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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:

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

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.

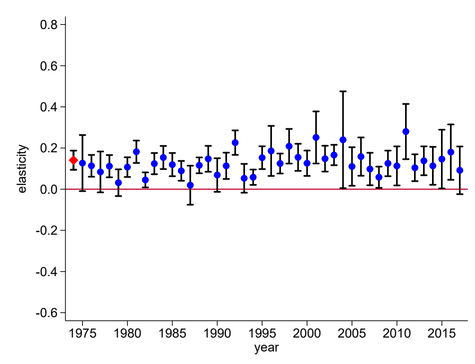
We also produced a set of elasticity estimates based on *cropland* acres as opposed to corn acres for the CONUS using the USGS+EPA data and the series of controls shown in Table A11. This analysis is limited to the Census-of-Agriculture (CoA) years because we use the CoA as our source of cropland acres. 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.

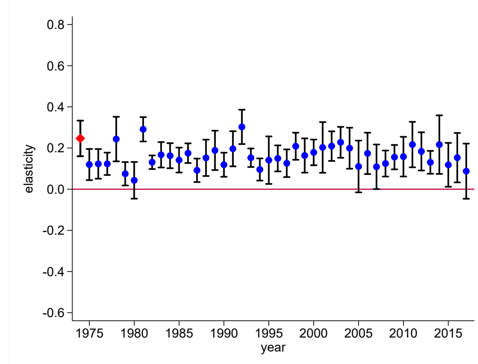
A notable observation regarding the cropland elasticity estimates is that additional controls (e.g., CRP acres, population, GDP, per-capita income) have a *de minimis* effect on their magnitude once we control for weather. The only exception is when we control for corn acres. For example, moving from 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

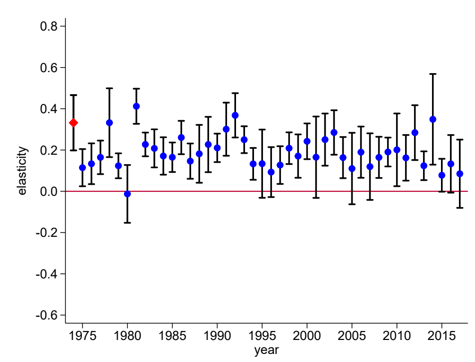
Figure A1. Corn acreage elasticities for cross-section regressions



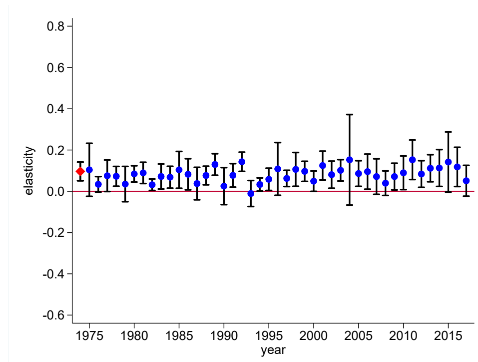
A. no fixed effects, 25% precipitation



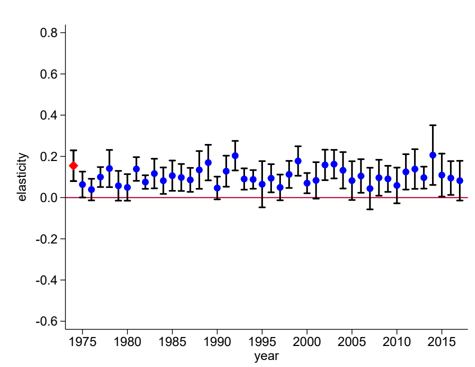
B. no fixed effects, 50% precipitation



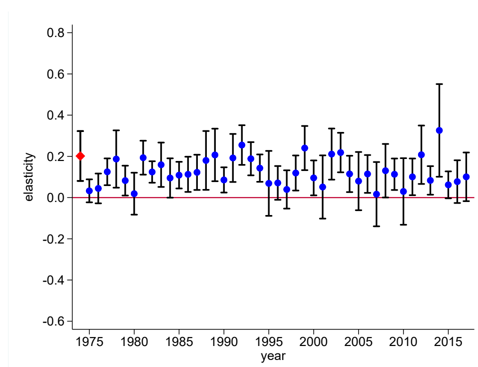
C. no fixed effects, 75% precipitation



D. HUC4 fixed effects, 25% precipitation



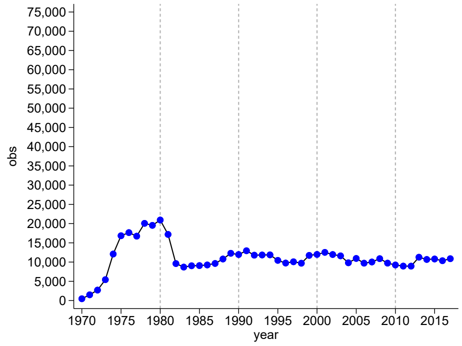
E. HUC4 fixed effects, 50% precipitation



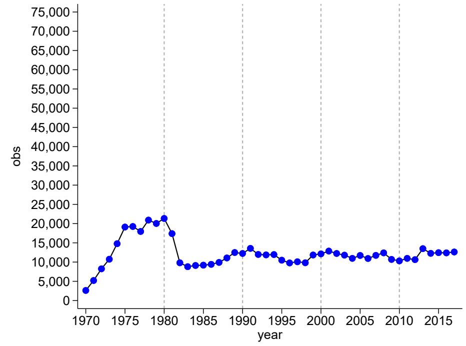
F. HUC4 fixed effects, 75% precipitation

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.

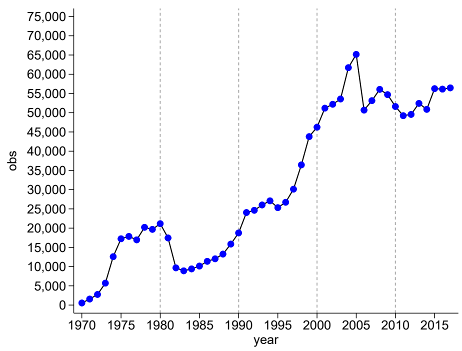
Figure A2. Alternative datasets used to track nitrogen concentration I



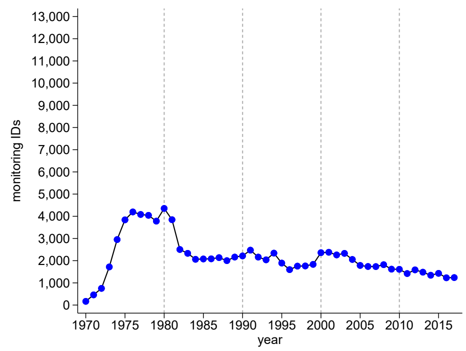
A. USGS-NWIS, site & date combs.



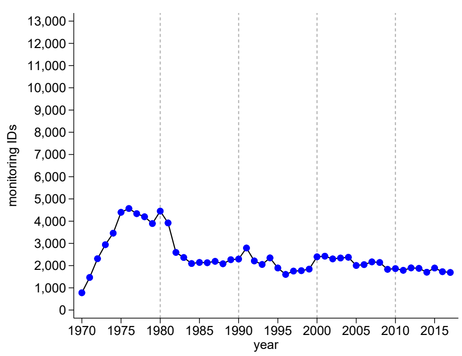
B. USGS-NWQN, site & date combs.



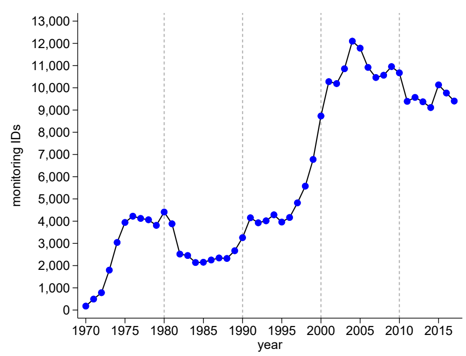
C. USGS+EPA, site & date combs.



D. USGS-NWIS, monitoring sites



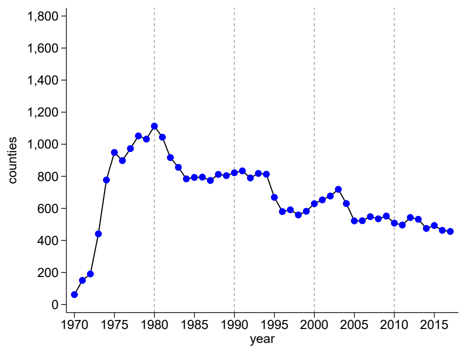
E. USGS-NWQN, monitoring sites



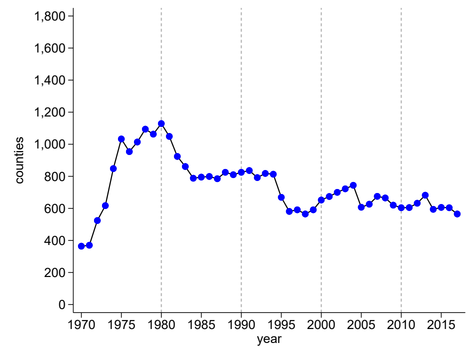
F. USGS+EPA, monitoring sites

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.

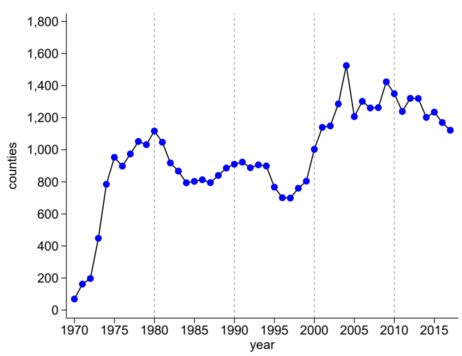
Figure A3. Alternative datasets used to track nitrogen concentration II



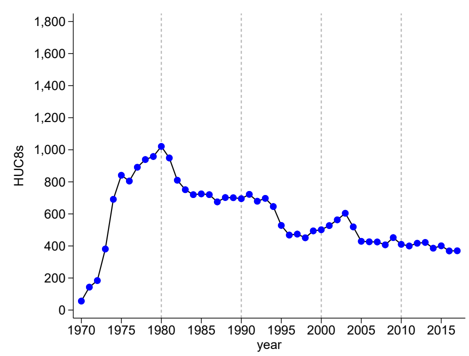
A. USGS-NWIS, counties



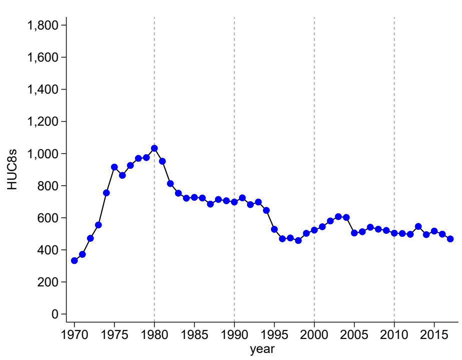
B. USGS-NWQN, counties



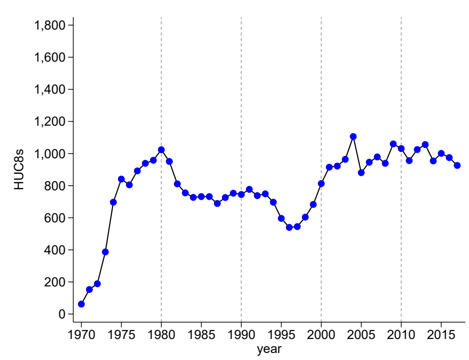
C. USGS+EPA, counties



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.