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The hydrologic model as a source of nutrient loading uncertainty in a future climate

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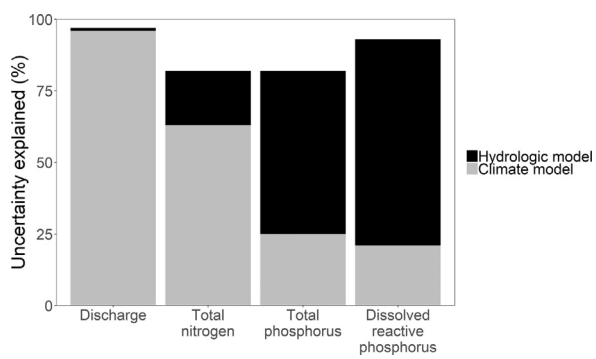
HIGHLIGHTS

- No clear change in mid-century water quantity or quality in a Great Lakes watershed
- Climate models are main source of uncertainty in discharge and nitrogen predictions.
- Hydrologic models are main source of uncertainty in phosphorus loading predictions.

GRAPHICAL ABSTRACT



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ABSTRACT

Hydrologic models are applied increasingly with climate projections to provide insights into future hydrologic conditions. However, both hydrologic models and climate models can produce a wide range of predictions based on model inputs, assumptions, and structure. To characterize a range of future predictions, it is common to use multiple climate models to drive hydrologic models, yet it is less common to also use a suite of hydrologic models. It is also common for hydrologic models to report riverine discharge and assume that nutrient loading will follow similar patterns, but this may not be the case. In this study, we characterized uncertainty from both climate models and hydrologic models in predicting riverine discharge and nutrient loading. Six climate models drawn from the Coupled Model Intercomparison Project Phase 5 ensemble were used to drive five independently developed and calibrated Soil and Water Assessment Tool models to assess hydrology and nutrient loadings for mid-century (2046–2065) in the Maumee River Watershed,the largest watershedsdraining to the Laurentian

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Uncertainty

Great Lakes. Under those conditions, there was no clear agreement on the direction of change in future nutrient loadings or discharge. Analysis of variance demonstrated that variation among climate models was the dominant source of uncertainty in predicting future total discharge, tile discharge (i.e. subsurface drainage), evapotranspiration, and total nitrogen loading, while hydrologic models were the main source of uncertainty in predicted surface runoff and phosphorus loadings. This innovative study quantifies the importance of hydrologic model in the prediction of riverine nutrient loadings under a future climate.

1. Introduction

Climate change influences water resources globally. Quicker onset and longer duration of droughts (Trenberth et al., 2014) and extreme precipitation events (IPCC, 2012) are expected to become more common in the next century. Subsequent changes in water quality could also occur given climate stress on water quantity (Murdoch et al., 2000; Whitehead et al., 2009). The direction and magnitude of these changes in water quantity and quality are of great interest to policy- and decision-makers because of its impacts on agriculture (Howden et al., 2007), drinking water supply (Delpla et al., 2009), and infrastructure (Gersonius et al., 2013).

A common method of forecasting the impacts of climate change on water resources is to drive a hydrologic model with projected temperature and precipitation from an ensemble of climate models. It is acknowledged that uncertainties associated with projected climate can be significant, and that the selection of climate model often affects the magnitude and direction of hydrologic change (Arnell, 1999; Jung et al., 2011; Kay et al., 2008; Prudhomme and Davies, 2009; Vetter et al., 2017; Wilby and Harris, 2006; Wilby et al., 2006). Using the ensemble range of temperature and precipitation predictions from multiple representative concentration pathways (RCP), climate models, and downscaling methods is assumed to characterize prediction uncertainty (e.g. Byun et al., 2019; Culbertson et al., 2016). This approach assumes most of the uncertainty comes from the climate projections rather than the hydrologic model.

There is extensive literature on water quantity prediction uncertainty (e.g. average discharge, 7-day low flow, flooding, etc.; Arnold et al., 2016), and the general consensus is that the dominant source of uncertainty is derived from the climate model, with the hydrologic model contributing a varying but lesser amount of uncertainty (e.g. Bosshard et al., 2013; Giuntoli et al., 2015; Karlsson et al., 2016; Kay et al., 2008; Prudhomme et al., 2014; Thober et al., 2018; Vetter et al., 2017). However, we found no study partitioning uncertainty in water quality predictions between climate models and hydrologic models. Water quality is more difficult than discharge to simulate accurately, and good performance metrics are rarely reported, especially in catchments dominated by non-point sources (Dean et al., 2009; Jackson-Blake et al., 2015; Moriasi et al., 2007; Moriasi et al., 2015). Therefore, one would expect predictions of water quality in watersheds dominated by non-point source contaminants to have greater uncertainty than predictions of discharge when compounded with climate change uncertainties.

This study aims to understand how future climate will alter nutrient loads in a Great Lakes watershed and how the uncertainty in those predictions is affected by both climate and hydrologic models. Using an ensemble of six climate models and five independently configured versions of the Soil and Water Assessment Tool (SWAT), we assess the magnitude and uncertainty of changes in average annual discharge, water balance, and nutrient loading from the Maumee River Watershed, the largest (~17,000 km^2 ODNR Ohio Department of Natural Resources, 2018) and one of the most intensely monitored of the Great Lakes' watersheds. The first objective is to assess the level of agreement in direction and magnitude of predicted changes in hydrology (discharge, tile discharge [i.e. subsurface drainage], surface runoff, and evapotranspiration) and water quality (total phosphorus, dissolved reactive phosphorus, and total nitrogen loadings). The second objective is to assess the extent to which climate and hydrologic models contribute to the uncertainty in predictions of hydrology and water quality.

2. Methods

2.1. Study area and importance

The Maumee River watershed, located in northwest Ohio and in portions of Indiana and Michigan (Fig. 1), is dominated by row crop agriculture (~70%), consisting primarily of soybean, corn, and winter wheat in rotation. Tile drains and surface ditches are used extensively because the soils are high in clay content and have poor natural drainage. The watershed is relatively flat with an average slope of ~0.8%.

The Maumee River Watershed is a prime case study for climate change effects on water quality due to a long-term record of daily water quality monitoring data, which allows for the models to be rigorously calibrated. This watershed has also been identified as a priority watershed for reducing the occurrence of harmful algal blooms (HABs) in the western Lake Erie basin (GLWQA Great Lakes Water Quality Agreement, 2016). Phosphorus is the primary driver of HABs in Lake Erie (Bertani et al., 2016; Bridgeman et al., 2013; Michalak et al., 2013; Obenour et al., 2014; Stumpf et al., 2016) and therefore phosphorus control measures are the focus of management strategies (GLWQA Great Lakes Water Quality Agreement, 2016); GLWQA Great Lakes Water Quality Agreement, 2018; Schindler et al., 2008; Schindler, 1974; Wilson et al., 2019). Reducing phosphorus from the Maumee River Watershed is a priority because it is the largest contributor of total phosphorus (TP) and the second largest contributor of dissolved reactive phosphorus (DRP) to Lake Erie (Maccoux et al., 2016). The Great Lakes Water Quality Agreement (GLWQA Great Lakes Water Quality Agreement, 2018) has set a target of a 40% reduction in phosphorus from the 2008 loads to reduce the extent of the blooms and hypoxia, and acknowledges the need for adaptive management to meet the target as climate changes. The influence of a changing climate on nutrient loading may be through changing discharge and/or phosphorus or nitrogen concentrations in the river, both being important constituents in fueling freshwater blooms (Newell et al., 2019; Paerl et al., 2016). Nutrient mobility, transformation, and retention by crops and soil can be affected as changing precipitation and temperature alter the pathways water travels through surface runoff, tile discharge, and evapotranspiration (Pease et al., 2017, 2018). The number of days with heavy precipitation and the overall average precipitation are expected to increase in the Midwest region (Basile et al., 2017; Pryor et al., 2014), which may increase phosphorus loadings and further fuel HABs (Jeppesen et al., 2009; Paerl and Paul, 2012). Taken together, the effects of future climate in the Maumee could alter the total reduction needed in phosphorus loads to achieve the Lake Erie target.

2.2. Climate model selection

We used downscaled precipitation and temperature data (~12 × 12 km resolution) from six General Circulation Models (GCMs) in the Coupled Model Intercomparison Project Phase 5 (CMIP5). The CMIP5 data were downscaled using the bias-corrected Constructed Analogues method (BCCA; Reclamation, 2013). BCCA downscaling

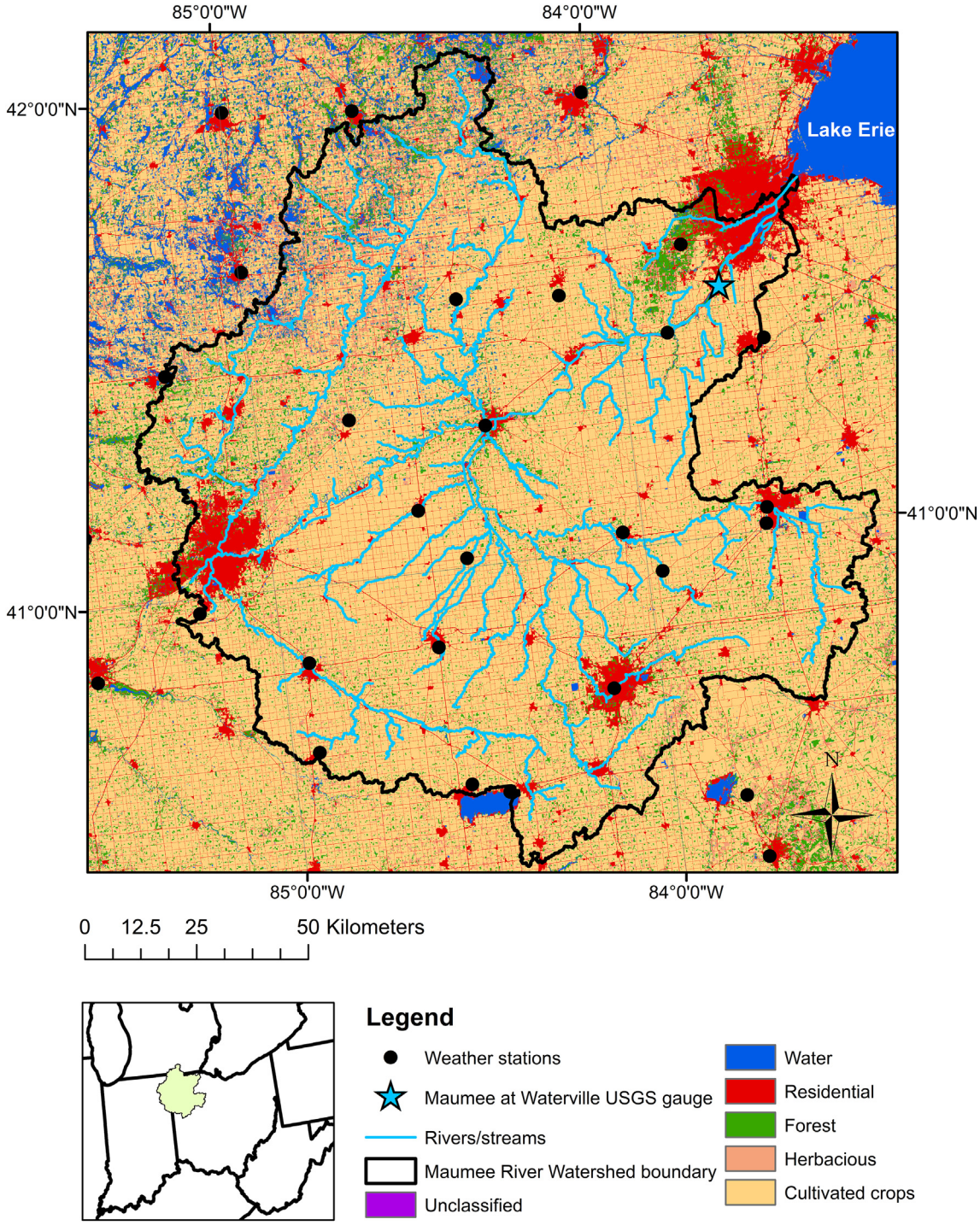

Fig. 1. Map of the Maumee River Watershed. The Maumee at Waterville gauge (USGS #04193500) is used for calibration of all five SWAT models.

produces daily precipitation (mm) as well as minimum and maximum air temperatures (°C). The spatial resolution varied among the models (Table 1). We used only the highest emissions scenario (RCP 8.5) because this scenario would drive the largest changes in temperature and precipitation, and therefore generate the greatest hydrologic response. We chose to focus on varying precipitation change because it is a significant driver of loads at the watershed scale (Michalak et al., 2013). Six GCMs from the CMIP5 ensemble were selected to represent climate change (Fig. S1). This is on the higher end of selected GCMs from similar model ensemble studies (median GCMs selected is 5, Table S5).

2.3. Hydrologic model ensemble

We used variations of the Soil and Water Assessment Tool (SWAT) to represent different hydrologic models. SWAT is a physically based watershed-scale model developed by the U.S. Department of Agriculture Research Service to evaluate the effects of land management on water quantity and quality (Arnold et al., 2012). SWAT runs on a daily timescale and requires, at a minimum, input data for land use and land cover, topography, and soils. SWAT can capture agricultural land-management practices, which is important for this watershed as most of the land-use is agricultural.

Table 1
Climate models for which outputs were used in this study. The models will be referenced by the abbreviation listed in this table in the remainder of this paper.

Abbreviation	Model	Institute	Resolution
CanESM	CanESM2	Canadian Center for Climate Modeling and Analysis	2.8° × 2.8°
CSIRO_r6	CSIRO-MK3-6-0	CSIRO Marine and Atmospheric Research	1.8° × 1.8°
CSIRO_r4	CSIRO-MK3-4-0	CSIRO Marine and Atmospheric Research	1.8° × 1.8°
CSIRO_r10	CSIRO-MK3-10-0	CSIRO Marine and Atmospheric Research	1.8° × 1.8°
MPI-ESM	MPI-ESM-LR	Max Planck Institute for Meteorology	1.9° × 1.9°
NorESM	NorESM1-M	Norwegian Climate Centre	1.875° × 2.5°

Five modeling groups independently developed and calibrated the ensemble suite of SWAT models for the Maumee River Watershed (Table 2). This model ensemble was used previously to assess agricultural management scenarios in the watershed for reducing nutrient delivery to Lake Erie (Scavia et al., 2017; Martin et al., 2019). While model inputs for historical climate, point sources, and some farm management practices were the same for all models, each modeling group made independent decisions about spatial resolution, many aspects of land management, and model calibration approach.

Land management and land use was determined using the National Land Cover Dataset and/or the NASS cropland data layer (Table S3). Each SWAT model was to be within pre-determined ranges of land management practices, but the exact placement or total area under a management practice could vary based on assumptions made. For instance, in the UM model cover crops were applied on 8.4% of cropland with a corn-soy-soy rotation; in the UT model, a cover crop was planted on 10% of cropland focusing on corn-soy rotations (Table S3). Land management operations were integrated into multi-year rotations that repeated throughout the calibration and validation period. For detailed information on differences in land management assumptions among the models, see Supplemental Information Table S3.

Each model was calibrated and validated near the watershed outlet, at the Maumee River at Waterville (USGS gauge 04193500), and was assessed using common model criteria for performance on monthly outputs using the correlation coefficient (R^2), Nash-Sutcliffe Efficiency (NSE), and percent bias (PBIAS) and standards in Moriasi et al. (2007). Differences in model parameters and subroutines are included in Supplementary Information (Tables S1 and S2). All models had at least satisfactory performance during the calibration and validation periods from 2005 to 2015 (Table 2). This method created an ensemble of models that simulate discharge and nutrient loads from the watershed in a historical period (2005–2015; Table 2, Figs. S2–S6) indicating each model has reasonable representations of watershed processes, but given their separate development, the individual models are considered unique. After calibration, model hydrologic processes at the HRU scale were further verified against field monitoring data on tile discharge, surface runoff, and crop yields (Table S4).

Cropland management for the entire period of the climate scenarios (1996–2065) remained the same as in the calibration and validation period of 2005–2015. This allowed us to predict the direction of change in discharge and nutrients if the watershed continues to be managed under a "business-as-usual" scenario. While it may have been more realistic to show projected land management changes simultaneously, by holding land management constant we were able to test the impact of climate alone.

2.4. Incorporation of climate data

To incorporate the climate model outputs of precipitation and temperature into each hydrologic model, the SWAT subbasin maps was overlain with the climate model grid, and each subbasin was given data from the climate model grid cell containing its centroid. Each SWAT model is unique in its number and spatial distribution of subbasins (Table 2). Hydrologic models were driven by all six climate models, for a total of 30 ensemble members. Due to the nature of the study and the large amount of coordinated model runs and processing time required, 30 potential futures (5 GCMs and 6 hydrologic models) was deemed adequate to represent the watershed. All models were run continuously from 1990 to 2065 and model outputs were processed for 1996–2015 (historical) and 2046–2065 (mid-century). A 20-year time window is appropriate for climate change studies based on the revised climate period from the World Meteorological Organization (Arguez and Vose, 2011; Basile et al., 2017).

2.5. Statistical approach

For objective 1, to assess agreement in direction and magnitude of hydrologic change, we used the signal-to-noise ratio, defined as the ensemble median divided by the inter-quartile range. A ratio of less than one is interpreted as little agreement in direction and/or large variation in magnitude of change, and greater than one as greater agreement and/or small variation (Giuntoli et al., 2015; Thober et al., 2018). The Wilcoxon Rank-Sum test (Wilcoxon, 1945) was used to test if the change between the historical and mid-century was significant. A

Table 2
Table of monthly calibration and validation statistics for discharge during the period 2005–2015 for the Maumee at Waterville gauge. *Model performance was rated according to standards in Moriasi et al. (2007).

		Criterion for **Good**/Satisfactory*	Model Average	University of Michigan	University of Toledo	Ohio State University	LimnoTech	Heidelberg University
PBIAS (%)	Discharge	**±15**/±25	−0.4	−0.8	0.9	2.7	−14.3	9.3
	TP	**±30**/±55	1.5	−1.4	14.0	−32.1	32.3	−5.3
	DRP		−1.3	−7.2	−24.3	36.1	10.4	−21.5
	TN		0.3	8.2	−29.7	33.1	12.1	−22.0
	Suspended solids	**±30**/±55	0.5	4.1	7.9	−24.6	20.8	−5.6
NSE	Discharge	>**0.65**/>0.50	0.89	0.94	0.84	0.90	0.91	0.88
	TP		0.70	0.61	0.66	0.71	0.77	0.73
	DRP		0.67	0.69	0.50	0.73	0.67	0.78
	TN		0.58	0.77	0.17	0.64	0.59	0.74
	Suspended solids		0.74	0.76	0.69	0.73	0.76	0.77
	Number of subbasins			358	97	1482	203	374

signal-to-noise ratio greater than one and a Wilcoxon Rank-Sum test result of significance would provide strong evidence of changes in climate and agreement in that direction of hydrologic change.

For objective 2, to assess the extent to which climate and hydrologic models contribute to the uncertainty in predictions of hydrology and nutrient loadings, we used a two-way, main effects ANOVA (Bosshard et al., 2013; Giuntoli et al., 2015; Vetter et al., 2017; von Storch and Zweirs, 1999; Yip et al., 2013) on the change between the historical and the mid-century output. The Shapiro-Wilk test was used to check for normality (Sharpiro and Wilk, 1965), required for use of the ANOVA method. Uncertainty in this study was defined as the range of predictions for each variable.

We did not weight hydrologic model outputs for three reasons. First, there was no evidence that a single model had superior performance based on calibration statistics alone. Second, calibration statistics can be misleading to use in a weighted approach because these non-linear models can successfully calibrate for the wrong reasons (Kirchner, 2006). For example, a calibrated model may simulate discharge at the outlet of the watershed correctly; however, this could be due to inaccurate but compensating representations of watershed processes (e.g. surface runoff, tile discharge, groundwater flow). Third, weighting of models in hydrologic climate change studies has also shown to not substantially alter results (Chen et al., 2017; Wilby and Harris, 2006).

3. Results

3.1. Precipitation and temperature

3.1.1. Historical bias (1996–2015)

All of the downscaled climate model outputs showed significant dry and warm biases in the historical time period (Table 3). The largest over-prediction for temperature was from CanESM (1.2 °C) and the largest under-prediction for precipitation from CSIRO-r10 (−10.7%). The warm and dry bias has been observed in other studies also using the BCCA downscaling technique (Gutmann et al., 2014). The standard deviation (Table 3) is for the monthly data in the entire historical period. The climate models captured historical interannual variability of precipitation and temperature, being either equal to or slightly greater than the standard deviation of the observed data. Some models had better prediction of average temperature and precipitation, while others were more able to capture the interannual variability (Table 3).

3.2. Influence of future climate on hydrology

3.2.1. Changes in average discharge

The signal-to-noise ratio for discharge (0.3) suggested there was little agreement about the direction of change in the ensemble, and most changes were not statistically significant (90% of the ensemble, Table 5). Across the ensemble, the increase in average annual discharge ranged from a 20% decrease to a 28% increase, with an ensemble average of a 4% increase (Fig. 2, Table S6). Climate models that projected decreased or slightly increased precipitation (MPI-ESM, CSIRO_r4) resulted in decreased discharge, while the models with increasing precipitation led to increased discharge.

The differences in discharge can mainly be explained by the range in climate models (96% of the variance, Table 4, Fig. 3). This is demonstrated by the greater variability in average annual changes in discharge across climate models than across the hydrologic models (Fig. 2, column A vs. column B), indicating the climate models were the largest factor in determining changes in average discharge. Note that while the ANOVA partitioned relative uncertainty for each variable (percent of variance contributed by hydrologic models and climate models), standard deviation and the range of results (Fig. 2, Table 4) better represented the absolute uncertainty (i.e., range of predictions).

3.2.2. Changes in evapotranspiration, tile discharge, and surface runoff

Signal-to-noise for ET (2.4) indicated strong agreement in change and most of the ensemble members had significant changes (90% of the ensemble, Table 4). Evapotranspiration increased from 1% to 13%, with an ensemble average of 7% (Fig. 2, Table S7). The increase in ET was expected given all climate models had an increase in temperature (the energy fueling ET) and many had an increase in precipitation (the source of water for ET). The range across hydrologic models was comparable to the range across climate models (Fig. 2). The variance from the hydrologic models was not negligible (24%) but the variance in climate models was the greatest source of uncertainty (64%, Table 4, Fig. 3).

The signal-to-noise for subsurface (tile) drainage (0.9) was slightly below the threshold to be considered strong agreement and approximately half of the ensemble showed significant change between the historical and mid-century (Table 5). All CSIRO_r10 and NorESM scenarios were significant, and both had the greatest increase in temperature (3 °C and 2.9 °C, respectively), likely corresponding to a shorter period of frozen ground conditions in winter. Change in tile discharge ranged

Table 3
Climate model bias as compared to the historical (1996–2015) observed on an annual basis, as well as overall changes from historical to mid-century period. The model(s) most closely matching historical climate are highlighted in grey based on the category (bias or variability).

Precipitation	Observed	CanESM	CSIRO_r4	CSIRO_r6	CSIRO_r10	MPI-ESM	NorESM
Historical (mm)	970	892	899	913	866	968	904
Mid-century (mm)	NA	996	915	957	980	921	985
Historical bias (mm)	NA	-78	-72	-57	-104	-2	-66
Historical bias (%)	NA	-8.1%	-7.4%	-5.9%	-10.7%	-0.2%	-6.8%
Standard deviation	118	118	145	136	122	142	120
Mid-century % change		12%	2%	5%	13%	-5%	9%
Temperature	Observed	CanESM	CSIRO_r4	CSIRO_r6	CSIRO_r10	MPI-ESM	NorESM
Historical (°C)	10.1	11.4	10.7	10.8	10.7	11.0	10.7
Mid-century (°C)	NA	14.2	13.2	13.3	13.6	13.5	13.5
Historical bias (°C)	NA	1.2	0.5	0.6	0.5	0.9	0.5
Standard deviation	0.86	0.69	1.03	0.87	0.97	1.02	0.90
Mid-century change (°C)		2.8	2.5	2.5	3.0	2.5	2.9

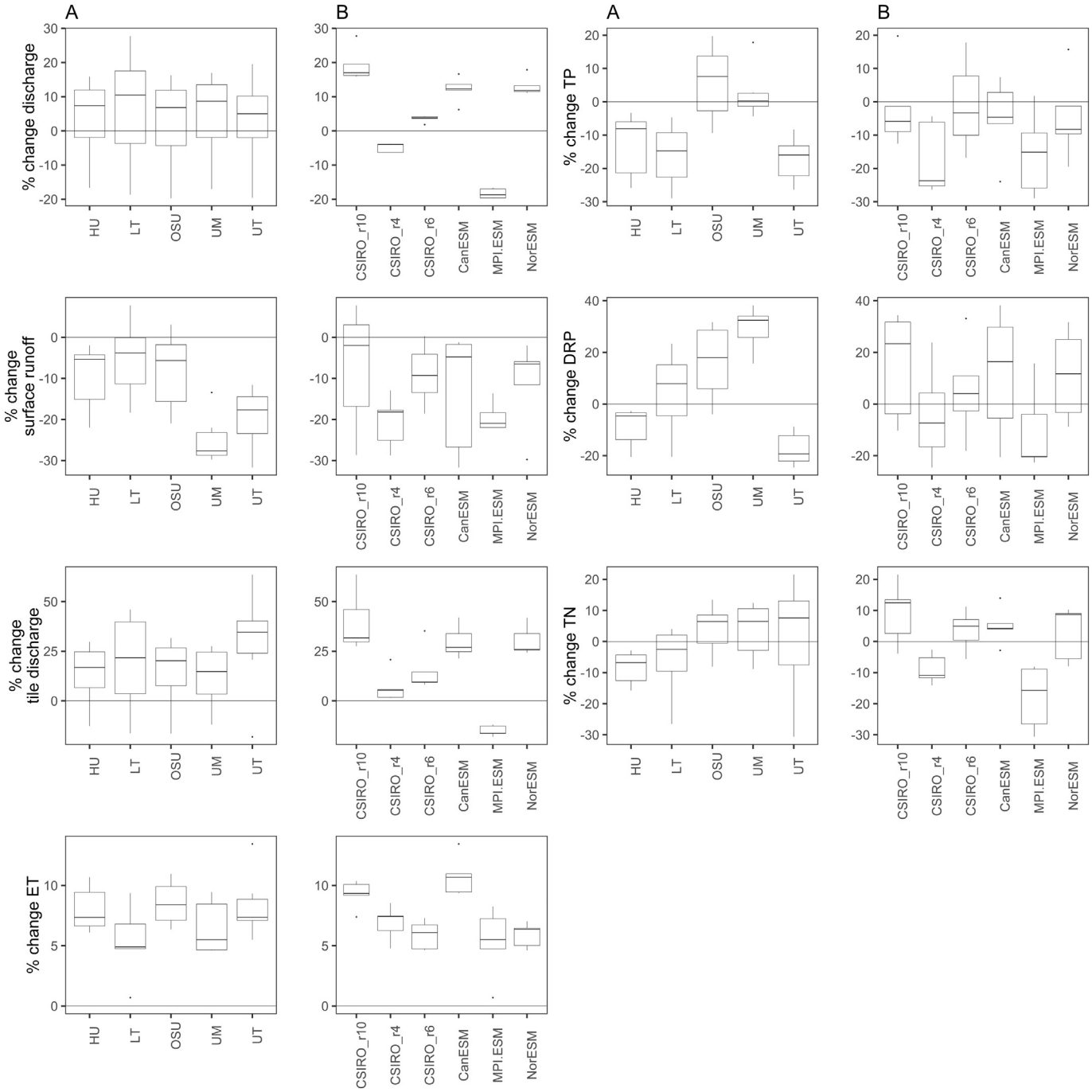

Fig. 2. Historical to mid-century changes in water balance (discharge at the calibration gauge and across the basin's tile discharge, surface runoff, and evapotranspiration (ET)) as well as water quality (loading at calibration gauge of TP, DRP, and total nitrogen (TN)). The first column (a) held each hydrologic model constant and plots the average change from the historical (1996–2015) to mid-century (2046–2065) for all six climate models as data within the boxplot. The second column (b) held each climate model constant and plots the average change in the five hydrologic model variations as the data within the boxplot. A box that crossed zero indicates no clear direction of change from the historical to mid-century. A larger range (a taller box) indicated greater uncertainty in the results than a small range within a given model.

from an 18% decrease to a 64% increase, with an ensemble average of an 18% increase (Fig. 2, Table S7). As with discharge, the variation among climate models was the main source of uncertainty for tile discharge (82%, Table 4), with some variation attributed to the hydrologic model (10%, Table 4). Tile discharge declined only under the decreasing precipitation climate scenario (MPI-ESM). In general, directional changes in tile discharge were consistent with directional changes in precipitation (Fig. 2, column B).

The signal-to-noise for surface runoff (0.8) and the minority of the ensemble showing significant changes (30%, Table 4) demonstrated disagreement in direction of future change. Changes in surface runoff ranged from a 32% decrease to an 8% increase, with an ensemble average of a 13% decrease (Fig. 2, Table S7). Most scenarios predicted a decrease or no change. However, the OSU and LT hydrologic models driven by CSIRO_r10 showed increased surface runoff. A larger portion of the uncertainty in surface runoff was contributed by the hydrologic model (49%) than the climate model (22%) in the ANOVA, though the residual was relatively large (29%), signifying the results are less clear in this case (Table 4, Fig. 3). This was most likely caused by the large variation in magnitude of decreased change (0% to −31%) combined with few hydrologic models having increased surface runoff in the climate scenario with the largest increase in precipitation (CSIRO_r10, Table S7).

Table 4
Summarized results of the signal-to-noise ratio, Wilcoxon Rank-Sum test, and ANOVA method for partitioning variance for hydrology and nutrient variables. The greatest contribution to uncertainty in the ANOVA results is highlighted dark grey and bolded and the second most is in light grey.

			Objective 1: detecting direction of future change		Objective 2: partitioning uncertainty between hydrologic models and climate models		
		Average change ± standard deviation [%]	Signal-to-noise ratio	Percent of significant changes	Hydrologic model [%]	Climate model [%]	residual [%]
Hydrology	Discharge	4 ±13	0.3	10	1*	**96**	3
	ET	7 ±3	2.4	90	24	**64**	12
	Tile discharge	16 ±19	0.9	47	10	**82**	8
	Surface runoff	-14 ±11	0.8	30	**49**	22	29
Nutrients	TP	-7 ±13	0.5	13	**57**	25	19
	DRP	5 ±20	0.0	33	**72**	21	6
	TN	-1 ±12	0.1	7	19	**63**	18

*Indicates non-significant ($p < .05$) in ANOVA results.

3.3. Influence of future climate change on water quality

3.3.1. Phosphorus loading

There was a wide range of phosphorus (P) predictions for the mid-century climate, and the signal-to-noise for TP (0.5) indicated little agreement in the ensemble, while the signal-to-noise ratio for DRP (0) indicated virtually no agreement (Table 4). The majority of the TP results were not significant (87%), but that fraction was smaller for DRP (67%, Table 4). Predicted TP load ranged from a 29% decrease to a 20% increase, with an overall average of a 7% decrease (Fig. 2, Table S8). Dissolved reactive P (DRP) ranged from a 25% decrease to a 38% increase, with an overall average of a 5% increase (Fig. 2, Table S8).

Despite this wide range, consistent patterns emerged among the hydrologic models. Under all climate models, the UT and HU hydrologic models predicted similar decreases in both TP (UT: −27% to −8%, with an average of −17%, HU: −26% to −3%, with an average of −13%, Table S8) and DRP loadings (UT: −25% to −9%, average = −17%, HU: −21% to −3%, average = −9%, Table S8). The UM model predicted both increasing (18%) and decreasing (−4%) results (average = 3%, Table S8) for TP across climate models. The UM model consistently predicted increased DRP loading (16 to 38%, average = 29%, Table S8) from all climate models, even for the climate model with decreased precipitation (MPI-ESM). The OSU model also showed mixed results for TP (−9 to 20%, average = 6%, Table S8), but the direction of change in TP loading is consistent with the direction of change in discharge (Fig. 4). The OSU model predicted DRP loading consistent with precipitation change (−4% to 32%, average = 16%, Table S8). The LT model predicted a decrease in TP (−29% to −5%, average = −16%, Table S8) across all climate models but has mixed results for DRP (−20 to 23%, average = 5%, Table S8). The climate models producing a decrease in DRP in the LT model are the same ones that produced decreased discharge (Fig. 4). The direction of change in TP and DRP load did not always follow directional changes in discharge (Fig. 4).

While uncertainty in hydrology was dominated by the variability in climate models, this was not true for phosphorus loads. Variability across hydrologic models and climate models showed similar ranges for TP (Fig. 2, column a vs. b), and we found the hydrologic model contributed more uncertainty (57%) than the climate model (25%, Table 4, Fig. 3). The results for DRP are almost the opposite of discharge; for DRP, the hydrologic model contributed more uncertainty (72%) than the climate model (21%, Table 4, Fig. 3).

3.3.2. Nitrogen loading

The low signal-to-noise (0.1) for total nitrogen (TN) indicated little agreement in the direction of future change, and the fraction of the ensemble exhibiting significant changes was small (7%, Table 4). Predictions of TN ranged widely from a 31% decrease to a 22% increase, with the ensemble average of a 1% decrease (Fig. 3, Table S9). All hydrologic models predicted decreasing TN loadings with decreased precipitation (MPI-ESM), but the range varied in magnitude (−31 to −8%, Table S9).

The changes in TN followed the changes in discharge closely; only five ensemble members showed decreased TN loads despite showing increased discharge (Fig. 4). Overall, the ensemble results suggest change in average discharge produced a similar direction of change in average TN loads. Indeed, the pattern of change for TN more closely followed changes in discharge and tile discharge compared to TP or DRP (Fig. 4), and variability in the climate models contributed much of the uncertainty (63% Fig. 3, Table 4). The climate model range being the main source of uncertainty and the low signal-to-noise ratio were similar to results for river discharge and tile discharge, which was not

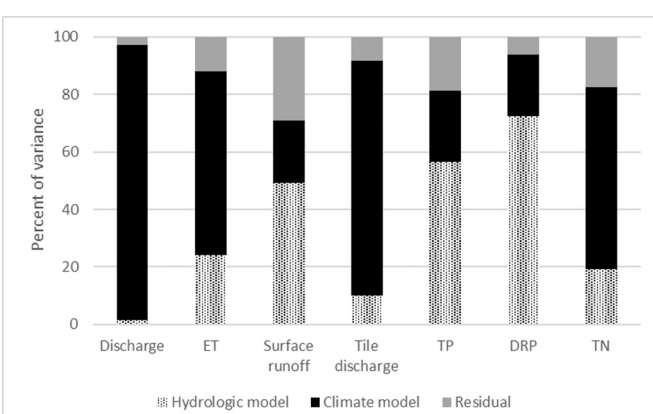

Fig. 3. Percent of variance partitioned using a two-way ANOVA, as in Table 4.

Table 5
Crop yield changes (kg/ha) from the historical to mid-century period, averaged across all climate models.

Crop/models	HU	LT	OSU	UM	UT
Corn	−21	−16	−13	−13	−14
Soy	−21	−17	−18	−6	−6
Winter wheat	−11	7	−7	−15	−14

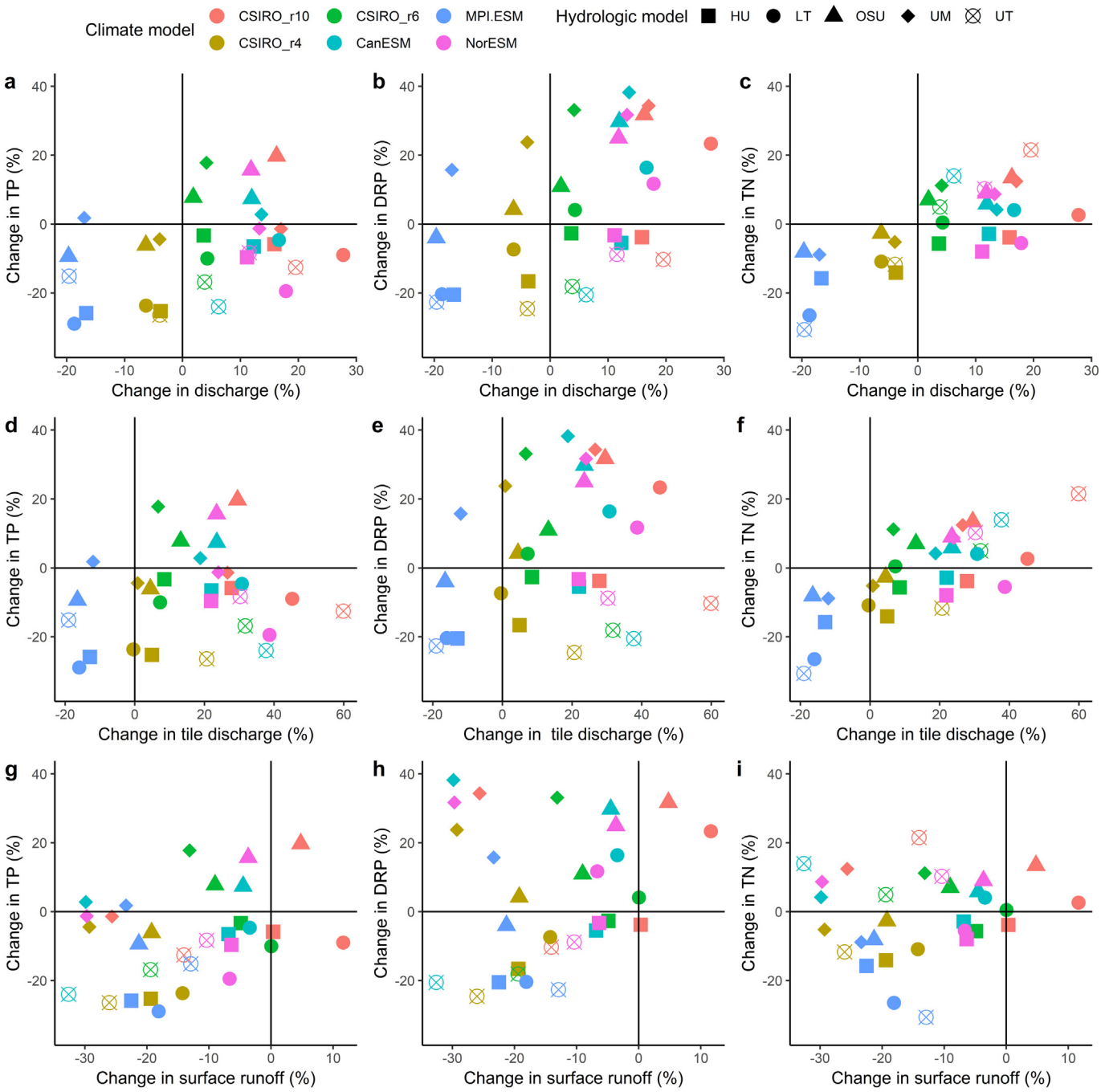

Fig. 4. Relationship between changes in water balance (discharge at outlet, tile discharge, and surface runoff, x-axis) and changes in nutrient loading (y-axis) for TP (first column), DRP (second column), and TN (third column). Expected results for average discharge (a,b,c) would have all points lying in the 1st (top-right) and 3rd (bottom-left) quadrants, meaning an increase in discharge caused an increase in nutrients. TN (c, f, i) follows this expected pattern more closely with few exceptions, whereas TP (a, d, g) and DRP (b, e, h) do not follow this expected pattern.

unexpected given TN has a stronger relationship to these variables (Fig. 4).

3.4. Crop yields

Crop yields may help to explain the difference in behavior between hydrology and water quality, as they control the amount of nutrients in the soil available for runoff. The majority of the ensemble members predicted decreased crop yields (Table 5). Decreases in corn ranged from 7% to 24%. Soybean yields ranged from an increase of 1% to a decrease of 24%. Wheat ranged from increases of 10% to decreases of 21%. Only the LT model for all climate runs and the OSU model with MPI-ESM predicted increased wheat yields. The UT model under the CSIRO_r4 climate predicted a 1% increase in soy yields. All other predictions show a decrease in yield (Table S10).

4. Discussion

4.1. Directional changes

Our first objective was to assess whether the climate and hydrologic model ensemble provides a clear direction of change in discharge and nutrients for the Maumee River Watershed. Many of the ensemble members indicated minimal changes in hydrology through mid-

century, even though there was robust agreement among models in increased evapotranspiration driven by increased temperatures, for which climate models have strong agreement. While there was not clear agreement in the direction of future change for most variables, we saw trends in physical processes that help to explain drivers of some of these changes. For example, there was a consistent pattern among ensemble members for increases in tile discharge and decreases in surface runoff. The processes behind these changes can be partially explained by warmer winter temperatures resulting in less snow-covered and frozen ground, which may increase infiltration and subsequently tile discharge in winter (Fig. S9). Similarly, the shorter duration of frozen ground, combined with higher rates of evapotranspiration, could have resulted in drier antecedent moisture conditions and therefore reductions in surface runoff (Fig. S8). If increased temperatures produced greater tile discharge and less surface runoff, it may become more significant later in the century when greater temperature changes are expected.

Predictions of mid-century phosphorus (P) loadings showed a wide variation of responses among hydrologic models and were not consistently correlated with changes in hydrology. Nutrient loadings from non-point sources are often assumed to follow riverine discharge, however, this was not always the case (Fig. 4). The differences in phosphorus prediction were partially due to the differences among hydrologic models in the routing of particulate P and dissolved reactive P (DRP). Particulate P loss from fields can only occur via surface processes within the SWAT models, such as loss of sediment-bound P, while dissolved nutrients (such as DRP) can be routed through surface or subsurface pathways (Neitsch et al., 2009; Arnold et al., 2012). One would then expect changes in particulate P, which makes up most of total P (TP), to track with changes in surface runoff. Overall, in 73% (22/30) of scenarios TP load decreased with decreased surface runoff or vice versa (Fig. 4). In reality, TP (simulated as the sum of particulate P and DRP) can travel in both surface runoff and tile drains and is hypothesized to enter tile drains through macropores and preferential flow paths (Smith et al., 2015). Tile discharge in SWAT is simulated when the perched water table rises above the tile depth (Neitsch et al., 2009; Qi and Qi, 2016). All SWAT models in this study were modified to include DRP loss through tiles (see Supporting Information in Kalcic et al., 2016 for source code modifications). The SWAT model does not yet simulate particulate P export through tiles (Qi and Qi, 2016). One might expect if particulate P was simulated in both surface runoff and tile discharge, results for TP may be more similar to those found for DRP.

We expected to see stronger links between changes in tile discharge and DRP as some nutrient balance studies have shown tile drains to account for over half of DRP export (Pease et al., 2018; Smith et al., 2015). However, those studies are mainly done at the field scale and may not apply to entire watersheds. Therefore, the underlying equations in the SWAT model allow for a diversity in simulation of DRP, given both subsurface and surface pathways, as well as options for soil phosphorus routine and macropore flow (Table S2). For example, only the UM model included a soil cracking routine which allowed for greater preferential flow and transport of DRP to tiles (Table S2). This parameter could partially explain why the UM model consistently demonstrates greater DRP predictions in the future climate. However, many interacting factors in SWAT influence DRP export (Tables S1–S3) and it is not unexpected that the models differ in their prediction of DRP under a future climate.

In this study most of the ensemble members predicted decreased crop yields (Table 5). Crop yields are related to nutrient export because increased crop growth can immobilize nutrients through uptake. Culbertson et al. (2016) predicted increased crop growth caused by increased atmospheric CO_2 concentrations, and they hypothesized this led to increased uptake and therefore overall decreased phosphorus losses. In this study, the inconsistencies in changes in phosphorus loading and the consistency of decreased crop yields does not suggest crop yields had a large role in changes in explaining the changes in phosphorus loss.

Unlike P, total nitrogen (TN) changes were similar to changes in discharge and tile discharge (Fig. 4). This was expected because the landscape is highly tile-drained and tile discharge has been shown to make up the majority of discharge in the watershed and account for the majority of TN export (Williams et al., 2015). TN loading exhibited the greatest increases in winter months (Dec, Jan, Feb), suggesting much of the increase may be due to increases in tile discharge during winter (Fig. S13). The TP and DRP ensemble median decreased in winter (Fig. S11–S12), suggesting phosphorus and nitrogen loads in the Maumee River Watershed may respond quite differently under the same future climate scenario.

4.2. Partitioning uncertainty

Our second objective was to determine to what extent the climate models or hydrologic models contributed to uncertainty in future hydrologic prediction. Our results are consistent with previous efforts showing that the majority of uncertainty for average discharge projections is from climate models (Addor et al., 2014; Hattermann et al., 2018; Karlsson et al., 2016). Our results are also similar to that of Dams et al. (2015), who found SWAT contributed to large variations in predicted surface runoff. In the present study, uncertainty for surface runoff from the hydrologic model (49%, Table 4) was greater than that of the climate model (22%, Table 4). Surface runoff was the only hydrology variable that had more uncertainty from the hydrologic than climate models (Table 4).

However, our analyses showed that hydrologic models can be a dominant source of uncertainty in water quality predictions. While climate models contributed the majority of uncertainty in TN prediction, most uncertainty in TP and DRP loads was derived from the hydrologic models. Therefore, for P, the hydrologic model is more important than the climate model when predicting future water quality. This contradicts previous studies showing the climate model uncertainty significantly outweighs uncertainty from the hydrologic model (e.g. Joseph et al., 2018; Kay et al., 2008; Poulin et al., 2011; Vetter et al., 2017; Wilby and Harris, 2006).

This variability among hydrologic models in this study is similar to the collection of other efforts simulating the effects of climate change on the Maumee River Watershed where only one hydrologic model was used across studies and results were mixed across discharge, TP, DRP, and TN loadings (Bosch et al., 2014; Cousino et al., 2015; Culbertson et al., 2016; Johnson et al., 2015; Kalcic et al., 2019; Verma et al., 2015; Table S11). Taken together, these results suggest that use of a single climate or hydrologic model may produce a misleading level of confidence to decision-makers seeking advice on managing watersheds with phosphorus impairments. Because the hydrologic model is the main source of uncertainty in P loading, we need not only improvements in climate models but also simultaneous improvement in nutrient simulation to better estimate water quality in a future climate.

4.3. Limitations and future work

A primary limitation of this work is generalizability to dissimilar watersheds. Studies that consider more than one watershed have found that different elements in the modeling chain (e.g. climate model, downscaling method, hydrologic model, etc.) contribute varying levels of uncertainty based on the watershed or area in question (Addor et al., 2014; Giuntoli et al., 2015; Kay et al., 2008; Thober et al., 2018; Velazquez et al., 2013; Vetter et al., 2017). Addor et al. (2014) found in Alpine catchments glacierized watersheds had comparable uncertainty from the hydrologic model as the climate model, whereas non-glacierized catchments was mainly from climate model. Giuntoli et al. (2015) found uncertainty in snow-dominated climates was from

hydrologic models, whereas in equatorial regions the uncertainty was mainly from the climate models. We expect a watershed not as intensively drained as the Maumee to exhibit different hydrologic patterns because the surface and subsurface drains act as direct conduits to rivers and increase nutrient mobility. It is unknown if the same uncertainty from the climate vs. hydrologic models (Table 4) will remain applicable in different landscapes (e.g. high slopes, well drained). The applications of this work could be expanded by examining watersheds that are not intensely drained, as well as considering changes in other hydrologic and nutrient extremes and indicators in addition to average changes from the historical to mid-century (Thober et al., 2018; Vetter et al., 2017).

This work is also limited in its ability to encompass all facets of uncertainty in climate and land use change. The study considers six GCMs under one emissions scenario, one downscaling approach, and one baseline land management. The selection of GCMs was comparable in size to similar studies on uncertainty (Table S5) and included a range of precipitation changes comparable to the CMIP5 ensemble range (Fig. S1). However, temperature changes were in a narrower range (approximately 0.5 °C) than the CMIP5 ensemble (2.6 °C, Table 3, Fig. S1). Including plausible land-management and land-use changes would be complex and dependent upon a variety of factors such as economics, technology, and social aspects; incorporating these scenarios accurately was outside the scope of this study. However, the use of multiple SWAT models allowed for a more holistic accounting of uncertainty in hydrologic modeling than is common practice. These include variations in parameterizations, land management assumptions, and spatial discretization. Despite being the same base model (SWAT), the models account for some structural variability as parameters in the model can turn entire subroutines on or off (e.g. soil cracking). The variation among the models is not negligible as evidenced by the differences in simulated nutrient changes (Fig. 2). Future work could more fully quantify the role of structural uncertainty by including other water quality models in addition to SWAT.

5. Conclusions

This study aimed to quantify future hydrologic change using ensembles of climate models and hydrologic models in the Maumee River watershed and to identify whether climate models or hydrologic models were the primary source of uncertainty in future prediction. The ensemble of climate and hydrologic models predicted a slight decrease in discharge and total phosphorus, no change for total nitrogen, and a slight increase in dissolved phosphorus loading from the historical (1996–2015) to the mid-century (2046–2065). However, the disparity across the ensemble dwarfs the predicted effects of climate change. For both discharge and nutrients, <50% of ensemble members for indicated a statistically significant change between the historical (1996–2015) and mid-century (2046–2065) and the signal-to-noise ratio demonstrated the ensemble did not agree in the direction and magnitude of change. Climate models introduced the greatest uncertainty for discharge and total nitrogen predictions, whereas for phosphorus predictions the hydrologic model produced the greatest uncertainty.

This study demonstrates to improve discharge or nitrogen predictions, improved climate predictions would reduce uncertainty. However, to reduce uncertainty in phosphorus prediction, significant improvements in the hydrologic model are needed. Improvements could be obtained if watershed processes were better calibrated, such as accurately partitioning phosphorus between surface and subsurface pathways. This study demonstrates it is crucial to include the hydrologic model uncertainties when examining climate change effects on phosphorus.

The implications of uncertainty in nutrient simulation is important not only for the Lake Erie region and harmful algal blooms, but also globally for management of eutrophication. Eutrophication is an international problem (Schindler et al., 2016) and adaptive management strategies for nutrient reductions are necessary to address the problem and resulting decreases in water quality (Watson et al., 2016), contaminated fisheries (Bukaveckas et al., 2017; Wituszynski et al., 2017), threats to irrigation and potable water supplies (Lee et al., 2017), and decreases in tourism, cultural activities, and coastal economies (Watson et al., 2016; Wolf et al., 2017). Predictions of nutrient load response to climate change are important for informing management and policy decisions to prevent further harm caused by eutrophication. Continuing to characterize and understand uncertainty that comes from both climate projections and hydrologic models is an important step in making climate change studies accessible to water managers and decision makers.

CRediT authorship contribution statement

Haley Kujawa: Writing - original draft, Formal analysis, Data curation, Visualization. **Margaret Kalcic:** Conceptualization, Writing - review & editing, Methodology, Software, Validation, Supervision, Funding acquisition, Resources. **Jay Martin:** Conceptualization, Writing - review & editing, Methodology, Supervision, Funding acquisition. **Noel Aloysius:** Conceptualization, Methodology, Software, Validation, Resources. **Anna Apostel:** Data curation, Visualization. **Jeffrey Kast:** Writing - review & editing, Data curation. **Asmita Murumkar:** Writing - review & editing, Visualization. **Grey Evenson:** Writing - review & editing. **Richard Becker:** Software, Validation. **Chelsie Boles:** Writing - review & editing, Software, Validation. **Remegio Confesor:** Writing - review & editing, Software, Validation. **Awoke Dagnew:** Software, Validation. **Tian Guo:** Writing - review & editing, Software, Validation. **Rebecca Logsdon Muenich:** Software, Validation. **Todd Redder:** Software, Validation. **Donald Scavia:** Writing - review & editing. **Yu-Chen Wang:** Software, Validation, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.138004.

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