

Tallis et al. (2019) analyze 5 financial mechanisms to increase adoption of beneficial practices in the Mississippi River Basin (MRB) aiming to reduce GHG emissions and nutrient runoff in Iowa, Illinois, Indiana, and Ohio. They estimate the nutrient runoff savings and the associated costs.[25] The 5 mechanisms could save up approximately 168,000 tons of nutrient runoff each year, which

[25] Examples of beneficial practices considered include cover crops, nutrient management, land retirement, conservation tillage, and sub-surface tile management. The five mechanisms are: crop insurance incentives, increased private technical services, expansion and redistribution of Farm Bill funds, creation of new state funds, redirection of federal disaster funds. In general, nutrient management costs include annualized installation and implementation costs, and foregone income associated with changes in crop yields net of savings from reduced commercial fertilizer purchases.

is equivalent to a 25% reduction (see their Table 1). This reduction exceeds the intermediate HTF target (20% reduction by 2025) and achieves more than half of the long-term HTF target (45% reduction). The reductions could be achieved at a cost of about $15 per kg of nitrate reduced for a total cost of $2.6 billion.

Marshall et al. (2018) model changes that would achieve the 45% reduction in nitrogen and phosphorous loads from cropland to the GoM at least cost to consumers and producers using 2 implementation scenarios, the USDA REAP model, and data from the USDA CEAP.[26] In the Gulf Constraints (GC) scenario, the objective is to reduce overall nutrient loads regardless of where they originate. In the Regional Constraints (RC) scenario, they require a 45% reduction in nutrient loads in each of the 135 REAP regions in the MRB. The study aims to identify the combination of conservation practices, crop rotations, tillage, irrigation, and land-use change that meets nutrient-reduction goals at least cost.

Under the GC scenario, domestic consumer surplus, falls an estimated 2.5%, or $1.9 billion relative to the baseline case. Under the RC scenario, consumer surplus drops an estimated 4.4%, or $3.3 billion. These dollar amounts do not account for benefits to the consumers due to improvements in water quality. Under the GC scenario, meeting a 45% nutrient-reduction goal at the Gulf is estimated to increase producer net returns within the MRB by 1.3%, or $847 million. The RC scenario, on the other hand, decreases producer net returns by 0.4% or $264 million. Hence, depending on the scenario, the reduction of 3,305 square miles in the average size of the summer hypoxic zone is at a cost between $1.053 (GC) and $3.564 (RC) billion. The implied cost is $123,015 per square kilometer (GC) to $416,358 per square kilometer (RC), which is of the same order of magnitude of the cost in Rabotyagov et al. (2014a) discussed below.

McLellan et al. (2016) use the SPARROW model to explore the downstream water quality impacts for a set of agricultural conservation and landscape restoration practices in the Upper Mississippi Ohio River basins (UMORB). Their modeling aims to identify scenarios (types and levels of practice implementation at various locations throughout the UMORB) capable of achieving the HTF target of 45% reduction in nitrogen loads delivered to the UMORB outlet at Cairo, Illinois. The authors consider adaptive nitrogen management (ANM) on 25% of the land in the UMORB, and cover crops on 20% of the land in the UMORB excluding Minnesota and Wisconsin. They then vary the levels and locations of implementation of the buffer, wetland, and stream practices, as needed to achieve a 45% reduction in nitrogen loads at the UMORB outlet. The annualized costs of implementing the proposed restoration scenario is about $1.48 billion in their Table 5 with a detailed breakdown provided in their Table 4.

[26] To give some context, this is the reduction required to limit the average size of the summer hypoxic zone in the Gulf from 5,236 square miles (13,561 square kilometers) to 1,931 (5,000 square kilometers, 5-year moving average).

Whittaker et al. (2015) use the SWAT model to simulate the reduction in nitrogen loads in the Upper Mississippi River Basin (UMRB) that would result from enrolling all row crop acreage in the USDA CRP. Nitrogen loads at the outlet of the UMRB are used to predict the areal of the hypoxic zone, and net cash farm rent is used as the price for participation in CRP.[27] Over the course of the 42-year (1960–2001) simulation, the direct CRP costs are more than \$388 billion (\$9.25 billion annually), and the assumed HTF goal (5-year moving average) of hypoxic area less than 5,000 square kilometers is met in only 2 years (see their graphical abstract).

In Rabotyagov et al. (2014a), a reduction of about 60% in the areal extent of the hypoxic zone in the GoM is required to achieve the goal of 5,000 square kilometers at a cost of \$2.7 billion per year using the HUMUS-CEAP model. Hence, the abatement cost is equal to $(2.7 \times 10^9)/7{,}500 =$ \$360,000 per square kilometer per year—a 60% reduction in 12,500 square kilometers implies 5,000 square kilometers. The reduction requires investment on approximately 178,000 square kilometers of cropland implying an average cost of \$62 per acre of cropland.

Kling et al. (2014) use the LUMINATE IAM combining SWAT with a land-use economic model (see their Figure 2) to analyze the costs and benefits of cover crop scenarios in the UMRB and the Ohio-Tennessee River Basin (OTRB).[28] The cover crop scenario in the paper consists of planting rye within the typical 2-year rotations of corn and soybeans or continuous corn, in which the rye cover crop was planted in the fall after corn or soybean harvest and then harvested shortly before planting of the following row crop in the spring. Based on the assumed costs of cover crop adoption from \$61.8–\$86.6 per hectare (\$25–\$35 per acre), the abatement cost of a kg of nitrogen is \$12.02–\$17.10 for the UMRB and \$7.74–\$10.88 for the OTRB (see their Table 4).

Compton et al. (2011) provide abatement costs for reducing nitrogen from various sources and from integrated projects (Table 3). The abatement cost for agriculture is \$10 per kg of nitrogen. The abatement cost for agricultural drainage water is \$2.71 per kg of nitrogen. Both of these abatement costs are from Birch et al. (2011). As a benchmark, the price of nitrogen fertilizer (private cost to the farmers), was 0.44 per kg of nitrogen from 1980—2000 and it was 1.21 per kg of nitrogen in 2008. Birch et al. (2011) report marginal abatement cost per ton of reactive nitrogen by source in 2000 in the Chesapeake Bay watershed. In the case of nitrate nitrogen from agriculture, the abatement cost per ton of reactive nitrogen is 10,000 according to their Table 2.

USEPA (2001) reports a range of TMDL implementation costs from under \$1 billion per year

[27] Although the CRP average price at the county level is available, where a large part of land goes into the CRP, the authors argue that the average cash rent price (for non-irrigated cropland) is a better estimate.

[28] As the authors discuss, winter cover crops including rye, oats, winter wheat or other close grown crops, are used in the Corn belt region to maintain and improve the quality of soil resources, and mitigate export of sediment and nutrients from cropland landscapes.

to \$4.3 billion per year depending on the efficiency of the TMDLs in Table ES-1. The table breaks down the costs by type of source (point and non-point). Table IV-1 shows leading causes of impairment—nutrients account for 11.5%—and leading sources of impairment (agriculture accounts for 24.6%) based on the States' 303(d) lists in 1998.

Ribaudo et al. (2001) analyze the cost effectiveness of intercepting nitrogen through wetland restoration of 0.4, 2.0, 4.0, and 7.0 million hectares (equivalently, 1, 5, 10, 18 million acres) targeted to maximize nitrogen reductions in the MRB using the USMP market equilibrium and the EPIC biophysical models. Restoring 1 million acres of wetlands was estimated to remove 97,000 tons of nitrogen from field runoff per year (see their Table 1). The welfare cost is \$1,022 million and the net welfare cost is \$468 million (equivalently, $(468 \times 10^6)/97{,}000 = \$4{,}824$ per ton of nitrogen removed). The cost per ton when restoring 5, 10, and 18 million acres is \$3,651, \$4,062, and \$4,620, respectively. Expressed in dollars per lb of nitrogen removed, the cost is \$1.7–\$2.2 depending on the wetland acreage. Expressed in dollars per acre of wetland, the cost of nitrogen removed is \$345–\$468. Assuming that these costs are expressed in \$2000 (it is not clear from the paper, hence, based on the year of publication), when expressed in \$2017 they would be close to 40% higher taking into account only the inflation (GDP implicit price deflator).[29]

Finally, in one of the earliest studies we are aware of, Doering et al. (1999) analyze the costs of the following nitrogen loss reduction strategies in the MRB: (1) EoF nitrogen loss reductions of 20%–60% through economically optimum actions; (2) fertilizer reductions of 20% and 45%, (3) 500% increase in fertilizer tax; (4) wetland acreage of 1–18 million acres (assuming filtering capacity of 15 grams of nitrogen per square meter per year); (5) 27 million acres acres of riparian buffers assuming filtering of 4 grams of nitrogen per square meter per year (equivalently, $4{,}046.86 \times 4/1{,}000 \approx 16.2$ tons per acre per year). The analysis is based on the USDA ERS USMP economic model coupled with the EPIC biophysical model (see Section 4.1 of Topic 6) using the 1997 USDA Economic Baseline and the 1992 NRI and is summarized in their Table 6.1. Depending on the loss reduction strategy, Doering et al. report net social costs of $-\$0.1$ (hence, savings are possible) to \$17.95 billion.

[29] According to the note in Table 2 of the paper, welfare costs include changes in consumer and producer surpluses plus wetland restoration costs. Government costs include restoration and easement costs. Net welfare costs include producer and consumer surplus, wetland restoration costs, erosion benefits, and wetland benefits. Government costs are shown for information only, and are already included under welfare costs. The cost of wetland restoration consists of permanent easement and restoration. Easement costs equal the full opportunity costs of removing productive cropland from production. Restoration costs are the one-time cost of converting cropland back into a functioning wetland. Landowners participating in wetland restoration sell a conservation easement to the government to restore and protect wetlands. The landowner and the NRCS develop a plan for the restoration and the maintenance of the wetland. The government pays for the easement and 100% of the costs of restoring the wetland.

A.2 Water Quality Portal Data

In this section, we provide some additional details regarding the data from the Water Quality Portal.

Table A2 shows that the split of surface- and ground-water monitoring sites is roughly 96% and 4%. According to Table A3, 94% of the activities are routine samples. Table A4 shows that approximately 14% of the nitrogen data are subject to censoring. In more detail, the reported value for nitrogen concentration is less than or equal to a historical lower reporting limit. The hydrologic event is equal to routine sample for about 88% of the data. Setting aside storms (5.6%), no other hydrologic event accounts for more than 3% of the data (Table A5). Finally, 98% of the result value measurements are actual with the remaining 2% being estimates (Table A6).

Table A7 shows a breakdown of the nitrogen data by decade keeping in mind that the 2010s stop in 2018. There is a steady decline in the number of monitoring sites, counties, and 8-digit hydrologic units. The decrease is more notable in 2010s and seems to be rather unlikely that the smaller number of years explain the decrease. For example, the number of monitors drops from about 12,700 in the 1970s to about 4,400. We also see a drop in the number of counties and 8-digit hydrologic units from 1,653 (1,334) to 871 (690). The drop in coverage across multiple dimensions documented here is consistent with the findings in Sprague et al. (2017).

Table A8 shows a breakdown of the nitrogen data by site type following the categories in Read et al. (2017). Stream (84%) and lake (8%) site types account for about 92% of all observations. No other site type accounts for more than 3.8%, which is the case of well sites.

Table A9 shows alternative calculations of nitrogen concentration based on parameter codes we identified in the technical information regarding the data and graphics on the U.S. Geological Survey National Water-Quality Assessment annual reporting Web site. These alternative calculations are based on sums of alternative parameter codes. As the table shows, our calculation of nitrogen concentration is essentially identical to those alternative ones.

A.3 Total Nitrogen Calculation using the USGS NWQN Methods

In this section, we describe the approach we followed to construct what we call the USGS-NWQN data for which the calculation of total nitrogen follows the NWQN methodology described here.

The steps for collecting the data associated with the relevant parameter codes are as follows. First, we downloaded the data from the WQP portal using web service calls based on parameter codes. Second, We limited the data to years 1970–2018 and to those for which the activity media name field is “water” and the activity media subdivision name field is “surface water” or “groundwater.” Finally, we excluded data with for which the organization identifier field is “usgs-ak,” “usgs-hi,” and “usgs-pr.”

We converted mg/L of nitrate or nitrite to mg/L of nitrogen following the NWQN methods. For the parameter codes 71850 and 71851, we multiplied the concentrations (result values) by 0.2259. For the parameter code 71856, we multiplied the concentrations by 0.3045. We calculated dissolved NO_3+NO_2 (nitrate plus nitrite) concentrations following the NWQN methods. Among the parameter codes used in these calculations, parameter code 00631 accounted for 51% of the observations for dissolved nitrate plus nitrite concentrations. Parameter code 00630 accounted for 29% of the observations for dissolved nitrate plus nitrite concentrations, and parameter code 00618 accounted for 13% of the observations. Parameter code 00620 accounted for 5% of the observations while the rest of the parameter codes accounting for the remaining 2% of the observations.

We calculated total organic nitrogen plus ammonia concentrations following NWQN methods. Parameter code 00625 accounted for 93% of the observations. Parameter codes 00605 and 00608 accounted for 5% of the observations, and parameter codes 00605 and 00610 for the remaining 2% of the observations.

We calculated total nitrogen concentrations using the following NWQN methods:

- Method 1: dissolved NO_3+NO_2 + total organic nitrogen plus ammonia (638,135 obs)
- Method 2: dissolved NO_3+NO_2 + 00623+45970 (19,818 obs)
- Method 3: 62854+45970 (16,542 obs)

Once we completed the steps described above, parameter code 00600 accounted for 91% of the observations for nitrogen concentrations. NWQN Method 1 accounted for the remaining 9% of the observations. In all, using imputed nitrogen concentrations following the NWQN methodology allowed us to have a sample of 681,313 obs while using parameter code 00600 allowed to have a sample of 620,816 observations, which is an increase of 9.7% in the number of observations; see Table A10.

A.4 Alternative Calculations of Total Nitrogen Concentration

For the USGS-NWIS data discussed in the main text, we use the USGS parameter code 00600. We accessed the data from the WQP portal using web service calls based on this parameter code.

Subsequently, we limited the data to those for the CONUS for which the activity media name is "water" and the activity media subdivision name is "surface" or "groundwater." Finally, we excluded observations for which the nitrogen concentration was negative or exceeded 50 mg/L.

For the USGS+EPA data, we used the NWIS parameter codes 00600, 71887, and 62855 in the case of the USGS data. Subsequently, we limited the data to those for the CONUS for which the activity media name is "water" and the activity media subdivision name is "surface" or "groundwater." Finally, we excluded observations for which the nitrogen concentration was negative or exceeded 50 mg/L. In the case of EPA STORET data, we limited the data to those for CONUS for which the activity media name is "water". We also limited the data to those for which the result measure unit code is "mg/L" or "μ g/L." and the characteristic name is one of the following: (i) nitrogen, mixed forms (nh3), (nh4), (ii) organic, (no2) and (no3), (iii) nutrient-nitrogen, (iv) total nitrogen, mixed forms, and (v) total nitrogen, mixed forms (nh3), (nh4), organic, (no2) and (no3).

A.5 Cross-Section Regressions

We estimate year-specific OLS regressions of the form:

$$y_{it} = \delta_i + \beta_1 a_{it} + \beta_2 a_{it} p_{it} + \mathbf{z}'_{it}\gamma + \varepsilon_{it}. \tag{A1}$$

We also estimate a "between" model using OLS regressions of the form:

$$\bar{y}_i = \delta_i + \beta_1 \bar{a}_i + \beta_2 \overline{a_i p_i} + \overline{\mathbf{z}'}_i \gamma + \varepsilon_i. \tag{A2}$$

Following our earlier notation, we use δ_i to denote various spatial FEs such as state FEs, and FEs for hydrologic units of different size. The between model in equation (A2), which allows us to assess longer-term impacts of agriculture on nitrogen pollution than the panel FE regression discussed earlier, resemble models used in hydrology (e.g., David et al. (2010)), and the Ricardian approach in accessing agricultural damages due to climate change (e.g., Mendelsohn et al. (1994)) taking into account adaptation. The similarity with the hydrology models is mainly due to the cross-sectional nature of the regressions and the controls considered keeping in mind that the hydrology models tend to employ nonlinear specifications often aiming to identify factors that best describe variation in nitrogen pollution as opposed to estimating causal effects.

The validity of the cross-section approach hinges on the assumption that there are no omitted variables correlated with both planting decisions and pollution that our spatial FEs fail to account for, in which case our estimates will be biased; a classical example of omitted variable bias (OVB).

For example, if counties that grow a lot of corn also tend to adopt more conservation efforts that our spatial FEs fail to account for, our cross-section regressions will be understating the true effect of acreage on nitrogen pollution. Numerous of our robustness checks in a subsequent section involve additional controls aiming to alleviate such OVB-related concerns.

We show our year-specific and between elasticity estimates based on the cross-section regressions using data for 1975–2017 in Figure A1. Our year-specific elasticities are based on equation (A1). Their between counterparts are based on equation (A2). Hence, we report 43 year-specific estimates and a single between estimate. We start our analysis in 1975 as opposed to 1970 due to the small number of observations in the early years of our sample for the year-specific regressions.[30]

We use the 6 panels to report results from two specifications that differ in the set of spatial FEs included: no spatial FEs (panels A–C), and HUC4 FEs (panels D–F). We also experimented with HUC2 and state FEs and obtain results that are very similar to those using HUC4 FEs. All specifications contain the same 48 weather controls and an interaction of acres with total annual precipitation as in panel C of Table 3. The standard errors are clustered at the HUC4 level. The reader should keep in mind the substantial variation in the number of counties when we discuss our year-specific estimates. In particular, the year-specific estimates are based on 802–1,915 counties depending on the year noting that there is a downward trend in the number of observations over time.

The vast majority of the elasticities are significant at conventional levels in the absence of spatial FEs without exhibiting a clear pattern, such as an upward or downward trend, over time. Depending on the precipitation quartile, the between elasticities are 0.141–0.332. They are of similar magnitude to those reported in column C1 of Table 3, which makes sense because that model excludes county FE and therefore identifies coefficients using cross-sectional variation. Their year-specific counterparts are 0.045–0.280 (first quartile), 0.075–0.303 (median) and 0.078–0.412 (third quartile). In the presence of HUC4 FEs, the between estimates are 0.096–0.202 and are somewhat smaller than those in the absence of spatial FEs. The year-specific elasticities are now 0.032–0.153 (first quartile), 0.063–0.206 (median), 0.062–0.326 (third quartile).[31]

[30]The 6 panels in the figure show elasticity estimates along with 95% CIs based on the same calculations as in the case of the panel FE regressions, namely using the mean concentration, mean acreage, and appropriate precipitation quartiles, all of which vary across years. In other words, the difference between the elasticities reported in the bottom of panel C of, say, Table 3 and the elasticities shown in Figure A1 is due to coefficient estimates, as well as summary statistics of the relevant components of the elasticity calculation. The same holds when we compare the elasticities in, say, 1980, to the elasticities in, say, 1995 in Figure A1.

[31]For the specifications without spatial FEs, all 48 weather-related controls are jointly significant in the case of the between regression. They are also jointly significant for the vast majority of the year-specific regressions. In the presence of HUC4 FEs, the 24 precipitation-related controls fail to be significant at conventional levels in the case of the between regression. Their moderate- and extreme-heat counterparts, however, are jointly significant. All 48 weather-related controls are jointly significant for most of the year-specific regressions.

A.6 Additional estimates

In the case of the panel FE regressions, we control for other sources of nitrogen pollution (economic activity, fossil-fuel combustion, atmospheric deposition, animal manure, point sources), as well as agricultural best management practices. We also control for the acres of other major crops (e.g., soybeans), acres enrolled to the Conservation Reserve Program, and fertilizer sales. Additionally, we explore heterogeneous effects exploring temporal (by decade) and spatial variation (e.g., counties in the MRB) in acreage effects, and alternative time windows (e.g., during the corn growing season) for the measurement of nitrogen concentration. Moreover, we interact corn acres with runoff as opposed to precipitation and we use alternative measures of nitrogen concentration accounting for streamflow (downstream monitoring sites) and stream levels. Furthermore, we examine the role of crop uptake by interacting corn acreage with heat and yield shocks and the idea that long-run acreage may matter more than its annual fluctuation. In addition, we explore the role of censoring in the measurement of nitrogen concentration and alternative data filters used in Keiser and Shapiro (2018). We use alternative datasets (e.g., EPA data from STORET) and extend the geographic scope of our analysis to the CONUS, we employ a flexible modeling of the interaction of acres and precipitation (splines), and alternative radii (100 and 200 miles) for the measurement of nitrogen pollution. We employ different data aggregation schemes performing monitoring-site- and hydrologic-unit-centric analyses. Finally, we perform statistical inference using alternative clustering schemes.

Discussion. Similar to the baseline results, the coefficient of the interaction of corn acreage and precipitation (coefficient β_2 in equation (1)) is positive and highly significant in the vast majority of the models we explored. Hence, the amount of precipitation matters for the magnitude of the estimated acreage elasticities. With very few exceptions, the corn acreage elasticities based on the second and third precipitation quartiles are highly significant. Their counterparts based on the first precipitation quartile are not. For the second precipitation quartile, the elasticities that are significant at conventional levels are 0.043–0.331. Their counterparts for the third precipitation quartile are 0.059–0.438. As a reminder, for our preferred baseline specification in column C8 of Table 3, the acreage elasticities are 0.076 and 0.118 for the second and third precipitation quartiles.

The acreage elasticity estimates are very similar for the specifications that include Bureau of Economic Analysis (BEA) series that vary by state and year aiming to control for overall economic activity that also contributes to nitrogen pollution; see models M1 and M2 in Table 4. Their counterparts for the specifications that include BEA series exhibiting variation by county and year (M3) are larger. Adding fuel consumption—an additional source of nitrogen pollution—from the Energy Information Administration State Energy Data System (EIA-SEDS) to the specifications has a very small effect on the magnitude of these elasticities (M4–M6). The specifications for which the beginning of our sample shifts to the mid 1990s and the number of observations drops from about 64,000 to somewhere between 24,000 (M7–M9, M12) or 33,500 (M10 and M11), imply elasticities that are not significant at conventional levels. We should note, however, that the main driver behind this finding is the shorter sample size and not the additional controls.[32] The specification with controls from the TREND nitrogen dataset of Byrnes et al. (2020) imply elasticities that are somewhat larger than their baseline counterparts. The elasticities that are significant at conventional levels and are based on the second precipitation quartile are between 0.075 and 0.164. Their counterparts based on the third precipitation quartile are 0.117–0.223. The high end of these elasticities are from a model where we also control for economic activity using data from the BEA regional economic accounts, fossil-fuel consumption from the EIA-SEDS, and nitrogen yields from waste water treatment plants (see model M13 in Table 4).

As Table 5 and Table 6 show, in the case of median precipitation, the elasticities are not significant at conventional levels in the following instances: (i) when we control for CRP acres and the acres of other major crops, (ii) when we explore temporal (1970s, 1990s, and 2010s) and spatial variation (MRB, northern states, southern states), (iii) when we consider alternative time windows during the year to track nitrogen concentration (all windows), (iv) when we use downstream monitoring sites (both on the mains stems and all tributaries), (v) when we use downstream monitoring sites located in rivers and streams of levels 1–3 (SL1–SL3). The range of the elasticities that are significant at conventional levels is 0.043–.0.331. We see the largest effect of corn acreage on nitrogen concentration tracked in downstream monitoring sites located in SL4 rivers and streams (see Downstream SL4 in Table 6). For the third precipitation quartile, the elasticities are not significant at conventional levels in the following instances: (i) when we explore temporal variation (1970s, 1990s, 2010s), (ii) when we explore spatial variation (northern states, southern states), and (iii) when we use downstream monitoring sites SL1 and SL2 rivers and streams. The range of the elasticities that are significant at conventional levels is 0.059–0.438.

A.6.1 Panel fixed-effect regressions: additional controls

In this section, we discuss a series of additional controls related to economic activity, fossil fuel combustion, atmospheric deposition, animal manure, point sources of nitrogen pollution, agricultural management practices, tillage, and drainage for the estimates reported in Table 4. In what follows, we discuss the rationale behind these additional controls and data sources.

[32] Our elasticities are either highly similar or smaller to the ones reported here when we use the shorter samples but we exclude the additional controls.

Economic activity. We use the BEA series SAEMP25 (total employment, number of jobs) and SAGDP2 (GDP by state, all industry total) to control for economic activity as a potential source of nitrogen pollution (e.g., urban non-point pollution). Both series exhibit variation by state and year. We also use three BEA series that exhibit variation by county and year, namely, CAINC30110 (per capita personal income, dollars), CAINC45190 (fertilizer and lime, incl. ag. chemicals 1978-fwd.), and CAINC45370 (farm earnings). The last economic series used to control for economic activity is the county-level monthly unemployment rate from the BLS Local Area Unemployment Statistics, which starts in 1990. We deflate all dollars using the GDP deflator.

Fossil-fuel combustion. We consider controls related to nitrogen pollution from fossil fuels. Fossil-fuel combustion releases nitrogen into the atmosphere, which is then redeposited on land and water through the water cycle—rain and snow. The first control is fossil-fuel consumption from the EIA State Energy Data System that exhibits variation by state and year. The second control is NO_x emissions from fuel combustion (electric utilities, industrial, and other) from the EPA Air Pollutant Emissions Trends data. The data on NO_x emissions exhibit variation by state and year and are available beginning in 1996.

Atmospheric deposition. Atmospheric deposition is a significant non-point source of nitrogen pollution (e.g., see Alexander et al. (2008) and Robertson and Saad (2006), among others). To control for atmospheric deposition, we use annual county level data on atmospheric deposition (kilograms of nitrogen per hectare per year) from Byrnes et al. (2020).

Animal manure. Animal manure can be a significant source of nitrogen and other nutrients needed for crop growth. Improper use or disposal of manure can lead to the buildup of nitrogen in soils and the loss of nitrogen to surface or ground water. We control for animal manure using annual county level data on manure from livestock (kilograms of nitrogen per hectares per year) from Byrnes et al. (2020).

Point sources of nitrogen pollution. Waste water treatment plants (WWTPs) and commercial and industrial point sources that discharge directly to streams are major contributors to surface-water nitrogen loads. We use data on the nitrogen yields (kilograms per square kilometer) for WWTPs in the EPA Clean Water Needs Survey (CWNS) from Dataset 16 in Falcone (2018) to control for point sources. The data are available for approximately two-year intervals between 1978 and 2012 at the 10-digit hydrologic unit level.

Agricultural management. Agricultural best management practices (BMPs) are designed to minimize the environmental impacts of agriculture while sustaining crop productivity (Dubrovsky et al. (2018)). BMPs reduce nutrient losses to streams through management of nutrient inputs on the land surface and through curtailment of erosion and runoff of nutrients from the land surface to streams. Three common BMPs are conservation tillage (see below), nutrient management plans, and conservation buffers. Comprehensive nutrient management plans help guide decisions on the placement, rate, timing, form, and method of nutrient application to avoid inputs in excess of crop requirements and to minimize loss to streams, groundwater, or the atmosphere. Nutrient management plans can incorporate a variety of agronomic tests to balance the amount of nutrients currently available in the soil against the amount required for crop production, and to identify the ideal timing for crop growth and irrigation to minimize runoff and leaching. Conservation buffers are areas of permanent vegetation often planted adjacent to streams, lakes, ponds, and wetlands or along the edges of agricultural fields to help reduce runoff or leaching of nutrients by filtering out nutrients and sediments, enhancing infiltration, and increasing plant uptake. We believe the spatial fixed effects (FEs) and spatially differentiated trends in our specifications adequately control for agricultural BMPs.

Tillage. Tillage is used to control weeds, incorporate crop residue, and prepare land for planting, but minimizing soil disturbance and maintaining soil cover are critical to improving soil health (Claassen et al. (2018)). Conservation tillage, particularly no-till or strip-till, used in conjunction with soil cover practices, such as conservation crop rotations and cover crops, entail numerous benefits, such as improved agricultural productivity, greater drought resilience, and better environmental outcomes. To name a few examples, compared to conventional tillage, conservation tillage increases water infiltration, and reduces water runoff and sediment yield (Capel et al. (2018)). Similar to the best management practices discussed above, we believe the spatial FEs and spatially differentiated trends in our specifications adequately control for tillage practices.

Drainage. Drain flow is water that moves off the landscape through artificial subsurface drains following rainfall or irrigation. Information on the location and areal extent of artificial drainage networks is crucial to understanding and quantifying their potential effects on water quality (Capel et al. (2018)). For example, subsurface tile drainage can provide both economic benefits for crop production through the removal of excess water from the soil column, and environmental improvements in soil and water quality through reductions in runoff, erosion, and phosphorous transport. Unfortunately, tile drains also transport nitrogen from fertilizer and other sources in water-soluble nitrate form more readily from the field to surface water.

The locations of surface drainage ditches are well known, because they are easily observable on the landscape. The extent of subsurface drainage systems, however, is poorly known in most areas because of their distributed nature, the extended period of installation, incomplete location maps, and a general lack of recent, systematic surveys of their spatial distributions. In addition to the lack of drainage information in recent decades, the lack of a consistent data collection method has resulted in great uncertainty as to the locations of subsurface drains throughout the country.

Networks of subsurface drainage systems have been installed beneath agricultural fields in the last few decades. In many cases, these systems have been installed as patterned drainage to improve control over soil water and thus increase crop yield. Landowners, however, are not required to report the installation of subsurface drainage systems or keep track of their locations. As a result, the locations of these networks are largely unknown.

The drainage-related datasets that we are aware off exhibit only spatial variation. The most recent dataset is based on a 30-meter resolution of tile-drained croplands using a geospatial modeling approach in Valayamkunnath et al. (2020).[33] We believe the spatial FE and spatially differentiated estimates of the effects of corn acreage on nitrogen pollution adequately control for drainage practices.

A.6.2 Panel fixed-effect regressions: other checks

The discussion in this section pertains to the additional estimates reported in Table 5, Table 6, and Figure 4 in the main text.

Conservation programs, acres of other major crops, and fertilizer sales. Agricultural conservation programs, ranging from voluntary technical assistance only to payment-based voluntary and cross-compliance programs, have been implemented since the Food Security Act of 1985 with an early focus on the viability of agricultural production through soil conservation. The Farm Security and Rural Investment Act of 2002 substantially increased the level of public funding for conservation and initiated the goal of maximizing environmental benefit. Subsequently, the Conservation Effects Assessment Project (CEAP) was established to provide science-based guidance on the best use of funding for conservation and to facilitate the alignment of conservation programs with national environmental protection priorities such as the restoration of the Gulf of Mexico (Garcia et al. (2016)).

We control for CRP acres, soybean acres, and wheat acres, as well as the acres of other major crops (cotton, rice, and sorghum) and fertilizer sales. Similar to the corn acres, we interact the acres of major crops, CRP acres, and fertilizer sales with precipitation. The major crops' acreage is from the USDA NASS. Annual county-level data on CRP acres is from Conservation Reserve Program

[33] Two older datasets have been compiled by USGS and are 30-meter resolution rasters. The first is for the CONUS in the early 1990s (Nakagaki et al. (2016)). The second is for 12 Midwest states in 2012 (Nakagaki and Wieczorek (2016)). Both datasets are built using information from the State Soil Geographic Database Version 2 (STATSGO2), the National Land Cover Dataset (NLCD), and Sugg (2007). The latter dataset also uses information on state-level acreages of agricultural land drained by tiles from the 2012 Census of Agriculture. The third dataset is from Sugg (2007), who combines information from the USDA STATSGO database and the 1992 NLCD to calculate the percent of cropland with subsurface drainage at the county level for 18 states, which include the Corn Belt and Lakes states.

Statistics from the USDA Farm Service Agency.[34] We use annual county-level data on fertilizer sales from Alexander and Smith (1990) and Brakeball and Gronberg (2017).

Temporal variation in corn acreage effects. We check whether acreage elasticities exhibit temporal variation by estimating decade-specific panel FE regressions.

Spatial variation in corn acreage effects. We check for spatial variation in the acreage elasticities by estimating different panel FE regressions for the top corn producing states, all other states (CONUS excluding the top corn states), and the Mississippi River Basin.[35]

Alternative time windows to measure nitrogen concentration, precipitation, and degree days. Transport of nutrients to streams and groundwater varies seasonally, in large part following seasonal patterns in human activities, such as fertilizer application in the beginning of the growing season. The transport of nutrients to streams also varies as precipitation and runoff change; loads and water discharge are usually highest during the late winter, spring, and early summer when runoff is highest. We consider several alternative windows during the year to measure nitrogen concentration, precipitation, and degree days, and estimate 4 different regressions. The first three windows (April–September, March–August, May–October) are around the typical U.S. crop growing season, which also stimulates spring and summer algae blooms directly influencing the hypoxic zone in the GoM. In the case of the fourth window (January–June), we aim to capture the effects of spring runoff.

Interacting corn acreage with runoff instead of precipitation. Runoff is water that flows over the landscape and directly into the surface waters that drain the watershed (for example, streams). The importance of runoff as a water flow path is affected by precipitation, vegetation, topography, and soil characteristics. Precipitation in excess of what the landscape can assimilate at a given time produces runoff (Capel et al. (2018)).[36] We use runoff data from Wolock and McCabe (2018) based on a water-balance model in Mccabe and Wolock (2011) to estimate a regression using the interactions of acres with runoff instead of precipitation.

Nitrogen concentration accounting for streamflow. We refine the measurement of pollution and acreage to account for streamflow. Using the NHD Plus data and R routines developed by the USGS, we are able to identify downstream monitoring sites for each county. We estimate two different regressions (based on main stems flowlines and tributaries flowlines) using nitrogen

[34] We set the CRP acres equal to zero for years 1975–1985.

[35] The top corn producing states are Iowa, Illinois, Minnesota, Nebraska, Indiana, South Dakota, Ohio, Wisconsin, Missouri, and Michigan. In the case of the Mississippi River Basin, we include counties lying the following HUC2s: Ohio (05), Tennessee (06), Upper Mississippi (07), Lower Mississippi (08), Missouri (10), Arkansas-White-Red (11).

[36] According to Table 6.2. in Goolsby et al. (1999) that pertains to a regression model for total nitrogen and nitrate yields in the Mississippi River Basin, runoff is included among the explanatory variables and is assumed to represent other unmeasured inputs such as atmospheric deposition, ground water discharge, soil erosion, etc.

concentration data for downstream monitoring sites.[37]

Nitrogen concentration accounting for streamflow and stream levels. We estimate 4 different regressions using downstream monitoring sites located in rivers and streams of levels 1–4. For the less familiar reader, and using the Mississippi River Basin flowline network as an example, the main stem of the Mississippi River is level 1, while the Ohio and Missouri rivers that discharge into the Mississippi River are level 2. Rivers and streams of level 3 (4) discharge into their counterparts of level 2 (3).

Lagged acreage. Our baseline results point to larger effects of corn acreage on nitrogen pollution in the absence of county FEs than in their presence. This finding is consistent with the notion that long-run corn acreage matters more than annual fluctuations. To investigate this conjecture further, we use time averages of corn acres in place of contemporaneous corn acres. We report results from three different regressions with the following acreage variables: (i) average of the current and prior year's corn acreage, (ii) average of the current and past two years' acreage, and (iii) average of the current and past three years' acreage.

Reporting limits in nitrogen concentration. In our baseline results, we exclude values of nitrogen concentration in excess of 50 mg/L noting that the 99% of the concentration empirical distribution is 20 mg/L. We also exclude values of nitrogen concentration that are identified as being lower than a reporting limit (e.g., less than 2.5 mg/L). We consider two robustness checks in terms of how we handle observations with values lower than the reporting limits. In the first regression, we set such values equal to zero. In the second regression, we set such values equal to the reporting limit.

Alternative radii. Our baseline results are based on USGS monitoring sites within 50-mile radii from the county centroids. We explore the sensitivity of our acreage elasticities to 100- and 200-mile radii. Apart from the effect on (potentially) altering the number of USGS monitoring sites and corn acreage used in the analysis, increasing the radii may alter (e.g., due to attenuation/removal) the share of the edge-of-field nutrient losses that reaches the monitoring sites where nitrogen concentration is measured.[38]

Data filtering. In this robustness check, we filter the nitrogen pollution data as in Keiser and Shapiro (2018). In particular, we only consider data for surface water and routine samples associated with lakes and streams.

Alternative datasets and extended geographic scope (CONUS). In our baseline results, we use

[37] See, for example, this link.

[38] In general, nutrient removal rates increase with transport distance and nutrient sources that are further upstream deliver smaller nitrogen loads (Marshall et al. (2018) and Robertson and Saad (2006)). As Kling (2011) discusses, the degree of attenuation depends not only on physical features but also on the land use choices that gives rise to non-constant diffusion coefficients.

the WQP data on parameter code 00600 to measure nitrogen pollution in the Eastern part of the country (east of the 100th meridian excluding Florida). We will refer to these data as the "USGS-NWIS" data. In what follows, we will use the term "EAST-100" to refer to the analysis pertaining to the Eastern U.S.. We also present results for the CONUS using the USGS-NWIS data. Moreover, we present results for the CONUS based on two additional datasets. The first dataset ("USGS-NWQN"), which is discussed in more detail in Section A.3, is based on imputation methods developed by the USGS. The second ("USGS+EPA") dataset, which is discussed in more detail in Section A.4, is based on a combination of the USGS-NWIS and EPA-STORET data and allow us to increase coverage in the later years of our analysis. Figure A2 and Figure A3 show the coverage in terms of monitoring site-date combinations, number of monitoring sites, number of counties, and number of 8-digit hydrologic units, by year for the alternative datasets. The use of the EPA STORET data allows us to increase significantly our sample size starting in the mid-1980s.

Alternative data aggregation. We explore two alternative data aggregation schemes that entail (h)ydrologic unit-centric and (m)onitoring-site centric analyses. C-centric type analyses are generally common in the economics literature and have been utilized to produce estimates of climate change on agriculture (e.g., Mendelsohn et al. (1994), Deschenes and Greenstone (2007)). M-centric and h-centric analyses are common in the environmental economics and science literature (e.g., Olmstead et al. (2013) and David et al. (2010)), and probably more so in the case of h-centric analyses, employing biophysical and water-quality models like the APEX, SPARROW, and SWAT. We calculate acres planted assuming a radius of 50 miles from the monitoring sites in the case of the m-centric analysis. For the h-centric analysis, we use monitoring sites and counties that lie within the HUC8 boundaries.

Statistical inference with alternative clustering schemes. We explore alternative clustering schemes for the purpose of statistical inference. In particular, we consider standard errors calculated by 2-digit hydrologic unit and year (HUC2 $\times$ year), by 4-digit hydrologic unit and year (HUC4 $\times$ year) and year.

A.6.3 Cross-section regressions

For the cross-section regressions described in Section A.5, we obtain a smaller set of additional estimates based on the following: (i) elimination of the acres' interaction with precipitation, (ii) alternative nitrogen concentration measurement adjusting for streamflow, and (iii) extended geographic scope plus additional data and specifications.

In this section, we discuss robustness checks to our baseline elasticity estimates for the cross-section regressions in Figure A1 of the main text. As a reminder, our baseline elasticity estimates for the between case are 0.141 (first precipitation quartile) to 0.332 (third precipitation quartile) in the absence of spatial FEs, and they are 0.096 (first quartile) to 0.202 (third quartile) in the presence of HUC4 FEs. Their year-specific counterparts that are significant at conventional levels ($\leq 10\%$) are 0.045–0.412 (no spatial FEs) and 0.032–0.326 (HUC4 FEs) depending on the year and the quartile of precipitation.

Elimination of acres' interaction with precipitation: In general, the elimination of the interaction of corn acres with precipitation entails elasticities that are smaller. Pooling the data across years (1975–2017), the corn acreage elasticities are 0.096 (without spatial FEs) and 0.138 (with HUC4 FEs). The year-specific elasticities that are significant at conventional levels are 0.047–0.239 (without spatial FEs) and 0.049–0.138 (with HUC4 FEs).

Streamflow: Adjusting for streamflow (using downstream USGS monitoring sites on main flowlines) the between corn acreage elasticities are 0.177 (first quartile)–0.307 (third quartile) in the absence of spatial FEs. With HUC4 FEs, the elasticities are 0.106 (first quartile)–0.170 (third quartile).

Extended geographic scope plus additional data and specifications. In a series of robustness checks that resemble in the panel FE regressions, we use additional data (USGS+EPA as opposed to the USGS-NWIS) and expand the geographic scope of our analysis from the EAST-100 to the CONUS. These additional data allow us to alleviate some of the concerns regarding the substantial variation in the number of observations used to obtain the year-specific elasticity estimates. For example, using data for all years (1975–2017), we have 3,029 counties. Moreover, we consider several additional controls to mitigate potential concerns for confounding factors (e.g., GDP, per-capita income, population) that introduce a bias in our baseline elasticity estimates (Table A11).

For the CONUS estimates using USGS+EPA data that pertain to the 48 CONUS states, 18 HUC2s and 205 HUC4s, there is still variation in the number of observations for the various years. The number of observations is between 2,055–2,758 depending on the set of additional controls. The range of the between elasticity estimates is 0.111–0.291 (first precipitation quartile), 0.094–0.296 (median), 0.078–0.299 (third quartile) depending on the set of additional controls and the spatial FEs.

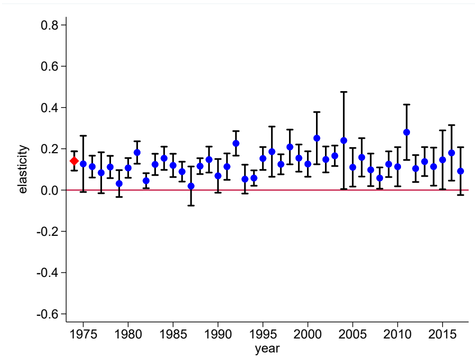
We also produced a set of elasticity estimates based on *cropland* acres as opposed to corn acres for the CONUS using the USGS+EPA data and the series of controls shown in Table A11. This analysis is limited to the Census-of-Agriculture (CoA) years because we use the CoA as our source of cropland acres. For the regressions that utilize cropland acres, we adjust our weather-related controls such that we use total annual precipitation and its square and the following annual degree days: 0C°, 5C°, 8C°, 10C°, 12C°, 20C°, 25C°, 29C°, 30C°, 31C°, 32C°, 33C°, 34C°. Hence, we use 2 as opposed to 24 precipitation-related controls and a much richer set of variables capturing degree days compared to the baseline models. Finally, the elasticity estimates are based on an increase in cropland acres and quartiles of precipitation. Similar to prior calculations based on corn acreage, we calculate these elasticities using mean cropland acres and mean nitrogen concentration.

For our between estimates based on CoA years, we have observations for approximately 2,350 counties. When we use data for a particular CoA year, the number of observations is between 1,733–2,146 depending on the set of additional controls. The range of the between elasticity estimates is 0.088–0.403 (first quartile), 0.055–0.428 (median), 0.086–0.448 (third quartile) depending on the set of additional controls and the spatial FEs.

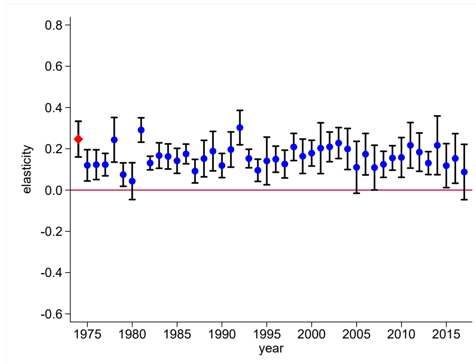
A notable observation regarding the cropland elasticity estimates is that additional controls (e.g., CRP acres, population, GDP, per-capita income) have a *de minimis* effect on their magnitude once we control for weather. The only exception is when we control for corn acres. For example, moving from the specification in which we control for CRP acres, population, GDP, and land area to the specification in which we *also* control for corn acres, the between cropland elasticities drop from 0.251 to 0.088 (first quartile), 0.279 to 0.101 (median), and 0.303 to 0.112 (third quartile) in the case of HUC4 FEs.

A Appendix Figures

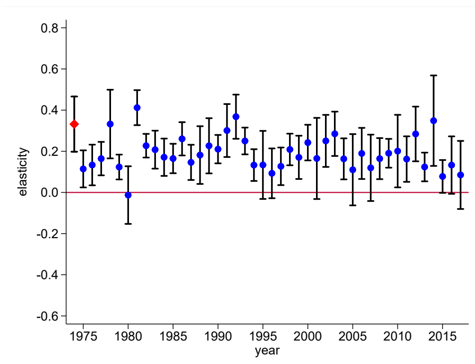
Figure A1. Corn acreage elasticities for cross-section regressions



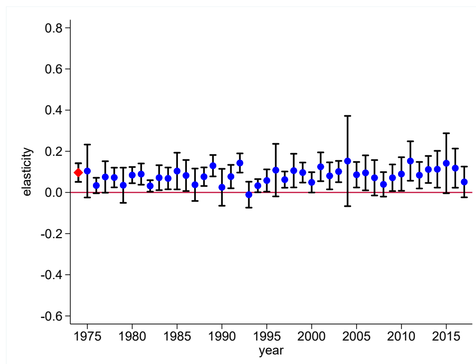
A. no fixed effects, 25% precipitation



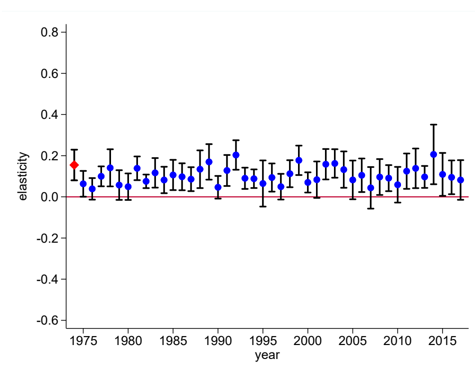
B. no fixed effects, 50% precipitation



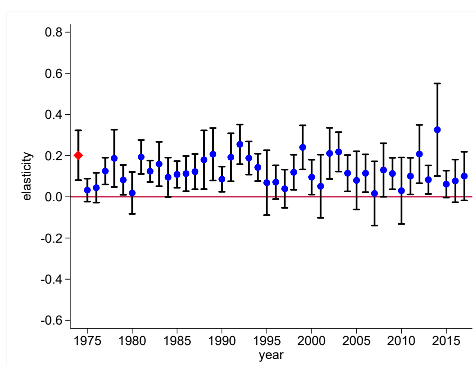
C. no fixed effects, 75% precipitation



D. HUC4 fixed effects, 25% precipitation



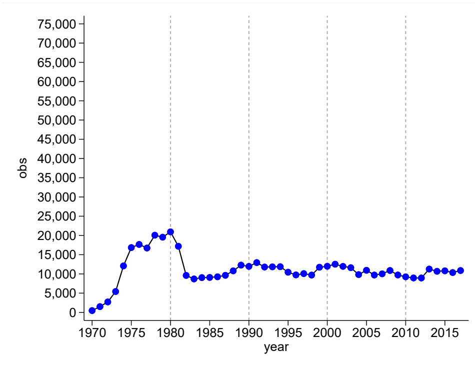
E. HUC4 fixed effects, 50% precipitation



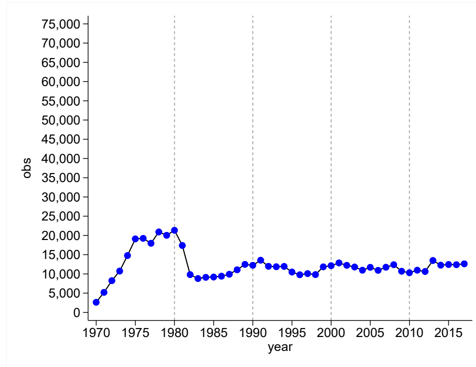
F. HUC4 fixed effects, 75% precipitation

Note: The figure shows point estimates and 95% confidence intervals (CIs) for the elasticity of nitrogen concentration with respect to corn acres based on equations (A1) and (A2) using three precipitation quartiles. The left-most point estimates (red diamonds) and their CIs are based on the between model in equation (A2). The standard errors are clustered by HUC4. The specifications control for weather (precipitation, squared precipitation, moderate heat, and extreme heat). For additional details, see Section A.5.

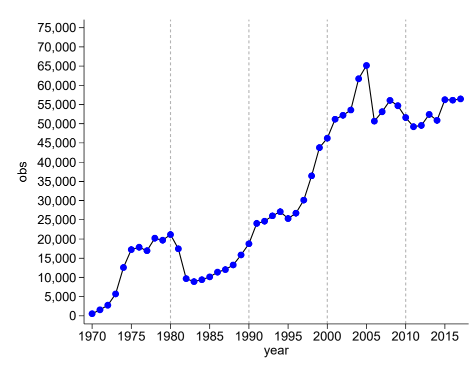
Figure A2. Alternative datasets used to track nitrogen concentration I



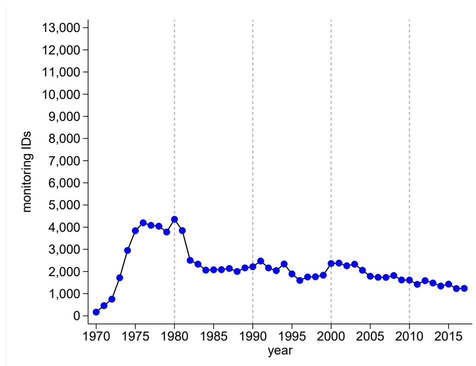
A. USGS-NWIS, site & date combs.



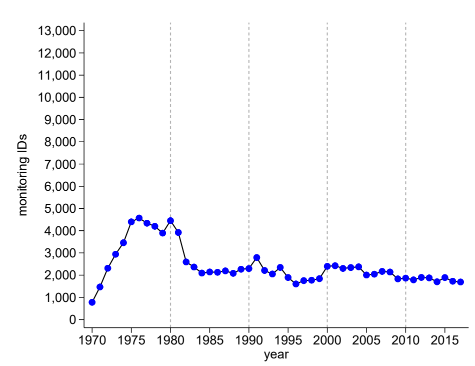
B. USGS-NWQN, site & date combs.



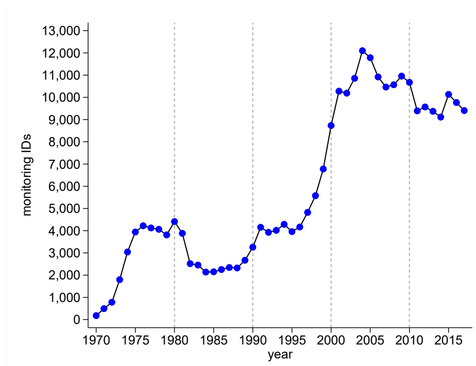
C. USGS+EPA, site & date combs.



D. USGS-NWIS, monitoring sites



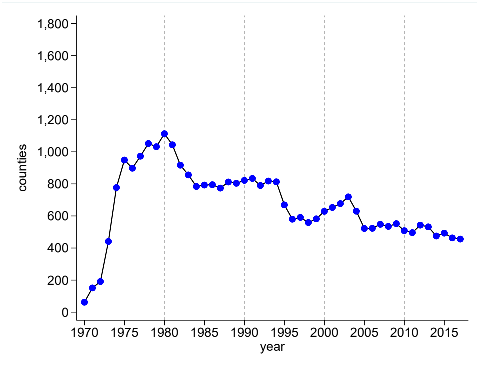
E. USGS-NWQN, monitoring sites



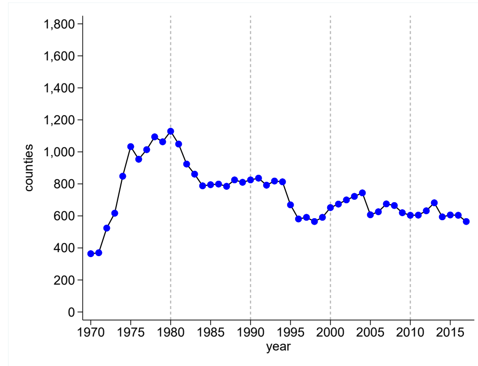
F. USGS+EPA, monitoring sites

Note: The figure shows the coverage implied by alternative datasets in terms of monitoring-site and date combinations in panels A–C, and monitoring sites in panels D–F, respectively. For additional details, see Section A.6.2.

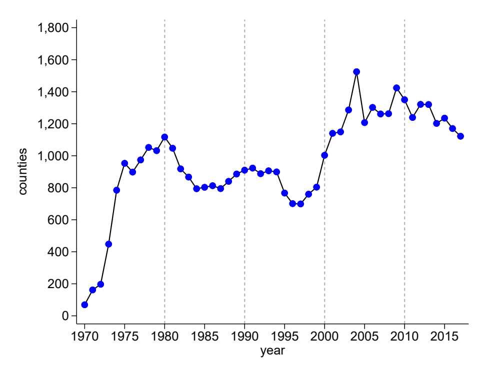
Figure A3. Alternative datasets used to track nitrogen concentration II



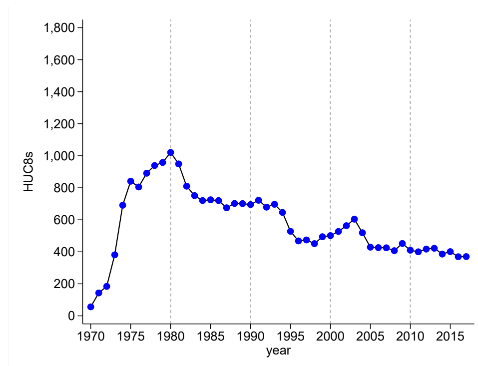
A. USGS-NWIS, counties



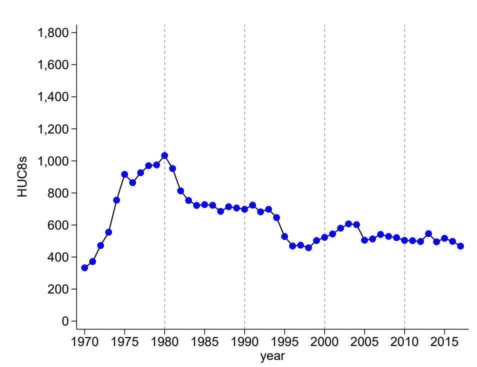
B. USGS-NWQN, counties



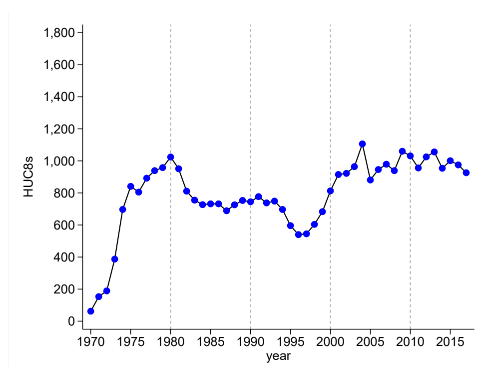
C. USGS+EPA, counties



D. USGS-NWIS, hydrologic units



E. USGS-NWQN, hydrologic units



F. EPA+STORET, hydrologic units

Note: The figure shows the coverage implied by alternative datasets in terms of monitoring-site and date combinations in panels A–C, and monitoring sites in panels D–F, respectively. For additional details, see Section A.6.2.

A Appendix Tables

Table A1. Ranking of top 20 corn producing states

rank	state	production	cumulative %
1	IA	81,235,491	19.035
2	IL	71,624,041	35.818
3	NE	48,475,417	47.177
4	MN	40,363,933	56.635
5	IN	34,377,920	64.690
6	OH	20,079,440	69.395
7	WI	16,704,529	73.310
8	SD	15,932,910	77.043
9	KS	13,118,720	80.117
10	MO	13,004,924	83.164
11	MI	11,429,575	85.842
12	TX	8,157,810	87.754
13	KY	6,546,971	89.288
14	CO	5,289,274	90.527
15	ND	5,234,568	91.754
16	PA	5,146,824	92.960
17	NC	4,405,036	93.992
18	TN	3,051,323	94.707
19	NY	2,759,176	95.354
20	GA	2,501,139	95.940

Note: We report total production for years 1970–2017 in 1,000 bushels. For additional details, see Section 5.1 in the main text.

Table A2. USGS-NWIS WQP data diagnostics, Activity Media Subdivision Name

value	obs.	obs. %
surface water	693,671	95.978
groundwater	29,068	4.022

Note: For additional details, see Section A.2.

Table A3. USGS-NWIS WQP data diagnostics, Activity Type Code

value	obs.	obs. %
sample-routine	680,274	94.124
not determined	18,174	2.515
sample-composite without parents	11,774	1.629
quality control sample-field replicate	11,670	1.615
quality control sample-field spike	446	0.062
quality control sample-field blank	202	0.028
quality control sample-reference sample	67	0.009
quality control sample-other	62	0.009
quality control sample-spike solution	39	0.005
quality control sample-reference material	13	0.002
quality control sample-blind	12	0.002
unknown	6	0.001

Note: For additional details, see Section A.2.

Table A4. USGS-NWIS WQP data diagnostics, Detection Quantitation Limit Type Name

value	obs.	obs. %
	612,111	84.693
historical lower reporting limit	103,289	14.291
laboratory reporting level	5,003	0.692
lower reporting limit	1,496	0.207
method detection limit (mdl)	795	0.110
upper reporting limit	39	0.005
lower quantitation limit	3	0.000
elevated detection limit	3	0.000

Note: For additional details, see Section A.2.

Table A5. USGS-NWIS WQP data diagnostics, Hydrologic Event

value	obs.	obs. %
routine sample	632,764	87.551
storm	40,579	5.615
not determined (historical)	19,404	2.685
regulated flow	8,238	1.140
snowmelt	6,469	0.895
flood	4,119	0.570
tidal action	3,475	0.481
not applicable	3,031	0.419
under ice cover	2,494	0.345
spring breakup	1,078	0.149
drought	644	0.089
hurricane	211	0.029
volcanic action	100	0.014
earthquake	79	0.011
spill	23	0.003
affected by fire	16	0.002
dambreak	9	0.001
backwater	6	0.001

Note: For additional details, see Section A.2.

Table A6. USGS-NWIS WQP data diagnostics, Result Value Type Name

value	obs.	obs. %
actual	709,831	98.214
estimated	12,908	1.786

Note: For additional details, see Section A.2.

Table A7. Breakdown of USGS-NWIS WQP nitrogen data

decade	monitors	dates	states	counties	HUC8s	obs R.	obs D.
1970	12,702	2,992	49	1,653	1,334	127,658	1,128
1980	11,700	3,393	49	1,626	1,332	139,579	29,308
1990	11,006	3,566	49	1,670	1,232	128,577	37,670
2000	10,349	3,252	49	1,387	1,029	117,701	18,963
2010	4,402	3,004	47	871	690	105,813	23,559
All	40,001	16,207	49	2,529	1,758	619,328	110,628

Note: The column "obs. R" indicates the number of observations for which the the Result Measure Value is available. The column "obs. D" indicates the number of observations for which the Detection Quantitation Limit Measure/Measure Value is available. For additional details, see Section A.2.

Table A8. Breakdown of WQP nitrogen data

group 1	group 2	obs.	obs. %
stream	stream	604,604	83.655
lake	lake	58,675	8.118
groundwater	well	27,306	3.778
facility	facility	11,932	1.651
marine	estuary	10,575	1.463
spring	spring	4,233	0.586
other	land	1,427	0.197
groundwater	subsurface	1,225	0.169
		854	0.118
marine	ocean	761	0.105
other	wetland	739	0.102
other	atmosphere	402	0.056
other	surface	6	0.001

Note: For additional details, see Section A.2.

Table A9. Alternative total nitrogen concentration calculations

calculation	obs.	R^2	intercept	slope
00625+00631	277,364	0.997	-0.001	0.998
49570+62854	15,723	0.998	0.007	0.996
00623+00631+49570	15,723	0.998	0.007	0.996

Note: An observation is identified as monitoring site-date combination. For each monitoring site, we collected the average daily Result Measure Value of the relevant parameter code and calculated the three sums indicated in the leftmost column of the table. The four rightmost columns report the results of a regression of the average daily Result Measure Value of parameter code 00600 used in the paper on the three alternative sums. There are 543,111 observations with non-missing values for parameter code 00600. See also the National Water Quality Network (NWQN) sample collection and reporting methods link. For additional details, see Section A.2.

Table A10. Alternative nitrogen concentration calculations

A. dissolved nitrate plus nitrite 00613				
calculation	obs.	intercept	slope	R^2
00630	63,860	-0.0459	1.0010	0.9762
00618	367,968	0.0191	1.0025	0.9952
00620	28,299	-0.0205	1.0073	0.9891
71851	366,995	0.0198	1.0025	0.9953
71850	487	0.1066	0.9667	0.9316
00620+00613	15,363	-0.0316	0.9922	0.9937
00620+71856	16,641	-0.0321	0.9922	0.9935
00620+00615	20,121	-0.0028	0.9711	0.9913
71851+00613	223,843	0.0055	1.0000	0.9941
71851+71856	233,714	0.0053	1.0000	0.9941
71851+00615	16,834	-0.0113	0.9998	0.9998
71850+00613	59	0.1474	0.9032	0.8090
71850+71856	99	0.0894	0.9747	0.9111
71850+00615	19	0.1841	0.5836	0.5362
B. total organic nitrogen plus ammonia 00625				
calculation	obs.	intercept	slope	R^2
00605+00608	271,805	0.0044	1.0000	1.0000
00605+00610	267,772	0.3535	0.7825	0.7961
C. total nitrogen 00600				
calculation	obs.	intercept	slope	R^2
method 1	577,683	0.0122	0.9980	0.9804
method 2	19,818	-0.0011	1.0001	0.9965
method 3	16,542	-0.0005	1.0001	0.9996

Note: An observation is identified as a monitoring site-and-date combination. For each monitoring site, we collected the average daily Result Measure Value for the relevant parameter code from the WQP. The four rightmost columns report the results of a regression of the average daily Result Measure Value for dissolved nitrate plus nitrite, total organic nitrogen plus ammonia, and total nitrogen, on the average daily Result Measure Value of the parameter codes indicated in the leftmost column. These parameter codes are based on the authors' review of USGS methodologies. For additional details, see Section A.3.

Table A11. Additional controls in cross-section regressions based on CONUS and USGS+EPA data

model	controls
1	none
2	weather
3	weather, population, GDP
4	weather, population, per-capita income
5	weather, CRP acres
6	weather, CRP acres, population, GDP
7	weather, CRP acres, population, per-capita income
8	weather, CRP acres, population, GDP, land area
9	weather, CRP acres, population, GDP, land area, corn acres

Note: For additional details, see Section A.6.3.