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Entitled
Climate Impacts on Nutrient Loading in Lake Erie

By
Tiffany M. Gentner

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the
Master of Science Degree in Geology

Richard Becker, Ph.D., Committee Chair

Kevin Czajkowski, Ph.D., Committee Member

James Martin-Hayden, Ph.D., Committee Member

Dr. Amanda Bryant-Friedrich., Dean
College of Graduate Studies

The University of Toledo

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The Maumee Watershed, the largest of the Great Lakes drainages, is located in NW Ohio, and is comprised of 70% agricultural land. In an effort to increase crop yields, fertilizer containing phosphorous (P) and nitrogen (N) are applied to the agricultural land. During large rain events or melt off periods these nutrients are mobilized, ultimately making their way to Lake Erie. Anthropogenic nutrient loading and increased water temperature allows for cyanobacterial harmful algal blooms (HABs) to prosper. Climate change is expected to increase both average temperature and precipitation events, potentially changing nutrient loading from runoff and influencing an increase in HABs. Best management practices (BMPs) have been utilized on agricultural land to help reduce and slow nutrient runoff. As HABs are detrimental to human health, understanding how climate change and BMPs interact to reduce nutrient loading is essential. A target reduction of 40% dissolved reactive phosphorus (DRP) nine years out of ten was established by the Ohio Phosphorus Task force, in an effort to reduce HAB occurrences. To investigate how climate change and BMPs interact, three climate models, MIROC, MRI, and CNRM, and a baseline scenario and two BMPs are run in a Soil and Water Assessment Tool (SWAT) model of the Maumee Watershed. MIROC predicts the

warmest and driest climate amongst the three climate models, while MRI foresees the coolest and wettest climate. MIROC and MRI both anticipate a decrease in P loading on average, with some decreases in P offset by climate change for MRI. Finally, CNRM anticipates a mild increase in temperature and precipitation, but increases P loading overall. Based on similar hindcast results to NOAA's measured data it is likely that CNRM is the most realistic climate model, but is inconclusive. BMPs are an effective practice in reducing P loading as scenario 2 and scenario 3 reduce P in reference to baseline management. More aggressive management will need to be implemented to help constrain algal growth in the future.

For my parents, sisters, and Ryan, thank you for believing in me and pushing me to do my best, always!

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List of Abbreviations

AOGCM.....	Atmosphere-Ocean General Circulation Model
BMP	Best Management Practice
CCSR	Center for Climate System Research
CEAP	Conservation Effects Assessment Project
Cerfacs	Centre Européen de Recherche et de Formation Avancée
CMIP5.....	Coupled Model Intercomparison Project Phase 5
CNRM.....	Centre National de Recherches Météorologiques
DEM.....	Digital Elevation Model
DRP	Dissolved Reactive Phosphorous
ENSO	El Niño Southern Oscillation
ET.....	Evapotranspiration
GCM	General Circulation Model
GLWQA.....	Great Lakes Water Quality Agreement
HAB	Harmful Algal Bloom
HRU	Hydrologic Response Unit
IPCC.....	Intergovernmental Panel on Climate Change
LLNL	Lawrence Liverpool National Library
MATLAB.....	Matrix Laboratory
MIROC	Model for Interdisciplinary Research on Climate
MRI.....	Meteorological Research Institute
N.....	Nitrogen
NIES.....	National Institute for Environmental Studies
NLCD.....	National Land Cover
NS	Nash-Sutcliffe
NUGIS	Nutrient Use Geographic Information System

PPhosphorous
 PCMDI.....Program for Climate Model Diagnosis and Intercomparison
 PETPotential Evapotranspiration

 RCPRepresentative Concentration Pathway

 SSURGO.....Soil Survey Geographic
 SWATSoil and Water Assessment Tool
 SWAT-CUPSWAT Calibration and Uncertainty Programs

 WCRPWorld Climate Research Programme

Chapter 1

Introduction

The Maumee River Watershed, the largest of the Great Lakes drainages, is located in NW Ohio, and is comprised of 70% agricultural land. Phosphorous (P) and nitrogen (N) are applied as fertilizer across the watershed. During rain events these nutrients can be mobilized, and travel through the river system, ultimately making their way to Lake Erie. Climate change is expected to increase both average temperature and precipitation events, potentially changing nutrient loading from runoff and impacting harmful algal blooms. Cyanobacterial harmful algal blooms (HABs) have been persistent and increasing in recent years as anthropogenic nutrients and water temperatures, both necessary for algal growth, have increased. In an effort to decrease HABs, best management practices (BMPs) have been employed on agricultural fields across the watershed to help reduce nutrient loading. As P is identified as a limiting nutrient to HABs, with the dissolved phase being particularly important, additional attention is paid to the effects of BMPs on P runoff. To assess if HABs can be reduced in the coming years, climate change and BMP interaction needs to be understood.

1.1 Study Area and Background

Lake Erie is the smallest, shallowest, most biologically productive, and southernmost of the five Great Lakes (Botts & Krushelnicki, 1987; LEIA, 2010; Millie et al., 2009). This Great Lake brings in \$50 billion annually for the regional economy through tourism, recreational boating, shipping, fisheries, and other industries. This region is home to 12 million individuals, and supplies drinking water for 11 million inhabitants (USEPA, 2016; Watson et al., 2016). Lake Erie is divided into three basins: the eastern, central, and western, with the western basin being the shallowest at less than 8 meters deep as the average (Botts & Krushelnicki, 1987). The Maumee Watershed drains an area close to 16,200 km² (6,500 mi²) into the western basin of Lake Erie and is designated as the Great Lake's largest drainage basin (Calhoun et al., 2002, ODNR, 2017). The Maumee watershed covers northwest Ohio and extends into Michigan and Indiana (Figure 1-1). Although seventeen metropolitan zones (defined as areas with more than 50,000 residents) lie within the Lake Erie drainage basin, it is dominated by agricultural land, which makes up approximately 70% of the Maumee Watershed (Figure 1-2) (Botts & Krushelnicki, 1987; ODNR, 2017; USEPA, 2016).

1.2 Problem Description

Although agriculture is a necessity for providing feed for cattle, food for our tables, and jobs to many Americans, the nutrient runoff poses a threat to the Lake Erie environment. Nutrient runoff influences many open waterbodies around the world and is well known within the Great Lakes region (Botts & Krushelnicki, 1987). P and N, two of the main nutrients that runoff agricultural land, are flushed from the Maumee watershed into nearby Lake Erie (Figure 1-3). The increased supply of nutrients causes

Figure 1-1: Maumee Watershed location in reference to surrounding states and major rivers. Adapted from Cousino et al., 2015.

Figure 1-2: Land use of the Great Lakes region based on a color diagram of the surrounding area. The study area is boxed in, showing colors ranging from orange and yellow to red; low to intense farming and urban areas, respectively. Edited from Botts & Krushelnicki, 1987.

eutrophication of the lake system, results in decreased water quality and plant growth, and creates a hypoxic environment (Fitzpatrick and Di Toro, 1999). To improve water quality, and reduce eutrophic environments, the Great Lakes Water Quality Agreement (GLWQA) was established in 1972 to place lake-wide regulations on a P loading limit (IJC, 1972). More recently, a 40% reduction of dissolved reactive phosphorous (DRP) was recommended by the Phosphorous Task Force to be met at least 9 out of every 10 years (USEPA, 2016). P is the main nutrient targeted, as research has identified it as the limiting nutrient in Lake Erie during eutrophic events (Figure 1-4) (Logan, 1987; Sonzogni et al., 1980). Strategies used to reduce P loading involve upgrading municipal water treatment systems, reducing the P content in soaps, detergents and lawn fertilizers, and establishing an array of agricultural practices (Bierman, 1979). The various agriculture approaches used to reduce nutrient runoff are referred to as Best Management

Figure 1-3: Depiction of how P and N can potentially impact soil, water, and air quality when farm inputs are shown as the source. Adapted from Sharpley & Wang, 2014

Figure 1-4: Computer generated map of P concentrations in the Great Lakes. The main map is from 1991/1992 while the insert is from 1980/1983, highlighting the P reductions set in place by the GLWQA. Although algal blooms are remaining persistent, as indicated by the colors referencing concentrations in mg/L, there has been a reduction in concentrations. The study area is focusing on Lake Erie. Edited from Botts & Krushelnicki, 1987.

Practices (BMPs), such as utilizing no-till farming, planting cover crops, and using filter strips. No-till practices are incorporated in BMPs as they lessen the amount of erosion due to crops remaining on the soil surface and, in most cases, having an intact root system holding the soil (Bosch et al., 2014). Cover crops are used as a similar practice to no-till, while filter strips slow runoff and allow for infiltration (Bosch et al., 2014). Wetland development is an additional BMP approach, utilized as a retention mechanism

to reduce nutrient runoff. Manure and fertilizer application practices and timing have also been placed into regulatory terms (Figure 1-5) (“Fertilizer Application Regulations...”, 2013; Sharpley & Wang, 2014; USDA ERS, 2017).

Figure 1-5: Schematic of the 4R's; decisions on applying the Right source at the Right rate, Right time, and Right place (IPNI, 2014). Adapted from Sharpley & Wang, 2014.

Total P concentrations were reduced in the 1970s and 1980s once various strategies were enacted in the Lake Erie basin, improving water quality (Ludsin et al., 2001). The GLWQA proved to be a short-term solution to increased water quality, as the eutrophic environment eventually returned. The GLWQA initially reduced nutrient loads, but around 2009 non-point sources and Lake Erie's tendency to retain P caused a return of the algal blooms (Cousino et al., 2015; LEA, 2016; Paerl et al., 2011; Schindler et al., 2008; Sonzogni et al., 1980). The return of algal blooms may have resulted from a lack of proactive work in implementing knowledge of how much P plants use, compared to the amount of fertilizer applied to fields. Tilman et al. (2001) found an increase in fertilizer application, but roughly only half of the N and P of the fertilizer is utilized by crops. This

allows the remaining fertilizer to become runoff during storm events, with nutrients transported as either particulate P bound to sediment or as DRP (Richards et al., 2010). Fertilizer application and tillage practices also affect the amount of nutrient influx into a waterbody. More nutrient runoff can be attributed to fertilizer being broadcast on the surface rather than being injected or plowed into the soil (Michalak et al., 2013; Sonzogni et al., 1980). No-till practices can increase nutrient loading when late fall fertilizer applications become potential surface runoff in winter months (Michalak et al., 2013).

1.2.1 Harmful Algal Blooms

Lake Erie has experienced annual occurrences of cyanobacterial blooms. These blooms are produced by anthropogenic nutrients and lake warming (Vollenweider et al., 1980). Recently, algal blooms have become more toxic, with these taxa known as microcystis (Munawar et al., 2008; Watson et al., 2016). Referred to as Harmful Algal Blooms (HABs), the microcystis cyanobacterial blooms are harmful based on significant levels of hepatotoxin microcystin (Watson et al., 2016). The toxin in these HABs is detrimental to the environment and economy. The blooms create a hypoxic lake environment, damages fisheries, diminishes water quality, disrupts recreational practices, and impacts drinking water quality. On August 2, 2014, the city of Toledo, Ohio was placed under a water advisory for three days as high levels of microcystin were present in treated water (Jetoo et al., 2015). This was a result of the toxic cyanobacterial bloom reaching Toledo's intake in the western basin of Lake Erie, and ultimately affecting the city's drinking water supply. If ingested, HABs can be damaging to human health affecting hepatopancreatic, digestive, endocrine, dermal, and nervous systems (Cousino et al., 2015; Paerl & Otten, 2013). For these HABs to prosper, there needs to be an influx

of nutrients (P and N) along with warming temperatures. In recent years the Great Lakes have been exposed to climate change, leading towards increased temperatures, decreased amounts of snow and ice cover, and a higher frequency of rain events (Bosch et al., 2014; Cousino, et al., 2015; Hayhoe et al., 2010; Michalak et al., 2013).

Figure 1-6: A migrating state analysis of Michigan shows how climate change can affect the state's climate. This type of analysis quantifies projected future climate conditions in a given location and uses present-day analogs to those conditions today. In this case, today's conditions of the lower midwest and southern United States match what Michigan is expected to look like in future years, making the state hotter and drier in the summers. Adapted from Hayhoe et al., 2010.

1.3 Climate Change

Figure 1-6, shows a migrating state analysis for Michigan, showing how climate change is expected to impact surrounding areas (Hayhoe et al., 2010). Many climatologists have been able to determine future climate by using General Circulation Models (GCMs), which simulate global climate and exhibits how an increase in CO₂ emissions will affect climate (Botts & Krushelnicki, 1987; LLNL, 2017). Hayhoe et al

(2010) and Bosch et al (2014) expect temperature to increase by 1.5-6° C, causing a replacement of snow precipitation with rain precipitation during winter months. The continued rise in air temperature will result with increased water temperature, influencing algal blooms to prosper. Additionally, increasing temperature influences the amount of evapotranspiration (ET), which may result in a reduced annual flow. This increased ET works against the otherwise expected increase in river flow from increased rainfall. An additional factor influencing flow is rain intensity. Bosch et al (2014) and Cousino et al (2015) noted that models predict the number of intense rain events to decrease, allowing rain to percolate through the uppermost soil, decreasing surface runoff. On the other hand, as infiltration increases, tile flow will likely increase, allowing for more surface runoff if the soil becomes oversaturated (Bosch et al., 2014). One amplifier of climate change impact on annual river discharge is centered on the geology, with focus placed on soil drainage of the Maumee Watershed (Figure 1-7). The majority of the watershed was shaped by the last retreating ice sheet, the Wisconsinan, approximately 14,000 years ago, followed by glacial Lake Whittlesey (Hansen, 1989). A lacustrine plain composed of predominate clay remains. The low-permeability, fine-grained soils caused much of the precipitation to flow as surface runoff to surface water bodies (Sonzogni et al., 1980). When an increase in precipitation is paired with the poorly drained soils of the region it will result in more surface runoff. There are a variety of ways to study climate change effects on the Maumee Watershed, which is why previous studies have utilized the Soil and Water Assessment Tool (SWAT) as this method addresses various aspects of climate change modeling on a modeled watershed.

1.4 Previous Research

Previous research on the Maumee Watershed and watersheds in general, utilized SWAT to simulate scenarios based on future impacts to watershed runoff and nutrient yield due to agricultural management and climate predictions. Cousino et al (2015) utilized Coupled Model Intercomparison Project Phase 5 (CMIP5) datasets to obtain

Figure 1-7: Soil drainage of the bordering states to the Great Lakes basin. The study area is boxed in, showing a dominance of moderately well to very poor soil drainage, with a few areas of bedrock exposed at the surface. Poor drainage is linked with fine-grained clay soils, allowing for surface runoff. Edited from Kling et al., 2003.

rainfall data and applied it to four climate drivers, RCP 2.6, 4.5, 6.0, and 8.5, and two time periods, 2046-2065 and 2080-2099. Different tillage practice scenarios were also applied to the SWAT model, reflecting the effect on sediment and nutrient loading in the Maumee Watershed. In that study, annual precipitation was expected to increase under all

scenarios, with an average increase of 2% for 2046-2065 and 5% for 2080-2099. End-of-century (2080-2099) average daily temperatures will likely increase from 3°C to 6°C for RCP 4.5 and RCP 8.5, respectively.

With the expected increase in average daily temperature, there is also a chance for an increase in potential evapotranspiration (PET) and ET. From 2046-2065 the models predicted that there will be a 10% increase in PET and 28% increase for ET, 2080-2099 is expected to see a 17% increase in PET and 46% increase in ET (Cousino et al., 2015). This results in a decrease in predicted average annual stream flow and a reduction in average annual sediment loads by 19%, regardless of an increase in average annual precipitation. Only one scenario, end-of-century RCP 8.5, shows results with an increase in sediment load. Overall, it was found that current agricultural practices will not be sufficient to reduce Lake Erie's HAB problem (Cousino et al., 2015).

Bosch et al (2014) conducted a similar SWAT model, studying moderate to pronounced climate change scenarios with three BMP practices of no-till, cover crops, and filter strips applied to four Lake Erie watersheds. All of the watersheds are expected to have increased annual precipitation by 6% under the pronounced climate scenario, while snow decrease is likely under both moderate (14%) and pronounced (35%). Surface runoff will increase 1-4% between the two climate futures, with sediment runoff likely to increase by 6-18% in the moderate scenario and 20-49% in the pronounced. Both climate scenarios will likely have a modest increase in nutrient yields: total P and N will increase, while DRP is likely to decrease under moderate conditions and increase under-pronounced. Bosch et al (2014) concluded that future climate will negate the gains of

most BMP implementation, that currently, they are sensitive to climate change but under high implementation might be able to offset the increased discharges.

HABs in Lake Erie have been increasing annually due to an increase in nutrient loading. In an effort to reduce HABs, the Ohio Phosphorous Task Force proposed a 40% goal reduction of DRP 9 out of 10 years by 2025. To assess if this goal is attainable, the interaction between climate change and BMPs needs to be better understood. 3 climate models were run against a baseline and two BMP scenarios during three time periods of historic, mid-century and end-of-century. The future time-periods were driven by RCP 4.5 and RCP 8.5 climate drivers. Based on background information, previous studies, and future climate models, it is likely that climate change will negatively impact the effectiveness of BMPs to constrain future algal blooms in Lake Erie. If BMPs cannot effectively constrain algal blooms, the goal set by the Ohio Phosphorous Task Force will not be attainable by 2025.

Chapter 2

Methods

2.1 Introduction to Methods

The present study aims to predict water and nutrient loads from the Maumee Watershed as a result of climate change and effectiveness of BMPs. Three climate models were selected from the most recent climate change predictions, CMIP5, generated by the World Climate Research Programme (WCRP) and Program for Climate Model Diagnosis and Intercomparison (PCMDI). WCRP's mission is to make climate, and effect of human activities on climate, predictable. To simulate climate change, daily data from climate models were incorporated as weather stations into a calibrated SWAT model of the Maumee Watershed. Each weather station and BMP scenario were run through multiple unique iterations to simulate future nutrient loading. All results of watershed yields were run under historic hindcast and future climate scenarios.

2.2 SWAT

2.2.1 Background

SWAT is a continuous-time, semi-distributed, process-based river basin model that explains the effects of climate change and land management practices on watershed yields (Arnold et al., 2012). To model processes within the watershed, SWAT integrates

weather, surface and groundwater hydrology, soil properties, pesticides, nutrients, and land management. Once a watershed is defined, it is divided into subbasins and even further into hydrologic response units (HRUs). Rather than being identified contiguously or spatially, HRUs are created by a representative percentage of homogenous land use, management, topographical, and soil characteristics (Arnold et al., 2012).

The driving mechanism behind all processes in SWAT is the hydrologic cycle which is driven by climatic variables including: daily precipitation, maximum and minimum temperatures, solar radiation, wind speed, and relative humidity (Arnold et al., 2012). The five variables used to calculate water balance are the same variables obtained from the Lawrence Liverpool National Library (LLNL) website and created into weather stations. The historic hindcast and predicted variables are simulated data from monthly averages generated from daily data in an excel macro. Simulated historic hindcast data gives a reference to future conditions.

2.2.2 SWAT-CUP

SWAT Calibration and Uncertainty Programs (SWAT-CUP) permits sensitivity analysis, calibration, validation, and uncertainty analysis of models. It is an interface for SWAT, providing a link between the input and output of the calibration and model calculations (Abbaspour, 2013).

2.3 Climate Models

Three individual models were selected from CMIP5: MIROC, MRI, and CNRM. CMIP5 is the most recent Coupled Model Intercomparison Project (CMIP) and was established to analyze the output of coupled atmosphere-ocean general circulation models (AOGCMs) methodically (LLNL-CMIP5, 2017, and Voldoire et al., 2013). CMIP5s

experimental design highlights decadal hindcasts and prediction simulations, long-term simulations, and atmosphere-only simulations (LLNL-CMIP5, 2017, Taylor et al., 2012 and Yukimoto et al., 2012). Hindcast is used to test mathematical models, where known or closely estimated inputs for past events are entered into the model. The outputs are compared to the known results to see how well they match. The overall goal of CMIP is model improvement of AOGCMs, along with conducting climate change studies and understanding past climates.

Figure 2-1: RCP scenarios plotted against year and global surface warming °C. Historic data is black, light blue represents climate driver RCP 4.5 and red highlights climate driver RCP 8.5. Climate driver RCP 4.5 appears to slowly decrease the rise in surface warming past 2070, while RCP 8.5 driver increases exponentially. Figure adapted from Knutti & Sedlacek (2013).

Selection criteria used in determining the AOGCMs were daily data models, higher spatial resolution, and atmosphere, ocean, land realms. Climate change scenarios

utilizing RCP 4.5 and RCP 8.5 models, along with hindcast data were required as well. The Intergovernmental Panel on Climate Change (IPCC) released two greenhouse gas emission scenarios: RCP 4.5 and RCP 8.5 (Van Vuuren et al., 2011). Representative concentration pathway (RCP) 4.5 demonstrates a 4.5 watts/m² increase of solar insolation, signifying how a moderate reduction in emissions would impact the amount of surface warming. RCP 8.5 is more extreme, with an 8.5 watts/m² increase of solar insolation, modeling a scenario with continued development at current trajectories (Figure 2-1) (Culbertson et al., 2016 and Knutti & Sedlacek, 2013). Within each of the climate models, average minimum and maximum temperatures, precipitation, humidity, wind speed, and solar radiation at Earth's surface were extracted to help simulate and predict climate impacts to the basin.

2.3.1 MIROC

The Model for Interdisciplinary Research on Climate (MIROC) was produced jointly at the Center for Climate System Research (CCSR) at University of Tokyo, National Institute for Environmental Studies (NIES), and Japan Agency for Marine-Earth Science and Technology (Watanabe et al., 2010). The current version of MIROC5 was updated from the previous version of MIROC3.2 and shows improvement in simulation of the mean climate, variability, and climate change due to anthropogenic radiative forcing (Watanabe et al., 2010). Increased developments in precipitation and more realistic El Niño Southern Oscillation (ENSO) were generated.

2.3.2 MRI

The Meteorological Research Institute (MRI) of Japan generated a new climate model, MRI-CGCM3. The model is an advancement of MRI-CGCM series 2, which was

included in the IPCC-AR4 and improvements based on feedback generated MRI-CGCM3, part of CMIP5. The upgrade consists of terrestrial biosphere carbon cycle processes, ocean biogeochemical processes, an atmosphere component that incorporates a land-surface model, and a global ocean-ice component. A good history of the development of this model is proved by Yukimoto et al., 2012.

2.3.3 CNRM

CNRM-GAME (centre National de Recherches Météorologiques-Grope d'études de l'Atmosphère Météorologique) worked jointly with Cerfacs (Centre Européen de Recherche et de Fromation Avancée) to generate another AOGCM: CNRM-CM5. Atmosphere, ocean, and sea ice models are coupled through OASIS in CNRM-CM5, along with a land surface scheme (Voldoire et al., 2013). OASIS is an addition since CMIP3 (CNRM-CM3 model), it helps avoid energy loss and spurious drifts. CNRM-CM5 shows increased sensitivity to observed natural and anthropogenic forcing's than predecessor, CNRM-CM3 (Voldoire et al., 2013).

2.4 Weather Stations

Simulated weather stations were built for model inputs on a regular grid spacing, using daily data of each climate model, downloaded from LLNL. To construct the stations, latitudes and longitudes within the watershed were selected and named in reference to nearby major cities. The daily temperature, precipitation, humidity, wind speed, and solar radiation data for the designated stations were extracted for historic hindcast and future time periods. Construction of weather stations required Matrix Laboratory (MATLAB) scripts to extract the time periods for each of the climate variables. Using the designated latitude and longitude, MATLAB scripts identified the

location and moved forward or backward in time along the z-axis, compiling daily data for future and historic hindcast time periods, respectively (Figure 2-2). Each of the climate models had scripts built for historic hindcasts (1970-2005) and predicted climate drivers RCP 4.5 and RCP 8.5 mid-century (2046-2065) and end-of-century (2076-2095). Refer to Appendix A for script example. Once the weather stations were constructed they were placed in a Microsoft Excel macro, built by Texas A&M University, compiling monthly averages from the daily data.

Figure 2-2: Weather stations were constructed in MATLAB for each climate model based on the conceptual image of MRI above. The x-axis is longitude, the y-axis is latitude, while the z-axis is daily time. To build the weather stations, labeled cells on the front, the latitude and longitude had to be specified and kept constant, from there the time was set to start at day one (January 1, 1970) and progress back to December 31, 2005. Dates, latitude, longitude, and weather stations were adjusted accordingly.

2.5 BMPs

In order to investigate if nutrient loading can be reduced in the future, SWAT models containing the BMPs were constructed to model runoff and P loading with the effects of climate change included. BMPs proposed for the Maumee Watershed were established by the Western Basin Conservation Effects Assessment Project (CEAP) to ensure the model inputs mimicked real-world agriculture operations. Nine operation schedules were constructed in total, with only three being utilized with climate change interactions. Management practices of a baseline (scenario 1), and two BMP scenarios (scenario 2 and scenario 3) were modeled.

Baseline scenario was constructed to mimic the typical practices in the current Maumee Watershed. To generate inputs from current agriculture operations, the following management practices are included in baseline as partial implementation (Table 2.1): cover crops, vegetative buffer strips, tile drainage, no-till, till incorporated fertilizer, manure application timing, and wetlands. Scenarios 2 and 3 contain more effective BMPs than the baseline scenario. Scenario 2 incorporates likely adoption rates of effective practices. Effective practices increase the use of cover crops to 60% of the Maumee Watershed, fertilizer injection was increased to 68%, and vegetative buffer strips were increased to 50% of watershed. The likely adoption scenarios were increased based on what is currently modeled in the Maumee Watershed. Scenario 3 is similar to scenario 2 but incorporates wetlands as a method of intercepting runoff and DRP. With respect to scenario 2, scenario 3 increases fertilizer injection to 50% in HRUs, cover crops to 58%, and the number of subbasins with wetlands to 78%.

Table 2.1 Management Scenarios for the baseline and BMP scenarios 2 and 3

Baseline (Scenario 1)	Scenario 2	Scenario 3
Partial Implementation of:	Likely adoption rates of BMPs:	Likely adoption rates of BMPs with wetlands:
Cover crops	Increase cover crops to 60% of watershed	Adoption of fertilizer injection to 50% of HRUs
Vegetative buffer strips		
Tile Drainage	Increase fertilizer injection to 68% of watershed	Increase cover crops to 58% of watershed
No till		
Wetlands		
Seasonal manure application	Increase vegetative buffer strip to 50% watershed	Create wetlands in 78% of sub-basins
Till incorporated fertilizer		

Agriculture management for scenarios 2 and 3 were selected based on feedback from stakeholders, and by which BMP shown effectiveness in previous models (Scavia et al., 2017). Likely adoption rates of BMPs were more effective in predicting reduced nutrient loading when implemented together, compared to when being implemented alone. Management practices were increased to a percent that farmers would likely adhere to, based on a survey conducted by collaborators. Increasing the number of wetlands was selected as a management practice to see how well they restrict nutrient runoff. Overall, management practices were selected based on their level of effectiveness in decreasing nutrient loading in a modeled watershed.

2.6 Model Setup

Reducing nutrient loading will help diminish HABs, and to see if this goal is attainable there needs to be a better understanding on how climate change and BMPs interact. This interaction is studied in a modeled watershed. The modeled Maumee Watershed utilized a 30 m digital elevation model (DEM) with 97 subbasins and 1,425 HRUs. Soil types and land use were incorporated from the USDA NRCS Soil Survey

Geographic (SSURGO) database and from 2011 National Land Cover Database (NLCD), respectively (USDA, 2017 and Homer et al., 2004). 299 registered point sources were identified and included in the DEM to ensure that nutrient runoff was well represented (Dehm, 2017). Agriculture operation schedules of fertilizer and manure application timing and practice were based on “Tri-State Fertilizer Recommendations” and checked against the Nutrient Use Geographic Information System (NUGIS) (Dehm, 2017 and Vitosh et al., 1995). NUGIS provides fertilizer sales data by county, to better reflect amount of fertilizer applied. Additionally, manure application rates were fact-checked based on livestock censuses. Land was managed with five to six crop rotations, with corn and soybean as the most dominant crop, based on USDA’s “Usual Planting & Harvesting Dates” and guidelines provided by a collaboration with the Western Lake Erie Basin Conservation Effects Assessment Project (CEAP) (Dehm, 2017, USDA, 1997). The collaboration goal was to ensure model inputs mimicked real-world applications.

Calibration and validation were completed prior to climate assessment on water and nutrient loading in Lake Erie under various BMPs. SWAT-CUP provided the uncertainty analysis for the model by calibration and validation. Calibration effectiveness was measured by Nash-Sutcliffe (NS) and R^2 values, which explain how well the best estimate values fit observed values (Abbaspour, 2013). While validation was measured by NS, R^2 , p-factor, and r-factor. NS calibration results were very good for flow and sediment, and satisfactory for total P and DRP. Validation results were good for flow and sediment, acceptable for total P, and unacceptable for total N and DRP (Dehm, 2017). Dehm (2017) stated calibrating total N, total P, and DRP together is difficult and future work is necessary to properly calibrate and validate DRP and total N.

2.7 Model Simulations

Once the model was calibrated, BMP scenarios were run with climate models to understand how they interact in reducing nutrient loading. Each climate model was run with historic, mid- and end-of-century time periods, under RCP 4.5 and RCP 8.5 climate drivers, baseline scenario, and BMP scenario 2 and scenario 3 (Figure 2-3). The following outputs were analyzed from subbasin 23 (flow out of model at the river mouth): annual flow out, evaporation, sediment out, DRP, total P, total N and compared against precipitation and temperature inputs. A combination of programs was essential in providing outputs, which include ArcSWAT, SWAT-CUP, and Cygwin.

BMPs were implemented in the modeled watershed by individually setting them as the default simulation in ArcSWAT and weather stations were imported. Each weather station was based on the respective climate model, time period, and climate driver. Once BMP scenarios and weather station were imported, a 5-year warm-up period was set and ArcSWAT run. The warm-up period was utilized to allow for nutrient and flow systems to stabilize before generating outputs (Dehm, 2017). ArcSWAT results were saved and uploaded into SWAT-CUP and file.cio was generated. File.cio is the master watershed file containing information related to modeling options, climate inputs, databases, and output specifications (Arnold et al., 2012). In SWAT-CUP, models were run with a 5-year warm-up during the correct time period and printed the six variables monthly results from subbasin 23. 100 realizations of the weather input were utilized to show variability inside of a single scenario with the same climate model. A Cygwin script (Appendix B) was developed to run swat.exe and read the file.cio created in SWAT-CUP. The script also changed the IGEN number for the climate model in file.cio from 1 to 100, creating

100 unique climate realizations. IGEN is the random generator seed code and it varies the weather sequences between runs (Arnold et al., 2012). Each BMP and climate model scenario had separate file.cio's, and after running in Cygwin gave 100 results for each variable previously mentioned.

			Baseline	Scenario 2	Scenario 3
MIROC	Hindcast		✓	✓	✓
	Mid-century	RCP 4.5	✓	✓	✓
		RCP8.5	✓	✓	✓
	End-of-Century	RCP 4.5	✓	✓	✓
		RCP 8.5	✓	✓	✓
MRI	Hindcast		✓	✓	✓
	Mid-century	RCP 4.5	✓	✓	✓
		RCP8.5	✓	✓	✓
	End-of-Century	RCP 4.5	✓	✓	✓
		RCP 8.5	✓	✓	✓
CNRM	Hindcast		✓	✓	✓
	Mid-century	RCP 4.5	✓	✓	✓
		RCP8.5	✓	✓	✓
	End-of-Century	RCP 4.5	✓	✓	✓
		RCP 8.5	✓	✓	✓

Figure 2-3: 45 scenario combinations of management practices and simulated weather stations. Management scenarios were implemented into the SWAT model first, followed by incorporation of simulated weather stations.

Chapter 3

Results

Results on climate change and BMP interaction are analyzed by comparing climate drivers RCP 4.5 and RCP 8.5 to the corresponding model's hindcast data, and comparing BMP scenarios 2 and 3 to baseline. Each climate model's hindcast results differ slightly between the other models due to different drivers and focus of each model. To compare results, values and percent change is provided. Outputs from model subbasin 23, which drains directly into Lake Erie, were used. Each figure is color-coded based on models: MIROC-green, MRI-red, CNRM-blue.

3.1 Climate Model Impacts on Climate

Comparing the predictions of the three climate models to the respective hindcast data indicates an overall increase in precipitation and temperature. Figure 3-1 compares average annual temperature to total annual precipitation for each model. MIROC predicts the greatest increase in temperature, with the smallest increase in precipitation, while MRI anticipates the least amount increase in temperature and the greatest increase in precipitation. Leaving moderate temperature and precipitation increases for CNRM. Each climate model predicts future climates similar to one another, but hindcast data varies

Figure 3-1: Each climate model's average annual temperature and total precipitation plotted. MIROC is shown in green, MRI in red, and blue denotes CNRM. Hindcast data for each climate model is plotted, along with NOAA weather data. Note the x-axis starts at 870 mm/y.

greatly. NOAA's measured historic data, from weather stations throughout the Maumee Watershed, were included in Figure 3-1 and shows that CNRM hindcast results closely resemble measured data. Hindcast results for MIROC are warmer and wetter than NOAA, while MRI hindcast is cooler and wetter. Change in temperature and precipitation, plotted in Figure 3-2, was calculated by comparing hindcast results to future predictions. CNRM sees the greatest percent change in precipitation at 31.53% increase (Table 3.1) during RCP 8.5 end-of-century scenario. This coincides with Figure 3-1 where the largest difference between CNRM hindcast and future is precipitation. MIROC results in Figure 3-2 anticipates the greatest increase in temperature change. This temperature change is apparent in Figure 3-1, as the predicted results have higher

temperatures than hindcast. MRI's predicted versus hindcast data shows the least change in temperature and precipitation.

Figure 3-2: Change in temperature and precipitation plotted for each climate model. Percent change in precipitation was calculated by comparing hindcast results to future predictions per climate model. Change in temperature was calculated by subtracting future temperature predictions from hindcast results per climate model. Mid-century results plotted as open symbols, while end-of-century symbols are closed.

MIROC predicts the driest climate and when viewing the models seasonally, RCP 4.5 mid-century scenario summer and fall shows decreasing precipitation compared to hindcast MIROC results (Figure 3-3). Additionally, end-of-century MIROC decreases in precipitation for both climate drivers and time periods in fall and summer. Although MRI predicts the wettest climate, RCP 4.5 mid-century fall and RCP 4.5 end-of-century fall and summer scenarios anticipate decreased changes in precipitation. Figure 3-3A and 3-3B shows a general pattern for all climate models, where RCP 8.5 forcing scenarios predict greater changes in temperature and precipitation than RCP 4.5 scenarios. An exception is mid-century CNRM fall, where RCP 4.5 climate driver predicts greater precipitation than RCP 8.5 driver.

Figure 3-3: Seasonal comparison between change in temperature and precipitation. Percent change in precipitation was calculated by comparing hindcast results to future predictions per climate model. Change in temperature was calculated by subtracting future temperature predictions from hindcast results per climate model. Winter months: December, January, and February. Spring months: March, April, and May. Summer months: June, July, and August. Fall months: September, October, and November. A) mid-century B) end-of-century. Designated symbols for each season, with climate driver RCP 4.5 open and climate driver RCP 8.5 closed.

Table 3.1 Precipitation and temperature data for each climate model

	Total Annual Precip (mm/y)	% Change in Precip	Avg Annual Temp °C	Change in Temp
MIROC Hindcast	1058.68	0.00	12.53	0.00
MRI Hindcast	1145.62	0.00	9.17	0.00
CNRM Hindcast	890.68	0.00	10.02	0.00
MIROC Mid-Century RCP 4.5	1065.86	0.68	15.68	3.15
MIROC Mid-Century RCP 8.5	1151.47	8.77	16.42	3.89
MRI Mid-Century RCP 4.5	1235.03	7.80	10.54	1.37
MRI Mid-Century RCP 8.5	1319.13	15.15	11.13	1.96
CNRM Mid-Century RCP 4.5	1123.98	26.19	12.11	2.09
CNRM Mid-Century RCP 8.5	1118.76	25.61	13.09	3.07
MIROC End-of-Century RCP 4.5	1081.29	2.14	16.13	3.60
MIROC End-of-Century RCP 8.5	1098.70	3.78	18.44	5.91
MRI End-of-Century RCP 4.5	1167.44	1.90	11.11	1.94
MRI End-of-Century RCP 8.5	1292.84	12.85	12.55	3.37
CNRM End-of-Century RCP 4.5	1113.51	25.02	13.06	3.04
CNRM End-of-Century RCP 8.5	1171.53	31.53	14.76	4.74

3.2 Climate Model Impacts on Evaporation and Flow

Flow and nutrient loading is dependent on precipitation and temperature. Another influence on flow is evaporation. Evaporation output from the climate models explains the average daily rate of water loss from subbasin 23 by evaporative processes (Arnold et al., 2012). The climate models cluster together in Figure 3-4 when comparing flow and evaporation. MIROC predicts the highest evaporation, at $0.2503\text{m}^3/\text{s}$ during RCP 8.5 end-of-century scenario (Table 3.2), and lowest increase in flow. MRI has a moderate increase in evaporation and the highest increase in flow at $333.67\text{ m}^3/\text{s}$ during RCP 8.5 mid-century scenario. Lowest increase in evaporation and moderate flow is predicted by CNRM. Both MRI and CNRM have higher values in evaporation and flow compared to their respective hindcast data (Figure 3-4). Comparing CNRM's hindcast and predicted

results gives a percent change of 24.95% (evaporation) and 64.67% (flow) during climate driver RCP 8.5 end-of-century scenario.

Figure 3-4: Evaporation and flow of hindcast data and predicted data. Mid-century results plotted as open symbols, while end-of-century symbols are closed. Climate driver RCP 4.5 is denoted as circles, while RCP 8.5 driver is denoted as squares. Note: the y-axis begins at 0.1820.

Table 3.2 Average and percent change of evaporation and flow. Highlighted cells denote a negative change in flow.

Models	Avg Evaporation (m ³ /s)	% Change Evaporation	Avg Flow (m ³ /s)	% Change Flow
MIROC Hindcast	0.2180	0.00	207.67	0.00
MRI Hindcast	0.2113	0.00	253.00	0.00
CNRM Hindcast	0.1830	0.00	122.67	0.00
MIROC Mid-Century RCP4.5	0.2340	7.34	161.67	-22.15
MIROC Mid-Century RCP8.5	0.2500	14.68	194.33	-6.42
MRI Mid-Century RCP4.5	0.2257	6.78	299.33	18.31
MRI Mid-Century RCP8.5	0.2330	10.25	333.67	31.88
CNRM Mid-Century RCP4.5	0.2150	17.47	201.65	64.39
CNRM Mid-Century RCP8.5	0.2240	22.40	188.33	53.53
MIROC End-of-Century RCP4.5	0.2357	8.10	176.00	-15.25
MIROC End-of-Century RCP8.5	0.2503	14.83	156.67	-24.56
MRI End-of-Century RCP4.5	0.2260	6.94	262.00	3.56
MRI End-of-Century RCP8.5	0.2360	11.67	312.67	23.58
CNRM End-of-Century RCP4.5	0.2197	20.04	188.67	53.80
CNRM End-of-Century RCP8.5	0.2287	24.95	202.00	64.67

3.3 Climate Model Impacts on Nutrients and BMPs

As P is the limiting nutrient in Lake Erie HABs, nutrient results are limited to P output data. Refer to Appendix C for N data.

Future predictions were compared to hindcast baseline outputs to determine modeled change (refer to Appendix D for total P loading values). Agriculture management practices were modeled with hindcast data to compare effectiveness against future predictions. This represents how flow and nutrient loading would have varied if scenarios 2 and 3 had been implemented with climate equivalent to the historic time period.

Figure 3-5: Change in MIROC P loading. To calculate a change in P, hindcast baseline was divided amongst the climate drivers and BMP scenarios. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Figure 3-5 shows MIROC's change in P loading for each time period, climate driver, and BMP scenario. Hindcast data shows that BMP adoption scenario 2 predicts reduced P loading, with scenario 3 being slightly more reduced. Comparing mid-century climate driver RCP 4.5 to hindcast results indicates a likely decrease in P loading overall, with RCP 8.5 producing a decrease as well but to a lesser extent. End-of-century climate driver's RCP 4.5 and 8.5 are also producing P output from the Maumee below hindcast baseline, indicating reduced P loading but reduced less than seen with respective mid-century climate drivers. In all the scenarios generated from MIROC predictions, management scenarios 2 and 3 predict lower P loading than baseline P loading.

Figure 3-6: Change in MRI P loading. Same analysis for MIROC was used for MRI. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Similar to MIROC hindcast results, MRI hindcast shows a decreasing trend in P loading when under management scenarios 2 and 3, respectively (Figure 3-6). Comparing mid-century MRI to hindcast shows a decrease in P in all management scenarios, with management scenarios 2 and 3 being most effective, and with climate driver RCP 4.5 predicting a greater reduction than RCP 8.5 driver. End-of-century time period shows a greater reduction in P loading than mid-century when comparing to hindcast. RCP 8.5 forcing scenario, during end-of-century, indicates P loading more reduced than RCP 4.5 scenario. For reference, Table 3.3 lists percent change in P loading for both climate drivers when comparing to hindcast results. There is a reduction in P when viewing BMP scenarios within each climate driver.

Figure 3-7: Change in CNRM P loading. Same analysis for MIROC was used for CNRM. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Comparing CNRM mid-century RCP 4.5 to hindcast data indicates a potential increase in P loading for all BMP scenarios (Figure 3-7). Mid-century RCP 8.5 climate driver predicts reduced P loading during baseline scenario but increased loading for management scenarios 2 and 3 when referenced to BMP scenarios 2 and 3 hindcast results (refer to Table 3.3). CNRM end-of-century P loading is expecting an increase as well when compared to hindcast data. Table 3.3 highlights cells indicating an increase in P loading when compared to same management practices. Viewing the climate drivers individually, BMP scenarios anticipate decreased P when compared to respective baseline scenarios.

Table 3.3 P loading (kg) of climate models. Percent P is the change in climate driver's P loading compared to hindcast data. Increased P loading is highlighted. Scenario 2 and 3 is denoted as s2 and s3, respectively

Model Scenario	Hindcast	RCP 4.5	RCP 8.5	% P loading RCP 4.5	% P loading RCP 8.5
MIROC Mid-Century Base	1.22E+06	7.87E+05	9.98E+05	-35.44	-18.14
MRI Mid-Century Baseline	2.66E+06	2.43E+06	2.55E+06	-8.69	-4.26
CNRM Mid-Century Baseline	1.32E+06	1.42E+06	1.28E+06	7.61	-2.93
MIROC Mid-Century s2	9.60E+05	6.41E+05	8.14E+05	-33.30	-15.22
MRI Mid-Century s2	2.10E+06	1.92E+06	2.01E+06	-8.69	-4.36
CNRM Mid-Century s2	9.84E+05	1.11E+06	1.00E+06	12.49	1.61
MIROC Mid-Century s3	9.22E+05	6.07E+05	7.76E+05	-34.12	-15.80
MRI Mid-Century s3	2.07E+06	1.88E+06	1.97E+06	-8.89	-4.58
CNRM Mid-Century s3	9.66E+05	1.07E+06	9.70E+05	11.19	0.38
MIROC End-of-Century Base	1.22E+06	9.48E+05	1.11E+06	-22.24	-8.52
MRI End-of-Century Baseline	2.66E+06	2.12E+06	2.07E+06	-20.27	-22.40
CNRM End-of-Century Base	1.32E+06	1.36E+06	1.44E+06	2.48	8.78
MIROC End-of-Century s2	9.60E+05	7.52E+05	8.82E+05	-21.70	-8.22
MRI End-of-Century s2	2.10E+06	1.66E+06	1.61E+06	-20.90	-23.30
CNRM End-of-Century s2	9.84E+05	1.04E+06	1.08E+06	5.18	9.33
MIROC End-of-Century s3	9.22E+05	7.17E+05	8.52E+05	-22.16	-7.59
MRI End-of-Century s3	2.07E+06	1.63E+06	1.57E+06	-21.18	-23.92
CNRM End-of-Century s3	9.66E+05	1.01E+06	1.05E+06	4.20	8.50

Figure 3-8 plots the three climate models together, indicating a greater predicted decrease in P loading for MIROC, followed by MRI, with a slight increase in P loading for CNRM, overall. In each climate driver, management scenario 2 decreases from baseline, with a slightly greater decrease in scenario 3. Table 3.4 has percent P loading comparing BMP scenarios to baseline. In each case, percent P loading in management scenario 3 (s3) reduces P more than management scenario 2 (s2).

Figure 3-8: Change in P loading for all three climate models. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Table 3.4 P loading (kg) for BMP scenarios. Percent P was calculated by comparing scenarios 2 and 3, individually, to baseline.

		Baseline	Scenario 2	Scenario 3	%P loading s2	%P loading s3
MIROC	Hindcast	1.22E+06	9.60E+05	9.22E+05	-21.20	-24.38
MIROC	RCP4.5	7.87E+05	6.41E+05	6.07E+05	-18.59	-22.83
Mid-Century	RCP8.5	9.98E+05	8.14E+05	7.76E+05	-18.39	-22.22
MIROC	RCP4.5	9.48E+05	7.52E+05	7.17E+05	-20.65	-24.30
End-of-Century	RCP8.5	1.11E+06	8.82E+05	8.52E+05	-20.94	-23.61
MRI	Hindcast	2.66E+06	2.10E+06	2.07E+06	-21.23	-22.38
MRI	RCP4.5	2.43E+06	1.92E+06	1.88E+06	-21.23	-22.56
Mid-Century	RCP8.5	2.55E+06	2.01E+06	1.97E+06	-21.31	-22.64
MRI	RCP4.5	2.12E+06	1.66E+06	1.63E+06	-21.85	-23.26
End-of-Century	RCP8.5	2.07E+06	1.61E+06	1.57E+06	-22.13	-23.90
CNRM	Hindcast	1.32E+06	9.84E+05	9.66E+05	-25.62	-26.96
CNRM	RCP4.5	1.42E+06	1.11E+06	1.07E+06	-22.24	-24.52
Mid-Century	RCP8.5	1.28E+06	1.00E+06	9.70E+05	-22.13	-24.46
CNRM	RCP4.5	1.36E+06	1.04E+06	1.01E+06	-23.65	-25.73
End-of-Century	RCP8.5	1.44E+06	1.08E+06	1.05E+06	-25.23	-27.14

Figure 3-9: Change in MIROC DRP. To calculate a change in DRP, hindcast baseline was divided amongst the climate drivers and BMP scenarios. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Figure 3-9 depicts change in DRP for MIROC. Outputs for this variable mimics change in P loading for MIROC, with the decreasing trend in BMP scenarios apparent. Table 3.5 lists DRP values for each of the climate models, time periods, and BMP scenarios in kg of P. Comparing Table 3.4 to Table 3.5, there is a visible kg loading difference between the two, where DRP values are below P. DRP outputs for MRI (Figure 3-10) mimics MRI P loading trends, except for climate driver RCP 8.5 mid-century. RCP 8.5 mid-century scenario indicates increased DRP outputs, while MRI P loading is likely to be reduced overall under this scenario. BMP scenarios are decreasing as management scenarios progress, except for hindcast results for MRI where scenario 3 DRP loading change is above scenario 2 (Table 3.5). Figure 3-11 plots changes in DRP outputs for CNRM, which follows P loading trends in Figure 3-7. Similar to MRI,

CNRM hindcast results show less of a decrease in DRP change during s3 than s2 management.

Figure 3-10: Change in MRI DRP. Same analysis for MIROC was used for MRI. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Figure 3-11: Change in CNRM DRP. Same analysis for MIROC was used for CNRM. Baseline is solid, while scenario 2 is denoted as diagonal lines, and scenario 3 is horizontally dashed.

Table 3.5 DRP loading (kg P) for BMP scenarios. Percent DRP was calculated by comparing scenarios 2 and 3, individually, to baseline. Highlight cells indicate s3 being reduced less than s2.

		Baseline	Scenario 2	Scenario 3	%DRP loading s2	%DRP loading s3
MIROC	Hindcast	4.78E+05	4.17E+05	3.99E+05	-12.75	-16.61
MIROC	RCP 4.5	3.16E+05	2.80E+05	2.63E+05	-11.43	-16.70
Mid-Century	RCP 8.5	3.91E+05	3.48E+05	3.30E+05	-11.01	-15.70
MIROC	RCP 4.5	3.67E+05	3.23E+05	3.07E+05	-11.75	-16.22
End-of-Century	RCP 8.5	3.82E+05	3.39E+05	3.32E+05	-11.16	-13.10
MRI	Hindcast	8.69E+05	7.68E+05	7.71E+05	-11.71	-11.28
MRI	RCP 4.5	8.61E+05	7.62E+05	7.58E+05	-11.42	-11.97
Mid-Century	RCP 8.5	9.15E+05	8.13E+05	8.06E+05	-11.15	-11.89
MRI	RCP 4.5	7.75E+05	6.83E+05	6.76E+05	-11.89	-12.70
End-of-Century	RCP 8.5	7.79E+05	6.93E+05	6.78E+05	-11.12	-12.96
CNRM	Hindcast	4.40E+05	3.72E+05	3.74E+05	-15.52	-15.12
CNRM	RCP 4.5	5.21E+05	4.58E+05	4.47E+05	-12.07	-14.18
Mid-Century	RCP 8.5	4.59E+05	4.00E+05	3.91E+05	-12.74	-14.75
CNRM	RCP 4.5	4.80E+05	4.18E+05	4.10E+05	-12.99	-14.72
End-of-Century	RCP 8.5	4.91E+05	4.29E+05	4.21E+05	-12.47	-14.29

Chapter 4

Discussion

Each climate model's variables are interpreted with a focus on precipitation and temperature input values and outputs for evaporation and flow. These variables influence nutrient runoff, explaining future impacts to Lake Erie HABs.

4.1 MIROC

MIROC predicts a warmer and drier climate than the other two climate models, increased evaporation and decreased flow. Seasonally, climate driver RCP 4.5 mid- and end-of-century, along with climate driver RCP 8.5 end-of-century summer and fall, anticipate a decrease in precipitation, corresponding to a drier climate and lower flow. Predictions of increased evaporation correlate to increased temperature. Increased evaporation contributes to a reduction of stream flow. Additionally, the negative values of percent change in flow indicate decreasing flow.

P loading in the RCP 4.5 forcing scenario during both time periods decreases more than in the RCP 8.5 scenario. Additionally, the RCP 4.5 scenarios predict less flow and evaporation than RCP 8.5 scenarios, explaining reduced P. Mid-century climate drivers are likely to decrease P more than end-of-century drivers, but shows a decrease in P loading overall when compared to hindcast baseline management. DRP mimics P

reductions but has lower loading values. MIROC's BMP scenarios are an effective practice in reducing P loading, as scenario 2 and scenario 3 resulted in model predictions that are reduced when compared to baseline management.

Due to predicted P loading results falling below hindcast baseline, MIROC's climate model appears to aid BMP scenarios. The positive interaction between climate change and BMP scenarios is explained when hindcast precipitation results are compared to NOAA's results and the predicted results. MIROC hindcast precipitation falls above NOAA's measured data and closer to predicted precipitation results. As a result, hindcast is wetter than reality and the small change between hindcast and predicted precipitation influences reduced P loading as flow increases less. Overall, MIROC predicts greater P reduction between climate models due to the drier climate, less flow, and higher evaporation.

4.2 MRI

MRI anticipates a cooler climate, as temperature increases the least among the climate models, and is the wettest. Even though MRI is identified as the wettest climate model, the percent change (difference between hindcast and predicted) in precipitation is mild compared to climate model CNRM's change in precipitation. This difference explains the slight decrease in precipitation during seasonal climate forcing of RCP 4.5 mid-century fall and climate forcing RCP 4.5 end-of-century fall and summer months. The mild change in precipitation is explained by MRI's hindcast precipitation results. Hindcast results are closer to predicted precipitation results than NOAA's measured data. Due to the slight increase in temperature, MRI predicts a mild increase in evaporation but not enough to decrease flow output as it predicts the largest flow among the models.

During mid-century time period, climate driver RCP 4.5 reduces P more than the RCP 8.5 scenario, while end-of-century climate driver scenarios predict the opposite effect in reducing P loading. Climate forcing RCP 8.5 end-of-century predicts higher evaporation values than RCP 4.5 scenario, creating less flow and thus less nutrient runoff. End-of-century MRI will likely reduce P more than mid-century, as management practices are effective and applied longer. Additionally, the models end-of-century time period predicts higher temperature and evaporation, leading towards less flow. P loading overall is reduced below hindcast baseline management. DRP follows P trends, except for climate driver RCP 8.5 end-of-century, indicating BMPs are less effective on DRP. Similar to MIROC, BMP scenarios are effective in reducing P for MRI.

MRI's climate model indicates that climate change will impact management scenarios, but not always offset P decrease. As noted in MIROC's climate model, MRI has a wetter hindcast than reality and shows climate change working with BMPs to reduce P loading. This statement is counteracted by MRI anticipating less decrease in P loading than MIROC and climate driver RCP 8.5 mid-century showing increased DRP loads. Overall, MRI is expected to reduce P the least when minimal increases in evaporation is paired with increased flow.

4.3 CNRM

Comparing CNRM to MIROC and MRI, it predicts a moderate increase in temperature and precipitation. A big player controlling P loading in CNRM is the change in temperature and precipitation input variables when comparing hindcast and predicted results. Hindcast results closely resemble measured NOAA precipitation and temperature but falls the furthest away from predicted. The biggest change is precipitation, with a

moderate increase in temperature. Because of this, CNRM has the highest percent change in precipitation of all climate models, influencing flow. When viewing flow and evaporation values, predictions fall with moderate and lowest increases, respectively. Change in precipitation overrides evaporative processes, causing CNRM evaporation to have the lowest increase compared to the other climate models.

CNRM RCP 8.5 mid-century baseline is the only variable that falls below hindcast baseline management, thus indicating an increase in P loading overall. During mid-century, climate driver RCP 4.5 increases P more than RCP 8.5 scenario. This difference in P loading is explained by an increase in flow and decrease in evaporation, leading towards increased nutrient loading. End-of-century RCP 4.5 scenario increases in P less than RCP 8.5 scenario. This is expected with RCP scenarios and is supported with lower predictions in flow and evaporation increases in climate driver RCP 4.5. CNRM mid-century has less P loading than end-of-century and can be explained by a lower increase in temperature and precipitation for mid-century. DRP also follows P trends, and like MRI, management scenario 3 for hindcast reduces DRP less than scenario 2. BMP scenarios are less effective on DRP but are an effective practice on reducing P when viewing individual climate driver scenarios. Overall, CNRM's climate change overrides BMP scenarios and P loading increases.

Chapter 5

Conclusion

HABs in the western basin of Lake Erie are annually persistent, increasing in intensity as anthropogenic nutrients and lake warming increases. As fertilizer application will likely continue, understanding the interaction between BMPs and climate change will help address a potential solution to reduce P loading. The goal of the Ohio Phosphorous Task Force is to reduce DRP loading by 40%, 90% of the time, by 2025. After running three climate models, during three time periods, under two climate drivers, and implementing a baseline scenario and two BMP scenarios, it is unlikely that the goal will be attainable with these model scenarios. MIROC predicts that the greatest decrease in P loading would be 34% by mid-century. This reduction was predicted using climate driver RCP 4.5 and scenario 3. MRI follows with P loading reduced by 24% during climate forcing RCP 8.5 scenario 3 end-of-century, with CNRM predicting an increase in P loading. DRP values closely follow P trends at lower loading volumes. Flow and evaporation, along with changes within the two variables when comparing hindcast to predicted results, were the main contributors influencing nutrient loading. Typically, when flow decreases and evaporation increases, nutrient loading will be reduced. Changes in flow and evaporation can offset one another. In the case of MRI and CNRM,

evaporation increased to a moderate level in the former climate model and increased to a lesser extent in the latter model, regardless of predicted temperature and precipitation increases.

Hindcast precipitation results help explain P loading when compared to NOAA's measured data and proximity to predicted results. MIROC and MRI hindcast results are wetter than NOAA's measured data and similar to respective model's predicted values, while CNRM hindcast is similar to measured values and drier than predicted results. MIROC and MRI both anticipate a relative decrease in P loading, with some decreases in P offset by climate change for MRI. CNRM anticipates a slight increase in P loading. Based on similar hindcast results to NOAA's measured data it is likely that CNRM is the most realistic climate model, reflecting future climate and P loading, but is inconclusive. Depending on climate model, climate change may offset nutrient decreases from implementing management scenarios. Most models show the 40% goal reduction in DRP 9 out of 10 years, by 2025, is not attainable with these model scenarios. Although BMP scenarios are an effective practice in reducing P loading, more aggressive management will need to be implemented to help constrain algal growth in the future.

MIROC and MRI climate models predicted unanticipated P loading results due to hindcast data being considerably more wet than NOAA's measured data. In the future, when selecting climate models emphasis should be placed on hindcast results that more closely resemble current and historic measured data. Other future work may incorporate increased or multiple growing seasons, as climate change may influence this type of environment. Additional focus should be placed on N loading; as on-going studies indicate microcystin levels are controlled by N abundance.

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Appendix A

MATLAB Scripts

MATLAB scripts extracted the necessary data from CMIP5 files to construct the weather stations utilized by the weather generator for ArcSWAT. Following is an example script for MIROC RCP 4.5 mid-century precipitation. Each of the climate models have similar scripts for both climate drivers, time-periods, and for all six variables. The only difference between variable scripts are the lines that convert units.

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```

```

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fprintf(fileID,'%s\r\n','12/31/2069');
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```

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B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\LEE45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-
20491231.nc';
pcp=ncread(file,'pr',[197,94,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40(isnan(pcp40))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20500101-
20591231.nc';
pcp=ncread(file,'pr',[197,94,1],[1,1,Inf],[1,1,1]);
pcp50=pcp*86400;
pcp50(isnan(pcp50))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20600101-
20691231.nc';
pcp=ncread(file,'pr',[197,94,1],[1,1,Inf],[1,1,1]);
pcp60=pcp*86400;
pcp60(isnan(pcp60))=-99.0;
A=[pcp40];

```

```

B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\DEF45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-
20491231.nc';
pcp=ncread(file,'pr',[198,94,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40(isnan(pcp40))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20500101-
20591231.nc';
pcp=ncread(file,'pr',[198,94,1],[1,1,Inf],[1,1,1]);
pcp50=pcp*86400;
pcp50(isnan(pcp50))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20600101-
20691231.nc';
pcp=ncread(file,'pr',[198,94,1],[1,1,Inf],[1,1,1]);
pcp60=pcp*86400;
pcp60(isnan(pcp60))=-99.0;
A=[pcp40];
B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\CLY45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-
20491231.nc';
pcp=ncread(file,'pr',[195,95,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40(isnan(pcp40))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20500101-
20591231.nc';
pcp=ncread(file,'pr',[195,95,1],[1,1,Inf],[1,1,1]);
pcp50=pcp*86400;
pcp50(isnan(pcp50))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20600101-
20691231.nc';
pcp=ncread(file,'pr',[195,95,1],[1,1,Inf],[1,1,1]);

```



```

pcp60=pcp*86400;
pcp60(isnan(pcp60))=-99.0;
A=[pcp40];
B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\MLM45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-
20491231.nc';
pcp=ncread(file,'pr',[196,95,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40(isnan(pcp40))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20500101-
20591231.nc';
pcp=ncread(file,'pr',[196,95,1],[1,1,Inf],[1,1,1]);
pcp50=pcp*86400;
pcp50(isnan(pcp50))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20600101-
20691231.nc';
pcp=ncread(file,'pr',[196,95,1],[1,1,Inf],[1,1,1]);
pcp60=pcp*86400;
pcp60(isnan(pcp60))=-99.0;
A=[pcp40];
B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\GRR45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-
20491231.nc';
pcp=ncread(file,'pr',[197,95,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40(isnan(pcp40))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20500101-
20591231.nc';
pcp=ncread(file,'pr',[197,95,1],[1,1,Inf],[1,1,1]);
pcp50=pcp*86400;
pcp50(isnan(pcp50))=-99.0;

```

```

file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20600101-
20691231.nc';
pcp=ncread(file,'pr',[197,95,1],[1,1,Inf],[1,1,1]);
pcp60=pcp*86400;
pcp60(isnan(pcp60))=-99.0;
A=[pcp40];
B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\ELS45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-
20491231.nc';
pcp=ncread(file,'pr',[198,95,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40(isnan(pcp40))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20500101-
20591231.nc';
pcp=ncread(file,'pr',[198,95,1],[1,1,Inf],[1,1,1]);
pcp50=pcp*86400;
pcp50(isnan(pcp50))=-99.0;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20600101-
20691231.nc';
pcp=ncread(file,'pr',[198,95,1],[1,1,Inf],[1,1,1]);
pcp60=pcp*86400;
pcp60(isnan(pcp60))=-99.0;
A=[pcp40];
B=[pcp50];
C=[pcp60];
fileID=fopen('D:\Tiffany\MIROC\4.5\r1\MAC45MIROCmid_pcp.txt','w');
fprintf(fileID,'%s\r\n','Text');
fprintf(fileID,'%s\r\n','01/01/2040');
fprintf(fileID,'%s\r\n','12/31/2069');
fprintf(fileID,'%0.2f\r\n',A,B,C);
fclose(fileID);

```

Following is a brief example script for MIROC RCP 4.5 mid-century temperature, highlighting the unit conversion.

```
file='D:\Tiffany\MIROC\4.5\tasmax\tasmax_day_MIROC5_rcp45_r1i1p1_20400101-20491231.nc';
tasmax=ncread(file,'tasmax',[195,93,1],[1,1,Inf],[1,1,1]);
tasmax40=tasmax-273.15;
tasmax40(isnan(tasmax40))=-99.0;
file='D:\Tiffany\MIROC\4.5\tasmin\tasmin_day_MIROC5_rcp45_r1i1p1_20400101-20491231.nc';
tasmin=ncread(file,'tasmin',[195,93,1],[1,1,Inf],[1,1,1]);
tasmin40=tasmin-273.15;
tasmin40(isnan(tasmin40))=-99.0;
```

Following is an example script for MIROC RCP 4.5 mid-century half hour rainfall, highlighting the unit conversion.

```
F=0.5;
G=24;
H=F./G;
I=(1/3);
E=H.^I;
file='D:\Tiffany\MIROC\4.5\pr\pr_day_MIROC5_rcp45_r1i1p1_20400101-20491231.nc';
pcp=ncread(file,'pr',[195,93,1],[1,1,Inf],[1,1,1]);
pcp40=pcp*86400;
pcp40=pcp40*E;
pcp40(isnan(pcp40))=-99.0;
```

Following is an example script for MIROC RCP 4.5 mid-century near-surface relative humidity, highlighting the unit conversion.

```
file='D:\Tiffany\MIROC\4.5\rhs\rhs_day_MIROC5_rcp45_r1i1p1_20400101-20491231.nc';
rhs=ncread(file,'rhs',[195,93,1],[1,1,Inf],[1,1,1]);
rhs40=rhs/100;
rhs40(isnan(rhs40))=-99.0;
```

Following is an example script for MIROC RCP 4.5 mid-century surface down welling shortwave radiation, highlighting the unit conversion.

```
file='D:\Tiffany\MIROC\4.5\rsds\rsds_day_MIROC5_rcp45_r1i1p1_20400101-20491231.nc';  
rsds=ncread(file,'rsds',[195,93,1],[1,1,Inf],[1,1,1]);  
rsds40=rsds*.0864;  
rsds40(isnan(rsds40))=-99.0;
```

Following is an example script for MIROC RCP 4.5 mid-century surface wind, highlighting the unit conversion.

```
file='D:\Tiffany\MIROC\4.5\sfcWind\sfcWind_day_MIROC5_rcp45_r1i1p1_20400101-20491231.nc';  
sfcWind40=ncread(file,'sfcWind',[195,93,1],[1,1,Inf],[1,1,1]);  
sfcWind40(isnan(sfcWind40))=-99.0;
```

Appendix B

Cygwin Script

Below is the Cygwin script, constructed to create 100 iterations using statistically equivalent weather generations to see how impacted the model. The script was designed to change the IGEN number from 0 to 100, to generate the 100 runs.

```
for number in {0..100}; do sed '13s/0/"$number"/g' ./filebase.txt > file.cio; ./swat.exe; mv 'output.std' 'output'$number'.std'; mv 'output.rch' 'output'$number'.rch'; done
```

Appendix C

N Loading

N loading total amounts of the three climate models: MIROC, MRI, and CNRM, with standard deviation.

Figure C-1: N loading during mid- and end-of-century for MIROC. Standard deviation is plotted.

Figure C-2: N loading during mid- and end-of-century for MRI. Standard deviation is plotted.

Figure C-3: N loading during mid- and end-of-century for CNRM. Standard deviation is plotted.

Appendix D

P and DRP Loading

P loading total amounts of the three climate models: MIROC, MRI, and CNRM, with standard deviation.

Figure D-1: P loading during mid- and end-of-century for MIROC. Standard deviation is plotted.

Figure D-2: P loading during mid- and end-of-century for MRI. Standard deviation is plotted.

Figure D-3: P loading during mid- and end-of-century for CNRM. Standard deviation is plotted.

Figure D-4: P vs DRP total loading values. Shades of green represent MIROC total P while orange represents DRP. Red is MRI total P and purple is DRP. Blue is CNRM total P and yellow is DRP. Time periods are abbreviated.