

**Assessing Hydrologic Vulnerability and Resilience of Critical Energy-Water
Infrastructures in a Changing Environment**

**A Dissertation Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville**

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December 2019**

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ACKNOWLEDGEMENTS

I express gratitude to my doctoral advisor, Dr. Shih-Chieh Kao, for his continuous guidance, support and encouragement throughout the Doctor of Philosophy program. His mentorship was not only crucial during the dissertation development, but also helped me grow as a research professional. I also thank my committee members Dr. Jon Hathaway, Dr. Forrest Hoffman, Dr. Ryan McManamay and Dr. John Schwartz for providing guidance and scientific inputs. I acknowledge several collaborators especially Dr. Bibi Naz, Dr. Moetasim Ashfaq and Deeksha Rastogi from Oak Ridge National Laboratory (ORNL), Dr. Benjamin Lee Preston from RAND Corporation, Dr. Alfred Kalyanapu and Tigstu Dullo from Tennessee Technological University, and Dr. Huilin Gao, Dr. Gang Zhao and Manqing Shao from Texas A&M University for sharing their scientific inputs, modeling tools, and/or required datasets to enable this research.

The studies that constitutes this doctoral dissertation were supported in parts by the US Department of Energy (DOE) Water Power Technologies Office, DOE Office of Science, Biological and Environment Research Program and U.S. Air Force Numerical Weather Modeling Program. I am also thankful for the Hydro Research Foundation Fellowship award that provided financial support for part of the work and networking opportunities with key industry partners. The research used resources of the Oak Ridge Leadership Computing Facility at ORNL.

ABSTRACT

Critical infrastructures, especially major hydropower reservoirs, play an important role in the energy-water nexus. These reservoirs are susceptible to evolving socio-environmental factors such as climate, urbanization, land use land cover (LULC) change, and population growth. This dissertation research, consists of four components, evaluates hydrologic vulnerability and resilience of such infrastructures in a changing environment through process-based hydrologic, hydraulic, and water management modeling frameworks for Alabama-Coosa-Tallapoosa (ACT) River Basin in the southeastern United States. The first component involves development of a high-resolution integrated hydro-meteorological framework consisting of Weather Research Forecasting (WRF) model and the distributed hydrology soil vegetation model (DHSVM) to assess probable maximum flood (PMF). The PMF, generally used as one of the design criteria for the critical infrastructures, is evaluated in a changing climate and its sensitivity to various factors such as meteorological forcing datasets, climate and LULC change, model parameters, and reservoir operation is assessed. The second component focuses on extending the above framework by incorporating a two-dimensional hydrodynamic model (Flood2D-GPU) to assess flood vulnerability through an ensemble-based approach. It enables development of probabilistic flood maps, providing additional information about probability of flooding in comparison with the flood maps obtained from the conventional deterministic PMF approach. The third component focuses on the generating ensemble future hydroclimate projections using a multi-model framework, including three process based hydrologic models (Precipitation Runoff Modeling System [PRMS], Variable Infiltration Capacity [VIC], and DHSVM) driven by 11 dynamically downscaled and bias-corrected Coupled Models Intercomparison Project phase 5 (CMIP5) Global Climate Models (GCMs) under historical and future climate scenarios. The ensemble projections are used to inform water resource managers regarding the hydrologic response in the region under future conditions and associated underlying uncertainties. The final component utilizes an integrated distributed hydrologic and water management model (DHSVM-Res) to evaluate the sensitivity of reservoir operations under various future scenarios including projected future water availability derived from an ensemble of dynamically downscaled CMIP5 model outputs, and hypothetical future water demand driven by increasing population projections. These studies inform the decision

makers about potential future risks and challenges associated with major reservoirs and their implications for water resources management.

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INTRODUCTION

Critical energy-water infrastructures such as hydropower reservoirs are crucial to meet the growing global water and energy demands (Moran et al., 2018). In the United States, hydropower constitutes 7 percent of annual electricity generation and has been one of the main providers of renewable energy (EIA, 2018). With the increase of more variable energy sources such as solar and wind, the operational flexibility of hydropower may provide further stability to the energy distribution grids (Tarroja et al., 2019). Additionally, most reservoirs are multi-purpose that provide the community a variety of benefits such as flood control, irrigation, municipal water supply, and recreational services besides hydropower. These infrastructures are capital intensive and usually have a long-life span of 50–100 years (Yüksel, 2010). However, most of these infrastructures were designed and constructed decades ago, during a time when we only had limited hydrometeorological observations and often assumed the natural variabilities to be statistically stationary. Considering the evolving socio-environmental factors such as climate, urbanization, land use land cover (LULC) change, and population growth, the vulnerability and resilience of these critical energy-water infrastructures in a changing environment deserve to be further evaluated.

From a hydrologic perspective, a changing climate is likely causing increases in temperature and air moisture holding capacity, modifications in precipitation volumes and variabilities, and intensified hydrologic cycles (Huntington, 2006). These variations can subsequent impact regional water availability at both seasonal and annual scales, increase frequency and intensity of extreme floods and droughts, and shift the timings of key hydrologic processes such as snowmelt and runoff generation (Barnett et al., 2005). The extreme flood events pose a direct physical threat to the safeguard of critical energy-water infrastructures (Wu et al., 2014). Dam failure under these circumstances could result in catastrophic damages and loss of human lives. On the other hand, droughts reduce water availability and challenge reservoirs to meet the competing water demands (Brekke et al., 2009) and minimum environmental/ecological flow requirements (Jager et al., 2018) through the current operation practice. Elevated temperatures can also cause enhanced evaporative losses from the reservoirs (Friedrich et al., 2018) and earlier snowmelt can result in untimely high streamflow that has serious implications for current reservoir operation and hydroelectric generation (Golombek et al., 2012). Additionally,

the stress on water resources is likely to further exacerbate under population growth and urbanization, resulting in increased water demands in the coming future (Duan et al., 2019).

In a changing environment, two important concerns for energy-water infrastructures include: 1) the elevated flood risks from intensified extreme flood events and, 2) operational resilience of current reservoirs to accommodate altered streamflow timing and variability. In this research, the vulnerability and resilience of key energy-water infrastructures is evaluated through a process-based hydrologic, hydraulic, and water management modeling framework. The research constitutes four components where the first component focuses on the development of a high-resolution hydro-meteorological modeling framework that can be used to assess extreme floods events and its sensitivity to various factors such as meteorological forcing datasets, climate change scenarios, LULC conditions, modeling parameters, and reservoir operation. The second component focuses on extending the above framework by incorporating a two-dimensional hydrodynamic flood model and assess flood vulnerability through ensemble-based approach to develop probabilistic flood maps to support decision making. The third component focuses on the development of high-resolution ensemble future hydroclimate projections using a multi-model framework to better represent different sources of underlying uncertainties. The final component utilizes the hydroclimate projections from the third study along with an integrated water management module to assess the robustness of current reservoir operation in a changing socio-climatic environment.

While the methodology and frameworks developed in this research are geographically transferrable, the proof of concept is demonstrated in the Alabama Coosa Tallapoosa (ACT) River Basin in the southeast United States. Apart from the need that the southeast United States is relatively underrepresented in existing hydroclimate impact assessments (Engström and Waylen, 2017), we select the ACT river basin also given its regional importance to water supply, hydropower generation, as well as flood risk management. The detailed description of each component is provided in later chapters and a brief summary is presented below:

1. Sensitivity of Probable Maximum Flood in a Changing Environment

The major hydropower reservoirs (and other critical infrastructures such as nuclear power plants) are typically designed to withstand the worst possible extreme flood events which are hypothetical yet physically plausible. Such adverse events are evaluated through the concepts of probable maximum precipitation (PMP) and flood (PMF). PMF occurs under a combination of

adverse hydro-meteorological conditions and is defined as “the largest flood that can reasonably be expected to occur at a given site” (United Nations, 1964; Cudworth, 1989). With likely increase of PMP in a changing climate (Rastogi et al., 2017), the critical infrastructures are subject to elevated risks. An integrated hydro-meteorological framework involving the Weather Research Forecasting (WRF) model and the Distributed Hydrologic Soil Vegetation Model (DHSVM) is developed to evaluate PMF in the ACT River Basin. A total of 120 relative humidity–maximized PMP storms under historic and projected future climate conditions are used to drive DHSVM in current and projected future LULC conditions. Multiple sensitivity tests are conducted by incorporating various factors such as meteorological forcing datasets, climate change scenarios, antecedent soil moisture contents, reservoir storage and LULC change to evaluate the sensitivity of PMF. The resulting ensemble of PMP and PMF simulations, along with their sensitivity, enable us to better quantify the potential risks associated with hydro-climatic extreme events to critical infrastructures for energy-water security.

2. Ensemble-based Flood Vulnerability Assessment for Probable Maximum Flood in a Changing Environment

This section evaluates flood vulnerability using an ensemble-based approach for PMF in a changing environment. The hydro-meteorological modeling framework (i.e., WRF and DHSVM) developed in Study 1 is extended by implementing a graphics processing unit (GPU)–accelerated 2-dimensional hydrodynamic model (Flood2D-GPU) to simulate the corresponding flood depth, velocity, and surface inundation area. Due to computationally expensive nature of hydrodynamic simulation, the study focuses on Etowah Watershed which is a sub-watershed within the ACT River Basin. A set of 120 PMF events are used to drive Flood2D-GPU to develop ensemble-based probabilistic flood maps based on best-available historic observations and future climate projections. These maps are compared with flood maps obtained from the conventional deterministic PMP/PMF approach to reveal added information regarding conditional probability of flooding. An application of these maps is demonstrated to examine the potential changes in the flood regime and its impacts on infrastructure/urban developments under projected future climate conditions. Additional sensitivity tests are conducted to explore the effects of various factors in the framework, such as meteorological forcing, antecedent hydrologic conditions, reservoir storage, and flood model input resolution and parameters. This approach provides ensemble-based information of key flood characteristics (including flood depth and duration), rather than the single

deterministic value obtained from the conventional approach. The ensemble-based method can better advise stakeholders regarding the probability and risk of inundation for a region of interest to enable well informed decisions.

3. Uncertainty quantification of future hydroclimate projections for water resource management

Hydroclimate projections are crucial information for water resource managers to inform future mitigation and adaption strategies for changing climate conditions and increasing water demands. However, hydroclimate projections are inevitably associated with a variety of uncertainties due to choices of climate and hydrologic models and other factors. To better understand the uncertainty of future hydroclimate projections, this section utilizes a high-resolution multi-model framework to assess the impacts of changing climate on water resources in the ACT river basin. An ensemble of hydrologic projections are generated using three distributed hydrologic models (Precipitation Runoff Modeling System [PRMS], Variable Infiltration Capacity [VIC], and DHSVM) driven by dynamically downscaled and bias-corrected future climate scenarios from 11 Coupled Models Intercomparison Project phase 5 (CMIP5) Global Climate Models (GCMs) under Representative Concentration Pathway (RCP) 8.5 emission scenario (Ashfaq et al., 2016). The hydroclimate projections are produced for 40-years in the baseline period (1966–2005) and 40 years in the future period (2011–2050). The hydroclimate responses are evaluated across various streamflow indices (high, low and seasonal flow) across various subbasins in ACT. The sources of uncertainties and relative contribution of climate and hydrologic models are disentangled using the analysis of variance (ANOVA) approach. The results from this section provide in-depth insights of hydroclimate uncertainties to support water resource managers identifying the main source of uncertainty to support well informed decisions.

4. Robustness of reservoir operation in a changing environment

A changing environment, resulting in non-stationary variations in precipitation and temperature, and a growing water demand owing to rapidly increasing population, is likely to stress the overall dynamics of current reservoir operation (Mateus et al., 2016). This section evaluates the robustness of current reservoir operation for selected major reservoirs in the ACT river basin under projected future hydroclimate conditions (from Study 3). A recently developed, integrated distributed hydrologic-reservoir model (DHSVM-Res), which includes the high-resolution DHSVM embedded with a multi-purpose reservoir module was implemented to study the dynamic

interaction between hydrologic variability and water demand. The DHSVM-Res is first calibrated to reproduce historic behavior of hydrologic parameters including reservoir storage, direct reservoir evaporation, and discharge. The sensitivity of reservoir operation under current operating rules is then evaluated against various future scenarios including 1) projected future water availability derived from an ensemble of dynamically downscaled CMIP5 meteorological forcings, and 2) hypothetical future water demands. This approach provides insights regarding the resilience of current reservoir operations in the southeastern US and implications for decision makers about potential future challenges.

CHAPTER I
SENSITIVITY OF PROBABLE MAXIMUM FLOOD IN A CHANGING
ENVIRONMENT

A version of this chapter was originally published as:

Gangrade, S., S.-C. Kao, B.S. Naz., D. Rastogi, M. Ashfaq, N. Singh, and B.L. Preston (2018), Sensitivity of probable maximum flood in a changing environment, *Water Resources Research*, 54(6), 3913-3936, doi:10.1029/2017WR021987.

Abstract

With likely increases in probable maximum precipitation (PMP) in a changing environment, critical infrastructures such as major reservoirs and nuclear power plants are subject to elevated risk. To understand how factors such as PMP variability, climate change, land use land cover (LULC) change, antecedent soil moisture conditions, and reservoir storage may individually or jointly affect the magnitude of probable maximum flood (PMF), integrated hydro-meteorological simulations were conducted involving both the Weather Research Forecasting model and the distributed hydrologic model (DHSVM) over the Alabama-Coosa-Tallapoosa (ACT) River Basin in the southeastern United States. A total of 120 relative humidity–maximized PMP storms under historic and projected future climate conditions were used to drive DHSVM in current and projected future LULC conditions. Overall, PMP and PMF are projected to increase significantly over the ACT River Basin. Sources of meteorological forcing data sets and climate change were found to be the most sensitive factors affecting PMF, followed by antecedent soil moisture, reservoir storage, and then LULC change. The ensemble of PMP and PMF simulations, along with their sensitivity, allows us to better quantify the potential risks associated with hydro-climatic extreme events to critical infrastructures for energy-water security.

1.1 Introduction

Flooding is a leading cause of weather-related deaths and damage to infrastructure globally (Das et al., 2011). Extreme flood events have shown an increasing trend in the United States over the past century (Pielke Jr and Downton, 2000) with direct flood damages of over \$7.96 billion per year and 82 fatalities per year during 1983–2014 (National Weather Service, 2016). For critical infrastructures such as major reservoirs and nuclear power plants, probable maximum precipitation (PMP) and flood (PMF) are the main concerns; and they have been used as design criteria by multiple US federal agencies, including the Bureau of Reclamation (Reclamation), US Army Corps of Engineers (USACE), Nuclear Regulatory Commission (NRC), and Federal Energy Regulatory Commission (England Jr., 2011; Hansen, 1987). While many studies demonstrate a likely projected increase of PMP in a warming environment (Kunkel et al., 2013; Beauchamp et al., 2013; Rousseau et al., 2014; Stratz and Hossain, 2014; Klein et al., 2016; Rastogi et al., 2017), the behavior of PMF remains uncertain. Given the severe consequences of critical infrastructure failure (e.g., the devastating August 1975 collapse of the Banqiao and Shimantan Dams [Si, 1997] and the Fukushima Daiichi Nuclear Power Plant incident [Chino et al., 2012]), understanding the sensitivity and reliability of PMF in a changing environment is of great importance to our energy-water security.

PMF occurs under a combination of adverse hydro-meteorological conditions and is defined as “the largest flood that can reasonably be expected to occur at a given site” (United Nations, 1964; Cudworth, 1989). PMF is mainly driven by PMP, which is the most extreme rainfall considered in hydrologic engineering (Reclamation, 2002; England Jr. et al., 2007). In addition, some hydrologic conditions, such as saturated antecedent soil moisture, high direct runoff, and rapid snowmelt, are assumed to occur concurrently to maximize flooding (e.g., Klein et al., 2016). In addition to providing riverine-scale PMF estimates that serve as an important criterion for the design of major dams, local-scale PMF driven by intense small area PMP is used to evaluate the ability of nuclear facilities to drain during critical events. *Given its extremely rare probability of occurrence (Shalaby, 1994; Chernet et al., 2014; Tofiq and Güven, 2015), the conventional probability-based flood frequency analysis procedure (e.g., Rao and Hamed, 2000) is unlikely to reasonably estimate PMF values.* A deterministic procedure generally involves PMP calculation, hydrologic rainfall-runoff modeling, and flood simulation.

The reliability of PMF calculation is largely dependent upon the reasonableness of the PMP, hydrologic models, and land surface conditions. PMP is defined as “theoretically the greatest depth of precipitation for a given duration that is physically possible over a given size of storm area” (Schreiner and Riedel, 1978; WMO, 2009). Among the various conventional PMP methods (see WMO, 2009; Hershfield, 1961, 1965; Hansen, 1987; Rakhecha and Singh, 2009), the most common approach is the storm moisture maximization, transposition, and envelopment method used in a series of US National Weather Service hydrometeorological reports (HMRs, e.g., HMR51 by Schreiner and Riedel, 1978). This method considers all historic storms that can be reasonably transpositioned to a site of interest, scales up the observed rainfall depth by maximizing the total precipitable water to its climatological maxima, and envelopes all maximized storms to get the deterministic upper bound (PMP) across various storm durations and areas. Multiple issues and criticisms have been raised regarding this conventional data-driven method, such as the approximation of total precipitable water using surface dew point temperature observations (Abbs, 1999; Chen and Bradley, 2006 and 2007), lack of uncertainty of PMP estimates (Micovic et al., 2015), linear assumption between the increase in precipitable water and rainfall depth (Rastogi et al., 2017), and reasonableness of a deterministic upper bound (Papalexiou and Koutsoyiannis, 2006). Some extreme storms were also reported to challenge HMR values (e.g., Hurricanes Floyd and Fran; Caldwell et al., [2011]), highlighting the need to update the conventional PMP estimates. While the World Meteorological Organization (WMO, 2009) stated that the PMP is derived “under modern meteorological conditions,” the subject of climate change was discussed comprehensively in Chapter 1.8 of WMO (2009). It suggested the likelihood that climate change may affect PMFs, and hence neglecting this change is not a reasonable option. Recent studies have started to use data from numerical weather forecasting models or regional climate models to estimate PMP (Ohara et al., 2011; Ishida et al., 2014 and 2015; Tan, 2010; Beauchamp et al., 2013; Rousseau et al., 2014; Klein et al., 2016; Rouhani and Leconte, 2016; Chen and Hossain, 2016; Rastogi et al., 2017), as well as to test how land use land cover (LULC) change may influence extreme precipitation (Woldemichael et al., 2012 and 2014). Rastogi et al. (2017) provides further discussion regarding issues related to PMP.

Nevertheless, although the reevaluation of PMP has received increasing attention in the past decade, issues specific to the estimation of PMF are less emphasized. For instance, how will rapid urbanization affect PMF, and how can we evaluate PMF in a stochastic manner? Although

various sophisticated methods have been developed for PMP, in practice, often a simple rainfall runoff model or unit hydrograph-based method is used to estimate PMF (England Jr. et al., 2007), such as HEC-1 (HEC, 1998), HEC-HMS (Feldman, 2000), and the Flood Hydrograph and Runoff model (Reclamation, 1990). While such conventional models may provide reasonable estimates of runoff and streamflow, they do not incorporate sufficient physical processes to address the effects of urbanization and changes in LULC or to capture the spatiotemporal variability of storms. Recent efforts have started to use process-based hydrologic models to study extreme floods (with annual exceedance probabilities of less than 10^{-4}) and PMFs, such as the Two-dimensional, Runoff, Erosion, and Export model by England Jr. et al. (2007 and 2014). Yigzaw and Hossain (2016) used the Variable Infiltration Capacity model (VIC; Liang et al., 1994) to evaluate the combined impact of a modified PMP on PMF and sediment yield. Chen et al. (2016) used the Watershed Environmental Hydrology model (Kavvas et al., 2004) to study the joint effects of PMP and snowmelt on PMF. Beauchamp et al. (2013) used the HSAMI hydrological model (Fortin, 2000) to simulate summer–fall PMF in Quebec, Canada, under projected future climate conditions. Jothityangkoon et al. (2013) used a distributed rainfall-runoff model to estimate the effects of both climate and LULC changes on PMF for the Upper Ping River in northern Thailand. Moving forward, integrated assessments considering multiple controlling factors (e.g., PMP scenarios, LULC, reservoir operation) will be beneficial for a heuristic understanding of future PMF.

In this study, I use an ensemble-based approach to quantify the uncertainty and sensitivity of PMF in a changing environment using integrated, physically based hydro-meteorological models over the Alabama–Coosa–Tallapoosa (ACT) River Basin in the Southeastern United States. The basin includes 15 large dams owned and operated by the USACE and Alabama Power Company and suburban areas of Atlanta (Kennesaw and Marietta), Georgia, and Birmingham, Montgomery, and Mobile, Alabama, which can benefit from the careful study of potential future impacts of PMF in the region. The PMF was simulated by the high-resolution Distributed Hydrologic Soil Vegetation Model (DHSVM; Wigmosta et al., 1994) for 120 PMP storms from Rastogi et al. (2017) that were simulated by the Weather Research Forecasting model (WRF; Skamarock et al., 2008), driven by both reanalysis and climate projection forcings. To improve the efficiency of DHSVM over a large scale and high resolution, parallel algorithms for the simultaneous computation of loosely coupled units (subbasins, in this case) were implemented. DHSVM can utilize high-resolution grid-based precipitation input and thus enables the

incorporation of spatiotemporal movement of storms. The main objectives of this study include testing the effects of climate change on PMF in the future and testing the sensitivity of PMF to climate and LULC change scenarios, antecedent watershed conditions, and compulsive approaches to drive hydrologic models. Because of the geographical location of the study area, the effects of snowmelt on PMF were not considered. Nevertheless, snowmelt is a dominant factor for watersheds with significant snowpack (e.g., Chen et al., 2016; Klein et al., 2016; Clavet-Gaumont et al., 2017).

This paper is structured as follows: Section 1.2 introduces the overall method, data, and study area; Section 1.3 illustrates and describes results; and Section 1.4 presents a summary and the conclusion of this study.

1.2 Methods

1.2.1 Study Area

The study area is the ACT River Basin that spans the northeastern and east-central parts of Alabama, northwestern Georgia, and small parts of Tennessee with an approximate drainage area of 59,100 km² (22,800 mi²; Figure 1.1, *Note: The tables and figures referred in this dissertation are located in Appendix at the end of this document*). The ACT basin is a four-digit hydrologic unit (HUC04) and consists of 14 eight-digit hydrologic units (HUC08). The topography of the ACT basin is relatively flat with a small mountainous region in the north. The elevation ranges from sea level to 1,278 m (4,193 ft), based on the United States Geological Survey (USGS) National Elevation Dataset (NED; Gesch et al., 2002). The soil types are mainly sandy loam and silty loam. The climate of ACT can be classified as humid subtropical, characterized by hot, humid summers and cool winters. It receives an average annual precipitation of 1,364 mm (53.7 inch) occurring throughout the year, predominantly as rainfall; light snow is received in the northern part of the basin. More than half of the basin consists of forested area with total evapotranspiration ranging from 762 to 1,067 mm (30–42 inches) per year, which is approximately 56–78% of the annual mean precipitation. There are 15 large dams in the ACT, mainly owned and operated by the USACE and Alabama Power Company. The major urban areas in the ACT include suburban areas of Atlanta (Kennesaw and Marietta), Georgia, and Birmingham, Montgomery, and Mobile, Alabama (USACE, 2013).

1.2.2 *Simulation of PMP*

An ensemble of 120 moisture-maximized storms was obtained from Rastogi et al. (2017). PMP was simulated using WRF version 3.6, a mesoscale numerical weather model, running with a double two-way nested domain at 9 km and 3 km horizontal spacing (WRF domain is shown in Figure 1.1). Both Climate Forecast System Reanalysis I (CFSR; Saha et al., 2010) and Community Climate System Model version 4 (CCSM4; Gent et al., 2011) were used as boundary forcings for WRF simulation. The storms include four sets:

- (1) **CFSR-CT**: Controlled simulation that includes the 30 largest historic storms during the 1981–2011 historic period driven by CFSR reanalysis. The largest historic storms were identified by sorting the 3-day (72 h) precipitation total calculated within the WRF inner domain (30.5°N–35.5°N and 84.5°W–88.5°W) encompassing the ACT River Basin.
- (2) **CCSM4-BL**: Baseline simulation that includes the 30 largest storms driven by both 1981–2005 in the historical period and 2006–2010 in a future period under an RCP8.5 scenario of CCSM4 experiments.
- (3) **CCSM4-F1**: Near-future simulation that includes the 30 largest storms driven by the 2021–2050 CCSM4 projection under an RCP8.5 scenario.
- (4) **CCSM4-F2**: Far-future simulation that includes the 30 largest storms driven by the 2071–2100 CCSM4 projection under an RCP 8.5 scenario.

Both Oregon State University's PRISM (Daly et al., 2008) and Oak Ridge National Laboratory's (ORNL) Daymet (Thornton et al., 1997) gridded precipitation data sets were used to evaluate the performance of the WRF simulation and to select the most appropriate parameterization scheme. CCSM4 was selected based on multi-model diagnostics as well as recommendations from recent literature (Rupp, 2016; Liu et al., 2013; Yoo et al., 2016). The Relative Humidity Maximization method (RHM; Ohara et al., 2011; Ishida et al., 2015) that adjusts relative humidity in the boundary conditions of the entire atmospheric column to 100% (i.e., fully saturated) was then used to simulate moisture-maximized storms to derive PMP. In addition, conventional PMP rainfall estimates were obtained using HMR51 and HMR52 to provide a reference and enable comparison with modeling-based results. For further technical details, see Rastogi et al. (2017).

In practice, after a deterministic PMP depth is chosen for a site of interest (e.g., from HMR51), additional steps (e.g., HMR52; USACE, 1984) are needed to convert the depth-area-

duration table into a spatiotemporal storm hyetograph as input for a hydrologic simulation. To avoid this simplification and to better reflect the structure of each storm, I have used the spatial hourly storm grids of each storm for hydrologic simulation directly. In other words, an ensemble hydrologic simulation was performed for all moisture-maximized storms to identify the most critical PMF event, instead of relying on one deterministic event based on the synthetic hyetograph. This ensemble-based approach can better capture the structure of each storm and help us understand the uncertainty associated with PMP.

1.2.3 Hydrologic Model

Distributed Hydrology Soil Vegetation Model (DHSVM)

The high-resolution, process-based distributed hydrologic model DHSVM (Wigmosta et al., 1994) was used to simulate streamflow in the ACT River Basin. DHSVM computes mass (water) and energy balance at each grid cell and accounts for hydrological processes such as evapotranspiration, snowmelt, canopy snow interception and release, soil moisture, subsurface flow, overland flow, and channel flow. Cuo et al. (2008) incorporated parameterization to simulate urban hydrological processes using parameters such as impervious area fraction, detention storage, and detention decay rate. This enhancement enabled DHSVM to capture the increased streamflow due to urbanization. The spatially distributed parameters include topography, soil, and vegetation. The model is driven using a set of meteorological inputs that includes precipitation, shortwave and longwave radiation, relative humidity, wind speed, and air temperature. A detailed description of DHSVM can be found in Wigmosta et al. (1994 and 2002) and Storck et al. (1998). Previous studies have demonstrated the applicability of DHSVM to studying the impacts of urbanization and climate change on future streamflow (Cuo et al., 2009; Safeeq and Fares, 2012). The DHSVM was selected for its ability to perform high-resolution modeling and to generate future projections under climate and LULC change scenarios.

DHSVM was setup at a fine 90-m horizontal resolution at 3-h time steps from 1980 to 2012, using 1980 for model spin-up. A 90-m resolution digital elevation model (DEM) was resampled from the 30-m resolution NED for ACT. DHSVM uses the DEM as the base map and requires other input data sets, including soil depth, soil type, and LULC type, at the same resolution of DEM. The river network from the National Hydrography Dataset Plus (McKay et al., 2012) was used for accurate representation of streams in the study area. Soil features were obtained from a multilayer contiguous US soil characteristics data set (Miller and White, 1998) that was derived

from the State Soil Geographic Database (Schwarz and Alexander, 1995). A dominant soil texture type was determined for every grid cell; and a set of soil-hydraulic properties such as porosity, hydraulic conductivity, wilting point, bubbling pressure, and field capacity were assigned to every soil texture type (Maidment, 1993). Subsequent adjustments to key soil parameters were made during the model calibration (described in a later section). The LULC maps were obtained from the USGS National Land Cover Database 2006 (NLCD; Fry et al., 2011). A set of vegetation properties including leaf area index, albedo, stomatal resistance, moisture threshold, and fractional coverage were assigned to every land cover type. Both LULC type and soil classification are shown as examples in Figure 1.2a and 1.2b.

DHSVM Parallelization

Given the large study area (over 59,100 km²) and fine spatial resolution (90 m), there are ~20 million grid cells; this number makes the conventional single-core DHSVM setup inefficient. To overcome such computational challenges in large-scale hydrologic simulations, general methods such as loosely coupled partitioning (Wang et al., 2011) and temporal-spatial discretization (Wang et al., 2013) have been proposed. In this study, I used temporal-spatial discretization (Wang et al., 2013), which partitions the entire simulation by space and time. This discretization allows large-scale hydrologic simulations to be divided into smaller and more manageable tasks and allows the incorporation of cluster computers to conduct these simulations simultaneously.

The first step in this technique involves spatial discretization of the basin by watersheds. The 14 ACT HUC08s were further divided into the 29 computing units shown in Figures 2c and 2d. The computing units were hydraulically linked so that each downstream unit could receive inflow from its connecting upstream unit(s). The spatial discretization was conducted so that it created minimum interactions between units. Each computing unit was then assigned an order number based on a hierarchy (from upstream to downstream, Figure 1.2d). An optimal discretization would involve fewer layers and similar drainage areas of computing units. A comparison of the parallelized DHSVM results with the single-core DHSVM results revealed that the streamflow hydrographs obtained from both approaches are almost identical, ensuring that no numerical error was introduced during parallelization.

For the complete 1981–2012 historical simulation (i.e., DHSVM driven by Daymet for the purpose of calibration and validation), the total simulation period of 33 years was discretized into

396 temporal units (one for each month). The simulation started by simulating the first temporal unit in the most upstream spatial unit. After the results were obtained and passed to the downstream spatial units, parallel simulations were performed, with upstream units calculating the next temporal unit and downstream units calculating the previous temporal unit. The process continued until the most downstream spatial unit calculated the final temporal unit. This algorithm enabled long-term and large-scale hydrologic simulation in a more efficient way, which is of particular importance for the calibration and validation of a computationally intensive model such as DHSVM.

Calibration and Validation

In this study, DHSVM calibration was performed individually for each of the 14 HUC08s. To generate meteorological forcing for the 1981–2012 historic simulation, daily precipitation and maximum and minimum temperatures were obtained from Daymet. The daily precipitation and maximum / minimum temperature were used to generate sub-daily incoming shortwave radiation and humidity using the MTCLIM algorithms (Kimball et al., 1997; Thornton and Running 1999). The sub-daily temperature values were calculated by interpolation of minimum and maximum air temperature time series. The humidity and temperature values were then used to infer longwave radiation values. A detailed description of these algorithms is presented in Bohn et al., (2013), Cuo et al., (2009), Thornton et al., (2000), and Prata (1996). In addition, the daily precipitation data were disaggregated uniformly into 3-h time steps as DHSVM radar rainfall inputs at 4-km resolution.

Calibration was performed by comparing simulated with observed streamflow at various USGS gauge locations. It involved three stages: (1) minimizing the absolute percentage bias (PBIAS; Moriasi et al., 2007), (2) maximizing the Nash-Sutcliffe Efficiency coefficient (NSE) and correlation coefficient (ρ), and (3) inspecting hydrographs. The initial soil and vegetation parameters were obtained from observed data sets and previous literatures. To determine parameter sensitivity to streamflow, a sensitivity analysis was carried out at one HUC08 by testing key parameters suggested in previous studies (Du et al., 2014; Kelleher et al., 2015). The saturated lateral hydraulic conductivity and its exponential decrease with depth were found to be the two most sensitive parameters. Other sensitive parameters included porosity, field capacity, overstory leaf area index, overstory fractional coverage, and moisture threshold. The calibration process was performed on cluster computers using a parallel computing algorithm described in the previous

section. Multiple simulations with a range of parameters (suggested by Kelleher et al., [2015] and the DHSVM website) were conducted to identify suitable parameters in each HUC08. The calibrated DHSVM was then used to simulate the PMF for each PMP storm.

1.2.4 Simulation of PMF

Given the smooth topography in the ACT region, a local intense storm that occurs in one location could also occur in other parts of the region. In other words, storms in ACT can generally be considered meteorologically transpositionable (similar concepts were also used in HMRs and England Jr. et al., [2014]). Therefore, to identify the most critical PMP input for a watershed of interest (e.g., a sub-watershed within ACT), the most intense portion of a storm must be identified and transpositioned. As a result, depending on the size and shape of a selected watershed, the transpositioned PMP storm inputs may be different. To focus the discussion, I selected four specific watersheds (Figure 1.1 and Table 1.1) for PMF simulation, including Buck Creek (A1), Conasauga (A2), Cahaba (A3), and the entire ACT (A4). Watersheds A1–A3 were selected primarily because of their geographic locations, which are relatively free of the presence of reservoirs and include urban areas where flooding may result in more significant impacts. The varying watershed sizes also allowed to study the effects of drainage area on PMF.

For each watershed (A1–A4) and for each of the 120 moisture-maximized storms from Rastogi et al. (2017), the most intense storm portion that would result in the largest 72-h average precipitation in each watershed was identified and transpositioned. The transpositioned WRF precipitation from Rastogi et al. (2017) was re-gridded to the same 4 km DHSVM radar rainfall format used for DHSVM calibration and validation. Given that WRF provided shortwave and longwave radiation, humidity, and other required DHSVM meteorological inputs, forcing disaggregation was not required.

1.2.5 Meteorological Sequence

Figure 1.3 illustrates the meteorological sequence used in this study. Following the NRC guidelines (Prasad et al., 2011), a meteorological sequence that included 40% of PMP in the first 72 h (antecedent precipitation—part A), followed by 72 h of no precipitation (part B), and then 72 h of full PMP (critical precipitation—part C) was used as the default setup to simulate PMF in each watershed (Figure 1.3). A meteorological sequence used by Beauchamp et al. (2013) that included 50% of PMP in the first 72 h, followed by 144 h of no precipitation, and then 72 h of full PMP was also compared in the sensitivity analysis. The simulation was continued for another 6

days (part D) to ensure the capture of peak flood hydrographs. PMF was eventually calculated from the ensemble of simulated DHSVM streamflow for each set of storms (CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2).

To compare the results with conventional PMF, PMP rainfall inputs were also calculated for watersheds A1–A4 using HMR51 and HMR52. The 72-h HMR PMP hyetograph was computed using a critically stacked temporal pattern, which was used to drive the DHSVM simulation. The critically stacked pattern allowed the occurrence of PMP for all durations (e.g., 1, 6, 12, 24, 48, 72 h) within a single storm of 72-h duration to generate a high-intensity storm (HMR52).

1.2.6 Future LULC Scenario

The projected LULC scenario for year 2030 was estimated using cellular automata (CA). The CA is a dynamic model that can be used to simulate the evolution of a wide variety of natural and human systems. CA has five basic components: (1) a grid tessellation on which the model acts, (2) a collection of cell states, (3) a neighborhood that influences the state of the central cell, (4) transition rules that determine the dynamics of the system, and (5) discrete time steps (Von Neumann, 1966). The CA models can reproduce complex global patterns and behaviors by simulating local interactions among individual cells (Wolfram, 1984). They are increasingly used for modeling various spatial phenomena, including LULC changes (e.g., Mitsova et al., 2011).

The NLCD LULC change from year 2001 to year 2011 was analyzed to estimate the transition probability matrix and transition areas matrix. The transition probability matrix recorded the probability of each land cover category to change, and the transition areas matrix recorded the number of pixels that were expected to change. Based on these probabilities, 2030 LULC was projected and a set of conditional probability images were created (not shown here), which report the probability of each land cover type at each pixel after the specified number of years (19 in our case, for projection from 2011 to 2030). The projected LULC was then converted to DHSVM parameters for sensitivity analysis.

Ideal Reservoir Operation

Since DHSVM in this study did not incorporate the rule-based reservoir operation module (e.g., Zhao et al., 2016), an ad hoc correction was performed after the DHSVM simulation to mimic the most ideal reservoir operation on PMF. This correction involved adjusting the PMF hydrograph immediately downstream of each reservoir location by subtracting a water volume equivalent to

the maximum storage capacity of the respective reservoir from the peak portion of the respective PMF hydrograph (i.e., using the full capacity to reduce peak discharge). This correction provided a maximum allowable impairment of PMF under a best-case ideal flood management scenario, which assumed a perfect PMF prediction and completely empty reservoirs at the beginning of the PMF event. It also assumed perfect coordination among all major reservoirs in the ACT River Basin. While actual operation will be different and more complex, this assessment can aid understanding of the maximum PMF retention capacity of the existing reservoirs.

1.3 Results and Discussion

1.3.1 DHSVM Performance

The calibration and validation were performed using 74 USGS gauges across the entire ACT (Table 1.2 and Figure 1.4). The periods of calibration and validation varied for each station depending on data availability (Table 1.2). A spatially split sample method (Pereira et al., 2016) was employed to calibrate DHSVM using 29 gauges and validate using 45 gauges. At least one calibration gauge, located near the watershed outlet, was selected to provide long-term observation in each HUC08. The calibration process started from the most upstream HUC08s. Once calibrated, the DHSVM outflow from each upstream HUC08 was passed downstream using a revised DHSVM routing algorithm, described by Zhao et al. (2016), that allows coupling of DHSVM simulations on connected watersheds. Table 1.2 summarizes statistics such as monthly and daily NSE, correlation coefficient (ρ), and PBIAS at each gauge. The monthly and daily NSE of each gauge is also illustrated in Figure 1.4. Of 29 USGS calibration gauges, roughly 90% of the gauges had NSEs greater than 0.6 at daily and monthly time scales. Of the validation gauges, roughly 56% and 82% had NSEs greater than 0.6 at daily and monthly time scales, respectively.

For the four selected watersheds (A1–A4), the simulated versus observed daily streamflow hydrographs at gauges closest to watershed outlets are presented in Figure 1.5. Their performance values are summarized as follows:

- Watershed A1 (USGS02413300) – $NSE_{daily} = 0.77$, $\rho_{daily} = 0.91$, $PBIAS = -7.3\%$
- Watershed A2 (USGS02387000) – $NSE_{daily} = 0.81$, $\rho_{daily} = 0.90$, $PBIAS = 2.2\%$
- Watershed A3 (USGS02425000) – $NSE_{daily} = 0.76$, $\rho_{daily} = 0.91$, $PBIAS = -6.7\%$
- Watershed A4 (USGS02428400) – $NSE_{daily} = 0.77$, $\rho_{daily} = 0.92$, $PBIAS = -5.9\%$

Note that the DHSVM reservoir operation module (e.g., Zhao et al., 2016) was not incorporated in this study. Therefore, the performance of a few USGS gauges, which are located immediately downstream of major reservoirs, was generally poor. Nevertheless, given the relatively smaller reservoir size in the southeastern United States (as opposed to the much larger reservoirs in the western United States), the effect of regulation by reservoirs on the historic hydrograph tended to dissipate quickly further downstream. Based on the results from Figures 4 and 5 and Table 1.2, an overall satisfactory DHSVM performance during 1981–2012 was observed.

1.3.2 Ensemble PMF Hydrographs

Figure 1.6 presents 3-h DHSVM streamflow hydrographs at the outlets of four watersheds for a total of 120 storms in 4 storm sets (i.e., CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2). In each set, the event resulting in the largest peak discharge is marked in a thick line. The peak discharge values of these events are also summarized as box plots in Figure 1.7.

Consistent with the large variability of PMP depth, as discussed by Rastogi et al. (2017), significant variability in DHSVM peak discharge was found. Additionally, the different spatiotemporal structures of the rainfall in each storm greatly affected other hydrograph features, such as timing of the peak and the shape of the hydrograph. While peak discharge is of the greatest importance for a site of interest, timing of the peak and the total peak volume are also important parameters to consider in designing hydraulic structures and preparing mitigation strategies. Largely influenced by the prescribed temporal distribution to produce a PMP hyetograph (following the HMR51 and HMR52 guidance), such variabilities in hydrograph shape and timing are typically more fixed in the conventional approach. The results show that these storm-specific features do affect hydrograph shape and timing and thus may provide a wider range of scenarios for consideration.

The hydrograph response simulated by distributed hydrologic models was significantly influenced by many factors, including the heterogeneity of hydrologic variables such as soil moisture and spatiotemporal rainfall distribution. Many previous studies have established that the shape, timing, and peak flow magnitudes of a hydrograph are largely dependent on the spatiotemporal variability of rainfall (Singh, 1997; Máca and Torfs, 2009). Zhao et al. (2013) found that ignoring spatial rainfall variability resulted in the underestimation of total streamflow volume for a given rainfall total in their study area.

To further illustrate this relationship for DHSVM, Figure 1.8(a) presents a scatter plot showing average 72-h cumulative rainfall depths and peak discharges from PMF hydrographs at watershed A1 for all 120 simulations. Although a high correlation between peak discharge and rainfall depth can be seen, spatiotemporal rainfall distribution also had a non-negligible effect. Two specific cases are further illustrated in Figure 1.8(b). Both cases have a similar magnitude of cumulative 72-h precipitation (Case 1 – 755.1 mm and Case 2 – 761.6 mm), but their streamflow responds differently, with peak values of 1839 m³/s and 718.5 m³/s in Case 1 and 2, respectively. These results demonstrate that a significant variation in the PMF due to spatiotemporal rainfall distribution is possible and highlight the benefit of using high-resolution distributed precipitation for PMF simulation. They also signify the benefits of using an ensemble-based approach and a distributed hydrologic model to estimate PMFs; such an approach can capture the effects of spatiotemporal distribution of rainfall that the simple lumped hydrologic models may not be able to capture.

1.3.3 Sensitivity of PMF

To explore and compare the sensitivity of PMF to various factors such as climate change scenario, LULC change, choice of meteorological forcing dataset, antecedent soil moisture condition, meteorological sequence, and reservoir operation, a set of sensitivity tests were performed. Six sets of sensitivity experiments (S2–S7) were conducted for each watershed (A1–A4) by changing one factor at a time and the results were compared with the baseline simulation (S1). The experiments included these:

- (1) **Scenario 1—baseline simulation (S1):** A set of 30 PMF simulations for each study area (A1–A4) using PMP driven by baseline CCSM4 forcings (CCSM4-BL), the default meteorological sequence (Figure 1.3), and year 2006 NLCD LULC.
- (2) **Scenario 2—alternative meteorological forcing (S2):**
 - S2-a:** A set of 30 PMF simulations for each study area (A1–A4) using PMP driven by the CFSR reanalysis forcing (CFSR-CT).
 - S2-b:** One PMF simulation for each study area (A1–A4) using HMR-based conventional PMP forcing (HMR).
- (3) **Scenario 3—climate change scenario (S3):**
 - S3-a:** A set of 30 PMF simulations for each study area (A1–A4) using PMP driven by 2021–2050 near-future CCSM4 climate forcing (CCSM4-F1).

S3-b: A set of 30 PMF simulations for each study area (A1–A4) using PMP driven by 2071–2100 far-future CCSM4 climate forcing (CCSM4-F2).

(4) **Scenario 4—LULC change (S4):** A set of 30 PMF simulations for each study area (A1–A4) using projected LULC at year 2030 and CCSM4-BL forcing.

(5) **Scenario 5—meteorological sequence (S5):** A set of 30 PMF simulations for each study area (A1–A4) using the Beauchamp et al. (2013) meteorological sequence that includes 50% PMP in the first 72 h (part A), followed by 144 h of no rainfall (part B), and then 72 h full PMP (part C). The PMF simulations were obtained using CCSM4-BL forcing.

(6) **Scenario 6—antecedent soil moisture:** A set of 30 PMF simulations for each study area (A1–A4) initiated with fully saturated soil moisture conditions at different timings.

S6-a: S1 with saturated soil moisture specified at the beginning of part A.

S6-b: S1 without meteorological sequence part A, saturated soil moisture specified at the beginning of part B.

S6-c: S5 without meteorological sequence part A, saturated soil moisture specified at the beginning of part B.

S6-d: S1 without meteorological sequence parts A and B, saturated soil moisture specified at the beginning of part C.

(7) **Scenario 7—reservoir operation (S7):** One PMF simulation for watershed A4 adjusted to reflect ideal reservoir operation.

The percentage change in the peak discharge at the outlet of each watershed (for each scenario with respect to S1) is summarized in Figure 1.9 and discussed in the following sections. S7 is applicable only in Watershed A4, as no major reservoir is presented in watersheds A1–A3.

Effects of Meteorological Forcing Sources (S2-a and S2-b)

Figure 1.10 presents a comparison among the largest events driven by CFSR-CT, CCSM4-BL, and conventional HMR for each watershed. Figures 1.9 and 1.10 suggest that peak discharges for all three cases (S1, S2-a and S2-b) are relatively comparable in magnitude for watershed A1, in which CFSR-CT produces the maximum peak discharge (1,646 m³/sec), followed by CCSM4-BL (1,561 m³/sec) and HMR (1,412 m³/sec). However, with an increase in watershed area, PMFs from CFSR-CT and CCSM4-BL become significantly higher than the HMR-based results, especially in watersheds A2 and A4. Similarly, the controlling event of CFSR-CT demonstrates a significantly higher peak discharge compared with the controlling event of CCSM4-BL. For watersheds A3 and

A4, the CFSR-CT peak discharge is almost twice the magnitude (+92.6% and +90.8% for watersheds A3 and A4, respectively) than CCSM4-BL (S2a in Figure 1.9).

This difference can mainly be attributed to the differences in PMP. As the PMPs simulated by WRF using CFSR-CT forcing were higher than the HMR PMPs, the effect was observed in the corresponding PMF as well. Overall, the possible reasons for high PMP estimates for CFSR-CT compared with those for a conventional approach include (a) the CFSR-CT storms being generally wetter than CCSM4-BL storms even before moisture maximization, (b) the modeling bias of both CFSR-CT and CCSM4-BL, (c) differences in the assumption of a linear relationship between change in precipitable water and change in rainfall depth, and (d) differences in the estimation of storm precipitable water between a conventional and a model-based (WRF) approach. A recent global precipitation inter-comparison study by Sun et al. (2018) compared more than 15 different precipitation datasets (including CFSR and other observations and reanalysis) and showed that CFSR is the wettest among all. Another study by Higgins et al. (2010) also showed that the summer CFSR precipitation is higher than observed precipitation. The high CFSR precipitation would suggest that PMP driven by CFSR may also be higher, and eventually results in the large difference between CCSM4-BL and CFSR-CT.

The results of scenario S2 suggest that there is high sensitivity related to the use of different meteorological forcing datasets, so the PMF simulation and decision should not rely on only one specific forcing dataset. However, recommendation about relative skillfulness of different datasets and/or models requires rigorous testing, which is beyond the scope of this study. Readers may see Rastogi et al. (2017) for further discussion regarding the uncertainty associated with PMP simulation, as well as the issue of linear assumption between change in precipitable water and change in rainfall depth in the conventional PMP assessment.

Effects of Climate Change (S3-a and S3-b)

The effects of climate change on PMF were examined by comparing the peak DHSVM hydrographs from future time periods (CCSM4-F1, 2021–2050; CCSM4-F2, 2071–2100) with respect to the baseline period (CCSM4-BL, 1981–2010) in Figure 1.11. Under the near-future climate scenario, an increase in peak discharge is observed for all four areas. The projected peak discharge in the near-future period increases by +37.9%, +7.6%, +42.0%, and +17.7%, respectively, for watersheds A1–A4 with respect to their corresponding baseline values. Under the far-future climate scenario, a further increase in PMF is observed for all four watersheds. The

PMFs increase significantly with respect to baseline values by +80.3%, +87.4%, +146.5%, and +68.7% for watersheds A1–A4 (Figure 1.9).

The significant increase in PMFs under climate change scenarios can be attributed to a large increase in projected PMPs in the near- and far-future periods. The far-future climate scenario projects a greater increase in PMPs due to stronger atmospheric warming and intensification of the hydrological cycle caused by a stronger increase in radiative forcing. These results highlight that accounting for the effects of a changing environment on PMF estimates is important from the perspective of infrastructure design; these effects are currently not captured by conventional PMP and PMF estimates. A similar issue is highlighted by another study that uses an ensemble of regional climate models to estimate PMF in a changing climate in five Canadian basins; it demonstrated a potential for increases in PMF in the range of –1.5% to +21.0% (Clavet-Gaumont et al., 2017).

Effects of LULC Change (S4)

LULC change is an integral part of a dynamic watershed, especially within an urban environment. Changes in LULC, such as increases in developed areas and reductions in forest cover, can alter the hydrologic response of a watershed. Using the method and data described in Section 1.2.6, Table 1.3 summarizes different land use category distributions for the years 2006 (observed) and 2030 (projected) for each watershed (A1–A4). In general, the developed, shrubland, grassland, and crop areas are projected to increase, and forest areas are projected to decrease, which suggests a potential loss of precipitation abstraction. Correspondingly, the projected LULC change results in an increase in PMF peak discharge by +5.23%, +1.27%, +1.90%, and +1.11% for watersheds A1 through A4 (Figure 1.9). The maximum sensitivity of LULC change is observed for watershed A1, compared with the larger watersheds A2–A4. Although this study accounts for only the effect of urbanization on hydrology, other studies raise the question whether LULC changes can also alter the governing storms (i.e., the PMP) for a given region via positive climate feedbacks (Yigzaw et al., 2012; Woldemichael et al., 2012).

Effects of Meteorological Sequence and Antecedent Soil Moisture (S5, S6-a to S6-d)

Rain events occurring before critical PMP storms (i.e., antecedent storms) can significantly raise the antecedent soil moisture content and result in enhanced maximum flooding (Zurndorfer et al., 1986). Various meteorologic sequences thus have been proposed to estimate PMF, depending on the catchment area and storm duration (Newton, 1983). To understand its sensitivity,

the effects of two different meteorological sequences that are used in practice (S1 and S5) were compared. As illustrated by Figure 1.9, watersheds A1 through A4 show slight differences of -0.02% , $+0.1\%$, $+2.1\%$, and $+0.9\%$ in the peak discharge. The results demonstrate that meteorological sequence itself is a less sensitive factor.

However, considering that the main purpose of the meteorological sequence is to increase the antecedent moisture in the watershed to maximize flooding, a different approach was also tested to directly maximize soil moisture within DHSVM (not achievable through the conventional lumped hydrologic models). Four different scenarios (S6-a to S6-d) were designed to directly enforce saturated soil moisture conditions at different stages of PMF simulation. The results shown in Figure 1.9 demonstrate that all experiments within Scenario S6 produce an increase in the PMF magnitude across all watersheds. In the case of scenario S6a, watersheds A1 through A4 show increases in PMF magnitude of $+7.8\%$, $+3.9\%$, $+32.8\%$, and $+52.1\%$, respectively. Similar behavior is observed in experiments 6b through 6d. These results indicate that antecedent soil moisture can play a significant role in the magnitude of PMF and using fully saturated soil conditions vs. fully unsaturated soil conditions can increase the PMF by $+52.1\%$ in ACT. Although conventional meteorologic sequences (S1 and S5) can increase the antecedent moisture in the watersheds, they seem to have an inconsistent effect depending on the size of the watershed (e.g., smaller A1 and A2 vs. larger A3 and A4). This inconsistency can be explained by the nature of the meteorologic sequence approach that uses a fixed ratio of PMP (40% or 50%) as the antecedent storms. Considering that the magnitude of PMP is higher in a more concentrated area (i.e., the depth-area-duration characteristic of PMP), the total depth of antecedent storms is higher in smaller watersheds (A1 and A2), so their antecedent soil moisture can be raised closer to full saturation (S6). For larger watersheds (A3 and A4), the antecedent storm depth is relatively weaker, so the soil moisture content may still be far from full saturation in the model. It is important to note that not every hydrologic model in practice can allow users to adjust soil moisture directly, so there is a need to revisit the reasonableness of meteorological sequence for larger watersheds.

Effects of Reservoir Operation

The presence of reservoirs in a basin can alter the natural runoff and streamflow and can impair PMF as well. Figure 1.12 presents the effect of a hypothetical regulation of PMF under the best-case scenario (which assumes complete knowledge of the PMF hydrograph, empty reservoirs at the beginning of the hydrograph, and a perfect coordination among the reservoirs in the system)

for watershed A4. The regulation was imposed on the maximum peak discharge obtained under CFSR-CT forcings, initiated under fully saturated soil moisture conditions, to obtain the highest flood hydrograph possible. The results of the modified PMF were demonstrated immediately downstream of 4 selected reservoirs (Allatoona Lake Dam, Logan Martin Dam, Martin Dam, and Claiborne Lock and Dam) out of 15 major reservoirs. The select reservoirs included the three largest reservoirs in ACT.

A significant reduction in peak discharge of –83% (Figure 1.12a) and –56% (Figure 1.12c) is possible for the upstream reservoirs Allatoona Lake Dam and Martin Dam, respectively; and a reduction of –38.4% (Figure 1.12b) is possible for the intermediate reservoir Logan Martin Dam. A potential reduction of –27.7% (Figure 1.12d) in peak discharge immediately downstream of Claiborne Lock and Dam is possible from the cumulative contribution of all the ACT reservoirs. These results show that certain upstream reservoirs in ACT can significantly help contain PMF, and the overall reservoir system can reduce the peak discharge by up to –27.7% of PMF (depending on their previous reservoir levels and joint operation). Therefore, incorporation of the reservoirs in the hydrologic models is important in evaluating PMF, depending on their locations with respect to the area of interest and their storage capacity.

However, caution is in order regarding the simplified nature of this sensitivity analysis. Flood risk management during an actual event involves various site- and event-specific considerations that could not be captured in this analysis. The main purpose is to demonstrate the maximum possible reduction in PMF through the series of reservoirs under assumed conditions that allow comparison of the importance of reservoirs relative to other contributing PMF factors.

Relative Sensitivity

This section discusses the relative sensitivity of PMF to various scenarios (S1 to S7). The results are summarized in Figure 1.9 for each of the watersheds (A1 through A4). Overall, PMF peak discharge is most sensitive to the choice of meteorological forcing dataset (CFSR-CT [S2a]) in watershed A4 and to climate change (CCSM4-F2 [S3b]) in watersheds A1–A3. Although both CCSM4-BL and CFSR-CT forcings represent the 1981–2010 historical period, S2a is consistently higher than S1 across all watersheds. This could be attributed mainly to variation in PMP estimates arising from potential factors such as uncertainties associated with the model structure and parameters, model calibration, and spatial resolution (discussed in Rastogi et al.,[2017]). Although

future climate change has a significant effect on PMF, the order of magnitude of change is comparable with changes arising from different meteorological forcing datasets. The antecedent soil moisture conditions can potentially impact PMF peak discharge significantly, by up to +50% for watershed A4 (S6a through S6d). The sensitivity of PMF peak discharge increases with the drainage area of the watersheds. Saturated soil moisture conditions have a pronounced impact compared with meteorological sequences (S5). The presence of reservoirs and their operation is also likely to be a significant factor and is likely to help reduce PMF peak discharge. The LULC change in this scenario had a comparatively smaller effect, which can be attributed to a relatively lower increase in developed areas in the selected watersheds A1–A4 (between 2.8 and 4.7%, Table 1.3). While the future LULC scenario developed in this study is dependent on the historical changes in LULC, the rate of urbanization in the future may differ from the historical rate. Therefore, the effect of LULC change on PMF may be relatively higher, depending on the scenario of future urbanization and site location. Moreover, the effects of urbanization are likely to produce more localized effects and may produce pronounced responses of hydrographs for smaller drainage areas and in shorter-duration flood events that are not the focus of this study.

1.4 Summary and Conclusions

In this study, a high-resolution modeling approach was used to generate ensemble estimates of PMF for multiple regions of varying area in the ACT River Basin and study the effects of various controlling factors on PMF, such as antecedent soil moisture conditions, changes in LULC, alternative meteorological sequences, and reservoir operation. A total of 120 relative humidity–maximized PMP storms under historical and projected future climate conditions from Rastogi et al. (2017) were used to drive PMF simulations. A calibrated hydrologic model (DHSVM) set up at 90 m spatial resolution was used to generate PMF estimates for four selected watersheds within the ACT River Basin.

Overall, it was found that PMF estimates are most sensitive to the sources of meteorological forcing datasets and climate change, followed by antecedent soil moisture, reservoir storage, and then LULC change. For the entire ACT, PMF driven by CFSR-CT is consistently higher (+91%) than PMF driven by CCSM4-BL and conventional HMR PMP (–34%). A significant increase in PMF was observed in a near-future period (+18%) and a far-future period (+69%) compared with the baseline for the ACT. These sensitivity tests also revealed antecedent

soil moisture as a sensitive factor affecting the PMF (+46%). Although conventional meteorological sequences can increase the antecedent moisture in the watersheds, they seem to have an inconsistent effect depending on the size of the watershed. Under the ideal reservoir operation assumption, certain upstream reservoirs in the ACT system can significantly help in containing PMF, and the overall reservoir system can reduce the peak discharge by up to -28% of PMF (depending on their previous reservoir levels and joint operation). While LULC change has comparatively less effect in this study (+1%), it is largely dependent on the scenario of future urbanization growth. Urbanization will have a more pronounced effect on shorter-duration flood events in more localized areas that are not specifically targeted in this study.

The results indicate that the choice of meteorological forcings can have one of the strongest influences on the magnitude of PMF (compared with all other affecting factors). While one might expect to see a similar magnitude of PMF between CCSM4-BL and CFSR-CT, a large dispersion was identified. The possible sources for such a large disagreement include the modeling bias of both CFSR-CT and CCSM4-BL, and differences in the estimation of storm precipitable water between a conventional and a model-based (WRF) approach. Given the relatively wetter tendency of CFSR reported in previous studies (Sun et al., 2018; Higgins et al., 2010), such differences cannot be solely attributed to the bias in climate models. Nonetheless, the larger sensitivity of meteorological forcings suggests that PMF simulations should not rely on only one particular meteorological forcing dataset. When resources are allowed, an ensemble-based approach, including multiple sources of reanalysis, numerical weather models, parameterizations within models, and all other affecting factors identified in this study, should be considered to provide a wider range of scenarios to support decision making.

The results also suggest a larger climate change-induced PMF sensitivity than some previous studies (e.g., Clavet-Gaumont et al., 2017), and this disagreement stems from differences in approaches to estimating PMP. Clavet-Gaumont et al. (2017) followed the concept of maximum precipitable water adjustment presented by the World Meteorological Organization (Paulhus and Miller, 1986) that assumed the increase of total precipitable water could be linearly translated to the increase of precipitation (and hence PMP). Therefore, the increase projected by Clavet-Gaumont et al. (2017) is largely controlled by the projected changes in total maximum precipitable water in the future climate. On the other hand, Rastogi et al. (2017) used RHM, proposed by Ohara et al. (2011), to simulate PMP through WRF. This approach modifies the atmospheric initial and

boundary conditions to full saturation (100%) and uses a numerical weather model to simulate the process based nonlinear PMP response. Therefore, the increase in PMP is not necessarily the same as the increase in total maximum precipitable water. The numerical simulation results of Rastogi et al. (2017) further suggested the increase in total precipitable water and the increase in rainfall depth had a large spread and did not fall near the 1:1 line. Since this simple linear increase assumption has not been thoroughly tested or validated in conventional studies, further evaluation regarding the validity of assumption is imperative.

This study employs a unique framework of process-based, high-resolution hydro-meteorological models to enable ensemble estimation of PMP and PMF in ACT. Further, it provides a tool to characterize the effects of non-stationarity of climate and hydrological processes on PMP and PMF. The novelty of the study lies in the comprehensive and robust sensitivity analysis of critical factors such as antecedent soil moisture conditions, meteorological forcings, LULC change, meteorological sequences, and reservoir operations affecting the PMF. Moreover, although the study was performed for one HUC04 basin in the southeastern United States, the methodology and framework it uses can be extended to similar climatic and geographical regions in other parts of the United States or the rest of the world. The output from this study has further applications in the generation of high-resolution flood regimes to assess potential flood risks for specific energy–water facilities.

Acknowledgment

This study was supported by the US Department of Energy, Office of Science, Biological and Environment Research, Integrated Assessment Program, and by Oak Ridge National Laboratory's (ORNL) Laboratory Directed Research and Development Program. The research used resources of the Oak Ridge Leadership Computing Facility at ORNL. The authors are employees of UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US Department of Energy. Accordingly, the US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US Government purposes. The sources of the input datasets used in the study are provided in the paper. The meteorological data used in this study were obtained from Rastogi et al, (2017). The hydrologic model DHSVM v3.1.1 used in this study is open source and available

at: <https://dhsvm.pnnl.gov/code.stm>. Other data questions can be directed to S.-C. Kao (kaos@ornl.gov) at the ORNL Climate Change Science Institute.

CHAPTER II

**ENSEMBLE-BASED FLOOD VULNERABILITY ASSESSMENT FOR
PROBABLE MAXIMUM FLOOD IN A CHANGING ENVIRONMENT**

A version of this chapter was originally published as:

Gangrade, S., Kao, S. C., Dullo, T. T., Kalyanapu, A. J., & Preston, B. L. (2019). Ensemble-based Flood Vulnerability Assessment for Probable Maximum Flood in a Changing Environment. *Journal of Hydrology*, 576, 342-355, doi: 10.1016/j.jhydrol.2019.06.027.

Abstract

The magnitude and frequency of hydro-meteorological extremes are expected to increase in a changing environment in ways that threaten the security of US energy-water assets. These include probable maximum precipitation (PMP) and probable maximum flood (PMF), which are used as hydraulic design standards for highly sensitive infrastructures such as nuclear power plants and main dams. To assess the flood vulnerability due to PMP/PMF, an integrated high-resolution process-based hydro-meteorologic modeling framework was used to develop ensemble-based probabilistic flood maps based on best-available historic observations and future climate projections. A graphics processing unit–accelerated 2-dimensional hydrodynamic model was used to simulate the surface inundation areas corresponding to a total of 120 PMF hydrographs. These ensemble based PMF maps were compared with flood maps obtained from the conventional deterministic PMP/PMF approach, revealing added information about conditional probability of flooding. Further, a relative sensitivity test was conducted to explore the effects of various factors in the framework, such as meteorological forcings, antecedent hydrologic conditions, reservoir storage, and flood model input resolution and parameters. The framework better illustrates the uncertainties associated with model inputs, parameterization, and hydro-meteorological factors, allowing more informed decision-making for future emergency preparation.

2.1 Introduction

Floods are one of the most destructive natural hazards, causing mortality, property loss, and infrastructure damage worldwide. The United States (US) alone has observed 29 billion-dollar-scale flood events in the period of 1980–2018 with a total of 543 deaths and roughly 122 billion dollars in inflation-adjusted losses (NCEI, 2018). The increasing frequency and magnitude of flood events under changing climate, population, and land use and land cover conditions require better predictability and preparedness for flood hazards. Flood inundation maps serve as a critical input to flood risk assessments and enable the development of informed floodplain management and mitigation strategies. In the US, the Federal Emergency Management Agency (FEMA) utilizes hydrologic and hydraulic models to delineate flood inundation zones associated with 1% and 0.2% annual exceedance probability (AEP) (or 100-year and 500-year return periods) to support the National Flood Insurance Program (FEMA, 2018). For critical energy-water infrastructures, including major hydropower dams and nuclear power plants, even rarer events ($AEP < 0.2\%$) or probable maximum flood (PMF) are the focus. Similar inundation maps developed for PMF-scale events may serve as useful tools to evaluate the vulnerability of critical infrastructures under worst-case flooding scenarios, as well as to identify regions with minimum flooding likelihood to support future site selection.

A general procedure to prepare flood inundation maps (hereinafter referred as a “modeling chain”) associated with PMF involves probable maximum precipitation (PMP) estimation, followed by hydrologic simulation and hydrodynamic/hydraulic modeling. Since the current practice of PMP/PMF assessment focuses on estimating the single deterministic maximum precipitation and streamflow event (that could occur under a series of adverse hydro-meteorological conditions), conventional PMF inundation maps are also deterministic in nature. However, deterministic maps inevitably mask out underlying uncertainties from decision makers or planners, given the binary (wet or dry) representation of the resulting flood inundation maps. While advanced deterministic maps employ process-based hydrologic and hydraulic models calibrated to historic events (Di Baldassarre et al., 2010), these maps are unable to capture the uncertainties arising from various other sources in the modeling chain, such as inaccurate input data, boundary conditions, model structure, and model parameterization (Alfonso et al., 2016; Di Baldassarre et al., 2010). Therefore, the value and potential of probabilistic flood maps (PFMs)

have been highlighted recently in the literature (Alfonso et al., 2016; Di Baldassarre et al., 2010; Papaioannou et al., 2017). Recent advances in computational power have allowed the use of computationally intensive hydrologic-hydraulic models to develop PFMs through multi-ensemble simulation (Neal et al., 2013). The uncertainty characterization may be performed at various stages of the modeling chain by varying factors such as precipitation (Caseri et al., 2016), spatiotemporal rainfall variability (Jenkins et al., 2017; Nuswantoro et al., 2016; Zischg et al., 2018), spatial dependence of flow from tributaries (Neal et al., 2013; Pattison et al., 2014), hydrologic model parameters or inputs (Domeneghetti et al., 2013), hydraulic model types (Papaioannou et al., 2016), hydraulic model roughness coefficient (Papaioannou et al., 2017), and different digital elevation models and observational data sets (Giustarini et al., 2016; Papaioannou et al., 2016).

Although a few studies have focused on the development of flood inundation maps for the largest historic events (e.g., Pedrozo-Acuña et al., 2015) or for events with return periods ranging from hundreds (Smemoe et al., 2007; Kalyanapu et al., 2012) to thousands of years (Büchle et al., 2006; Prime et al., 2016), studies evaluating flood inundation maps for rare hydroclimatic extreme events such as PMP/PMF are limited (Zischg et al., 2018). Further, recent studies have suggested that PMP/PMF are sensitive to the changing climatic conditions (e.g., Kunkel et al., 2013; Beauchamp et al., 2013; Rousseau et al., 2014; Stratz and Hossain, 2014; Klein et al., 2016; Rastogi et al., 2017; Gangrade et al., 2018) and challenged the deterministic treatment of PMP/PMF. It has also been suggested that both epistemic and aleatoric uncertainties are involved in the estimation of PMP (Micovic et al., 2015). For instance, PMP and PMF estimates are often derived for a point location of interest without considering variability originating from spatiotemporal rainfall distribution or watershed heterogeneity. Through Monte Carlo simulation, Zischg et al. (2018) demonstrated that the spatiotemporal distribution of PMP has significant effects on the resulting PMF inundation maps. Other factors such as meteorological forcings, antecedent soil moisture, land-use land-cover conditions, and reservoir operation (Gangrade et al., 2018) may introduce further uncertainties to the PMF estimate and consequently the resulting surface inundation area. The 2017 Hurricane Harvey precipitation near Houston, Texas, is reported to exceed the Hydrometeorological Report No. 51 (HMR51; Schreiner and Riedel, 1978) 72-h PMP estimates at 5,000 mi² and 10,000 mi² scales (Kao et al., 2019), suggesting that an extremely large PMP-scale storm is physically possible. Considering that there has not been a focused federal effort since the publication of HMRs, it is of critical importance to advance our concept and

practice from the conventional, deterministic treatment of PMP/PMF to an ensemble-based, probabilistic flood mapping approach to better analyze and quantify the vulnerability of critical energy-water infrastructures in a changing environment.

In this study, building upon our prior work involving PMP/PMF simulations (Rastogi et al., 2017; Gangrade et al., 2018), we present a high-resolution, process-based, hydro-meteorological modeling framework to produce probabilistic flood inundation maps for PMF. The main objectives of the study are (1) to employ an ensemble-based approach to translate uncertainties associated with PMP to flood inundation maps, (2) to prepare probabilistic flood inundation maps illustrating uncertainties with the flood hazard modeling chain of PMF, and (3) to quantify the potential impacts of environmental change on the inundation areas of PMF. The study area includes areas immediately upstream and downstream of the Allatoona Dam in Georgia, US. For PMP, we used Weather Research Forecasting (WRF), a numerical weather simulation model (Skamarock et al., 2008) to create an ensemble of 120 storms. The input forcings to the WRF model is provided by reanalysis as well as climate projections as detailed in Rastogi et al. (2017). These 120 PMP storms were then used to conduct PMF estimates using the Distributed Hydrologic Soil Vegetation Model (DHSVM; Wigmosta et al., 1994) as described by Gangrade et al. (2018). The ensemble of PMF hydrographs was further used to drive a high-resolution, graphics processing unit– (GPU) accelerated 2-dimensional (2D) dynamic wave flood model (Flood2D-GPU; Kalyanapu et al., 2011) to simulate the spatiotemporal evolution of PMF and to develop ensemble-based PFMs. Apart from better quantifying uncertainties, compared with the deterministic approach, the ensemble-based flood mapping approach allowed us to better visualize the potential impacts of PMF through a spatially explicit, more intuitive manner. This study is the first of its kind that implements a high-resolution modeling framework to assess changes in flood regime through an ensemble-based approach for PMF to account for a changing climate and other factors. The study also includes a relative sensitivity experiment to evaluate the sensitivity of various factors in the modeling chain, including inputs such as precipitation, hydrologic model antecedent conditions, and hydraulic model parameters. Although the study is presented for a selected watershed, the methodology can also be adopted for other locations with similar climates and geographical settings for broader applications.

This study is organized as follows: Section 2.2 provides an overview of the study area, methodology, and data; Section 2.3 presents results and associated discussion; and Section 2.4 summarizes and concludes the study.

2.2 Methods

2.2.1 Study Area

This study focuses on the Etowah Watershed located in the northwestern Georgia, US. This watershed is selected because it includes a major reservoir and urban areas and lies in a relatively flat topographic region, allowing transposition of PMP storms. The Etowah Watershed has an estimated drainage area of 4821 km² (1861 mi²; Figure 2.1) and is a part of the Alabama-Coosa-Tallapoosa (ACT) River Basin. It drains parts of 15 counties in Georgia and covers major urban areas including the city of Cartersville and parts of Atlanta's metropolitan area such as Woodstock, Marietta, and Alpharetta. The Etowah Watershed includes a large multi-purpose reservoir, Allatoona Lake and Dam, owned and operated by the US Army Corps of Engineers (USACE), with a maximum storage capacity of roughly 826.5 million m³ (the second-largest dam in the ACT River Basin). While the headwaters of Etowah Watershed include mountainous areas (such as the Piedmont mountains), the topography of the rest of the watershed is moderate, with elevations ranging from 176 m (577 ft) to 1,147 m (3,763 ft) as per the National Elevation Dataset (NED; Gesch et al., 2002). The region receives roughly 1,336 mm of annual precipitation, predominantly in the form of rainfall, with light snowfall in the headwater region. The major soil types include silty loam and sandy loam. According to the National Land Cover Database 2006 (Fry et al., 2011), 61% of the basin is covered by forests, 18.5% lies under small vegetation, and 18.5% falls in the developed category.

The main critical infrastructure located in the Etowah Watershed is the Allatoona Dam which produces hydroelectric power for the region. The PMFs developed through the WRF and DHSVM cover both the upstream and downstream areas of the Allatoona Lake and Dam. To further demonstrate the applicability of probabilistic flood maps for other energy infrastructures, 16 selected electric substations (obtained from Homeland Infrastructure Foundation-Level Data; Figure 2.1) were also evaluated in the watershed. Four different types of modeling/analysis domains were used in this study. The WRF meteorological and DHSVM hydrologic modeling domains covered the Etowah Watershed as well as the entire ACT River Basin (see Rastogi et al.,

[2017] and Gangrade et al., [2018] for domain details). Two Flood2D-GPU modeling domains (i.e., 358 km² ME01-Flood2D-GPU and 507 km² ME02-Flood2D-GPU in Figure 2.1) were set up within the Etowah Watershed, and final analysis was performed for two slightly smaller analysis domains (ME01 and ME02). The two regions, upstream (ME01) and immediately downstream (ME02) from Allatoona Dam, were selected such that they cover parts of the Atlanta metropolitan region and the City of Cartersville in the Etowah Watershed. The computational domains of Flood2D-GPU were set to be larger than the analysis domains to avoid potential backwater effects and computational domain boundary artifacts.

2.2.2 Simulation Setup

A process-based, high-resolution modeling framework is used to develop multi-ensemble flood inundation maps associated with PMF estimates. The main steps involved (1) simulation of PMP storms, (2) simulation of PMF hydrographs, and (3) simulation of flood regimes. A brief overview of the methods follows.

Simulation of PMP

The simulation of PMP storms was performed using a mesoscale numerical weather model, WRF version 3.6. The WRF model is driven using boundary forcings from: a) a reanalysis dataset: Climate Forecast System Reanalysis I (CFSR; Saha et al., 2010), and b) a global climate model: Community Climate System Model version 4 (CCSM4; Gent et al., 2011). The WRF model, setup at a 9km and 3km (double nested) horizontal grid resolutions, was driven for 120 selected storms (Table 1) using relative humidity maximization (RHM) method to simulate PMP. Before PMP estimation, WRF parameterization was selected by testing the simulated 3-day rainfall depth against PRISM (Daly et al., 2008) and Daymet (Thornton et al., 1997) precipitation datasets to assess and compare WRF performance. PMP was then estimated using the selected parameterization with RHM method which maximizes the relative humidity of the entire atmospheric column to 100 % at initial and boundary conditions following Ohara et al. (2011) and Ishida et al. (2015). The PMP outputs were stored at 1-hourly temporal resolution. The readers are referred to Rastogi et al. (2017) for further technical details regarding PMP estimation and WRF performance evaluation.

In addition, Hydrometeorological Report (HMR) 51 (Schreiner and Riedel, 1978) and HMR52 (USACE, 1984) were used to obtain conventional PMP rainfall estimates for the study area. This enables a comparison of ensemble-based simulations with the conventional

deterministic approach and serves as a reference. The ensemble approach relies on identifying the most critical PMF event based on hydrologic and hydraulic simulations for each of the PMP storms, as opposed to one deterministic event under conventional approach estimated using synthetic hyetographs. The ensemble-based approach leads to better understanding of the uncertainty associated with PMP estimates.

Simulation of PMF

The PMF simulations were conducted by using each of the 120 moisture maximized storms as the meteorological forcing input to drive a high-resolution DHSVM. DHSVM was selected because of its wide applications in hydroclimate impact assessments and its capability to generate high-resolution streamflow data required to drive the consequent hydrodynamic flood models. DHSVM is a distributed, process-based model and performs water/energy balance calculations to account for various hydrological processes. The model uses precipitation, air temperature, radiation (both longwave and shortwave), wind speed and relative humidity as input datasets (Wigmosta et al., 1994 and 2002; Storck et al., 1998). The DHSVM setup for the Etowah Watershed was obtained from Gangrade et al. (2018), which is a part of a larger modeling effort performed for the ACT River Basin. The DHSVM simulation was performed at the 3-hourly time step and 90-m horizontal grid resolution from 1980–2012. The 90-m NED is used as the base digital elevation model (DEM) map for DHSVM simulation. Further, the soil (Miller and White, 1998) and land-use and land-cover data (NLCD; Fry et al., 2011) were resampled at the base map resolution to serve as inputs to hydrologic simulation. The stream network was obtained from the National Hydrography Dataset Plus (McKay et al., 2012). Readers are referred to Gangrade et al. (2018) for associated detailed technical descriptions regarding setup, calibration and validation.

To simulate PMF specifically for the Etowah Watershed, for every storm listed in Table 2.1 (Section 2.2.1), the largest 72-h average precipitation (which is the largest duration commonly used by HMR reports to estimate PMP) over the watershed was identified from the WRF output and transpositioned to the center of the Etowah Watershed as an input for DHSVM. Given the relatively smooth topography in the ACT River Basin (compared with other mountainous regions in the US), storms within the basin can be considered meteorologically transpositionable. This enables identification of the most critical PMP input for the study area and ensures that the PMP storm is captured by the watershed. The simulated precipitation depth from the most inner WRF domain (as explained in Section 2.2.1) was further re-gridded/aggregated as 3-hourly inputs to

DHSVM at a 4-km horizontal grid resolution radar rainfall format. Following the Nuclear Regulatory Commission guidelines, a critical meteorological sequence was used for PMF estimation (Prasad et al., 2011). The meteorological sequence included 40% of 72-hr PMP (antecedent precipitation), followed by no precipitation for 72 hours, and then a full (100%) 72-hr PMP (critical precipitation). Fully saturated moisture conditions were used at the beginning of the DHSVM simulations. This approach provides an ensemble of simulated DHSVM streamflow hydrographs for each set of storms sets as specified in Table 2.1 (i.e., CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2).

The ensemble PMF hydrographs obtained above were also compared against conventional PMF driven by conventional PMP rainfall estimates calculated for Etowah Watershed using HMR51 and HMR52. The detailed methodology is described in Gangrade et al. (2018).

Simulation of Flood Regime

The hydrodynamic flood simulation was performed using the computationally enhanced version of the 2D hydraulic model Flood2D-GPU (Marshall et al., 2018), originally developed by Kalyanapu et al. (2011). Flood2D-GPU uses a first-order accurate upwind finite difference scheme in solving the nonlinear hyperbolic shallow water Saint Venant equations, which are a simplified version of the Navier-Stokes equations with horizontal momentum and continuity equations integrated over water depth. The model implements on a structured grid to take advantage of the uniform grid structure of the DEM data. The computational performance of the Flood2D-GPU model was improved using a hybrid Message Passing Interface (MPI) and Compute Unified Device Architecture (CUDA). The model speed-up for the MPI + multiple GPU version was up to 18× compared with an identical single-process Open Multi-Processing (OpenMP) version (Marshall et al., 2018). Benefitting from GPU acceleration, the high performance of Flood2D-GPU allowed us to perform ensemble simulation for two domains: ME01 (~400,000 grid cells, 360 km²) and ME02 (~563,000 grid cells, 507 km²). The simulations were conducted on the Titan supercomputer maintained by the Oak Ridge Leadership Computing Facility and used ~1 million computing hours for ensemble flood simulation.

The key input data required for Flood2D-GPU include DEM, surface roughness (Manning's n value), inflow source locations, and the corresponding streamflow hydrographs. In this study, both 30-m and 10-m resolution DEM data were obtained from NED. Several commonly used Manning's n values were tested and 0.035 was selected as the default value (discussed in

Section 2.3). For the selection of inflow locations (Figure 2.1), the main upstream NHDPlus channel segments that flow into the Flood2D-GPU simulation domain were identified. A series of additional NHDPlus segments (with approximately 50 km² incremental drainage areas) were then selected to input the incremental streamflow hydrographs. The corresponding hydrographs for each of the 120 storms were extracted using high-resolution hydrologic outputs from DHSVM at 3-h time-steps for both domains (i.e., ME01 and ME02). The Flood2D-GPU was driven by 5-day hydrographs that capture the peak discharge of each storm event and the output was stored at a 10 minutes temporal resolution for each storm. The Flood2D-GPU performance is evaluated and presented in the Results and Discussion section. The current model setup captures riverine or fluvial floods; the pluvial flood simulation, an important aspect for flood maps generation to support decision making, shall be incorporated in the future model improvements.

Apart from the default simulations driven by simulated PMF hydrographs, an additional set of 120 flood simulations were conducted for ME02 (downstream of Allatoona Dam) with modified upstream inflow to understand the maximum flood retention capacity under idealized reservoir operation (denoted as ME02R). At the stream segment immediately downstream of the Allatoona Lake and Dam, the volume equal to the maximum storage capacity of the Allatoona reservoir (i.e., 826.5 million m³) was subtracted from the peak of the PMF hydrograph. In other words, this ME02R simulation assumes that the reservoir can be fully emptied right before a PMF event, remains structurally intact throughout the entire event, and is operated optimally to reduce the peak discharge of a PMF event. The modified hydrograph in addition to natural flow from other tributaries served as an input for ME02 to drive Flood2D-GPU for each of the 30 storm sets from CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2. This hypothetical discharge scenario is mainly used to identify the maximum possible downstream flood inundation area reduction under the most optimistic flood management operation. Given that the actual reservoir operation is unlikely to beat this optimal scenario, the actual PMF inundation area under the protection of a reservoir should be within the range between ME02 and ME02R.

2.2.3 Probabilistic Flood Map

For each simulated PMF flood event (realization), the Flood2D-GPU simulation outputs were stored at a 10-minute temporal resolution for the duration of the flood. These outputs were first post-processed to obtain the maximum flood inundation extents arising from the event. A minimum threshold of 10 cm flood depth was used to differentiate a cell as flooded vs. not flooded

(Kalyanapu et al., 2011) during the post-processing step. Using the maximum flood inundation extents for every flood event as an input, the probabilistic value of flooding for any given cell was then calculated using Eq. (1) (Kalyanapu et al., 2012). Given that these moisture maximized storms were selected by the 30 largest storms within a 30-year period (Rastogi et al., 2017), each storm is weighed equally in this study. This approach was used to produce one PFM for each of the storm sets (i.e. CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2) for both ME01 and ME02.

$$P_{cell} = \frac{\sum_{i=1}^{i=N} X_i}{N} \quad (\text{Eq. 2.1})$$

where

P_{cell} = probability to flood for any given cell

$X_i = 0$ (dry) or 1(wet) for realization ‘ i ’

N = total number of realizations/flood event simulations

The PFM presents a spatial map of conditional probability of flooding given a moisture-maximized extreme storm event has occurred at the region of interest. The PFMs were generated for the two model domains ME01 and ME02 for each of the 30 storm sets for CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2. The flood simulations are referenced by adding the subscript ME01, ME02, and ME02R after the name of the storm set. For example, CFSR-CT-ME01, CFSR-CT-ME02, and CFSR-CT-ME02R refer to PFMs generated for CFSR-CT storms for model domains ME01 and ME02 under natural flow and ME02 under reservoir regulation, respectively.

2.3 Results and Discussion

2.3.1 Flood2D-GPU Performance

The performance of Flood2D-GPU was evaluated by comparing the simulated 100-year flood inundation extents against a benchmark data set from FEMA (100-year flood zones or Zone A/AE; Wing et al., 2017; Alfieri et al., 2014) for ME01. The first step in the process involved the estimation of a 100-year peak streamflow (Q_{100}) through standard frequency analysis at the outlet of ME01 using guidelines from Bulletin 17B prepared by the Interagency Advisory Committee on Water Data (1982). The continuous streamflow data from the control simulation (i.e., DHSVM driven using observed historic precipitation from Daymet) for a period of 32 years (1981–2012) served as inputs for frequency analysis. The annual maximum series (AMS) of peak discharge ($Q_{\max, \text{year}}$) was extracted from the hydrograph at the outlet of ME01. A log-Pearson Type III distribution was then fitted to the AMS using a skewness parameter obtained for the region based

on Plate 1 of Bulletin 17B. The results from the flood frequency analysis are illustrated in Figure 2.2. Based on the annual maximum peak discharges for a period of 32 years, a Q_{100} value of 18,956 ft^3/s is obtained at outlet of ME01.

In the next step, an ensemble-based approach is employed to validate Flood2D-GPU, as a single storm might not be able to capture the spatial variability across the watershed and might result in underestimation of flood extents. For each annual maximum peak discharge event, the hydrographs at each inflow location (Figure 2.1) were abstracted (i.e., 32 events from 1981 through 2012). These hydrographs were then re-scaled to match the estimated 100-year peak discharge value and then served as inputs to Flood2D-GPU to conduct the simulation at 30-m spatial resolution. The rescaling of hydrographs was performed by multiplying the hydrographs with a rescaling factor (R_{yr}) calculated at each year as $R_{\text{yr}} = Q_{100}/Q_{\text{max, yr}}$, so that the peak streamflow at the domain outlet of each simulation is controlled at the same Q_{100} value. This approach retains the relative streamflow magnitude across all tributaries and allows us to explore the spatial variability and uncertainty across the ensemble members. The ensemble simulation resulted in 32 flood inundation maps. The maximum inundation area was then identified from the 32 maps and compared against a FEMA 100-year flood map rasterized to the same 30-m resolution. The flood maps were compared based on a binary (flooded = 1, not flooded = 0) classification scheme, as presented in Table 2.2. The comparison was performed for the analysis domain ME01 and the smaller stream segments which did not have any inflow locations (due to modeling constraints/limitations) were excluded. The vector-based FEMA flood extents for the region of interest were rasterized to the Flood2D-GPU grid to enable a direct comparison.

Figure 2.3 presents a comparison of 100-year flood inundation extents obtained from Flood2D-GPU and FEMA. A visual inspection reveals that the 100-year flood zones simulated by Flood2D-GPU are largely consistent with the FEMA flood zones. While there may also be inaccuracies and uncertainties associated with FEMA flood zones, this study uses the FEMA data as a benchmark to evaluate the overall reasonableness of Flood2D-GPU.

Four key metrics including critical success (C), hit rate (H), false alarm (F), and error (E) were estimated to quantify Flood2D-GPU performance (Table 2.3). H provides a measure of the model to accurately predict benchmark flood extents; however, it does not penalize for overprediction. Flood2D-GPU obtained $H = 0.82$ for ME01, revealing the model can accurately predict 82% of the FEMA flood zones. F, which measures overprediction, is estimated as 0.17,

demonstrating that 17% of the grid cells were falsely reported as flooded by the model. The metric C equivalent to the F-squared statistics, a common measure to evaluate spatial extents for flood studies (Bates and De Roo, 2000), is estimated as 0.70, providing an overall measure of fit. The C metric adds a penalty to H for any overprediction and underprediction. In addition, the fact that E for Flood2D-GPU is less than 1 (0.93) suggests an overall tendency of the model to underpredict, predominantly in the upstream reaches close to inflow boundary conditions.

These key metrics suggest that Flood2D-GPU performance is on par with the acceptable range of these metrics provided in the literature (Alfieri et al., 2014; Wing et al., 2017). For instance, Alfieri et al. (2014) obtained H values between 0.59 and 0.78, and C values between 0.43 and 0.65 for a flood simulation at 100-m resolution across selected areas in Germany and the United Kingdom compared with national/regional hazard maps. Wing et al. (2017) performed a similar evaluation for validation of a flood hazard model for the conterminous US using FEMA flood zones as a benchmark, with H values as 0.685 and 0.815 and C values of 0.55 and 0.50 for 90 m and 30 m spatial resolutions, respectively. The results indicate overall satisfactory performance of the Flood2D-GPU in comparing spatial extents for 1 in 100-year event against the equivalent flood inundation zone obtained from FEMA.

2.3.2 Ensemble PMF Hydrographs and Comparison with Deterministic Approach

This section presents the ensemble PMF hydrographs for each of the four sets of moisture-maximized storms (i.e., CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2) at the outlet of the Etowah Watershed (Figure 2.4). The hydrographs with the largest peak discharge are presented in thick lines in Figure 2.4 and are individually presented in Figure 2.5a. For further comparison, the PMF hydrograph from the conventional approach (HMR based) is also presented for the Etowah Watershed (Figure 2.5a). The range of peak discharge values for these events is presented in Figure 2.5b for Etowah Watershed and at the outlets of computational Flood2D-domains ME01 and ME02 in Figure 2.5c and 5d, respectively.

The results indicate that peak discharges obtained for CCSM4-BL and HMR are comparable in magnitude with maximum peak discharge values of 21,874 m³/s and 18,654 m³/s, respectively. Although the deterministic HMR peak discharge is less than the maximum event in each set of the hydrographs, it is larger than more than 75% of the ensemble members and lies among the top quartile of all events. In addition, the HMR based deterministic peak discharge is

82% larger than the ensemble mean peak discharge of all CCSM4-BL members (Table 2.4), suggesting the relative conservativeness of the deterministic HMR approach.

The maximum peak discharge of CFSR-CT (27,732 m³/s) is greater for CCSM4-BL. This higher discharge could be attributed to higher PMP estimates for CFSR-CT, demonstrating the effect of the choice of meteorological forcings on PMF (Gangrade et al., 2018). The effects of climate change on maximum peak discharge indicate a significant increase in peak discharge magnitude, with an increase of approximately 58% for the near future time period (CCSM4-F1; 2021–2050) and 109% for the far-future period (CCSM4-F2; 2071–2100). The comparison is performed with reference to the peak discharge magnitude obtained from the CCSM4-BL baseline period. These changes could be attributed to increased PMP estimates projected in the future periods resulting from the intensification of hydrologic cycle caused by atmospheric warming. Readers are referred to Rastogi et al. (2017) and Gangrade et al. (2018) for further technical details.

The results demonstrate a large variability in the hydrograph shapes and peak discharge values (Figures 2.4, 2.5b, 2.5c and 2.5d). In addition to the key factor (e.g., PMP magnitude), the variability in the hydrographs can be attributed to spatiotemporal rainfall structure and watershed heterogeneity. The results also highlight the range of uncertainties captured in terms of streamflow estimates, which are often missing in the conventional, deterministic estimation of PMF. Here the main focus lies on the range of streamflow variability that corresponds to a set of moisture-maximized storms. Similar concepts can also be followed to develop ensemble hydrographs that address other possible sources of uncertainties (e.g., timing, parameterization).

2.3.3 Development of Probabilistic Flood Maps

An ensemble-based approach involves analyzing a collection of simulated flood events corresponding to multiple hydrographs and peak discharge magnitudes. Generally, the most extreme or worst-case scenario is selected by choosing the single PMF hydrograph with the maximum peak discharge. In this section, the effects of ensemble PMF are analyzed in terms of flood inundation area by translating these hydrographs into probabilistic flood inundation maps and comparing the results with flood extents obtained via the conventional deterministic approach. This comparison intends to illustrate flood damages/extents resulting from PMF events and associated uncertainties.

The PFMs are presented for each of the 30 moisture-maximized storms (Figure 2.6, Panels a through d for ME01, Panels e through h for ME02, and panels i through l for ME02R). The

results are presented in term of conditional probability of flooding for a given cell, assuming a moisture-maximized storm has occurred in the region. Panels a and e also include the deterministic flood extents obtained from Flood2D-GPU driven by conventional HMR PMF, presented as white contours overlaid on top of the probabilistic flood maps. In addition, the range of maximum flood inundation area associated with each storm event is presented in Figure 2.7 for ME01 (Panel a), ME02 under natural flow condition (Panel b), and ME02R under ideal reservoir regulation (Panel c).

A comparison of the maximum flood inundation extent for the domain upstream of Allatoona Lake and Dam (ME01; Figure 2.6a) obtained from the conventional (HMR-based) approach (15.56 km^2) is very similar to the maximum flooding extent of CFSR-CT-ME01 (16.83 km^2) and CCSM4-BL-ME01(16.32 km^2), resulting in 8.2 % and 4.9% respective increments in inundation area compared with HMR. On the other hand, the downstream domain (ME02; Figure 2.6e) has a larger difference in flood extent obtained from the HMR approach (96.6 km^2) compared with the maximum flood extents of CFSR-CT-ME02 (117.9 km^2) and CCSM4-BL-ME02(101.5 km^2); the results are 22.1 % and 5.1% respective increments in inundation area compared with HMR. A comparison of panels 6e and 6i in Figure 2.6 reveals the maximum possible flood reduction by the Allatoona reservoir due to its regulation of PMF-scale events in the immediate downstream areas. Ideal reservoir operation results in a decrease in the maximum flood inundation area of 9.5% in the CFSR-CT case.

Given the projected future climate conditions, the simulated maximum inundation area reveals a likely increase in both near future (CCSM4-F1) and far future (CCSM4-F2) periods. For ME01, the projected maximum inundation areas are 17.6 km^2 for CCSM4-F1 and 19.1 km^2 for CCSM4-F2, which suggest 8% and 17% increases when compared with the 16.3 km^2 CCSM4-BL-M01 baseline value (Figure 2.7a). Similarly, a total of 121.2 km^2 (108.7 km^2) and 135.7 km^2 (128.4 km^2) in the maximum inundation area is projected for ME02 (ME02R) for CCSM4-F1 and CCSM4-F2, and they suggest 19% (22%) and 34% (44%) increases when compared with the 101.5 km^2 (88.9 km^2) CCSM4-BL-ME02 (CCSM4-BL-ME02R) baseline value. The results indicate that the percentage increase in maximum inundation area is projected to be higher for ME02R than for ME02, mainly due to a smaller ME02R baseline value.

Given the wide range of areal extents produced for each set of moisture-maximized storms, further insight into flood characteristics (e.g., flood inundation area, gauge height) using

hydrologic/meteorological parameters can improve the understanding of flood zones. The relationship between peak discharge and maximum flood inundation area is presented in Figure 2.8. Although the maximum flood inundation area is highly correlated to the peak discharge at the outlet of each model, the relationship is nonlinear, with a higher variance observed for ME02 (Figure 2.8b) than for ME01 (Figure 2.8a). This finding was mainly attributed to the relatively flat topography in ME02. The variability demonstrates that a similar peak discharge could result in varying extents of flood inundation which could be attributed to hydrograph characteristics (including timing, sequence, and total flood volume) and spatial variations in streamflow. For instance, two storms with maximum peak discharges of 11,112 m³/s and 11,504 m³/s, respectively, can produce maximum flood inundation areas of 102.1 km² and 81.32 km² for ME02 (Figure 2.8b).

The results suggest that a single peak discharge value for PMF obtained using the conventional approach cannot capture such variations in flood impacts. The results further highlight the value of an ensemble-based approach compared with current deterministic methods for more comprehensive understanding of flood damage resulting from an extreme event.

2.3.4 Potential Changes in Flood Impacts Arising from PMF

In this section, the PFM are used to examine the potential changes in the flood regime and its impacts on infrastructure/urban developments under projected future climate conditions. To illustrate how the conditional probability of flooding due to moisture maximized storms changes in different periods, the difference in probability of flooding at each grid among CCSM4-BL, CCSM4-F1, and CCSM4-F2 for each domain ME01, ME02 and ME02R was calculated and is summarized in Figure 2.9. The grid cells that are consistently flooded (i.e., probability = 1) or non-flooded (i.e., probability = 0) in all inundation maps across all storms (CCSM4-BL, CCSM4-F1, and CCSM4-F2) were excluded from the analysis.

The results indicate that the overall probability of flooding will increase by up to 30% in CCSM4-F1 across ME01, ME02, and ME02R, where most grid cells show increasing probability ranging between 0 and 0.15. Similarly, the histogram for CCSM4-F2 indicates that the overall probability of flooding will increase by up to 60% for CCSM4-F2 for each domain ME01, ME02, and ME02R, with most cells showing positive increases ranging between 0 and 0.25. This process allows the identification of other areas that may be more susceptible to PMF-scale flooding in addition to the most vulnerable areas (i.e., probability = 1).

To demonstrate the potential application of this framework, the analysis was further expanded to demonstrate the utility of PFMs as a tool to identify potential hazards to electricity grid infrastructure arising from PMF events. The vulnerability of 16 selected electric substations (from the Homeland Infrastructure Foundation-Level Data; Figure 2.1) for ME02 was evaluated and additional ensemble information, such as duration of flooding and median flood depths, is presented in Figure 2.10.

These results identify the substations at risk of flooding given a PMF event has occurred. Of 16 substations, 8 substations (#6, 7, 9, 10, 12, 13, 14, and 15) demonstrated a high probability of flooding (>0.75) for ME02 under unregulated flow condition for CCSM4-BL. The mean duration of flooding and median flood depths is likely to show an increase in CCSM4-F1 and CCSM4-F2 compared with CCSM4-BL. Similarly, the substations currently not at risk of flooding in CCSM4-BL (for instance, #1, 2, 3, 5, and 8) have a higher chance of flooding in future time periods (i.e., CCSM4-F1 and CCSM4-F2). Further, additional information from the ensemble approach—such as distribution of duration of flooding and median floods depths—has the potential to reduce the likelihood of Type I and Type II decision errors in risk management. Such risk identification research can help improve current flood mitigation features while also equipping decision makers with information that can be used in strategic planning and development of future urban areas and/or critical infrastructure.

2.3.5 Sensitivity Analysis

To understand the overall and relative sensitivity of flood inundation to various factors—such as meteorological forcings, climate change, hydraulic and hydrologic model inputs, and parameters—a comprehensive sensitivity test was performed, as explained in Table 2.5. The simulation results from scenarios S2 through S7 are compared with reference to the control scenario (S1) in Figure 2.11.

The relative sensitivity reveals that climate change (S3a and S3b) and meteorological forcings (S2a) are the most sensitive factors for flood inundation area and the median flood depths for ME02. Climate change is likely to cause increases of up to 33.7% and 46.5 % in inundated area and median flood depth, respectively. These differences in inundation areas for the aforementioned scenarios can be attributed mainly to changes in PMP values, revealing that precipitation is the most sensitive factor affecting flood regimes. Reservoir operations (S7) can also contribute moderately by reducing the overall flood inundation area by approximately 13.2 % compared with

S1. Note that the reduction is calculated under an ideal reservoir operation scenario and will be directly controlled by the maximum storage capacity of the reservoir. The other two sensitive parameters in this order include the effects of antecedent moisture conditions in the hydrologic model (S6) and the effects of using a high-resolution DEM (S4). They produce relative changes of -8.6% and $+6.7\%$, respectively, for the inundation area. The effect of the Manning's roughness coefficient was found to be the least sensitive factor in this case. A similar trend was also noticed for median flood depths. It should be noted that a minimum depth threshold of 10 cm was utilized to calculate the maximum inundation area post-hydrodynamic simulation. We also repeated our analysis using a 1 cm threshold which lead to minimal impacts for our watershed. However, it can have a stronger influence in flat topographies or other regions.

2.4 Summary and Conclusions

This study demonstrates a high-resolution process-based hydro-meteorological modeling framework to generate ensemble-based PFMs for two selected domains for the worst-case flood scenarios (i.e., PMF). An ensemble of 120 moisture maximized PMP storms were acquired from Rastogi et al. (2017) for historical time period and future climate projections. PMF estimates were then generated by driving DHSVM at a 90-m grid resolution. The 3-hour hydrographs obtained from DHSVM for each storm were used to drive a 2D GPU-accelerated hydraulic model (Flood2D-GPU) at 30-m and 10-m spatial resolutions to produce flood maps for each storm. The probability of inundation was then calculated at each grid cell of the flood domain, which was then used to generate PFMs. Further, the relative sensitivity of flood inundation area and median flood depth was evaluated for various factors such as meteorological forcings, climate change, antecedent moisture conditions, and hydraulic model inputs and parameters.

The results indicate that the peak discharge from the PMF hydrograph is likely to increase significantly for the Etowah Watershed region under a changing climate. The region downstream of Allatoona Lake is likely to observe an increase of up to 58% in peak discharge magnitude in the near future period (2021–2050, CCSM4-F1), and up to 109% in the far future period (2071–2100, CCSM4-F2) under RCP8.5 compared with the baseline period (1981–2010, CCSM4-CT). These changes in PMF translate into approximately 19% and 33% increases in the flood inundation area. An evaluation of probabilistic inundation maps revealed that the probability of flooding is likely to increase by up to 30% and 60%, respectively, under the near future and far future scenarios. For

the 16 selected electric substations, the vulnerability assessment suggests that over 50% of the selected substations have more than 75% probability of flooding during PMF events in the baseline period. The probability of flooding increases significantly in the projected near and far future periods. For far future scenario CCSM4-F2, all substations are projected to be inundated in at-least one of the ensemble simulations. Additionally, the high-resolution outputs may also provide additional key information such as duration of flooding and flood depths under these scenarios.

The relative sensitivity experiments further demonstrated that precipitation is the most sensitive factor affecting the flood regime, including flood inundation areas and depth. The choice of meteorological forcings can contribute to up to a 16% change in the flood inundation area. Further, the flood inundation elasticity relationships developed between peak streamflow and corresponding flood inundation area revealed the uncertainties associated with the shape and timing of hydrographs originating from the spatiotemporal variability in precipitation and the watershed heterogeneity.

The proposed hydro-meteorological modeling framework can enable the generation of probabilistic flood inundation maps through ensemble-based PMP and PMF simulation. The uncertainties associated with the most sensitive factor (i.e., extreme precipitation) and others can be successfully captured with an ensemble approach as presented in this study. The comprehensive relative sensitivity analysis and its effects on flood regime further identify the most important factors causing changes to flood regimes. Although the study focused on a particular HUC08 basin, the framework can be extended to other regions to generate ensemble-based probabilistic flood inundation maps. These maps can serve as an important tool and provide ensemble-based information regarding key flood characteristics (including flood depth and duration) to decision makers, rather than deterministic values obtained from the conventional approach. Such an evaluation of a region not only determines the regions under flood risk but also informs stakeholders regarding the probability of inundation to enable informed decisions.

Acknowledgment

SG and SCK were supported by the Hydro Research Foundation and US Department of Energy (DOE) Water Power Technologies Office under Award Number DE-00006506. SCK was also partially supported by the U.S. Air Force Numerical Weather Modeling Program. AJK and TTD are supported by the Tennessee Tech University Center for the Management, Utilization and

Protection of Water Resources. The research used resources of the Oak Ridge Leadership Computing Facility. Some of the co-authors are employees of UT-Battelle, LLC, under contract DE-AC05-00OR22725 with DOE. Accordingly, the US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US Government purposes. The input data sets are cited throughout the paper, as appropriate. The meteorological data was acquired from Rastogi et al, (2017), while the hydrologic model setup was acquired from Gangrade et al, (2018). The open source version of hydrological model (DHSVM) is available at <https://dhsvm.pnnl.gov/code.stm>. Any data questions can be directed to S.-C. Kao (kaos@ornl.gov) at ORNL.

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CHAPTER III

**MULTI-MODEL AND MULTI-RESOLUTION HYDROCLIMATE
PROJECTIONS FOR THE ALABAMA-COOSA-TALLAPOOSA RIVER
BASIN IN THE SOUTHEASTERN UNITED STATES**

A version of this chapter has been submitted for peer review:

Gangrade, S., Kao, S. C., & McManamay, R. A. (2019). Multi-model and Multi-resolution Hydroclimate Projections for the Alabama-Coosa-Tallapoosa River Basin in the Southeastern United States. Scientific Reports, submitted.

Abstract

This study utilizes high-resolution, process-based, modeling framework to assess the impacts of changing climate on water resources for Alabama Coosa Tallapoosa (ACT) River Basin in the southeastern United States. A 33 member ensemble of hydrologic projections was generated using three distributed hydrologic models (PRMS, VIC, and DHSVM) of variant spatiotemporal resolution and complexity. These hydrologic models were driven by dynamically downscaled and bias-corrected future climate simulations from 11 CMIP5 global climate models under RCP 8.5 emission scenario, with 40-years each in baseline (1966–2005) and future (2011–2050) period. The hydroclimate response, in general, projects an increase in mean seasonal precipitation, runoff and streamflow. The high and low flows are projected to increase and decrease, in general, respectively suggesting increased likelihood of extreme rainfall events and intensification of hydrologic cycle. The uncertainty associated with the ensemble hydroclimate response, analyzed through an analysis of variance (ANOVA) technique, suggests that the choice of climate model is more critical than the choice of hydrologic model for our region. This study provides in-depth insights of hydroclimate response and associated uncertainties to support water resource managers and informed decisions.

3.1 Introduction

Changing climate is projected to intensify the hydrologic cycle globally and regionally (Huntington 2006; Déry et al., 2009). These alterations in hydrologic cycles will potentially increase frequency and magnitudes of hydroclimate extremes such as flood and droughts; and impact water resources availability due to changes in seasonality of streamflow and runoff (Allan and Soden 2008; Giorgi et al., 2011; Milly et al., 2005). The future hydrologic projections are, therefore, important to inform mitigation and adaptation strategies aimed at addressing impacts of climate change in addition to increasing water demands. Moreover, reliable estimates of hydroclimate extreme trends can ensure better preparedness of society and infrastructure from threats arising from extreme events and their socioeconomic impacts (Paiva et al., 2012).

Studies assessing climate change impacts on future hydrology at regional or catchment scales often adapt a standard procedure involving the use of a hierarchical hydro-meteorological framework (hereinafter “modeling framework”), including selection of following key elements: a) greenhouse gas emission scenario, b) global climate model (GCM), c) downscaling methods (statistical or dynamical), d) bias correction of downscaled data (if required) and e) hydrologic model (Bosshard et al., 2013; Chen et al., 2011; Meresa and Romanowicz 2016; Hattermann et al., 2018). These hydrologic projections are inevitably associated with uncertainties introduced at each stage of the modeling framework. In addition to external factors such as natural variability and the choice of emission scenarios, a large amount of uncertainties is model-related, such as model assumptions, structures, accuracy, initial conditions, calibration procedures, training datasets, and the spatial and temporal scale of implementation (Bosshard et al., 2013; Mendoza et al., 2015; Pechlivanidis et al., 2016). An ideal, but non-pragmatic, way to characterize these uncertainties would encompass producing ensemble hydroclimate projections utilizing a complete sample of uncertainty sources. However, given the limited resources, most impact assessment studies can only focus on a subset of these choices resulting in underestimation of the uncertainties in hydroclimate projections (Bosshard et al., 2013; Her et al., 2019).

Given the plethora of choices in the above-mentioned modeling framework and their significance in hydroclimatic projections, many studies have investigated effects of individual sources of uncertainties (Gutmann et al., 2014; Madhusoodhanan et al., 2017; Mendoza et al., 2016), as well as combined uncertainties due to different methodological choices within the

modeling framework (Bosshard et al., 2013; Chen et al., 2011; Xu et al., 2011; Wilby and Harris 2006; Vetter et al., 2016; Thompson et al., 2017; Schewe et al., 2014; Van Beusekom et al., 2016; Chegwiddden et al., 2019). Several studies, at global and regional scale, indicate that the uncertainties from climate models is the most important source over other factors such as greenhouse gas emission scenarios and hydrologic model structures (Chen et al., 2017; Pechlivanidis et al., 2016; Vetter et al., 2016; Chen et al., 2011). On the other hand, Bosshard et al. (2013) revealed that the prominent sources of uncertainty vary by season in the Alpine region, where uncertainties arising from climate models dominate during summer and fall, whereas choices of statistical processing methods and hydrologic models are more prevalent during winter and spring (Bosshard et al., 2013). Similarly, Chegwiddden et al. (2019) demonstrate that choice of GCM and greenhouse emission pathways are the dominant contributor to annual streamflow volume, and the choices of hydrologic model and parameters are prominent in capturing low flow uncertainties over the US Pacific Northwest (Chegwiddden et al., 2019). While multiple climate models and greenhouse emission scenarios have been utilized to capture the ensemble of climate scenarios in the last two decades, such studies are often limited to the choice of a single hydrologic model (Xu et al., 2011; Thompson et al., 2017; Van Beusekom et al., 2016; Zhao et al., 2019; Naz et al., 2018; Naz et al., 2016). Despite studies indicating that choice of hydrologic model can produce substantial differences in hydrologic projections at times exceeding the mean signal from climate scenarios (Mendoza et al., 2015), the use of multiple hydrological models has only begun to gain traction (Krysanova et al., 2017; Schewe et al., 2014; Huang et al., 2018).

The selection of appropriate hydrologic model(s) in the modeling framework remains a challenge (Tran et al., 2018) as such a decision, subjective in nature, requires careful consideration of several factors including model applicability, suitable spatiotemporal scale of implementation, availability of computational resources, quality of meteorological forcings and land surface parameters, and the overall technical feasibility. While certain applications, such as hydrodynamic modeling applied at watershed scales, warrant fine-scale outputs from hydrologic modeling (<100 m) (Gangrade et al., 2019), the scalability of these implementations at regional scales is an obvious challenge. Studies have demonstrated that lumped or coarse-scale semi-distributed hydrologic models may yield similar hydroclimate projections compared to fine-scale hydrologic models (Tran et al., 2018). However, a more elaborate comparison among models with very distinct spatial scales and structures is still lacking.

The goal of this study is to assess the impacts of changing climate on water resources through multi-model, multi-resolution ensemble hydroclimate projections for the Alabama-Coosa-Tallapoosa River Basin (ACT) in the southeast United States (SEUS). While SEUS is considered “water-rich”, water allocation conflicts within two major river basins including ACT have created a political issue between states of Georgia, Alabama and Florida. The increasing water demand due to population growth and urbanization is further likely to deepen water stress in the future (Seager et al., 2009). In addition, SEUS is relatively underrepresented in the existing climate impact assessments on hydrology (Engström and Waylen, 2017). While some studies at regional scale have been conducted, this study aims to provide a more comprehensive, ensemble-based hydroclimate evaluation over the ACT River Basin.

Overall, the main objectives of this study are to: a) develop an ensemble of high-resolution hydroclimate projections for ACT, b) analyze the relative uncertainty contribution between climate and hydrologic models, and c) explore whether the complexity and spatial resolution of hydrologic models may yield different insights of future projections. To accomplish these objectives, a hierarchical multi-model framework with process-based hydro-meteorological models over the ACT River Basin is utilized. An ensemble of 33 hydroclimate projections using a combination of 11 GCMs and 3 distinct hydrologic models is produced for 1966–2005 baseline and 2011–2050 future periods under Representative Concentration Pathway 8.5 (RCP8.5) scenario. Various hydrologic metrics including long term seasonal mean and high and low streamflow are investigated, and the effects of various sources of uncertainties are also analyzed. Through the incorporation of a high-resolution modeling framework, this assessment expects to provide fine scale ensemble hydroclimate projections to support local stakeholders, including water resource managers from major reservoirs and city planners from several urban areas (including Atlanta), for more uncertainty informed decisions.

3.2 Study Area

The study area consists of Alabama-Coosa-Tallapoosa (ACT) River Basin covering the northeastern and east central parts of Alabama, northwestern Georgia and small parts of Tennessee (Figure 3.1). The ACT River Basin, classified as a US Hydrologic Subregion (HUC04 = 0315), has an approximate drainage area of 59,100 km² and includes 14 US Hydrologic Subbasins (HUC08s). The Alabama river is formed by the confluence of the Coosa and Tallapoosa Rivers

near Montgomery, AL. The Coosa River flows through HUC08s 03150101 to 03150107, while the Tallapoosa River flows through HUC08s 03150108 to 03150110. The subregion has a relatively flat topography with a small mountainous region in the north. Elevation ranges from sea level to 1278 m based on the National Elevation Dataset (Gesch et al., 2002). The soil type consists mainly of sandy loam and silty loam. The ACT River Basin receives an annual average of 54.3 inches of precipitation primarily from rainfall with minimal influence of snow on runoff. Forest is the major landcover type in ACT that results in high evapotranspiration ranging from 30–42 inches (56%–78% of annual precipitation), generally increasing from north to south. The study area includes 13 large reservoirs including 5 federal dams (USACE, 2013). The major urban areas in ACT include suburban areas of Atlanta (Kennesaw and Marietta, GA); Birmingham, Alabama; Montgomery AL; and, Mobile AL. The selected US Geological Survey (USGS) streamflow gauges utilized in the study (assigned a five-character unique id for brevity, a reference table is provided in Table 3.2) and HUC08s are marked on Figure 3.1 for reference.

3.3 Data and Methods

3.3.1 General Modeling Framework

Various choices available along the hierarchical hydro-meteorological modeling chain necessitates an evaluation of all potential options while designing a climate change impact assessment study. The modeling framework employed in this study mainly constitutes two elements contributing to uncertainty: 1) downscaling of coarse resolution GCM data to the regional scale, and 2) utilizing regional scale meteorological forcings to drive calibrated hydrologic models. This modeling framework is employed after careful consideration of the goals of the study, availability of computational resources, time-constraints, and stakeholder needs. A multi-model ensemble of hydrologic projections is created using a combination of eleven climate models and three distinct hydrologic models. Each combination of 11 climate models and 3 hydrologic models are employed thereby producing 33 sets of hydroclimate projections.

3.3.2 Climate Models

The climate projections used in this study were generated by dynamically downscaling of 11 Coupled Model Inter-comparison Project Phase 5 (CMIP5) GCMs using Regional Climate Model version 4 (RegCM4) to a horizontal spatial resolution of 18 km (Ashfaq et al., 2016). These climate projections were further statistically bias corrected by the 1966–2005 Parameter-elevation

Relationships on Independent Slopes Model (PRISM) meteorological data using quantile mapping technique (Ashfaq et al., 2013; Ashfaq et al., 2010). The climate projections provide key meteorological forcing data such as daily precipitation, maximum and minimum daily temperature, and wind speed for hydrologic models for 40 years in the baseline period (1966–2005) and another 40 years in the future period (2011–2050). The future projections are obtained under RCP8.5 business as usual case scenario, which assumes high population and slow income growth.

3.3.3 Hydrologic Models

This study utilizes three distinct hydrologic models of varying complexity and spatiotemporal resolution, including the Precipitation Runoff Modeling System (PRMS, roughly ~7.5 km spatial resolution at daily timestep), Variable Infiltration Capacity model (VIC, 4km at three-hourly timestep), and Distributed Hydrology Soil Vegetation Model (DHSVM, 90 m at three-hourly timestep). These models were selected due to their wide range of applications in the climate change studies (Christiansen, Markstrom, and Hay 2011; Cristea et al., 2014; Cuo et al., 2009; Naz et al., 2016; Naz et al., 2018). In addition, these models can simulate hydrologic processes at a fine spatial resolution using distributed process-based equations allowing them to better capture meteorological and basin heterogeneity. For model calibration and validation, all three hydrologic models were implemented for historic period of 1980-2012 using the same meteorological forcings obtained from Daymet dataset (Thornton, Running, and White 1997). The year 1980 was used for model spin-up. The model performance was evaluated for 62 USGS gauges across ACT. A detailed description of these models and their calibration strategies is presented as follows:

Precipitation Runoff Modeling System

Precipitation Runoff Modeling System (PRMS) is a deterministic, process-based model, distributed hydrologic model developed by the United States Geological Survey (Leavesley et al., 1983). PRMS has a modular framework to enable use of alternative algorithms to simulate several hydrologic processes such as precipitation, evapotranspiration, runoff, infiltration, groundwater etc. (Markstrom et al., 2015). PRMS has been widely utilized to study climate change impacts at watershed scale (Hay et al., 2011; Najafi et al., 2011). In this study, PRMS is implemented using NHM-PRMS (Regan et al., 2018) which utilizes Geospatial Fabric (Viger & Bock, 2014) for spatial discretization to obtain hydrologic response units (HRUs) and stream segments, while the initial parameters were obtained through National Hydrologic Model Parameter Database (Driscoll

et al., 2017). PRMS was setup for a period of 1980-2012 and first year was used a spinup. Six sensitive parameters to runoff and streamflow response were identified from literature (Markstrom et al., 2016) to calibrate PRMS using particle swarm optimization algorithm. The calibration was first carried out by maximizing Nash Sutcliffe Efficiency (NSE) values individually at HUC08 level by comparing the simulated runoff with observed monthly runoff obtained from USGS WaterWatch runoff dataset at monthly scale. Finally, the “K_coef” parameter was adjusted for all the channel segments to maximize daily NSE values for USGS gages within the HUC08 progressively starting from upstream to downstream.

Variable Infiltration Capacity Model (VIC)

VIC is a semi-distributed, grid-based, macroscale hydrologic model which solves energy and water balance equations using physical process-based equation (including hydrologic process such as evaporation, runoff, baseflow, energy fluxes etc.) within grid cell. The model utilizes a variable infiltration capacity curve to determine the infiltration and surface runoff process, while empirical Arno curve is used to generate base flow. VIC allows to represent sub-grid variability by accounting for topography, precipitation and vegetation (Liang et al., 1994). The grid cells do not interact with each other during the simulation; therefore, the streamflow estimates are produced by routing the surface runoff and baseflow from each grid cell to desired location through the river network based on a linear reservoir model (Lohmann et al., 1996 and 1998).

In this study, the VIC hydrologic model was setup at $1/24^\circ$ (~4 km) grid resolution with a three-hourly time step using five elevation bands for each grid cell. The model was calibrated for each HUC08 by comparing the simulated runoff with observed monthly runoff obtained from USGS WaterWatch runoff dataset (Brakebill et al., 2011). The WaterWatch data provides aggregated monthly runoff derived from USGS National Water Information System gauges. Additional model setup details are available from Naz et al. (2016) and Oubeidillah et al. (2014).

Distributed Hydrology Soil Vegetation Model

Distributed Hydrology-Soil-Vegetation Model (DHSVM) is a physical process based distributed hydrologic model typically implemented at 30-200 m resolution (VanShaar et al., 2002). DHSVM is primarily a saturation excess model (Cuo et al., 2009) which solves energy balance and mass (water) balance equations at each grid cell. DHSVM utilizes spatially distributed parameters including topography, soil, soil depths, and vegetation type where each grid cell represents one soil type and one vegetation type. The input meteorological data comprises mainly

of precipitation, incoming shortwave and longwave radiation, relative humidity, air temperature and wind speed. It captures the hydrological processes such as evapotranspiration, snowmelt, canopy snow interception and release, unsaturated soil moisture, saturated subsurface flow, overland flow and channel flow. A detailed description of DHSVM and physical process-based equations can be found in (Storck et al., 1998; Wigmosta et al., 1994 and 2002).

A calibrated DHSVM setup utilized in this study is obtained from Gangrade et al. (2018). The model is implemented at a 90-meter spatial resolution at sub-daily temporal scale (3-hourly). The calibration and validation of DHSVM was performed individually at sub-basin level employing 74 USGS gauges. Additional details about the calibration, validation and model setup are available from Gangrade et al. (2018).

3.3.4 Climate Change Indices

The calibrated PRMS, VIC, and DHSVM models were utilized to generate hydroclimate for each of the 11 GCMs resulting in a 33-member ensemble. The first year of meteorological data was repeated during the hydrologic simulation in both the baseline and future periods to initiate hydrologic model spin-up and has been discarded in the analysis. The outputs of hydrologic models included runoff at the aggregated HUC08 level and daily streamflow values at the gauge level for 62 selected gauges were used for analysis and comparison (Figure 3.1, gauges are assigned a five character unique id for the sake of brevity, an association table is provided in Table 2).

Three types of indices were selected to evaluate changes in hydrologic response from baseline (1966–2005) to future periods (2011–2050). They include:

- a) Mean seasonal percent change in precipitation (ΔP), runoff (ΔR) and streamflow (ΔQ)
- b) Mean percentage change in high runoff/streamflow ($\Delta R_{95}/\Delta Q_{95}$), where high runoff/streamflow indicates the 95th percentile runoff/streamflow statistics.
- c) Mean percentage change in low runoff/streamflow ($\Delta R_{05}/\Delta Q_{05}$), where low runoff/streamflow indicates the 5th percentile runoff/streamflow statistics.

In all cases, percentage change is calculated with reference to baseline values (i.e., $100 \times (\text{future} - \text{baseline}) / \text{baseline}$). The following breakdown of months was utilized to characterize seasons: Winter (December, January and February), Spring (March, April and May), Summer (June, July and August), and Fall (September, October and November).

3.3.5 Uncertainty Quantification

Analysis of variance (ANOVA) was utilized to quantify the of relative contribution of uncertainties in hydroclimate projections arising from different sources and their interactions, similar to other studies (Bosshard et al., 2013; Meresa and Romanowicz 2016; Osuch et al., 2016; Chegwiddden et al., 2019). Based on this technique, the total variance can be explained by the sum of variances introduced by individual components and their interactions. Since, this study focuses on two main sources of uncertainties arising from a) 11 climate models, and b) 3 hydrologic models, the following equation was developed:

$$Y_{i,j} = \mu + CM_i + HM_j + (CM * HM)_{ij} + e \quad \text{Eq. (1),}$$

where Y is the climate change indicator for ith climate model and jth hydrologic model, μ and e denotes overall mean and error respectively. The terms CM, HM and CM*HM denotes the relative contribution of each sources of uncertainties arising from climate models, hydrologic models and interaction of climate and hydrologic models respectively. The analysis was performed for the climate change indices including ΔQ for each season, $\Delta Q95$ and $\Delta Q05$.

3.4 Results and Discussion

3.4.1 Model Performance:

The historic model performance of the hydrologic models was evaluated for two different hydrologic variables including runoff (monthly, aggregated at HUC08 level) and streamflow (both daily and monthly for 62 gauges) due to different calibration procedures for the hydrologic models. While VIC was calibrated to monthly USGS WaterWatch runoff and DHSVM was calibrated to daily streamflow at USGS Gauge locations, PRMS was calibrated in a two-step fashion where the first step involved runoff calibration at HUC08 level to monthly USGS WaterWatch and the second step involved calibration of streamflow against USGS gauge data at daily time scale.

The time series of simulated monthly runoff was compared with the observed runoff from USGS WaterWatch for each HUC08. The key statistics including aggregate annual runoff, Nash Sutcliffe Efficiency (NSE) and percent bias (PBIAS) are presented (Figure 3.2, Table 3.2). The NSE values at monthly time step ranged between 0.43–0.93 for VIC, 0.59–0.92 for PRMS and 0.74–0.91 for DHSVM. For all hydrologic models, 11 out of 14 HUC08s demonstrate NSE values greater than 0.8 exhibiting a good skill of hydrologic models. Since the WaterWatch data include

gauges under influence of regulation, basins with large reservoir storage could show a potential bias.

The next comparison included evaluation of daily streamflow for 62 USGS gauges spread over the entire ACT basin covering every HUC08 (Figure 3.2). Table 3.2 summarizes the locations of USGS Gauges and summary statistics of NSE at both daily and monthly time steps for each hydrologic model. At monthly scale, all three model demonstrate a good skill to recreate historic USGS streamflow. For instance, the monthly NSE values are greater than 0.7 for roughly 79% USGS gauges for VIC, 92% for PRMS, and 89% of USGS Gauges for DHSVM (Figure 2d, 2e, 2f, and Table 3.2). However, the VIC model has a lower performance at daily scale when compared with DHSVM and PRMS (Figure 3.2a, 3.2b, 3.2c and Table 3.2). The USGS gauge closest to outlet of ACT demonstrate a similar level of performance for all three models with monthly NSE values of 0.89, 0.90 and 0.91 for PRMS, VIC and DHSVM respectively. It is important to note that the current hydrologic model setup for each all three models does not incorporate the effects of reservoirs on the streamflow; therefore, performance of model is affected for the USGS gauges located immediately downstream of big reservoirs. The effect of regulation from reservoirs on hydrograph response tends to dissipate for the gauges further downstream. Overall, the results suggest a satisfactory performance of hydrologic models in the historic period.

3.4.2 Future Hydroclimate Projections

Precipitation

The mean seasonal change in precipitation (ΔP) averaged over the ACT river basin is projected to increase across all the seasons (Figure S1). The multi-model mean precipitation exhibited an increase by +2.3%, +4.4%, +1.9% and +3.5% during winter, spring, summer and fall, respectively. During winter and spring seasons, the increase is generally observed across the entire basin with minor spatial variability. However, summer and fall exert greater spatial variabilities in ΔP , with slight decrease projected over the northeastern part of ACT.

Runoff

Figure 3.3(a-d) and Table 3.1 present projected mean seasonal change in runoff (ΔR) using all the 33 ensemble members summarized at the HUC08 level for ACT. The ΔR aggregated for the ACT (Table 3.1) suggests that average runoff is likely to increase by 2.3%, 5.5%, 8.0%, and 12.0% in winter, spring, summer and fall, respectively. The spatial distribution of ΔR indicates that the lower half of the basin may potentially observe a larger increase in runoff along Alabama

River as compared to the upstream tributaries of Coosa River (HUC08s such as 03150102 and 03150104). Furthermore, the spatial variability in ΔR is largest in fall and summer as compared to winter and spring. The spatial patterns and seasonal changes in ΔR are generally consistent with ΔP . Changes in low runoff (Figure 3.3e) indicate a projected decrease by -1.74 % while high runoff is projected to increase by +6.6 % averaged across the ACT. Low runoff is projected to change within a range of -6.6 % to +1.6 % for roughly 72 % of the HUC08s. Similarly, high runoff is projected to increase for all HUC08's within a range of +1.5 % to +10.8%.

The robustness of hydrologic projections is evaluated for each variable and for each HUC08 in Figure 3.3. The HUC08s with more than two thirds of ensemble members indicating a same sign of change are marked and labeled as 'A', or 'N' otherwise. These results suggest that roughly 35%, 42%, 57% and 79 % of HUC08s indicate an agreement during spring, summer, fall and Q95, while no agreement is observed during winter and Q95.

Streamflow

Next, future changes in streamflow for 62 selected USGS Gauges in ACT are evaluated. Although runoff provides a good sense of overall water distribution in the basin, the evaluation of streamflow can provide a direct indication of water availability in the channels. Therefore, the response of streamflow, particularly high and low flows, under climate change is of interest to water managers. Figure 3.4a-d presents projected changes in average seasonal streamflow (ΔQ) for each of the USGS gauge locations with detailed statistics presented in Table 3.3. The projected range of changes in seasonal streamflow for 62 USGS gauges is as follows: winter (-1.2% to +5.2 %), spring (+0.9% to +10%), summer (-2.3% to +18.1%) and fall (-2.2% to 23.4%). Maximum changes are projected in the months of summer and fall with up to a +23% increase in the streamflow in future. The spatial distribution of changes in streamflow indicates a larger increase in the lower half of the basin, whereas a moderate change is observed in the upper half of the basin. While the spatial pattern of ΔQ is consistent with runoff changes, the magnitudes of projected changes in ΔQ are larger than ΔR .

Figure 3.4e and 3.4f show projected percent changes in streamflow extremes $\Delta Q05$ and $\Delta Q95$ respectively for each USGS gauge location. The $\Delta Q95$ is projected to increase between +1.8% to +11.1% across all gauges. In general, $\Delta Q95$ will increase approximately +4.0 % averaged across gauges located in Coosa River (HUC08s 03150101 through 03150107), and approximate 7.2 % averaged across gauges in Tallapoosa and Alabama river (Table 3.3). A similar evaluation

for ΔQ_{05} (Figure 3.4e, Table 3.3) reveals that ΔQ_{05} is projected to decrease across 84 % of the gauges along with greater spatial heterogeneity across the ACT. A majority of gauges located in the upstream HUC08s (03150101, 03150102 and 03150104) exhibit an average projected decrease of 4.7 % in low flows with a maximum change of approximately -19.7 %. The rest of gauges in the lower half of ACT exhibit an average decrease of roughly -1.6 % in the low flows.

A comparison of the hydrologic projections generated by different hydrologic models for gauge A0096 (USGS gauge closest to outlet of ACT) reveals that PRMS, VIC and DHSVM suggest a mean change (ensemble range) in projected streamflow by +3.2% (-23.3% - +16.0%) , +6.4% (-19.0% - +21.1%) and +6.0% (-13.1% - +21.1 %) respectively. In general, the PRMS results in relatively lower change in mean streamflow signal response, compared to VIC and DHSVM. However, the ensemble range is much larger and comparable for each hydrologic model, suggesting that despite the differences in the model structures, resolution, calibration and validation, these three hydrologic models provide similar insights in hydrologic projections.

3.4.3 Role of Climate vs. Hydrological Models and Uncertainty Evaluation

As discussed in the introduction, uncertainties are evident in future hydroclimate projections derived through the hierarchical modeling chain introduced due to various factors. While ensemble mean values of projections can be beneficial, ranges in ensemble values for future projections can also serve as important information from the perspective of water resource management. As indicated in previous section, the mean hydrologic response from each hydrologic model captures similar information in streamflow change; this analysis further provides a breakdown for seasonal and high and low flows presented for gauge A0096 as an example. The range associated with change in hydroclimate response, in addition to mean hydrologic signal, is also presented in Figure 3.5 for different streamflow variables (ΔQ at seasonal scale, ΔQ_{05} and ΔQ_{95}) arising from 33 sets of hydroclimate projections. Each sub-figure (Figure 3.5a-f), provides an ensemble range of ΔQ arising from individual hydrologic models PRMS, VIC and DHSVM, and compared with “Total” (ensemble range from 33 members). In each subfigure, the spread of the distribution of relative change in flow obtained by individual hydrologic model is very similar to each other. In other words, the distribution is not significantly different from each other. This indicates that the choice of hydrologic model is not as significant compared to that of selecting a climate model, as the total spread is largely driven by uncertainties associated with precipitation arising from different climate models. In general, a similar trend is observed in most of the

remaining USGS gauge locations (results for rest of the 61 locations are not shown). However, higher uncertainty was observed in the simulation of ΔQ during summer and fall and in ΔQ_{05} for a few gauges located in the northeastern part of ACT.

The ANOVA also provides the relative contribution of uncertainties arising from climate models and hydrologic models to total ensemble uncertainty. The variance decomposition suggested that CM was the dominant source of variability and explains over 90% of total variance for all the six variables (Figure 3.6). The second largest source of variability arises from the interaction of climate and hydrologic model (CM*HM). The contribution of hydrologic model (HM) is relatively low compared to other factors, while the residual error ϵ is almost negligible in all the cases. An increase in relative contribution from HM is observed for summer flow and low flow conditions, indicating a relatively stronger influence of the choice of hydrologic models in conditions where baseflow constitutes a larger portion of stream flow. However, since all the hydrologic models used in this study were robustly calibrated, the lesser influence of hydrologic model choice is expected over the southeast region, whereas the opposite may be expected for drier or snow-dominated regions.

3.4.4 Discussion and Potential Implication

The projected changes in seasonal hydrology demonstrate that the ACT, in general, is expected to observe an increase in total runoff and streamflow in future, which could be attributed to an overall increase in the seasonal precipitation over the region. However, the magnitude of increase in runoff is not linearly proportional to the increase in precipitation. It is interesting to note that a small increase of +1.9% percent in precipitation potentially causes an increase of +8.0% in runoff during summer. A similar behavior is also exhibited during the fall season. This could be attributed to high hydrologic sensitivity of runoff which indicates that even a small increase in precipitation could yield significant increase in runoff response (Goudie 2006). Moreover, increases in high intensity storm events can trigger high runoff response signals despite relatively marginal increases in total seasonal precipitation. This suggests that the summer and fall seasons in the Southeast could observe an increase in precipitation intensity. This explanation corroborates the results of other studies indicating ongoing intensification of summer (Wang et al., 2010; Li et al., 2013) and fall (Bishop et al., 2019) precipitation in southeastern United States based on historic observed and reanalysis datasets. The projected changes in high flows further indicate that climate change is likely to affect the frequency and magnitude of high flow events consistently throughout

the ACT, which may be further exacerbated if urbanization and deforestation occur under future conditions in the region (not accounted for explicitly in hydrologic models). The changes are more prominent for the lower half of the basin including the gauges located around reservoirs Martin, Jordan, Robert F. Henry, Millers Ferry and Claiborne. The changes in low flows are more prominent in the north-western parts of the ACT. Projected increases in high flows and ubiquitous decreases in low flows across the majority of gauges in the ACT suggest an intensification of extremes in the hydrologic cycle in the region under future climatic conditions.

The projected seasonal and high/low streamflow changes provide valuable information to water resource managers and other reservoir operators in the region. Despite only moderate increases projected for high flows, such information is still beneficial for infrastructure design and safety. Likewise, projected decreases in low flows during summer and fall for the upper half of the ACT could influence reservoir operations, especially during periods when reservoir operations are balancing competing demands, such as water supply, hydropower, minimum environmental and recreational flow etc.

Based on our uncertainty quantification for the ACT River Basin, the choice of GCM is the most important factor when designing the hierarchical modeling framework for impact studies. The choice of the hydrologic models plays an insignificant role in uncertainty of hydrologic regimes in the region relative to the uncertainties arising from the climate projections. The complex and computationally intensive hydrologic model like DHSVM provides similar insights in hydrologic projections compared to VIC and PRMS in this region, suggesting that water managers and other stakeholders can place greater emphasis on the selection of climate models for any future hydroclimate studies designs.

It is important to note that internal variability of GCMs is not explicitly calculated, as this commonly requires generating multiple simulations for a given GCM using different initial conditions but similar external forcings (Lafayesse et al., 2014). Since the meteorological forcings for this study were only limited by one run per GCM, the internal variability is therefore integral with GCM uncertainty for the purpose of this study. Nevertheless, the findings of this study align with other studies performed over various regions (Chen et al., 2011; Hattermann et al., 2018; Meresa and Romanowicz 2016; Osuch et al., 2016; Chegwiddden et al., 2019) that focus on quantifying the major sources of uncertainty.

3.5 Summary and Conclusions

Evaluations of future water resources under a changing climate requires reliable hydroclimate projection. These projections are often generated by driving calibrated hydrologic models using meteorological outputs from GCMs. In this study, a hydro-meteorological framework of process-based models was developed. A set of 33-member ensemble hydrologic projections over ACT river basin using a combination of eleven dynamically downscaled GCMs and three calibrated hydrologic models were produced. The future projections were generated under RCP8.5 emission scenario for a 40 years period of 2011–2050, which were compared with reference to baseline simulations (1966–2005). The high resolution simulated hydrologic outputs variables were analyzed and sources of uncertainties arising from climate models and hydrologic models were quantified.

Overall, models are reasonably able to simulate baseline hydroclimate comparable to the observations. The future projections show an increase in multi-model mean seasonal precipitation during all seasons by +1.9% to +3.5% relative to baseline. The runoff signal exhibits a similar behavior; however, the changes in runoff are not linearly proportional to the increase in precipitation. For instance, the summer season observe an +8% increase in runoff while precipitation increases only by +2%. This indicates future intensification of summer rainfall consistent with existing trend also documented in other studies. The consistent increase projected in high flow further suggests an increasing trend of high intensity rainfall across ACT, while the projected low flow exhibits a decreasing trend for a majority of gauge locations indicating potential slight intensification of hydrological cycle in the region. The increased magnitudes of high flow events could put additional stress on the major reservoirs with primary goal of flood control in ACT. On the other hand, the decreased low flow magnitudes could make reservoir more vulnerable when meeting competing water demands. The analysis of changes in seasonal and extreme flows close to outlet of ACT shows a large spread in the distribution, which is consistent across most gauges. A quantification of sources of uncertainties using ANOVA method revealed that climate models are the dominant source of uncertainties in the region. These results are consistent across all measures of streamflow. The results suggest that selection of hydrologic model does not yield different insights about hydroclimate projection at the watershed scale, therefore suggesting that in-lieu of resources, the water managers can utilize a relatively coarser hydrologic model to capture

the hydrologic projections effectively. Although, this study considered two sources of uncertainties, other sources may be incorporated in future. A more comprehensive analysis would include additional sources of uncertainties by including other emission scenarios, climate models, downscaling approaches, sets of hydrologic parameters and future land use cover. Despite the limitations, this study can set a path forward with the applications of the proposed framework in many aspects of water resources including investigation of future flood risks, water supply, reservoirs operations and hydropower production in ACT river basin.

Acknowledgment

This study was supported by the US Department of Energy (DOE) Water Power Technologies Office as a part of the SECURE Water Act Section 9505 Assessment. The research used resources of the Oak Ridge Leadership Computing Facility at Oak Ridge National Laboratory (ORNL). The authors are employees of UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US DOE. Accordingly, the US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US Government purposes.

CHAPTER IV
ROBUSTNESS OF RESERVOIR OPERATION IN A CHANGING
ENVIRONMENT

Abstract

The role of reservoirs is vital for water resource management with benefits such as freshwater storage and supply, flood risk management, and hydropower generation. A changing environment, resulting in non-stationary variations in precipitation and temperature, and a growing water demand owing to rapidly increasing population, are likely to stress the overall dynamics of reservoir operations. Therefore, it is important to evaluate the robustness of current reservoir operations in the projected future hydro-climate conditions for optimal water resources management decisions. This study utilizes an integrated distributed hydrologic-reservoir model (DHSVM-Res) which includes the high-resolution Distributed Hydrology Soil Vegetation Model (DHSVM) embedded with a multi-purpose reservoir module to study the key hydrologic and water demand interactions for selected major reservoirs in the Alabama-Coosa-Tallapoosa (ACT) River Basin in the southeastern United States. The reservoirs in ACT are multi-purpose and provide benefits such as flood control, hydropower generation, and water supply for states of Alabama and Georgia (including the Atlanta metropolitan area). DHSVM-Res was first calibrated, depending on observed data availability, to reproduce historic behavior of key hydrologic parameters including reservoir storage, direct reservoir evaporation, and discharge. The sensitivity of reservoir operations under current operating rules was then evaluated against various future scenarios including 1) projected future water availability derived from an ensemble of dynamically downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) model outputs, and 2) hypothetical future water demand. This study will provide insights regarding the resilience of current reservoir operations in the southeastern US and have implications for the decision makers about potential future challenges.

4.1 Introduction

Reservoirs play an important role in water resource management by reducing natural and/or anthropogenic hydrologic variabilities to meet our constant needs (Ehsani et al., 2017). Many reservoirs serve multiple purposes to provide benefits such as flood control, hydropower generation, recreation, navigation and municipal, industrial and agricultural water supply (Lehner et al., 2011). Given that many of these objectives are competing in nature, effective reservoir operations become crucial for sustainable water management. With intensified hydroclimate extreme events such as floods and droughts, the reservoirs can face more severe challenges in mitigating the increasing variability. Unfortunately, such occurrences are projected in the future under a changing socio-environmental scenario triggered by factors such as climate change, land use landcover change, urbanization and population growth, and will further stress the current reservoir operation practice (Ehsani et al., 2017; Giorgi et al., 2011; Watts et al., 2011). The reservoir operations are affected by interannual hydrologic variability, increasing frequencies of floods and droughts, shifts in timings of seasonal and annual streamflow, and increasing evaporation, etc. Under prolonged droughts with reduced water availability, reservoirs may not meet the competing water demands, and/or comply with minimum environmental / ecological flow requirements (Batalla et al., 2004; Brekke et al., 2009; Jager et al., 2018). For instance, elevated temperatures can cause enhanced evaporative losses from the reservoirs (Friedrich et al., 2018) and earlier snowmelt, resulting in untimely high streamflow that could have serious implications on the current reservoir operations and hydroelectricity generation (Golombek et al., 2012). Additionally, the stress on water resources is likely to further exacerbate under the compound effects of climate change and increased water demands arising from population growth and urbanization (Mehran et al., 2017).

An evaluation of reservoir operations under these non-stationary hydrologic conditions are hence required. Such modeling involves estimation of discharge and storage by accounting for inflow, maximum and minimum storage capacities, downstream water requirements and operation rules. Many regional and large-scale hydroclimate projection studies do not capture the effects of reservoir operations and only produce naturalized flow projections (Naz et al., 2016). The implementation of reservoir operations is either hindered due to a lack of multi-purpose reservoir components in the models (Zhao et al., 2016), or the lack of pertinent reservoir information or

operational rules (Shin et al., 2019). A simplified version to simulate releases using weir equations (Meigh et al., 1999), implementation of neural network-based approaches to simulate reservoir operations (Celeste and Billib, 2009; Ehsani et al., 2016; Rungee and Kim, 2017), and alternate statistical techniques for indirect assessment of dam regulations (McManamay, 2014) have been utilized in the literature. However, the implementation of such techniques may not be appropriate under a changing climate scenario given their inability to account for physical processes such as evaporation and sedimentation and may result in biases under future scenarios. Therefore, this study utilizes a high resolution distributed hydrologic model along with an embedded multi-purpose reservoir module to understand the impacts of changing environment on current reservoir operations.

The main objectives of this study are to: 1) generate high resolution regulated hydroclimate projections under historic and future conditions for selected major reservoirs in the Alabama-Coosa-Tallapoosa (ACT) river basin, and 2) evaluate the resilience of current reservoir operations due to a changing environment including the effects of climate change and increased water demands. The study area located in the southeast United States, underrepresented in current hydroclimate impact assessment studies (Engström and Waylen, 2017), is one of the two major river basins that has water allocation issues between states of Georgia, Alabama and Florida. This study can provide decision makers better understanding of future climate impacts on hydrology and water resources at a regional scale to support more informed decisions.

4.2 Methods

4.2.1 Study Area

The study area focuses on ACT River Basin which covers northeastern and east central parts of Alabama, northwestern Georgia and small parts of Tennessee (Figure 4.1). ACT river basin includes 13 large reservoirs (Figure 4.1) with 5 federal dams (USACE, 2013) operated by the US Army Corps of Engineers (USACE). Other major dams are operated by a utility company headquartered in Birmingham, Alabama. The combined conservation storage for ACT river basin from these major reservoirs is roughly 2.6 million acre-feet (Table 4.1). The water resources in ACT basin are managed to serve multiple purposes including hydropower generation, flood risk management, navigation, water supply, recreation. The major urban areas in ACT include suburban areas of Atlanta (Kennesaw and Marietta), GA; Birmingham, AL; Montgomery, AL; and

Mobile, AL. The ACT river basin is a major source of water supply and accounts for roughly 20% and 13% of public water supply for the states of Georgia and Alabama respectively (USACE, 2013). The USGS gauges, HUC08s and reservoir locations are shown in the Figure 4.1. A detailed description about ACT is provided in sections 1.2.1 and 3.2.

This study will focus on 4 major reservoirs namely Allatoona, Carters, Harris and Martin which collectively accounts for ~70% of the total conservation storage of ACT. These reservoirs are selected based on the availability of pertinent reservoir information such as observed inflow, discharge and storage, area-elevation-volume relationships, minimum and maximum permissible reservoir discharge etc. This information was largely derived from the following references: ACT Master Control Manual (USACE, 2013).

4.2.2 DHSVM-RES Description

This study utilizes a high-resolution, process-based Distributed Hydrology Soil Vegetation Model (DHSVM) along with a multi-purpose reservoir module (DHSVM-RES; Zhao et al., 2016). DHSVM-RES performs grid-based mass and energy balance calculation to simulate various hydrologic processes such as evapotranspiration, snowmelt, canopy snow interception and release, soil moisture, subsurface flow, overland flow, and channel flow, along with added capability to simulate multiple reservoirs at fine spatiotemporal scales. The reservoir module embedded within DHSVM-RES treats reservoirs as a point-based reservoir located on a selected channel assigned by the users. It considers streamflow reaching a segment as inflow to the reservoir and performs the water balance calculations at every time step by accounting various process including evaporation, water demands, storage, release, sedimentation, recharge, etc. The discharge from the reservoir is calculated through a threshold-based release scheme dependent on the reservoir pool elevation at any given timestep. The reservoir storage is divided into several pools termed as inactive, conservation, flood control and surcharge pools. At any given simulation time-step, if the reservoir elevation enters the surcharge pool, any excess water is discharged immediately. If the reservoir elevation is between conservation and flood control pool elevation, water released is calculated in proportion to elevation difference between current pool and conservation pool using a bathymetry-based area-elevation-volume (AEV) relationship. However, such a release is still regulated by the maximum discharge limit of the reservoir to avoid flooding at downstream locations. Below the conservation pool, the release is constrained to meet preassigned water demands and the release is restricted completely if the reservoir pool falls below the inactive pool.

The reservoir conservation pool can be varied at monthly timestep which allows the use of reservoir operational rule (or guide curves). At every simulation timestep, the direct open water evaporation from reservoir is calculated using Penman equation on estimated surface area of the reservoir derived using AEV relationships. A detailed description of DHSVM and relevant process-based equations can be found in Storck et al. (1998), Wigmosta et al. (2002) and (1994). Readers are also referred to Zhao et al. (2016) for more detailed description of the reservoir module.

4.2.3 DHSVM-Res Setup and Implementation

A calibrated DHSVM setup, obtained from Gangrade et al., (2018), was used as the base for this study. The above setup implements DHSVM at a 90-meter spatial resolution at sub-daily temporal scale (3-hourly), also explained in Section 1.2.3. The DHSVM requires meteorological inputs including precipitation, temperature, relative humidity, wind speed, longwave and shortwave radiation. The hydrologic simulation is implemented for historic period of 1980–2012 using the meteorological forcings obtained from the Daymet dataset (Thornton et al., 1997). The calibration and validation of DHSVM is performed by comparing simulated streamflow against observed streamflow at 74 USGS gauges (Gangrade et al., 2018). The above setup does not account for reservoir operations, which were introduced in this study through DHSMV-RES, a dynamically linked reservoir module with DHSVM, for selected major reservoirs in ACT river basin to reproduce historic reservoir discharge and storage. The setup details are presented using reservoir Allatoona, one of the most upstream reservoirs in ACT, as an example. The DHSVM-RES was setup using the pertinent reservoir information from the ACT Water Control Manual. The initial control simulation is setup from 1981–2009 with 1981–1994 used for calibration and 1995–2009 used for validation. Since Allatoona has sufficiently good historic inflow observation, the flow within DHSVM setup immediately upstream of the reservoir is replaced with observed reservoir inflow during calibration. The calibration is conducted using the Nelder-Mead simplex algorithm by simultaneously maximizing NSE values for release and storage at weekly timestep. The simulated release is compared with USGS gauge located immediately downstream of the reservoir. A similar approach was utilized to setup DHSVM-RES for rest of the selected reservoirs in ACT. The calibration was performed using data from best available sources (USACE or USGS; rescaled where necessary based on the drainage area between USGS gauge and the reservoir location). The calibration was restricted to used only weekly release where the observed storage values were

unavailable. The reservoirs in ACT do not operate on a single conservation pool elevation throughout the year. Instead, the reservoirs observe a drawdown in advance of the flood season as a flood risk management. Further depending on wetter/drier than normal conditions, the reservoir operates under different action zones. However, due to a lack of information regarding the deciding factors of a reservoir to operate following a specific rule, a general guide curve is derived as an average of the two extreme guide curves (wettest and driest) wherever applicable. More details regarding model setup are presented in Table 4.2.

4.2.4 *Climate Change Forcing and Simulations*

The climate projections used in this study were generated by 11 dynamically downscaling Coupled Model Inter-comparison Project Phase-5 (CMIP5) GCMs using Regional Climate Model version 4 (RegCM4) to a horizontal spatial resolution of 18 km (Ashfaq et al., 2016). These climate projections were further statistically bias-corrected using a quantile mapping technique (Ashfaq et al., 2010; Ashfaq et al., 2013) to a spatial resolution of 4-km. The 1966–2005 Parameter-elevation Relationships on Independent Slopes Model (PRISM) precipitation, daily maximum and minimum temperature dataset was then used as the ground truth to support bias-correction.

The climate projections provide key meteorological forcing data such as daily precipitation, daily wind speed, daily maximum and minimum temperature for hydrologic models for 40 years in the baseline period (1966–2005) and for 40 years in the future period (2011–2050). These climate forcings were then used to drive DHSVM to generate the hydrologic projects immediately upstream of the reservoir locations. To avoid any potential biases arising from the hydrologic modeling, the streamflow data were further bias corrected using quantile mapping technique for each individual reservoir location to characterize a more accurate representation of climate signal on reservoir operation. The bias corrected climate driven historic and future streamflow data was used as input to capture the effects of four selected reservoirs using calibrated DHSVM-RES. The regulated hydrologic projections under climate scenarios for 40 years in the baseline period (1966–2005) and 40 years in the future period (2011–2050) using dynamically downscaled meteorological data for 11 GCMs.

4.2.5 *Analysis*

A reservoir specific analysis was conducted for each of the selected reservoirs which were evaluated through following indices:

- a) Mean streamflow at weekly and monthly timesteps for both inflow and discharge from the reservoir
- b) Q95: the 95th percentile weekly flow statistics as a proxy for high flow conditions
- c) Q05: the 5th percentile weekly flow statistics as a proxy for low flow conditions
- d) OD: The operational departures calculated as percent deviation of reservoir storage from its operational target, methodology adopted from Patterson and Doyle (2018) who used this approach to conduct a nationwide assessment of 233 USACE reservoirs to evaluate their performance in meeting the operational targets.

$$\text{Operational Departure (OD)} = \frac{\text{Reservoir Storage}}{\text{Operational Target}} * 100$$

These analyses were conducted for each of the 11-ensemble member in baseline and future period independently. The percent changes, wherever applicable, were calculated as: future-baseline with respect to baseline. The analysis to capture the seasonal variations included following time periods: Fill-up (F; January-April), Conservation (C; May-August) and Drawdown (D; September – December)

4.3 Results and Discussion

4.3.1 DHSVM-Res Performance

The DHSVM-RES calibration and validation included comparison of simulated release and storage against observed streamflow and storage, where applicable. These weekly statistics (along with monthly) are presented in Table 4.2. The periods of calibration and validation varied for each station depending on data availability. The time series time-series of weekly release for each reservoir is presented in Figure 4.2 a through d. In addition, time series of weekly storage is presented for Allatoona Lake (Figure 4.2e). The results indicate a satisfactory performance at weekly time step to simulate the release (NSE = 0.62), and a good performance to simulate the storage (NSE = 0.83) for Allatoona. Table 4.2 and Figure 4.2 demonstrates that DHSVM-RES was satisfactorily able to capture the release dynamics for reservoirs Carters, Harris and Martin at weekly and monthly timesteps.

4.3.2 Climate Impacts on Inflow

The first analysis focus on evaluation of impacts of climate change on the streamflow volume which generally dictates the water availability for any given reservoir. At annual scale, the reservoirs Allatoona, Carters, Harris and Martin demonstrate a change of +2.8%, +1.9%, +8.7%

and +9.5% in the projected multi- model mean streamflow. A further breakdown of projected multi-model mean percent change in monthly reservoir streamflow along with the ensemble range is presented in Figure 4.3.

The results indicate that while the multi-model mean demonstrate a slight to moderate increase in the streamflow, it is accompanied with a large variability and associated uncertainties arising due to the ensemble climate forcings under future time period. Generally, the reservoirs located in the lower half of the ACT river basin observe a greater increase in streamflow availability as opposed to their counterparts in the upper ACT river basin (more discussion in Chapter III). While the multi-model mean streamflow projects an increased water availability at annual scale for all the reservoirs, the analysis of high flows and low flows indicates a projected increase in hydrologic extremes (Figure 4.4). In general, the Q95 is expected to increase for all reservoirs showing that flood events of higher magnitude are more likely to occur in future climate conditions. Similarly, the Q05 demonstrate a projected decrease for all reservoirs under future climate conditions demonstrating the increased variability in hydrologic extremes potentially posing a challenge for the reservoir operators.

The increase in Q95 is more pronounced for the reservoirs Harris and Martin especially in the Conservation period, whereas reservoirs Allatoona and Carters show a stronger signal in projected low flow decrease during the same time period. The decreased water availability during the conservation period may lead to overall water stress for the reservoir in case of competing water demands.

4.3.3 *Climate Impacts on Reservoir Discharge and Storage*

This section explores the impacts of climate change on the simulated reservoir release and storage dynamics. While the reservoirs are expected to maintain their storage close to their operational target, the water level within the reservoir are likely to fluctuate depending on the reservoir's attempt to meet its objectives. The DHSVM-RES attempts to mimic the same by trying to meet all the water requirements and provide flood control benefits to maximum possible extent (as discussed in Section 4.2.2) and regulates the storage to the monthly guide curves. At monthly time scales, the reservoir release and storage changes arising from the ensemble members is presented in Figure 4.3 for each reservoir. A quick glance at any given reservoir's inflow release and storage dynamics (Figure 4.3) suggests that the mean inflow in future exhibit a large variability. A similar variability is reflected within each reservoir's release compared with the

reservoir's inflow, which indicates that reservoirs mainly absorb the variability arising from the inflows by modifying its release and thereby maintaining a more stable storages at monthly timescale in future conditions. Since, monthly mean response smooths out extremities of the reservoir release and storage, Figure 4.5 presents percent change in median reservoir release at weekly time step arising from ensemble climate projections during fill-up (F), conservation (C) and drawdown (D) periods for each reservoir. The results demonstrate that for each reservoir the median weekly release is projected to increase, in general, during the fill-up period. However, all the reservoirs demonstrate a projected decrease in median weekly release during the conservation and draw-down periods. For instance, the multi-model median change in weekly release projects a decrease of -12% and -7% for reservoirs Martin and Harris respectively.

Further, as the release and storage of the reservoir are intertwined, the impacts of altered water availability or hydrologic extremes will impact the reservoir storages as well. While the mean monthly storages under future conditions may not demonstrate a large deviation due to absorption of inflow variability at that time scale by the reservoirs, increase in flood magnitudes can still result in some large divergence in the reservoir storage at daily or weekly timestep from its operational target. A potential explanation of such behavior stems from the indication that southeastern US has observed an ongoing intensification of precipitation during summer and fall seasons (Wang et al., 2010; Li et al., 2013; Bishop et al., 2019). Further, the reservoir inflow suggests a larger variability of hydrologic extremes under future climate conditions. Therefore, the increased magnitude of flood events results in immediate release of water as soon as practical after the event to prepare the reservoir for any future flood events. But at the same time, the lower availability of water during the low flow periods can stress the reservoir thereby resulting in lower releases in general.

To further capture the effects of climate impacts on reservoir storage, the operational departures at weekly time step are calculated for each reservoir under baseline and future climate conditions separately. The operational departures can then be used to identify how frequently any reservoir exceeds or drops below a certain percent deviation from operational target. This information summarized as storage duration curves is presented for each reservoir under baseline and future time periods (Figure 4.6). The shaded portions indicate the range of 5th percentile and 95th percentile storages under baseline and future time periods. In general, the storage duration curve of a reservoir should align with the reference (i.e. 100% in this case) for most of the duration

except for the tail ends to account for deviations arising from flood events or water withdrawals. Under baseline time period, the reservoirs Carters and Martin operate more closely to their operational targets, followed by Harris. A greater deviation is observed for Allatoona.

The operational departure greater than 100 indicates that reservoir operates in surplus zone. For instance, for each reservoir, the magnitude of operational departure increases under future climate conditions in the surplus zone, which further stresses the fact that due to increased magnitude of flood extremes, the reservoir is likely to observe much higher storages to accommodate the flood event. While it may be deemed as increased water availability, the reservoir operating in excess of operational targets are vulnerable and can be triggered by any additional flood events of even a smaller magnitude.

Similarly, the operational departures less than 100 percent indicate that reservoirs operate in shortage and are more vulnerable to decreased water availability. Figure 4.6 suggest that deviations in the operational departures when in shortage are not as severe as the reservoir attempts to conserve as much water as possible by reducing the release from the reservoir in these circumstances. However, the reservoirs meeting competing water demands such as Allatoona are more influenced during reduced water availability.

While the future climate conditions exacerbate the reservoir operations, especially resulting in a much higher reservoir storages compared to baseline, the reservoirs have been in general resilient enough under current operations to accommodate and rebound from these fluctuations. It is important to note that this type of analysis is significantly dependent on the size of the reservoir along with overall conservation storage, inactive and flood control volume, and minimum and maximum water withdrawal requirements and monthly scale guide curve as an input data to the DHSVM-RES. Further, these analysis for baseline and future conditions is performed using simulated storage which may have potential biases introduced through the hydrologic simulations. It is also important to note that above analysis for reservoir Carters was performed by adding the conservation volume of Carters reregulation dam to the general operational target of the Carters main dam.

4.3.4 Impacts of Increased Water Demands

Additional set of simulations were conducted for reservoir Allatoona to explore the impacts of increased water demands in conjunction with climate change signal to provide a more comprehensive view of water resources under future conditions. These simulations were

conducted specific to reservoir Allatoona as it plays an important role to maintain water supply for the Atlanta metropolitan area. These additional set of simulations were designed as follows:

- a) Baseline: 11-member ensemble simulation during baseline time period (same as explained in Section 4.2.4) which uses 50 million gallon per day (mgpd) as water demand
- b) Future-S1: 11-member ensemble simulation during future time period (same as explained in Section 4.2.4), 50 mgpd as water demand
- c) Future-S2: 11-member ensemble simulation during future time period (same as Future-S1) with 95 mgpd as water demand
- d) Future-S3: 11-member ensemble simulation during future time period (same as Future-S1) 145 mgpd as water demand

Figure 4.7 shows the boxplots demonstrating the weekly storage and discharge (release from the reservoir) for each scenario arising from 11-member ensemble. As expected, the increased water demands consistently lead to lower median discharge from the reservoirs for scenarios Future-S1, Future-S2 and Future-S3. In addition, the increased water demands exhibit a greater impact on the minimum storage values of the reservoirs especially during the conservation and drawdown period (not shown here).

4.3.5 Sensitivity Analysis

A systematic set of simulations were designed for each reservoir to evaluate the impacts of variability in reservoir inflow on reservoir release and storage in a more comprehensive method. Such information can help deduce the relative impacts of water availability and evaluate the resilience of reservoirs operations. Four set of simulations were conducted for each reservoir:

Control – Calibrated DHSVM-RES driven by historic observed reservoir inflows

Scenarios S1 - S4 - same setup as Control, for each reservoir, with the observed reservoir inflows adjusted as -50%, -25% +25% and +50% of the reservoir inflows compared to Control.

The resulting changes in median weekly reservoir storage (relative to control simulations; Figure 4.8a) and frequency of reservoir exceeding +/- 10% of its operational target at weekly time-step (assumed value for the analysis), were evaluated for each reservoir in Figure 4.8b and c respectively. The results indicate that for Allatoona, S1, S2, S3 and S4 results in -63.7%, -32.5%, +30.4% and +61.3% changes in reservoir release, respectively, when compared against the

reservoir release under control scenario. Reservoirs Carter, Harris and Martin also show a similar behavior.

As expected, the changes in release occur in tandem with changes in storages. In general, altered water availability results in more deviations for the reservoir from its operational target. The increased water availability i.e. Scenarios S3 and S4 result in a greater number of times a reservoir exceeds its operational departure from +10% threshold, which at the same time lead to reduction in frequency OD fall shorts of -10% threshold. Similarly, an opposite behavior is expected in the reduced water availability i.e. Scenarios S1 and S2. In some cases, such as reservoir Harris, and Carters, reduced water availability may lead to more pronounced impacts on reservoir storage under shortages compared to surplus, as evident from Figure 4.8b and c.

4.4 Summary and Conclusions

The goal of this study is to capture the reservoir storage and release dynamics under a changing environment to determine the resiliency of current reservoir operations to non-stationary factors like climate change and projected increased water demands. A set of 11-member ensemble hydrologic projections over ACT river basin using dynamically downscaled GCMs and DHSVM-RES, a high-resolution process-based hydrologic model embedded with a dynamically linked multi-purpose reservoir module, were produced for four selected major reservoirs namely Allatoona, Carters, Harris and Martin. The future projections were generated under RCP8.5 emission scenario for a 40 years period (2011–2050) and compared with the baseline simulation values (1966–2005).

The simulated reservoir inflow, release and storages were evaluated for each reservoir, generally indicating an overall increase in projected multi-model mean streamflow for the reservoirs by up to 9.5% for reservoir Martin at annual scale. However, a further analysis of high flow (Q95) and low flow (Q05) indicate a general increase in Q95 and decrease in Q05 under projected climate, thereby suggesting a greater variability in projected hydrologic regimes. Such effects are more pronounced during summer/fall season aligning with conservation and drawdown periods of reservoirs. As the reservoir operations are more susceptible to increased variability in hydrologic regimes, a general decrease in reservoir release is observed during conservation and drawdown periods. This behavior is more noticeable for reservoirs Martin and Harris and could have potential implications for their hydropower generation which is largely dependent on

reservoir release. A further analysis of storage duration curves for each reservoir indicates that reservoirs are likely to observe larger magnitude deviations from their operational target under future climate conditions. However, the reservoirs have been in general resilient enough under current operations to accommodate and rebound from these fluctuations. Additional set of simulations were conducted to explore the impacts of increased water demands on reservoir Allatoona. As expected, the reservoir is likely to observe a greater water stress in conjunction of climate change especially during the conservation and drawdown periods, resulting in lower reservoir release as well.

This study provides a baseline analysis for selected major reservoirs in ACT to provide a comprehensive view of overall water resources availability and its interactions with various potential future changes arising from changing climate or water demand interaction using hydrologic and reservoir models. While this approach is crucial to capture the non-stationarity, given its high dependence on a variety of reservoir specific information, this approach has limited applicability to data limited environments. For instance, many other reservoirs in ACT were excluded from this analysis due to lack of data availability. Relatively, greater availability of reservoir specific information for reservoir Allatoona allows for a more robust check of simulated results compared to its counterparts and limiting the uncertainties arising from the modeling chain. Nonetheless, the simulations in this study provides a general guidance regarding potential reservoir behaviors under varying factors and set path forward for future studies.

Acknowledgment

This study was supported by the US Department of Energy (DOE) Water Power Technologies Office as a part of the SECURE Water Act Section 9505 Assessment. The research used resources of the Oak Ridge Leadership Computing Facility at Oak Ridge National Laboratory (ORNL). The authors are employees of UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the US DOE. Accordingly, the US government retains and the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US Government purposes.

SUMMARY

This dissertation conducts a comprehensive analysis to evaluate hydrologic vulnerability and resilience of selected major hydropower reservoirs in the ACT River Basin. It was accomplished through four interdependent studies. The first study utilized a high resolution, process-based modeling framework to generate estimates of PMF in a changing climate. The framework including WRF and DHSVM produced an ensemble of PMF hydrographs for 120 moisture maximized storms under historic and future climate conditions. We find that under near and far future climate conditions, PMF is projected to increase significantly across ACT. The second study extends the WRF-DHSVM framework by employing a GPU accelerated 2D hydraulic model (Flood2D-GPU) to develop high resolution probabilistic flood maps under PMF events. The uncertainties arising from the ensemble approach are captured in the conditional probability of flooding under PMF, thereby providing flood risks information in a comprehensive fashion to decision makers. As revealed by multiple relative sensitivity tests in both the studies, the PMF and associated flood regimes are most sensitive to meteorological forcing datasets (precipitation) among other factors including antecedent soil moisture, reservoir operations, hydraulic model resolution and parameters, and LULC change (Gangrade et al., 2018; Gangrade et al., 2019). The third study generated 33-member ensemble hydrologic projections for ACT river basin under baseline (1966–2005) and RCP 8.5 future (2011–2050) climate scenario. It was accomplished using a combination of eleven dynamically downscaled GCMs and three process based hydrologic models of different spatiotemporal resolution. The future climate projections demonstrate a projected increase in multi-model seasonal precipitation, runoff and streamflow which is accompanied with a large range of uncertainties from the ensemble. The high flow is projected to increase across all gauges evaluated across ACT, while low flow is projected to decrease for majority of them. Based on analysis of variance, hydrologic projections in the region are greatly affected by the choice of the GCMs as opposed to the choice of hydrologic models. The fourth study develops the regulated hydroclimate projections for four selected major hydropower reservoirs in ACT to evaluate the robustness of reservoir operations under future climate scenarios. This was accomplished by using DHSVM-Res model, a dynamically linked reservoir module with DHSVM to capture the storage and release dynamics. The increased hydrologic variability results in a general decrease in reservoir release during conservation and

drawdown periods, further exacerbated under increased water demand scenario. The reservoirs also observe a stronger deviation from the operational target to accommodate increased magnitude of flood events. Despite such deviations, the evaluated reservoirs are resilient enough under current operation conditions to accommodate and rebound from these fluctuations.

Overall, this dissertation has performed a robust evaluation of hydrologic projections for ACT river basin, an under-represented area in hydroclimate studies, through process-based hydro-meteorological frameworks. The results from this research can be useful to provide information to water resource managers and other stakeholders regarding potential risks to critical infrastructure associated with hydro-climatic extreme events. The research presented can also prove beneficial to future modeling studies in the similar geographical areas.

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APPENDIX

Table 1. 1 Summary of selected study areas A1–A4 including HUC ID, drainage area, centroid, and extents

Study Area	HUC ID	Drain Area (km ² / mi ²)	Centroid		Extents			
			Long.	Lat.	West	East	North	South
A1 – Buck Creek	0315010805	360 / 139	–85.05°	33.68°	–85.18°	–84.91°	33.80°	33.56°
A2 – Conasauga	03150101	1880 / 727	–84.81°	34.85°	–85.08°	–84.50°	35.15°	34.54°
A3 – Cahaba	03150202	4720 / 1820	–87.00°	33.03°	–87.39°	–86.42°	33.75°	32.31°
A4 – ACT	0315	58900 / 22700	–86.05°	33.19°	–87.95°	–83.99°	35.15°	31.02°

Table 1. 2 Summary statistics for USGS gauges, including NSE, ρ , and PBIAS.

PBIAS is calculated as $([\text{observed flow} - \text{simulated flow}] * 100 / [\text{observed flow}])$.

No.	USGS ID	Drainage Area (km ² / mi ²)	Data Coverage	NSE		PBIAS (%)	ρ	
				Daily	Monthly		Daily	Monthly
Gauges Used for Calibration								
C01	02388320	43 / 16.6	1982–2012	0.65	0.82	−14.9	0.82	0.92
C02	02395120	85.7 / 33.1	1980–2012	0.49	0.70	10.6	0.80	0.92
C03	02425200	92.7 / 35.8	1972–1985	0.83	0.91	8.7	0.91	0.96
C04	02397410	169 / 65.3	1981–2012	0.66	0.78	−22.5	0.82	0.95
C05	02390000	231 / 89	1939–2012	0.50	0.46	18.0	0.78	0.88
C06	02427700	253 / 97.5	1958–1996	0.77	0.86	−12.7	0.88	0.95
C07	02392780	360 / 139	2005–2012	0.63	0.74	−14.7	0.81	0.91
C08	02401390	365 / 141	1965–2012	0.66	0.82	14.0	0.86	0.93
C09	02407514	368 / 142	2005–2012	0.76	0.88	5.1	0.88	0.95
C10	02406500	388 / 150	1900–2012	0.73	0.80	0.2	0.86	0.93
C11	02401000	471 / 182	1943–2012	0.78	0.90	−2.8	0.88	0.95
C12	02415000	492 / 190	1952–2012	0.67	0.80	27.6	0.84	0.94
C13	02422500	526 / 203	1938–2012	0.75	0.79	−4.4	0.88	0.94
C14	02380500	611 / 236	1938–2012	0.53	0.37	4.7	0.86	0.87
C15	02400100	653 / 252	1962–2012	0.76	0.78	−12.3	0.89	0.94
C16	02427250	676 / 261	1989–2012	0.80	0.85	−14.0	0.90	0.96
C17	02408540	681 / 263	1980–2012	0.68	0.89	12.8	0.83	0.95
C18	02421000	751 / 290	1952–2012	0.62	0.85	−13.2	0.79	0.93
C19	02419000	862 / 333	1939–2012	0.76	0.88	−9.2	0.89	0.95
C20	02423555	868 / 335	1995–2012	0.79	0.88	−12.4	0.91	0.95
C21	02398300	948 / 366	1959–2012	0.80	0.83	−12.1	0.92	0.96
C22	02413300	1050 / 406	1975–2012	0.77	0.84	−7.3	0.91	0.95
C23	02412000	1160 / 448	1952–2012	0.78	0.84	−1.7	0.88	0.94
C24	02404400	1250 / 481	1960–2012	0.79	0.87	7.6	0.91	0.95
C25	02392000	1590 / 613	1900–2012	0.70	0.59	8.9	0.88	0.90
C26	02387000	1780 / 687	1937–2012	0.81	0.91	2.2	0.90	0.96
C27	02425000	4570 / 1770	1938–2012	0.76	0.92	−6.7	0.91	0.97
C28	02420000	38900 / 15000	1927–2012	0.75	0.88	−1.1	0.93	0.97
C29	02428400	54400 / 21000	1975–2012	0.77	0.91	−5.9	0.92	0.98
Gauges Used for Validation								
V01	02393377	9.3 / 3.6	2007–2012	0.14	0.47	7.1	0.45	0.75
V02	02410000	12.7 / 4.9	1953–1987	0.39	0.77	8.0	0.63	0.92
V03	02384540	21.2 / 8.2	1985–2012	0.59	0.76	2.6	0.77	0.90
V04	02381600	25.6 / 9.9	1974–2012	0.38	0.27	−15.8	0.69	0.84
V05	02388300	38.1 / 14.7	1968–1989	0.64	0.90	−2.7	0.84	0.96
V06	02393419	38.3 / 14.8	2005–2012	0.14	0.41	−10.7	0.40	0.64
V07	02423130	51 / 19.7	1988–2012	0.52	0.78	−1.9	0.73	0.89

Table 1.2 Continued

No.	USGS ID	Drainage Area (km ² / mi ²)	Data Coverage	NSE		PBIAS (%)	ρ	
				Daily	Monthly		Daily	Monthly
V08	02401470	57.8 / 22.3	1982–1995	0.59	0.87	3.1	0.80	0.94
V09	02423400	63.2 / 24.4	1986–2012	0.53	0.79	0.0	0.81	0.93
V10	02392950	66 / 25.5	1998–2012	0.49	0.76	–21.2	0.71	0.90
V11	02392975	89.6 / 34.6	1998–2012	0.49	0.71	–28.8	0.73	0.91
V12	02385500	104 / 40	1943–2012	0.61	0.76	5.8	0.79	0.91
V13	02401370	117 / 45	1978–1995	0.58	0.84	15.3	0.82	0.95
V14	02418760	119 / 45.8	2002–2012	0.55	0.73	–13.6	0.77	0.89
V15	02400680	143 / 55.4	2002–2012	0.68	0.78	–26.7	0.84	0.95
V16	02392360	146 / 56.5	2005–2012	0.58	0.76	13.1	0.76	0.91
V17	02387600	162 / 62.6	2005–2012	0.69	0.64	–26.4	0.86	0.92
V18	02385800	166 / 64	1960–2012	0.62	0.82	–0.0	0.80	0.91
V19	02390475	177 / 68.2	2005–2012	0.49	0.44	–14.1	0.77	0.91
V20	02388900	181 / 69.7	2005–2012	0.45	0.44	14.1	0.81	0.87
V21	02418230	185 / 71.3	1999–2012	0.73	0.87	6.1	0.85	0.94
V22	02388975	252 / 97.3	2007–2012	0.49	0.47	6.8	0.80	0.87
V23	02397500	298 / 115	1942–2012	0.60	0.40	–40.3	0.85	0.94
V24	02389150	339 / 131	2002–2012	0.41	0.34	3.0	0.82	0.88
V25	02423380	363 / 140	1980–2012	0.74	0.90	8.1	0.86	0.96
V26	02385170	456 / 176	2005–2012	0.64	0.81	–0.5	0.80	0.91
V27	02403310	495 / 191	2002–2011	0.84	0.90	8.6	0.92	0.96
V28	02398000	497 / 192	1937–2012	0.80	0.84	–10.4	0.90	0.95
V29	02405500	500 / 193	1951–2012	0.66	0.83	12.6	0.88	0.94
V30	02399200	515 / 199	1958–2012	0.65	0.85	11.4	0.83	0.94
V31	02423425	521 / 201	1975–2012	0.67	0.77	–31.6	0.87	0.95
V32	02424940	570 / 220	1975–1987	0.71	0.81	–16.6	0.89	0.97
V33	02388350	580 / 224	2005–2012	0.76	0.91	–9.3	0.89	0.96
V34	02413210	635 / 245	2000–2012	0.72	0.80	–18.8	0.87	0.93
V35	02384500	653 / 252	1981–2012	0.70	0.84	5.1	0.85	0.92
V36	02411930	704 / 272	1999–2012	0.71	0.68	–19.9	0.87	0.93
V37	02383500	2150 / 831	1938–2012	0.38	0.63	5.0	0.85	0.91
V38	02424000	2660 / 1027	1901–2012	0.59	0.84	–13.9	0.85	0.97
V39	02424590	3830 / 1480	1987–2011	0.75	0.89	–8.3	0.92	0.97
V40	02387500	4150 / 1600	1900–2012	0.79	0.84	4.0	0.92	0.95
V41	02414500	4340 / 1680	1923–2012	0.65	0.82	10.7	0.83	0.93
V42	02414715	5330 / 2060	1985–2012	0.70	0.83	17.8	0.86	0.94
V43	02388500	5480 / 2120	1939–2012	0.81	0.88	–2.4	0.92	0.96
V44	02419890	12000 / 4646	1995–2012	0.70	0.82	7.9	0.89	0.93
V45	02411000	25900 / 10000	1912–2012	0.69	0.91	–1.6	0.87	0.97

Table 1. 3 Land use land cover (LULC) categories for year 2006 (observed) and 2030 (projected) at each study area

LULC Categories	A1 – Buck Creek			A2 – Conasauga			A3 – Cahaba			A4 – ACT		
	2006 (%)	2030 (%)	Change (%)	2006 (%)	2030 (%)	Change (%)	2006 (%)	2030 (%)	Change (%)	2006 (%)	2030 (%)	Change (%)
Water	1.6	2.0	+0.4	0.4	0.5	+0.1	0.9	1.2	+0.3	1.9	2.3	+0.4
Developed	10.0	12.9	+2.9	11.8	16.5	+4.7	12.4	15.8	+3.4	8.4	11.2	+2.8
Barren	0.3	0.1	-0.2	0.2	0.1	-0.1	0.5	0.2	-0.3	0.3	0.1	-0.2
Forest	50.2	38.1	-12.1	60.8	50.9	-9.9	62.0	48.6	-13.4	58.5	46.8	-11.7
Shrubland / Grassland / Crops	36.0	44.9	+8.9	25.9	31.1	+5.2	19.7	29.6	+9.9	25.6	34.3	+8.7
Wetland	1.9	2.0	+0.1	0.9	0.9	0	4.5	4.6	+0.1	5.3	5.3	0

Table 2. 1 List of 120 events used to generate moisture maximized storms under historic and future climate forcings.

Storm Set	No of storms	Time Period	Forcings Source
CFSR-CT	30	1981–2011	CFSR Reanalysis (Control Simulation)
CCSM4-BL	30	1981–2005 (historical) 2006–2010 (RCP 8.5)	CCSM4 (Baseline Simulation)
CCSM4-F1	30	2021–2050 (RCP 8.5)	CCSM4 (Near Future Simulation)
CCSM4-F2	30	2071–2100 (RCP 8.5)	CCSM4 (Far Future Simulation)

Table 2. 2 Contingency table for the analysis domain in ME01 represented as a fraction of total number of cells in the analysis domain.

Cells	Wet in Model (M1)	Dry in Model (M0)
Wet in FEMA (B1)	0.0804 (M1B1)	0.0175 (M0B1)
Dry in FEMA (B0)	0.0162 (M1B0)	0.8859 (M0B0)

Table 2. 3 Key flood model performance metrics calculated for ME01 for a 100-year ensemble flood event. Adopted from Wing et al., (2017).

Criterion	Formula	Calculated Value	Range	Description
Hit rate (H)	$M1B1 / (M1B1 + M0B1)$	0.82	0 – 1	Measure of tendency of model to accurately predict the benchmark flood extents
False alarm ratio (F)	$M1B0 / (M1B0 + M1B1)$	0.17	0 – 1	Measure of tendency to overpredict flood extent
Critical success index (C)	$M1B1 / (M1B1 + M0B1 + M1B0)$	0.70	0 – 1	Measure of fit with penalty for overprediction and underprediction
Error (E)	$M1B0 / M0B1$	0.93	0 – infinity	Measure of tendency toward overprediction or underprediction

Table 2. 4 Key ensemble PMF peak discharge statistics for domain ME01, ME02 and at the outlet of Etowah Watershed

Scenario	Etowah Watershed				ME01				ME02			
	Min (cfs)	Mean (cfs)	Median (cfs)	Max (cfs)	Min (cfs)	Mean (cfs)	Median (cfs)	Max (cfs)	Min (cfs)	Mean (cfs)	Median (cfs)	Max (cfs)
CFSR-CT	3,628	11,883	10,645	27,731	692	2,255	1,951	4,453	3,326	11,061	9,761	25,726
CCSM4-BL	4,815	10,255	8,996	21,874	843	1,850	1,657	4,038	4,459	9,594	8,507	21,379
CCSM4-F1	4,874	12,184	10,923	34,591	943	2,246	2,013	5,219	4,592	11,319	10,382	32,555
CCSM4-F2	4,925	16,704	16,098	45,660	1,144	2,800	2,517	6,523	4,485	15,517	14,824	42,312
HMR	18,653				3,618				17,322			

Table 2. 5 Scenarios for relative sensitivity test. The Default* setting indicates 30-m for Flood2D-GPU grid resolution and 0.035 as Manning's n value.

Experiment	Scenario ID	Flood2D-GPU Driven by	Flood2D-GPU Resolution	Manning's n
Baseline simulation	S1	PMF hydrographs associated with the event with maximum peak discharge (out of 30 events) obtained from CCSM4 forcings (CCSM4-BL)	Default*	Default*
Alternative meteorological forcings	S2a	PMF hydrographs with maximum peak discharge obtained from CFSR forcings (CFSR-CT)	Default*	Default*
	S2b	PMF hydrographs with maximum peak discharge obtained from conventional approach (HMR51 and HMR52)	Default*	Default*
Climate change	S3a	PMF hydrographs with maximum peak discharge obtained from near future CCSM4 forcings (CCSM4-F1)	Default*	Default*
	S3b	PMF hydrographs with maximum peak discharge obtained from far future CCSM4 forcings (CCSM4-F2)	Default*	Default*
Horizontal grid resolution for Flood2D-GPU	S4	Same as S1	10-m	Default*
Manning's roughness coefficient	S5a	Same as S1	Default*	0.015
	S5b	Same as S1	Default*	0.055
Antecedent moisture conditions	S6	Same as S1, with unsaturated soil moisture conditions at the beginning of hydrologic simulation	Default*	Default*
Reservoir operations	S7	Same as S1, with adjustment to reflect ideal reservoir operations	Default*	Default*

Table 3. 1 Summary statistics for mean ensemble percent change in runoff observed under climate change summarized by HUC08s in ACT River Basin

HUC08	Change in Runoff (%)					
	Winter	Spring	Summer	Fall	Q05	Q95
3150101	-0.34	0.49	5.15	0.47	0.72	1.46
3150102	-0.32	0.40	0.13	-0.82	-3.25	2.24
3150103	0.01	1.84	6.86	2.60	-0.41	2.46
3150104	0.51	1.87	0.02	0.22	-3.12	3.89
3150105	0.64	2.43	7.70	6.36	1.68	3.70
3150106	1.50	3.93	6.10	9.14	-2.67	5.15
3150107	3.22	6.20	8.70	13.02	-2.49	6.71
3150108	3.60	3.38	2.12	7.16	-3.20	4.51
3150109	3.29	6.25	6.19	11.41	-6.56	8.34
3150110	4.13	8.33	10.56	17.73	-3.05	10.78
3150201	4.06	9.16	12.35	19.42	-0.08	9.77
3150202	2.28	6.80	9.28	13.89	-3.70	7.30
3150203	2.55	8.99	15.07	22.39	1.34	9.16
3150204	2.26	7.72	12.10	21.85	1.31	7.61
ACT	2.28	5.53	7.97	11.99	-1.74	6.60

Table 3.2 Historic hydrologic model performance evaluation summarized for each USGS gauge location.

Unique ID	USGSID	Longitude	Latitude	Drainage Area (sq. miles)	Data Availability		NSE monthly			NSE daily		
							VIC	DHSVM	PRMS	VIC	DHSVM	PRMS
'A0001'	'USGS02380500'	-84.51	34.68	236	1938	2013	0.85	0.37	0.75	0.29	0.53	-0.14
'A0002'	'USGS02381600'	-84.47	34.57	9.99	1974	2013	0.65	0.27	0.20	0.15	0.38	0.06
'A0007'	'USGS02383500'	-84.83	34.56	831	1938	2013	0.89	0.63	0.87	0.31	0.38	0.46
'A0008'	'USGS02384500'	-84.85	34.83	252	1981	2013	0.78	0.84	0.92	0.28	0.70	0.79
'A0009'	'USGS02384540'	-84.72	34.87	8.24	1985	2013	0.51	0.76	0.82	0.12	0.59	0.63
'A0010'	'USGS02385170'	-84.88	34.74	176	2005	2013	0.71	0.81	0.87	0.28	0.64	0.70
'A0011'	'USGS02385500'	-84.97	34.79	40	1943	2013	0.73	0.76	0.90	0.23	0.61	0.49
'A0012'	'USGS02385800'	-84.77	34.72	64	1960	2013	0.76	0.82	0.79	0.15	0.62	0.67
'A0013'	'USGS02387000'	-84.93	34.67	687	1937	2013	0.85	0.91	0.92	0.53	0.81	0.83
'A0014'	'USGS02387500'	-84.94	34.58	1602	1900	2013	0.92	0.84	0.93	0.76	0.79	0.82
'A0016'	'USGS02388300'	-85.27	34.37	14.7	1968	1989	0.54	0.90	0.89	0.25	0.64	0.73
'A0017'	'USGS02388320'	-85.26	34.37	16.6	1982	2013	0.60	0.82	0.82	0.28	0.65	0.64
'A0018'	'USGS02388350'	-85.14	34.36	224	2005	2013	0.73	0.91	0.85	0.38	0.76	0.75
'A0019'	'USGS02388500'	-85.14	34.30	2115	1939	2013	0.92	0.88	0.94	0.78	0.81	0.85
'A0023'	'USGS02390000'	-84.21	34.43	89	1939	2013	0.88	0.46	0.76	0.05	0.50	0.33
'A0029'	'USGS02392000'	-84.49	34.24	613	1900	2013	0.88	0.59	0.82	0.35	0.70	0.53
'A0031'	'USGS02392780'	-84.50	34.12	139	2005	2013	0.71	0.74	0.82	0.20	0.63	0.51
'A0038'	'USGS02395120'	-84.89	34.24	33.1	1980	2013	0.58	0.70	0.79	0.14	0.49	0.33
'A0042'	'USGS02397410'	-85.26	34.00	65.3	1981	2013	0.82	0.78	0.12	0.11	0.66	0.23
'A0043'	'USGS02397500'	-85.31	34.06	115	1942	2013	0.85	0.40	0.69	0.19	0.60	0.54
'A0044'	'USGS02398000'	-85.34	34.47	192	1937	2013	0.88	0.84	0.92	0.27	0.80	0.80
'A0046'	'USGS02398300'	-85.51	34.29	366	1959	2013	0.89	0.83	0.91	0.45	0.80	0.72
'A0047'	'USGS02399200'	-85.68	34.29	199	1958	2013	0.73	0.85	0.72	0.24	0.65	0.65
'A0048'	'USGS02400100'	-85.61	34.07	252	1962	2013	0.86	0.78	0.87	0.44	0.76	0.69
'A0049'	'USGS02400680'	-85.77	34.44	55.4	2002	2013	0.77	0.78	0.88	0.12	0.68	0.63
'A0050'	'USGS02401000'	-86.04	34.10	182	1943	2013	0.85	0.90	0.90	0.43	0.78	0.83

Table 3.2 continued

Unique ID	USGSID	Longitude	Latitude	Drainage Area (sq. miles)	Data Availability		NSE monthly			NSE daily		
							VIC	DHSVM	PRMS	VIC	DHSVM	PRMS
'A0051'	'USGS02401370'	-86.38	33.81	45	1978	1995	0.72	0.84	0.88	0.21	0.58	0.72
'A0052'	'USGS02401390'	-86.26	33.84	141	1965	2013	0.68	0.82	0.78	0.28	0.66	0.71
'A0055'	'USGS02403310'	-85.79	33.60	191	2002	2011	0.84	0.90	0.88	0.53	0.84	0.70
'A0056'	'USGS02404400'	-86.10	33.55	481	1960	2013	0.89	0.87	0.89	0.52	0.79	0.74
'A0057'	'USGS02405500'	-86.39	33.45	193	1951	2013	0.59	0.83	0.73	0.31	0.66	0.67
'A0058'	'USGS02406500'	-86.23	33.36	150	1900	2013	0.86	0.80	0.87	0.24	0.73	0.75
'A0060'	'USGS02407514'	-86.50	33.32	142	2005	2013	0.67	0.88	0.82	0.39	0.76	0.68
'A0061'	'USGS02408540'	-86.27	32.92	263	1980	2013	0.89	0.89	0.91	0.21	0.68	0.72
'A0062'	'USGS02410000'	-86.13	32.68	4.91	1953	1987	0.35	0.77	0.49	-0.08	0.39	0.25
'A0063'	'USGS02411000'	-86.25	32.61	10000	1912	2013	0.91	0.91	0.91	0.56	0.69	0.64
'A0065'	'USGS02411930'	-85.34	33.74	272	1999	2013	0.73	0.68	0.77	0.21	0.71	0.31
'A0066'	'USGS02412000'	-85.51	33.62	448	1952	2013	0.80	0.84	0.90	0.36	0.78	0.77
'A0068'	'USGS02413210'	-85.28	33.49	245	2000	2013	0.75	0.80	0.87	0.46	0.72	0.50
'A0069'	'USGS02413300'	-85.40	33.44	406	1975	2013	0.80	0.84	0.90	0.48	0.77	0.57
'A0070'	'USGS02414500'	-85.56	33.12	1675	1923	2013	0.84	0.82	0.86	0.49	0.65	0.65
'A0072'	'USGS02414715'	-85.74	32.98	2058	1985	2013	0.84	0.83	0.86	0.51	0.70	0.71
'A0073'	'USGS02415000'	-85.88	33.07	190	1952	2013	0.88	0.80	0.86	0.18	0.67	0.75
'A0074'	'USGS02418230'	-85.59	32.63	71.3	1999	2013	0.74	0.87	0.85	0.10	0.73	0.75
'A0076'	'USGS02418760'	-85.48	32.55	45.8	2002	2013	0.55	0.73	0.71	0.06	0.55	0.57
'A0077'	'USGS02419000'	-85.69	32.48	333	1939	2013	0.82	0.88	0.85	0.40	0.76	0.61
'A0078'	'USGS02419890'	-86.20	32.44	4646	1995	2013	0.84	0.82	0.83	0.66	0.70	0.62
'A0080'	'USGS02420000'	-86.41	32.41	15000	1927	2013	0.91	0.88	0.90	0.70	0.75	0.65
'A0081'	'USGS02421000'	-86.30	32.31	290	1952	2013	0.66	0.85	0.81	0.19	0.62	0.65
'A0083'	'USGS02422500'	-86.90	32.58	203	1938	2013	0.69	0.79	0.71	0.08	0.75	0.44
'A0084'	'USGS02423130'	-86.60	33.62	19.7	1988	2013	0.65	0.78	0.68	0.12	0.52	0.52
'A0085'	'USGS02423380'	-86.71	33.48	140	1980	2013	0.77	0.90	0.71	0.27	0.74	0.65

Table 3.2 continued

Unique ID	USGSID	Longitude	Latitude	Drainage Area (sq. miles)	Data Availability		NSE monthly			NSE daily		
							VIC	DHSVM	PRMS	VIC	DHSVM	PRMS
'A0086'	'USGS02423400'	-86.61	33.50	24.4	1986	2013	0.76	0.79	0.80	0.18	0.53	0.62
'A0087'	'USGS02423425'	-86.74	33.42	201	1975	2013	0.77	0.77	0.86	0.28	0.67	0.59
'A0088'	'USGS02423555'	-86.88	33.28	335	1995	2013	0.80	0.88	0.81	0.37	0.79	0.63
'A0089'	'USGS02424000'	-87.14	32.95	1027	1901	2013	0.87	0.84	0.93	0.40	0.59	0.70
'A0090'	'USGS02424590'	-87.20	32.53	1480	1987	2011	0.90	0.89	0.92	0.73	0.75	0.82
'A0091'	'USGS02424940'	-87.09	32.53	220	1975	1987	0.87	0.81	0.84	0.68	0.71	0.11
'A0092'	'USGS02425000'	-87.18	32.44	1766	1938	2013	0.91	0.92	0.93	0.76	0.76	0.81
'A0094'	'USGS02427250'	-87.07	32.00	261	1989	2013	0.81	0.85	0.91	0.23	0.80	0.78
'A0095'	'USGS02427700'	-87.56	32.02	97.5	1958	1996	0.76	0.86	0.90	0.17	0.77	0.79
'A0096'	'USGS02428400'	-87.55	31.62	21000	1975	2013	0.90	0.91	0.88	0.70	0.77	0.61

Table 3.3 Summary statistics for percent change in mean seasonal streamflow (ΔQ), high flow ($\Delta Q95$) and low flow ($\Delta Q05$) observed under climate change summarized by each USGS gauges location in ACT River Basin

Unique ID	USGSID	Drainage Area (sq. miles)	Change in streamflow (%)					
			Winter	Spring	Summer	Fall	Q05	Q95
'A0001'	'USGS02380500'	236	-0.79	0.88	-0.97	-1.53	-7.31	2.31
'A0002'	'USGS02381600'	9.99	-1.23	1.03	-0.62	-1.34	-6.94	1.77
'A0007'	'USGS02383500'	831	-0.71	1.36	-0.07	-1.23	-5.20	2.60
'A0008'	'USGS02384500'	252	-0.06	0.97	3.91	0.47	-7.33	3.02
'A0009'	'USGS02384540'	8.24	0.04	1.23	4.26	1.22	-19.68	2.95
'A0010'	'USGS02385170'	176	-1.06	1.75	8.76	0.25	-3.39	2.36
'A0011'	'USGS02385500'	40	-0.86	2.16	7.46	1.07	-2.42	2.50
'A0012'	'USGS02385800'	64	-0.42	1.20	2.13	0.43	-10.30	2.51
'A0013'	'USGS02387000'	687	-0.40	1.40	5.13	0.15	-4.28	3.05
'A0014'	'USGS02387500'	1602	-0.57	1.42	1.84	-0.71	-4.55	2.99
'A0016'	'USGS02388300'	14.7	1.20	3.39	9.38	5.23	2.37	4.10
'A0017'	'USGS02388320'	16.6	0.86	3.18	8.77	4.81	-0.14	4.01
'A0018'	'USGS02388350'	224	0.09	2.57	8.08	2.68	-2.16	3.26
'A0019'	'USGS02388500'	2115	-0.48	1.71	2.75	-0.22	-3.69	3.29
'A0023'	'USGS02390000'	89	-0.68	1.49	-0.23	-2.15	-5.68	1.94
'A0029'	'USGS02392000'	613	-0.51	1.58	-0.48	-1.18	-5.96	2.33
'A0031'	'USGS02392780'	139	0.50	1.70	-2.26	1.09	-7.40	2.42
'A0038'	'USGS02395120'	33.1	1.82	3.19	0.90	-1.01	1.93	2.96
'A0042'	'USGS02397410'	65.3	2.78	3.69	2.86	5.69	-5.22	4.58
'A0043'	'USGS02397500'	115	2.58	3.57	2.82	5.22	-4.94	4.43
'A0044'	'USGS02398000'	192	-0.50	2.54	8.51	3.10	-0.19	2.96
'A0046'	'USGS02398300'	366	0.02	2.98	11.34	5.28	2.16	3.83
'A0047'	'USGS02399200'	199	-0.06	3.08	11.49	7.64	2.25	4.20
'A0048'	'USGS02400100'	252	2.63	3.35	4.43	7.02	-2.50	4.89
'A0049'	'USGS02400680'	55.4	-0.60	3.10	9.46	8.07	-0.21	4.03
'A0050'	'USGS02401000'	182	-0.61	2.84	7.00	6.92	-0.64	3.66
'A0051'	'USGS02401370'	45	0.26	4.65	5.12	10.72	-4.63	4.30
'A0052'	'USGS02401390'	141	0.54	4.46	5.77	10.45	-4.45	4.19
'A0055'	'USGS02403310'	191	3.73	4.54	6.20	10.95	-2.32	5.75
'A0056'	'USGS02404400'	481	3.32	4.95	6.12	10.30	-2.57	6.25
'A0057'	'USGS02405500'	193	1.77	5.51	6.69	12.41	-3.76	5.41
'A0058'	'USGS02406500'	150	2.93	5.46	6.93	11.22	-2.43	6.41
'A0060'	'USGS02407514'	142	3.01	6.09	6.67	10.60	-1.75	6.33
'A0061'	'USGS02408540'	263	3.74	5.90	6.66	11.54	-1.18	7.88
'A0062'	'USGS02410000'	4.91	3.90	8.92	9.18	13.55	0.77	9.68

Table 3.3 continued

Unique ID	USGSID	Drainage Area (sq. miles)	Change in streamflow (%)					
			Winter	Spring	Summer	Fall	Q05	Q95
'A0063'	'USGS02411000'	10000	1.24	3.77	4.50	4.82	-1.91	5.58
'A0065'	'USGS02411930'	272	3.45	3.96	1.70	5.82	-2.17	5.66
'A0066'	'USGS02412000'	448	3.69	3.81	2.13	6.47	-1.63	5.94
'A0068'	'USGS02413210'	245	3.14	3.58	2.03	6.73	-2.02	5.59
'A0069'	'USGS02413300'	406	3.26	3.56	2.12	7.07	-2.00	5.99
'A0070'	'USGS02414500'	1675	3.56	4.10	2.76	7.84	-2.49	6.91
'A0072'	'USGS02414715'	2058	3.48	4.49	3.11	8.16	-2.36	6.89
'A0073'	'USGS02415000'	190	3.76	5.66	6.83	11.13	-4.01	7.08
'A0074'	'USGS02418230'	71.3	2.69	6.92	7.40	11.37	0.03	7.95
'A0076'	'USGS02418760'	45.8	3.33	6.33	6.98	12.24	-0.39	7.22
'A0077'	'USGS02419000'	333	4.57	7.82	9.14	16.07	0.82	9.13
'A0078'	'USGS02419890'	4646	3.87	6.42	6.31	11.46	-0.76	8.91
'A0080'	'USGS02420000'	15000	2.04	4.66	5.30	6.91	-1.68	6.76
'A0081'	'USGS02421000'	290	4.37	9.68	12.95	20.45	1.97	10.66
'A0083'	'USGS02422500'	203	5.17	8.51	11.09	17.98	1.99	11.06
'A0084'	'USGS02423130'	19.7	0.28	5.36	5.39	9.33	-5.48	4.45
'A0085'	'USGS02423380'	140	0.80	5.42	5.46	9.69	-2.47	4.88
'A0086'	'USGS02423400'	24.4	1.70	5.85	5.65	7.55	-2.30	4.92
'A0087'	'USGS02423425'	201	1.04	5.53	5.40	9.26	-2.76	5.14
'A0088'	'USGS02423555'	335	1.43	5.85	5.11	9.05	-2.65	5.82
'A0089'	'USGS02424000'	1027	2.15	6.88	7.98	11.86	-1.32	6.76
'A0090'	'USGS02424590'	1480	2.43	7.23	9.29	13.24	-1.26	7.32
'A0091'	'USGS02424940'	220	3.76	8.74	12.96	19.58	-0.67	8.85
'A0092'	'USGS02425000'	1766	2.59	7.41	9.83	14.13	-1.32	7.70
'A0094'	'USGS02427250'	261	3.39	9.00	14.10	23.29	3.93	8.01
'A0095'	'USGS02427700'	97.5	2.66	10.05	18.01	23.22	-1.49	8.38
'A0096'	'USGS02428400'	21000	2.37	5.71	7.14	10.10	-0.63	7.58

Table 4. 1. List of major reservoirs in Alabama Coosa Tallapoosa River Basin along with their conservation storage volumes. The reservoirs selected for analysis in this study are presented in bold. (USACE, 2013)

Reservoir	Conservation Storage (acre-feet)	Percent of total storage
Allatoona	284,580	10.8%
Carters	157,402	6.0%
Weiss	263,417	10.0%
H.Neely Henry	118,210	4.5%
Logan Martin	144,383	5.5%
Lay	92,352	3.5%
Mitchell	51,577	2.0%
Jordan/Bouldin	19,057	0.7%
Harris	207,317	7.9%
Martin	1,202,340	45.7%
Yates	6,928	0.3%
R.F.Henry	36,450	1.4%
Millers Ferry	46,704	1.8%
Total	2,630,717	

Table 4. 2 Calibration and Validation Statistics.

Reservoir Name	Data Source				Calibration		Calibration/Validation Period	NSE (Calibration/Validation)			
	AEV Relationship	Inflow	Outflow	Storage	Release	Storage		Release (weekly)	Release (monthly)	Storage (weekly)	Storage (monthly)
Allatoona	USACE	USACE	USGS	USACE	Yes	Yes	1981-1994 / 1995-2009	0.63 / 0.63	0.81 / 0.81	0.83 / 0.71	0.83/0.70
Carters	USACE	USACE*	USGS	USACE**	Yes	No	1981-1994 / 1995-2009	0.83 / 0.70	0.93 / 0.88	0.39 / 0.76	0.37 / 0.77
Harris	USACE	USGS*	USGS*	NA	Yes	No	1984-1994 / 1995-2009	0.84 / 0.83	0.88 / 0.88	NA	NA
Martin	USACE	USGS*	USGS*	NA	Yes	No	1981-1994 / 1995-2004	0.71 / 0.52	0.84 / 0.67	NA	NA
* Indicates Rescaled Flow at reservoir location based on drainage area ** Observed Storage is adjusted by adding the conservation volume of Carters reregulation dam, since the DHSVM-RES setup for Carters treat the entire system as one unit instead of separate reservoirs.											

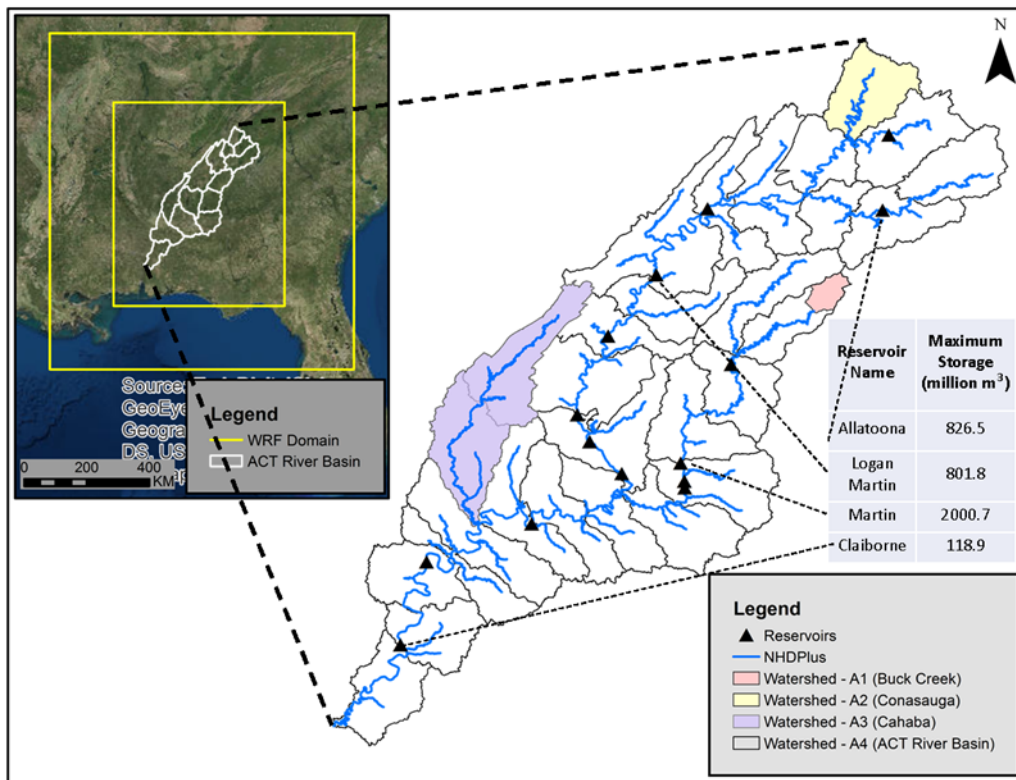


Figure 1.1. Major river segments and reservoirs in the Alabama–Coosa–Tallapoosa (ACT) River Basin.

The inserted panel at left shows the double nested WRF domain used by Rastogi et al., (2017). The four sub-watersheds (A1–A4) and four reservoirs plotted in Figure 1.12 are marked.

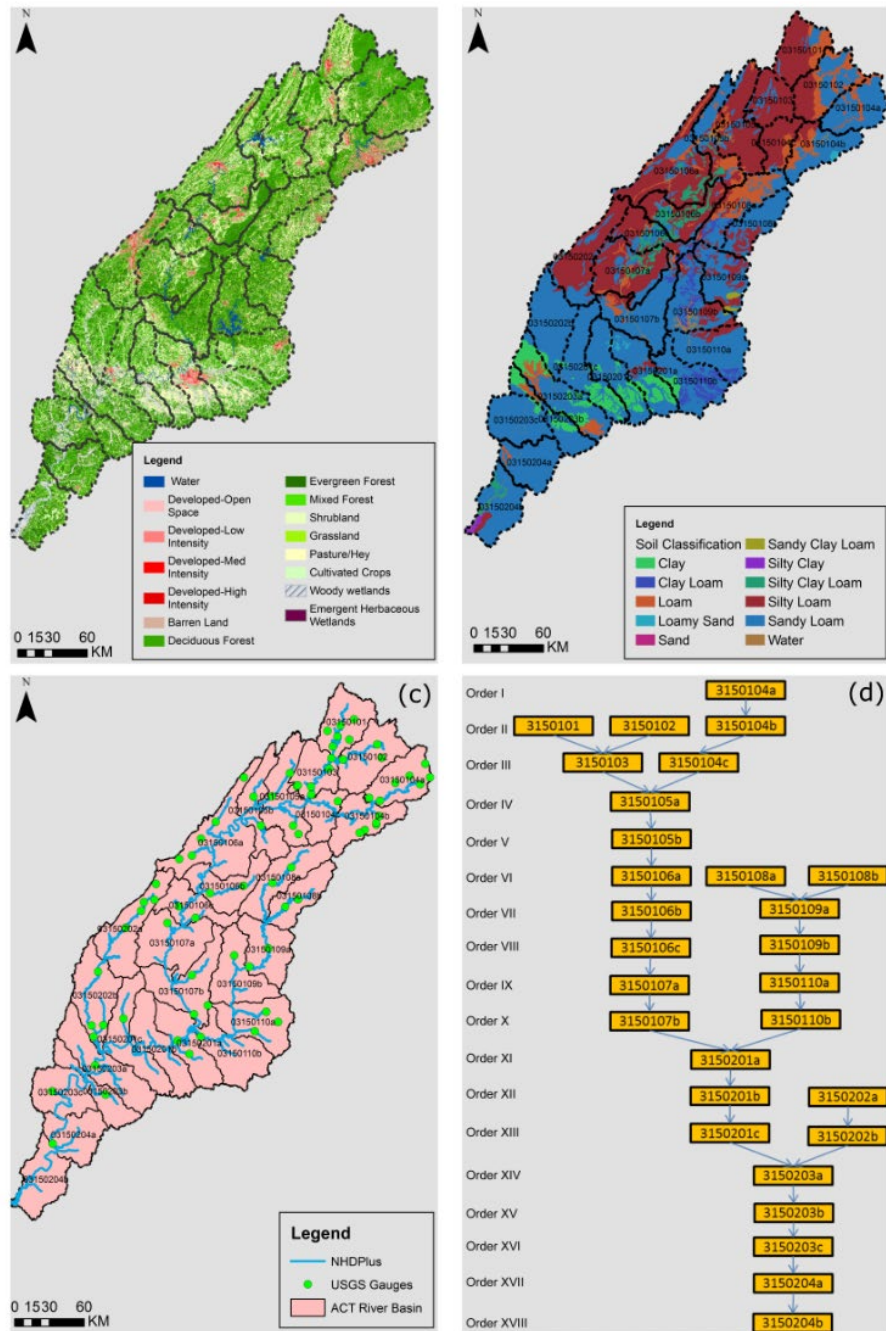


Figure 1.2. The setup of DHSVM in ACT.

Panel (a) shows LULC from NLCD 2006. Panel (b) shows the dominant soil texture from Miller and White (1998). Panel (c) shows the 29 spatially discretized DHSVM computational units. Panel (d) shows the computing order of the DHSVM spatial units.

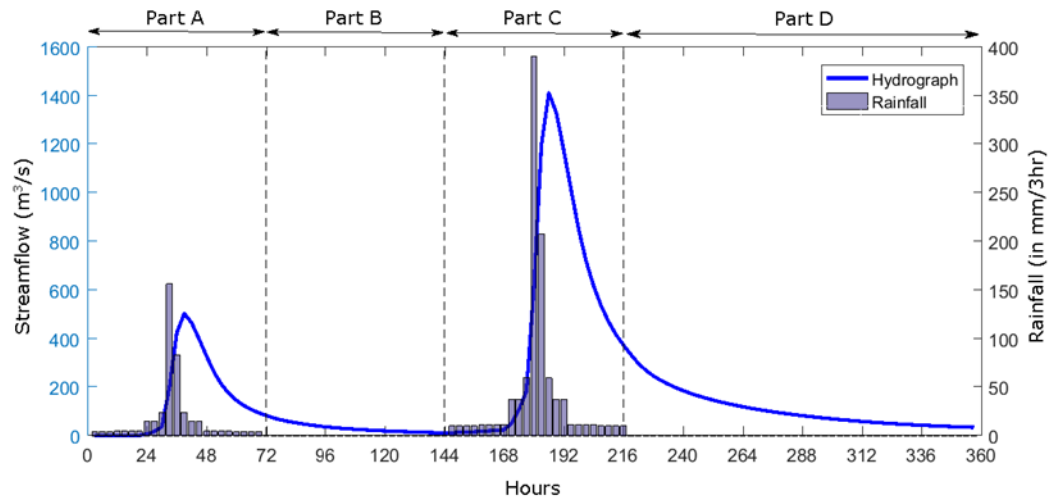


Figure 1.3. Meteorological sequence used to drive DHSVM. Parts A, B, and C along the x axis illustrate 72 hours of 40% PMP, 72 hours of no rain, and 72 hours of 100% PMP, respectively.

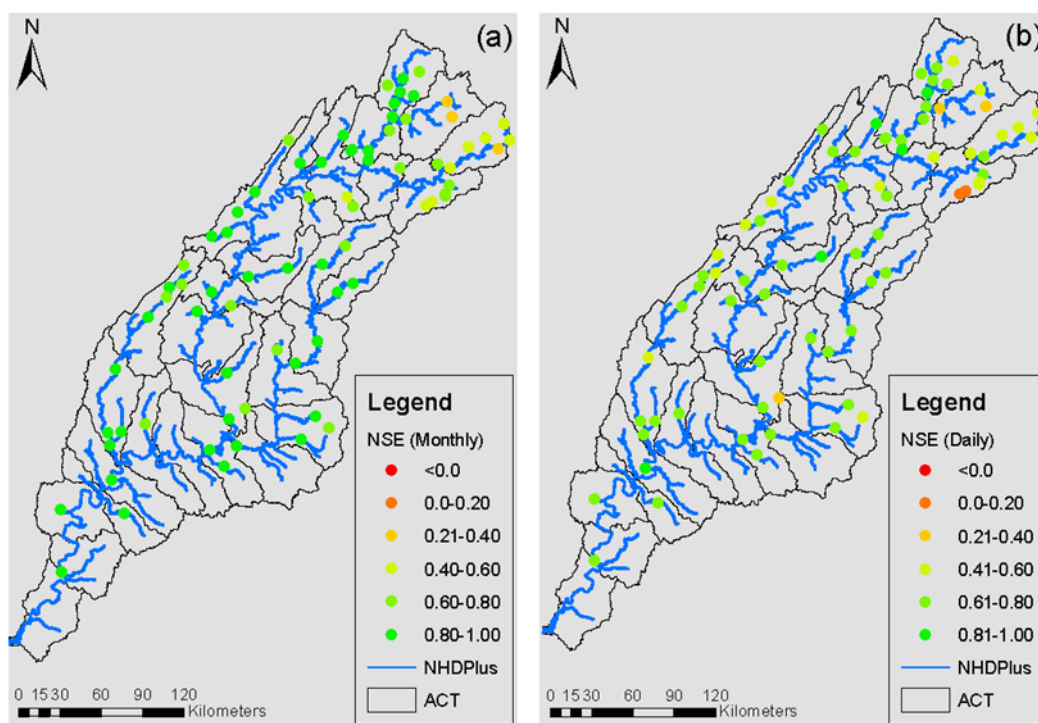


Figure 1.4. Summary of DHSVM performance at 74 USGS gauge locations.

Panel (a) shows the monthly NSE values during 1981–2012; panel (b) shows the daily NSE values.

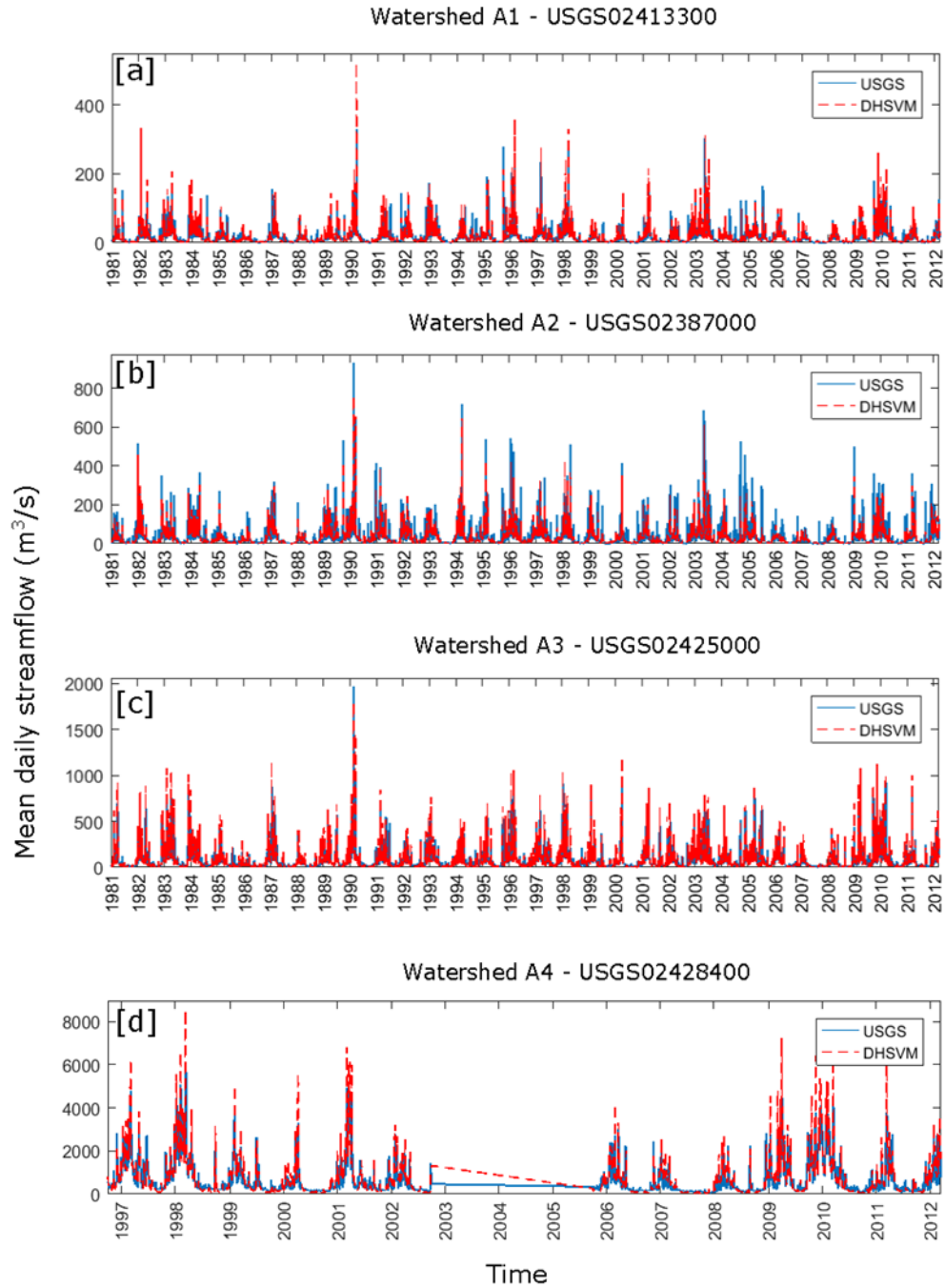


Figure 1.5. Figure summarizing simulated (red) versus observed (blue) daily streamflow during 1981–2012 for watersheds (a) A1 – USGS02413300, (b) A2 – USGS02387000, (c) A3 – USGS02425000, and (d) A4 – USGS02428400 (observed data record is not available during October 2002 to 2005).

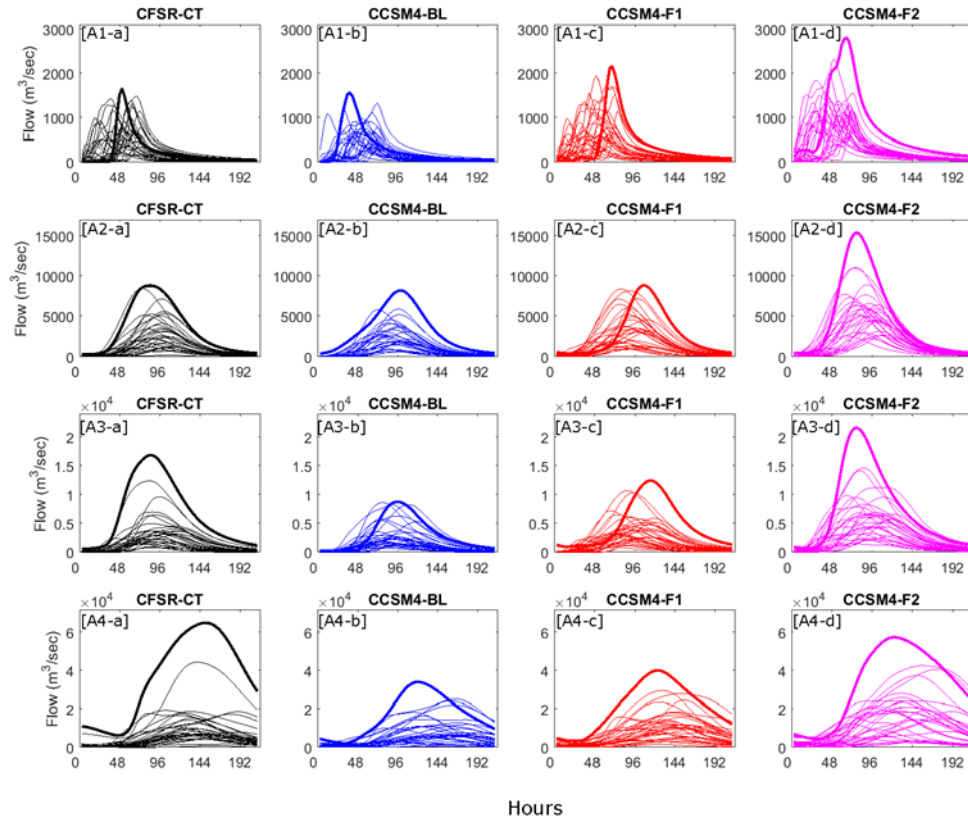


Figure 1.6. Ensemble PMF hydrographs for each set of PMP storms (CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2). The hydrograph resulting in peak discharge is presented as a thick line. The panels are labeled based on their corresponding watersheds (A1–A4).

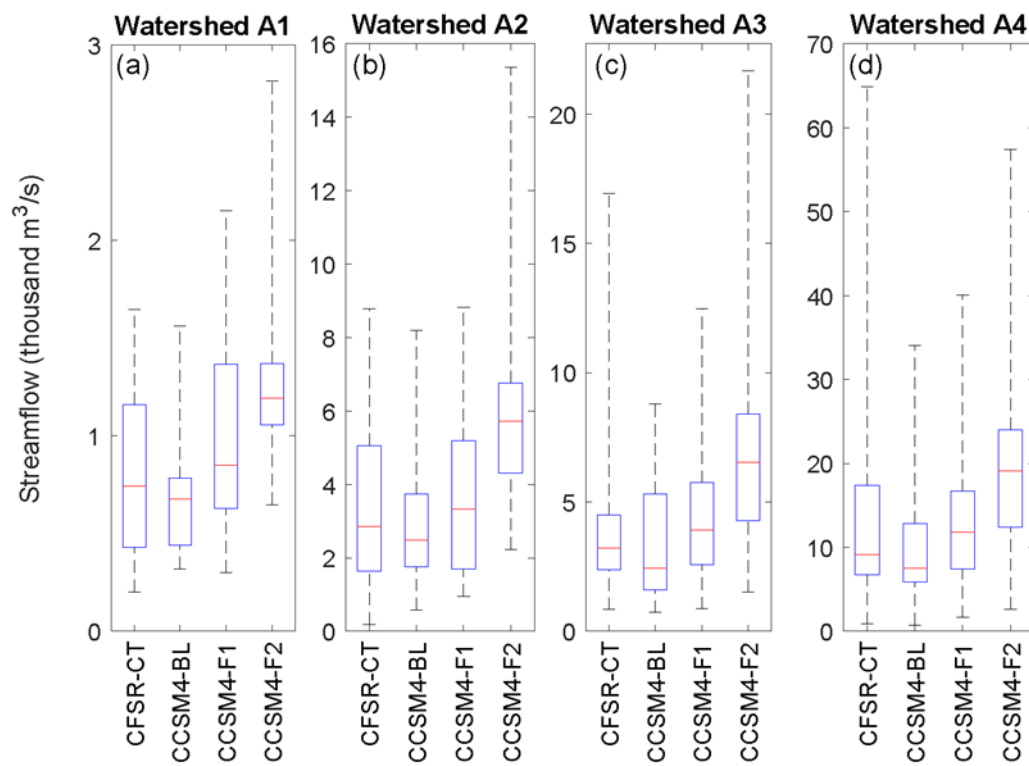


Figure 1.7. Range of peak discharge for each study watershed (A1–A4) and each set of simulations (CFRS-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2).

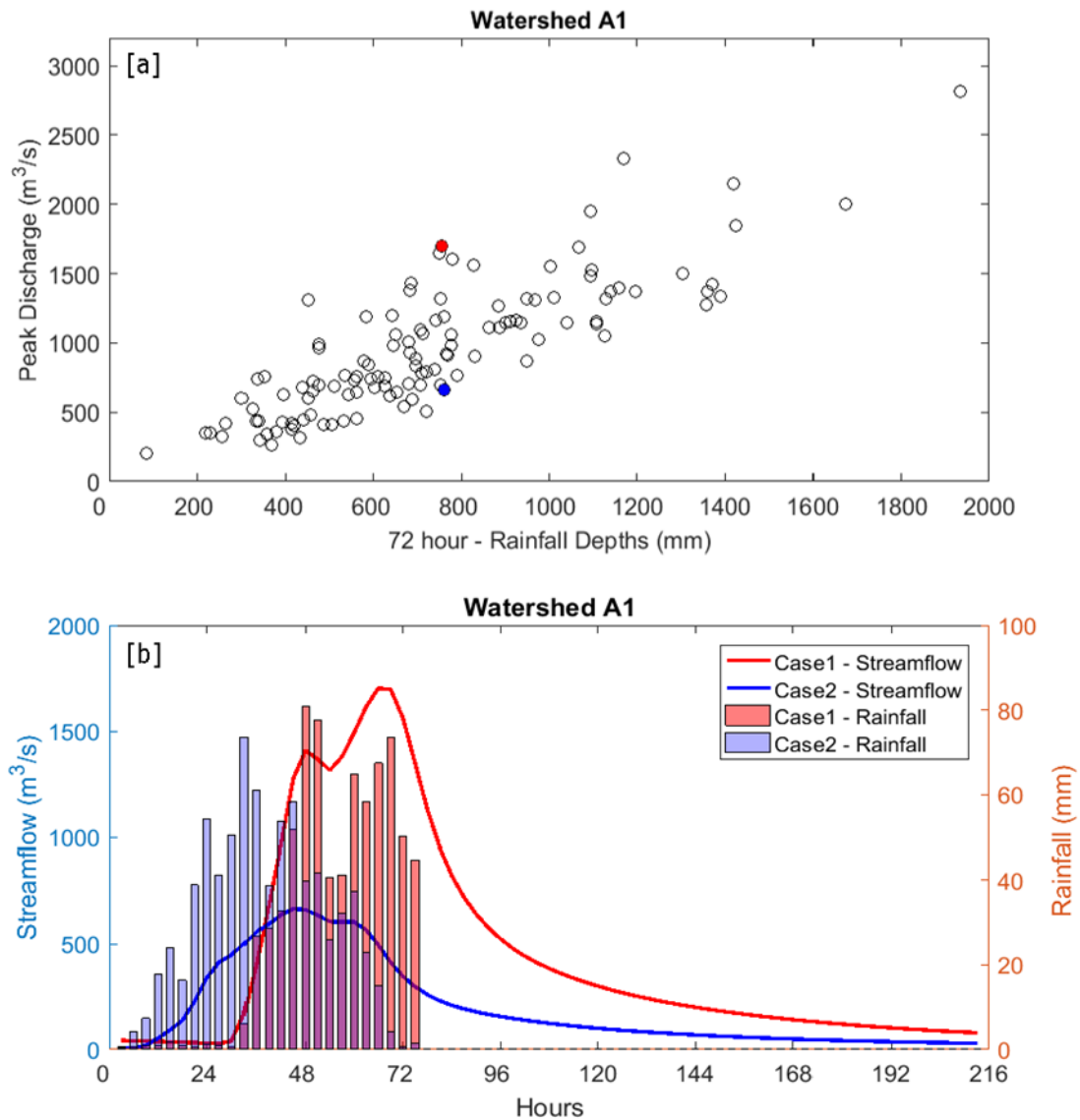


Figure 1.8. Relationship between PMP and PMF.

Panel (a) shows a scatterplot demonstrating the relationship between peak discharge (m^3/s) and watershed averaged 72 hour-rainfall depth (mm) for 120 events simulated in watershed A1. Panel (b) shows two cases with similar total 72-h PMP depth but varying PMF hydrographs.

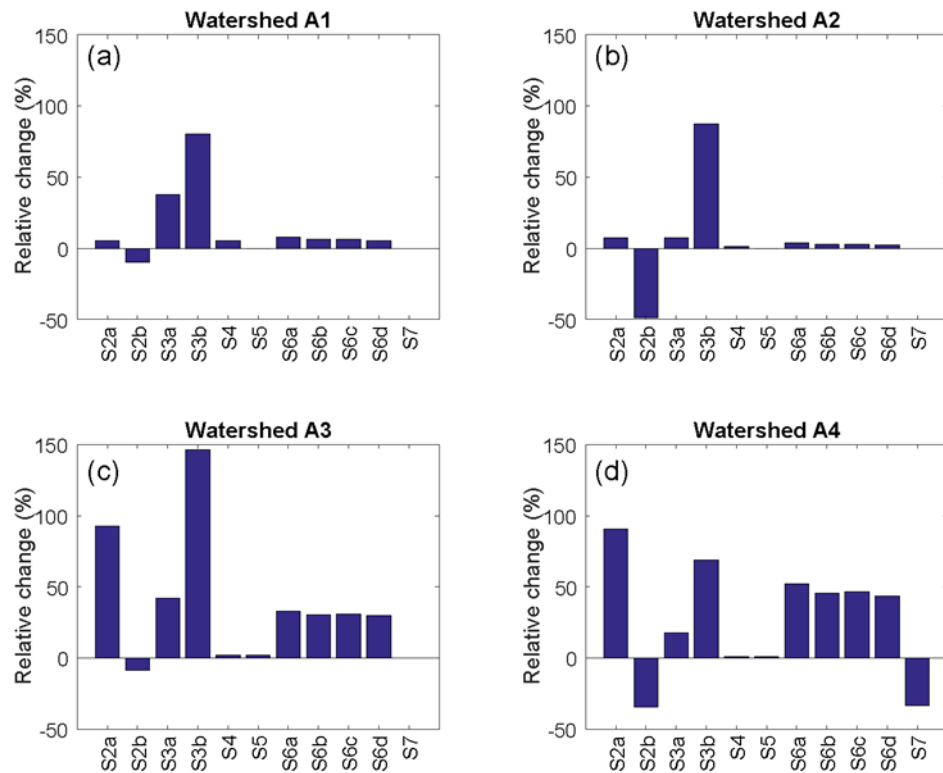


Figure 1.9. Figure summarizing relative sensitivity of peak hydrograph discharge from each scenario with reference to scenario 1 (S1).

S7 is applicable only in Watershed A4 since no major reservoir is located in watersheds A1–A3. The relative change is calculated by comparing the percentage change in the peak discharge magnitude of the largest hydrograph in each scenario with reference to the control scenario (S1).

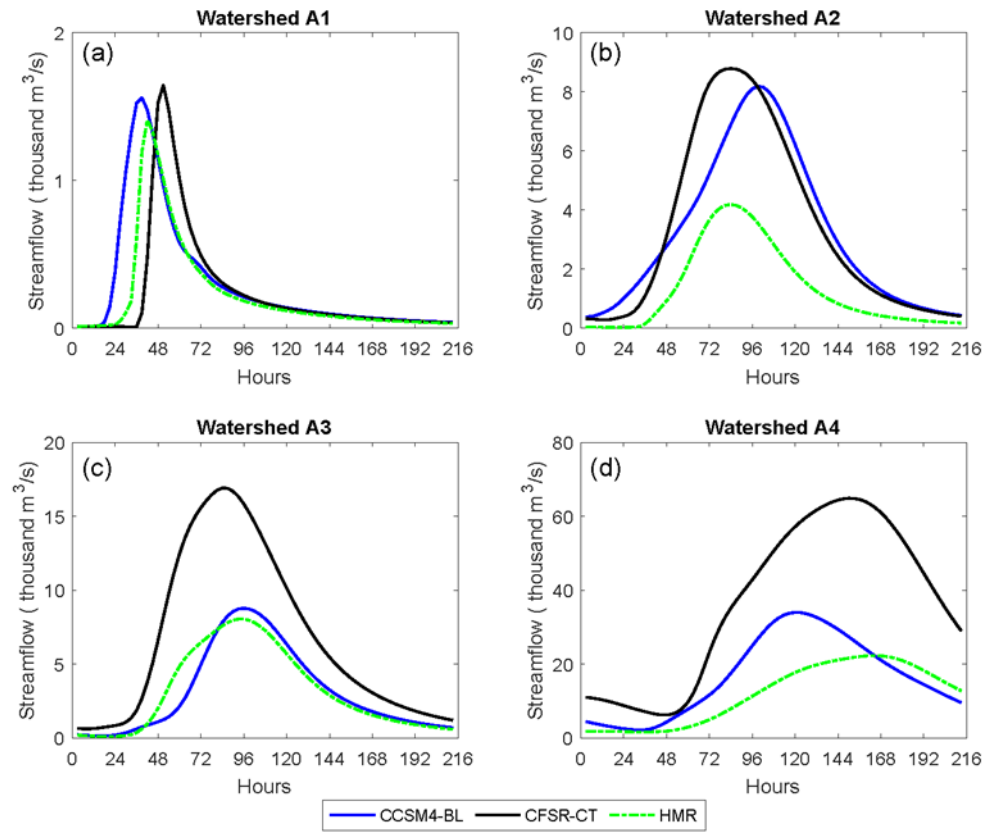


Figure 1.10. Figure summarizing the peak PMF hydrograph for CFSR-CT, CCSM4-BL, and HMR for watersheds (a) A1, (b) A2, (c) A3, and (d) A4.

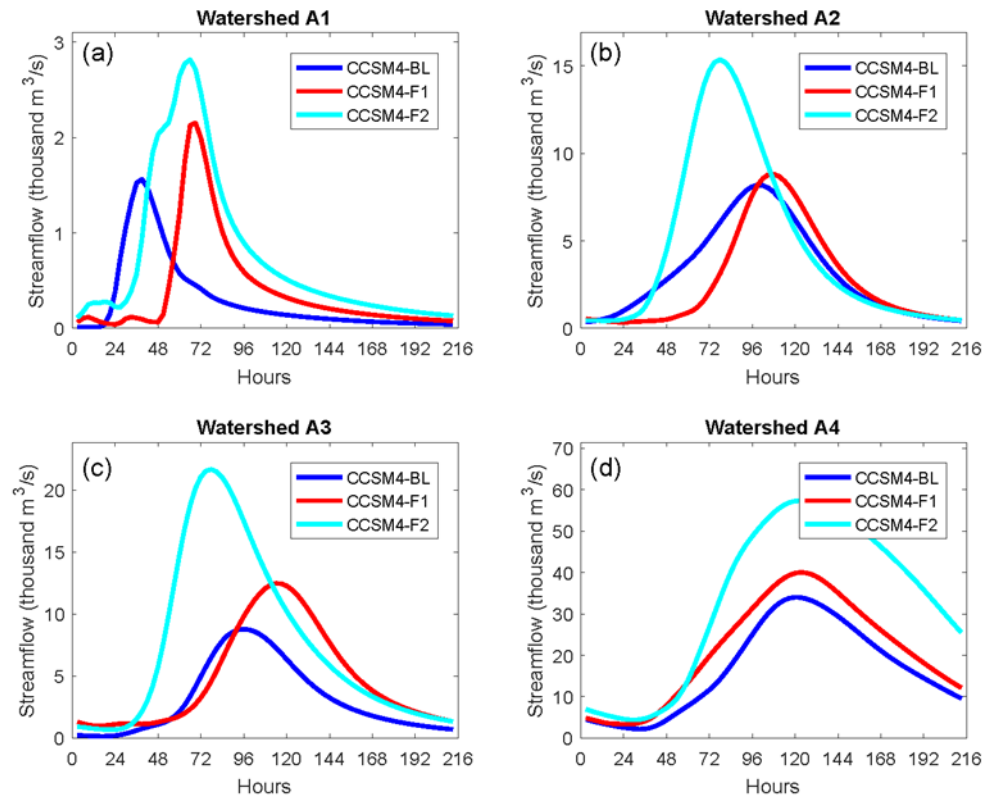


Figure 1.11. Figure summarizing selected PMF hydrographs under climate change scenario for CCSM4-BL, CCSM4-F1, and CCSM4-F2 case for watershed (a) A1, (b) A2, (c) A3, and (d) A4.

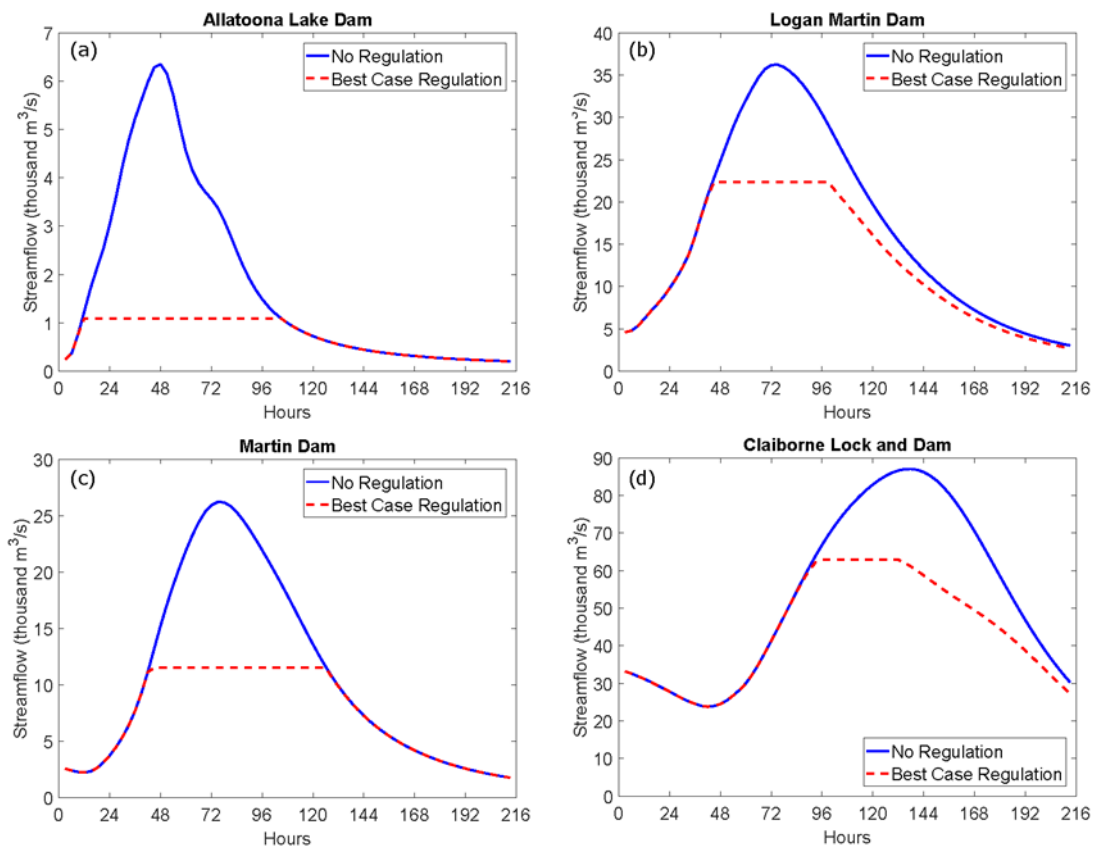


Figure 1.12. Figure demonstrating the effect of ideal reservoir operation on PMF for four selected reservoir locations in ACT.

Panel a: Allatoona Lake Dam, panel b: Logan Martin Dam, panel c: Martin Dam, and panel d: Claiborne Lock and Dam

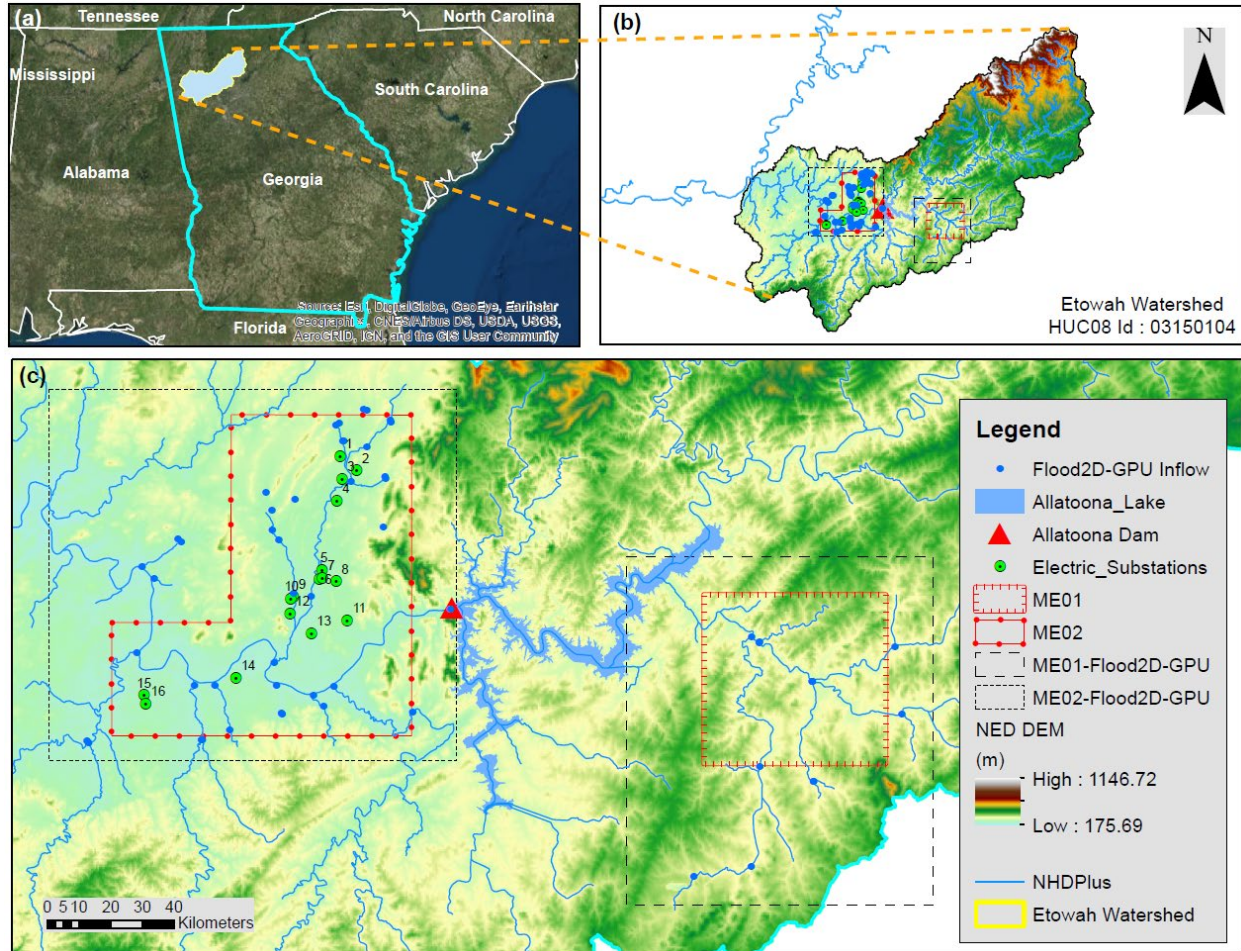


Figure 2.1. Etowah Watershed with two selected areas of interest, ME01 and ME02, along with Flood2D-GPU setup including computational domains, DEM, inflow locations, and stream network (Panel c).

The inserted panels (a and b) shows the overall location of Etowah Watershed in Georgia, US.

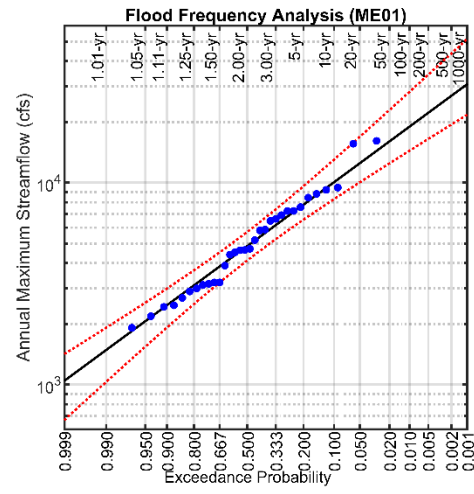


Figure 2.2. Standard flood frequency analysis for ME01 according to the guidelines of Bulletin 17B.

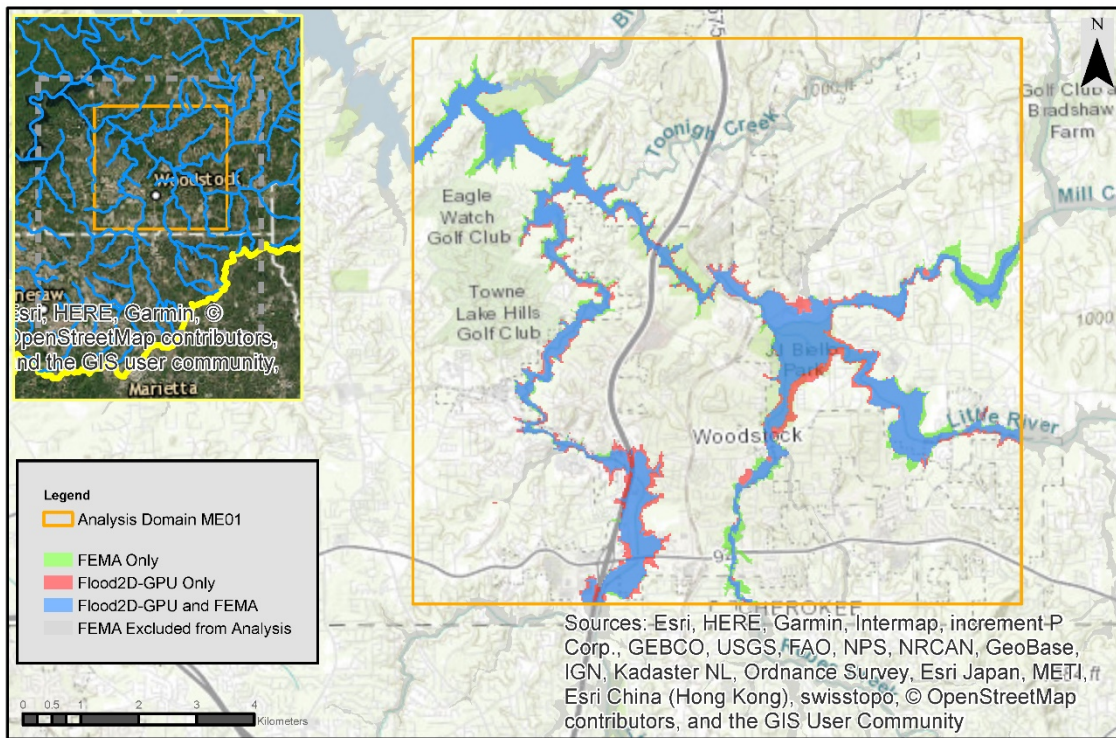


Figure 2.3. A comparison of flood inundation spatial extents obtained from Flood2D-GPU and FEMA for 100-year flood events.

The regions flooded with both Flood2D-GPU and FEMA flood zones are presented in blue. The regions in red/green represent the cells flooded only by Flood2D-GPU/FEMA. The FEMA zones excluded from this evaluation because of model or other data limitations are presented in gray.

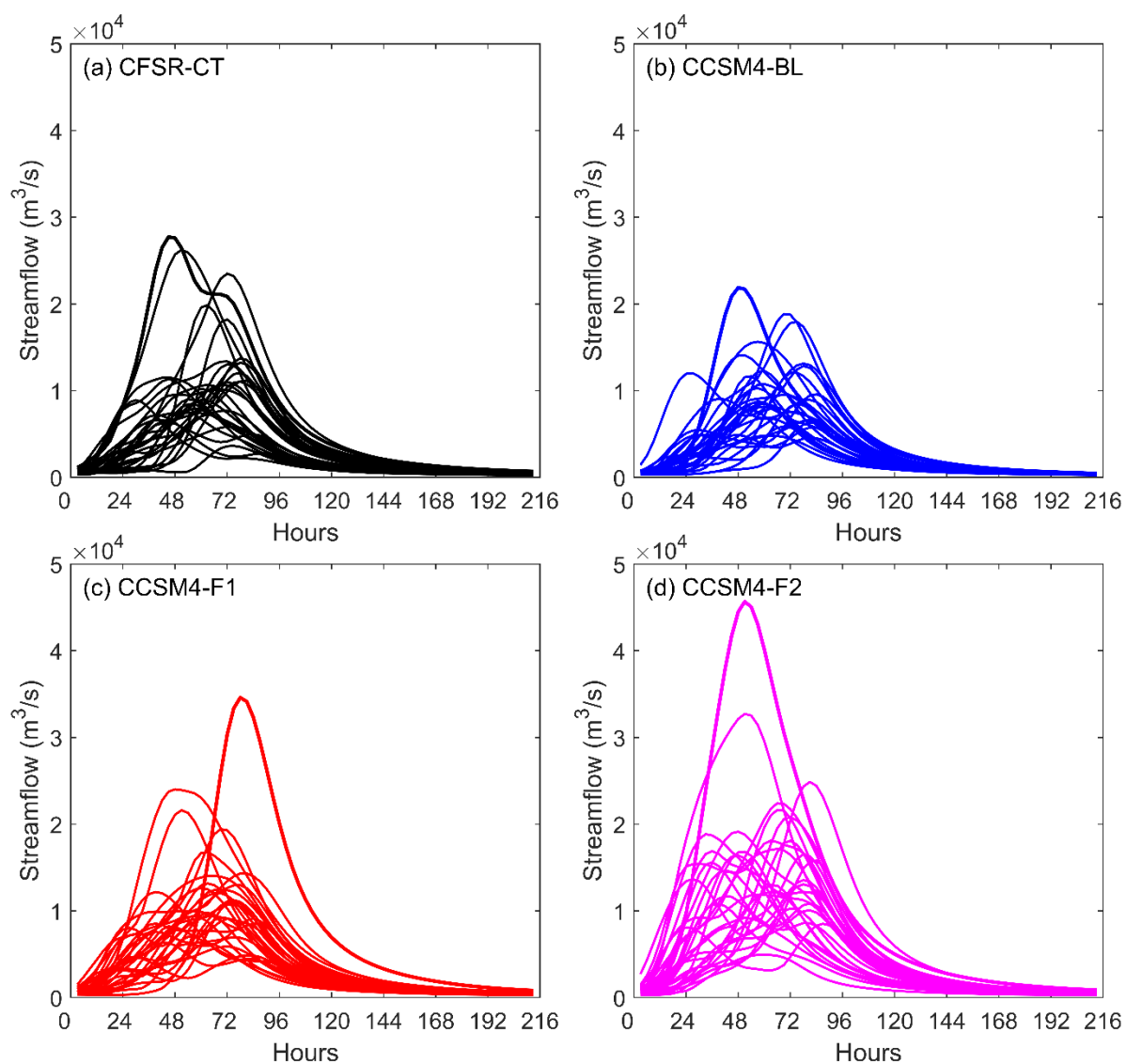


Figure 2.4. Ensemble PMF hydrographs for each set of the moisture maximized storms (listed in Table 1) at the outlet of Etowah Watershed.

The hydrograph yielding the highest peak discharge in each set of storms is highlighted with a thick line.

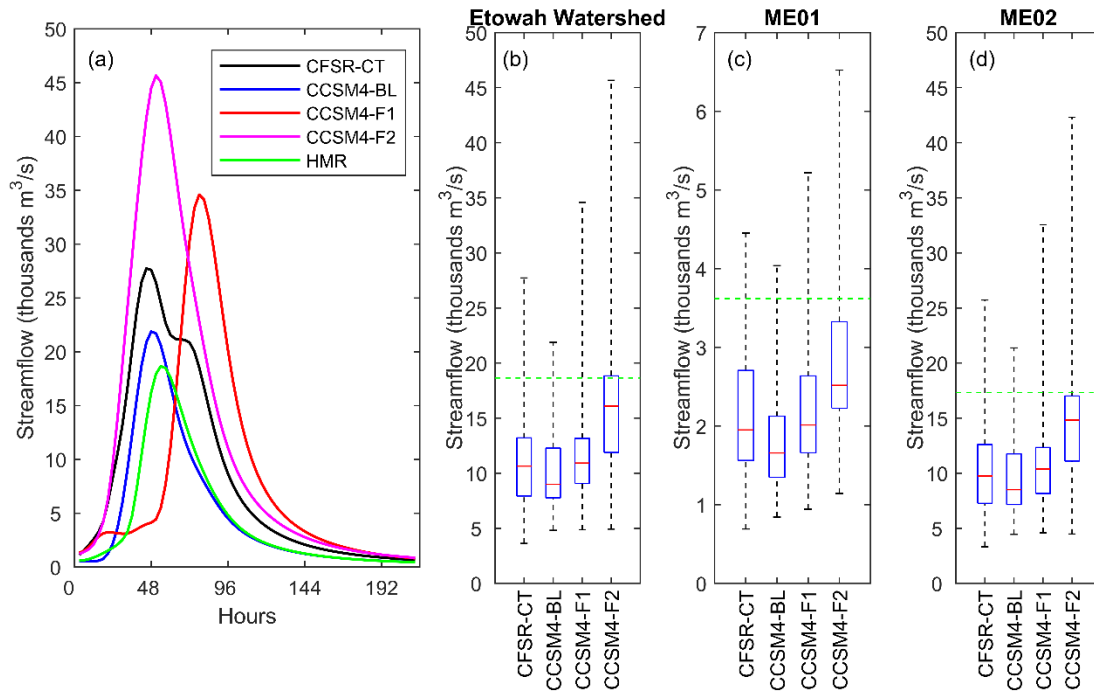


Figure 2.5. PMF hydrographs selected based on peak discharge for Etowah Watershed (Panel a) and range of peak discharge for each set of simulations (CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2), with corresponding HMR scenario values marked as green dash line, for Etowah Watershed and ME01 and ME02 (Panels b, c and d respectively).

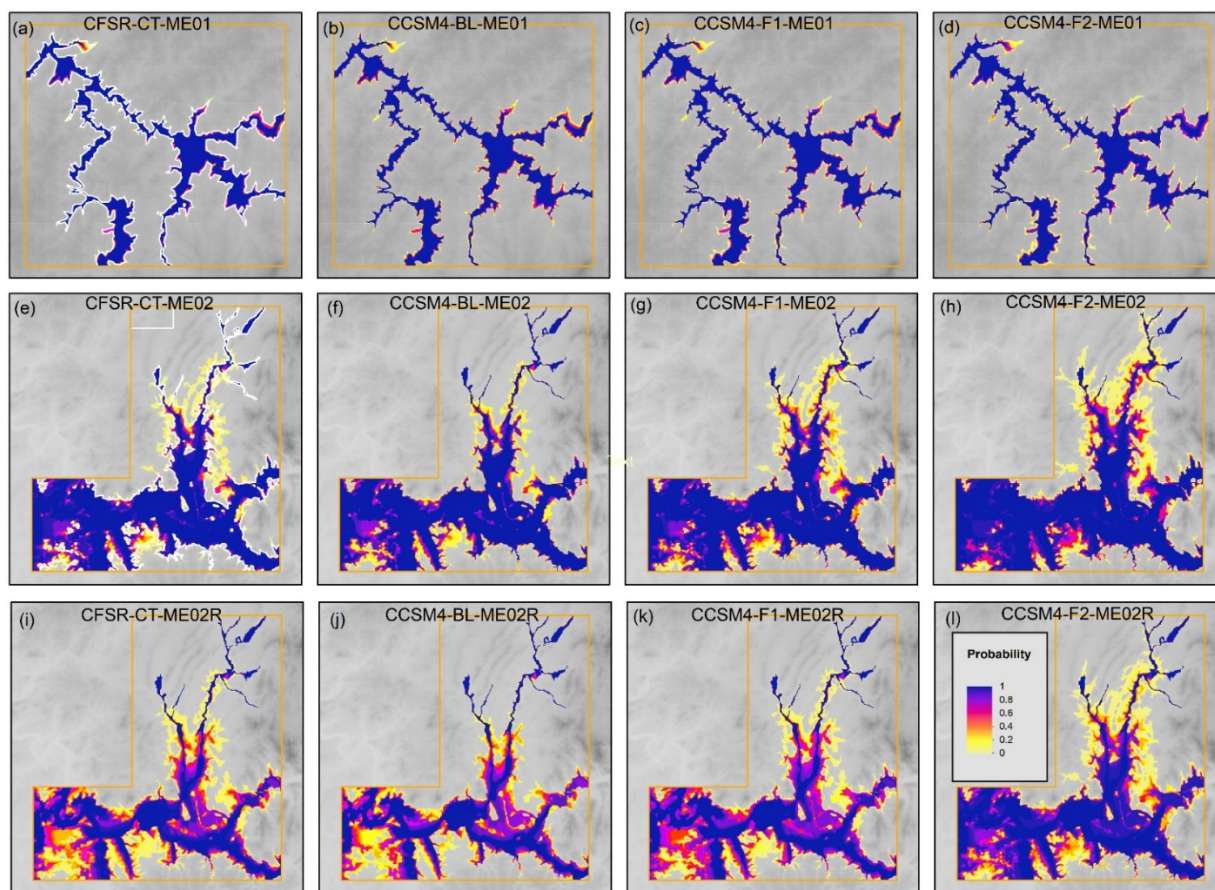


Figure 2.6. Ensemble flood maps for domain upstream of Allatoona lake ME01 (a through d), and domain ME02 downstream of Allatoona lake (e through h), and ME02 with reservoir regulation (i through m) for each of the storm sets CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2. Panels a and e also show HMR52-based flood extents in white contour.

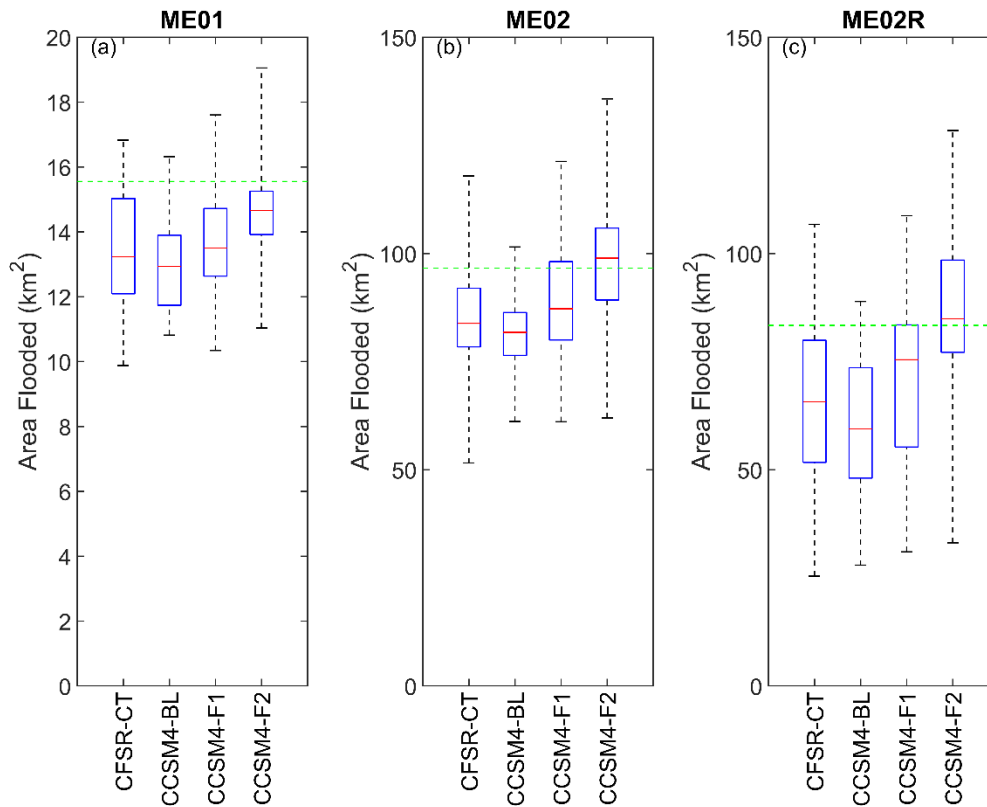


Figure 2.7. Boxplot showing the range of area under inundation for each of the storm sets for domain upstream of Allatoona lake ME01 (Panel a), and domain ME02 downstream of Allatoona lake under natural flow condition (Panel b), and ME02 under reservoir regulation (Panel c). The area inundated under HMR scenario is marked with green dash line in each of the panels.

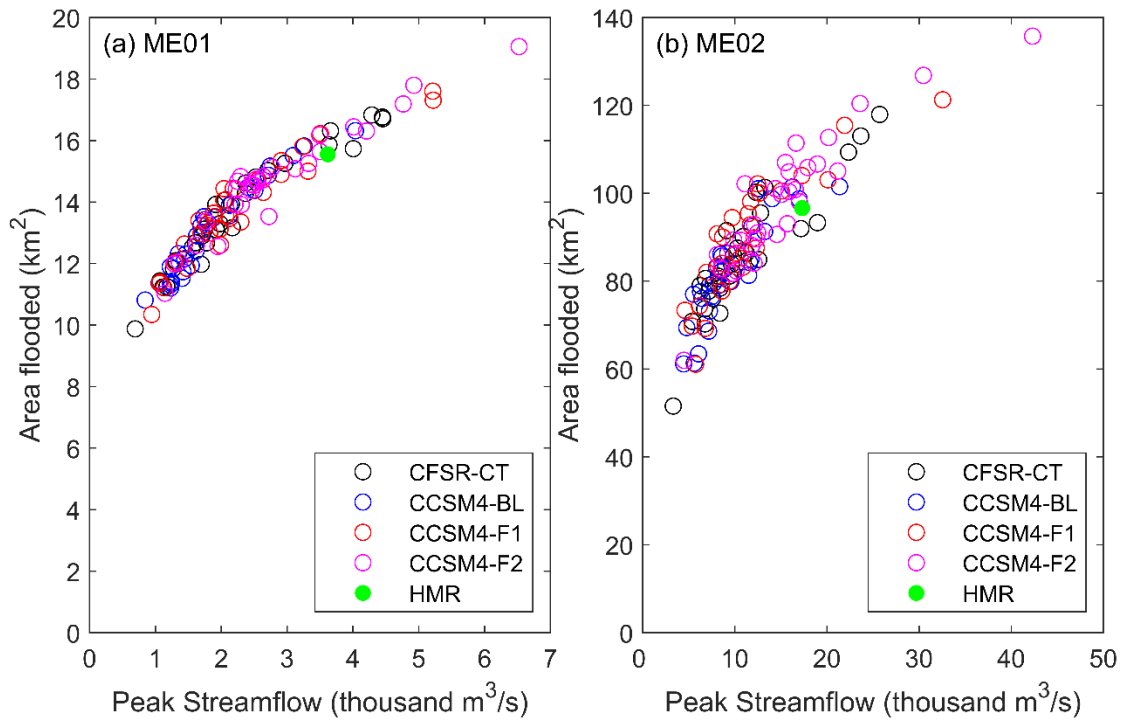


Figure 2.8. Flood inundation elasticity with respect to peak discharge for each set of simulations (CFSR-CT, CCSM4-BL, CCSM4-F1, and CCSM4-F2) for ME01 and ME02.

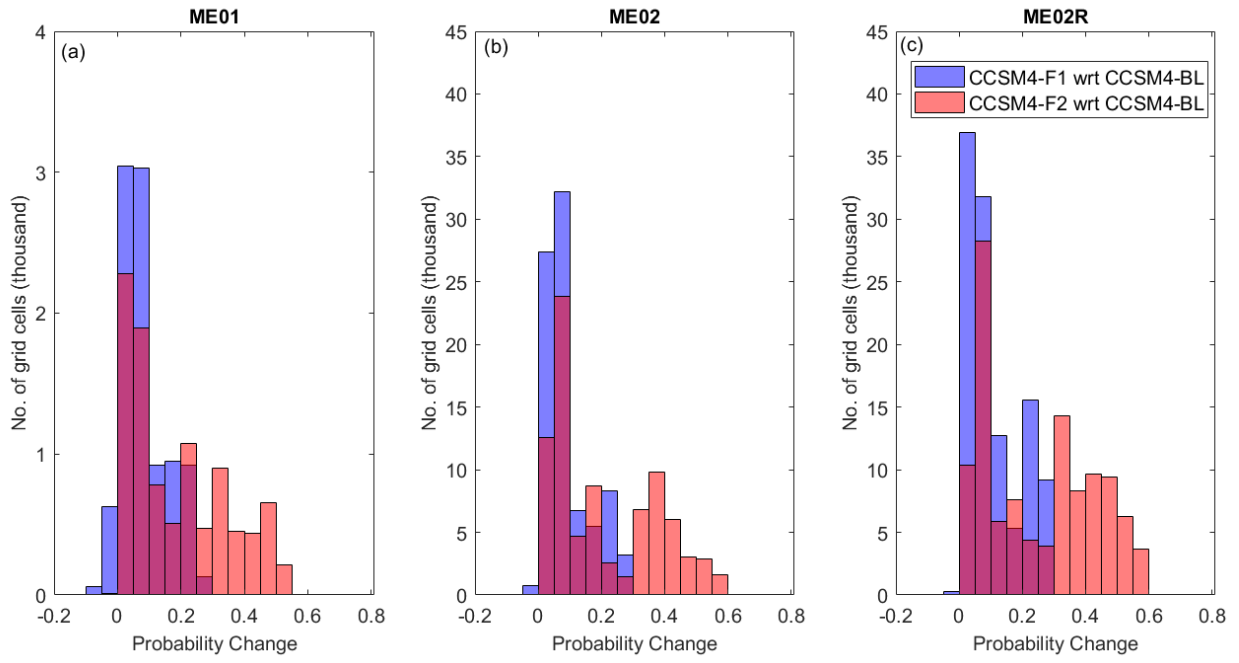


Figure 2.9. Changes in flood inundation probability for near future (CCSM4-F1) and far future (CCSM4-F2) periods

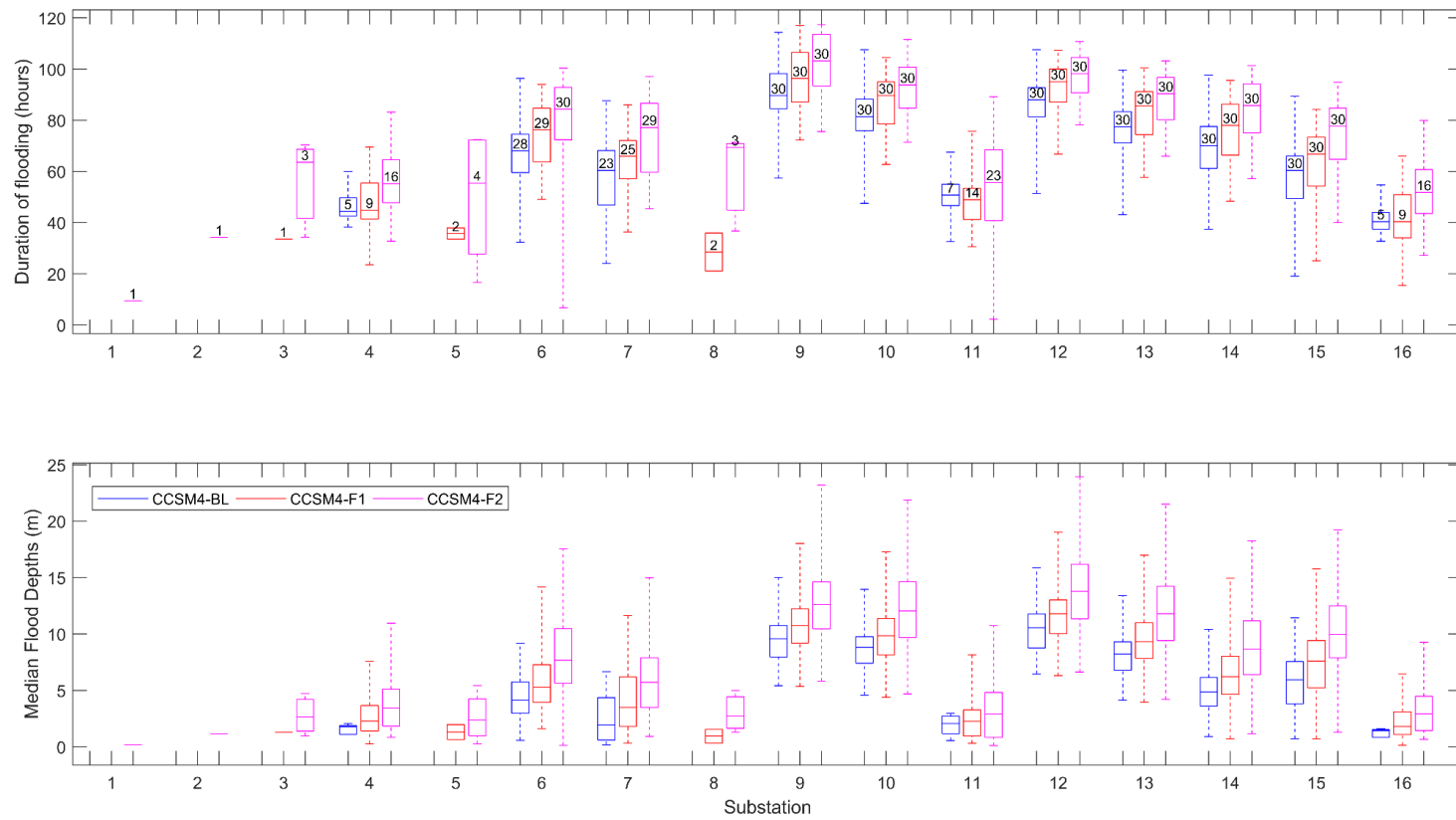


Figure 2.10. Flood vulnerability analysis for 16 selected substations for each storm set (i.e., CCSM4-BL, CCSM4-F1, and CCSM4-F2 for ME02).

The boxplots for duration of flooding and median flood depths are presented in panels a and b, respectively. The number of storms (maximum of 30 storms for each storm set) in which a substation is likely to be flooded is also indicated above the mean of the box plot in Panel a

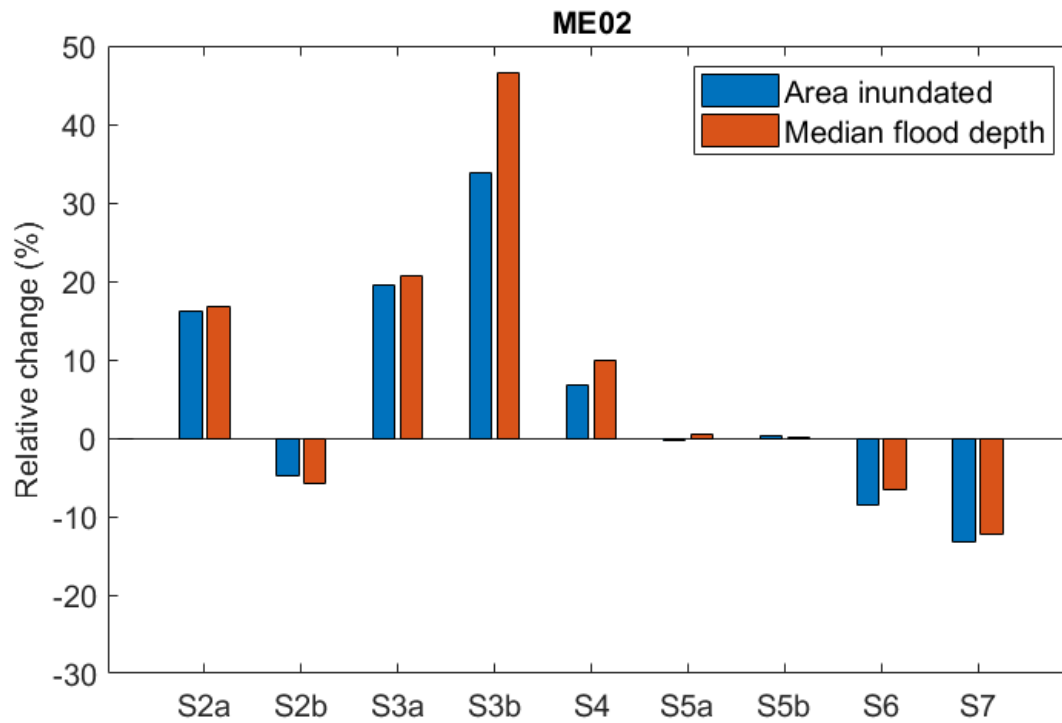


Figure 2.11. Figure summarizing the relative sensitivity of area inundated and median flood depths from each scenario with reference to scenario 1 (S1).

S2a and S2b are the Alternative meteorological forcing scenarios, S3a and S3b are the Climate change scenarios, S4 is the varying grid resolution scenario, S5a and S5b are the varying Manning's coefficient scenarios, S6 is the antecedent moisture condition scenario, and S7 is the reservoir operation scenario. Scenario details are provided in Table 2.5.

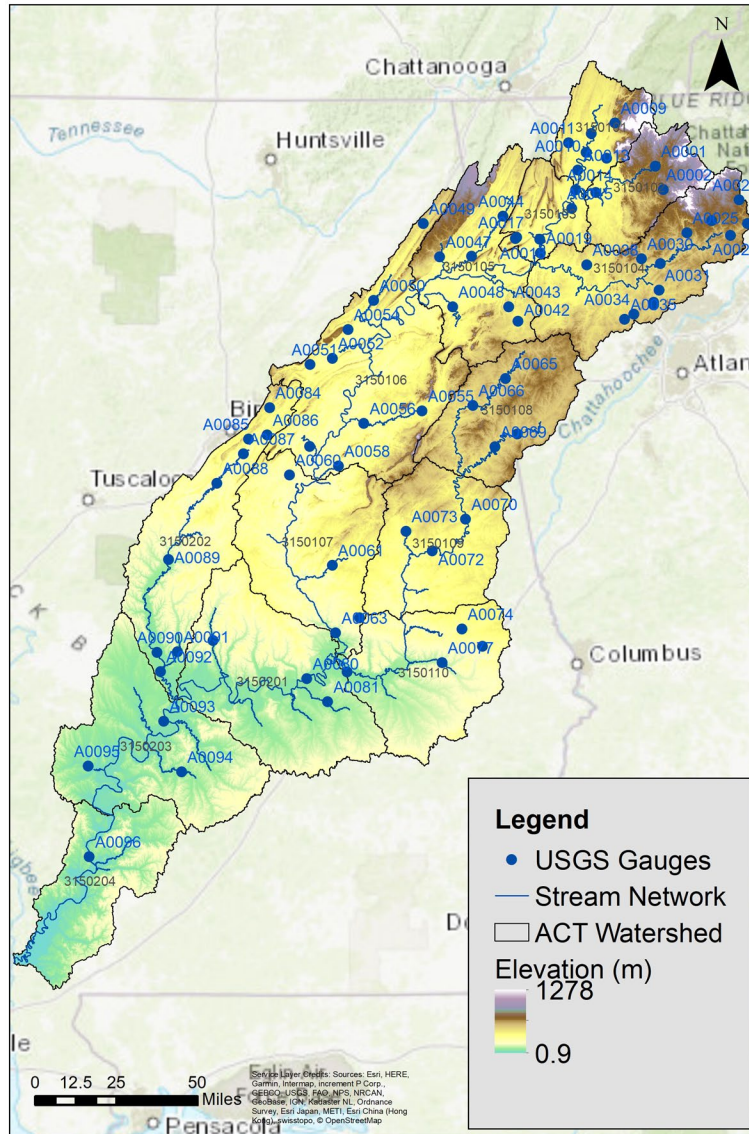


Figure 3.1. The study area showing Alabama Coosa Tallapoosa River Basin along with major stream network and USGS Gauges utilized in analysis

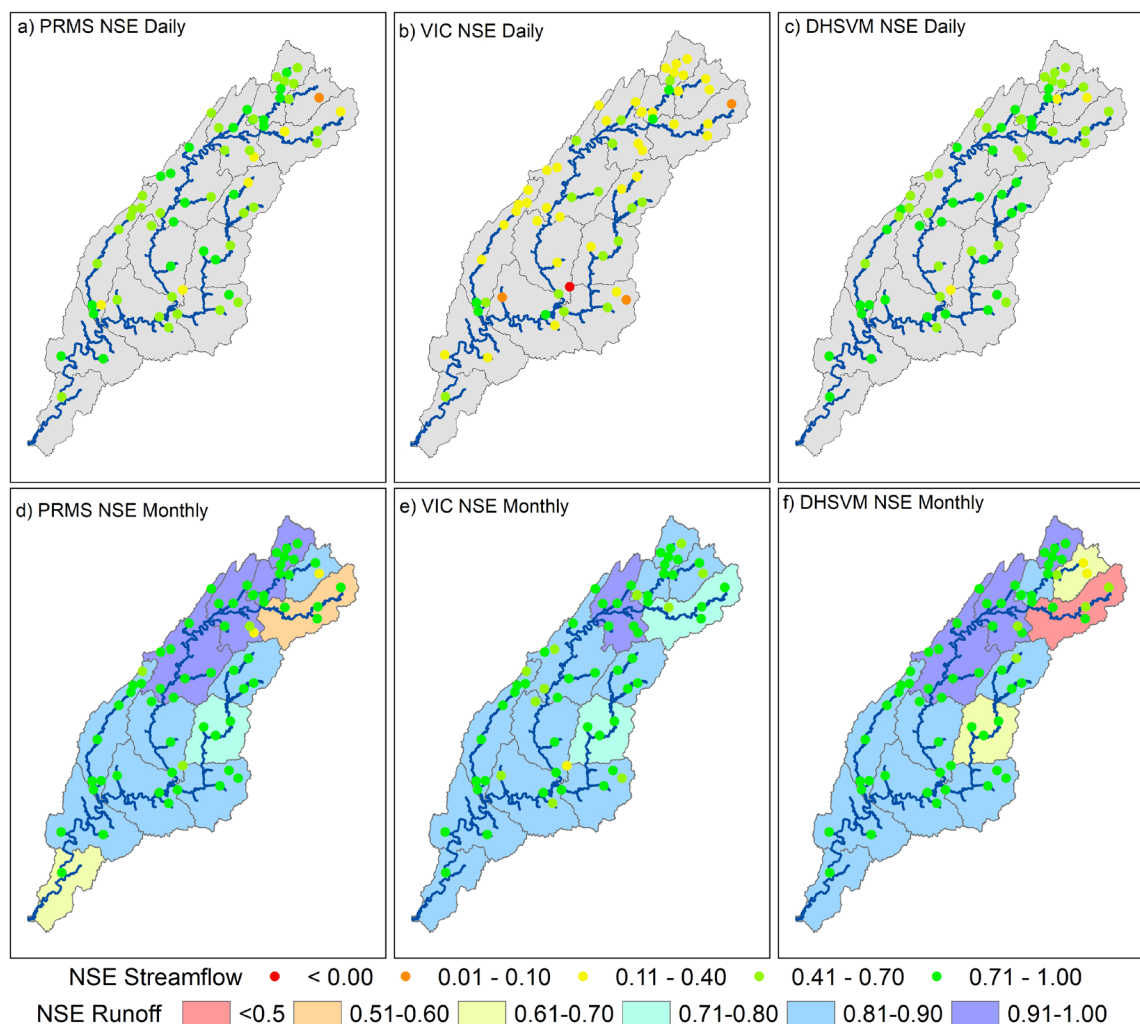


Figure 3.2. Historic model performance at daily and monthly scale for each of the three hydrologic models.

The HUC08s and USGS gauge locations are color coded based on NSE values. The simulated streamflow values are compared with corresponding observed historic USGS streamflow, while the simulated runoff was compared with USGS WaterWatch runoff as benchmark for the period of 1981-2012.

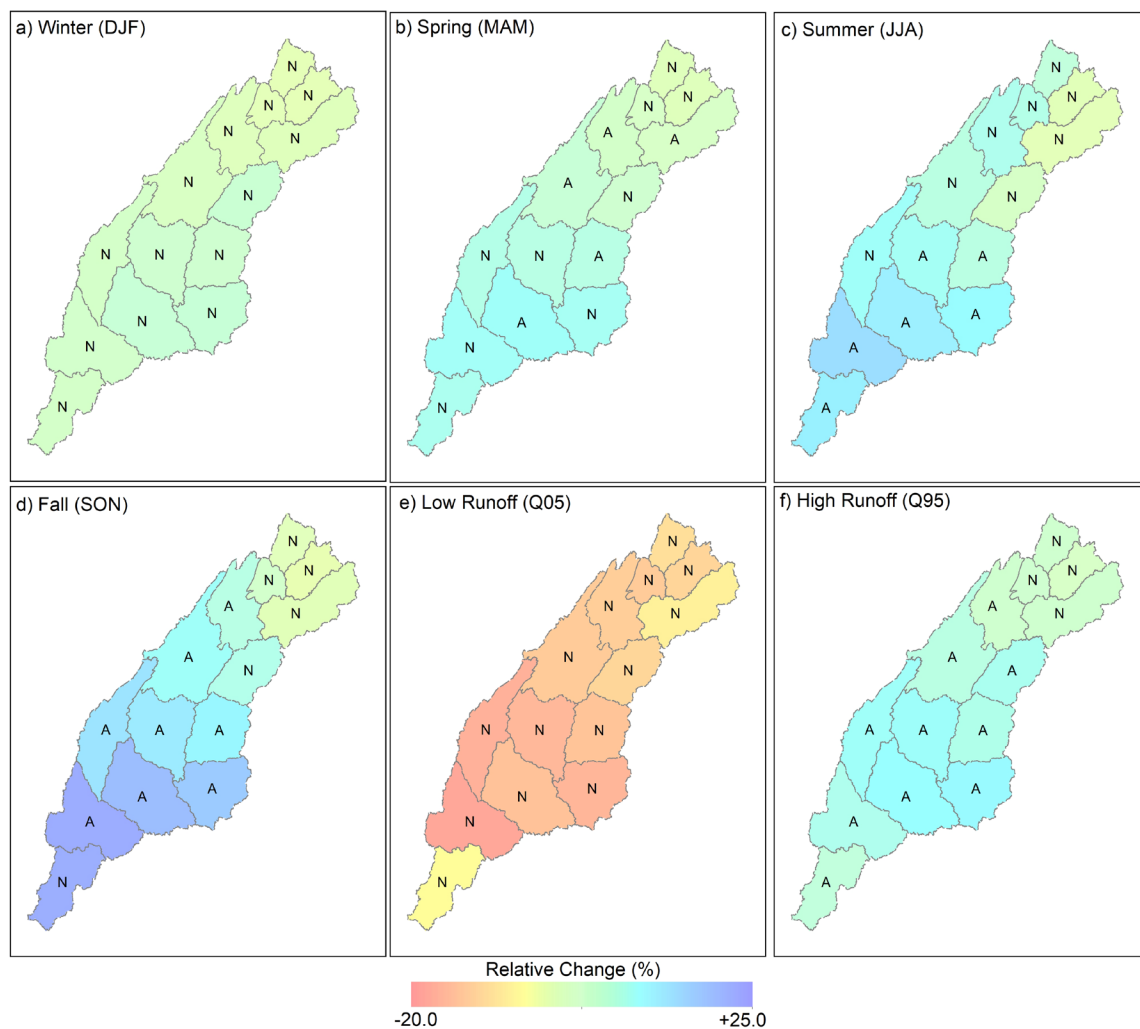


Figure 3.3. Projected changes in average monthly seasonal runoff (a, b, c, d), low runoff (e) and high runoff (f) over ACT aggregated at HUC08 levels.

The HUC08s with more than two thirds of ensemble members indicating a same sign of change are marked and labeled as 'A', or 'N' otherwise.

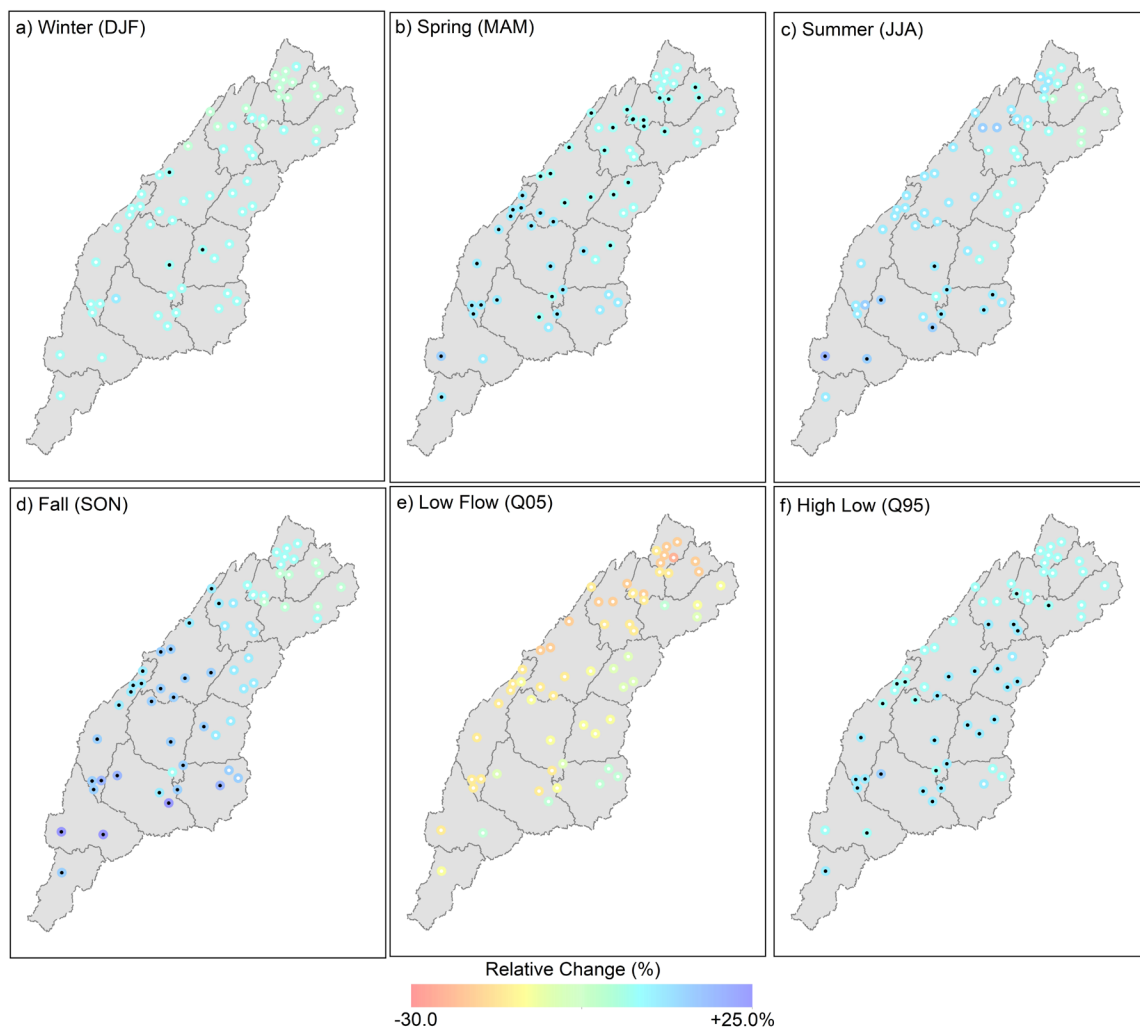


Figure 3.4. Projected changes in average monthly seasonal streamflow (a, b, c, d), low flow (e) and high flow (f) over ACT for each USGS gauge location.

The gauge locations with more than two thirds of ensemble members indicating a same sign of change are stippled in black.

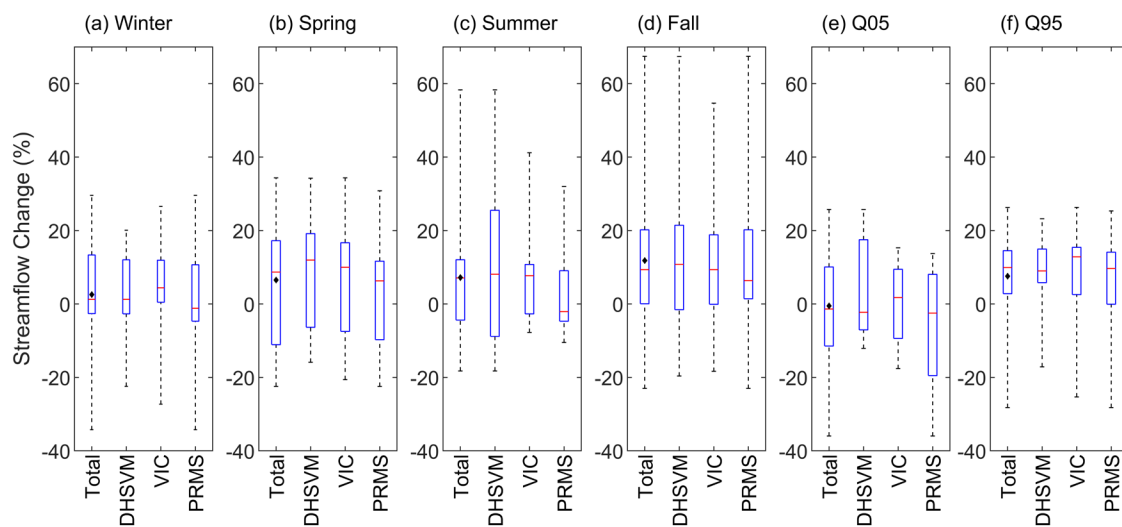


Figure 3.5. . Distribution of percent change in mean, high and low streamflow for a selected USGS Gauge close to the outlet of ACT. In each panel, “Total” represents distribution obtained from all 33 set of projections, while DHSVM and VIC represents distribution obtained from the respective choice of hydrologic model. The multi-model mean for total ensemble is shown as black diamond

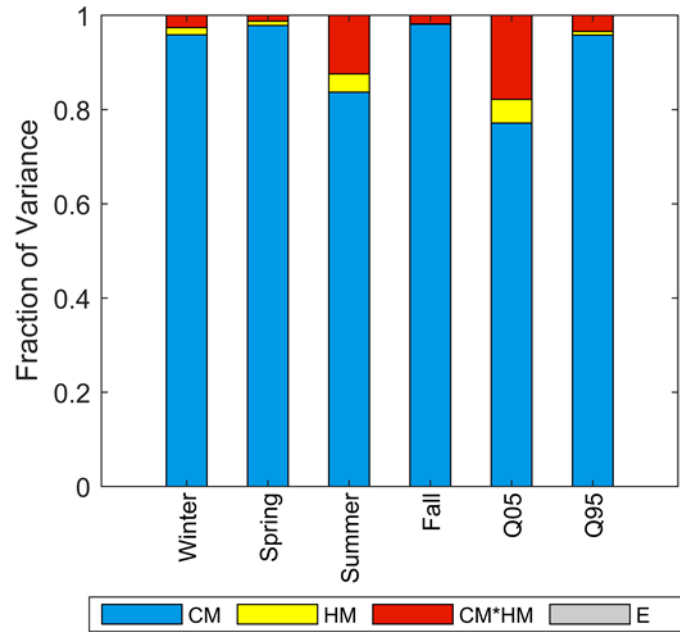


Figure 3.6. Relative contribution of different sources of uncertainty to total variance for each climate indices respectively. The CM, HM, CM*HM and E represents variance caused by climate models, hydrologic models, interaction of climate and hydrologic models, and error.

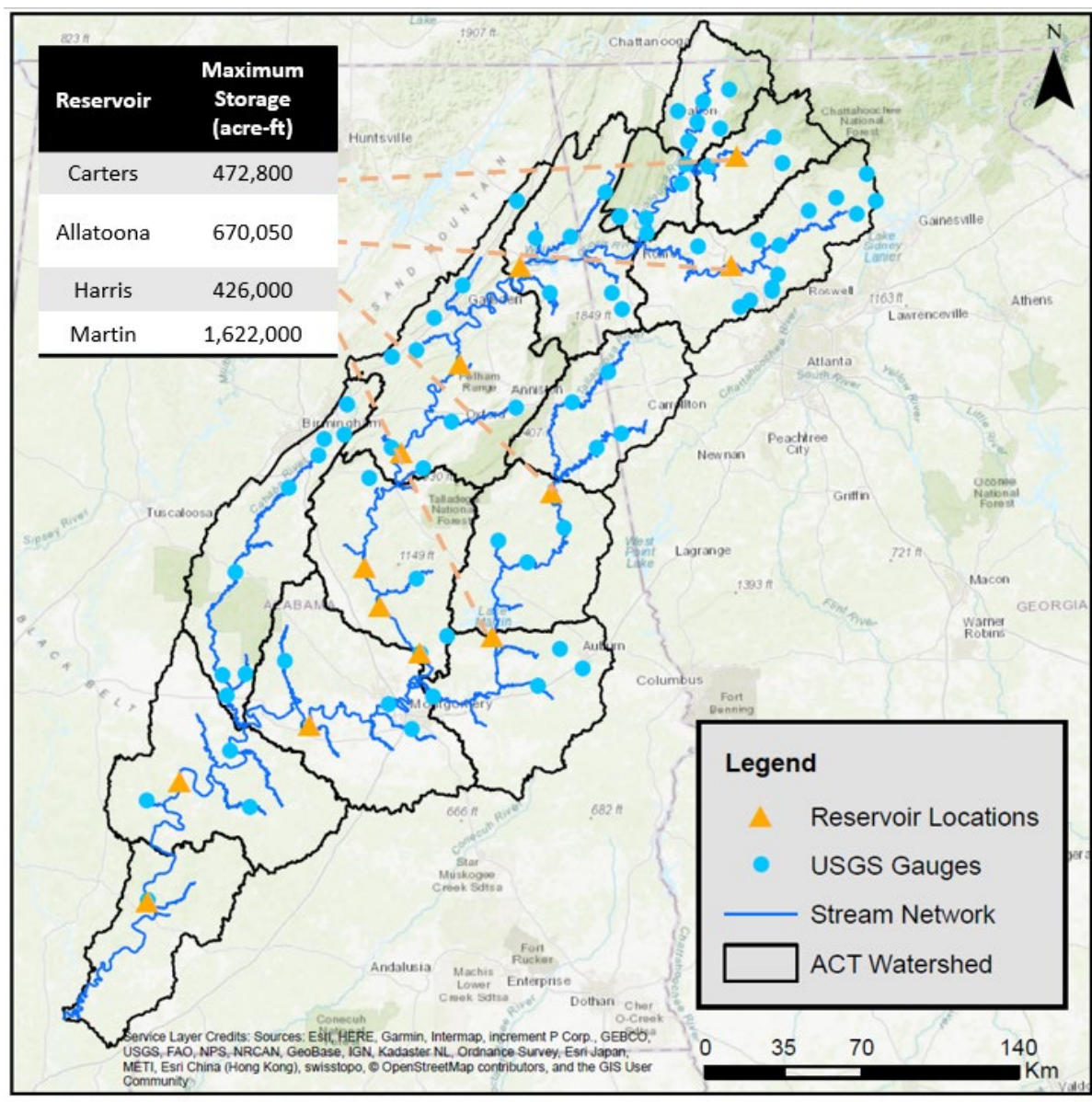


Figure 4.1 Alabama Coosa Tallapoosa (ACT) River Basin in southeastern United States.

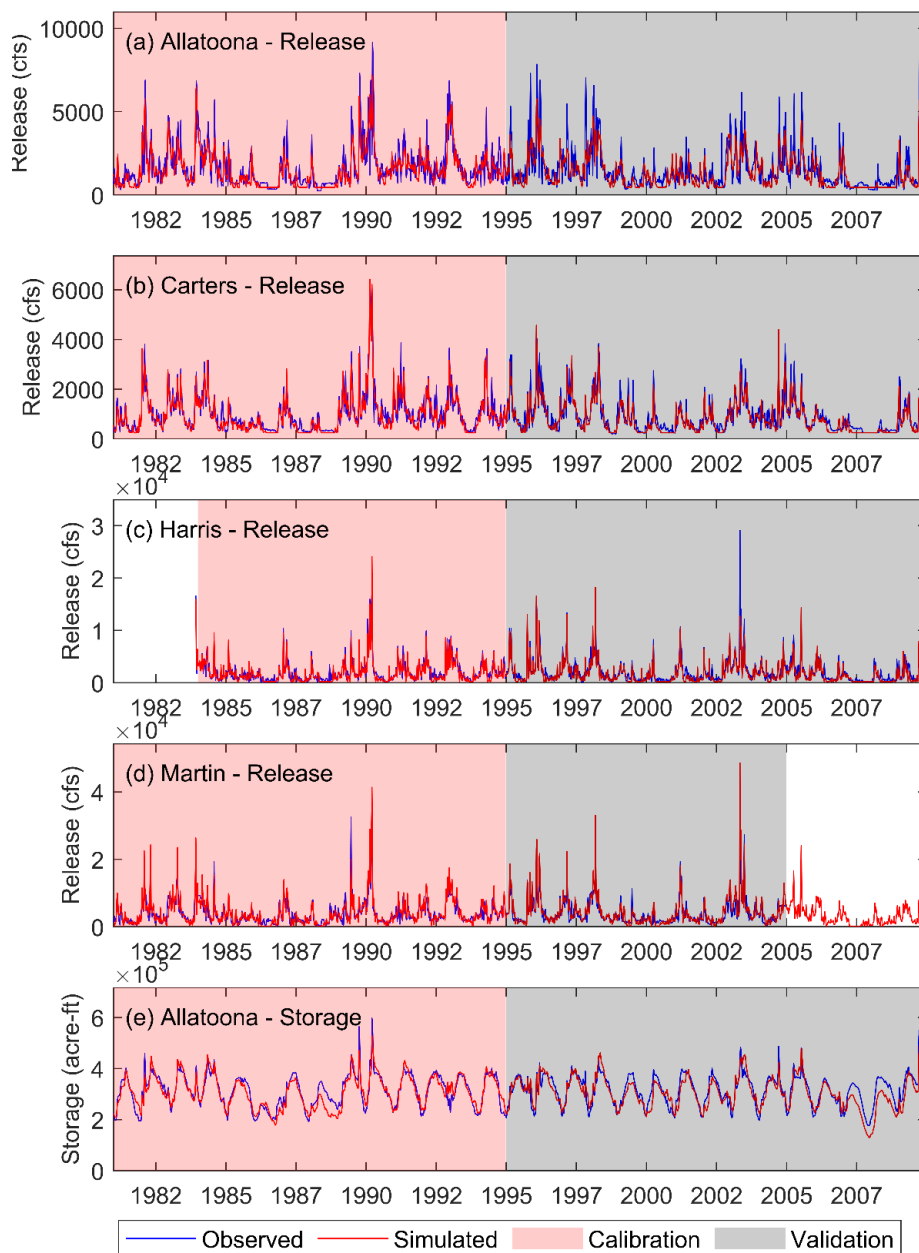


Figure 4.2 Historic DHSVM-RES performance for each reservoir.

Additional details about the calibration and validation time periods and data sources is referred in Table 4.2

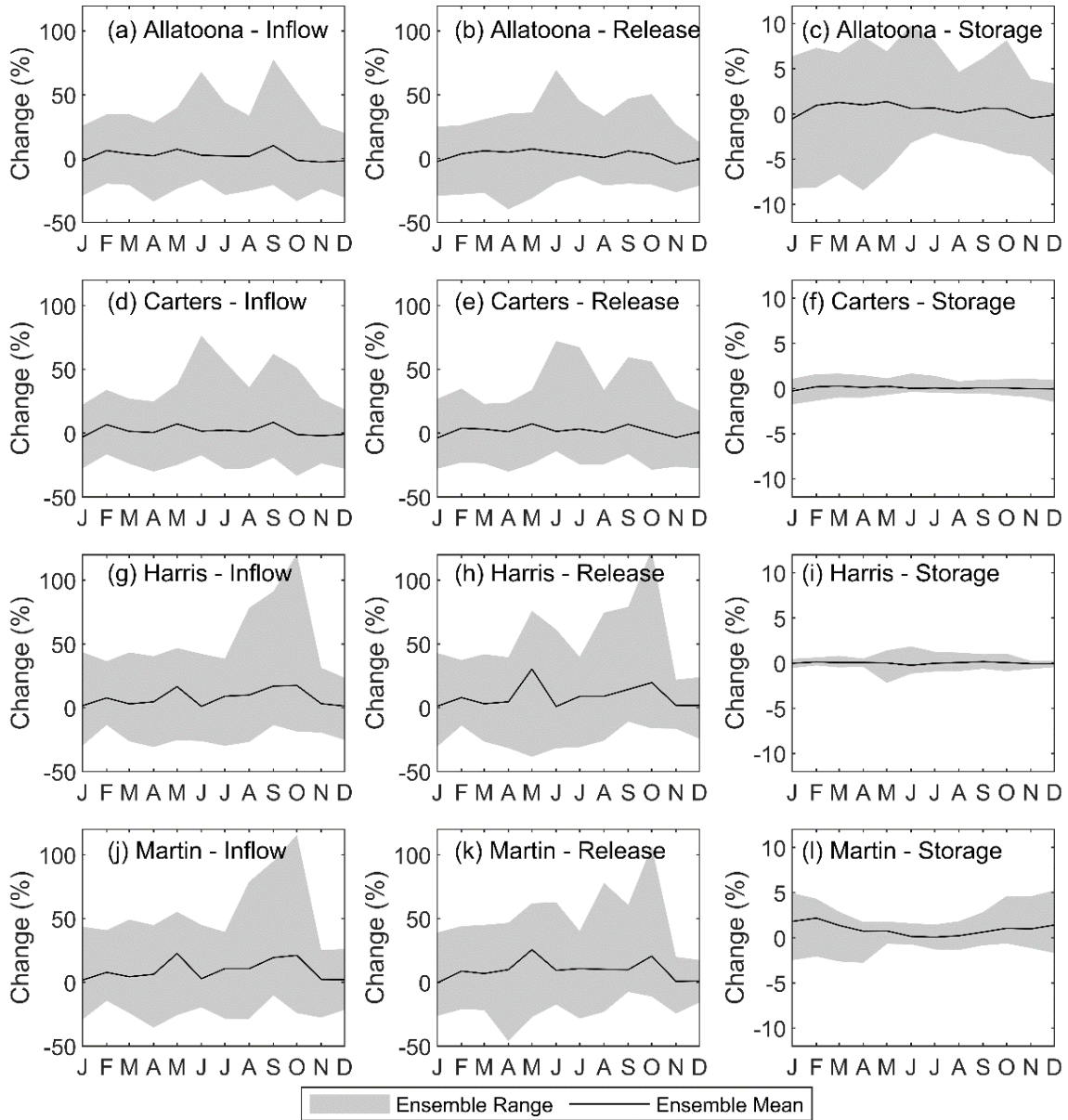


Figure 4.3 Relative change in monthly reservoir inflow, release and storage for each reservoir under future climate projections compared with baseline time period.

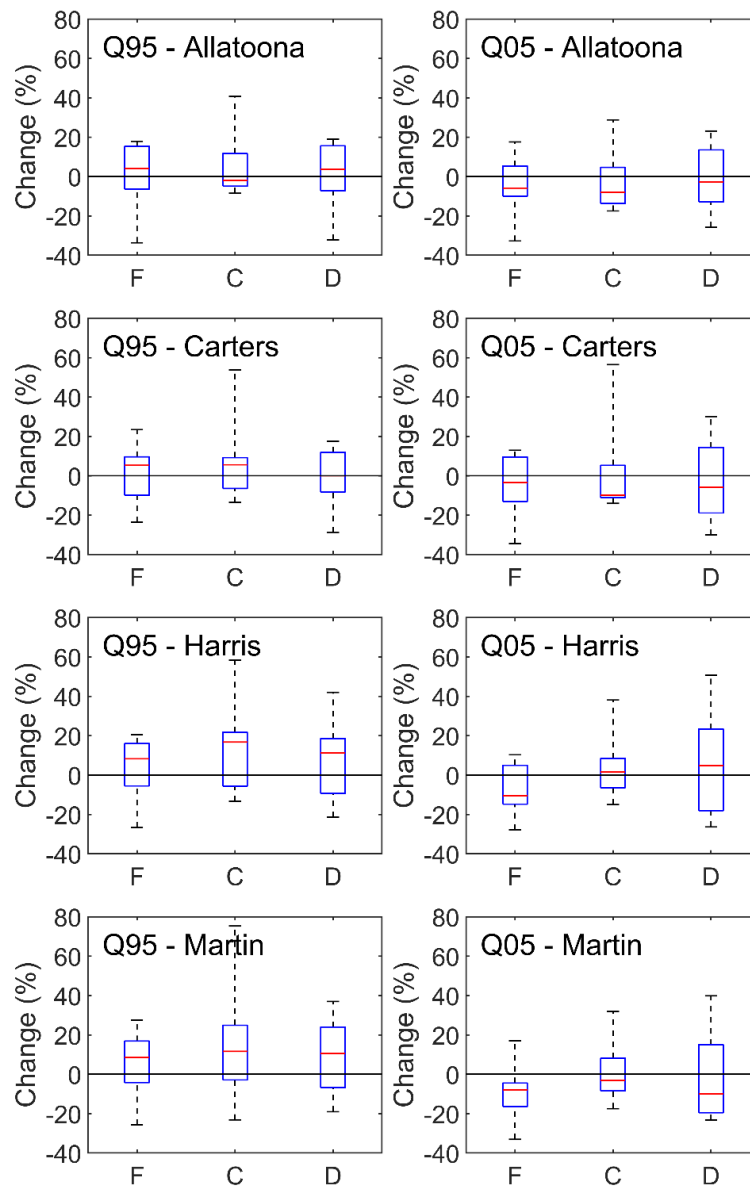


Figure 4.4 Relative change in inflows to the reservoirs. The high flow (Q95) and low flow (Q05) are calculated under future climate projections and compared with baseline time period.

The breakdown is presented at seasonal levels indicating Fill-up(F) , Conservation (C) and Drawdown (D) periods.

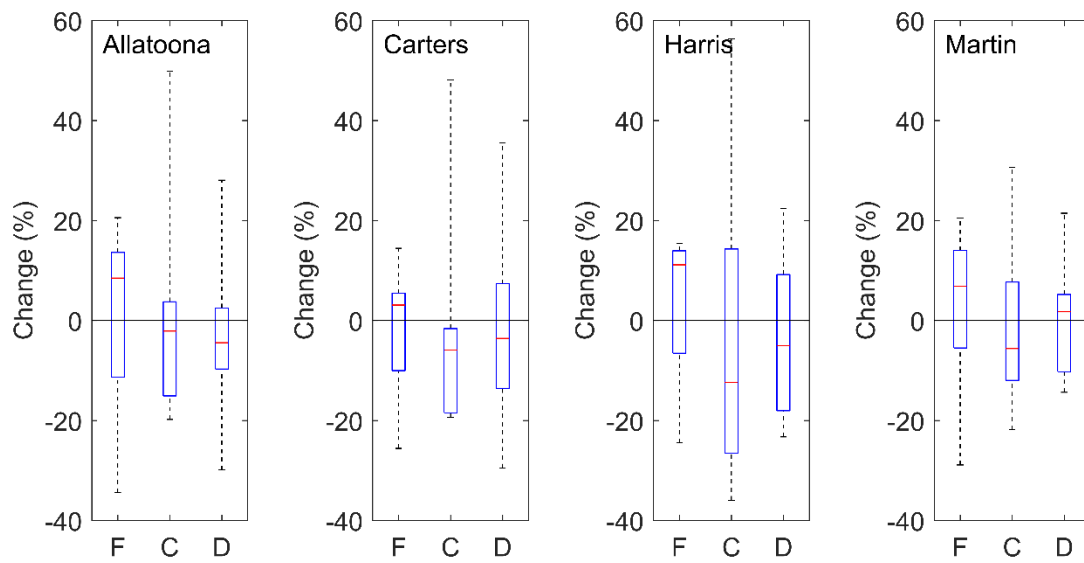


Figure 4.5. Relative change in median reservoir release under future climate projections compared with baseline time period. The breakdown is presented at seasonal levels indicating Fill-up (F) , Conservation (C) and Drawdown (D) periods.

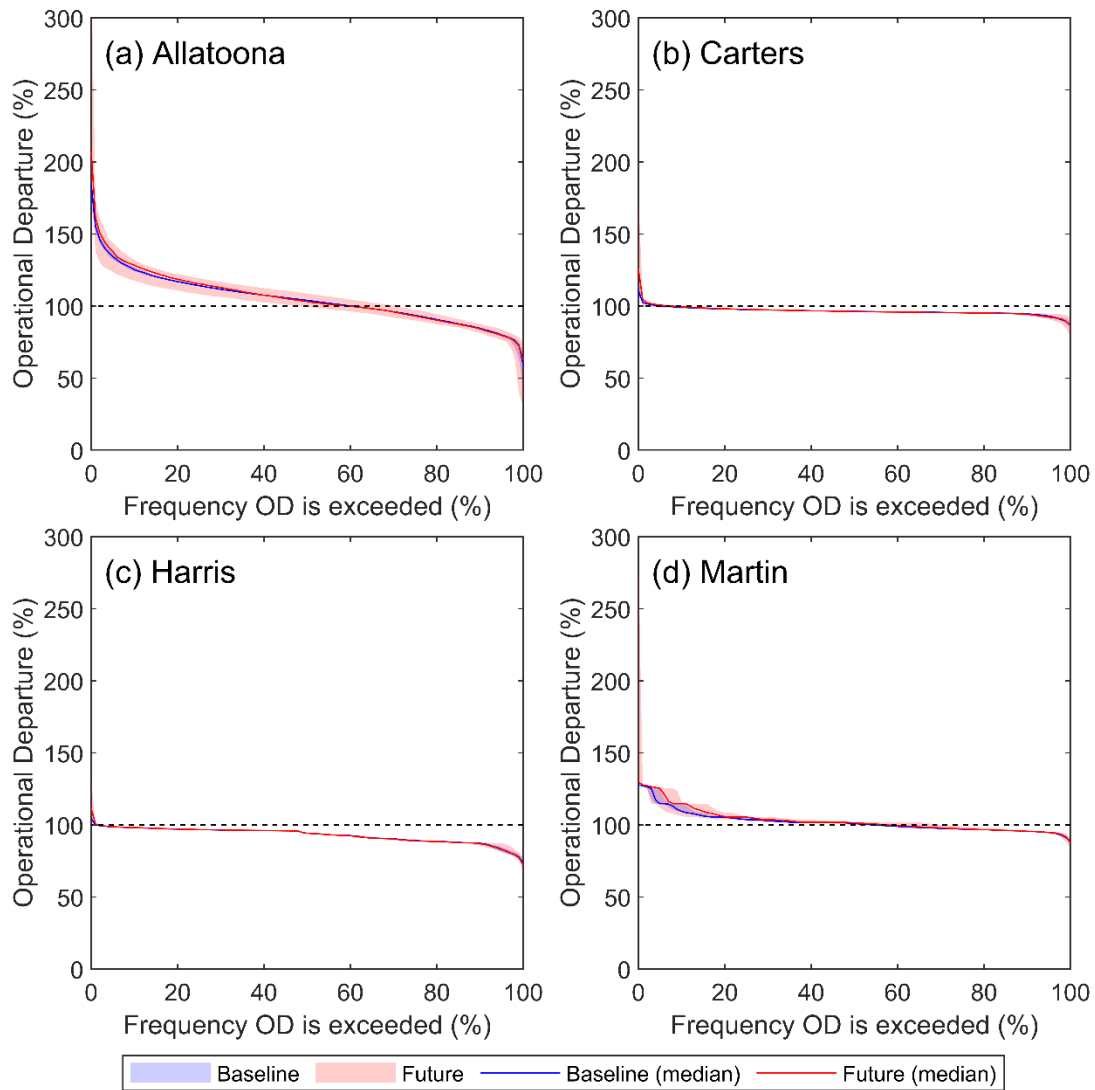


Figure 4.6 Storage Duration Curves for each reservoir under baseline and future time periods. The shaded portions indicate the range of 5th percentile and 95th percentile storages under baseline and future time periods.

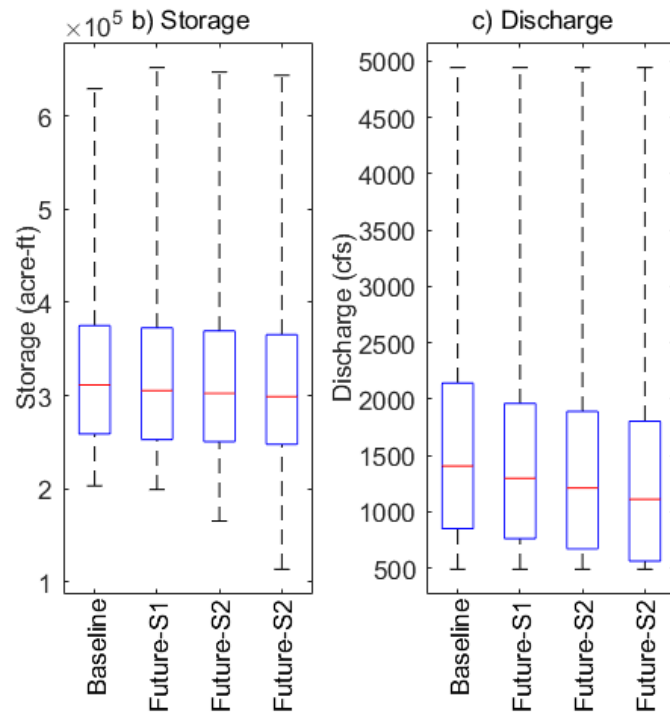


Figure 4.7. Impacts of increased water demands in conjunction with climate impacts on reservoir Allatoona.

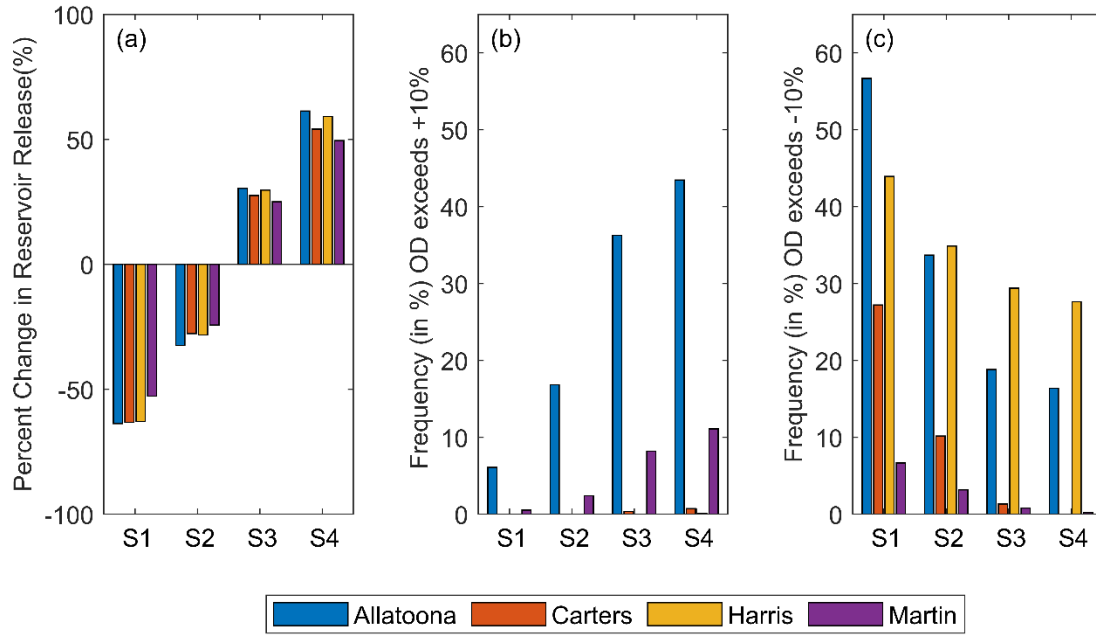


Figure 4.8 Sensitivity test results for Scenarios S1-S4, with -50%, -25% +25% and +50% of the reservoir inflows respectively, on reservoir release (panel a) and operational departures (panel b) for each reservoir.

VITA

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