Impact of Global Climate Change on Extreme Streamflow: A Case Study of the Great Miami River Watershed in Southwestern Ohio

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ABSTRACT

There is a widespread concern that climate change will lead to an increased frequency and intensity of extreme weather events in the 21st century. It is essential, from a watershed management point of view to understand how these alterations in the hydrologic regime would affect the existing water resources. This research, therefore, provides an overview of the hydrologic impacts on the Great Miami River Watershed in Ohio, USA due to projected climatic changes on both low flows and high flows. An extensively used hydrological model, the Soil and Water Assessment Tool (SWAT) was to evaluate the hydrological impacts of climate change. The multi-site model calibration and validation were performed using the SUFI-2 algorithm within SWAT-CUP. The model was calibrated (2005 - 2014) and validated (1995 - 2004) for monthly stream flows at the outlet resulting in Nash - Sutcliffe Coefficients of 0.86 and 0.83, respectively. An ensemble of ten downscaled and bias-corrected climate models from Fifth Phase Coupled Model Intercomparison Project (CMIP5) under two Representative Concentration Pathways (RCPs) 4.5 and 8.5 were used to generate a probable set of climate data (precipitation and temperature). The climate data were then fed into the SWAT model and hydrological changes in the stream in terms of daily discharge were produced for three time-frames: (2016 - 2043) as 2035s, (2044 - 2071) as 2055s, and (2072 - 99) as 2085s and compared against the baseline period (1988 - 2015).

The findings from this research showed that low flows using both hydrological and biological indices would increase more than 100% in 2035s but eventually decrease slightly in the later part of the century (2085s). However, the Max Planck Institute Earth System Model (MPI-ESM-LR) used in this study predicted that the biological indices under RCP 8.5 would increase slightly at the beginning but decrease considerably in the middle and later part of the century. Analysis showed that the variability of the average 7-day low flows in each year would increase considerably for both emission scenarios. Furthermore, 75th percentile exceedance frequency of monthly low flows was found higher in September, October, and November during the study period.

As for high flow analysis, the hydrological index for high flows (7Q10) from an ensemble of 10 climate models predicted to decrease consistently in future. When the results from the two RCPs are compared, high flows would decrease maximum by 22% in 2055s under RCP 8.5 and 21% in 2085s under RCP 4.5. However, the MIROC5 model in RCP 4.5 showed 1.2% increase in 7Q10 high flows during 2035s. The frequency of the 75th percentile non-exceedance flows was also projected to increase in the future. Under the RCP 4.5, the frequency becomes higher in 2055s whereas under the RCP 8.5 most frequent 75th percentile flow would occur in 2085s. Meanwhile, on a monthly scale, the peak would increase more on every month except January and December than that of historical records. The variability of peak discharge was also expected to increase in every other month in both scenarios. The peak would increase considerably especially in August, September, and October when compared to historical months, indicating relatively wetter months in the future years. Finally, this study has demonstrated the effects of changing climates projected by the climate models on extreme flow condition in the large agricultural watershed. The next step of the research will focus on further bias correction on simulated climate data and analysis for future.

Keywords: Climate Change, Greenhouse Gas Emission Scenarios, CMIP5 Climate Models, Low flows, High flows, SWAT, and Great Miami River Watershed

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LIST OF ABBREVIATIONS

AOGCM	Atmosphere-Ocean Global Circulation Models
BCCA	Bias Corrected Constructed Analogs
CMIP	Coupled Model Intercomparison Project
DEM	Digital Elevation Model
GCM	Global Circulation Model
GHG	Greenhouse Gas
HRU	Hydrologic Response Unit
IPCC	Intergovernmental Panel on Climate Change
NCDC	National Climatic Data Center
NLCD	National Land Cover Dataset
NPDES	National Pollutant Discharge Elimination System
NSE	Nash-Sutcliffe's Efficiency
OEPA	Ohio Environmental Protection Agency
PBIAS	Percentage Bias
R^2	Coefficient of determination
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
RSR	RMSE Standard Deviation Ratio
STATSGO	State Soil Geographic
SSURGO	Soil Survey Geographic
SUFI	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Procedures
USACE	United States Army Corps of Engineers
USDA	United States Department of Agriculture
USGS	United States Geological Survey
WCRP	World Climate Research Program

Chapter 1. Introduction

Over the past few decades, climate change has emerged as one of the leading global concerns for sustainable management of natural resources. The Earth's average surface temperatures are expected to rise continuously that could bring major alteration in hydrologic as well as energy cycles (IPCC, 2001). More than 97 percent of climate scientists agree that anthropogenic greenhouse gas emissions contribute to climate change and global warming (Oreskes, 2004). However, there are still plenty of uncertainties regarding the identification of the causes of climate change and especially about its future implications (McCarthy et al., 2001). Based on the research conducted by the climate scientists involved in the Intergovernmental Panel on Climate Change (IPCC), the key impacts of climate change on the hydrologic cycle include changing precipitation patterns, increased the occurrence of extreme weather events, frequent flooding, intense droughts, and desertification (IPCC, 2007).

Past studies have suggested that streams would exhibit higher flows during extreme storms events and smaller base flows during droughts caused by climate change. This is because warmer air can hold more water vapor and tends to accelerate water movement in the atmosphere leading to intensification of precipitation and causing increased surface runoff and soil saturation (Huntington, 2006). On the other hand, droughts could become more severe in regions that may realize an increase in precipitation. In a warmer climate, increased evaporation from soils and evapotranspiration from plants can potentially lead to rapid drying of existing soil layers and offset any additional rainfall from the surface (Sheffield et al., 2012).

Climate researchers around the world have attempted to illustrate the connection between extreme events and climate change with the help of Global Circulation Models (GCMs). These models are constructed based on the physical processes that involve atmosphere, ocean, and land surface in order to provide consistent estimates of climate change throughout the planet (Cubasch et al., 1990). Thousands of peer-reviewed papers have been published about model-based studies. However, due to lack of proper understanding of the exact processes within climate models, a number of uncertainties exist in estimating future atmospheric conditions (Refsgaard et al., 2007). In order to cope with such uncertainties, a new set of GCMs has been generated by the World Climate Research Program (WCRP), known as Coupled Model Inter-comparison Project phase five (CMIP5) (Taylor et al., 2012). The CMIP5 models include simulations of 20th century climate, and projection of 21st century climate under different greenhouse gas emission scenarios known as Representative Concentration Pathways (RCPs) (Moss et al., 2010).

In addition to climate models, hydrologic models are also important components for assessment of climate change effects on water resources. These hydrologic models are generally combined with climate models to simulate hydrologic processes. One of the widely accepted hydrological models for climate impact analysis is the Soil and Water Assessment Tool (SWAT). The SWAT model incorporates different climatic components such as precipitation, temperature, CO_2 concentration, and relative humidity.

The overall purpose of this study is to evaluate the impacts of climate change on extreme hydrologic regime using downscaled climate models under different greenhouse gas emission scenarios. Both the SWAT model and the CMIP5 climate models will be used to examine the effects of climate change on stream flows in the Great Miami River Watershed.

Scope and Objectives

An intensifying water cycle due to climate change can potentially alter the hydrological regime especially during extreme low and peak flow events. Hydrologists and engineers should, therefore, have a good understanding of stream flows within a watershed. Stream low flows could change the chemical, physical and biological processes within the watershed environment, which can degrade the water quality and cause considerable harm to aquatic life. Moreover, the National Pollutant Discharge Elimination System (NPDES) uses the low flows primarily estimated based on the hydrological and biological design flow conditions (7Q10, 1Q10, 4B3, and 4B1) using historical data.

Almost 40 percent of the streams in the Great Miami River Watershed are below the water quality standards even though many of the point sources discharged to a section of the rivers meets the water quality standards (MCD, 2017). The pollution problems in these streams are primarily nonpoint sources from upstream agricultural runoff.

Furthermore, intense precipitation would increase the rate of runoff, subsequently cause frequent floods and increase the risk of property losses to the affected areas (Pathak, 2016). In addition, streams monitoring during the high flows period is essential because of the high pollutant concentration from non-point sources that become more predominant during these periods.

The climate change, streamflow, and water quality in every watershed are interlinked. This study focuses on utilizing climate change models to simulate future flows for the 21st century to analyze flow patterns specifically during extreme flow events such as low and high flows. Although quantitative results from this study may be represented for this particular watershed only, the relevant knowledge about the watershed process and its response to different climate change models can be shared and compared with other watershed studies throughout the world.

The specific research objectives of this study are:

1. To assess the potential impact of climate change on low flows during the 21st century;
2. To assess the potential impact of climate change on high flows during the 21st century.

To accomplish these objectives, the following tasks were completed: 1) Delineate land catchment, stream segments, and reservoirs for the Great Miami River Watershed; 2) Prepare the necessary input data for SWAT simulation, such as meteorological data (precipitation and temperature), soil, land use, reservoir and point source data; 3) Simulate flow, calibrate and validate the model using United States Geological Survey (USGS) streamflow records; 4) Download the bias corrected and fine downscaled CMIP5 climate model; 5) Select top 10 models based on the correlation (R^2) with the observed precipitation in the watershed; 6) Develop future climate scenarios from selected models under two emission scenarios from 2016 to 2099; 7) Run the SWAT simulations for three allotted future period of 2035s (2016 - 2043), 2055s (2044 - 2071), and 2085s (2072 - 2099) to simulate flow based on downscaled climate scenarios; 8) Analyze future flows from each scenario in terms of low flows and high flows; and 9) Compare the simulated results with the historical data (1988 - 2015).

Thesis Structure

This thesis is divided into four chapters. Chapter 1 covers the background, scope, objectives, and overall thesis organization. Next two chapters are organized in journal paper format; therefore, readers may find some repetition in the content.

Chapter 2 documents the process involved during SWAT model development of the Great Miami River Watershed, which includes delineation, preparation of input data, calibration and validation of the model. In addition, generation of climate data from various general climate models, which represents the climate change in the watershed, is also discussed in this chapter. Different regulatory low flows criteria including hydrological and biological low flows statistics are estimated for future (2016 - 2099) and compared with the historically observed flow condition (1988 - 2015).

In Chapter 3, the SWAT model and climate data from different CMIP5 models developed in Chapter 2 are used to assess the potential impact of climate change on the high flows of the stream. This chapter simply discusses the possible change in high flow frequency and magnitude in the watershed. The study periods established for the low flows analysis are also used for the study of high flows and compared with same period of historical records.

Lastly, Chapter 4 summarizes the project accomplishment against the set objectives. This chapter also outlines some recommendation for future exploration.

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Chapter 2. Impact of Global Climate Change on Low Flows: A Case Study of the Great Miami River Watershed

Abstract

Several studies have indicated that climate change will profoundly affect hydrological processes at various temporal and spatial scales. Since climate has the capacity to change stream flow regimes, the regulatory low flows criteria for waste load allocation and point source permitting needs to be reviewed. This study aims to assess the alteration of water resource availability and low flows frequencies driven by the changing climates in different time periods of the 21st century. In addition, this analysis evaluates the adaptability of prevailing Global Circulation Models (GCMs) through flow regimes in channels. The study was conducted in the Great Miami River Watershed, Ohio by analyzing historical and future low flows using climate model outputs and the Soil and Water Assessment Tool (SWAT). The climate change scenarios from ten downscaled CMIP5 climate models, each one under two emission scenarios, "Representative Concentration Pathways", RCP 4.5 and RCP 8.5, were selected based on the correlation of daily precipitation with the observed records and model outputs. The streamflow for three future periods: 2016 - 2043, 2044 - 2071 and 2072 - 2099 (2035s, 2055s, and 2085s, respectively) were independently analyzed using each climate model and compared with a baseline condition (1988 - 2015). The output from ten climate models projected that low flows in the Great Miami River would increase significantly in the 21st century for both scenarios. The average 7-day low flows have a two-fold increase during 2035s but decrease slightly during 2085s. This trend was also consistent for both hydrological and biological low flows statistics 7Q10, 1Q10 and 4B3, 1B3, respectively. The large increase in low flows could be caused by the high variability in precipitation that is projected by GCMs and the inadequacy of climate models to represent appropriately the uncertainties associated with extreme weather events. However, the MPI-ESM-LR model predicted more reliable and analogous low flows conditions. The model suggested that biologically based low flows statistics, 4B3, and 1B3 would significantly decrease in the later part of the century (-41.6% and -36.1% respectively) under RCP 8.5 scenario, meanwhile the majority of the climate models showed a consistently increasing pattern.

Keywords: Climate Change, Low Flows, SWAT, Climate Models, Great Miami River Watershed

Introduction

Stream water quality is greatly affected by the low flows conditions in terms of dissolved oxygen (Haag et al., 2008), nutrient levels and the quality of aquatic habitat (Gibson et al., 2000). Moreover, stream low flows might have detrimental implications on water supply, power generation, navigation, and waste load allocation (Kundzewicz et al., 2008; Moser et al., 2008; Saunders III et al., 2004). Therefore, understanding low flows events and its effects on river ecosystem are essential for effective and sustainable water resource management (Burn et al., 2008). Many factors including soil infiltration, catchment hydraulics, topography, vegetation types, evapotranspiration rates, and local climatic conditions have an influence on low flows regimes (Smakhtin, 2001). Likewise, anthropogenic activities may alter the above-mentioned factors and potentially influence the low flows conditions in a stream.

The changing climate may lead to a more intensifying hydrological cycle (Lettenmaier et al., 2008) including an increase in inconsistent precipitation (Pathak et al., 2016), change in evaporation rates (Abtew et al., 2013) and early snowmelt. The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC, 2014) has estimated an increase in global temperature based on different emission scenarios over the 21st century. An increase in global temperature will enhance the rate of evapotranspiration and speed up the water cycle process. As a result, an uneven distribution of moisture in the atmosphere would take place leading to heavy precipitation in one region and an extreme drought in the other (Hayhoe et al., 2007).

Many research in the past have been conducted to comprehend streamflow variability due to climate change (Huang et al., 2013; Wilby et al., 2006; Vaze et al., 2010; Gain et al., 2013). Most research scientists around the world have utilized the Global Circulation Models (GCMs) for regional climate simulations and their impacts under different global warming scenarios (IPCC, 2014). A number of climatic models and versions have been developed based on a variety of numerical techniques and parameterizations. However, many systematic biases exist in some of the models when compared to actual climatic conditions (Takle et al., 1999; Rinke et al., 2006). These biases considerably vary from one model to another, which generally limits the strengths and weaknesses of simulation. Therefore, it is crucial to validate the applicability of the outputs of these climatic models for regional hydrological impact analysis (Mohammed et al., 2015).

A study by Middelkoop et al., 2001 on the Rhine River in Europe used two GCMs and predicted that low flows would occur more frequently and lasted longer during the summer period. In the same river, Shabalova et al., 2003 used a single climate model that revealed a tendency of increasing winter flows of 30% and decreasing summer flows of 30% in the 21st century. Gunawardhan et al., 2012, in a study in Italy based on 10 GCMs, estimated that the magnitude of 7-day 10 years low flows (7Q10) increased by 25% during the winter season in the later part of the 21st century.

Similarly, in the United States, a study by Small et al., 2006 in the Upper Mississippi and the Great Lakes river basins suggested that an increase in precipitation during the fall season resulted in an increase in the low flows. Albeit, some researchers have suggested that low flows would likely become more severe in the upcoming years due to climate change. Schoen et al., 2007, studied 160 watersheds of Mid-Atlantic region, showed a decrease in the 7Q10 low flows during the 21st century. Similarly, Eheart et al., 1999 estimated low flows such as 7Q10 and 1Q10 would decrease by 63% in a stream of the Midwestern United States due to 25% decrease in mean precipitation.

Most of the studies in the past were based on previously established GCMs, derived from phase three of the Coupled Model Inter-comparison Project (CMIP3). Advancing low flows science in a changing climate could not be successfully assessed without considering recent climate models and emission scenarios (Pal et al., 2015). Therefore, in this study, recently published CMIP5 model outputs and updated greenhouse gas emission scenarios are used to assess the impacts of climate change on stream low flows in the Great Miami River Watershed. In addition, an appropriate hydrologic model is necessary to link climate change outputs and water yields (daily discharge) in the watershed (Jothityangkoon et al., 2001). A widely used Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) were prepared and utilized for this analysis. The results from this study would be beneficial for policymakers and water resource engineers in developing sustainable management of water resources and strategies to combat the hydrological effects of climate change.

Theoretical Description

CMIP5 Model

The impacts of climate change on hydrologic regimes requires inputs from meteorological variables such as temperature and precipitation. These variables are mainly generated from climatic models, which have been known to provide acceptable results (Wilby et al., 2006) despite the existence of uncertainties (Jenkins et al., 2003). In recent years, the fifth phase of the Coupled Model Intercomparison Project (CMIP5) has incorporated new GCMs that have been extensively used for impact assessment due to climate change (Taylor et al., 2012). These newly disseminated models have more comprehensive greenhouse-gas emission scenarios and include finer spatial resolution of 1/8° latitude-longitude (12 km by 12 km) (Meehl et al., 2014).

Based on the greenhouse gas emissions including mitigation measures, the atmospheric concentration of air pollutants and land use, four Representative Concentration Pathways (RCPs), which are RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, were developed to assess their impacts on climate change (Moss et al., 2010). Among the four scenarios, RCP 2.6 is the most stringent mitigation scenario and targets to balance global warming below 2^0C from pre-industrial temperature (before 1750). On the other hand, RCP 8.5 scenario has very high greenhouse gas emissions resulting from limited additional efforts to constrain emissions, while RCP 4.5 and RCP 6.0 are two intermediate scenarios (IPCC, 2014).

SWAT Model

Soil and Water Assessment Tool (SWAT) is a widely accepted watershed model especially suited for forested and agricultural watersheds (Borah et al., 2003). SWAT is a process-based and semi-distributed hydrologic simulation model developed by United States Department of Agriculture (USDA) in the 1990s. The SWAT model uses the following water balance equation (1) to simulate the streamflow (Neitsch et al., 2011).

$$SW_t = SW_o + \sum_{i=1}^{t} \left(R_{day} - Q_{surf} - ET_i - W_{seepi} - Q_{gw}\right) \qquad (1)$$

SW_t and SW_o are soil water contents at the end and the start of the day (mm H_2O). R_{day} and Q_{surf} are rainfall amounts and surface runoff in mm H_2O. ET_i and W_{seepi} are the amounts of evapotranspiration and water in the vadose zone. Lastly, Q_{gw} represents the return flow (mm H_2O).

The SWAT model consists of two hydrological parts: i) land phase of the hydrological cycle, and ii) routing of runoff through the reaches. In land phase modeling, the river basin is partitioned into multiple sub-basins consisting of one or more Hydrological Response Units (HRUs), an area that consists similar amount of land cover, soil types, and slopes. Calculation of water balance is subsequently accomplished for additional HRUs within each sub-basin. In SWAT, different sub-basin outlets are connected together by stream networks and the routing phase determines the flow of water through those networks.

The SWAT model uses either the Curve Number (CN) method or the Green and Ampt infiltration method to calculate the total volume of runoff. While the CN method is lumped over time and used when precipitation data is provided in daily time steps (Johnson, 1998), the Green and Ampt method require input data at sub-daily time resolution.

Materials and Methods

Study Area

The Great Miami River watershed is one of the major sub-basins of the Ohio River, located in southwestern Ohio (Figure 2.1). The watershed covers an area approximately 3,870 square miles, which includes fifteen counties in Ohio and four counties in Indiana. The watershed lies between latitudes 39º8'43.67" N to 40º38'28.27" N and longitudes 83º33'0.67"W to 84º54'25.77"W. Similarly, the elevation of the watershed ranges from 459 ft to 1545 ft with an average of 981 ft above the mean sea level.

The distribution of land uses in this watershed includes agriculture (70%), residential, commercial and industrial (18%), forests (11%), and water bodies and wetlands (1%). Major wastewater treatment facilities and industries are located along the downstream reaches of the Great Miami River (Figure 2.1), thus compromising the water quality of the river during the dry periods.

The Great Miami River watershed has four major river sub-basins: Upper Great Miami, Mad River, Stillwater River, and the Lower Great Miami River. These sub-basins contain numerous tributaries that create a number of smaller sub-basins. Highly productive sand and gravel aquifers, known as buried valley aquifers, are the main features of the watershed. These aquifers are the primary sources of groundwater for adjoining river channels. As a result, some of the rivers within the watershed are able to sustain flow even during periods of prolonged drought.

SWAT Model Inputs

The data required for the SWAT modeling include a Digital Elevation Model (DEM), land use, soils, climate data, reservoir and point sources information. A DEM contains all the information about watershed terrain and streams networks. Several 30 m resolution DEMs were downloaded from the USGS National Elevation Dataset (NED) and mosaicked together to cover the entire watershed. This DEM was utilized to delineate the watershed and created 144 sub-basins. Similarly, the most recently available land use dataset was acquired from the National Land Cover Dataset (NLCD). The distribution of land use in the watershed is presented in Table 2.1. As for the soil data, the State Soil Geographic (STATSGO) and Soil Survey Geographic (SSURGO) are the two commonly used databases. Since the watershed is relatively large and the SSURGO data is extremely detailed, the STATSGO soil data was downloaded from the USDA Geospatial Data Gateway to avoid computational complexity. The threshold values for land use (5%), soils (15%) and slope (15%) were subsequently used to generate 2676 HRUs.

The climate data including precipitation, temperature, solar radiation, wind speed and relative humidity are essential for hydrological modeling. The SWAT model requires either a user defined weather data or simulated data from an inbuilt weather generator function (Winchell et al., 2013). In this study, historical weather dataset including precipitation, maximum and minimum temperature was downloaded from the National Climatic Data Center (NCDC). Nineteen precipitation stations and 10 temperature stations with continuous records for 36 years (1980 - 2015) were available within the watershed (Figure 2.1). However, the remaining climatic datasets were simulated using the weather generator function in the SWAT model. Since reservoirs and dams are used for water storage and flood control, 3 major reservoirs and 5 relatively large dams were incorporated into the model during the watershed delineation process (Figure 2.1). Useful information and data related to these reservoirs and dams were obtained from the Miami Conservancy District (MCD) and the United States Army Corps of Engineers (USACE) (Table 2.2). In addition, 28 major point sources including wastewater treatment facilities and industries (Table 2.3) that discharge effluents greater than 0.5 million gallons per day were downloaded from the Ohio Environmental Protection Agency (OEPA) and incorporated in the modeling process.

Model Setup, Calibration, and Validation

The SWAT Model was set up and run from 1988 to 2015 in daily time steps using a 3-year warm up period (1985 - 1987). The model was calibrated by using observed streamflow from 2005 to 2014 at 9 USGS gauge stations located within the watershed (Figure 2.1). Both manual and automatic parameter optimization procedures were utilized in model calibration. The automatic multi-site model calibration and sensitivity analysis were performed by the help of Swat Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour, 2007). In SWAT-CUP, a semi-automatic inverse modeling procedure algorithm known as Sequential Uncertainty Fitting version 2 (SUFI-2) was selected in order to find the most favorable model parameters. Manual calibration was also performed after automated calibration to fine-tune the calibration parameters. Twenty different parameters shown in Table 2.4 were chosen based on the similarity of past studies (Sharma et al., 2015). These model parameters were then independently validated using observed streamflow data from 1995 to 2004 in the respective locations.

Model Evaluation Criteria

The performance of the SWAT model was evaluated through certain statistical criteria such as Nash - Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), Percentage Bias (PBIAS), and Root Mean Square Error (RMSE) - observations standard deviation ratio (RSR). These indicators are mathematically represented by equations (2) through (5).

$$NSE = 1- \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs}-Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs}-Y^{mean}\right)^2}\right] \tag{2}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_{obs}^{mean}\right)\left(Y_i^{sim} - Y_{sim}^{mean}\right)}{\left[\sum_{i=1}^{n} \left(Y_i^{obs} - Y_{obs}^{mean}\right)^2 \sum_{i=1}^{n} \left(Y_i^{sim} - Y_{sim}^{mean}\right)^2\right]^{0.5}} \right)^2 \tag{3}$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{sim}\right) X\ 100}{\sum_{i=1}^{n} \left(Y_i^{obs}\right)} \right] \tag{4}$$

$$RSR = \left[\frac{\sqrt{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{sim}\right)^2}}{\sqrt{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_{obs}^{mean}\right)^2}} \right] \tag{5}$$

Here, “n” is the total number of observations and Y_i^{obs} and Y_i^{sim} are the ith values of observed and simulated flows. Similarly, Y_{obs}^{mean} and Y_{sim}^{mean} are the mean of observed and simulated flows, respectively.

NSE is commonly used to test the model performance whose values range from $-\infty$ to 1. A model is considered as good if its values range from 0.5 and 1 (Moriasi et al., 2007). The R^2 represents the relationship of simulated data with observed. The values of R^2 lies between 0 to 1 and value nearer to 1 shows a strong relationship. PBIAS indicates whether the simulated data is larger or smaller than the observed data. Simulated data having PBIAS value 0 is considered perfectly harmonizing with observed data while a positive or negative value represents the model underestimation or overestimation respectively. Similarly, RSR is defined as the ratio of RMSE and observations standard deviation. An RSR of 0 is considered a perfectly simulated model.

Future Climate Scenarios

Precipitation and temperatures dataset from ten climate models under two forced GHGs emission scenarios, RCP 4.5 and RCP 8.5, were downloaded from the freely available downscaled CMIP5 climate projection archive (Brekke et al., 2013). This archive contains high-resolution translations of climate projections based on global climate projections from Coupled Model Intercomparison Project for the contiguous United States. Climate projections available in the archive were developed by using the daily Bias Correction Constructed Analogs (BCCA) downscaled technique (Maurer et al., 2008).

In order to make a realistic comparison between simulated results versus observed data, projected precipitation and temperature dataset were segregated into three time intervals which were (2016 - 2043) as 2035s, (2044 - 2071) as 2055s, and (2072 - 2099) as 2085s having each of 28 years period.

Low Flows Statistics

Several methods have been developed to assess low flows regimes. The Frequency Duration Curve (FDC) is commonly used method to display the low flows (Smakhtin, 2001). Other specific low flows indices used in the United States are hydrologically based low flows such as 7-day 10 years low flows (7Q10) and 1-day 10 year low flows (1Q10), which are defined as the lowest flows occurring 7 consecutive days and 1 day respectively with a recurrence interval of 10 years. The recurrence interval of a particular consecutive day low flows events was calculated by fitting the annual low flows series to a log-Pearson Type III distribution (Riggs, 1972). Another method used to examine low flows is a biologically based design flow, 1B3 (1-day 3 years) for criterion maximum concentration and 4B3 (4-day 3 years) for criterion continuous concentration. Further literature on Criterion Maximum Concentration and Criterion Continuous Concentration can be found in Dilks et al., 1992 and Stephan et al., 1985. In this study, we used the DFLOW tool (US EPA, 2016) to calculate hydrologically and biologically based low flows indices by providing daily discharge simulated from ten climate models and observed records. Some other low flows indices used in this study were annual average 7-day low flows and 95th percentile low flow (Q_{95}), which are generally used to assess the stream waste-load assimilative capacity (US EPA, 2016).

Results and Discussions

SWAT Model Performance

The model performance was assessed based on daily and monthly flows at nine USGS gauge stations. Average monthly discharge from simulated vs observed flow during the calibration period (2005 - 2014) at the outlet gauge station (USGS 03274000) of the watershed are graphically plotted in Figure 2.2. Similarly, a comparison between simulated and observed flows during the validation period (1995 - 2004) is shown in Figure 2.3. Statistical indicators used to measure the performance of the model at different gauge stations in the watershed are given in Table 2.5. The performance indicators NSE, R^2, PBIAS, and RSR for monthly flows at the outlet were 0.86, 0.89, 2.86%, and 0.38 respectively during the calibration period. Similarly, the respective model indicators were 0.83, 0.86, 0.82%, and 0.41 at the outlet during the validation period.

The simulated peak flows during calibration (Figure 2.2) and validation (Figure 2.3) were slightly underestimated by the model perhaps due to the unequal distribution of meteorological stations within the watershed. For example, the amount of precipitation simulated from SWAT could be slightly different from the actual precipitation in the basin. Nevertheless, according to the values of performance indicators, the calibrated model good to use for hydrological analysis (Moriasi et al., 2007).

Climate Model Evaluation

Since it was very tedious and time-consuming to utilize all downscaled climate models from CMIP5 for hydrologic assessment, we considered only 10 climate models, listed in Table 2.6 based on the performance of their daily precipitation with the observed data in the past. A continuous precipitation dataset from 1980 to 2015 at Dayton International Airport station (00093815) was used to compare the projected precipitation from the 19 climate models with recorded precipitation for the same time period. Although the simulated daily precipitations performed poorly i.e. low R^2, the average monthly precipitation performed much better. The 10 climate models that performed well in terms of R^2 are presented in Table 2.7.

Furthermore, the comparison among projected daily precipitations from the 10 climate models from the referenced time period with the observed precipitation of historical period was also inspected through box plots as shown in Figure 2.4. In the observed period, the variability of daily precipitation in the first two quartiles range (first and second) was found very narrow, indicating less variability of rainfall during the observed period. However, future precipitation from model simulations was found a comparatively high variability for the first and second interquartile range in each time span in future. Moreover, the median of daily precipitation from each climate models for the three periods was projected to increase significantly than that of historical precipitation.

Climate Change Impact on Streamflow

Figure 2.5 shows the average annual streamflow in the Great Miami River from an ensemble of 10 climate models for RCP 4.5 and RCP 8.5. The annual flow was estimated to increase throughout the 21st century when compared with the historical data, which was true for both scenarios. However, the increasing trends were not consistent within each scenario. Under the RCP 4.5, average annual flow was estimated to increase by 21% in the first 28 years (2035s), followed by a 2% increase in 2055s and finally decrease by 4% in the late century (2085s). On the other hand, under RCP 8.5, the average annual flow was projected to increase by 21% in 2035s followed by a 2% decrease in 2055s and again increase of 1% in 2085s.

Similarly, outputs from 10 climate models were aggregated for monthly scale as shown in Figure 2.6 (a) and (b) for both scenarios respectively. The flow pattern for each month was found to almost similar for both emission scenarios. However, when compared to the historical data, monthly flows were predicted to increase in all months except for March and April, where average flow decreased by a maximum of 14% in 2085s. A large increase in monthly flow during 2035s could be seen in August (114%), September (126%), October (80%) and November (65%) under the RCP 4.5 and 113%, 121%, 75%, and 61%, respectively for the same months under the RCP 8.5. However, in almost every month in the later part of the century, flows are expected to decrease in RCP 4.5 scenario but not in RCP 8.5.

Impacts on Low Flows

The 7 consecutive days low flows simulated from an ensemble of 10 climate models under two emission scenarios are summarized in box plots (Figure 2.7). The future flows based on the average of 7-day low flows showed higher variability in each time span with larger interquartile ranges as compared to observed flow. Historical streamflow data suggested that the median of 7-day low flows was 641 cfs. While analyzing the output from climate models, 7-day low flows during the 21st century were predicted to increase more than 100% and became 1421 cfs in 2035s. The box plots show that the median value of 7-day low flows in future would be the highest in 2055s for the both RCPs. Similarly, box plots in Figure 2.8 show the 7-day low flows from 10 individual climate models under both emission scenarios to illustrate the variation in low flows predictions from each model. Every single model showed a large and sudden increase in the 7-day low flows in the earlier part of the century, with a high degree of variability as compared to the historical data. However, the trend and the degree of variability was not consistent in all models.

Furthermore, Figure 2.9 shows the flow duration curve of the average 7-day low flows from an ensemble of 10 climate models with the observed low flows data at the outlet of the watershed. From the flow duration curve, 95th percentile low flows (Q_{95}) which exceeded 95% of the time during 28 years of each study period were found to increase by two folds in future simulation period under both emission scenarios.

Hydrological and Biological Based Low Flows

Hydrologically and biologically based low flows indices, (7Q10, 1Q10) and (4B3, 1B3) respectively are important indices for the water quality analysis. Figure 2.10 shows the

7Q10 from 10 different models and their average of each model under RCP 4.5 and RCP 8.5. In 2035s, 7Q10 under RCP 4.5 was projected to increase by 107%. In the later period (2055s), it would again increase by 6% and decrease by 9% in 2085s. Similarly, for RCP 8.5, 7Q10 was be expected to increase by 112% in 2035s and decrease in 2055s and 2085s (5% and 4% respectively). A similar trend was exhibited by 1Q10 shown in Figure 2.11. Even though simulated 7Q10 and 1Q10 values decreased in the late century, the low flows values were still significantly higher (almost double) when compared to the baseline condition.

Biologically based design flows; 4B3 and 1B3 were also calculated and presented in Figure 2.12 and Figure 2.13, respectively. The 4B3 and 1B3 from an ensemble of 10 models with forced scenario RCP 4.5 and RCP 8.5 followed the same trend as 7Q10 and 1Q10. In 2035s under RCP 4.5, 4B3 was expected to increase by 127% (736 cfs) as compared to historical 4B3 (324 cfs). This trend continued to increase slightly (by 1%) until 2055s and eventually decreased (by 4.24%) in 2085s. Under RCP 8.5, 4B3 values increased in 2035 (134%) and started to decrease in 2055s and 2085s (8.27% and 37.8% respectively).

After analyzing the individual model projections, we could see among 10 different models, MPI-ESM-LR showed relatively less difference in low flows measured in terms of all indices (7Q10, 1Q10, 4B3, and 1B3) when compared with historical records. In fact, simulated low flows using climate data from other models were higher when compared to the historically observed streamflow records than streamflow simulated using MPI-ESM-LR climate output. It is interesting to note that the performance of this climate model was relatively better than that of other climate models. During 2035s, simulated 4B3 flow from the MPI-ESM-LR model under RCP 8.5 was predicted to be 418 cfs in 2035s, which was

29% greater than the baseline. In 2055s, its value increased again by 49% (623 cfs), but in the late century (2085s) 4B3 surprisingly decreased to 189 cfs, which is 42% lower than the baseline condition (324 cfs). A similar trend was predicted in the case of 1B3 as well where MPI-ESM-LR showed a 36% reduction in 2085s under RCP 8.5.

Surprisingly, the every simulated low flow for the periods 2035s, 2055s and 2085s almost doubled suddenly when compared to the historical data. Such large changes in flows, therefore, can only be justified by the different pattern and variability of temperature and precipitation projected from climate models (Small et al., 2011; Douglas et al., 2000). The low flows indicators including 7-day low flows are directly linked with daily streamflow. If the intensity of daily precipitation increases, an excessive amount of surface runoff will be produced as a result daily streamflow in the channel increases.

In this study, the SWAT model was setup for an equal number of 28 years and used 3 years of warm up period in each simulation in order to avoid any discrepancy from the model. Additionally, the model performance indicators suggested that the model was able to follow the trend of the observed streamflow with reasonable accuracy in the watershed. Therefore, after careful inspection of precipitation data in each study period, increased interquartile range and median values of daily projected precipitation data along with high variability as shown in Figure 2.4 could be the result of uncorrected biases present in the downscaled CMIP5 climate models that might be responsible for the increased low flows condition in the watershed.

Conclusion

There is no doubt that climate change has potential to change the hydrologic cycle and affect water resources. Therefore, this study was aimed at investigating the impacts of climate change, especially on low flows regime. In this regard, we prepared a hydrological model to generate daily streamflow from the Great Miami River Watershed with the help of the SWAT tool. Projected climate change from 10 recently published CMIP5 climate models under two scenarios RCP 4.5 and RCP 8.5 were deployed in the SWAT model to estimate future low flows in the watershed.

Low flows analysis was conducted in the watershed outlet, where a maximum number of point source discharging facilities were located. The results indicated that low flows in the Great Miami River in the 21st century would likely increase by more than 100%. In addition, the pattern of future monthly flows depicted the likelihood of increasing flows during the months of August, September, October, and November. Furthermore, the average 7-day low flows in the beginning of 21st century would likely to increase two-fold compared to the observed data.

The assessment of hydrological and biological low flows indices reinforced the results of the 7-day low flows and predicted an increase in future under both emission scenarios. The reason for such increases in low flows could be from increased precipitation intensity projected by the climate models. All models predicted that the trend of low flows would increase during 2035s and may remain constant or decline slightly based on the emission scenarios in the middle of the century. Both hydrologically and biologically based low flows were expected to increase in the first half of the century but decrease in the late century.

Interestingly, the predicted low flows from all climate models were significantly higher compared to the historical data. This indicates that the BCCA downscaling of CMIP5 models in terms of precipitation in the watershed still need to be reviewed during the study of extreme flows at the watershed. However, the MPI-ESM-LR model, which showed superior correlation with observed precipitation, showed a convincing projection of future low flows. Thus, besides MPI-ESM-LR, other CMIP5 models do not seem to be adequately representing the local behavior to reproduce the daily distribution of climate variables.

Outwardly, assimilating capacity of the stream seems to be increasing due to increase in low flows although there are other factors such as temperature, available dissolved oxygen, and characteristics of waste load and microorganisms that could affect the assimilative power of the stream. Besides, the assessment of low flows based on the MPI-ESM-LR model showed a decrease in the biological low flows under the RCP 8.5 in the later part of the century. These indices must be satisfied while developing the necessary modification in the permit limits.

Even though the CMIP5 data products are widely used for impact analysis of regional climate change, the uncertainty associated with future climate predictions are inevitable especially extreme flow events. Moreover, all climate models could have a lot of biases, using such datasets to develop water resource management, policy-making and formulation of rules and regulations may not be appropriate if not properly rectified. Therefore, further analyses are necessary to understand the hydrological influences due to climate changes.

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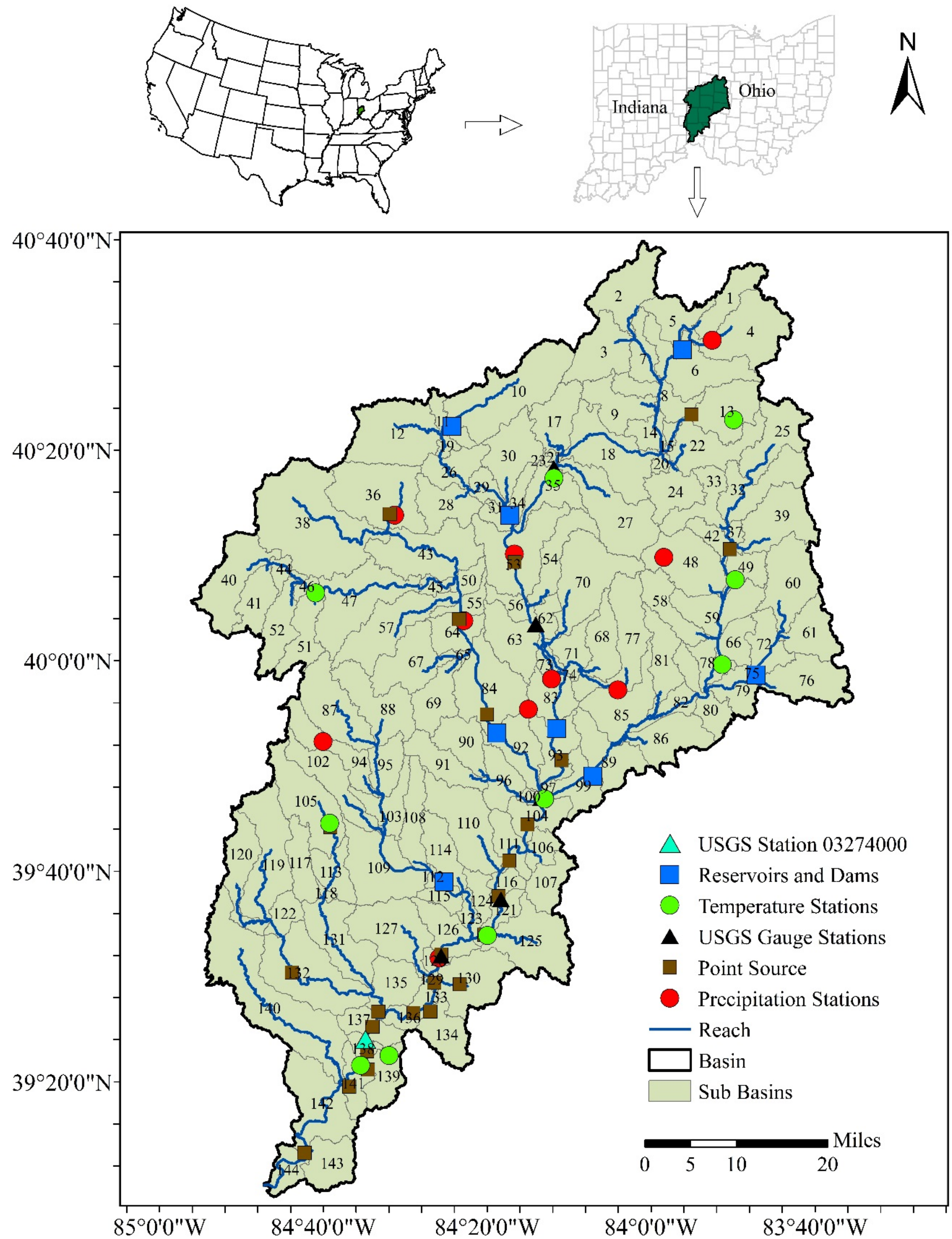


Figure 2.1 Study area of the Great Miami River watershed consisting sub-basins, gauge stations, climate stations, location of point sources and reservoirs

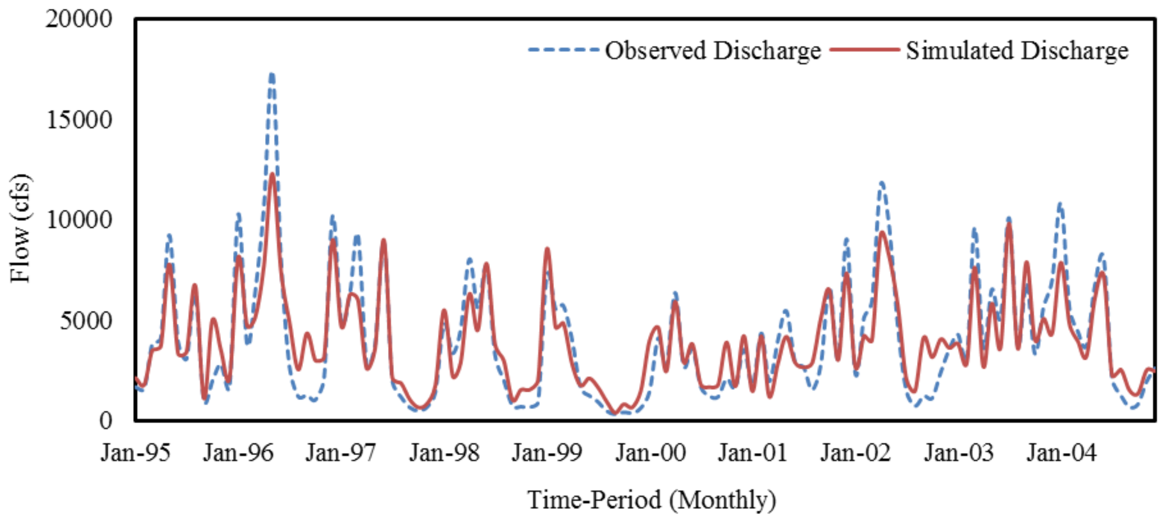


Figure 2.2 Streamflow calibration at the watershed outlet (USGS Gauge 03274000) from January 2005 to December 2014

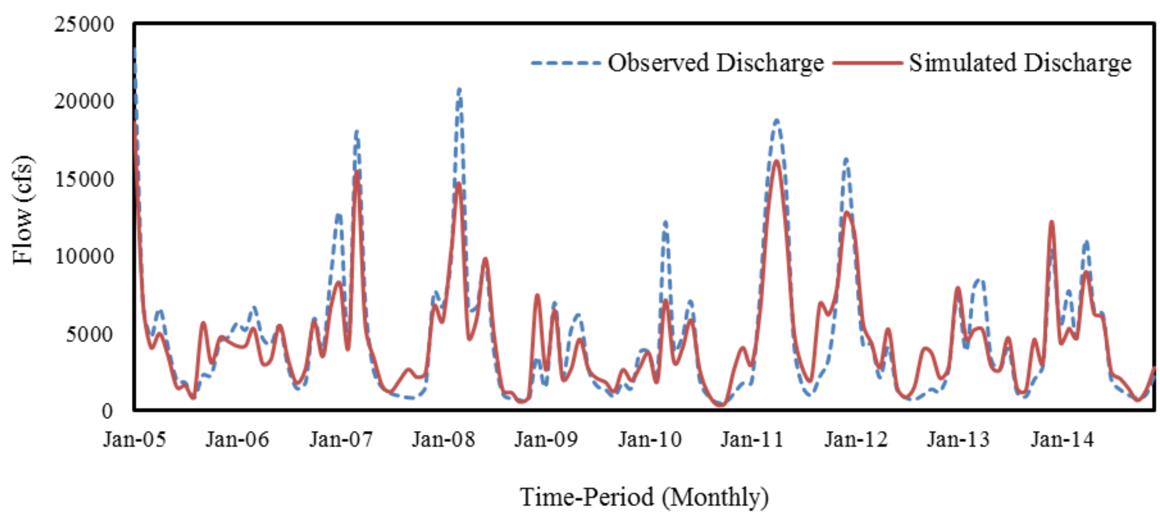


Figure 2.3 Streamflow validation at the watershed outlet (USGS Gauge 03274000) from January 1995 to December 2004

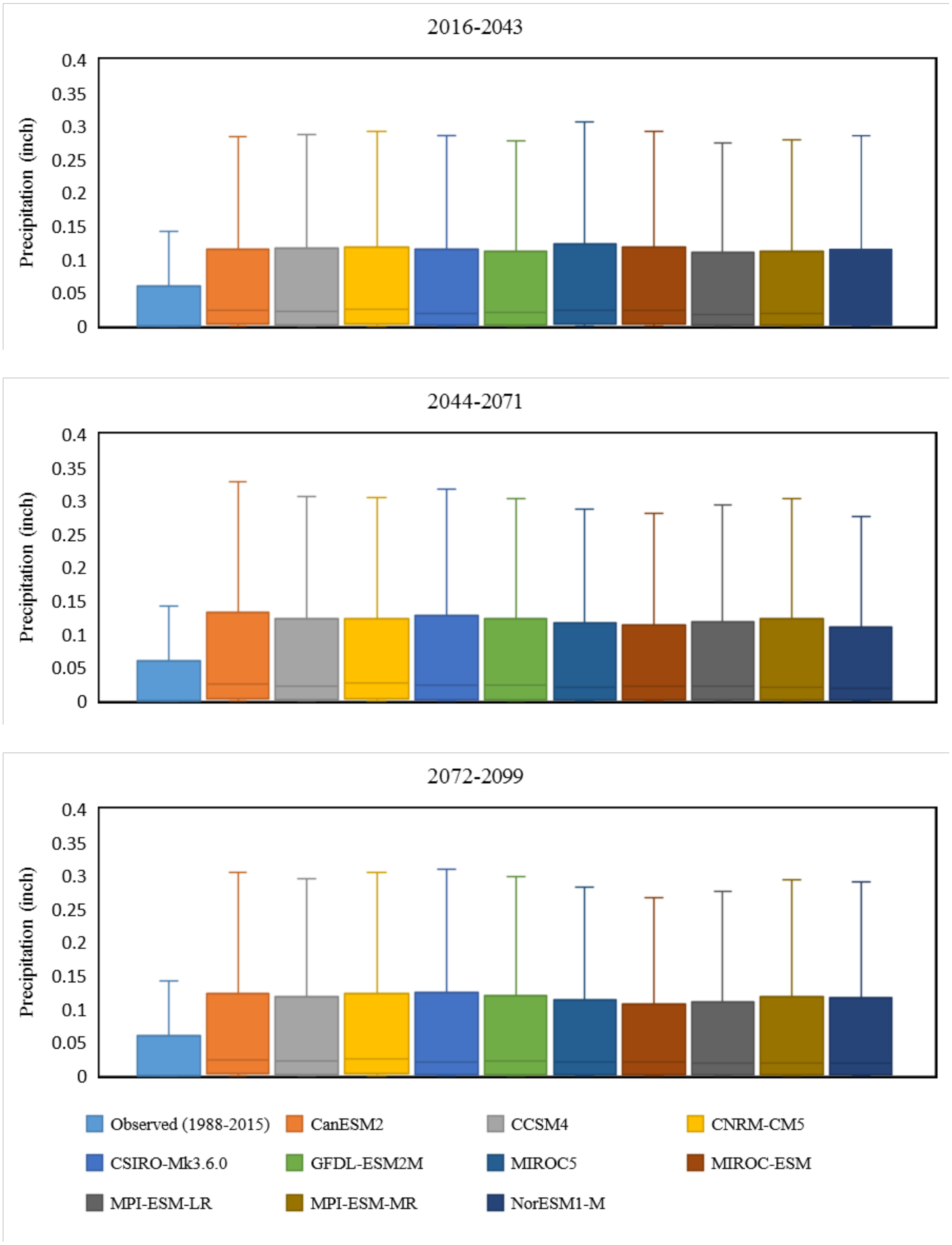


Figure 2.4 Comparison of precipitation data from 10 climate models at three time spans (2016-2043, 2044-2071, and 2072-2099) with observed precipitation (1988-2015) at station 0093815 under RCP 4.5

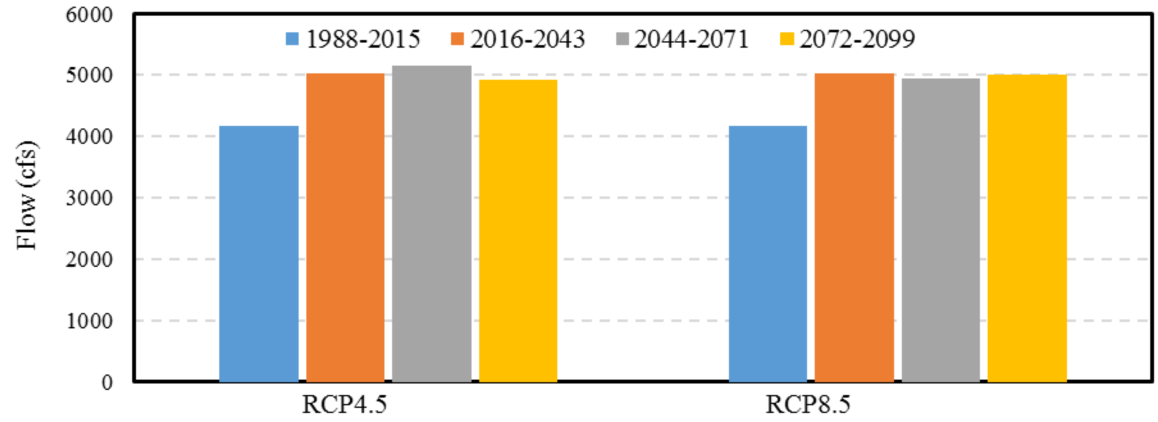


Figure 2.5 Average annual flow from ensemble of 10 models under RCP 4.5 and RCP 8.5

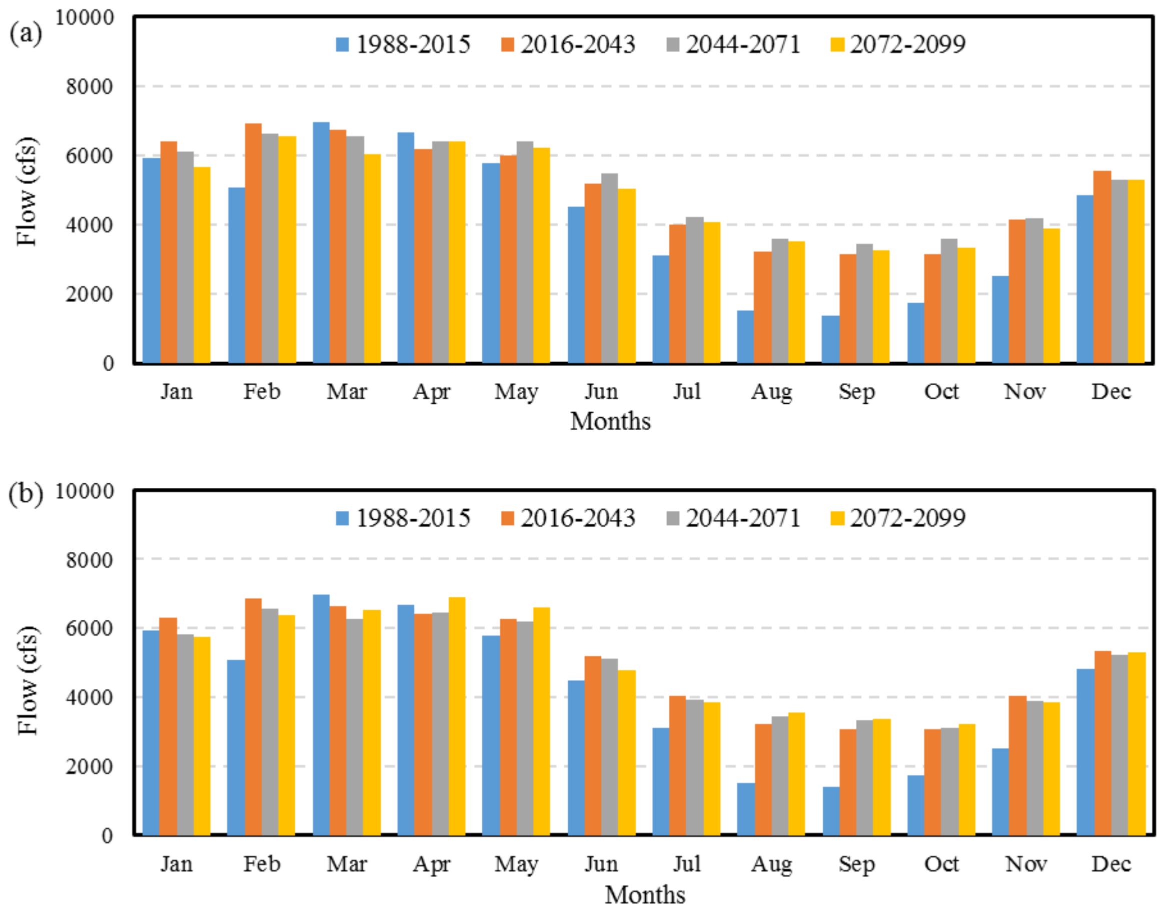


Figure 2.6 Average monthly flow from ensemble of 10 climate models under RCP 4.5 (a) and RCP 8.5 (b)

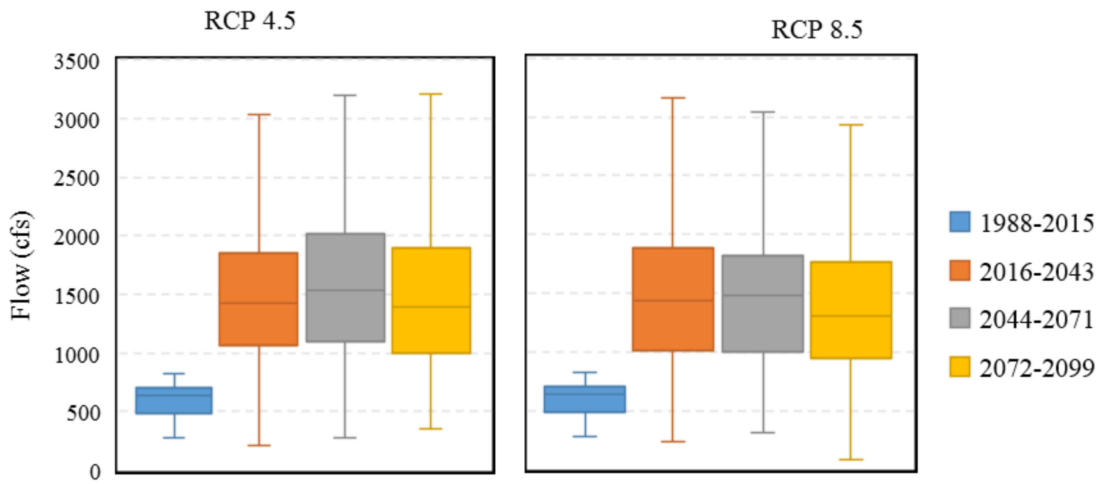
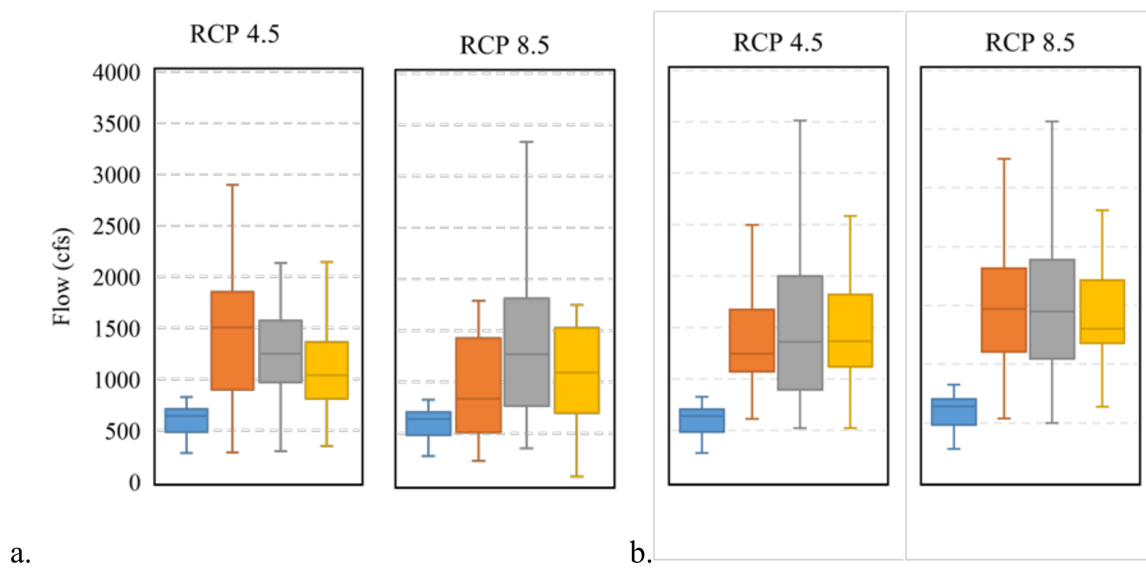
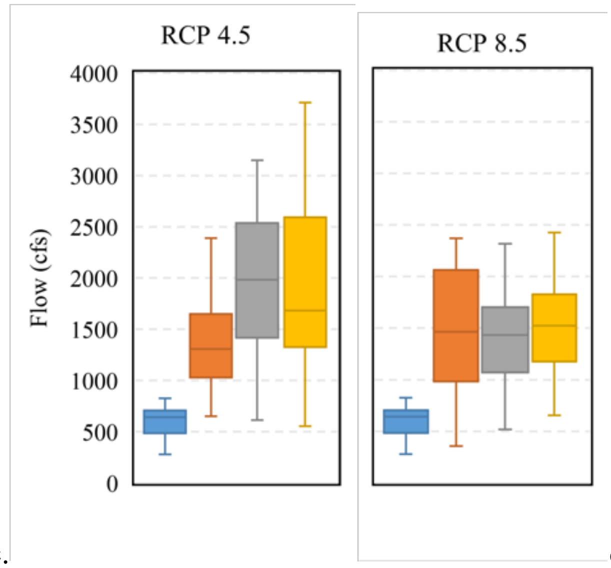
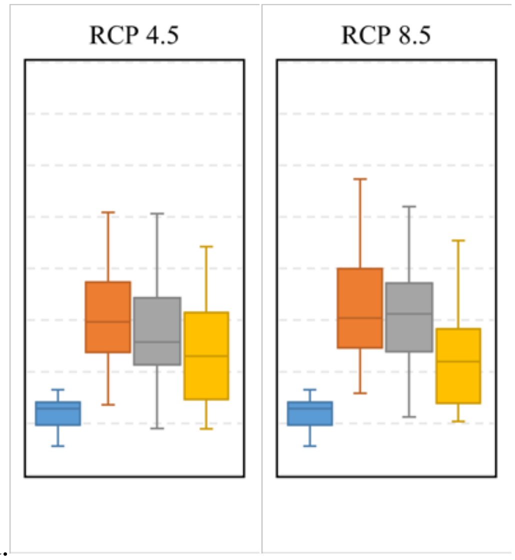


Figure 2.7 Box plots annual 7-day low flows from ensemble of 10 climate models

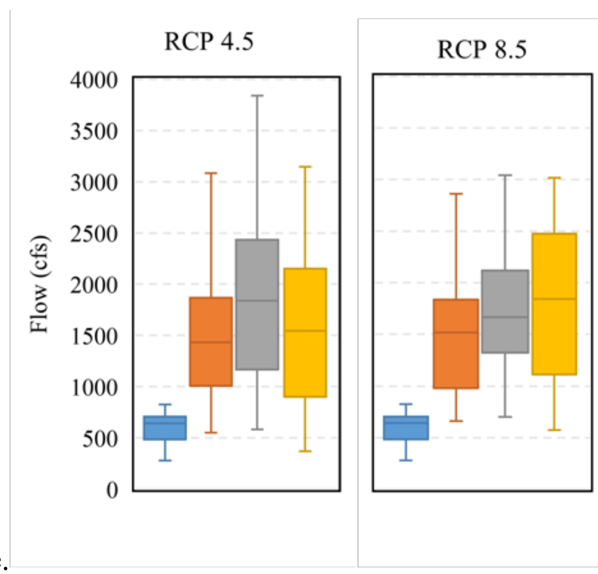



RCP 4.5
RCP 8.5
Flow (cfs)
4000
3500
3000
2500
2000
1500
1000
500
0

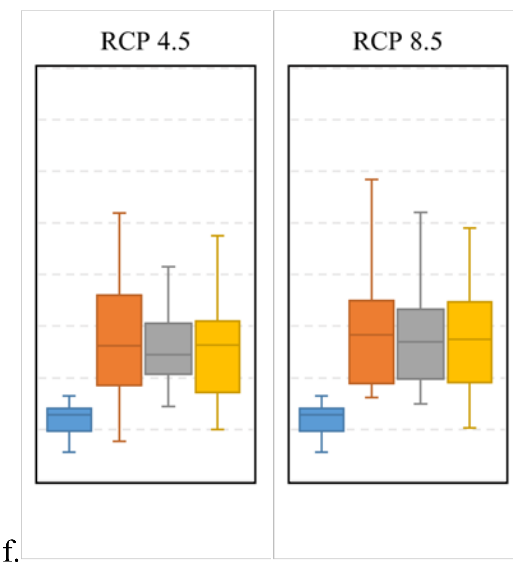
c.


RCP 4.5
RCP 8.5

d.


RCP 4.5
RCP 8.5
Flow (cfs)
4000
3500
3000
2500
2000
1500
1000
500
0

e.


RCP 4.5
RCP 8.5

f.

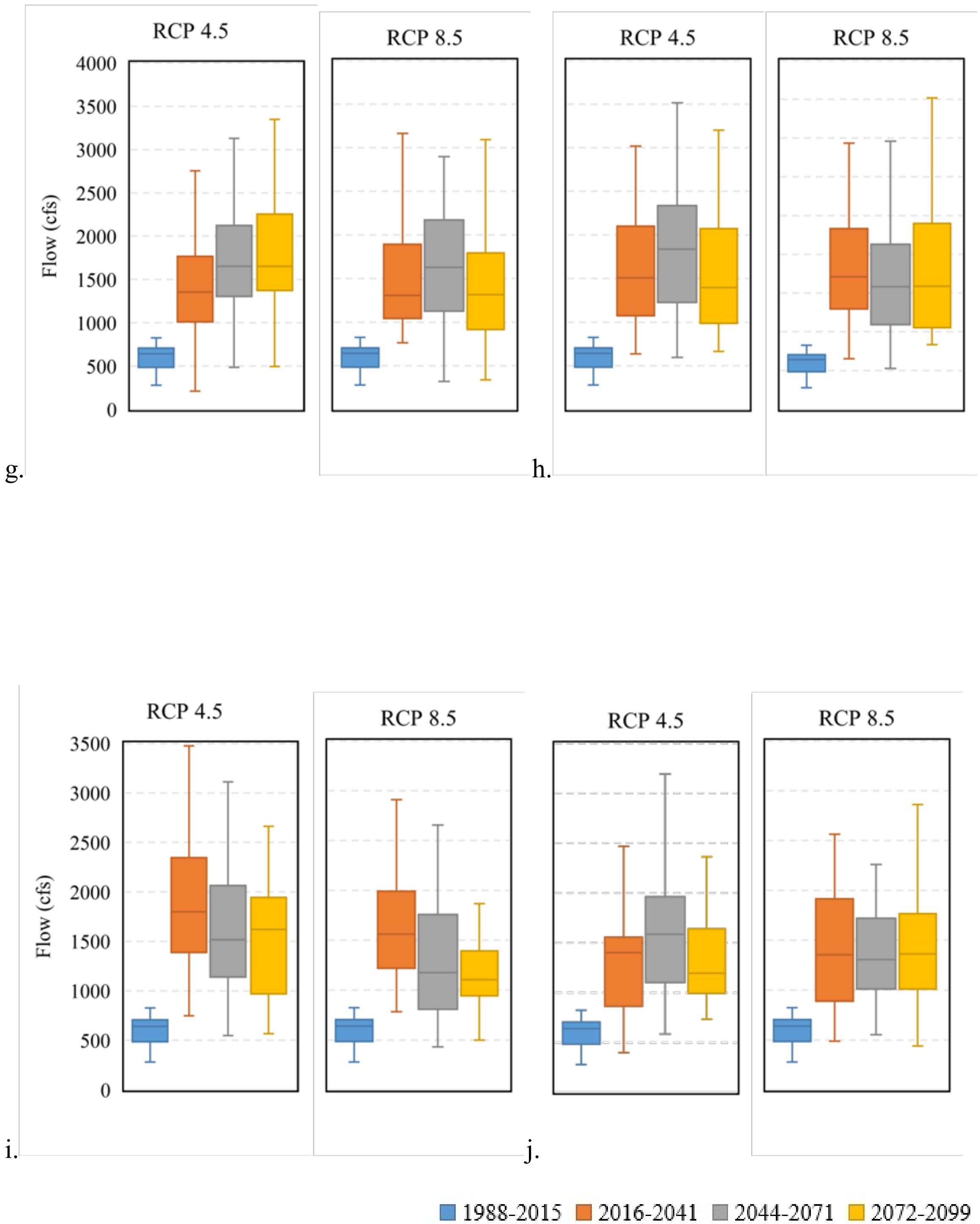


Figure 2.8 Box and Whisker plots of annual 7-day low flows for 10 different climate models under RCP 4.5 and RCP 8.5 scenarios (a) MPI-ESM-LR (b) MPI-ESM-MR (c) CSIRO-Mk3.6.0 (d) MIROC5 (e) CanESM2 (f) NorESM1-M (g) GFDL-ESM2M (h) CNRM-CM5 (i) MIROC-ESM (j) CCSM4

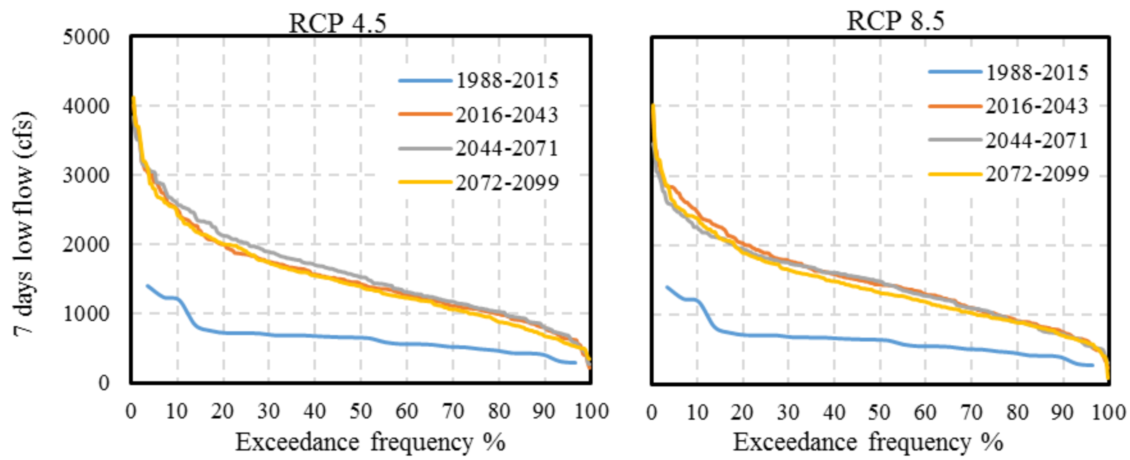


Figure 2.9 Flow duration curves for 7-day low flows from ensemble of 10 climate models and historical data

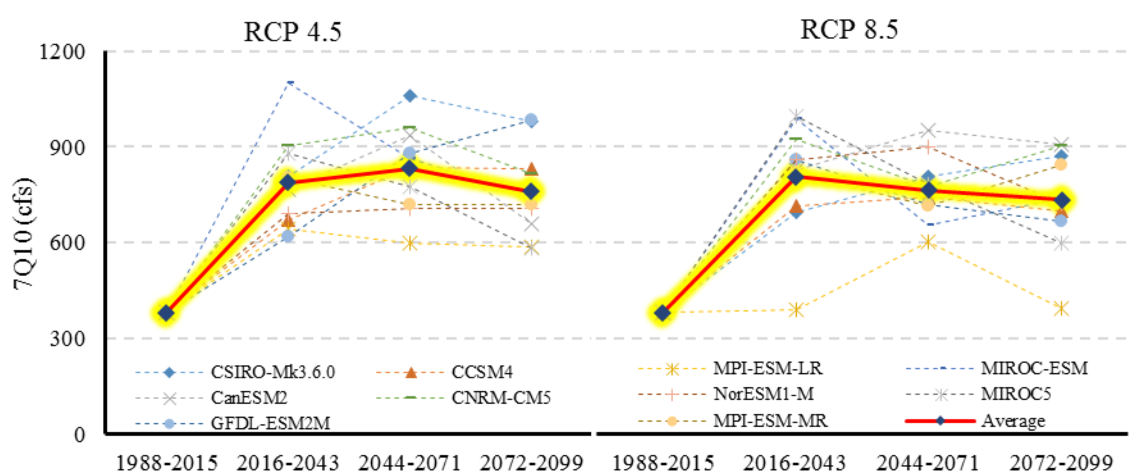


Figure 2.10 7Q10 low flows from 10 climate models

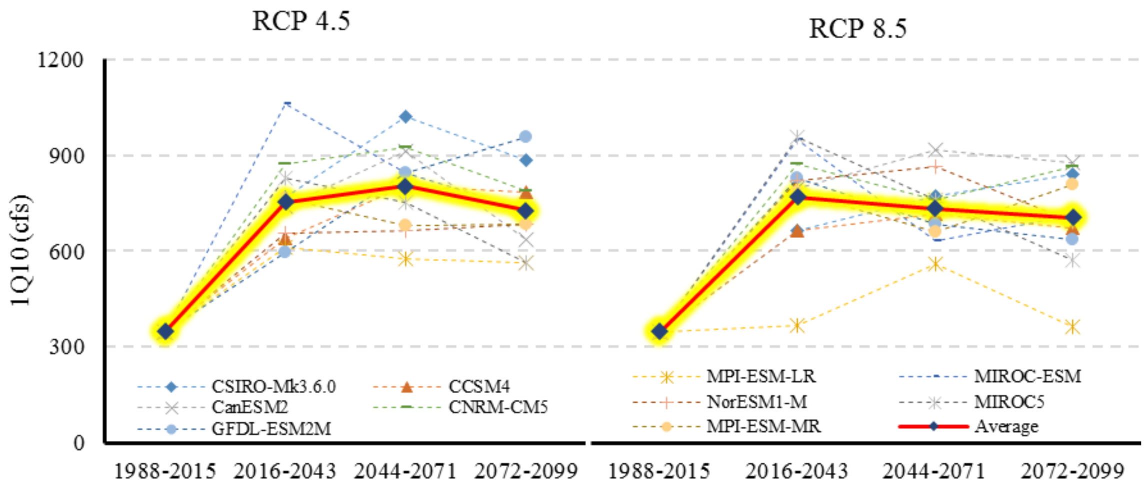


Figure 2.11 1Q10 low flows from 10 climate models

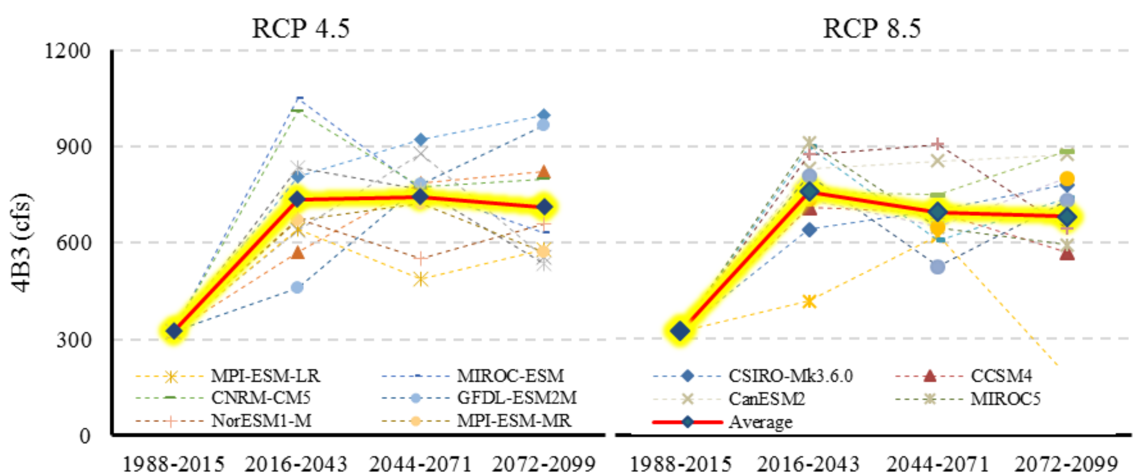


Figure 2.12 4B3 flows from 10 climate models

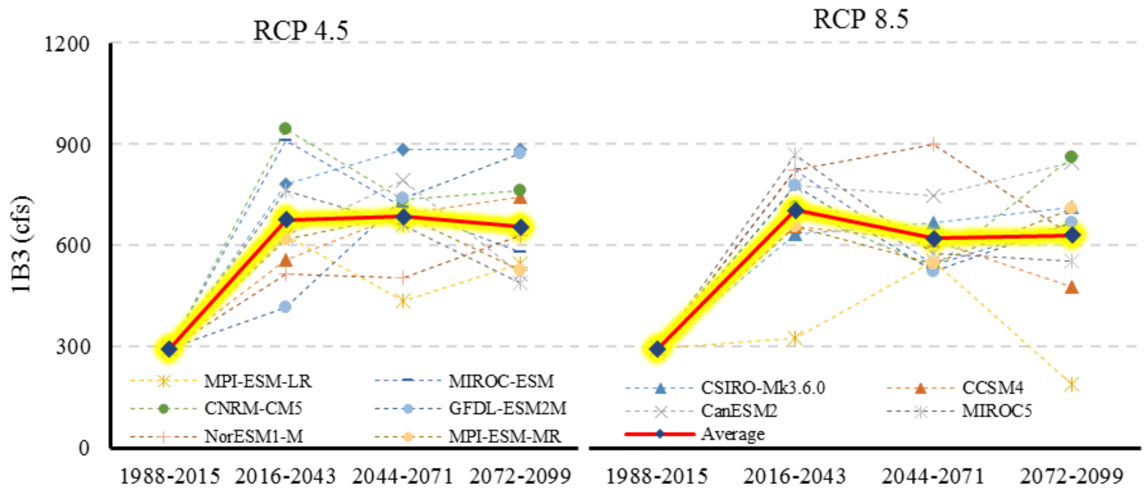


Figure 2.13 1B3 flows from 10 climate models

Table 2.1 Percentage of land cover in the GMR watershed

Land Cover	Percentage (%)
Open Water	1.37
Developed, Open Space	6.04
Developed, Low Intensity	3.08
Developed, Medium Intensity	1.18
Developed, High Intensity	0.51
Barren Land	0.11
Deciduous Forest	21.87
Evergreen Forest	0.56
Mixed Forest	0.04
Shrub/Scrub	0.33
Herbaceous	1.52
Hay/Pasture	7.31
Cultivated Crops	54.55
Woody Wetlands	1.30
Emergent Herbaceous Wetlands	0.23

Table 2.2 Reservoirs and dams in the watershed

Name	County	River	Max Design Discharge (cfs)	Max Design Storage (Acre-ft)	Drainage Area (mi^2)
Clarence J Brown Lake	Clark	Buck Creek	50000	63700	82
Englewood Dam	Montgomery	Stillwater River	41250	413000	651
Germantown Dam	Montgomery	Twin Creek	22294	142000	275
Huffman Dam	Greene	Mad River	204186	297000	671
Indian Lake	Logan	Great Miami River	18015	69900	98
Lockington Dam	Shelby	Loramie Creek	25000	165000	255
Loramie Lake	Shelby	Loramie Creek	8548	12900	78
Taylorsville Dam	Montgomery	Great Miami River	112381	386000	1133

Table 2.3 Point sources in the watershed

Point Sources	Sub-basin
Bellefontaine WWTP	13
Versailles WWTP	36
Urbana WTP	42
Piqua WWTP	53
Pleasant Hill WWTP	64
Union WWTP	84
Tri-cities North Regional WW Authority	93
Dayton WWTP	104
Eaton WWTP	105
West Carrollton WWTP	111
Dayton Power & Light Co	116
Miamisburg Water Reclamation Facility	116
US Department of Energy OU-1	116
Franklin Regional WWTP	125
Magellan Aerospace	126
Sorg Paper Co.	126
Wausau Paper Towel and Tissue LLC	126
Middletown WWTP	129
AK Steel Corporation	130
Oxford WWTP	132
Lesourdsville Water Reclamation Facility	134
New Miami WWTP	135
Miller Brewing Co.	136
Hamilton Municipal Electric Pl	137
Hamilton Water Reclamation Facility	138
Fairfield WWTP	139
Rumpke Sanitary Landfill	141
Hamilton Co Taylor CRK Treatment	142

Table 2.4 Model parameters used in the SWAT calibration

Parameters	Calibrated value
Available water capacity of the soil layer (relative)	0.0002
Base flow alpha factor (days)	0.8600
Base flow alpha factor for bank storage	0.9700
Deep aquifer percolation fraction	0.4300
Effective hydraulic conductivity in main channel alluvium	127.6300
Groundwater "revap" coefficient	0.0400
Groundwater delay (days)	74.0400
Manning's "n" value for the main channel	0.0600
Maximum melt rate for snow during year	0.7100
Minimum melt rate for snow during the year	0.8100
Plant uptake compensation factor	0.8600
Saturated hydraulic conductivity (relative)	0.0015
SCS runoff curve number (relative)	0.0003
Snow melt base temperature	0.1300
Snow pack temperature lag factor	0.7800
Snowfall temperature	0.0500
Soil evaporation compensation factor	0.8100
Surface runoff lag time	2.0000
Threshold depth of water in shallow aquifer for return flow to occur	1004.4000
Threshold depth of water in the shallow aquifer for revap to occur	285.0000

Table 2.5 The statistical criteria measuring the performance of the SWAT model

USGS Gauge Stations	Station Name	Sub-basin	Time Scale	Calibration				Validation			
				NSE	R^2	PBIAS	RSR	NSE	R^2	PBIAS	RSR
3274000	Great Miami River, Hamilton	137	Monthly	0.86	0.89	2.86	0.38	0.83	0.86	0.82	0.41
			Daily	0.81	0.81	2.86	0.44	0.78	0.78	0.80	0.47
3272100	Great Miami River, Middletown	126	Monthly	0.86	0.89	4.22	0.38	0.82	0.84	0.96	0.42
			Daily	0.80	0.81	4.22	0.44	0.77	0.77	0.93	0.48
3271601	Great Miami River, Miamisburg	116	Monthly	0.87	0.89	1.45	0.35	0.85	0.87	-0.58	0.39
			Daily	0.80	0.80	1.47	0.45	0.77	0.77	-0.61	0.48
3272000	Twin Creek, Germantown	112	Monthly	0.79	0.83	0.87	0.45	0.77	0.81	0.80	0.48
			Daily	0.66	0.68	0.94	0.58	0.63	0.65	0.76	0.61
3270500	Great Miami River, Dayton	98	Monthly	0.88	0.89	-4.43	0.35	0.85	0.87	-5.39	0.39
			Daily	0.79	0.79	-4.40	0.46	0.77	0.77	-5.41	0.48
3266000	Stillwater River, Englewood	84	Monthly	0.81	0.84	4.15	0.43	0.83	0.87	5.78	0.42
			Daily	0.69	0.69	4.18	0.56	0.71	0.72	5.80	0.54
3263000	Great Miami River, Taylorsville	83	Monthly	0.86	0.89	-8.47	0.38	0.83	0.85	-8.24	0.42
			Daily	0.75	0.76	-8.46	0.50	0.74	0.74	-8.24	0.51
3262700	Great Miami River, Troy	56	Monthly	0.84	0.87	-13.95	0.40	0.80	0.85	-16.93	0.45
			Daily	0.75	0.75	-13.98	0.50	0.74	0.75	-16.91	0.51
3261500	Great Miami River, Sidney	23	Monthly	0.80	0.84	-17.48	0.45	0.77	0.81	-16.69	0.48
			Daily	0.71	0.72	-17.53	0.54	0.73	0.74	-16.72	0.52

Table 2.6 Top 10 climate models selected for the analysis of low flows

Institute	Model
Canadian Centre for Climate Modelling and Analysis, Canada	CanESM2
National Center for Atmospheric Research, USA	CCSM4
Centre National de Recherches Meteorologiques, Meteo-France	CNRM-CM5
Commonwealth Scientific and Industrial Research Organization, Aus.	CSIRO-Mk3.6.0
NOAA Geophysical Fluid Dynamics Laboratory, USA	GFDL-ESM2M
Model for Interdisciplinary Research On Climate, Japan	MIROC5
Model for Interdisciplinary Research On Climate, Japan	MIROC-ESM
Max Planck Institute for Meteorology, Germany	MPI-ESM-LR
Max Planck Institute for Meteorology, Germany	MPI-ESM-MR
Norwegian Climate Center's Earth System Model	NorESM1-M

Table 2.7 R^2 of observed vs model predicted precipitation in weather station 00093815

Climate Models	Daily	Average Monthly	Average Annually	Monthly
CanESM2	0.00001	0.002	0.001	0.782
CCSM4	0.00001	0.025	0.028	0.826
CNRM-CM5	0.00013	0.018	0.020	0.760
CSIRO-Mk3.6.0	0.00017	0.014	0.016	0.775
GFDL-ESM2M	0.00006	0.010	0.012	0.759
MIROC-ESM	0.00003	0.017	0.008	0.735
MIROC5	0.00017	0.017	0.019	0.864
MPI-ESM-LR	0.00005	0.027	0.029	0.767
MPI-ESM-MR	0.00009	0.007	0.008	0.662
NorESM1-M	0.00057	0.037	0.040	0.742

Chapter 3. Impact of Global Climate Change on High Flows: A Case Study of the Great Miami River Watershed

Abstract

A climate-induced extreme flow event such as flooding is one of the major natural calamities, which can significantly damage human lives and properties. This study uses watershed level hydrologic modeling and analysis to examine the effects of climate change on the high flows conditions at Great Miami River Watershed under two RCPs 4.5 and RCP 8.5. The 21st century streamflow was simulated by utilizing widely used SWAT model and 10 different climate data from the Coupled Model Intercomparison Project phase 5 (CMIP5). The future streamflow was divided into three equal periods: 2016 - 2043 (2035s), 2044 - 2071 (2055s) and 2072 - 2099 (2085s) and independently analyzed to compare with high flows of baseline condition (1988 - 2015). The results of this analysis predicted that 7-day high flows in each simulation period would likely to decrease by 25% than historical records. A similar trend was demonstrated by 7Q10 high flows. However, the MIROC5 model in RCP 4.5 showed 1.2% increase in 7Q10 high flows in 2035s followed by a slight decrease in 2055s and 2085s. The projected future 50-year and 100-year flood for the study area were most likely to decrease by 29% and 36% respectively. Similarly, the peak flows for each year were predicted to decrease by 21% and 16% under RCP 8.5 and RCP 4.5 respectively in the future. The analysis suggested that peak on monthly basis would increase more during the months of August, September, and October compared to the historical period.

Keywords: Climate Change, High flows, SWAT, and Great Miami River Watershed

Introduction

Human activities have been responsible for modifying the global atmospheric composition including greenhouse gases sufficiently that anthropogenic climate change is already being experienced (Bernstein et al., 2007). Due to an increase in greenhouse gas concentrations in the atmosphere and subsequent global warming, the Earth's hydrologic cycle is being altered in multiple ways over different geographic regions at various temporal scales (Vitousek et al., 1997). These changes in the hydrological cycle eventually lead to more precipitation and extreme rainfall which results in increased water runoff and flood risks (Graham et al., 2010).

Extreme rainfall events and flooding in the Midwest have increased during the last century up to 20% in some locations, and these trends are expected to continue in the future (Pathak et al., 2016). The 2008 flooding in the Midwest caused 24 deaths and losses of billions of dollars in terms of reduced agricultural yields and disrupting some key transportation routes (Pryor et al., 2013). Therefore, it is essential to assess the impact of extreme storm events and flows due to climate change in order to mitigate its impacts and build a resilient society.

Projected climate dataset, developed from the Global Circulation Models (GCMs) are being used been utilized to investigate the impacts associated with climate change on extreme events (Kharin et al., 2005; Wang et al., 2008). However, uncertainties within the GCM models are known to affect future hydrological simulations (Xu et al., 2013). Moreover, some biases might be present in these climate models, which have to be adjusted before using in the simulation process. In the United States, different downscaling techniques have been used to generate unbiased climate data (Hayhoe et al., 2007; Christensen et al., 2007). Recently published Coupled Model Intercomparison Projects (CMIP) multi-model ensemble data are projected with the downscaling technique of daily bias correction and constructed analogs (BCCA) (Taylor et al., 2012, Meehl et al., 2014).

In Midwestern United States, scientists have analyzed the impact of climate change and projected risk of flooding as well as increasing trend of water yield in different watersheds (Pathak et al., 2016). An experiment by Milly et al., 2005, based on 12 GCMs, showed that total runoff is expected to increase by 10 - 25% in Midwestern United States by the end of 2050. Similarly, in the Upper Great Miami River Watershed, Shuang-Ye Wu, 2010 used 14 GCMs and Monte Carlo simulation technique to estimate the flood risk due to climate change. The study depicted that the aggregated 100-year peak flow was expected to increase by 13% and concluded.

As a case study, we selected the Great Miami River Watershed to explore the responses of climate change on high flows. Even though the impact of climate change in this watershed has been explored in a previous research, there were several limitations such as:

i) the study was based on the former set of CMIP3 data which needs to be revised as CMIP5 datasets are currently available;

ii) the study was simply based on regression equations although distributed watershed models are needed for appropriate analysis;

iii) the study was focused only on the Upper part of the Great Miami River but not on the entire Great Miami River;

iv) the study did not make a comprehensive climate change assessment in various aspects of water resources.

Therefore, the major focus of this chapter is to predict the impact of climate change based on 10 climate models from CMIP5 dataset and two GHG emission scenarios RCP 4.5 and RCP 8.5 using a widely accepted hydrological model SWAT. The RCP 4.5 scenario assumes that global annual GHGs emission measured in terms of CO_2 equivalents becomes maximum at the 2040s and then starts to reduce, whereas, in the RCP 8.5, the emission is expected to rise continuously throughout the 21st century (Meinshausen et al., 2011).

Methodology

Study Area

The Great Miami River Watershed is situated mostly in the southwestern part of Ohio (Figure 2.1). Details about the study area are presented in chapter 2. The watershed is primarily dominated by agricultural land and has been experienced a hydrologic drought (1930-1936) and severe destructive floods from time to time. A catastrophic flood of 1913 was attributed to a combination of snowmelt and intense precipitation leading to overflows in the Great Miami River, the Mad River, and the Stillwater River. Over 300 lives were lost and property damages exceeding $2 billion in today's currency (MCD, 2016). As a result, flooding is still considered one of the biggest challenges in this watershed.

SWAT Model Inputs

Temperature data from 10 different stations for the period 1980 to 2015 and precipitation data for the same period were incorporated from 19 meteorological stations. Other input parameters such as DEM, Land use, Soil data were described in chapter 2.

Model Calibration and Validation

The SWAT model calibration and validation procedure using the SUFI-2 program has already been discussed in Chapter 2 under the heading "Model Calibration and Validation".

Scenario Analysis

Out of the 20 GCMs in CMIP5, 10 models were used for RCP 4.5 and RCP 8.5. Selected GCMs are tabulated in Chapter 2. The output from each model includes daily precipitation and maximum and minimum temperature for the baseline period 1988 - 2015 and the future period 2016 - 2099. The observation dataset of monthly precipitation at station 0093815 was used to validate the model performance with the help of coefficient of correlation (R^2). Future period (2016 - 2099) was subdivided into three time frames as follows: 2035s as (2016 - 2043), 2055s as (2044 - 2071) and 2085s as (2072 - 2099) and compared to that of the baseline period.

High flows Analysis

The SWAT model provides a long-term daily streamflow from each sub-basin. We analyzed high flows from the simulated and observed discharge at outlet station of the watershed (USGS 03274000). For climate change impacts assessment on high flows, we examined five high flows variables based on the ensemble of 10 climate models and 2 scenarios. High flows variables incorporated in our analysis includes 7-day high flows, 7Q10 high flows, annual and monthly peak discharges, 75th percentile flow, and flood frequency analysis. The 7-day high flows are the maximum flow from the average of 7 days consecutive flows in a year. Similarly, 7Q10 high flows are defined the maximum 7 days high flows that have a probability of occurring once in every 10 years (EPA, 1991). In addition, peak discharges from each year as well as months were also estimated to capture the extreme high flow events. For the flood frequency analysis of streamflow data PeakFQ program (Flynn et al., 2006) was used. PeakFQ uses the Bulletin 17B and Expected Moments Algorithm to estimate flood magnitudes with different recurrence intervals. The streamflow series simulated by SWAT model for 2035s, 2055s, and 2085s were separately fed into the program and results were compared against historical records.

Results

Model Simulation

As described in the earlier chapter, the SWAT model calibration and validation were performed on a daily and monthly time step. The model performance was satisfactory during calibration and validation period with reasonable accuracy, which was assessed through a visual inspection and statistical criteria. Figure 3.1 shows scatter plots and R^2 values of the observed vs simulated discharges for the Great Miami River at (USGS 03274000) to verify the robustness of model performance. The statistical criteria NSE, R^2, PBIAS, and RSR on a daily and monthly scale from different stations throughout the watershed were described in chapter 2.

Model Prediction

Since data from climate model need to be validated before regional hydrological impacts analysis, the variability of each CMIP5 outputs under RCP 4.5 was compared with the observed precipitation data at the same station. The extreme precipitations represented by the dots in the box-plots in Figure 3.2, which are the daily precipitation greater than the 90th percentile are more frequent for the observed period compared to climate model outputs. The coefficient of correlation (R^2) in terms of daily precipitation output, when compared to observe data, was relatively very less (discussed in chapter 2). This indicates that data from the climate models have issues in capturing the general trend of observed precipitation and variabilities that might persist when applied in a smaller region.

Change in Streamflow

The primary outputs of the above-mentioned modeling runs were daily streamflow for 2016-2099 at subbasin outlets (USGS 03274000). Table 3.1 presents the results of average annual streamflow from 10 climate models and two emission scenarios for three reference periods. The annual streamflow recorded from baseline condition was 4166 cfs. The simulation from the nine models projected a future increase in annual flow under both scenarios, but MPI-ESM-LR model during 2035s projected a decrease of annual flow under RCP 8.5 by 2.2%. The trend in annual flow drastically increases at the beginning of the century and subsequently decreases in a mid and late century. In addition, the increment under RCP 4.5 scenario was the largest compared to RCP 8.5. The maximum increase in annual flow was projected from CSIRO-Mk3.6.0 model under RCP 4.5 (41.5%). The annual stream flows predicted from the climate models showed an increase of 21%, 23%, and 18% for the 2035s, 2055s, and 2085s, respectively under RCP 4.5, and an increase of 21%, 19%, and 20% for the 2035s, 2055s, and 2085s, respectively under RCP 8.5.

Impact of Climate Change on High Flows

Even though the annual flow was predicted to increase in each period, both emission scenarios showed a decrease in 7-day maximum flow in all periods (Figure 3.3). The median value of 7-day maximum flow from an ensemble of 10 models in three time periods reduced significantly (25%) than an observed period. Under RCP 4.5, the median decreased gradually from 2035s to 2085s while in RCP 8.5 the median decreased in 2055s and increased in 2085s. Similarly, annual peak also decreased in projected periods compared to the historical condition. The pattern of peak flows in each time-period were found similar in both scenarios as shown in Figure 3.4. The median of annual peak flow decreased from 14% to 21% in RCP 4.5 and 13% to 16% in RCP 8.5.

Peak flow was also calculated on monthly basis for both emission scenarios, which are presented in Figure 3.5 for RCP 4.5 and Figure 3.6 for RCP 8.5. The model outputs predicted that peak flow would increase from February to November in general. The maximum increase in monthly peaks was found in August, September, and October for both RCPs.

In order to see the 10 years recurrence of high flows, the calculated 7Q10 for high flows from each model was compared to the historical data. The graph in Figure 3.7 showed that the 7Q10 high flows from model ensemble would decrease in the 21st century; however, some climate models predicted an increase in a certain period. For example, the MIROC5 model during 2035s showed 1.2% increase in 7Q10 under RCP 4.5 and then decreasing trend was predicted. Similarly, CanESM2 and CSIRO-Mk3.6 showed higher values of 7Q10 in different periods of the 21st century. The decreasing pattern from two different emission scenarios had some changes in 7Q10 high flows. Under RCP 4.5, 7Q10 high flows were expected to be the least on 2085s, while it was expected to be the least in 2055s for RCP 8.5.

Furthermore, the frequency of future flows having greater value than the 75th percentile threshold of observed flow was analyzed separately in Figure 3.8. The median of frequencies for RCP 4.5was found 135 times in 2035s, whereas it was 146 and 135 during 2055s and 2085s, respectively. In RCP 8.5, the median value followed the similar trend but during 2055s, its value was decreased to 134 (lower than RCP 4.5).

Changes in flood magnitude from an ensemble of 10 climate models in the Great Miami River with different recurrence intervals are shown in Figure 3.9 for RCP 4.5 and Figure 3.10 RCP 8.5 respectively. The 2, 5, 10, 25, 50, and 100 years flood frequencies in the 21st century were estimated to decrease rapidly from observed frequency. Box plots showed that as recurrence interval increased, the change in flood frequency also increased in both scenarios. One of the reasons of such relationship could be the limited number of flow data for calculating each flood frequency. Similarly, the reduction in 50 years recurrence flood would become maximum during 2035s (median value of -33%) and gradually increase in subsequent period for both RCPs. The 100 years flood under RCP 4.5 were predicted to reduce greatly in 2035s by -36% (median value), however, the variability of the reduction in the flood was found larger in 2085s (from -43% to -10%). Unlike RCP 4.5, interquartile range of the box plot in 100 years floods did not vary significantly for future. The flood frequency of 2 years flood was predicted to change less than that of other flood frequencies.

It would reduce from -10 % to -29% in RCP 4.5 and -8% to -29% in RCP 8.5 in future periods.

Flood protection system in the Great Miami River Watershed comprises several dams and levees, which might be vulnerable during the time of high flows. Therefore, the high flows analysis in four major reservoirs is shown in Figure 3.11 - Figure 3.18. Since it was very difficult to analyze the results using all models, only two climate models namely MPI-ESM-LR and NorESM1-M, which had good correlation with observed data, were considered for monthly peak flows analysis. Results showed that all dams in August, September, October, and November are vulnerable in terms of high flows as peak flow in these months from both scenarios were expected to exceed the observed peak flow. In addition, peak flow from MPI-ESM-LR in February was also predicted to exceed the observed peak value except for Germantown dam. The NorESM1-M model under both scenarios also followed a similar trend of peak flows. The results from two climate models showed that among the four major dams, the peak flows in Huffman dam are expected to cross the historical peak limits in almost all months.

Conclusion

The climate scenarios generated from the 10 CMIP5 climate models under two emission scenarios became very helpful to illustrate the impact of climate change on streamflow regime, especially during high flows periods in Great Miami River Watershed. The watershed model, SWAT, was chosen to simulate stream flows after calibration and validation at different locations of the watershed.

The average annual stream flows for both emission scenarios were projected to increase for all simulation periods. The significant increase in peak flow as compared to historical period was expected to occur in the months of July, August, September. However, flood frequency from all climate models suggested that major flood events in future such as the 50-year and the 100-year flood would decrease. 7-day high flows from an ensemble of 10 models were estimated to decrease in the future but the variability of flow in each period of study remained similar under both emission scenarios. Similarly, 7Q10 high flows showed a dramatic decrease from 1988-2015 to consecutive periods. Under RCP 4.5, 7Q10 value was expected to be the lowest in 2085s but in RCP 8.5, the lowest 7Q10 was estimated in 2055s.

This analysis was also conducted to see the difference in the flood frequency of 2, 5, 10, 50 and 100 years to get a better idea about the upcoming major flood events. All models predicted the flood values would be smaller than the observed flood magnitude in a future period. Furthermore, the results from the high flows analysis concluded that peak flow from August to November would exceed the recorded peaks near major dams of Great Miami River watershed. While high flows were estimated to be critical in the months of February for RCP 4.5, the months of February and May would be critical for RCP 8.5. Among four major dams, the high flows in Huffman dam were significantly influenced by climate change under both scenarios and climate models especially during the month of February.

Even though the model projected the decrease in the high flows in the 21st century, the projected streamflow presented in this analysis are inherently uncertain. It is clear from the analysis that CMIP5 climate data may not be adequate for the extreme flow analysis of the watershed. We demonstrated that the outputs from the 10 climate models might result in a large difference in high flows. The failure of CMIP5 data to capture the trend of extreme events could be due to lack of extreme precipitation events in the model outputs. Since precipitation is the major component of the hydrologic cycle, the hydrologic flow regime resulting from such flat precipitation input could have produced unrealistic output. This uncertainty of CMIP5 climate output cast a doubt over the projected datasets and careful validation of new climate data should be carried out prior to being used.

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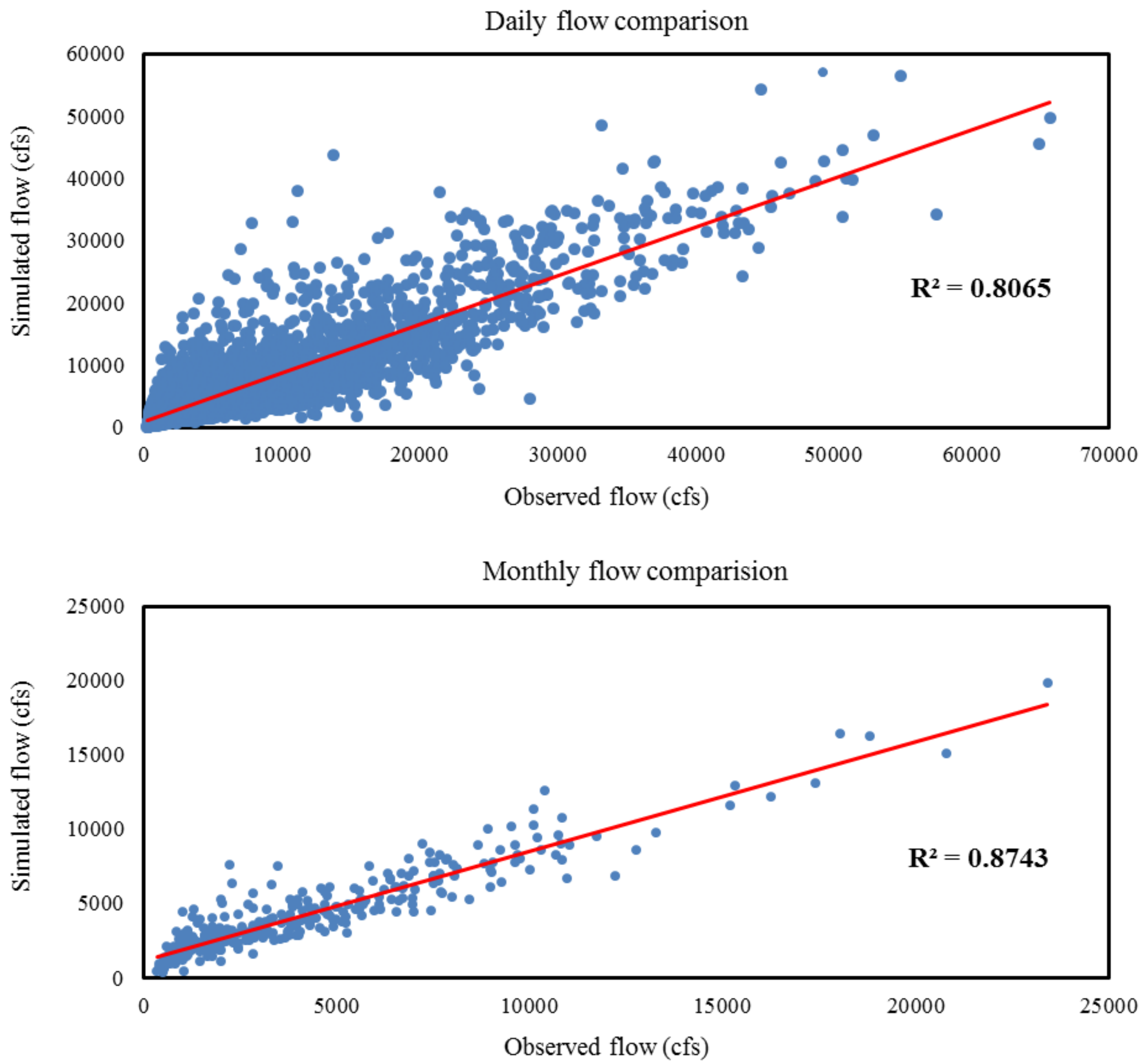

Figure 3.1 Scatter plots of daily and monthly observed vs simulated flows for station 03274000 in the Great Miami River during 1988-2015

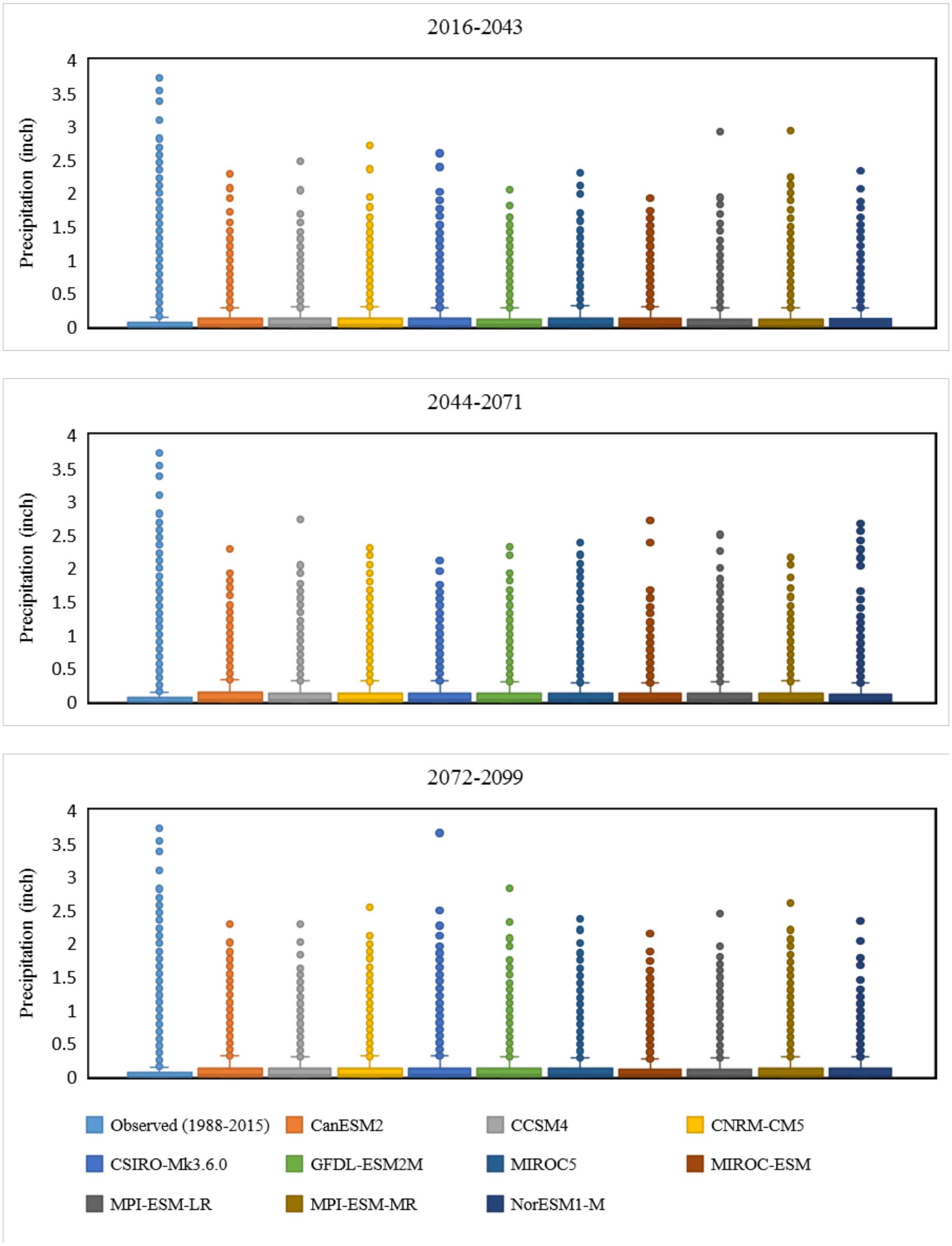

Figure 3.2 Comparison of extreme storm events from 10 climate models at three time spans for future with observed precipitation at station 0093815

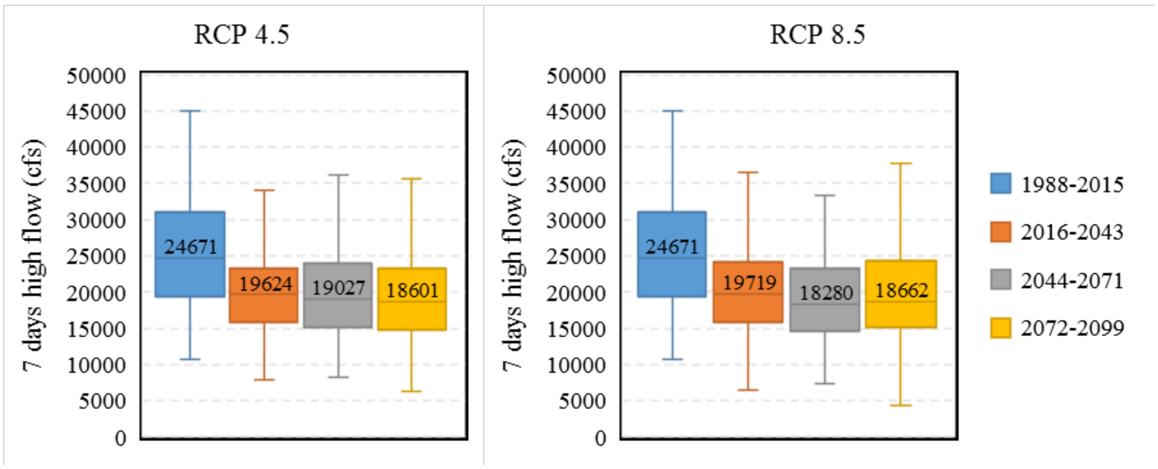

Figure 3.3 7-day high flows from ensemble of 10 climate models and observed records in both RCPs

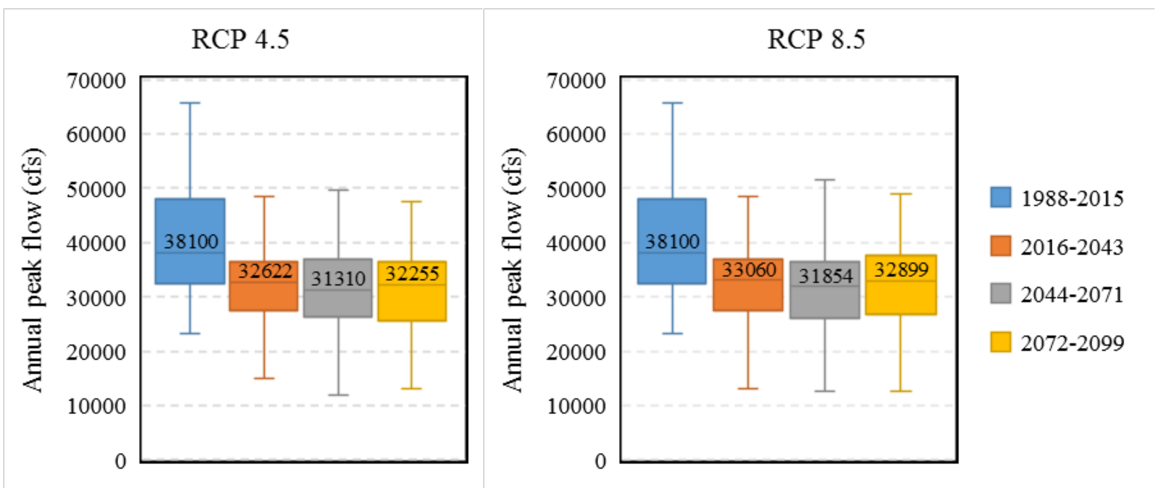

Figure 3.4 Annual peak flow from ensemble of 10 climate models and historical flows

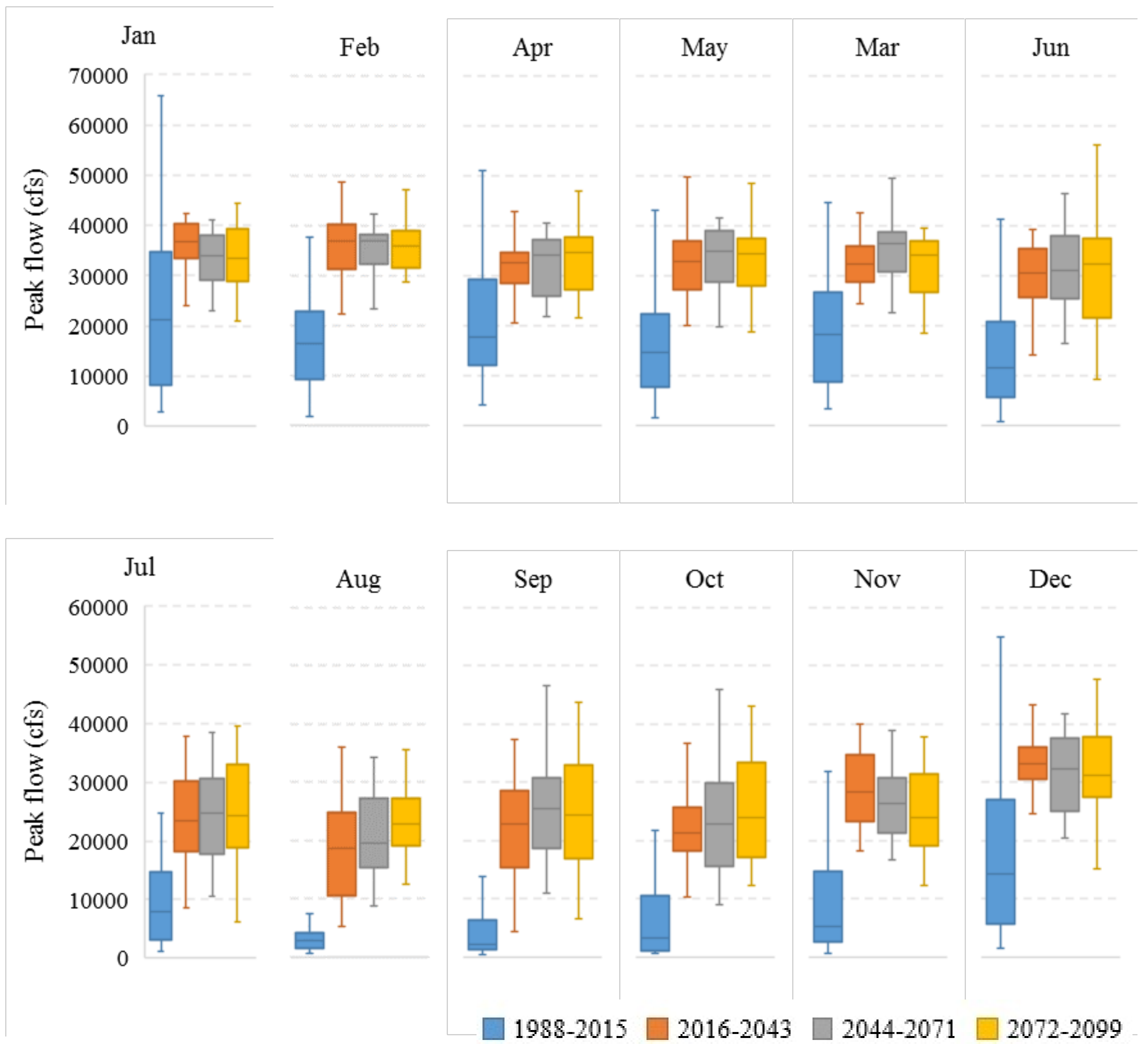

Figure 3.5 Monthly peak from ensemble of 10 climate models under RCP 4.5 and historical flows

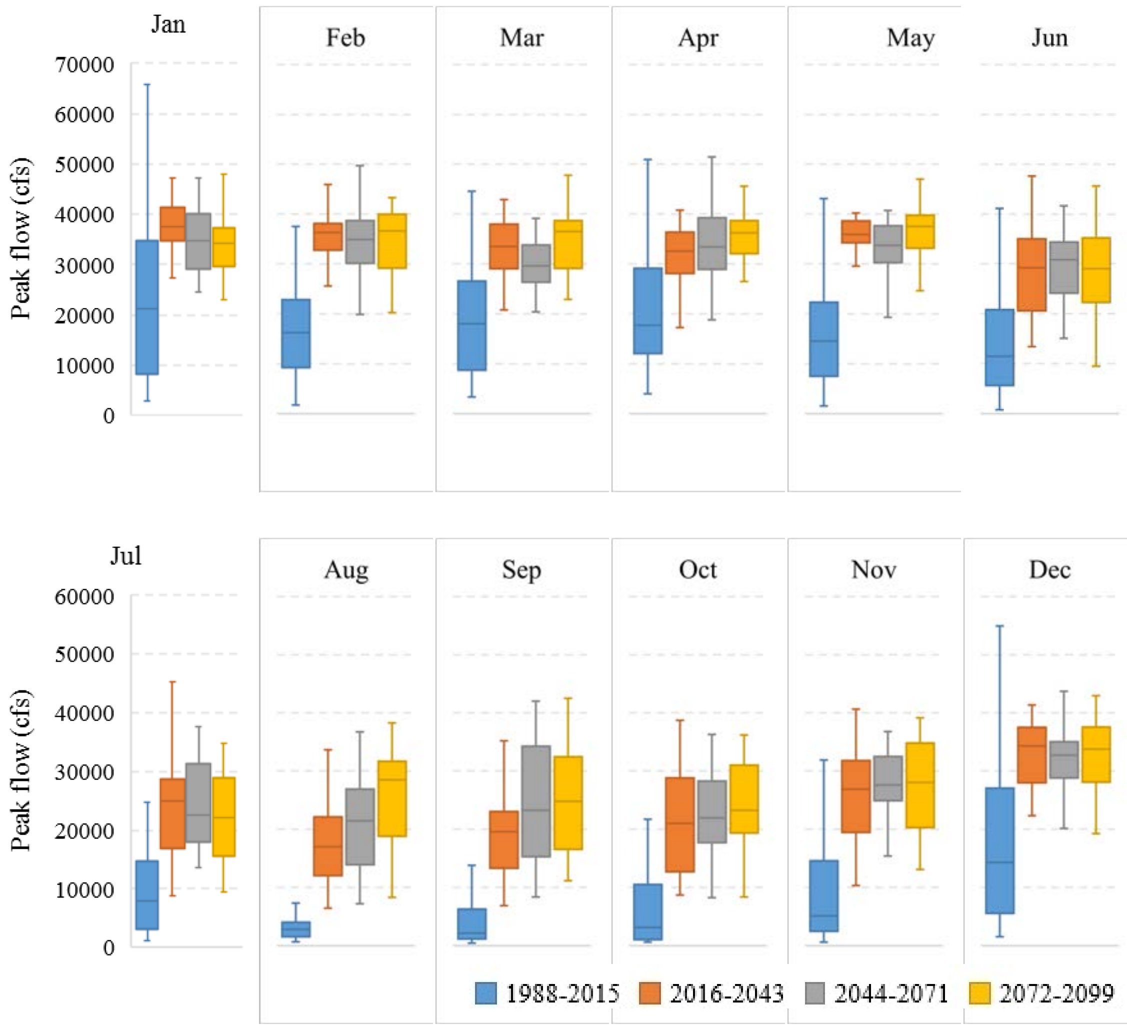

Figure 3.6 Monthly peak from ensemble of 10 climate models under RCP 8.5 and historical flows

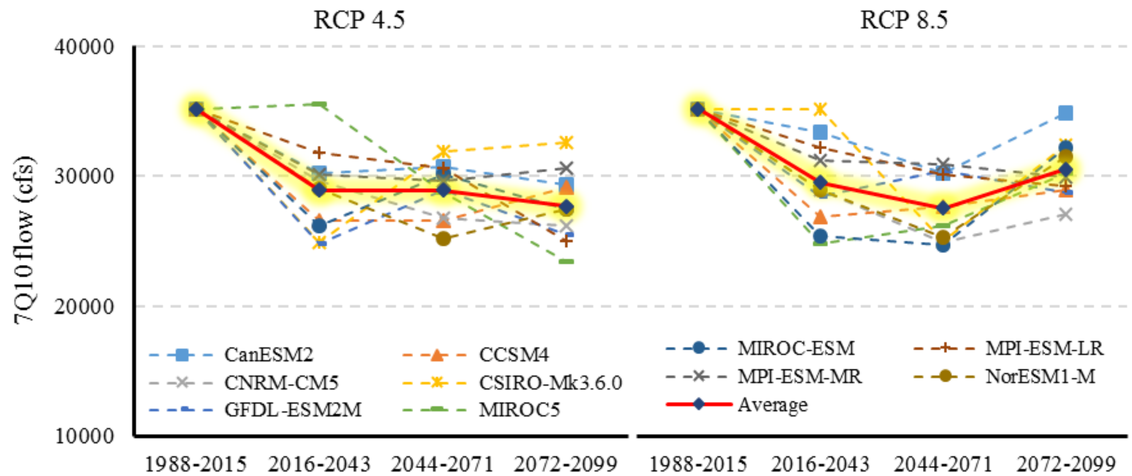

Figure 3.7 7Q10 high flows from ensemble of 10 climate models and historical flows

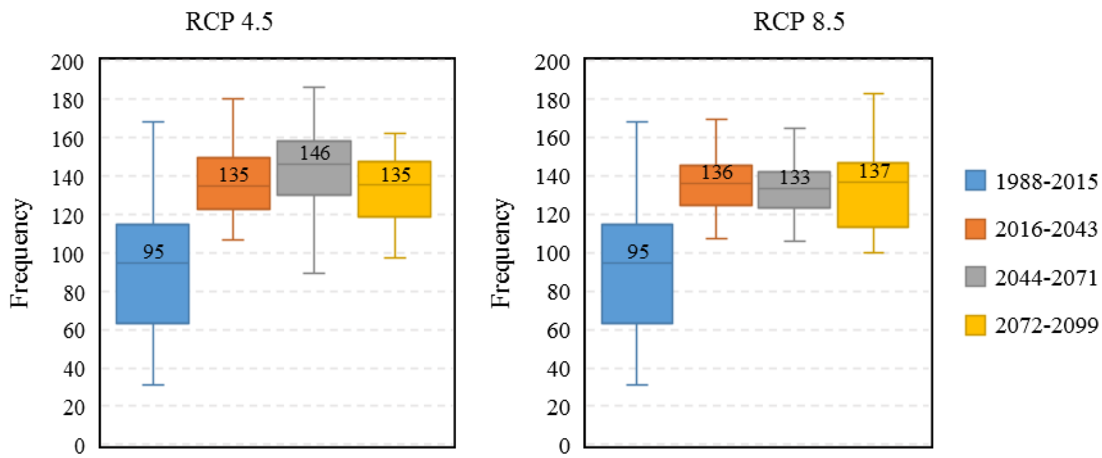

Figure 3.8 Frequency of 75th percentile flows from ensemble of 10 climate models

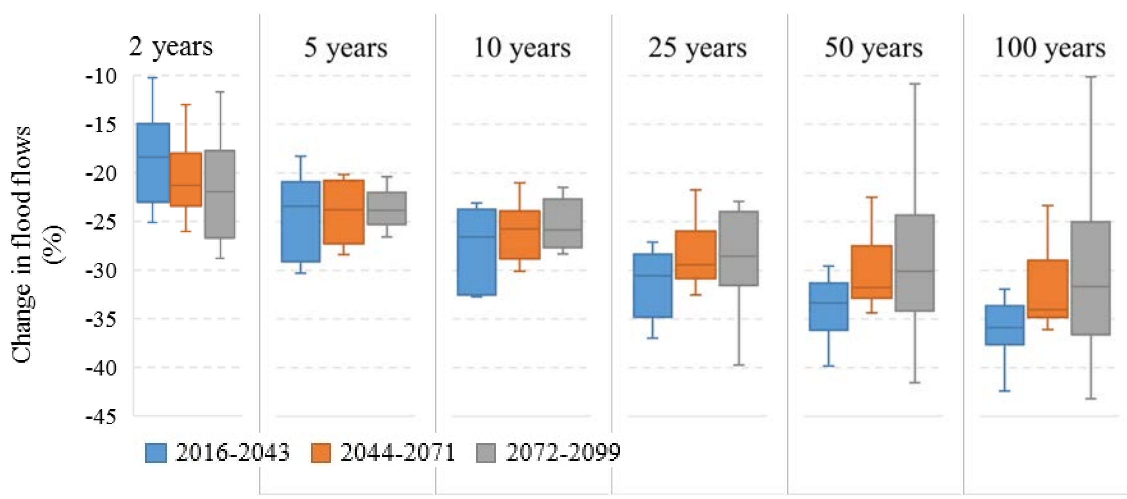

Figure 3.9 Change in flood magnitudes for recurrence intervals of 2, 5, 10, 25, 50, and 100 years from 10 climate models with respect to observed period for RCP 4.5

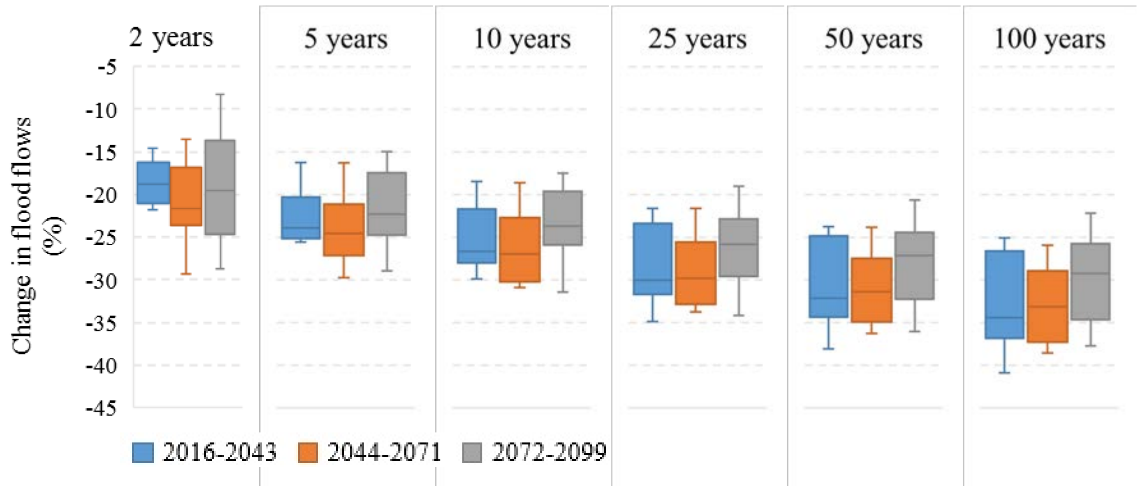

Figure 3.10 Change in flood magnitudes for recurrence intervals of 2, 5, 10, 25, 50, and 100 years from 10 climate models with respect to observed period for RCP 8.5

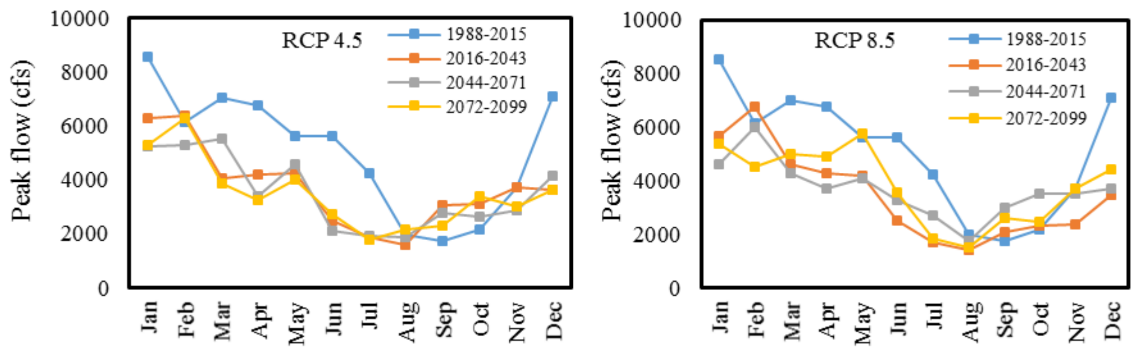

Figure 3.11 Monthly peak flow near Taylorsville dam from MPI-ESM-LR model

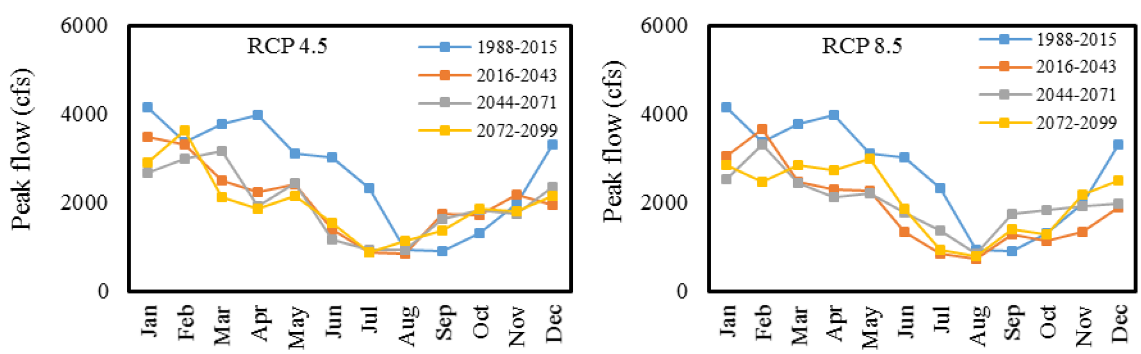

Figure 3.12 Monthly peak flow near Englewood dam from MPI-ESM-LR model

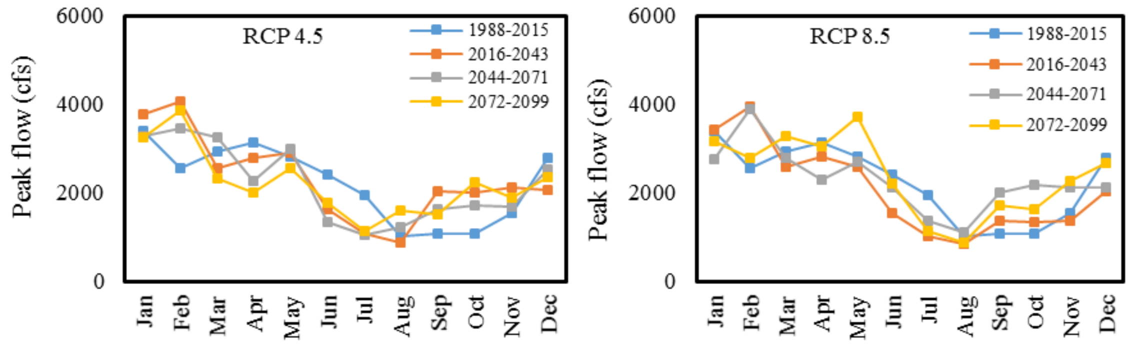

Figure 3.13 Monthly peak flow near Huffman dam from MPI-ESM-LR model

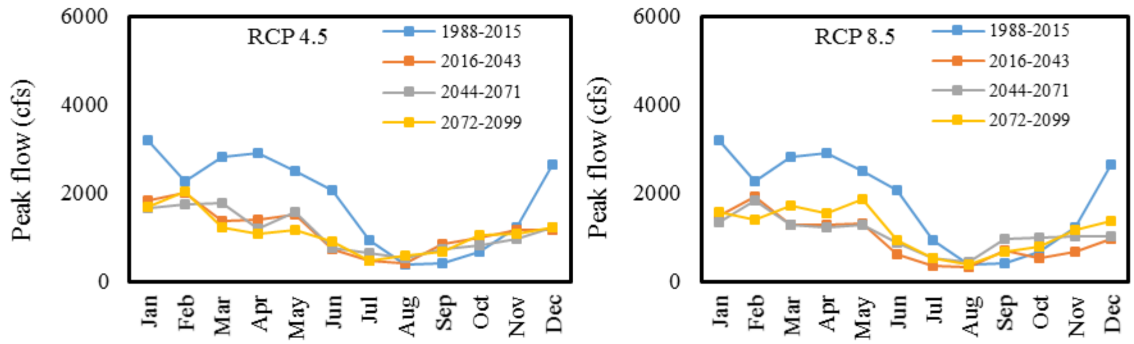

Figure 3.14 Monthly peak flow near Germantown dam from MPI-ESM-LR model

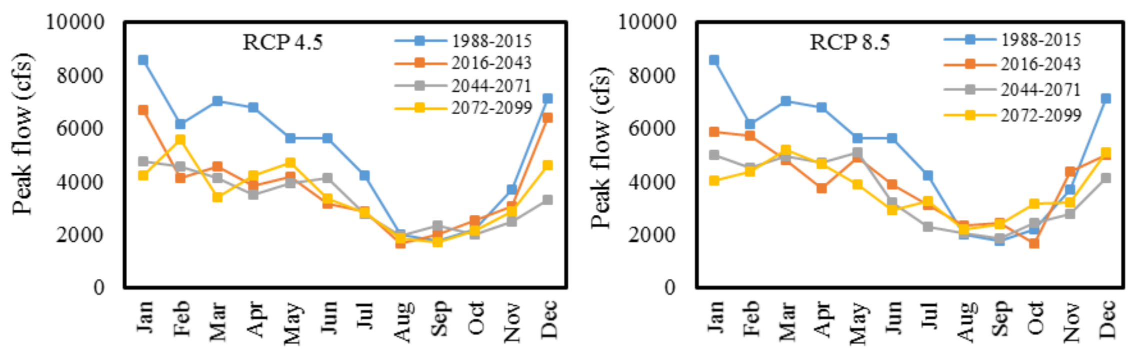

Figure 3.15 Monthly peak flow near Taylorsville dam from NorESM1-M model

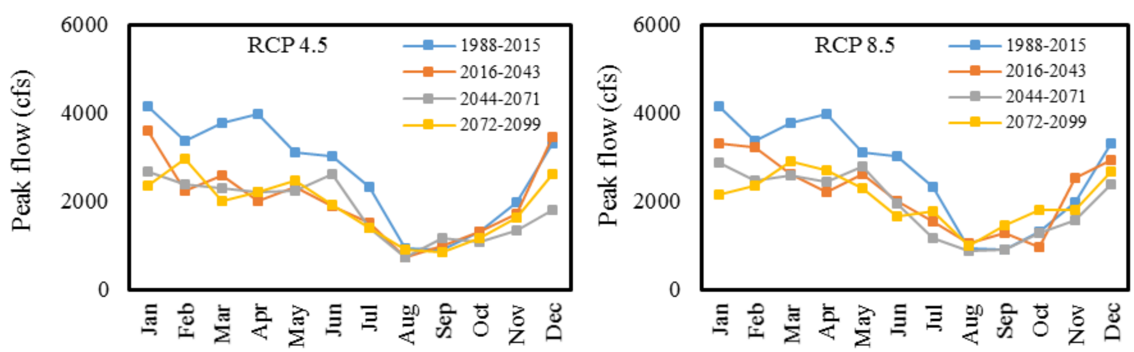

Figure 3.16 Monthly peak flow near Englewood dam from NorESM1-M model

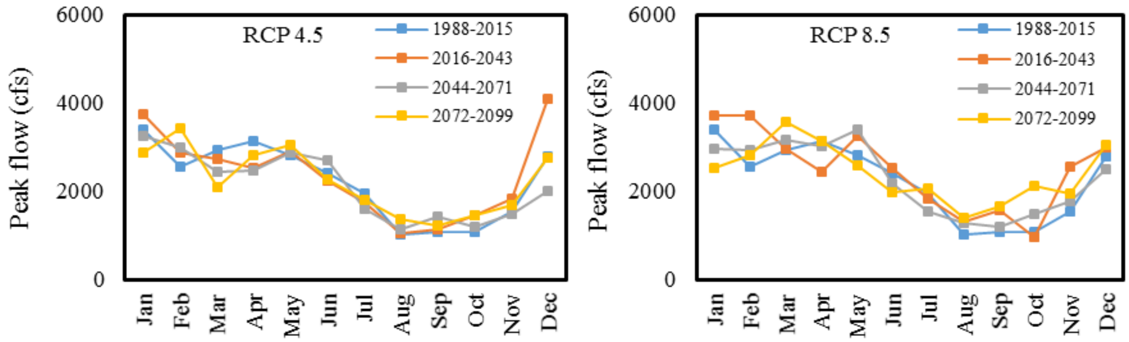

Figure 3.17 Monthly peak flow near Huffman dam from NorESM1-M model

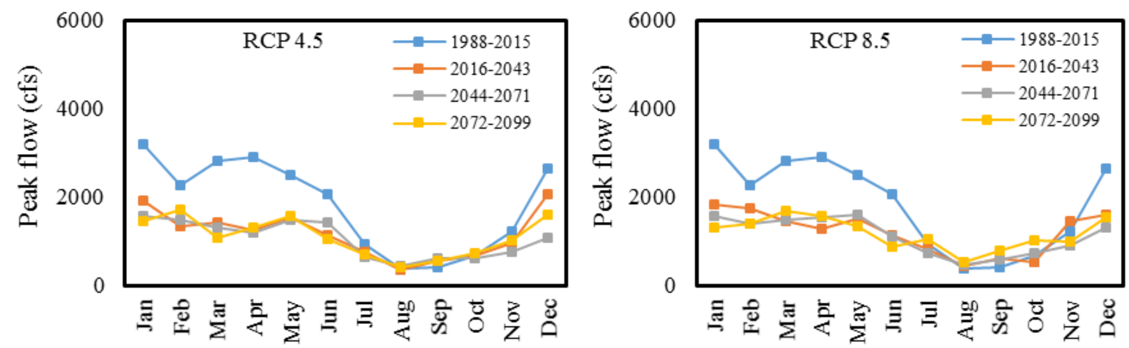

Figure 3.18 Monthly peak flow near Germantown dam from NorESM1-M model

Table 3.1 Change in annual streamflow from 10 climate models and under 2 RCPs compared to observed annual flows

Emission Scenarios		RCP 4.5		RCP 8.5	
Models	**Period**	**Flows (cfs)**	**% Change**	**Flows (cfs)**	**% Change**
Observed (Baseline)	1988 - 2015	4166.20	-	4166.20	-
MPI-ESM-LR	2016 - 2043	4939.60	18.60	4074.60	-2.20
	2044 - 2071	4707.70	13.00	4691.90	12.60
	2072 - 2099	4493.80	7.90	4613.40	10.70
NorESM1-M	2016 - 2043	4887.10	17.30	5139.20	23.40
	2044 - 2071	4349.40	4.40	4834.90	16.00
	2072 - 2099	4497.60	8.00	5062.40	21.50
CSIRO-Mk3.6.0	2016 - 2043	5048.40	21.20	5055.80	21.40
	2044 - 2071	5896.50	41.50	4758.20	14.20
	2072 - 2099	5805.70	39.40	5227.90	25.50
MIROC5	2016 - 2043	5237.90	25.70	5134.20	23.20
	2044 - 2071	4850.40	16.40	5037.20	20.90
	2072 - 2099	4293.40	3.10	4341.60	4.20
CanESM2	2016 - 2043	5014.10	20.40	4955.00	18.90
	2044 - 2071	5533.40	32.80	5396.20	29.50
	2072 - 2099	5103.10	22.50	5594.10	34.30
MPI-ESM-MR	2016 - 2043	4728.90	13.50	5442.00	30.60
	2044 - 2071	5097.90	22.40	5089.20	22.20
	2072 - 2099	4953.00	18.90	5621.90	34.90
GFDL-ESM2M	2016 - 2043	4892.50	17.40	5215.80	25.20
	2044 - 2071	5564.30	33.60	5432.50	30.40
	2072 - 2099	5535.90	32.90	5087.80	22.10
CNRM-CM5	2016 - 2043	5250.00	26.00	5371.60	28.90
	2044 - 2071	5688.40	36.50	5088.50	22.10
	2072 - 2099	5300.60	27.20	5065.20	21.60
MIROC-ESM	2016 - 2043	5597.70	34.40	5166.60	24.00
	2044 - 2071	4943.30	18.70	4453.30	6.90
	2072 - 2099	4851.90	16.50	4465.70	7.20
CCSM4	2016 - 2043	4768.10	14.40	4648.70	11.60
	2044 - 2071	4818.50	15.70	4613.70	10.70
	2072 - 2099	4476.90	7.50	4932.20	18.40

Chapter 4. Conclusions and Recommendations

Over the 21st century, it is likely to expect that climate change will affect water resources mainly through affecting the process of watershed hydrology and water resource cycles. The aim of this study was to investigate the effects of climate change in the context of extreme events in a large agricultural watershed. The key question in this study was to see how and at what degree these hydrological variations due to climate change would affect high flows and low flows in the river basin.

The Soil and Water Assessment Tool (SWAT) model was employed to the Great Miami River Watershed, which covers approximately 4000 square miles area in Southwest Ohio. The model offers a high level of spatial detail, continuous-time simulation and efficient appraisal of hydrological changes in the watershed. To evaluate the model performance in simulating watershed hydrology, multi-site model calibration and validation were conducted using the SUFI-2 algorithm in SWAT-CUP program. Flow calibration and validation were performed for 2005 - 2014 and 1995 - 2004, respectively at nine different USGS gauge stations throughout the watershed. Model performance was evaluated by using four statistical measures: NSE, R^2, RSR, and PBAIS, which were found within the range recommended by Moriasi et al., 2007. Calibration and validation provided a good insight on model input parameters and enabled the model to simulate hydrological processes very well.

The SWAT model was next utilized for the climate change study. The projected climate data from 10 different climate models under two emission scenarios were generated from downscaled CMIP5 model dataset. Each dataset containing future precipitation, maximum temperature, and minimum temperature were provided to the SWAT model to simulate the daily discharge from the outlets. The simulated flows at the outlet (USGS 03274000) were then analyzed separately for three future periods comprising an equal number of years. Subsequently, potential impacts of climate change on extreme flow regimes in terms of different flow parameters were calculated and compared with historical data.

The analysis projected that the climate change will significantly affect most of the low flows indices in Great Miami River. Significant differences were observed on the future scenarios for hydrological and biological low flows when compared to historical data. The average 7-day low flows were expected to increase by two folds during 2035s. However, results from different models were not consistent and the magnitude of low flows varied within each scenario.

Furthermore, the analysis indicated that September, October, and November would have a high number of low flows events. In general, simulation under high emission scenario (RCP 8.5) demonstrates a reduction in 7-day low flows after 2035s, whereas, under medium emission scenario (RCP 4.5), low flows increase slightly after 2035s until 2055s but eventually decrease around 2085s. From all climate models, there was slight fluctuation in low flows within the three periods, however, the difference in low flows with respect to historical data was substantially higher.

Results from this study indicate that some elements of climate including precipitation, which are provided by the CMIP5 models, are not enough to capture extreme weather events in a watershed scale because the spatial resolution of each climate projection model is 12km by 12km. It is also evident from the box plot of precipitation that the minimum precipitations in model outputs are comparatively higher than that of actual precipitations recorded in the historical time. This could be the main reason for increased simulated low flows in the river while using climate model output.

Similarly, the impact of climate change was assessed for high flows for the same periods. Results indicate an increase in the magnitude of the 50-year and the 100-year in the later part of the 21st century. However, peak flows are projected to reduce significantly in future when compared to the historical data. Both 7-day high flows and annual peak flow from an ensemble of 10 models in each period are projected to decrease. The analysis also shows that monthly peak flows from the months of July to October will increase. This reduction in high flows is probably due to the lack of a large number of extreme storm events in the downscaled climate output.

This study provides the foundation for the calculation of low flows and high flows and the awareness towards climate change models. However, extensive assessment of potential impacts due to climate change should be performed based on further bias corrected and downscaled climate models along with improved land use and soil data.