Climate change and water pollution: the impact of extreme rain on nutrient runoff in Wisconsin

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May 18, 2022

Agriculture remains a leading source of water pollution in the United States, even after decades of efforts to address the problem. Climate change may further challenge the relationship between agriculture and water quality. Field and micro-watershed level data have shown that increased frequency of heavy rainfall and flooding will impact runoff from farms, but research has yet to quantify nutrient runoff triggered by rainfall at a multi-watershed scale. We quantify the effects of high rainfall events on manure runoff and water pollution in dairy- and crop-producing watersheds in Wisconsin. We begin by analyzing the specific temporal effects of rainfall, including the magnitude of the effect by rainfall severity, the lagged effects up to four days after a rainfall event, and the effects by season. Our results align with the conclusions of simulations and small-scale studies, supporting the accuracy of our methods in identifying the effects of rainfall on water quality. We then study how land use and agricultural practices affect a watershed's susceptibility to extreme rainfall events. Our work highlights which agricultural practices lessen these impacts, shedding light on methods that can be adopted to protect water quality in a scenario with more frequent extreme-rain events.

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1 Introduction

Agriculture remains a leading source of water pollution in the United States, even after decades of efforts to address the problem (Rabotyagov et al., 2014; Ribaudo and Shortle, 2019). Most agricultural pollution is deemed non-point source pollution and falls outside of the enforcement arm of the Clean Water Act, which has meant its pollution problems have not responded to the policy tools that have effectively addressed point-source pollution (Kling, 2011; Shortle et al., 2012).[1] Modelling, measuring, and regulating non-point pollution across space presents numerous challenges to researchers and policy makers alike, leaving the problem under-researched and lightly regulated (McDowell et al., 2016).

Climate change may further challenge the relationship between agriculture and water quality due to increased extreme weather events. Field- and micro-watershed-level data have shown that increased frequency of heavy rainfall and flooding will impact agricultural runoff (Ockenden et al., 2016; Lisboa et al., 2020; Liu et al., 2019), but research has yet to quantify nutrient runoff triggered by rainfall at a multi-watershed scale. Better understanding the role of extreme rainfall in driving water pollution from agriculture can help shape best-practices and policies to prevent climate driven non-point source pollution. Mitigation and adaptation to climate change requires such timely and accurate information.

We contribute to the literature by quantifying the effects of high rainfall events on nutrient runoff and water pollution in dairy- and crop-producing watersheds in the state of Wisconsin.[2] We begin by analyzing the specific temporal effects of rainfall, including the magnitude of the effect by rainfall severity, the lagged effects up to four days after a rainfall event, and the effects by season. We then study how land use and agricultural practices affect a watershed's susceptibility to extreme rainfall events. Our work highlights which agricultural practices lessen these impacts, shedding light on methods that can be adopted to protect water quality in a scenario with more frequent extreme-rain events.

The efforts to curb non-point source water pollution are a patchwork of state and local policies and voluntary programs to increase use of best management practices (CITE WI LAW REVIEW). There is only limited causal evidence that some of these non-point policies can be effective (Skidmore et al., 2022; **?**). This is a stark contrast to the point-source pollution literature, where numerous authors have found that policies of the Clean Water Act improved water quality (**?**Cohen and Keiser, 2017; Grant and Grooms, 2017; Keiser and Shapiro, 2019; Shapiro and Walker, 2015). Similarly, there are few causal studies on the effects of best management practices on water quality, and few studies (causal or otherwise)

[1] Funding for non-point source pollution is provided to states under the Clean Water Act Section 319. As such, the non-point program of the CWA is largely supportive, in terms of funds and training, rather than punitive.

[2] Manure runoff from animal agriculture is a major contributor to non-point source pollution, especially in settings like the dairy industry where small unregulated family farms dominate and decentralized local decision-making and regulation predominate (Agouridis et al., 2005; Hooda et al., 2000; Mulla et al., 1999). Crop agriculture serves as the other source of non-point pollution from agriculture; the recent work by Paudel and Crago (2020) provides the first nation-wide estimate of the negative impact of agricultural fertilizer on water quality. Wisconsin presents a good laboratory to study these effects because of its mix of animal and crop agriculture.

at a multi-watershed scale.

There is, however, a strong body of very micro-level work using edge-of-field or watershed-level water quality readings (see, among others Meals et al. (2010); King et al. (2018); Zopp et al. (2019); Kim et al. (2019)). This work, carried out by academic and on-the-ground researchers, consistently supports the importance of the "4 Rs" for nutrient management in conjunction with land management practices (King et al., 2018; Skidmore et al., 2022; Ockenden et al., 2016). King et al. (2018) describe the 4Rs as "apply the right source of fertilizer (i.e., matching source and type with crop requirements) at the right rate (i.e., applying the right amount to meets crop requirements), at the right time (i.e., ensuring timely nutrient availability), and at the right place (i.e., locating nutrients for efficient use)." Following this practice, often using a field-specific nutrient management plan, reduces the availability of excess nutrients on the soil that are at risk of running off to water sources. In contrast, land management practices such as cover cropping, buffers, and diversion waterways improve water quality by slowing nutrient's transport along the surface and/or reducing erosion (**?**).

Heavy rainfall events pose a particular challenge for water quality, as rainfall, irrigation, and snow melt transport excess nutrients from the soil's surface to water sources (Xia et al., 2020; Zopp et al., 2019). Moreover, they may result in erosion, whereby soil itself is transported to surface water. During erosion, the soil brings with it sedimentized nutrients, especially phosphorous, that are bound to it (Duncan et al., 2019). These sedimentized nutrients are referred to as "legacy" nutrients, as they are the legacy of nutrient use and management practices from years prior (Sharpley et al., 2013). Efforts to reduce non-point source pollution must contend with continued impacts of legacy nutrients; they challenges not only improvements in water quality but also the detection of the impacts of current interventions (Skidmore et al., 2022; King et al., 2017).

Climate change may exacerbate the impact of agriculture on water quality by increasing the frequency of heavy rainfall events that trigger runoff and erosion (Ockenden et al., 2017). Edge-of-field- and watershed-level studies have confirmed this vulnerability (Ockenden et al., 2017; Lisboa et al., 2020; Zhang et al., 2012). The above mentioned literature, however, has not integrated these two strands of knowledge to measure how extreme rainfall can affect water quality at a large scale.

We contribute to this literature by producing the largest-to-date retrospective analysis of water quality after heavy rainfall events. We study water quality over fifteen years in nearly 50 HUC8 in the state of Wisconsin. Our sample includes nearly 4,000 cases of over a half inch of rain in a single day and 2,000 of over one inch of rain. The scale of our data allows for novel detail into the effects of rainfall on water quality. At the same time our focus on the watersheds in a single state allows us to accurately measure farm practices, locations, and county level policies that may influence outcomes in a way that would be difficult in a national study.

Our results align with the conclusions of simulations and small-scale studies, supporting the accuracy of our methods in identifying the effects of rainfall on water quality. We thus extend our analysis to study the interaction of land-use and management practices and rainfall events. Our study is the most comprehensive of its kind, as we consider the effects of small-scale and CAFO crop agriculture and crop agriculture.

We study Wisconsin as a snapshot of many of the models of agriculture across the United Station. Agriculture provides $104.8 billion to the state's economy annually and accounts for 11.8% of employment. Both crop and livestock agriculture are present, with dairy, soybeans, and corn leading the industry. The landscape of agriculture is changing; small family-owned dairy farms have consolidated and the number of farms in the state has fallen by half in fifteen years. Concentrated animal feeding units (CAFOs) have increased in frequency (Raff and Meyer, 2019), even while small farms that are exempt from the Clean Water Act still predominate (McCarthy, 2020). Recent EPA estimates show that non-point source pollution from small-scale livestock farms and crop production is responsible for 82% of impairment to Wisconsin's rivers and streams and 57% of impairment to lakes, ponds, and reservoirs (Environmental Protection Agency, 2016).

Wisconsin is also a relevant laboratory to study the impacts of climate change. Climate models predict that Wisconsin will experience climate similar to those previously seen 200 - 500 kilometers south (Veloz et al., 2012). Key components of those predictions include more variability in rainfall, with a higher frequency of heavy rainfall and flooding, as well more extreme temperatures (Schuster et al., 2012). Such a combination of economically strong non-point polluting sources in dairy and crop agriculture, an important economic demand for clean water, a novel regulatory environment at the county level (**?**), and increasing vulnerability to extreme rain events makes Wisconsin an important laboratory to assess climate effects on non-point pollution.

The paper proceeds as follows: section 2 introduces our data and empirical strategy, section 3 presents the results, and section 4 concludes.

2 Methods

2.1 Data

The data used in our estimations comes from a number of public sources compiled by the authors. For our outcome variables, we obtain filtered ammonia and total phosphorus concentration data from the Water Quality Portal (WQP) from 2008 to 2020. The WQP combines data from the United States

Geological Service (USGS) National Water Information System (NWIS), the Environmental Protection Agency (EPA) STOrage and RETrieval (STORET) Data Warehouse, and the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) Sustaining The Earth's Watersheds - Agricultural Research Database System (STEWARDS). The data are collected by state, federal, tribal, and local agencies as well as watershed groups, volunteer groups, universities, and public and private utilities. We include readings from rivers, streams, lakes, reservoirs, impoundments, and estuaries and restrict the sample to routine surface water readings that were collected during routine hydrologic events. Following Keiser and Shapiro (2019), we winsorize water quality measurements at the 99^{th} percentile.

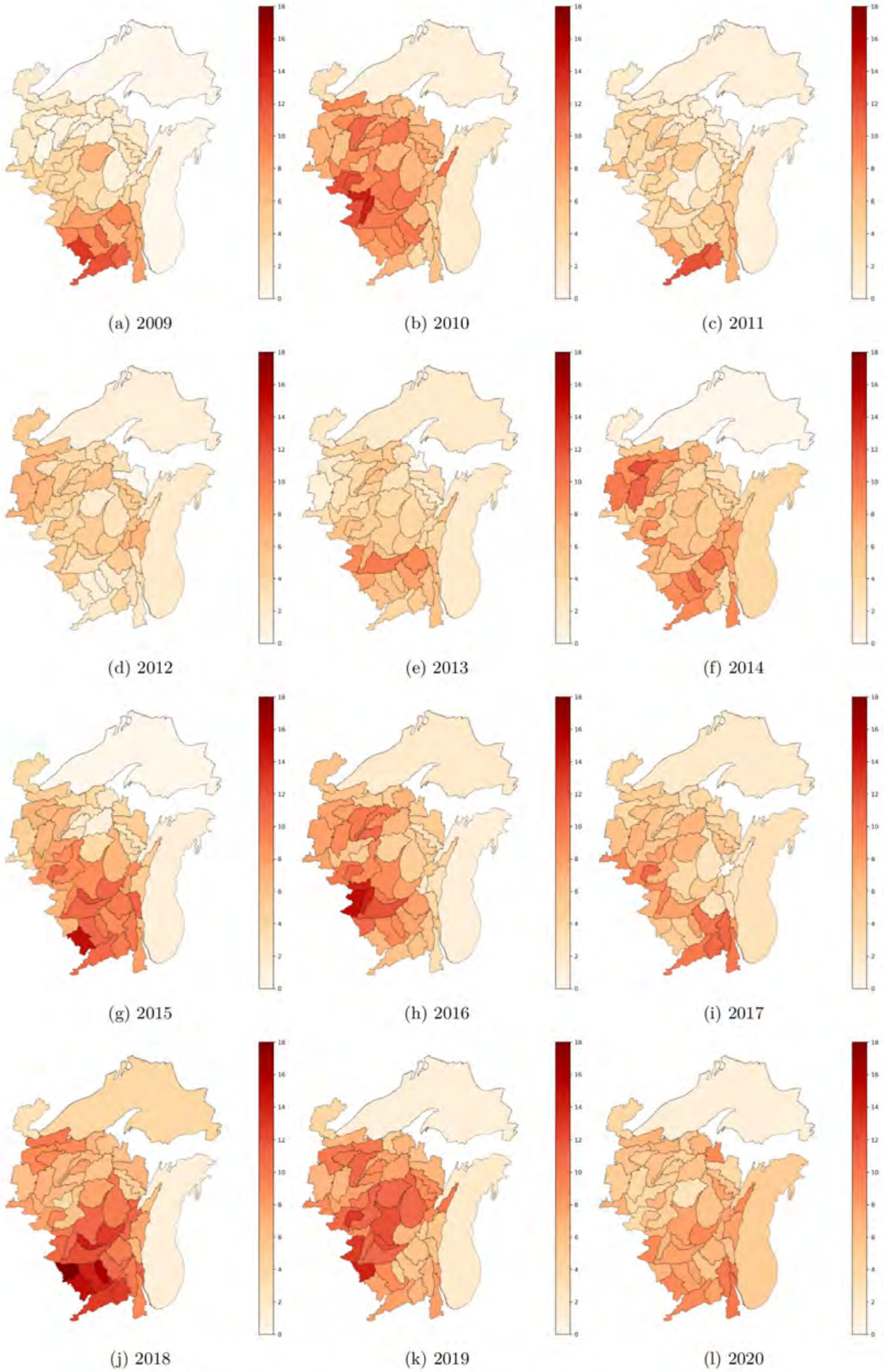
Weather data comes from the PRISM Climate Group, which processes data from a variety of weather monitoring networks to provide 4 km resolution raster data sets for various weather variables. To obtain HUC8 level measures of precipitation and temperature, we take the mean of the raster cells within the HUC8 for each weather variable. Figure 1 presents maps of the number of days with greater than one inch of precipitation by year. HUC8s in the southwest tend to experience more days with extreme rainfall events while HUC8s in the northwest have fewer days with extreme rainfall events.

We also include control data on other factors that might affect water quality: counts of livestock farms, cropped acres, and point-source pollution permits. We obtain farm addresses and operating dates from the WI-DATCP; which allows us to geolocate all dairy farms in the state. These overall dairy farm numbers are supplemented with data on current CAFO permits from WI-DNR and Raff and Meyer (2019) to help us identify which dairy farms are non-point-source emitters (non-CAFO dairy farms).[3] Using these addresses and locations, we obtain the geographic coordinates of the farm and use those coordinates to locate farms within a county and within a HUC8.[4] Figure 2 presents a map of both CAFO and non-CAFO farms.

We obtain raster data on annual crop acreages for major crops (i.e., corn, soy and wheat) from the United States Department of Agriculture (USDA) Cropland Data Layer (CDL). The CDL is a raster data layer with with crop-specific information for the conterminous US. We calculate the area planted with each crop type in a HUC8 by taking the sum of the areas of the raster cells for each crop type within a HUC8. Lastly, we obtain data on the number of non-CAFO point-source pollution permits

[3]The DNR provides a list of current CAFO permits with the issue date and expiration date of that permit. We pair this with Raff and Meyer's data to create a consistent panel using the following steps: (1) we assumed that any permits that were operating until December 2017 (i.e. the end of Raff and Meyer's time series) and that have an issue date after January 2018 were active during the interim period (2) DNR provided the permit expiration dates of all permits that appeared in Raff and Meyer's data up to December 2017 but do not have an active permit (3) we confirmed that all CAFOs with permit expiration dates in 2018 - 2020 remained active through and appeared expired in the data due to a pending permit renewal.

[4]We use OpenCage Geocoder to obtain the geographic coordinates from farm addresses Measurement error may occur in determining the geographic coordinates. However, this error is of concern only if the measurement error leads to incorrect assignment of farms to a county or HUC8. OpenCage Geocoder provides information the precision and accuracy of the match. We flag farms whose distance to the nearest boundary is smaller than the precision of the match. We are confident that between 87.6% and 92.77% of farms are correctly placed within a county and between 85.3% and 92.18% within a HUC8.



(a) 2009 (b) 2010 (c) 2011

(d) 2012 (e) 2013 (f) 2014

(g) 2015 (h) 2016 (i) 2017

(j) 2018 (k) 2019 (l) 2020

Figure 1: Number of days with greater than one inch of precipitation

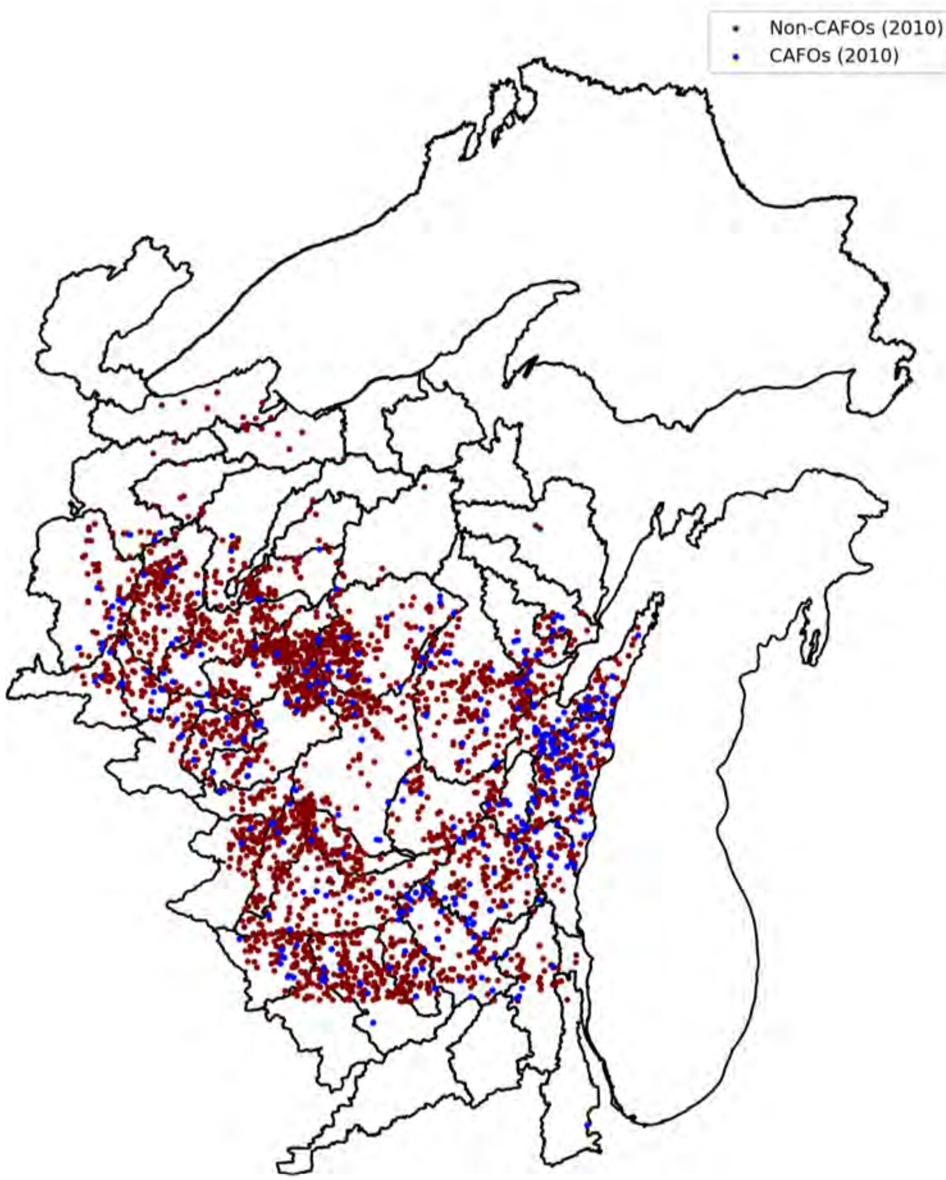


Figure 2: Locations of CAFO and non-CAFO Farms

Table 1: Summary statistics of daily rainfall and annual HUC8-level activities

	Mean	SD	Min	Max
Rainfall (cm)	4.179102	9.33735	0	121.5622
Rain > half inch (0/1)	.0762389	.2653807	0	1
Rain > 1 inch (0/1)	.0411384	.1986109	0	1
Rain > 2 inch (0/1)	.00628	.0789972	0	1
Observations	169428			
Cafo count	4.828777	6.074988	0	40.91667
Number farms	71.82302	74.01995	0	382
Percent crops	.1673415	.1260705	.0002122	.653508
Point source	4.639928	5.470606	0	33
Point source	6.956835	8.047764	0	41
Observations	695			

from the Integrated Compliance Information System (ICIS) for National Pollution Discharge Elimination System (NPDES). The Discharge Monitoring Reports (DMRs) from NPDES contain information on the pollutants discharged by each facility which we use to identify facilities that are likely contributors to ammonia and phosphorus pollution. Then, we use the coordinates of those facilities to locate them inside HUC8s and calculate the number of ammonia and phosphorus non-CAFO point sources at the HUC8-level.

2.2 Empirical strategy

We estimate how rainfall affects the nutrient concentration in a HUC8 using the following equation:

$$Q_{st} = \alpha + \beta P_{ht} + \lambda_y + \mu_m + \omega_h + \epsilon. \tag{1}$$

Our outcome, Q_{st} refers to the concentration (milligrams per liter) of phosphorus or ammonia at monitoring station s, located in HUC8 h, at time t. We estimate models using untransformed values (i.e., levels) and using the logarithmic transformation.

The treatment variable of interest, P_{ht}, is the precipitation in the HUC-8 at that time, for which we construct a number of different measures of rainfall events. As a baseline, we use a set of mutually exclusive categories indicating the amount of daily rainfall: whether there was less than one-half in of rain (the base category), one-half inch to one inch, one inch to two inches, or more than two inches in that day. To better specify extreme events, we employ binary variables indicating whether rainfall exceeded a cutoff (one-half inch or one inch) in a single day, and finally we use a continuous measure of the total rainfall (in inches) in a single day.

We control for other variations in water quality using year-fixed effects (λ_y) for annual variations, month-fixed effects (μ_m) for seasonal variation, and HUC8-fixed effects (ω_h) for variations in characteristics inherent to the HUC-8. After controlling for time and location fixed effects, extreme weather events can be considered “as good as random” (Tambet and Stopnitzky, 2021). Thus, our empirical strategy causally identifies the effects of weather shocks on our outcomes of interest.

We cluster standard errors at the level of the HUC8-year, as we believe that this captures the level of treatment since water quality is influenced by all activity within a HUC8, and is influenced by the weather and activities taking place within a given year. For robustness, we test the model clustering standard errors at the HUC8 (44 clusters) and using wild-bootstrapped standard errors while clustering in the HUC8.

In order to capture the temporal nature of runoff, we further explore the effects of rainfall past the day of the rainfall event by including lagged values of rainfall in the following equation:

$$Q_{ht} = \alpha + \Sigma_{l=0}^{4}\Big(\beta_l P_{h(t-l)}\Big) + \lambda_y + \mu_m + \omega_h + \epsilon. \tag{2}$$

Here, l is an integer running from 0 to 4 and all other variables are described as above.

We then explore how HUC8-level agricultural and other potentially water polluting activity interacts with rainfall events using the following equation:

$$Q_{ht} = \alpha + \beta P_{ht} + \gamma \mathbf{X}_{ht} + \delta P_{ht} * \mathbf{X}_{ht} + \lambda_y + \mu_m + \omega_h + \epsilon. \tag{3}$$

We capture the point- and non-point source pollution activity in the HUC-8 in H_{ht}, including the number of CAFO dairy farms and NPDES permits (point activity) and non-CAFO dairy farms and the number of crop acres (non-point activity). Our coefficient of interest, δ captures the interaction between extreme rainfall and each of these activities.

3 Results

3.1 Ammonia and phosphorus levels spike after rainfall

Both ammonia and phosphorus concentrations increase immediately after a rainfall event, and the effect increases with the amount of rainfall. Table 2 shows estimates of the effect of day-of rainfall from 0.5 - 1 inch, 1 - 2 inches, or more than 2 inches on ammonia and phosphorus concentration. For ammonia, we find a 45% increase with 0.5 - 1 inch, a 63% increase with 1 - 2 inches, and a 75% increase with 2 or more inches. The increase falls by around half by the next day; there is a 25% increase following 0.5 - 1 inches, a 33% increase following 1 - 2 inches, and a 34 % following 2 or more inches. The effect is starker for phosphorus; we find a 50% increase with 0.5 - 1 inch, a 79% increase with 1 - 2 inches, and a 130% increase with 2 or more inches. The following day, there is a 21% increase following 0.5 - 1 inches, a 40% increase following 1 - 2 inches, and a 66 % following 2 or more inches.

We also find large increases in both ammonia and phosphorus concentrations in the model with untransformed nutrient concentrations. For ammonia, we find a 0.04 mg/L increase with 0.5 - 1 inch, a 0.09 mg/L increase with 1 - 2 inches, and a 0.04 (not statistically significant) increase with 2 or more inches. These compare to a mean ammonia concentration of 0.19 mg/L in our sample. For phosphorus, we find a 0.12 mg/L increase with 0.5 - 1 inch, a 0.22 mg/L increase with 1 - 2 inches, and a 0.43 mg/L increase with 2 or more inches. Phosphorus has a mean concentration of 0.14 mg/L in our sample. Thus, the results of this level model suggest much larger effects a percent increase compared to the log model. This is likely due to the right-skew in the data, despite the fact that we winsorize the data. The top 1% of phosphorus readings have a concentration of over 1.4 mg/L; and 23% of these occurred on a day with at least a half inch of rain. The top 1% of ammonia readings have a concentration of over 2.6 mg/L, although only 8% of these occurred on a day with over a half inch of rain.

Next, we consider the effect on the day of the rain and the following four days using a single cutoff for extreme rain (table 3). We test this separately using cutoffs at a half inch and one inch. For ammonia we find that concentration increases by 55% on the day of the event using the half inch cutoff and by 62% the day of the event using the one inch cutoff. The following day this falls to a 29% using the half inch cutoff and 32% using the one inch cutoff; the third day, this falls to a 10% inch increase using both cutoffs. There is no statistically significant effect on the fourth or fifth day after an extreme rainfall event.

For phosphorus, however, table 3 shows continued significant effects up to four days after the rainfall event. We again observe that the effect falls by half after the first day and then falls further on the third through fifth days. Using a half inch cutoff, a 68% increase in concentration on the rainfall event day falls to a 31% increase the following day; with the one-inch cutoff, a 84% increase the day of falls to a 42% increase the following day with the one-inch cutoff. The elevated levels of phosphorus continue two through four days after the rainfall event, with a 10 - 20 % increase two to four days later using the half-inch cutoff and 19 - 17% increase using the one-inch cutoff.

We consider seasonality of the effect of rainfall by interacting the rainfall dummy (one inch cutoff) with a dummy for month of year. Figure 3 shows the total effect of rainfall in a given month (i.e., the sum of the main effect and the interaction of the rainfall dummy and month dummy).[5] As expected, we see that rainfall has particularly strong effects for both nutrients in spring (i.e., March - April). The

[5] We drop all observations for January and February from the model, as there are only three and five observations, respectively, with more than one inch of rain.

potency of spring runoff events is attributable to the build up of nutrients applied in late fall or through the winter, sometimes on frozen soil, and often without a crop to take up the nutrients (Zopp et al., 2019). We still see significant effects of rainfall on both runoffs in the summer months (i.e., June to August) when farmers are applying manure and fertilizer to their main-season crops. We do not see a significant effect for ammonia outside of spring and summer. For phosphorus, however, we observe an even larger effect in the fall and early winter (ie., October - December). This likely reflects late fall manure applications that are not readily taken up by crops as well as runoff effects of legacy phosphorus.

These results reflect known differences in the environmental behavior of ammonia and phosphorus. Phosphorus binds readily to soil, resulting in stronger legacy effects (Sharpley et al., 2013). This may explain two differences in our results between the ammonia and phosphorus results. First, we do not observe increases in ammonia outside of the seasons in which we would expect the most excess nutrients on the soil's surface (i.e., spring and summer), suggesting that the mechanism for ammonia is through the runoff of soluble nutrients on the soil's surface. In contrast, we observe a nearly year-round spike in phosphorus due to extreme rainfall, suggesting that available legacy nutrients are also contributing to the effect of rainfall on phosphorus concentrations. Second, the longer effect that we observe of extreme rainfall on phosphorus is also what we would expect in the context of a sedimentized nutrient. These nutrients will take longer to move through the system than soluble nutrients.

3.2 Heterogeneous effects of extreme rain by agricultural practices

Next, we explore how the activity in a HUC8 interacts with extreme rain. We explore practices both in terms of the type of agriculture (i.e., animal or crop) and the production methods (i.e., tillage and cover-crop rates).

Table 4 shows the main and interaction effect of large-scale (i.e., CAFO) dairy farns, non-CAFO dairy farms, area in crops, and point-source pollutions permits. We use both a half inch and one inch cutoff for extreme rain. We again find that concentrations of both ammonia and phosphorus spike the day of an extreme rainfall event. Phosphorus concentrations rose 39% with a half inch of rain and 56% with an inch of rain, while ammonia rose by 46% with a half inch of rain and 55% with an inch of rain.

We find heterogeneous results for ammonia and phosphorus. We find that phosphorus concentration spikes following rainfall are higher in regions with (1) more CAFO farms and (2) more cropped area. We also observe that baseline phosphorus levels are higher with more point-source pollution permits. We find that ammonia concentration spikes following rainfall are higher in regions with more non-CAFO dairy farms. We find, however, that the interactions effect was negative for cropped area and point source pollution permits. When we test this using a continuous measure of rainfall in table 5 and find the same

Table 2: Effect of rainfall in current or previous using mutually exclusive severity categories

	Ammonia		Phosphorus	
	Level	Log	Level	Log
0.5in - 1in	0.043*	0.449***	0.120***	0.496***
	(0.022)	(0.051)	(0.012)	(0.032)
1in - 2in	0.086***	0.627***	0.222***	0.787***
	(0.025)	(0.056)	(0.017)	(0.039)
2+ in	0.044	0.752***	0.433***	1.294***
	(0.028)	(0.112)	(0.056)	(0.089)
0.5in - 1in t - 1	0.007	0.245***	0.034***	0.207***
	(0.016)	(0.053)	(0.008)	(0.028)
1in - 2in t - 1	0.004	0.331***	0.076***	0.392***
	(0.020)	(0.049)	(0.010)	(0.031)
2+ in t-1	-0.003	0.341***	0.085***	0.659***
	(0.027)	(0.091)	(0.019)	(0.067)
Observations	14695	14695	42995	42995

Note: Observations are at the monitoring-station-day level. Standard errors are clustered at the HUC8-year.

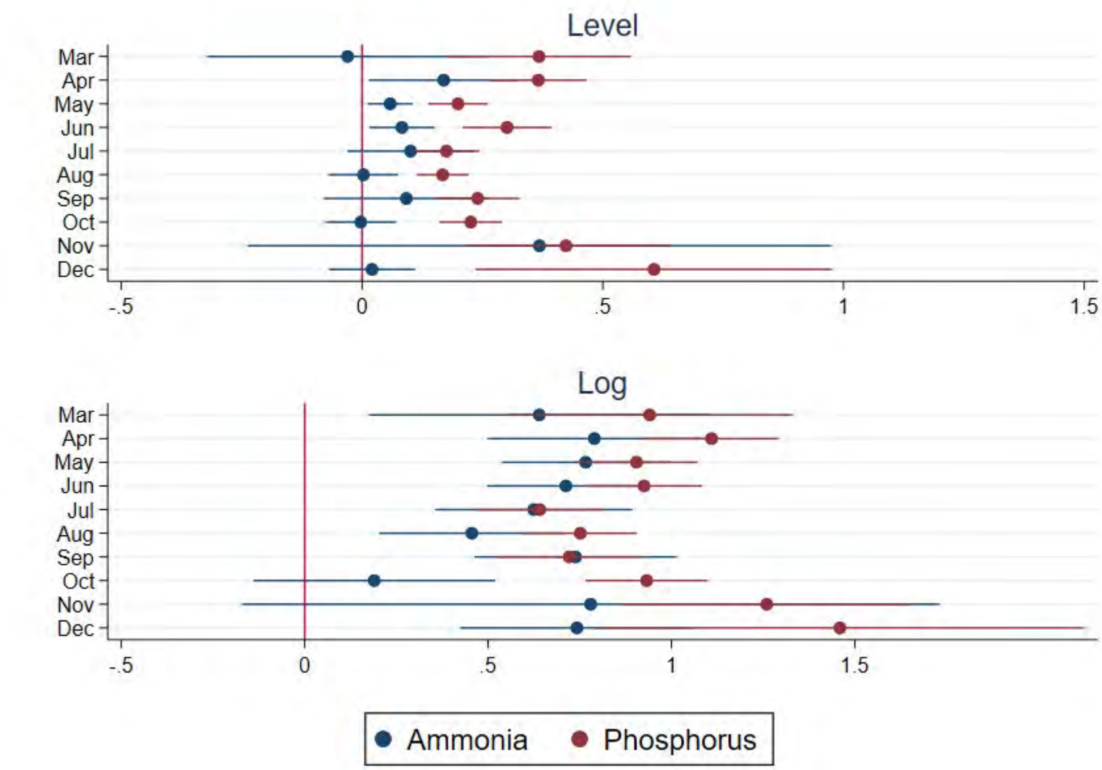


Figure 3: Effect of extreme rain (> 1in) by month. Note: Observations are at the monitoring-station-day level. Standard errors are clustered at the HUC8-year.

Table 3: Effect of rainfall in current or previous days using binary definition of extreme rain and half inch or 1 inch cutoffs

	Ammonia				Phosphorus			
	Half inch		1 inch		Half inch		1 inch	
	Level	Log	Level	Log	Level	Log	Level	Log
Extreme rain	0.062***	0.551***	0.079***	0.622***	0.184***	0.676***	0.245***	0.837***
	(0.017)	(0.041)	(0.022)	(0.052)	(0.014)	(0.031)	(0.019)	(0.038)
Extreme rain t-1	0.004	0.286***	0.004	0.323***	0.055***	0.308***	0.078***	0.418***
	(0.011)	(0.036)	(0.018)	(0.044)	(0.006)	(0.022)	(0.009)	(0.029)
Extreme rain t-2	-0.008	0.105***	-0.029***	0.098**	0.022***	0.157***	0.026***	0.172***
	(0.013)	(0.037)	(0.011)	(0.049)	(0.005)	(0.020)	(0.007)	(0.028)
Extreme rain t-3	-0.010	0.030	-0.038***	0.011	0.009*	0.086***	0.010	0.097***
	(0.015)	(0.040)	(0.010)	(0.052)	(0.005)	(0.020)	(0.008)	(0.028)
Extreme rain t-4	-0.015	0.058*	-0.019	0.055	0.019***	0.133***	0.024***	0.150***
	(0.010)	(0.034)	(0.013)	(0.048)	(0.005)	(0.020)	(0.008)	(0.027)
Observations	14692	14692	14692	14692	42991	42991	42991	42991

Note: Observations are at the monitoring-station-day level. Standard errors are clustered at the HUC8-year.

conclusions.

One major contributor to nutrient pollution is chemical fertilizers (Paudel and Crago, 2020). We partially account for this by controlling for both cropped area and dairy production; fertilizer use should increase in cropped area, and a smaller ratio of dairy production to cropped area should imply more chemical fertilizer use. This, however, implicitly assumes uniform fertilizer application rates across space. Unfortunately, there is no spatially or temporally explicit data on fertilizer use (Mitchell, 2021). We thus add a third proxy for fertilizer use: corn yield. One challenge is that current corn yield is a classic "bad control," as extreme rainfall during the growing season will directly impact corn yield. To account for this, we interact current rainfall with the mean corn yield in the HUC8. We similarly estimate the mean value of all the agricultural practices we previously explored. This method precludes the inclusion of main effects, as they are absorbed by the HUC8 fixed effect term.

Table 6 shows that a HUC8 with higher corn yield does experience a larger spike in phosphorus after rainfall. We also observe a larger spike in HUC8s with more non-CAFO dairy farms. For ammonia, we find a modest interaction between rainfall and the mean number of non-CAFO dairy farms. Notably, the main effect on extreme rain now is negative, but this does not reflect a negative total effect of rainfall for the average HUC8. A HUC8 with the mean value of all the activities experiences a 60% increase in

Table 4: Effect of rainfall in current day using binary definition of extreme rain and half inch or 1 inch cutoff and interacted with activities in the HUC8

	Ammonia				Phosphorus			
	Half inch		1 inch		Half inch		1 inch	
	Level	Log	Level	Log	Level	Log	Level	Log
Extreme rain	0.099***	0.459***	0.131**	0.550***	0.074***	0.390***	0.119***	0.561***
	(0.032)	(0.084)	(0.051)	(0.107)	(0.016)	(0.054)	(0.022)	(0.074)
Cafo count	0.004	0.008	0.004	0.008	0.002	0.009	0.002	0.009
	(0.003)	(0.008)	(0.003)	(0.008)	(0.002)	(0.008)	(0.002)	(0.008)
Cafo count * ppt	0.002	0.005	0.003	0.007	0.004	0.011**	0.004	0.011*
	(0.002)	(0.007)	(0.002)	(0.009)	(0.002)	(0.005)	(0.003)	(0.006)
Number farms	0.000	-0.002*	0.000	-0.002*	-0.000	0.000	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Number farms * ppt	0.000	0.002**	0.000	0.002***	0.000	0.001	0.001**	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Percent crops	-0.272	-1.441***	-0.287	-1.521***	-0.117	-0.540	-0.106	-0.510
	(0.182)	(0.476)	(0.180)	(0.480)	(0.163)	(0.425)	(0.158)	(0.414)
Percent crops * ppt	-0.273**	0.024	-0.304*	0.008	0.248**	1.061***	0.223*	1.092***
	(0.135)	(0.427)	(0.176)	(0.482)	(0.098)	(0.258)	(0.130)	(0.313)
Point source	-0.002	-0.006	-0.002	-0.007	0.002**	0.004	0.002**	0.004
	(0.002)	(0.006)	(0.002)	(0.006)	(0.001)	(0.004)	(0.001)	(0.004)
Point source * ppt	-0.004*	-0.020**	-0.006**	-0.033***	-0.001	-0.005	-0.003	-0.011*
	(0.002)	(0.009)	(0.003)	(0.012)	(0.002)	(0.005)	(0.002)	(0.006)
Observations	10945	10945	10945	10945	32975	32975	32975	32975

Note: Observations are at the monitoring-station-day level. Standard errors are clustered at the HUC8-year.

ammonia and an 84% in phosphorus on a day with one inch of rainfall.

4 Conclusion

This work highlights the importance of mitigating non-point source water pollution during extreme rainfall events. As climate change driven rainfall events in places like Wisconsin with both animal and crop agriculture get more extreme, our results suggest that this will significantly increase pollution of both phosphorus and ammonia from agricultural production. This work demonstrates an unexplored way that future climate change may cause adverse economic and environmental outcomes in the US. In

Table 5: Linear effect of rainfall in current period and activities in HUC8

	Ammonia		Phosphorus	
	Level	Log	Level	Log
Extreme rain	0.004***	0.018***	0.003***	0.016***
	(0.001)	(0.003)	(0.001)	(0.002)
Cafo count	0.004	0.007	0.002	0.009
	(0.003)	(0.008)	(0.002)	(0.008)
Cafo count * ppt	0.000	0.000	0.000**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Number farms	0.000	-0.002*	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)
Number farms * ppt	0.000	0.000***	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Percent crops	-0.239	-1.368***	-0.107	-0.529
	(0.181)	(0.461)	(0.159)	(0.414)
Percent crops * ppt	-0.011***	-0.008	0.003	0.023**
	(0.004)	(0.013)	(0.003)	(0.009)
Point source	-0.002	-0.005	0.002**	0.004
	(0.002)	(0.006)	(0.001)	(0.003)
Point source * ppt	-0.000	-0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10945	10945	32975	32975

Note: Observations are at the monitoring-station-day level. Standard errors are clustered at the HUC8-year.

Table 6: Effect of rainfall in current day using binary definition of extreme rain and half inch or 1 inch cutoff and interacted with mean levels of activities in the HUC8

	Ammonia				Phosphorus			
	Half inch		1 inch		Half inch		1 inch	
	Level	Log	Level	Log	Level	Log	Level	Log
Extreme rain	0.254	-0.572	0.679*	0.341	-0.730***	-1.127*	-1.031***	-1.275*
	(0.263)	(0.642)	(0.379)	(0.848)	(0.269)	(0.602)	(0.324)	(0.699)
Cafo count * ppt	-0.001	0.004	-0.001	0.003	0.002	-0.000	0.001	-0.001
	(0.004)	(0.009)	(0.005)	(0.013)	(0.003)	(0.008)	(0.003)	(0.009)
Number farms * ppt	-0.000	0.002**	0.000	0.002**	0.001*	0.001	0.001**	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Percent crops * ppt	0.341	0.208	0.654	0.834	-0.349	0.004	-0.685*	-0.261
	(0.298)	(0.808)	(0.399)	(0.966)	(0.325)	(0.692)	(0.381)	(0.753)
Corn yield * ppt	-0.001	0.008	-0.004*	0.001	0.006***	0.011**	0.009***	0.013**
	(0.002)	(0.005)	(0.003)	(0.006)	(0.002)	(0.005)	(0.003)	(0.005)
Point source * ppt	-0.010	-0.041**	-0.005	-0.040*	-0.000	0.012	0.001	0.009
	(0.009)	(0.016)	(0.011)	(0.024)	(0.003)	(0.009)	(0.004)	(0.011)
Observations	14697	14697	14697	14697	42998	42998	42998	42998

Note: Observations are at the monitoring-station-day level. Standard errors are clustered at the HUC8-year.

addition, this work highlights how different farm sizes and production practices on the land affect how extreme rainfall affects nutrient pollution. The results run somewhat counter to the popular perception that CAFOs are the worst polluters and suggests that all animal agriculture is vulnerable to extreme rain.

Our work highlights the need for further research to determine the policy mechanisms that effectively reduce non-point source pollution, as climate change will increase extreme rainfall events and may further exacerbate nutrient runoff. This work suggests that policy makers may want to focus on all animal agriculture as well as specific practices on crop farms if they want to mitigate the climate impacts on water bodies around the US. Future research that quantified the proportion of nutrient pollution due to extreme rainfall events compared to everyday runoff would also be important for understanding appropriate policies to implement on the landscape.

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