Algal Blooms and the Social Cost of Fertilizer

Charles A Taylor*

Geoffrey Heal†

May 2021

Abstract

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

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

*School of International and Public Affairs, Columbia University. Author received support from the Center for Environmental Economics and Policy (CEEP), Columbia University.

†Columbia Business School; National Bureau of Economic Research (NBER)

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

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 are 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 mostly 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 also inhibit efficient regulation of this market.

First, the economic impacts of hypoxia and algal blooms and the related external 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 an analysis of contributors to the dead zone in the Gulf of Mexico, David et al. 2010 found that the highest nitrogen yields occurred in the tile-drained Corn Belt of Minnesota, Iowa, Illinois, Indiana, and Ohio—areas 1,500 km 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 is the lack of temporally-consistent and spatially-relevant data on water quality (Brooks et al. 2016) 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 overcome this problem, 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.

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).

There is also evidence that nitrates in drinking water may have a negative effect on human health. Best documented is the 'blue baby syndrome', formally known as *methemoglobinemia*, a condition in which nitrites derived from nitrates combine with hemoglobin and prevent oxygenation of the blood. There is additionally some evidence that nitrates are associated with colorectal cancer, thyroid disease, and neural tube defects, but these connections are not rigorously established and are controversial (Ward et al. 2018; Hilborn et al. 2014).

Here we focus only on the direct economic effects of algal blooms generated by nitrate fertilizers and omit any consideration of the health effects, so that our estimates must be seen as lower bounds for the total external costs of these fertilizers. However, hypoxia and algal-related externalities linked to public health may to some degree be captured in our measure of county income to the extent that they affect labor or other economic outcomes.

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 widely-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 the use of phosphate and potash-based fertilizers has flattened 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.

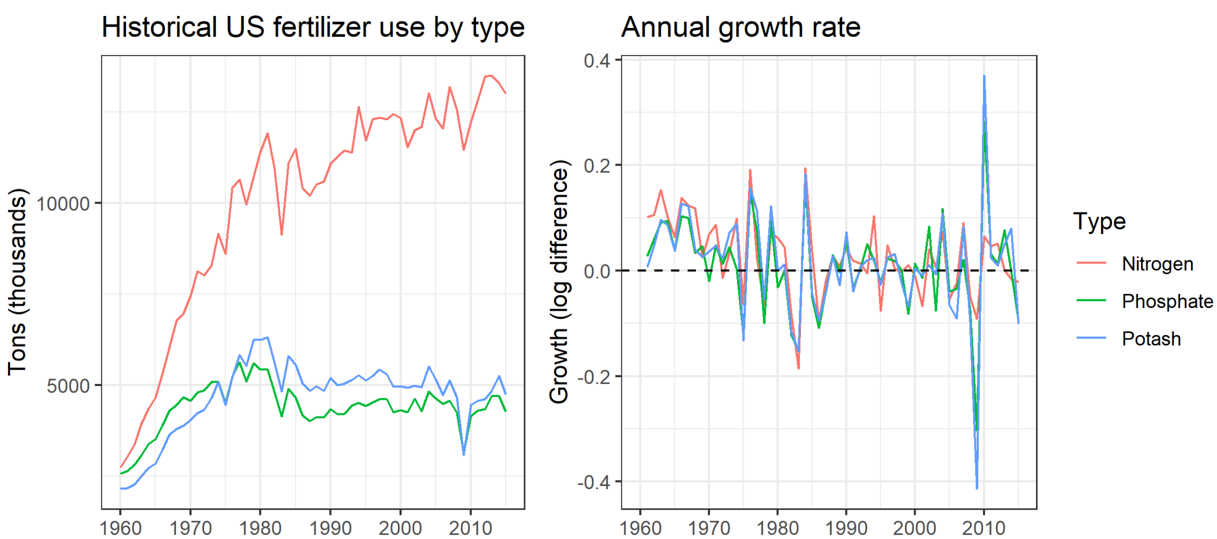


Figure 1: USDA ERS fertilizer use aggregated nationally by fertilizer type and year

Determining the socially-optimal level of nitrogen use requires equating the marginal private benefits of fertilizer to its consumers (i.e., farmers) with the private and external marginal cost of fertilizer.[2] The private benefit is conceptually straightforward and based on agronomic relationships between yield and fertilizer use,[3] 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

[2] There may also be external social benefits of fertilizer use, such as reducing the cost of food to the benefit of low-income groups. Here we focus exclusively on the external costs.

[3] Optimal nitrogen calculator: http://cnrc.agron.iastate.edu/nRate.aspx

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 have a strong incentive to optimize their fertilizer use in a way that takes into account marginal yield increases relative to the marginal cost of fertilizer.

The external 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, estimating 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[4] 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),[5] 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.[6] However, using 2021 prices 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 median estimate of a left-skewed 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 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.[7] The wide gap in the estimated costs of algal blooms and

[4] Fertilizer Use and Price: www.ers.usda.gov/data-products/fertilizer-use-and-price

[5] Source: http://agfax.com

[6] 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.

[7] However, it is worth noting that their estimate is more in line with Dodds et al. 2009's estimated cost of

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 in water reliant regions (i.e., coastal areas) and economic sectors (fishing, tourism, hunting, recreation). We calculate a back-of-the-envelope cost estimate of $580 per ton of nitrogen [range $370 to $1,400], 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 relation to geographies outside of the United States.

2 Data

Fertilizer: We utilize the 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 2017 (Falcone 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 from over three decades of Landsat satellite imagery and processed using computing power available through Google Earth Engine.[8] 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 Resolu-

algal blooms in the US of $2.2 billion per year.

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

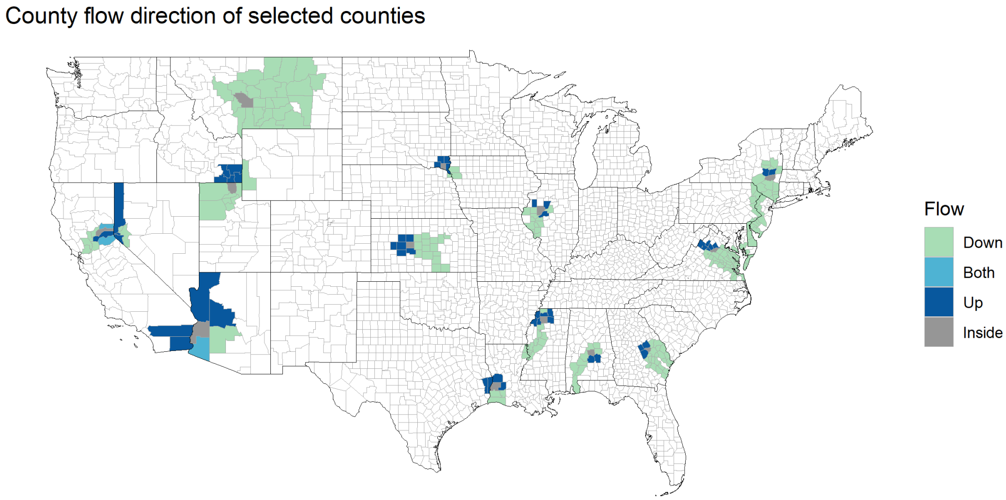


Figure 2: Watershed classification of counties based on their relative location within the USGS hydrologic unit code HUC-4 watershed boundary. Thirteen randomly-selected counties are shown in gray. Green areas represent counties that are at least partly within the same HUC-4 and downstream from the gray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

tion 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 build on Ho et al. 2019's approach to analyzing 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). In matching the Landsat 5 with Landsat 7 we subtract the satellite bias based on the difference in county-level bloom values during the years in which the products overlapped.

We filter out all images with over 25% cloud cover. Unlike Ho et al. 2017, we do not filter out pixels beyond a certain hue threshold. We then take the temporal average of the bloom measure across all the 16-day revisit periods 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. We exclude counties lacking significant water features (less than 5 km^2 of surface water), dropping about 25% of US counties. However, the results are robust to their inclusion.

It is worth noting that our calculated index is not a direct measure of either concentrations of chlorophyll or 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).

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.[9] 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.

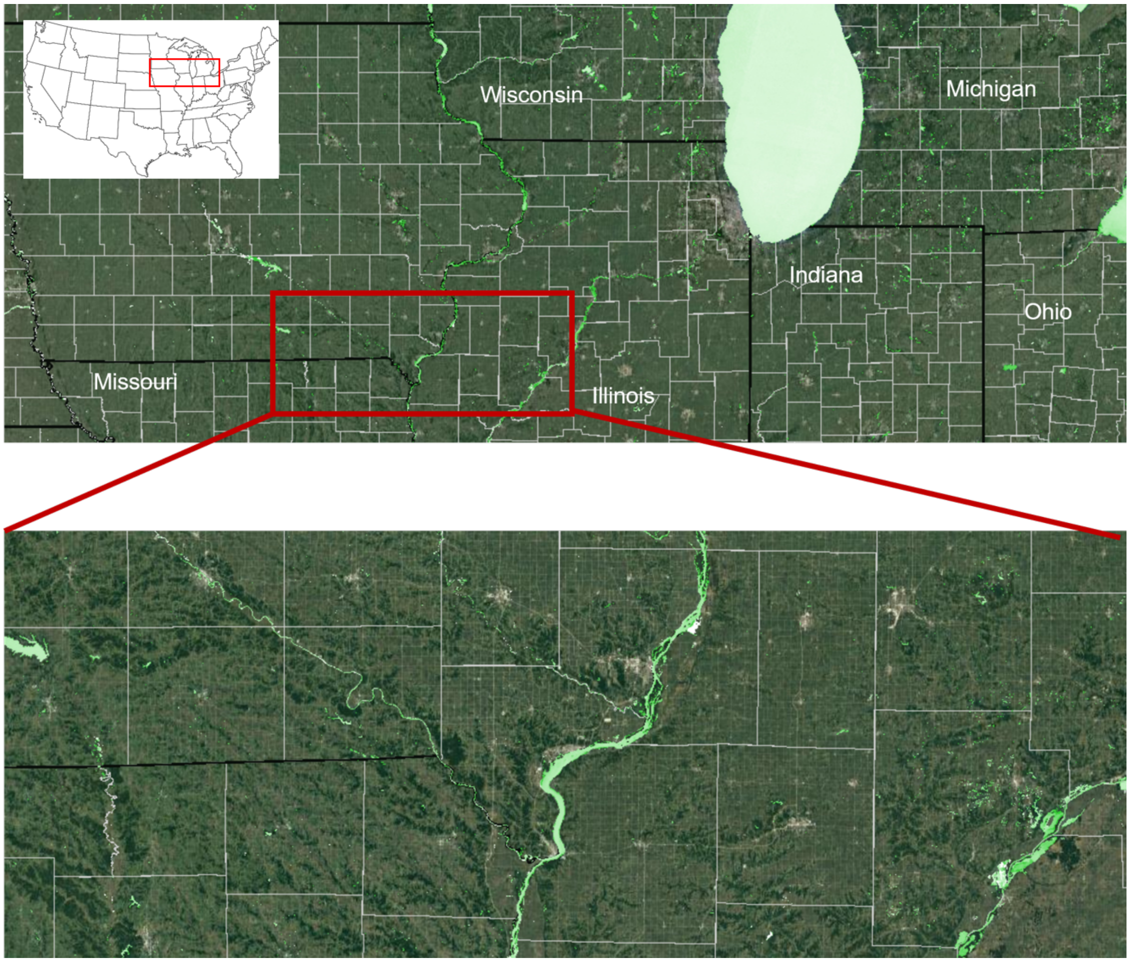
2.1 Satellite-derived bloom intensity trends

The contribution 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$^{\text{th}}$ meridian.

Figure 5 graphs average annual bloom intensity by US region from 1984 to 2020. Most locations appear flat. A trend of decreasing bloom intensity in the US Southeast (South Atlantic) signifying potential water quality improvement may be attributable to a reduction in cropland area in that region. In line with the pattern shown on the map in Figure 4, algal blooms have intensified in the upper Midwest (West North Central) beginning in the mid-2000s. This may be linked to Corn Belt cropland expansion and intensification

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

Panel A



Panel B

Houston-Beaumont, TX

1999 2019

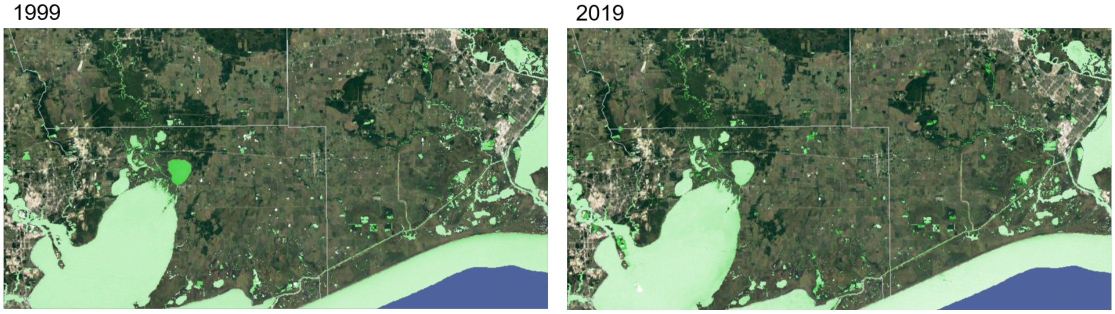
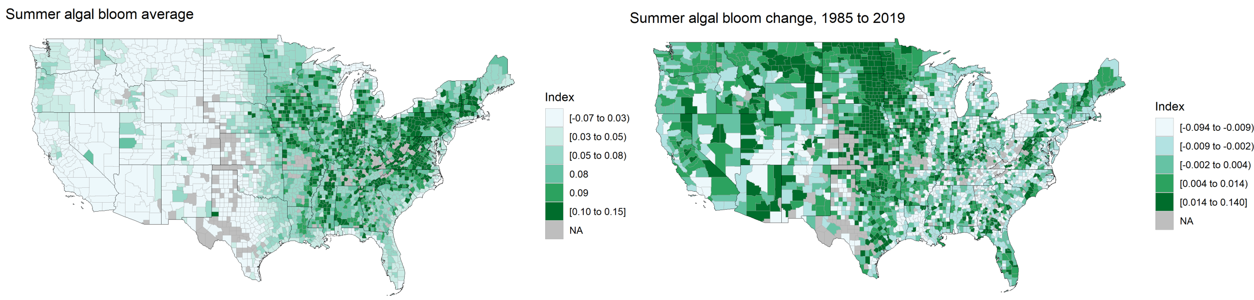


Figure 3: Panel A shows late summer bloom index averaged over 20 years from 1999 to 2019 in the US Corn Belt, then with a close-up of the boundary region of Iowa, Illinois and Missouri where the Des Moines River meets the Mississippi. Panel B shows the late summer algal bloom index at two discrete points 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 from 1985 to 2019 using three-year averages around the endpoints (i.e., 1984-1986 for 1985). Gray counties lack enough surface water for a reading.

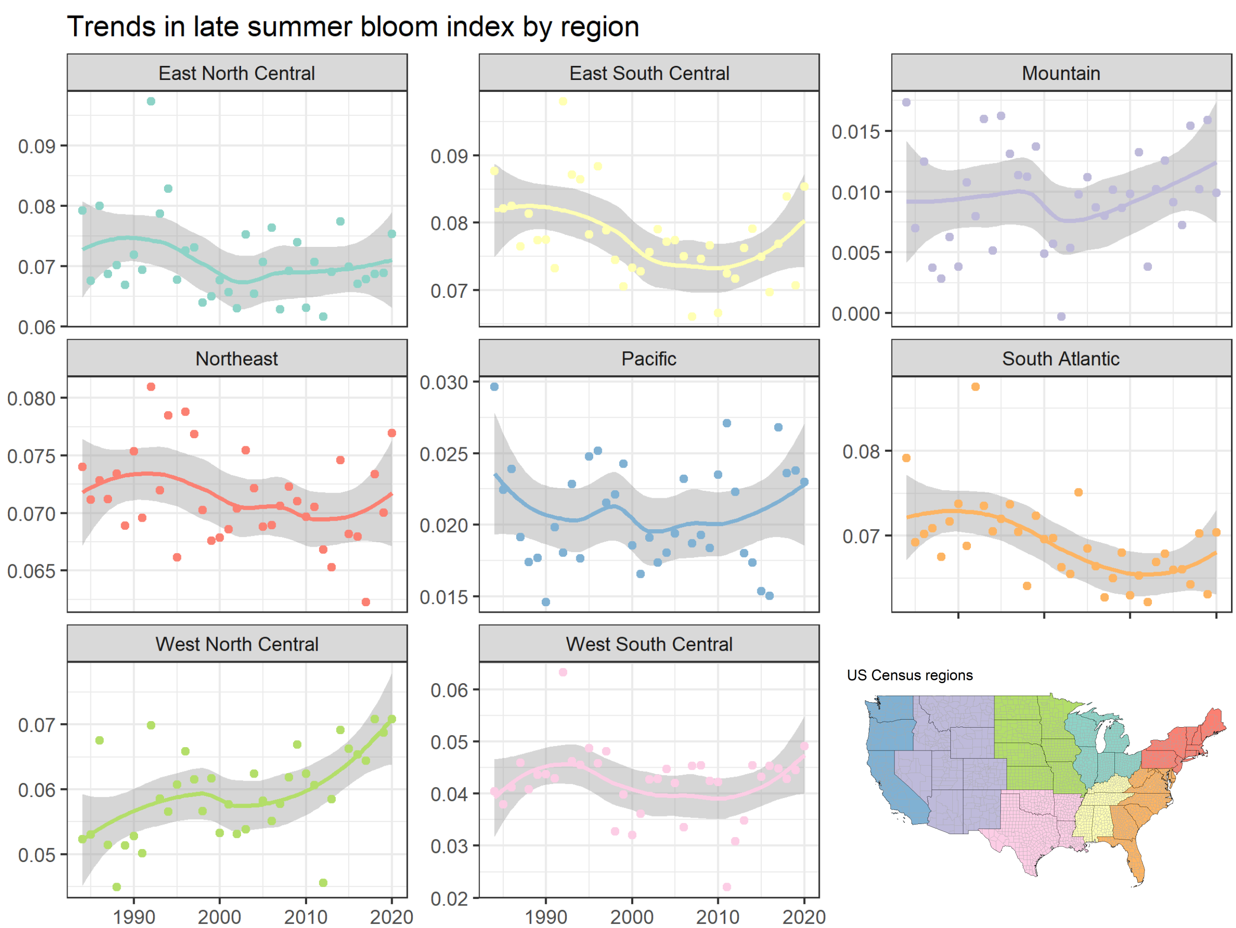


Figure 5: Trends in late summer algal bloom intensity from 1984 to 2020 by US Census region. 'Northeast' includes New England and the Middle Atlantic. Color coded legend map on bottom right.

driven by ethanol demand in response to the Energy Policy Act of 2005. Note that four of the five largest ethanol producers in the US are included in the West North Central region (Iowa, Nebraska, South Dakota, Minnesota).

3 Empirical Strategy

We employ several empirical approaches: a difference-in-difference approach using a panel of county-year observations to assess annual variation, a five-year panel to assess intermediate variation, and a long-difference cross-sectional approach to assess longer-term effects. We apply 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

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

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

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. $\mathbf{W}$ is a vector of climate controls including mean summer *temp* and *precip*.

We use county-level fixed effects α to demean the observations and allowing for interannual comparisons, as well as year level fixed effects γ to account for national level variation (i.e., commodity prices). State-specific annual time trends *state* are also included to account for differential state-level policy. Standard errors are clustered at state level s.

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

$$\Delta bloom_i = \beta_1 \Delta fert_i + \beta_2 \Delta \mathbf{W}_i + state_s + \epsilon_i \tag{3}$$

$$\Delta income_i = \beta_1 \Delta bloom_i + \beta_2 \Delta bloom_i * feature_i + \beta_3 \Delta \mathbf{W}_i + state_s + \epsilon_i \tag{4}$$

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, $\Delta\ fert$ and $\Delta \mathbf{W}$ represent the change in each variable at the county level over that same time period. We also employ state-level fixed effects *state* to isolate within-state variation. Standard errors are again clustered at the state level. Note we restrict our analysis to the continental US. We drop counties with little surface water (less than 5 km^2), as well as counties with no cropland area. However, results are robust to the inclusion of such counties.

Five-year panel

As a final approach, we estimate 'intermediate' effects with a panel of five-year intervals using rolling-window moving averages calculated over our annual panel dataset. 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 subsequent years. For this intermediate analysis, we utilize the five-year panel of county-level fertilizer data developed by (Falcone 2021).

4 Results

4.1 Drivers of fertilizer use

We first analyze the drivers of fertilizer use at the county level. For an individual farmer, the yield-response of fertilizer is well-known. As described earlier, nitrogen fertilizer accounts for a large cost component of commercial farm operations (∼10% of production value). There is a strong incentive 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 not concerned 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 use 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 use (1,000 tons)			
	(1)	(2)	(3)	(4)
Crop area	0.009***	0.012***	0.009***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Corn-soy ratio		0.929***		0.920***
		(0.252)		(0.248)
CRP acres			−0.008***	−0.010**
			(0.003)	(0.004)
County FE	X	X	X	X
Year FE	X	X	X	X
State-Yr trends	X	X	X	X
Observations	83,094	51,538	82,804	51,458
R^2	0.954	0.956	0.954	0.956

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. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Overall, these results reassure us that fertilizer use is responding to the 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 of nitrogen use over upstream counties within the county's watershed. We further control for weather conditions and and county and year fixed effects, as well as state-year trends, as described earlier.

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	1.409***	0.589*		
	(0.440)	(0.320)		
Nitrogen, upstream			1.576***	0.529
			(0.448)	(0.471)
County FE	X	X	X	X
Year FE	X	X	X	X
State-Yr trend		X		X
Controls	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State
Observations	61,020	61,020	54,221	54,221
R^2	0.856	0.858	0.858	0.860

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. Counties with less than 5 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Figure 6 plots the coefficients for the annual panel, a five-year panel, and long difference cross-section over thirty years from 1987 to 2017. We see that algal bloom intensity responds to nitrogen use across short term, medium term, and long term horizons.

There are valid concerns about the extent to which weather is a potential confounder given its influence on farm-level decisions (e.g., reducing fertilizer use in response to adverse weather) as well as bloom intensity directly through phytoplankton biological processes. While we cannot completely untangle this relationship, in Appendix Figure A2 we run the analyses from Figure 6 but omit the controls for growing season precipitation and temperature. The resulting coefficients are quite similar.

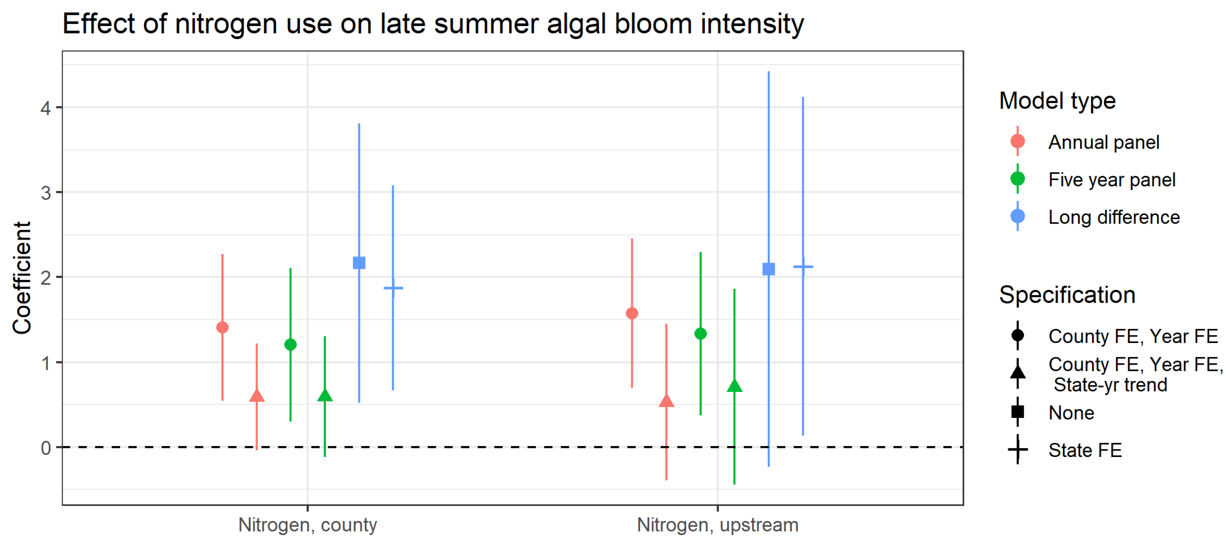


Figure 6: Coefficient plot. Red lines include the same specification as Table 2. Green lines includes observations every five years from 1987 to 2017, using average values in the year prior through the year after each point. Blue lines are the results of the cross-sectional long difference from 1987 to 2017, similarly using three year average values around the endpoints. All models control for average weather conditions. Counties with less than 5 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

4.3 Income effect

We test the relationship between algal bloom intensity and income in Table 3. Model (1) shows that bloom intensity alone has little effect on 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 a high proportion of surface area covered by water, 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 sub-periods and 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 (5) in Table 3. The non-interacted bloom term is again close to zero, and the

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	0.03	0.04	0.06	0.06	−0.04	−0.02	−0.03	−0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Bloom:Coastal		−0.26**			−0.18*			
		(0.10)			(0.09)			
Bloom:Water Prop			−0.98***			−0.77**		
			(0.34)			(0.31)		
Bloom:Fishing High				−0.19***			−0.14***	−0.12**
				(0.05)			(0.04)	(0.06)
Bloom:Farm Income High					0.40***	0.40***	0.40***	0.40***
					(0.12)	(0.12)	(0.12)	(0.12)
County FE	X	X	X	X	X	X	X	X
Year 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	81,231	81,231	81,231	81,231	81,231	81,231	81,231	73,305
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97

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. Counties with less than 5 km^2 of water dropped from analysis. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

interacted terms behave similarly: blooms are associated with reduced income in coastal counties and positive income in farm-intensive counties—although the relationship weakens after 2000.

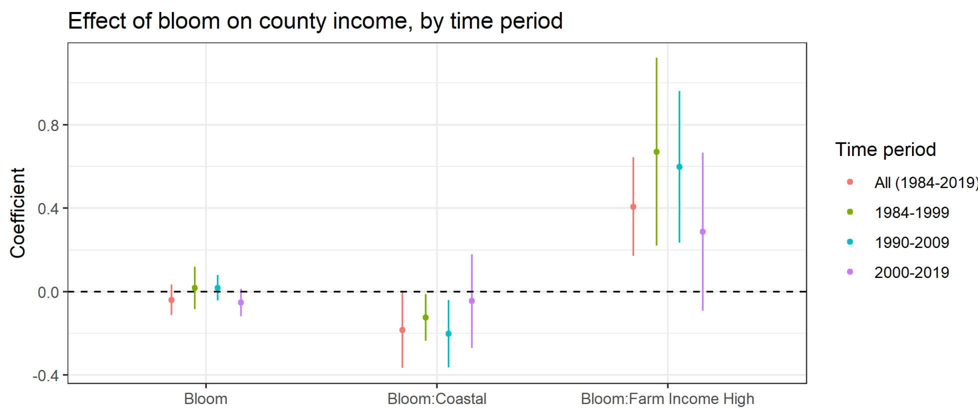


Figure 7: Coefficient plot using Model (4) specification in Table 3. Fishing High and Farm Income High are indicators for counties with high levels of fishing income and farm income, respectively (top quintile). All models control for average weather conditions. Counties with less than 5 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

4.4 Robustness

The Appendix includes several robustness tests. 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 effect of blooms on economic outcomes from Table 3 but drop the weather covariates. The resulting coefficients in Table A1 are unchanged. While this does not illuminate the complex weather-agriculture-ecological interactions, it at at least ensures that weather anomalies are not driving our results. Substituting average growing season temperature with a non-linear measure of crop growing degree days above and below 29°C as per Schlenker and Roberts 2009 does not change results either.

We also utilize non-log transformed county income as our outcome variable in Table A2, as well as alternate measures of farm income that include both continuous and time-varying values in Table A3. For the latter, our non-interacted bloom coefficients become negative, implying that within-year increases in farm income may be driving observed “positive” income associations with algal blooms—although this should be interpreted with caution given the correlation between overall income and farm income.

We next test whether the relationship holds over longer time periods, and not just year-to-year: i.e., is it the case that places where blooms are getting worse experience less income growth over time. Figure 8 plots the interacted coefficients from the annual panel in Table 3 along with coefficients from models using the five-year panel and long difference cross-section spanning 30-plus years.

Overall, the estimates for the five-year panel and the long difference are less precisely estimated, partly because of fewer observations. We see a clear and increasingly negative effect of blooms on medium and long-term income growth in counties with a high proportion of water. For coastal counties the negative effect of blooms increases in the medium term, implying there may be lagged and/or cumulative impacts on tourism, industry, or real estate. However, we no longer see an association over the course of three decades. The long-term relationship is less clear in fishing-intensive counties, which could imply a shift away from fishing as a response to water pollution 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 over longer time periods. The estimates are negative, albeit imprecise, suggesting that fertilizer use may coincide with higher year-to-year income, but that otherwise blooms do not benefit farm-intensive counties.

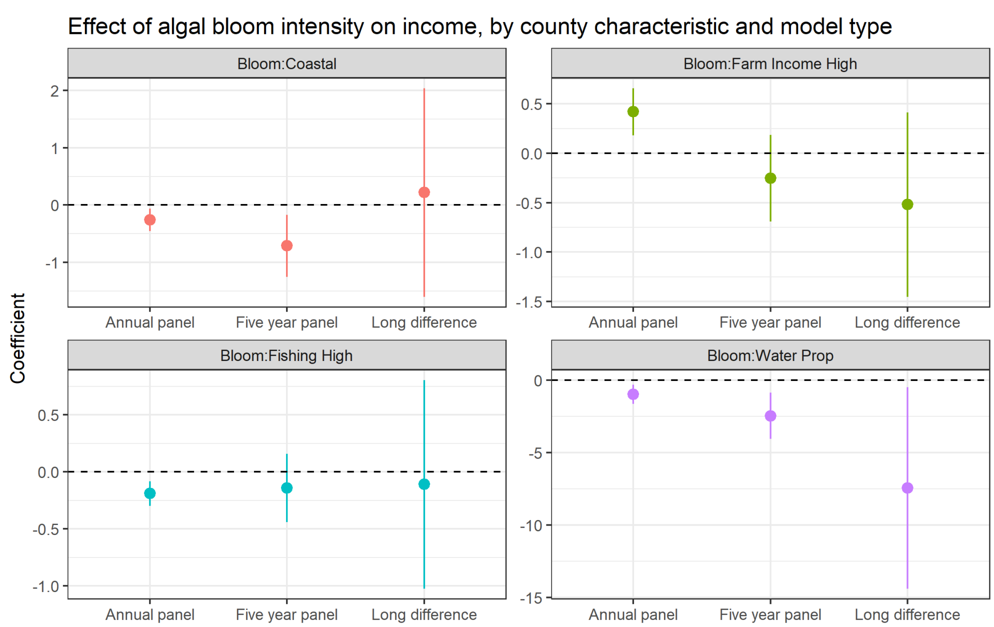


Figure 8: Coefficient plot. ‘Annual panel’ plots the interacted coefficients from models in Table 3. ‘Five year panel’ includes observations every five years from 1987 to 2017, using average values in the year prior through the year after each point. ‘Long difference’ is a cross-sectional long difference from 1987 to 2017, similarly using three year average values around the endpoints. Annual and five-year panels include fixed effects for county, year, and state time trends. State fixed effects included in the long difference. The four panels show bloom intensity interacted with counties by whether they are coastal (top left), in the top quintile of fishing income (bottom left) and farming income (top right), and their water area proportion (bottom right). All models control for average weather conditions. Counties with less than 5 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

4.5 Combined model estimation

We next combine the two models to assess the economic impact of blooms using 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 an optimal instrument given that fertilizer use is related to income through non-water quality channels. 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 (2) of Table 2. We include the F-statistic for the excluded instrument, nitrogen use. There is some evidence of a weak instrument when clustering at the state-level, which is the standard error treatment we use in this analysis. 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 less significant.[10] The non-interacted bloom terms become large in the IV, perhaps capturing the general economic value of increased fertilizer use, or alternatively the weaknesses described surrounding this instrument.

[10] Alternatively, we bootstrap the IV standard errors of the interacted bloom coefficient 1,000 times which produces lower standard error values: Bloom:Coastal (0.205), Bloom:Water Prop (0.438), Bloom:Fishing High (0.111), Bloom:Farm Income High (0.217)

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

	Dependent variable:							
	County income per capita (log)							
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	0.09**	5.27*	0.10**	5.13*	0.10**	5.30*	−0.003	4.76*
	(0.05)	(2.65)	(0.05)	(2.66)	(0.05)	(2.67)	(0.03)	(2.66)
Bloom:Coastal	−0.34***	−1.72***						
	(0.10)	(0.60)						
Bloom:Water Prop			−0.91**	−1.87*				
			(0.36)	(0.96)				
Bloom:Fishing High					−0.20***	−0.91***		
					(0.06)	(0.20)		
Bloom:Farm Income High							0.39***	0.91*
							(0.14)	(0.49)
County FE	X	X	X	X	X	X	X	X
Year 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	61,016	61,016	61,016	61,016	61,016	61,016	61,016	61,016
R^2	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
Adjusted R^2	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97

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 at the county level. Time series from 1987 to 2017 when both fertilizer and bloom data is available. Counties with less than 5 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 account for nutrient pollution from the fertilizer utilized upstream from the county, we do not explicitly assess downstream impacts. A proportion of all fertilizer applied across the entire Mississippi River basin (3.2 million km^2 and about 40% of the the continental US, and including the entire Midwestern Corn Belt) reaches the Gulf of Mexico via the Mississippi River (and the nearby Atchafalaya river). This upstream nutrient loading creates hypoxic conditions in the Gulf of Mexico (Rabotyagov et al. 2014). Appendix Figure A3 shows the correlation between upstream nitrogen and phosphate use and the size of the Gulf of Mexico hypoxic zone. We see the strong correlation between nitrogen and phosphate fertilizer use, as well as a positive but weaker correlation with hypoxic zone extent.

In Table 5 we estimate the impact of upstream nutrients on the extent of the hypoxic zone. We take the inverse distance-weighted average of fertilizer use across all counties in the Mississippi river basin. Since weather also affects hypoxia via its impact on water flow and phytoplankton activity, we flexibly control for precipitation and temperature 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 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 6% increase in hypoxic extent in km^2. We also show the results for phosphates, the another important 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**	3.702*	4.633*			
	(2.087)	(1.960)	(2.409)			
Log Nitrogen				6.571**	5.448**	5.709*
				(2.902)	(2.577)	(3.241)
Weather upstream		X	X		X	X
Weather coastal			X			X
Observations	26	26	26	26	26	26
R^2	0.155	0.375	0.398	0.176	0.455	0.456
Adjusted R^2	0.120	0.290	0.247	0.142	0.380	0.320
F Statistic	4.417**	4.407**	2.641*	5.128**	6.117***	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

Next, we estimate the external cost of nitrogen fertilizer. Table 3 contains results from an annual panel regression of county-level income on late summer algal bloom intensity. The standard deviation in algal bloom intensity across time and counties is 0.04. Using Models (5)-(7), a one standard deviation increase in algal bloom intensity is associated with a 0.7% decline in coastal counties (0.04 x 0.18) and a 0.5% decline in fishing-intensive counties (0.04 x 0.14). For each additional 12% of county area that is water, which is the standard deviation across US counties, there is a 0.3% decline in income (0.04 x .77 x 0.12). We see an opposite effect in relation to agriculture: a one standard deviation increase in bloom intensity equates to a 1.5% increase in income in farming-reliant counties (0.04 x 0.4).

We can link these estimates back to Table 2, the annual panel regression of algal bloom intensity on fertilizer use. The standard deviation in nitrogen use (tons per county km^2 land) across time and counties is 0.002. Therefore, using coefficients from Models (1) and (3) in Table 2, a one standard deviation increase in fertilizer is associated with a 0.003 increase in algal bloom intensity (0.002 x 1.5). Using the Bloom:Coastal coefficient in Model (5) of Table 3 (0.18) and the fertilizer-driven increase in algal bloom intensity, we would expect a reduction in coastal county income by 0.05% (0.003 x 0.18). Similarly, in fishing-reliant counties this equates to 0.04% (0.003 x 0.14).

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, or $14 billion per county and $32,000 per capita. In terms of nitrogen use, a one standard deviation is 5,000 tons within-county and 19,000 tons upstream of a county, or 12,000 tons on average. So one ton of nitrogen results in a cost of $580 [range $370 to $1,400] to downstream coastal counties ([1/5,000 to 1/19,000] x 0.0005 x 14 billion). Interestingly, this is in the range of 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 from 1984 to 2020.

We find significant geographic variation in where blooms occur, and where bloom intensity has increased and decreased over time. On average bloom levels have been relatively flat with the exception of an upward trend in the upper Great Plains and along the 100^{th} meridian starting in the mid 2000s. This may be linked to Corn Belt cropland expansion and intensification driven by ethanol demand in response to the Energy Policy Act of 2005.

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). Using our reduced form estimates, we compute a back-of-the-envelope estimate of $580 per ton of nitrogen [range $370 to $1,400] to downstream coastal counties, which is roughly in line with its market value ($880 per ton N). Note that this figure does not include any health damages associated with the use of nitrate fertilizers or climate impacts of nitrous oxide or methane emissions.

In terms of policy, a nitrogen fertilizer tax could help internalize the externality and move the market toward efficiency. In addition to limiting fertilizer use, there are other policies that may mitigate the negative externality, including land use programs like the USDA's 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).

Further, we hope that this new satellite product of water quality, can be tested, refined, and utilized in research on other policy-relevant questions, including the valuation of wetlands and other ecosystem services—in both the United States and internationally.

References

Anderson, Donald M. 1989. "Toxic algal blooms and red tides: a global perspective." *Red tides: biology, environmental science and toxicology:* 11–16.

Barbier, Edward B. 2012. "Progress and challenges in valuing coastal and marine ecosystem services." *Review of Environmental Economics and Policy* 6 (1): 1–19.

Bechard, Andrew. 2020. "External costs of harmful algal blooms using hedonic valuation: The impact of karenia brevis on Southwest Florida." *Environmental and Sustainability Indicators* 5:100019.

Brakebill, JW, and JM Gronberg. 2017. "County-level estimates of nitrogen and phosphorus from commercial fertilizer for the conterminous United States, 1987–2012." *US Geological Survey, United States.*

Breitburg, Denise L, J Kevin Craig, Richard S Fulford, Kenneth A Rose, Walter R Boynton, Damian C Brady, Benjamin J Ciotti, RJ Diaz, KD Friedland, JD Hagy, et al. 2009. "Nutrient enrichment and fisheries exploitation: interactive effects on estuarine living resources and their management." *Hydrobiologia* 629 (1): 31–47.

Brooks, Bryan W, James M Lazorchak, Meredith DA Howard, Mari-Vaughn V Johnson, Steve L Morton, Dawn AK Perkins, Euan D Reavie, Geoffrey I Scott, Stephanie A Smith, and Jeffery A Steevens. 2016. "Are harmful algal blooms becoming the greatest inland water quality threat to public health and aquatic ecosystems?" *Environmental toxicology and chemistry* 35 (1): 6–13.

Clark, John M, Blake A Schaeffer, John A Darling, Erin A Urquhart, John M Johnston, Amber R Ignatius, Mark H Myer, Keith A Loftin, P Jeremy Werdell, and Richard P Stumpf. 2017. "Satellite monitoring of cyanobacterial harmful algal bloom frequency in recreational waters and drinking water sources." *Ecological indicators* 80:84–95.

David, Mark B, Laurie E Drinkwater, and Gregory F McIsaac. 2010. "Sources of nitrate yields in the Mississippi River Basin." *Journal of Environmental Quality* 39 (5): 1657–1667.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics* 4 (3): 66–95.

Diaz, Robert J, and Rutger Rosenberg. 2008. "Spreading dead zones and consequences for marine ecosystems." *science* 321 (5891): 926–929.

Dodds, Walter K, Wes W Bouska, Jeffrey L Eitzmann, Tyler J Pilger, Kristen L Pitts, Alyssa J Riley, Joshua T Schloesser, and Darren J Thornbrugh. 2009. *Eutrophication of US freshwaters: analysis of potential economic damages.*

Doney, Scott C. 2010. "The growing human footprint on coastal and open-ocean biogeochemistry." *science* 328 (5985): 1512–1516.

Duan, Hongtao, Yuanzhi Zhang, Bai Zhang, Kaishan Song, and Zongming Wang. 2007. "Assessment of chlorophyll-a concentration and trophic state for Lake Chagan using Landsat TM and field spectral data." *Environmental monitoring and assessment* 129 (1-3): 295–308.

Erisman, Jan Willem, James N Galloway, Sybil Seitzinger, Albert Bleeker, Nancy B Dise, AM Roxana Petrescu, Allison M Leach, and Wim de Vries. 2013. "Consequences of human modification of the global nitrogen cycle." *Philosophical Transactions of the Royal Society B: Biological Sciences* 368 (1621): 20130116.

Falcone, James A. 2021. *Estimates of county-level nitrogen and phosphorus from fertilizer and manure from 1950 through 2017 in the conterminous United States.* Technical report. US Geological Survey.

Falconer, Ian R. 1999. "An overview of problems caused by toxic blue–green algae (cyanobacteria) in drinking and recreational water." *Environmental Toxicology: An International Journal* 14 (1): 5–12.

FAO. 2018. *World fertilizer trends and outlook to 2018.*

Fleming, Lora E, Barbara Kirkpatrick, Lorraine C Backer, Judy A Bean, Adam Wanner, Andrew Reich, Julia Zaias, Yung Sung Cheng, Richard Pierce, Jerome Naar, et al. 2007. "Aerosolized red-tide toxins (brevetoxins) and asthma." *Chest* 131 (1): 187–194.

Glibert, Patricia M. 2020. "Harmful algae at the complex nexus of eutrophication and climate change." *Harmful algae* 91:101583.

Gourevitch, Jesse D, Bonnie L Keeler, and Taylor H Ricketts. 2018. "Determining socially optimal rates of nitrogen fertilizer application." *Agriculture, Ecosystems & Environment* 254:292–299.

Gruber, Nicolas, and James N Galloway. 2008. "An Earth-system perspective of the global nitrogen cycle." *Nature* 451 (7176): 293–296.

Hallegraeff, Gustaaf M. 1993. "A review of harmful algal blooms and their apparent global increase." *Phycologia* 32 (2): 79–99.

Hilborn, Elizabeth D, and Val R Beasley. 2015. "One health and cyanobacteria in freshwater systems: animal illnesses and deaths are sentinel events for human health risks." *Toxins* 7 (4): 1374–1395.

Hilborn, Elizabeth D, Virginia A Roberts, Lorraine Backer, Erin DeConno, Jessica S Egan, James B Hyde, David C Nicholas, Eric J Wiegert, Laurie M Billing, Mary DiOrio, et al. 2014. "Algal bloom–associated disease outbreaks among users of freshwater lakes—United States, 2009–2010." *MMWR. Morbidity and Mortality Weekly Report* 63 (1): 11.

Ho, Jeff C, Anna M Michalak, and Nima Pahlevan. 2019. "Widespread global increase in intense lake phytoplankton blooms since the 1980s." *Nature* 574 (7780): 667–670.

Ho, Jeff C, Richard P Stumpf, Thomas B Bridgeman, and Anna M Michalak. 2017. "Using Landsat to extend the historical record of lacustrine phytoplankton blooms: a Lake Erie case study." *Remote sensing of environment* 191:273–285.

Hoagland, Porter, Donald M Anderson, Yoshi Kaoru, and Alan W White. 2002. "The economic effects of harmful algal blooms in the United States: estimates, assessment issues, and information needs." *Estuaries* 25 (4): 819–837.

Hudnell, H Kenneth. 2008. *Cyanobacterial harmful algal blooms: state of the science and research needs.* Vol. 619. Springer Science & Business Media.

Huisman, Jef, Geoffrey A Codd, Hans W Paerl, Bas W Ibelings, Jolanda MH Verspagen, and Petra M Visser. 2018. "Cyanobacterial blooms." *Nature Reviews Microbiology* 16 (8): 471–483.

Keeler, Bonnie L, Jesse D Gourevitch, Stephen Polasky, Forest Isbell, Chris W Tessum, Jason D Hill, and Julian D Marshall. 2016. "The social costs of nitrogen." *Science Advances* 2 (10): e1600219.

Kling, Catherine L. 2013. "State level efforts to regulate agricultural sources of water quality impairment." *Choices* 28 (316-2016-7675).

Larkin, Sherry L, and Charles M Adams. 2007. "Harmful algal blooms and coastal business: economic consequences in Florida." *Society and Natural Resources* 20 (9): 849–859.

Michalak, Anna M, Eric J Anderson, Dmitry Beletsky, Steven Boland, Nathan S Bosch, Thomas B Bridgeman, Justin D Chaffin, Kyunghwa Cho, Rem Confesor, Irem Daloğlu, et al. 2013. "Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends consistent with expected future conditions." *Proceedings of the National Academy of Sciences* 110 (16): 6448–6452.

Mitsch, William J, John W Day, Li Zhang, and Robert R Lane. 2005. "Nitrate-nitrogen retention in wetlands in the Mississippi River Basin." *Ecological engineering* 24 (4): 267–278.

Morgan, Kimberly L, Sherry L Larkin, and Charles M Adams. 2009. "Firm-level economic effects of HABS: A tool for business loss assessment." *Harmful Algae* 8 (2): 212–218.

Nixon, Scott W. 1995. "Coastal marine eutrophication: a definition, social causes, and future concerns." *Ophelia* 41 (1): 199–219.

Olmstead, Sheila M. 2010. "The economics of water quality." *Review of Environmental Economics and Policy* 4 (1): 44–62.

Paerl, Hans W, and Jef Huisman. 2008. "Blooms like it hot." *Science* 320 (5872): 57–58.

Rabotyagov, Sergey S, Catherine L Kling, Philip W Gassman, Nancy N Rabalais, and Robert Eugene Turner. 2014. "The economics of dead zones: Causes, impacts, policy challenges, and a model of the Gulf of Mexico hypoxic zone." *Review of Environmental Economics and Policy* 8 (1): 58–79.

Rohlich, GA. 1969. "Eutrophication: causes, consequences, correctives." In *National Academy of Sciences, Washington,* vol. 307.

Schlenker, Wolfram, and Michael J Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of sciences* 106 (37): 15594–15598.

Shortle, James, and Richard D Horan. 2001. "The economics of nonpoint pollution control." *Journal of economic surveys* 15 (3): 255–289.

———. 2013. "Policy instruments for water quality protection." *Annu. Rev. Resour. Econ.* 5 (1): 111–138.

Smayda, Theodore J. 1997. "What is a bloom? A commentary." *Limnology and Oceanography* 42 (5part2): 1132–1136.

Sobota, Daniel J, Jana E Compton, Michelle L McCrackin, and Shweta Singh. 2015. "Cost of reactive nitrogen release from human activities to the environment in the United States." *Environmental Research Letters* 10 (2): 025006.

Steffen, Will, Katherine Richardson, Johan Rockström, Sarah E Cornell, Ingo Fetzer, Elena M Bennett, Reinette Biggs, Stephen R Carpenter, Wim De Vries, Cynthia A De Wit, et al. 2015. "Planetary boundaries: Guiding human development on a changing planet." *Science* 347 (6223).

Stewart, Ian, Penelope M Webb, Philip J Schluter, Lora E Fleming, John W Burns, Miroslav Gantar, Lorraine C Backer, and Glen R Shaw. 2006. "Epidemiology of recreational exposure to freshwater cyanobacteria–an international prospective cohort study." *BMC Public Health* 6 (1): 93.

Taylor, Charles A, and Hannah Druckenmiller. 2021. "Draining the Swamp: Wetlands, Flooding, and the Clean Water Act." *Working Paper.*

Tebbs, EJ, JJ Remedios, and DM Harper. 2013. "Remote sensing of chlorophyll-a as a measure of cyanobacterial biomass in Lake Bogoria, a hypertrophic, saline–alkaline, flamingo lake, using Landsat ETM+." *Remote Sensing of Environment* 135:92–106.

Turner, R Eugene, and Nancy N Rabalais. 2013. "Nitrogen and phosphorus phytoplankton growth limitation in the northern Gulf of Mexico." *Aquatic Microbial Ecology* 68 (2): 159–169.

Tyler, AN, E Svab, T Preston, M Présing, and WA Kovács. 2006. "Remote sensing of the water quality of shallow lakes: A mixture modelling approach to quantifying phytoplankton in water characterized by high-suspended sediment." *International Journal of Remote Sensing* 27 (8): 1521–1537.

Van Grinsven, Hans JM, Mike Holland, Brian H Jacobsen, Zbigniew Klimont, Mark A Sutton, and W Jaap Willems. 2013. "Costs and benefits of nitrogen for Europe and implications for mitigation." *Environmental science & technology* 47 (8): 3571–3579.

Vitousek, Peter M, John D Aber, Robert W Howarth, Gene E Likens, Pamela A Matson, David W Schindler, William H Schlesinger, and David G Tilman. 1997. "Human alteration of the global nitrogen cycle: sources and consequences." *Ecological applications* 7 (3): 737–750.

Wang, Menghua, and Wei Shi. 2007. "The NIR-SWIR combined atmospheric correction approach for MODIS ocean color data processing." *Optics Express* 15 (24): 15722–15733.

Ward, Mary H, Rena R Jones, Jean D Brender, Theo M De Kok, Peter J Weyer, Bernard T Nolan, Cristina M Villanueva, and Simone G Van Breda. 2018. "Drinking water nitrate and human health: an updated review." *International journal of environmental research and public health* 15 (7): 1557.

Wolf, David, Will Georgic, and H Allen Klaiber. 2017. "Reeling in the damages: Harmful algal blooms' impact on Lake Erie's recreational fishing industry." *Journal of environmental management* 199:148–157.

Wolf, David, and H Allen Klaiber. 2017. "Bloom and bust: Toxic algae's impact on nearby property values." *Ecological economics* 135:209–221.

8 Appendix

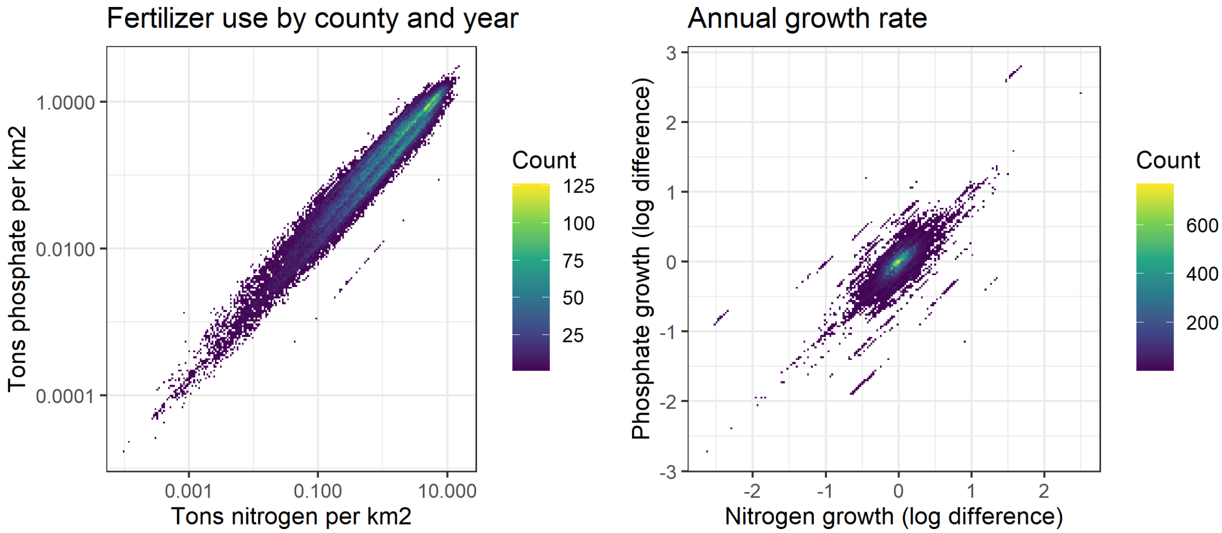


Figure A1: Scatter plot of USGS county-level farm nitrogen and phosphate use per km^2. Left panel shows annual levels, right panel shows annual change in term of growth rate

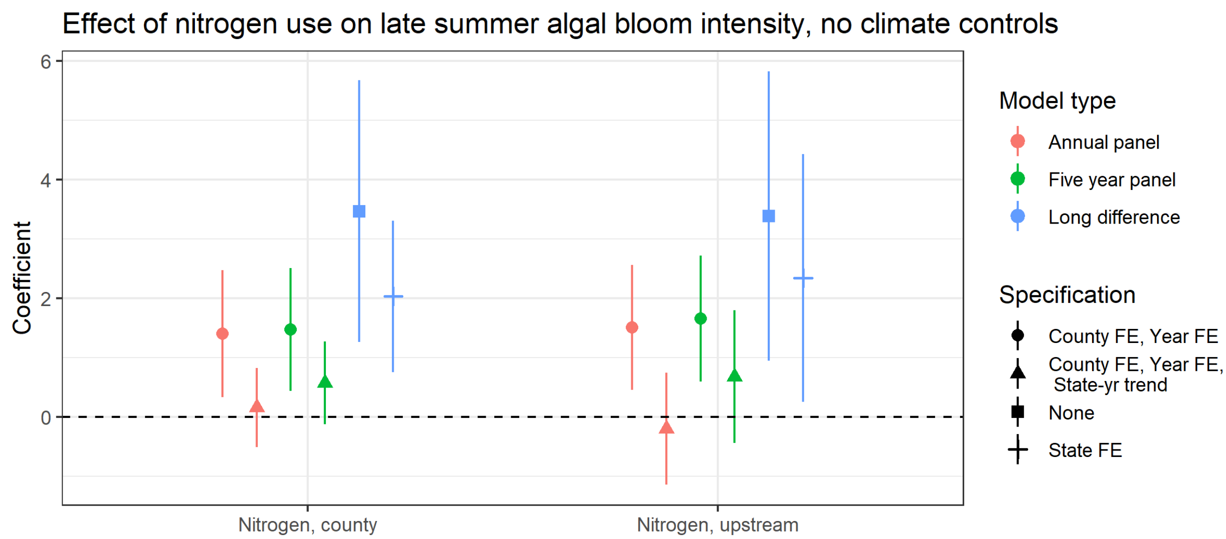


Figure A2: Coefficient plot. Same as Figure 6 except does not include weather controls. Red lines include the same specification as Table 2. Green lines includes observations every five years from 1987 to 2017, using average values in the year prior through the year after each point. Blue lines are the 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 5 km^2 of water dropped from analysis. Standard errors clustered at the state level. Error bars are at the 95% confidence range.

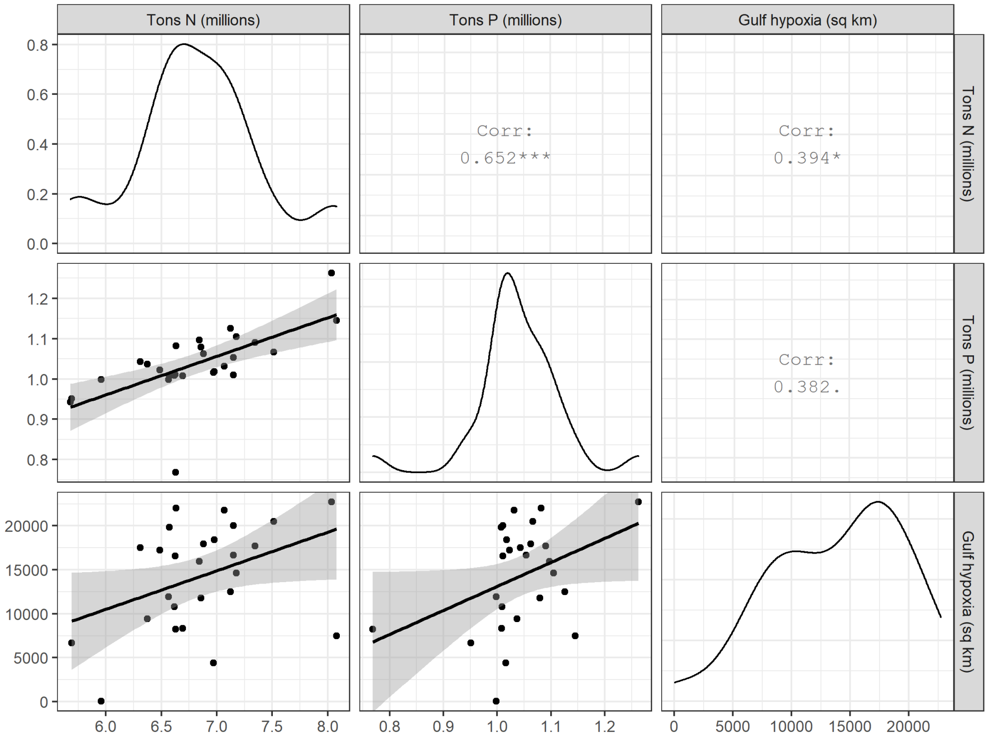


Figure A3: Scatter plots with line of best fit for weighted upstream basin fertilizer use of nitrogen (N) and phosphate (P) in millions of tons and Gulf of Mexico hypoxic zone extent in km^2. Diagonal line is kernel density plots showing distribution of annual values.

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	0.04	0.06	0.08	0.07	−0.03	−0.01	−0.01	−0.02
	(0.05)	(0.05)	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
Bloom:Coastal		−0.28**			−0.20**			
		(0.11)			(0.10)			
Bloom:Water Prop			−1.02***			−0.80**		
			(0.36)			(0.32)		
Bloom:Fishing High				−0.20***			−0.14***	−0.12**
				(0.06)			(0.04)	(0.06)
Bloom:Farm Income High					0.41***	0.41***	0.41***	0.41***
					(0.13)	(0.13)	(0.12)	(0.12)
County FE	X	X	X	X	X	X	X	X
Year 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	81,231	81,231	81,231	81,231	81,231	81,231	81,231	73,305
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97

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. Counties with less than 5 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 income per capita, 1984-2019

	Dependent variable:							
	County income per capita ($1,000s)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bloom	0.22	1.39	2.71	2.23	−1.12	0.21	−0.37	−0.18
	(1.72)	(1.83)	(1.87)	(1.96)	(1.22)	(1.19)	(1.33)	(1.26)
Bloom:Coastal		−17.15***			−14.85**			
		(6.32)			(6.23)			
Bloom:Water Prop			−67.85***			−61.50***		
			(19.06)			(18.57)		
Bloom:Fishing High				−11.52***			−9.98***	−9.18**
				(2.79)			(2.52)	(3.49)
Bloom:Farm Income High					12.29**	11.89**	12.21**	11.87**
					(5.20)	(5.16)	(5.10)	(5.06)
County FE	X	X	X	X	X	X	X	X
Year 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	81,231	81,231	81,231	81,231	81,231	81,231	81,231	73,305
R^2	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92

Notes: Linear regression. Dependent variable is county-level income per capita ($1,000s). Bloom is county-level average bloom intensity from July to September in areas with water. Time series from 1984 to 2019. Counties with less than 5 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)
Bloom	0.026	−0.053	−0.143***	−0.305***
	(0.046)	(0.034)	(0.040)	(0.047)
Bloom:Farm Income High		0.414***		
		(0.122)		
Bloom:Farm Income Avg			0.210***	
			(0.044)	
Bloom:Farm Income Annual				0.323***
				(0.014)
County FE	X	X	X	X
Year FE	X	X	X	X
State-Yr trend	X	X	X	X
Sample	All	All	All	All
Controls	Weather	Weather	Weather	Weather
SE cluster	State	State	State	State
Observations	81,231	81,231	81,231	81,231
R^2	0.976	0.976	0.976	0.978

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. Counties with less than 5 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: nitrogram fertilizer use on late summer algal blooms

	Dependent variable:			
	County income per capita (log)			
	(1)	(2)	(3)	(4)
Nitrogen	0.59***	0.59***	0.59***	0.59*
	(0.13)	(0.15)	(0.08)	(0.32)
SE cluster	None	County	Ecoregion	State
County FE	X	X	X	X
Year FE	X	X	X	X
State-Yr Trend	X	X	X	X
Controls	Weather	Weather	Weather	Weather
F-stat	20.5	14.8	59	3.4
Observations	61,016	61,016	60,782	61,016
R^2	0.86	0.86	0.86	0.86
Adjusted R^2	0.85	0.85	0.85	0.85

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 at the county level. Time series from 1987 to 2017. F-stat is for nitrogen, the excluded instrument. Counties with less than 5 km^2 of water dropped from analysis. Standard errors clustered as described. *p<0.1; **p<0.05; ***p<0.01