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Evaluating the impact of climate change on fluvial flood risk in a mixed-used watershed

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ABSTRACT

Predicting flood risk is important for climate change adaptation. We quantify fluvial flood risk due to changing climate in a mixed-use watershed in Michigan, USA. We apply two approaches to project future climate change: an ensemble of temperature and precipitation perturbations on the historical record and an ensemble of global and regional climate models. We incorporate climate projections into the Soil and Water Assessment Tool (SWAT) to estimate daily streamflow, then quantify flood risk using indices related to flood probability, duration, magnitude, and frequency. Results indicate rising temperatures may counteract small increases in precipitation, likely due to increased evapotranspiration. Climate model data without bias correction used in SWAT produced reasonable future streamflow changes—similar to the perturbation of historical climate—therefore retaining the predicted change in the flood frequency distribution. This work advances the application of climate models in SWAT for flood risk evaluation at watershed scales.

Software availability

The SWAT program and source code is freely available for download at this website: http: //swat. tamu.edu/

MATLAB and R scripts we used to calculate flood indices and result datasets can be freely downloaded at this GitHub repository: https: //github.com/yuchenw/Flood-Index

1. Introduction

Flooding is one of society's most devastating natural hazards, and predicting potential flood risk is an important element of climate change adaptation (Adger et al., 2005; Naess et al., 2005; Wilby et al., 2008). Statistical analysis of the global historical flooding record shows a trend towards greater flooding over the course of the twentieth century (Milly et al., 2002), and modeling at the global scale suggests a warmer climate carries a greater risk of flooding to continue in the future (Hirabayashi et al., 2013). Previous studies have evaluated future flood risk by analyzing climate change trends from the historical climate record (Milly et al., 2002; Wilby et al., 2008), or used global climate models to assess large-scale future risk (Hirabayashi et al., 2013; Prudhomme et al., 2014; Arnell and Gosling, 2016). However, global trends can mask the spatial variability of land use and climate change at smaller scales relevant for adaptation (Adger et al., 2005; Garner et al., 2015), and routing future climate data through watershed-scale models can fill this gap towards quantifying flood risk at local to regional scales.

The Soil and Water Assessment Tool (SWAT) is one such watershed-scale model, developed to study watershed hydrology and nutrient cycling in response to agricultural management scenarios, land use change, and climate (Arnold et al., 1998), and is commonly and increasingly used to estimate the hydrologic

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influences of climate change. However, there is no scientific consensus on the most appropriate method to incorporate future climate data to drive watershed models. Previous studies have applied several methods of integrating future climate information into SWAT: 1) generate climate input as a simple increment of temperature and percentage change of precipitation, either by adjusting climate model output (Fan and Shibata, 2015) or by adjusting observed station data (Liu et al., 2013; Steinschneider et al., 2015), which avoids the bias in climate models but may not account for changes in climate regime predicted by climate models, such as the potential change in frequency, intensity, and seasonality of precipitation; 2) use Regional Climate Models (RCM) or downscaled General Circulation Models (GCM) as the input (Bouraoui et al., 2002; Abbaspour et al., 2009; Deb et al., 2015; Kharel and Kirilenko, 2015), which preserves all features of the modeled climate dynamics, but is also subject to bias; 3) apply statistical transformation on climate model output to correct some bias in distribution of precipitation and/or temperature (Salathe et al., 2014; El-Khoury et al., 2015; Goldstein and Tarhule, 2015; Carvalho-Santos et al., 2016; Walters and Babbar-Sebens, 2016), which is a compromise between the simple increment method (assuming no distribution change) and the climate model method (assuming distribution change is not biased). While bias correction is a common approach to deal with climate model biases for historical conditions, the use of this technique may create difficulties when evaluating future climate. Specifically, present-day biases may change in the future such that the statistical correction may no longer be applicable. It is also important to consider an ensemble of various models, since the uncertainty of climate models has been found to be larger than the uncertainty of hydrologic simulation in some cases (Prudhomme et al., 2003). The first goal of this project is to test and provide guidance on the use of future climate data for prediction of streamflow in SWAT.

The second goal of this work is to assess multiple indicators of flood risk under future climate using SWAT-modeled streamflow outputs. Approaches currently used with watershed models to estimate flooding either describe temporal patterns, including magnitude of flooding, or identify spatial patterns and trends. A common approach to describe the temporal pattern of flooding is to calculate the exceedance probability, which is the probability of flow rate exceeding a given threshold. For instance, Cheng et al. (2013) defined the Flood Hazard Index as the recurrence probability during the entire study period when daily flow rate exceeds the bankfull discharge. A more holistic approach to flow management would consider flood characteristics such as flood duration, frequency, and magnitude (Postel and Richter, 2012). Researchers focused on ecosystem services and functions have suggested that incorporating multiple indicators may be important for properly assessing flooding regimes (Richter et al., 1996; Logsdon and Chaubey, 2013). Logsdon and Chaubey (2013) proposed the Flood Regulation Index to quantify flood regulation ecosystem services by combining flood duration, frequency, and magnitude into one index. In this study, we separated the components of Flood Regulation Index and Flood Hazard Index to assess flood hazard on four aspects, i.e. recurrence probability, frequency, duration, and magnitude.

The overall purpose of this study was to evaluate fluvial flooding under future climate change in a mixed-use watershed to provide guidance for modelers and managers. To test the approach, we used multiple methods to estimate future climate change and to assess flood risk. We applied a watershed model of the Huron River watershed in Michigan, USA, built with SWAT to estimate daily streamflow, drove the model with climate data from both statistically-generated climate scenarios and physically-based climate models, and evaluated four indices to quantify separate aspects of flood risk.

2. Methods

2.1. Study area

The Huron River is located in southeast Michigan, and drains to Lake Erie's western basin. Its drainage area is 2380 km^2, and contains nearly 600 km of stream channel (MDNR, 2002). Among all major rivers draining to Lake Erie's western basin, the Huron River is unique in many aspects. A large proportion of the watershed falls in the Detroit metropolitan area and it contains most of the city of Ann Arbor, therefore over 30% of the watershed is urbanized (Fig. 1). The river has over 100 dams on its main stem and tributaries, and numerous artificial and natural lakes cover more than 4% of the watershed. The percentage of streamflow coming from baseflow, referred to as baseflow index, is higher in the Huron River watershed (74%) (Bosch et al., 2011) than other nearby watersheds draining to western Lake Erie (10–30%) (USGS, 2003).

While it is challenging to build a watershed model for this highly-populated watershed with complex hydrology (Bosch et al., 2011), there is a need to evaluate flood risk under future climate among stakeholders in the area. Extreme rainfall events and flooding in the Midwest and around the Great Lakes region have intensified in the past several decades and these trends are likely to continue (Pryor et al., 2014). Nevertheless, despite most climate models projecting increases in the frequency and intensity of extreme precipitation events, changes in precipitation and temperature differ seasonally and geographically over the Great Lakes region (Bartolai et al., 2015). It is thus timely to assess flood risk specifically for this area, given the large number of people that could be exposed to future flooding.

2.2. Study design

This study (Fig. 2) builds upon previous work conducted by Cheng et al. (2013, 2017), and was initiated as a portion of the study overviewed in Cheng (2016). In this work we go beyond the single flood hazard index in Cheng (2016) and assess sensitivity of the watershed model driven by alternative estimates of climate change. A SWAT model was developed and calibrated for the Huron River Watershed based on daily flow data from 2001 to 2005, then model performance was verified from 1981 to 2010. After calibration and verification, we applied two approaches to simulate future climate. The first approach was a climate sensitivity analysis that applied step-wise temperature and precipitation perturbations to historical station data. The second approach used output from an ensemble of global and regional climate models. For both approaches, we incorporated temperature and precipitation data in SWAT to simulate daily flow data for each sub-basin. Four flood indices (flood exceedance probability, flood duration, flood frequency, and flood magnitude) were calculated based on simulated streamflow at every sub-basin outlet. Finally, we compared the flood indices of future and historical scenarios to assess future flood risk.

2.3. SWAT model calibration and verification

The SWAT model was set up in ArcSWAT 2012 (SWAT Revision 635) for ArcGIS 10.1, using a 30 m-resolution Digital Elevation Model (DEM) (downloaded from http://viewer.nationalmap.gov/viewer/), the National Land Cover Database (NLCD) for 2006 (downloaded from http://www.mrlc.gov/nlcd06_data.php), and the Soil Survey Geographic Database (SSURGO; downloaded from http://www.arcgis.com/apps/OnePane/basicviewer/index.html). Stream flowlines from the National Hydrography Dataset (NHD) medium resolution dataset were burned into the DEM before stream definition. The watershed was divided into 57 sub-basins

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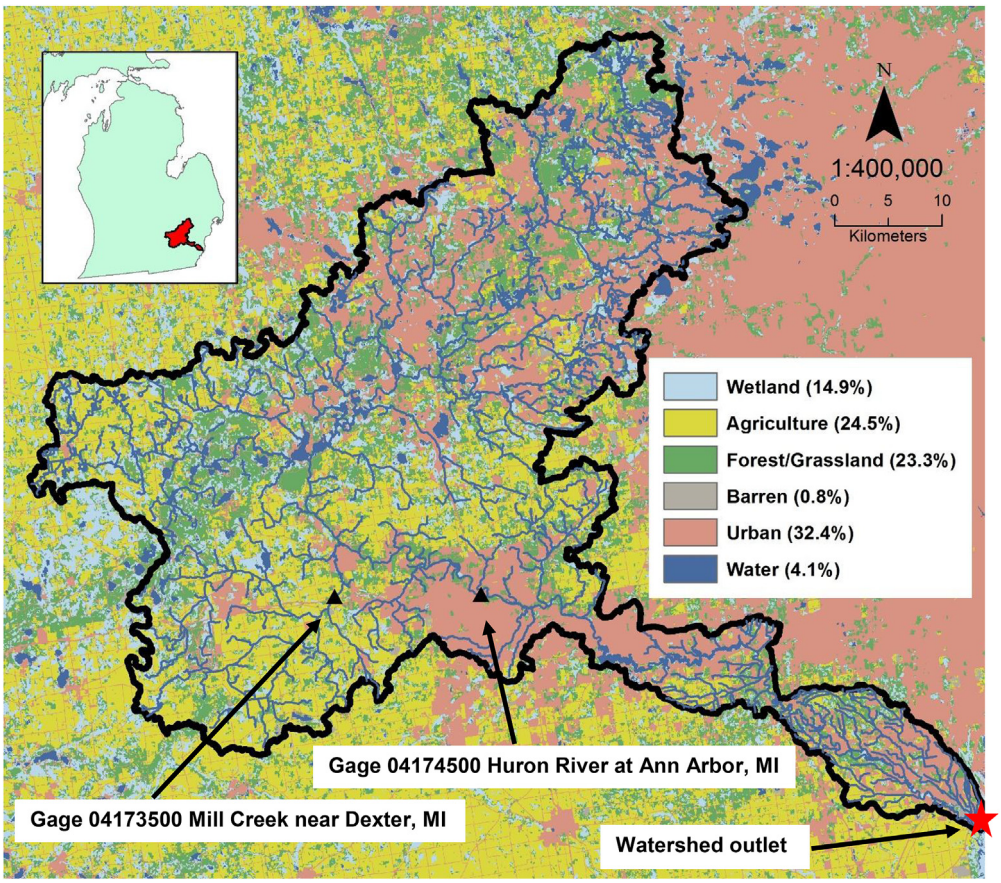

Fig. 1. Location of the Huron River Watershed in southeastern Michigan (inset map), along with the 2006 NLCD land use (percentage of each land use category in parentheses).

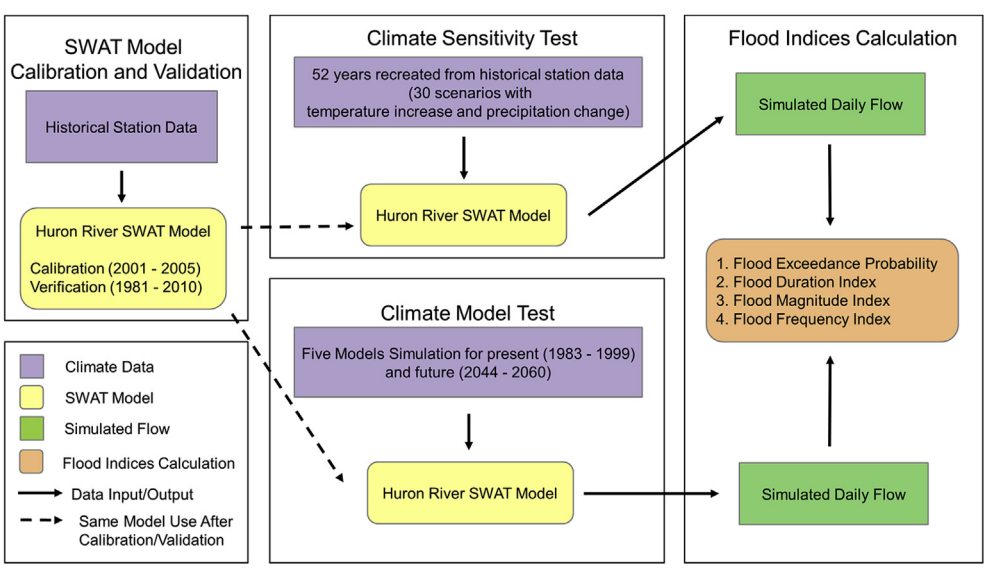

Fig. 2. Flowchart of the study design.

and 1890 HRUs, using a stream threshold of 4000 ha, and including all HUC12 outlets as well as USGS flow gages as additional sub-basin outlets. The average size of a sub-basin was 41.8 km^2, and, using HRU definition thresholds of 0% for land use, 10% for soils, and a single slope, the average size of an HRU was 1.26 km^2. Cropland HRUs were divided into two rotations of corn, soybean, and wheat based on the most common rotations determined by overlaying the Cropland Data Layer (CDL) from 2007 to 2012 (SI-A). For six reservoirs on the main stem of the Huron River, where dam operation information was available from stakeholder surveys, dam

operations were simulated by maintaining designated reservoir storage volumes (parameter STARG, target storage volume, in .res files) in winter months (November to April) (SI-B). Other impoundments were simulated as uncontrolled reservoirs (intersecting the stream channel) or ponds (not intersecting the stream channel) (SI-B).

A SWAT parameter sensitivity test was run in SWAT-CUP to choose the parameters to which streamflow is most sensitive parameters for manual calibration. A detailed list of parameters adjusted in calibration and example input files can be found in Table S1. Considering distinct hydrologic properties of agricultural land compared to forested and urban lands, we adjusted three parameters most sensitive to surface runoff in agricultural HRUs separately from other land uses: initial SCS runoff curve number for moisture condition II (CN2), maximum canopy storage (CANMX), and surface runoff lag coefficient (SURLAG_HRU). The model was run with SWAT2012 revision 635. Daily streamflow records from USGS flow gage sites 04174500 (Huron River at Ann Arbor, MI) and 04173500 (Mill Creek near Dexter, MI) were used for calibration (2001–2005) and verification (1981–2010). Gage 04174500 is the flow gage closest to the basin's outlet, draining 80% of the watershed. Gage 04173500 is close to the outlet of the agriculturally-dominated sub-watershed draining to Mill Creek. Due to availability of flow gage data, streamflow at the Mill Creek gage was only verified from 1995 to 2010. For calibration and verification, the correlation coefficient (R^2), Nash-Sutcliffe Efficiency coefficient (NSE), percent bias (PBIAS), and root mean square error-observation standard deviation ratio (RSR) statistics were calculated for streamflow at daily and monthly timescales (Moriasi et al., 2007; Bennett et al., 2013). In addition to quantitative measures of model fit, we sought to visually match the flow duration curves of observed and simulated streamflow, as the distribution of high flow events is essential in predicting flood risk.

2.4. Climate sensitivity test and climate model test

For climate sensitivity analysis, we generated an ensemble of potential climate data from the historical station record (1981–2010) using a bootstrapping method similar to Steinschneider and Brown (2013), given permutations of a temperature increase of 0, 1, 2, 3, 4, and 5 °C and precipitation changes of 0%, ±10%, and ± 20%. A total of 30 scenarios (five precipitation changes multiplied by six temperature changes) were generated to produce 55-year time series of daily temperature and precipitation data. Flood indices were calculated on 51 years of data, because the first three years were used to spin-up the SWAT model, and use of the water year for data summaries eliminated an additional year from the dataset. The scenario with no temperature or precipitation change compared to historical record was used as the baseline condition for comparison within the climate sensitivity datasets. Climate sensitivity analyses have been widely used around the world including the Great Lakes region (Moody and Brown, 2013), Midwestern US (Steinschneider et al., 2015), and South Asia (Yang et al., 2016) for uncertainty assessments of climate change impact. The set of possible future temperature and precipitation conditions allows us to determine which factors, at what range of values, affect environmental outcomes (Pianosi et al., 2016). The 30 scenarios were used to drive the Huron River SWAT model to produce daily streamflow time series.

For the climate model approach, an ensemble of climate models including one global (CESM1-CAM5), two regional (CRCM-CGCM3, RCM3-GFDL), and two dynamically-downscaled regional (RCM4-GFDL, RCM4-HadGEM) climate models were selected for the business-as-usual emissions scenarios (RCP 8.5 or A2) based on their general performance in the region (Basile et al., 2017; Table 1). For each model, we selected historical (1983–1999) and future (2044–2060) conditions for comparison. The five climate models predict that the Huron River watershed would see an increase of 1.69–3.32 °C in annual average temperature and annual precipitation change of −3% to 12% by the mid-21st century (2044–2060) compared to the historical period (1983–1999).

In both future climate approaches, we changed only temperature and precipitation inputs and allowed the SWAT model to automatically generate the other three weather inputs—solar radiation, relative humidity, and windspeed—as we had during the historical calibration and verification periods. We also did not alter the atmospheric carbon dioxide concentration in future climate scenarios because it is not a common practice among SWAT climate modeling studies, and a recent study that did change carbon dioxide concentrations in the current SWAT outlined some of its limitations (Culbertson et al., 2016).

2.5. Flood indices

To quantify flood risk, we calculated four indices based on simulated daily flow rate at each sub-basin outlet in the SWAT model (specific equations are presented in Table 2). A 2-year flood threshold was used in all indices, because it has been used as a proxy to bankfull discharge and threshold for flood events in past studies (Cheng et al., 2013). For the two different future climate approaches, we calculated 2-year flood values based on the present climate simulation (the baseline scenario in the sensitivity test, or the historical climate output of each climate model). The flow exceedance probability index, which is similar to the flood hazard index in Cheng et al. (2013), is defined as the probability of daily flows above the 2-year flood, calculated as the fraction of days with simulated flow above or equal to the 2-year flood in a given water year (October-September), then averaged across the simulation period, expressed as a percentage.

The other three indices were modified from the Flood Regulation Index designed by Logsdon and Chaubey (2013), which combines duration, magnitude, and frequency patterns of floods based

Table 1
Climate Model Information and Characteristics (more information on these climate models and their suitability for the region is available in Basile et al., 2017).

	Model Type	CO_2 Emission Scenario	Model Resolution	Temperature Increase (°C)[a]	Precipitation Change (%)[b]
CESM1-CAM5	Global climate model	RCP 8.5	~200 km	3.32	4.35
CRCM-CGCM3	Regional climate model - NARCCAP	A2 emissions scenario	50 km	2.58	8.56
RCM3-GFDL	Regional climate model - NARCCAP	A2 emissions scenario	50 km	2.19	1.33
RCM4-GFDL	Regional dynamically downscaled model	RCP 8.5	25 km	1.69	−3.05
RCM4-HadGEM	Regional dynamically downscaled model	RCP 8.5	25 km	2.71	12.13

[a] Temperature increase indicates the increase of future condition (2044–2060) compared to historical condition (1983–1999) in annual average temperature of the entire watershed.
[b] Precipitation change indicates the percentage change of future condition (2044–2060) compared to historical condition (1983–1999) in annual average precipitation of the entire watershed.

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Table 2
Equations for flood indices.

Flood Indices	Equations	Definitions
Flood Exceedance Probability Index (FEPI)	$FEPi = Di/Dy$ $FEPI = \frac{\sum_{i=1}^{N} FEPi}{N} \times 100\%$	*FEPi*: Flood Exceedance Probability of water year[a] *i* *Di*: Number of days when flood happens (discharge is larger than or equal to the 2-year flood) in year *i* *Dy*: Total number of days in one water year (365 for non-leap year, 366 for leap year) *N*: Total number of years in simulation period *FEPI*: Average Flood Exceedance Probability for a sub-basin
Flood Duration Index (FDI)	$FDi = Di/FFi$ $FDI = \frac{\sum_{i=1}^{N} FDi}{N}$	*FDi*: Flood Duration of water year *i* *Di*: Number of day when flood happens (discharge is larger than or equal to the 2-year flood) in year *i* *FFi*: Number of flood events in water year *i* *N*: Total number of years in simulation period *FDI*: Average Flood Duration Index for a sub-basin
Flood Magnitude Index (FMI)	$FMj = \frac{\sum_{m=1}^{n} Qm}{n}$ $FMi = \frac{\sum_{j=1}^{k} FMj}{k}$ $FM = \frac{\sum_{i=1}^{N} FMi}{N}$ $FMI = FM/Q2$	*FMj*: The average daily discharge of flood event *j* *Qm*: The daily discharge of day *m* *n*: Total number of days in one flood event *FMi*: The average flood discharge of water year *i* *k*: Total number of flood events in one water year *FM*: Flood Magnitude for a sub-basin *N*: Total number of years in simulation period *Q2*: 2-year flood *FMI*: Standardized expression of Flood Magnitude Index for a sub-basin adjusted for *Q2*
Flood Frequency Index (FFI)	$FFI = \frac{\sum_{i=1}^{N} FFi}{N}$	*FFi*: Number of flood events in water year *i* *N*: Total number of years in simulation period *FFI*: Average Flood Frequency Index for a sub-basin

[a] Water year refers to the period October 1–September 30.

on daily flow records. In this study, to further interpret the flood pattern of these individual components, we used flood duration, flood magnitude, and flood frequency separately based on simulated daily flow of each sub-basin from the SWAT model. For these indices we defined a flood event as one or more consecutive days when the daily flow rate exceeds a 2-year flood. Flood duration is defined as the number of consecutive days of flooding in a flood event. We averaged the flood duration for all flood events in a water year, then calculated the average for all years to derive the flood duration index. The flood magnitude index is an indicator of the relative magnitude of flood events compared to the 2-year flood. We calculated the average amount of discharge per day for each flood event. We then calculated the average discharge of flood events in a water year. After that, we calculated the average for all years to derive the flood magnitude index. The final average is further divided by the 2-year flood for each sub-basin to standardize across sub-basins with large and small drainage areas. Finally, the flood frequency index is defined as the average number of flood events in a water year across the observation period.

For the climate sensitivity test we compared the flood indices for each of the 29 climate change scenarios to the 51-year baseline condition. For each model in the climate model ensemble we compared the flood indices under future conditions (2044–2060) to the historical conditions (1983–1999). We present findings as a percentage change in flood indices between future and historical conditions to assess if the flood risk of each sub-basin increases or decreases under future climate.

3. Results and discussion

3.1. SWAT model calibration and verification

Given the difficulty in calibrating to multiple gaging stations, and the hydrologic complexity of this mixed-use watershed, including dozens of impoundments, this SWAT model adequately simulated daily flow rate using observed precipitation and temperature time series as input (Table 3), and can thus be applied to study climate-change-induced flood risk change in the Huron River Watershed. Daily and monthly flow rate at both gages had satisfactory calibration (Moriasi et al., 2007), and the simulated flow

Table 3
Calibration and verification statistics at daily and monthly time-scales for the Huron River SWAT model.

		Calibration		Verification	
		Whole basin (Ann Arbor gage)	Agricultural subwatershed (Mill Creek Gage)	Whole basin (Ann Arbor gage)	Agricultural subwatershed (Mill Creek Gage)
Period		2001–2005	2001–2005	1981–2010	1995–2010
Daily	R^2	0.69	0.58	0.54	0.54
	NS	0.60	0.57	0.43	0.47
	PBIAS	−9%	8%	8%	1%
	RSR	0.626	0.650	0.754	0.728
Monthly	R^2	0.77	0.64	0.60	0.58
	NS	0.72	0.63	0.52	0.51
	PBIAS	−9%	8%	8%	1%
	RSR	0.522	0.604	0.689	0.700

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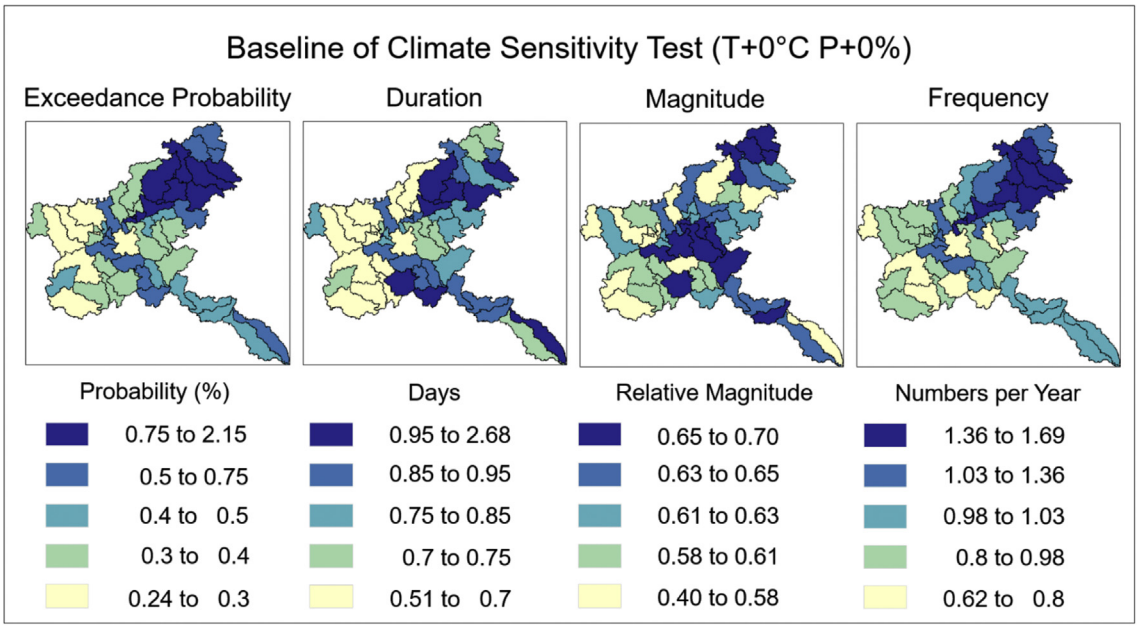

Fig. 3. Four flood risk indices under baseline scenario.

duration curve for both gages matched the observations well (Figs. S1–S4). Calibration at two outlets with different dominant land uses demonstrates how spatial heterogeneity in land use interacts with hydrology and further affects flood risk distribution in this watershed. Generally, the SWAT model showed slight underprediction of flow rate in agricultural lands and slight overprediction from other land uses in calibration. The small bias in SWAT-modeled flow rate is insignificant in predicting flood risk change, because present and future climate scenario simulations are subject to the same model bias.

3.2. Flood risk under the baseline condition

The spatial distribution of all four flood indices for the baseline case (T+0 °C P+0%) agrees across much of the watershed, and generally shows greater flood risk in the northern headwaters of the Huron River (Fig. 3). The relatively high flood indices in northern headwaters may be explained by the fact that this area coincides with urbanized lands in this watershed (Fig. 1). Urbanized lands are likely to expand the area of impervious surface (Paul and Meyer, 2001), which reduces infiltration and increases surface runoff (Dunne and Leopold, 1978). Many studies have shown that urbanization may alter the stream hydrology, leading to increase in flood magnitude (White and Greer, 2006) or frequency (Moscrip and Montgomery, 1997; Garner et al., 2015). The spatial distribution of flood risk under baseline conditions confirms that the SWAT model captured the impact of urbanized land on stream discharge, and the urbanized headwaters of the Huron River could be a focus area for flood mitigation.

Despite the overall agreement among the flood indices, not all four indices show consistent levels of risk for each sub-basin. Some sub-basins had high values in only one or two flood indices but low values for others (Fig. 3), suggesting that these indices are capturing unique components of flooding in different areas. For example, a sub-basin having an elevated flood frequency and a small flood magnitude may have many small flooding events throughout the year, and flood mitigation efforts in this sub-basin should be focused differently than in an area with low flood frequency and large flood magnitude.

Where there is a disagreement among the four indices, the flood magnitude index was often the most distinct from the others. Pearson Correlation analysis on flood indices of all sub-basins shows that, under baseline conditions, flood exceedance probability was positively correlated with flood duration and flood frequency, but not correlated with flood magnitude (Fig. S5). Correlations between the four indices were all positive in the 30 scenarios from the climate sensitivity test, but the correlation between flood exceedance probability and flood magnitude was the lowest (Fig. S6). This is unsurprising given that the equation for flood magnitude index (Table 2) is indeed different from the others, and it is the only index considering the total amount of flow above the 2-year return interval. Flood duration and magnitude are more related to exceedance probability, but sometimes these three indices show different patterns. When viewed together these indices paint a more nuanced and complete picture of flood risk, and managers may find them more helpful for prioritizing mitigation efforts than relying on a single index.

3.3. Future flood risk under climate sensitivity testing

The climate sensitivity test reveals overall flood risk under different scenarios and areas sensitive to climate change. Watershed-level flood risk for each index was summarized by averaging that index weighted by sub-basin area (Figs. S7–S10). As expected, all four indices exhibited the highest area-weighted average when precipitation increased by 20% with no increase in temperature (Scenario T+0 °C P+20%), and all indices increased by over 100%. In contrast, all four indices were the lowest when precipitation decreased by 20% with a temperature increase of 5 °C (Scenario T+5 °C P-20%), with many index values near zero. There was a gradual change in flood indices between the scenario T+0 °C P+20% and the scenario T+5 °C P-20% (Figs. S7–S10). Generally speaking, more precipitation tended to perpetuate flood risk, while warmer temperature tended to reduce flood risk. Additionally, this demonstrates the need to evaluate flood risk with respect to both temperature and precipitation change.

Spatial heterogeneity of flood risk change was seen at the sub-basin level based on different land use and hydrologic properties

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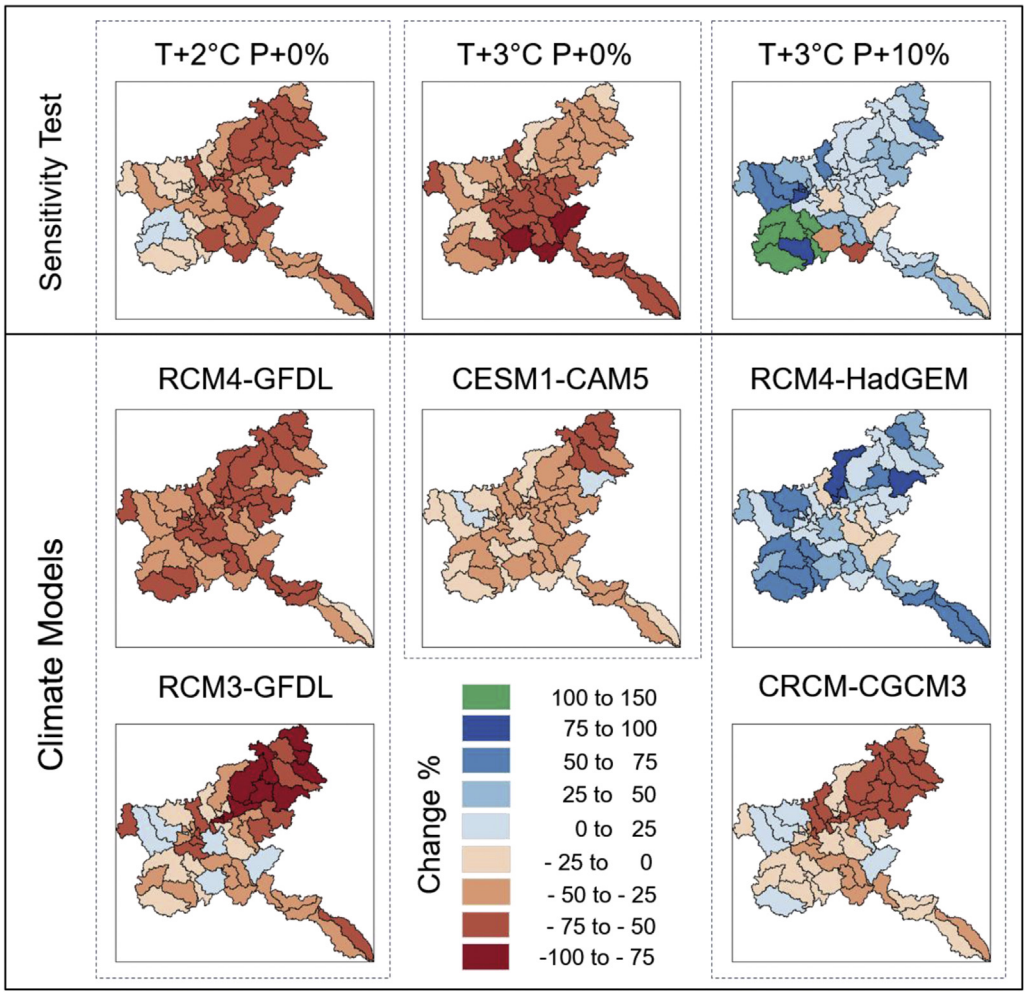

Fig. 4. The percentage change of flood exceedance probability index between future and historical climate conditions. The top three maps are of the sensitivity tests with the most similar temperature and precipitation change to the climate models shown beneath.

(Figs. S11–S14). When precipitation decreased by 10% or 20%, flood indices of all sub-basins were lower than the baseline scenario; however, when precipitation increased by 10% or 20%, not all sub-basins saw flood index increases from the baseline. Warmer temperatures caused a decrease in water yield, which counteracted the increase in precipitation. Therefore, in the sub-basins more sensitive to temperature change, flood indices were lower compared to the baseline scenario despite precipitation increases. For flood exceedance probability and flood duration, the headwater area exhibited considerable change when precipitation increased, indicating that headwaters were more sensitive to higher precipitation in terms of these two components of flood risk. However, for flood magnitude and flood frequency, the level of change seems to be consistent across the watershed, suggesting that precipitation and temperature change have a more consistent impact on flood magnitude and frequency. These findings, again, illustrate the value of applying multiple flood indices to assess flood risk since the response of each individual flood components can be different under the same precipitation and temperature condition.

The climate sensitivity scenarios showed that when precipitation increased by 0%–10% and temperature increased 2–3 °C not all sub-basins exhibited a consistent direction of change compared to the baseline scenario (Figs. S11–S14), suggesting flooding within the basin is sensitive to the interacting effects of temperature and precipitation, as well as land use. At the scale of the entire basin, this balance suggests a threshold around a 10% increase in precipitation (Figs S7–S10); above this threshold, greater precipitation leads to greater flood risk, while below it rising temperature may counteract the influence of increased precipitation.

3.4. Future flood risk under climate model predictions

Most of our climate/SWAT model results predicted reduced flood risk in the future (Tables S2–S5). The five climate models projected precipitation increases of 0–10% and temperature increases of 2–3 °C (Table 1). Considering the 10% precipitation increase threshold we identified in the climate sensitivity test, it is not surprising that most future flood indices decreased. Flood exceedance probability and flood duration decreased over the entire watershed with four out of the five climate models (RCM4-HadGEM was the exception; Figs. 4 and 5, Fig. S15). The other two flood indices show less certainty about the direction of change. Flood magnitude differed among the climate models; RCM3-GFDL and RCM4-GFDL showed a decrease of 22% between future and historical condition, whereas CESM1-CAM5 showed a slight increase of 9% and both CRCM-CGCM3 and RCM4-HadGEM showed an increase of 46% (Fig. 6, Table S4, Fig. S15). Flood frequency increased for two of the five models. Among these models, RCM4-HadGEM showed the largest increase, almost 100% (Fig. 7, Table S5, and Fig. S15).

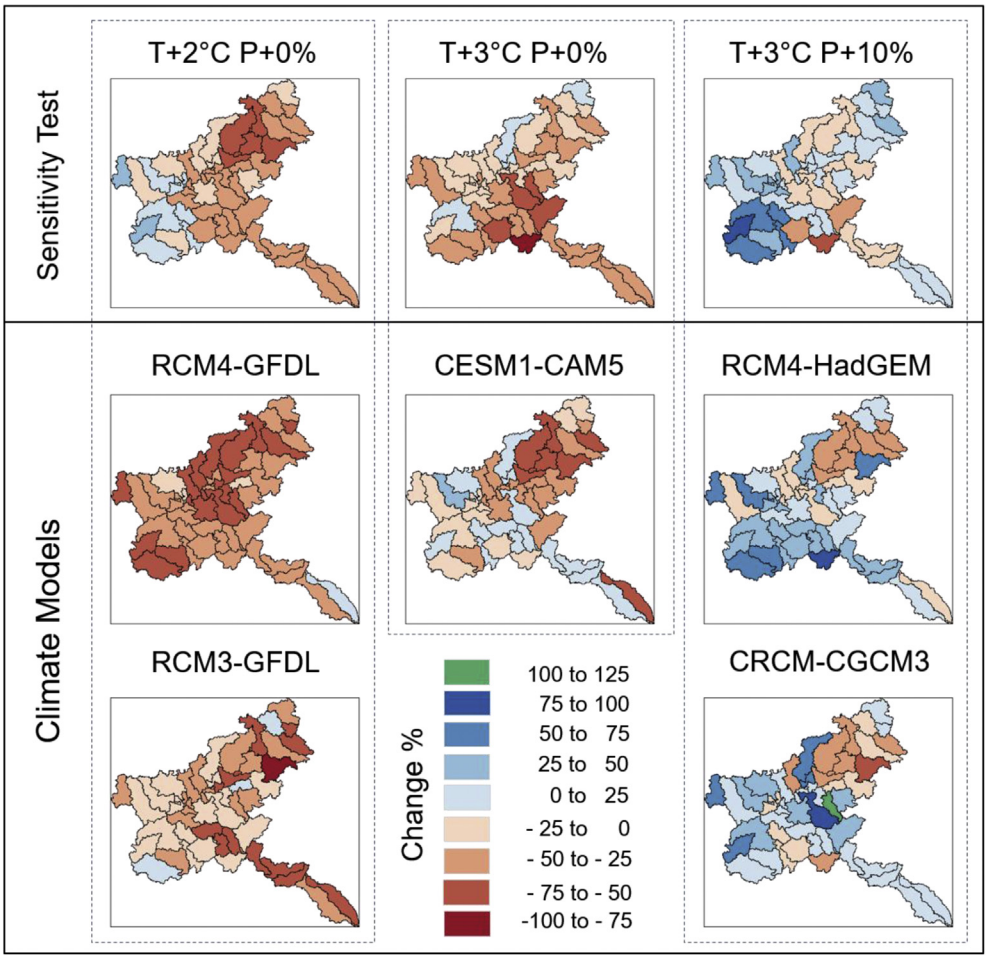

Fig. 5. The percentage change of flood duration index between future and historical climate conditions. The top three maps are of the sensitivity tests with the most similar temperature and precipitation change to the climate models shown beneath.

Spatial patterns of flood indices and their magnitudes of change are similar between the two approaches for projecting future climate. In most cases, SWAT results driven by the five climate models align with results driven by scenarios from the sensitivity tests with the closest temperature and precipitation change (Figs. 4–7). However, there are also notable exceptions where results using the climate model were considerably different from its closest sensitivity test scenario (e.g., flood exceedance probability from CRCM-CGCM3 and its closest sensitivity test, T+3 °C, P+10%, Fig. 4). Results using climate models also generally showed greater reduction of flood duration than sensitivity test scenarios. Flood magnitude was more variable in comparison between climate models and sensitivity tests, with RCM3-GFDL producing the greatest increase despite a relatively small change in annual precipitation. Finally, there was a marked difference in the spatial patterns of flood frequency among climate models and sensitivity tests, with some of the greatest decrease predicted by CRCM-CGCM3 despite a relatively large increase in precipitation. Some of the differences in flood risk under climate model simulations may have resulted from different distribution patterns of temperature and precipitation in the models (Figs. S16–S17). For example, when comparing future and historical conditions, RCM4-HadGEM displays the greatest precipitation increase in the spring. Springtime is generally the beginning of the flooding season in the Huron River (Fig. S18), so these precipitation increases may be expected to influence flooding more than precipitation increases occurring at other times of the year.

Differences among climate model scenarios highlight the value of incorporating multiple climate model predictions in SWAT analyses. While climate models produce different future seasonal or spatial patterns of temperature and precipitation, statistically generated climate sensitivity tests do not. Using climate models more likely captures key changes in spatiotemporal patterns of temperature and precipitation. Using multiple climate models is also valuable because it is not clear which models produce the most accurate futures, or where model bias is influencing results. While we were not able to tease apart the impact of bias in the climate models, the fact that the sensitivity tests produced similar percentage changes and spatial patterns of flood risk suggests that even though the climate models used were not bias-corrected, they resulted in a similar frequency distribution of streamflow in the hydrologic model.

There was substantial agreement between sensitivity test scenarios and climate models suggesting that a precipitation increase above 10% will likely increase flood risk sharply for all four flood indices. Below this 10% precipitation increase, temperature rise can balance the precipitation effect. This threshold may provide important insight for managers in the Huron River watershed in assessing and managing future flood risk.

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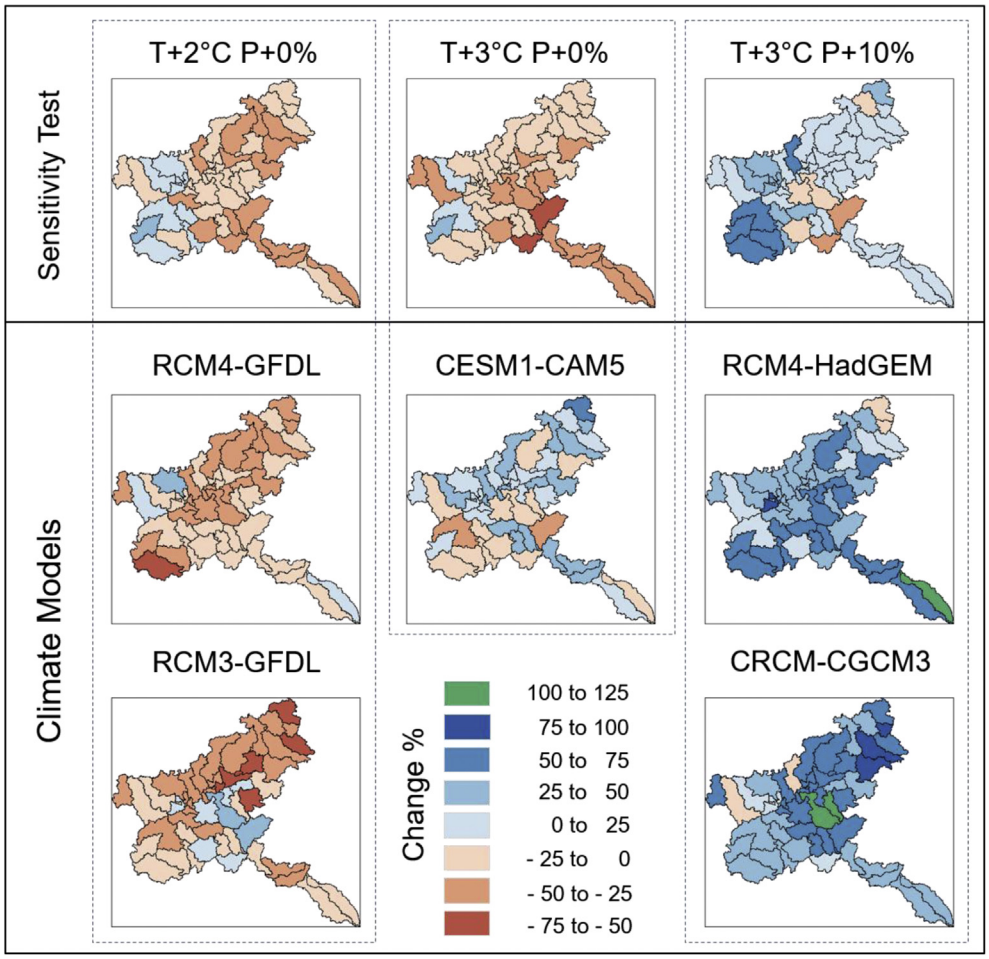

Fig. 6. The percentage change of flood magnitude index between future and historical climate conditions. The top three maps are of the sensitivity tests with the most similar temperature and precipitation change to the climate models shown beneath.

4. Conclusions

We compared the effects of two approaches to simulating climate change on the SWAT model using four indices for estimating flood risk across the watershed. Our findings contribute to the following broader lessons:

- We used four flood indices to identify spatial patterns of flood risk within the watershed, and while ***each flood index produced unique results*** that paint a more comprehensive picture of flood risk than using one index alone, we found that the four indices showed ***higher risk in urban areas in the headwaters and lower risk in agricultural areas.***
- The SWAT model produced similar patterns of change in flooding due to temperature and precipitation driven either by climate models or sensitivity analysis. While passing climate data with known bias through a watershed model that is sensitive to those biases may produce unreasonable results, we found that using unaltered climate model data produced reliable predictions of percent changes in flood risk.
- Unlike results from many global and regional studies, our results suggest this watershed is likely to experience a ***reduction in flood risk under a future, mid-century climate*** as long as the precipitation increase is less than 10% because increased evapotranspiration induced by higher temperatures will balance that precipitation increase. Above a 20% increase in precipitation, flood risk will most likely escalate.

While these findings shed light on approaches commonly used for implementing climate change research, as well as the relationship between climate change and flood risk, there are some aspects to consider and expand upon in the future:

- Tying the climate and watershed modeling work to a DEM-based analysis of inundation area would provide local and regional managers with more detailed analysis of projected changes in ***water level and areas inundated.***
- Simulation of climate change in SWAT is ***not limited to inputs of temperature and precipitation.*** A modeler can also change SWAT's simulation of solar radiation, humidity, and wind speed, which could influence soil moisture and runoff. Additionally, there is an option to update atmospheric carbon dioxide concentrations, which would alter plant respiration and water requirements. Few modelers change these settings, and more work in this area is needed to more fully capture the hydrologic changes from a future climate.
- While it is common practice to drive a watershed model with climate model output, in larger watersheds it would be preferable to ***couple watershed and climate models*** so that landscape processes feed back into the climate model, as in Goodall et al. (2013).

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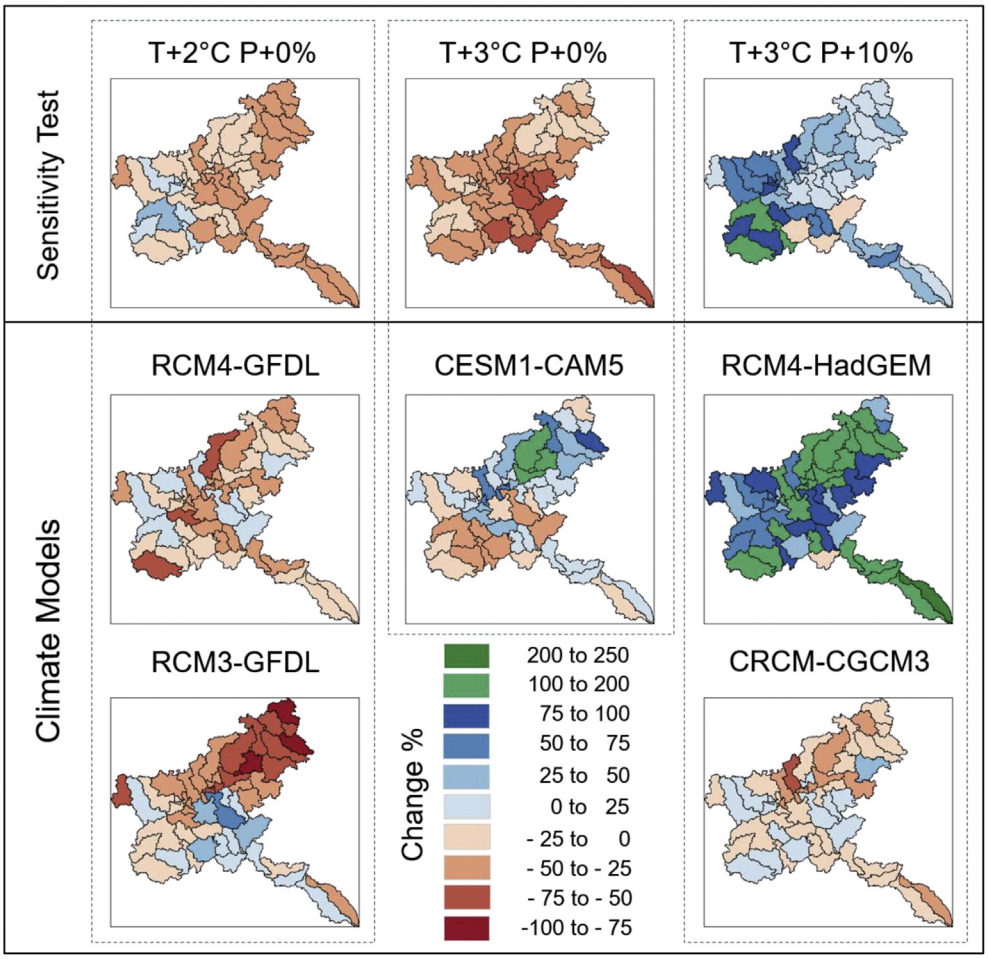

Fig. 7. The percentage change of flood frequency index between future and historical climate conditions. The top three maps are of the sensitivity tests with the most similar temperature and precipitation change to the climate models shown beneath.

Finally, in this study we did not consider human interaction with and impact on future climate change. The future climate trajectory could be different if mitigation efforts were taken, and shifting land uses could alter hydrologic regime and flood risk in the watershed. Flood and drought mitigation efforts and technological advances could further reduce the vulnerability of the community.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2017.07.013.

References

Abbaspour, K.C., et al., Oct 28 2009. Assessing the impact of climate change on water resources in Iran. Water Resour. Res. 45. ISSN 0043–1397.

Adger, W.N., Arnell, N.W., Tompkins, E.L., Jul 2005. Successful adaptation to climate change across scales. Glob. Environ. Change-Human Policy Dimensions. ISSN: 0959-3780 15 (n. 2), 77–86.

Arnell, N.W., Gosling, S.N., Feb 2016. The impacts of climate change on river flood risk at the global scale. Clim. Change. ISSN: 0165-0009 134 (n. 3), 387–401.

Arnold, J.G., et al., Feb 1998. Large area hydrologic modeling and assessment - Part 1: model development. J. Am. Water Resour. Assoc. ISSN: 0043-1370 34 (n. 1), 73–89.

Bartolai, A.M., He, L., Hurst, A.E., Mortsch, L., Paehlke, R., Scavia, D., 2015. Climate change as a driver of change in the great lakes st. Lawrence river basin. J. Gt. Lakes. Res. 41 (Suppl. 1), 45–58.

Basile, S., Rauscher, S., Steiner, A., June 2017. Projected precipitation changes within the great lakes and Western Lake Erie basin: a multi-model analysis of intensity and seasonality. Int. J. Climatol. Available online, DOI: http://dx.doi.org/10.1002/joc.5128.

Bennett, N.D., et al., 2013. Characterising performance of environmental models. Environ. Model. Software 40, 1–20.

Bosch, N.S., Allan, J.D., Dolan, D.M., Han, H., Richards, R.P., 2011. Application of the soil and water assessment tool for six watersheds of Lake Erie: model parameterization and calibration. J. Gt. Lakes. Res. 37 (2), 263–271.

Bouraoui, F., Galbiati, L., Bidoglio, G., Apr 2002. Climate change impacts on nutrient loads in the Yorkshire Ouse catchment (UK). Hydrology Earth Syst. Sci. ISSN: 1027-5606 6 (n. 2), 197–209.

Carvalho-Santos, C., et al., Feb 2016. Assessing the effects of land cover and future climate conditions on the provision of hydrological services in a medium-sized watershed of Portugal. Hydrol. Process. ISSN: 0885-6087 30 (n. 5), 720–738.

Cheng, C., et al., 2013. Rethinking stormwater management in a changing world: effects of detention for flooding hazard mitigation under climate change scenarios in the Charles River watershed. Landsc. Res. Rec. 1 (n. 1), 214–228.

Cheng, C., 2016. Spatial climate justice and green infrastructure assessment: a case study for the Huron River watershed, Michigan, USA. GI Forum 1, 176–190.

Cheng, C., et al., 2017. Assessing climate change-induced flooding mitigation for adaptation in Boston's Charles River watershed, USA. Landsc. Urban Plan. 167, 25–36.

Culbertson, A.M., et al., 2016. Anticipated impacts of climate change on 21st century Maumee River discharge and nutrient loads. J. Great Lake. Res. 42 (6), 1332–1342.
Deb, D., Butcher, J., Srinivasan, R., Mar 2015. Projected hydrologic changes under Mid-21st century climatic conditions in a sub-arctic watershed. Water Resour. Manag. ISSN: 0920-4741 29 (n. 5), 1467–1487.
Dunne, T., Leopold, L.B., 1978. Water in Environmental Planning. W. H. Freeman, ISBN 9780716700791.
El-Khoury, A., et al., Mar 15 2015. Combined impacts of future climate and land use changes on discharge, nitrogen and phosphorus loads for a Canadian river basin. J. Environ. Manag. ISSN: 0301-4797 151, 76–86.
Fan, M., Shibata, H., Mar 2015. Simulation of watershed hydrology and stream water quality under land use and climate change scenarios in Teshio River watershed, northern Japan. Ecol. Indic. ISSN: 1470-160X 50, 79–89.
Garner, G., et al., Dec 2015. Hydroclimatology of extreme river flows. Freshw. Biol. ISSN: 0046-5070 60 (n. 12), 2461–2476.
Goldstein, J.C., Tarhule, A., Feb 28 2015. Evaluating the impacts of climate change and switchgrass production on a semiarid basin. Hydrol. Process. ISSN: 0885-6087 29 (n. 5), 724–738.
Goodall, J.L., et al., 2013. Coupling climate and hydrological models: Interoperability through Web Services. Environ. Model. Software 46, 250–259.
Hirabayashi, Y., et al., Sep 2013. Global flood risk under climate change. Nat. Clim. Change. ISSN: 1758-678X 3 (n. 9), 816–821.
Kharel, G., Kirilenko, A., Oct 2015. Considering climate change in the estimation of long-term flood risks of devils lake in North Dakota. J. Am. Water Resour. Assoc. ISSN: 1093-474X 51 (n. 5), 1221–1234.
Liu, T., et al., 2013. Modeling the production of multiple ecosystem services from agricultural and forest landscapes in Rhode Island. Agric. Resour. Econ. Rev. 42 (n. 1), 251–274.
Logsdon, R.A., Chaubey, I., May 2013. A quantitative approach to evaluating ecosystem services. Ecol. Model. ISSN: 0304-3800 257, 57–65.
MDNR, 2002. Huron River Plan. RESOURCES, M. D. O. N..
Milly, P.C.D., et al., Jan 2002. Increasing risk of great floods in a changing climate. Nature. ISSN: 0028-0836 415 (n. 6871), 514–517.
Moody, P., Brown, C., Jun 2013. Robustness indicators for evaluation under climate change: application to the upper Great Lakes. Water Resour. Res. ISSN: 0043-1397 49 (n. 6), 3576–3588.
Moriasi, D.N., et al., May-Jun 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. Asabe. ISSN: 0001-2351 50 (n. 3), 885–900.
Moscrip, A.L., Montgomery, D.R., Dec 1997. Urbanization, flood frequency, and salmon abundance in Puget Lowland streams. J. Am. Water Resour. Assoc. ISSN: 0043-1370 33 (n. 6), 1289–1297.
Naess, L.O., et al., Jul 2005. Institutional adaptation to climate change: flood responses at the municipal level in Norway. Glob. Environ. Change-Human Policy Dimensions. ISSN: 0959-3780 15 (n. 2), 125–138.
Paul, M.J., Meyer, J.L., 2001. Streams in the urban landscape. Annu. Rev. Ecol. Syst. ISSN: 0066-4162 32, 333–365.
Pianosi, F., et al., 2016. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environ. Model. Software 79, 214–232.
Postel, S., Richter, B., 2012. Rivers for Life: Managing Water for People and Nature. Island Press.
Prudhomme, C., et al., Mar 2014. Hydrological droughts in the 21st century, hotspots and uncertainties from a global multimodel ensemble experiment. Proc. Natl. Acad. Sci. U. S. A. ISSN: 0027-8424 111 (n. 9), 3262–3267.
Prudhomme, C., Jakob, D., Svensson, C., Jun 2003. Uncertainty and climate change impact on the flood regime of small UK catchments. J. Hydrology. ISSN: 0022-1694 277 (n. 1–2), 1–23.
Pryor, S.C., Scavia, D., Downer, C., Gaden, M., Iverson, L., Nordstrom, R., Patz, J., Robertson, G.P., 2014. Ch. 18: Midwest, climate change impacts in the United States: The third national climate assessment. In: Melillo, J.M., Richmond, Terese (T.C.), Yohe, G.W. (Eds.), U.S. Global Change Research Program, pp. 418–440. http://dx.doi.org/10.7930/J0J1012N.
Richter, B.D., et al., Aug 1996. A method for assessing hydrologic alteration within ecosystems. Conserv. Biol. ISSN: 0888-8892 10 (n. 4), 1163–1174. Disponível em: < <Go to ISI>://WOS: A1996VC10300033 >.
Salathe, E.P., et al., Oct 2014. Estimates of twenty-first-century flood risk in the Pacific Northwest based on regional climate model simulations. J. Hydrometeorol. ISSN: 1525-755X 15 (n. 5), 1881–1899.
Steinschneider, S., Brown, C., Nov 2013. A semiparametric multivariate, multisite weather generator with low-frequency variability for use in climate risk assessments. Water Resour. Res. ISSN: 0043-1397 49 (n. 11), 7205–7220.
Steinschneider, S., Wi, S., Brown, C., Jun 2015. The integrated effects of climate and hydrologic uncertainty on future flood risk assessments. Hydrol. Process. ISSN: 0885-6087 29 (n. 12), 2823–2839.
USGS, 2003. Base-flow index grid for the conterminous United States. http://water.usgs.gov/GIS/metadata/usgswrd/XML/bfi48grd.xml.
Walters, K.M., Babbar-sebens, M., Apr 2016. Using climate change scenarios to evaluate future effectiveness of potential wetlands in mitigating high flows in a Midwestern US watershed. Ecol. Eng. ISSN: 0925-8574 89, 80–102.
White, M.D., Greer, K.A., Jan 2006. The effects of watershed urbanization on the stream hydrology and riparian vegetation of Los Penasquitos Creek, California. Landsc. Urban Plan. ISSN: 0169-2046 74 (n. 2), 125–138.
Wilby, R.L., Beven, K.J., Reynard, N.S., Jul 2008. Climate change and fluvial flood risk in the UK: more of the same? Hydrol. Process. ISSN: 0885-6087 22 (n. 14), 2511–2523.
Yang, Y.C.E., et al., Mar 2016. The future nexus of the Brahmaputra River Basin: climate, water, energy and food trajectories. Glob. Environ. Change-Human Policy Dimensions. ISSN: 0959-3780 37, 16–30.

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