

# Chronic and Acute Water contamination from Animal Feeding Operations

Claire Palandri\*

*Latest version [online](#)*

## Abstract

Over the past century, U.S. livestock production has shifted from many small farms to fewer, increasingly larger operations. Today, most animals are raised in confined Animal Feeding Operations (AFOs), where manure is stored on-site and eventually applied to fields. This concentration of waste has long raised concerns about pollution, yet credible causal evidence on its impacts remains scarce.

In this paper, I assemble new panel data linking permitted AFOs in Iowa (2004–2017) and North Carolina (2014–2020) to downstream water monitoring records. To reflect the hydrological structure of pollutant transport, I delineate station-specific drainage basins and match them to upstream facilities. I then employ two empirical strategies tailored to each state’s regulatory and data context: in Iowa, a difference-in-differences design exploiting spatio-temporal variation in the number and size of AFOs; in North Carolina, an event-study approach leveraging extreme precipitation shocks at the precise location of facilities. Across both settings, I find that AFOs significantly degrade surface water quality. In Iowa, an additional operation in a drainage area increases downstream total phosphorus by 6.0% and total reactive nitrogen by 1.6%, while reducing dissolved oxygen by 0.7%, relative to mean levels. In North Carolina, an additional extreme rainfall event over an upstream AFO increases fecal coliforms by 0.21% and nutrient concentrations by 0.08–0.14%. Effects are larger for swine facilities, scale with herd size, and are detected from facilities below the current federal permitting threshold.

With global livestock production projected to grow and intensify further, and with regulatory changes in some regions moving toward weaker environmental oversight, these findings provide timely evidence on the pollution risks of large-scale operations. By establishing causal effects along the water exposure pathway, I identify and quantify a mechanism through which industrial production generates externalities with direct implications for ecosystems and risks for public health.

---

\*Harris School of Public Policy, University of Chicago, Chicago, IL 60637. clairepalandri@uchicago.edu

# 1 Introduction

Over the last century, U.S. livestock production has undergone a structural transformation from many small farms to fewer and increasingly larger operations (MacDonald & McBride, 2009). The total number of animal farms in the U.S. declined from around 1,517,000 in 1982 to 868,000 in 2022, while sales of U.S. animal products increased from 179 to 262 billion US dollars (in dollars of 2022) (USDA NASS, 1984, 2024). In the hog production sector, in the largest producing state—Iowa—the number of farms dropped by 89% (45,800 to 5,300), while the annual number of hogs sold rose from 24 to 60 millions in total across farms, and from 500 to 9,700 on average per farm. These trends were achieved by the gradual transition to large and intensive confined operations, called Animal Feeding Operations (AFOs), which now represent the overwhelming majority of animal farms across states (MacDonald & McBride, 2009; McBride & Key, 2013).

In these industrial operations, animals are mostly kept in confinement buildings, and produce manure which is temporarily stored on site. While the animals themselves are subject to FDA regulation, there is limited oversight of the pollutants emitted by these operations. Yet they represent a potentially large threat to environmental and public health as well as rural quality of life. Indeed, a single farm can produce more manure than all the sanitary waste generated by a city of 1.5 million residents (U.S. GAO, 2008), yet unlike city sewage, animal waste is untreated (Hribar, 2010). This waste releases harmful gases as it decomposes, such as ammonia and hydrogen sulfide, and contains various pollutants, including excess nutrients and harmful pathogens (U.S. EPA, 2013). In all, U.S. AFOs produce over 1.2 billion tons of waste annually, reaching levels potentially severe enough to have triggered a 2005 Congressional hearing titled “Superfund Laws and Animal Agriculture” (U.S. House of Representatives, 2005). In addition, residues from the frequent administration of antimicrobials—often at low doses and over extended periods—if disseminated, may contribute to the spread of antimicrobial resistance and increase the risk of resistant infections in human populations. The confinement buildings themselves also emanate particulate matter. The environmental and public health concern is that through airborne and waterborne transmission, these contaminants do not stay enclosed in feeding operations but instead put the surrounding communities at risk of environmental exposure (Mallin, 2000). The water exposure pathway is of particular concern for operations that store manure in liquid form, which is the case for the vast majority of swine and dairy operations.

Numerous studies document environmental exposures and their impacts on both ecosystems and human health. However, these impacts have either not been assessed at large scale or not been robustly quantified. Afflictions associated with proximity to AFO practices include respiratory problems, digestive disorders, impaired mental health, low birth weight, and infant mortality, and are thought to be mediated by air and water transmission. Some causal evidence has been provided for the airborne exposure pathway; outcomes analyzed include air pollution measures (Sneeringer, 2010), birth outcomes (Sneeringer, 2009) and property values (Isakson & Ecker, 2008; Kim & Goldsmith, 2009; Lawley, 2021; Palmquist et al., 1997). The water exposure pathway, by contrast, has not yet been robustly assessed for causal impacts, despite concerns about both surface water and groundwater pollution. Raff and Meyer (2021) analyzes impacts on surface water nutrient concentrations of AFOs, focusing on the largest dairy operations in the state of Wisconsin. Wing and Wolf (2000)

relies on a matching identification strategy and finds increased occurrences of gastrointestinal problems with proximity to swine operations, suggesting contamination through water exposure, but is limited by a small sample size (155 survey respondents).

Understanding the extent of the impact of environmental exposure to the pollutants from such facilities is ever more important, for multiple reasons. First, global animal production is projected to increase in the short- to medium-term, and in the U.S. as well as abroad, much of this growth seems planned to occur through the expansion of such industrial operations. World meat production is expected to rise by 13% by 2030, with half of this increase corresponding to chicken production and a third to pigmeat ([OECD & FAO, 2021](#)). In the U.S., by 2031, all types of animal production are expected to increase substantially, notably milk by 9.1%, pork by 7.9%, and chicken and egg by around 14% ([USDA, 2022](#)). Two important features of the projected increases in swine production are worth noting: (i) 66% of the global increase would come from Asian countries, particularly China and Vietnam, where the imported model of industrial swine operations is supported by development banks;<sup>1</sup> (ii) the 8% growth in the Americas should be driven notably by "further intensification of production systems". International organizations also promote the system's "sustainable intensification" by its "sustainable industrialization" ([FAO, 2018](#)).

Second, in many countries, including the U.S. (as detailed in the next section), regulatory frameworks governing large-scale animal operations commonly rely on size thresholds to trigger meaningful environmental oversight. Following an initial 2017 petition for rule-making filed by environmental interest groups, the U.S. Environmental Protection Agency (U.S. EPA) initiated in 2023 an evaluation of whether to revise its regulations or pursue non-regulatory initiatives. Most recently, in France, similar thresholds were raised substantially—from 40,000 to 85,000 heads of poultry, and from 2,000 to 3,000 swine—while beef operations were exempted, and the process of public consultation for establishing new operations was simplified.<sup>2</sup> These regulatory revisions are unfolding in a context where robust causal evidence on their impacts remains scarce, yet the accumulation of suggestive evidence points to potentially serious threats to both environmental and human health.

Simultaneously, nuisance lawsuits against AFOs have been on the rise across the U.S. ([Hines, 2018](#); [Sellers, 2017](#); [Smart, 2016](#)), as residents of nearby rural communities claim persistent harms to their quality of life and property values. In response, a second generation of state "right-to-farm" laws has emerged, designed to shield agricultural producers from such litigation.<sup>3</sup> These laws often expand protections by exempting from nuisance claims activities

---

<sup>1</sup>Development banks directly invest in the expansion of industrial swine production in Asia. Most recently in February 2022, a US\$52 million investment from the World Bank's private sector arm, the International Finance Corporation (IFC), was approved to finance the expansion of one of the main vertically integrated pork producer, meat processor, feed mill operator, and veterinary health products manufacturer in Vietnam (<https://disclosures.ifc.org/project-detail/ESRS/45292/mavin>). The IFC further funds industrial animal agriculture in other parts of the world both directly, such as through the expansion of industrial broiler chicken operations in Uganda (<https://disclosures.ifc.org/project-detail/SII/44775/yokuku-mezz>), and indirectly, through proposed loans to support massive monoculture of crops used as feed for the industrial livestock sector, such as soy and corn in Brazil (<https://disclosures.ifc.org/project-detail/ESRS/44281/ldc-brasil>).

<sup>2</sup>These provisions were initially introduced by decree in June 2024, then enshrined in law in 2025.

<sup>3</sup>Starting in the 1970s, when suburban encroachment on rural areas was bringing new residents close to industrial animal operations, the threat of nuisance lawsuits with costs that would push farmers out of

defined as "normal agricultural practices" or "minor changes" in operation. Yet this raises a critical question: should, e.g., the conversion of cropland into an intensive animal feeding operation, or the substantial expansion of an existing AFO, be considered a "minor change" within the scope of normal farming? The very large damages awarded by courts—upwards of the millions of dollars per affected household ([Gore, 2020](#); [Pollard, 2020](#); [Anderson v. Murphy-Brown LLC, 2018](#))—which threaten the economic viability of these operations and point to the magnitude of the externalities they seem to generate, highlight how much turns on where the legal boundary of "normal agriculture" is drawn. At the same time, rigorous causal evidence quantifying the pollution harms of AFOs remains limited, leaving policy and legal debates to proceed in a context of suggestive but not yet definitive scientific findings.

Understanding the causal impact of AFOs on human health through the environmental exposure pathway is therefore both timely and of high policy relevance.

While substantial evidence links AFOs—particularly swine operations—to adverse local outcomes through water-borne pollution, there are still no robust causal estimates of these externalities. This paper addresses this gap by providing causal evidence on surface water contamination and thereby the larger waterborne exposure pathway from intensive livestock production. I focus on the two leading hog-producing states, Iowa and North Carolina, which account for 31.4% and 12.3% of the U.S. swine inventory, respectively ([USDA NASS, 2024](#)).<sup>4</sup> Specifically, I test whether AFOs measurably degrade downstream surface water quality, and I estimate the magnitude of their impacts across multiple pollution indicators of importance for environmental and public health. The empirical strategy differs across states due to variation in both AFO data and institutional settings. In Iowa, where AFOs expanded substantially between 2004 and 2017 but are only observed at the zip code level, I implement a difference-in-differences design with continuous treatment intensity. This enables me to capture the chronic effect of industrial animal production. In North Carolina, by contrast, the number of liquid-manure operations has been fixed since a 1997 moratorium. Here I exploit exogenous precipitation shocks at precisely geolocated AFO sites to identify pollution effects. I further incorporate geospatial data on unpermitted dry poultry operations (available as a single 2014 snapshot), restricting the North Carolina analysis to the period after 2014.

---

business or prevent them from investing in their farm led states to legislate the "right to farm" (RTF). The first generation of RTF legislation prohibited nuisance lawsuits by new neighboring residents against farmers when "normal farming operations" preexisted their move. An individual could file a claim only if a new operation was developed after their arrival, or if an existing farm became industrialized (with a significant change on the farm, e.g., in size, hours of operation or technology used). Since the 2000s and especially in the last few years, a second generation of RTF laws has emerged to expand the right to farm. Some states are expanding the scope of their existing legislation, i.e., reducing the circumstances under which farms can be held liable for nuisance — e.g., Indiana in 2005, Florida in 2021 — others are enshrining this right in their constitution — e.g., Missouri in 2014; West Virginia introduced two RTF constitutional amendments in 2021 which failed.

<sup>4</sup>Depending on the year and on the exact metric considered — namely, whether production in tons of animal product (from surveys) or animal inventory (from the Agricultural census and surveys) — Minnesota and North Carolina dispute the second position; both states represent around 12%.

## 2 Background

**Regulation** While the animals themselves are subject to FDA regulation, federal oversight of pollution from AFOs is limited ([U.S. GAO, 2008](#)). Air emissions remain unregulated,<sup>5</sup> and only large or so-called concentrated AFOs, or "CAFOs", which hold more than 1,000 animal units,<sup>6</sup> are considered point sources under the Clean Water Act, and are thus subject to the National Pollutant Discharge Elimination System (NPDES) permit regulations. Other provisions, such as Section 404 permitting, also exempt AFOs under the rubric of "normal farming" activities.

The enforcement of the NPDES program is delegated by the U.S. EPA to state agencies in most states.<sup>7</sup> An NPDES permit is required for a facility to open or expand, but notably the permit covers only the waste management system rather than the operation itself—in effect considering CAFOs as manure-production facilities in the context of environmental oversight. Indeed, the disposal of that manure is the primary environmental concern.

Two broad types of systems are distinguished: dry-manure facilities (mostly poultry) and wet-manure facilities (swine and cattle). The latter pose the greatest risk to water quality. In swine operations in particular, manure is typically liquefied and stored in open pits or "lagoons" on-site before being extracted and applied to sprayfields. Permits require Nutrient Management Plans (NMPs), which must demonstrate that the permit holder has sufficient land available with the right soil composition for nutrients to be applied at "agronomically appropriate" rates under effluent limitation guidelines. However, NMPs regulate only nutrient application and do not address antibiotics, pathogens, or other contaminants—in contrast with the regulation of sewage sludge, for which the EPA has established limits on pathogens and heavy metals.

Most states are authorized to administer the base NPDES program and may impose additional requirements so long as they are at least as stringent as federal standards. In practice, most states have developed AFO-specific programs with their own provisions. In Iowa, all confinement feeding operations above 1,000 animal units (about 2,500 finishing hogs) require both construction permits and manure management plans, in addition to NPDES coverage.

---

<sup>5</sup>A priori, any facility that emits hazardous air pollutants in quantities such that it would constitute a "major source" would trigger Clean Air Act "Title V" operating permit requirements or reporting requirements under the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) and the Emergency Planning and Community Right-to-Know Act (EPCRA). However, such pollutants generated by AFOs remain unregulated, for two reasons: (1) The EPA has not finalized the development of reliable emission estimating methodologies to determine whether AFOs are subject to these requirements ([U.S. EPA OIG, 2017](#)); (2) The EPA, countering the 2017 court ruling of *Waterkeeper Alliance et al. v. EPA*, published final rules exempting farms from reporting air emissions from animal waste under CERCLA (August 2018) and EPCRA (June 2019).

<sup>6</sup>The U.S. EPA defines animal units in the regulations that govern NPDES permits [40 C.F.R. § 122]. 1,000 animal units are equivalent to the following animal quantities: 700 mature dairy cows, 1,000 veal calves or beef cattle, 2,500 swine above 55 lbs, 10,000 swine under 55 lbs, 30,000 laying hens or broilers if the poultry AFO uses a liquid manure handling system, and 125,000 chickens or 82,000 laying hens if the poultry AFO uses other than a liquid manure handling system. The term "animal unit" was removed in 2003, but the same animal-equivalent quantities apply.

<sup>7</sup>In Iowa, the Department of Natural Resources is responsible for implementing the NPDES program, and notably issuing permits directly to the discharging facilities. In North Carolina, the Division of Water Resources within the Department of Environmental Quality holds this mandate.

North Carolina, by contrast, has implemented a comprehensive water-quality permitting program that extends beyond federal requirements: since 1993, all AFOs using liquid waste management systems must obtain a permit once they exceed 100 cattle, 75 horses, 250 swine, 1,000 sheep, or 30,000 birds.

**Water pollution from manure** The infrastructure and the management practices required under the NMPs do not fully prevent spillage or runoff risks. Open-air lagoons, where most swine facilities store liquid manure, are prone to leaks, breaks, or overflows, and manure spread on saturated soils can leach from the surface (Armstrong et al., 2010; Mallin, 2000; Simpkins et al., 2002).

The sheer volume of waste therefore raises persistent concerns, and there is suggestive evidence of both chronic contamination of waterways—through lagoon leakage and spray-field runoff—and acute spikes during heavy precipitation, as lagoons overflow and soils become saturated. Local analyses downstream of sprayfields show that manure is not fully absorbed, with substantially elevated contaminant levels in both groundwater and surface waters (Harden, 2015; Karr et al., 2001). Through both pathways—lagoons and sprayfields—pollutants reach water bodies, and risks are amplified after heavy rains.<sup>8</sup> The contaminants of concern include excess nutrients—nitrogen (notably in the forms of nitrate and ammonia) and phosphorus—as well as heavy metals and pathogens. At high concentrations these create both environmental and human health hazards. Coliform bacteria have been linked to gastroenteritis outbreaks; elevated nitrate intake can cause infant methemoglobinemia ("blue baby syndrome"). Nutrient over-enrichment can also have large consequences on ecosystems, as it drives eutrophication, leading to algal blooms, subsequent oxygen depletion, and finally hypoxic "dead zones," and, in extreme cases, fish die-offs.

**Evidence of environmental exposure to AFO pollutants and consequences** A large literature documents positive relationships between proximity to AFO locations and practices and environmental pollution, particularly excess nutrients and pathogens—see for example (Heaney et al., 2015; Mallin, 2000; Messier et al., 2014; Wing et al., 2008). However, most studies rely on limited site samples or document correlations, without establishing causal mechanisms. Raff and Meyer (2021) is one exception: they find positive impacts of animal production on surface water concentrations of ammonia and phosphorus in Wisconsin. Yet this analysis covers only CAFOs—i.e., the upper tail of industrial operations—and almost exclusively dairies. Prior work suggests that externalities are in fact larger for hog operations (Wing & Wolf, 2000) and for facilities below the 1,000-animal unit cutoff. Moreover, the study uses Hydrologic Unit Codes (HUCs) as spatial units, which are administrative subsegments rather than true topographic watersheds and often much smaller than actual drainage basins (Omernik et al., 2017). This mismatch may obscure the true upstream–downstream

---

<sup>8</sup>In the days before the most extreme of such high precipitation events to hit North Carolina, namely Hurricane Florence in 2018, the handling of manure by hog operators was observed. Many illegally sprayed waste onto fields that were to be soaked in rain. This revealed at the same time how AFO operators may adopt averting behavior to prevent lagoons from overflowing, by preemptively emptying them — and thereby violating their permit — but yet do not prevent the manure from entering the water resources, due to saturated soils (Ouzts, 2018).

relationships and thereby underestimate spillovers.

An equally abundant literature has documented links between AFOs and human health outcomes. Already in 2008, the Government Accountability Office flagged "15 studies that linked animal waste from industrial livestock farms with widespread health problems" (U.S. GAO, 2008). Since then, suggestive evidence has grown substantially, with numerous studies showing associations between AFO proximity and adverse conditions, including respiratory illness (Mirabelli et al., 2006; Poulsen, Pollak, Sills, Casey, Nachman, et al., 2018; Radon et al., 2007; Rasmussen et al., 2017; Sigurdarson & Kline, 2006), digestive disorders (Poulsen, Pollak, Sills, Casey, Rasmussen, et al., 2018), impaired mental health (Donham et al., 2007), and adverse birth outcomes such as low birth weight and infant mortality (Kravchenko et al., 2018).

While this literature suggests potentially important effects of AFOs on human health—from morbidity, including both mental and physical health, to mortality rates—through the environmental exposure pathway, the observed relationships are generally not causally interpretable due to selection effects. Households living near AFOs may differ systematically in other dimensions, such as socioeconomic status, baseline health, or other environmental risks, that make them at higher risk of deleterious health outcomes independently of AFO exposure, thereby confounding observed correlations. Two studies provide some causal evidence. Wing and Wolf (2000) use a matching design and find increased rates of several respiratory and gastrointestinal problems with proximity to swine operations, suggesting multiple contamination pathways including water exposure, though their analysis relies on a small sample (155 respondents). Sneeringer (2009) uses changes in county-level animal units to estimate impacts on infant health, and finds that increases in industrial production worsen infant morbidity and mortality, with evidence suggesting an air pollution channel, but is inconclusive regarding a potential water channel.<sup>9</sup>

Taken together, this evidence base paints a consistent picture: AFOs seem to generate substantial environmental and health risks, but the magnitude and causal attribution remain uncertain. The current regulatory context, projected production growth, and the methodological limitations of prior work underscore the need for robust quantification of water pollution and its downstream health consequences.

### 3 Data

**Animal Feeding Operations** I focus on the top two swine-producing states, Iowa and North Carolina, which together account for about 40% of U.S. swine production. For both states, I compile and harmonize AFO permit records from the relevant state agencies. These permits report each operation's location, start date, past expansions, animal capacity by species, and waste management practices, including manure storage structures and acreage for land application. I use the information on capacity by animal type to compute estimates of livestock intensity in "animal units", to be used as proxy for the quantities of manure generated—which are unreported—as supported by the literature (Copeland, 2010).

---

<sup>9</sup>The analysis does not test for a statistical difference between the effects for counties with low/medium/high well usage, and does not have sufficient statistical power to detect an effect on the rates of infant death with causes related to water pollutants associated with livestock production.

The permit databases do not include the locations of sprayfields. However, manure transport is costly, especially liquid manure, making it reasonable to assume that sprayfields lie close to the lagoons where liquid waste is stored. Survey evidence from [Ali et al. \(2012\)](#), based on 3,000 Iowa and Missouri livestock farmers, supports this assumption: among the 27–29% of swine producers who reported transporting manure, the average maximum distance was only 2.95 miles for nursery operations (swine weighing less than 55 pounds) and 4.25 miles for finishing operations (swine over 55 pounds).

The temporal coverage, scope of operations, and spatial precision of permit data vary by state, leading to important differences between the Iowa and North Carolina panels. In Iowa, construction permits are required for operations exceeding 1,000 animal units (about 2,500 finishing hogs). The data obtained from the state permitting agency cover the period 2004–2017, and provide counts of operations and their animal capacities at the zip code level. The data obtained from the state permitting agency cover 2004–2017 and provide animal capacity counts aggregated to the zip code level. The situation is very different in North Carolina. A moratorium on new or expanded swine operations was imposed in 1997 and made permanent in 2007 for facilities using anaerobic lagoons. As a result, the number and geographic distribution of swine AFOs in the state has remained largely unchanged since 1997. Permit requirements are also stricter than in Iowa, applying to all operations with more than 250 swine or 100 cattle that use some liquid waste management system. The dataset from the North Carolina Department of Environmental Quality covers the period 1997–2020 and provides exact building coordinates. The top panel of Figure 1 maps the permitted AFOs. In addition, I incorporate the hand-validated predictions of unpermitted dry poultry AFOs generated by [Handan-Nader and Ho \(2019\)](#) from 2014 NAIP remote sensing imagery. This enables me to capture the rapid expansion of dry poultry production that followed the 1997 moratorium on open-air liquid-manure operations, but also imposes my restricting the North Carolina sample to the period post-2014. The bottom panel of Figure 1 shows the spatial distribution of the facilities in the combined NC panel.

Figure 2 shows the resulting coverage of facilities in the two panels. To benchmark this coverage, I use the *NPDES CAFO Permitting Status Report*, published annually by the EPA since 2011. It compiles state-reported data and distinguishes between CAFOs (i.e., facilities above 1,000 animal units that fall under federal regulation) and those CAFOs that have actually obtained an NPDES permit. As required under 40 CFR 122.23(d)(1), only CAFOs that discharge must hold an NPDES permit, though states may impose additional requirements. Two patterns stand out. First, in both states there is a striking gap between the number of CAFOs with NPDES permits (light blue) and the total number of CAFOs (dark blue), suggesting that the overwhelming majority of federally regulated operations above 1,000 animal units operate without an NPDES permit. Second, my constructed panels provide extensive coverage across three policy-relevant categories: (i) federally regulated and permitted CAFOs, (ii) federally regulated but unpermitted CAFOs, and (iii) smaller AFOs below 1,000 animal units that fall outside federal regulation altogether.

**Water quality outcomes** I collect water quality data from the Water Quality Portal ([Read et al., 2017](#)) which aggregates all records from the U.S. EPA and the USGS dating back to the early 20th century. The analysis aims to quantify the changes in water quality caused by AFOs, in particular the concentrations of pollutants known to pose risks to

public health. I therefore examine three categories of indicators: (1) pathogens originating exclusively from food animals and which can cause severe gastrointestinal illness, (2) excess nutrients in multiple forms, and (3) dissolved oxygen as a general indicator of water quality.

Fecal coliform bacteria, which reside in the digestive tracts of food animals and are present in their manure, are pathogens that, under short-term exposure, can induce severe gastrointestinal illness such as diarrhea, vomiting, and cramps ([U.S. EPA, 2009](#)). Their presence in surface waters is a strong indicator of contamination from AFOs. The U.S. EPA has established a national primary drinking water regulation with a strict Maximum Contaminant Level (MCL) of 0 cfu/100mL for fecal coliforms (see Table [A2](#) for a summary of drinking water standards and recommended surface water quality criteria).

Excess nutrients—specifically nitrogen and phosphorus—threaten aquatic ecosystems, recreational water use, and human health. Several forms of each nutrient are present in aquatic environments. Total Nitrogen (TN) refers to the sum of all nitrogen forms (expressed as N), and Total Phosphorus (TP) the sum of all phosphorus forms (expressed as P). While no drinking water standards regulate nutrient levels, the EPA has established recommended criteria for surface water quality: at the national level for phosphorus (0.1 mg/L in flowing waters, 0.05 mg/L in streams entering lakes), and at the ecoregion level for both N and P (see Table [A2](#)).

Nitrogen compounds include ammonia ( $\text{NH}_3$ ), nitrate ( $\text{NO}_3^-$ ), nitrite ( $\text{NO}_2^-$ ), and organic nitrogen. Pregnant women and infants under six months are particularly vulnerable to nitrate and nitrite, with excessive ingestion linked to shortness of breath and methemoglobinemia or "blue baby syndrome". High nitrate and nitrite levels also cause environmental problems, in particular eutrophication in lakes and streams, and thereby indirectly affect aquatic life. Ammonia, by contrast, has direct toxic effects on aquatic life at concentrations below 1 mg/L. Humans are less sensitive to ammonia in water, though long-term ingestion may still have harmful consequences. Because direct TN measurements are limited, I consider nitrogen compounds with sufficient coverage: ammonia (and its ionized form ammonium,  $\text{NH}_4^+$ ), and Total Kjeldahl Nitrogen (TKN), also referred to as total reactive nitrogen, which combines ammonia-nitrogen and organic nitrogen.

Phosphorus is present in water primarily as part of phosphate molecules, either organic phosphate or inorganic orthophosphates and polyphosphates. Phosphates are not toxic to humans unless they are present at very high levels. The main concern with phosphorus pollution is the risk of eutrophication, and its chain of consequences leading to oxygen depletion and potential hypoxic "dead zones." I extract all existing measures of TP taken within the states and periods of interest.

Finally, I extract measurements of dissolved oxygen (DO), which reflects the amount of oxygen available to aquatic life and serves as a standard proxy for overall water quality ([Keiser & Shapiro, 2019](#)). In the North Carolina setting, where water temperature measures are widely available, I further convert DO readings into dissolved oxygen deficit: a normalized measure of oxygen depletion relative to saturation, which provides a sharper indicator of eutrophication risk.

Figure [3](#) shows the locations of the water monitoring stations with measurements of these water quality parameters, along with their number of observations, in both states over each state's respective study period. Examples are provided for one parameter from each of the

three categories. Because measurement methods differ across stations, the same pollutant may appear in the Water Quality Portal under different characteristic names and units. For instance, ammonia levels may be reported either as "ammonia as NH<sub>3</sub>" in milligrams of NH<sub>3</sub> or as "ammonia-nitrogen as N" in parts per million of N. Appendix A.1 lists all characteristic names used and summarizes the harmonization steps applied to these outcome data.

**Drainage areas** I then construct the relevant spatial units for the analysis: the stations' drainage basins. Using the National Hydrography Dataset Plus High Resolution (NHDPlus HR)—a detailed representation of the U.S. surface hydrological network that encodes flow direction for each stream segment—I delineate the exact drainage basin for each monitoring station. This allows me to identify all AFOs located within a station's drainage area, define them as upstream, and measure their hydrological distances from the station outlet. By definition, all runoff from these AFOs flows downslope into the stream at the monitoring site. Importantly for identification, the drainage basin boundaries are orthogonal to administrative units such as counties, along which AFOs may choose to locate.

**Extreme precipitation events** For precipitation, I use the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset, which provides daily precipitation levels at 4-km resolution for the entire U.S. from 1981 onward ([PRISM, 2020](#)). I use these data both to control for daily precipitation within the drainage areas and to identify extreme precipitation events for the event-study analysis. To define extremes, I process the data in two steps designed to preserve the relevant dimension of weather variation. First, I compute the "extremeness" of precipitation at the grid-cell level, at the exact location of each AFO. Second, I aggregate these values across all AFOs within a drainage area. An extreme precipitation event is defined relative to the local climatology: specifically, rainfall that is substantially higher than what is normal for that location, season, and period—where seasons are defined by three-month groupings (JFM, AMJ, JAS, OND). To construct the reference climatology, I use daily precipitation levels over a 30-year reference period (1981–2010), following World Meteorological Organization guidelines ([WMO, 2017](#)). For each grid cell, I recover the standard deviation of the seasonal precipitation distribution, and define an extreme event as daily rainfall exceeding two standard deviations above the mean. Finally, for each drainage area and period, I count the number of AFOs experiencing such extreme precipitation.

**Controls** Because crop agriculture near AFOs may act as an important confounder, I also include controls for the presence and intensity of crop agriculture. For this, I use the USGS National Land Cover Database (NLCD), a gridded dataset that classifies land cover for the entire U.S. at 30-meter resolution ([Dewitz & USGS, 2021](#)). I aggregate the cell-level classifications to the drainage basin level and compute annual shares of land classified as cultivated, wetlands, and developed. These variables capture crop intensity, hydrologically sensitive areas, and the potential for other non-point source pollution. In addition, I compute the total precipitation falling within each drainage area over the study period to include as control—and its square. Finally, because water temperature directly affects biological activity and nutrient dynamics, I include temperature controls. When dissolved oxygen

deficit is the outcome, this adjustment is unnecessary since the measure already embeds water temperature. When direct water temperature readings are missing for many water quality observations, I use the daily maximum air temperature from PRISM, measured at the monitoring station location, as a proxy.

**Final samples** The relatively low frequency of outcome data, combined with the complicated patterns of pollutant persistence and reaction in surface waters, renders a day-level analysis infeasible. In addition, one might be concerned that the timing of water sampling is partially endogenous to the occurrence of intense precipitation events. To address both issues, I aggregate the data to coarser time intervals and conduct the analysis at the week and month levels.

Table 1 provides summary statistics of the main explanatory and outcome variables for the week samples. Some differences between the two state settings are striking. Due to the topography of the states, average drainage areas are roughly 33 km<sup>2</sup> in Iowa, compared with more than 1,200 km<sup>2</sup> for North Carolina monitoring stations. As expected, the number of AFOs per drainage area also differs sharply: slightly above one in Iowa, versus an average of 82 in North Carolina. Pollution levels show equally large contrasts. The average concentrations of all pollutants are higher in Iowa surface waters, with fecal coliforms especially elevated. In both states, average concentrations of total phosphorus exceed the national and ecoregion-specific recommended limits (see Table A.2).

## 4 Empirical strategy

**Identification strategies** The ideal research design, from a statistical standpoint, would be a randomized experiment in which the opening or the expansion of an AFO is randomly assigned in time and space, while all other characteristics are held constant. This would ensure that variation in pollution exposure is independent of factors impacting the outcomes of interest. In practice, I approximate this ideal design using two complementary identification strategies tailored to the regulatory and data contexts of the two states considered. In Iowa, where the number and sizes of AFOs vary over time and across space during my study period (2004-2017), but locations are only observed at the zip code level, I adopt a difference-in-differences design with continuous treatment intensity. Specifically, I exploit spatio-temporal variation in the number and size of AFOs by drainage area to estimate the causal effect of increases in animal production on downstream water quality. In North Carolina, by contrast, the number of liqui-manure operations has remained virtually constant since the moratorium implemented in 1997. Here, I leverage exogenous realizations of high precipitation levels over the AFO locations to capture water pollution caused by existing operations. In my main specifications, the treatment variable is the sum of daily precipitation shocks experienced by upstream AFOs over the relevant week or month.<sup>10</sup>

---

<sup>10</sup> Alternatively, the importance of total precipitation levels over the period compared to what the given area would ‘normally’ receive over such a period, could be considered the relevant time scale of analysis. In Appendix A.3, I present the results of specifications defining a shock as a period-total amount of precipitation above two standard deviations of the climatological period-total for the grid cell. In these models, the final treatment variable captures the count of AFOs which received extreme rain for the period.

**Modeling and inference** For the difference-in-differences analysis, the model estimated is the linear regression model (1), where  $\text{WQ}_{it}^k$  is the average level of the water quality indicator  $k$ , recorded at station  $i$  in period  $t$ .  $\text{AP}_{it}$  is a measure of the intensity of animal production—which can be captured by AFOs or AUs—located in the drainage area of station  $i$  during the period,  $X_{it}$  is a vector of time-varying controls which include the total amount of precipitation that fell over the area during the period and its square, the average maximum temperature at the monitoring station, and shares of land cover categories.  $\alpha_i$  and  $\omega_t$  are station and period fixed effects, respectively. Year fixed effects absorb state-wide factors evolving over time, such as policies targeting non-point source water pollution, while month fixed effects capture the seasonality of pollutant levels. Standard errors are clustered at the drainage area level, which is the level of identifying variation, to account for spatial correlation within watersheds.

$$\text{WQ}_{it}^k = \beta \text{AP}_{it} + X'_{it}\gamma + \alpha_i + \omega_t + \epsilon_{it}, \quad \forall i = 1, \dots, N, t = 1, \dots, T \quad (1)$$

$\beta$  is the main parameter of interest, it captures the average treatment effect of an increase in animal production on downstream water quality. In my main specifications,  $\text{AP}_{it}$  corresponds to the number of permitted AFOs. I also present results of specifications using alternative measures of production intensity, namely the numbers of swine AFOs and of all animal units, in Appendix A.3.

For the precipitation-event analysis, the model estimated is the linear regression model (2):

$$\text{WQ}_{it}^k = \beta |\text{ppt\_events}|_{it} + X'_{it}\gamma + \alpha_i + \omega_t + \epsilon_{it}, \quad \forall i = 1, \dots, N, t = 1, \dots, T \quad (2)$$

The outcome variable, fixed effects, and clustering strategy mirror that of model (1). Controls  $X_{it}$  include the average water temperature at station  $i$  over period  $t$ , and the shares of relevant land cover categories in the drainage area. The treatment variable  $|\text{ppt\_events}|_{it}$  is defined as the number of high precipitation events affecting upstream AFOs during period  $t$ , with  $\beta$  capturing their average causal effect.

Because some water monitoring stations have more readings than others within a given period—and thereby may provide a more reliable measure of the outcome—I use the number of measurements available for the relevant water quality parameter at each station over the period as analytic weight in all regressions.

**Restricted sample to account for upstream-downstream connectivity** The data generating process of water quality levels follows a specific upstream-downstream structure. Some monitoring stations are nested within the drainage areas of others, such that their pollutant readings are partly determined by the levels experienced at upstream stations whose drainage areas are subsumed under the larger area of the downstream station (see Figure A1). If two such connected stations present measurements of a given parameter in the same time period, then including both in the sample without adjustment could bias precision.

To address this, I identify the full hydrological network of monitoring stations—the "watershed matrix"<sup>11</sup>—which delineates upstream–downstream connectivity. I then restrict the

---

<sup>11</sup>Given a spatial directed network of  $J$  units, the  $J \times J$  watershed matrix characterizes all adjacent and

sample so that, for each parameter  $k$  and period  $t$ , I retain only stations that are not downstream of another station reporting measurements of  $k$  in that period. In other words, I exclude ‘nesting’ observations. This ensures independence across station-period observations used in the estimation.

## 5 Results

### 5.1 Chronic contamination from AFO activity (IA)

The top panel of table 2 presents the results of the week-level difference-in-differences analysis. In each table, the top row presents the direct regression coefficients and the rows underneath interpret these estimates relative to the sample mean levels of the pollutants. I find that an additional AFO leads to an increased contamination of downstream surface water with multiple pollutants. Specifically, the marginal AFO in a station drainage area leads to average increases of 6.0% in total phosphorus and 1.6% in total reactive nitrogen, and a 0.7% decrease in dissolved oxygen, relative to sample mean levels. The analysis is unable to detect significant effects on downstream levels of fecal coliforms, or ammonia, notably due for the first parameter to the low number of readings available which shrinks the statistical power.

The temporal resolution of a week might still suffer from the limitations aforementioned, of endogenous sampling and delayed release or persistence of pollutants. I therefore also estimate model (1) at the aggregated month-level. The bottom panel of table 2 presents the results of the drainage area-month level analysis, and shows similar effects for all water quality indicators.

**Robustness** I consider alternative measures of production intensity, in particular the number of swine AFOs and the number of animal units, and estimate model (1) with these variables. Results are presented in the Appendix in Tables A3 and A4. When considering swine AFOs, I find higher average effects across water quality indicators, as well as a significant effect on ammonia. On average, an additional upstream swine AFO decreases dissolved oxygen by 1.2%, and increases ammonia, total reactive nitrogen, and total phosphorus by +11.7%, +3.8%, and +10.9%, respectively—with again very similar effects when considering a 4-week period instead of one week. These results provide evidence to the existing hypothesis from the literature that the waste management systems of swine operations raise a higher potential threat than that of the average AFO. When considering total animal units, the magnitudes of effects are fairly consistent with that obtained at the AFO level.

---

non-adjacent connectivity between units. In our setting, a value of 1 at row  $i$  and column  $j$  indicates that station  $i$  is located upstream from station  $j$ , although multiple other stations may be located at intermediary locations along this flow path, such that the water entering station  $i$  drains into other stations before entering station  $j$ . The watershed matrix thereby accounts for the full downstream connectivity of subwatersheds. It can be computed from the more common adjacency matrix, which only indicates adjacent connections.

## 5.2 Acute contamination from extreme precipitation events (NC)

The top panel of table 3 presents the results of the week-level analysis. We observe a clear deleterious effect of precipitation events at the location of AFOs on each category of water quality indicators. For the average drainage area, an upstream AFO experiencing an intense rainfall event in the preceding week causes average increases in downstream dissolved oxygen deficit (i.e., decrease in oxygen available for aquatic life) of 0.12%, and in concentrations of fecal coliforms, ammonia, total reactive nitrogen, and total phosphorus of 0.21%, 0.12%, 0.08%, and 0.14%, respectively, relative to sample mean levels.

Similarly to the previous setting, I conduct the same analysis with data aggregated by month. Results are presented in the bottom panel of Table 3. Attenuated effects are observed across indicators—with the exception of fecal coliforms for which no effects are detectable—suggesting indeed that the pollution from acute events is most impactful closer to the event timing, within a few weeks window. The slopes estimates for the coefficient of the land cover control variables also reveal interesting patterns: the share of wetlands is associated with lower pollutant concentrations, across all categories, while the inverse is observed with the share of land that is cultivated or used as pasture.

**Robustness** I consider alternative definitions of precipitation shocks. The total level of precipitation received over the given period relative to the amount that the given area would ‘normally’ receive over such a period, could be considered the relevant time scale of analysis, rather than the count of anomalous daily events. An unusually high precipitation event is then defined as a period-total amount of precipitation above two standard deviations of the climatological period-total at the given location. In these specifications, the final treatment variable captures the count of AFOs which received extreme rain for the period. Appendix A5 presents the results obtained using these alternative definitions of the treatment variable. At the week-level, I find higher changes by a factor between x1.5 and x2 across all water quality indicators. At the month-level, changes in the concentrations of fecal coliforms and total phosphorus are no longer associated with the aggregated high precipitation levels.

I also run an analysis on the subsample excluding measurements from stations ‘nesting’ another station with measurements of the same water quality parameter in the same time period. Results are presented in Table A6. Owing to the large range of sizes of the drainage areas in North Carolina, a substantial number of these areas are nested within others, such that sample sizes are noticeably reduced. In this restricted sample which omits the potential precision bias from the dependence between stations, and in effect restricts the size of drainage areas considered, I find here as well higher changes by a factor between x1.5 and x2 across all water quality indicators; however the average effect on ammonia concentrations is no longer precise.

## 6 Discussion

This study combines two complementary identification strategies, tailored to the regulatory and data contexts of Iowa and North Carolina, to estimate the reduced-form effects of industrial animal operations on downstream surface water quality. In Iowa, I exploit spatio-temporal variation in the number of AFOs and animal units between 2004–2017. In North

Carolina, where liquid-manure operations have been virtually frozen since the 1997 moratorium, I leverage plausibly exogenous precipitation shocks over confinement sites to capture the acute release of pollutants. Both approaches are motivated by the mechanisms suggested in prior work: chronic contamination from lagoon leakage and sprayfield runoff, and the amplification of these risks during heavy rainfall.

I find consistent evidence that upstream AFOs degrade downstream water quality across all three indicator categories: (1) pathogens (fecal coliforms), (2) excess nutrients (nitrogen- and phosphorus-based compounds), and (3) dissolved oxygen, a general marker of ecosystem health. In Iowa, an additional permitted AFO in a drainage area leads to average downstream increases of 6.0% in total phosphorus and 1.6% in total reactive nitrogen, and a 0.7% decrease in dissolved oxygen, relative to sample mean levels. These effects are larger than those found by [Raff and Meyer \(2021\)](#), who focus mainly on dairies, and are especially pronounced for swine operations. This supports concerns in the literature that the spatial concentration of liquid waste poses disproportionately high risks. In North Carolina, I find acute effects of high rainfall events on downstream water quality. Each additional upstream AFO experiencing extreme precipitation increases average dissolved oxygen deficit by 0.12%, fecal coliforms by 0.21%, and excess nutrients by 0.08–0.14%, relative to sample means. Together, these results highlight both the chronic and acute dimensions of water pollution from intensive animal production.

This article makes important contributions along several dimensions. First, by combining data from Iowa and North Carolina, it provides multi-state evidence across multiple livestock species and measures of production intensity, ranging from facility counts to animal units. Second, it tests and finds that AFOs affect water quality through both chronic pathways, associated with the persistent accumulation of waste in concentrated areas, and acute pathways, where extreme precipitation events trigger sharp spikes in contamination. Third, due to my constructed panels including a large number of operations below the federal CAFO threshold of 1,000 animal units—in addition to virtually all those above—I am able to detect pollution effects from facilities that fall outside federal oversight yet represent the majority of operations. Finally, by using animal units as a measure of production intensity, I show that pollution impacts are not merely a function of the number of operations but scale with herd size, underscoring the environmental consequences of industrial concentration in livestock production.

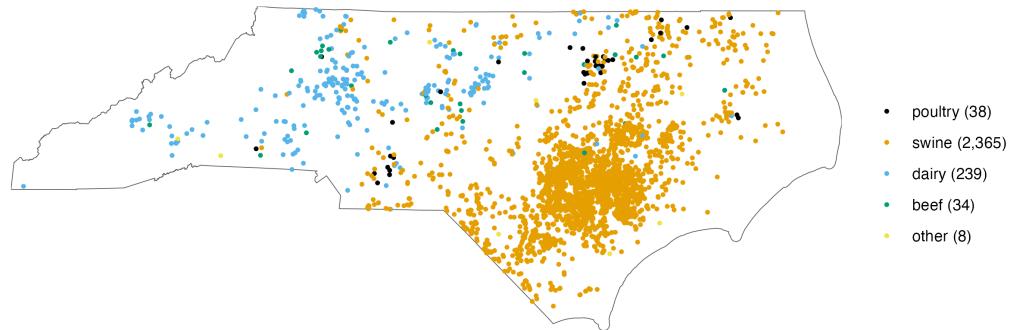
Quantifying the pollution caused by AFOs is particularly timely, as the number of industrial animal operations and the animal density within such operations continue to increase in the U.S. and abroad. In North Carolina, while swine AFOs have remained capped since the 1997 moratorium, poultry operations have proliferated rapidly, raising new concerns. At the same time, climate change is projected to increase the frequency of extreme precipitation events,<sup>12</sup> further elevating the risk of acute contamination from existing facilities.

---

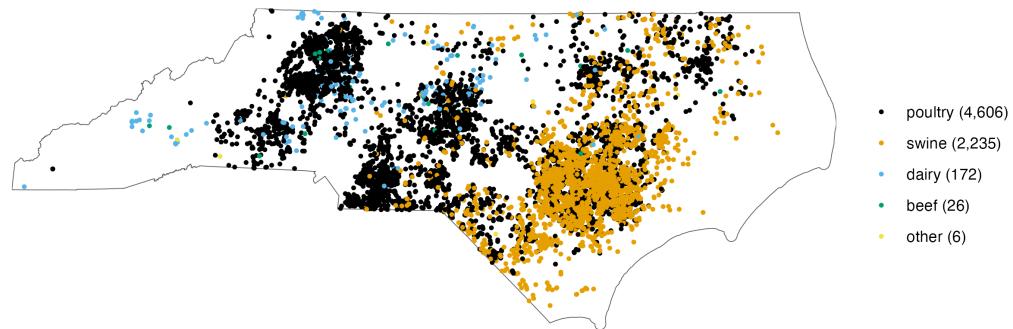
<sup>12</sup>The state's latest climate science report, which defines a "heavy rainfall event" for North Carolina as a day on which rainfall totals 3 inches (76.2 mm) or more, reports an observed upward trend in the number of such events, with the period 2015–2018 having seen the greatest number of events since 1900. Its projections for the end of the century state that "it is *likely* that annual total precipitation for North Carolina will increase", and "*very likely* that extreme precipitation frequency and intensity in North Carolina will increase", due to increases in atmospheric water vapor content ([Kunkel et al., 2020](#)).

The estimates of surface water pollution obtained in this study put forward the notion of the carrying capacity of an ecosystem, here illustrated in its water dimension, and it is important to interpret them in this context. They suggest that the concentration of farm animals in space—and therefore that of their manure—in industrial scales, is such that sprayfields cannot retain and surface water sufficiently dilute the quantities of contaminants that the waste releases. Similarly, [Joy et al. \(2022\)](#), in the context of dairy operations in New Zealand, estimates the farms' nitrate grey water footprint—the amount of water needed to dilute nitrogen leached to meet water nitrate standards—and finds that having healthy water under the same level of production would require either 12 times more rainfall in the region or a 12-fold reduction in cows. In other words, and as the paper summarizes, "dairy farming at this intensity is unsustainable and if not reduced could pose a significant risk to human health". Because of the high transportation costs of manure, and potential lack of suitable land and demand for such manure in other states, the present paper suggests that the current density of industrial operations in space may be similarly unsustainable.

These results open to an array of questions that are beyond the scope of this study and that call for further research. In particular, the present analysis cannot distinguish whether most of the pollution comes from lagoon failures or sprayfield runoff. Data on the precise location of sprayfields, as is reported in most permit applications, would enable to assess the precise source of externality, and thereby formulate recommendations for short-term policies to limit such water pollution, and is the object of future work. The research designs also capture only one part of the potential water pollution caused by animal operations, that is the contamination of surface water. However, pollutants may also enter groundwater, and affect populations downstream through this channel, notably those relying on domestic wells for water supply. Indeed, local analyses of pollution found higher levels of contaminants in both surface water and groundwater downstream from sprayfields ([Harden, 2015](#); [Karr et al., 2001](#)). This contamination has not been robustly causally assessed to date. The total population using domestic-well water in the contiguous U.S. was estimated to reach around 37.29 million in 2010 (the year of the latest available decennial census) ([Johnson et al., 2019](#)), and North Carolina is the leading state in the number of estimated housing units using wells, above 1.5 million ([Murray et al., 2021](#)). The estimates of increased concentrations of pollutants of all categories found for surface water by the present study suggest potential similar contamination of groundwater, with serious implications for human health.



(a) Registered AFOs (1997-2020 database)



(b) Registered AFOs (2014-2020 database) and poultry facilities from remote sensing imagery (2014)

Figure 1: Location of AFOs in North Carolina by animal type

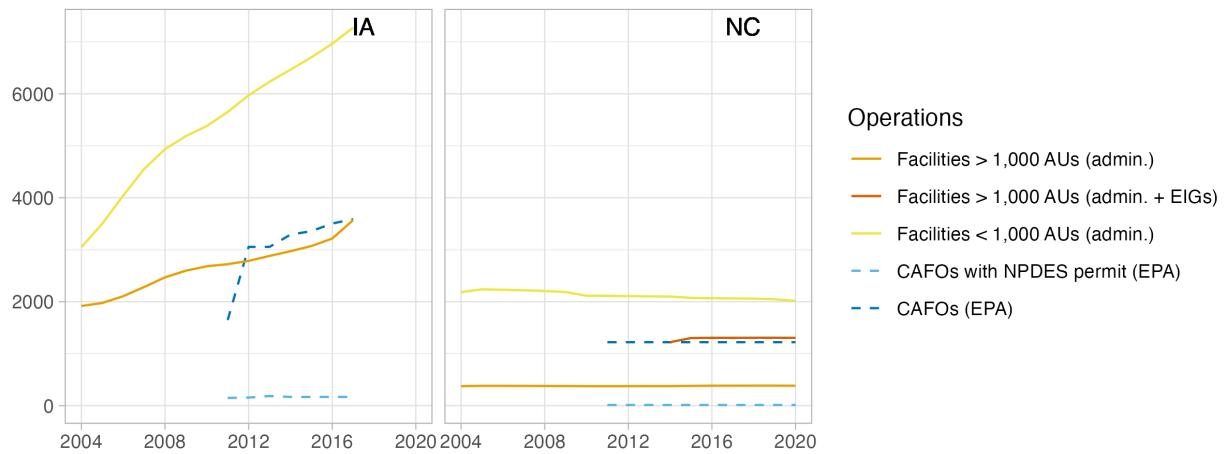


Figure 2: Coverage of the state AFO panels wr.t. size and regulation: total AFO counts by category. Notes: The red line corresponds to the addition of the manually validated poultry operations from remote sensing imagery

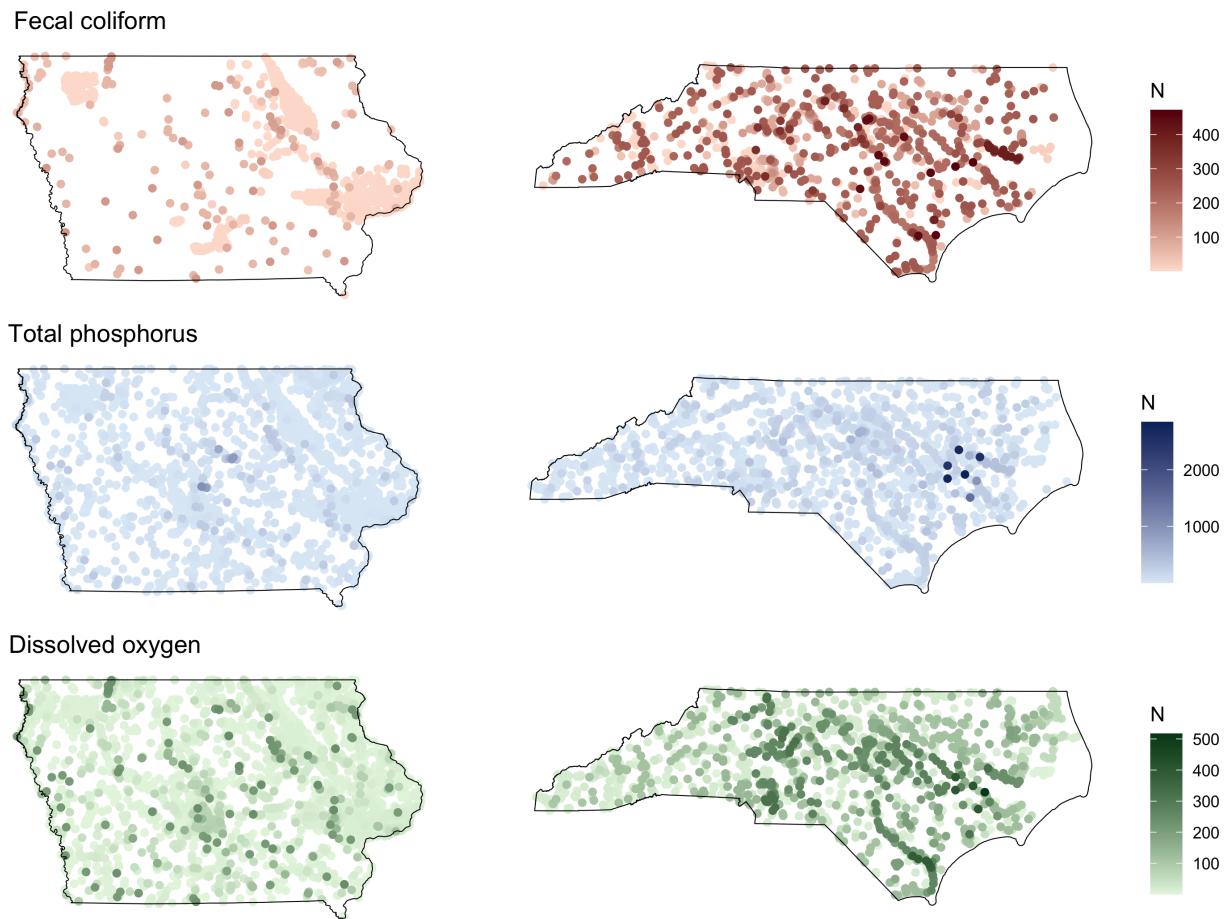


Figure 3: Location and number of observations of water monitoring stations, in Iowa (2004-2017) and North Carolina (1997-2020), with measurements of fecal coliforms (top), total phosphorus (middle) and dissolved oxygen (bottom), respectively.

Variable	Unit	IA (2004-2017)		NC (2014-2020)	
		Mean	SD	Mean	SD
<i>Water quality indicators</i>					
DO	mg/L	9.21	2.72	7.90	2.71
DO deficit	%			15.1	13.7
Fecal coliform	cfu/100mL	3,946	75,268	349	793
Ammonia	mg/L as N	0.09	0.47	0.05	0.12
TKN	mg/L as N	1.08	1.46	0.58	0.40
TP	mg/L as P	0.29	1.27	0.13	0.23
<i>Explanatory variables</i>					
AFOs		1.2	2.3	82.3	218
T <sup>max</sup>	°C	20.6	9.3	23.2	7.8
T <sub>water</sub>	°C			16.3	7.2
Ppt	mm	20.8	24.9	27.1	28.3
% developed	%	10	18	19	22
% planted	%	72	23	19	15
% wetlands	%	3	4	8	13
Drainage area size	km <sup>2</sup>	32.7	24.4	1206.7	3621.9

Table 1: Sample summary statistics. All variables are at the drainage area by week level.

	DO	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b>AFOs</b>					
Regression coefficient	<b>-0.065**</b> (0.026)	-5,603 (5,007)	0.003 (0.002)	<b>0.017**</b> (0.009)	<b>0.018***</b> (0.005)
Sample mean	9.21	3,946	0.09	1.08	0.29
Relative effect	<b>-0.70%</b>	-142%	+3.9%	<b>+1.6%</b>	<b>+6.0%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	60,916	7,043	32,957	32,155	48,422
Adjusted R <sup>2</sup>	0.473	0.059	0.297	0.186	0.795

(a) Week level estimates (drainage area–week panel)

	DO	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b>AFOs</b>					
Regression coefficient	<b>-0.060**</b> (0.027)	-5,527 (4,997)	0.004 (0.002)	<b>0.018**</b> (0.009)	<b>0.020***</b> (0.006)
Sample mean	9.21	3,946	0.09	1.08	0.29
Relative effect	<b>-0.65%</b>	-140%	+4.0%	<b>+1.6%</b>	<b>+6.7%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	48,685	4,973	29,866	28,670	40,536
Adjusted R <sup>2</sup>	0.504	0.118	0.305	0.234	0.838

(b) Month level estimates (drainage area–4-week panel)

Table 2: Effects of AFOs on downstream surface water quality (Iowa, 2004–2017). Standard errors are clustered by drainage area. Significance codes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

	DO deficit	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b> AFO-day &gt; 2<math>\sigma</math> </b>					
Regression coefficient	<b>0.017***</b> (0.005)	<b>0.716***</b> (0.238)	<b>5.8E-5***</b> (2.2E-5)	<b>4.9E-4***</b> (0.0001)	<b>1.8E-4***</b> (3.9E-5)
Sample mean	15.1	349	0.05	0.58	0.13
Relative effect	<b>+0.12%</b>	<b>+0.21%</b>	<b>+0.12%</b>	<b>+0.08%</b>	<b>+0.14%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	16,986	11,705	10,780	11,512	12,443
Adjusted R <sup>2</sup>	0.6405	0.1386	0.2332	0.5718	0.5324

(a) Week level estimates (drainage area–week panel)

	DO deficit	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b> AFO-day &gt; 2<math>\sigma</math> </b>					
Regression coefficient	<b>0.012***</b> (0.0016)	0.041 (0.054)	<b>2.7E-5***</b> (1E-5)	<b>1.7E-4***</b> (2.9E-5)	<b>2.8E-5***</b> (1.0E-5)
Sample mean	15.1	349	0.05	0.58	0.13
Relative effect	<b>+0.078%</b>	+0.012%	<b>+0.054%</b>	<b>+0.030%</b>	<b>+0.021%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	16,767	11,663	10,661	11,387	12,317
Adjusted R <sup>2</sup>	0.6447	0.1252	0.2353	0.5685	0.5357

(b) Month level estimates (drainage area–4-week panel)

Table 3: Effects of extreme precipitation events at the location of AFOs on downstream surface water quality (North Carolina, 2014–2020). Standard errors are clustered by drainage area. Significance codes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## References

- Ali, S., McCann, L., & Allspach, J. (2012). Manure transfers in the midwest and factors affecting adoption of manure testing. *J. Appl. Agric. Econ.*, 44, 533–548. <https://doi.org/10.1017/S1074070800024093>
- Armstrong, S. D., Smith, D. R., Owens, P. R., Joern, B., & Williams, C. (2010). Manure spills and remediation methods to improve water quality. In E. Lichtfouse (Ed.), *Genetic engineering, biofertilisation, soil quality and organic farming* (pp. 201–215). Springer Netherlands. [https://doi.org/10.1007/978-90-481-8741-6\\_7](https://doi.org/10.1007/978-90-481-8741-6_7)
- Copeland, C. (2010, February 16). *Animal waste and water quality: EPA regulation of concentrated animal feeding operations (CAFOs)* (research rep. No. RL31851). Congressional Research Service.
- Dewitz, J., & U.S. Geological Survey. (2021, July 8). *National land cover database (NLCD) 2019 products (ver. 2.0, june 2021)*. <https://doi.org/10.5066/P9KZCM54>
- Donham, K. J., Wing, S., Osterberg, D., Flora, J. L., Hodne, C., Thu, K. M., & Thorne, P. S. (2007). Community health and socioeconomic issues surrounding concentrated animal feeding operations. *Environ. Health Perspect.*, 115, 317–320. <https://doi.org/10.1289/ehp.8836>
- FAO. (2018). *Shaping the future of livestock* (research rep. No. I8384EN/1/1.18). Food and Agriculture Organization of the United Nations. <http://www.fao.org/3/i8384en/I8384EN.pdf>
- Gore, T. (2020). Silent but deadly. *Journal of Animal & Environmental Law*, 12, 26–43. <https://www.louisvillejael.com>
- Handan-Nader, C., & Ho, D. E. (2019). Deep learning to map concentrated animal feeding operations. *Nature Sustainability*, 2, 298–306. <https://doi.org/10.1038/s41893-019-0246-x>
- Harden, S. L. (2015). *Surface-water quality in agricultural watersheds of the north carolina coastal plain associated with concentrated animal feeding operations* (research rep.). US Geological Survey. <https://doi.org/10.3133/sir20155080>
- Heaney, C. D., Myers, K., Wing, S., Hall, D., Baron, D., & Stewart, J. R. (2015). Source tracking swine fecal waste in surface water proximal to swine concentrated animal feeding operations. *Sci. Total Environ.*, 511, 676–683. <https://doi.org/10.1016/j.scitotenv.2014.12.062>
- Hines, N. W. (2018). Here we go again: A third legislative attempt to protect polluting iowa CAFOs from neighbors' nuisance actions. *Iowa L. Rev. Online*, 103, 41. [https://heinonline.org/hol-cgi-bin/get\\_pdf.cgi?handle=hein.journals/iowalrb9%C2%A7ion=5](https://heinonline.org/hol-cgi-bin/get_pdf.cgi?handle=hein.journals/iowalrb9%C2%A7ion=5)
- Hribar, C. (2010). *Understanding concentrated animal feeding operations and their impact on communities* (M. Schultz, Ed.; research rep.). National Association of Local Boards of Health. <https://stacks.cdc.gov/view/cdc/59792>
- Isakson, H. R., & Ecker, M. D. (2008). An analysis of the impact of swine CAFOs on the value of nearby houses. *Agric. Econ.*, 39, 365–372. <https://doi.org/10.1111/j.1574-0862.2008.00339.x>

- Johnson, T. D., Belitz, K., & Lombard, M. A. (2019). Estimating domestic well locations and populations served in the contiguous U.S. for years 2000 and 2010. *Sci. Total Environ.*, 687, 1261–1273. <https://doi.org/10.1016/j.scitotenv.2019.06.036>
- Joy, M. K., Rankin, D. A., Wöhler, L., Boyce, P., Canning, A., Foote, K. J., & McNie, P. M. (2022). The grey water footprint of milk due to nitrate leaching from dairy farms in canterbury, new zealand. *Australasian Journal of Environmental Management*, 1–23. <https://doi.org/10.1080/14486563.2022.2068685>
- Karr, J. D., Showers, W. J., Gilliam, J. W., & Andres, A. S. (2001). Tracing nitrate transport and environmental impact from intensive swine farming using delta nitrogen-15. *J. Environ. Qual.*, 30, 1163–1175. <https://doi.org/10.2134/jeq2001.3041163x>
- Keiser, D., & Shapiro, J. (2019). Consequences of the clean water act and the demand for water quality. *Q. J. Econ.*, 134, 349–396. <https://doi.org/10.1093/qje/qjy019>
- Kim, J., & Goldsmith, P. (2009). A spatial hedonic approach to assess the impact of swine production on residential property values. *Environ. Resour. Econ.*, 42, 509–534. <https://doi.org/10.1007/s10640-008-9221-0>
- Kravchenko, J., Rhew, S. H., Akushevich, I., Agarwal, P., & Lyerly, H. K. (2018). Mortality and health outcomes in north carolina communities located in close proximity to hog concentrated animal feeding operations. *N. C. Med. J.*, 79, 278–288. <https://doi.org/10.18043/ncm.79.5.278>
- Kunkel, K. E., Easterling, D. R., Ballinger, A., Bililign, S., Champion, S. M., Reide Corbett, D., Dello, K. D., Dissen, J., Lackmann, G. M., Luettich, R. A., Jr, Baker Perry, L., Robinson, W. A., Stevens, L. E., Stewart, B. C., & Terando, A. J. (2020). *North Carolina Climate Science Report* (tech. rep.). North Carolina Institute for Climate Studies.
- Lawley, C. (2021). Hog barns and neighboring house prices: Anticipation and post-establishment impacts. *Am. J. Agric. Econ.*, 103, 1099–1121. <https://doi.org/10.1111/ajae.12203>
- MacDonald, J., & McBride, W. (2009, January). *The transformation of U.S. livestock agriculture: Scale, efficiency, and risks* (research rep.). U.S. Dept. of Agriculture, Economic Research Service. [https://www.ers.usda.gov/webdocs/publications/44292/10992\\_eib43.pdf?v=0](https://www.ers.usda.gov/webdocs/publications/44292/10992_eib43.pdf?v=0)
- Mallin, M. A. (2000). Impacts of industrial animal production on rivers and estuaries. *Am. Sci.*, 88, 26. <http://search.proquest.com/openview/e2e3a1c3c6847d1c185654848ebd7abb/1?pq-origsite=gscholar&cbl=40798>
- McBride, W., & Key, N. (2013, October). *U.S. hog production from 1992 2009: Technology, restructuring, productivity growth* (research rep. No. ERR-158). U.S. Department of Agriculture, Economic Research Service.
- Messier, K. P., Kane, E., Bolich, R., & Serre, M. L. (2014). Nitrate variability in ground-water of north carolina using monitoring and private well data models. *Environ. Sci. Technol.*, 48, 10804–10812. <https://doi.org/10.1021/es502725f>
- Mirabelli, M. C., Wing, S., Marshall, S. W., & Wilcosky, T. C. (2006). Asthma symptoms among adolescents who attend public schools that are located near confined swine feeding operations. *Pediatrics*, 118, e66–e75. <https://doi.org/10.1542/peds.2005-2812>
- Murray, A., Hall, A., Weaver, J., & Kremer, F. (2021). Methods for estimating locations of housing units served by private domestic wells in the united states applied to 2010. *J. Am. Water Resour. Assoc.*, 57, 1–16. <https://doi.org/10.1111/1752-1688.12937>

- OECD & Food and Agriculture Organization of the United Nations. (2021, July 5). *OECD-FAO agricultural outlook 2021-2030*. <https://play.google.com/store/books/details?id=3eE2EAAAQBAJ>
- Omernik, J. M., Griffith, G. E., Hughes, R. M., Glover, J. B., & Weber, M. H. (2017). How misapplication of the hydrologic unit framework diminishes the meaning of watersheds. *Environ. Manage.*, 60, 1–11. <https://doi.org/10.1007/s00267-017-0854-z>
- Ouzts, E. (2018, September 21). In north carolina, hog waste pollution a familiar result. will things ever change? <https://www.ehn.org/hurricane-florence-floods-north-carolina-hog-farms-2606610607.html>
- Palmquist, R. B., Roka, F. M., & Vukina, T. (1997). Hog operations, environmental effects, and residential property values. *Land Econ.*, 73, 114–124. <https://doi.org/10.2307/3147081>
- Pollard, A. (2020). This little piggy caused a nuisance: Analyzing north carolina's 2018 amendment to its right-to-farm act. *Liberty University Law Review*, 14. [https://digitalcommons.liberty.edu/lu\\_law\\_review/vol14/iss3/5](https://digitalcommons.liberty.edu/lu_law_review/vol14/iss3/5)
- Poulsen, M. N., Pollak, J., Sills, D. L., Casey, J. A., Nachman, K. E., Cosgrove, S. E., Stewart, D., & Schwartz, B. S. (2018). High-density poultry operations and community-acquired pneumonia in pennsylvania. *Environmental Epidemiology*, 2, e013. <https://doi.org/10.1097/EE9.0000000000000013>
- Poulsen, M. N., Pollak, J., Sills, D. L., Casey, J. A., Rasmussen, S. G., Nachman, K. E., Cosgrove, S. E., Stewart, D., & Schwartz, B. S. (2018). Residential proximity to high-density poultry operations associated with campylobacteriosis and infectious diarrhea. *Int. J. Hyg. Environ. Health*, 221, 323–333. <https://doi.org/10.1016/j.ijheh.2017.12.005>
- PRISM Climate Group, Oregon State University. (2020). *Gridded climate data*. <http://prism.oregonstate.edu>
- Radon, K., Schulze, A., Ehrenstein, V., van Strien, R. T., Praml, G., & Nowak, D. (2007). Environmental exposure to confined animal feeding operations and respiratory health of neighboring residents. *Epidemiology*, 18, 300–308. <https://doi.org/10.1097/01.ede.0000259966.62137.84>
- Raff, Z., & Meyer, A. (2021). CAFOs and surface water quality: Evidence from wisconsin. *Am. J. Agric. Econ.*, 104, 161–189. <https://doi.org/10.1111/ajae.12222>
- Rasmussen, S. G., Casey, J. A., Bandeen-Roche, K., & Schwartz, B. S. (2017). Proximity to industrial food animal production and asthma exacerbations in pennsylvania, 2005–2012. *Int. J. Environ. Res. Public Health*, 14, 362. <https://doi.org/10.3390/ijerph14040362>
- Read, E. K., Carr, L., De Cicco, L., Dugan, H. A., Hanson, P. C., Hart, J. A., Kreft, J., Read, J. S., & Winslow, L. A. (2017). Water quality data for national-scale aquatic research: The water quality portal. *Water Resour. Res.*, 53, 1735–1745. <https://doi.org/10.1002/2016wr019993>
- Sellers, S. M. (2017, May 2). As factory farms spread, so do toxic tort cases. <https://news.bloomberglaw.com/environment-and-energy/as-factory-farms-spread-so-do-toxic-tort-cases>

- Shaughnessy, A. R., Wen, T., Niu, X., & Brantley, S. L. (2019). Three principles to use in streamlining water quality research through data uniformity. *Environ. Sci. Technol.*, 53, 13549–13550. <https://doi.org/10.1021/acs.est.9b06406>
- Sigurdarson, S. T., & Kline, J. N. (2006). School proximity to concentrated animal feeding operations and prevalence of asthma in students. *Chest*, 129, 1486–1491. <https://doi.org/10.1378/chest.129.6.1486>
- Simpkins, W. W., Burkart, M. R., Helmke, M. F., Twedt, T. N., James, D. E., Jaquis, R. J., & Cole, K. J. (2002). Potential impact of earthen waste storage structures on water resources in iowa. *J. Am. Water Resour. Assoc.*, 38, 759–771. <https://doi.org/10.1111/j.1752-1688.2002.tb00995.x>
- Smart, C. M. (2016). The right to commit nuisance in north carolina: A historical analysis of the right-to-farm act. *NCL Rev.*, 94, 2097. <https://scholarship.law.unc.edu/nclr/vol94/iss6/6>
- Sneeringer, S. (2009). Does animal feeding operation pollution hurt public health? a national longitudinal study of health externalities identified by geographic shifts in livestock production. *Am. J. Agric. Econ.*, 91, 124–137. <https://doi.org/10.1111/j.1467-8276.2008.01161.x>
- Sneeringer, S. (2010). A national, longitudinal study of the effects of concentrated hog production on ambient air pollution. *Am. J. Agric. Econ.*, 92, 821–835. <https://doi.org/10.1093/ajae/aap030>
- U.S. Dept of Agriculture. (2022, February). *USDA agricultural projections to 2031* (research rep. No. OCE-2022-1). U.S. Dept of Agriculture.
- U.S. District Court, E.D. North Carolina. (2018). Anderson v. Murphy-Brown LLC [No. 7:14-CV-183-BR].
- U.S. Environmental Protection Agency. (2009, May). *National primary drinking water regulations* (research rep. No. 816-F-09-004). U.S. Environmental Protection Agency. <https://www.regulations.gov/document/EPA-HQ-OPPT-2009-0477-0003>
- U.S. Environmental Protection Agency. (2013, July). *Literature review of contaminants in livestock and poultry manure and implications for water quality* (research rep. No. EPA 820-R-13-002). U.S. Environmental Protection Agency.
- U.S. Environmental Protection Agency, Office of the Inspector General. (2017, September 19). *Eleven years after agreement, EPA has not developed reliable emission estimation methods to determine whether animal feeding operations comply with clean air act and other statutes* (research rep. No. 17-P-0396). U.S. Environmental Protection Agency, Office of Inspector General.
- U.S. Government Accountability Office. (2008, September). *Concentrated animal feeding operations: EPA needs more information and a clearly defined strategy to protect air and water quality from pollutants of concern* (research rep. No. GAO-08-944). <http://www.gao.gov/products/GAO-08-944>
- U.S. House of Representatives. (2005, November). Superfund laws and animal agriculture : Hearing before the subcommittee on environment and hazardous materials of the committee on energy and commerce, house of representatives, one hundred ninth congress, first session, november 16, 2005. <https://www.govinfo.gov/content/pkg/CHRG-109hhrg27001/pdf/CHRG-109hhrg27001.pdf>

- USDA National Agricultural Statistics Service. (1984). *1982 census of agriculture*. USDA-NASS, Washington, DC. [www.nass.usda.gov/AgCensus](http://www.nass.usda.gov/AgCensus)
- USDA National Agricultural Statistics Service. (2024). *2022 census of agriculture*. [www.nass.usda.gov/AgCensus](http://www.nass.usda.gov/AgCensus)
- Wing, S., & Wolf, S. (2000). Intensive livestock operations, health, and quality of life among eastern north carolina residents. *Environ. Health Perspect.*, 108, 233–238. <https://doi.org/10.1289/ehp.00108233>
- Wing, S., Horton, R. A., Marshall, S. W., Thu, K., Tajik, M., Schinasi, L., & Schiffman, S. S. (2008). Air pollution and odor in communities near industrial swine operations. *Environ. Health Perspect.*, 116, 1362–1368. <https://doi.org/10.1289/ehp.11250>
- World Meteorological Organization. (2017). WMO guidelines on the calculation of climate normals.

# Appendix

## A.1 Harmonization of the water quality data

The measurements recorded in the Water Quality Portal (WQP) are provided by multiple agencies, and present many inconsistencies in reporting, such as being labeled under different "characteristic names" as well as reported in various units. [Shaughnessy et al. \(2019\)](#) notes that among the most inconsistently reported water quality parameters are some of the most important (and indeed those of interest in this paper): nutrients, including the various nitrogen-containing compounds (e.g., nitrate, nitrite, ammonia) and forms of phosphorus (e.g., orthophosphate, total phosphorus). Indeed, I find in the raw collected data that a unique pollutant, e.g., nitrite, can appear as a concentration *as element* (e.g., "Nitrite-N" in mg/L as N), as a concentration *as polyatomic* (e.g., "Nitrite" in mg NO<sub>2</sub>/L), but often also ambiguously as a concentration in mg/L of "Nitrite", without specifying whether the quantity is in polyatomic or elemental mass. Some measurements are also actually recorded twice, both in polyatomic and elemental mass concentrations.

I harmonize the data by extracting from the WQP all the "characteristic names" that correspond to the parameter of interest, and convert all measures to elemental mass concentrations. I average all measurements by station-by-day, to avoid cases of double reporting that would induce the over-representation of specific stations in my final sample. The list of characteristic names considered and the corresponding number of observations collected — pre-data processing — is detailed in Table A1.

Water quality data are also prone to measurement error, which may lead to extreme values beyond the natural value range (e.g., levels of dissolved oxygen exceeding 20 mg/L) or beyond the detection upper bound of the test used. Measurements below the given test's detection lowerbound, i.e., "non-detects", are also sometimes erroneously labeled as "0" values. For records on the left tail of the distribution, I follow the approach of the existing literature and transform measures of zero and non-detects as positive values ([Keiser & Shapiro, 2019](#)), specifically to half of the smallest positive value in the sample, following [Raff and Meyer \(2021\)](#). I apply a different correction on the right tail of the distribution, which is generally much larger: I censor data to the maximum physically possible level when one exists (such as for dissolved oxygen), and winsorize at the 99.5% level otherwise.

## A.2 Water quality standards and recommended criteria

The U.S. EPA develops drinking water regulations, which impose notably maximum contaminant levels (MCL) for key pollutants of concern. For numerous other compounds present in water, while there is no enforceable national standard, the U.S. EPA provides recommended ambient water quality criteria (AWQC) for the different types of waterbodies, notably rivers and streams. For example, in 2013, the final acute AWQC for protecting freshwater organisms from the toxicity of ammonia was set to 17 mg/L total ammonia nitrogen, and the final chronic AWQC for ammonia to 1.9 mg/L (in the conditions of a pH of 7.0 and a temperature of 20°C) ([EPA 822-R-13-001](#)).

For nutrient concentrations, specifically total nitrogen and total phosphorus, recommended criteria are provided for each of the fourteen major "ecoregions" of the country,

alongside guidelines for states and authorized tribes for establishing their own water quality standards, in order to protect three designated uses: aquatic life, recreation, and drinking water supply. The criteria proposed differ across ecoregions in order to account for unique local conditions. However, neither North Carolina nor Iowa has developed numeric water quality criteria for nitrogen and phosphorus.<sup>13</sup>

Table A2 summarizes the national drinking water standards and recommended surface water quality criteria for the nutrient and pathogen concentrations of concern. Most of Iowa is located in Ecoregion VI ("Corn Belt And Northern Great Plains"), and North Carolina belongs, from East to West, to Ecoregions XIV ("Eastern Coastal Plain"), IX ("Southeastern Temperate Forested Plains and Hills") and XI ("Central and Eastern Forested Uplands").

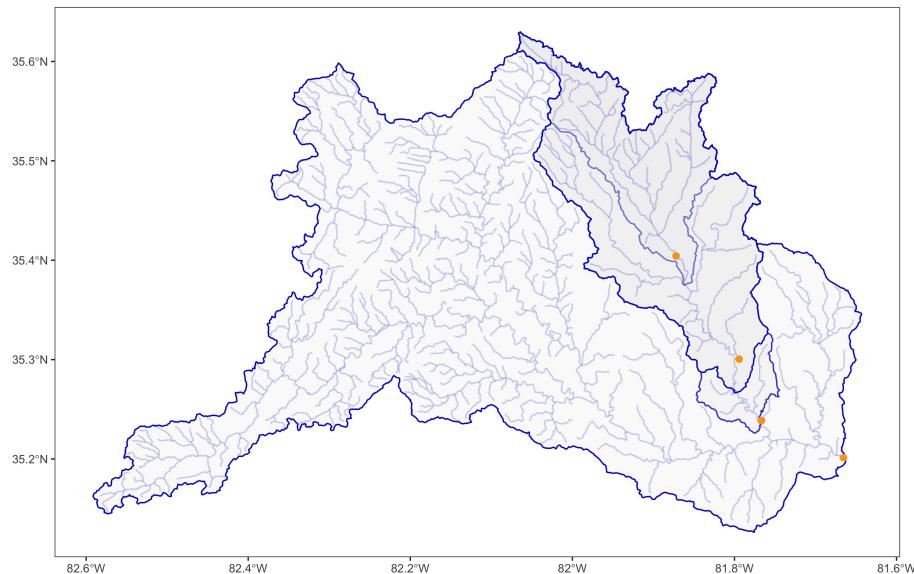


Figure A1: Example of nested drainage areas (North Carolina)

---

<sup>13</sup>The U.S. EPA publishes the status of states' numeric nutrient criteria development online: <https://www.epa.gov/nutrient-policy-data/state-progress-toward-developing-numeric-nutrient-water-quality-criteria>

Parameter	Unit	Characteristic Name	NC, 97-20	IA, 02- 18
Ammonia-Ammonium (NH <sub>3</sub> -NH <sub>4</sub> )	mg/L as N	Ammonia	9,288	5,144
		Ammonia as NH <sub>3</sub>	59	1,721
		Ammonia uptake	0	0
		Ammonia-nitrogen	81,478	36,785
		Ammonia and ammonium	22,236	13,602
		Ammonia-nitrogen as N	49,547	22,028
		Nitrogen, ammonia (NH <sub>3</sub> ) as NH <sub>4</sub>	0	0
		Ammonium	8,678	37
		Ammonium as N	0	0
		Ammonium as NH <sub>4</sub>	404	0
Total Kjeldahl nitrogen (TKN)	mg/L as N	Ammonium-nitrogen	0	0
		<b>TOTAL</b>	<b>171,690</b>	<b>79,317</b>
		Kjeldahl nitrogen	152,276	53,031
		Nitrogen Kjeldahl	0	0
		Total Kjeldahl nitrogen	0	0
Total Phosphorus (TP)	mg/L as P	Total Kjeldahl nitrogen (Organic N & NH <sub>3</sub> )	0	6
		<b>TOTAL</b>	<b>152,276</b>	<b>53,037</b>
		Total Phosphorus, mixed forms	704	434
		Phosphate	0	18,173
		Phosphate-phosphorus	168	40,052
		Phosphate-phosphorus as P	49,802	22,519
		Phosphate-phosphorus as PO <sub>4</sub>	0	160
Dissolved Oxygen (DO)	mg/L	Phosphorus	108,842	9,036
		Phosphorus as P	0	0
		<b>TOTAL</b>	<b>159,516</b>	<b>90,374</b>
		Dissolved oxygen	0	0
		Dissolved oxygen (DO)	396,213	103,434
Fecal coliform	cfu/100mL	Dissolved oxygen uptake	0	0
		<b>TOTAL</b>	<b>396,213</b>	<b>103,434</b>
Fecal coliform	cfu/100mL	Fecal Coliform	134,200	14,337

Notes: CFU = colony-forming units.

Table A1: Characteristic names recorded on the Water Quality Portal, and corresponding number of measurement records by state and period

Parameter	Unit	Drinking water standard	Surface water quality criteria
Ammonia-Ammonium	mg/L as N	none <sup>a</sup>	chronic (30-day rolling average) = 1.9; acute (1-h average) = 17
Total Nitrogen	mg/L as N		By Ecoregion: (VI) 2.18, (IX) 0.69, (XI) 0.31, (XIV) 0.71
Total Phosphorus	µg/L as P		National recommended limits: 100 in flowing waters, 50 in streams entering lakes. By Ecoregion: (VI) 76.25, (IX) 36.56, (XI) 10, (XIV) 31.25
Fecal coliform	cfu/100mL	MCL = 0; Public health goal = 0	

Notes: CFU = colony-forming units; MCL = maximum contaminant level.

<sup>a</sup> The National Academy of Science recommends, and many European nations have adopted, a drinking water standard of 0.5 mg/L.

Table A2: National drinking water standards and recommended surface water quality criteria for nutrient and pathogen concentrations

### A.3 Robustness checks

	DO	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b>Swine AFOs</b>					
Regression coefficient	<b>-0.106***</b> <b>(0.039)</b>	-11,512 (10,204)	<b>0.010**</b> <b>(0.004)</b>	<b>0.041**</b> <b>(0.016)</b>	<b>0.032***</b> <b>(0.007)</b>
Sample mean	9.21	3,946	0.09	1.08	0.29
Relative effect	<b>-1.2%</b>	-292%	<b>+11.7%</b>	<b>+3.8%</b>	<b>+10.9%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	60,916	7,043	32,957	32,155	48,422
Adjusted R <sup>2</sup>	0.473	0.059	0.297	0.187	0.795

(a) Week level estimates (drainage area–week panel)

	DO	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b>Swine AFOs</b>					
Regression coefficient	<b>-0.099**</b> <b>(0.040)</b>	-11,376 (10,207)	<b>0.011**</b> <b>(0.004)</b>	<b>0.041**</b> <b>(0.016)</b>	<b>0.035***</b> <b>(0.008)</b>
Sample mean	9.21	3,946	0.09	1.08	0.29
Relative effect	<b>-1.07%</b>	-288%	<b>+12.0%</b>	<b>+3.8%</b>	<b>+12.1%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	48,685	4,973	29,866	28,670	40,536
Adjusted R <sup>2</sup>	0.504	0.119	0.305	0.234	0.838

(b) Month level estimates (drainage area–4-week panel)

Table A3: Effects of *swine AFOs* on downstream surface water quality (Iowa, 2004–2017). Standard errors are clustered by drainage area. Significance codes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

	DO	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b>Animal Units</b>					
Regression coefficient	<b>-6.1E-5***</b> <b>(2.1E-5)</b>	-4.10 (3.87)	<b>5.2E-6**</b> <b>(2.6E-6)</b>	<b>2.1E-5**</b> <b>(9.0E-6)</b>	<b>1.9E-5***</b> <b>(5.6E-6)</b>
Sample mean	9.21	3,946	0.09	1.08	0.29
Relative effect	<b>-0.001%</b>	-0.104%	<b>0.006%</b>	<b>0.002%</b>	<b>0.007%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	60,916	7,043	32,957	32,155	48,422
Adjusted R <sup>2</sup>	0.473	0.060	0.297	0.186	0.795

(a) Week level estimates (drainage area–week panel)

	DO	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b>Animal Units</b>					
Regression coefficient	<b>-5.5E-5***</b> <b>(2.1E-5)</b>	-4.05 (3.86)	<b>5.5E-6**</b> <b>(2.5E-6)</b>	<b>2.2E-5**</b> <b>(9.0E-6)</b>	<b>2.2E-5***</b> <b>(6.0E-6)</b>
Sample mean	9.21	3,946	0.09	1.08	0.29
Relative effect	<b>-0.001%</b>	-0.103%	<b>0.006%</b>	<b>0.002%</b>	<b>0.007%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	48,685	4,973	29,866	28,670	40,536
Adjusted R <sup>2</sup>	0.504	0.120	0.305	0.234	0.838

(b) Month level estimates (drainage area–4-week panel)

Table A4: Effects of *animal units* on downstream surface water quality (Iowa, 2004–2017). Standard errors are clustered by drainage area. Significance codes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

	DO deficit	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b> AFO-period &gt; 2<math>\sigma</math> </b>					
Regression coefficient	<b>0.035***</b> (0.006)	<b>1.81***</b> (0.580)	<b>9.5E-5***</b> (3.3E-5)	<b>7.3E-4***</b> (1.6E-4)	<b>3.5E-4***</b> (7.0E-5)
Sample mean	15.1	349	0.05	0.58	0.13
Relative effect	<b>+0.23%</b>	<b>+0.52%</b>	<b>+0.19%</b>	<b>+0.13%</b>	<b>+0.27%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	16,986	11,705	10,780	11,512	12,443
Adjusted R <sup>2</sup>	0.6406	0.1389	0.2331	0.5714	0.5324

(a) Week level estimates (drainage area–week panel)

	DO deficit	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b> AFO-period &gt; 2<math>\sigma</math> </b>					
Regression coefficient	<b>0.076***</b> (0.008)	0.593 (0.530)	<b>1.6E-4***</b> (3.2E-5)	<b>6.1E-4***</b> (1.3E-4)	3.2E-5 (7.7E-5)
Sample mean	15.1	349	0.05	0.58	0.13
Relative effect	<b>+0.50%</b>	+0.17%	<b>+0.33%</b>	<b>+0.11%</b>	+0.03%
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	16,767	11,663	10,661	11,387	12,317
Adjusted R <sup>2</sup>	0.645	0.1253	0.2353	0.5679	0.5356

(b) Month level estimates (drainage area–4-week panel)

Table A5: Effects of a *period* of extreme precipitation at the location of AFOs on downstream surface water quality (North Carolina, 2014-2020). Standard errors are clustered by drainage area. Significance codes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

	DO deficit	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b> AFO-day &gt; 2<math>\sigma</math> </b>					
Regression coefficient	<b>0.045***</b> (0.011)	<b>1.62***</b> (0.55)	3.5E-5 (4.4E-5)	<b>0.0012***</b> (3.3E-4)	<b>3.2E-4**</b> (1.3E-4)
Sample mean	15.1	349	0.05	0.58	0.13
Relative effect	<b>+0.30%</b>	<b>+0.47%</b>	+0.07%	<b>+0.20%</b>	<b>+0.24%</b>
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	14,600	10,259	9,320	9,691	10,506
Adjusted R <sup>2</sup>	0.6419	0.1444	0.2315	0.5852	0.5342

(a) Week level estimates (drainage area–week panel)

	DO deficit	F.coliform	NH <sub>3</sub> -NH <sub>4</sub>	TKN	TP
<b> AFO-day &gt; 2<math>\sigma</math> </b>					
Regression coefficient	<b>0.019***</b> (0.0038)	0.104 (0.093)	<b>4.5E-5***</b> (1.5E-5)	<b>2.1E-4***</b> (5.7E-5)	2.5E-5 (2.1E-5)
Sample mean	15.1	349	0.05	0.58	0.13
Relative effect	<b>+0.13%</b>	+0.03%	<b>+0.09%</b>	<b>+0.04%</b>	+0.02%
Station FEs	✓	✓	✓	✓	✓
Year & month FEs	✓✓	✓✓	✓✓	✓✓	✓✓
Observations	14,404	10,221	9,219	9,582	10,396
Adjusted R <sup>2</sup>	0.6448	0.1325	0.2334	0.583	0.5377

(b) Month level estimates (drainage area–4-week panel)

Table A6: Effects of extreme precipitation events at the location of AFOs on downstream surface water quality (North Carolina, 2014-2020, *restricted sample: no nesting drainage areas*). Standard errors are clustered by drainage area. Significance codes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .