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Estimating Potential Climate Change Effects on the Upper Neuse Watershed Water Balance using the SWAT Model

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Research Impact Statement: The results of this study can aid planning for the RTP's future hydrologic and water supply conditions and expand the knowledge of local impacts of climate change on critical watersheds.

ABSTRACT: Climate change poses water resource challenges for many already water stressed watersheds throughout the world. One such watershed is the Upper Neuse watershed in North Carolina, which serves as a water source for the large and growing Research Triangle Park region. The aim of this study is to quantify possible changes in the watershed's water balance due to climate change. To do this, we used the Soil and Water Assessment Tool (SWAT) model forced with different climate scenarios for baseline, mid-century, and end-century time periods using five different downscaled General Circulation Models. Before running these scenarios, the SWAT model was calibrated and validated using daily streamflow records within the watershed. The study results suggest that, even under a mitigation scenario, precipitation will increase by 7.7% from the baseline to mid-century time period and by 9.8% between the baseline and end-century time period. Over the same periods, evapotranspiration (ET) would decrease by 5.5 and 7.6%, water yield would increase by 25.1 and 33.2%, and soil water would increase by 1.4% and 1.9%. Perhaps most importantly, the model results show, under a high emission scenario, large seasonal differences with ET estimated to decrease by up to 42% and water yield to increase by up to 157% in late summer and fall. Planning for the wetter predicted future and corresponding seasonal changes will be critical for mitigating the impacts of climate change on water resources.

(**KEYWORDS:** watershed modeling; SWAT; climate change; water resources.)

INTRODUCTION

Climate change is expected to alter the water cycle across global to regional scales (Hagemann *et al.*, 2013). The high level of uncertainties embedded in the assessment of climate change impacts on hydrologic processes and this dynamic across spatial scales makes it necessary to investigate impacts for watersheds and regions across the globe. There is a growing body of research aimed at providing insight to climate change impacts at a regional-scale (e.g., Jha *et al.*, 2006; Pradhanang *et al.*, 2013). Investigating local impacts for watersheds across the globe is important to better understand general trends and controlling factors for global water resource impacts due to climate change. Therefore, a motivation for this study is to add to the growing literature of watershed-scale climate change impacts by studying potential climate change impacts on the Upper Neuse Watershed, an important water supply source for the large and growing Research Triangle Park (RTP) region.

In addition to climate change, population increase is also expected to result in water stress in the RTP region and throughout the Southeast United States (Sun *et al.*, 2008). In previous years, the Southeast United States region has experienced multiple droughts (1986–1988, 1998–2002, 2007–2008, 2016) (Weaver, 2005; Keellings and Engström, 2019), increasing the vulnerability of the region to water deficits. The Upper Neuse watershed includes the public water supplies for most of Wake and Durham counties. Falls Lake supplies drinking water to Wake County, where Raleigh is located, and upstream lakes (Little River reservoir and Lake Michie) supply drinking water to Durham County (Li *et al.*, 2014; Palmer and Characklis, 2009). Prior research suggests that the Upper Neuse watershed will experience a 14% decrease in water supply due to climate change and will experience a 21% increase in water demand due to industrialization and growth (Marion *et al.*, 2014). While they made use of a General Circulation Model (GCM), Marion *et al.* did not use a locally calibrated watershed model forced with downscaled GCM outputs. Some studies addressed the water deficit problem in the RTP region by exploring inter-basin transfer (IBT) (e.g., Li *et al.*, 2014 and Palmer and Characklis, 2009). However, these studies focused primarily on historical data and did not explicitly consider future climate effects on the RTP region. This study advances on these prior studies within the region by making use of downscaled climate projection datasets along with a calibrated watershed-scale hydrologic simulation model to gain insight into potential water balance changes within the watershed by the end of the century.

Golembesky et al. (2009) and Devineni et al. (2008) estimated short-term inflow to Falls Lake, the drinking water source for Wake County, using historical streamflow and weather records along with GCM climate change projections. Both studies addressed the record shortages in North Carolina's local and statewide water supply systems by developing multi-model streamflow forecast methods for decision makers to take appropriate conservation measures before a period of drought. However, these studies focused on short-term decision making and did not take advantage of GCMs for long-term impact assessments in their methodology. The current study also makes use of multiple GCMs and different emission scenarios to better understand how variability across projections impacts uncertainties in watershed-scale water balance terms, but does so for long term rather than short term planning.

Sun et al. (2008) used future climate data from two GCMs along with future population and land use change scenarios to estimate water supply and water demand on 8-digit Hydrologic Unit Code (HUC) watersheds in the Southeast United States, including the 8-digit HUC Upper Neuse watershed. Similarly, Marion et al. (2014) calculated water supply and water demand on 8-digit HUC watersheds in the Southeast using four different climate models for future climate projections. Although both studies gave insight into the future water deficit problem in the

Southeast US and the Upper Neuse watershed, they used generalized models on a monthly time step with a coarse spatial resolution (8-digit HUC). In this study, we use a more detailed physically-based hydrological model and 5 downscaled GCMs to gain more insight into changes that may occur to hydrological processes and water balances within the watershed by the mid-century and end-century periods.

One example of using physically-based hydrological models with GCMs for other watersheds and regions is illustrated by Jha et al. (2006). The researchers used a semi-distributed model, Soil and Water Assessment Tool (SWAT), to assess the effect of future climate change on hydrologic components of the Upper Mississippi River Basin. The SWAT model was calibrated and evaluated with historical observations and used future precipitation and temperature data from 6 different GCMs. They also evaluated the sensitivity of the Upper Mississippi River Basin to atmospheric, precipitation, and temperature changes. Their results indicated that the basin was very sensitive to the climate change scenarios and that, when forced with GCM climate change projections, mean annual streamflow generally increased, with one GCM resulting in a 51% increase in mean annual streamflow. Another example is Pradhanang et al. (2013) who studied climate change effects in a New York City water supply watershed by using SWAT with an ensemble of 9 GCMs. Their study results suggest increased winter discharge and greatly decreased spring discharge due to early melting of snow in the watershed. Similar SWAT model studies were able to identify specific changes in local hydrology and ecosystem consequences due to climate change for other watersheds across the globe (Bajracharya *et al.*, 2018; Chattopadhyay *et al.*, 2017; Ficklin *et al.*, 2013; Meaurio *et al*. 2017; Moradkhani *et al.*, 2010; Park *et al.*, 2011; Reshmidevi *et al.*, 2018; Sunde *et al*., 2017; Ye and

Grimm, 2013). This study builds on this growing body of research by focusing on a key watershed for the expanding Research Triangle Park region.

In summary, the objective of this study is to better understand the hydrological impacts of climate change for the Upper Neuse watershed, an important water supply source for the growing Research Triangle Park region of North Carolina. The SWAT model was calibrated and validated for the watershed using historical observational data, and then an ensemble of five GCMs were used within the SWAT model to quantify how future weather conditions and future projections of atmospheric CO_2 concentrations would change key water balance terms in the watershed. The results of this study can aid decision makers in the region when planning for future hydrologic and water supply conditions. Additionally, the results serve as a contribution to the growing literature using physically-based hydrology models to investigate local impacts of climate change on critical watersheds across the globe.

MATERIALS AND METHODS

Study Area

The Upper Neuse Watershed in North Carolina has a total drainage area of 1,373 km^2 with gently rolling topography, is the head watershed of the Neuse River Basin (Figure 1), and serves as a public water source for the growing Research Triangle Park region of North Carolina. The Upper Neuse Watershed contains three main tributaries: the Flat, Little, and Eno Rivers. Each of these tributaries includes a streamflow gauging station maintained by the United States Geological Survey (USGS). Little Reservoir Lake and Lake Michie in the Upper Neuse Watershed provide drinking water to the City of Durham. Moreover, the upper part of the Neuse watershed drains into Falls Lake, which provides drinking water for Raleigh and six other municipalities in eastern Wake County. This region is one of the fastest growing in the US and has issues with the availability of enough fresh water (Sun *et al.*, 2008).

[Figure 1 goes here]

Hydrological Model Setup and Data Preparation

The SWAT model for the Upper Neuse Watershed was created using USGS 10-m resolution National Elevation Datasets (NED), the 30-m resolution 2011 National Land Cover Dataset (NLCD) (both NED and NLCD are obtained from: U.S. Geological Survey, The National Map. Accessed December 2018, https://viewer.nationalmap.gov/basic/#startUp), the United States Department of Agriculture (USDA) Soil Survey Geographic (SSURGO) soil dataset (Soil Survey Staff, 2018), and weather data from historical gauges and radar observations. Using the method presented by Ercan and Goodall (2012), NEXRAD-derived radar rainfall from National Oceanic and Atmospheric Administration (NOAA) National Weather Service (NWS) (NOAA National Weather Service (NWS) Radar Operations Center, 1991) and gauge observed rainfall from NOAA's National Climatic Data Center (NCDC) (NOAA National Centers for Environmental Information, 2001) were combined to derive an area-average time series for the watershed. From the DEM, elevation in the Upper Neuse watershed ranges from 50 to 255m and has an average elevation of 162.5m. The slope of the watershed ranges from 0 to 223.6%, with an average slope of 6.9%. From the NLCD dataset, the watershed is dominated by forest (mostly deciduous forest) (54.4%), pasture lands (19.4%), and developed area (mostly open space development) (14.1%) (Figure 2). Herbaceous, scrub, wetland, open water, cultivated crops, and barren land cover 5%, 2.6%, 2%, 1.5%, 0.8%, 0.1% of the watershed, respectively. From SURRGO dataset, the dominant soil types in the watershed are silt loam and sandy loam, and the hydrologic soil groups are mainly B and D (Figure 2). The watershed was divided into subbasins based on the USGS streamflow station locations and the drainage structure within the watershed. Threshold values of 10%, 14%, and 14%, for soil, slope, and land cover, respectively, were used to define Hydrologic Response Units (HRUs) to represent variability within the subbasins. In the final model, there were 932 HRUs for 93 subbasins, which is in line with the HRU/subbasin ratio range of 1-10 recommended in the SWAT manual (Arnold *et al.*, 2012). The Natural Resources Conservation Service (NRCS) Curve Number (CN) surface runoff method (Boughton, 1989), the Penman-Monteith evapotranspiration method (Allen, 1986), and the variable storage channel routing method (Williams, 1969) were used in our SWAT model. Further detail on the data and methods used to create the SWAT model can be found in Ercan and Goodall (2014 and 2016).

[Figure 2 goes here]

We identified the most sensitive model parameters using the Generalized Likelihood Uncertainty Estimation (GLUE) in the SWAT CUP program (Abbaspour, 2007) based on 25 parameters effecting streamflow (Beven and Binley, 1992) (Table 1). Then, we calibrated the SWAT model using these most sensitive parameters and the Non-Sorting Genetic Algorithm II (NSGA-II) method (Deb *et al.*, 2002) by comparing the average daily simulated streamflow against the records data. The freely available NSGA-II Python tool for SWAT model calibration described in Ercan and Goodall (2016) was used for calibration because of its auto-calibration capability based on multi-objective genetic algorithms (MOGAs). The Flat, Little and Eno watershed outlets were set as objective-sites for maximizing the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and minimizing Percent Bias (PB) as goodness of fit criteria for the simulated streamflow. Therefore, a total of six objective functions (3 streamflow sites * 2 fitness measures) were used to calibrate the model. The observed daily flow data for the 3 watershed outlets were obtained using USGS National Water Information System (U.S. Geological Survey, National Water Information System. Accessed December 2018, https://waterdata.usgs.gov/nwis). When evaluating the performance of the calibrated model, in addition to NSE and PB, we used RMSE-observations standard deviation ratio (RSR) (Moriasi, et. al, 2007) and coefficient of determination (R^2). 2003-2004 was used as the simulation warm-up period and 2005-2008 was used as the calibration period. The model evaluation period was 2009-2011.

Downscaled Future Climate Data

General Circulation Models (GCMs) are used to project climatic conditions by coupling various earth system models, such as the atmosphere, solid and liquid water bodies, and the land surface (Fowler *et al.*, 2007). Each GCM contains differences in model structures, physical representations, and parameterizations. Furthermore, different emission scenarios for each model will result in different future projections. Therefore, multiple GCMs along with multiple emission scenarios as a model ensemble can be used to represent a range of future projections when studying climate change impacts (Brekke *et al.*, 2008; Pierce *et al.*, 2009; Reichler and Kim, 2008).

Although GCMs offer the potential to study climate change and variability, they are relatively coarse, only a few hundred kilometers in spatial resolution, for use in local watershed impact studies (Gates, 1985). Two types of downscaling techniques, dynamical and statistical, are typically used for downscaling coarse GCM data to finer resolutions for watershed level studies (Fowler *et al.*, 2007). Dynamical downscaling models are Regional Climate Models (RCMs) with a finer resolution focusing on certain regions embedded within a GCM. These models are computationally intensive and strongly dependent on GCM boundary forcing with a limited number of scenario ensembles available for them. Statistically downscaled models are able to translate coarse GCM outputs to finer resolution climate projections based on spatial trends within historical climate observations. These models are computationally inexpensive, easily transferable to other regions, and based on standards and accepted statistical procedures (Fowler *et al.*, 2007).

In this study, the statistically downscaled World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model dataset was used. We used the Localized Constructed Analog (LOCA) downscaled CMIP5 daily climate projections (Pierce et al., 2014; Pierce et al., 2015) obtained in NetCDF format at $1/16^{o}$ resolution, which is between 5.6 and 5.8km grid cell size in our study area. The downscaled field in LOCA is produced point-by-point from a single best match analog day, while in the other constructed analog methods, multiple analog days are averaged to obtain the downscaled field. LOCA has been shown to obtain a better downscaled field compared to other constructed analog methods by avoiding issues associated with averaging numerous analog days (e.g., high spatial autocorrelation, a reduction in extremes, and the production of days with low levels of precipitation). The bias correction method that was used to develop the high resolution ($1/16^{o}$) LOCA downscaled CMIP5 daily projections are described by Pierce et al. (2015). The projections obtained from LOCA, include three daily variables: precipitation, maximum temperature, and minimum temperature. We converted the downscaled CMIP5 data from the NetCDF format to the format required by SWAT for use in our climate scenarios in the Upper Neuse watershed. We used an areal average spatial interpolation method to convert daily precipitation, and maximum and minimum temperature values, from the downscaled CMIP5 data grids into our Upper Neuse SWAT model subbasins (Figure 1).

Representative Concentration Pathways (RCPs) predict a range of future changes in the atmospheric greenhouse concentration as a result of human activities (Taylor et al, 2012). Among the RCPs, we used RCP4.5, called the mitigation scenario, and RCP8.5, called the high emission scenario. The RCP4.5 scenario assumes a world using technologies and strategies leading to stabilized radiative forcing before 2100 at 4.5 W m^{-2}. Conversely, in the RCP8.5 scenario, high population growth and lack of highly developed technologies leads to radiative forcing reaching to a high level, i.e., 8.5 W m^{-2} in 2100 (van Vuuren et al., 2011).

The 5 GCMs shown in Table 2 were used along with the calibrated SWAT model to estimate climate change impacts. The results focus on three key water balance terms: evapotranspiration, water yield, and amount of water in the soil profile. Historical simulations, and future projections for daily precipitation, maximum surface temperature, and minimum surface temperature are available for the periods of 1950-2005 and 2005-2099, respectively. The base conditions (base period), mid-century and end-century are defined as the 1961-2000, 2046-2065 and 2081-2099 time periods, respectively. We ran SWAT for each length of time with the first 5 years in the period as warm-up. The average atmospheric CO_2 concentrations were obtained from the literature. We used CO_2 concentrations of 330ppm for the base period (Jha *et al.*, 2006; Wu *et al.*, 2012), 490 (RCP4.5) and 575ppm (RCP8.5) for the mid-century period, and 522 (RCP4.5) and 838ppm (RCP8.5) for the end-century period (Yang *et al.*, 2018). Unavailable weather data for historical simulations and future projections such as humidity, solar radiation and wind speed were generated by the SWAT weather generator file (Arnold *et al.*, 2012). Like prior studies on this topic (e.g., Pradhanang *et al*. 2013), we assumed no significant changes to land cover or land use over the study period to isolate the impact of climate change on water resources.

RESULTS AND DISCUSSION

Calibration and Validation Results

Table 1 shows the selected calibration parameter values from the Pareto solutions that were produced at the end of the calibration process. The “range” and “change type” columns give the defined parameter limits and the approach used to adjust the parameter values in the SWAT files. SWAT model calibration with the NSGA-II Python tool (Ercan and Goodall, 2016) gave multiple sets of parameters that have the best calibration performance. From the multiple sets of calibration parameters that were identified as having a good match with observed streamflow, additional properties of the watershed were then used to select the final set of calibration parameters used in the subsequent analysis (Table 1). Most noteably, parameters were selected so that the baseflow contribution to total streamflow were in line with expected values based on regional analysis by the United States Geological Survey base-flow index Grid estimate (Wolock, 2003). The ratio in our calibrated model is 0.45 which is comparable to the USGS base-flow index Grid estimate of 0.31 for our study area. This difference may be justified by knowing that the simulation years used by USGS to calculate base-flow index grid for the conterminous United States may not completely match with our baseline period, and the USGS uses the actual measured discharge at fixed observation locations but we simulated the discharge throughout the study watershed using the downscaled precipitation and maximum and minimum daily temperature (the downscaling technique and the selection of the GCMs introduce some uncertainties here as well). Also, certain parameter values, such as the main channel hydraulic conductivity (ch_k2), Manning's n for the main channel (Ch_N2), and Curve Number (CN2) were selected from among that calibrated parameter sets to realistically match assumed conditions within the study watershed and to be consistent with estimated values for these parameters derived from baseline soil and land use/land cover datasets.

Following calibration for the 2005-2008 time period, the final selection of calibrated parameters was used in the SWAT model in a validation model run for the 2009-2011 time period (Table 3). The guidelines for hydrological model evaluation introduced by Moriasi et al. (2007; 2015) were used to evaluate both the calibration and validation periods of the SWAT model. According to Moriasi et al. (2015), a discharge simulation is satisfactory at a daily or monthly time step when NSE > 0.5, PBIAS < 15% and $R^2 > 0.6$. At a monthly time step the discharge simulation is satisfactory when NSE > 0.5, PBIAS < 25% and RSR ≤ 0.7 (Moriasi et al., 2007). Based on these guidelines, our SWAT model is satisfactory for the daily and monthly time steps during the calibration period. The analysis of the validation daily and monthly statistics indicates satisfactory performance with the exception of daily R^2 for the Little watershed (0.59), which is slightly below the satisfactory range. Figure 3 shows a comparison between observed and SWAT simulated streamflow at the Flat, Little and Eno watershed outlets. The daily observed and simulated streamflow values were accumulated to monthly values for comparison. The agreement between the graphical representations of the observed streamflow and the SWAT simulated streamflow for all three outlets also provides a visual measure of the model's predictive skill.

[Figure 3 goes here]

Overall Impact of Climate Change Scenarios on Water Balance Terms

Using the calibrated SWAT model along with the downscaled climate projections resulted in a consistent increase in precipitation, water yield and soil water, and a decrease in evapotranspiration (Table 4). Precipitation, on average, increased by 7.8 and 9.8% over the baseline for the mitigation scenario for the mid-century and end-century, respectively. For the high emission scenario, average precipitation increased by 9.4 and 13.7% over the baseline for the mid-century and end-century, respectively. Both the mitigation and high emission scenarios predicted that, on average, the rate of precipitation increase for the end-century period will be considerably more than the mid-century period.

The decrease in evapotranspiration is substantial in the high emission scenario because of the high atmospheric CO_2 concentrations projected in the RCP8.5 scenario (575 and 838ppm for mid-century and end-century compared to 330ppm for baseline). The increased atmospheric CO_2 concentration results in decreased transpiration due to plants having more efficient water use (Battipaglia *et al.*, 2013; Kauwe *et al.*, 2013; Lammertsma *et al.*, 2011; Morison, 1987). On the other hand, evaporation depends mainly on temperature and water availability. The projected increased precipitation ensures that there will be enough water available for evaporation. Both minimum daily temperature and maximum daily temperature for both mid-century and end-century periods under both emission scenarios are projected to increase. Under the mitigation scenario, the minimum daily temperature is projected to increase by 1.9 and 3.3 °C for the mid-century and end-century, respectively; the high emission scenario projects minimum daily temperature increases of 2.7 and 4.6 °C for the mid-century and end-century, respectively. Maximum daily temperature is projected to increase by 2.1 and 2.7 °C for the mitigation scenario and by 2.8 and 4.6 °C for the high emission scenario for the mid-century and end-century, respectively. Despite these changes, the differences in temperature and precipitation that would drive more evapotranspiration are outweighed by changes in atmospheric CO_2 concentration. Therefore, evapotranspiration will decrease due to the large decrease in transpiration. These results show the important role that transpiration plays in the water cycle, especially for regions like the Upper Neuse Watershed that are dominated by forest cover and cultivated crops.

The precipitation increases and evapotranspiration decreases resulted in increases in the amount of water stored in the soil profile and the water yield. The amount of water in the soil profile (or soil water, for short) increased by 1.9% and 2.5% under the mitigation scenario for the mid-century and end-century periods, respectively. A greater increase in soil water, 2.6% for mid-century and 5.2% for end-century, was predicted under the high emission scenario given the larger decreases in evapotranspiration. Water yield, the total amount of water from HRUs that contributes to stream flow, increased substantially for the end-century high emission scenario (70.9%), indicating the effect of large decreases in evapotranspiration and the considerable increase in precipitation.

Water yield has three main components: surface runoff, lateral flow, and groundwater discharge (Table 5). According to the models, the largest contributor to water yield (19.89mm per month for the baseline period) is the groundwater discharge (about 9.05mm per month for the baseline period). The surface runoff contributed 7.13mm per month for the baseline period while lateral flow contributed 3.70mm per month for the same period. The model results showed that all three components increased for the mid-century and end-century periods under both the mitigation and high emission scenarios. For the mitigation scenario, surface runoff increased by 25.8 and 33.1%, lateral flow increased by 18.4 and 24.0%, and groundwater discharge increased by 29.5 and 40.1% for the mid-century and end-century, respectively. For the high emission scenario, surface runoff increased by 32.5 and 71.3%, lateral flow increased by 25.3 and 45.5%, and groundwater discharge increased by 42.2 and 80.9% for the mid-century and end-century, respectively.

Seasonal Impact of Climate Change Scenarios on Water Balance Terms

A monthly aggregation of the water balance terms provides a means for understanding potential seasonal changes in the Upper Neuse watershed (Figure 4). On a monthly time step, precipitation under the mitigation and high emission scenarios for both mid-century and end-century periods shows clear increases compared to the baseline conditions (except for the mid-century period under the high emission scenario in August, and the end-century period under the high emission scenario in June which both experience a decrease, and the mid-century period under the mitigation scenario in July which remains almost unchanged). The largest increase in precipitation, 18mm (17%) for the mitigation scenario and 25mm (23%) for the high emission scenario, was seen in September. The lowest increases in precipitation occurred in November with 5mm (7%) for the mitigation scenario and 3mm (4%) for the high emission scenario.

[Figure 4 goes here]

Evapotranspiration also had clear seasonal patterns, decreasing from baseline conditions for all months. The winter to mid-spring months had smaller decreases in evapotranspiration of between 0.8 to 9.5 mm (3-27%); the mid-spring to mid-fall month had larger decreases in evapotranspiration from 2 mm (3%) to 18 mm (23%). The smaller decrease during winter and spring was due primarily to increased temperature while the larger decrease during summer and fall was due to decreases in transpiration caused by increased atmospheric CO_2 concentration. Plant activities play a major role in evapotranspiration during summer and fall when plants are actively developing and there is often less precipitation compared to spring months (Allen *et al.*, 1998).

Water yield expectedly increased, due largely to the increase in precipitation and the decrease in evapotranspiration. It increased from between 2.2mm (11%) to 22mm (102%)

happening in August for the mid-century period under the high emission scenario and in September for the end-century period under the high emission scenario, respectively. Soil water increased during May to January while experiencing less increase from February to April. This increase in the seasonal water cycle could result in increased flooding risk caused by higher antecedent soil moisture conditions in particular in the summer and fall in the RTP region.

To this point of increased flood risk, Figure 5 shows the average monthly water yield terms for the baseline, mid-century and end-century periods under the mitigation and high emission scenarios. Future surface runoff projections show substantial increases for September and March, but less increase for the other months of the year (except for the mid-century period under the RCP8.5 scenario which shows a decrease during August). Both lateral flow and groundwater discharge also consistently increases across all months, with the largest increase happening during September, October and March compared to the base conditions for both the mid-century and end-century periods. Overall, the modeled impact of climate change on water yield terms during the end-century period is often twice as much as the mid-century for the high emission scenario. The mitigation scenario, however, shows much less difference between the mid-century and end-century time periods.

[Figure 5 goes here]

Variability Across GCMs

It is important to also consider the variability of model results derived from using different GCMs to understand the uncertainty of future climate impacts on the Upper Neuse Watershed hydrology. Figure 6 shows the changes in the water balance terms from the base period to the mid-century period for the two emission scenarios across the five GCMs; Figure 7 does the same for the end-century period. Most GCMs predict increased precipitation across all months for both emission scenarios and the mid-century and end-century periods, despite the expected uncertainty about future conditions. The variation in the SWAT simulated evapotranspiration across the models is much lower compared to the other water balance terms. This may be because the atmospheric CO_2 concentration, which seems to have a substantial effect on evapotranspiration in the model, is considered to be the same across all GCMs in a given emission scenario and time period. For almost all GCMs under both emission scenarios and time periods, evapotranspiration decreased across all months. Water yield tends to respond to the variation in precipitation across the GCMs while soil water tends to respond to the seasonal pattern of evapotranspiration. This is expected as larger decreases in evapotranspiration due to more efficient transpiration during growing seasons would result in more water remaining in the soil profile rather than being transpired by plants (Kruijt *et al.*, 2008). Soil water in winter and mid spring, when plants are not transpiring, is projected to remain relatively constant (all GCMs show low variation during those months).

[Figure 6 goes here]

[Figure 7 goes here]

Table 6 provides average changes in water balance terms for each individual GCM under both the mitigation and high emission scenarios for the mid-century and end-century periods. All models consistently predicted reduced evapotranspiration for both the mid-century and end-century periods for both the mitigation and high emission scenarios. For any given GCM and time period, the evapotranspiration value decreases more for the high emission scenario compared to the mitigation scenario. Also, for any given GCM and emission scenario, the evapotranspiration decreases more for the end-century period compared with the mid-century period.

All GCMs show increased precipitation for both time periods under both emission scenarios (except for MIROC5 for the end-century period under the high emission scenario, which shows a decrease of -1.3 mm). For any given time period and model, the high emission scenarios predict more precipitation compared to the mitigation scenario (with the exception for MIROC5). The magnitude of precipitation change, as expected, correlated with that of water yield; soil water change, however shows slightly less correlation with precipitation. Water yield and soil water both increased from mid-century to end-century (except for MIROC5 where both soil water and water yield under the mitigation scenario decreased from mid-century to end-century). Water yield consistently increased from the mitigation to high emission scenario (except for MIROC5 during the mid-century period). Soil water followed a similar pattern (except for CNRM-CM5 and MIROC5 during the mid-century which they decrease from mitigation to high emission scenario).

Looking into the components of water yield provides more detail about differences across the GCMs (Figure 8 for mid-century period and Figure 9 for end-century period). For all three components, the variation between GCMs tends to be greater under the high emission scenario. The mid-century period showed a similar pattern to the end-century period across GCMs with a single distinct characteristic that end-century changes in water yield components moved upward. During the mid-century period under both emission scenarios, all water yield components tend to increase across the GCMs as expected. Also, during the mid-century period both emission scenarios show similar variations across the GCMs. The change in variation for all water yield components throughout the months and models seems to be similar, as expected. Generally, for any given time-period and emission scenario the variations in all water yield components are high during June to October months while overall the lowest variation is experienced in April. The variation in surface runoff predictions is generally low during the months that the amount of surface runoff is low (e.g., April and May for mid-century and end-century periods).

[Figure 8 goes here]

[Figure 9 goes here]

Table 7 shows the average changes in the modeled water yield components for each individual GCM for the mid-century and end-century periods under the mitigation and high emission scenarios. For any given GCM and time period, all water yield components increase more for the high emission scenario compared to the mitigation scenario (with the exception of MIROC5 which shows less increase from the mitigation to high emission scenarios during the mid-century period). Also, for any given GCM and emission scenario, all water yield components show increase from mid-century to end-century periods (except for all water yield components for MIROC5, lateral flow for CNRM-CM5, and surface runoff for MIROC-ESM under the mitigation scenario). Among the water yield components, the groundwater discharge experienced the highest changes followed by surface runoff and lateral flow. The MIROC-ESM based SWAT simulation gives the highest increase in water yield components under the mitigation scenario for the mid-century (37.7%) period. The NorESM1-M based simulation, on the other hand, shows the largest increase in that component for the end-century (52.3%) period. Under the high emission scenario, the NorESM1-M based SWAT simulation gives the highest increase in water yield components for both the mid-century (48.3%) and end-century period (87.5%). This was expected as MIROC-ESM and NorESM1-M experienced the highest increase in projected precipitation during the corresponding future periods (mid-century or end-century) and emission scenarios (mitigation or high emission) compared to other GCMs, which leads to the highest increase in water yield components. In total, the results suggest that average monthly surface runoff could increase anywhere between 0.7mm (9.8%) and 6.5mm (91.2%), average monthly lateral flow could increase anywhere between 0.7mm (18.9%) and 2.4mm (64.9%), and average monthly groundwater discharge would increase anywhere between 1.0mm (11.0%) and 10.3mm (113.8%) depending on the specific GCM used in the analysis as well as the time period (mid-century or end-century) and emission scenario (mitigation or high).

CONCLUSIONS

A study of the potential climate change impacts to key water balance terms for the Upper Neuse watershed was conducted using the SWAT hydrologic model. The model was calibrated on a daily time step for three streamflow stations (Flat, Little, and Eno River watersheds) and two fitness criteria (NSE and PB) using a multi-objective calibration approach (NSGA-II). Overall, the calibrated model was satisfactory for both the calibration and validation periods based on established guidelines (Moriasi *et al.*, 2015). Downscaled precipitation and minimum daily and maximum daily temperature outputs from five General Circulation Models (GCMs) along with projected future atmospheric CO_2 concentrations were then used as input into the calibrated SWAT model. We ran simulations for each GCM output for both the mitigation and high emission scenarios for baseline (1961-2000), mid-century (2046-2065) and end-century (2081-2099) time periods.

Overall, the ensemble of GCMs projected wetter conditions in the future. This was due to increases in precipitation for both the mitigation and high emission scenarios for both the mid-century and end-century periods. Additionally, due to increased atmospheric CO_2 concentration evapotranspiration decreased for both scenarios and time periods. The increased precipitation and decreased evapotranspiration result in increases to water yield and soil water. Seasonally, the projected wetter future led to increases in water yield components for all months. The greatest increase in surface runoff occurred in the summer and fall months, while the greatest increase in groundwater flow occurred in the spring months. The decrease in evapotranspiration was greatest during growing seasons and is correlated with increases in soil water. Past research has shown the importance of how the evapotranspiration process is represented within a watershed model, but this study highlights the importance of transpiration in the RTP region. Future research should test the sensitivity of these results to the representation of transpiration within the watershed model, given that this research has shown the importance of the process to future water resources in the region. The results of this study have management implications for both the Upper Neuse and similar watersheds. Despite the history of drought in the region, the projected increases in precipitation and decreases in transpiration indicate wetter conditions in the future. These changes could positively impact water supply, but could also increase the risk of flooding without proper management. As the Research Triangle Park continues to grow, population and land use changes will have a significant impact on the region’s hydrology. With the results of this study, and by incorporating changes in population and land use, water managers will be able to plan for and adapt to future hydrological conditions in the region caused by a changing and uncertain climate.

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REFERENCES

Abbaspour, K. C. 2007. *User manual for SWAT-CUP, SWAT Calibration and Uncertainty Analysis Programs*. Swiss Federal Institute of Aquatic Science and Technology, Eawag, Duebendorf, Switzerland.

Allen, R.G. 1986. “A Penman for All Seasons.” *Journal of Irrigation and Drainage Engineering* 112 (4): 348-368. https://doi.org/10.1061/(ASCE)0733-9437(1986)112:4(348)

Allen, R.G., L.S. Pereira, D. Raes, and M. Smith. 1998. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56. FAO, Rome, 300 (9)), D05109.

Arnold, J.G., J.R. Kiniry, R. Srinivasan, J.R. Williams, E.B. Haney, and S.L. Neitsch. 2012. “Soil and Water Assessment Tool Input/Output Documentation Version 2012.” *Texas Water Resources Institute Technical Report 429.* http://swat.tamu.edu/documentation/2012-io/.

Bajracharya, A. R., S. R. Bajracharya, A. B. Shrestha, and S. B. Maharjan. 2018. “Climate Change Impact Assessment on the Hydrological Regime of the Kaligandaki Basin, Nepal.” *Science of the Total Environment* 625: 837-848. https://doi.org/10.1016/j.scitotenv.2017.12.332.

Battipaglia, G., M. Saurer, P. Cherubini, C. Calfapietra, H.R. McCarthy, R.J. Norby, and M. Francesca Cotrufo. 2013. “Elevated CO2 Increases Tree-Level Intrinsic Water Use Efficiency: Insights from Carbon and Oxygen Isotope Analyses in Tree Rings across Three Forest FACE Sites.” *New Phytologist* 197 (2): 544–554. https://doi.org/10.1111/nph.12044.

Bentsen, M., I. Bethke, J. B. Debernard, T. Iversen, A. Kirkevåg, Ø. Seland, H. Drange, C. Roelandt, I.A. Seierstad, C. Hoose, and J. E. Kristjánsson. 2013. “The Norwegian earth System Model, NorESM1-M—Part 1: Description and Basic Evaluation of the Physical Climate.” *Geosci. Model Dev* 6 (3): 687-720. https://doi.org/10.5194/gmd-6-687-2013.

Beven, K. and A. Binley. 1992. “The Future of Distributed Models: Model Calibration and Uncertainty Prediction.” *Hydrological Processes*” 6 (3): 279–298. https://doi.org/10.1002/hyp.3360060305.

Boughton, W. C. 1989. “A Review of the USDA SCS Curve Number Method.” *Soil Research* 27 (3): 511-523. https://doi.org/10.1071/SR9890511.

Brekke, L.D., M.D. Dettinger, E.P. Maurer, and M. Anderson. 2008. “Significance of Model Credibility in Estimating Climate Projection Distributions for Regional Hydroclimatological Risk Assessments.” *Climatic Change* 89 (3-4): 371–394. https://doi.org/10.1007/s10584-007-9388-3.

Chattopadhyay, S., D.R. Edwards, Y. Yu, and A. Hamidisepehr. 2017. “An Assessment of Climate Change Impacts on Future Water Availability and Droughts in the Kentucky River Basin.” *Environmental Processes* 4 (3): 477–507. https://doi.org/10.1007/s40710-017-0259-2.

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan. 2002. “A Fast and Elitist Multiobjective

Genetic Algorithm: NSGA-II.” *IEEE Transactions on Evolutionary Computation* 6 (2): 182–197. https://doi.org/10.1109/4235.996017.

Devineni, N., A. Sankarasubramanian, and S. Ghosh. 2008. “Multimodel Ensembles of Streamflow Forecasts: Role of Predictor State in Developing Optimal Combinations.” *Water Resources Research* 44 (9). https://doi.org/10.1029/2006WR005855.

Ercan, M.B. and J.L. Goodall. 2012. “Estimating Watershed-Scale Precipitation by Combining Gauge and Radar Derived Observations.” *Journal of Hydrologic Engineering* 18 (8): 983-994. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000687.

Ercan, M.B. and J.L. Goodall. 2014. “A Python Tool for Multi-Gage Calibration of SWAT Models Using the NSGA-II Algorithm”. *Proceedings of the 7th International Congress on Environmental Modelling and Software (iEMSs), June 15-19, San Diego, CA, USA*: 2325–2331. https://doi.org/10.13140/2.1.3865.4407.

Ercan, M.B. and J.L. Goodall. 2016. “Design and Implementation of a General Software Library for Using NSGA-II with SWAT for Multi-Objective Model Calibration.” *Environmental Modelling & Software* 84: 112–120. https://doi.org/10.1016/j.envsoft.2016.06.017.

Ficklin, D.L., I.T. Stewart, and E.P. Maurer. 2013. “Effects of Projected Climate Change on the Hydrology in the Mono Lake Basin, California.” *Climatic Change* 116 (1): 111–131. https://doi.org/10.1007/s10584-012-0566-6.

Fowler, H.J., S. Blenkinsop, and C. Tebaldi. 2007. “Linking Climate Change Modelling to Impacts Studies: Recent Advances in Downscaling Techniques for Hydrological Modelling.” *International Journal of Climatology* 27 (12): 1547–1578. https://doi.org/10.1002/joc.1556.

Gates, W.L. 1985. “The Use of General Circulation Models in the Analysis of the Ecosystem Impacts of Climatic Change.” *Climatic Change*, 7 (3): 267-284. https://doi.org/10.1007/BF00144171.

Golembesky, K., A. Sankarasubramanian, and N. Devineni. 2009. “Improved Drought Management of Falls Lake Reservoir: Role of Multimodel Streamflow Forecasts in Setting up Restrictions.” *Journal of Water Resources Planning and Management* 135 (3): 188–197. https://doi.org/10.1061/(ASCE)0733-9496(2009)135:3(188).

Hagemann, S., C. Chen, D.B. Clark, S. Folwell, S.N. Gosling, I. Haddeland, N. Hanasaki, J. Heinke, F. Ludwig, F. Voss, and A.J. Wiltshire. 2013. “Climate Change Impact on Available Water Resources Obtained Using Multiple Global Climate and Hydrology Models.” *Earth System Dynamics* 4 (1): 129–144. https://doi.org/10.5194/esd-4-129-2013.

Jha, M., J.G. Arnold, P.W. Gassman, F. Giorgi, and R.R. Gu. 2006. “Climate Change Sensitivity Assessment on Upper Mississippi River Basin Streamflows Using SWAT.” *Journal of Water Resources Planning and Management* 42 (4): 997-1015. https://doi.org/10.1111/j.1752-1688.2006.tb04510.x.

Kauwe, M.G., B.E. Medlyn, S. Zaehle, A.P. Walker, M.C. Dietze, T. Hickler, A.K. Jain, Y. Luo, W.J. Parton, I.C. Prentice, and B. Smith. 2013. “Forest Water Use and Water Use Efficiency at Elevated CO2: A Model-Data Intercomparison at Two Contrasting Temperate Forest FACE Sites.” *Global Change Biology* 19 (6): 1759–1779. https://doi.org/10.1111/gcb.12164.

Keellings, D. and J. Engström. 2019. “The Future of Drought in the Southeastern US: Projections from Downscaled CMIP5 Models.” *Water* 11 (2): 259. https://doi.org/10.3390/w11020259.

Kruijt, B., J.M. Witte, C.M.J. Jacobs, T. Kroon. 2008. “Effects of Rising Atmospheric CO_2 on Evapotranspiration and Soil Moisture: A Practical Approach for the Netherlands.” *Journal of Hydrology* 349 (3-4): 257-267. https://doi.org/10.1016/j.jhydrol.2007.10.052.

Lammertsma, E.I., H.J. de Boer, S.C. Dekker, D.L. Dilcher, A.F. Lotter, and F. Wagner-Cremer. 2011. “Global CO_2 Rise Leads to Reduced Maximum Stomatal Conductance in Florida Vegetation.” *Proceedings of the National Academy of Sciences* 108 (10): 4035-4040. https://doi.org/10.1073/pnas.1100371108.

Li, W., A. Sankarasubramanian, R.S. Ranjithan, and E.D. Brill. 2014. “Improved Regional Water Management Utilizing Climate Forecasts: An Interbasin Transfer Model with a Risk Management Framework.” *Water Resources Research* 50 (8): 6810-6827. https://doi.org/10.1002/2013WR015248.

Marion, D.A., G. Sun, P.V. Caldwell, C.F. Miniat, Y. Ouyang, D.M. Amatya, B.D. Clinton, P.A. Conrads, S.G. Laird, Z. Dai, and J.A. Clingenpeel. 2014. “Managing Forest Water Quantity and Quality under Climate Change.” In: *Climate Change Adaptation and Mitigation Management Options*, 249-305. ROUTLEDGE in association with GSE Research

Meaurio, M., A. Zabaleta, L. Boithias, A. M. Epelde, S. Sauvage, J. M. Sánchez-Pérez, R. Srinivasan, and I. Antiguedad. 2017. “Assessing the Hydrological Response from an Ensemble of CMIP5 Climate Projections in the Transition Zone of the Atlantic Region (Bay of Biscay).” *Journal of Hydrology* 548: 46-62. https://doi.org/10.1016/j.jhydrol.2017.02.029.

Moradkhani, H., R.G. Baird, and S.A. Wherry. 2010. “Assessment of Climate Change Impact on Floodplain and Hydrologic Ecotones.” *Journal of Hydrology* 395 (3): 264–278. https://doi.org/10.1016/j.jhydrol.2010.10.038.

Moriasi, D. N., J. G. Arnold, M. W. Van Liew, R. L. Bingner, R.D. Harmel, and T. L. Veith. 2007. “Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations.” *Transactions of the ASABE* 50 (3):885–900. https://doi.org/10.13031/2013.23153.

Moriasi, D. N., M. W. Gitau, N. Pai, and P. Daggupati. 2015. “Hydrologic and Water Quality Models: Performance Measures and Evaluation Criteria.” *Transactions of the ASABE* 58 (6): 1763-1785. https://doi.org/10.13031/trans.58.10715.

Morison, J.I.L. 1987. “Intercellular CO_2 Concentration and Stomatal Response to CO_2 James I. L Morison.” In: *Stomatal Function*, edited by E. Zeiger, G.D. Farquhar and I.R.Cowan 229-251. Stanford, CA, USA: Stanford University Press.

Nash, J. E. and J. V. Sutcliffe. 1970. “River Flow Forecasting Through Conceptual Models Part I—A Discussion of Principles.” *Journal of Hydrology* 10 (3): 282-290. https://doi.org/10.1016/0022-1694(70)90255-6.

NOAA National Centers for Environmental Information, 2001. Global Surface Hourly [subset used: Global Summary of the Day]: NOAA National Centers for Environmental Information. (available online https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00516; access date 12/18/2018)

NOAA National Weather Service (NWS) Radar Operations Center, 1991. NOAA Next Generation Radar (NEXRAD) Level 2 Base Data: NOAA National Centers for Environmental Information, https://doi.org/10.7289/V5W9574V. (available online: https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00345; access date 12/18/2018)

Palmer, R.N. and G.W. Characklis. 2009. “Reducing the Costs of Meeting Regional Water

Demand through Risk-Based Transfer Agreements.” *Journal of Environmental Management* 90 (5): 1703–1714. https://doi.org/10.1016/j.jenvman.2008.11.003.

Park, J.Y., M.J. Park, S.R. Ahn, G.A. Park, J.E. Yi, G.S. Kim, R. Srinivasan, and S.J. Kim. 2011. “Assessment of Future Climate Change Impacts on Water Quantity and Quality for a Mountainous Dam Watershed Using SWAT.” *Transactions of the ASABE* 54 (5) :1725–1737. https://doi.org/10.13031/2013.39843.

Pierce, D. W., T.P. Barnett, B.D. Santer, and P.J. Gleckler. 2009. “Selecting Global Climate Models for Regional Climate Change Studies.” *Proceedings of the National Academy of Sciences* 106 (21): 8441–8446. https://doi.org/10.1073/pnas.0900094106.

Pierce, D. W., D. R. Cayan, and B. L. Thrasher. 2014. “Statistical Downscaling Using Localized Constructed Analogs (LOCA).” *Journal of Hydrometeorology* 15 (6), 2558-2585. https://doi.org/10.1175/JHM-D-14-0082.1.

Pierce, D. W., D. R. Cayan, E. P. Maurer, J. T. Abatzoglou, and K. Hegewisch. 2015. “Improved Bias Correction Techniques for Hydrological Simulations of Climate Change.” *Journal of Hydrometeorology* 16 (6), 2421-2442. https://doi.org/10.1175/JHM-D-14-0236.1.

Pradhanang, S.M., R. Mukundan, E.M. Schneiderman, M.S. Zion, A. Anandhi, D.C. Pierson, A. Frei, Z.M. Easton, D. Fuka, and T.S. Steenhuis. 2013. “Streamflow Responses to Climate Change: Analysis of Hydrologic Indicators in a New York City Water Supply Watershed.” *Journal of the American Water Resources Association* (JAWRA) 49 (6):1308–1326. https://doi.org/10.1111/jawr.12086.

Reichler, T. and J. Kim. 2008. “How Well Do Coupled Models Simulate Today’s Climate?” *Bulletin of the American Meteorological Society* 89 (3): 303–311. https://doi.org/10.1175/BAMS-89-3-303.

Reshmidevi, T. V., D. Nagesh Kumar, R. Mehrotra, and A. Sharma. 2018. “Estimation of the Climate Change Impact on a Catchment Water Balance Using an Ensemble of GCMs.” *Journal of Hydrology* 556: 1192–1204. https://doi.org/10.1016/j.jhydrol.2017.02.016.

Soil Survey Staff, 2018. Soil Survey Geographic (SSURGO) Database: Natural Resources Conservation Service, United States Department of Agriculture. (available online: https://sdmdataaccess.sc.egov.usda.gov; access date 12/18/2018).

Sun, G., S.G. McNulty, J.A. Moore Myers, and E.C. Cohen. 2008. “Impacts of Multiple Stresses on Water Demand and Supply Across the Southeastern United States.” *Journal of the American Water Resources Association* (JAWRA), 44 (6): 1441-1457. https://doi.org/10.1111/j.1752-1688.2008.00250.x.

Sunde, M. G., H. S. He, J. A. Hubbart, and M. A. Urban. 2017. “Integrating Downscaled CMIP5 Data with a Physically Based Hydrologic Model to Estimate Potential Climate Change Impacts on Streamflow Processes in a Mixed-use Watershed.” *Hydrological Processes* 31 (9): 1790-1803. https://doi.org/10.1002/hyp.11150.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl. 2012. “An Overview of CMIP5 and the Experiment Design.” *Bulletin of the American Meteorological Society*, 93 (4): 485-498. https://doi.org/10.1175/BAMS-D-11-00094.1.

Van Vuuren, D.P., J. Edmonds, M. Kainuma, K. Riahi, A. Thomson, K. Hibbard, G.C. Hurtt, T. Kram, V. Krey, J.F. Lamarque, and T. Masui. 2011. “The Representative Concentration Pathways: an Overview.” *Climatic Change* 109 (1-2): 5. https://doi.org/10.1007/s10584-011-0148-z.

Voldoire, A., E. Sanchez-Gomez, D. S. y Mélia, B. Decharme, C. Cassou, S. Sénési, S. Valcke,

I. Beau, A. Alias, M. Chevallier, and M. Déqué. 2013. “The CNRM-CM5. 1 Global Climate Model: Description and Basic Evaluation.” *Climate Dynamics* 40 (9-10): 2091-2121. https://doi.org/10.1007/s00382-011-1259-y.

Watanabe, M., T. Suzuki, R. O’ishi, Y. Komuro, S. Watanabe, S. Emori, T. Takemura, M. Chikira, T. Ogura, M. Sekiguchi, and K. Takata. 2010. “Improved Climate Simulation by MIROC5: Mean States, Variability, and Climate Sensitivity.” *Journal of Climate* 23 (23): 6312-6335. https://doi.org/10.1175/2010JCLI3679.1.

Weaver, J.C. 2005. “The Drought of 1998-2002 in North Carolina: Precipitation and Hydrologic Conditions.” *U.S. Geological Survey Scientific Investigations Report 2005-5053.* https://pubs.er.usgs.gov/publication/sir20055053.

Williams, J.R. 1969. “Flood Routing with Variable Travel Time or Variable Storage Coefficients.” *Transactions of the ASAE 1969*, 12 (1), 100–103. https://doi.org/10.13031/2013.38772.

Wolock, D.M.. 2003. “Estimated Mean Annual Natural Ground-water Recharge Estimates in the Conterminous United States.” *U.S. Geological Survey Open-File Report 2003-311*. https://pubs.er.usgs.gov/publication/ofr03311.

Wu, Y., S. Liu, and O.I. Abdul-Aziz. 2012. “Hydrological Effects of the Increased CO_2 and Climate Change in the Upper Mississippi River Basin Using a Modified SWAT.” *Climatic Change* 110 (3-4): 977–1003. https://doi.org/10.1007/s10584-011-0087-8.

Yang, Q., X. Zhang, J. E. Almendinger, M. Huang, G. Leng, Y. Zhou, K. Zhao, G.R. Asrar, X. Li, and J. Qiu. 2018. “Improving the SWAT Forest Module for Enhancing Water Resource Projections: A case study in the St. Croix River Basin.” *Hydrological Processes* 33 (5):

864-875. https://doi.org/10.1002/hyp.13370.

Ye, L. and N.B. Grimm. 2013. “Modelling Potential Impacts of Climate Change on Water and Nitrate Export from a Mid-Sized, Semiarid Watershed in the US Southwest.” *Climatic Change* 120 (1-2): 419–431. https://doi.org/10.1007/s10584-013-0827-z.

Yukimoto, S., Y. Adachi, M. Hosaka, T. Sakami, H. Yoshimura, M. Hirabara, T.Y. Tanaka, E. Shindo, H. Tsujino, M. Deushi, and R. Mizuta. 2012. “A New Global Climate Model of the Meteorological Research Institute: MRI-CGCM3—Model Description and Basic Performance—.” *Journal of the Meteorological Society of Japan*. Ser. II, 90: 23-64. https://doi.org/10.2151/jmsj.2012-A02.

Table 1: The calibration parameter values, acceptable ranges and replacement operations.

Change type*	Parameter	Description	Range	Best Fitted Value
v	Ch_K2	Main channel hydraulic conductivity	0.00-150.00	7.14
r	Cn2	Curve number	±0.25	0.04
v	Alpha_Bf	Base flow alpha factor	0.00-1.00	0.90
r	Sol_Awc	Available water capacity	±0.25	0.11
v	Ch_N2	Manning's n value for main channel	0.00-0.30	0.031
v	Esco	Soil evaporation compensation factor	0.00-1.00	0.78
r	Sol_Z	Depth from soil surface to bottom of layer	±0.25	0.20
v	Epco	Plant uptake compensation factor	0.00-1.00	0.16
v	RCHRG_DP	Deep aquifer percolation fraction	0.00-1.00	0.62
r	SOL_K	Saturated hydraulic conductivity	±0.25	-0.05
a	GW_REVAP	Groundwater “revap” coefficient	±0.036	-0.01
a	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occure	±1000.00	-746.03

* “v”: The default parameter is replaced by a given value; “r”: The existing parameter value is changed relatively “a”: The existing parameter is changed absolutely.

Table 2: The GCMs used and their corresponding average annual changes in precipitation (PCP), minimum daily temperature (TMIN) and maximum daily temperature (TMAX) for mid-century (2046-2065) and end-century (2081-2099) projections for both mitigation (RCP4.5) and high emission (RCP8.5) scenarios from the baseline (1961-2000) period.

		TMIN (°C)		TMAX (°C)		PCP (mm)	
	GCMs	**Mid**	**End**	**Mid**	**End**	**Mid**	**End**
RCP 4.5	CNRM-CM5[1]	1.9	2.8	1.8	2.4	7.7	7.1
	MIROC-ESM[2]	2.4	2.9	2.4	3.4	11.0	10.9
	MIROC5[3]	2.4	2.7	2.9	3.3	4.3	2.8
	MRI-CGCM3[4]	1.2	4.7	0.7	1.1	2.9	9.5
	NorESM1-M[5]	1.9	3.3	2.5	3.1	10.3	15.6
	Mean	1.9	3.3	2.1	2.7	7.2	9.2
RCP 8.5	CNRM-CM5	2.7	4.4	2.6	3.9	8.3	16.6
	MIROC-ESM	3.4	5.7	3.7	6.1	11.3	12.5
	MIROC5	3.0	4.7	3.6	5.3	2.3	-1.3
	MRI-CGCM3	1.9	3.3	1.2	2.4	7.0	16.0
	NorESM1-M	2.6	4.7	3.1	5.3	15.0	20.2
	Mean	2.7	4.6	2.8	4.6	8.8	12.8

[1] National Center for Meteorological Research, France (Voldoire et al., 2013), [2] Japan Agency for Marine-Earth Sciences and Technology, Atmosphere and Ocean Research and National Institute for Environmental Studies, Japan (Watanabe et al., 2010), [3] Japan Agency for Marine-Earth Sciences and Technology, Atmosphere and Ocean Research and National Institute for Environmental Studies, Japan (Watanabe et al., 2010), [4] Meteorological Research Institute, Japan (Yukimoto et al., 2012), [5]

Norwegian Climate Center, Norway (Bentsen et al., 2013); The spatial resolutions for the GCMs before downscaling are 1.4°×1.4°, 2.8°×2.8°, 1.4°×1.4°, 1.4°×1.4°, and 2.5°×1.8°, respectively.

Table 3: Calibration and validation statistics for the Flat, Little and Eno watersheds.

	Calibration Period[a] (2005-2008)						Validation Period (2009-2011)					
Watershed	**NSE_d**	**NSE_m**	**R^2_d**	**R^2_m**	**$PB_{m,d}$**	**RSR_m**	**NSE_d**	**NSE_m**	**R^2_d**	**R^2_m**	**$PB_{m,d}$**	**RSR_m**
Flat	0.68	0.63	0.70	0.63	6.8	0.61	0.63	0.69	0.67	0.73	8.0	0.55
Little	0.73	0.63	0.76	0.65	13.4	0.60	0.57	0.59	0.59	0.60	8.4	0.63
Eno	0.55	0.59	0.66	0.62	1.7	0.64	0.67	0.73	0.67	0.74	-9.2	0.52

[a] NSE: Nash-Sutcliff Efficiency, R^2: coefficient of determination, PB: percent bias (values shown in %), RSR: RMSE-observations standard deviation ratio, d: daily, m: monthly

Table 4: Average of each water balance term (mm per month) for baseline (1961-2000), mid-century (2046-2065) and end-century (2081-2099) projections for both mitigation (RCP4.5) and high emission (RCP8.5) scenarios. Values in parentheses represent percent change from baseline conditions.

		Mitigation (RCP4.5)		High Emission (RCP8.5)	
	Baseline	**Mid**	**End**	**Mid**	**End**
Precipitation	93.53	100.78 (7.8)	102.71 (9.8)	102.32 (9.4)	106.33 (13.7)
Evapotranspiration	58.89	56.36 (-4.3)	55.23 (-6.2)	54.12 (-8.1)	45.63 (-22.5)
Water Yield	19.89	25.07 (26.1)	26.76 (34.6)	26.96 (35.6)	33.97 (70.9)
Soil Water	227.62	232.03 (1.9)	233.2 (2.5)	233.51 (2.6)	239.51 (5.2)

Table 5: Average of each water yield component (mm per month) for baseline (1961-2000), mid-century (2046-2065) and end-century (2081-2099) projections for mitigation (RCP4.5) and high emission (RCP8.5) scenarios. Values in parentheses represent percent change from baseline conditions.

		Mitigation (RCP4.5)		High Emission (RCP8.5)	
	Baseline	**Mid**	**End**	**Mid**	**End**
Surface Runoff	7.13	8.97 (25.8)	9.49 (33.1)	9.45 (32.5)	12.21 (71.3)
Lateral Flow	3.7	4.38 (18.4)	4.59 (24.0)	4.64 (25.3)	5.39 (45.5)
Groundwtr Dschr	9.05	11.72 (29.5)	12.68 (40.1)	12.87 (42.2)	16.37 (80.9)

Table 6: Average changes in water balance terms (mm per month) for mid-century (2046-2065) and end-century (2081-2099) relative to the baseline period (1961-2000) for each GCM

		Precip[a]		ET[b]		WtrYield[c]		SoilWtr[d]	
	GCMs	**Mid**	**End**	**Mid**	**End**	**Mid**	**End**	**Mid**	**End**
RCP 4.5	CNRM-CM5	7.7	7.1	-3.2	-4.6	5.7	6.2	6.0	8.2
	MIROC-ESM	11.0	10.9	-3.0	-4.3	7.5	8.1	5.6	6.4
	MIROC5	4.3	2.8	-2.6	-3.4	3.8	3.0	4.4	3.9
	MRI-CGCM3	2.9	9.5	-1.8	-2.6	2.9	6.8	-0.1	2.7
	NorESM1-M	10.3	15.6	-2.0	-3.4	6.1	10.4	6.2	6.6
RCP 8.5	CNRM-CM5	8.3	16.6	-5.3	-14.6	7.2	16.7	4.4	13.4
	MIROC-ESM	11.3	12.5	-4.8	-13.6	9.0	15.0	8.8	11.9
	MIROC5	2.3	-1.3	-4.7	-13.1	3.6	6.2	2.0	7.1
	MRI-CGCM3	7.0	16.0	-4.2	-11.0	6.0	15.3	4.8	12.4
	NorESM1-M	15.0	20.2	-4.9	-14.0	9.6	17.4	9.4	14.6

[a] Precipitation, [b] Evapotranspiration, [c] Water yield, [d] Amount of water in soil profile

Table 7: Average changes in water yield components (mm per month) for mid-century (2046-2065) and end-century (2081-2099) periods relative to the baseline period (1961-2000) for each GCM

		SrfcRnff[a]		LtrlFlw[b]		GwDschr[c]	
	GCMs	**Mid**	**End**	**Mid**	**End**	**Mid**	**End**
RCP 4.5	CNRM-CM5	1.9	2.0	0.8	0.7	3.1	3.4
	MIROC-ESM	2.8	2.6	0.9	1.1	3.8	4.4
	MIROC5	1.3	0.7	0.5	0.4	2.0	1.9
	MRI-CGCM3	1.6	2.8	0.3	0.8	1.0	3.2
	NorESM1-M	1.6	3.7	0.9	1.3	3.6	5.3
RCP 8.5	CNRM-CM5	2.5	5.9	0.9	2.1	3.8	8.7
	MIROC-ESM	3.7	6.5	1.0	1.5	4.2	7.0
	MIROC5	1.2	1.9	0.5	0.7	2.0	3.6
	MRI-CGCM3	2.2	6.5	0.7	1.7	3.1	7.1
	NorESM1-M	2.1	4.6	1.5	2.4	6.0	10.3

[a] Surface Runoff, [b] Lateral Flow, [c] Groundwater Discharge

Figure 1: Study area, the Upper Neuse Watershed in North Carolina, USA.

Figure 2: (a) NLCD 2011 land use and (b) SSURGO soil hydrologic groups within the Upper Neuse watershed study area

Figure 3: Monthly-accumulated streamflow observations and SWAT simulations at the Flat, Little and Eno watershed outlets

Figure 4: Average monthly water balance terms for baseline (1961-2000), mid-century (2046-2065) and end-century (2081-2099) periods under the mitigation (RCP45) and high emission (RCP85) scenarios

Figure 5: Average monthly water yield terms for baseline (1961-2000), mid-century (2046-2065) and end-century (2081-2099) periods under mitigation (RCP45) and high emission (RCP85) scenarios

Figure 6: Water balance terms variations for mid-century period (2046-2065) with respect to the baseline (1961-2000) between GCMs throughout the months under mitigation (RCP45) and high emission (RCP85) scenarios

Figure 7: Water balance term variations for end-century period (2081-2099) with respect to the baseline (1961-2000) between GCMs throughout the months under mitigation (RCP45) and high emission (RCP85) scenarios

Figure 8: Water yield component variations for mid-century period (2046-2065) with respect to the baseline (1961-2000) between GCMs throughout the months under mitigation (RCP45) and high emission (RCP85) scenarios

Figure 9: Water yield component variations for end-century period (2081-2099) with respect to the baseline (1961-2000) between GCMs throughout the months under mitigation (RCP45) and high emission (RCP85) scenarios