Deadzone Agriculture:

Algal Blooms and the Social Cost of Fertilizer

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PRELIMINARY DRAFT - DO NOT SHARE

Abstract

Fertilizer is critical to agricultural productivity, but its use results in negative externalities downstream in the form of hypoxic zones and harmful algal blooms. The economic cost of fertilizer has yet to be quantified at a large-scale, partly because farm pollution is mostly unregulated under the Clean Water Act in the United States, and partly due to the lack of a widespread and temporally consistent dataset on algal blooms. This study utilizes a novel satellite-derived measure of water quality that spans 30-plus years and encompasses lakes, riparian, and coastal aquatic resources. We document a positive relationship between nitrogen fertilizer use and algal bloom intensity. We then find a significant negative economic impact in places downstream from agricultural areas, as well as water-reliant regions (e.g., coastal areas) and economic sectors (e.g., fishing, tourism, recreation). From these results, we estimate the social cost of nitrogen fertilizer.

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1 Introduction

The US Environmental Protection Agency considers nutrient pollution one of the "most widespread, costly and challenging environmental problems."[1] Increasing flows of nitrogen have far exceeded earth's handling capacity and have impaired ecosystem functioning (Vitousek et al. 1997; Gruber and Galloway 2008; Erisman et al. 2013), and nitrogen and phosphorus levels are far past the zone of certainty under the planetary boundaries analysis (Steffen et al. 2015).

Nutrient enrichment, hypoxia, and algal blooms are interrelated environmental phenomena. They are caused by excess nitrogen and phosphorus, coming primarily from fertilizer use but also from human and industrial waste. These nutrients leach into waterways and feed the growth of phytoplankton in a process called eutrophication (Nixon 1995). Eutrophication can produce algal blooms which are considered harmful when concentrations of algae (e.g., cyanobacteria) achieve sufficient density to create negative environmental or health effects (Smayda 1997).

Occurring in both fresh and salt water, algal blooms can be produced by excess nutrients and/or climactic anomalies like warmer water temperatures (Paerl and Huisman 2008; Michalak et al. 2013; Ho et al. 2019). Algal blooms are often followed by hypoxia events, defined by dissolved oxygen levels below two ml per liter, as dead phytoplankton sink to the seafloor and get decomposed by bacteria. Sustained low oxygen levels, in turn, can result in aquatic dead zones.

Algal blooms have increased in frequency and intensity over the decades (Anderson 1989; Hallegraeff 1993; Hudnell 2008; Huisman et al. 2018; Ho et al. 2019). The quantity and extent of dead zones have also increased across the globe (Diaz and Rosenberg 2008). Dead zones are now considered a major threat to the health of aquatic ecosystems (2008; Doney 2010). While natural processes like upwelling of nutrient-rich ocean water contribute to eutrophication, anthropogenic nutrient loading is increasingly the driver of algal blooms and hypoxia events.

Fertilizer use is mainly exempt from federal regulation under the Clean Water Act despite being the major source of water quality impairment in the US (Olmstead 2010), and individual states have been hesitant to regulate agricultural inputs (Kling 2013). While regulation of agriculture is politically difficult to implement, several other challenges inhibit efficient regulation of this market.

[1] Source: www.epa.gov/nutrientpollution/issue, accessed December 9, 2020

First, the economic impacts of hypoxia and algal blooms and the related social cost of fertilizer are difficult to quantify (Rabotyagov et al. 2014; Barbier 2012). This is partly due to the inherent challenges of estimating the costs of nonpoint pollution (Shortle and Horan 2001; 2013), in which those negatively affected are not those responsible for the pollution. In the case of the dead zone in the Gulf of Mexico, David et al. 2010 estimated fertilizer runoff and found that the highest nitrogen yields occurred in the tile-drained corn belt of Minnesota, Iowa, Illinois, Indiana, and Ohio–areas 1,500km upstream from the pollution culmination point at the mouth of the Mississippi River.

A second challenge to rigorous estimation of the social cost of fertilizer has been the lack of temporally-consistent and spatially-relevant data on water quality that can be linked to economic outcomes. Most past studies of the impact of algal blooms have been limited to specific geographies or relatively short time frames. To this end, we construct a measure of county-level algal bloom intensity that is derived from over three decades of Landsat satellite imagery, as well as a spatially-weighted measure of fertilizer use linked to watersheds. We utilize aggregate county-level income to estimate the cost of fertilizer-driven algal blooms.

Algal blooms can affect income through several potential channels: studies have documented that blooms affect water-based industries and water treatment systems (Rohlich 1969; Dodds et al. 2009), fisheries and fishing revenues, (Breitburg et al. 2009; Wolf et al. 2017), and tourism (Larkin and Adams 2007; Morgan et al. 2009). Hedonic analyses show a response to algal blooms in local housing prices (Wolf and Klaiber 2017; Bechard 2020). County-level income should capture many of these direct economic effects.

Hypoxia and algal-related externalities linked to public health may also be captured in our measure of county income to the extent that they affect labor or other economic outcomes. Drinking water containing toxins from algal blooms has been associated with negative health effects including dermatologic, gastrointestinal, respiratory, and neurologic illnesses (Hilborn et al. 2014). Recreational exposure to algal blooms has been linked to headaches and allergic reactions (Falconer 1999; Stewart et al. 2006), as well as asthma and respiratory issues from the inhalation of algal aerosols (Fleming et al. 2007). Algal-related wildlife and livestock illnesses have been reported in a number of species (Hilborn and Beasley 2015).

However, externalities from the nitrate pollution that drives algal blooms, including GHG emissions and air pollution, are unlikely to be captured in county-level income. It is also likely that some of the public health effects are not reflected. Thus our estimates consti-

tute a lower bound on the external costs of fertilizer use.

Studies have attempted to aggregate the cost of algal blooms for the US: Dodds et al. 2009 look across fourteen EPA ecoregions and estimate the total cost of freshwater algal blooms to be $2.2 billion per year via its impact on real estate values, recreation, wildlife protection, and water treatment. In an earlier analysis, Hoagland et al. 2002 estimate the cost of algal blooms to be $50 million per year across several coastal states with public health and fisheries being the largest components. However, these estimates are limited by the data available on algal blooms, as well as uncertainties involved in generalizing cost estimates derived for specific context at the national level.

We focus on nitrogen-based fertilizer in part because it is the most consumed fertilizer nutrient of the three crop macro-nutrients. Nitrogen usage has steadily increased over the last couple of decades, aided by the Haber Bosch process and low-cost energy (Glibert 2020), while phosphate and potash-based fertilizers have stayed flat or declined, as shown in Figure 1. However, phosphates are also an important driver of algal blooms. Appendix Figure A1 plots the relationship between nitrogen and phosphate use at the county level. Again, we see a very high correlation. We replicate some of our analyses for phosphates in Appendix [XXX].

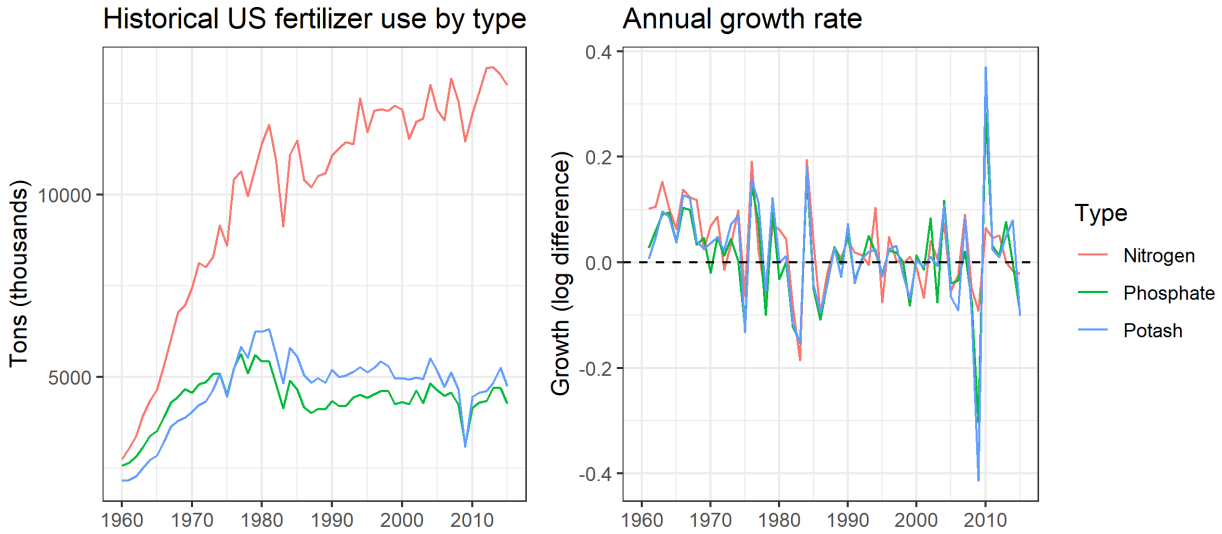


Figure 1: USDA ERS fertilizer use aggregated nationally by fertilizer type and year

Determining the socially-optimal level of nitrogen use requires equating the marginal private benefits of fertilizer to consumers (i.e., farmers) with the private and external marginal cost of fertilizer. The private benefit is conceptually straightforward and based on agro-

nomic relationships between yield and fertilizer use,[2] as well as crop prices. Private marginal costs are simply the cost of fertilizer.

Fertilizer is among the highest cost input in a farmer's production function. For example, if we assume 200 bushels per acre corn, 200 lb nitrogen (using the one-to-one bushels to pounds convention), and a price of nitrogen at \$0.4/lb, this equates to \$80 of nitrogen per acre. At a \$4 per bushel corn price, an acre yields \$800 in revenue, and nitrogen fertilizer alone accounts for 10% of the production value. Therefore farmers are strongly incentivized to optimize their fertilizer use in such a way that takes into account marginal yield increases relative to the marginal cost of fertilizer.

The external cost (or social cost) of fertilizer is more complex given the nonpoint nature of the pollution, as well as the issues related to the variety of nitrogen forms, numerous end-user impacts, and questions about spatial and temporal scale. Existing estimates of the aggregate cost of nitrogen fertilizer tend to be higher than those looking at the impact of algal blooms. Sobota et al. 2015 estimates that nitrogen use in agriculture costs the US \$59–340 billion annually through its impact on aquatic habitat and eutrophication. This component alone is 75% of their aggregate nitrogen cost estimate, which also includes the climate change-related cost of N2O emissions. Van Grinsven et al. 2013 find similarly high costs in Europe, estimated the cost of nitrogen pollution from agriculture in the range of €35-230 billion per year, exceeding the private benefit to farmers.

In 2015, nitrogen fertilizer consumption in the US was 13 million tons[3] and world nitrogen demand was 119 million tons in 2019 (FAO 2018). At the current price of \$0.4 per lb nitrogen equivalent (or 0.88/kg and \$880 per ton),[4] this equates to a market value of \$11 billion in the US and \$105 billion globally. In the US, for example, this means that the social cost of fertilizer of \$59–340 billion estimated by Sobota et al. 2015 is 5-31x the private cost.[5] However, the average private benefit from fertilizer via increased yields is 2-3x the commodity cost.

Gourevitch et al. 2018 derive a more conservative estimate of \$0.50 per kg for the social cost of nitrogen in Minnesota, which is the midpoint estimate of a very broad distribution ranging from \$0.05 to \$10. Their estimate is driven primarily by public health costs and WTP surveys for clean drinking water. Assuming US consumption of 13 million tons of nitrogen, this equates to an aggregate cost of \$6.5 billion per year, which is notably lower

[2] Optimal nitrogen calculator: http://cnrc.agron.iastate.edu/nRate.aspx
[3] Fertilizer Use and Price, www.ers.usda.gov/data-products/fertilizer-use-and-price
[4] Source: http://agfax.com
[5] This study appears to rely on an estimate of the eutrophication cost of nitrogen of \$16/kg (from Van Grinsven et al. 2013), which is 18x the current cost \$0.88/kg of fertilizer.

than the nitrogen cost estimated by Sobota et al. 2015, a discrepancy that could be due to less nitrogen exposure among the Minnesota population. The study also does not include the impact of nitrogen on eutrophication and hypoxia, citing data constraints and the lack of credible estimates.[6] The wide gap in the estimated costs of algal blooms and nitrogen fertilizer showcase the complexity of the issue. Keeler et al. 2016 shows that estimates of nitrogen cost can span several orders of magnitude depending on the specific location, form of N, and endpoints of interest.

This study utilizes a novel satellite-derived measure of water quality that spans 30-plus years and encompasses lakes, riparian, and coastal aquatic resources. We document a positive relationship between nitrogen fertilizer use and algal bloom intensity. We then find a significant negative economic impact in places downstream from agricultural areas, as well as water reliant regions (i.e., coastal areas) and economic sectors (fishing, tourism, hunting, recreation). We calculate a back-of-the-envelope cost estimate of [$900] per ton of nitrogen, which is roughly in line with its market value.

To our knowledge, this study is the first to 1) analyze the impact of algal blooms on aggregate income, 2) link this to a social cost of fertilizer, and 3) perform the analysis at a national-wide scale that includes both inland and coastal waters. We also hope that the satellite product of water quality that we developed can be utilized in research on many policy-relevant questions, including in geographies outside of the United States.

2 Data

Fertilizer: We utilize US Geological Survey (USGS)'s annual county-level estimates of nitrogen and phosphorus use from 1987 to 2012 (Brakebill and Gronberg 2017), which was recently updated for the year 2017Falcone 2021. We normalize values by the land area in a given county. We further calculate the sum of fertilizer use in upstream counties within a given watershed (HUC 4) from a county. The upstream-downstream relationship for a random subset of counties can be visualized in Figure 2.

Our main measure is farm fertilizer use, but results are robust to including non-farm fertilizer use as well. We also utilize an alternative dataset of fertilizer sales compiled by the fertilizer industry body AAPFCO which is available for a subset of states.

Algal blooms: We construct a county-level measure of algal bloom intensity derived

[6] However, it is worth noting that their estimate is more in line with Dodds et al. 2009's estimated cost of algal blooms in the US of $2.2 billion per year.

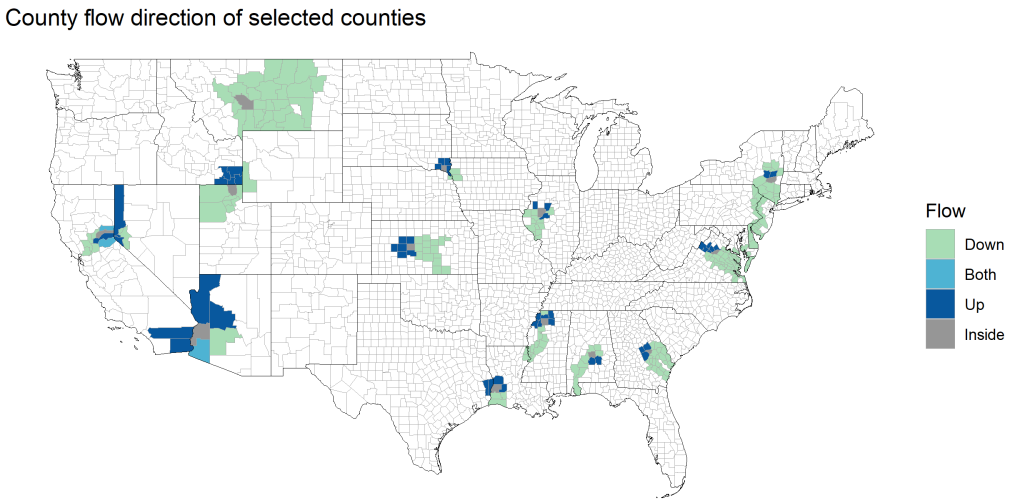


Figure 2: Watershed classification of counties based on their relative location within the USGS hydrologic unit code HUC-4 watershed boundary. Thirteen randomly selected counties are shown in grey. Green areas represent counties that are at least partly within the same HUC-4 and downstream from the grey county, as determined by their overlap with finer resolution HUC-12 watersheds. Likewise, blue counties are upstream from grey counties. Finally, the light blue 'Both' includes counties which have land area that is both upstream and downstream from grey counties.

from over three decades of Landsat satellite imagery and processed using computing power available through Google Earth Engine.[7] Several satellite products have been used to detect and monitor algal blooms, including the European Space Agency's Medium Resolution Imaging Spectrometer (MERIS) product (Clark et al. 2017) and a Moderate Resolution Imaging Spectroradiometer (MODIS) product for ocean color which measures chlorophyll levels at 500m resolution in the ocean and large inland lakes. Each satellite product has its own tradeoffs around duration, revisit time, resolution, and geographic extent. We opt for Landsat given its longer time series and the higher spatial resolution at 30m, which allows us to better capture small inland water bodies and rivers.

We adopt an approach that builds on Ho et al. 2019's analysis of global lakes. We use Landsat Thematic Mapper top-of-atmosphere (TOA), combining Landsat 5 (1984-2000) and Landsat 7 (2000-present). The bloom algorithm is based on the near infrared (NIR) band with an atmospheric correction for short wave radiation (SWIR): B4 - 1.03*B5 (Wang and Shi 2007).

We filter all images with over 25% cloud cover. Unlike Ho et al. 2017, we do not filter out pixels below a certain hue threshold, [though general results hold if this is implemented]. We then take the temporal average of the bloom measure across all the 16-day revisit peri-

[7] Google Earth Engine, urlhttps://earthengine.google.com

ods during the peak bloom time in late summer (July-Sept). We then take the US county-level mean over a 30m water mask from the National Land Cover Dataset (NLCD) for the maximum water extent from 2001 to 2016. US state boundaries extend three nautical miles from the coast, and this area is included in each state's county calculations of bloom intensity. Thus we include both saline coastal waters as well as inland freshwater.

In our regression models, we use county-level fixed effects to demean the observations, which allows for interannual comparisons. We also drop counties with very little surface water (less than $1km^2$), which comprise about 3% of our sample. However, the results are robust to their inclusion.

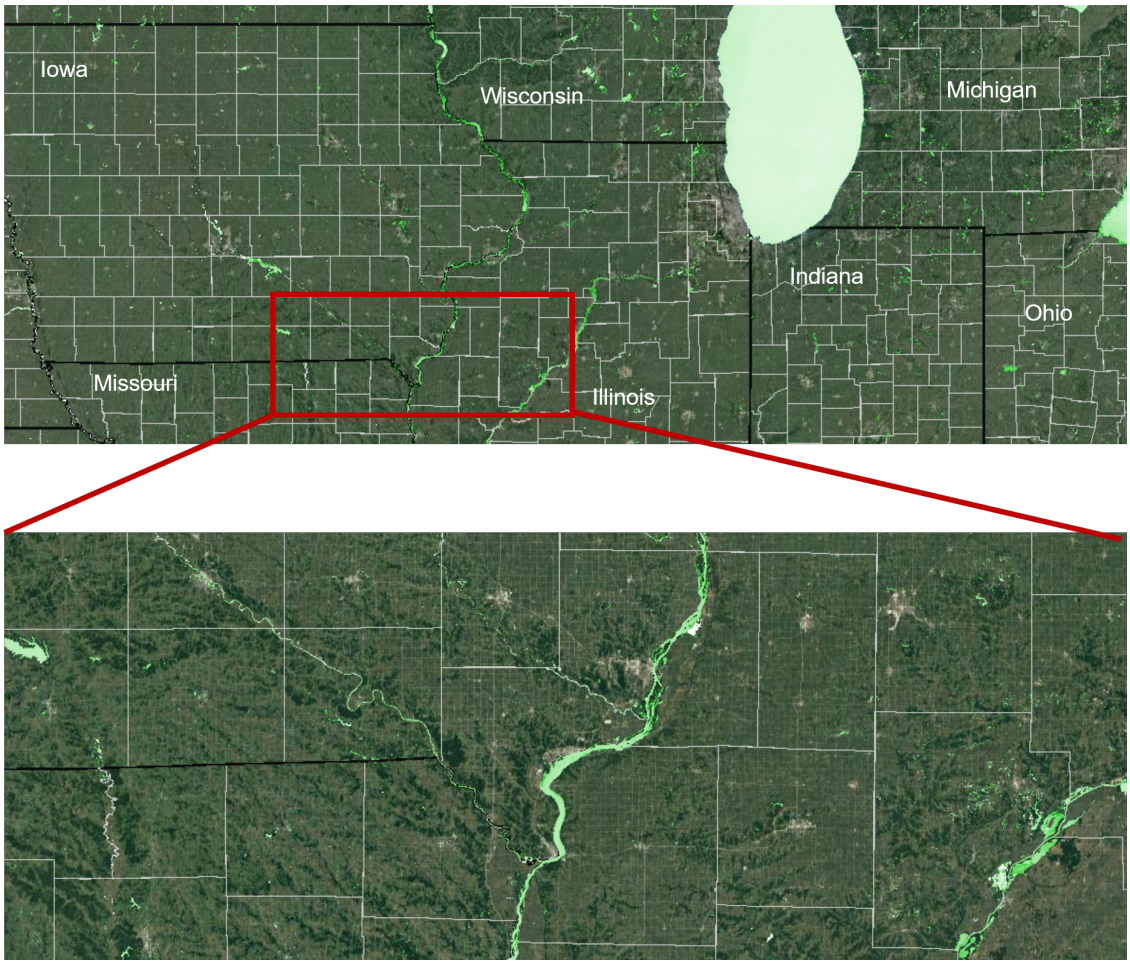
It is worth noting that this index is a direct measure of the concentration of neither chlorophyll nor any specific algal species. Rather it measures relative greenness in the upper layer of the water column. Many studies over the years have used Landsat to identify algal blooms (Tyler et al. 2006; Duan et al. 2007; Tebbs et al. 2013). This specific algorithm has been validated on-the-ground in Lake Erie (Ho et al. 2017) and globally through tests of how the index reflects the spatial gradients of chlorophyll-a levels within lakes (Ho et al. 2019). The calculation of the bloom index can be visualized in Panel A of Figure 3, along with how the bloom index changes over time in Panel B.

Figure 4 showcases the temporal and spatial patterns of the constructed bloom index across US counties. As expected, bloom intensity is higher in agricultural regions. There is significant geographic variation in where bloom intensity increased and decreased, although there seems to be a general upward trend in the upper Great Plains and along the 100^{th} meridian. The third panel shows an overall decline in bloom intensity over time along with an uptick in recent years.

Additional datasets include the following: watershed boundaries of hydrologic unit code HUC-4 and HUC-12 from USGS. County-level climate data comes from NOAA's Climate Divisional Database (nCLIMDIV) of monthly temperature and precipitation levels. Annual estimates of hypoxic extent in the northern Gulf of Mexico spanning 1985 to 2019 from Nancy Rabalais, LUMCON, and R. Eugene Turner, LSU.[8] County-level data on agricultural yields come from the US Department of Agriculture's historical census and National Agricultural Statistics Service (NASS). County-level socioeconomic data come from the Department of Commerce's Bureau of Economic Analysis.

[8] Source: https://www.epa.gov/ms-htf/northern-gulf-mexico-hypoxic-zone

Panel A



Panel B

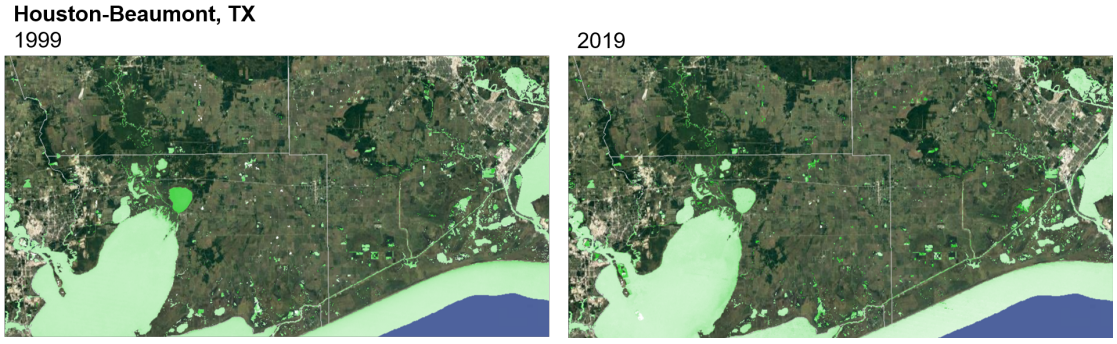
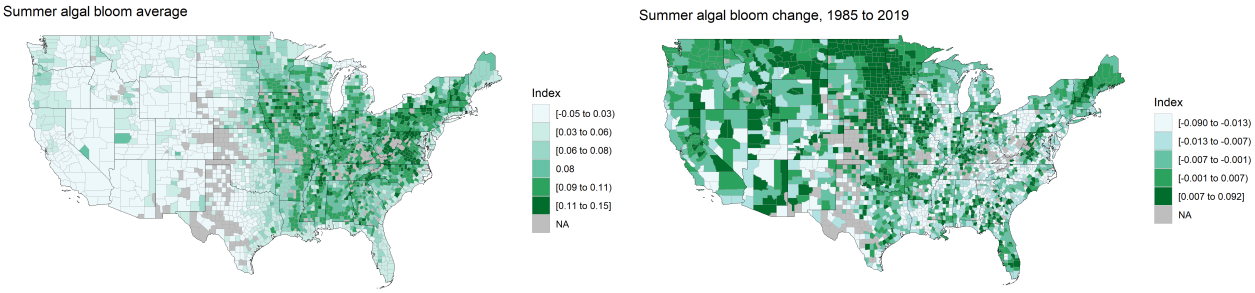


Figure 3: Panel A shows late summer bloom index averaged over 20 years from 1999 to 2019 in the US Corn Belt, then with a close-up of the boundary region of Iowa, Illinois and Missouri where the Des Moines River meets the Mississippi. Panel B shows the late summer algal bloom index at two discrete points in time, 1999 and 2019, in the Houston-Beaumont region.



Panel A Panel B

Figure 4: Panel A plots the county-level late summer bloom index averaged over the entire sample time period from 1984 to 2020. Panel B plots long-term change between from 1985 to 2019 using three-year averages around the endpoints (i.e., 1984-1986 for 1985).

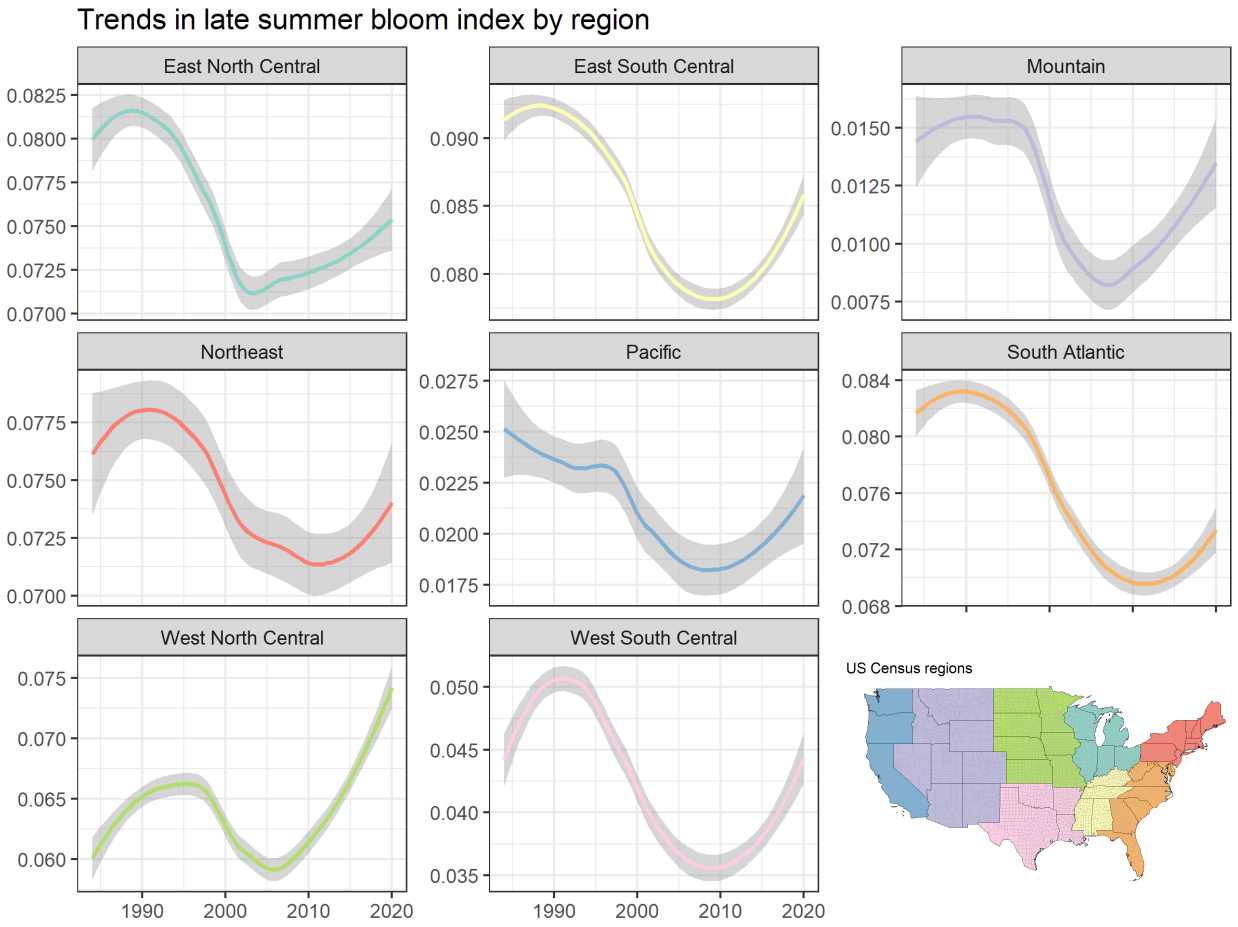


Figure 5: Trends in late summer algal bloom intensity average by US census region. 'Northeast' includes both New England and Middle Atlantic. Color coded legend map on bottom right.

3 Empirical Strategy

We employ two empirical approaches: first a difference-in-difference approach using a panel of county-year observations to assess annual variation, and second a long-difference cross-sectional approach to assess longer-term effects. We apply both these approaches to a first stage that estimates the impact of fertilizer on algal blooms, and then a second stage that estimates the impact of algal blooms on income.

Difference-in-difference model

$$bloom_{it} = \beta_1 fert_{itw} + \beta_2 \mathbf{W}_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad (1)$$

$$income_{it} = \beta_1 bloom_{it} + \beta_2 bloom_{it} * feature_i + \beta_3 \mathbf{W}_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad (2)$$

In the first model, the outcome variable, *bloom*, is the satellite-derived measure of late summer algal bloom intensity in county i and year t. $fert$ is tons of nitrogen fertilizer in county i and year t, or alternatively the sum of fertilizer use in counties upstream of county i but within its watershed w. Fertilizer values are normalized by dividing by land area. Phosphate fertilizer use can be used as well. $\mathbf{W}$ is a vector of climate controls including mean summer *temp* and *precip*. Fixed effects are at the county level α and year level γ. State-level time trends included in some specifications. Standard errors are clustered at state level.

In the second model the outcome variable, *income*, is log income per capita in county i and year t, *bloom* is the satellite-derived measure of late summer algal bloom intensity in county i and year t. $feature$ is an interaction variable based on some non-time varying characteristic of county i. This can include the proportion of a county that is water, or a dummy for coastal counties, or a dummy if the county income is highly reliant on certain sectors (i.e., fishing, recreation, farming). Other variables are the same as above.

Long-difference model

$$\Delta bloom_i = \beta_1 \Delta fert_i + \beta_2 \Delta \mathbf{W}_i + \epsilon_i \quad (3)$$

$$\Delta income_i = \beta_1 \Delta bloom_i + \beta_2 \Delta bloom_i * feature_i + \beta_3 \Delta \mathbf{W}_i + \epsilon_i \quad (4)$$

The outcome variable, Δ *bloom*, is the change in our satellite-derived measure of late summer algal bloom intensity between 1987 and 2017, each period calculated as a three year average (i.e., period 1987 is the average of 1986 to 1988) to reduce the likelihood of anomalous years influencing outcomes. Similarly, Δ $fert$ and Δ $\mathbf{W}$ represent the change in each

variable at the county level over that same time period. Standard errors are again clustered at the state level.

Note we restrict our analysis to the continental US. We drop counties with very little surface water (less than 1km^2), which comprise about 3% of our sample, as well as counties with no cropland area. However, results are robust to the inclusion of such counties.

In summary, we estimate short-term effects with a difference-in-differences model on annual panel data and long-term effects with a long-difference model on cross-sectional data. As a further test, we estimate 'intermediate' effects with a panel of five-year intervals using rolling-window moving averages. This allows us to account for a multi-year process. For example, it often takes several years for fertilizer to leach into downstream waterways (Rabotyagov et al. 2014), and likewise, fertilizer use over a multi-year period may result in elevated bloom intensity over the course of several years. In addition, one could imagine that the economic effects of the algal blooms could spill over into proceeding years. For this analysis, we utilize a five-year panel of county-level fertilizer data (Falcone 2021), which may be less prone to interpolation.

4 Results

4.1 Drivers of fertilizer use

We first analyze the drivers of fertilizer use at the aggregate, county level. At the individual farmer-level, we understand the drivers of fertilizer use: as described earlier, nitrogen fertilizer accounts for a large cost component of commercial farm operations (10% of production value). The yield-response of fertilizer is well-known and farmers are strongly incentivized to apply an amount that optimizes yield response relative to the marginal cost of fertilizer. Since fertilizer and crops have transparent commodity pricing, we are less worried about pricing differentials across location driving changes in input use.

At the county-level we expect fertilizer use to be driven by changes in land use. In Table 1, we regress county-level nitrogen on several potential land use variables: total harvested acres of the four major crops in the US (corn, soy, wheat, cotton), the ratio of corn-to-soy acres, and acres of land enrolled under the USDA Conservation Reserve Program (CRP). Cropland area is strongly related to nitrogen use. We would expect that places that increased corn production relative to soy production would increase their nitrogen fertilizer use given that soybeans are a nitrogen-fixing leguminous plant that require less nitrogen

compared to corn. Finally, we see a negative relationship with CRP enrollment, which makes sense given that this program entails taking land out of active farm production.

Table 1: Drivers of farm nitrogen use

	Dependent variable:			
	Nitrogen			
	(1)	(2)	(3)	(4)
Crop area	0.010***	0.012***	0.010***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Corn-soy ratio		0.575***		0.578***
		(0.158)		(0.157)
CRP acres			−0.008***	−0.010**
			(0.003)	(0.004)
County FE	X	X	X	X
State-yr trends	X	X	X	X
Observations	77,858	53,825	77,620	53,742
R^2	0.954	0.955	0.954	0.955
Adjusted R^2	0.952	0.953	0.952	0.953

Notes: Linear regression. Dependent variable is aggregate farm-level nitrogen use (1,000s of tons) at the county level. Crop area is the total harvested acres of corn, soy, wheat, and cotton. Corn-soy ratio is the amount of corn acres divided by the sum of corn and soybean acres. CRP acres is the amount of acres under the USDA Conservation Reserve Program. Time series to 1987 to 2012 and 2017. Sample size varies based on extent of counties with both corn and soy production and CRP data. County-level fixed effects and state-level time trends included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Overall, these results reassure us fertilizer use is responding to individual and aggregate-level factors that one would expect, and that our nitrogen use data is capturing meaningful variation across counties and over time.

4.2 Fertilizer on blooms

We next test the relationship between nitrogen use and algal bloom intensity at the county level, as captured by a satellite measure of late summer water greenness. In Table 2 we separately test for effects of nitrogen use in the county and the sum over upstream counties within the watershed. We further control for weather conditions and various county, state, and year trends.

Figure 6 plots the coefficients for the annual panel, a five-year panel, and a cross-section of long differences over thirty years from 1987 to 2017. Included are various combinations of

Table 2: Late summer algal bloom intensity and fertilizer use per km^2

	Dependent variable:			
	Algal boom intensity			
	(1)	(2)	(3)	(4)
Nitrogen, in county	1.408***	1.015**		
	(0.456)	(0.393)		
Nitrogen, upstream			1.634***	1.311**
			(0.499)	(0.580)
County FE	X	X	X	X
Year FE	X		X	
State-Yr trend		X		X
Controls	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State
Observations	73,176	73,176	64,087	64,087
R^2	0.864	0.859	0.866	0.862
Adjusted R^2	0.858	0.854	0.861	0.856

Notes: Linear regression. Dependent variable is county-level average bloom intensity from July to September in areas with water. Nitrogen is 1,000s of tons of farm-level use per km^2 land area of either county or counties upstream within the HUC4 watershed. Time series to 1987 to 2012 and 2017. County-level fixed effects and either year fixed effects of state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

fixed effects and state-level trends. We see that algal bloom intensity responds to nitrogen use across short term, medium term, and long term horizons.

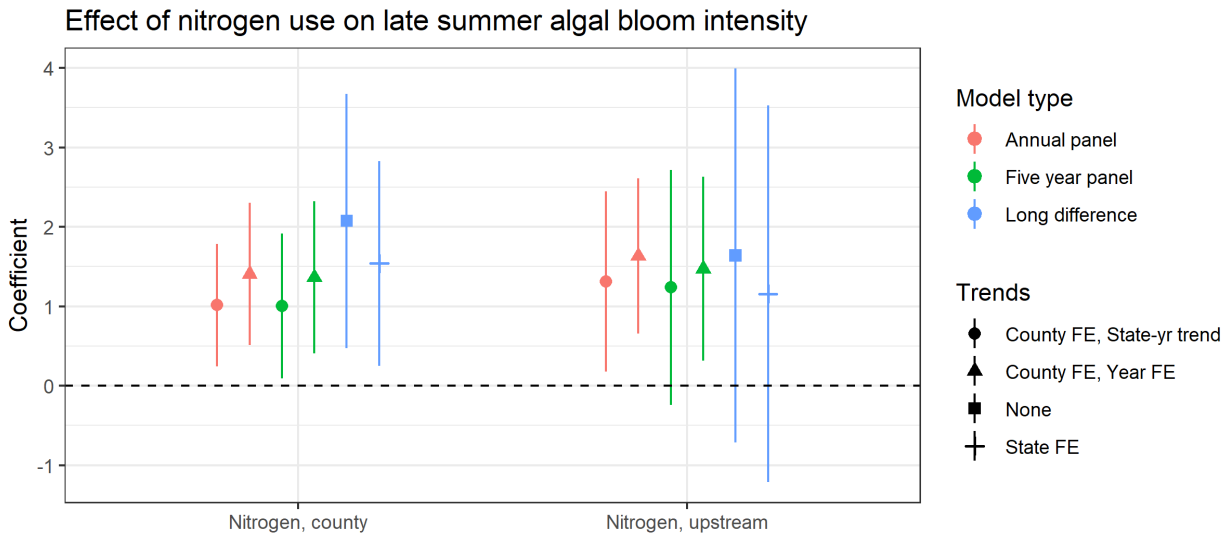


Figure 6: Coefficient plot. Red lines include the same specification as Table 2. Green lines includes observations every five years from 1987 to 2017, using average values in the year before through the year after each point. Blue lines are the results of the cross-sectional long difference from 1987 to 2017, similarly using three year average values around the endpoints. All models control for average weather conditions. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

There are valid concerns about weather being a potential confounder given that it may influence both farm decisions (e.g., compensate for bad weather with additional fertilizer) as well as bloom intensity directly through phytoplankton biological processes. While we cannot completely untangle this relationship, in Appendix Figure A2 we run the analysis shown in Figure 6 but omit the controls for growing season precipitation and temperature. The resulting coefficients are a bit less precisely estimated, as may be expected, but the results are largely unchanged.

4.3 Income effect

We test the relationship between algal bloom intensity and county-level income in Table 3. Note that going forward we include county and state-year trends in all of our models. Model (1) shows that bloom intensity is negatively related to county level income. Models (2)-(7) include interaction terms to determine if there are differential effects by county characteristics. Model (8) drops coastal counties to test whether effects are present in inland waterways.

We find that the negative effect of blooms are larger in coastal counties, counties with high

Table 3: Impact of late summer algal blooms on county income, 1984-2019

	Dependent variable:							
	County income per capita (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	−0.131***	−0.109**	−0.080	−0.096*	−0.205***	−0.174***	−0.197***	−0.200***
	(0.047)	(0.050)	(0.052)	(0.050)	(0.048)	(0.050)	(0.048)	(0.049)
Bloom:Coastal		−0.504***			−0.418**			
		(0.166)			(0.169)			
Bloom:Water Prop			−2.043***			−1.805***		
			(0.649)			(0.646)		
Bloom:Fishing High				−0.247***			−0.199***	−0.169**
				(0.070)			(0.070)	(0.072)
Bloom:Farm Income High					0.331***	0.316***	0.335***	0.331***
					(0.095)	(0.095)	(0.095)	(0.095)
County FE	X	X	X	X	X	X	X	X
State-Yr trend	X	X	X	X	X	X	X	X
Sample	All	All	All	All	All	All	All	Non-coastal
Controls	Weather	Weather	Weather	Weather	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State	State	State	State	State
Observations	97,391	97,391	97,391	97,391	97,391	97,391	97,391	89,471
R^2	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.966
Adjusted R^2	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.965

Notes: Linear regression. Dependent variable is county-level log income per capita. Bloom is county-level average bloom intensity from July to September in areas with water. Time series from 1984 to 2019. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

proportion of water area, and counties with high levels of fishing income (top quintile). On the contrary, the relationship is positive in counties with high levels of farm income.

We interpret the results to mean that places more dependent on water resources for industry, recreation, tourism, and real estate are more negatively affected by algal blooms. Farm-intensive counties see higher income which likely reflects the fact that farmers are using more fertilizer in these places, and thus getting higher yields. This in turn results in higher county income, especially during times of high crop commodity prices.

We split the sample into decadal sub-periods can confirm that the results generally hold across the 35 years in which satellite-derived algal bloom data is available. Figure 7 plots coefficients from Model (4) in Table 3. The non-interacted bloom term is no longer consistently negative, but the interacted terms largely behave the same. During 2000-2019, the coefficient for counties reliant on fishing is negative but no longer significant, but in this case, the overall bloom term is statistically significant and negative. Blooms are consistently associated with higher income in farm-intensive counties.

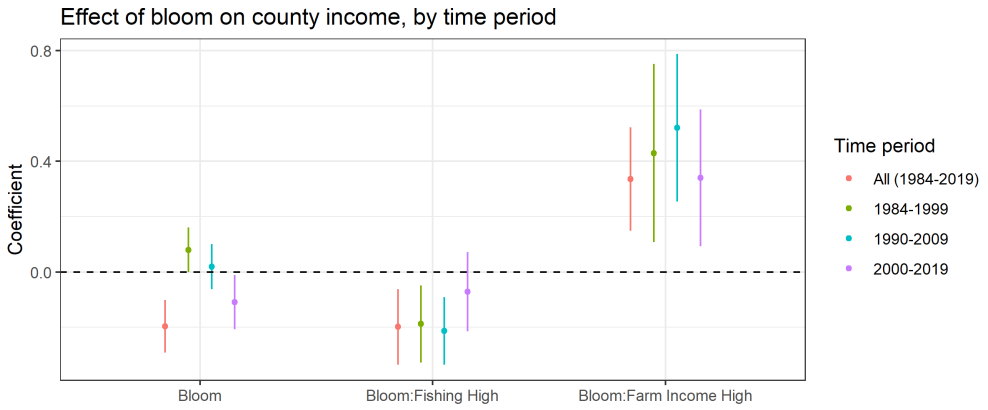


Figure 7: Coefficient plot using Model (4) specification in Table 3. Fishing High and Farm Income High are indicators for counties with high levels of fishing income and farm income, respectively (top quintile). All models control for average weather conditions. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

4.4 Robustness

We provide several alternate models in the Appendix. As discussed earlier, while weather influences bloom intensity directly, it also affects economic outcomes through channels unrelated to algal blooms (Dell et al. 2012). To this end, we replicate the analysis of the impact of bloom intensity on economic outcomes from Table 3 but drop the weather covariates in Table A1. The resulting coefficients are unchanged. While this does not illumi-

nate the complex weather-agriculture-ecological interactions, it at at least ensures us that weather is not driving our results.

We also use aggregate county income instead of per capita income in Table A2, as well as alternate measures of farm income that include both continuous and time-varying values in Table A3.

We showcase potential non-linearities in Figure 8 based in algal bloom intensity quintile across subsets of the data consisting of counties that are coastal as well as in the top quintile of water area, fishing income, and farming income. For all except farm-intensive counties, the response appears to be relatively linearly, with the negative effect of blooms increasing with bloom intensity quintile. This implies there may not be a discrete cut-off when algal blooms become detrimental based on the level of average water greenness.

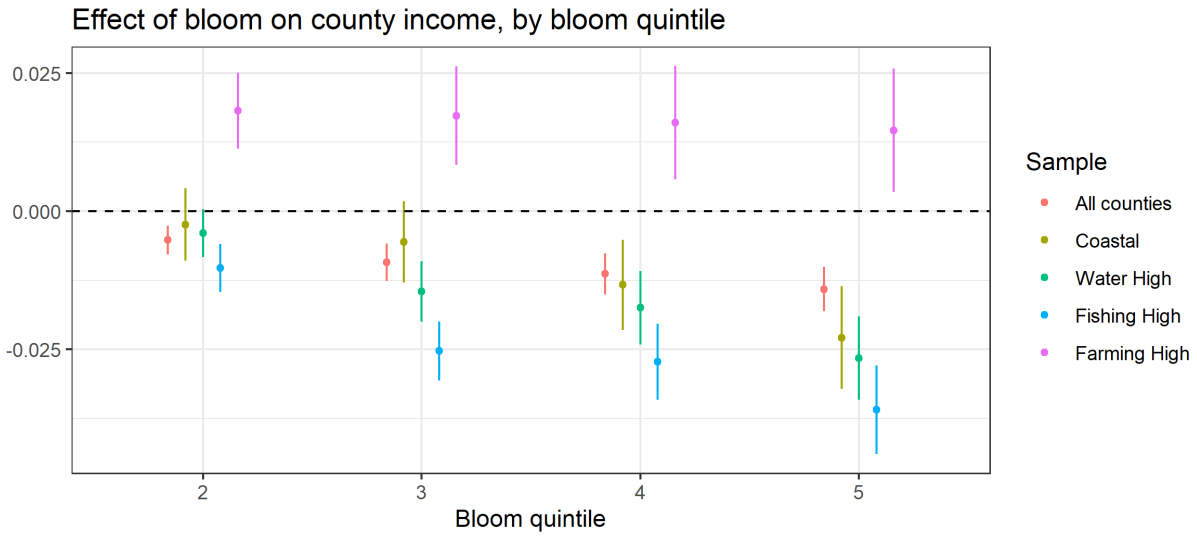


Figure 8: Coefficient plot. Magnitudes are relative to the low bloom omitted category (first quintile of bloom intensity). Samples are subsets of the data consisting of counties that are coastal as well as in the top quintile of water area, fishing income, and farming income. All models control for average weather conditions. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

We next test whether the relationship holds over longer time periods: i.e., is it the case that places where blooms are getting worse experience less income growth over time. Figure 9 plots the interacted coefficients from the models in Table 3 using an annual, as well as the same outcomes for a five-year panel and a thirty-year long difference cross-section. Overall, the estimates for the five-year panel and the long difference are less precise, partly because of the fewer number of observations. We see a clear and increasingly negative effect of blooms on medium and long-term income growth in coastal counties and counties with a high proportion of water. The long-term relationship is less clear in fishing-intensive counties, which could imply a shift away from fishing as a response to water pol-

lution or an adaptive response given the complex interactions between fish populations and nutrient enrichment (Breitburg et al. 2009). Interestingly, we no longer see a positive relationship for farm-intensive counties. This suggests that fertilizer use is boosting incomes in the short term, but that blooms do not otherwise benefit farm-intensive counties.

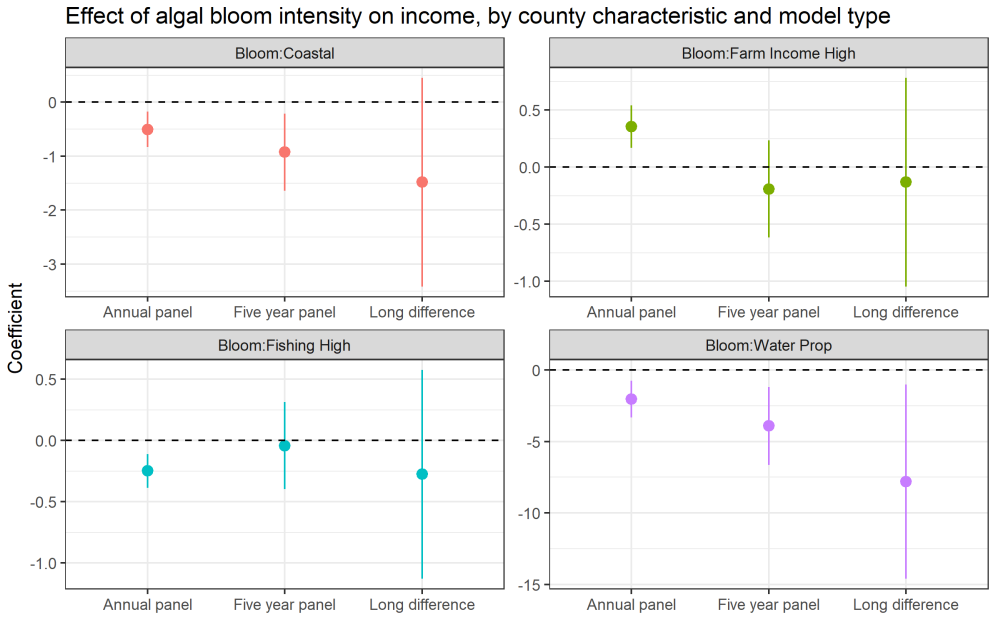


Figure 9: Coefficient plot. 'Annual panel' plots the interacted coefficients from models in Table 3. 'five year panel' includes observations every five years from 1987 to 2017, using average values in the year before through the year after each point. 'Long difference' is a cross-sectional long difference from 1987 to 2017, similarly using three year average values around the endpoints. State fixed effects included in the long difference. The four panels show bloom intensity interacted with counties by whether they are coastal, in the top quintile of fishing income and farming income, and their water area proportion. All models control for average weather conditions. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

4.5 Instrumental variable

[PRELIMINARY AND SUBJECT TO REVISION]

We next combine the two models to assess the economic impact of blooms using upstream fertilizer use as an instrumental variable. The general idea is that we seek to isolate the variation in bloom levels that is driven by fertilizer use, and then estimate the resulting economic impact from that variation. We note that this is not a perfect instrument because fertilizer use is related to impact in ways unrelated to water quality. As discussed earlier, farmers may apply more fertilizer when the economy is good (e.g., credit is easily available), and increased fertilizer use can increase crop production and increase county income, particularly during periods of high commodity prices.

The first stage regression is shown in Appendix Table A5 using the same specification as

Model (4) of Table 2. We include the F-statistic for the excluded instrument, nitrogen use. There is evidence of a weak instrument when clustering at the state-level, which is the standard error treatment used in this analysis. However, other clustering approaches yield a much stronger relationship. Nevertheless, caution is warranted when interpreting the results.

Table 4 shows the IV results with proximate OLS estimates like in Table 3, except restricted in years to when fertilizer use data is available. We consistently see that the IV coefficients for the interaction with water-reliant counties (e.g., the bloom impact in coastal areas) are negative and larger in magnitude than OLS. For farm intensive counties the IV coefficient is still positive but no longer significant. The non-interacted bloom term becomes large in the IV, perhaps capturing the economic value of increased fertilizer use. Appendix Table A6 replicates the IV with the five year panel data to assess the medium-term effects.

Table 4: IV (Annual panel): Impact of late summer algal blooms on county income, instrumented by nitrogen use upstream

	Dependent variable:							
	County income per capita (log)							
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	0.071	7.050**	0.089	6.907**	0.078	6.951**	−0.044	6.700**
	(0.056)	(3.098)	(0.056)	(3.097)	(0.058)	(3.114)	(0.049)	(3.102)
Bloom:Coastal	−0.684***	−1.886***						
	(0.168)	(0.578)						
Bloom:Water Prop			−1.907***	−2.157**				
			(0.605)	(0.998)				
Bloom:Fishing High					−0.278***	−0.575**		
					(0.080)	(0.256)		
Bloom:Farm Income High							0.306**	0.602
							(0.140)	(0.601)
County FE	X	X	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X	X	X
Controls	Weather	Weather	Weather	Weather	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State	State	State	State	State
Observations	64,083	64,083	64,083	64,083	64,083	64,083	64,083	64,083
R^2	0.965	0.965	0.965	0.965	0.965	0.965	0.965	0.965
Adjusted R^2	0.964	0.964	0.964	0.964	0.964	0.964	0.964	0.964

Notes: Linear regression. Dependent variable is county-level log income per capita. Bloom is county-level average bloom intensity from July to September in areas with water. Nitrogen is 1,000s of tons of farm-level use per km^2 land area in counties upstream within the HUC4 watershed. Time series from 1987 to 2017 when both fertilizer and bloom data is available. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

5 Gulf of Mexico effect

This paper has focused on the within-county impact of algal blooms on economic outcomes in that same county. While we take into account nutrient pollution from the fertilizer utilized upstream from the county, we do not look explicitly at downstream impacts. However, a proportion of all the fertilizer applied across the entire Mississippi River basin (3.2 million km^2 and about 40% of the the continental US, including the entire Midwestern corn belt) reaches the Gulf of Mexico via the Mississippi River (and the nearby Atchafalaya river). These upstream nutrient levels create hypoxic conditions in the Gulf of Mexico (Rabotyagov et al. 2014).

Figure 10 shows the correlation between upstream nitrogen and phosphate use and the size of the Gulf of Mexico hypoxia zone. We see the strong correlation between nitrogen and phosphate fertilizer use, as well as a positive but weaker correlation with hypoxia extent.

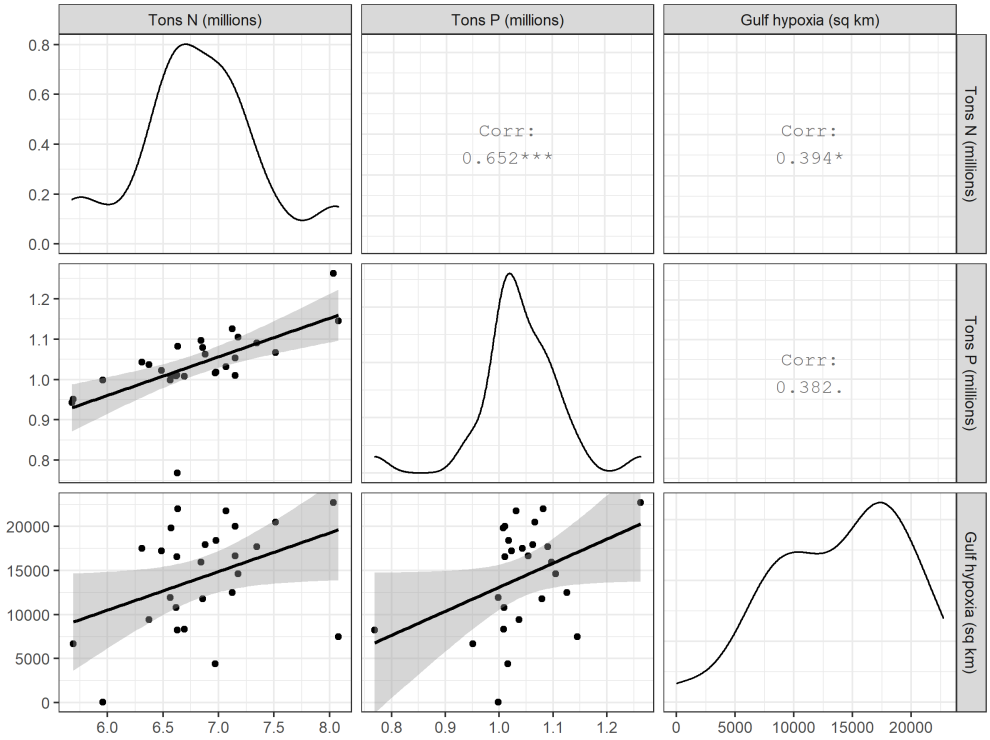


Figure 10: Correlation and density plots with line of best fit for weighted upstream basin fertilizer use of nitrogen (N) and phosphate (P) in millions of tons and Gulf of Mexico hypoxia extant in km^2

In Table 5 we estimate the impact of upstream nutrients on the hypoxia zone extent. We take the inverse distance-weighted average of fertilizer use across all counties in the Mississippi river basin. Weather also affects hypoxia via its impact on water flow and phytoplankton activity. To this end, we flexibly control for precipitation and temperature both

across the Mississippi River basin and along the coast. We find a somewhat weak but persistently positive relationship between nitrogen use and hypoxic extent: a 1,000 ton increase in upstream nitrogen adds 4-5 km^2 to the hypoxic zone in the gulf. The average hypoxic zone during this time period was 14,000 km^2. In log form, we see that a 1% increase in nitrogen is associated with about a 5% increase in hypoxic extent in km^2. We also show the results for the phosphorus, the other major limiting factor in phytoplankton growth (Turner and Rabalais 2013), in Appendix Table A4.

Table 5: Mississippi River basin annual nitrogen use and Gulf hypoxia extent

	Dependent variable:					
	——Hypoxia (sq km)——			——Log Hypoxia (sq km)——		
	(1)	(2)	(3)	(4)	(5)	(6)
Nitrogen	4.386**	4.106*	4.633*			
	(2.087)	(2.083)	(2.409)			
Log Nitrogen				6.571**	5.340*	5.709*
				(2.902)	(2.746)	(3.241)
Weather upstream		X	X		X	X
Weather coastal			X			X
Observations	26	26	26	26	26	26
R^2	0.155	0.371	0.398	0.176	0.454	0.456
Adjusted R^2	0.120	0.285	0.247	0.142	0.380	0.320
F Statistic	4.417**	4.325**	2.641*	5.128**	6.107***	3.356**

Notes: Linear regression. Dependent variable is Gulf of Mexico summer hypoxic extent as defined by the estimated area where bottom-water dissolved oxygen is below 2 mg/L. Nitrogen is measured in 1,000s of tons for farm use, inverse weighted by distance from the mouth of the Mississippi River and summed across all counties in the Mississippi river basin. Weather controls include average temperature and precipitation from January to June of the given year for all counties in the Mississippi River basin (upstream) and counties along the coast of the Gulf of Mexico (coastal). Time period from 1985 to 2019. *p<0.1; **p<0.05; ***p<0.01

6 External cost

[PRELIMINARY AND SUBJECT TO REVISION]
Next, we estimate the external cost of nitrogen fertilizer. Table 3 is an annual panel regression of county-level income on summer algal bloom intensity. The standard deviation in algal bloom intensity across time and counties is 0.04. Therefore, a one standard deviation increase in algal bloom intensity is associated with a 1.2% increase in per capita income in farming counties (0.04 x 0.3), and a 2% decline in coastal counties (0.04 x 0.5), a 0.8% decline in fishing-intensive counties (0.04 x 0.2). Each additional 12% of county area that is water, which is the standard deviation across US counties, there is a 1% decline in income (0.04 x 2 x 0.12).

We can link this back to Table 2, the annual panel regression of algal bloom intensity on fertilizer use. The standard deviation in upstream nitrogen use (tons per county km^2 land) across time and counties is 0.002. Therefore, a one standard deviation increase is associated with a 0.0026 increase in algal bloom intensity (0.002 x 1.3). Based on the coefficients in Table 3, this fertilizer-driven 0.0026 increase in algal bloom intensity reduces income in coastal counties by 0.125% (0.0026 x 0.5).

Coastal counties account for about one-third of US income. During our sample period from 1984 to 2019, the average aggregate income of coastal counties was $3 trillion per year, $32,000 per capita, or $14 billion per county. In terms of total upstream nitrogen use from a county, a one standard deviation is 20,000 tons. So one ton used upstream is equivalent to about $900 in damages (1/20,000 x 0.00125 x 14 billion) to downstream coastal counties. Interestingly, this is near the market price of nitrogen fertilizer cited earlier at $880 per ton.

7 Discussion

In this study, we seek to estimate the economic cost of fertilizer via water quality. This exercise has been challenging to date due to the fact that farm pollution is largely exempt under the Clean Water Act as well as the lack of annual panel on water quality linked to an administrative level. We create such a dataset using a satellite algorithm to approximate algal bloom intensity at the US county level. We find a significant negative economic impact in places downstream from agricultural areas, as well as water reliant regions (i.e., coastal areas) and economic sectors (fishing, tourism, hunting, recreation). We calculate a back-of-the-envelope cost estimate of [$900] per ton of nitrogen, which is roughly in line

with its market value.

In addition to limiting fertilizer use, there are other policies that may mitigate the negative externality, including land use programs like the Wetlands Reserve Program. The protection and restoration to wetlands of lowland area under crop cultivation has been shown to significantly reduce downstream nutrient pollution in the Mississippi basin (Mitsch et al. 2005). Wetlands also have the added benefit of reducing flood damages (Taylor and Druckenmiller 2021).

We hope that this new satellite product of water quality can be utilized in research on other policy-relevant questions, including the valuation of wetlands and other ecosystem services—in both the US and geographies outside of the US.

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8 Appendix Tables

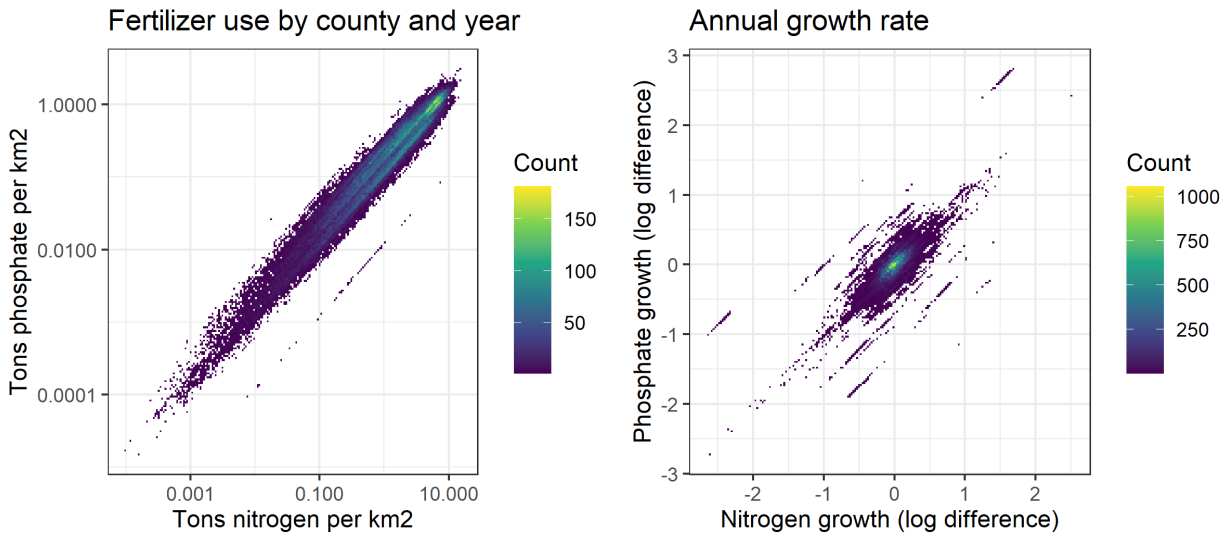


Figure A1: Scatter plot of USGS county-level farm nitrogen and phosphate use per km^2. Left panel shows annual levels, right panel shows annual change in term of growth rate

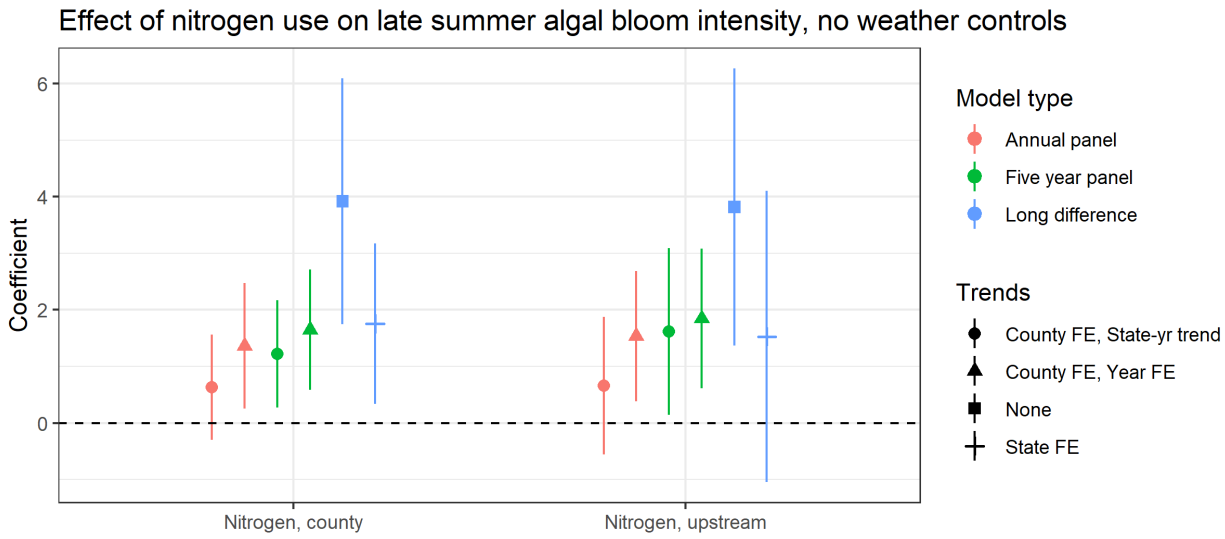


Figure A2: Coefficient plot. Same as Figure 6 except does not include weather controls. Red lines include the same specification as Table 2. Green lines includes observations every five years from 1987 to 2017, using average values in the year before through the year after each point. Blue lines are the results of the cross-sectional long difference from 1987 to 2017, similarly using three year average values around the endpoints. All models control for average weather conditions. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

Table A1: Impact of late summer algal blooms on county income, 1984-2019, no weather controls

	Dependent variable:							
	County income per capita (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	−0.049	−0.025	0.002	−0.012	−0.123**	−0.094*	−0.114**	−0.116**
	(0.049)	(0.052)	(0.054)	(0.053)	(0.050)	(0.052)	(0.051)	(0.051)
Bloom:Coastal		−0.564***			−0.478**			
		(0.177)			(0.178)			
Bloom:Water Prop			−2.079***			−1.836***		
			(0.658)			(0.652)		
Bloom:Fishing High				−0.270***			−0.221***	−0.177**
				(0.072)			(0.070)	(0.073)
Bloom:Farm Income High					0.334***	0.323***	0.340***	0.334***
					(0.101)	(0.102)	(0.101)	(0.101)
County FE	X	X	X	X	X	X	X	X
State-Yr trend	X	X	X	X	X	X	X	X
Sample	All	All	All	All	All	All	All	Non-coastal
SE cluster	State	State	State	State	State	State	State	State
Observations	97,391	97,391	97,391	97,391	97,391	97,391	97,391	89,471
R^2	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.966
Adjusted R^2	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.965

Notes: Linear regression. Dependent variable is county-level log income per capita. Bloom is county-level average bloom intensity from July to September in areas with water. Time series from 1984 to 2019. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A2: Impact of late summer algal blooms on county aggregate income, 1984-2019

	Dependent variable:							
	County aggregate income (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	−0.290***	−0.264***	−0.247***	−0.260***	−0.438***	−0.425***	−0.444***	−0.432***
	(0.056)	(0.059)	(0.066)	(0.064)	(0.070)	(0.078)	(0.076)	(0.078)
Bloom:Coastal		−0.616***			−0.461*			
		(0.228)			(0.238)			
Bloom:Water Prop			−1.758			−1.308		
			(1.274)			(1.266)		
Bloom:Fishing High				−0.216			−0.128	−0.175
				(0.171)			(0.183)	(0.205)
Bloom:Farm Income High					0.600***	0.598***	0.614***	0.588***
					(0.149)	(0.152)	(0.152)	(0.150)
County FE	X	X	X	X	X	X	X	X
State-Yr trend	X	X	X	X	X	X	X	X
Sample	All	All	All	All	All	All	All	Non-coastal
Controls	Weather	Weather	Weather	Weather	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State	State	State	State	State
Observations	97,391	97,391	97,391	97,391	97,391	97,391	97,391	89,471
R^2	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.992
Adjusted R^2	0.993	0.993	0.993	0.993	0.993	0.993	0.993	0.992

Notes: Linear regression. Dependent variable is county-level log aggregate income. Bloom is county-level average bloom intensity from July to September in areas with water. Time series from 1984 to 2019. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A3: Impact of late summer algal blooms on county income, by farm income measure, 1984-2019

	Dependent variable:				
	County income per capita (log)				
	(1)	(2)	(3)	(4)	(5)
Bloom	-0.131^{***}	-0.109^{**}	-0.205^{***}	-0.274^{***}	-0.420^{***}
	(0.047)	(0.050)	(0.048)	(0.051)	(0.054)
Bloom:Coastal		-0.504^{***}	-0.418^{**}	-0.382^{**}	-0.265
		(0.166)	(0.169)	(0.167)	(0.168)
Bloom:Farm Income High			0.331^{***}		
			(0.095)		
Bloom:Farm Income Avg				0.142^{***}	
				(0.031)	
Bloom:Farm Income Annual					0.195^{***}
					(0.042)
County FE	X	X	X	X	X
State-Yr trend	X	X	X	X	X
Sample	All	All	All	All	All
Controls	Weather	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State	State
Observations	97,391	97,391	97,391	97,391	97,391
R^2	0.967	0.967	0.967	0.967	0.969
Adjusted R^2	0.966	0.966	0.966	0.966	0.968

Notes: Linear regression. Dependent variable is county-level log aggregate income. Bloom is county-level average bloom intensity from July to September in areas with water. Farm Income High is a non-time varying indicator for counties with average farm income in the top quintile. Farm Income Avg is a non-time varying continuous measure of average farm income. Farm Income Annual is a time-varying measure of farm income per capita. Time series from 1984 to 2019. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A4: Mississippi River basin annual phosphate use and Gulf hypoxia extent

	Dependent variable:					
	——Hypoxia (sq km)——			——Log Hypoxia (sq km)——		
	(1)	(2)	(3)	(4)	(5)	(6)
Phosphate	27.314*	26.447**	26.622*			
	(13.499)	(12.068)	(13.379)			
Log Phosphate				3.159	3.207	3.239
				(2.908)	(2.487)	(2.671)
Weather upstream		X	X		X	X
Weather coastal			X			X
Observations	26	26	26	26	26	26
R^2	0.146	0.404	0.404	0.047	0.390	0.415
Adjusted R^2	0.110	0.323	0.255	0.007	0.307	0.269
F Statistic	4.094*	4.975***	2.714**	1.180	4.691**	2.836**

Notes: Linear regression. Dependent variable is Gulf of Mexico summer hypoxic extent as defined by the estimated area where bottom-water dissolved oxygen is below 2 mg/L. Phosphate is measured in 1,000s of tons for farm use, inverse weighted by distance from the mouth of the Mississippi River and summed across all counties in the Mississippi river basin. Weather controls include average temperature and precipitation from January to June of the given year for all counties in the Mississippi River basin (upstream) and counties along the coast of the Gulf of Mexico (coastal). Time period from 1985 to 2019. *p<0.1; **p<0.05; ***p<0.01

Table A5: IV First Stage: Upstream nitrogram fertilizer use on late summer algal blooms

	Dependent variable:			
	County income per capita (log)			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Nitrogen	1.311***	1.311***	1.300***	1.311**
	(0.158)	(0.202)	(0.120)	(0.580)
County FE	X	X	X	X
State-Yr Trend	X	X	X	X
Controls	Weather	Weather	Weather	Weather
SE cluster	None	County	Ecoregion	State
F-stat	68.6	41.9	117.1	5.1
Observations	64,083	64,083	63,903	64,083
R^2	0.862	0.862	0.862	0.862
Adjusted R^2	0.856	0.856	0.856	0.856

Notes: Linear regression. Dependent variable is county-level average bloom intensity from July to September in areas with water. Nitrogen is 1,000s of tons of farm-level use per km^2 land area in counties upstream within the HUC4 watershed. Time series from 1987 to 2017. F-stat is for nitrogen, the excluded instrument. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered as described. *p<0.1; **p<0.05; ***p<0.01

Table A6: IV (5-Year Panel): Impact of late summer algal blooms on county income, instrumented by nitrogen use upstream

	Dependent variable:							
	County income per capita (log)							
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	−0.826***	5.896	−0.780***	5.814	−0.861***	5.588	−0.799***	5.974
	(0.118)	(4.622)	(0.118)	(4.632)	(0.114)	(4.670)	(0.145)	(4.824)
Bloom:Coastal	−1.133***	−2.991**						
	(0.334)	(1.129)						
Bloom:Water Prop			−3.866***	−3.912*				
			(1.300)	(2.222)				
Bloom:Fishing High					−0.082	0.134		
					(0.185)	(0.481)		
Bloom:Farm Income High							−0.251	−2.211
							(0.229)	(1.468)
County FE	X	X	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X	X	X
Controls	Weather	Weather	Weather	Weather	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State	State	State	State	State
Observations	16,840	16,840	16,840	16,840	16,840	16,840	16,840	16,840
R^2	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971
Adjusted R^2	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966

Notes: Linear regression. Dependent variable is county-level log income per capita. Bloom is county-level average bloom intensity from July to September in areas with water. Nitrogen is 1,000s of tons of farm-level use per km^2 land area in counties upstream within the HUC4 watershed. Time series from 1987 to 2017 when both fertilizer and bloom data is available. County-level fixed effects and state-level time trends included. Counties with less than 1 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01