

Climate change impacts on water resources in the Greenbrier  
basin in West Virginia

by

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Thesis submitted in partial fulfillment of  
the requirements for the degree of  
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Civil and Environmental Engineering in the Graduate School  
of Duke University

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ABSTRACT

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## Abstract

This paper investigates climate change impact on the water resources in the Greenbrier basin using a distributed hydrological model VIC and future climate series. The GCM outputs under the SRES A2 greenhouse gas emission scenario is downscaled and bias-corrected by the BCCAQ method to obtain the future climate series. The VIC model performance is satisfactory with the Nash–Sutcliffe efficiency coefficient (NSE) of 0.62 and 0.58 in calibration and validation periods. The bias-corrected precipitation and temperature indicate a warmer and more humid climate with precipitation and temperature increase by 14% and 1.8°C in the future. Under climate change background, the mean annual cycles of water balance components keep similar seasonal fluctuation but have larger magnitudes in the future. The discharge in the future also has close monthly distribution with that in the historical observations. The results show that the future discharge is larger than historical observation, implying water resources would be more abundant in summer from 2046 to 2065. The hydrological simulations in the Greenbrier basin have a system error of underestimating the peak flows, and the extreme discharge would be larger and more frequent in the mid of 21st century.

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# 1. Introduction

Intergovernmental Panel on Climate Change (IPCC) has shown strong evidence of global warming. Most of the increases in global surface air temperature since the mid-20th century are very significant due to the increase in anthropogenic greenhouse gas concentrations (IPCC, 2007). Climate change can significantly influence all aspects of the earth, data especially the hydrological cycle, which will be intensified with more evaporation and precipitation (Arnell, 1999). These effects are amplified more significantly in runoff (Chiew et al., 2009; Sankarasubramanian et al. 2001; Wigley et al., 1985), leading to remarkable changes in the distribution of water resources over many regions over the past century. Based on the greenhouse gas emission scenarios for the 21st century, climate change will continue causing increased temperatures and significant precipitation variation and then changes in water resources and water availability (Nakicenovic et al.,2000). Such hydrological changes could have severe impacts on many aspects of the environment, society, and human development, which are dependent on water resources. The potential changes in runoff and water distribution require a careful and considerate water resource planning and management policy.

Massive studies have assessed the impact of climate change on past and future water resources. The approaches they estimate the impact could be generally divided into four categories (Sankarasubramanian et al. 2001). The first uses hydrological models

forced by varying meteorological inputs and then evaluates the discharge's resulting changes (Jeton et al., 1996; Chiew et al., 2009; Hagemann et al., 2013). Another approach is analyzing the sensitivity of the streamflow regarding the model parameters (Schaake, 1990). The third one is to empirically investigate discharge changes resulted from historical changes in climate (Risbey et al., 1996). A fourth approach is to use statistical methods to analyze the relationship between historical climate and streamflow (Revelle et al., 1983). Among the above-mentioned methods, the hydrological modeling approach is performed in most cases and regions because it is much more objective, and many other variables of interest in the hydrological cycle (e.g., evaporation, soil moisture and baseflow) could be modeled. Usually, in the hydrological modeling approach, the model is first calibrated against observed discharge data and then forced by future climate series with the same optimal parameter values. The resulting simulated future discharge is compared and analyzed with the historical streamflow to estimate the climate change impact (Schaake, 1990; Xu, 1999; Chiew et al., 2002).

One essential step in the hydrological modeling approach is developing the future climate series. Many previous studies have suggested obtaining future series based on general circulation models (GCM) (Gleick, 1986; Arnell, 1998; Wood et al., 2004). The ICPC concludes that GCMs are the best tools available to simulating the present climate and predict future climate change. Since GCMs are conceptually designed to simulate average, large-scale atmospheric circulation (Holton, 1992), they

are inherently unable to provide accurate and high-resolution meteorological variables on the earth's surface and unqualified to use directly in hydrological studies (Xu, 1999). Also, GCM outputs must be handled with caution as they usually exhibit great systematic bias caused by imperfect conceptualization, discretization, and spatial averaging within grid cells (Teutschbein and Seibert, 2012), comparing with observed climate variables (Varis et al., 2004; Randall et al., 2007; Teutschbein and Seibert, 2010). Consequently, a spatial downscaling and bias-correction method should be performed on the GCM outputs before coupling with any hydrological models.

There are a plethora of studies in the literature on downscaling and bias correction methods of GCM outputs. A diverse range of downscaling techniques has been developed, evaluated, and reviewed over the past few years to post-process the GCM outputs, transforming synoptic-scale climate series into catchment-scale. The basic assumption is that the relationship between GCM-outputs and local climate series remains unchanged (Wilby et al., 1998; Boé et al., 2006). There are two general types of downscaling: dynamic and statistical (Maurer et al., 2008). Dynamic techniques employ high-resolution models with GCM outputs being initial and lateral boundary conditions over a region of interest (Gordon et al., 1997;). Though dynamic approaches maintain spatial correlation and plausible physical relationships, they are laborious and computationally intensive to perform in many regions and scales (Chiew et al., 2009). Based on the direct quantitative relationships between the climate variables at the two

spatial resolutions (Wigley et al., 1990; Karl et al., 1990), statistical downscaling is computationally efficient and easy to implement, making them more common than dynamic ones (Ahmed, 2013). They usually lie in three broad categories (Chen et al., 2011): regression methods (Wilby and Wigley, 1997), stochastic weather generators (Richardson, 1981; Racsco et al., 1991), and weather typing schemes (van den Dool, 1994; Hunter et al., 2005).

In either category, before downscaled GCM outputs can be used in climate studies, some adjustments to account for the GCM biases must be performed (Haerter et al., 2011). Bias correction methods are designed to mitigate the systematic bias presented by climate model outputs, such as the overestimation of wet days with negligible rain or extreme temperature errors (Ines et al., 2006), or incorrect precipitation magnitude and seasonal variations (Christensen et al., 2008; Terink et al., 2009). Numerous bias correction approaches have been proposed, including statistical downscaling, histogram equalizing, rank matching, and quantile mapping (QM). Most of them form a transfer function based on cumulative distribution functions (CDFs) of climate variables from the observations and climate model outputs and the assumption that the bias between observed and simulated climate variables keep unchanged in both historical and future periods (Piani et al. 2010). Previous studies have already evaluated and compared various bias correction techniques. Teutschbein and Seibert (2012), for instance, have reviewed and assessed six bias correction methods. Based on the comparison of quantile

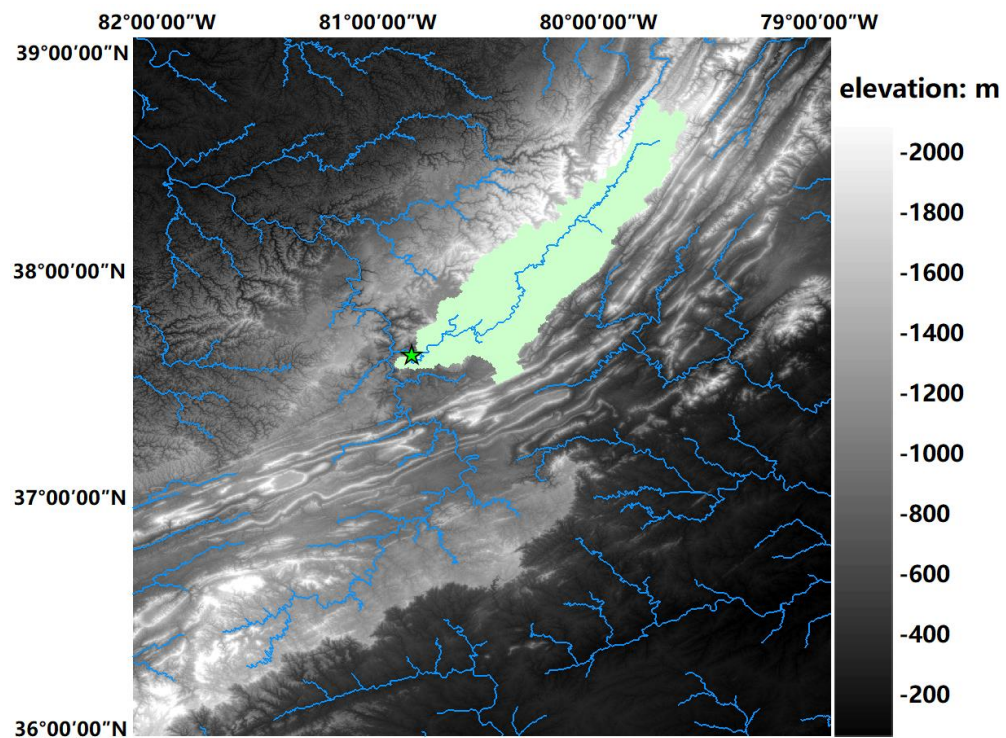
distribution, quantile mapping methods are the most widely used and successful among the above-mentioned ones. Some lumped methods combining spatial downscaling and bias corrections have been designed, such as bias correction and spatial downscaling (BCSD) (Wood et al., 2002) and recently developed BCCAQ (Cannon et al., 2015; Murdock et al., 2014).

This study's motivation is to describe a modeling method for estimating climate change impact on water resources across a small basin in West Virginia, US. This modeling method is performed by coupling VIC hydrological model with GCMs. To achieve this, this study develops the future climate series based on outputs of GCM as input into the hydrology model to estimate the future discharge and water resources of the selected basin. The GCMs use the SRES A2 greenhouse gas emission scenario (IPCC) to simulate the future climate. "Study region and Data" presents the selected region's basic information and the data used in this study. Then, "Methodology" described the methods to obtain the future climate series and VIC model and its application. The results of future climate simulations, climate change impact on water resources, and the corresponding analysis and discussion are demonstrated in "Results and Discussion".

## 2. Study region and Data

### 2.1 Study region

The study region is the Greenbrier river basin, located in southeastern West Virginia, in the United States. As one of the longest and most influential rivers in West Virginia, it is 261 km long, draining 4,290 km<sup>2</sup>. Via the New, Kanawha and Ohio rivers, it is part of the Mississippi River watershed. It is also the longest free-flowing stream in West Virginia with no part of the river or its branches being dammed.



**Figure.1 The study region.** The green area is the Greenbrier basin, and the star is the location of the discharge gauge station.

## **2.2 Data**

### **2.2.1 Observed discharge data**

Daily discharge is from United States Geological Survey (USGS) at the gauge station USGS 03184000 GREENBRIER RIVER AT HILLDALE, located at Latitude 37°38'24", Longitude 80°48'19" (<https://waterdata.usgs.gov/usa/nwis/uv?03184000>). Observed data ranges from calibration (1991 - 2000) to validation period (2001 - 2010).

### **2.2.2 Forcing data for the VIC model**

The observed meteorological data used to force the hydrology model are hourly time-series atmospheric ERA 0.1° \* 0.1° gridded data ranges from 1991 to 1999 (calibration period) and 2001 to 2010 (validation period). Seven meteorological variables are used to extract the forcing data of VIC model in this study.

### **2.2.3 GCM outputs**

To entirely cover the forcing climate variables required by the VIC model, future climate projections are based on two GCM outputs from CMIP Phase 3 (CMIP3) following the IPCC emission scenarios A2 (Nakicenovic et al., 2000): CCSM of the National Center for Atmospheric Research and INGV of National Institute of Geophysics and Volcanology. The selection of GCMs for this study was subject to the availability of meteorological variables necessary to force the VIC model. The domain roughly stretched over the latitude 36–39N and longitude 79–82E, entirely covering the Greenbrier basin.

## **3. Methods**

### ***3.1 Hydrological model and its application***

The hydrology model used to simulate discharges is the Variable Infiltration Capacity (VIC) model (Liang et al., 1994, 1996). The VIC model is a semi-distributed, grid-based hydrologic model (Liang et al. 1994; Nijssen et al. 1997, 2001) based on the variable infiltration curve (Zhao et al., 1980) to describe soil moisture distribution and runoff generation. It uses multiple soil layers to simulate the effects of vegetation, topography, and soil moisture and energy exchange between land and atmosphere (Zhao et al., 2013). Since the VIC model only simulates the runoff of each soil grid independently, a routing model described by Lohmann et al. (1996, 1998) is employed to calculate the channel flow based on the runoff of the soil grids in the upstream of the outlet. With many updates (Cherkauer et al., 2003; Bowling et al., 2004), the VIC model has been extensively used in studies on topics ranging from water resources management (Nijssen et al., 2001; Abdulla et al., 1996;) to climate change impacts (Guo et al., 2009; Hagmann et al., 2011).

The primary meteorological data to force the VIC model are precipitation, temperature. In this study, the forcing data is slightly different in temporal resolution and extraction algorithms of some variables during two periods. In calibration (1991 - 2000) and validation (2001 - 2010) processes, the model runs hourly in  $0.1^\circ * 0.1^\circ$  grided cells. Required vapor pressure is estimated by the August-Roche-Magnus (or Magnus-

Tetens or Magnus) equation based on 2-meter dew temperature. When simulating future discharge (2046 - 2065), the forcing data is daily at 0.1° \* 0.1° spatial resolution. Vapor pressure and longwave radiation are calculated according to specific humidity and algorithms developed by the Konzelmann formula (Konzelmann et al., 1996), respectively.

The VIC model has been well calibrated in many large river basins over the continental US and the globe (Abdulla et al., 1996; Zhu and Lettenmaier, 2007; Guo et al., 2009; Zhao et al., 2013). In the greenbrier basin, seven parameters with specific ranges are acquired based on the experience gained in previous VIC applications to maximize the objective function. In this study, the hydrological model is calibrated and validated against 1991 to 2000 and 2001 to 2010 by observed daily streamflow using Shuffled Complex Evolution - University of Arizona (SCEUA) (Duan, 1993), one of the most popular parameter optimization methods in hydrological studies. The seven calibrated parameter values are identical for each grid cell within the Greenbrier basin.

To quantify the model performance, the Nash–Sutcliffe efficiency coefficient NSE (Nash and Sutcliffe, 1970) is employed as the objective function, calculated by the equations below:

$$NSE = 1 - \frac{\sum_{i=1}^{i=N} [Q_s(i) - Q_o(i)]^2}{\sum_{i=1}^{i=N} [Q_s(i) - \bar{Q}_o(i)]^2}$$

where  $i$  is the time step (in this study, daily),  $N$  is the number of time steps,  $Q_s$ ,  $Q_o$  are simulated discharge, observed discharge and the mean of  $Q_o$  of all time steps.

### **3.2 Future climate series development**

Future climate series are used to force the hydrological model to simulate the discharge in the future. While GCMs are a useful tool to model detailed future climate evolution, the outputs must be downscaled and corrected due to resolution mismatch and significant system bias before used as future climate series in climate impact studies. In this study, future climate series is informed by simulated precipitation and temperature of some general circulation models with the IPCC A2 emission scenario from 2000 to 2070 to cover the study period (2046 - 2065). The downscaling and bias correction method is Bias Correction/Constructed Analogues with Quantile mapping reordering (BCCAQ) (Murdock et al., 2014).

BCCAQ is a lumped downscaling and bias correcting method that combines the results from Climate Analogues (CA) (van den Dool, 1994), climate imprint (CI) (Hunter et al., 2005), and quantile delta mapping (QDM) (Cannon et al., 2015), which has been tested and used in many climate studies (Cannon et al., 2015; Werner et al., 2016).

CI is a downscaling method by mapping daily weather conditions. Climate averages of a long period (i.e., 30 years) from the fine-scale data provide a "spatial imprint" representing climate gradients in the study region. The ratio (for precipitation) or difference (for temperature) of daily to average monthly values is multiplied or

subtracted by the fine-scale monthly values for a grid to get the daily values. The climate imprint (CI) method is described in detail in Hunter et al. (2005). CA estimates the target climate pattern by a linear combination of observed historical patterns (library) like the target pattern. This downscaling method builds a library of observed coarse-resolution and corresponding high-resolution climate patterns of the target variable (Hidalgo et al., 2008). Then 30 most similar days from the coarse-scale library to a given simulated day are selected. The weights for the 30 days are calculated via ridge regression, and the 30 corresponding patterns from the fine-scale library are identified and combined with the same weights (Maurer et al., 2010). The process of CA is clearly demonstrated in Hidalgo et al. (2008). As a bias correction method based on QM (Quantile mapping), Quantile delta mapping (QDM) preserves the changes in quantiles using techniques from the quantile delta change (Olsson et al. 2009) and quantile perturbation (Willems et al., 2011) and corrects the bias in quantiles of a modeled climate series concerning observed values. The GCM outputs are detrended by quantiles and bias-corrected by QM with the transfer function according to CDF (cumulative distribution function) built in the calibration period. Then the projected ratio (for precipitation) or difference (for temperature) changes in quantiles are subtracted or multiplied to the bias-corrected climate series (Cannon et al., 2015). The three components in BCCAQ have been widely used and evaluated in many studies (Ahmed et al., 2013; Maurer et al., 2010; Tong et al., 2020).

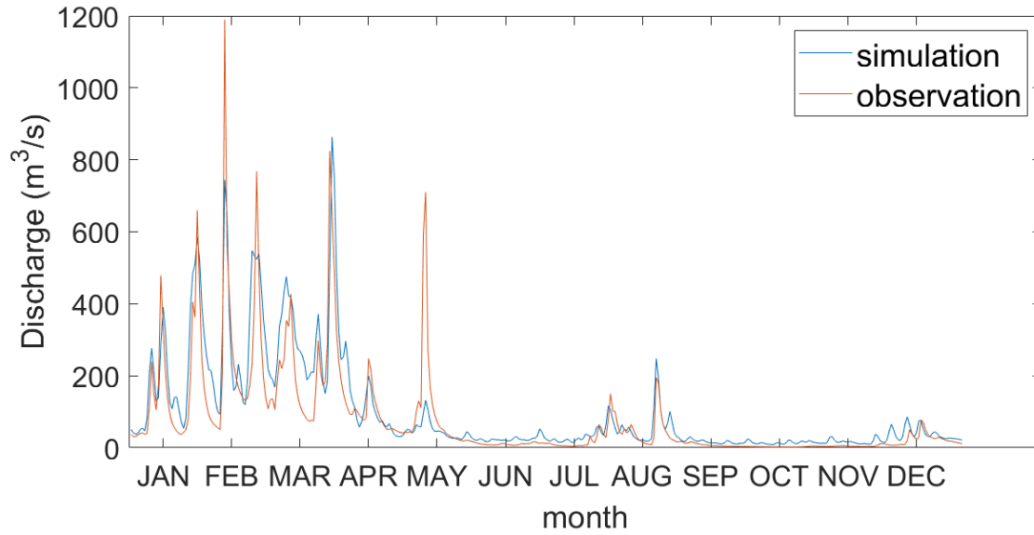
In BCCAQ, the GCM outputs are first downscaled and corrected the bias by CI and QDM, respectively. The results at each fine-scale are then reordered within a given month according to CA ranks. Reordering data within a month eliminates the excessively smooth representation of sub-reanalysis-grid-scale spatial variability inherited from bias-corrected CI outputs (Maraun, 2013), making the outcomes more realistic.

## **4. Results and discussion**

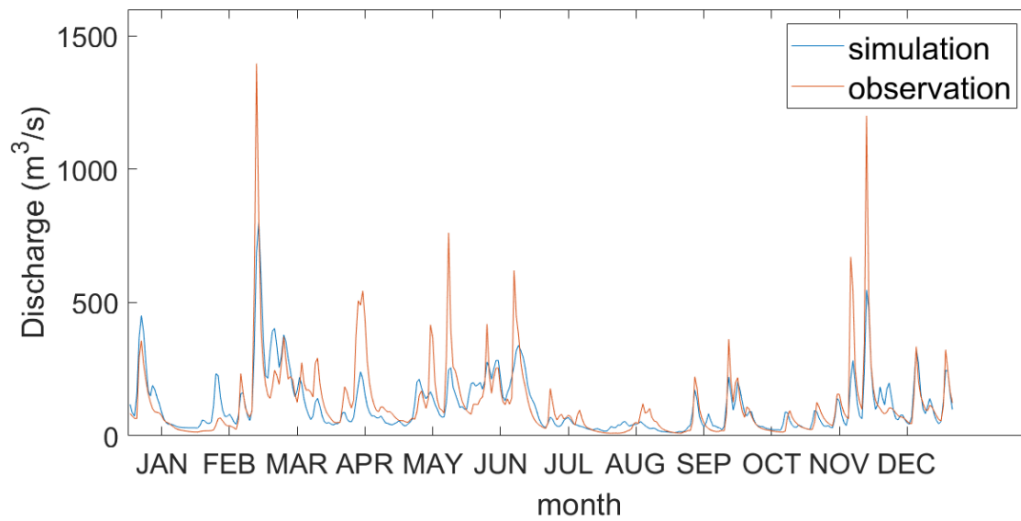
### ***4.1 Calibration and validation of VIC model***

Figures. 2 and 3 display the simulated and observed discharge in 1994 and 2003, sampled from calibration and validation periods, respectively. These figures demonstrate that while the VIC model can make timely responses to all rainfall events and predict most daily streamflow well, it shows a systematic bias of underestimating the peak flows, which would cause significant uncertainty in flood frequency analysis.

The Nash–Sutcliffe model efficiency coefficient (NSE) is used to assess hydrological models' predictive power. NSE ranges between  $-\infty$  and 1.0, with NSE =1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas a negative value indicates that the mean observed value is a better predictor than the simulated value indicating unacceptable performance (Moriiasi et al., 2007).



**Figure. 2 The simulated and observed discharge in 1994.**



**Figure. 3 The simulated and observed discharge in 2003.**

In the calibration period (1991 - 2000), the NSE is 0.62, and the validation (2001 - 2010) is 0.58, reasonably slightly lower than calibration. As suggested by Ritter et al., 2013, 0.5 is the threshold to be the sufficient quality threshold. The model has enough

satisfaction in the calibration period and acceptable in the validation period. So, in this study, the VIC model with the optimal parameters can simulate streamflow with enough quality in the Greenbrier basin.

Even though the metrics are above the satisfactory threshold, the VIC model's application on the Greenbrier Basin could not perfectly represent the land phase of the hydrological cycle, resulting in uncertainty in representing the reality and future water resource prediction that cannot be ignored, especially in the peak discharge. Multiple factors lead to uncertainty. Apart from the model structure and calibration method, there are uncertainties in the forcing data, vegetation parameters, and soil parameters. The spatial resolution of forcing data is 9km, downscaled from 30km, and the soil and vegetation parameters are linearly interpolated from 0.125°. In a complex terrain like the Greenbrier basin, the downscale methods would undoubtedly cause significant uncertainty.

## 4.2 Changes of future precipitation and temperature

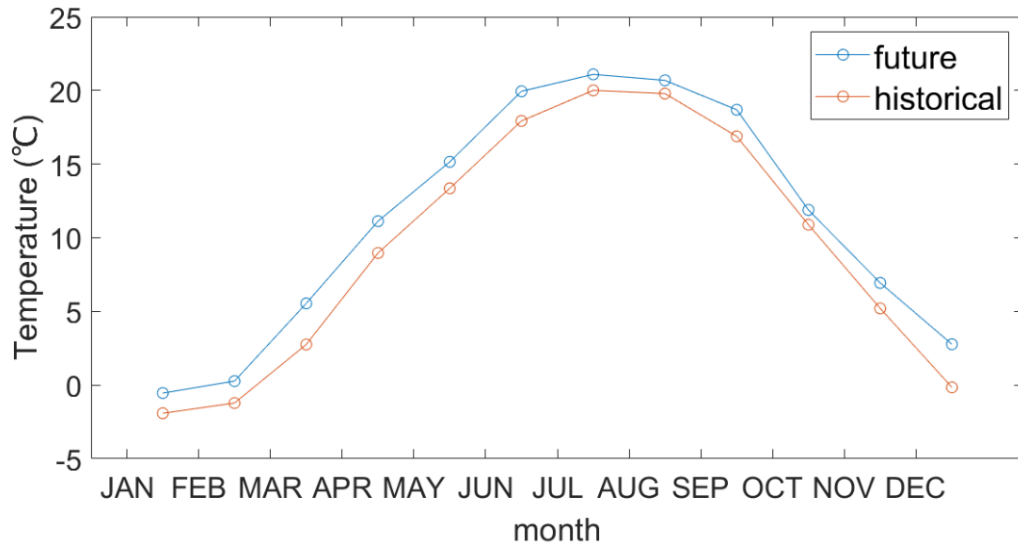


Figure. 4 Mean annual cycle of temperature.

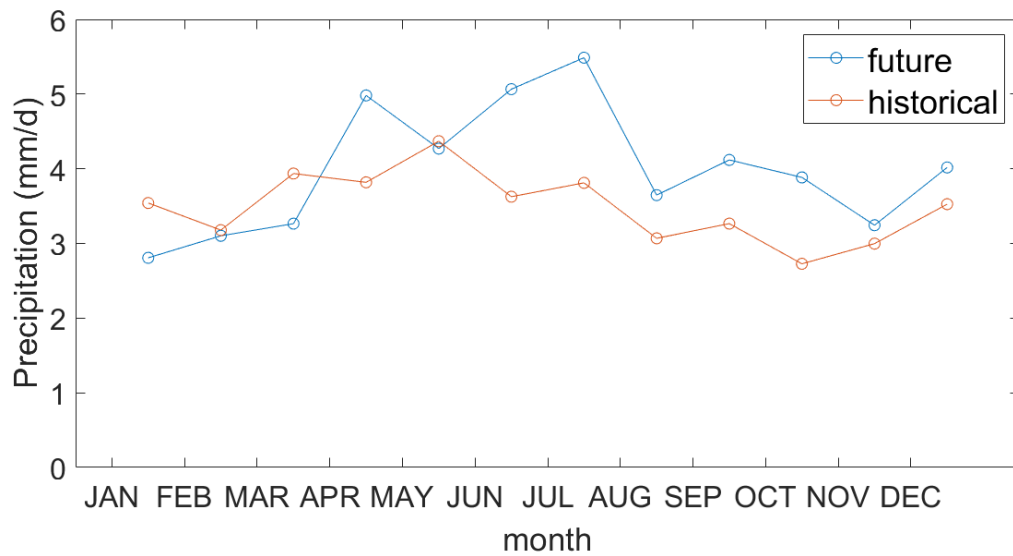


Figure. 5 Mean annual cycle of precipitation.

**Table.1 Seasonal changes of mean temperature and precipitation, from future (2046 - 2065) relative to historical records (1991 - 2010) with winter from Oct to Mar and Summer from Apr to Sep**

	<b>Winter</b>	<b>Summer</b>	<b>Annual</b>
<b>Temperature change (°C)</b>	1.6	1.9	1.8
<b>Precipitation change (%)</b>	2	25	14

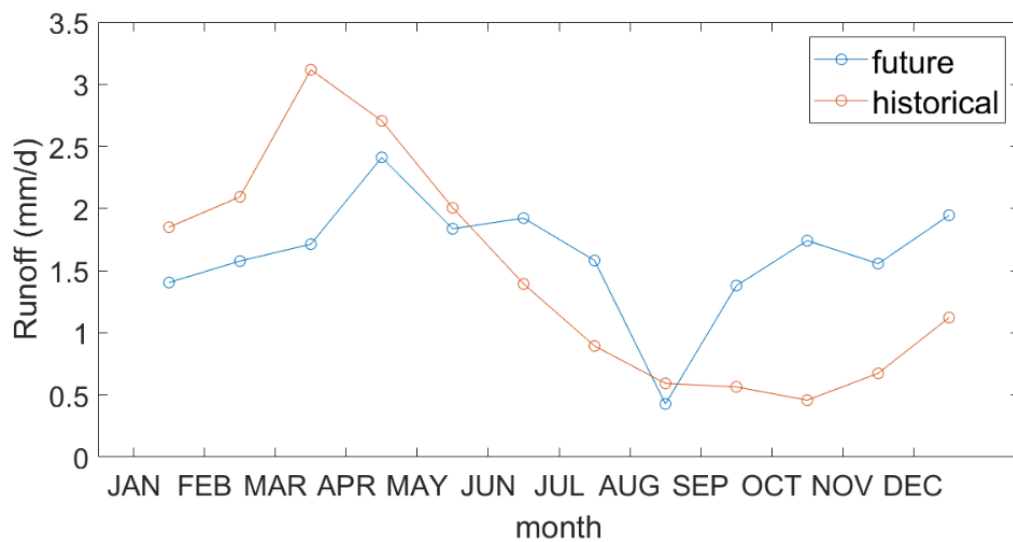
The mean annual cycles of temperature and precipitation for the present and simulated future climate in the Greenbrier basin are presented in Figure. 4 and 5, respectively. The monthly average temperature indicates an apparent warmer climate in the next few decades. For both the historical (1991 - 2010) and future (2046 - 2065) periods, the temperature reaches the highest in July and lowest in January. Table. 1 presents the seasonal changes in temperature and precipitation from future (2046 - 2065) relative to historical records (1991 - 2010) in the Greenbrier basin. The rise of annual mean temperature in the mid of the century is up to 1.8 °C compared to the start. The warming is more substantial during the winter and spring season compared to the late Summer and Fall. Warming since 1991 in simulated climate has been 0.32°C per decade, similar to 0.32~0.34°C per decade from studies by Brohan et al. (2006) and within the average temperature increase range in North Hemisphere land (IPCC, 2007).

The GCM estimates a rise in annual mean precipitation (up to 14%) in the mid of the 21st century. The increase in precipitation is observed in most months except Jan, Feb, and Mar. Generally, the increase concentrates on the second half-year with a

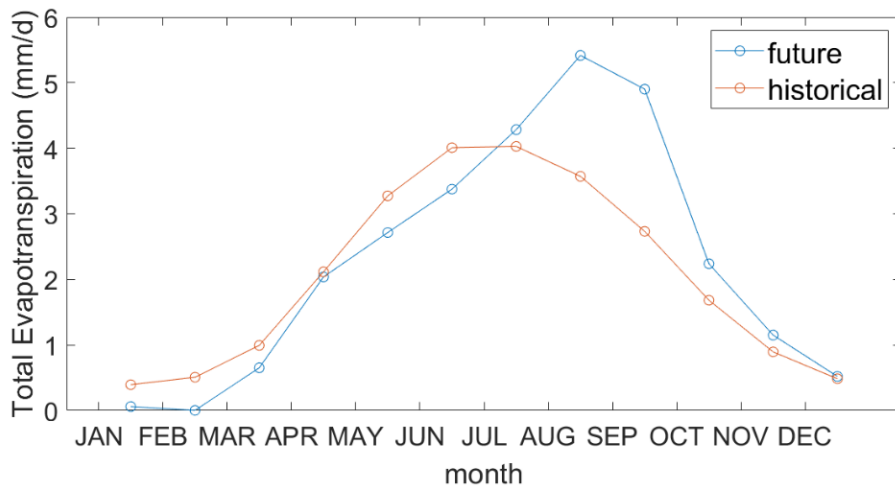
considerable rise in the summer than in the winter. While the average increase in precipitation is slightly higher than that in the past century (10%), it is consistent with the projected increase by 12% up to 22% in the mid of the 21st century in the neighboring Mississippi river basin (Arnell, 1999).

### **4.3 Climate change impact on water resources**

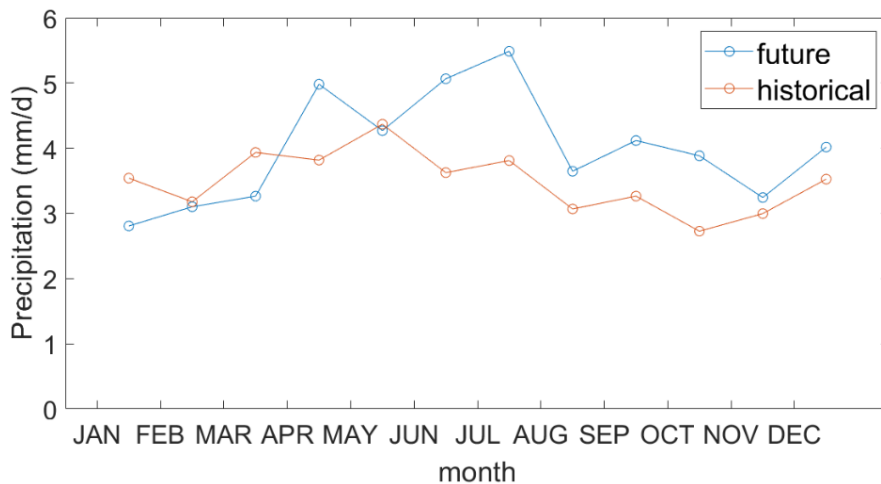
#### **4.3.1 Impact on water balance**



**Figure. 6 Mean annual cycle of runoff.**



**Figure. 7 Mean annual cycle of total evapotranspiration.**



**Figure. 8 Mean annual cycle of precipitation.**

Figure. 6 - 8 shows the average annual cycles of major water balance components, including runoff, evapotranspiration, and precipitation in history (1991 - 2010) and future (2046 - 2065) periods under the IPCC emission scenarios A2.

Generally, the average annual water balance cycles in future simulations and historical observations have similar seasonal patterns with relatively uniform

precipitation, lower runoff in the summer, and higher evapotranspiration in the second half-year. While both cycles agree with general fluctuations in temperature, discharge, and the water balance components, historical observation is much smoother, closer to the real hydrological processes in nature. This is mainly caused by the systematic bias in GCM-simulated meteorological variables like vapor pressure or net solar radiation.

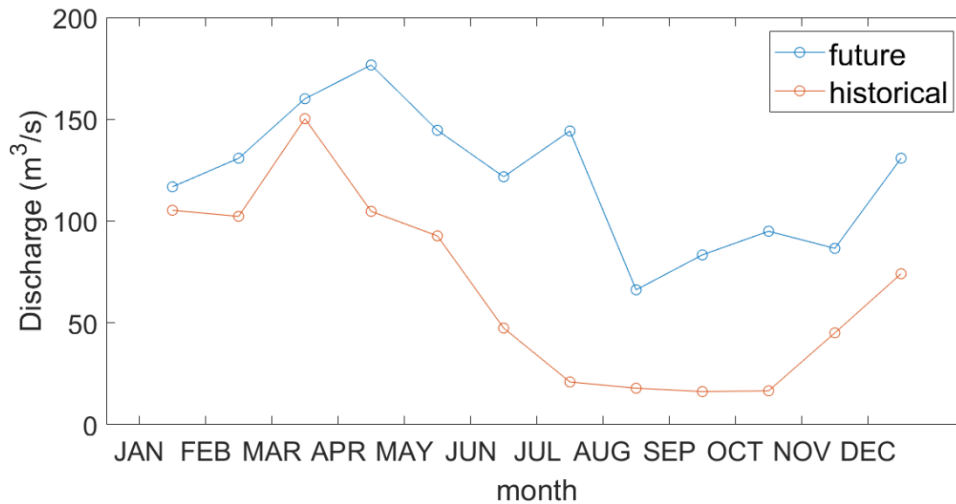
In future water balance simulations, monthly average runoff is higher in all seasons except spring, showing a potential of less water in spring but more in the second half-year in the mid of 21st century. A problem in hydrological calibration is the equality of multiple parameter combinations with similar satisfactory model performance. In this study, several parameter combinations have an NSE of 0.62, with the parameter  $b_i$  ranging from 0.14 to 0.18. Since  $b_i$  is the infiltration curve parameter, it controls the surface runoff and its variation reducing runoff prediction's confidence level. It is not enough to conclude the water resource change only according to runoff. The available water resources are addressed based on average monthly discharge in the next discussion section. A significant decrease in runoff occurs in Aug. It is because of a substantial reduction in rainfall compared to the prior month and very high evapotranspiration. The evapotranspiration reaches highest in Aug, a month later than that in historical observation and temperature. It might be because other meteorological factors like wind speed or vapor pressure deficit reach the extreme in Aug in the future,

or time offset errors accumulated by GCMs over 20 years. Anyhow, this temporal offset should not modify the general trend of future water resources on a yearly basis.

The average total evapotranspiration increase in the second half-year is 20% and 10% of the whole year, consistent with the projected annual increase by up to 13% in the mid of the 21st century in the adjacent Mississippi river basin (Arnell, 1999).

In general, the average monthly water balance components in future simulations and historical observations have similar temporal distributions, while the former has higher magnitudes due to increasing precipitation, indicating a more humid climate and the environment in the mid of 21st century.

#### 4.3.2 Impact on discharge cycle



**Figure. 9 Mean annual cycle of discharge**

Figure. 9 shows the mean annual discharge cycle of historical observation and future simulation in the Greenbrier basin. Concurrent with the corresponding

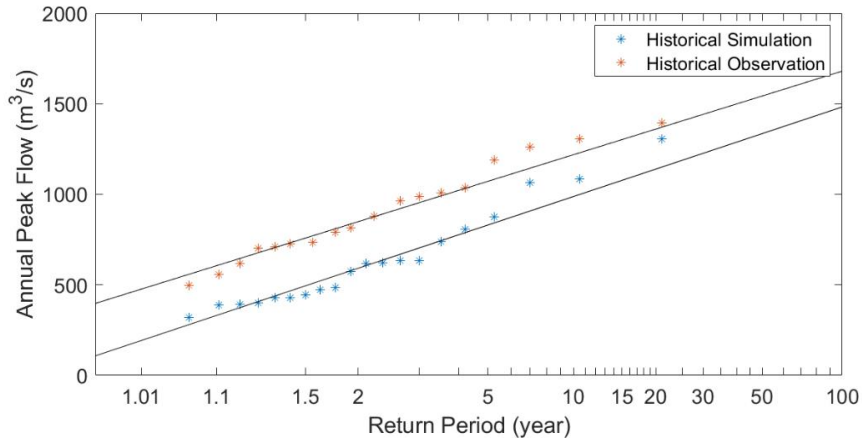
precipitation and evapotranspiration, both discharge cycles show similar seasonal variations with high flow in spring and low in late summer and fall.

From 2046 to 2065, the flow stays high from Jan to May. It reaches highest in Apr under the combining effect of most extensive rainfall and relatively small evapotranspiration, which means more available water resources at this period from the 2040s to 2060s. Even though rainfall in July is highest, the intense evapotranspiration makes the discharge lower than that in Apr. Stronger evapotranspiration and less rainfall drastically reduce the streamflow to the minimum in Aug. Because the precipitation is evenly distributed over months in the historical period, the discharge fluctuation is mainly controlled by the evapotranspiration. Since the total evapotranspiration is much larger in summer, the Greenbrier basin usually has a high flow from Jan to May, indicating more abundant water resources in spring and winter.

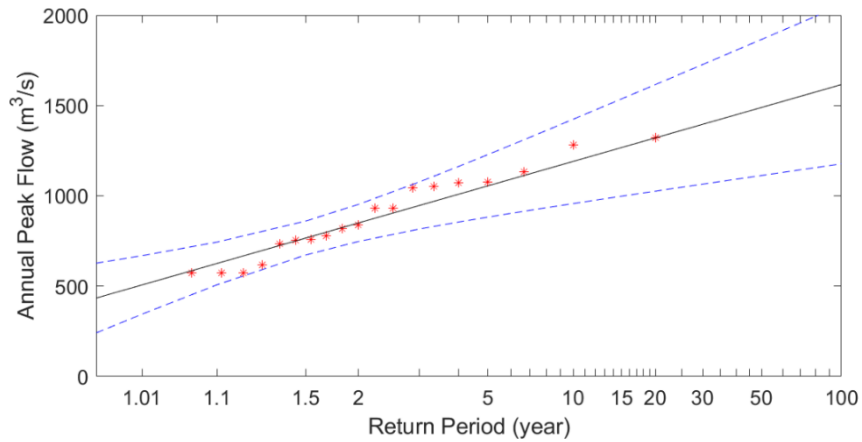
While the streamflow cycles resemble each other in season distribution, flow's magnitude of future simulation is larger than that of historical observation, especially from Apr to Dec. Based on figure. 9, the future streamflow from Jan to Apr is slightly higher than historical observations. However, considering the systematic error in hydrological simulation, the truth maybe not or even less. But the prediction demonstrates that the discharge from early summer to early winter would increase with confidence even considering the uncertainty caused by the hydrology model. Thus, under the IPCC A2 emission scenarios, climate change would result in more available

water resources in the Greenbrier basin in the 2040s to 2060s, significantly reducing the water resource stresses in summer.

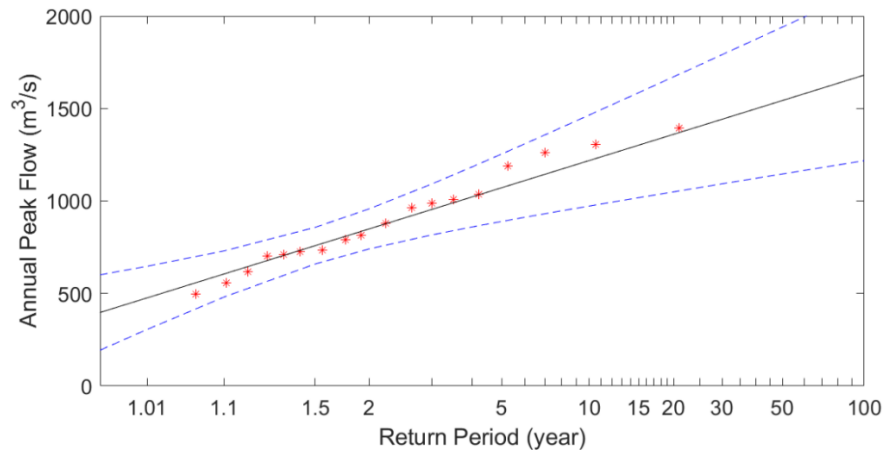
### 4.3.3 Impact on discharge peaks



**Figure. 10 Annual peak flow of future simulations and historical observations over return period.**



**Figure. 11 Annual peak flow of future simulations over return period. Dashed lines are ranges with 95% confidence level.**



**Figure. 12 Annual peak flow of historical observations over return period. Dashed lines are ranges with 95% confidence level.**

Based on the Gumbel extreme value distribution, peak flow analysis is performed to estimate climate change's impact on floods for the Greenbrier basin. The maximum discharge per hydrological year is extracted from both historical observations and future simulations as the flood series.

To estimate the VIC model's error in simulating the peak discharges, flood frequency analysis is carried out. Figure. 10 shows the return years of two peak flow series: historical simulations and observations. The peak flow of historical simulated annual maximum discharge demonstrates a general concurrence with observations in distribution trends over frequency, illustrating that the VIC model can significantly respond to heavy precipitation as reality. However, the simulation keeps underestimating the flood magnitude at all return levels, showing a systematic bias of predicting lower peak discharge. As a return period, thirty years correspond to an annual peak flow of 1200 and 1400 m<sup>3</sup>/s, and 1000 m<sup>3</sup>/s has a return period of 4 and 10

years for observations and simulations, respectively. Analysis of the peak flow is based on relatively few extreme flood events (1 per year, 20 years), making the interpolation and large return period extrapolation highly susceptible to uncertainty.

Figure. 11 and 12 present the peak discharge analysis of future simulations and historical observations, respectively. Obviously, the relationships between flow and return periods of two series have remarkable similarity (e.g., 1500 m<sup>3</sup>/s has a return period of about 50 years in both figures). However, VIC model's application has a systemic error of underestimating the peak discharge. So, the future peak discharge will have shorter return periods, and floods will be more frequent. Under the SRES A2 greenhouse gas emission scenario, climate change would cause more frequent and higher peak flows, increasing the pressure of flood control in the Greenbrier basin by the 2060s.

## 5. Conclusion

This paper investigates the impact of climate change on water resources in the Greenbrier basin in the future. It uses the VIC model to simulate essential hydrological variables. Even though the simulation cannot perfectly present the hydrological cycle, the performance is qualified with the satisfactory NSE metrics of 0.62 and 0.58 in calibration (1991 - 2000) and validation (2001 - 2010) periods, respectively. Based on the BCCAQ method, the precipitation and temperature of CCSM can be successfully downscaled and bias-corrected. From 2046 to 2065, the bias-corrected precipitation and temperature increase by 14% and 1.8 °C, respectively, demonstrating a warmer and more humid climate in the mid of 21st century under the SRES A2 greenhouse gas emission scenario.

The average annual cycles of the water balance components in future simulations and historical observations have similar seasonal variations with relatively uniform precipitation, lower runoff in the spring, and higher evapotranspiration in the second half-year. Generally, major water balance components have larger magnitudes due to increased precipitation and temperature, indicating a more humid environment in the mid of 21st century.

Both discharge cycles are concurrent with the corresponding precipitation and evapotranspiration and showing similar fluctuations over time, with high in spring and low from Jun to Nov. The magnitude of discharge in the future is larger than that of

historical observation, especially from Apr to Dec. Though considering the hydrological model uncertainty, the streamflow from early summer to winter would increase.

Climate change under A2 emission scenarios would result in more abundant water resources in the Greenbrier basin in the 2040s to 2060s, significantly relieve the water use stresses in future summer.

The VIC model can rapidly make the respond to intense precipitation. However, there is a significant systematic bias of predicting lower peak flow according to the comparison between simulated and observed historical discharge analyses. The extreme discharge would be larger and more frequent because the flood-frequency relations of modeled and observed flow are very close to each other, and the model tends to underestimate the flood magnitudes. Thus, climate change under the A2 scenario would lead to a higher risk of encountering severe floods in the Greenbrier basin from 2046 to 2065.

Even though the future climate series are successfully processed, and the hydrological performance is satisfactory, the whole climate and hydrological coupling process have significant uncertainty caused by multiple factors, making the prediction of future water resources less confident. In fact, this paper has simply discussed the uncertainty from hydrological parts, but the largest uncertainty from GCM has not been addressed. Until multiple GCMs and hydrological models are employed and combined

to reduce the uncertainty, it is impossible to assess climate change impacts on water resources quantitatively.

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