

Impacts of Projected Climate Change on Sediment Yield and Dredging Costs

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Abstract

Changes in climate may significantly affect how sediment moves through watersheds into harbors and channels that are dredged for navigation or flood control. Here we applied a hydrologic model driven by a large suite of climate change scenarios to simulate both historical and future sediment yield and transport in two large, adjacent watersheds in the Great Lakes region. Using historical dredging expenditure data from the US Army Corps of Engineers (USACE) we then developed a pair of statistical models that link sediment discharge from each river to dredging costs at the watershed outlet. While both watersheds show similar slight decreases in streamflow and sediment yield in the near-term, by mid-century they diverge substantially. Dredging costs are projected to change in opposite directions for the two watersheds; we estimate that future dredging costs will decline in the St. Joseph River by 8-16% by mid-century but increase by 1-6% in the Maumee River. Our results show that the impacts of climate change on sediment yield and dredging may vary significantly by watershed even within a region, and that agricultural practices will play a large role in determining future streamflow and sediment loads. We also show that there are large variations in responses across climate projections that cause significant uncertainty in sediment and dredging projections.

1 Introduction

Changes in climate have the potential to significantly alter the movement of sediment through watersheds and directly affect dredging needs in rivers and harbors. There are over sixty-three commercial harbors in the Great Lakes and over 600 miles of navigation channel maintained by the U.S. Army Corps of Engineers (USACE). In 2014, an estimated 132 million tons of commodities were transported to and from U.S. ports located on the waterways of the Great Lakes system (USACE, 2014). Many of the harbors are located at the outlets of rivers that can convey large amounts of sediment, necessitating periodic dredging to maintain the navigation channels. In spite of the importance of this system, previous studies have not examined the potential impacts of projected future climate changes on both sediment yield (sediment eroded from the landscape and delivered to the river) and the dredging requirements in this region.

Current climate change projections generally show increasing temperatures and precipitation in the Great Lakes region of the United States, although the magnitude and seasonality of these changes depends on the emissions scenario and climate model (Hayhoe et al., 2010; IPCC, 2014; Pryor et al., 2013). Precipitation is expected to increase in the winter and spring, but decline in the summer; temperatures are projected to increase more in the winter during the early part of the century, with changes in summer temperatures catching up by mid-century (Hayhoe et al., 2010). The Third National Climate Assessment found that extreme rainfall and flooding events, and their associated erosion, are on an upward trend in the Midwest, including Indiana, Michigan, and Ohio (Pryor et al., 2014).

Numerous studies have examined the potential implications of climate change on streamflow and sediment yield (e.g. Mukundan et al., 2013; Park et al., 2011; Serpa et al., 2015). In the Upper Midwest and Great Lakes regions, O'Neal et al. (2005) found that variability in soil loss would increase due to changes in crops. Two separate studies looked at climate change effects on northern Illinois watersheds and found that streamflows would decrease, based on the projected climate change scenarios (Cherkauer and Sinha, 2010; Chien et al., 2013). Several Soil and Water Assessment Tool (SWAT) models of the Maumee River have examined the potential effects of climate change scenarios. For example, Bosch et al. (2014) modeled four watersheds that drain to Lake Erie and projected that flow and sediment yield would increase, based on climate projections from two emissions scenarios and three General Circulation Models (GCMs). In contrast, a more narrowly focused study on the Maumee that utilized three GCMs and a single emissions scenario found that annual average flow and sediment loads will decrease by mid-century (2045 to 2055), although there was significant variability in the monthly sediment loads (Verma et al., 2015). As part of a nationwide study of 20 watersheds with SWAT simulations, Johnson et al. (2015) found that five of their six climate change scenarios would likely increase flow and sediment delivery in the Maumee by mid-century (2041 to 2070).

Dredging quantities are imperfectly correlated to sediment discharge (the sediment delivered to the mouth of the river) since they depend on downstream water levels (for example, Lake Michigan levels varied 1.9 m over the last 30 years), the location where the sediment settles out relative to the navigation channels, and on the amount of funding available to conduct the dredging operations. Some studies that discuss dredging in the context of climate change do so through the lens of rising water levels (Schwartz et al., 2004; Smith, 1991) rather than looking at

changes in delivery of sediment from rivers. Schwarz et al. (2004) used both future projections and an arbitrary scenario of Great Lakes water levels to estimate increased dredging costs at Goderich, Ontario, on Lake Huron, but did not consider the possibility of changing riverine sediment input to the harbor. Other authors consider the dredging as either one component of the overall sediment budget (Morang et al., 2013; Templeton and Jay, 2013) or as a causative effect of increased sediment delivery (Zhang et al., 2010). We are not aware of any studies that directly link projected future riverine sediment delivery to changes in dredging needs.

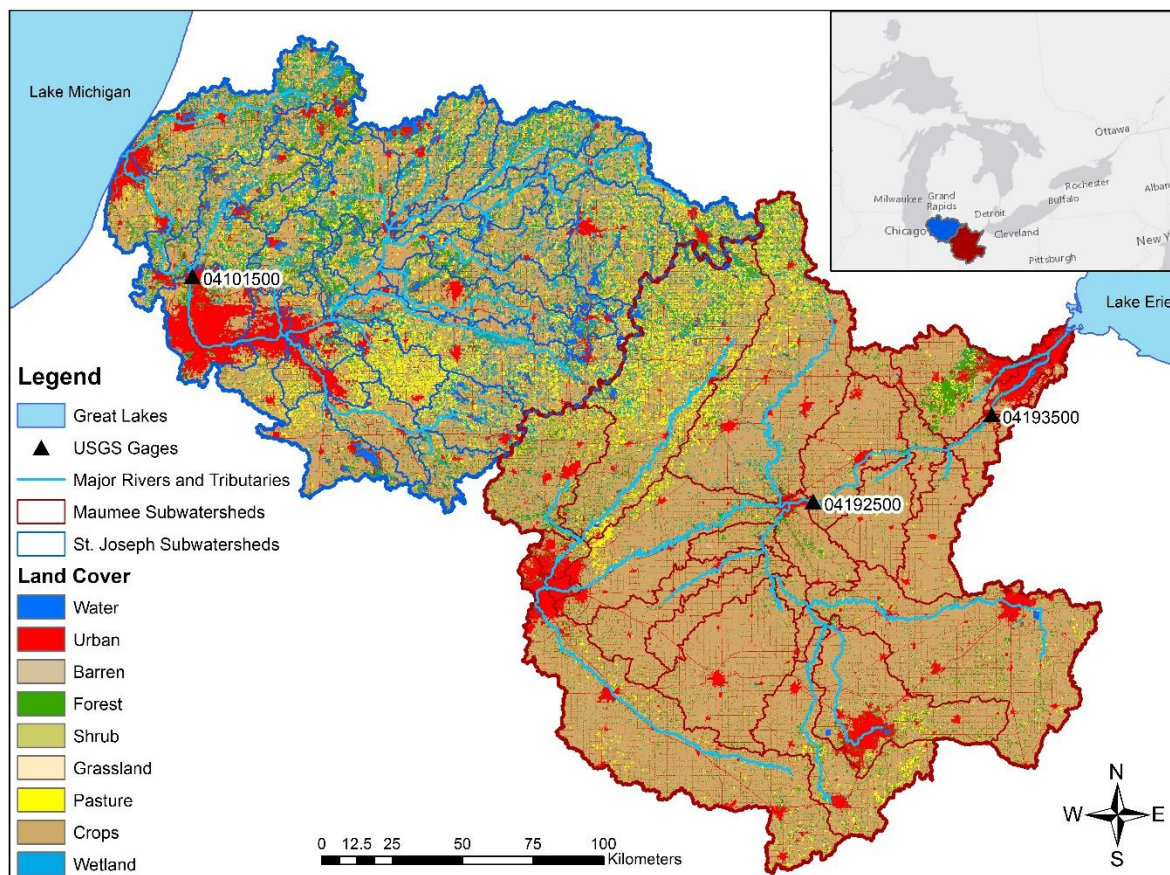
In this study, we used SWAT models of two large US watersheds draining into the Great Lakes to quantify the likely effects of climate change on the streamflow, sediment yield to the river, and sediment discharge at the mouth of the river. SWAT-calculated sediment loads are then input to two different statistical sediment dredging models calculated from historical dredging costs for each system. We then drive these linked models with both historical climate and future climate simulations based on downscaled scenarios from the 5th Coupled Model Intercomparison Project (CMIP5) for both “Contemporary” (~2011-2030) and “Mid-Century” (2031-2050) periods. We run the whole suite of 234 climate models ensemble members included in the CMIP5 dataset to better understand how climate forecast uncertainties will propagate through the paired SWAT sediment transport and statistical dredging models. In the body of the paper, we discuss results for Representative Carbon Pathways (RCPs) 6.0 and 8.5, while results for the remaining RCPs (2.6 and 4.5) are in the Supporting Information. These results provide both a more comprehensive view of how climate may impact sediment yield differentially in these neighboring watersheds and a first quantification of how dredging costs may respond to climate changes.

99 2 Methods

100 2.1 Study Domain

101 Two large, adjacent watersheds in the southern Great Lakes were selected for this study: the St.
102 Joseph River and the Maumee River (Figure 1). We chose these two watersheds because of their
103 size, proximity to each other, and dredging requirements at the river mouths in the Great Lakes.
104 The St. Joseph River watershed covers parts of northern Indiana and southwestern Michigan and
105 generally flows northwest into Lake Michigan at St. Joseph, MI. According to the 2006 National
106 Land Cover Database (NLCD) (Fry et al., 2013), this 12,138 km² watershed consists of 49.3%
107 agricultural row crops, 23.8% forest, 13.0% urban, and 12.2% pasture. The average annual flow
108 at the USGS gage at Niles, MI (#04101500) between 1990 and 2009 was 113.6 cms. Long-term
109 sediment data was not available for the St. Joseph River. The USACE dredges the harbor at St.
110 Joseph, MI.

111
112 The Maumee River watershed is located in northeastern Indiana, southeastern Michigan, and
113 northwestern Ohio. The main channel flows northeast to Toledo, OH and Lake Erie. This
114 17,015 km² watershed is more heavily agricultural and significantly less forested than the St.
115 Joseph, consisting of 74.7% agricultural row crops, 10.8% urban, 8.2% forest, and 5.2% pasture.
116 The average annual flow of the Maumee River in Waterville, OH (USGS gage 04193500)
117 between 1990 and 2009 was 172.6 cms. The average annual suspended sediment load at this site
118 between 1990 and 2003 was 1.2 million tonnes. The USACE performs dredging operations at
119 both a Maumee River and a Maumee Bay site.



121

122 *Figure 1. Map of the St. Joseph and Maumee River watersheds, subwatersheds, and their 2006 land use/land cover.*

123

124 2.2 SWAT Model Development and Calibration

125 The Soil and Water Assessment Tool (SWAT) is a semi-distributed, lumped parameter
 126 hydrologic model developed by researchers at the U.S. Department of Agriculture's Agricultural
 127 Research Service (USDA-ARS) (Arnold et al., 2012; Neitsch et al., 2011). It is often used for
 128 sediment yield studies (Alighalehbabakhani et al., 2017; Gassman et al., 2014; Krysanova and
 129 White, 2015) and is increasingly used to examine climate change impacts (Chaplot, 2007; Chien
 130 et al., 2013; Ficklin et al., 2009; Johnson et al., 2015). SWAT models split their domain into

subwatersheds and then subset these into Hydrologic Response Units (HRUs). HRUs are the basic computational units of a SWAT model, which represent all of the area within a subwatershed with similar soils, slopes, and land uses.

We developed SWAT models independently for each watershed using the ArcSWAT 2012.10.0.7 plugin for ArcGIS, and used SWAT 2012 rev. 622. Digital elevation models with a resolution of 1 arc-second were obtained from the National Elevation Dataset and used to delineate the watersheds. The 2006 National Landcover Dataset was used to determine land use/land cover types and we used the default crop and harvest management parameters from ArcSWAT. Soil types and soil hydraulic properties were determined using the SSURGO database from the Natural Resources Conservation Service. Information on dams in the watersheds was obtained from the National Inventory of Dams maintained by the U.S. Army Corps of Engineers and those we deemed significant because of size or location were included in the models. We selected dams with storage greater than 1,233,000 m³ for inclusion in the models. We also included the St. Joseph River Dam, in Fort Wayne, IN, which only has a storage of 1,078,000 m³ while draining over 16% of the Maumee basin. These datasets were all imported into ArcSWAT and used to determine watersheds, subwatersheds for modeling purposes (shown in Figure 1), and HRUs. The St. Joseph SWAT model consisted of 32 subbasins and 278 HRUs, along with 17 dams. The Maumee SWAT model had 24 subbasins, 307 HRUs, and 5 dams.

The United States Department of Agriculture's Agricultural Research Service (ARS) provides weather data, in SWAT format, for all counties across the US. The daily data covers January

1950-December 2009, with the exception of January 2002. January 2002 was filled using SWAT's weather generation routines that create typical weather time series for the location and time period. We included 2002 in our simulations, but to avoid biasing further analyses due to the weather generation routine excluded January 2002 from goodness-of-fit calculations, and excluded the entire 2002 year from the downscaling bias analyses.

After initial set up of the models in ArcSWAT, we calibrated them using the SWAT Calibration and Uncertainty Programs (SWAT-CUP) tool (Abbaspour, 2015). We ran both models from 1980 through 2009, using a daily time step, with at least a five year spin-up period. Monthly outputs from the models were used for all comparisons. We began our calibration by using the Sequential Uncertainty Fitting version 2 algorithm (SUFI2) in SWAT-CUP to determine the sensitivity of the parameters in the SWAT models, based on the full allowable range of each parameter. We then focused our efforts in succeeding calibration iterations on those parameters that had the most significant effect on the model outputs. As a final step in the model parameterization, we tested the removal of each calibration parameter to arrive at a parsimonious set of calibration parameters.

The St. Joseph River model was calibrated to the streamflow at the USGS gage at Niles, MI (#04101500). The model was run from 1985 to 2009, with 1990-1999 used for calibration and 2000-2009 for validation. Sediment discharge was then calibrated and validated for the same periods using a streamflow:sediment discharge curve for the harbor in St. Joseph, MI. This curve was developed for a previous U.S. Army Corps of Engineers study of the St. Joseph River watershed (USACE, 2007).

177

178 We calibrated the Maumee River model by first matching the hydrology using the USGS gages
179 at Waterville, OH (#04193500) and Defiance, OH (#04192500). The model was run from 1980
180 to 2003, with 1991-1999 used for calibration to match up with the period used for the St. Joseph
181 model. The validation period was split between October 1985 to December 1990 and January
182 2000 to September 2003, based on the availability of USGS sediment discharge data. We
183 calibrated and validated the simulated sediment discharge to data from the USGS Gage at
184 Waterville, OH (#04193500) using periods matching the streamflow.

185

186 2.3 Dredging Cost Estimation

187 The U.S. Army Corps of Engineers provided us with dredging quantities for St. Joseph Harbor,
188 the lower Maumee River, and the Maumee Bay (M. Mahoney, personal communication, 20-Sep-
189 2013). We created two models for dredging costs: 1) a linear regression, fit to historical
190 dredging data and simulated modeled sediment fluxes, and; 2) a simpler 1:1 correlation between
191 simulated sediment discharge and dredging costs (or percentage change in each). Our use of two
192 models provides an estimate of cost model structural uncertainty, and allows us to evaluate a
193 range of possible outcomes. To fit each model, dredging data from 1989-2009 was used for St.
194 Joseph Harbor and 1990-2009 for the Maumee River and Maumee Bay dredging sites.

195

196 We created linear regression models between the annual dredging costs, converted to 2009
197 dollars using the U.S. Bureau of Labor Statistics Consumer Price Index data, and the modeled
198 sediment discharge from the SWAT models run using the historic gage data. To evaluate
199 possible time-lagged responses between sediment discharge and dredging, regressions were

tested using simulated sediment results from the same calendar year as the dredging; the same water year as the dredging; the prior calendar and water years; and one and two year (calendar and water year) moving averages of sediment discharge. As there are two dredging sites in the Maumee Watershed, in the River itself and in the bay at its mouth, we examined regressions to the Maumee River and Bay dredging sites both separately and as a combined amount. We also added long-term average monthly water levels of Lakes Michigan and Erie to the regressions for the St. Joseph and Maumee dredging sites respectively.

2.4 Climate Model Scenarios

The analyses presented in the main paper utilized the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al., 2012) multi-model dataset. We acquired bias-corrected, spatially downscaled versions of these datasets from a publicly available archive created by the United States Bureau of Reclamation and others (Brekke et al., 2013). The temperature and precipitation data in this archive are available at a monthly time step and a spatial resolution of $1/8^\circ$. This data needed to be further disaggregated for use with the SWAT models, which use daily data at a single weather gage location for each sub-basin. We utilized all 234 CMIP5 model projections available from the archive. The CMIP5 dataset consists of multiple Representative Carbon Pathways (RCPs), run across a large number of individual models. To consider a larger ensemble, additional analyses were run with 112 CMIP3 scenarios (Meehl et al., 2007) and the results are included in the Supporting Information for this paper.

For brevity, analysis in this paper is limited to CMIP5 RCP 6.0 (Masui et al., 2011; 37 projections) and RCP 8.5 (Riahi et al., 2011; 71 projections), which represent a plausible range of CO₂ emissions given no additional conservation efforts. These RCPs are particularly relevant given the 2011 – 2050 simulation period of this study. RCP 6.0 is most similar to the older B2 Special Report on Emissions Scenarios (SRES; Nakicenovic and Swart, 2000), while RCP8.5 is similar to SRES A2/A1F1 (IPCC, 2014). Results for the other climate change scenarios are presented in the Supporting Information.

Two forecast periods were run: 2011 – 2030, hereafter called the Contemporary period, and; 2031 – 2050, called the Mid-Century period. SWAT model outputs for each period are individually averaged and presented below as both climate ensemble medians and ranges, as stated in figures and tables.

We matched individual, observed gage locations used by the SWAT models with the closest spatial grid cell for the downloaded climate data. These climate datasets were then spatially disaggregated from the grid cells to the individual gages and temporally disaggregated for 1980 to 2050 using the methodology from Maurer and Hidalgo (2008) and Wood et al. (2004) based on the ARS weather data described previously. This procedure involved randomly selecting months from the historical data to serve as a template for temporal distribution. Temperatures at each gage location were adjusted using a monthly additive factor to match the average temperature for each month of the GCM results. The precipitation data were adjusted using a monthly multiplier to match the total monthly precipitation for each month in the GCM results

while maintaining the proportion of monthly rainfall across individual days. The same sequence of reference months was used to downscale each of the climate change scenarios.

To evaluate remaining bias in the climate simulations, we compared the downscaled precipitation and temperature data with the historical gage data. Bias was calculated by comparing the distribution of annual average temperature and total annual precipitation for the downscaled climate scenarios with that of the historical gage data from 1988-2008, excluding 2002. The SWAT models were then run using the historical gage data for 1985-2009, and for each climate model scenario for 1985-2050. To explicitly examine how biases in downscaled climate would propagate through the SWAT model streamflow and sediment discharge predictions, we compared the 1988-2008 (again excluding 2002) period for each scenario run to the same period run using gage data.

3 Results and Discussion

3.1 Model Calibration and Validation

Results for the calibration and validation of the SWAT models are shown in Figure 2 and Figure 3, with goodness-of-fit statistics summarized in Table I. Hydrologic calibration and validation of monthly outputs for the St. Joseph River model were both good, with Nash-Sutcliffe efficiencies of 0.78 for calibration and 0.72 for validation. The sediment discharge calibration and validation for the St. Joseph model resulted in biases of -3.2% and +10.5%, respectively, which are both considered very good, based on the percent bias criterion of Moriasi et al. (2007).

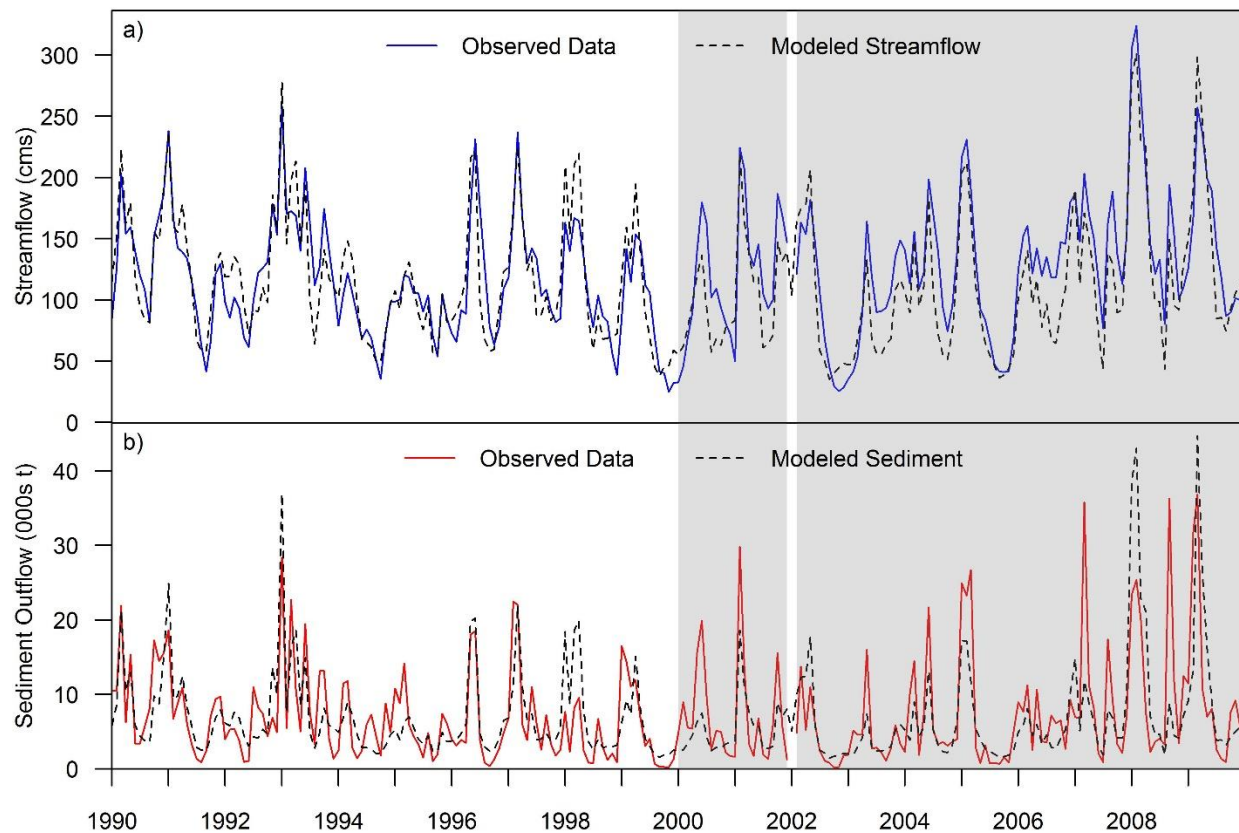


Figure 2. Calibration and validation of St. Joseph River SWAT model for (a) monthly streamflow and (b) monthly sediment discharge. The validation months are indicated by the grey shaded boxes. The gap in the validation period for January 2002 is due to missing weather data.

The calibration of the Maumee River model had nearly identical goodness-of-fit statistics for monthly flows at both stream gage sites. The calibration Nash-Sutcliffe efficiency was 0.79 at Waterville, OH and 0.80 at Defiance, OH (see Figure 1 for locations). Validation Nash-Sutcliffe efficiencies were 0.79 at Waterville and 0.82 at Defiance. Sediment discharge at Waterville produced a very good percent bias both for the calibration period (+4.6%) and the validation period (+2.5%).

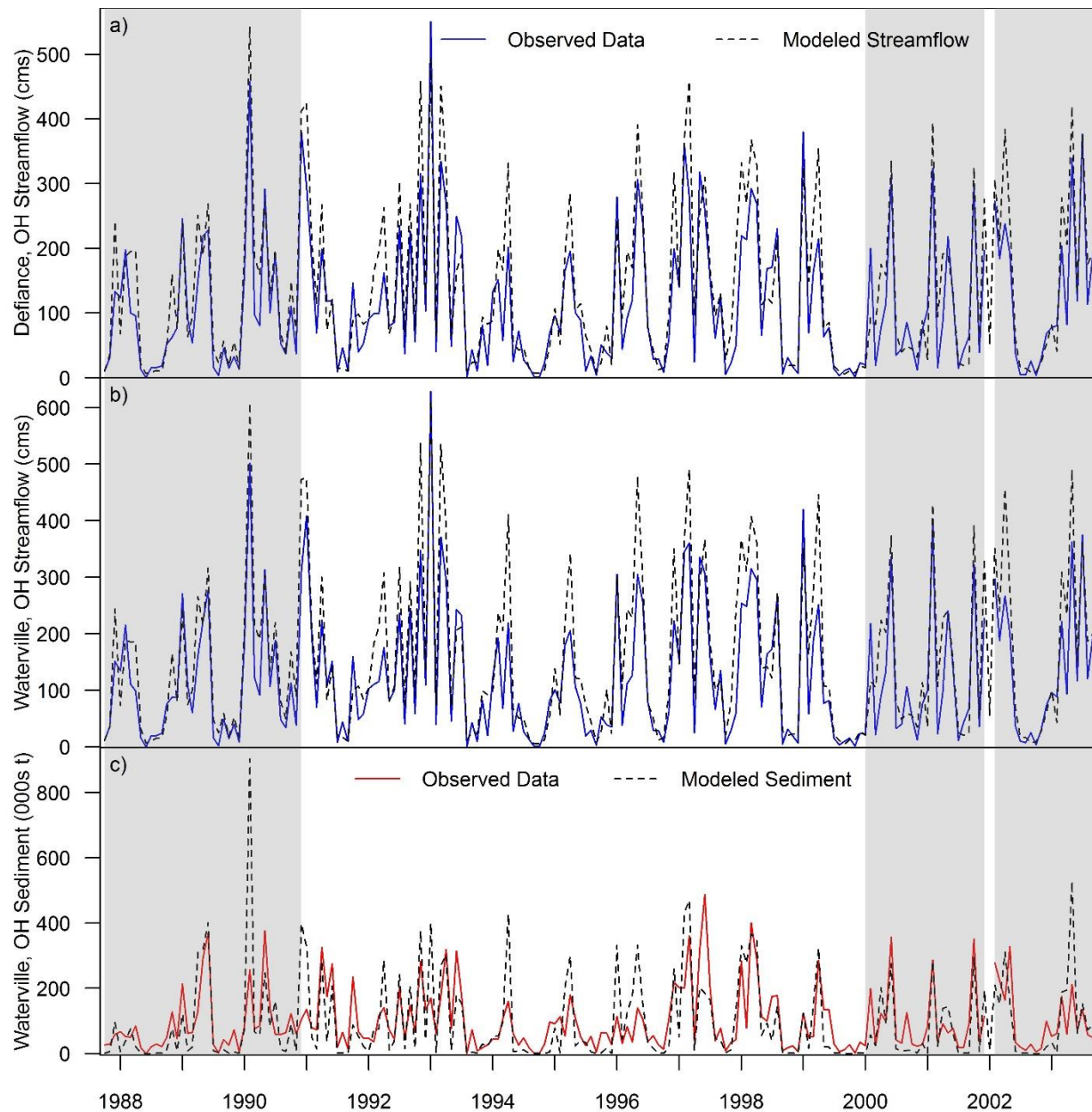


Figure 3. Calibration and validation of Maumee River SWAT model for (a) monthly streamflow at Defiance, OH and (b) at Waterville, OH, and (c) monthly sediment discharge at Waterville, OH. The validation months are indicated by the grey shaded boxes and were selected to maintain a common calibration period with the St. Joseph model while maximizing the use of available sediment data. The gap in the validation period for January 2002 is due to missing weather data.

Table I. Summary of Calibration and Validation Statistics: R^2 , Nash-Sutcliffe Efficiency (NSE), and % Bias. *Note that January 2002 was excluded from the goodness-of-fit calculations due to missing weather data for that month.*

			Calibration		Validation	
Calendar Years			1990-1999		2000-2009	
St. Joseph River at Niles, MI	Flow	R ²	0.78		0.83	
		NSE	0.78		0.72	
	Sediment	R ²	0.59		0.47	
		NSE	0.52		0.29	
		% Bias	-3.2%		+10.5%	
Water Years			1991-1999	Oct 1987-Dec 1990, Jan 2000-Sep 2003		
Maumee River at Waterville, OH	Flow	R ²	0.86		0.86	
		NSE	0.79		0.79	
	Sediment	R ²	0.53		0.49	
		NSE	0.52		0.48	
		% Bias	+4.6%		+2.5%	
Maumee River at Defiance, OH	Flow	R ²	0.84		0.86	
		NSE	0.80		0.82	

3.2 Downscaled Climate Model Bias

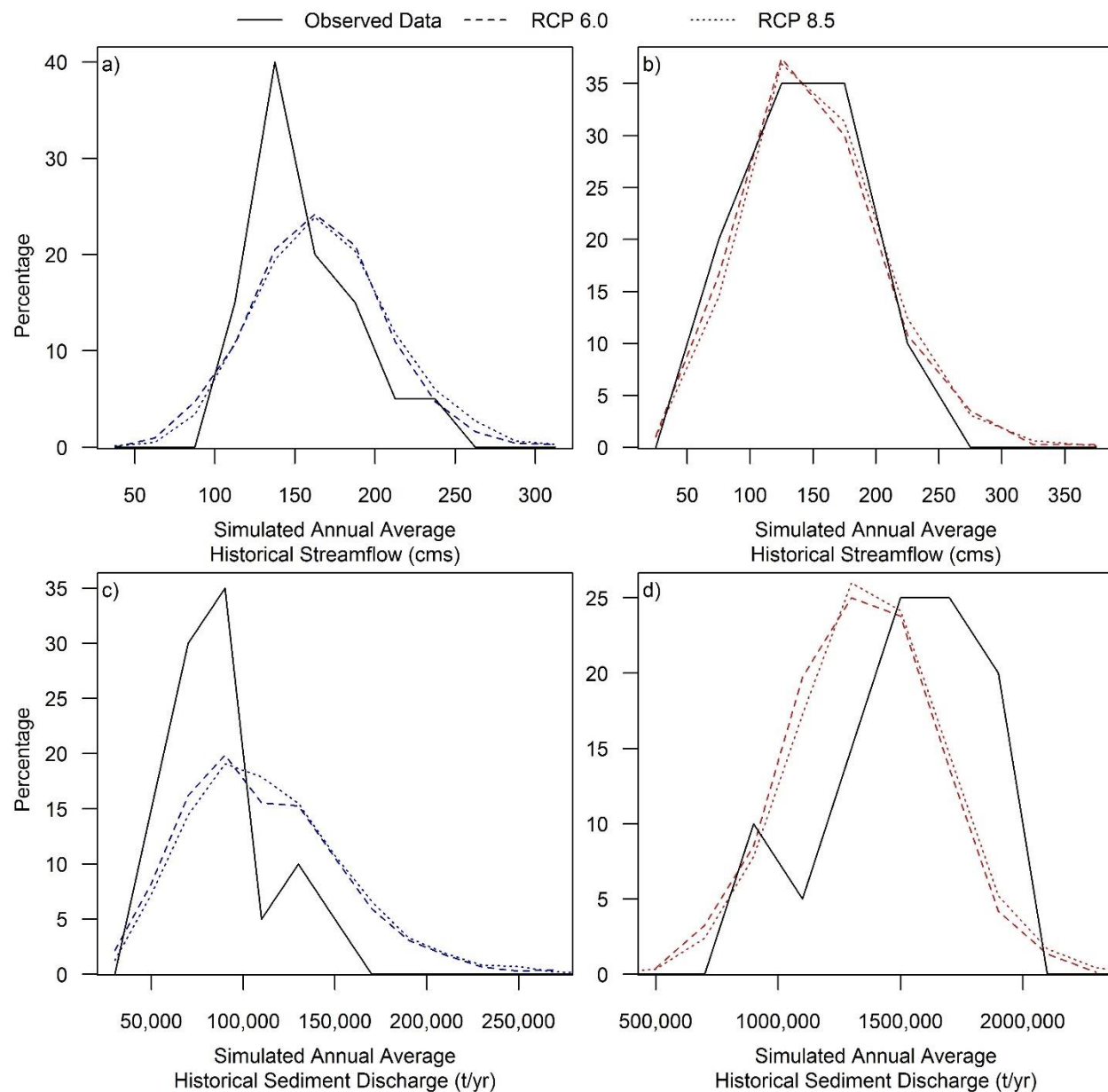
We looked at Probability Density Functions (PDFs) of the mean annual temperatures and annual precipitation from both the downscaled climate model historical runs and observed station data (Figure S1 in the Supporting Information) in order to determine if they represented the same distribution as the observed data. The overlap and similarities between the PDFs of the observed data and those of the downscaled climate data indicates that they likely represent the same distribution. When interpreting Figure S1, it is important to understand that the bias correction performed on the climate model data by Brekke et al. (2013) utilized a temperature and

precipitation dataset that was scaled to match long-term (1961-1990) average statistics (Maurer et al., 2002). The downscaled climate model temperatures have a mean annual bias of +0.02 °C and a standard deviation of 0.01 °C for both RCP 6.0 and 8.5, relative to the gage observations. The precipitation values for RCP 6.0 and 8.5 have mean annual biases of -49.5 mm/yr (-5.1% of mean observed precipitation) and -48.9 mm/yr (-5.0%), respectively. The standard deviation of the precipitation values is 25.0 and 29.0 mm/yr for RCP 6.0 and 8.5 respectively. It is also important to note that the sample sizes for the two RCPs discussed are different, as there were 37 RCP 6.0 scenarios and 71 RCP 8.5 scenarios available from the archive.

Biases in the downscaled climate inputs have the potential to propagate into the SWAT model outputs. Figure 4 shows the PDFs of the simulated historical streamflow and sediment discharge at the mouth of each river. Generally, the PDFs all follow similar patterns to the observed data. Potential differences may exist due to the small sample size of the observations. Streamflow and sediment discharge for the St. Joseph River have a slight high bias, while sediment discharge for the Maumee River has a slight low bias. The Maumee streamflow PDFs for the RCP 6.0 and 8.5 scenarios reasonably match the observed PDF. In order to limit the potential influence of this on our analysis, we used anomalies (differences between projected and historical time periods from the same data set) for the remaining analysis. Results for CMIP3 scenarios and additional CMIP5 RCP scenarios are summarized in the Supporting Information of this paper.

The biases in SWAT model outputs, when using the downscaled projections to simulate the historical time period, are most likely due to the biases in the downscaled and disaggregated

316 CMIP precipitation and temperature data. This may be attributed to a combination of the spatial
 317 and temporal disaggregation processes used and the climate models themselves.



318
 319 *Figure 4. Probability density functions of: a) annual average streamflow for the St. Joseph River, b) annual average*
 320 *streamflow for the Maumee River, c) annual average sediment discharge for the St. Joseph River, and d) annual*
 321 *average sediment discharge for the Maumee River. All PDFs are for the historical period (1988-2001, 2003-2008),*
 322 *simulated using observed climate data and downscaled climate data.*

3.3 Dredging Model Results

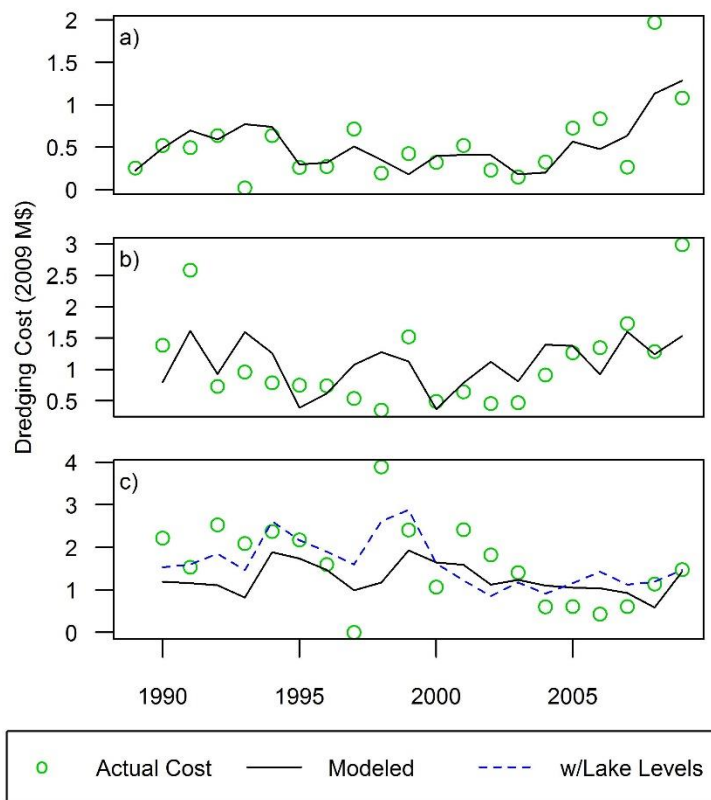


Figure 5. Actual and modeled historical costs using multiple linear regression for: a) St. Joseph Harbor, b) Maumee Bay, and c) Maumee River. The Maumee River modeled historical costs are shown both with and without including Lake Erie levels in the multiple linear regression.

The actual annual dredging expenditures and the modeled costs are shown in Figure 5. Table II shows the fit and parameters for the best linear model of dredging costs at each location, where $Q_{S, WY}$ is the sediment discharge for the water year of interest, $Q_{S, WY-1}$ is the sediment discharge for the preceding water year, $Q_{S, CY-1}$ is the sediment discharge for the preceding calendar year, and $D_{S, WY}$ is the deposition in the downstream reach of the Maumee River for the current water year. The estimate of St. Joseph Harbor dredging costs had an R^2 of 0.48. The cost of dredging the two sites associated with the Maumee River were estimated as the sum of the Maumee Bay ($R^2=0.30$) and Maumee River ($R^2=0.15$) costs.

336

337 *Table II. Dredging cost linear models for each dredging location*

Dredging Location	Model R ²	Equation				
		Intercept, <i>b</i> (\$)		Slope, <i>m</i> (\$)		Predictor Variables
St. Joseph Harbor	0.48	-693,700	+	14.30	*	$(Q_{S,WY} + Q_{S,WY-1})/2$
Maumee Bay	0.30	-859,800	+	1.26	*	$Q_{S,CY-1}$
Maumee River	0.15	3,519,000	+	16.88	*	$D_{S,WY}$

338

339 The multiple linear regressions including water levels showed no significant improvement over
 340 the simple linear regression for either the St. Joseph Harbor or the Maumee Bay dredging sites.
 341 Inclusion of Lake Erie water levels did improve the model fit for the Maumee River site
 342 ($R^2=0.38$). This improved estimate is shown as the dashed blue line in Figure 5c. While climate
 343 change will affect future lake levels, it is unclear what the effect will be and we opted not to
 344 include it in our estimates of future dredging.

345 3.4 Effects of Climate Change on Streamflow, Sediment Yield, Sediment Discharge, 346 and Dredging

347 The SWAT results are reported for three relevant outputs: streamflow at the river mouth,
 348 sediment yield from the entire watershed to the river, and sediment discharge at the river mouth.
 349 The SWAT outputs for the Contemporary (scenario years 2011-2030) and Mid-Century
 350 (scenario years 2031-2050) climate change scenarios are summarized in the Supporting
 351 Information in Tables S1 and S2, respectively.

352

353 The median streamflow values from the summary tables show small differences from the current
 354 climate. In contrast, the box plots in Figure 6 illustrate that the changes in median monthly

streamflow are small relative to the variability across climate scenarios for the Contemporary period. This is also true for the St. Joseph River in the Mid-Century period. However, the Mid-Century Maumee streamflows have a median increase of 6.1 cms for the RCP 6.0 scenarios and 3.9 cms for the RCP 8.5 scenarios.

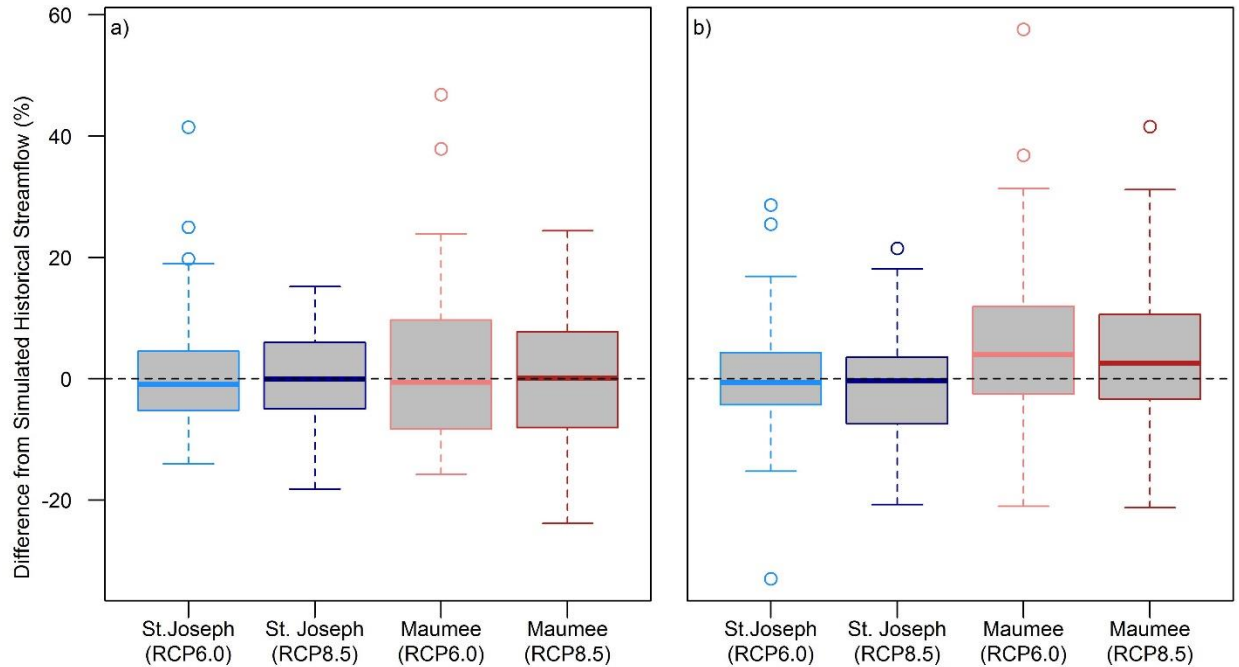


Figure 6. Differences in modeled streamflow between current (1989-2008), and both Contemporary (a, 2011-2030) and Mid-Century (b, 2031-2050) CMIP5 scenarios.

Median sediment yield estimates for both the St. Joseph and Maumee appear to decrease slightly in the Contemporary scenarios, as seen in Figure 7. Sediment yields in the St. Joseph watershed continue to decrease during the Mid-Century scenarios. In contrast, there is a slight increase in the Mid-Century sediment yields for the Maumee River under both RCP 6.0 and 8.5 scenarios.

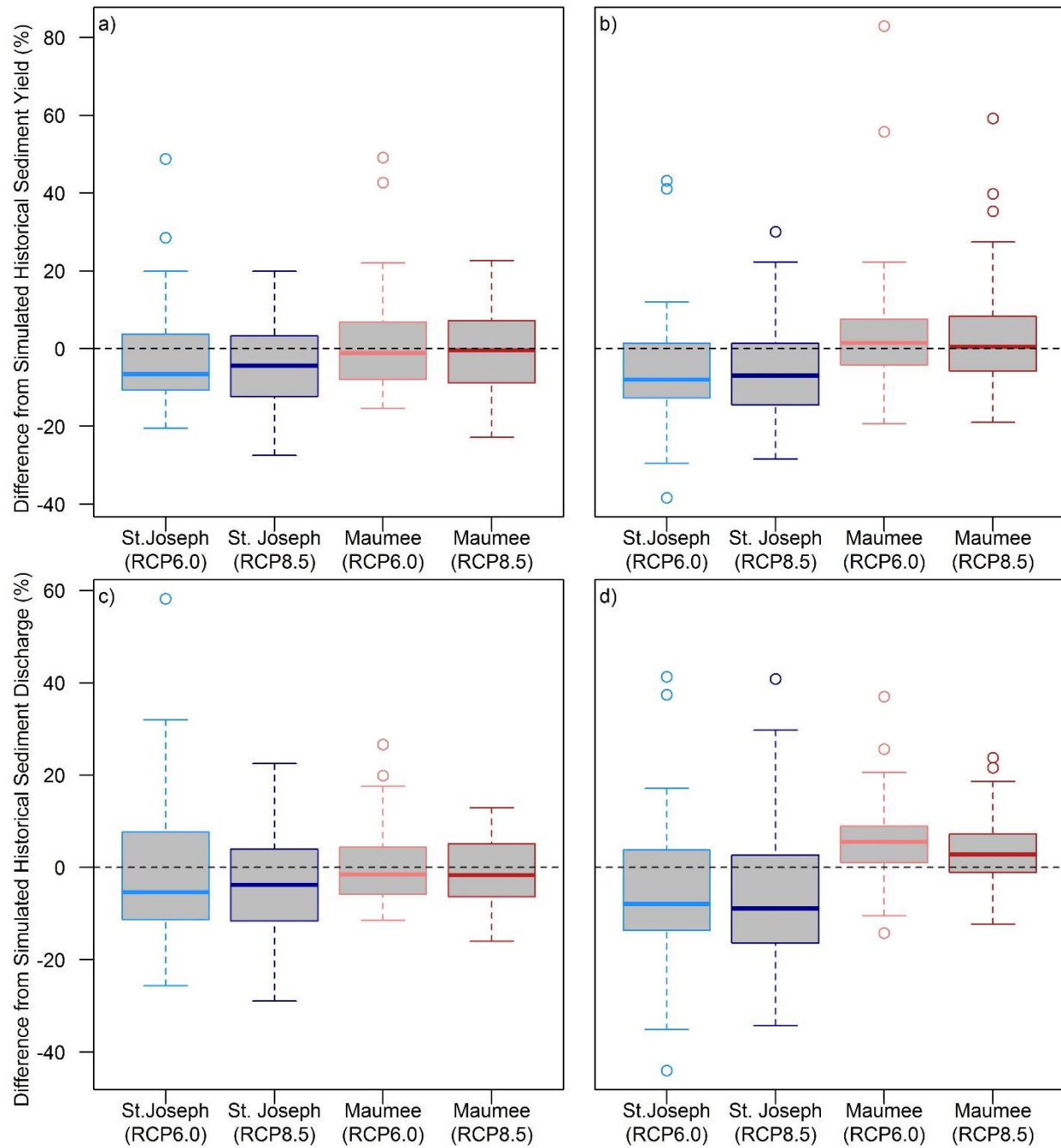


Figure 7. The top row shows differences in modeled sediment yield between historical (1989-2008) and both Contemporary (a, 2011-2030) and Mid-Century (b, 2031-2050) CMIP5 scenarios. The bottom row presents the differences in modeled sediment discharge between historical and Contemporary (c) and Mid-Century (d) CMIP5 scenarios.

Sediment discharge follows the same patterns as the sediment yield (Figure 7). The most significant difference is that over 75% of RCP 6.0 scenarios show an increase in sediment discharge for the Maumee relative to the current values. The percentage changes in the sediment discharge for the Maumee are similar to the simulated changes in streamflow. The sediment discharge changes in the St. Joseph, however more closely resemble the changes in sediment yield. There is a large amount of variability in these results and, with the exception of the Maumee RCP 6.0 sediment discharge, at least 25% of the scenarios fall on the opposite side of the no change line.

Several other studies have examined climate change in the Maumee River, although they used the CMIP3 climate scenarios and had differences in methodologies and study periods. Results from both Johnson et al. (2015) and Cherkauer and Sinha (2010) suggested little change in the average flows by mid-century, while Bosch (2014) projected a 6-18% increase in flow; these results are within the middle two quartiles of those presented here. Verma et al. (2015) projected a reduction in flow of 8.5%, which would be in the lowest quartile of our results. The sediment results from these studies are similar to those projected for streamflows, with Johnson et al. (2015) projecting very small (0.6%) increases in TSS, Bosch et al. (2014) projecting larger increases of 8-32%, and Verma et al. (2015) projecting decreases of 10.4%. With the exception of the high estimate of 32% from Bosch et al., these estimates are within the range of our results, with the results from Johnson et al. (2015) being closest to our median.

The responses of the two adjacent watersheds are similar, with the exception of the Mid-Century period in which median streamflow, sediment yield, and sediment discharge all start to increase in the Maumee River watershed, while they continue to decline in the St. Joseph River

396 watershed. A deeper investigation of model outputs revealed that this difference is due to the
397 much greater proportion of agricultural land in the Maumee (Figure 1). Sediment yield from
398 agricultural land can be significantly affected by the cover practices used, with low or no-till
399 practices and cover crops significantly reducing the soil erosion. This also implies that the timing
400 of large precipitation events that coincide with periods of bare ground can produce a large
401 proportion of the annual sediment yield. The effects of climate change will depend on the
402 coincident timing of these precipitation events and conditions, also suggesting that management
403 will be important to mitigate the effects of climate change on sediment yield in agricultural
404 watersheds.

405
406 The higher temperatures in the Mid-Century scenarios lead to simulated faster crop growth,
407 producing earlier and larger harvests. This increase in agricultural production can be seen in
408 Figure 8, which shows the change in harvested yield per hectare. A similar increase in future
409 crop yield due to longer growing seasons has been identified as a potential effect of climate
410 change (Pryor et al., 2014). In the model, once a crop is harvested, the land lays fallow, with
411 little to no transpiration, until the next growing season. This allows small increases in the
412 modeled sediment yield (due to erosion from the bare earth) as well as increased runoff that
413 translates into increased streamflow and sediment discharge. This model phenomenon, as
414 evidenced by a shift in evapotranspiration earlier in the year, was also noted by Ficklin et al.
415 (2009) for a SWAT model of a highly agricultural watershed in California. This example shows
416 the importance of looking closely at both the model results and the underlying processes.

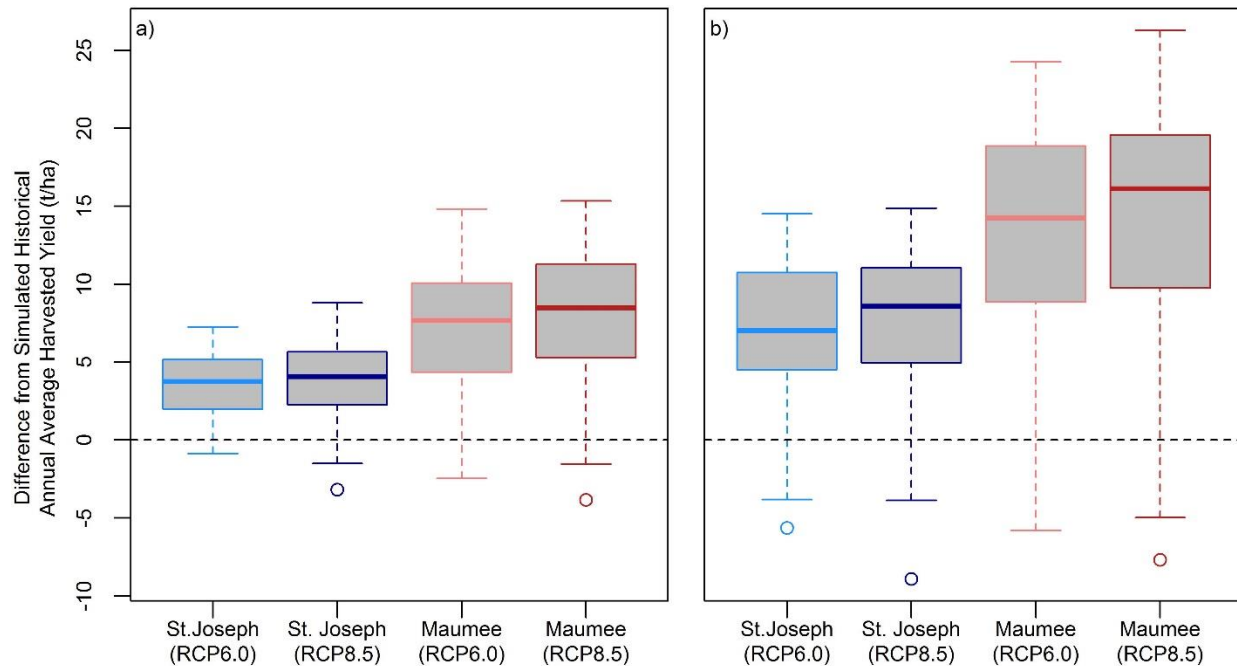


Figure 8. Difference in annual harvested yield per hectare estimated by the SWAT models for a) Contemporary (2011-2030) and b) Mid-Century (2031-2050) time periods. As harvested yield increases, more land is left fallow in the SWAT models, leading to increased runoff and sediment yield. Note that the values of the change in harvested yield are reflective of both area of cultivation, which is much greater in the Maumee, and increasing temperatures under climate change scenarios. In our models, once the crops were harvested, SWAT treated the land as fallow, allowing increased runoff and sediment yield.

It is possible that this phenomenon would be more limited in the real world. If crops are harvested early enough, farmers may plant a second crop, increasing evapotranspiration and offsetting the effects on sediment and streamflow. Alternatively, they may start to plant longer season crops that benefit from the increased temperatures. Both possibilities would also likely be accompanied by the use of additional fertilizers and possibly increased irrigation from groundwater.

432 Whatever the outcome of future management decisions, these results point to the sensitivity of
433 sediment yield and [discharge](#) to agricultural management. [Research is needed](#) to quantify the
434 likely effects of climate changes and to translate scientific results into potential policies to adapt
435 to a changing climate. While hydrologists and atmospheric scientists are prepared to discuss the
436 physical aspects of the water cycle, agricultural specialists and social scientists can better predict
437 how farmers will respond to the changing climatic conditions.

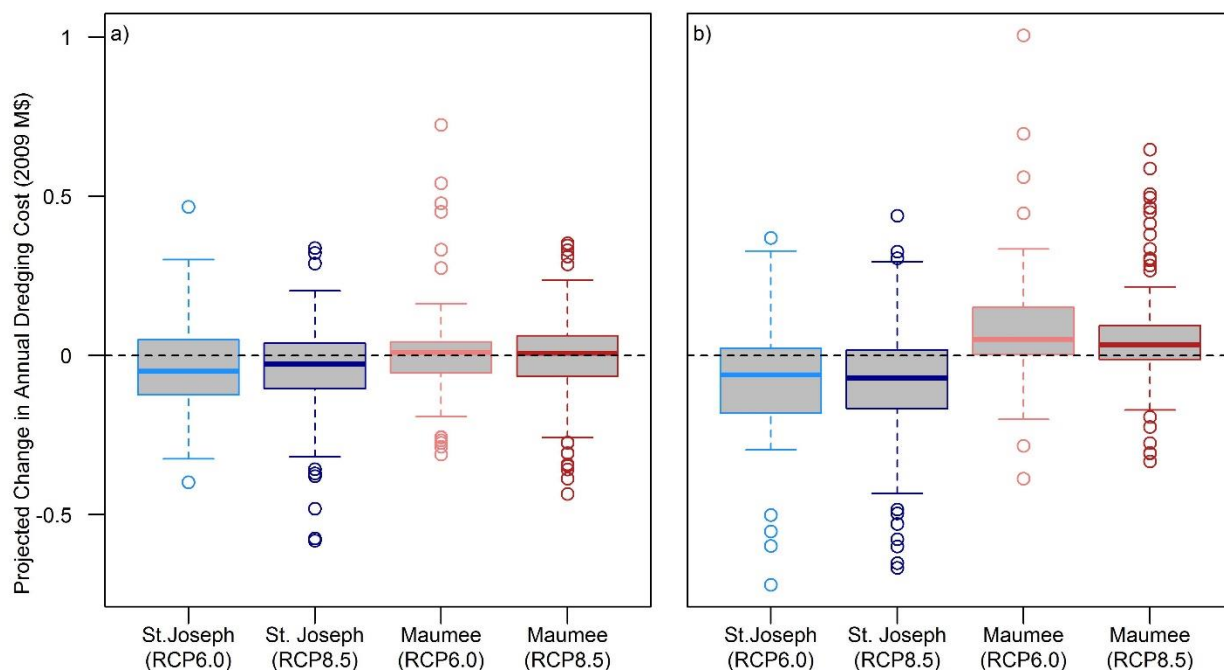
438
439 Recent (1989-2009) dredging of St. Joseph Harbor averaged \$517k per year (in 2009 dollars).
440 Relative to modeled historical dredging costs, median estimates using the regression equation
441 decline 5-13% in the Contemporary scenario and 14-16% in the Mid-Century time period
442 **(Error! Reference source not found., Figure 9).** (The upper quartiles ranged from +6-12% in
443 the Contemporary and +2-6% in the Mid-Century while the lower quartiles were -18% in the
444 Contemporary and -25-28% in the Mid-Century.) The decreases in median dredging costs
445 estimated using the 1:1 sediment discharge:dredging cost relationship were only about half as
446 much, 4-5% in the Contemporary and 8-9% in the Mid-Century time periods. (The upper
447 quartiles for the 1:1 cost relationship ranged from +4-8% in the Contemporary and +3-4% in the
448 Mid-Century while the lower quartiles were -11-12% in the Contemporary and -14-16% in the
449 Mid-Century.)

450
451 The average dredging cost for the combination of the Maumee River and Maumee Bay sites
452 between 1990 and 2009 was \$2.7M (in 2009 \$). The median estimated future dredging costs
453 (Table S3, Figure 9) based on the regression equation estimates show an increase of 1% or less
454 for both the Contemporary and Mid-Century scenarios, with upper quartiles of 1-2% and lower

quartiles of 0%. The estimates that are based on the 1:1 sediment discharge:dredging cost relationship are more variable, with median decreases of 2% in the Contemporary and 3-6% increases in the Mid-Century time period. The upper quartiles for the 1:1 relationship are 4-5% in the Contemporary and 7-9% in the Mid-Century time periods, while the lower quartiles indicate a decrease of 6% in the Contemporary and a change of $\pm 1\%$ by Mid-Century.

The changes in dredging costs vary between the two watersheds, the modeled time periods, across the climate models, and between the two different estimates of costs. Of note is that, for the St. Joseph River, the regression equation estimates show greater changes and variability than the 1:1 sediment discharge:dredging cost relationship, while the opposite is true for the Maumee. This difference in response between the two approaches to estimating the future dredging costs indicates the potential importance of examining multiple approaches when using empirical models.

The historical dredging was not driven solely by the amount of sediment being delivered by the river. The areas dredged are coastal harbors on the Great Lakes and are affected by longshore transport of sediment, short time period seiche events (over hours to days), and variations in lake levels on seasonal, annual, and decadal time scales (Gronewold & Stow, 2014; Quinn, 2002). In particular, our modeling shows that the Maumee River site dredging appears to be driven by lake level variations on Lake Erie (Figure 5c). Dredged volumes are also affected by the limited budget available to the U.S. Army Corps of Engineers in any given year; there is a backlog of dredging need across the Great Lakes (USACE, 2015).



478

479 *Figure 9. Projected changes in dredging costs for: a) Contemporary (2011-2030) and b) Mid-Century (2031-2050)*480 *scenarios, relative to historical (1989-2008) costs. Data shown includes both cost estimation methods, which are*481 *given equal weight, doubling the sample size.*482

4 Conclusions

483 We modeled future conditions in two large watersheds, the Maumee and St. Joseph Rivers, using

484 108 different sets of climate change inputs representing a plausible range of CO₂ emissions. In485 general, the [median results](#) suggest small decreases in streamflow in both watersheds, with

486 similar decreases in sediment delivery to the river mouths. The exception to this is the Mid-

487 Century scenario (2031-2050) for the Maumee River Watershed, where [its](#) managed agricultural488 landscapes are [likely](#) to drive the sediment and streamflow response of the watershed. This

489 implies that the response of farmers to the changing climate will significantly impact the

490 streamflow and sediment yield in agricultural areas.

491

There is a large amount of variation in the climate change model [projections](#) that drive similarly large variations in the predicted sediment yield and sediment discharge response. Even though averages across climate model ensembles tend to show little change, the variance is large. Of note, the differences between RCP 6.0 and RCP 8.5 scenarios are smaller than the variation across models within each scenario. The responses will also vary between watersheds depending on the dominance of agricultural lands, farming practices, soil types, [and other factors](#).

We also estimated dredging costs using two methods and, in general, they decrease slightly at St. Joseph, MI (~ 4-8% median decrease in the Contemporary, 8-18% median decrease in the Mid-Century). The Maumee dredging costs are likely to remain near the current range in the Contemporary, but are projected to increase slightly in the Mid-Century period (median increase of 1-6% in the Mid-Century). This will depend on the responses of farmers in the watershed to climate change. The model variance also indicates a significant uncertainty in outcomes.

This study focused on the aggregated effects of a large number of downscaled climate scenarios but only a single sediment modeling framework [using SWAT](#). Our understanding of the potential impacts of climate change could benefit by extending this research to include other sediment models and to examine the differences and variability within the CMIP5 projections. There is also a need to explore the likely responses of farmers to lengthening growing seasons and the impacts [of climate-induced changes in agricultural and management practices](#) on the sediment regime of watersheds.

Supporting Information

Interested readers may view additional model results in the Supporting Information accompanying this paper. Figure S1 shows the PDFs of observed and downscaled temperature and precipitation. Figure S2 shows the PDFs of mean annual temperature and precipitation for both the CMIP3 and CMIP5 scenarios. We have provided the results for all of the CMIP3 scenarios modeled and the A1b scenarios as Figures S3 to S7. CMIP5 results for all RCPs combined, as well as for RCPs 2.6 and 4.5 are presented in Figures S8 to S12. Tables S1 and S2 report the SWAT model outputs for the Contemporary and Mid-Century periods, respectively. Table S3 reports the estimated change in dredging costs.

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539

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