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Climate Change-Legacy Phosphorus Synergy Hinders Lake Response to Aggressive Water Policy Targets

Asim Zia[1,2,3,4], Andrew W. Schroth[5,6], Jory S. Hecht[7,8], Peter Isles[6,9], Patrick J. Clemins[2,7], Scott Turnbull[7], Patrick Bitterman[4,7,10], Yushio Tsai[7,11], Ibrahim N. Mohammed[7,12], Gabriela Bucini[7,13], Elizbeth M. B. Doran[4,7], Christopher Koliba[1,4], Arne Bomblies[4,7,14], Brian Beckage[2,4,15], Jonathan Winter[16], Elizabeth C. Adair[4,6], Donna M. Rizzo[2,4,14], William Gibson[17], and George Pinder[14]

[1]Department of Community Development & Applied Economics, University of Vermont, Burlington, VT, USA, [2]Department of Computer Science, University of Vermont, Burlington, VT, USA, [3]Institute for Environmental Diplomacy & Security, University of Vermont, Burlington, VT, USA, [4]Gund Institute for Environment, University of Vermont, Burlington, VT, USA, [5]Department of Geology, University of Vermont, Burlington, VT, USA, [6]Rubenstein School of Environment & Natural Resources, University of Vermont, Burlington, VT, USA, [7]Vermont EPSCoR, University of Vermont, Burlington, VT, USA, [8]Integrated Modeling and Prediction Division, Water Resources Mission Area, U.S. Geological Survey, Reston, VT, USA, [9]Department of Aquatic Ecology, Swiss Federal Institute of Aquatic Sciences and Technology, Dübendorf, Switzerland, [10]School of Global Integrative Studies, University of Nebraska-Lincoln, Lincoln, NE, USA, [11]School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ, USA, [12]Hydrological Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, MD, USA, [13]Department of Plant and Soil Science, University of Vermont, Burlington, VT, USA, [14]Department of Civil and Environmental Engineering, University of Vermont, Burlington, VT, USA, [15]Department of Plant Biology, University of Vermont, Burlington, VT, USA, [16]Department of Geography, Dartmouth College, Burlington, VT, USA, [17]Department of Economics, University of Vermont, Burlington, VT, USA

Key Points:

- A novel model examines the ability of policy targets to meet Water Quality Standards (WQS) in eutrophic lakes under future climate scenarios
- The WQS of 0.025 mg/L total phosphorus in Missisquoi Bay is unlikely to be met by 2035 in all climate scenarios
- Synergies between climate change and legacy nutrients hinder significant reduction in cyanobacteria blooms despite aggressive policy targets

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

A. Zia,
Asim.Zia@uvm.edu

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Author Contributions:

Conceptualization: Asim Zia, Andrew W. Schroth, Christopher Koliba, Arne Bomblies, Brian Beckage, Jonathan Winter, Elizabeth C. Adair, Donna M. Rizzo
Data curation: Patrick J. Clemins, Scott Turnbull
Formal analysis: Asim Zia, Jory S. Hecht, Patrick Bitterman, Yushio Tsai, Ibrahim N. Mohammed
Funding acquisition: Asim Zia, Andrew W. Schroth, Christopher Koliba, Arne Bomblies

Abstract

With mounting scientific evidence demonstrating adverse global climate change (GCC) impacts to water quality, water quality policies, such as the Total Maximum Daily Loads (TMDLs) under the U.S. Clean Water Act, have begun accounting for GCC effects in setting nutrient load-reduction policy targets. These targets generally require nutrient reductions for attaining prescribed water quality standards (WQS) by setting safe levels of nutrient concentrations that curtail potentially harmful cyanobacteria blooms (CyanoHABs). While some governments require WQS to consider climate change, few tools are available to model the complex interactions between climate change and benthic legacy nutrients. We present a novel process-based integrated assessment model (IAM) that examines the extent to which synergistic relationships between GCC and legacy Phosphorus release could compromise the ability of water quality policies to attain established WQS. The IAM is calibrated for simulating the eutrophic Missisquoi Bay and watershed in Lake Champlain (2001–2050). Water quality impacts of seven P-reduction scenarios, including the 64.3% reduction specified under the current TMDL, were examined under 17 GCC scenarios. The TMDL WQS of 0.025 mg/L total phosphorus is unlikely to be met by 2035 under the mandated 64.3% reduction for all GCC scenarios. IAM simulations show that the frequency and severity of summer CyanoHABs increased or minimally decreased under most climate and nutrient reduction scenarios. By harnessing IAMs that couple complex process-based simulation models, the management of water quality in freshwater lakes can become more adaptive through explicit accounting of GCC effects on both the external and internal sources of nutrients.

Plain Language Summary

Water quality policies for freshwater systems generally do not consider synergies between legacy benthic nutrients and climate change. While some governments require water quality targets to consider climate change, few tools are available to model the complex interactions between climate change and benthic legacy nutrients. We present a novel integrated assessment model (IAM) that simulates phosphorus and potentially harmful cyanobacteria bloom dynamics in Missisquoi Bay of Lake Champlain under alternate nutrient reduction and climate change scenarios. Results illustrate biophysical and ecological challenges associated with meeting water quality standards and suppressing harmful cyanobacteria blooms due to warming water temperatures interacting with legacy pools of benthic nutrients. IAMs can inform policy for considering synergies between climate change and legacy nutrients to maintain or improve future water quality.

Investigation: Asim Zia, Andrew W. Schroth
Methodology: Asim Zia, Andrew W. Schroth, Jory S. Hecht, Patrick J. Clemins
Project Administration: Asim Zia, Andrew W. Schroth, Christopher Koliba, Arne Bomblies
Resources: Asim Zia, Andrew W. Schroth
Software: Asim Zia, Jory S. Hecht, Patrick J. Clemins, Scott Turnbull, Yushio Tsai, Ibrahim N. Mohammed, Gabriela Bucini, Elizbeth M. B. Doran, Brian Beckage, Jonathan Winter
Supervision: Asim Zia, Andrew W. Schroth, Patrick J. Clemins, Christopher Koliba, Arne Bomblies, Brian Beckage, Jonathan Winter, Elizabeth C. Adair, Donna M. Rizzo
Validation: Asim Zia, Jory S. Hecht, Patrick J. Clemins, Scott Turnbull, Patrick Bitterman, Yushio Tsai, Ibrahim N. Mohammed
Visualization: Jory S. Hecht, Patrick J. Clemins, Scott Turnbull, Patrick Bitterman, Gabriela Bucini
Writing – original draft: Asim Zia, Andrew W. Schroth, Jory S. Hecht
Writing – review & editing: Asim Zia, Andrew W. Schroth, Jory S. Hecht, Patrick J. Clemins, Scott Turnbull, Patrick Bitterman, Yushio Tsai, Ibrahim N. Mohammed, Gabriela Bucini, Elizbeth M. B. Doran, Christopher Koliba, Arne Bomblies, Brian Beckage, Jonathan Winter, Elizabeth C. Adair, Donna M. Rizzo, William Gibson, George Pinder

1. Introduction

Global climate change (GCC) has been expected and observed to promote eutrophication and potentially harmful cyanobacteria blooms (CyanoHABs) in waterbodies worldwide (Chapra et al., 2017; Michalak et al., 2013; Vorosmarty et al., 2000; Zia et al., 2016). Warmer water temperatures, and, in some cases, greater thermal stratification from reduced wind speeds (Michalak et al., 2013) can (a) increase internal loading from benthic phosphorus (P) and nitrogen (N) pools by promoting manganese, nitrate, and iron reduction around the sediment-water interface (Giles et al., 2016; Jeppesen et al., 2014; Orihel et al., 2017), (b) raise CyanoHAB growth rates (Chapra et al., 2017) and (c) favor the buoyancy regulation abilities of cyanobacteria (Carey et al., 2012). These mechanisms could synergistically elevate nutrient concentrations and increase the frequency and severity of CyanoHABs, particularly in shallow waterbodies where benthic nutrients are potentially bioavailable upon release (Giles et al., 2016; Paerl & Huisman, 2008, 2014). However, while increasing water temperatures and riverine inputs due to climate change have been frequently observed (e.g., Isles et al., 2017 for Lake Champlain), and the mechanisms for climate change synergistically interacting with legacy nutrient reserves are well-established (e.g., Nazarai-Sharabian et al., 2018; Orihel et al., 2017), we are not aware of observational studies that have conclusively demonstrated such an effect over time. This is partly because it can be difficult to disentangle internal versus external drivers of change in highly dynamic shallow lake systems (Schmidt et al., 2019).

Process-based hydrologic models that have the capacity to simulate changes in watershed loading driven by policy, land use and/or climate change, when linked with lake models that have the capacity to simulate internal loading of nutrients due to reducing conditions at the sediment-water interface, are particularly useful integrated tools to disentangle: (a) the role of external versus internal loading in meeting water quality targets under different GCC scenarios, and (b) the capacity of internal loading of legacy P to sustain or enhance cyanobacteria blooms in GCC-induced warmer waters, even when aggressive watershed load reductions are implemented. Indeed, we have developed such an integrated tool (see schematic in Figure 1 and for more detail on P cycling, Figure S4 in Supporting Information S1) that is capable of simulating these processes in the watershed and its receiving water (Hecht et al., 2022; Zia et al., 2016). The integrated tool allows us to disentangle the impacts of internal versus external loading on the system's capacity to meet nutrient concentration-based Water Quality Standards (WQS) under GCC and watershed nutrient reduction scenarios.

As shown in the conceptual integrated process model (Figure 1), the GCC induced changes in air temperature and precipitation directly influence external nutrient loading from the watershed and indirectly influence internal benthic sediment loading of legacy nutrients due to hypoxia driven by changes in sediment oxygen demand. Numerous studies have examined potential GCC impacts on lakes using coupled climate-watershed-lake models (Chapra et al., 2017; Couture et al., 2018; Me et al., 2018; Rolighed et al., 2016; Zia et al., 2016). However, few studies have assessed the synergistic effects of GCC and benthic nutrient loading on CyanoHABs under climate change projections (Couture et al., 2018; Me et al., 2018; Rolighed et al., 2016). Furthermore, studies accounting for this synergy have not investigated policy implications of specific nutrient load reduction targets or bloom suppression goals (Me et al., 2018). Indeed, this conceptually well-established, yet frequently overlooked synergism may have far-reaching implications for water quality regulations under GCC. To address this knowledge gap, we examine the extent to which synergistic relationships between GCC and legacy P release could compromise the ability of existing water quality policies to attain nutrient reduction and bloom management goals in the eutrophic Missisquoi Bay of Lake Champlain (Figure 2).

With mounting scientific evidence demonstrating adverse GCC impacts on water quality, water quality management policies, such as Total Maximum Daily Loads (TMDLs) for impaired waters as mandated by the U.S. Clean Water Act (CWA) and policies described in the European Union (EU)'s Seventh Environment Action Program (EEA, 2018), have begun accounting for GCC effects. In both frameworks, policy targets have been mandated for nutrient (nitrogen and phosphorus) reductions. Section 303(d) of the United States. CWA, for example, requires that states develop TMDLs for listed impaired waters (40 CFR 130.7). While some TMDLs and jurisdictions specify numeric WQS for chlorophyll *a* and other CyanoHAB indicators (Poikane et al., 2014), many water bodies that suffer from CyanoHABs remain regulated using target nutrient concentrations. Overall, policies safeguarding against societal and ecological risks from CyanoHABs in the context of GCC can be designed using one or more of the following metrics as policy targets: (a) reduction in riverine nutrient fluxes; (b) reduction in lake nutrient concentrations; (c) reduction in biological indicators of lake eutrophication (e.g., Chl-a concentrations); (d) reduction in exceedances of thresholds of human and ecological health.

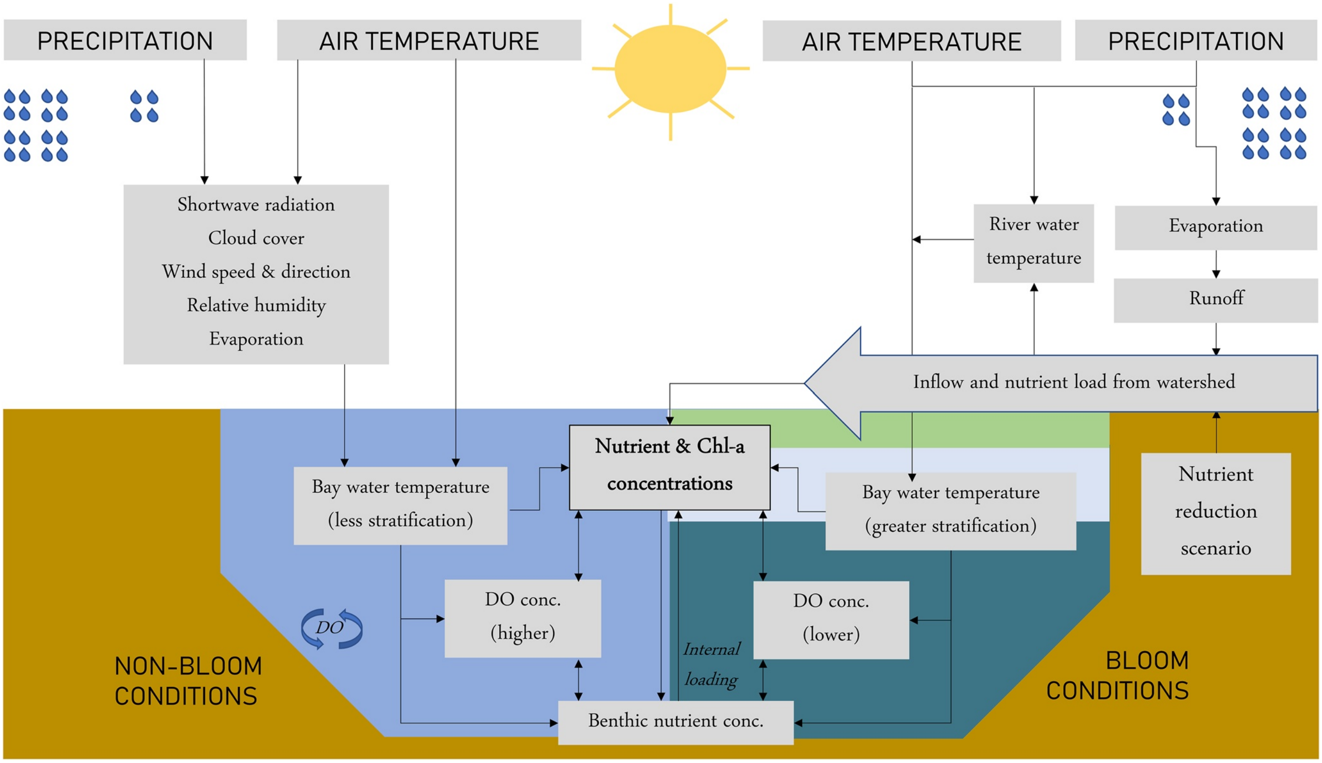

Figure 1. A conceptual integrated process model of Global climate change (GCC) induced changes in air temperature and precipitation that directly influence external nutrient loading from the watershed and indirectly influence internal benthic sediment loading of legacy nutrients due to hypoxia driven by changes in Dissolved Oxygen (DO) concentration and greater duration and intensity of stratification in Bay water temperature. Detailed process of benthic sediment loading for both bloom and non-bloom conditions is shown in Figure S4 in Supporting Information S1. The combined effects of both external and internal nutrient loading increase Chl-a concentrations and sustain CyanoHABs in shallow bays under GCC induced changes in air temperature and precipitation patterns.

Simulation modeling provides a tool for assessing the impacts of GCC scenarios to each of these metrics for configuring policy targets. In the case of watershed loading reduction targets, only the coupling of climate and watershed models is necessary, whereas the other three options based on lake water quality metrics require linking a hydrodynamic-biogeochemical lake model to the climate-watershed modeling sequence. Importantly, these three latter options also can evaluate the impacts of internal nutrient loading from benthic sediments in addition to watershed (external) loading. In this study, we demonstrate the ability of an integrated assessment model to evaluate climate impacts to all four of these metrics in the Missisquoi Bay and Watershed of the Lake Champlain (Figure 2). In turn, this showcases an approach for using integrated modeling to understand how the choice of WQS policy targets can influence policy outcomes aiming to curtail CyanoHABS under different GCC scenarios. Specifically, in the legal and policy context of the eutrophic Missisquoi Bay (Figure 2), this study evaluates the technical feasibility of TMDL-approved nutrient reductions for these four metrics, that is, reductions in riverine nutrient fluxes, lake nutrient concentrations, biological indicators of lake eutrophication and exceedances of thresholds of human and ecological health, that could be considered for setting water quality policy targets under GCC.

2. Materials and Methods

2.1. Study Site and Its Legal and Policy Context

Given the TMDL policy framework established by the United State Environmental Protection Agency (EPA), coupled with the dynamic internal and external drivers of phosphorus loading that are potentially sensitive to different components of GCC (e.g., temperature, wind, and precipitation), Missisquoi Bay is an ideal test bed to implement a process-based IAM linking climate, watershed, and lake models to explore these interactions and their policy implications. This shallow, polymictic bay, situated on the U.S.-Canada border, has been the subject

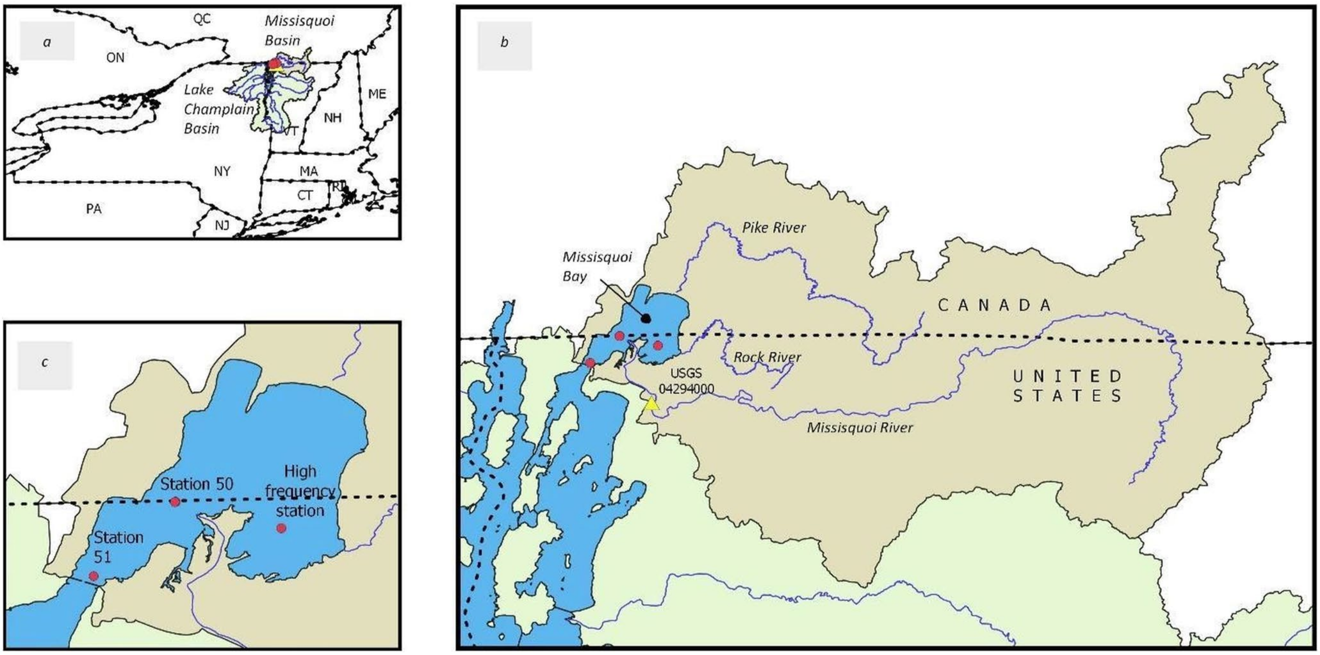

Figure 2. Study area: (a) Missisquoi Bay and its contributing watershed lie within the transboundary Lake Champlain basin that extends across the U.S.-Canada border, (b) Missisquoi Bay inflow and nutrient loads come from three principal tributaries: the Missisquoi, Pike, and Rock Rivers. The integrated model domain encompasses Missisquoi Bay and the Missisquoi River watershed. Inflow and nutrient fluxes from the Pike and Rock Rivers are also accounted for through their statistical relations with observed Missisquoi River inflows and concentrations (see Supporting Information S1) and (c) Missisquoi Bay water-quality monitoring stations used in model development and validation.

of numerous nationally mandated regulations and binational treaties. Its watershed's long history of extensive agricultural land use combined with its high watershed to lake area/volume ratio and shallow depth, average depth at mean annual low water = 2.8 m, with a maximum depth of 4.75 m (Isles et al., 2015), makes it especially vulnerable to high rates of both watershed (external) phosphorus loading as well as internal loading from its benthic sediments. The most current WQS in both the United States and Canada stipulate annual average TP concentration not to exceed 0.025 mg/L. Further, Missisquoi Bay was the only bay for which EPA used GCC projections to set up nutrient reduction targets in the Lake Champlain TMDL.

The EPA has designated Missisquoi Bay as a 303(d) impaired water body, as required by the Clean Water Act. The EPA approved its first TMDL for Lake Champlain in 2002 to address nutrient loading associated with agricultural practices in its basin (Levine et al., 1999). However, these agreements did not improve the water quality of Missisquoi Bay. Annual average (2001–2010) concentrations in the bay were 0.042 ± 0.015 mg/L—or almost double the current 0.025 mg/L target–at Station 50 in the bay, where VT DEC's Lake Champlain Long-Term Monitoring Project (https://dec.vermont.gov/watershed/lakes-ponds/monitor/lake-champlain) has been collecting biweekly samples between May and early November since 1992. In 2008, the Conservation Law Foundation filed a lawsuit against the EPA on four grounds, including "climate change considerations associated with the loading capacity and hydrologic base year" (EPA, 2016, p. 5). A 2010 settlement called for a new TMDL to address these climate change considerations. Then, EPA and VT DEC explicitly considered a suite of 6 GCC scenarios to account for "margin of safety" in setting up TMDL targets (EPA, 2016). The "margin of safety" embedded in the TMDL accounting formula is intended to account for both "known" and "unknown" uncertainties, including changes in both temperature and precipitation induced by GCC.

Ultimately, a revised TMDL was approved in 2016. The EPA allocated a 5% margin of safety and "considered whether it was necessary to increase the MOS above 5% to account for uncertainties related to potential climate change effects. Given that: (a) any increases in [watershed] phosphorus loads to the lake due to climate change from 2040 to 2070 are likely to be modest (i.e., 15%), and (b) the State's implementation strategy includes measures that will mitigate possible increases in loads due to climate change, EPA determined that it was not necessary to increase the MOS above the 5% already identified to account for possible, far-term effects of climate change"

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(EPA, 2016, p. 26). Using this 5% MOS, EPA estimated that TP loading in Missisquoi needs to be reduced by 64.3% compared with the 2001–2010 flow-averaged baseload of 208.6 t/year. The TP load reductions needed to meet TMDL allocations vary by sector: 82.8% from agriculture, 65.3% from streambanks, 60% from forest, 30.1% from developed land and 51.9% from wastewater. This agreement mandated an annual average in-lake P concentration not exceeding 0.025 mg/L and a 64.3% watershed P load reduction target to be met by 2035 (US EPA, 2016). However, models used to set these criteria were only available for examining the effects of GCC on external P loads and not potential changes to in-lake conditions that drive internal loading and the frequency, severity, and duration of CyanoHABs (Giles et al., 2016; Isles, Xu, et al., 2017). In this legal and policy context, this study evaluates the technical feasibility of TMDL approved 64.3% nutrient reductions for all four policy metrics for setting water quality policy targets under GCC.

2.2. Integrated Assessment Modeling Approach

To accomplish the study goals, we implemented a process-based IAM for this impaired bay and its watershed under different GCC and nutrient reduction scenarios (see Zia et al., 2016) and the Materials and Methods). Water quality impacts of seven P-reduction scenarios were examined under downscaled and bias-corrected (Winter et al., 2016) 17 GCC scenarios defined by available combinations of five Global Climate Models (GCMs) and four Representative Concentration Pathways (RCPs): 2.6, 4.5, 6.0 and 8.5 (See 2.2 in Supporting Information S1 for complete list). GCMs were chosen based on ability to reproduce warm-season precipitation dynamics in the northeastern United States (Thibeault & Seth, 2015) and capture a range of climate futures. The lake model was forced with North American Regional Reanalysis (NARR) (Mesinger et al., 2006) meteorological data from 2001 to 2014 to enable comparisons to observations, and then with the 17 GCC scenarios from 2015 to 2050. The Regional Hydroecologic Simulation System (RHESSys Version 5.18.2 watershed model was forced with the 17 GCC scenarios for the entire 2001–2050 study period. Phosphorus reduction scenarios developed under stakeholder guidance ranged from 0% to 100% and included the 64.3% reduction specified under the current TMDL (US EPA, 2016). All phosphorus flux reductions were implemented instantaneously in 2016 in the simulations.

We force the watershed and lake models using daily precipitation and temperature (both minimum and maximum) time series from five downscaled GCMs across four different emissions scenarios (RCP 2.6, 4.5, 6.0, and 8.5) from the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor et al., 2012). Daily time series of additional meteorological variables (air pressure, cloud cover, relative humidity, shortwave radiation, wind speed, and direction), needed only for the lake model, are generated using an analog approach detailed in 2.3 in Supporting Information S1 (also see Clemins et al., 2019). Watershed hydrology is modeled using RHESSys (Regional Hydro-Ecologic Simulation System) while watershed nutrient loads (carbon, nitrogen, and phosphorus) are estimated as a function of RHESSys-generated streamflow based on observed associations between stream discharge and water quality concentrations (see 2.4 in Supporting Information S1). Following a recent study in Lake Erie (Rucinski et al., 2016), the phosphorus reduction scenarios that reflect improved nutrient management are implemented by applying percent-reduction scalars to each of estimated phosphorus concentration time series. Section 2.3 in Supporting Information S1 provides details about the overview, assumptions, calibration, and validation results of the RHESSys model. To model the hydrodynamics and water quality of Missisquoi Bay, we use the three-dimensional Advanced Aquatic Ecosystem Model (A2EM), which consists of coupled hydrodynamic (EFDC) and water quality models (RCA) that provide estimates of nutrient and phytoplankton concentrations in Missisquoi Bay. This includes a digenesis model that has the capacity to simulate internal loading due to mineralization of organic matter/P and redox driven loading of P (promoted by low oxygen levels in bottom water due to thermal stratification and high sediment oxygen demand) following the equations described in Di Toro (2001). Our model (Zia et al., 2016) has been shown to accurately simulate water column P concentrations where the dominant process has been confirmed by monitoring data to be almost exclusively sourced in internal loading (e.g., summer 2012, Isles et al., 2015, 2016), as well as spring and fall periods where the overwhelmingly dominant supply of P in Missisquoi Bay is watershed/external loading (e.g., Isles et al., 2016, 2017). While the model can simulate up to 4 different phytoplankton species depending on conditions, our analysis focuses on Chl-a concentration output so that we can use a threshold of 20 μg/L to indicate an ecosystem likely to be dominated by cyanobacteria blooms, a threshold based on the trophic state index metric originally developed by Carlson (1977) as used by the North American Lake Management Society and many water resource management entities (https://www.nalms.org/secchidipin/monitoring-methods/trophic-state-equations/). A suite of cyanobacteria species in varying proportions has indeed been shown to be the

Table 1
Differences in Projected Daily Mean Temperature and Precipitation by GCM-Ensembles of Four RCPs for the Post-Treatment Period (2016–2050) Compared to the Pre-Treatment Period (1981–2015)

	Mean daily temperature (°C)(individual GCM means)	Mean daily precipitation (mm/day) (individual GCM means)
RCP 2.6	1.20 (0.80, 0.88, 1.37, 1.77)	0.10 (0.06, 0.07, 0.08, 0.19)
RCP 4.5	1.15 (0.56, 0.72, 0.95, 1.52, 2.00)	0.04 (−0.01, 0.00, 0.04, 0.05, 0.12)
RCP 6.0	0.85 (0.71, 0.91, 0.94)	0.04 (0.02, 0.02, 0.07)
RCP 8.5	1.34 (0.81, 0.99, 1.16, 1.64, 2.07)	0.08 (0.01, 0.08, 0.08, 0.08, 0.13)

dominant form of phytoplankton in Missisquoi Bay in warmer months during periods of high chlorophyll (Shambaugh et al., 1999; Smeltzer et al., 2012), but assessing the prevalence of different species over model runs is beyond the scope of this work given the lack of species-specific monitoring data available to calibrate the model. More information about A2EM and the statistical analysis conducted to calibrate and validate each of its component models EFDC and RCA are presented in 2.4 in Supporting Information S1 in S. Zia et al. (2016) provides additional details about this IAM, which also includes an agent-based land-use model (Tsai et al., 2015). Only the business-as-usual scenario, as described in 2.2 in Supporting Information S1 of Zia et al. (2016), is used in this study to simulate the baseline 0% Phosphorus reduction scenario. Finally, IAM integration and computational workflow methodology is presented in 2.5 in Supporting Information S1.

The IAM generates the four types of water-quality policy target metrics identified in Section 1 under different GCC scenarios:

1. Daily watershed *P* loads
2. Daily lake TP concentrations from April–November (areal average of TP concentrations in the surface layer, the uppermost of five vertical layers used in the lake model).
3. Daily lake Chl-a concentrations from April–November (areal average of TP concentrations in the surface layer, the uppermost of five vertical layers used in the lake model)
4. Days with Chl-a concentrations above mild and moderate recreational contact thresholds of 10 and 50 μg/L (Chorus & Welker, 2021) and above an ecological threshold of 20 μg/L from April–November, the latter of which has been used in numerous recent studies (Carey et al., 2012; Giles et al., 2016; Isles, Xu, et al., 2017).

We also conducted a multivariate analysis on the IAM results to better understand the sensitivity of water-quality response metrics to climate drivers and water policy targets while controlling for other mediating factors. For quantifying the pre- and post-treatment effects of stakeholder informed phosphorus reduction scenarios under different GCC conditions, a difference-in-difference generalized linear model (GCM) was computed, which is a standard approach in policy analysis literature for informing the efficacy of alternate policy designs (Lechner, 2011; Shadish et al., 2002).

3. Results and Discussion

Compared with the baseline period (1981–2015), the air temperature was warmer in almost all simulations (2016–2050), and the precipitation increased in many projections as well (Table 1, Figure S13 in Supporting Information S1). However, the differences in climate between the pre- and post-treatment periods of this study across the different RCPs were not very large due to the relative similarity of the greenhouse gas emissions scenarios and internal climate variability (Table 1) even though across GCMs, there are larger differences in temperature and precipitation (Figure S13 in Supporting Information S1). For the Northeast United States, persistent temperature differences across RCPs do not develop until the latter half of the 21st century. These projected changes in both temperature and precipitation are consistent with previous studies (Guilbert et al., 2014; Mesinger et al., 2006; Winter et al., 2014).

The TMDL WQS of 0.025 mg/L total phosphorus (TP) is unlikely to be met by 2035 under the mandated 64.3% reduction for all GCC scenarios, even with the simulated unrealistic instantaneous reduction of watershed P loads (Figure 3; and Figures S15–S18 in Supporting Information S1). This projected failure is primarily due to the

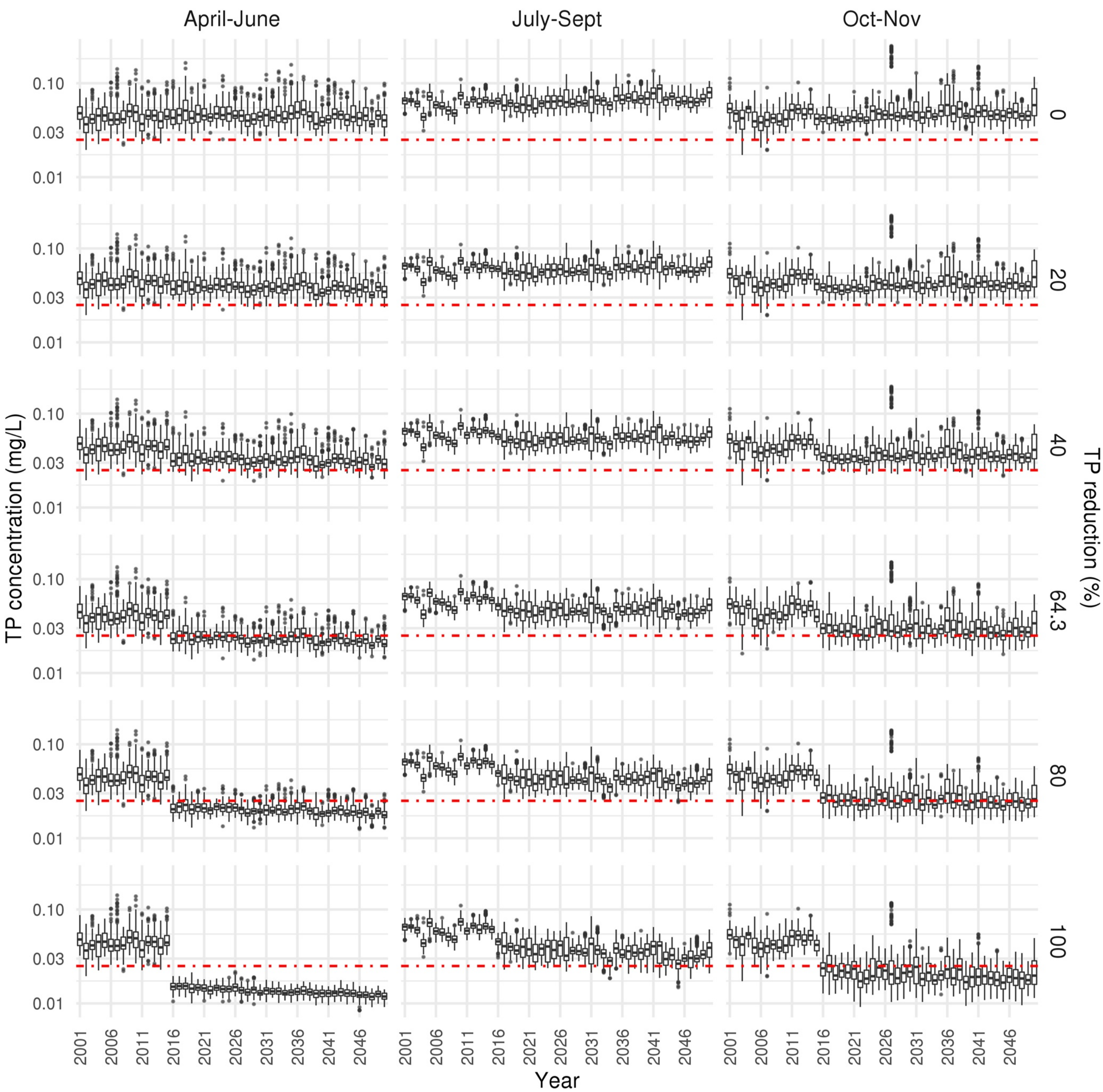

Figure 3. Projected Missisquoi Bay total phosphorus (TP) concentrations averaged by spring, summer and fall seasons under GCC RCP 4.5 scenario for different TP load reduction scenarios. TMDL WQS of 0.025 mg/L (dashed red lines). Projections under other RCPs are shown in Figures S15–S21 in Supporting Information S1.

internal loading of benthic legacy phosphorus during warmer summer months (July–September) (Figure 4). Due to the simulated instantaneous 64.3% reduction in riverine P loading, Bay phosphorus concentrations sometimes reach the WQS in spring (April–June) and fall (October–November) months when reduced riverine nutrient loads are the dominant source of P (Rosenberg & Schroth, 2017), but remain almost double the WQS during summer months under RCP 4.5 (Figure 3). However, with an 80% reduction of riverine phosphorus entering the bay, the annual average WQS (0.025 mg/L TP) is slightly more likely to be met across GCC scenarios by driving spring and fall concentrations well below the WQS. Therefore, the WQS has a greater chance of being achieved under all GCC scenarios with additional, relatively more expensive increase (∼15%) in the policy-mandated reduction of riverine P loads. Yet even with an instantaneous 100% P load reduction and 35 subsequent years

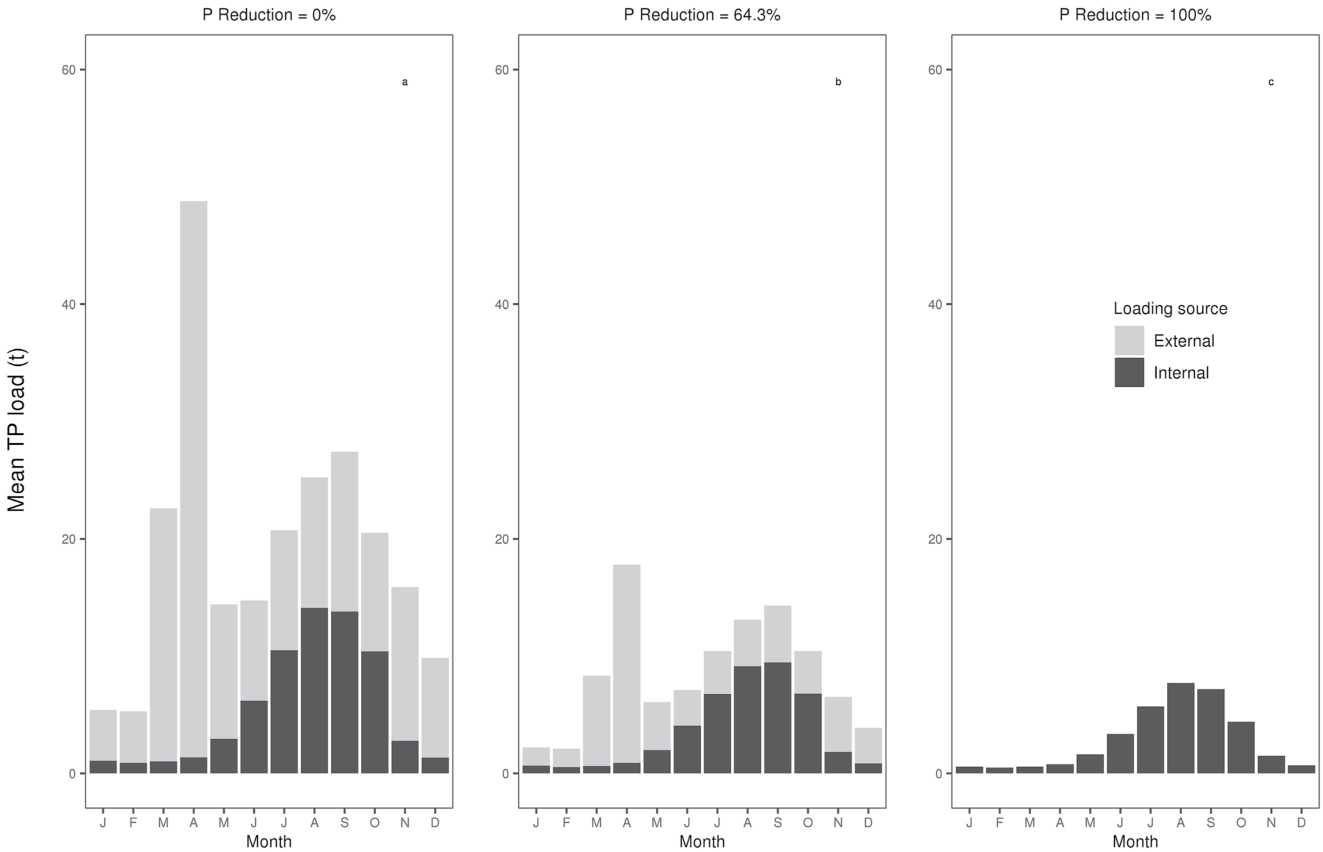

Figure 4. Simulated average monthly external versus internal total phosphorus (TP) loads in metric tons (t) for 2001–2050 for 0% (a), 64.3% (b) and 100% (c) external TP load reductions under RCP 4.5 ensemble. Projections under other Representative Concentration Pathways (RCPs) are shown in Figures S22–S23 in Supporting Information S1.

without any riverine phosphorus input, summer concentrations remain well above the WQS in 2050 (Figure 3), even when the annual average WQS is met. Given that phosphorus loading from the river is zero under this scenario (Figure 4c), the range of 0.002–0.05 mg/L TP (below to double the TMDL) (Figure 3, as well as Figure 9 and Figure S31 in Supporting Information S1) can be considered the range of average ice-free season phosphorus concentrations that would be derived purely from internal loading under simulated climate scenarios. Internal loading does also decrease with external loading reductions since there are positive feedbacks between internal and external loading inherent to the model (Figure 4). Previous studies have suggested that the P flux from the sediment can be anywhere from 50% to 300% of the riverine P load to the bay from June through September when CyanoHABs are prevalent (Isles et al., 2015; Limnotech, 2012), and this is evident in our 0% reduction scenario where fall and spring fluxes are overwhelmingly dominated by external loading, while summer fluxes are in similar range (Figure 4a). Furthermore, known CyanoHAB-nutrient dynamics in Missisquoi Bay (Giles et al., 2016; Isles, Rizzo, et al., 2017) confirm that release of benthic legacy P often drives these persistent elevated summer P concentrations, which often initiate and sustain CyanoHABs, the major water quality concern to stakeholders.

Indeed, IAM simulations show that the frequency and severity of summer (July–September) CyanoHABs (inferred by a simulated chlorophyll *a* threshold concentration of ≥20 ug/L as derived from the Trophic State Index (Carlson, 1977; Carlson & Simpson, 1996) and commonly used by water management and stakeholder communities such as the North American Lake Management Society) increased or minimally decreased under most climate and nutrient reduction scenarios (Figures 5 and 6). The projected failure of implemented policies in reducing CyanoHABs is due to persistently high summer P concentrations, coupled with warmer waters that further promote cyanobacteria growth and dominance. Attainment of WQS under RCP4.5 will have a minimal impact on reducing bloom duration or severity, even with unrealistically aggressive instantaneous implementation of mandated P reductions (Figure 5). Furthermore, chlorophyll *a* concentrations under many worst-case climate scenarios where the WQS or load reduction target is met suggest that CyanoHABs will become more frequent

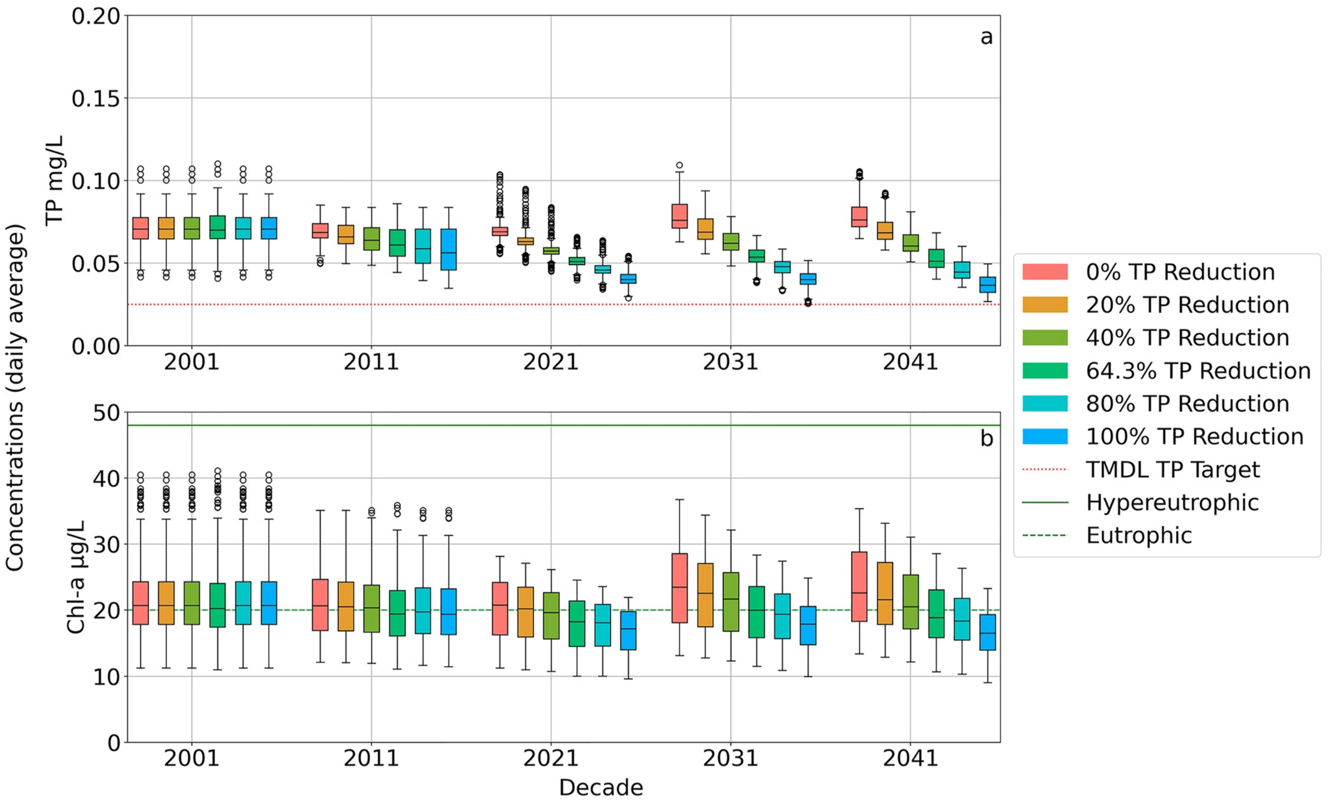

Figure 5. Projected decadal average TP (a) and Chl-a (b) concentrations in the month of August under global climate change (GCC) scenario Representative Concentration Pathways (RCP) 4.5 for 0%, 20%, 40%, 64.3%, 80%, and 100% TP load reductions. Figures S24–S30 in Supporting Information S1 show remaining combinations of GCC RCPs for the months of August and September.

and severe during the peak tourism months of July and August (Figure 6) due to warmer waters and ample legacy P (Figures 2–4). There are even scenarios where the WQS is met due to aggressive watershed P reductions, but the principal stakeholder concern, CyanoHABs, did not improve or worsened due to climate change synergy with legacy nutrient reserves. Given projected CyanoHAB persistence after decades of presumed taxpayer investment and mandated aggressive nutrient reduction implementation (e.g., Figure 5b), such a scenario could compromise citizen confidence in water policy and governance, unless expectations are tempered. For example, citizens may be informed that substantial increases in bloom severity and frequency are generally constrained to GCC scenarios when watershed P load reductions are 40% or less under RCP 4.5, suggesting that the 64.3% load reduction target would at least preserve the current trophic state of the system through 2050 (Figures 5 and 6).

Difference-in-difference random effects generalized linear models (GLMs) quantify the average effect sizes of nutrient management reductions on TP and Chl-a concentrations under alternate GCC scenarios (Table S1 in Supporting Information S1). Since nutrient management reductions were implemented from 0% to 100% in 2016, the pre-treatment effects are computed for 2001–2015 and post-treatment effects for 2016–2050. The interaction variables between nutrient scenario and treatment present quantitative estimates of reducing external riverine loading. The TMDL implementation of 64.3% riverine P reduction is projected to reduce the average April to November TP concentration by 37.3% ($p < 0.0001$), which falls short by ~62.7% in reducing the pre-treatment TP levels of 0.05 to the EPA target of 0.025 (Figure 5). The 64.3% reduction in external loading is projected to reduce the average April to November Chl-a concentration by 15.3% ($p < 0.001$).

The effects of individual GCC scenarios are also significant. In particular, we find that the choice of a GCM has relatively stronger effects on TP and Chl-a projections, while the differences in the effects of RCPs in the mid-century projections are not as strong yet they are significant at $p < 0.05$. Compared with RCP2.6, which is consistent with the Paris Agreement goal of limiting anthropogenic climate change to 1.5 C above pre-industrial levels, RCP4.5 increases TP by 0.5% ($p < 0.001$) and Chl-a by 0.2% ($p < 0.05$). The average effects of RCP6 are significant for Chl-a, and RCP8.5 on increasing TP. The effects of RCPs, however, are influenced by the choice of GCM ensemble members.

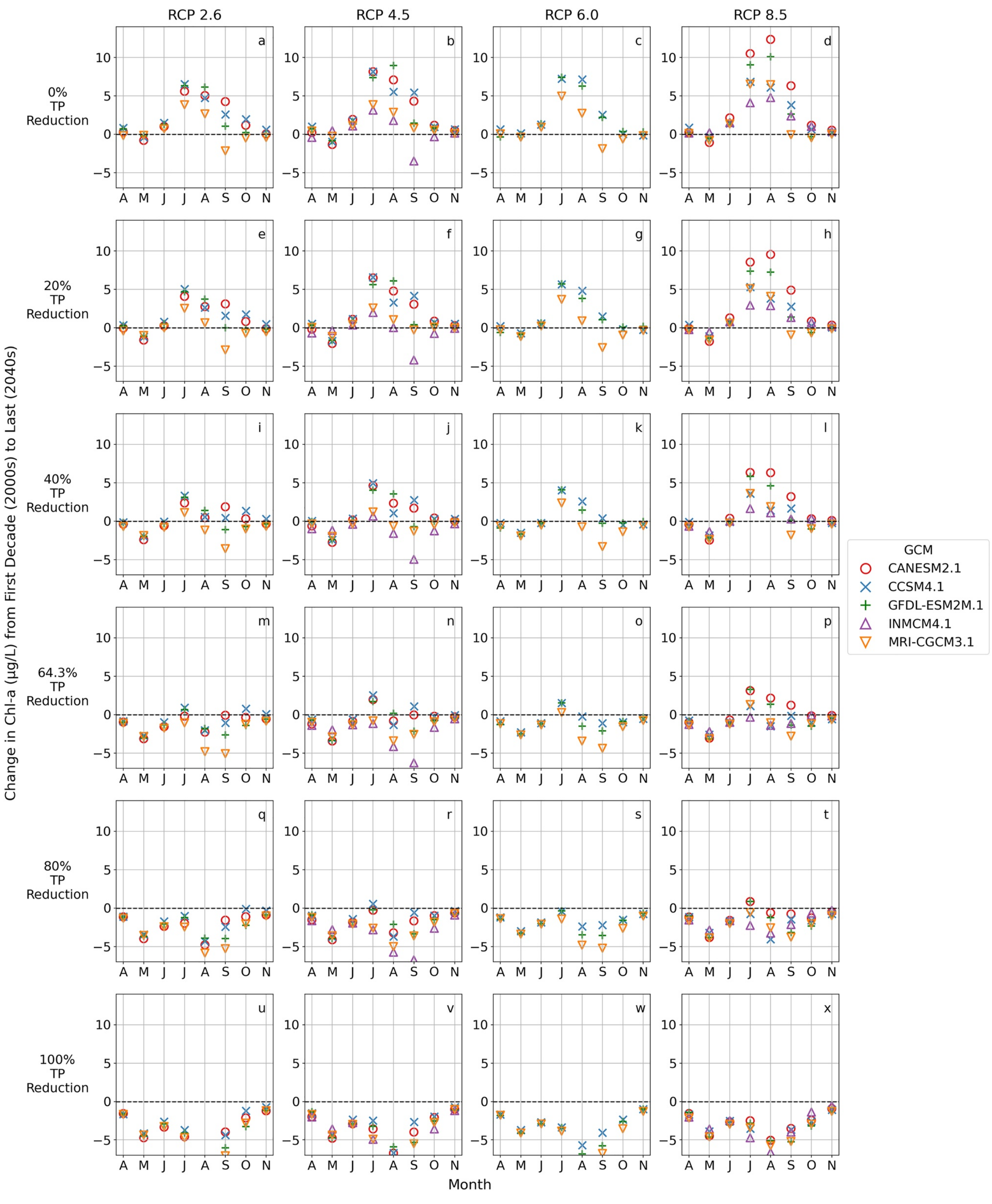

Figure 6. Differences in projected monthly (April–November) mean Chl-a concentrations (µg/L) for the post-treatment mid-century period (2041–2050) compared to the pre-treatment period (2001–2010). Results shown for combinations of four GCC scenarios (columns) and TP load reduction scenarios (rows). Figure S31 in Supporting Information S1 presents projected changes in monthly average TP concentrations.

Compared with CANESM2.1, the CCSM4.1, GFDL-ESM2.1 and MRI-CGCM3.1 project 4.5% ($p < 0.001$), 7.5% ($p < 0.001$) and 5.0% ($p < 0.001$) higher TP reductions. The choice of GCM in projecting Chl-a also induce similar significant effects. Compared with CANESM2.1, all other four GCMs project 1.4%–6.2% higher Chl-a reductions.

Although the GLM findings presented in Table S1 provide important insights about the mean changes in the water quality of the shallow bay of a freshwater lake due to synergistic effects of GCC and internal versus external loading of nutrients, the process-based IAM can also project non-linear effects of threshold based impacts on water quality, such as the average number of the days per month with CyanoHABs above an established eutrophication threshold (Chl-a >20 μg/L) (Figure 7), the likelihood of exceeding the WHO moderate recreational

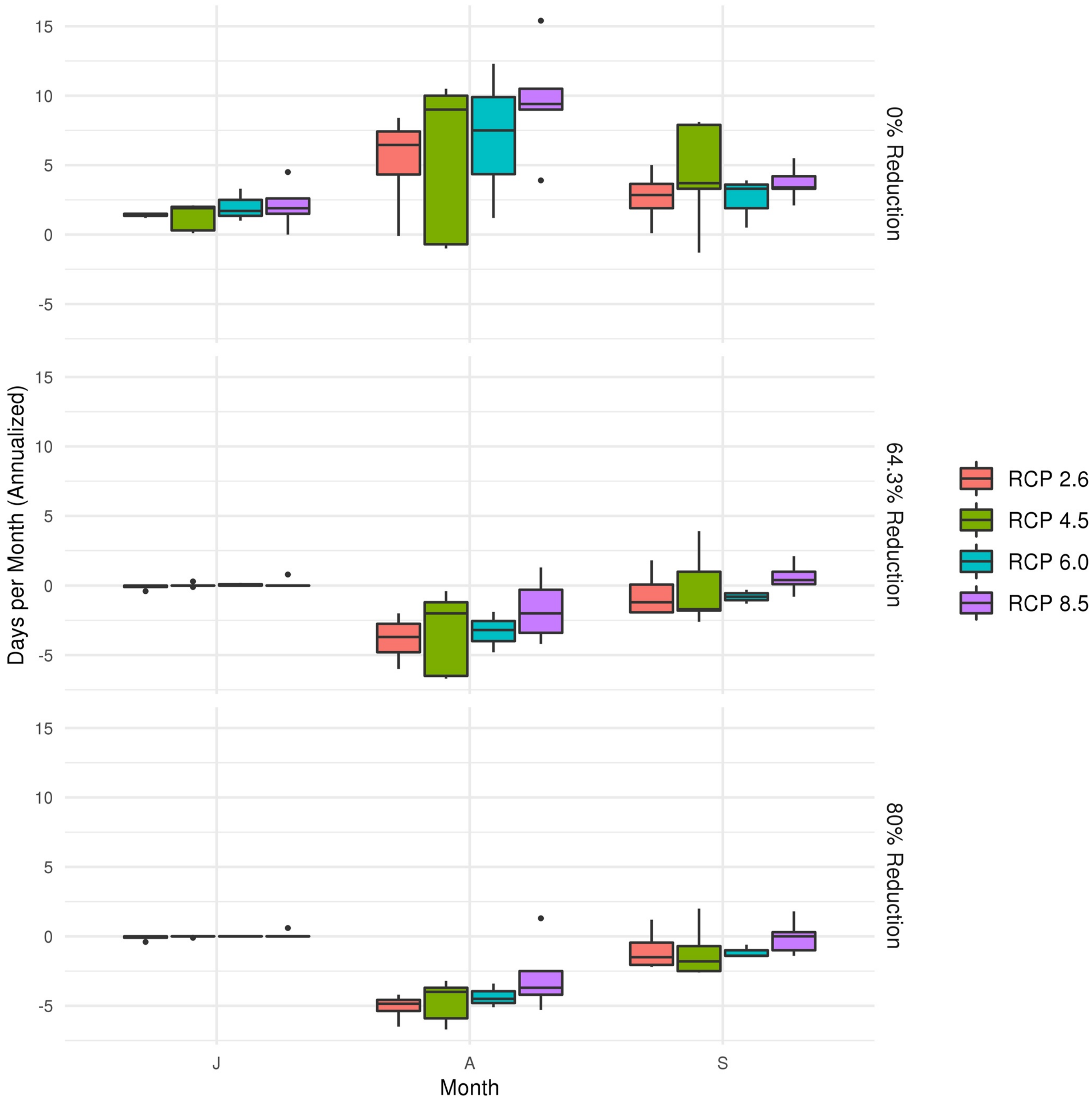

Figure 7. Days per month in the summer and fall months when the WHO Chl-a moderate recreational contact threshold (50 μg/L) is not met under alternate nutrient reduction and Representative Concentration Pathways (RCP) scenarios for 2041–2050, compared with the baseline period of 2001–2010.

contact threshold (Figure 8) and the cumulative probability of non-compliance with in-lake TMDL policy targets (Figure 9) under alternate nutrient management and RCP scenarios. The persistence of this water quality problem under GCC, even under aggressive watershed phosphorus reductions, is clearly evident when analyzing IAM output this way. While there was some improvement in the number of days below the eutrophication threshold in the 64.3% and 80% reductions during the months of July, August and September, the majority of summer days remain above the threshold even under an 80% reduction (Figure 7), and even under a 100% reduction, the probability of exceeding the threshold remains. Furthermore, the challenges for meeting the TMDL WQS target are also illustrated in Figure 9, given that with an 80% reduction in riverine P, 87.5%–94% of the simulations fail to meet the WQS target, and with a 100% reduction, there remains a 12%–20% chance that the target will not be met. Given that even meeting the TMDL 64.3% reduction level mandated by the TMDL will be challenging, this indicates that an engineering solution designed to suppress legacy P release will likely be needed to meet the EPA's target within the allotted 30-year time frame.

4. Conclusions

The ability of our process-based IAM and similar complex systems modeling tools to capture commonly unconsidered feedbacks and synergies is important for assessing the efficacy of policy options under GCC. We show a shallow bay example where these IAMs can be deployed at basin scales to capture the synergistic effects of GCC, internal legacy nutrient loading, and watershed nutrient management on lake water quality. Our results highlight the importance of coupling climate, watershed, and lake models together for shallow bay settings where internal loading comprises a large fraction of the nutrient budget. The Missisquoi Bay case study shows that water-quality policies focused solely on regulating external nutrient loads (currently implemented policy metric)

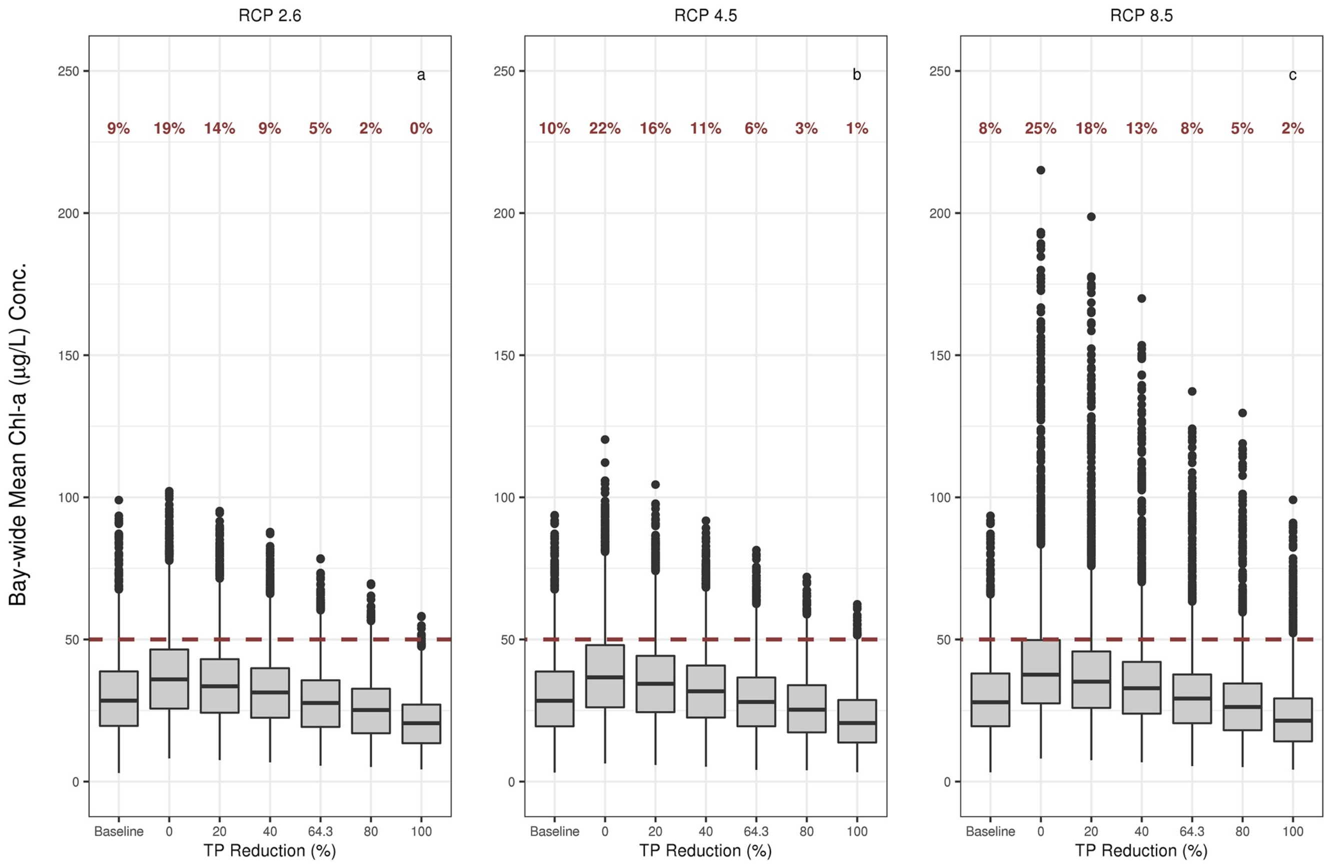

Figure 8. Projected likelihood (%) of bay-wide average mean Chl-a concentration (µg/L) exceeding WHO Chl-a moderate recreational contact threshold (50 µg/L) (dashed red line) in July-September under alternate P reduction scenarios between 2041 and 2050 compared with 2001–2010 (baseline) for RCP 2.6 (a), RCP 4.5 (b) and RCP 8.5 (c).

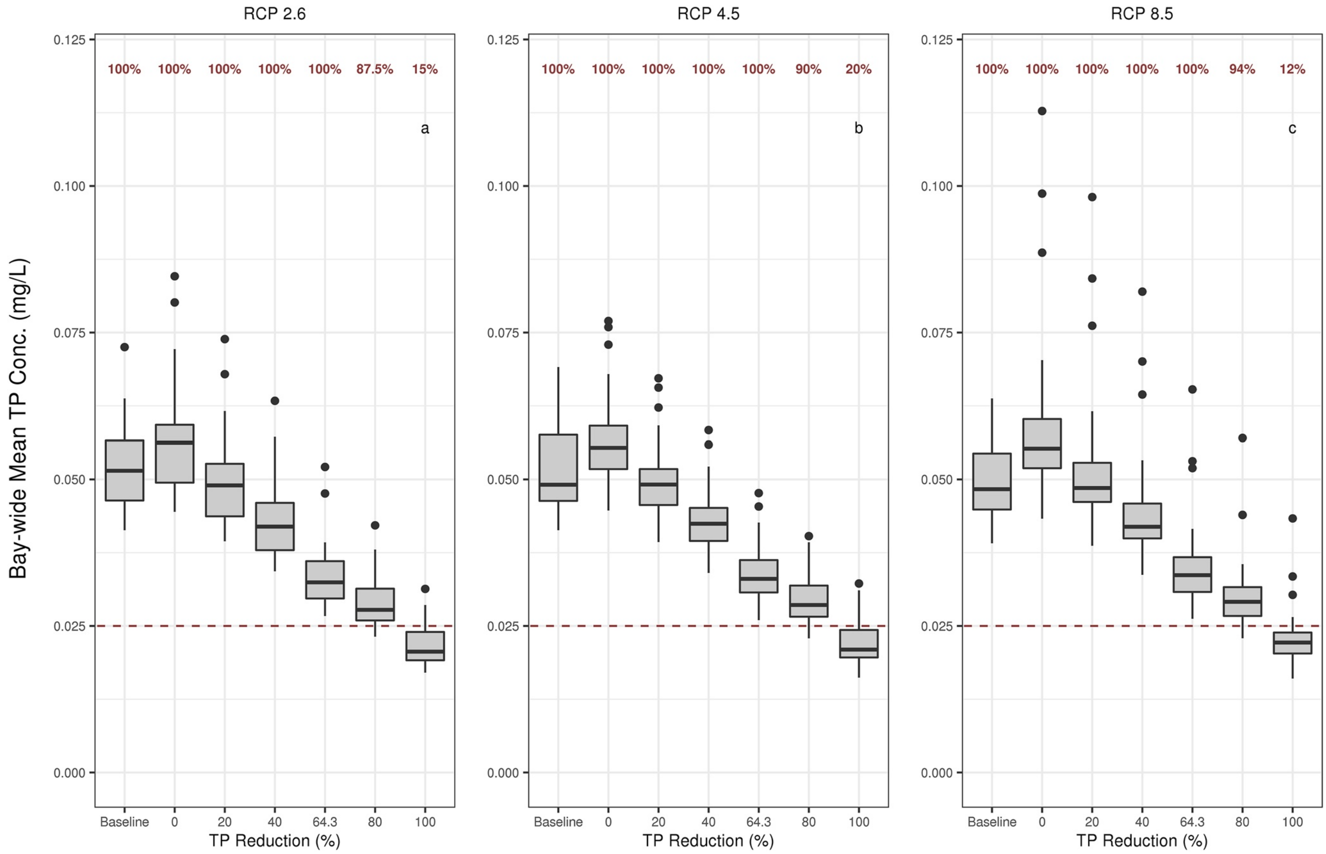

Figure 9. Projected likelihood of non-compliance with in-lake TP WQS policy target (0.025 mg/L TP, dashed red line) based on bay-wide average mean TP concentration (μg/L) under alternate P loading reduction scenarios in Jul-Sep between 2041 and 2050 compared with 2001–2010 (baseline) for RCP 2.6 (a), RCP 4.5 (b) and RCP 8.5 (c).

are insufficient for safeguarding the water quality of shallow bays from GCC. Moreover, our analysis highlights the importance of basing water quality management around indicators of human and ecological impacts in lieu of simply using WQS based on concentrations sampled in lakes. This includes aligning the timescales over which the attainment of WQS is assessed with those of the water-quality hazards. Our study shows that immediately achieving a TMDL-mandated load reduction of 64.3% would only roughly offset the impacts of climate change to CyanoHABs (as inferred from Chl-a indicators). Immediately eliminating external loading would only achieve a moderate reduction in the exceedance of key bloom impact thresholds during summer months in the last decade of the simulation. These results motivate future research on challenges in shifting TMDL and other policies, commonly based on currently implemented policy metric 1 (i.e., reductions in riverine nutrient fluxes), to approaches that consider water-quality impact metrics more meaningful to stakeholders (e.g., metrics 2, 3, and 4 focused on lake nutrient concentrations, biological indicators of lake eutrophication and exceedances of thresholds of human and ecological health).

IAMs can enable WQS to be set adaptively as social-ecological system knowledge evolves to better reflect the adverse impacts induced by the complex ongoing interaction of climate, land use and socio-economic change across multiple timescales. Furthermore, these tools can help temper short-term expectations of lake water-quality remediation efforts and promote transparency with stakeholders and citizens by clearly demonstrating the challenges that this GCC-legacy nutrient synergy poses to CyanoHABs suppression. This is particularly important considering the temporal offset and lags associated with flushing legacy nutrient reserves after load reductions are achieved (often many decades) relative to shorter-term policy timescales (Goyette et al., 2018; Haas et al., 2019). The unrealistic instantaneous watershed reductions that are employed in this study demonstrate the potential impact of water quality management actions. These optimistic scenarios do not consider temporal lags in policy implementation. Moreover, the extreme P reduction scenarios do not reflect the slow recovery of anthropogenic phosphorus pollution in watersheds due to legacy soil phosphorus (Goyette et al., 2018). Managers could therefore leverage IAM output to inform decisions regarding complementary investments in evolving technologies focused on the in-lake suppression of benthic P releases and CyanoHABs (Bormans et al., 2016) and further demonstrate the urgency of addressing GCC.

Our study of Missisquoi Bay shows that the US Clean Water Act (CWA) and nutrient management policy tools embedded in such policies, for example, TMDLs, may only account for GCC effects in setting WQS targeting watershed nutrient load reduction goals through evaluations of the "margin of safety" in TMDL calculations. According to this policy, the "margin of safety" embedded in the TMDL accounting formula for nutrient reductions presumably accounts for both "known" and "unknown" uncertainties, including temperature and precipitation non-stationarities induced by GCC. In this paper, we have demonstrated that current TMDL approach to managing water quality by only focusing on reducing external loading is insufficient for addressing the adverse impacts of GCC in eutrophic lakes where internal loading from legacy nutrients is a dominant driver of poor water quality, as measured through the incidence and duration of CyanoHABs. In addition to reducing riverine nutrient fluxes, IAM simulations lead us to recommend that the GCC adaptation policy targets also consider other water quality management metrics that can transparently account for the effects of GCC on the lake nutrient concentrations, biological indicators of lake eutrophication (e.g., Chl-a concentrations) and the likely exceedances of thresholds of human and ecological health.

Data Availability Statement

We would like to thank many data providers for making the calibration and validation of the IAM possible (see Section 2 and Supporting Information S1 for details). The World Climate Research Programme's Working Group on Coupled Modeling produced Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections. The weather estimator used North American Regional Reanalysis data from the National Centers for Environmental Prediction (NCEP) and obtained from NOAA/OAR/ESRL PSD, Boulder, Colorado, USA. The Land use agent-based model (ABM) is described in (Zia et al., 2016) and references therein benefits from 2001 National Land Cover Data, the 2007 USDA Census of Agriculture and 2013 E911 parcel data. The RHESSys watershed hydrology model utilized historical climate data for calibration runs (Maurer et al., 2002), NLCD for land cover, the National Elevation Data set, surface soil texture data from the Vermont Center for Geographic Information and Soil Landscapes of Canada, and USGS daily streamflow data. The lake model uses long-term monitoring data from the Lake Champlain Basin Program, along with high-frequency sensor data from previous research (Giles et al., 2016; Isles, Rizzo, et al., 2017). We also acknowledge high-performance computing support from the National Center for Atmospheric Research's Cheyenne high-performance computer (Computational & Information Systems Laboratory, 2017). The IAM output data and STATA code for estimating GLMs is made available in a public repository: https://doi.org/10.4211/hs.76b1e433cd2a41a0b50170511fec68ac

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