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A retrospective analysis of climate and land management drivers of nutrient export from the western Lake Erie watershed: 1980-2019

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The return of harmful algal blooms to western Lake Erie has heightened the focus on managing nutrient loading from its watershed, and particularly the large, agricultural Maumee River Watershed (MRW). Increased dissolved reactive phosphorus (DRP) loads over the last twenty years are suspected to be a primary cause of the recurrence and severity of these blooms. The primary cause of increasing DRP is still unclear, and therefore management efforts to reverse this trend are difficult to develop. We used a refined model of the MRW to investigate changes in climate and land management between 1980 and 2019 to identify key factors driving trends in DRP as well as discharge and other nutrient forms that impact algal biomass and toxicity. We found that the dominant drivers of discharge and nutrients varied: historical climate trends drove discharge and nitrogen concentrations, while historical management changes were more responsible for changing phosphorus concentrations. Among the land management changes examined, the rising adoption of minimal- and no-tillage strategies had the greatest impact on nutrient trends, leading to reductions in total phosphorus (TP), total nitrogen (TN), and nitrate (NO_3), yet increases in DRP. We posit that a better understanding of the water quality impacts of past land management enables modelers and managers to more accurately predict the impacts of potential future management changes.

Keywords: Soil and Water Assessment Tool, nutrient loading, historical farm management, climate impacts

Introduction

In the 1960s and 1970s, Lake Erie suffered from significant algal blooms and hypoxia as a result of excess phosphorus (P) loading that impacted drinking water, limited recreational use, and threatened local fish and wildlife populations (Ohio EPA, 2010). As a result, the International Joint Commission (IJC) instituted a P loading limit of 11,000 metric tons per year under the Great

Lakes Water Quality Agreement (GLWQA, 1978). Subsequently, P controls that primarily focused on point source contributors were widely adopted, and by the 1980s nuisance and harmful algal blooms (HABs) and hypoxia were less prevalent.

However, HABs and hypoxia returned in the 1990s with greater frequency, extent, and toxicity over the next two decades. This resurgence occurred despite meeting the lake-wide water quality target for P. This led to the establishment of new targets by the GLWQA in 2016 that called for greater reductions in P loads (GLWQA, 2016). An additional focus was placed on dissolved reactive P (DRP) from the Maumee River, which decreased between the 1970s and the 1990s and then increased two-fold (Johnson et al., 2014; Scavia et al., 2014; Smith et al., 2015; Stow et al., 2015). Streamflow and total P (TP) exhibited a similar, but less pronounced, "u-shape" (Stow et al., 2015), suggesting climate variations may be partially responsible. Land management also likely contributed to trends in nutrient loads. Jarvie et al. (2017) suggested that 35% of the increase in DRP load after 2002 was related to increased streamflow and the remaining 65% was attributed to greater DRP delivery from the land to the river. While it remains unclear why the DRP load to the river changed, a review of 25 possible causes of the resurgence of HABs in Lake Erie suggested changes in agricultural practices were responsible for a disproportionate amount of the increases (Smith et al., 2015). The primary focus of most HAB management has been on P loading as research suggests P loads drive the size of blooms (Stumpf et al., 2012), and yet nitrogen (N) controls the relative abundance of varying bloom species and toxicity levels (Jankowiak et al., 2019; Harke et al., 2016; Gobler et al., 2016; Newell et al., 2019). This highlights the need for understanding driving forces behind both P and N, especially because patterns in N loading trends are the inverse of those for P (Stow et al., 2015).

Watershed models have been used to investigate the impacts of changes in climate and land management on discharge and nutrient (N and P) loads (Kalcic et al., 2016; Keitzer et al., 2016; Muenich et al., 2016; NRCS CEAP, 2016; Scavia et al., 2016a; Apostel et al., 2021). However, few have used these models to address long-term, historical impacts of management changes. Jarvie et al. (2017) assessed the relative roles of climate and delivery mechanisms on increased DRP loading through use of empirical models. To our knowledge, Daloğlu et al. (2012) is the only process-based watershed modeling study that attempted to reproduce historical trends in loads in the Maumee River. They simulated changes in agricultural practices and field conditions from the 1970s through the 2000s but were constrained by limited access to changes in field-level management practices. In addition, neither Jarvie et al. (2017) nor Daloğlu et al. (2012) focused on both P and N.

This study aims to understand the influence of historical changes in agricultural management practices and climate on P and N loading from the Maumee River. The specific objectives are to:

1. Simulate long-term trends in discharge and nutrient export using historical climate and agricultural management data,
2. Assess the relative roles of climate and land management in driving those trends, and
3. Identify the relative impacts of individual management practices on discharge and nutrient export.

Methods

Study area

The Maumee River Watershed (MRW) is a largely agricultural landscape located primarily in northwest Ohio, with boundaries that cross into Indiana and Michigan (Figure 1). Greater than 70% of the roughly 8,000 mi^2 basin is row cropland (primary crops of corn, soybean and wheat). This region is characterized by flat topography with an abundance of poorly drained soils that have been drained through surface ditches and subsurface ("tile") drains. The outlet of the Maumee River drains directly into the western basin of Lake Erie near Toledo, Ohio. While the Detroit River dominates the discharge into Lake Erie, the waters of the Maumee River have much higher P concentrations (Maccoux et al., 2016) and this riverine P load has been shown to drive the extent of annual algal blooms (Scavia et al., 2016b).

Watershed model

The Soil and Water Assessment Tool (SWAT) is a watershed-scale model created to assess the impacts of land management on water quality in large, un-gauged basins (Arnold et al., 2012). It is a semi-distributed, physically-based model commonly used in agricultural settings as it permits implementation of detailed field conditions and management schedules. It has also been used extensively to predict water quality under climate change (e.g. Kujawa et al., 2020; Yuan et al., 2020).

In this study, we altered an existing SWAT2012 model of the MRW to test our three objectives (Figure 2). The existing model was developed by Apostel et al. (2021) using management practices for 2005-2015, a calibration period that coincides with the latter portion of this study period. This model's Hydrological Response Units (HRUs) approximate the resolution and location of individual farm fields. Apostel et al. (2021) used discharge, TP, DRP, total nitrogen (TN), and suspended sediment in a manual calibration (2005-2015) and validation (2000-2004) process at both daily and monthly timescales near the watershed outlet at Waterville. While they did not originally calibrate for nitrate (NO_3), back-validation reported 'good' performance (Apostel et al., 2021) (Table S1 available on-line through the publisher's website). Calibration and validation goodness-of-fit statistics included the coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), and percent bias (PBIAS) following 'good' model performance recommendations (Moriasi et al., 2015). In the MRW, point sources are responsible for a small fraction of nutrient load. Because we lacked point source data for the majority of the historical period, we removed point sources from the model so all changes in nutrient loading are associated strictly with changing land management practices.

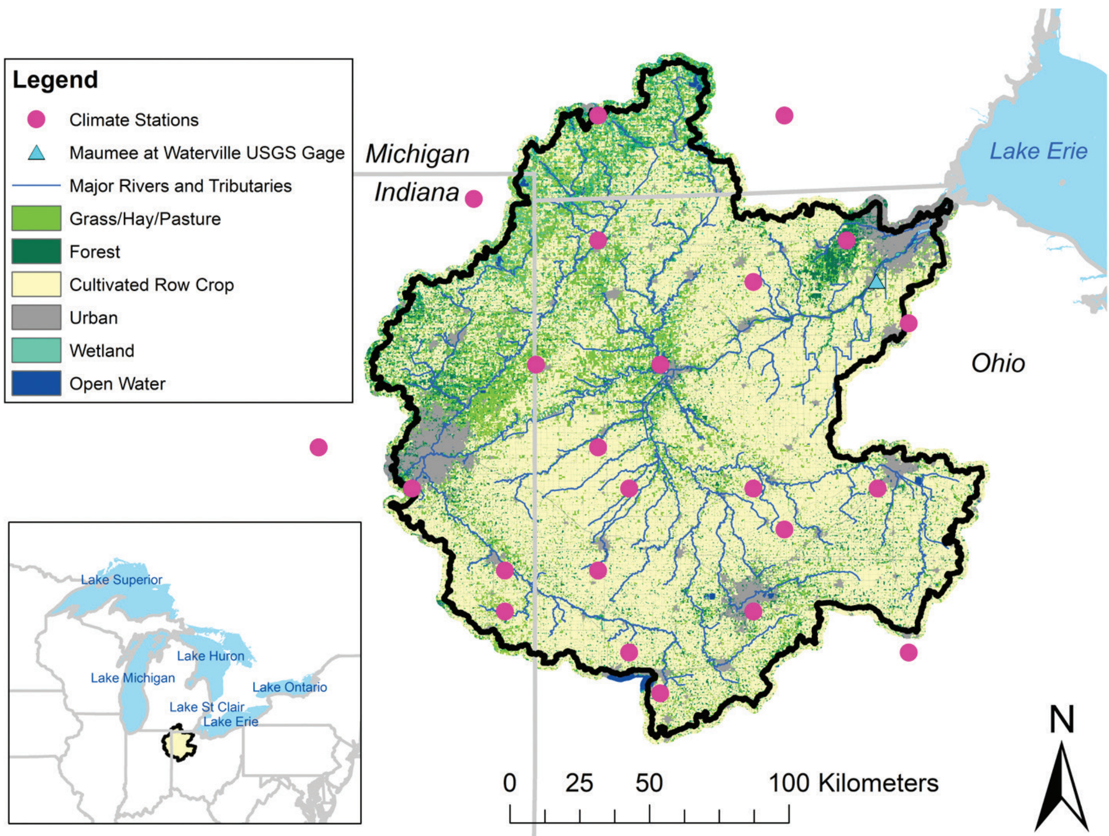

Figure 1. Map of Maumee River Watershed (MRW) within the Laurentian Great Lakes Region. USGS gauge #04193500, Maumee at Waterville, is used for calibration and historical trend analysis.

Climate data

To capture historical changes in climate, we obtained daily precipitation and temperature data from the National Climatic Data Center's Global Historical Climatology Network (GHCND) (Menne et al., 2012). We eliminated climate stations missing >20% of daily precipitation or temperature data from 1980-2019, resulting in 24 stations within or adjacent to the watershed (Figure 1). We used a Haversine distance calculation, which accounts for earth surface curvature, to gap fill missing data from stations based on the next closest station with available data on that day.

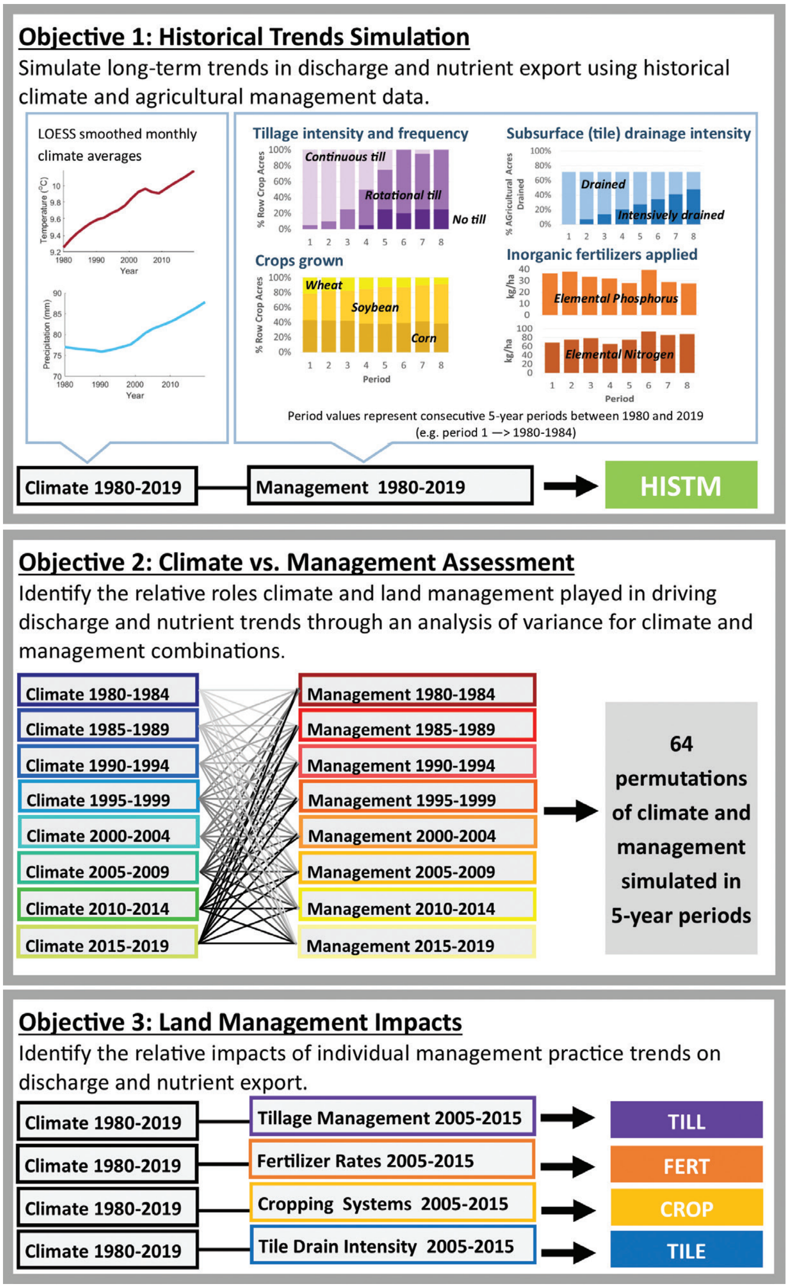

Figure 2. Methodology diagram depicting the combinations of climate and management data used for each objective.

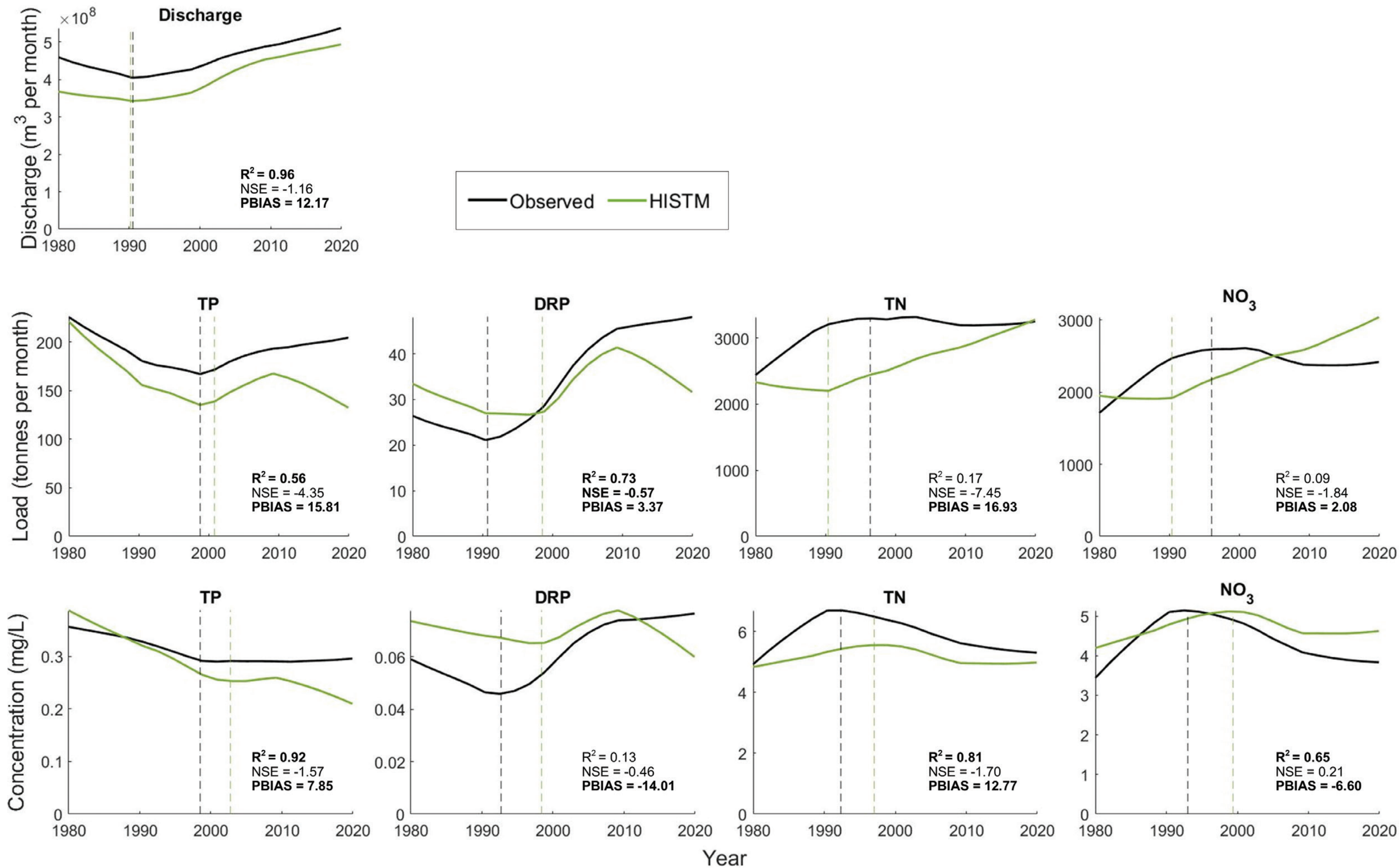

Figure 3. Long-term trends for observed and SWAT-simulated (HISTM) Maumee River discharge and nutrient outputs (1980-2019) at the watershed outlet. Vertical dotted lines represent the breakpoint for the observed (black) and simulated (green) trends. Goodness-of-fit measures (R2, NSE, and PBIAS) are shown on each panel. Bolded goodness of fit measures meet minimum satisfactory criteria according to Moriasi et al. (2015) standards.

Land management

To assess changes in land management practices, we collected historical (1980-2019) land management data on tillage management (Smith et al., 2015; Jarvie et al., 2017), crops (NASS CDL, 2016), inorganic fertilizer application rates (IPNI, 2011), and intensity of tile drainage (Jarvie et al., 2017; NRCS CEAP, 2016; Kumar et al., 2009). We used best available data from current and historical surveys, fertilizer sales, and agricultural inventories as described below.

We altered the Apostel et al. (2021) model to represent management changes in the 1980-2019 period that have been deemed influential in the region and for which data exists that can be implemented in the model. We hereafter refer to this as the historical management model (HISTM). We will also refer to management practices as the four practices which were modified in the model according to available historical data. Scenarios will refer to any model runs with changes made to the HISTM model. Because many of the relevant parameters that change over time are static inputs within SWAT2012, meaning they cannot be varied over time within a model run, we implemented a piecewise approach with HISTM using eight consecutive five-year model runs following 5-year warmup periods. We ran each segment independently holding all other conditions constant between runs. To maintain consistency, we used this approach for all scenarios regardless of whether a scenario required a change in parameters. The following describes the data implemented into HISTM to modify it from the original Apostel et al. (2021) model.

Tillage management

For tillage management changes over time, we separated tillage into three categories: continuous tillage, rotational tillage (only before corn), and no tillage. Apostel et al. (2021) used NRCS CEAP reports to establish 2005-2015 distributions of practices. For the historical period (1980-2019), we relied on residue management data obtained from the National Resource Inventory surveys for Ohio, Indiana, and Michigan every 5 years beginning in 1982 (Jarvie et al., 2017), and percentage of fields under each category changed at each 5-year time interval (Figure 2; Figure S5, Table S6-available on-line through the publisher's website).

Cropping systems

We obtained general trends for the relative amounts of corn, soybean, and wheat planted in Ohio, Indiana, and Michigan from USDA-NASS for 1980 through 2019 (NASS CDL, 2016). To maintain model continuity, we made the following assumptions based on the data: 1) the total row crop area remained constant, and 2) there was no change in crops or crop variety, but only changes in relative abundance. We based both assumptions on survey

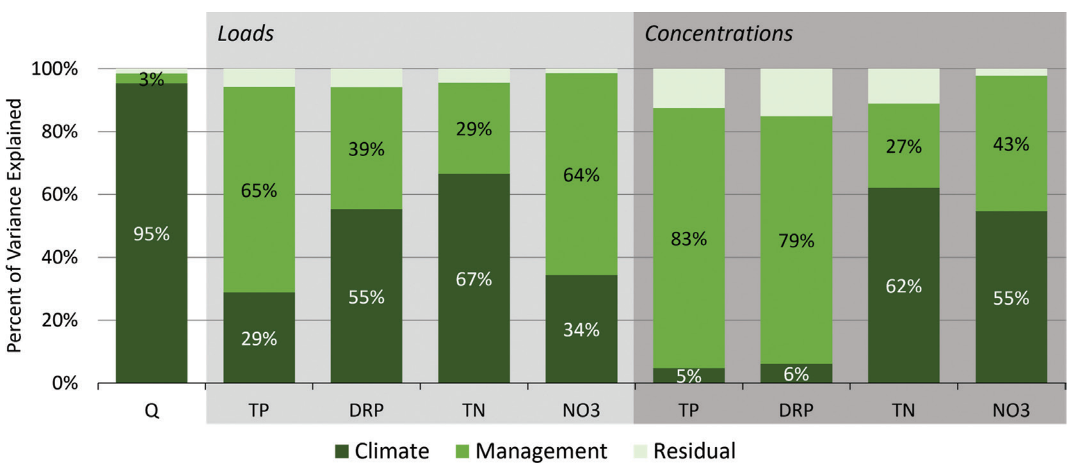

Figure 4. Contribution to trend variance. Percent variation explained by climate and land management using a two-way ANOVA for rank normalized transformed discharge, load, and concentrations. All results reported significant values ($p < 0.05$).

data which showed that that the total area planted for all row crops remained constant, but the relative abundance of the three crops changed (NASS CDL, 2016). We then used tri-state historical crop data to determine a percent change in planted area for each crop in each state. These values we then scaled based on the relative area of each state within the watershed and then calculated percent changes of corn, soybean, and wheat of each 5-year historical period from the 2005-2015 period in the original model. With these percent changes, we adjusted the relative abundances of rotations to meet changes in individual crops on a 5-year basis (Figure 2; Figure S3-available on-line through the publisher's website).

Inorganic fertilizer application rates

For the historical period, we used a watershed-wide change in application rates from the 1985-2019 average based on data from the International Plant Nutrition Institute (IPNI, 2011). Within each 5-year period, we determined an average application rate and then calculated the percent changes from the 2005-2015 calibration period. No data was available for 1980-1984, and so we used a linear regression on 1985-2019 data to fill in the missing data. Apostel et al. (2021) based their original fertilizer rates on county-level fertilizer sales which were then scaled to meet crop needs. We utilized this same approach (Figure 2; Figure S4 available on-line through the publisher's website).

Tile drainage

Approximately 70-78% of the western Lake Erie basin cropland was estimated to have subsurface drainage (NRCS CEAP, 2016); however, detailed information on the extent and intensity of tile drainage was limited. Kumar et al. (2009) suggested that while the total area under tile drainage may have changed little over the past 40 years, the density, or "intensity," of tile drainage increased. We assumed a steady increase in tile intensity between 1980 and 2019 (Figure S7-available on-line through the publisher's website). The Apostel et al. (2021) model contained tile drainage on 71.5% of agricultural row crops, with 41% of that area having a higher density of tile drains. We implemented historical intensification of drainage into the model by decreasing tile spacing (SDRAIN) and increasing the drainage coefficient in the model (DRAIN_CO) (Figure 2; Figure S8-available on-line through the publisher's website).

Long-term trend decomposition

We obtained daily monitoring data for 1980-2019 from the National Center for Water Quality Research (https://ncwqr.org/) for the Maumee River at Waterville OH (USGS gauge number 04193500). Using this data, we calculated nutrient loads from discharge and nutrient concentrations. Daily discharge and load values were summed to aggregate the data to a monthly timestep; monthly loads were then divided by monthly discharges to obtain a monthly concentration. We used a best fit linear regression model between discharge and loads at this location as presented in Obenour et al. (2014) to gap fill missing data.

We used a seasonal trend decomposition using LOESS (locally estimated scatterplot smoothing) to display trends, as presented in Stow et al (2015). Similar to Stow et al. (2015), we used the window lengths of 48 and 250 months for seasonal and long-term trends, respectively, but our time frame was adjusted to incorporate six additional years of data and to remove the late-1970s period that contained several years of missing discharge data.

Historical trends simulation

For Objective 1, to simulate long-term trends in discharge and nutrient export using historical climate and agricultural management data, we developed the final historical model, HISTM, using the Apostel et al. (2021) baseline model and incorporating the 1980-2019 climate and management data described in the sections above (Figure 2). We compared long-term data trends from HISTM with observed trends for discharge, nutrient loads, and nutrient concentrations. Both loads and concentrations were included as each has been shown to influence HABs (Gobler et al., 2016; Harke et al., 2016). We assessed the model's ability to replicate the observed trends using standard model performance statistics including the coefficient of determination (R^2), Nash-Sutcliffe efficiency coefficient (NSE), and percent bias (PBIAS). To further examine model trend performance, we conducted a piecewise regression analysis in the software program R (R Core Team, 2020) with the package segmented (Muggeo, 2008) and a single breakpoint. This analysis resulted in two separate periods of interest around a breakpoint for which we fit linear pre- and post-breakpoint regression lines. We compared long-term trends based on breakpoints and slopes of trends in loads and concentrations. We considered breakpoints estimated within a 48-month range similar due to the window length used in trend decomposition. We used a two sample T-test to compare pre- and post-breakpoint slopes.

Climate vs. management assessment

For Objective 2, to assess the relative roles of climate and land management in driving long-term trends, we developed 64 scenarios of all permutations of climate and land management in the historical period: eight 5-year climate segments multiplied by eight 5-year management segments (Figure 2). We quantified the relative impacts of climate and management as the variance explained by each using a two-way main effects ANOVA on annual mean outputs for each permutation. Because the SWAT model is deterministic—only one realization is output for each permutation—the ANOVA considers only one case per treatment; consequently, we did not include an interaction term.

To evaluate if the results meet the necessary conditions for ANOVA, we performed a Shapiro-Wilks test to determine normality and the score for non-constant error variance to test heteroscedasticity of residuals (Sharpiro and Wilk, 1965). We transformed discharge, TP, and DRP data to meet the normality requirements using rank normalization (Shapiro-Wilk test, $p < 0.05$). We compared the ANOVA with transformed data to non-transformed data and found that the transformation had little to no impact on results.

Land management impacts

For Objective 3, to identify the relative impacts of individual management practices on discharge and nutrient export, we designed sensitivity scenarios for one-at-a-time changes such that each aspect of land management was held constant at the calibration levels (2005-2015) in HISTM (Figure 2). We determined changes in discharge and nutrient loads and concentrations for the period prior to the simulated breakpoint in the HISTM model by comparing mean values from HISTM to the individual management scenario runs and reported these as a percent change. To determine the significance of variation in the means, we used a two-sample t-test on the pre-breakpoint period for HISTM and management practice scenario.

Results

Historical trends simulation

We built a model capable of testing the role of historical land management and climate on water quality trends in the MRW. We estimated historical changes in agricultural management that scientists have suggested were responsible for shifting nutrient loads as they had an ability to impact nutrient export and experienced considerable changes in the historical period. In comparing the model output from the historical (HISTM) scenario to observed trends, we can assess the extent to which the model was able to capture observed trends through the combination of climate and land management changes. This tells us whether the proposed factors were likely to be the primary drivers of historical nutrient load changes. It also confirms whether the model replication of historical trends is sufficient for use in Objectives 2 and 3.

Simulated trends in discharge and nutrient loads and concentrations are similar to the observed as shown in Figure 3. On visual inspection, it is evident that the general shapes of the simulated trend curves are not dissimilar to the observed for discharge and P. There is however a divergence in trend in the 2010-2019 period for TP and DRP components where the observed demonstrates a flattening curve and the modeled a decline (Figure 3). While N concentrations showed visually similar patterns, N loads were less successful at replicating long-term trends. The Moriasi et al. (2015) performance criteria confirm these findings: by R^2 we see strong correlation between observed and simulated discharge, P loads, and TP and N concentrations; the more stringent NSE shows that simulated DRP loads reasonably capture observed trends; PBIAS indicates the magnitudes of simulated trends are within 25% of the observed for discharge and all nutrient concentrations and loads.

The location of breakpoints in observed and simulated trends further confirmed that the model exhibited an inflection in discharge and nutrient export towards the middle of the historical period (Table S9-available on-line through the publisher's website). Such behavior not only supported the shape of the trends, but also the method used in Objective 3 to use simulated breakpoints for assessing watershed sensitivity to historical trends in practices one-at-a-time through scenarios. Breakpoints were most accurately identified for TP and DRP loads, as inaccuracies in simulation of discharge and P concentration breakpoints balanced one another out.

The discharge and nutrient export trends before and after our breakpoints were also indicators of how well the HISTM model replicated observed historical trends. Most model outputs produced statistically similar slopes to the observed trendlines, highlighting the model's ability to capture the direction and steepness in trend (Table S9-available on-line through the publisher's website). The exceptions were the statistically significant differences in pre- and post-breakpoint slopes for discharge and TN and NO_3 loads ($p < 0.05$), a pre-breakpoint slope mismatch in TN load and a slope direction mismatch in NO_3 load simulations

For the most part, long-term simulated trends produced by HISTM largely resembled observed hydrology and water quality trends in the Maumee River visually and according to Moriasi et al. (2015) performance criteria (Figure 3). While in many cases the simulated magnitudes and breakpoints of discharge and nutrients disagreed with the observed data, we were most interested in capturing the overall patterns in trends to determine whether the model could be used to test Objectives 2 and 3, and this indeed was the case.

Climate vs. land management

From the two-way ANOVA on the 64 permutations of climate and land management changes we found that change in climate over time was responsible for 95% of the variability in discharge, while water quality had a mixed response to historical climate and land management changes (Figure 4). Land management played a greater role than climate in explaining TP and DRP concentrations and TP load variance, as well as NO_3 load. DRP and TN loads, as well as TN and NO_3 concentrations, were more strongly influenced by climate (Figure 4).

Land management practices

The sensitivity analysis in which scenarios were run where individual land management practices were held constant one at a time at 2005-2015 rates supported the finding that long-term trends in discharge were primarily driven by climate, as there was little variation among scenarios (Table 1, Figure S14-available on-line through the publisher's website). For instance, the greatest impact on discharge was from the TILE scenario, and it was only a minimal (2%) increase due to tile drainage intensity held at the relatively higher 2005-2015 value.

In contrast, scenario results showed that individual management practices greatly influenced nutrient concentrations and load patterns (Table 1). The movement from continuous tillage towards rotational tillage (2005-2019 tillage management in the TILL scenario) resulted in considerable shifts in P loading, increasing DRP (16 %) while simultaneously decreasing TP (-22%), such that DRP assumed a much larger proportion of the P load. The impact of fertilizer trends was clear and intuitive, with an increase in N and decrease in P fertilizer (2005-2019 rates in the FERT scenario) resulting in greater TN and NO_3 loads (7% and 9%, respectively) and concentrations (6% and 7%, respectively) and lesser TP and DRP loads (-8% and -14%, respectively) and concentrations (-8% and -14%, respectively). Reducing the abundance of wheat and soybean, while increasing that of corn, in the CROP scenario resulted in decreased fluxes of P (Load, TP: -5%; Load DRP: -3%; Concentration TP: -4%; Concentration DRP: -2%) and increased N (Load, TN: 10%; Load NO_3: 12%; Concentration TN: 4%; Concentration NO_3: 6%). A greater intensity of tile drainage (TILE) resulted in decreased P, with TP and DRP loads and concentrations decreasing between 3% and 5% in the pre-breakpoint period. More intense tile drainage had smaller impacts on N, with TN and NO_3 loads increasing by no more than 3% and concentrations decreasing by 1%.

Comparing the relative impacts of management scenarios on individual outputs, each of the four trends in farm management practices served as a dominant driver of at least one water quality output (Table 1). The trend in tillage (TILL) was particularly impactful, driving changes in TP, DRP and TN loads and concentrations. Trends in fertilization (FERT) had the greatest impact on NO_3 concentrations. Shifts in crop abundance (CROP) had the largest impact on NO_3 loads. More detail on individual impacts of individual management scenarios and resulting curve patterns can be found in SI section 5.

Discussion

Simulating observed trends

The goal of this study is to understand the drivers of long-term trends in nutrient loads and concentrations in the Maumee River draining to Lake Erie. While the focus of policy in the MRW has been primarily on reductions in P loads, flow weighted mean concentrations are considered an additional metric to assess P reduction progress in the region as this limits the impacts of inter-annual climate variability on nutrient contribution patterns (GLWQA, 2015). Therefore, concentrations may be more indicative of impacts of land management changes. Driven by estimates of observed climate and land management changes, the HISTM model was able to reasonably replicate long-term loading and concentration trends. This replication was of the general shape of the trends, as well as the magnitude of discharge and nutrient export over time. This suggests the factors included by the model that change over time--climate and land management—were able to explain much of the observed trends, giving us confidence that we can learn more from this model about the drivers of these trends.

While the model explained much of the observed trends, it did not capture trends fully. We would not expect a perfect match between simulated and observed historical trends for several reasons. First, the original model was calibrated to discharge and nutrient loads but not concentrations, and therefore would not be expected to perform as highly for concentrations. Second, the model was calibrated during the latter part of the historical period, and as expected, was better able to match observations closer to the calibration period than in the earlier period. Model parameters were established in this later period and hydrological system changes, which are represented by static model parameters, may not be adequately representing earlier realities. For example, the soil partitioning coefficient (PHOSKD) parameter is static in the model, and yet there is evidence that changes in soil P availability and transport from a variety of changes including the increase of soil pH over time (Smith et al., 2015). While our piecewise modeling approach allowed us to modify static parameters over time, we set PHOSKD based on data from more recent edge-of-field monitoring, and lacked an estimate of how the parameter may have changed throughout the historical period. Third, model inputs are less certain in the early period. For example, point sources likely had larger contributions in the past—due to reductions through permitting taking a number of years to implement after the initial Great Lake Water Quality Agreement (GLWQA, 1978; Scavia et al., 2014)-but were not included because of limited data, an assumption that they constituted a small fraction of nutrient load, and our focus being on non-point sources. Due to the steady nature of point source pollution due to permitting, the inclusion of these would likely only have resulted in magnitude shift, not a significant change in the shape of long-term trends. Given that a perfect match is unlikely, and the evidence that the simulated long-term trends are similar to the observed, we conclude that this model can be used to gain knowledge of nutrient loading impacts of climate and specific management changes in Objectives 2 and 3.

Roles of climate and land management

Understanding the extent to which nutrient loads is driven by changing land management vs. climate is critical for managing expectations of how the watershed will respond to future management strategies. While climate is known to play a key role in driving discharge and loading in general, it has been shown to have only a partial role in the MRW (Stow et al., 2015; Jarvie et al., 2017; Dodd and Sharpley, 2016; King et al., 2018). Our results demonstrate that climate has been a significant driver of long-term trends in discharge and water quality, contributing between 5% and 67% of the variation in trends across all nutrient loads and concentrations. These results are consistent with studies that evaluated the impact of climate on P loads (Jarvie et al., 2017; Daloğlu et al., 2012) and N loads (Choquette et al., 2019). We found 53% (11%) of the variability in DRP loadings (concentration) were driven by climate, whereas Jarvie et al. (2017) reported that 35% of the change in load delivery was due to greater discharge volumes, which represented their climate mechanism. Therefore, our study suggests a greater role of climate in driving DRP export than previously thought. Continued climate changes, with projected increases in precipitation and a greater likelihood of intense storms (Angel et al., 2018; Williams et al., 2020), will need to be considered when developing future management strategies.

And yet, the finding that trends in climate did not always dominate the watershed's water quality response in a changing management regime provides an optimistic message: that decisions farmers make in managing their lands are impactful and can improve water quality substantially. While climate has a strong role in transport, management decisions at the field level impact P type (fertilizer type), location (placement), and transport pathways (tile drainage, overland flow), which plays a substantial role in controlling the amount of nutrient available to be transported into a waterway (King et al., 2018; Pease et al., 2017). We see this impact in this study by the influence of management practice scenarios as drivers of TP and DRP concentrations.

N trends at locations within the MRW have been reported (Stow et al., 2015; Choquette et al., 2019); however, ours is the first to simultaneously model climate and land management drivers of these trends. Consistent with trends discussed by Stow et al. (2015) and Choquette et al. (2019), TN and NO_3 load and concentration trends are inversely related to discharge trends. TN load and concentration were primarily climate-driven (67% and 62% respectively). For NO_3, load was more strongly controlled by land management and concentration by climate. The dominant impact of climate on concentration are counter to the expected management drivers, however, these trends suggest a potential dilution effect for TN, a result of limited changes in transport/delivery capacity through limited changes in N focused management combined with increased discharge over time (Choquette et al., 2019). For NO_3, the increased management control of this bioavailable form suggests it is more sensitive to changes in fertilizer application (Renwick et al., 2018; Hubbard et al., 2013). Due to the impact of N on bloom toxicity in the Western Lake Erie basin (Jankowiak et al., 2019; Newell et al., 2019), being able to manage a large portion of the bioavailable NO_3 is a promising message under current future climate change projections.

These results highlight the relative importance of historical changes in both land management and climate. While nutrients can be controlled through management practices, high discharges are likely to lead to larger loads regardless (Rittenburg et al., 2015). Managing these strongly climate-driven components is more difficult with the management options explored here because they showed little impact on discharge at the watershed outlet. For future management, it may be wise to also consider management controls capable of reducing discharge, such as drainage water management (Heathwaite and Dils, 2000).

Land management drivers of nutrient export trends

Even in cases where climate variability is a stronger driver of loading trends, having better information on the relative influence of land management options is important to guide policy and practices. The sensitivity analysis that isolated the effects of historical changes in individual management practice scenarios allowed us to identify which practices were likely most influential in driving long-term nutrient trends. Here we summarize the significance of each individual driver:

Tillage

Tillage represented our dominant management driver, an expected result based on the extent of adoption of minimal and no-tillage practices during our period of interest (Jarvie et al., 2017) combined with the known impacts of tillage on

Table 1. Summary table for management scenario impacts on discharge and nutrients compared to HISTM during the simulated pre-breakpoint period. Each scenario is a one-at-a-time sensitivity run, where one practice was held constant at the Apostel et al. (2021) values (2005-2015) and run with other management changes and climate from the historical (1980-2019) period. Highlighted values in each column under % change in outputs represent the scenario with the largest relative change for discharge or nutrient load/concentration. Values with an asterisk denote a non-significant p-value in differences among pre-breakpoint means between scenario and HISTM. Additional information on breakpoint means and p-values is located in SI table S10 (available on-line through the publisher's website).

	Scenario Description	Change in Management compared to HISTM	% Change in output for simulated pre-breakpoint period								
			Q	Load				Concentration			
				TP	DRP	TN	NO3	TP	DRP	TN	NO3
	Breakpoint Dates		*Apr 1990*	*Oct 2000*	*Sep 1998*	*Jun 1990*	*May 1990*	*Sep 2002*	*Jun 1998*	*Feb 1997*	*Jun 1999*
TILL	Rates of continuous tillage (CT), rotational tillage (RT), and continuous no-till (NT) practice were held at 2005-2015 rates.	A decrease in CT and increase in RT and NT	<1*	**-22**	**16**	**-9**	-4	**-19**	**18**	**-6**	-3
FERT	Rates of inorganic fertilizer application for both N and P were held at 2005-2015 rates.	A decrease in P applied and increase in N applied	<1*	-8	-14	7	9	-8	-14	**6**	**7**
CROP	Cropping system were held constant at 2005-2015 rates.	Abundance of corn decreased, soybeans and wheat increased	<1	-5	-3	10	**12**	-4	-2	4	6
TILE	Total acreage and intensity of tile drained fields were held constant at the 2005-2015 distribution.	Increasing intensity of tile drainage	**2**	-4	-4	2	3	-5	-3	1	2

nutrient transport pathways (Tiessen et al., 2010). Reductions in tillage are known to reduce sediment export from a field, which thereby reduces particulate-bound P—a major fraction of TP—from entering waterways (Tiessen et al., 2010). However, reduced tillage is also known to increase DRP by means of greater stratification of P in surface soil layers (Dodd and Sharpley, 2016). This is precisely what we found, with reduced tillage yielding greater DRP losses despite reductions in TP. While Jarvie et al. (2017) showed a similarity in changing tillage practice trends with changes in DRP loading, this modeling work shows the direct impact of these tillage trends on regional water quality. Tillage management has also been shown to play a significant role in N soil cycling and transport. Increased denitrification in soils under conservation tillage practices has been shown to decrease NO_3 concentrations (García et al., 2016) and may increase the rate of N volatilization from the soil (Renwick et al., 2018), which we saw through the impacts on TN loads and concentrations.

Drainage tiles

We expected tile drainage to have the most significant impact on discharge because tiles affect the hydrological structure of the system by creating direct conduits into local waterways (Heathwaite and Dils, 2000). When the more closely spaced tile drainage of the calibration period replaced the lower density of tiles in the early period, discharge increased as expected. This was also reflected in greater N loads, as more N is exported in tile drainage than in surface runoff (Williams et al., 2015). As N loads increased, concentrations remained steady. Concentrations of NO_3 in runoff and drainage are strongly impacted by nitrification and plant up-take rates in the soil, which were held constant in our model, while most watershed loads occur through drainage systems in highly drained fields (Williams et al., 2015). DRP load and concentrations, however, decreased with more intense tile drainage. These findings were consistent with findings from King et al. (2014) and Williams et al. (2015), as DRP concentrations are typically greater in surface runoff compared to tile drainage (King et al., 2014). Therefore, as tile drainage increased, the overland flows carrying a higher concentration of DRP would decrease, resulting in an overall decrease in DRP at edge-of-field and downstream.

Fertilizer

Fertilizer application rates were important drivers of nutrient load changes. While the shape of curves changed minimally, the magnitude of loads and concentrations did show decreases across the management scenarios. Rates of fertilizer application are a key determinant of the amount of fertilizer available for both plant consumption and offsite transport. Using the 2005-2015 application rate in the FERT scenario resulted in reduced P fertilizer and increased N fertilizer applications and corresponding decreases in P load and increases in N load in the early part of the 40-year simulation. While this scenario focused only on the impacts of fertilizer rates and not application method or timing, it highlights the importance of fertilizer rate applications in driving nutrient loads and concentrations.

Cropping systems

Setting the relative abundance of crops grown to that of the 2005-2015 period was the least impactful scenario for nutrients, despite its suspected importance in driving some of the changing trends in the region (Smith et al., 2015). The most evident impact of this change was increased N in the CROP scenario due to a larger abundance of N-fixing soybean. Relative row crop abundance may have less impact on nutrient pollution and management practices surrounding changing cropping systems (e.g. tillage management for different styles of crop rotations and watershed wide fertilizer application to meet crop needs) play a more substantial role.

Other than tillage, the P focus practices showed an inverse impact on P and N contributions. Increases in N in the Western Lake Erie Basin have been linked to a rise in toxicity in algal blooms in the region (Jankowiak et al., 2019; Newell et al., 2019). The ability to impact N components through management sends a promising message that under an uncertain climate, there is potential to manage this nutrient. However, efforts need to be made in management practices specifically design for N management, as current P focused practices have shown to result in increased N component contributions, which may in turn lead to smaller, but likely more toxic blooms.

Overall, our findings show that each management change that occurred over time impacted nutrient export. The most pronounced impact was that of changing tillage practices on P loading. Of greatest significance may be the tradeoff among P forms corresponding to reduction of tillage in the watershed, which simultaneously drove the greatest reduction in TP and greatest increase in DRP export to waterways. No-tillage has been encouraged in the watershed for both soil health and water quality benefits, and we found these benefits in reduced sediment-bound P and N to be appreciable. And yet with growing awareness of the role of DRP in the eutrophication of Lake Erie, it is timely to consider ways to lessen the stratification of P at the surface layers of the soil that may be responsible for elevated losses of DRP in no-till agriculture.

Future work

Simulating long-term trends can provide key understanding for effective management. Such analyses also build confidence in using a model outside of the period for which it was developed (e.g. future climate change impact assessments), provide better understanding of dominant processes, and aid in identifying model uncertainties. This work identified two key drivers of model uncertainty: model stationarity and data availability.

Model rigidity is a key challenge in the SWAT2012 model. While SWAT is regarded as effective for modeling long-term impacts of agricultural management practices (Arabi et al., 2008), it does not allow for dynamically changing all parameters affected by management practices such as biological mixing associated with reduced tillage and drainage coefficient and spacing. Because there was no option to change key parameters over time, we conducted piecewise analysis of consecutive 5-year model runs. We suggest future work in developing the model so that it can handle these dynamic parameter changes over time as SWAT models are increasingly being used in longer-term scenario assessments, especially in future climates, where maintaining static management practices and system representation is unrealistic.

Data limitations are often a key challenge, especially for longer-term historical analyses. While our scenarios replicated some facets of the observed trends, we were unable to match the timing of the DRP trend changes as well as the 2010-2020 curve for TP and DRP. Lack of robust information on historic management trends may preclude capturing those phase shifts. Our assumption of a linear change in tile intensity is an example of how required simplified management implementation could have smoothed a key transition and in turn may have resulted in smoothed modeled trends. The discrepancy between modeled and observed long term trends during the 2010-2020 period for phosphorus could represent a change in management practices in the region that was not included, such as animal numbers which have increased in the region since 2015 (Bahe et al., 2022), or the impacts of legacy P in streams which is not well represented in the SWAT model (White et al., 2014). Future study in this area could include gathering more refined data on land management for analyzing the water quality impact of specific management actions over time and space.

Conclusions

Lake Erie's Western Basin has garnered significant policy attention as the size and toxicity of algal blooms has grown despite the continued adoption of conservation and nutrient management practices. Using a hydrologic watershed-scale model of the Maumee River Watershed, we sought to replicate historical trends of nutrient export, understand the roles of agricultural management practices and climate in driving these trends, and specifically identify management practices of greatest influence. Key findings include:

- The SWAT model was able to replicate the general shape of historical trends in discharge and N and P loading and concentrations.
- Changes in climate over the 1980-2019 period were the dominant driver of trends in discharge.
- Trends in TP and DRP concentrations, as well as TP load, were predominantly driven by changing land management, while DRP

loads were controlled by both climate and management.

- Trends in TN and NO_3 concentrations and TN loads were primarily climate-driven, while NO_3 loads were primarily management-driven.
- Among the land management changes simulated, the rising adoption of minimal- and no-tillage had the greatest impact on nutrient trends, leading to reductions in TP, TN, and NO_3, and increases in DRP.
- Historical changes in fertilizer application rates also drove nutrient trends, with positive relationships between nutrient application rates and resultant losses.

Our finding that management has had a substantial impact on nutrient trends highlights the importance of continued focus on land management strategies in the face of a changing climate. Differing patterns in N and P controlled by climate and land management highlight the need to examine both nutrients simultaneously when developing management plans, as both contribute to the eutrophication issues plaguing Lake Erie. We found certain management actions showed clear tradeoffs among nutrient forms, in particular the move away from continuous tillage driving increases in DRP despite overall decreases in TP and N. The use of models like this one to assess progress towards nutrient loading targets can help managers and policymakers anticipate water quality outcomes into the future and enable adaptive management to occur on shorter timescales than seen in Lake Erie's past.

Supplementary material

Supplementary material is available for this manuscript online through the publisher's website. The supplementary information contains detailed information on Apostel et al. (2021) MRW SWAT model development and set up including assumptions, model calibration and validation details, as well as detailed information regarding historical data collection and assumptions.

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