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RESEARCH ARTICLE

Remotely sensed imagery reveals animal feeding operations increase downstream dissolved reactive phosphorus

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Abstract

In this paper, we use remotely sensed imagery to identify the location and size of animal feeding operations in the Maumee River Watershed, a key drainage area to Lake Erie's Western Basin, which has recently experienced severe harmful algal blooms. We then estimate the relationship between the intensity of animal feeding operations in the watershed and surface water body concentrations of dissolved reactive phosphorus (DRP), the pollutant most responsible for algal growth. We find that stream reaches with relatively larger increases in upstream animal feeding exposure experience significantly higher increases in concentrations of DRP. The average marginal upstream animal feeding operation in the watershed increases downstream DRP concentrations by between 10% and 15%. In contrast, when restricting the analysis to include only permitted operations, coefficient estimates are practically zero and statistically insignificant. Our work presents evidence that the increasing intensity of animal feeding operations contributes to water quality problems. Permitting and identification of animal feeding operations is therefore important for managing runoff and correctly attributing the causes of excess nutrients in surface water bodies.

KEYWORDS
aerial imagery, animal feeding operations, dissolved reactive phosphorus, remote sensing, stream and river network, surface water quality

1 | INTRODUCTION

Anthropogenic eutrophication is a major cause of impairment in freshwater lakes and reservoirs worldwide, causing predictable increases in algae biomass and harmful algal blooms (Heisler et al., 2008; Smith, 2003). Eutrophication and its associated algal blooms impose billions of dollars of annual economic damages on residents of the United States (U.S.) (Dodds et al., 2009) through reduced property values, degraded recreational usages, and increased water treatment costs (Heberling et al., 2022). The eutrophication of surface water bodies and the algal production process have long been topics of research (Lund, 1967). Briefly, nitrogen and phosphorus pollution jointly contribute to eutrophication, but the limiting nutrient for algal production, and therefore the more important nutrient to control, depends on the specific conditions of each water body (Wurtsbaugh et al., 2019). In the U.S. Midwest and freshwater systems in general, there exists higher relative nitrogen levels than phosphorus levels in surface water bodies (Dodds & Smith, 2016; EPA, 2013; Wurtsbaugh et al., 2019). Phosphorus is therefore the nutrient that constrains eutrophication and the associated algal blooms in surface water bodies in that region (Carpenter, 2008; Schindler, 1974; Schindler et al., 2008).

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Research Impact Statement

Streams with larger increases in upstream animal feeding operations experience larger increases in dissolved reactive phosphorus concentrations in an agricultural watershed over a 10-year period.

In many parts of the U.S., agricultural nonpoint source pollution is the primary source of excess phosphorus in surface water bodies (Carpenter et al., 1998; Mooney et al., 2020). More generally, phosphorus loading is one of the main drivers of incident threat to global human water security and biodiversity (Vörösmarty et al., 2010). However, food and environmental policy agendas of international conventions and most countries largely neglect phosphorus management (Brownlie et al., 2021).

To date, commercial fertilizer has been the primary focus of research on agricultural nonpoint source phosphorus pollution. However, animal feeding operations (AFOs), where many animals are held in confined spaces, are also an important nonpoint source contributor to phosphorus loads in many watersheds (e.g., Cahoon et al., 1999; Glasgow & Burkholder, 2000). Across the U.S., for example, manure phosphorus production increased by 92% from 1930 to 2012 (Yang et al., 2016). But many studies assume that manure application from AFOs has remained constant over time (IJC, 2018). Additionally, prior empirical work on the relationship between AFOs and surface water quality typically relies on case studies and correlational evidence. We seek to improve on this evidence by using causal identification methods and longitudinal data over a large spatial scale in the present study.

One limitation of the existing literature estimating the source contribution to phosphorus loads is that there is a lack of reliable, publicly available information about where and how many AFOs exist in many watersheds and the amount of manure and phosphorus that they produce. Livestock operations in the U.S. above a certain size threshold are subject to regulation by government agencies. But many AFOs are below this threshold and therefore do not require Clean Water Act permits that would provide more detailed information about the operation's location, size, and other characteristics. Additionally, many states do not issue permits to all AFOs that are above the relevant size thresholds because of differences in state-level Clean Water Act implementation and state agency interpretation of operations considered as potential dischargers (GAO, 2003; Raff & Meyer, 2022). As a result, researchers and governmental agency officials have had little detailed information about the scope of livestock production in many watersheds. To overcome these and other "on the ground" data issues, researchers have recently begun using remote sensing and satellite imagery to identify the sources of pollutants (e.g., Dasgupta et al., 2020; Nian, 2023) or ambient pollutant levels in the water (e.g., Wolf et al., 2022; Wolf & Kemp, 2021) and air (e.g., Currie et al., 2023; Hammer et al., 2020; von Donkelaar et al., 2019). Directly applicable to our purposes, Shea et al. (2022) use radar and multispectral imagery to identify probable hog manure spreading locations for concentrated animal feeding operations (CAFOs) in North Carolina. In this paper, we use remotely sensed imagery to identify likely AFO location and size to examine the effects of increased animal agriculture on surface water quality.

To answer our research questions, we focus on the Maumee River Watershed (MRW), which is a major contributor of phosphorus loadings to Lake Erie. Lake Erie, and its Western Basin in particular, has a history of eutrophication and provides an illustrative case study of the effects of excess phosphorus. Our study therefore uses novel data collection techniques to account for more refined sources of phosphorus loadings to the lake than previous studies.

Lake Erie is particularly susceptible to environmental impacts from sediment and nutrient loads. Lake Erie is the shallowest and warmest of the Great Lakes, and of its three main basins, the Western Basin is the shallowest. To control nutrient pollution in Lake Erie, several international agreements and regulations in the 1970s primarily targeted point sources of phosphorus and resulted in water quality improvements that lasted until around 1990 (Baker & Richards, 2002; Paytan et al., 2017). However, harmful algal blooms in Lake Erie began re-appearing in the early 2000s and have increased in severity over time (D'Anglada et al., 2018; Michalak et al., 2013; Scavia et al., 2014; Watson et al., 2016). The blooms, which impose millions of dollars of economic costs each year on residents (e.g., Wolf et al., 2022; Wolf & Klaiber, 2017), are primarily caused by excess dissolved (i.e., soluble) reactive phosphorus (DRP), which upstream tributary watersheds deliver to the lake through streams and rivers. Like many watersheds in the U.S. and around the globe, nonpoint source agricultural release is recognized as the single largest source of excess phosphorus to Lake Erie's Western Basin (Dolan & Chapra, 2012; IJC, 2018). Importantly, trends point to decreasing commercial fertilizer application in the Lake Erie Watershed since the 1990s. DRP loads to the lake, however, increased until the mid-2000s before stabilizing (IJC, 2018; Rowland et al., 2021).

Leading current hypotheses to explain increasing DRP loads into Lake Erie include legacy phosphorus in the soil, tile drainage, and tillage practices (OEPA, 2010). Relatedly, Baker et al. (2014) find that, while total phosphorus (TP) loads to Lake Erie have continued to decline, DRP export from the MRW substantially increased beginning in the 1990s. This increase in bioavailable DRP corresponds to the period of Lake Erie's re-eutrophication, suggesting that DRP concentrations and loads are important (Baker et al., 2014).

Maccoux et al. (2016) provide an accounting of TP and DRP loadings to Lake Erie by basin and source type and demonstrate that nonpoint sources now dominate point sources as contributors to phosphorus loadings. For Lake Erie as a whole, 76% of the TP load stems from tributaries. Most of the load is from nonpoint sources (71% of total Lake Erie TP load) versus point sources. Five percent of Lake Erie's TP comes from point sources upstream of tributary monitoring locations and 14% comes from industrial and municipal point sources discharged directly to the lake or downstream of monitoring locations (Maccoux et al., 2016). Furthermore, 60% of the TP loading in Lake Erie comes from the Western Basin (Maccoux et al., 2016). The International Joint Commission estimates that 80% of agricultural phosphorus generated in the Western Lake Erie Basin derives from commercial fertilizer, whereas approximately 20% derives from manure from AFOs (IJC, 2018). Kast et al. (2021) estimate that manure sources of phosphorus contribute 8% of the TP load in the watershed, given their modeling assumptions about manure spreading practices.

The MRW, which is a largely agricultural watershed, is especially important to study because the Maumee River is the largest source of phosphorus loadings to both Lake Erie overall and its Western Basin (Maccoux et al., 2016). The MRW spans over 17,000 km^2 of Northwest Ohio, Northeast Indiana, and South Central Michigan, making it the largest drainage basin of any river system in the Great Lakes Watershed (ODNR, 2018). Importantly, manure nutrients produced by AFOs in the MRW have increased considerably over the past several decades (Yang et al., 2016).

In this paper, we leverage remotely sensed imagery to determine the size and scope of livestock operations in the MRW, obviating the need for permit information. We then combine this information about livestock operations with publicly available water quality data at downstream locations. We focus on DRP because it is the most bioavailable form of phosphorus and previous research recognizes its importance in explaining eutrophication and harmful algal blooms (Baker et al., 2014; Bertani et al., 2016; De Pinto et al., 1986; Richards et al., 2010; Stumpf et al., 2016). We then empirically estimate the aggregate effect of upstream AFOs on downstream DRP concentrations, controlling for permanent differences in DRP concentrations across stream reaches and for unobservable factors common to the MRW that change over time. Intuitively, changes in DRP concentrations at stream reaches that experience little upstream expansion in AFO exposure serve as counterfactual outcomes to observed changes in DRP concentrations at stream reaches that experience more substantial increases in AFO exposure.

We make three primary contributions to the literature with this paper. First, we demonstrate the usefulness of remotely sensed imagery data for producing a historical record of AFO geolocations and intensity. As mentioned, AFO counts from governmental permit data miss many operations, so remotely sensed AFO counts fill an important knowledge gap in the literature. We are not aware of previous studies linking remotely sensed imagery-derived AFO intensity measures to downstream nutrient concentrations.

As a second contribution, we leverage the National Hydrography Dataset Plus v2.1 (NHD) to determine the flow networks of streams and rivers in our sample and link each AFO to downstream stream reaches. This methodological approach is an improvement over recent work on nonpoint source pollution that relies on less precise spatial measures, such as averages over a Hydrologic Unit Code 8 (HUC8) hydrologic unit watershed (Grant & Langpap, 2019; Paudel & Crago, 2021; Raff & Meyer, 2022; Skidmore et al., 2023). However, several previous studies apply a geospatial approach like ours using the Spatially Referenced Regressions on Watershed Attributes (SPARROW); Brakebill et al. (2011) and Brakebill and Schwarz (2016) provide a review of the applications of the SPARROW model. We discuss some similarities and differences between our approach and the SPARROW model in Section 4.

Finally, as our third contribution, we provide evidence linking AFO expansion to downstream DRP concentrations using an empirical approach that relies only on longitudinal ex post, observational data. Previous studies assessing water quality and policy primarily rely on ex ante hydrological simulations using models such as the Soil and Water Assessment Tool to predict the impacts of agricultural and land management changes on nutrient concentrations and loads in the MRW (Bosch et al., 2013; Cousino et al., 2015; Kast et al., 2021; Martin et al., 2021; Muenich et al., 2016; Scavia et al., 2017). These models require quantity and locational assumptions about the application of manure and other nutrients; conclusions about linkages in the watershed therefore depend on the modeling assumptions. Several existing studies statistically correlate AFO operations with downstream water quality. Cox et al. (2013) document significant positive correlations between TP concentrations and the intensity of upstream poultry operations in the Illinois River watershed of Arkansas and Oklahoma. Likewise, Romeis et al. (2011) find significantly higher TP levels in commercial poultry-pasture sites as compared to forested headwater streams. Additionally, Ciparis et al. (2012) find significant positive correlations between the density of AFOs and dissolved inorganic nitrogen in Virginia's Shenandoah River watershed and Weldon and Hornbuckle (2006) find elevated nitrate levels near Iowa CAFOs. More broadly, Mainali et al. (2019) survey alternative spatial approaches to modeling water quality as a function of many factors including agricultural land use. Our approach differs in that we leverage within-stream reach variation in upstream AFO intensity to identify the downstream water quality effects.

2 | STUDY AREA

In this section, we describe our study area. First, we discuss the MRW and the Western Basin of Lake Erie. Then, we discuss animal agriculture and manure management in the basin.

2.1 | The MRW

The MRW, which drains into the Western Basin of Lake Erie at Toledo, Ohio, spans over 17,000 km^2 of Northwest Ohio, Northeast Indiana, and South Central Michigan (Figure 1). There are seven HUC8 subbasins within the MRW; Supporting Information Figure A1 maps these

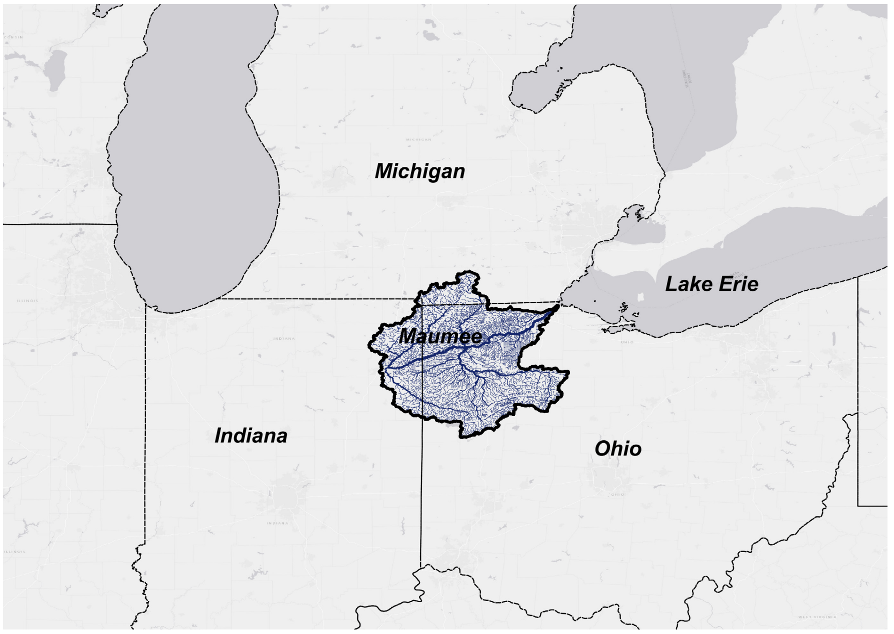

FIGURE 1 Location of the Maumee River Watershed. This map shows the location of the Maumee River Watershed, along with state borders for Indiana, Michigan, and Ohio.

subbasins. Land use in the MRW is heavily agricultural, with many AFOs and over 70% coverage with row crop agriculture (Muenich et al., 2016; OEPA, 2010). The watershed is characterized by flat topography and heavy, clayey soils with poor natural drainage. As a result, roughly 62% of cropland in the 25 counties that make up the MRW is drained by subsurface tile (USDA-NASS, 2017).

2.2 | Animal agriculture and manure management in the MRW

It is important to consider how manure from livestock operations likely reaches surface water bodies. AFOs use two stages to manage manure. First, AFOs may store manure onsite. Swine and dairy operations most often store manure within surface "lagoons", whereas poultry operations typically store manure under tarps or in buildings. Second, after storing onsite, livestock operations typically spread manure onto farmland, sometimes at agronomically inappropriate rates and/or times (Osterberg & Wallinga, 2004; Raff & Meyer, 2022). Nonpoint source water pollution, or runoff, can happen in either storage stage. In the first stage, manure lagoons are frequently insecure and do not contain linings or retaining walls (Hribar, 2010). As such, especially during precipitation events, manure can runoff from lagoons or other storage locations into surface water bodies or leach into groundwater (Waller et al., 2021). In the second stage, if manure is spread onto surrounding farmland at inappropriate rates and/or times (e.g., on frozen ground, without plant cover), the soil does not fully absorb nutrients from the manure (EPA, 2001; Gollehon et al., 2016). Rain or melting snow can then transport the manure nutrients to surface water bodies. Moreover, artificial drainage tile systems, like those common in the MRW, can quickly transfer excess nutrients directly from farm fields to nearby streams.

The Ohio EPA requires all CAFOs—AFOs with over 1000 animal units (AUs) in confined spaces (one AU is equivalent roughly to 1000 pounds of live animal weight, Raff & Meyer, 2022)—to submit manure management plans (MMPs) when they apply for a permit to operate. The MMPs include, among other things: information on timing and method of manure spreading, amount of manure generated onsite and spread, manure storage facilities onsite, current and historical soil phosphorus tests, and maximum number of animals onsite. Kast et al. (2019) studied the MMPs for all 48 operational CAFOs in the Ohio portion of the MRW. These CAFOs consist of 18 dairy, one beef, 23 swine, and six poultry operations. Among the fields controlled by the CAFOs, the average distance from a swine CAFO's holding barn to the receiving fields where manure is spread is 2 km. For cattle, this distance is roughly 3 km. Much of the manure is unaccounted for because of Distribution and Utilization, in which the manure is legally transferred from the CAFO to another entity. Over 75% of CAFO manure phosphorus is transferred in this way, including 100% of all poultry manure phosphorus. However, Distribution and Utilization only helps manage the manure of 48 CAFOs in Ohio. Our study examines all 774 AFOs in the MRW that operate between 2010 and 2018. The operations that engage in Distribution and Utilization practices therefore represent only a small portion of the AFOs that we study, so the impact of their manure management is likely small.

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3 | DATA

For our empirical analysis, we aggregate data from several sources. In this section, we describe these data sources, the construction of our analysis sample, and provide descriptive analyses and statistical summaries.

3.1 | Water quality

First, we gather water quality data from the publicly available Water Quality Portal (NWQC, 2022). The National Water Quality Council aggregates data from three sources to include in the Water Quality Portal: USGS National Water Information System (NWIS), EPA Storage and Retrieval (STORET), and USGS Biodata. To gather these data, we use the "dataRetrieval" package in R (De Cicco et al., 2018), which uses a web services approach to make targeted retrievals from several national databases and organizes the data into a form that is ready for analysis. We use the package to gather all nutrient readings for Ohio, Indiana, and Michigan, which we then filter for DRP readings for the MRW. Few DRP readings are available in the portal before 2010, so we begin our sample in 2010, when data are readily available. For our analysis, we retain only water quality readings from streams and rivers, rather than, for example, lakes and ditches. Like previous studies with few non-detected measurements, we transform zero and non-detected measurements (494 of 27,662 total readings) to ½ of the smallest positive value in the sample (Chen et al., 2019; Keiser & Shapiro, 2019; Raff & Meyer, 2022), as recommended by US EPA (2006) and Shoari and Dubé (2018). This substitution value is 0.00005 mg/L. Results are robust to alternative substituted values (0.0005 and 0.005 mg/L) and to an alternative random effects Tobit model that retains non-detect information. The magnitudes of the average partial effects increase with the correlated random effects Tobit model as compared to our baseline linear fixed effects estimates. Our baseline model imposes fewer assumptions on the correlation between unobserved stream reach-level characteristics and observed AFO intensity, so we present the more conservative linear fixed effects estimates. Alternative estimation results are available from the authors upon request.

We complement the data from the Water Quality Portal with long-term monitoring data from the Heidelberg Tributary Loading Program (HTLP). Heidelberg University's National Center for Water Quality Research (NCWQR) initiated the HTLP in 1974 as part of state and federal programs to improve water quality in Lake Erie. The NCWQR collects hundreds of water samples from each monitored location each year, analyzes the water samples to calculate concentrations of multiple pollutants, and publicly shares these data via the HTLP Data Portal (2022). There are nine HTLP monitoring locations in the MRW; of these, eight provide DRP readings for at least 1 year of our sample period. We use all available DRP measurements from the HTLP Data Portal. The HTLP reports DRP measurements for one station dating back to 1975, for three other locations beginning in 2007, and for four other upstream tributary locations in 2018. As the longest-running and most detailed program of its kind in the U.S. (NCWQR, 2022), these data help establish long-term trends in DRP concentrations in the MRW. In total, there are 7324 stream reaches in the study area, but most stream reaches are unmonitored. Combining the Water Quality Portal and HTLP data results in 27,662 DRP observations from 74 stream reaches during our study period. We do not include unmonitored stream reaches in our analysis.

There could be a concern that governmental agencies, researchers, and citizen volunteers are more likely to sample water quality on days that they expect nutrient concentrations to be elevated, particularly following precipitation events. We note that this concern is unlikely to bias our analysis. The only potential concern would be if the probability of sampling following a precipitation event was to increase differentially at stream reaches with more upstream AFOs. Raff and Meyer (2022) provide evidence from a similar geography (Wisconsin) that sampling timing is not endogenous to precipitation and that sampling does not differentially increase in areas with more CAFOs following precipitation events. Nevertheless, to avoid potentially overweighting certain locations that were monitored more frequently and to smooth daily noise in the data, we follow other studies and aggregate surface water quality readings to the monthly level (Keiser & Shapiro, 2019). Here, we average all DRP readings along each stream reach, resulting in 1673 stream reach-month observations. Our measure of water quality is therefore an average reading of DRP concentrations at the stream reach-month level, from 2010 to 2018.

3.2 | Animal agriculture

Next, we obtain data on the location, type (i.e., animal), and size of livestock operations in the MRW from 2010 to 2018 using aerial imagery. In the watershed, only 20% of livestock operations have Clean Water Act (or other) permits (ELPC, 2019), so it is difficult to identify their locations and the overall intensity of animal agriculture in the watershed. We therefore use USDA's National Agriculture Imagery Program (NAIP) aerial photography (1 m ground sample distance) (USDA, 2023), to visually locate AFOs in the MRW. Consistent imagery was available on a biennial basis across the study area beginning in 2005, so we match on available DRP data and begin our study in 2010. Supporting Information Table A1 displays NAIP availability by state and year. For each AFO, we attribute several characteristics of the operation: the year in which the operation is first evident, the number of barns and their total square footage, animal type (poultry, swine, beef cattle or dairy cattle), and the year of expansion, if any. We update square footage measurements corresponding to the AFO expansion year.

When available, we assign animal type using permit data for each operation. When unavailable, we assign animal type to each operation based on several attributes unique to each facility, including the size and shape of each barn, the presence and number of feed bins, the location of fans, and the presence of lagoons and of visually identifiable animals. We also use Google Street View (Google, 2019) to ground truth the assignments. In addition, we remove facilities from the analysis if they appear abandoned, as evidenced by dilapidated roofs or removal of infrastructure. Supporting Information Appendix D describes the photointerpretation methodology in detail. Our photointerpretation approach includes a detailed literature review of industry standards, use of permitted operations as visual training data, and the use of independent AFO attribution by multiple analysts. We obtain state permit data for AFOs in the MRW from the Ohio Department of Agriculture, MIWaters website, and the Indiana Department of Environmental Management. Where possible, we match these permit data to mapped facilities.

By the end of our sample period, we identify, with location information, 774 AFOs in the MRW; we map these operations along with the streamflow network and monitoring locations in Figure 2. Overall, only 20% of AFOs that we identify in the MRW via remotely sensed imagery were permitted at the end of our sample period. We estimate animal counts and manure production for each facility by dividing the mapped square footage of each barn by a square footage per animal. We obtain recommended square footage per animal from a literature review of standards, which, along with their source, we provide in Supporting Information Table A2. We estimate animal counts for each barn in the MRW and provide total counts in Supporting Information Table A3. For permitted facilities, we use the permitted animal count rather than the estimates.

Supporting Information Table A4 shows how AFOs expanded in the MRW during our period of analysis. Between 2010 and 2018, an average of 15 AFOs were added each year in the MRW. Considering the composition of these AFOS, this increase translates to an additional 29,155 AUs per year and an additional 5 million metric tons of manure per year. In addition to new AFO construction, 12% (75) of the AFOs present in 2010 expanded in size at least once between 2010 and 2018, and 5% (30 AFOs) expanded in size twice or more. As a result, the mean barn size

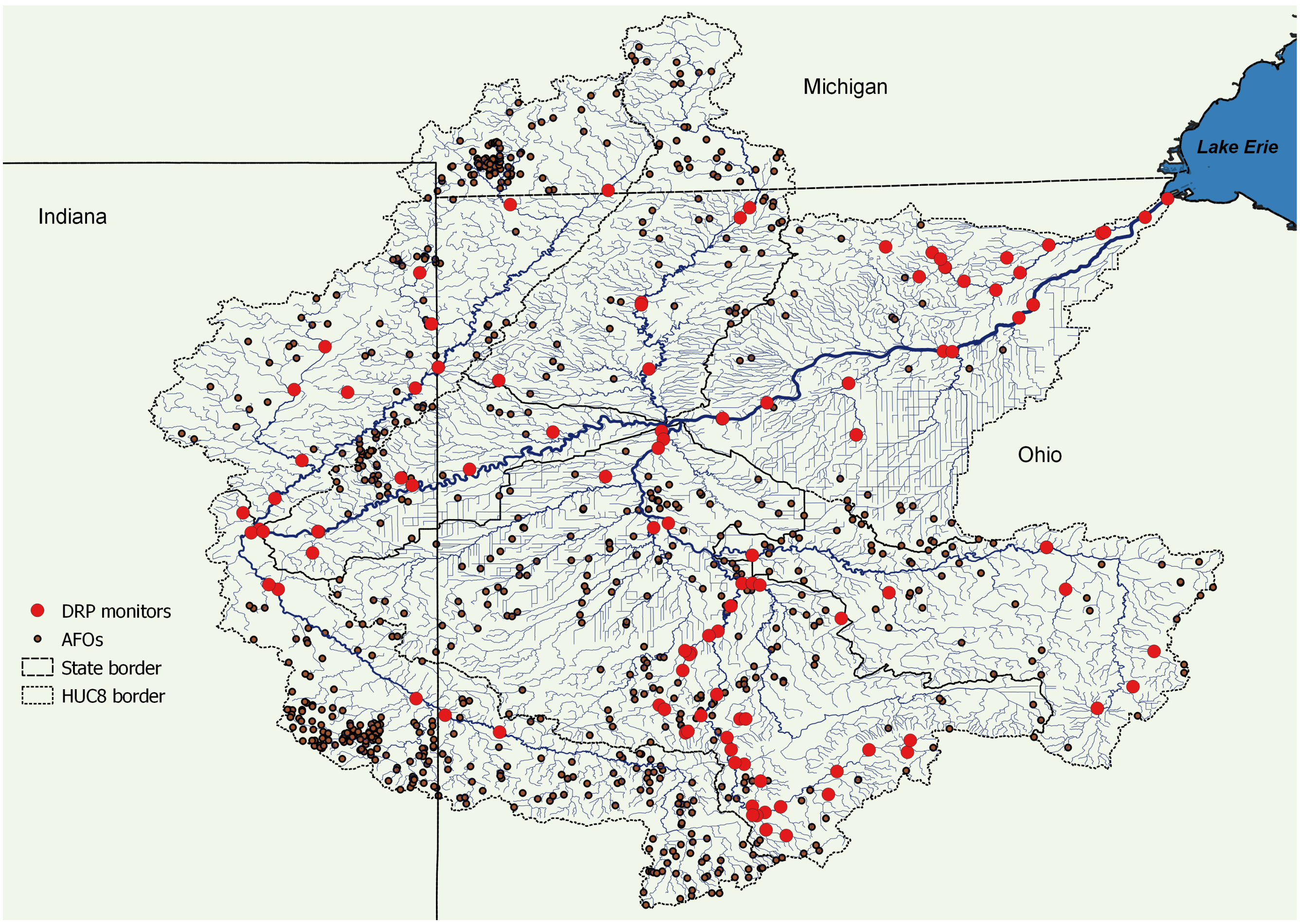

FIGURE 2 The Maumee River Watershed with the National Hydrography Dataset (NHD) stream network, dissolved reactive phosphorus (DRP) monitors, and animal feeding operation (AFO) locations. This map shows the locations of monitors with at least one DRP reading from 2010 to 2018. It also shows all AFOs within the Maumee River Watershed (2018), along with stream reaches of the NHD stream and river network.

and the number of animals per facility increased. This notable increase aligns with findings from the International Joint Commission (IJC, 2018), that show increased consolidation of livestock agriculture in the Western Lake Erie Basin.

Indiana, Ohio, and Michigan have their own requirements for livestock operations to obtain a permit, based mainly on the number of animals at each operation and the state's interpretation of potential dischargers (GAO, 2003; Raff & Meyer, 2022). Permit data allow for an accuracy assessment of the square footage methodology that we use to assign animal counts to unpermitted AFOs. For each permitted facility, we calculate the prediction error by subtracting the permitted animal counts from the animal counts estimated from remote imaging. We find a mean error of −139 AU per dairy operation ($n=31$), −1266 AU per poultry operation ($n=16$), +65 AU per swine operation ($n=74$), and +46 AU ($n=2$) for cattle operations. We observed the largest variability for poultry AFOs, for which the square footage approach underestimated animal counts as compared to permitted AFOs. This is an expected result given the challenges in determining poultry production system (layers, broilers, pullets, turkeys) and barn height (which is important for modern high-rise poultry facilities) using a remote sensing approach. We identified only two permitted cattle AFOs in the MRW at the time of this study. While additional beef cattle facilities may be permitted in the MRW, exact locations were not always provided and could therefore not be spatially matched to an identified AFO. In Indiana, for example, agencies only provide AFO data at a township scale at the time of this analysis, and we included only those operations that could be spatially matched to an identified AFO within that township in the accuracy assessment.

Swine and dairy operations were permitted at the highest frequency, with 32% and 31% of facilities permitted, respectively. Only 12% of poultry and 2% of cattle facilities had permits in 2018. The overall low percentage of permitted facilities highlights the importance of identifying AFOs by means outside of official permits.

3.3 | Surface water body network

We gather data from the Watershed Boundary Dataset v2.3 (WBD) (USGS, 2021b) and the NHD (USGS, 2021a) to determine watershed boundaries for each AFO and stream reach and to determine the flow networks of streams and rivers in our sample, respectively. The WBD and NHD are national geospatial surface water frameworks that EPA and USGS developed through a collaborative partnership. The datasets contain information on stream and river flow paths, watershed and catchment boundaries, and other important features in the U.S. hydrological network, such as USGS gage stations and catchment outlets. The NHD provides information about the U.S. streamflow network at the stream reach level for all perennial streams and rivers in the conterminous U.S. Figure 2 depicts the NHD streamflow network for the MRW. A stream reach typically consists of a 1–5 km section of the water body, depending on if it is part of the mainstem or a tributary. The NHD provides information on, among other things, the type of water body, its streamflow direction, its outlet, the type of stream reach (e.g., mainstem vs. tributary), and flow. From this streamflow network, we can navigate upstream and downstream from AFOs and DRP monitoring stream reaches. The WBD allows us to place each stream reach into its appropriate HUC12 subwatershed, which we then use to develop variables that capture the characteristics of the area surrounding AFOs and stream reaches.

3.4 | Control variables

In our empirical analysis, we control for time-varying characteristics of surface water bodies and watersheds that, if omitted and correlated with the treatment regressors, may bias our estimates. Inclusion of covariates can also reduce the variance of the error term and hence improve the precision of our estimates. In our empirical analysis, we include the following variables as controls: precipitation (including its square), land cover, and commercial fertilizer application. We discuss each variable in turn. First, we control for precipitation in all specifications because it is well known that precipitation events affect nutrient runoff and observed concentrations (Waller et al., 2021; Williams & King, 2020). We gather precipitation data from Schlenker and Roberts (2020) who use PRISM climate data (PRISM, 2023) and weather monitoring stations to create daily precipitation data for 2.5- by 2.5-mile grids throughout the conterminous U.S. We geocode each stream reach to the nearest PRISM grid centroid to get the average daily precipitation (cm) at each stream reach in the MRW for each month of our sample. Next, in some empirical model specifications, we control for land cover and fertilizer usage. We gather land cover data from the National Land Cover Database (NLCD) (MRLC, 2021). The NLCD classifies land cover at 30 m resolutions and we overlay the NLCD maps onto HUC12 subwatersheds and calculate the percentage of each HUC12 that is developed (NLCD classes 21, 22, 23, and 24), planted/cultivated (NLCD classes 81 and 82), and wetlands (NLCD classes 90 and 95). Finally, the literature suggests that runoff from commercial fertilizer is a source of phosphorus in surface water bodies in the MRW (e.g., IJC, 2018; Kast et al., 2021). We therefore control for commercial fertilizer application of phosphorus, both on- and off-farm. We gather these county-level data from Falcone (2020) and convert them to HUC12-level measures by using ArcGIS Pro to reweight the measures based on the percentage of each county that is in each HUC12. For land cover and fertilizer usage, which USDA and the NLDC collect annually and semi-annually, respectively, we linearly interpolate values to the monthly level while assuming a constant rate of change between the two known values. All regression tables indicate which controls we include in each specification.

3.5 | Construction of analysis sample and descriptive analysis

We derive an AFO intensity measure that is more spatially fine than an aggregate watershed approach (e.g., Raff & Meyer, 2022) by using ArcGIS Pro to spatially match each water quality monitoring location and AFO to the nearest stream reach in the NHD. For our analysis sample, we match each AFO's barn centroid to the nearest stream reach. Because there exist many stream and river segments in the MRW, each AFO is located within 2 km of the nearest stream reach. We then calculate the level of upstream AFO exposure to each stream reach with DRP concentration readings over time. For each stream reach, we aggregate the number of upstream AFOs within these distances and their associated animal counts (in AU) and their estimated manure production (in metric tons). We therefore have three treatment regressors at the stream reach-month level, from 2010 to 2018, within several distance measures: (1) number of upstream operating AFOs, (2) number of upstream AUs, and (3) amount of upstream manure production. Our final analysis sample is a 1673-observation stream reach-month level panel dataset from 2010 to 2018. The mean stream reach-month observation has a DRP concentration of 0.155 mg/L. The mean observation is exposed to nearly 3.5 AFOs, almost 4700 total AUs, and 24,500 metric tons of manure production at AFOs within 20 km upstream. Some stream reaches have observations from all months (108 maximum possible observations per stream reach), but many stream reaches in our data have sporadic DRP monitoring. Of the 74 stream reaches in the analysis sample, the mean number of observations is 22.6 and the median number of observations is 11.

We provide complete summary statistics in Supporting Information Table A5 and assess the variation in the key regression measures in Supporting Information Appendix C. In Figure 3, we show the number of AU that are within 20 km upstream of each stream reach in 2018; thicker blue lines represent stream reaches downstream of higher intensities of AFOs. Figure 3 also shows 2018 HUC12-level average DRP concentrations. We use HUC8-level average DRP concentrations in this figure for HUC12 subwatersheds without DRP monitoring. Darker areas, with higher average DRP concentrations, tend to be in the same areas with stream reaches receiving the highest upstream AFO intensity. These maps represent a snapshot from one point in time and hence do not establish a causal relationship. However, a strong spatial correlation between AFO intensity and average DRP concentrations is evident and motivates our empirical analysis.

We provide a series of maps of the MRW to visualize spatial variation in our main variables of interest. In each map (except Supporting Information Figure A5), we use the Jenks optimization method to cluster variable levels into classes. These natural breaks minimize the variation within each class while maximizing variation across the classes. Supporting Information Figure A2 shows the number of AFOs in each HUC12 in 2018. Likewise, Supporting Information Figure A3 shows the number of AU in each HUC12 in 2018. These figures reveal considerable variation in the intensity of AFO presence across the MRW.

Supporting Information Figures A4 and A5 visualize average DRP concentrations for each HUC12 in the MRW. In Supporting Information Figure A4, we average all available DRP concentrations from 2017 to 2019 and use the Jenks optimization method to cluster DRP levels into classes. Then, in Supporting Information Figure A5, we visualize average DRP levels according to proposed as target concentrations. For example, the Annex 4 Objectives and Targets Task Team (2015) recommends a flow weighted mean target DRP concentration of 0.05 mg/L for the Maumee River. The same report also details average flow weighted mean DRP concentrations of approximately 0.10 mg/L for the Maumee River from 2012 to 2015. In Supporting Information Figure A5, we see that virtually all HUC12 subwatersheds exceed average concentrations of 0.05 mg/L and most also exceed average concentrations of 0.10 mg/L.

4 | EMPIRICAL APPROACH

We use linear regression analysis to identify the effects of AFO exposure and intensity on stream reach-month level DRP concentrations. This approach allows us to model the aggregate effect of upstream AFOs on downstream DRP concentrations. We perform our analysis first measuring upstream exposure using the intensity measures from remotely sensed imagery and second measuring upstream exposure using only permitted operations. Our empirical approach facilitates the inclusion of treatment variables with varying intensities (number of operating AFOs, animal counts, or manure production) which is important in the MRW where there are closely clustered AFOs throughout the watershed. We estimate the following regression specification:

$$\ln\left(Y_{jhmt}\right) = \beta_1 \mathrm{AFO}_{jhmt} + \boldsymbol{P}'_{\boldsymbol{jmt}}\beta_2 + \boldsymbol{X}'_{\boldsymbol{hmt}}\beta_3 + \gamma_j + \psi_m + \lambda_t + \varepsilon_{jhmt}, \tag{1}$$

where Y_{jhmt} is the mean DRP concentration (in mg/L) of stream reach j in HUC12 h in month m of year t. Here, we log-transform the outcome for two reasons. First, the outcome is skewed away from zero, so log-transforming normalizes its distribution. Second, log-transforming the outcome allows for interpretation of the primary treatment regressors in percentage terms (rather than in level terms), which is more appropriate for variables of interest with wide distributions. Next, we code AFO_{jhmt} as the count of upstream: (1) operating AFOs, (2) number of AUs at AFOs, and (3) amount of manure production at AFOs; that are present on the month of the mean DRP readings.

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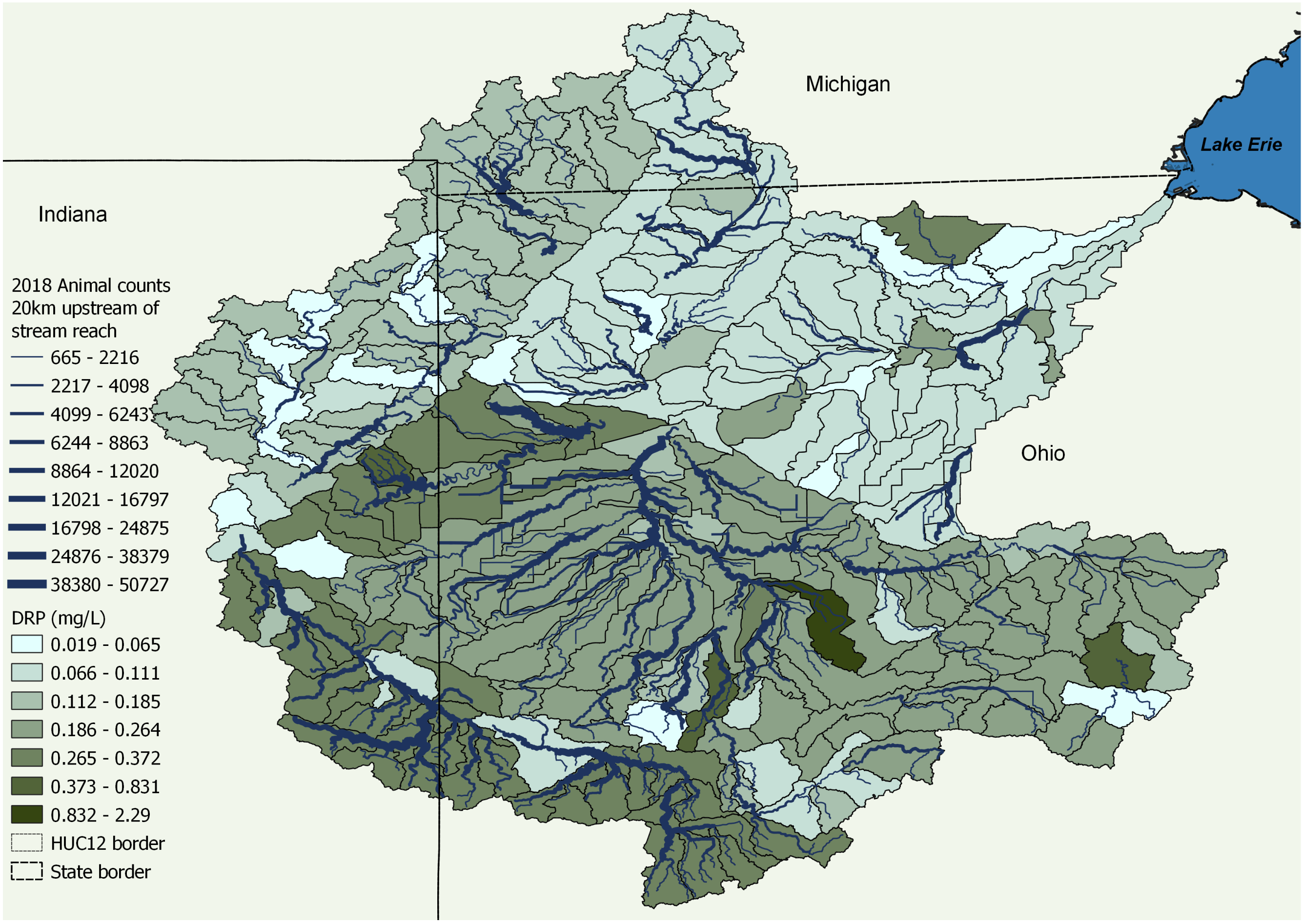

FIGURE 3 DRP concentrations and stream reach exposure to upstream AFOs in the Maumee River Watershed. This map shows average DRP concentrations in the Maumee River Watershed from 2017 to 2019 within each Hydrologic Unit Code 12 (HUC12) subwatershed and the number of AUs present in 2018 within 20 km upstream of each stream reach. HUC8 averages are used for HUC12 subwatersheds without DRP readings. Wider lines indicate more upstream animal units.

Additionally, only 20% of the AFOs that we identify in the MRW via remotely sensed imagery are permitted. It is therefore difficult for state agencies and researchers to correctly identify the effects of these operations on DRP concentrations in surface water bodies, because there is relatively little information available to these groups on AFO locations and sizes. Accordingly, we estimate two separate specifications for each treatment regressor. First, we define AFO_{jhmt} as the upstream exposure using the intensity measures from remotely sensed imagery. Second, we define AFO_{jhmt} as the upstream exposure using only permitted operations.

Importantly, Equation (1) contains a series of fixed effects. γ_j are stream reach fixed effects that control for time-invariant stream reach-level characteristics that correlate with DRP concentrations. There are permanent differences in average DRP concentrations across stream reaches because of land slope, soil type, or other geographic/hydrologic characteristics near or at each stream reach. By including stream reach fixed effects in our model specification, we identify the effects of upstream AFO exposure using only within-stream reach variation. These fixed effects therefore control for the permanent differences in DRP concentrations at different stream reaches across time. ψ_m are month fixed effects that control for the seasonality of DRP concentrations and λ_t are year fixed effects that control for unobservable factors common to the entire watershed that change over time, for example, regional or national policies to control water pollution. During our sample period, there were several policy changes that could possibly affect surface water quality in the MRW, including changes in the permitting requirements for AFOs. The year fixed effects absorb the common changes in DRP concentrations due to these policies.

Next, $\boldsymbol{P}_{jmt}$ and $\boldsymbol{X}_{hmt}$ are vectors of time-varying controls at the stream reach- and HUC12-month level, respectively. Inclusion of these controls can reduce the variance of the error term and improve the precision of our estimates. First, $\boldsymbol{P}_{jmt}$ controls for precipitation at the nearest PRISM grid centroid. Rain and snow events affect how much nonpoint source runoff occurs. Dilution occurs during the runoff process, so we control for both the mean of daily total precipitation and its square to model a nonlinear relationship between precipitation and our outcome. Second, $\boldsymbol{X}_{hmt}$ is a vector that contains measures for land cover and land use. $\boldsymbol{X}_{hmt}$ includes NLCD land cover classifications in percentages, such as the percent of the HUC12 that is planted. These land cover measures control for the likelihood that other, non-AFO, nonpoint source pollution occurs in each HUC12. These measures also capture the likelihood of urban runoff, which can affect nutrient concentrations in surface water bodies. Certain land uses can also serve as a phosphorus "sink", such as wetlands, which would decrease the amount of runoff phosphorus that ultimately ends up in surface water bodies. $\boldsymbol{X}_{hmt}$ contains measures for the percentage of land in each HUC12 that is planted, developed, or wetlands. Finally, commercial fertilizer contributes to phosphorus runoff in the MRW. We therefore include within $\boldsymbol{X}_{hmt}$ a control measure for the amount of phosphorus added to the land through commercial fertilizer application, both on- and off-farm, on a per acre basis (Falcone, 2020). ε_{jhmt} is the exogenous error term. We cluster standard errors at the stream reach level, which is our level of identifying variation, to allow for within-stream reach correlation in the error term (spatial and serial correlation). In the Supporting Information Appendix, we also demonstrate the stability of the results when clustering standard errors at the HUC10 (watershed) level. Falcone (2020) provides annual, not monthly, commercial fertilizer data so we also show results for specifications that interact month fixed effects with commercial fertilizer. These specifications allow commercial fertilizer to have differential effects on DRP concentrations by month, reflecting the reality that farmers do not uniformly apply fertilizer throughout the year.

Our regression specification represents a two-way fixed effects model, where identification of our coefficient of interest, β_1, comes from changes in DRP concentrations within a stream reach coincident with variation in upstream AFO presence and intensity. Our identifying assumption is the standard parallel trends assumption for a two-way fixed effects model. Conditional on covariates, and in the absence of any changes to upstream AFO presence and intensity, average downstream DRP concentrations would have trended in parallel at monitoring locations with varying intensities of upstream AFO expansion.

Our empirical approach shares some features with SPARROW models, which were originally developed by USGS scientists in the 1990s (Smith et al., 1997). Brakebill and Schwarz (2016), Preston et al. (2009, 2011), and USGS (2019) provide helpful overviews of SPARROW. First, both approaches leverage a stream reach network such as the NHD to link water quality monitoring sites to upstream watershed characteristics. Second, both approaches estimate the effects of various pollution sources and environmental factors on downstream water quality.

However, there are notable differences between our approach and that of SPARROW. First, SPARROW standardizes predictions of mean annual nutrient loads and sources to a single year referred to as the "base year," reflecting what would occur in stream during a mean annual flow year. Thus, SPARROW focuses more on long-term average relationships between contaminant sources and downstream nutrient levels. In contrast, our approach leverages temporal variation and spatial variation to provide statistical identification. Second, SPARROW is based on mass balance, whereas our approach does not impose any mass balance constraints. Third, SPARROW predicts water quality conditions at unmonitored stream locations; we only use data from actual stream monitoring. Fourth, SPARROW predicts nutrient concentrations and loads, whereas we focus only on concentrations. Finally, SPARROW models often include geologic measures such as soil permeability or basin slope. SPARROW therefore facilitates estimation of the importance of time-invariant landscape factors to downstream nutrient delivery because it focuses on long-term mean annual relationships. Alternatively, our approach holds these time-invariant factors constant with the stream reach fixed effects but does not estimate their effect on downstream water quality.

5 | RESULTS

The primary independent variable in regression specification (1) is AFO_{jhmt}, the upstream AFO intensity measure. An important question is the distance cutoff to use when linking upstream AFOs to downstream water quality monitors. As stated, manure is typically spread near the animal holding barns. Clearly, phosphorus from manure travels downstream further than the area where operators spread it. However, due to dilution and stream uptake, an empirical question remains: how far downstream does one AFO significantly affect DRP concentrations? We therefore modify Equation (1) to empirically test how AFOs within different upstream distance bins (less than 10 km, 10–20 km, 20–30 km, 30–50 km, and 50–100 km) affect downstream DRP concentrations. We estimate:

$$\ln\left(Y_{jhmt}\right) = \beta_1 \mathrm{AFO}\left[0\_10\right]_{jhmt} + \beta_2 \mathrm{AFO}\left[10\_20\right]_{jhmt} + \beta_3 \mathrm{AFO}\left[20\_30\right]_{jhmt} + \beta_4 \mathrm{AFO}\left[30\_50\right]_{jhmt} + \beta_5 \mathrm{AFO}\left[50\_100\right]_{jhmt} + \boldsymbol{P}^{\prime}_{jmt}\boldsymbol{\beta}_6 + \boldsymbol{X}^{\prime}_{hmt}\boldsymbol{\beta}_7 + \gamma_j + \psi_m + \lambda_t + \varepsilon_{jhmt}, \tag{2}$$

where all notation follows that of Equation (1). Table 1 presents the results of this estimation. Table 1 shows that AFOs within 10 km upstream have a small and statistically insignificant effect on downstream DRP concentrations (when controlling for the number of AFOs further upstream). In contrast, additional AFOs within 10–20 km upstream have a large and statistically significant effect on downstream DRP concentrations (when controlling for AFOs at other distances upstream). Likewise, we find that additional AFOs within 20–30 km upstream have a positive and statistically significant effect on downstream DRP concentrations (although not as large as the estimated effect for AFOs 10–20 km upstream). We do not find any practical or statistically significant effect of additional AFOs beyond 30 km upstream. These results suggest that a distance measure of 10 km upstream of a monitoring location may not be sufficient to fully incorporate the effects from all manure spreading from AFOs. On the other hand, 20 km appears to be a sufficient distance for upstream AFO manure to affect a monitoring location. Beyond 20 km, the effects are not as detectable, likely due to dilution. Therefore, we select 20 km as the preferred distance to measure upstream AFO intensity. In the main text, we

TABLE 1 Upstream distance and the effect of AFO exposure on DRP concentrations.

Variable	(1) Operating AFO	(2) Operating AFO	(3) Animal count	(4) Animal count	(5) Manure produced	(6) Manure produced
Treatment bins						
Upstream distance < 10 km	−0.0151 (0.0808)	0.0317 (0.0811)	0.0734 (0.0854)	0.0909 (0.122)	0.00500 (0.0238)	0.00530 (0.0352)
10 km < upstream distance < 20 km	0.257** (0.106)	0.269*** (0.0948)	0.0774 (0.0705)	0.0766 (0.0637)	0.0198 (0.0148)	0.0210* (0.0126)
20 km < upstream distance < 30 km	0.133** (0.0537)	0.147* (0.0745)	0.132*** (0.0326)	0.157** (0.0606)	0.0230** (0.0100)	0.0285 (0.0173)
30 km < upstream distance < 50 km	0.000853 (0.0239)	0.0152 (0.0300)	−0.00841 (0.0105)	−0.0154 (0.0117)	−0.00134 (0.00217)	−0.00304 (0.00243)
50 km < upstream distance < 100 km	−0.00688 (0.0181)	−0.0138 (0.0195)	0.0227 (0.0245)	0.0258 (0.0250)	0.00301 (0.00418)	0.00364 (0.00428)
Precipitation (cm)	0.0897*** (0.0169)	0.0885*** (0.0168)	0.0881*** (0.0170)	0.0862*** (0.0168)	0.0880*** (0.0170)	0.0860*** (0.0168)
Precipitation^2 (cm)	−0.00199*** (0.000498)	−0.00194*** (0.000495)	−0.00196*** (0.000500)	−0.00188*** (0.000493)	−0.00195*** (0.000499)	−0.00187*** (0.000491)
Stream reach FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Additional controls		X		X		X
R^2	0.542	0.544	0.544	0.546	0.543	0.544
Observations	1673	1673	1673	1673	1673	1673

Note: Each column presents OLS regression results from a separate specification of Equation (2). The dependent variable is the log-transformed concentration of DRP at the stream reach-month level. This table presents results for remotely sensed AFO exposure within distance bins upstream of the stream reach, in km traveled via the stream and river network. Additional controls are planted %, developed %, wetlands %, and commercial fertilizer/acre. Robust standard errors in parentheses are clustered at the stream reach level.

Abbreviations: FE, fixed effects; OLS, ordinary least squares.

$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

report results for operations within 20 km upstream of the monitoring stream reach via the stream and river network. In Supporting Information Tables A6 and A7, we provide results for AFO exposure within 10 km and 30 km of the monitoring stream reach.

In Tables 2 and 3, we tabulate results for the primary regression analysis. Table 2 presents results where we define treatment based on cumulative remotely sensed AFO exposure up to 20 km upstream from each stream reach that monitors DRP concentrations during our sample period. In the MRW, permitted operations represent 20% of those that we identify using remotely sensed imagery. Therefore, Table 3 tabulates results for these same AFO exposure measures, but where we define treatment based on official AFO permit data. For each table, we examine three definitions of treatment, or AFO exposure: (1) count of operating AFOs, (2) number of AUs at these operations, and (3) metric tons of manure produced at the AFOs. For the primary specification, we use permitted "on the ground" counts for (2) and (3) for AFOs with permits, but we use estimated counts (as described in Section 3) for remotely sensed operations. The permitted and estimated animal count and manure production measures are highly correlated: $r = 0.882$ and $r = 0.936$, respectively; both correlations are statistically different than zero ($p = 0.000$). Within each table, Columns 1, 3, and 5 present results for the parsimonious regression specification, where we include only our measures of treatment and precipitation on the righthand side, while columns 2, 4, and 6 add HUC12-level time-varying controls to add precision to our estimates. Below, we focus our discussion on the marginal effects of the model with the full set of controls but note that coefficient point estimates are qualitatively similar in models without the additional controls.

First, we discuss the results for the estimation sample where we examine upstream AFO exposure based on remotely sensed imagery (standard errors are in parentheses). In our sample, the marginal AFO that is within 20 km of a monitoring stream reach increases the concentration of DRP at that downstream location by 13.0% (±3.9%). Here, the marginal effect represents the impact of any livestock operation, regardless of size, animal type, or other characteristics of the AFO, on downstream DRP concentrations. Because larger operations produce more manure in a concentrated location, it is likely that there exists heterogeneity in the effects of AFO exposure on downstream DRP levels.

The fourth column of Table 2 shows that the addition of 1000 AUs within 20 km upstream of a stream reach that monitors DRP increases these levels by 9.7% (±3.4%). To put this value into greater perspective, in the last year of our sample period, the average (mean) AFO in the MRW contained 1061 AU. Our results therefore suggest that the addition of an average size AFO, which here, is above the size threshold set by EPA to require a Clean Water Act permit, increases downstream DRP concentrations by 10.3% (±3.6%).

Nearly all AFOs, both in the MRW and throughout the U.S., spread their manure onto nearby agricultural land, most often within 3 km of the operation (Kast et al., 2019; Long et al., 2018). Therefore, the livestock operations that produce more manure can have a larger effect on downstream DRP concentrations, through greater contributions to runoff, than AFOs that produce less manure. Using onsite manure production as a treatment regressor allows us to again examine the differences in effects not only by the size of the AFO, but also by the type of operation, because different livestock types produce different amounts of manure each day. Column 6 of Table 2 shows that for every 1000 metric tons of manure production from upstream AFOs, downstream DRP concentrations increase by roughly 2.3% (±0.83%). Again using an average (mean) AFO to put this effect into context, the average AFO in our sample produced 6488 metric tons of manure in 2018. The addition of one AFO, that produces the sample average amount of manure onsite, to the watershed results in an increase in downstream DRP levels of approximately 15% (±5.3%). Therefore, larger operations have a larger effect on downstream DRP concentrations and industry trends to more concentrated and larger operations will likely result in more substantial nutrient loads in the future. Supporting Information Tables A6–A10 show that these results are robust to alternative upstream distance measures (10 and 30 km), when using estimated animal counts for all treatment measures, when interacting month fixed effects with commercial fertilizer, and when clustering standard errors at the HUC10 level.

Next, Table 3 presents the estimation results where we examine upstream AFO exposure using only permitted operations. These treatment measures, which omit 80% of operations in the MRW, capture less intense animal agriculture in the watershed than the regressors that measure intensity via remotely sensed imagery. As shown in Table 3, exposure to only permitted upstream AFOs does not significantly impact DRP concentrations in the MRW. Regardless of the inclusion of control variables, there is a practically zero and statistically insignificant effect of each (permitted) AFO intensity measure on DRP concentrations. (Supporting Information Tables A6 and A7, which contain estimation results using alternative distance measures, present results that are qualitatively and quantitatively like the primary estimation results presented in the main text.)

We are primarily interested in the effect of increased upstream AFO intensity on downstream DRP concentrations. Our research design does not depend on the inclusion of the control variables for unbiased estimates of our effect of interest if our identifying assumptions hold. Therefore, we principally include the controls, especially commercial fertilizer application and land cover, to reduce the variance of the error term and hence improve precision in our estimates. However, if there are time-varying characteristics of surface water bodies and watersheds that are omitted and correlated with the treatment regressors, this would bias our estimates of the downstream effects of AFOs. Demonstrating the stability of results with and without the additional controls therefore helps support the research design.

Finally, we note that the signs and stability of control variable coefficients throughout all regression specifications lend support to the internal validity of our study. As expected, precipitation is positively correlated with DRP concentrations in the MRW while its square is negatively correlated; both signs reinforce the impact of precipitation on runoff and increasing pollutant concentrations in surface water bodies, and that dilution occurs during the runoff process, as precipitation's effect on DRP concentrations exhibits diminishing returns. The land use measures also have the expected signs, although they are imprecisely estimated. Again, as expected, more developed land is associated with

TABLE 2 Effect of upstream AFO exposure on DRP concentrations, remotely sensed AFOs.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Treatment measures						
Operating AFO	0.106** (0.0445)	0.130*** (0.0390)				
Animal count (000 au)			0.0858** (0.0381)	0.0971*** (0.0343)		
Manure produced (000 metric tons)					0.0201** (0.00921)	0.0227*** (0.00828)
Control variables						
Precipitation (cm)	0.0894*** (0.0169)	0.0881*** (0.0167)	0.0887*** (0.0169)	0.0873*** (0.0167)	0.0887*** (0.0169)	0.0873*** (0.0167)
Precipitation^2 (cm)	−0.00198*** (0.000497)	−0.00193*** (0.000491)	−0.00196*** (0.000496)	−0.00191*** (0.000490)	−0.00196*** (0.000496)	−0.00190*** (0.000490)
Planted %		0.00714 (0.278)		0.0188 (0.278)		0.0176 (0.277)
Developed %		0.249 (0.356)		0.255 (0.346)		0.252 (0.346)
Wetlands %		−3.10 (2.16)		−3.09 (2.14)		−3.09 (2.14)
Commercial fertilizer/acre (kg)		0.561* (0.325)		0.542* (0.321)		0.540* (0.321)
Stream reach FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.542	0.543	0.542	0.543	0.542	0.543
Observations	1673	1673	1673	1673	1673	1673

Note: Each column presents OLS regression results from a separate specification of Equation (1). The dependent variable is the log-transformed concentration of DRP at the stream reach-month level. This table presents results for remotely sensed AFO exposure within 20 km upstream of the stream reach, in km traveled via the stream and river network. Robust standard errors in parentheses are clustered at the stream reach level.

Abbreviations: FE, fixed effects; OLS, ordinary least squares.

$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

TABLE 3 Effect of upstream AFO exposure on DRP concentrations, permitted AFOs.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Treatment measures						
Operating AFO	−0.0141 (0.0464)	0.00948 (0.0451)				
Animal count (000 au)			−0.00565 (0.0185)	0.00379 (0.0180)		
Manure produced (000 metric tons)					−0.00134 (0.00441)	0.000902 (0.00429)
Control variables						
Precipitation (cm)	0.0890*** (0.0169)	0.0876*** (0.0168)	0.0890*** (0.0169)	0.0876*** (0.0168)	0.0890*** (0.0169)	0.0876*** (0.0168)
Precipitation^2 (cm)	−0.00196*** (0.000496)	−0.00191*** (0.000489)	−0.00196*** (0.000496)	−0.00191*** (0.000489)	−0.00196*** (0.000496)	−0.00191*** (0.000489)
Planted %		−0.0359 (0.278)		−0.0359 (0.278)		−0.0359 (0.278)
Developed %		0.167 (0.366)		0.167 (0.366)		0.167 (0.366)
Wetlands %		−3.20 (2.22)		−3.20 (2.22)		−3.20 (2.22)
Commercial fertilizer/acre (kg)		0.519 (0.332)		0.519 (0.332)		0.519 (0.332)
Stream reach FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.542	0.543	0.542	0.543	0.542	0.543
Observations	1673	1673	1673	1673	1673	1673

Note: Each column presents OLS regression results from a separate specification of Equation (1). The dependent variable is the log-transformed concentration of DRP at the stream reach-month level. This table presents results for permitted AFO exposure within 20 km upstream of the stream reach, in km traveled via the stream and river network. Robust standard errors in parentheses are clustered at the stream reach level.

Abbreviations: FE, fixed effects; OLS, ordinary least squares.

$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

higher DRP concentrations, while more area in the HUC12 containing wetlands is associated with lower DRP concentrations. For commercial fertilizer usage, estimation results confirm the hypothesized positive relationship between fertilizer application and DRP concentrations. Increasing commercial fertilizer phosphorus spreading in the HUC12 by 1 kg per acre (a 25% increase relative to the mean) leads to increases in DRP concentrations that are comparable to adding four upstream AFOs.

6 | DISCUSSION AND CONCLUSIONS

Our estimation results using remotely sensed imagery provide evidence that increased upstream AFO exposure significantly increases downstream DRP concentrations relative to counterfactual stream reaches with less AFO exposure. The results of our analysis using remotely sensed imagery therefore suggest that animal agriculture in the MRW contributes to the water quality problems in the watershed and to the presence of harmful algal blooms in the Western Lake Erie Basin. However, when omitting the unpermitted operations from our analysis, we find a practically zero and statistically insignificant effect of upstream AFO exposure on downstream DRP concentrations. This finding reinforces the fact that using alternative measures of AFO identification, such as remotely sensed imagery, rather than relying solely on permits is imperative in identifying the effects of AFOs on surface water quality. Our results also highlight the importance of permitting these operations, especially those larger operations that have thousands of AUs and produce much manure onsite. Importantly, our estimation results are consistent with those of the recent literature. As one example, Rowland et al. (2021) find that DRP concentrations and loads in the MRW remained constant during the period of our study. However, during that same period, commercial fertilizer usage in the watershed decreased considerably (IJC, 2018). Our results therefore suggest that the stabilization of DRP concentrations in the MRW is because the increasing DRP from AFOs is in essence “replacing” that from the decreases from commercial fertilizer usage.

Our results have implications for regulating AFOs in general and specifically in the MRW. First, the lack of permits and local regulations in the watershed likely contribute to the runoff. In some states (e.g., Wisconsin), all AFOs of a certain size must be permitted, but all AFOs (regardless of size) are subject to local regulations, such as the requirement to complete a nutrient management plan (Skidmore et al., 2023). In addition, previous studies on surface water quality degradation in the MRW likely underestimate the contributions of AFOs because of a lack of data on their presence and size. Future studies will need to expand their data collection to include AFOs not covered by official permits to better account for animal agriculture's contributions to nonpoint source pollution. Second, previous work has shown that the external costs to water quality from increasingly concentrated livestock operations are the result of the land being unable to assimilate the excess manure phosphorus (Jones et al., 2018; Kellogg et al., 2014; Raff & Meyer, 2022). Comparing present DRP concentrations to targets proposed by the Annex 4 Objectives and Targets Task Team (2015), it is difficult to see how DRP loading targets are reached if more AFOs are added to the MRW, unless other, more substantial, nonpoint source reductions in DRP are made to compensate for the additional loads from new or expanded AFOs.

Our findings also motivate additional needed work. In addition to locational information about AFOs, there are several other knowledge gaps surrounding AFOs. First, we echo the conclusions of Kast et al. (2019) that more knowledge is needed about what happens to manure from livestock operations below CAFO thresholds and from CAFOs engaging in Distribution and Utilization practices. This additional knowledge about where AFOs apply manure could help in designing incentives and policies to decrease its environmental impact. Another knowledge gap related to nonpoint source pollution stems from regulatory and monitoring efforts focusing only on large tributaries (Mooney et al., 2020). A major obstacle to targeting nonpoint source pollution reduction programs is the lack of monitoring data at refined scales (Fleming et al., 2022). As we have shown, most livestock operations in the MRW are near the outside edges of the watershed, not necessarily near the mouth of the Maumee River at Lake Erie. This paper shows that AFOs substantially increase downstream DRP concentrations in the monitored tributaries. However, many tributaries remain unmonitored. Total DRP loads entering Lake Erie are estimated using the downstream monitoring stations in the mainstems of contributing rivers before they reach the lake. A crucial question is how much of that nutrient load stems from AFOs relative to other sources. A precise answer to this question would require increased monitoring efforts at upstream tributaries where the AFOs are located.

AUTHOR CONTRIBUTIONS

Andrew Meyer: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Zach Raff:** Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Sarah Porter:** Data curation; investigation; resources; writing – original draft.

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CONFLICT OF INTEREST STATEMENT

Andrew Meyer and Zach Raff acknowledge funding from Lake Erie Waterkeeper (LEW) that supported this work. LEW provided remuneration for the work, but had no input into the conceptualization, design, data collection, analysis, or publication of the project. Andrew Meyer declares that he has no other relevant or material financial interests that relate to the research described in this paper. Zach Raff declares that he has no other relevant or material financial interests that relate to the research described in this paper. Sarah Porter acknowledges funding received by the Environmental Working Group from the Fred A. and Barbara M. Erb Family Foundation and the Joyce Foundation. This funding enabled the geolocation and attribution of the animal feeding operation dataset that was used in this work. Sarah Porter declares that she has no other relevant or material financial interests that relate to the research described in this paper.

DATA AVAILABILITY STATEMENT

Data to replicate empirical analysis and tabulated results in this paper can be found in the Harvard Dataverse at https://doi.org/10.7910/DVN/ZYCSJB.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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