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Climate Change and Nutrient Loading in the Western Lake Erie Basin: Warming Can Counteract a Wetter Future

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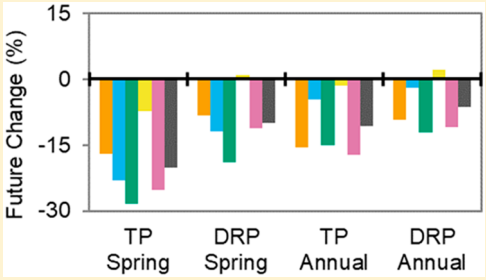
Supporting Information

ABSTRACT: In the past 20 years, Lake Erie has experienced a resurgence of harmful algal blooms and hypoxia driven by increased nutrient loading from its agriculturally dominated watersheds. The increase in phosphorus loading, specifically the dissolved reactive portion, has been attributed to a combination of changing climate and agricultural management. While many management practices and strategies have been identified to reduce phosphorus loads, the impacts of future climate remain uncertain. This is particularly the case for the Great Lakes region because many global climate models do not accurately represent the land−lake interactions that govern regional climate. For this study, we used midcentury (2046−2065) climate projections from one global model and four regional dynamically downscaled models as drivers for the Soil and Water Assessment Tool configured for the Maumee River watershed, the source of almost 50% of Lake Erie's Western Basin phosphorus load. Our findings suggest that future warming may lead to less nutrient runoff due to increased evapotranspiration and decreased snowfall, despite projected moderate increases in intensity and overall amount of precipitation. Results highlight the benefits of considering multiple environmental drivers in determining the fate of nutrients in the environment and demonstrate a need to improve approaches for climate change assessment using watershed models.



INTRODUCTION

In response to increased harmful algal blooms (HABs), low bottom-water oxygen concentrations (hypoxia), and increased nearshore algae growth,[1−4] in 2012, the United States and Canada agreed to a 40% reduction in phosphorus loads to Lake Erie from 2008 levels.[5] State and provincial policymakers set 2025 as the year for reaching the 40% phosphorus reduction goal, but continued blooms in Western Lake Erie suggest that meeting these goals is an evolving challenge. To combat persistent HABs in western Lake Erie, the Maumee River watershed has an additional target to reduce the March−July total phosphorus (TP) and dissolved reactive phosphorus (DRP) loads by the same percent. In recognition that it may not be possible to meet that target in years with exceptionally high rainfall, this target is to be met 9 out of every 10 years. This adds an additional test for models of the load responses to actions in the watershed. The Maumee River watershed, which dominates the Western Lake Erie watershed in areal extent, contributes almost 50% of Lake Erie's Western Basin phosphorus load and has been specifically identified as the primary driver of the lake's HABs.[2,6−8] Along with the Detroit River, it also contributes to low bottom-water dissolved oxygen concentration (hypoxia) in the Central Basin.[9,10]

An ensemble of models using the Soil and Water Assessment Tool (SWAT), a water quality and quantity watershed model, identified potential pathways to that 40% reduction goal for the Maumee River watershed.[11] Model results suggested that while there are several pathways to achieve the target loads, any successful pathway will require large-scale implementation of multiple agricultural conservation practices. This work only looked at meeting the target on average, so reaching the targets

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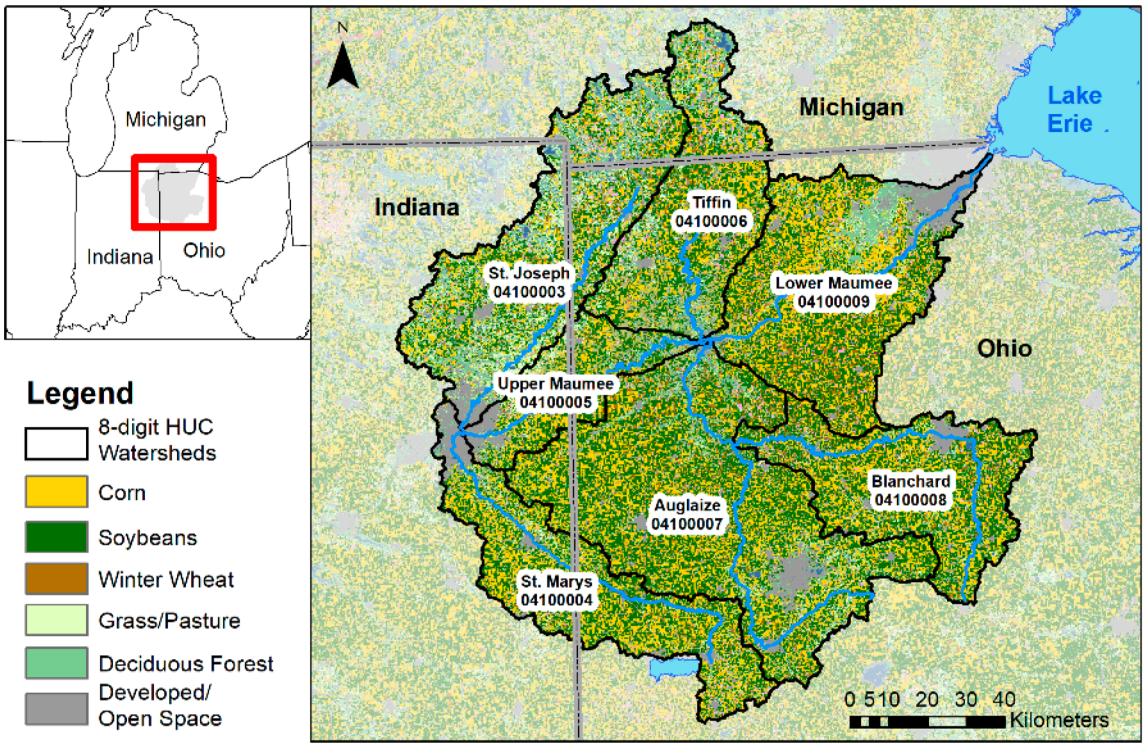

Figure 1. Location and land-use of the Maumee River watershed. Land-use data are from the 2015 National Agricultural Statistics Service Cropland Data Layer; only the top six land-use categories are shown.

would be even more difficult than they suggest. However, that analysis did not account for potential impacts of climate change, a driver that will likely be significant. For example, Daloglu et al.[12] showed that the interaction of climate change and agricultural practices over the last half of the 20th century was a potential cause of the increasing fraction of the phosphorus load in the dissolved form, and through riverine analysis on Lake Erie tributaries, Jarvie et al.[13] estimated increased DRP loads in the early 2000s were due to both increased runoff and increased DRP delivery rates. Bosch et al.[14] suggested that a warmer climate with wetter springs will increase phosphorus loads to Lake Erie.

However, none of these studies directly used future climate model data to assess the impacts of a changing climate on nutrient runoff. Rather, these studies utilized analyses of historical data or altered observed climate data rather than using climate model output directly in the SWAT model. A recent continental-scale study[15] reported that future precipitation increases would increase nitrogen loads to the coasts and Great Lakes using climate model outputs to drive an empirically based model. However, that study only included the effects of precipitation alone and did not consider impacts to phosphorus loads. Another study of the contiguous U.S. showed primarily decreases in nitrogen yield using the SPAtially Referenced Regression on Watershed attributes model and 14 global climate models.[16] While these large-scale studies can give some idea of future changes, Reichwaldt and Ghadouani[17] note that the relationship between rainfall patterns and harmful algal blooms is complex and strongly dependent on site dynamics. A broad-scale study of multiple U.S. watersheds, including the Maumee, used climate model precipitation and temperature projections to drive watershed models and found changes in TP loads ranging from a 4.6% decrease to a 38% increase.[18] For the Maumee watershed specifically, they predicted a slight increase (1.3%) in TP loads due to increased urbanization alone and a total of ∼25% increase due to urbanization and mid-21st century climate combined.

More recent studies focused specifically on the Maumee River report of varying effects of climate change on runoff and nutrient loads. Using observed historical climate data with a change factor developed from global climate models, Verma et al.[19] predicted that Maumee River nutrient loads would decrease by midcentury (2045−2055) and increase by the end of the century (2089−2099). Using a perturbation approach with the weather generator in SWAT, Cousino et al.[20] reported reduced annual sediment loads by midcentury (2046−2065) under all representative concentration pathway (RCP) scenarios and reported an increase in sediment load only for end-of-century (2080−2099) climate under the RCP8.5 scenario, though they found seasonal variability. Driving SWAT with an ensemble of 15 global climate models that were bias-corrected at the monthly scale and downscaled to higher temporal resolutions, Culbertson et al.[21] found that phosphorus loads may decrease both early and late in the century due to decreased surface runoff in the winter and increased plant uptake. However, they projected an increase in phosphorus loading if fertilizer application more closely matched the increased plant uptake from heightened CO_2 levels.

The comparison of SWAT-based climate studies for the Maumee watershed is complicated because studies use different approaches to integrate climate model output into SWAT (SI Table S-1). However, all studies to date either do not directly incorporate climate model data into SWAT[14,18−20] or they used global models that may not simulate the regional climate of the Great Lakes region well.[21] Assessing the impact of climate change in Great Lakes watersheds is particularly

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Table 1. Climate Model Sources and Details[a]

ID in Paper	Model	Model Category	Emissions Scenario	Grid Cell Resolution (km)	Annual change between future (2046−2065) and historical (1980−1999) time periods in the Maumee River watershed	
					ΔTemp (°C)	ΔPrecip. (%)
CESM1	CESM1-CAM5	Global model	CMIP5 - RCP 8.5	∼200	3.53	6
CRCM	CRCM-CGCM3	Regional dynamically downscaled model - NARCCAP	CMIP3 - A2	50	2.73	8
RCM3-GFDL	RCM3-GFDL	Regional dynamically downscaled model - NARCCAP	CMIP3 - A2	50	2.43	1
RCM4-GFDL	RCM4-GFDL	Regional dynamically downscaled model	CMIP5 - RCP 8.5	25	2.19	1
RCM4-Had	RCM4-HadGEM	Regional dynamically downscaled model	CMIP5 - RCP 8.5	25	3.09	11

[a]See Basile et al.[23] for more information.

difficult because the lakes regulate regional climate,[22] and their role on the physical climate is not represented in most climate models.[23] Herein, we add to the existing literature on climate change in the Maumee to explore the potential influence of climate change on future phosphorus loads as well as the feasibility of using unaltered climate data to drive the SWAT model from different, mostly regional, climate models that have been shown to work well in the region. While the primary focus of this study is not on a comparison of methods of climate model integration into watershed models, this is one of the first studies, to our knowledge, to apply this integration and present results in terms of the impact on nutrient loading.

■ MATERIALS AND METHODS

Study Area. The Maumee River watershed occupies over 17000 km^2 in northwest Ohio, northeast Indiana, and southeast Michigan and covers seven 8-digit hydrologic unit code (HUC) areas (Figure 1). The land is characterized by low-sloping to flat topography and heavy, clayey soils with poor natural drainage. Productive agriculture has only been possible through widespread installation of subsurface drainage, commonly referred to as "tile drains". Row crop agriculture dominates this watershed (∼70%) consisting primarily of corn, soybean, and winter wheat in rotation.

Model Descriptions. *SWAT.* SWAT is a semidistributed hydrologic and water quality model.[24,25] Within SWAT, data on land use, land management, soils, and topography are used to characterize the watershed, and the model is driven at a daily time-scale with meteorological inputs of temperature, precipitation, solar radiation, relative humidity, and wind speed. The model simulates crop/plant growth, hydrologic processes, and nutrient and sediment dynamics across the landscape and in streams and rivers. SWAT has been widely used across a variety of climatic zones and land types, though it is especially suited to agricultural watersheds.[26]

We applied a previously developed and calibrated SWAT model of the watershed. This model was previously calibrated for 2001−2005, validated for 2006−2010, and further verified for 1981−2010.[24] Agricultural croplands were simulated as rotations of corn and soybean, with 45% of cropland including winter wheat in the rotation. Fertilizer applications were based on county-level fertilizer sales;[27] manure applications were based on reported county-level animal abundance,[28] and tillage was based on surveys from the Conservation Technology Innovation Center database.[29] The model was calibrated manually to ensure reliable estimates of streamflow and loading of TP, DRP, sediment, and total nitrogen (TN) near the watershed outlet. The overall model performance was very good based on common model evaluation criteria and the monthly and daily scale.[30] The percent of streamflow and loads from subsurface drains was within observed ranges, and crop yields were similar to reported values. For more details on the model development, see the Supporting Information, Tables S-2 and S-3, and Kalcic et al.[24]

Climate Models and Model Integration. We assembled a 5-member ensemble of climate models (Table 1), including one global model from the Intergovernmental Panel on Climate Change Climate Model Intercomparison Project version 5 (IPCC CMIP5:[31] CESM1-CAM5), two regional models from the North American Regional Climate Change Assessment Program that are dynamically downscaled from CMIP version 3 (NARCCAP:[32] CRCM-CGCM3, RCM3-GFDL), and two regional models dynamically downscaled from CMIP5 (RCM4-GFDL, RCM4-HadGEM).[33] We chose these five models on the basis of their performance against historical temperature and precipitation data in the Great Lakes region[23] and the ability of the regional models to represent the lakes and capture land−lake interactions.[33] Future climate is simulated using the emissions projections from the RCP 8.5 for CMIP5 models and the A2 scenario for CMIP3 models, both of which represent a high-emissions future and would likely drive the strongest climate response.

To incorporate climate model output in SWAT, we used temperature (°C; daily min and max) and precipitation (mm/day) projections from the climate models and simulated the other key weather inputs (solar radiation, relative humidity, wind speed) using SWAT's weather generator. Solid-phase precipitation was calculated based on SWAT temperature parameters. Like recently published studies simulating climate change in SWAT,[19,20] we did not alter the carbon dioxide concentrations for future scenarios because of known limitations in associated model algorithms that do not fully capture the effects of increased carbon dioxide on plant processes. For example, in their paper on future climate in the Maumee River watershed given changing carbon dioxide concentrations, Culbertson et al.[21] highlight as a key limitation of their work the uncertainty regarding the impacts of carbon dioxide on crops. This uncertainty is a general research need, but it is a known problem in the SWAT model, as its algorithms were developed from enclosure studies that have been shown to considerably overestimate the increase in crop yields due to elevated carbon dioxide levels.[21] Additionally, we

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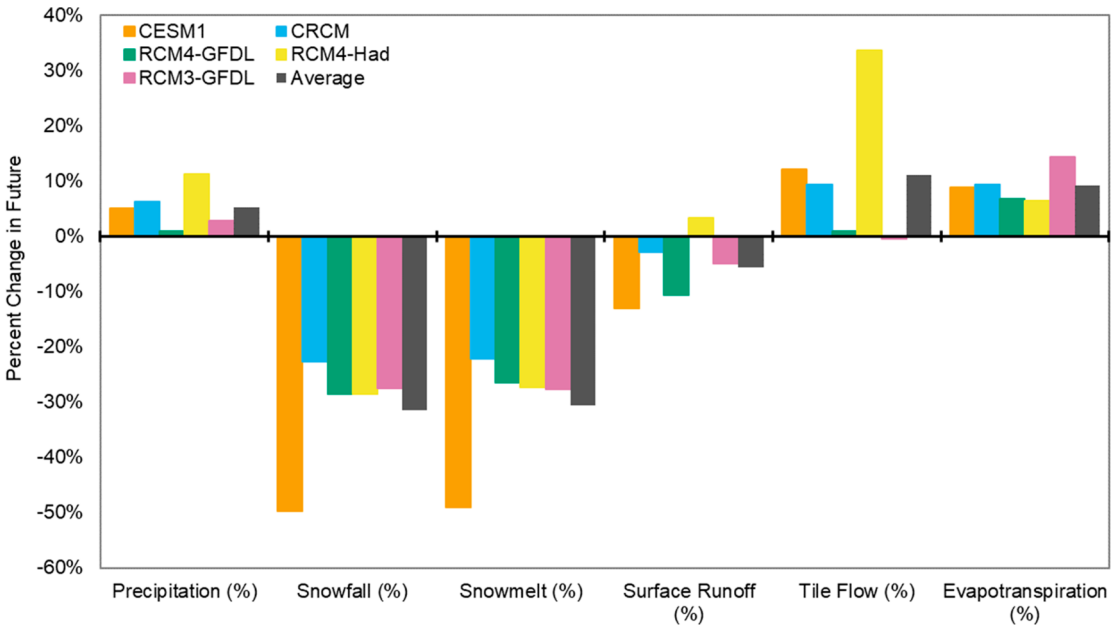

Figure 2. Annual average changes (%) in hydrologic water budget components between SWAT simulations driven by historical climate (1980−1999) and midcentury future climate (2046−2065). For magnitude plots see Supporting Information, Figure S-6.

did not simulate changing management actions in response to climate change, such as potential changes in the timing of planting and harvest, the timing and amounts of nutrient applications, or the types of crops grown by midcentury. Our crop management files were developed using scheduling by day to ensure these management practices did not change. We drove the SWAT model with midcentury predicted climate (2046−2065) and with historical period climate (1980−1999) and examined changes in hydrology and nutrient processes at the watershed scale.

Although bias between the five climate models and historical observations exists for both temperature and precipitation (see SI, Table S-4), we did not perform bias-correction on the input climate data but rather incorporated the unaltered climate model data directly into SWAT. While bias correction methods are a common approach to ensure that the climate model predictions reproduce observed historical data, it is uncertain if the present-day biases based on historical conditions will apply under a future climate.[34] Chen et al.[35] found that bias correction methods may increase uncertainty in future hydrology predictions. The assumption of stationarity of these statistical relationships has been shown to be particularly inaccurate when applied to precipitation.[36] The bias correcting of climate models also decouples the interactive effects of temperature and precipitation[37] and may result in inconsistent responses that are not representative of the physical climate system. Additionally, it may result in the models becoming more alike, artificially reducing the range of predictions expected from different climate models. For example, Xu et al.[38] demonstrated that the interdependency of temperature and precipitation creates a precipitation threshold below which warming temperature is the primary driver of hydrology and above which precipitation is the primary driver. Therefore, we apply the unaltered, historical and future climate model data directly to SWAT and evaluate the percent differences between historical and future simulations to account for climate model bias. We compare our results to previous studies and discuss the bias of the individual models and how this impacts future simulated changes and the multimodel mean. Finally, given that we are using models that have been shown to represent the regional climate well, we provide all climate model results individually as well as in a multimodel mean as each model can be considered one representation of the possible future.

RESULTS

Hydrologic Futures. All five SWAT-climate model combinations projected increased precipitation, decreased snowfall, and increased evapotranspiration (Figure 2) by midcentury, compared to historical data. Similar patterns in precipitation and temperature were seen in a recent ensemble study of 10 global climate models selected for their ability to represent the Midwest and Great Lake regional climate well.[39] RCM4-GFDL projects the smallest annual precipitation increase (+1%) and RCM4-Had projects the largest (+11%). However, increased total precipitation was accompanied by a 24−50% annual decrease in snowfall as simulated in SWAT (Figure 2), representing a significant change in the phase of the incoming precipitation, which has direct effects on the quantity and timing of nutrient loss. During March−July, the season when the phosphorus load is especially important for HAB development, the models simulated an average of 65% decrease in snowfall, ranging from 54%−93% among models (see SI, Tables S-5−S-9). The increased precipitation was mitigated to some extent by 7%−12% increases in evapotranspiration, likely due to warming that ranged from 2.2 °C (RCM4-GFDL) to 3.5 °C (CESM1).

Estimates of subsurface drainage (tile flow) from SWAT either stayed the same or increased (Figure 2), with significant variation among models, ranging from no change (RCM3-GFDL) to a 30% increase (RCM4-Had). The large increase in tile flow with RCM4-Had is likely due to the projected 11% increase in precipitation, combined with a slight cool bias in the summer resulting in a dampened increase in evapotranspiration. Surface runoff is projected to decrease in all but the RCM4-Had model. The projected decrease was especially pronounced in March−July, when the change in ensemble

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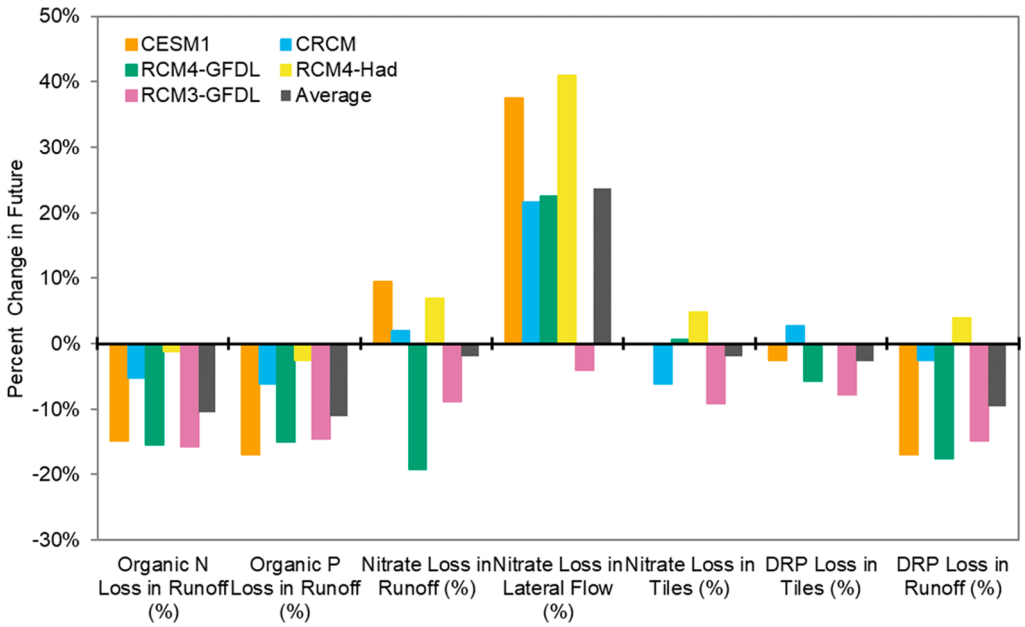

Figure 3. Annual average changes (%) in nutrient loss pathways between SWAT simulations driven by historical climate (1980−1999) and midcentury future climate (2046−2065).

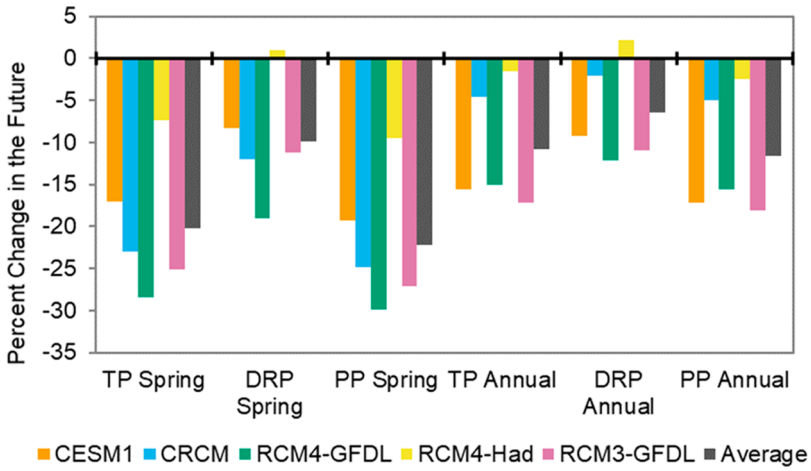

Figure 4. March−July and annual average percent change (%) in phosphorus loads near the outlet of the Maumee River to Lake Erie between SWAT simulations driven by historical climate (1980−1999) and midcentury future climate (2046−2065).

average runoff was −13%, with individual models ranging from −35% to +4%. Peak runoff shifted to an earlier month for all of the regional models but not with the global CESM1 model.

Nutrient Futures. Across the five climate models, N loading showed more variability than phosphorus (Figure 3). On average, models showed decreased nitrate loading through tiles (average: −2%; range: −9% to +3%) and decreased organic N (average: −11%; range: −15% to −1%) and nitrate (average: −2%; range: −19% to +10%) loading through surface runoff. While nitrate lost in surface runoff varied more among the models, its magnitude is much less than that of tile flow (see SI, Figure S-6 to S-8 for corresponding magnitude change plots). While lateral N flows show the largest percent change, they only account for a small quantity of N flows in the system (see SI, Figure S-8). Organic phosphorus showed more consistent decreases across climate models (average: −11%; range: −17% to −3%); however, the amount of phosphorus lost through tiles (average: −3%; range: −8% to +3%) and runoff (average: −10%; range: −18% to 4%) was more variable. Interestingly, for the RCM4-Had model, while tile flow increased significantly (33%), the nitrate and DRP lost through tiles did not have a similarly large increase (+5% and 0% change, respectively). This may be due to the fact that the RCM4-Had model was the only model that increased surface runoff, which may reduce the amount of nutrients available to leach through the soil and into the tiles. It may also be due to increased plant uptake of these more plant-available forms of nutrients (see SI, Figure S-9, for plant uptake figures).

Despite the variability in phosphorus dynamics at the landscape scale, changes in loads near the watershed outlet were consistent across climate models: TP loads are projected to decrease both in March−July (−20%) and annually (−11%; Figure 4) and, with the exception of RCM4-Had, DRP loading is also expected to decrease in March−July (−10%) and annually (−6%) by midcentury. As described above, input from RCM4-Had resulted in much greater increases in tile flow when compared to the other models; this may explain why the RCM-Had model differs from the other four models in future

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DRP loading projections. Given that DRP and particulate phosphorus (PP) have varying strategies for management,[13] we calculated PP based on Baker et al.[40] as TP minus DRP (Figure 4). While this may be a slight overestimate of PP, it can help improve discussions around P management. At the watershed level, our modeling suggests that while both PP and DRP show decreases overall, the most significant decreases occur in PP.

We also examined the influence of climate change on the timing of phosphorus loading (see SI, Figure S-5, for monthly results) because March−July loads are the most critical for HAB development in Western Lake Erie. For TP, the CESM1 and RCM3-GFDL models produce future phosphorus loading patterns similar to the past, except for sharper decreases in March−July loads, specifically in March for CESM1 and March−April for RCM3-GFDL. The other three models (CRCM, RCM4-GFDL, RCM4-HadGEM) produced similar decreases in March−July loads but were accompanied by more marked load increases in winter, specifically in December−February, January−February, and February, respectively. This winter increase may be due to the fact that projected winter precipitation changes dramatically from snow to rain, increasing wintertime runoff and decreasing snowpack.

■ DISCUSSION

Unlike most previous studies on future climate impacts in the Maumee River Watershed, we used five climate models on the basis of their ability to capture the dynamics of the weather patterns in the Western Lake Erie Basin watersheds and we input their outputs to SWAT without alteration. This method preserves the simulated relationships between temperature and precipitation in the climate models, avoiding issues with stochasticity assumptions between present and future climates. Our findings suggest that because of climate warming, Maumee River phosphorus loads may actually decrease from the present by the midcentury because increases in precipitation are mitigated by warmer temperatures that increase evapotranspiration and changes snowfall to rain. These findings are counter to those found by Johnson et al.[18] who found increases in TP loads but directionally similar to Verma et al.[19] and Culbertson et al.[21] who projected decreased Maumee River phosphorus loads in the midcentury (2045−2055; 2040−2069). Cousino et al.[20] reported reduced midcentury (2046−2065) sediment loads across all emissions scenarios as well, though they did not simulate phosphorus. While our results agree with Culbertson et al.[21] in the direction of change, their study attributed the reduced load to increased plant phosphorus uptake spurred by increasing CO_2 concentration. Our model did not account for changing CO_2 concentrations, and we suggest that decreases in snowfall and higher evapotranspiration are the dominant drivers of the simulated decreased loads. Given that plant phosphorus uptake increases with increased CO_2 concentration,[21] it is likely that if we included this effect in the model, plant phosphorus uptake would increase, reducing phosphorus available for loss and subsequently decreasing simulated phosphorus loads even further.

One difficulty in comparing these results to other regional studies is that climate model output was used differently across watershed models. Most studies in this region only applied a change factor to observed data,[14,18,19] thus simulating future climate indirectly and potentially not accounting for feedbacks in the climate system. While Culbertson et al.[21] simulated future climate model output after downscaling and bias correction, we directly incorporated the unaltered climate model output into SWAT to fully capture the changes between historical and future scenarios and to maintain the relationships between temperature and precipitation.

To further understand the impact the direct input approach could have on our results, we applied the common "delta change" method to correct bias in modeled temperature (both in the historical and future simulations) for comparison (temperature bias was greater than precipitation bias). The results (provided in the SI, Figures S-2 and S-3) show that bias correction can make a substantial impact on the watershed model outputs, particularly nutrient loads, for certain climate models, primarily those with large temperature biases that affect crop growth. Bias correction altered nutrient loading primarily through changes to crop yields in both historical and future simulations (SI, Figure S-3). The climate models displaying the greatest reductions in future nutrient loading prior to bias correction (RCM4-GFDL and RCM3-GFDL) produced depressed historical crop yields and considerable increases in future crop yields. These increases, which are reflected in increased nutrient use by plants, result in less nutrients available for loading to the lake (see SI, Figure S-9). When driven with bias-corrected climate model output, crop yields showed less of a change from present to future time periods. The direction of change across the five bias-corrected models still shows decreasing nutrient loads, yet the reduction is smaller with less agreement among models. This, along with the variation in results (e.g., direct integration vs bias correction) from the methods used for climate model integration into watershed models in this region, highlights the need for an improved understanding of how climate integration methods affect nutrient load estimates. While method comparisons like this have been completed in many studies to examine the impact on hydrological change,[41] to our knowledge, this is the first study to demonstrate the potential impact on nutrient loads, but a more focused, methodological study is still needed.[37]

Recent studies suggest that while there are several pathways to achieve the 40% load reduction targets for Lake Erie, any successful pathway will require large-scale implementation of multiple practices.[11,42] Our results suggest that a warmer climate may make reaching those targets less daunting, at least in the midcentury, though studies with similar results found that nutrient loads could increase in late-century. Our analysis (Figure 4) indicates that on average, across the climate model inputs, March−July TP and DRP loads would decline by 20% and 10%, respectively; while annual TP and DRP loads would decrease by 11% and 6%, respectively. The majority of this decrease is due to reductions in particulate P, rather than DRP which has implications for bioavailability.[40] It is difficult to compare these numbers with absolute values of loading targets given bias in the climate data, but the identification of direction of change relative to a baseline can help in understanding potential future impacts.

While decreases in nutrient loading induced by a warming climate may make it easier to reach the 40% load reduction targets, the 40% reduction targets were based on load−response curves developed from models that did not account for the effects of climate change on lake dynamics.[7] Increasing temperatures and longer periods of lake stratification can lead to an earlier and longer HAB growing season, as well as increased production and decomposition of organic matter that promote larger regions of hypoxic waters. For example,

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Rusinski et al.[9] showed that variation in meteorology (via lake thermal stratification) explained almost nine times as much interannual variability in hypoxic area compared to variation in phosphorus loading, and that deeper stratification caused by warmer, longer summers led to larger hypoxic areas. In addition to considering in-lake dynamics, further work should evaluate the impact specifically of extreme events, which have been shown to increase in the future. Given that there was bias in our climate model data, our results are presented as averages. To advance scientific progress and better inform management, the interactions between climate and land management, as well as climate impacts within the lake, must be better evaluated to assess future changes in HABs and hypoxia in Lake Erie.[22] Overall, this work has demonstrated that the variability introduced by climate models not suited for a given region, as well as the methodological approach for integrating this data within watershed models, must be considered for future management strategies that desire to incorporate the impacts of climate change.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.9b01274.

Detailed summary of existing future climate model simulations in the Maumee River watershed, details on the development of the SWAT model used in this study, demonstration of the impact of bias correction on model results, monthly SWAT results, results by magnitude instead of percentage, and data on simulated plant uptake (PDF)

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The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript.

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Notes

The authors declare no competing financial interest.

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■ ABBREVIATIONS

CAM5	Community Atmosphere Model (version 5.0)
CESM1	Community Earth System Model (1.0 public release)
CGCM3	Canadian Global Circulation Model Version 3
CMIP	Coupled Model Intercomparison Project
CO_2	carbon dioxide
CRCM	Canadian Regional Climate Model
DRP	dissolved reactive phosphorus
GFDL	Geophysical Fluid Dynamics Laboratory
HAB	harmful algal bloom
HadGEM	Hadley Global Environmental Model
HUC	hydrologic unit code
IPCC	Intergovernmental Panel on Climate Change
N	nitrogen
RCM3	Regional Climate Model version 3
RCM4	Regional Climate Model version 4
RCP	representative concentration pathways
SWAT	Soil and Water Assessment Tool
TN	total nitrogen
TP	total phosphorus

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