WATER BALANCE CHANGE UNDER CLIMATE AND LANDUSE/LANDCOVER VARIABILITY IN THE NORTH CAROLINA PIEDMONT

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Abstract

YURI KIM: WATER BALANCE CHANGE UNDER CLIMATE AND LANDUSE/LANDCOVER VARIABILITY IN THE NORTH CAROLINA PIEDMONT
(Under the direction of Lawrence E. Band)

Fresh water availability is an important concern for human society as well as ecosystems. In this dissertation, water resources trends in the North Carolina Piedmont were analyzed to understand historical trends and provide potential future scenarios in response to different climate and landuse/landcover (LULC) dynamics. North Carolina Piedmont has experienced a large scale LULC conversion from farmland to naturally grown forest, followed by recent urbanization, in the last century. Simulation with the Soil and Water Assessment Tool (SWAT) indicates that forest regrowth mitigated the impact of increased precipitation on stream discharge in areas that reforested from abandoned agricultural fields due to increasing water consumption. For projected climate conditions, nested global and regional circulation model results from the North American Regional Climate Change Assessment Program (NARCCAP) were evaluated for bias relative to current measurements in North Carolina. For historical NARCCAP output (1971-2000), precipitation shows seasonal bias pattern and, there is a general trend of NARCCAP temperature cold bias. After applying bias correction methods, NARCCAP climate simulation outputs have significant reduction of seasonal biases in precipitation temperature except for a few extreme events. For future projections of monthly runoff production, a set of scenarios are used for SWAT simulations with increasing carbon dioxide (CO₂), projected climate and LULC. Under future climate conditions,
evapotranspiration (ET) is projected to increase in winter and spring while annual water yield (WY) would show various changing patterns, with greater dependence on projected CO$_2$ and precipitation. When only future climate scenario was included, the highest WY was produced by combining increasing CO$_2$ and future precipitation while future temperature alone produced the lowest WY. When projected LULC is applied, future urban growth may cause decreased ET and increased WY because of the imperviousness increment. However, interaction between climate and LULC change can mitigate these effects. Most of the simulation scenarios projected WY similar or slightly lower than current WY on an annual basis due to the offsetting effects of increasing temperature and urbanization. Therefore, it is necessary to incorporate interactions of all factors, CO$_2$, climate and LULC change, to simulate future water availability in the North Carolina Piedmont.
This dissertation is dedicated

To my husband and precious daughter, Taehee and Arwen

To my parents, Guison Kim and Jongwon Kim
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Chapter 1: Introduction

Fresh water availability is an important concern for human society as well as ecosystems. In the Southeast of the United States, as in other locations around the globe, increases in population and demand for water along with the potential for significant change in watershed runoff production is creating challenges and uncertainty in water security. Impacts and interactions between climate change, land use conversion and ecosystem adjustment in terms of resulting hydrologic changes are important to evaluate and de-convolve to inform water resources planning and watershed management. The main objective of this study is the integration of climate and LULC change scenarios to model and project historic and future changes in freshwater availability in the North Carolina Piedmont. Therefore, water resources trend of the North Carolina Piedmont in past and future times in response to individual and combined effects of all three of these drivers were analyzed and simulated by hydrologic model in order to understand historical trends and provide information on potential future scenarios in response to different climate and land cover dynamics.

The study area, the North Carolina Piedmont, has experienced a large scale landuse conversion from farmland to forest in the last century (Billings 1938; Oosting 1942; Christensen and Peet 1984). At the same time, between 2000 and 2010 the North Carolina population increased by 18.5% (2010 US Census). In the North Carolina Triangle area, Wake County (Raleigh-Cary area) experienced a 41.8 % increase between 2000 and 2010 (2010 US Census), the 4th fastest-growing county in the US. Other Triangle (Orange, Durham, and Wake counties) and Triad (Guilford and
Forsyth counties) regions of North Carolina Piedmont experienced unprecedented population growth rates of from 10% to 25% (2010 US Census). According to the Spatially Explicit Regional Growth Model (SERGoM) (Theobald, 2005) from the spatial allocation model of Integrated Climate and Land Use Scenarios (ICLUS) by EPA (2009), some watersheds of the North Carolina Piedmont area could have a twofold increase in urban land compared to current landcover in the future, 2060, as well. Therefore, the North Carolina Piedmont is characterized by rapid urban growth while retaining a large area of forest cover in the recent past and is expected to maintain that trend over the next few decades.

For future climate, the North American Regional Climate Change Assessment Program (NARCCAP) is selected for projected climate scenarios. NARCCAP is an international program developed to produce high resolution climate change simulations in order to investigate uncertainties in regional scale projections of future climate and generate climate change scenarios for use in impacts research (http://www.narccap.ucar.edu). It provides a set of regional climate models (RCMs) nested within a set of atmosphere-ocean general circulation models (AOGCMs) over a domain covering the conterminous United States, most of the Canada, and Northern Mexico. The Integrated Climate and Land Use Scenarios (ICLUS) (EPA, 2009) program is used to project LandUse/LandCover (LULC) scenarios, and is focused on urban growth. This is basically an urban expansion model using forecasted population growth and transportation infrastructure as land-use change drivers. Selected future climate CO₂ concentrations and LULC scenarios are based on the same economic storyline, the Special Report on Emission Scenario (SRES) (IPCC, 2000) A2 emissions scenario for the 21st century.

The hydrologic model used to evaluate runoff impacts of LULC and climate scenario simulations in this study is the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Neitsch
et al., 2009). It is a process-based model, which requires specific information about weather, topography, soil, and LULC (i.e. vegetation, land cover and land management practices) as model input. The physical processes associated with water storage and flux, sediment transport, crop growth, nutrient cycling etc. are simulated by SWAT in a watershed. The National Elevation Dataset (NED) (http://ned.usgs.gov/) and 1:24,000 stream network data (http://www.cgia.state.nc.us/) are used for watershed and sub-watershed delineation. Each sub-watershed is divided into smaller segments, Hydrologic Response Units (HRUs), by unique LULC, soil, and management combinations. The Generalized Likelihood Uncertainty Estimation (GLUE) (Free and Binley, 1992) is applied to calibrate the model for daily runoff data under current land cover and represent uncertainty in the model predictions. GLUE is a Monte Carlo simulation-based method, developed from the Generalized Sensitivity Analysis (GSA) of Spear and Hornberger (1980). The basic concept of GLUE is that there is no one optimal parameter set for a given watershed; a number of combinations of parameters that simulate observed discharge data can exist. The GLUE method evaluates sensitivity of each parameter and suggests acceptable parameter value combinations based on a likelihood function. The sensitivity of parameters can be explained as “behavioral” and “non-behavioral” by certain criteria for model rejection. SWAT-CUP4 software (Abbaspour, 2011), which provides for sensitivity analysis, calibration, validation, and uncertainty analysis for the SWAT model, is used for GLUE application.

The three related themes of this dissertation are:

1. The influence of forest re-growth on stream discharge in the North Carolina Piedmont watersheds in the past century
2. Evaluation and bias correction of General Circulation Model (GCM) based Regional Climate Models (RCMs) precipitation and temperature in North Carolina for future water yield change scenario applications

3. Simulation of future water yield under the conditions of changing CO\textsubscript{2}, climate and landuse/landcover (LULC) in the North Carolina Piedmont

Chapter 2 focuses on the relationship between historical landuse/landcover (LULC), recent climate trends and stream discharge with the following scientific question:

- How has historical forest re-growth from abandoned agricultural areas affected stream discharge of the North Carolina Piedmont catchments?

- Hypothesis

  \(H_0\): A hydrologic model with consistent land use explains historical behavior of watersheds that have had changing land uses.

  \(H_1\): The apparent difference in runoff can be explained by land use change.

Chapter 3 is about the evaluation and bias correction of dynamically downscaled climate model information required for watershed simulation in North Carolina. The performance of a set of the nested global and regional circulation model (GCM-RCM) results from the North American Regional Climate Change Assessment Program (NARCCAP) is evaluated for bias relative to current measurement in North Carolina.

- Are systematic biases found in NARCCAP produced GCM-RCM daily precipitation, and maximum and minimum temperature in the North Carolina region?

- If there are systematic biases, can we apply statistical methods to efficiently correct the biases?
• Is bias correction of NARCCAP necessary for its application to hydrologic modeling? To what extent can bias corrected NARCCAP output improve hydrologic modeling performance?

Finally in Chapter 4, future water yield change sensitivity under increasing carbon dioxide (CO₂), projected climate and Landuse/Landcover (LULC) variability in the North Carolina Piedmont is evaluated.

• How will evapotranspiration (ET) and water yield (WY) be affected by future CO₂ level and climate scenarios which generally include temperature increases and stable or moderate increases in precipitation?

• How will water balance, especially ET and WY be altered under the synergistic condition of projected CO₂, climate and LULC change?
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Chapter 2: The influence of forest re-growth on the stream discharge in the North Carolina Piedmont watersheds

2.1 Abstract

This study focuses on the relationship between historical landuse/landcover (LULC), recent climate trends and stream discharge. A major problem recognized in water resources is the issue of non-stationarity in climate and watershed conditions, and impacts on forecasting and explaining hydrologic behavior. Over the 20th century, landuse/landcover in the Southeast US, particularly the North Carolina Piedmont, has evolved from a more dominantly agricultural to an extensively forested landscape, and more recent localized urbanization. The re-growth of forests has an important influence on the hydrology of the region as it enhances ecosystem interaction with recent climate change. During the time period of this study, 1920’s-2009, the amount of precipitation in some parts of the North Carolina Piedmont forest re-growth area showed increasing trends without corresponding increments in stream discharge. To understand the effect of LULC on runoff, we employed long-term the Soil and Water Assessment Tool (SWAT) to simulate hydrologic behavior for several watersheds in North Carolina with different LULC histories: (1) LULC conversion from agricultural to forested area, and (2) long-term stable forest cover with no significant LULC conversion. Comparing stream discharge simulated with SWAT with the assumption of constant LULC with USGS-measured stream discharge, we found significant stream discharge under-prediction by SWAT in two LULC conversion watersheds during the early simulation period (1920’s) with differences gradually decreasing by mid-1970’s. However, SWAT simulation for a watershed
with long-term stable forest cover does not show this under-prediction bias; simulated and measured stream discharge show similar patterns during the entire study time period. Monthly scale residual analysis in reforested watersheds also shows significant seasonal patterns in stream discharge differences before and after forest re-growth. Therefore, the under-prediction bias of SWAT from the 1920’s to the mid-1970’s indicates that forest re-growth mitigated the impact of increased precipitation on stream discharge in the reforested area from abandoned agricultural fields due to increasing water consumption driven by changes in vegetation.

2.2 Introduction

Recent severe hydrologic droughts in the North Carolina in past decades have raised significant concerns about the adequacy of water resource systems in this area given significant population increases and potential changes in hydro-climate. In 2002 and again from 2007 to 2008, USGS stream discharge data for the Flat River in the North Carolina Piedmont (site number 0208550) documented record low flows, with zero stream discharge in October 2007 and almost zero stream discharge in summer of 2007 and 2008 (http://waterdata.usgs.gov/nc/nwis). These no-flow conditions had not been previously experienced in 83 years of discharge records. Non-stationarity in the processes controlling watershed hydrology has been recognized as a major challenge for evaluating and planning for water resources (Milly et al., 2008). In the Southeast United States, major shifts in land cover and climate may have produced large changes in expected runoff, as well as hydrologic extremes of floods and droughts. Therefore, planning for water security based on only past hydrologic records may not be as reliable as it appears by leading to significant bias in estimation of available water.
Over the past century, a general increase in stream discharge has been found in most of the US, particularly in the eastern half (McCabe and Wolock, 2002) and is correlated with a trend of increasing precipitation (Lins and Slacks 1999, 2005; Andreadis 2006; Small et al. 2006). However, Lins and Slacks (2005) noted that stream discharge in the South Atlantic-Gulf region shows a decreasing trend especially in the annual minimum, Q₀ percentile flow. This implies that either precipitation is anomalous compared to most of the US or another factor, LULC change, may affect decreasing stream discharge trend in Southeast US.

The stream discharge is affected by precipitation and landuse/landcover (LULC) of a watershed. North Carolina climate is characterized as humid subtropical climate—hot and humid summers and generally mild and cool winters—, and there has been no significant average annual total precipitation change over the past century though greater inter-annual variability and increasing precipitation are found in some area (The University of North Carolina at Chapel Hill Institute for the Environment, 2009). Therefore, if precipitation has not shown a decreasing signal, there may be other factors that cause more low flow duration in the North Carolina Piedmont. LULC change can be another driver for increased drought frequency in the North Carolina Piedmont. LULC change has an influence on the hydrology, and more specifically, reforestation has been shown to increase drought frequency in other regions as well (Trimble et al., 1987; Scott and Smith 1997; Farley et al., 2005). Therefore, this study focuses on the stream discharge change in the context of climate and LULC characteristics of the North Carolina Piedmont.
Figure 2.1: Historical Palmer Drought Severity Index (PDSI) and Palmer Hydrological Drought Index (PHDI) in North Carolina by water year scale. Climate Division 3 is the Northern Piedmont, and Climate Division 1 is the Southern Mountain (NOAA Satellite and Information Service, http://www.ncdc.noaa.gov)
Other observations suggest that LULC change may play a key role in increased drought vulnerability in North Carolina Piedmont. Figure 2.1 shows the drought indices of the Northern Piedmont (Climate Division 3) and Southern Mountain (Climate Division 1) of North Carolina. The Palmer Drought Severity Index (PDSI) is based on a water balance derived from precipitation and temperature, and Palmer Hydrological Drought Index (PHDI) is based on the hydrological impact of drought, such as reservoir and groundwater levels (NOAA Satellite and Information Service, [http://www.ncdc.noaa.gov](http://www.ncdc.noaa.gov)). Comparing these two indices in these two Climate Divisions, the lowest value of indices in Southern Mountain shows similar timing between PDSI and PHDI, whereas Northern Piedmont shows a little different timing. In the North Carolina Piedmont, the recent water shortage in 2002 recorded as the lowest hydrologic drought event in PHDI, but PDSI shows more severe meteorological droughts in 1920’s and 1930’ than 2002. Differences in timing and severity between meteorological and hydrological droughts are further evidence that factors aside from climate may be involved in drought conditions in the North Carolina Piedmont region.

We hypothesize that the severity of hydrologic drought in recent years in the North Carolina Piedmont has been influenced by LULC, i.e., forest re-growth in abandoned agricultural field during the 20th century. Reforestation can reduce annual water yield from a watershed (e.g. Hibbert 1967; Bosch and Hewlett, 1982; Trimble et al., 1987; Scott and Smith 1997; Farley et al., 2005; Huxman et al., 2005; Scott et al., 2006; Buttle, 2011). Specifically, runoff reduction by forest re-growth has a much higher impact in the dry season and in areas that have low base flow (Trimble et al., 1987; Scott and Smith 1997; Farley et al., 2005). In terms of the amount of reforestation, even a relatively small increase in forest, e.g. 10% in total area, can cause noticeable decreases in water yield (Trimble et al., 1987). Therefore, the hypothesis in this study area is that increasing water consumption, i.e. evapotranspiration (ET) by gradual forest re-growth, could be the major source of water consumption that is offsetting increased precipitation.
Scientific question and hypothesis addressed in this study is:

- How has historical forest re-growth from abandoned agricultural areas affected stream discharge of the North Carolina Piedmont catchments?

Then, two hypothesis of this question are:

- $H_0$: A hydrologic model with consistent land use explains historical behavior of watersheds that have had changing land uses.
- $H_1$: The apparent difference in runoff can be explained by land use change.

2.3 Methodology

2.3.1 Study areas

The North Carolina Piedmont has experienced a large scale landuse conversion from farmland to forest (Billings 1938; Oosting 1942; Christensen and Peet 1984). Since the region’s climate is favorable to agriculture with rolling topography with mild and humid weather, large forest areas were cleared for agricultural activity during early settlement in the eighteenth century through the mid-nineteenth century. However, erosion and loss of the top soil reduced productivity, and cultivated patches had been gradually abandoned (Oosting, 1942). This process was hastened by food imported from the Midwest and the economic depression of the 1930’s. Current forested area of the North Carolina Piedmont mostly results from extensive secondary succession from abandoned farms.

Two watersheds in the North Carolina Piedmont were chosen for study of forest re-growth due to: (1) their history of landuse conversion from farmland to forest; and (2) a long record of stream discharge (1925 – current) and meteorological data (1900 – current). The Flat River
watershed, located in Person County and the Eno River watershed, in Orange County, satisfy these two conditions (Figure 2.2 (b)). Additionally, these two watersheds are headwater for Durham and Raleigh water supply. Therefore, drought signals of these head water catchments can be a direct sign of water shortage for these areas. Drainage areas, length of discharge records and current land use for each watershed are given in Table 2.1.

Another study watershed with long-term forested LULC was selected to compare hydrologic behavior difference between LULC conversion and non-conversion watershed. Agriculture to forest conversion was widespread in the Piedmont of North Carolina, and there are no watersheds with long-term runoff records with consistent forest cover for comparison. However, the adjacent Blue Ridge Mountains has had consistent forest cover, although the structure of the forest has changed due to extensive past logging. The Linville river watershed which keeps a long history of meteorological and stream discharge data in the Blue Ridge Mountains of the North Carolina is used as a long-term consistent LULC watershed (Figure 2.2 (a)). This watershed drains an area of 174 km$^2$ and nearly 80% is forested (Table 2.1). Although the geomorphic characteristics, such as elevation, slope and soil etc., of the Linville River watershed are different from those of watersheds in the Piedmont, the differences in historical trends in stream discharges between the two sites can still provide significant insight regarding the effect of LULC on watershed hydrology.
Figure 2.2: The geographic division of North Carolina: Mountain (left), Piedmont (middle), and Coastal plain (right). (a) is the long-term forested Linville River watershed, and (b) shows the reforested the Flat and the Eno River watersheds. The Flat and the Eno River watersheds are headwater area of Falls Lake.

Table 2.1: Current percent LULC condition of three study watersheds by NLCD 2006 (http://www.mrlc.gov/nlcd06_data.php)

<table>
<thead>
<tr>
<th>LULC Type</th>
<th>Flat (384 Km²)</th>
<th>Eno (171 Km²)</th>
<th>Linville (174 Km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential-Low Density</td>
<td>4.3</td>
<td>8.4</td>
<td>9.7</td>
</tr>
<tr>
<td>Residential-Medium Density</td>
<td>1.2</td>
<td>2.2</td>
<td>0.6</td>
</tr>
<tr>
<td>Residential-High Density</td>
<td>0.2</td>
<td>0.3</td>
<td>0.0</td>
</tr>
<tr>
<td>Forest-Deciduous</td>
<td>48.8</td>
<td>46.8</td>
<td>66.2</td>
</tr>
<tr>
<td>Forest- evergreen</td>
<td>5.4</td>
<td>6.9</td>
<td>8.9</td>
</tr>
<tr>
<td>Forest-Mixed</td>
<td>3.3</td>
<td>2.6</td>
<td>5.1</td>
</tr>
<tr>
<td>Agriculture</td>
<td>1.2</td>
<td>0.7</td>
<td>0.1</td>
</tr>
<tr>
<td>Pasture</td>
<td>26.8</td>
<td>24.3</td>
<td>5.7</td>
</tr>
<tr>
<td>Others (water, wetland, grass, commercial)</td>
<td>8.9</td>
<td>7.8</td>
<td>3.8</td>
</tr>
</tbody>
</table>
2.3.2 LULC change history

USDA agricultural census data for the North Carolina Person County (Figure 2.3) shows that both “All land in farms” and “Crop land” decreased by almost half from the 1920’s to the mid-1970s. The “All land in farms” (Figure 2.3 (a)) category is the sum of total crop land, total pasture land, total woodland, and all other land in farm. The detailed LULC snap shots of 1925 and 1978 show that approximately half of farm land was registered as “Total woodland.” Thus, not “All land in farms” but rather “Crop land” change needs to be analyzed in detail for tracking farm land conversion to forest. In Figure 2.3 (b), “Total Crop land”, the sum of harvested crop land, failed crop land, idle, and plowable pasture land, covered roughly 30% of Person County in the 1920’s and has decreased to about 20% by 2007. Also, “The total pasture land” could be other sources of forest re-growth.

Though the agricultural census has data limitation, it showed decreased total pasture land by 7% of Person County area from 1925 to 1978 (Figure 2.3 (a)). Therefore, at least 17% of the area (10% from “Total crop land” and 7% from “Total pasture land”) could be the source of forest re-growth in Person County. As approximately 90% of the Flat River watershed is located in Person County and sub-county level agricultural census data do not exist, we assume that agricultural area change in the watershed is similar to that of the county, as shown in agricultural census data (Figure 2.3 (b)).
Figure 2.3: An example of the agricultural statistics of the North Carolina Piedmont, Person County. (a) Farm land change from 1900 to 2007 (All land in farms = total crop land + total pasture land + total woodland + all other land in farm), and (b) total crop land and harvested crop land change from 1925 to 2007 (Total Crop land = harvested crop land + failed crop land + idle + plowable pasture land) (USDA Agricultural census, http://www.agcensus.usda.gov/Publications/Historical_Publications/index.php).
In addition to county level agricultural census information, aerial photos in 1955 (USDA aerial photography, 1955) are used to compare land cover with current conditions. In Figure 2.4, a decrease in agricultural land use and an increase in forest cover can be detected by comparing the 1955 aerial photo with the 2006 National Land Cover data (NLCD). Numerous agricultural patches found in the 1955 aerial photos were identified as forests in the 2006 NLCD. The aerial photo of the Flat river watershed was classified with on screen digitization (Song 2012, personal communication) (Figure 2.5(a)). While care needs to be taken comparing aerial photographic interpretation with the NLCD product, the significant shift in land use is evident. Table 2.2 shows that the major LULC changes in the Flat River watershed between 1955 and 2006 were 1) forest transition from mixed forest to deciduous forest (20%) and 2) forest re-growth from farmland to forest, i.e., from Agriculture/Pasture to Deciduous, Evergreen, and Mixed forest (13%).

Both agricultural census data of Person County and the 1955 aerial photo classification show a similar forest re-growth in the Flat River watershed over this 50-year period. Another LULC change to note is urban areas; only a 5% increase in urban area has occurred in the Flat River watershed, with most of the urban increase categorized as residential-low density area from agricultural area. Therefore, we can infer that the Flat River watershed has not urbanized extensively, but natural vegetation succession significantly advanced after decreasing agricultural activity.
Figure 2.4: Person County landuse/landcover (LULC) change in 1955 (by aerial photo) and current (by NLCD 2006)

Figure 2.5: Flat River watershed classified LULC: (a) 1955 air photo classification and (b) NLCD 2006
Table 2.2: Major LULC changes from 1955 to 2006 in the Flat River watershed

<table>
<thead>
<tr>
<th>From (1955)</th>
<th>To (2006)</th>
<th>% of the Flat River watershed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest-Mixed</td>
<td>Forest-Deciduous</td>
<td>20.2</td>
</tr>
<tr>
<td><strong>Agriculture + Pasture</strong></td>
<td><strong>Forest-Deciduous</strong></td>
<td><strong>9.4</strong></td>
</tr>
<tr>
<td>Forest-Evergreen</td>
<td>Forest-Deciduous</td>
<td>7.3</td>
</tr>
<tr>
<td>Agriculture + Pasture</td>
<td>Urban-Low Density</td>
<td>2.4</td>
</tr>
<tr>
<td><strong>Agriculture + Pasture</strong></td>
<td><strong>Forest-Evergreen</strong></td>
<td><strong>2.3</strong></td>
</tr>
<tr>
<td>Agriculture + Pasture</td>
<td>Forest-Mixed</td>
<td>1.2</td>
</tr>
</tbody>
</table>
According to vegetation community analysis in the North Carolina Piedmont by Oosting (1942), pine commonly emerged from the grass cover approximately five years after farm abandonment, grew rapidly, and decreased in density by transitioning to broad leaf forest. Comparing 1955 and 2006 vegetation component (Table 2.2), we can find this secondary succession as well; 20% of the Flat River watershed changed from mixed forest area in 1955 to deciduous forest by 2006. Therefore, the Flat river watershed in Person County appears to be representative of the general forest re-growth patterns from abandoned agricultural area.

2.4 Simulation with SWAT and Weather Data

A before and after forest re-growth water yield comparison is required to test the hypothesis of this study. Since paired control catchments (i.e., forest re-growth watershed vs. watershed without substantial LULC change) in the same geographic location are not available, we use hydrologic simulation with the process-based Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Neitch et al., 2011) 2008 version to investigate land use impact on stream discharge trends from two forest re-growth watersheds and the consistent forest watershed in the last century. We also test for a trend in the differences of simulated and observed monthly and annual runoff, coincident with the major changes in LULC, can be found. National Elevation Dataset (NED) (http://ned.usgs.gov/) and 1:24,000 stream network data (http://www.cgia.state.nc.us/) are used for watershed and sub-watershed delineation. Each sub-watershed is divided into smaller segments, Hydrologic Response Units (HRUs), by unique LULC and soil combination. In this study, the National Land Cover Data (NLCD) 2006 is used for LULC (http://www.mrlc.gov/nlcd06_data.php) and STATSGO, already embedded in the ArcSWAT interface program, is used for soil data.
The basic meteorological data required for SWAT include daily precipitation, as well as minimum and maximum temperature. This information was downloaded from the National Climate Date Center. Other data, such as net radiation, wind speed, relative humidity, etc. are also required to simulate Penman-Monteith evapotranspiration, but these are produced by the SWAT weather generator. There is one National Weather Service COOP station inside the Flat River watershed (Roxboro COOP station, site number 317516), but it has substantial missing data. Therefore, two other stations near this area (Durham (site number 312515) and Butner (site number 311285) COOP stations) are additionally considered; averaged weather data of these three stations are used as input precipitation and temperatures for SWAT simulation. In the Linville River watershed, weather data are more problematic; COOP stations do not cover the entire watershed spatially and temporally. To compensate for the lack of a consistent record from a station in the watershed, 9 stations around the Linville River watershed area are averaged for SWAT simulations. We tested the effect of averaged precipitation stations to SWAT simulation with the Eno River watershed, i.e. separate and one averaged meteorological stations. The result showed that these two SWAT simulation setting do not show significant difference though SWAT with averaged precipitation stations produced a little higher stream discharge than that of SWAT with separate precipitation stations (result is not presented). The effects of averaging meteorological records among a set of stations, particularly for precipitation, leads us to use monthly, rather than daily model predictions as our basic unit of analysis for long term trends. This is appropriate for water supply evaluation given storage effects of reservoirs.

For SWAT calibration and validation, measured stream discharge data were downloaded from the USGS National Water Information System (http://waterdata.usgs.gov/nwis). Stream flow data are available since 1926 in the Flat River watershed (site number 0208550), 1926 in the Eno River watershed (site number 0208500), and 1922 in the Linville river watersheds (site number
Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992) is applied to calibrate for daily runoff under current land cover and represent uncertainty in the model predictions. GLUE is a Monte Carlo simulation-based method, developed from the Generalized Sensitivity Analysis (GSA) of Spear and Hornberger (1980). The basic concept of GLUE is that there is no one optimal parameter set for a given watershed; other combinations of parameters that simulate observed discharge data could also exist. The GLUE method evaluates sensitivity of each parameter and suggests acceptable parameter value combinations based on likelihood function. The sensitivity of parameters can be explained as “behavioral” and “non-behavioral” by certain criteria for model rejection. SWAT-CUP (SWAT Calibration and Uncertainty Procedures) (http://www.eawag.ch/forschung/siam/software/swat/index) software is used for GLUE application. SWAT-CUP provides various calibration and uncertainty analysis methods, including GLUE, for SWAT.

As the goal of hydrologic simulation for this study is to analyze long term trends in annual stream flow in terms of LULC change, we first calibrate SWAT with up-to-date and accurate land cover data. Behavioral parameter sets for recent time periods are then applied to the entire long term-period, from 1926 to 2009. This simulation keeps historical weather conditions (e.g. precipitation and temperature), but LULC is assumed to be current LULC instead of historical conditions (for which accurate, spatially explicit land cover data is generally not available). Therefore, the resulting simulations may explain what runoff would have been if current forest land cover had been consistent since 1920, instead of the actual historical LULC conversion from agriculture. In addition, the LULC of 1955, estimated from rectified air photos is applied to the Flat River watershed, one of the watersheds where agriculture to forest conversion took place, to simulate long-term stream discharge trends with fixed 1950’s LULC conditions (i.e., more agricultural activity and less forest cover than current LULC).
SWAT simulations in the Flat and the Eno River watersheds were calibrated and validated for two years each at daily time step first to verify the parameter behavior: 1998 - 1999 for calibration and 1996 - 1997 for validation. For the Linville River watershed, the calibration period is 1990 -1991, with 1992 - 1993 used as the validation period because of the precipitation data availability, avoiding the time period with missing data. Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) is applied to stream discharge as a goodness of fit to emphasize peak flows and to logarithmic scale stream discharge to emphasize low flows. NSE is defined as:

\[
NSE = 1 - \frac{\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T}(Q_o^t - \overline{Q_o})^2}
\]  

where \(Q_o\) is observed discharge, \(Q_m\) is modeled discharge, and \(\overline{Q_o}\) is averaged of stream discharge from time \(t = 1\) to \(T\).

2.5 Results

2.5.1 Precipitation and Stream Discharge trends

Figure 2.6 shows annual scale weather and stream discharge trends for past decades in the Flat, the Eno, and the Linville River watersheds. In the Flat and the Eno River watershed, averaged precipitation from the nearest three (for the Flat River watershed) and two (for the Eno River watershed) stations show significant increase since the 1920’s, whereas the Flat River watershed USGS stream discharge has no trend (95% significance level of nonparametric Mann-Kandall and Spearman’s rho tests as well as student’s t test). Stream discharge trend analysis of the Eno River watershed is problematic due to the missing data period from 1972 to 1985 though it generally shows decreasing tend. In detail, precipitation showed a step increase after 1970, consistent with McCabe and Wolock’s (2002) observation at a national level, whereas stream discharge did not
show this trend. Therefore, increasing precipitation input has not induced increasing stream
discharge in the Flat or Eno River watersheds, suggesting increased water consumption, export or
evapotranspiration inside the watershed. In contrast, both stream discharge and precipitation show
the same trend in the Linville River watershed; both have a small increase or no trend at 95%
significance level of nonparametric Mann-Kendall and Spearman’s rho tests as well as student’s t
test. A major difference between these watersheds is LULC; the Flat and the Eno River watershed
experienced significant forest re-growth, whereas the Linville River watershed has maintained a
consistent forest cover. Therefore, these two watershed behaviors suggest that landuse has been
the major driver of watershed response change in these watersheds.
Figure 2.6: Examples precipitation and stream discharge trends of LULC conversion from agricultural to forest area (the Flat and the Eno River watersheds in North Carolina Piedmont) and long term consistent forest area (the Linville River watershed) in North Carolina Mountain (http://waterdata.usgs.gov/nwis; http://climod.srcc.lsu.edu/
2.5.2 SWAT Calibration and validation

Figure 2.7, 2.8, 2.9 and Table 2.3 show calibration and validation results in the two Piedmont watersheds with LULC change and the Linville watershed. The number of simulation realizations for calibration and validation is 2000 each. Out of the 2000 simulations, the best simulated parameter sets are selected using a threshold NSE value of 0.5 for both NSE of stream discharge and logarithmic scale stream discharge for the 95% confidence boundary in simulation results. The stream discharge is transformed from volume (m$^3$/s) to depth (mm) by dividing by each watershed area and adjusting units. In the Flat and the Eno River watersheds, the best fit results tend to underestimate some peak flows and overestimate some low flows in the calibration period. Logarithmic scale plots show that simulated falling limbs and extreme low flows show bias to the observed data for the highest NSE simulation. However, because the amount of this unmatched base flow is small, e.g., 0.004mm/day, these biases seem to be insignificant for monthly to annual water supply calculation. In addition, the observed flow is contained within the 95% confidence limits of simulated flow.
Table 2.3: Daily scale calibration and validation results of three study watersheds by Nash-Sutcliff Efficiency (NSE) of stream discharge (Q). Calibration and validation period are two years each

<table>
<thead>
<tr>
<th>Best result (NSE_Q / NSE_logQ)</th>
<th>Flat River watershed</th>
<th>Eno River watershed</th>
<th>Liville River watershed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>Validation</td>
<td>Calibration</td>
<td>Validation</td>
</tr>
<tr>
<td>0.68 / 0.71</td>
<td>0.86 / 0.63</td>
<td>0.81 / 0.70</td>
<td>0.74 / 0.72</td>
</tr>
<tr>
<td>0.74 / 0.72</td>
<td>0.66 / 0.74</td>
<td>0.66 / 0.78</td>
<td></td>
</tr>
</tbody>
</table>
Figure 2.7: Flat River watershed calibration (left) and validation (right) result in arithmetic scale (upper) and logarithmic scale (lower) in daily scale. The 95% confidence boundary in simulations results is drawn from simulations with a threshold of 0.5 for both NSE of stream and logarithmic scale stream discharge.
Figure 2.8: Eno River watershed calibration (left) and validation (right) result in arithmetic scale (upper) and logarithmic scale (lower) in daily scale. The 95% confidence boundary in simulations results is drawn from simulations with a threshold of 0.5 for both NSE of stream and logarithmic scale stream discharge.
Figure 2.9: Linville River watershed calibration (left) and validation (right) result in arithmetic scale (upper) and logarithmic scale (lower) in daily scale. The 95% confidence boundary in simulations results is drawn from simulations with a threshold of 0.5 for both NSE of stream and logarithmic scale stream discharge.
2.5.3  Water year scale SWAT simulation since 1920

For long-term SWAT simulation, the acceptable daily scale SWAT simulations (with NSE=0.5 as a threshold value in both normal and logarithmic scale of simulated stream discharge during calibration and validation periods) are aggregated to monthly scale. Then these monthly scale results are re-selected with threshold value NSE=0.5, same as daily scale selection, on the monthly scale in 1986–2009 for SWAT application from 1920’s to current in the three watersheds. Table 2.4 shows the best SWAT simulation results at monthly time scales. While additional land use change occurred during this period, most of the forest re-growth in the Flat and the Eno River watersheds had occurred earlier, and each of these have shown only slow development as they are protected as water supply catchments. The long-term SWAT modeling scenarios of the three watersheds (1927-2009 for the Flat and Linville, and 1929-2009 for the Eno) assumes constant 2006 LULC during the whole simulation period, whereas the observed annual hydrograph is produced by gradual LULC conversion from agricultural to forested area during the early through middle part of the 20th century. Simulated results for the Flat and Eno watersheds show a noticeable annual stream discharge under-prediction compared with measured discharge for the first few decades of simulation. Observed runoff during this time is typically above the 95% confidence interval simulated by SWAT. This difference became smaller by mid-1970 and SWAT and measured data seems to agree well thereafter in the Flat River watershed. The Eno River watershed has missing data from 1970-1985 but shows a similar trend with the Flat river watershed, although it appears that early period under-prediction may have closed earlier in the Eno River watershed. The long term water yield in the consistently forested Linville watershed shows a different result. Unlike the Flat and Eno, long-term simulation agrees well with measured data during the entire period without the consistent under-prediction bias in the first few decades. Occasional lack-of-fit in some years may be mainly caused by missing precipitation data. This non-biased SWAT simulation result implies
that the current forest LULC extent is capable of producing acceptable simulations for the full
historical period in the Linville River watershed with stable LULC. Therefore, the discrepancy
between the stream discharge from SWAT simulations and observation for the Flat and the Eno
watersheds can be attributed to LULC change. Also, the results of three study watersheds indicate
that the altered LULC, dominated by forest re-growth, produced progressively less water than prior
LULC under the same meteorological regime.
Table 2.4: Monthly scale SWAT simulation best result of three study watersheds by Nash-Sutcliff Efficiency (NSE) of stream discharge (Q) from 1986 to 2009.

<table>
<thead>
<tr>
<th>Monthly (1986~2009)</th>
<th>Flat River watershed</th>
<th>Eno River watershed</th>
<th>Liville River watershed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best simulation result (NSE_Q and NSE_logQ)</td>
<td>0.75 / 0.74</td>
<td>0.75 / 0.73</td>
<td>0.78 / 0.73</td>
</tr>
</tbody>
</table>
Figure 2.10: Long-term SWAT scenario simulations of the Flat and the Eno river watershed (LULC conversion watersheds), and Linville river watershed (long-term forested watershed) in water year scale. The 95% confidence boundary in simulations results is drawn from simulations with a threshold of 0.5 for both NSE of stream and logarithmic scale stream discharge.
2.5.4 Monthly scale stream discharge residual analysis

Vegetation change causes changes in magnitude and phenology of evapotranspiration, and leads to changed seasonal patterns of stream discharge (Hibbert, 1967). Forest, specifically conifer and mature forest cover, will intercept and transpire at a greater rate and for a longer period than crops of any other vegetation (Swank and Douglas, 1974; Bosch and Hewlett, 1982; Zhang et al., 2001; Stoy et al., 2006). While pasture cover is perennial, it will evapotranspire at lower rates than forests. We expect that forest re-growth from agricultural fields, which manifested as coniferous stands first, would decrease stream discharge by increasing water consumption. Figure 2.11 depicts monthly scale residuals (USGS minus SWAT) in the Flat River watershed from 1926 to 2009. It shows a decreasing trend in most of the seasons. Spring seasons (March - May) show the most significant trends; the slope and $R^2$ are high and the $p$ value is less than 0.001. This implies that agricultural land use may produce more stream discharge than forested area especially in spring. Early growing season stream discharge may differ significantly for forested and agricultural watersheds (Schilling and Libra, 2003). Crop emergence delays the onset of significant evapotranspiration, while broadleaf forests transpire rapidly following leaf out, and conifers show consistent evapotranspiration once temperatures become moderate. By comparison, residual patterns of Linville River watershed do not show a consistent increasing or decreasing trend in residuals (slope -0.22 - 0.10), $R^2$ are low (0.00 - 0.08), and the trend line also does not show significance ($p$-value < 0.9). Since this area does not have a significant LULC change history, any differences seems to be due to random modeling error, commonly found in hydrologic simulation. Therefore, these different behaviors between watershed with forest re-growth and consistently forested watershed in seasonal model residual trends can explain the relationship between historical water yield change and forest re-growth; re-growing forest consumes more water than crops, especially in the early growing season.
Figure 2.11: Flat River watershed monthly scale stream discharge residual (USGS – SWAT, mm/month) patterns in month by month from 1926 to 2009 (*** p < 0.001, ** p < 0.01, * p < 0.05).
Figure 2.12: Linville River watershed monthly scale stream discharge residual (USGS – SWAT, mm/month) patterns in month by month from 1926 to 2009 (*** p < 0.001, ** p < 0.01, * p < 0.05).
2.5.5 SWAT simulation with 1955 LULC

Using the same calibration and validation process as with NLCD 2006-based SWAT simulations, the Flat River watershed was simulated with 1955 LULC derived from aerial photographs. Since LULC in 1955 contained more agricultural and less forested land than 2006 LULC, we expect that SWAT residual bias pattern with 1955 LULC would be different from SWAT residual bias pattern with 2006 LULC. In other words, if the under-predicted bias of SWAT with 2006 LULC in 1927 – mid-1970 is due to the amount of forested land, this bias could be mitigated with SWAT simulation with 1955 LULC.

Figure 2.13 is the result of SWAT simulations for the Flat River watershed with 1955 LULC with NSE of Q = 0.82 and NSE of logQ = 0.81 at monthly time scales as one of the best simulated result. The stream discharge difference between USGS and SWAT with the 1955 LULC shows a different trend compared with the SWAT simulations using the 2006 LULC. The water year scale SWAT with 1955 LULC shows a better fit to USGS measured stream discharge from 1927 to mid-1970’s, whereas simulated stream discharge became significantly higher than USGS measurements after the mid-1990’s. This pattern suggests that 1955 LULC, i.e. less forest and more agriculture/pasture than 2006 LULC, provided more stream discharge than the current LULC with higher forest cover. This simulated result confirm our hypothesis that LULC change, in this case forest re-growth, is a significant influence on long-term stream discharge trends in the North Carolina Piedmont, consistent with the SWAT simulated stream discharge bias with 2006 LULC.
Figure 2.13: The Flat River watershed SWAT simulation using 1955 LULC as a landuse input in water year scale. The 95% confidence boundary in simulations results is drawn from simulations with a threshold of 0.5 for both NSE of stream and logarithmic scale stream discharge.
2.5.6 SWAT simulation differences between 1955 and 2006 LULC

Detailed SWAT simulated hydrologic components analysis explains the differences in hydrologic condition between 1955 and 2006 LULC in the Flat River watershed (Figure 2.14). In SWAT, total water yield (WY) as stream flow from each HRU is the sum of runoff from surface, shallow aquifer, and lateral flow from soil profile, and subtraction of transmission loss from channel bed and pond extraction. The transmission loss was excluded in this water balance analysis because it is so small, less than 1mm a month, and pond extraction was not considered in Flat River watershed SWAT simulation. Figure 2.14 represents hydrological behavior difference between 1955 LULC (i.e., more agriculture and less forest than current LULC) and 2006 LULC (i.e., forest re-growth). The monthly average water yields for 1926-2009 based on 1955 LULC is generally higher than those based on 2006 LULC, and the difference during May – December is higher than that of January - April. More specifically, water yield based on 1955 LULC is mostly composed of surface runoff which has some seasonality—low in summer and high in fall and winter. The amount of groundwater and lateral flows are much smaller than surface runoff in simulation with 1955 LULC. However, the hydrologic components based on 2006 LULC show different trends from those based on 1955 LULC. Both surface runoff and groundwater flow contribute to total WY, and groundwater and lateral flows from 2006 LULC are higher than those from 1955 LULC. It implies that forest re-growth increase groundwater recharge to produce more sub-surface runoff in SWAT algorithm. With 2006 LULC simulation, surface runoff does not show seasonality, but groundwater flow has distinctive seasonal patterns: lower in forest peak growing season (June – October) and higher in non-growing or early growing season (September – May). It seems that groundwater rises during non-growing season because the forest does not consume ground water as it does during growing season and there is significant recharge in this period. It also can explain the residual trends in Figure 2.11. In the residual analysis of watershed with forest re-growth, March – May showed noticeable residual
trends. This matched the season when groundwater flow from forested conditions peak. Therefore, the large amount of surface runoff of more agricultural LULC in 1955 and groundwater seasonality of more forested LULC in 2006 appear to be the major reasons for the stream discharge different in the two historical times.
Figure 2.14: The Flat River watershed SWAT simulated hydrologic components with 2006 and 1995 LULC. Total Water Yield (WY) from Hydrologic Response Unit (HRU) to stream channel = Surface runoff + Groundwater flow from shallow aquifer + Lateral Flow from soil profile – transmission loss from stream bed – reservoir extraction. Transmission loss and reservoir extraction are not considered because these are negligible amount.
2.6 Discussion

SWAT simulations for watersheds in the northern Piedmont of North Carolina experiencing forest re-growth show significant bias in the early decades of simulations assuming constant LULC, and not accounting for forest re-growth. This suggests that if current canopy cover existed through the full time period, this area would have produced less water yield than the actual, i.e., more agricultural, LULC condition. This bias is largely absent by the mid-1970’s, consistent with the approach of watershed conditions to current LULC. As simulated hydrographs are produced by measured historical weather conditions, i.e., precipitation and temperature, it can be assumed that the difference between simulated and measured stream discharge in the Flat and Eno River watersheds is due to the LULC change.

Given the limited availability of long-term LULC history for the study area, we have used USDA agricultural census, 1955 aerial photo classification, and NLCD 2006 classification. Table 2.2 and Figure 2.4 show that 13% of the agricultural/pasture area may be converted to forest since 1955. Since USDA agricultural census data (Figure 2.4) showed more agricultural activity in 1920’s, we can infer that the amount of forest re-growth since the 1920’s could be more than the amount of forest re-growth since 1955. We estimate 17% of Flat River watershed area as forest re-growth with USDA agricultural census data. Trimble et al. (1987) showed that water yield reduction by 4 to 21 % in annual stream discharge was found with a relatively small increase of forest, e.g. 10 - 28% of total watershed area in US Southern Piedmont watersheds. This also supports the hypothesis that the water yield reduction of the Flat and the Eno River watersheds may be due to forest re-growth from abandoned cultivated land.
In order to analyze the change in three month for the purpose of water resources management in forest re-growth watershed, three month moving average monthly stream discharge of the Flat River watershed simulated by SWAT is presented as a cumulative distribution function (CDF). Figure 2.15 shows the CDFs in 1926 – 2009 of 1) USGS stream discharge, which represents stream discharge with historical LULC change by forest re-growth, 2) SWAT with lulc2006, which means simulated stream discharge with the static forest condition of 2006, and 3) SWAT with lulc1955, which implies simulated stream discharge with the static LULC condition as more agricultural land and less forest cover than 2006. SWAT with lulc2006 produces least amount of stream discharge, and SWAT with lulc1955 tends to simulate more stream discharge than SWAT with lulc2006 except extremely high stream discharge. USGS stream discharge tends to take its position between SWAT with lulc 2006 and SWAT with lulc1955 in below average stream discharge (i.e, CDF less than 0.5 level), which implies stream discharge condition by LULC transition from agricultural to forested cover. The high flow statistics, especially extreme high flow (i.e., CDF greater than 0.95 level) seems not to show significant variation between simulated and USGS stream discharge comparing with low flow portion. This result indicates that the effect of forest re-growth on water resources management needs to be more weighted to low flow than high flow period.

Overall results imply that naturally re-growing forest from abandoned agricultural land plays important role in water yield of the North Carolina Piedmont. Also, these result support the idea that stationarity assumption of nature which traditionally used for water resources management and planning seems not to be applicable any more (Milly et al., 2008). Instead of consistency of natural variability, every aspects of dynamic change of LULC should be considered in current and future hydrologic change and water resources studies.
Figure 2.15: Three month average monthly SWAT simulated stream discharge cumulative distribution function in the Flat River watershed in 1926 – 2009.
2.7 Conclusion

The simulations and analysis presented in this paper suggest that the lack of a definitive trend of increasing annual stream discharge of the Flat and the Eno River watersheds in the North Carolina Piedmont may be due to the offsetting impacts of increasing precipitation and forest regrowth. In the past with greater agricultural area, the runoff ratio of this region was higher than that of current forested conditions; less precipitation and more stream discharge in the past, compared with current more precipitation though with similar water yields as the past. This fact is confirmed by SWAT scenario simulations over the past century, which suggests that forested areas produce less water than agricultural areas in Piedmont with drier weather conditions similar to those of the past. As forests re-grow in abandoned agricultural fields, evapotranspiration gradually increases, especially during the vegetation growing season in spring and summer. If increasing vegetation water consumption is combined with less precipitation during the growing season, water shortage problem may be exacerbated. As a result, increasing water consumption by increasing forest water use may contribute to recent trends in hydrologic drought in the North Carolina Piedmont.

However, forest cover is also beneficial to health of watershed and water ecosystem because it reduces flash flood, land slide, and sediment and nutrients discharged to water body (van Dijk et al., 2007). Therefore, water resources management should consider every aspects of dynamic change of LULC, different from traditional statistical methods which assume stationary of nature (Milly et al., 2008).
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Chapter 3: Evaluation and bias correction of NARCCAP nested General Circulation Models (GCMs) and Regional Climate Models (RCMs) precipitation and temperature in North Carolina for hydrologic model application

3.1 Abstract

The aim of this chapter is the evaluation and bias correction of dynamically downscaled climate model information required for watershed simulation in North Carolina. The performance of a set of nested global and regional circulation model (GCM-RCM) results from the North American Regional Climate Change Assessment Program (NARCCAP) is evaluated for bias relative to current measurements in North Carolina. Though there are pattern variations in the five selected NARCCAP models, fall precipitation tends to be significantly less than measured precipitation, and spring and winter precipitation are generally overestimated in NARCCAP. The general trend of NARCCAP temperature error is cold bias. The degree of bias shows inter-model differences, but daily maximum temperature (Tmax) cold bias tends to be maximized in winter season. Monthly scale averaged Tmax shows a 3.5 – 9.6°C range of cold bias which depends on climate models. Tmax cold bias tends to be minimized or even warm biased in summer as much as 5.0°C – 6.6°C in monthly average values, also varying among climate models. Daily minimum temperature (Tmin) also shows cold bias especially in cold season though the magnitude of bias is less than Tmax, and the amount of bias decreases gradually in spring and summer. Simple statistical methods were applied for bias correction so that model output could be more reliably used to simulate both current watershed hydrology and future projected hydrologic behavior. The LOCal Intensity (LOCI) scaling method
(Widmann et al., 2003) was applied to precipitation bias, and Tmax and Tmin biases were corrected by Fourier functions. After applying bias correction methods, NARCCAP climate simulation outputs have significant reduction of seasonal biases in precipitation, Tmax and Tmin except for a few extreme events. Application of raw and bias-corrected NARCCAP to a hydrologic model, the Soil and Water Assessment Tool (SWAT) shows that SWAT with bias-corrected NARCCAP simulated more reliable stream discharge than SWAT with raw NARCCAP simulation. Therefore, though these bias correction methods still show some errors, especially with extreme events, bias corrected data can be more appropriately used for not only current and future climate simulations but also hydrologic model application.

3.2 Introduction

The aim of this chapter is the evaluation and bias correction of dynamically downscaled climate model information required for watershed simulation in North Carolina. The performance of climate models to simulate current climate should be acceptable before using future climate prediction output. Un-biased climate model data is pre-requisite for not only climate change studies but also further applications, such as watershed hydrologic modeling. A set of the nested global and regional circulation model (GCM-RCM) results from the North American Regional Climate Change Assessment Program (NARCCAP) with current time simulations, are selected for model evaluation and bias correction.

General Circulation Models (GCMs) are commonly used for predicting future climate conditions but often have significant shortcomings in their ability to reproduce observed climate conditions especially at the regional to local time scale. Current time simulated climate by GCMs is often significantly biased, and there are inter-model discrepancies in future projected climate by
multiple models (Intergovermental Panel on Climate Change (IPCC), 2007). The Southeast US in particular is an area in which simulated climate information does not agree well with observed climate (Nigam and Ruiz-Barradas 2006). For example, simulated annual precipitation is too large, summertime wetness is much too high, and winter precipitation simulation is dry with some models. One of the possible reasons which make Southeast US challenging area for climate modeling is its geographical location (Sobolowski and Pavelsky, 2012); the climate of this region is affected by the different ocean sources (i.e., Gulf of Mexico and Atlantic Ocean) as well as by mountainous topography (i.e., Appalachian and Blue Ridge Mountains).

There are several reasons why GCMs have problems with simulating current climate and by extension, predicting future climate conditions. GCMs are generally composed of three-dimensional numerical simulations of the atmosphere, ocean and land surface, which are represented by relevant dynamical and physical processes (Noguer et al., 1998; Li et al., 2010). There are inherent errors of GCMs in formulating dynamics of each of these sub-systems and also their interactions (Goddard et al. 2001; Koster et al. 2000).

Modeling results of surface energy balance in GCM tend to be biased. One of the major reasons for this bias is that there are significant uncertainties in land surface parameters about vegetation thermal heterogeneity (Nasonova et al. 2011). For instance, if surface temperature is positively biased, latent heat flux is underestimated (overestimated) in summer (winter), and sensible heat flux is overestimated (underestimated) in summer (winter) (Chen et al. 1997). Soil moisture affects vegetation root-zone available water as well as runoff. Therefore, this may also cause significant modeling problems in the Southeast US with dense vegetation cover.

The complexity of atmosphere-sea-land interactions contributes to model problems in simulating climate phenomenon as well. Parameterizing both atmosphere and ocean are complex
and non-linear (Goddard et al. 2001). Moreover, even though we assume that SSTs could be simulated and predicted perfectly, chaotic atmospheric dynamics and limited land surface simulation can cause significant limits on precipitation simulation (Koster et al. 2000). Another serious problem about the interactions in atmosphere, sea, and land is that these three components have different time scales for mathematical formulation; i.e. a few days of atmosphere, and more than a couple of months or longer of ocean conditions (Goddard et al. 2001). So initializing of each component makes the models much more complex. Overall, the discrepancy between simulations and observations may be due to a number of reasons, such as neglected physical processes in the models, uncertainty about important parameter values, lack of detailed descriptions of the specific conditions, lack of atmospheric forcing data before the year that would allow appropriate spin-up, or the assumption that simulation results with coarse grid resolution, and simplification of the natural heterogeneity of the climate system that exist at finer spatial scales (Chen et al. 1997; Li et al., 2010).

The coarse spatial resolution of GCM does not provide important smaller scale details that may significantly influence regional to local climate. To attempt to solve this problem, higher resolution Regional Climate Models (RCMs) can be embedded within GCMs. This approach uses the GCM to set boundary conditions for the RCM and is referred to as dynamic downscaling (Noguer et al., 1998; Hay and Clark, 2003; Fowler et al., 2007). RCMs have the potential to more realistically simulate regional climate features, like orographic precipitation, extreme climate events and regional scale climate anomalies (Wilby et al., 2000; Fowler, 2007; Wang et al., 2009) but typically cannot be operated for the full globe. Thus this meso-scale, e.g., 50km, regional climate variable can help to produce more plausible climate change scenarios than GCM simulation alone. This nested GCM and RCM approach has been used in a set of projects, such as Prediction of Regional scenarios and Uncertainties for defining European Climate change risks and Effects (PRUDENCE) project,
Ensembles-Based Predictions of Climate Changes and Their Impacts (ENSEMBLES) program and the North American Regional Climate Change Assessment Program (NARCCAP) project (Themeßl et al., 2010).

However, RCMs could add additional error and uncertainty even though the largest sources of modeling uncertainties may be inherited from the driving GCM (Noguer et al., 1998; Fowler et al., 2007; de Elia et al., 2008). In RCM simulations, inadequate representations of local forcing, such as orography, land-sea contrast and vegetation cover, may still bring errors in the finer scale simulations (Noguer et al., 1998; Fowler et al., 2007). For example, overestimated precipitation of RCM may be due to inaccurate parameterizations of large-scale condensation and convection schemes, poor soil parameterizations, lack of moisture advection into the region, or poor simulation of snow-albedo feedback (Fowler et al., 2007). Thus, regional systematic errors can be introduced by RCM physical processes to the GCM framework.

Other GCM downscaling tools are statistical methods which establish empirical relationships between GCM and local climate variables. In the review paper of Fowler et al. (2007), they classified and compared statistical downscaling methods in several groups, including change factors, simple analogue methods, regression models, weather typing schemes, and weather generators. They found that GCM precipitation considerably improved by simple statistical methods, a finding supported by other studies (Zortia and von Storch, 1999; Widmann et al., 2003; Schmidlie et al., 2006). As dynamical downscaling alone has not led to large improvements in bias relative to GCM output alone, a combination of dynamical and statistical approaches has been used to gain an improvement over their use alone (Diez et al., 2005).

Although statistical bias correction methods do not explain the process basis for model bias, key advantages are the lower computation requirements and relatively good skill, at least for
present climate conditions (Wilby et al., 2000; Hay and Clark, 2003; Wilby and Wigley, 2000; Wood et al., 2004; Li et al., 2010). This is one of the reasons why statistical methods are widely used in climate impact related studies. However, the key weakness of statistical methods is the stationarity assumption in statistical models (Li et al., 2010). This weakness can be partially alleviated by specific statistical model application strategies. For example, Salathe (2003) divided time period on the basis of Pacific Decadal Oscillation (PDO) phase change for the scale factor application; 1958~1976 is downscaled with scale factors for data of 1977~1994 and vice versa. In this manner, the statistical model fitting process can reflect the effect of the shifts in the natural climate.

Not only NARCCAP bias correction alone, but also the applicability of NARCCAP to watershed hydrologic model is the goal of this study as well. Therefore, both raw and bias-corrected NARCCAP precipitation and temperature are applied to the Soil and Water Assessment Tool (SWAT) in one of the major water supply basins in the North Carolina Piedmont to compare the effect of raw and bias corrected NARCCAP to hydrologic modeling.

In this study, we pose the following questions:

1) Are systematic biases found in NARCCAP produced GCM-RCM daily precipitation, and maximum and minimum temperature in the North Carolina region?
2) If there are systematic biases, can we apply statistical methods to efficiently correct the biases?
3) Is bias correction of NARCCAP necessary for its application to hydrologic modeling? To what extent can bias corrected NARCCAP output improve hydrologic modeling performance?
3.3 Methods

3.3.1 Evaluation of North American Regional Climate Change Assessment Program (NARCCAP)

GCM-RCM precipitation and temperature

The North American Regional Climate Change Assessment Program (NARCCAP) is an international program to produce high resolution climate change simulations in order to investigate uncertainties in regional scale projections of future climate and generate climate change scenarios for use in impacts research (http://www.narccap.ucar.edu). It provides a set of regional climate models (RCMs) driven by a set of atmosphere-ocean general circulation models (AOGCMs) over a domain covering the conterminous United States, most of the Canada, and northern Mexico. The AOGCMs in NARCCAP have been forced with the Special Report on Emission Scenario (SRES) (IPCC, 2000) A2 emissions scenario for the 21st century. SRES is the green house gas emission scenarios for future climate change. The A2 scenario is a worst-case scenario, in which CO$_2$ emission over 2000-2099 will increase to be 350 – 850 ppm. It is based on an economic storyline with high population growth, regionally oriented economic development, and slow technological change. Simulations with the NARCCAP models were also produced for the current (historical) period. The RCMs are nested within the AOGCMs for 1971-2000 and for a future period 2041-2070.

A major advantage of NARCCAP output is the provision of daily time scale weather data. Since one of the main purposes of climate data evaluation and bias correction in this study is preparing input weather data for hydrologic models which requires daily weather input data, NARCCAP is one of the appropriate data sources for watershed hydrologic simulation.

Since both driving global model (GCM) and regional process (RCM) are the sources of uncertainty (de Elia et al., 2008), the choice of GCM and RCM is important for climate impact on a study area. Because each model has different error sources and performances, a multi-model
approach is also required for climate change and its application to characterize climate model output uncertainty. Therefore, model performance evaluation by comparing simulation and observations are a necessary step before choosing GCM-RCMs. For further application of future climate projections as well as analyzing future climate trends, each GCM-RCM’s ability to simulate the historical climate condition should be evaluated in advance.

In this study, five GCM-RCM combinations, with both current and future time simulations, are selected for the model evaluation:

1. CCSM-CRCM (NCAR Community Climate System Model – Canadian Regional Climate Model),
2. CGCM3-CRCM (Canadian Global Climate Model v.3 – Canadian Regional Climate Model),
3. CGCM3-RCM3 (Canadian Global Climate Model v.3 – Regional Climate Model v.3),
4. GFDL-RCM3 (Geophysical Fluid Dynamics Laboratory GCM – Regional Climate Model v.3)
5. GFDL-ECP2 (Geophysical Fluid Dynamics Laboratory GCM – Experimental Climate Prediction Center).

The 3-hour precipitation and surface air temperature data are extracted and aggregated to daily scale precipitation, maximum and minimum temperature. Measured data used for model evaluation is National Weather Service COOP station data. All measured data within a 50 km GCM-RCM output grid is averaged to a single value to evaluate climate model simulation output.

NARCCAP evaluation and bias correction of the Southeast US is found in Sobolowski and Pavelsky (2012)’s study, which is based on multi-model mean of NARCCAP. They found clear cold bias in temperature, especially winter, spring and fall, and significant precipitation underestimation (overestimation) in western (eastern) part of the Southeast US. They also reduced those biases by applying a performance-based weighting scheme. In this study, we tried to evaluate and bias-
correct the five NARCCAP output each and narrow the study area to North Carolina and its geographical regional divisions. NARCCAP grids are divided by three regions according to the North Carolina geography: mountain, piedmont, and coast. Figure 3.1 is one of the examples of NARCCAP regional climate model boundary, RCM3. The number of grid cells with more than one weather station available is approximately 20 for the Mountain, 25 for the Piedmont, and 30 for the Coastal Plain. For temperature, there are less available weather stations, so the number of grid cells used for NARCCAP-National Weather Service stations comparisons are slightly less than precipitation grids.
Figure 3.1: An example of NARCCP regional climate model boundary, Regional Climate Model version 3 (RCM3), in North Carolina
3.3.2 Bias correction of NARCCAP GCM-RCM precipitation and temperature

The time period of historical NARCCAP output is 1971~2000, or 1971-1999 for CRCM regional climate model outputs. The model bias correction calibration and validation period are simply divided into two 15 year periods. Bias correction methods are calibrated for the uncorrected GCM-RCM output for the first 15 years and validated with the other 15 years. These two 15 year time periods are switched for calibration and validation, i.e. last 15 years for calibration and first 15 years for validation, to check how this random time division scheme affects bias correction results.

Figure 3.2 is monthly observed regional precipitation, mean daily maximum and minimum temperature statistics in North Carolina for two 15 year periods: 1971-1985 and 1986-2000. There are regional differences in temperature. Tmax and Tmin are low in the mountain area and gradually increase in the Piedmont and the Coastal Plain. The mean and inter-quartile range of meteorological data are similar between the two time periods though some extreme precipitation events occurred in 1986-2000 especially in the Piedmont and the Coast. This represents an increase in extreme events, i.e., tropical storm, to the late 1990’s, which may affect precipitation statistical bias correction. Other than these precipitation extremes, the weather characteristics look similar in the two 15 year periods.
Figure 3.2: Monthly scale observed regional precipitation, maximum and minimum temperature statistics in North Carolina for two 15 year periods: 1971-1985 and 1986-2000
3.3.2.1 Precipitation

While many statistical downscaling methods use circulation-based predictors, such as geopotential height, wind and humidity at five pressure levels, various surface flux variables (Hay and Clark, 2003), Widmann et al. (2003) proposed a relatively simple statistical method, Local intensity scaling (LOCI). This is one of the statistical approaches using GCM or RCM precipitation directly as a predictor for precipitation. The key advantages of LOCI are relative simplicity and independence of data distributions (Themeßl et al., 2010). This method is confirmed by Salathe (2003), Schmidli et al. (2006), and Themeßl et al. (2010) as well.

The downscaled or bias corrected daily precipitation series \( \hat{P} \) is calculated as:

\[
\hat{P}(t) = \max (P^0_{WD} + s(P^m(t) - P^m_{WD}), 0) \quad (1)
\]

Where,

\( P^0_{WD} \): Wet-day threshold from the daily observed series, 1mm/day

\( P^m_{WD} \): Wet-day threshold determined from daily climate model precipitation, mm/day

\( P^m(t) \): Climate model precipitation, mm/day

\( s \): Scaling factor

A wet day threshold of climate model \( (P^m_{WD}) \) is determined by the value of the climate model precipitation with a frequency which equals the wet-day frequency in the observed data \( (P^0_{WD}) \). \( P^0_{WD} \) was set to 1mm/day, and \( P^m_{WD} \) was calculated month by month in this study. The number of wet days in observed precipitation series is defined as days in which precipitation
amount is greater or equal than 1mm/day. So $P_{WDT}^m$ is defined as the modeled precipitation value which matches the same number of wet days observed precipitation data.

A scaling factor $s$, the ratio of wet-day intensities between observation and climate model with the wet-day threshold of observation and climate model each, is calculated by:

$$s = \frac{\langle P^o: P^o \geq P_{WDT}^o \rangle - P_{WDT}^o}{\langle P^m: P^m \geq P_{WDT}^m \rangle - P_{WDT}^m}$$  \hspace{1cm} (2)

The angle brackets indicate long-term averages; monthly scale is used in this study for the long-term averages.

This kind of statistical post-processing of RCMs is often not carried out in climatological studies. Due to the concept of perfect prognosis (Wilks, 1995), traditional empirical-statistical downscaling methods, which build the relationship between suitable large-scale observation data and local observations, are often preferred. However, since climate information at the point scale are not always available, empirical-statistical transfer functions are useful to provide applicable climate scenario data for future climate impact studies (Widmann et al., 2003; Schmidli et al., 2006; Themßl et al., 2010).

### 3.3.2.2 Temperature

Temperature residual (i.e., observed - modeled) analysis of NARCCAP outputs show a distinctive seasonal pattern, well explained by a Fourier function. Fourier analysis is a signal processing approach which breaks down a signal into constituent sinusoids of different frequencies:

$$f(x) = a_0 + \sum_{n=1}^{\infty} (a_n \cos(x \cdot w) + b_n \sin(x \cdot w))$$  \hspace{1cm} (3)
where,

\[ a_0, a_n, \text{ and } b_n: \text{ coefficients} \]

\[ x: \text{ time, day of year} \]

\[ w: \text{ frequency} \]

In this study, first we calculate daily scale residuals (i.e. modeled – measured) for calibration period (i.e. 15 years) and average the residuals by Day of Year (i.e. 365 days a year). We then calibrate the Fourier function for each NARCCAP grid by daily scale, and then add estimated residual temperature for Day of Year to the original modeled data. To evaluate these Fourier transformed temperatures, daily scale raw NARCCAP output and Fourier transformed data are averaged to monthly scale Tmax and Tmin temperature, and are compared by cumulative distribution function. The Fourier analysis has also been applied to a NARCCAP precipitation study in the region where the seasonal cycling pattern is prominent (Wang et al., 2009).

3.3.3 Raw and bias-corrected NARCCAP GCM-RCM precipitation and temperature application to SWAT modeling

Both NARCCAP bias correction alone and the applicability of NARCCAP to watershed hydrologic model is the goal of this study. Therefore, both raw and bias-corrected NARCCAP daily precipitation and temperature are applied to the process-based Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Neitch et al., 2011) in the Haw River basin (Figure 3.3), one of the major water supply basins in the North Carolina Piedmont, to compare the effect of raw and bias-corrected NARCCAP to hydrologic modeling. The Haw River basin is calibrated for 1998-1999 and validated for 2000-2001 at the daily time scale. This four year period includes the highest, average, and lowest
water yield years on record. Using the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992) in SWAT-CUP4 software (Abbaspour, 2011), 2000 realizations of parameter combinations are used, and the best results are chosen and presented at the monthly time scale. For goodness of fit, Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) is applied to stream discharge to emphasize peak flows and to logarithmic scale stream discharge to emphasize low flows.
Figure 3.3: Haw River basin in North Carolina Piedmont, the study watershed which is simulated by hydrologic model, SWAT, with raw and bias-corrected NARCCAP
3.4 Results

3.4.1 Evaluating NARCCAP output

To present a comparison between measured and NARCCAP data, daily scale precipitation is aggregated to monthly scale precipitation, mm/month, and daily maximum and minimum temperatures are averaged to monthly scale. Monthly averages are then aggregated to each geographical region.

3.4.1.1 Precipitation

Generally, precipitation agreement between modeled and observed is noticeably poorer than temperature agreement, especially in warmer and wetter climate condition (Christensen et al., 2008). Since North Carolina is a relatively warm and wet area, this area may show significant precipitation bias with climate model simulation.

Though there are pattern variations in NARCCAP models, Figure 3.3 shows that simulated fall precipitation in all regions and late summer precipitation in Coastal Plain are significantly less than measured precipitation, and spring and winter precipitation are generally overestimated in NARCCAP. The geographical differences of precipitation seem not to be reflected in NARCCAP results well; NARCCAP outputs show consistent monthly patterns in all areas though measured precipitation shows some differences. For example, measured cold season precipitation is a little higher in the Mountains than the Piedmont and the Coast, and high fall season precipitation appears only in the coast. It appears that NARCCAP does not capture high precipitation in fall and late summer, which can be caused by tropical cyclones.
### 3.4.1.2 Daily maximum and minimum temperature (Tmax and Tmin)

The general trend of NARCCAP temperature error is cold bias (Figure 3.3). The degree of bias shows inter-model differences, but Tmax cold bias tends to be maximized in winter season, with a range of 3.5 – 9.6°C in monthly average, and minimized in summer or even warm biased with two CRCMs, by 5.0°C – 6.6°C in monthly scale averaged value, which depends on climate models. This underestimated temperature pattern is also found in other studies (Noguer et al., 1998; Hay and Clark, 2003; Randall et al., 2007), and winter temperature is known to be relatively straightforward to correct (Fowler et al., 2007). It might be explained by the circulation error and tropospheric cold bias. Tropospheric cold bias in GCMs is common and a main factor in atmospheric circulation systematic errors (Noguer et al., 1998). Thus, in GCM simulation, the Jet Stream tends to be shifted southward and the Subtropical Jet is weakened, which can bring winter season cold bias in the US Southeast.

Two GFDL driven regional climate models show the largest bias in Tmax. GFDL-EPC2 and GFDL-RCME have the maximum of 9.6°C and 9.5°C cold bias each in February of the mountain area. CRCM is the only regional climate model which has a noticeable warm bias in warm season; August CCSM-CRCM shows maximum warm bias by 6.6°C in Piedmont and coastal area. Tmin also shows cold bias especially in cold season though the magnitude of bias is less than Tmax, and the amount of bias decreases gradually in spring and summer (Figure 3.3). Two CGCM3 driven regional climate models show the least bias, closer to the observed value.

In terms of geographical differences, there is no different bias pattern found in Tmax and Tmin except degree of value; both Tmax and Tmin biases of NARCCAPs are the greatest in the Mountains, decrease in the Piedmont, and least in Coastal Plain. So it seems that NARCCAP basically reflects the geographical differences.
Figure 3.3: Raw NARCCAP monthly scale averaged (a) precipitation, (b) maximum, and (c) minimum daily temperature for 1971~1999 in the Mountain, Piedmont, and Coast of North Carolina
3.4.2 NARCCAP bias correction: Calibration and Validation

3.4.2.1 Precipitation

For precipitation bias correction, two parameters of Equation (1), $P^m_{\text{WDT}}$ and s, need to be calculated. Analyzing the patterns of these two parameters also can show more detailed diagnosis of NARCCAP bias patterns showed in Figure 3.3.

Figure 3.4 shows five NARCCAP precipitation monthly scale wet day threshold for 1) two time periods for calibration and validation, 1971~1985 (upper) and 1986~2000 (lower), and 2) geographical regions. Though there are inter-model differences in bias pattern and magnitude, the general trend is that the wet-day threshold value of NARCCAP is greater than 1mm/day, the wet day threshold in observed precipitation, except September. This means that there are more wet-days (i.e. days with precipitation > 1mm/day) in NARCCAP than measured data in both calibration time periods. The wet-day bias peaks in March through June, is lowest in September, and increases again in November and December in all five NARCCAP simulations. A noticeable difference between the two time periods is a sudden drop in May with the 1971-1985 period, whereas the 1986-2000 period shows a bias peak in May. This implies that wet days (i.e. days with precipitation > 1mm/day) of May are more overestimated in 1986-2000 than 1971-1895 period. NARCCAP wet day frequency of September and August was close to observed wet days and is the least biased value. Geographical differences are found in some of the NARCCAPs; for example, the Mountain area has a little less wet-day threshold than other regions especially with CGCM3-CRCM and GFDL-ECP2 in both periods, and RCM3s in spring. This means that wet days tend to be less biased in the Mountain than the Piedmont and Coastal plain.
Figure 3.4: Five NARCCAP precipitation monthly scale “wet day threshold” for 1) two time periods for calibration and validation, 1971~1985 (upper) and 1986~2000 (lower), and 2) geographical region

Figure 3.5: Five NARCCAP precipitation monthly scale “scaling factor” for 1) two time periods for calibration and validation, 1971~1985 (upper) and 1986~2000 (lower), and 2) geographical regions
Another precipitation bias parameter, the scaling factor \( s \), which is the ratio between averaged value of observed and modeled average precipitation greater or equal to wet-day thresholds. In Figure 3.5, the scaling factor generally is greater than 1 especially from August to October; this means that the amount of modeled precipitation in late summer and fall is underestimated and needs to be amplified by the scale factor. Peak values approach 4 – 5, suggesting large bias in raw NARCCAP precipitation amounts. In terms of regional differences, there are no significant pattern differences in the Mountain, Piedmont and Coastal areas except in 1986 – 2000 period; the mountain area has the least bias and coastal area has a little higher scaling factor. This may be related with increasing precipitation intensity by a recent increase in tropical cyclone frequency trend in the coastal zone, and some of the NARCCAPs do not simulate these extreme events.

Figure 3. 6 is the seasonal precipitation CDF of measured, raw, and two LOCI biased corrected NARCCAP products for the NARCCAP historical data (1971 – 1999) by geographical regions. “Corrected 1” is the bias corrected result of 1971–1999 by the 1971–1985 period calibration and “Corrected 2” is by the 1986–2000. Both Corrected 1 and 2 generally show reduced bias in all seasons and areas except a few extreme events of certain kind of NARCCAPs. For example, the Mountain area winter extreme of GFDL-RCM3 appeared not to be corrected, and the Piedmont and the Coast spring extreme were exaggerated in Corrected 1. Fall extremes also tended to be exaggerated in Corrected 1 and 2 especially in the Mountain and Piedmont. This may be because some of the extreme events are over amplified by scaling factor, \( s \). Therefore, LOCI method has weakness for bias correction of extreme precipitation events.
Figure 3.6: Seasonal precipitation CDF of monthly scale averaged precipitation bias correction by 1971-1985 calibration (Corrected 1) and 1986-2000 calibration (Corrected 2) in 1971-1999
3.4.2.2 Daily maximum temperature (T$_\text{max}$) and Minimum temperature (T$_\text{min}$)

A basic aim of this statistical bias correction is to make the correction equation as simple as possible to avoid overfitting. Using AIC, R$^2$, RMSE, and 95% confidence values of chosen parameters as references, second order Fourier equation for daily T$_\text{max}$, and third order Fourier equations for daily T$_\text{min}$ were selected for residual fitting.

Figure 3.7 shows five NARCCAP T$_\text{max}$ and T$_\text{min}$ residual curve fitting by Fourier transformation, averaged over 15 years (1985-2000) by day of year. Since the temperature residual is defined by observed minus NARCCAP, positive value of residual means underestimated temperature in NARCCAP. T$_\text{max}$ show larger model residuals than T$_\text{min}$. NARCCAP temperatures also show seasonal pattern of cold and sometimes warm biases, and the bias pattern is more distinctive in T$_\text{max}$ than in T$_\text{min}$; R$^2$ is generally higher with T$_\text{max}$ than T$_\text{min}$ (Table 3.1 and 3.2). T$_\text{max}$ tends to have larger cold bias in cold season and lower cold bias in warm season, which shows sinusoidal pattern of T$_\text{max}$ residual curve fitting. Though the sinusoidal patterns are similar in five NARCCAP analyses, the residual magnitude and values are somewhat different in the models. The magnitude of cold bias in T$_\text{max}$ is the highest in GFDL driven regional climate models (GFDL-RCM3 and GFDL-ECP2), and two CRCM regional climate models have cold bias in cold season and even warm bias in summer. CCSM-CRCM has the most distinctive bias pattern, i.e. high R$^2$ out of five NARCCAPs in all geographical regions (Table 3.1). In T$_\text{min}$, two GFDL driven regional climate models show more consistent bias pattern (Table 3.2) and also tends to have cold bias in the cold season with decreasing cold bias in the warm season (Figure 3.7). Two RCM3 models (CCSM-RCM3 and CGCM3-RCM3) have close to 0.0 residuals in summer, while two GFDL driven regional climate model have warm bias in summer (Figure 3.7). These consistent bias patterns with each GCM or RCM group show consistent patterns of temperature bias sources for each GCM and RCM.
### Table 3.5: Daily maximum temperature (Tmax) second order Fourier transformation results, $R^2$

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<tr>
<td>CCSM-CRCM</td>
<td>0.81</td>
<td>0.81</td>
<td>0.80</td>
<td>0.82</td>
<td>0.79</td>
<td>0.81</td>
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<td>CGCM3-CRCM</td>
<td>0.56</td>
<td>0.74</td>
<td>0.57</td>
<td>0.76</td>
<td>0.55</td>
<td>0.73</td>
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<tr>
<td>CGCM3-RCM3</td>
<td>0.42</td>
<td>0.59</td>
<td>0.41</td>
<td>0.61</td>
<td>0.31</td>
<td>0.52</td>
</tr>
<tr>
<td>GFDL-RCM3</td>
<td>0.66</td>
<td>0.70</td>
<td>0.62</td>
<td>0.72</td>
<td>0.54</td>
<td>0.59</td>
</tr>
<tr>
<td>GFDL-ECP2</td>
<td>0.69</td>
<td>0.76</td>
<td>0.70</td>
<td>0.75</td>
<td>0.49</td>
<td>0.58</td>
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### Table 3.6: Daily minimum temperature (Tmin) third order Fourier transformation results, $R^2$

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<tr>
<td>CCSM-CRCM</td>
<td>0.32</td>
<td>0.42</td>
<td>0.26</td>
<td>0.28</td>
<td>0.22</td>
<td>0.25</td>
</tr>
<tr>
<td>CGCM3-CRCM</td>
<td>0.19</td>
<td>0.34</td>
<td>0.21</td>
<td>0.19</td>
<td>0.18</td>
<td>0.12</td>
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<tr>
<td>CGCM3-RCM3</td>
<td>0.18</td>
<td>0.50</td>
<td>0.19</td>
<td>0.41</td>
<td>0.18</td>
<td>0.33</td>
</tr>
<tr>
<td>GFDL-RCM3</td>
<td>0.60</td>
<td>0.71</td>
<td>0.54</td>
<td>0.68</td>
<td>0.44</td>
<td>0.55</td>
</tr>
<tr>
<td>GFDL-ECP2</td>
<td>0.52</td>
<td>0.68</td>
<td>0.46</td>
<td>0.64</td>
<td>0.37</td>
<td>0.61</td>
</tr>
</tbody>
</table>
Figure 3.7: Daily scale residual fitting by Fourier second order in Tmax (left) and Fourier third order Tmin (right) Fourier transformation curve fitting (1986 – 2000 averaged value)
The residual curves in Figure 3.7 show that there are also bias pattern differences in each geographical region. The Mountain region tends to have the highest Tmax cold bias value followed by the Piedmont and the Coast. Some exceptions are found in GFDL-ECP2; it shows similar bias pattern in the Mountain and the Piedmont, but distinctive patterns in the Coast. In Tmax, Mountain area residual curves show more fluctuation than the other two areas; it shows the highest cold bias in cold season and the highest warm bias in summer.

Bias correction significantly improved the fit of simulated and observed Tmax and Tmin. Figure 3.8 is CDF of monthly scale averaged Tmax bias correction by 1971-1985 calibration (Corrected 1) and 1986-2000 calibration (Corrected 2) in 1971-1999 time period. These two 15 year calibrations generally seem to show similar bias corrected results in CDF. In winter (DJF), biases are generally corrected, but extremely high temperature was found in both Tmax and Tmin with bias corrected GFDL-ECP2. Summer (JJA) seemed to be the most challenging season with Tmax; after bias correction, some cold bias still remained below 0.5 CDF of the temperature distribution and a little warm bias was found in more than 0.95 CDF temperature, maximum of 3.6 °C difference each. This after-bias-correction biases tends to be less in Corrected 2 than Corrected 1. Daily minimum temperature (Tmin) shows lower residuals than Tmax, but Tmin bias correction produced values similar to the observed Tmin (Figure 3.9). Tmin also showed a similar problem with exaggerated winter extreme temperature in GFDL-ECP2 as well. Comparing CDFs of Corrected 1 and Corrected 2, the two calibration periods performed similarly in temperature bias correction.

Figure 3.10 is the overall bias correction results of precipitation, Tmax, and Tmin in North Carolina geographical regions in month by month average. Since the two calibration periods performed similarly in bias correction according to ANOVA test, 1985-2000 period calibration methods were applied for presenting the bias correction results in overall historical period, 1971-
2000. Comparing Figure 3.10 with uncorrected NARCCAP data in Figure 3.3, the simple bias correction method seems to significantly reduce NARCCAP model errors.
Figure 3.8: Seasonal precipitation CDF of monthly scale averaged Tmax bias correction by 1971-1985 calibration (Corrected 1) and 1986-2000 calibration (Corrected 2) in 1971-1999
Figure 3.9: Seasonal precipitation CDF of monthly scale averaged Tmin bias correction by 1971-1985 calibration (Corrected 1) and 1986-2000 calibration (Corrected 2) in 1971-1999
Figure 3.10: Monthly by month averaged bias corrected NARCCAP by 1986-2000 calibration. Monthly precipitation sum and monthly averaged temperatures (Tmax and Tmin) were averaged for 1971-1999
3.4.3 NARCCAP application to a hydrologic modeling

For comparison of raw and bias corrected NARCCAP applicability to hydrologic modeling, the Haw River basin is calibrated for 1998-1999 and validated for 2000-2001 at the daily time scale with National Weather Service COOP station precipitation and temperature as a reference simulation. This four year period includes the highest, average, and lowest water yield years on record.

Figure 3.11 is one of the best calibration results, which monthly NSE (NSE_Q) is 0.88 and logarithmic scale stream discharge of NSE (NSE_logQ) is 0.73 from 1974 to 2000 (Figure 3.11). Figure 3.12 is monthly average SWAT simulated and measured stream discharge in the historical time period (1974 – 2000) in the Haw River basin. When applying raw NARCCAP to past time data to SWAT, the simulated stream discharge shows seasonal bias comparing with both SWAT with National Weather Service COOP stations data (black bold line) and USGS stream discharge (gray dashed line). Except for CCSM-CRCM, which underestimated stream discharge in all seasons, the other four NARCCAP generated stream discharge tended to be overestimated in winter and spring, and underestimated in late summer and fall. SWAT simulation with biased-corrected NARCCAP, however, decreased seasonal biases. This reinforces the need for climate model output to be evaluated and bias corrected before being applied to hydrologic models.
Figure 3.11: Haw River basin SWAT calibration result in monthly scale

Figure 3.12: Haw River basin SWAT simulation with raw NARCCAP (left) and bias corrected NARCCAP (right)
3.5 Discussion

One of the major purposes of this study is preparation of climate model precipitation and temperature for watershed hydrologic modeling. SWAT requires daily scale weather input, and NARCCAP is an appropriate climate model product for SWAT application by aggregating and extracting in daily time scale. The basic requirement for GCM application for hydrological study should be the GCM’s capability of reproducing historical observed condition (Wood et al., 2004). Therefore, NARCCAP output performance to hydrologic model simulation for the current time can be evaluated by applying raw and bias-corrected NARCCAP daily precipitation, maximum and minimum temperature to the historical time period (1971-2000).

Figure 3.13 shows the separate and synergistic effects of raw NARCCAP precipitation and temperature to SWAT simulation in the Haw River basin, located in the North Carolina Piedmont. For example, Figure 3.13 (b) shows only raw NARCCAP temperature effect to SWAT simulation by applying raw NARCCAP temperature and NWS COOP precipitation. In the same way, Figure 3.13 (c) shows only raw NARCCAP precipitation effect to SWAT simulation. Figure 3.13 (a) shows a synergistic effect of both precipitation and temperature of raw NARCCAP to SWAT simulation. The bias patterns of raw NARCCAP seem to be reflected in SWAT simulated stream discharge according to Figure 3.13. The raw NARCCAP precipitation alone applied SWAT result (Figure 3.13 (c)) basically seems to follow the precipitation seasonal bias pattern of the North Carolina Piedmont in Figure 3.3, especially fall underestimation and winter overestimation. Though the amount of stream discharge bias by raw NARCCAP temperature is small (Figure 3.13 (b), some models, i.e. CCSM-CRCM and GFDL-ECP2, noticeably reflect temperature bias patterns. According to the five NARCCAP temperature evaluation result (Figure 3.3), CCSM-CRCM Tmax shows least amount of cold bias and even warm biased in warm season. Besides, it is the only model which shows warm bias through a year in Tmin, especially from January to October by up to 2.3°C (in April) in five selected NARCCAPs.
This warm biased temperature could lead to simulate higher evapotranspiration (ET) than SWAT with other climate models to produce low stream discharge. GFDL-ECP2 Tmax and Tmin show the largest amount of cold bias in five NARCCP, especially from January to June. On the contrary to SWAT with CCSM-CRCM temperature, GFDL-ECP2 cold bias simulates less ET and makes stream discharge higher than SWAT with reference and other climate models. Both raw NARCCAP precipitation and temperature applied SWAT results (Figure 3.13 (a)) indicate that though the amount of stream discharge bias by temperature is small, temperature bias effect seems to affect SWAT stream discharge simulation by a little exaggerating over or under prediction of stream discharge. Therefore, though SWAT simulated stream discharge basically depends on precipitation bias pattern, temperature bias pattern also combined to result seasonal biases of NARCCAP produces higher or lower stream discharge compared to measured weather data by SWAT simulation. These results emphasize that both climate model produced temperature and precipitation need to be bias corrected for better performance of watershed hydrologic modeling.

Limitations of bias correction also seem to effect on hydrologic modeling results. SWAT simulation with bias-corrected NARCCAP in Figure 3.12 still shows some remained bias patterns, i.e. stream discharge underestimation in May – July and overestimation in October, though hydrologic modeling performance is significantly improved. These remained biases in stream discharge also seem to reflect errors which still exist in bias-corrected NARCCAP, especially precipitation. Figure 3.10 shows that bias-corrected NARCCAP precipitation tend to a little underestimate May and June precipitation and overestimate September and October precipitation in the North Carolina Piedmont. Therefore, some caveats are still required in interpreting hydrologic modeling result with climate model application.
Figure 3.13: Haw River basin SWAT simulated monthly average stream discharge with both National Weather Service (NWS) COOP stations and raw and bias-corrected NARCCAP in 1974 – 1999: (a) SWAT with raw NARCCAP precipitation and temperature, (b) SWAT with NWS COOP precipitation and raw NARCCAP temperature, and (c) SWAT with raw NARCCAP precipitation and NWS COOP temperature.
3.6 Conclusion

As there are strong demands for predicting future climate conditions and concerns for use of future climate projections in areas such as water resources change, future climate model simulation is a required and useful tool despite the presence of predictive uncertainty and bias. Therefore, we need to focus on how we can make climate model output more useful by evaluating model simulation performance and reducing model bias.

Though there are pattern variations in NARCCAP models, precipitation of the five selected NARCCAP climate models tend to be slightly underestimated in fall and generally overestimated in spring and winter. The general trend of NARCCAP temperature error is cold bias though the degree of bias shows inter-model differences. Daily maximum temperature (Tmax) cold bias tends to be maximized in winter season; monthly scale averaged Tmax shows 3.5 – 9.6°C range of cold bias which depends on climate models. Tmax cold bias tends to be minimized or even warm biased in summer as much as 5.0°C – 6.6°C in monthly scale averaged value which is also determined by climate models. The bias pattern of daily minimum temperature (Tmin) is similar with Tmax, but the magnitude of bias is less than Tmax cold bias. The amount of Tmin bias decreases in the warm season, and a few models show close to measured value.

Usually both dynamical and statistical methods have lower skill in simulating precipitation than temperature (Wilby et al., 2000), and this was also found in this study. After applying bias correction methods, NARCCAP climate simulation outputs have significant reduction of seasonal biases in precipitation, and daily minimum and maximum temperature. This study shows the potential of significantly reducing bias with simple empirical-statistical bias correction methods, LOCal Intensity scaling (LOCI), for precipitation, and signal analysis, Fourier analysis, for temperature. Though these methods still show weaknesses especially with extreme events, the bias
corrected data can be more reliable as scenario weather data for future climate prediction. SWAT simulations with both bias-uncorrected and corrected NARCCAP shows that SWAT with bias-uncorrected NARCCAP produced seasonally biased stream discharge. However, this bias pattern in simulated stream discharge is significantly reduced in SWAT with bias-corrected NARCCP. Therefore, the simple bias correction methods for climate model output do significantly improve watershed hydrologic model simulations, justifying the evaluation and bias correction methods.
References


Chapter 4: Simulation of future water yield under the condition of changing CO₂, climate and landuse/landcover (LULC) in the North Carolina Piedmont

4.1 Abstract

This study focuses on future water yield change sensitivity to the individual effects and interaction of increasing carbon dioxide (CO₂), projected climate and Landuse/Landcover (LULC) variability in the North Carolina Piedmont. Increasing CO₂ from 330 to 600 ppm, bias corrected future climate scenarios from the North American Regional Climate Change Assessment Program (NARCCAP) and projected LULC by Spatially Explicit Regional Growth Model (SERGoM) (Theobald, 2005) from the spatial allocation model of Integrated Climate and Land Use Scenarios (ICLUS) by EPA are used to parameterize a hydrologic model, the Soil and Water Assessment Tool (SWAT). In the North Carolina Piedmont, NARCCAP scenarios simulate future precipitation to be similar or have a small increase with a temperature increasing by 1 – 5°C in 2041 – 2070. ICLUS projections suggest some watersheds of the North Carolina Piedmont would have a twofold increase in urban land compared to current landcover. Water yield change sensitivity in the future was assessed by deconvolving as well as finding the synergistic effects of increasing CO₂, warmer and more urbanized conditions. Under future climate condition evapotranspiration (ET) is projected to increase noticeably especially in winter and spring while water yield (WY) would show various changing patterns, with greater dependence on projected CO₂ and precipitation. When only future climate scenario (no change in LULC) was included, the highest WY was produced by combining increasing CO₂ and future precipitation while future temperature alone produced the lowest WY. When
projected LULC is applied, future urban growth may cause decreased ET and increased WY because of the imperviousness increment. However, interaction between climate and LULC change can mitigate these effects. Most of the simulation scenarios projected WY similar or a slightly lower than current WY on an annual basis due to the offsetting effects of increasing temperature and urbanization. Therefore, consideration of individual factors may be misleading, and it is necessary to incorporate interactions of all factors, CO₂, climate and LULC change, to simulate future water availability in the North Carolina Piedmont.

4.2 Introduction

Future water availability is an important concern for human society as well as ecosystems. Many studies have developed hydrologic change scenarios by future environments characterized by climate warming, increased carbon dioxide (CO₂) level, adjustment of ecosystem canopies, and more urban development (Band et al., 1996; Jha et al., 2006; Johnson et al., 2011; Wu et al., 2012). In this study, future water yield changes are projected by a set of hydrologic modeling scenarios with separate and synergistic effect of modeled CO₂ increase, climate change and Landuse/Landcover (LULC) change.

General Circulation Models (GCMs) are commonly used for predicting future climate conditions. Though GCMs were not originally designed for the assessment of watershed hydrological response to climate change, they have become widely used for future water related study (Wilby et al., 2000; Xu, 1999). There are many examples of hydrological climate change impact studies with climate model outputs; applying raw GCM output directly (Hejazi and Moglen, 2008), dynamically downscaled GCM output (Wood et al., 2004; Graham et al., 2007a, b), bias-corrected dynamically downscaled output (Wood et al., 2004; Fowler and Kilsby, 2007; Fowler et al., 2007), and simple
statistical approaches such as multiple regression relationships (Evans and Schreider, 2002). Combining Regional Climate Models (RCMs) with GCMs have considerably reduced some of the bias of GCMs, but RCMs still typically show systematic errors (e.g. Frei et al., 2003; Hagemann et al., 2004; Suklitsch et al., 2008, 2010). As daily precipitation highly depends on model resolution and parameterization, raw RCM precipitation usually cannot be applied directly in future climate impact studies (Fowler et al., 2007; ThemeBl et al., 2010). This is a reason why the bias evaluation and correction need to be developed before applying climate model output to hydrologic simulation. Bias correction methods developed for current NARCCAP output are applied to future climate as well. The key weakness of this method is that we assume the same bias pattern in historical (1971 – 2000) and future (2041 – 2070) time periods.

A number of LULC change models have been developed for projecting future change (Veldkamp and Lambin, 2001). The Integrated Climate and Land-Use Scenarios (ICLUS) project is one of the projected landuse/landcover change models output focused on urban growth (U.S. Environmental Protection Agency, 2009). This is based on the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) development storylines (A1, A2, B1, and B2), a demographic model for population change, and the Spatially Explicit Regional Growth Model (SERGoM) (Theobald, 2005) for the spatial allocation of population. The future land-use model results are provided in a GIS grid format with 1ha spatial resolution and from 2010 to 2100 with decadal temporal resolution. This is basically an urban expansion model with population growth and transportation infrastructure as land-use change drivers. The uniqueness of SERGoM which makes it different from other existing urban growth models as it considers comprehensive land-use change and housing density patterns from urban to rural. However, since it only focuses on urban related LULC, other types of landcover change, such as vegetation transition, is not included in its mechanism.
Another factor which needs to be considered for future hydrologic change simulations in the North Carolina Piedmont is the dynamics of forest characteristics. Most urban hydrologic studies tend to include lawn as urban land cover but do not consider forest as urban ecosystem. However, a significant amount of area in North Carolina is covered by forest even in urban area; most of the low density urban area in North Carolina Piedmont has a considerable amount of forest, and it may play important role in urban hydrology. As an example, climate warming would affect forest development change by extended growing season (Menszel et al., 2006; Dragoni and Rahman, 2012; Gunderson et al, 2010). Increasing CO$_2$ levels can also affect the physiological response of forest, such as stomatal conductance and Leaf Area Index (LAI) (Schafer et al, 2002; Warren et al., 2011). These forest changes in physiology and phenology would impact evapotranspiration (ET), a significant amount of water consumption in North Carolina, and consequent Water Yield (WY) change. Therefore, forest characteristics, including urban forest, must be carefully considered for projected water yield change both under climate and urban development in the North Carolina Piedmont.

Specific scientific questions are;

1) How will evapotranspiration (ET) and water yield (WY) be affected by future CO$_2$ level and climate scenarios which generally include temperature increases and stable or moderate increases in precipitation?

2) How will water balance, especially ET and WY be altered under the synergistic condition of projected CO$_2$, climate and LULC change?
4.3 Study area

Figure 4.1 shows four study watersheds in the North Carolina Piedmont. One of the significant aspects of the chosen watersheds is the past century’s development history and future development potential. Between 2000 and 2010 the North Carolina population increased by 18.5% (2010 US Census, 2010). In the Triangle area, Wake County (Raleigh-Cary area) experienced 41.8% increase between 2000 and 2010, the 4th fastest-growing county in the US. Other Triangle (Orange, Durham, and Wake counties) and Triad (Guilford and Forsyth counties) regions of North Carolina Piedmont experienced unprecedented population growth rates of from 10% to 25% (2010 US Census). This rate of population growth leads to land use development which can have important effects on local water bodies by adding new impervious area and creating additional water demand. This historical population growth also indicates high future urban growth potential in the Piedmont area. The set of watersheds in the Triangle regions show a significant range of projected urban expansion by SERGoM output, making them appropriate for hydrologic simulation by LULC change application (Figure 4.2 and Table 4.2).
Figure 4.1: Four study watersheds in the North Carolina Piedmont with NCAR Community Climate System Model (CRCM) grid points from North American Regional Climate Change Assessment Program (NARCCAP)
Figure 4.2: Projected LULC change by ICLUS SERGoM of two Piedmont basins (Haw and Neuse River, top) and (a) the Eno River, (b) the New Hope Creek, and (c) the Crabtree Creek watersheds
The study watersheds are used for

1) climate change scenario application alone,

2) LULC change scenario application alone, and

3) both climate and LULC change scenario together

The Haw River basin is useful for estimating climate change impact from multiple projected scenarios because the drainage area is largely unregulated, i.e. no major impoundments, and large (3,300 Km$^2$) enough to be covered by 5 – 6 grids points of the NARCCAP output. Another important point is that it is one of the major water resources watersheds located in the North Carolina Piedmont area; runoff from this area drains into Jordan Lake, a 56 km$^2$ multiuse impoundment. Therefore, water availability of Jordan Lake is significantly affected by hydrologic change of Haw River basin.

For projected LULC simulation, three watersheds in the North Carolina Piedmont are selected for different degrees of future urban growth. According to ICLUS SERGoM results (Table 4.2), the Eno River watershed is not likely to show much development whereas the New Hope Creek watershed and Crabtree Creek watershed are projected to increase urban area by one and half and two times each. Therefore, hydrologic simulation of these three watersheds with future LULC can show the range of projected water yield change in North Carolina Piedmont.

Current LULC condition by NLCD 2006 (Table 4.1) shows that four study watersheds have different areas of urban and vegetation cover as well. In the Haw and Eno River watersheds, 50% of the area is forest, 25% is pasture, and 20% is urban area. New Hope and Crabtree Creek watersheds have more urban and less vegetation cover than the Haw River basin: urban is 40% and 64%, and forest cover is 45% and 28% in New Hope and Crabtree Creek watershed each.
Table 4.1: Landuse/Landcover (LULC) of three study watersheds in current time by NLCD 2006 (%)

<table>
<thead>
<tr>
<th>Landuse</th>
<th>Haw River</th>
<th>Eno River</th>
<th>New Hope Creek</th>
<th>Crabtree Creek</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1.4</td>
<td>1.3</td>
<td>0.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Residential-Low Density</td>
<td>9.4</td>
<td>8.5</td>
<td>24.5</td>
<td>33.8</td>
</tr>
<tr>
<td>Residential-Medium Density</td>
<td>5.9</td>
<td>2.2</td>
<td>10.1</td>
<td>17.5</td>
</tr>
<tr>
<td>Residential-High Density</td>
<td>1.0</td>
<td>0.3</td>
<td>1.1</td>
<td>2.5</td>
</tr>
<tr>
<td>Commercial</td>
<td>2.1</td>
<td>0.9</td>
<td>4.8</td>
<td>10.3</td>
</tr>
<tr>
<td>Forest-Deciduous</td>
<td>35.3</td>
<td>46.8</td>
<td>29.4</td>
<td>14.1</td>
</tr>
<tr>
<td>Forest-Evergreen</td>
<td>7.6</td>
<td>7.0</td>
<td>12.5</td>
<td>11.5</td>
</tr>
<tr>
<td>Forest-Mixed</td>
<td>2.3</td>
<td>2.6</td>
<td>3.3</td>
<td>2.4</td>
</tr>
<tr>
<td>Scrub/Shrub</td>
<td>1.4</td>
<td>1.8</td>
<td>0.7</td>
<td>0.2</td>
</tr>
<tr>
<td>Range-Grasses</td>
<td>4.1</td>
<td>3.1</td>
<td>2.6</td>
<td>2.0</td>
</tr>
<tr>
<td>Pasture</td>
<td>27.9</td>
<td>24.3</td>
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<tr>
<td>Agricultural Land-Generic</td>
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<td>0.2</td>
</tr>
<tr>
<td>Wetlands</td>
<td>0.9</td>
<td>0.7</td>
<td>5.3</td>
<td>1.1</td>
</tr>
</tbody>
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Table 4.2: LULC change by EPA ICLUS SERGoM A2 scenario (%)

<table>
<thead>
<tr>
<th></th>
<th>Haw River basin (3,298 Km²)</th>
<th>2010</th>
<th>2040</th>
<th>2050</th>
<th>2060</th>
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</thead>
<tbody>
<tr>
<td>Non-urban</td>
<td>17.5</td>
<td>13.5</td>
<td>13.3</td>
<td>13.3</td>
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<tr>
<td>Exurban</td>
<td>69.6</td>
<td>71.0</td>
<td>70.4</td>
<td>69.8</td>
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<tr>
<td>Suburban</td>
<td>8.5</td>
<td>11.0</td>
<td>11.6</td>
<td>12.1</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>1.1</td>
<td>1.3</td>
<td>1.4</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>Commercial/Industrial</td>
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<td>0.8</td>
<td>0.8</td>
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</tr>
<tr>
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<table>
<thead>
<tr>
<th></th>
<th>Eno River watershed (171 Km²)</th>
<th>2010</th>
<th>2040</th>
<th>2050</th>
<th>2060</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-urban</td>
<td>75.4</td>
<td>83.6</td>
<td>82.6</td>
<td>80.8</td>
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<td>Exurban</td>
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<td>8.1</td>
<td>9.8</td>
<td>11.6</td>
<td></td>
</tr>
<tr>
<td>Suburban</td>
<td>0.3</td>
<td>0.5</td>
<td>0.6</td>
<td>0.6</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>Commercial/Industrial</td>
<td>0.0</td>
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<td>0.0</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>NoData</td>
<td>19.7</td>
<td>7.7</td>
<td>6.9</td>
<td>6.8</td>
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<table>
<thead>
<tr>
<th></th>
<th>New Hope Creek (197 Km²)</th>
<th>2010</th>
<th>2040</th>
<th>2050</th>
<th>2060</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-urban</td>
<td>3.1</td>
<td>0.9</td>
<td>0.6</td>
<td>0.6</td>
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</tr>
<tr>
<td>Exurban</td>
<td><strong>50.4</strong></td>
<td>41.5</td>
<td>39.5</td>
<td><strong>36.5</strong></td>
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<tr>
<td>Suburban</td>
<td><strong>28.7</strong></td>
<td>38.5</td>
<td>40.4</td>
<td><strong>42.6</strong></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
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<td>6.3</td>
<td>6.7</td>
<td><strong>7.4</strong></td>
<td></td>
</tr>
<tr>
<td>Commercial/Industrial</td>
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<td>3.0</td>
<td>3.0</td>
<td>3.0</td>
<td></td>
</tr>
<tr>
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<table>
<thead>
<tr>
<th></th>
<th>Crabtree Creek (315 Km²)</th>
<th>2010</th>
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<th>2050</th>
<th>2060</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-urban</td>
<td>0.2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Exurban</td>
<td><strong>34.2</strong></td>
<td>20.6</td>
<td>18.3</td>
<td><strong>16.4</strong></td>
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</tr>
<tr>
<td>Suburban</td>
<td><strong>38.5</strong></td>
<td>47.8</td>
<td>48.4</td>
<td><strong>48.5</strong></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td><strong>7.0</strong></td>
<td>11.3</td>
<td>13.1</td>
<td><strong>14.9</strong></td>
<td></td>
</tr>
<tr>
<td>Commercial/Industrial</td>
<td>8.7</td>
<td>8.7</td>
<td>8.7</td>
<td>8.7</td>
<td></td>
</tr>
<tr>
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<td>11.5</td>
<td>11.5</td>
<td>11.5</td>
<td>11.5</td>
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</tbody>
</table>
4.4 Method

4.4.1 Climate model output: North American Regional Climate Change Assessment Program (NARCCAP)

The North American Regional Climate Change Assessment Program (NARCCAP) is an international program to produce high resolution climate change simulations in order to investigate uncertainties in regional scale projections of future climate and generate climate change scenarios for use in impacts research (http://www.narccap.ucar.edu). It provides a set of regional climate models (RCMs) driven by a set of atmosphere-ocean general circulation models (AOGCMs) over a domain covering the conterminous United States, most of the Canada, and the Northern Mexico. The AOGCMs in NARCCAP have been forced with the Special Report on Emission Scenario (SRES) (IPCC, 2000) A2 emissions scenario for the 21st century. SRES is the green house gas emission scenarios for future climate change. The A2 scenario is a worst-case scenario, in which CO$_2$ emission over 2000-2099 will increase to be 350 – 850 ppm. It is based on an economic storyline with high population growth, regionally oriented economic development, and slow technological change.

Simulations with the NARCCAP models were also produced for the current (historical) period. The RCMs are nested within the AOGCMs for 1971-2000 and for a future period 2041-2070.

In this study, five GCM-RCM combinations, with both current and future time simulations, are selected for the model evaluation: CCSM-CRCM (NCAR Community Climate System Model-Canadian Regional Climate Model), CGCM3-CRCM (Canadian Global Climate Model version 3-Canadian Regional Climate Model), CGCM3-RCM3 (Canadian Global Climate Model version 3-Regional Climate Model version 3), GFDL-RCM3 (Geophysical Fluid Dynamics Laboratory GCM-Regional Climate Model version 3) and GFDL-ECP2 (Geophysical Fluid Dynamics Laboratory GCM – Experimental Climate Prediction Center). The 3-hour precipitation and surface air temperature data
are extracted and aggregated to daily scale precipitation, maximum and minimum temperature. Before application to hydrologic modeling, the NARCCAP data were evaluated and bias-corrected by Local intensity scaling (LOCI) method (Widmann et al. 2003) in precipitation and Fourier transformation method in temperature (Chapter 3).

4.4.2 LULC map for SWAT application

As NARCCAP uses SRES A2 scenario, ICLUS SRES A2 scenario output is also selected for this study. The A2 scenario ICLUS simulation tends to show less compact growth and more housing in suburban and exurban settings (US EPA, 2009). Also, because the projected NARCCAP output is for 2041-2070, ICLUS SERGoM was also selected with a comparable development scenario. Since SERGoM has only 5 categories, non-urban (> 60 minutes travel time from the nearest urban/suburban core from major road), exurban (30-60 min.), suburban (10-30 min.), urban (0-10 min.), and commercial/industrial (US EPA, 2009), without any vegetation information, it is useful to run SWAT with more detailed LULC since the study watersheds contain significant amount of forest. Therefore, a combining information from the NLCD 2006 and SERGoM 2010a2, a map was used for current time LULC for hydrologic simulation. Before combining with NLCD 2006, the SERGoM housing density categories were re-classed following NLCD 2006 categories. For example, exurban becomes Urban Low Density (URLD), Suburban is Urban Medium Density (URMD), and Urban is Urban High Density (URHD). Also, non-urban and no data category of SERGoM was treated same as NLCD 2006, while commercial/industrial was directly incorporated. As a result, if a composite pixel contains URLD by NLCD 2006 and Suburban by SERGoM 2010 A2, the new pixel was designated as URMD. The projected LULC composite map in 2060 was created by combining NLCD 2006 and accumulated SERGoM map from 2010 to 2060.
4.4.3 Hydrologic model simulation (SWAT) with both measured and climate model output in historical time period

The basic requirement for GCM application for hydrological studies should be the GCM’s capability of reproducing historical observed condition (Wood et al., 2004). By applying bias corrected NARCCAP output to the historical time period (1971-2000), NARCCAP output performance to hydrologic model simulation for current time can be evaluated. After confirming NARCCAP’s capability of application to current hydrologic model simulation, NARCCAP future climate scenario output can be used for predicting future water resources.

The Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998; Neitch et al., 2011) was calibrated in four study watersheds with National Weather Service weather data (http://www.weather.gov/), USGS stream discharge data (http://waterdata.usgs.gov/nc/nwis), NLCD2006 (http://www.mrlc.gov/nlcd06_data.php) for historical time hydrologic simulation. Instead of NLCD2006, a composite map of NLCD 2006 and SERGoM 2010 A2 scenario result is used as a reference LULC for future LULC change scenario simulations. The study watersheds are calibrated for 1998-1999 and validated for 2000-2001 at the daily time scale. This four year period includes the highest, average, and lowest water yield years on record. By Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992) in SWAT- CUP4 software (Abbaspour, 2011), 2000 realizations of parameter combinations are used, and the best results are chosen and presented at the monthly time scale. The simulation period was set on the basis of the study purpose and available USGS records for the study watersheds. For example, the Haw River basin hydrologic simulation is only for the future climate change application. Thus, the simulation period is 1974-2000 because the USGS stream discharge record started in 1973. NARCCAP data for the
current period is only until 2000. However, the three watersheds for projected LULC scenarios, the Eno River, New Hope Creek and Crabtree Creek watersheds, have shorter USGS records than the Haw River watershed. Monthly scale simulations were developed for the observation period for these watersheds for 1991-2010 to compare with projected hydrologic simulation.

One of the important characteristics of SWAT simulation in North Carolina Piedmont watersheds is forest cover. The forest growth parameters of each species in SWAT vegetation growth database, such as Maximum LAI, canopy height, etc. were adjusted to be appropriate for the North Carolina Piedmont using Gray and Song (2012) as a reference. Maximum stomatal conductance was set to 0.006 m/s (Kelliher et al. 1995). Also, “urban forest” was introduced in low density residential area in this study. Though the default SWAT setting of urban vegetation is Bermuda grass, urban area, especially low density residence, contains significant amount of forest in North Carolina. The “urban forest” in this simulation is characterized as mixed forest with a maximum LAI=4.0, referenced by Gray and Song (2012).

4.4.4 Hydrologic model simulation with projected CO₂ concentration and climate

With a calibrated parameter set with current climate and LULC, projected runoff variability was simulated with future climate scenarios derived from NARCCAP. To analyze the sensitivity of each climate factor separately, historical and projected CO₂, temperature and precipitation were used to set scenarios in a factorial design (Table 4.3). As NARCCAP and selected ICLUS LULC are based on SRES A2 scenario, projected CO₂ level also followed the same emission scenario, set to 600 ppm in 2070. In Table 4.3, there are two reference simulations (Reference 1 and 2) and 7 scenario simulations from the combination of CO₂, current measured climate data, and future climate model projections. “Reference1” is the baseline historical CO₂ of 330 ppm (default value of SWAT), and
“Measured” weather data in 1974-2000. “Reference2” uses historical NARCCAP data instead of measured weather to compare the SWAT simulation results generated by measured and NARCCAP. “CO₂ = 600” keeps the measured data and increasing CO₂ level to 600 ppm. S1-S6 are the combination of “Future NARCCAP”, bias corrected NARCCAP climate data in 2044-2070, 300 and 600 ppm level of CO₂, and measured weather data.

As projected climate has increasing temperatures (Figure 4.4), forest growth parameters also need to be adjusted according to the changing environment. SWAT adapted a temperature based Heat Unit theory (Boswell, 1926; Magoon and Culpepper, 1932; Barnard, 1948; Phillips, 1950) for plant growth cycles. A Heat Unit (HU) is the difference between the average daily temperature \( \bar{T}_{\text{av}} \) and plant minimum temperature for growth \( T_{\text{base}} \) when \( \bar{T}_{\text{av}} > T_{\text{base}} \). Potential Heat Unit (PHU) is the summation of Heat Unit from the day of planting to maturity. For forests, the growing season is defined from the time when forests develop buds to the time that forest seeds to reach maturation. The forest growing season of the study area was set May – October for conifer, Mar – October for deciduous and April – October for mixed forest with reference from Gray and Song (2012) to modify PHU in the future scenario. Also, the base zero heat unit (PHU₀) also needs to be calculated for non-growing season. This is the total number of heat units greater than 0°C in a year and calculated from 30 year (2040-2070) average values of the selected five NARCCAP models used in this study.

4.4.5 Hydrologic model simulation with projected LULC

The three study watersheds showed different degrees of projected urbanization; Eno River watershed has the lowest, New Hope Creek watershed intermediate, and Crabtree Creek watershed the highest potential of future urbanization.
Since there was less significant urban increase between 2040 and 2060 in ICLUS (Table 4.2), the ET and WY differences before and after urbanization is analyzed by comparing current and 2060 LULC hydrologic simulation results. The simulated ET and WY results in 2040, 2050, and 2060 do not show much difference (results are not shown here). The calibrated parameter set of SWAT with NLCD 2006 + ICLUS SERGoM 2010 LULC is applied to SWAT with ICLUS SERGoM 2060 LULC under the same climate condition (1991-2010). Therefore, the simulation results imply how ET and WY would change only by the LULC change.

4.4.6 Hydrologic model simulation with projected CO$_2$, climate and LULC

600 ppm CO$_2$, bias corrected projected NARCCAP scenario data (2061-2070) and ICLUS projected LULC of 2060 were used as weather and land cover input for SWAT. This simulation is expected to show combined effect of projected CO$_2$, climate and LULC in the North Carolina Piedmont watersheds. The SWAT simulation for historical time period is 1991-2000 when both measured stream discharge and NARCCAP historical data are available. The future SWAT simulation was also carried out for the 10 year time period to 2061-2070. Table 4.5 shows water balance change scenarios by combining projected CO$_2$, climate, and LULC.

4.5 Results

4.5.1 NARCCAP bias correction in historical data

Figure 4.3 shows the five before and after bias corrected NARCCAP outputs in the North Carolina geographical regions (Mountain, Piedmont, and Coastal Plain) with historical time period (1971 – 2000) by monthly average. Precipitation seasonal bias, such as fall underestimation and
spring/winter overestimation, are moderated by the LOCI method. Fourier transformation method also reduced cold and warm bias in NARCCAP daily maximum and minimum temperature to better match measured data.

These bias correction methods are also applied to future NARCCAP data in 2041 – 2070. Figure 4.4 is month by month averaged projected NARCCAP in 2041-2070 after applying bias correction methods. The Haw River basin is covered by 5-6 NARCCAP grids, and 1-2 grids are applied to the Eno River, the New Hope Creek and the Crabtree Creek watersheds. The bias-corrected NARCCP grid cells inside each study watersheds are averaged to present projected climate. It shows that precipitation varies in climate models, but seasonal patterns tend to be similar with historical data or show a small increase especially in summer and fall. The temperature shows warming by 1 – 5°C; summer and fall tend to show more temperature increase than spring and winter in both maximum and minimum daily temperature.
Before bias correction

After bias correction

Figure 4.3: Before and after bias corrected five NARCCAP outputs in the North Carolina geographical regions (Mountain, Piedmont, and Coastal Plain) with historical time period (1971 – 2000) by month by month average
Figure 4.4: Four study watersheds NARCCAP bias corrected projected precipitation and temperature in month by month average (2041 – 2070)
4.5.2 Hydrologic simulation with historical time

Figure 4.5 is the best fit SWAT calibration results of four study watersheds with NLCD 2006 + 2010 A2 LULC and measured climate. The Crabtree Creek watershed is the best hydrologic modeling performance in four study watersheds (Nash-Sutcliff Efficiency of stream discharge (NSE_Q) is 0.95 and logarithmic stream discharge (NSE_logQ) is 0.94) because of the high percentage of urban area (64%) and good quality meteorological station data (Raleigh – Durham International Airport station (COOP ID 317069)). The New Hope Creek watershed shows the lowest modeling performance: NSE_Q is 0.69 and NSE_logQ is 0.67. One of the possibilities to make New Hope Creek watershed challenging for hydrologic modeling is stream discharge data from USGS (site number 02097314). The gauge is located near an impoundment and was temporarily moved 300 ft upstream from January 3, 2005 to April 17, 2008 for bridge replacement (http://wdr.water.usgs.gov/wy2011/pdfs/02097314.2011.pdf). Another possibility is that forest area may not be parameterized well enough during calibration. These calibrated parameter sets were used for further SWAT simulations of this study, e.g., simulation with historical NARCCAP data and scenario simulation by Table 4.3 and 4.4.

Figure 4.6 is month by month average simulated and measured stream discharge in the historical time period of each watershed: 1974-2000 for Haw River basin and 1991-2000 for Eno River, Hew Hope Creek and Crabtree Creek watersheds. When applying raw NARCCAP to SWAT, the simulated stream discharge shows seasonal bias in four study watersheds. Except for CCSM-CRCM, which underestimated stream discharge in all seasons, the other four NARCCAP generated stream discharge tended to be overestimated in winter and spring, and underestimated in late summer and fall. These simulations results reflected bias patterns of raw NARCCAP. The SWAT simulated stream discharge pattern basically followed the seasonal pattern of precipitation, and temperature cold bias tends to exaggerate over or under prediction of stream discharge. For example, the noticeable
temperature cold bias in winter and spring makes ET lower in SWAT simulation, so stream discharge became even more over-predicted. Therefore, combined effect of temperature cold bias and precipitation seasonal biases of NARCCAP produces higher or lower stream discharge compared to measured weather data by SWAT simulation. SWAT simulation with biased-corrected NARCCAP, however, decreased seasonal biases though the amount of bias in 10 year averaged stream discharges in Eno River, New Hope and Crabtree Creek watersheds are larger than the remaining discharge bias in the Haw River basin. This reinforces the need for climate model output to be evaluated and bias corrected before being applied to hydrologic models.
Figure 4.5 SWAT calibration results of four study watersheds in monthly scale
Figure 4.6: Four study watersheds SWAT simulation with NARCCAP bias uncorrected (left) and bias corrected (right) precipitation and temperature
4.5.3 Hydrologic simulation with future changing environment

These scenario simulations focus on the sensitivity of projected CO\textsubscript{2}, climate, and LULC on ET and WY when applied separately as well as in combination. Since SWAT simulation with bias-corrected NARCCAP still shows residual bias (Figure 4.6), future water balance changes were compared by SWAT with historical time NARCCAP, i.e. “Ref.2” in Table 4.4, instead of measured weather data, “Ref.1.”

4.5.3.1 Increasing CO\textsubscript{2} effect: The Haw River basin

Figure 4.7 is the monthly scale averaged SWAT simulated ET and WY with measured weather data in the Haw River basin by “Ref.1” and “CO\textsubscript{2} = 600” scenarios in Table 4.3. The only difference between two simulation results is CO\textsubscript{2} level; 330 ppm is current CO\textsubscript{2} concentration and 600 ppm represents CO\textsubscript{2} concentration in 2060 under the SRES A2 scenario. The results indicate that increasing CO\textsubscript{2} causes an ET decrease especially in spring and summer, which can be explained by the relationship between stomatal conductance and CO\textsubscript{2} concentration in SWAT algorithm (Estering et al., 1992). SWAT decreases stomatal conductance by 40% when CO\textsubscript{2} increased from 330 to 660 ppm, which also produces decreased ET. This decreased ET by CO\textsubscript{2} increment also results in WY increase in Figure 4.7.
Table 4.3: Future water availability by projected CO\textsubscript{2} and climate scenarios. “Measured” data is observed data in 1974-2000 “Historical NARCCAP” is climate model output in 1974-2000, and “Future NARCCAP” is climate model output in 2044-2070

<table>
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<th>Scenarios</th>
<th>CO\textsubscript{2} (ppm)</th>
<th>Temperature</th>
<th>Precipitation</th>
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</thead>
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<td>Ref.1</td>
<td>330</td>
<td>Measured</td>
<td>Measured</td>
</tr>
<tr>
<td>Ref.2</td>
<td>330</td>
<td>Historical NARCCAP</td>
<td>Historical NARCCAP</td>
</tr>
<tr>
<td>CO2=600</td>
<td>600</td>
<td>Measured</td>
<td>Measured</td>
</tr>
<tr>
<td>SC1</td>
<td>330</td>
<td>Future NARCCAP</td>
<td>Measured</td>
</tr>
<tr>
<td>SC2</td>
<td>300</td>
<td>Measured</td>
<td>Future NARCCAP</td>
</tr>
<tr>
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<td>Future NARCCAP</td>
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</tr>
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<td>SC6</td>
<td>600</td>
<td>Future NARCCAP</td>
<td>Future NARCCAP</td>
</tr>
</tbody>
</table>

Figure 4.7: SWAT simulated Evapotranspiration (ET) and water yield (WY) change by increasing CO\textsubscript{2} from 330 to 600 ppm in the Haw River basin
4.5.3.2 Projected climate and CO$_2$ effect: The Haw River basin

SC1-SC6 in Table 4.3 are combinations of historical and projected CO2, temperature, and precipitation. Figure 4.8 is SWAT simulated monthly average ET by SC1-SC6 for 1974-1999 in the Haw River. Comparing reference 1 and 2, historical NARCCAP applied SWAT ET does not show major a discrepancy with measured weather data though minor overestimation in summer and underestimation in February can be seen. ET change is more sensitive to future temperature than future precipitation; future temperature only (SC1) showed no ET increase from July to September, and from April to June showed the largest increase in a year. Future precipitation only simulation (SC2), however, did not show any distinctive change. When both future temperature and precipitation were applied (SC3), simulated ET showed combined pattern of S1 and S2: more overestimated in June and July, and a little underestimated in February than reference ET. Comparing CO$_2$ = 330 scenarios (SC1, SC2, and SC3) and CO$_2$ = 600 (SC4, SC5, and SC6), year round ET patterns are similar, but amount of ET is lower in CO$_2$ = 600 simulations. Therefore, it seems that CO$_2$ and NARCCAP projected temperature (i.e., increasing temperature) show more impact than NARCCAP projected precipitation (i.e., similar or a little increasing precipitation) to ET.
Figure 4.8: Monthly scale averaged (1974 – 1999) SWAT simulated Evapotranspiration (ET) change by projected CO$_2$ and climate change scenarios in the Haw River basin.
In water yield simulation results (Figure 4.9), increasing future temperature (SC1) leads to water yield decrease because of the increased water consumption by forest ET. When future temperature is combined with increasing CO$_2$ (SC4), the decreasing water yield trend moderates as ET decreased with increasing CO$_2$. In the case of future precipitation related simulations, a variety of water yield change results because each NARCCAP future precipitation has more variation than temperature trend. However, similar WY patterns in reference time period (i.e., over-prediction in cold season and under-prediction in summer) are still found in the future precipitation related WY scenarios though the amount of future WY seems higher than reference WY.

Since projected LULC change does not show significant urban growth in 2060 in the Haw River watershed area (Table 4.2), the major projected change should be CO$_2$ and climate. Figure 4.10 is monthly scale water yield in warm (March - September) and cold (October - February) seasons by each NARCCAP output in 2044-2070; September was added to warm season because of the relatively warm temperature in September of the study area. Projected water yield showed a little difference in each NARCCAP, but the general pattern is that future precipitation and CO$_2$ change combination (SC5) showed the largest increase. Future temperature only application (SC1) showed the largest decrease of WY in both seasons with more significant WY reduction in cold season. However, the water yield simulation combined with projected CO$_2$, temperature, and precipitation (SC6) did not show significant change compared with Reference simulations. This means that although each factor shows a significant effect on water yield, combining all of the three future conditions may offset each effect to produce water yield similar to the historical condition.
Figure 4.9: Monthly scale averaged (1974 – 1999) SWAT simulated total Water Yield (WY) change by projected CO$_2$ and climate change scenarios in the Haw River basin
Figure 4.10: Haw River basin water yield change by projected changing CO$_2$ and climate scenarios in warm and cold seasons. This box plot indicates median (central mark in box), 25$^{th}$ and 75$^{th}$ percentiles in each lower and upper edge, and extreme values with whiskers. Outliers are excluded in this plot, and average value of each scenario result is presented with dot inside the box.
4.5.3.3 Projected LULC effect: Eno River, New Hope and Crabtree Creek watersheds

In this simulation, future ET and WY change are modeled only as a function of projected LULC; with current weather conditions, “Reference” used NLCD 2006 + 2010 A2 map and “LULC change” used ICLUS 2060 A2 as the LULC map for the SWAT simulation. Figure 4.1 shows the monthly scale averaged ET and WY results of the three study watersheds in 1991-2010. The Eno River watershed does not show changes in ET and WY with LULC change scenario because it does not have significant urban growth with ICLUS LULC scenario in 2060 (Table 4.2). The other two watersheds showed ET decreasing and WY increasing with the projected LULC.
Table 4.4: Future water availability by projected CO$_2$, climate, and LULC scenarios. “Measured” climate data is observed data in 1974-2000, “Current” LULC is NLCD 2006 + ICLUS 2010 A2 composite map, “Future NARCCAP” is climate model output in 2041-2070, and “Future (2060)” LULC is for ICLUS 2060 A2 LULC.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>CO$_2$ (ppm)</th>
<th>Climate</th>
<th>LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref.1</td>
<td>330</td>
<td>Measured</td>
<td>Current</td>
</tr>
<tr>
<td>Ref.2</td>
<td>330</td>
<td>Historical NARCCAP</td>
<td>Current</td>
</tr>
<tr>
<td>SCL1</td>
<td>330</td>
<td>Historical NARCCAP</td>
<td>Future (2060)</td>
</tr>
<tr>
<td>SCL2</td>
<td>600</td>
<td>Historical NARCCAP</td>
<td>Future (2060)</td>
</tr>
<tr>
<td>SCL3</td>
<td>330</td>
<td>Future NARCCAP</td>
<td>Current</td>
</tr>
<tr>
<td>SCL4</td>
<td>600</td>
<td>Future NARCCAP</td>
<td>Current</td>
</tr>
<tr>
<td>SCL5</td>
<td>330</td>
<td>Future NARCCAP</td>
<td>Future (2060)</td>
</tr>
<tr>
<td>SCL6</td>
<td>600</td>
<td>Future NARCCAP</td>
<td>Future (2060)</td>
</tr>
</tbody>
</table>
Figure 4.11: SWAT simulated Evapotranspiration (ET) and total Water Yield (WY) change by ICLUS SERGoM projected LULC in 2060
4.5.3.4 *Projected LULC, climate, and CO$_2$ effect: Eno River, New Hope and Crabtree Creek watersheds*

4.5.3.4.1 ET change

Figure 4.12 shows warm season SWAT simulated ET change by scenarios (Table 4.4). Future LULC only (SCL1) shows decreasing ET in New Hope and Crabtree Creek watersheds because of the decreased vegetated area and increased impervious surface by urban growth. This trend is exacerbated by increased CO$_2$ (SCL2). Projected climate scenario based SWAT simulated ET, SCL3 – SCL6, shows increasing ET compared to reference ET with increasing temperature. LULC change seems not to cause significant differences under projected climate comparing SCL3 and S5 though increased CO$_2$ effect (i.e., decreasing ET) still can be found. The Eno River watershed shows more extreme ET change than New Hope and Crabtree Creek watershed, especially with RCM3, as this watershed still keeps significant forest cover in the projected LULC. Cold season SWAT simulated ET (Figure 4.13) shows similar patterns with warm season ET though magnitude is smaller. As a result of projected ET change, decreased ET by urban growth can be offset or even become higher than current conditions because of the future temperature warming.
Figure 4.12: Warm season (March – September) ET change by projected changing environment (CO$_2$, climate, and LULC) scenarios in 2061 – 2070. This box plot indicates median (central mark in box), 25$^{th}$ and 75$^{th}$ percentiles in each lower and upper edge, and extreme values with whiskers. Outliers are excluded in this plot, and average value of each scenario result is presented with dot inside the box.
Figure 4.13: Cold season (October – February) ET change by projected changing environment (CO₂, climate, and LULC) scenarios in 2061 – 2070. This box plot indicates median (central mark in box), 25th and 75th percentiles in each lower and upper edge, and extreme values with whiskers. Outliers are excluded in this plot, and average value of each scenario result is presented with dot inside the box.
4.5.3.4.2 WY change

Interaction between climate and LULC change makes the water balance change more complicated. In Figure 4.14 and 4.15, projected WY change simulated by SWAT showed that WY will increase because of the urban growth and decrease because of the future climate change. In other words, WY is increased by projected urbanization because of the imperviousness increment (SCL1 and SCL2), but projected climate, especially increasing temperature, results in ET higher than current, producing a WY decrease (SCL3 – SCL6). Depending on the climate models, WY from all three factors (CO2, climate, and LULC) change (SCL6) shows similar or decreasing trend. For example, CCSM-CRCM and GFDL-ECP2 driven WY in S6 tend to project decreased WY in both warm and cold season mainly because projected precipitation of these two models in 2061 – 2070 are lower than historic precipitation in 1991 – 2000 (results are not shown here).
Figure 4.14: Warm season (March – September) WY change by projected changing environment (CO₂, climate, and LULC) scenarios in 2061 – 2070. This box plot indicates median (central mark in box), 25th and 75th percentiles in each lower and upper edge, and extreme values with whiskers. Outliers are excluded in this plot, and average value of each scenario result is presented with dot inside the box.
Figure 4.15: Cold season (October – February) WY change by projected changing environment (CO₂, climate, and LULC) scenarios in 2061 – 2070. This box plot indicates median (central mark in box), 25th and 75th percentiles in each lower and upper edge, and extreme values with whiskers. Outliers are excluded in this plot, and average value of each scenario result is presented with dot inside the box.
4.6 Discussion

4.6.1 Uncertainty in interaction between CO\textsubscript{2} increasing, forest ET and growth

In calculating the Penman-Monteith potential evapotranspiration under increasing CO\textsubscript{2} environment, SWAT decreases stomatal conductance by 40% when CO\textsubscript{2} increased from 330 to 660 ppm by the following equation (Estering et al., 1992):

\[ g_{l,\text{CO}_2} = g_l [1.4 - 0.4 \left( \frac{\text{CO}_2}{330} \right)] \]

Where \( g_l \) is the maximum leaf conductance, \( g_{l,\text{CO}_2} \) is the modified leaf conductance to reflect CO\textsubscript{2} effect, and CO\textsubscript{2} is the atmospheric CO\textsubscript{2} concentration. This linear decline of stomatal conductance by CO\textsubscript{2} enhancement tends to cause overestimation of ET reduction. The over-reduction of ET in SWAT by increasing CO\textsubscript{2} has been discussed in previous studies (Eckhardt and Ulbrich, 2003; Jha et al., 2006; Ficklin et al. 2009). In addition, the stomatal conductance change by elevated CO\textsubscript{2} varies with different kinds of vegetation. For example, stomatal conductance decrease in deciduous is higher than conifer (Saxe et al., 1998) and also C3 and C4 grass have different stomatal conductance reduction (Field et al., 1995; Kanp et al., 1996). Therefore, the current SWAT has limitations to simulate stomatal conductance response to elevated CO\textsubscript{2} in various kinds of vegetation.

Another problem with simulating CO\textsubscript{2} concentration and vegetation ET is the relationship between increasing CO\textsubscript{2} and LAI. Previous studies showed that CO\textsubscript{2} increase causes increased agricultural productivity (Allen et al., 1993). Some studies in vegetation ET suggested that increasing CO\textsubscript{2} may not significantly decreased ET because LAI is also increased by increasing CO\textsubscript{2} (Band et al., 1996; Wand et al., 1999; Saxe et al., 1998; Pritchard et al., 1999). However, the current SWAT does not include LAI increasing feedback though there is biomass production adjustment algorithm under changing CO\textsubscript{2} concentration (Ficklin et al., 2009). In SWAT, Radiation Use Efficiency (RUE),
(kg/ha)/(MJ/m²), is the potential vegetation growth rate per unit of photosynthetically active radiation and is sensitive to atmospheric CO₂ concentration. According to the vegetation database and modified RUE equation by Stockle et al. (1992) in SWAT, vegetation biomass would increase with increasing CO₂. However, the total biomass increment seems not to be related to LAI increasing in SWAT simulation. Simulated LAI in Figure 9 even shows a small decrease in summer and fall with increasing CO₂. Therefore, there is a possibility of overestimating ET decreases in future CO₂ simulation because of the limitations in the relationships in CO₂, stomatal conductance, and LAI in SWAT. Wu et al. (2012) modified current stomatal conductance and maximum LAI response to increasing CO₂ by vegetation types, such as crop, forest species (deciduous, coniferous, and mixed), and pasture. In their study, forest stomatal conductance reduction by doubling CO₂ is lower, 8 – 24%, than that of current SWAT, 40%, and LAI will increase by 7%. If these kinds of modification are applied to the forested watersheds of the North Carolina Piedmont, there could be moderation of ET reduction and WY increment, projected by current SWAT.

Another suggestion about the relationship in effect of CO₂ to ET and LAI is that the existing studies of decreasing stomatal conductance and increasing LAI under increasing CO₂ condition may not be applicable to some forest conditions. Some forest species, for example, *P. taeda* and *U. alata*, do not respond to elevated CO₂, and mature forest seemed not to increase LAI by CO₂ increasing in the North Carolina Piedmont (Schafer et al., 2002). Therefore, there could be various assumptions about vegetation water consumption change under projected CO₂ level, and the SWAT model simulation needs to be viewed as simplified and just one of the possible mechanisms.
4.6.2 ET and LAI pattern change by projected CO\(_2\) and Climate

These ET change patterns (Figure 4.8) tend to follow the change in Leaf Area Index (LAI) patterns in each scenario (Figure 4.16). By the Heat Unit theory adopted in SWAT, vegetation growth is mainly affected by temperature change, and simulated LAI seems to reflect this change in the future. The potential Heat Unit (PHU) value increases in SWAT simulation with projected climate because of the increased temperature. Increased PHU also means extended vegetation growth potential. Simulated LAI with future climate showed an earlier LAI green-up, and the maximum LAI value is higher than current LAI though the amount depends on the NARCCAP model. This earlier growing onset was also found in some studies with actual field measurement (Menzel et al, 2006; Granderson et al., 2012), and end of growing seasons can be prolonged under the increased temperature (Dragoni and Rahman, 2012; Granderson et al., 2012). The simulated LAI in Figure 4.9 does not seem to delay the fall growing season. However, if the LAI simulation shows more extended growing season than currently simulated LAI, the WY reduction by increasing temperature would show more reduction than in the current SWAT simulated WY.

Another factor that regulates LAI in SWAT is vegetation actual growth factor. In SWAT actual growth part, there are four stress factors that determine vegetation biomass as well as LAI: water, temperature, nitrogen, and phosphorous. Vegetation growth factor on a day is calculated by,

\[
y_{reg} = 1 - \max(wstrs, tstrs, nstrs, pstrs)
\]

where \(y_{reg}\) is the vegetation growth factor (0.0 – 1.0), \(wstrs\) is the water stress, and \(tstrs\) is the temperature stress, \(nstrs\) is the nitrogen stress, and \(pstrs\) is the phosphorous stress for a give day. This vegetation growth factor adjusts the actual LAI increase on a given day with following equation:

\[
\Delta LAI_{act,i} = \Delta LAI_{i} \cdot \sqrt{y_{reg}}
\]
Where $\Delta LAI_{act,i}$ is the actual leaf area added on day $i$, $\Delta LAI_i$ is the potential LAI on day $i$.

Figure 4.17 show the four monthly scale average SWAT simulated growth stress components (water, temperature, nitrogen, and phosphorous) which are required to calculate the vegetation growth factor. In ref.2 simulation, temperature (from September to April) and nitrogen (from April to September) are two main components which decide the vegetation growth factor. However, when future temperature is applied (SC1, SC3, SC4, and SC6), water stress days in each month becomes dominant from July to November. Figure 4.18 also shows that water stress and nitrogen stress are noticeably changed by CO$_2$ and climate change scenarios (Figure 4.18). These stress factor change patterns seem to affect patterns of LAI change. SC1 in Figure 4.9 shows that future temperature simulated LAI is higher than current conditions especially in spring and summer. Also, SWAT simulated LAI starts to increase and peak timing is shifted to earlier than current temperature conditions due to increasing temperature. However, there is inconsistent LAI decline pattern within models because of the water stress and temperature warming differences by each climate model. Three NARCCAP temperature-driven LAIs in SC1 are lower than current LAIs from September to November. LAI with GFDL-ECP2 and CGCM3-RCM3 are still a little higher than current value in September. Future precipitation applied LAI (SC2) did not show noticeable change except minor decrease from May to November, and this might be caused by the nitrogen stress increment (Figure 4.18). In both future temperature and precipitation applied simulation (SC3), LAI pattern also showed combined effect of SC1 and SC2, and increased CO$_2$ tends to moderate LAI increase by future climate condition (SC4 – SC6). Therefore, these LAI changing patterns can explain the ET changing pattern of each CO2 and climate change combination scenarios in Figure 4.8.
Figure 4.16: Monthly scale averaged (1974 – 1999) SWAT simulated Leaf Area Index (LAI) change by projected CO₂ and climate change scenarios in the Haw River basin
Figure 4.17: Monthly average values of SWAT simulated stress factor (water, temperature, nitrogen, and phosphorous) changes by projected CO2, and CCSM-CRCM temperature and precipitation change scenarios (2044 – 2070)
Figure 4.18: Monthly average values of SWAT simulated stress factor (water, temperature, nitrogen, and phosphorous) changes by projected CO2, and NARCCAP temperature and precipitation change scenarios (2044 – 2070)
4.6.3 SWAT simulated ET difference between coniferous and deciduous forest under projected CO₂ and climate

Inter-species ET change under the future changing environment is another concern under future changing climate and CO₂ for not only current forest species composition but also potential forest transition in the future. Figure 4.19 is SWAT simulated monthly scale averaged ET of deciduous (FRSD) and coniferous (FRSE) forest by climate and CO₂ change scenarios in 2044 – 2070. SWAT with five NARCCAP (CCSM-CRCM, CGCM3-CRCM, CGCM3-RCM3, GFDL-RCM3, and GFDL-ECP2) results are averaged in order to present as an ensemble. In Ref.2 simulation (with current climate data), SWAT simulated FRSE ET is higher than FRSD ET from February to May, and FRSD ET is a little higher than FRSEET in summer, from June to October. When projected temperature is applied (SC1, SC3, SC4 and SC6), FRSD ET especially increased in May – October, so ET difference between FRSD and FRSE becomes higher than ET with current climate condition (Ref.2). These SWAT scenario simulations show that deciduous forest ET might be more sensitive than coniferous forest ET under future increasing temperature condition.

Figure 4.20 shows boxplots of SWAT simulated monthly scale deciduous and coniferous forest ET change by projected CO₂ and climate scenarios in warm and cold seasons in the Haw River basin. Comparing ET change pattern with each scenario in both species and seasonal points of view, cold season coniferous ET shows distinctive patterns. For example, ET with CO₂ increasing and future climate (SC6) tends to increase or is similar with current condition except conifer ET in cold which shows lower average and shorter inter-quartile range than current ET (Ref.2). This means that under future climate and increased CO₂ condition, ET from conifer might be lower and more uniform than current condition.
Figure 4.19: SWAT simulated monthly scale averaged ET (2044 – 2070) of deciduous (FRSD) and coniferous (FRSE) forest under climate and CO₂ changing environments in the Haw River basin. Presented value is the average of five NARCCAP applied SWAT results.
Warm season (Mar. – Sep., 2044 – 2070)

Cold season (Oct. – Feb., 2044 – 2070)

Figure 4.20: Monthly scale deciduous and coniferous forest ET change by projected changing CO₂ and climate scenarios in warm and cold seasons in the Haw River basin. Presented value is the average of five NARCCAP applied SWAT results. This box plot indicates median (central mark in box), 25th and 75th percentiles in each lower and upper edge, and extreme values with whiskers. Outliers are excluded in this plot, and average value of each scenario result is presented with dot inside the box.
4.6.4 SWAT simulated WY change in watersheds with ICLUS SERGoM A2 urban growth scenario in 2060

In watersheds with urban growth, extreme events, including water yield change in high flow because of the flooding but also in low flow are important concerns for securing stream health and water resources. In order to analyze the change in three month, 10 percentile low-flow changes for the purpose of water resources management, three month moving average monthly water yield simulated by SWAT is presented as a cumulative distribution function (CDF) (Figure 4.21) with future environment changing scenarios (Table 4.4) of the three study watersheds. All study watersheds show simulated increased water yield with urban growth alone scenarios (SCL1 and SCL2) but decreasing water yield when future climate change are involved (SCL3 – SCL6). However, since three watersheds are projected by different degrees of urbanization in 2060, water yield also changes differently in accordance with projected urbanization in each watershed. Table 4.5 is the three month water yield change in CDF 0.1 level (the 10th percentile) as an example of low flow portion. The Eno River watershed, which represents a forest head-watershed for fresh water supply, produces the smallest amount of low flow and does not show noticeable change with future LULC alone scenario (SCL1) because planned urban portion in 2060 is almost same with current. On the other hand, the other two urban-growth projected watersheds, New Hope Creek and Crabtree Creek watersheds, show increase in low flow. When both CO₂ increment and urban growth are applied (SCL2), the amount of water yield in the low flow portion from all three watersheds increases significantly because of the forest cover. Since the North Carolina Piedmont is projected to hold significant amount of forest cover in spite of urban growth, these SWAT simulated WY change reflected the relationships in CO₂, ET, and WY in SWAT: when CO₂ increased, ET decreased and water yield increased. Scenarios with future climate alone application (SCL3) simulated 23 – 25% water yield decreases in CDF 0.1 level in all three watersheds because of the ET increasing by future...
temperature increment. After compensating LULC and climate change effects on water yield, SWAT simulated water yield combining all three future changing factors scenario (SLC6) show that low flow from the Eno River and the New Hope Creek watersheds would be almost similar with current, but the Crabtree Creek watershed projected decreased low flow by around 17%. This means that the amount of water yield in low flow period from urban growing watershed could be much lower than current condition. In terms of the water management in urban watershed, it also suggest that watershed with projected urban growth might produce low quantity as well as low quality water when combined with future climate and CO₂ condition. Therefore, the Best Management Practices (BMPs) for watershed with future urban growth might be flexible enough to consider not only urban flash flood but also much drier hydrologic condition.

One caveat of water yield simulation in this study is that though urban development is projected by ICLUS SERGoM, a significant amount of forest would exist in the future in the North Carolina Piedmont area. As ET simulation suggested, the water consumption by forest is one of the major components for hydrologic balance of the North Carolina Piedmont area. However, ICLUS SERGoM does not account for LULC change except urban landuse categories. Therefore, other LULC change models which simulate vegetated area transition as well, such as the Conversion of Land Use and its Effect (CLUE) model (Verburg et al., 2002) can complement the limitation of LULC projection of this study.
Figure 4.21: Three month average monthly water yield cumulative distribution function in watersheds with projected climate, LULC, and CO$_2$ in 10 year period (reference: 1991 – 2000 and scenario: 2061 – 2070). Presented values are the average of five NARCCAP applied SWAT results.

Table 4.5: Three month averaged monthly scale WY change in low flow (CDF 0.1 level) under projected climate, LULC, and CO$_2$ in 10 year period (reference: 1991 – 2000 and scenario: 2061 – 2070). Presented values are the average of five NARCCAP applied SWAT results.

<table>
<thead>
<tr>
<th>Study watersheds</th>
<th>Ref.2 WY (mm)</th>
<th>WY change in mm and %</th>
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</thead>
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<tr>
<td></td>
<td>SCL1</td>
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</tr>
<tr>
<td>Eno River watershed</td>
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</tr>
<tr>
<td></td>
<td>7.8</td>
<td></td>
</tr>
<tr>
<td>New Hope Creek watershed</td>
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<td>(+33.7%)</td>
</tr>
<tr>
<td></td>
<td>4.1</td>
<td></td>
</tr>
<tr>
<td>Crabtree Creek watershed</td>
<td>23.24</td>
<td>(+17.9%)</td>
</tr>
</tbody>
</table>
4.6.4  Inter-annual variability of ET and WY in projected changing environment

Another concern about hydrologic change under future changing environment is whether inter-annual variability will change. Figure 4.22 presents annual ET and WY standard deviations under CO$_2$ and climate change scenarios in the Haw River basin for 27 years (2044 – 2070). Comparing scenario simulations with the reference, future precipitation with CO$_2$ change scenarios (SC2 and SC5) shows the most variable in inter-annual WY, and future temperature with CO$_2$ change scenarios (SC1 and SC6) tend to show the most variability in ET. These results indicate that WY variation sensitively responds to precipitation change and ET variation to temperature change. Simulation with the synergistic effects of all three change factors (SC6) tends to produce inter-annual variability similar with current condition which depends on climate models in both WY and ET. In results with some climate models (e.g., CGCM3-CRCM and GFDL-ECP2), decrease or increase trends by hydrologic simulations with individual future changing factors (CO$_2$, precipitation, and temperature) tend to offset each other to produce no significant differences in ET and WY variability with current and future environmental condition.

Inter annual variability tends to increase further when LULC change is combined with CO$_2$ and climate change. Figure 4.23 is the SWAT simulated WY and ET inter-annual variability in watersheds with projected CO$_2$, climate, LULC by scenarios in Table 4.4. In CO$_2$ and LULC change scenarios (SCL1 and SCL2), urban growth projected watersheds, New Hope Creek and Crabtree Creek watersheds, show increasing variability in WY, and decreasing variability in ET because of the forest cover reduction. When climate change factors are added (SCL3 – SCL6), WY inter-annual variability increases in all three study watersheds because NARCCAP projected precipitation inter-annual variability tend to increase comparing with current precipitation (Figure 4.4). Decreased ET variability by LULC change increased variation because of the projected temperature warming
effect. It implies that though the area of forest cover is reduced by future urban growth, future climate change might make annual ET variability increase more than current LULC condition.
Figure 4.22: Haw River basin SWAT simulated water year scale WY and ET inter-annual variability for 27 years (reference: 1974 – 2000 and scenario: 2044 – 2070)
Figure 4.23: SWAT simulated water year scale WY and ET inter-annual variability for 10 years (reference: 1991 – 2000 and scenario: 2061 – 2070) in watersheds with projected climate, LULC, and CO₂ concentration. Presented value is the average of five NARCCAP applied SWAT results.
4.7 Conclusion

While recognizing the modeling projection uncertainties deriving from climate and LULC projections, model calibration and structural limitations, the important point is that future forest phenology and growth changes appear to play an important role in future water resources of North Carolina Piedmont under the assumption of current projected climate and LULC change scenarios. We can conclude that increasing temperature is important for water budget in North Carolina Piedmont as it significantly increases ET, and it is directly related to forest growth change in timing as well as amount.

Before applying climate model projections to hydrologic models, climate model bias needs to be identified and corrected. In this study, uncorrected NARCCAP projections produce significant WY bias, while the simple bias correction significantly reduces water yield bias. Under projected climate conditions, i.e. increasing temperature, diverse precipitation pattern and increasing CO₂, ET would increase especially in winter and spring, while CO₂ increase would moderate ET increase, especially for heavily forested watersheds. Water yield would show various changing patterns but tend to decrease by temperature warming and increase by projected precipitation and CO₂. Future urban growth may result in ET reductions and WY growth at monthly and annual time scale because of the imperviousness increment for the more urban catchments. Interaction between climate and LULC change makes the water balance change more complicated. For example, increased WY by urban growth is decreased by projected climate to make the projected WY similar or a little lower than current WY. Therefore, considering interactions of all factors, climate, urban growth, and forest ecophysiological response to CO₂, temperature and precipitation changes, are required to simulate future water availability in the North Carolina Piedmont.
References


Intergovernmental Panel on Climate Change (IPCC), 2000. Emission Scenarios. Cambridge University Press, UK. pp 570


Chapter 5: Summary and Conclusions

The purpose of this dissertation is to analyze the drivers of past and future water resources in the North Carolina Piedmont. Stream discharge of some watersheds in the North Carolina Piedmont have had repeated record low flows in the last decade. A major shift in land cover over the last century has been a significant re-growth in forest cover. In the future, the Intergovermental Panel on Climate Change (IPCC), climate model (NARCCAP) and landuse/landcover (LULC) model (US EPA ICLUS, 2009) project increasing carbon dioxide, temperature warming and more urban development in the North Carolina Piedmont. A major interest in the area is both historical and potential future trends in freshwater availability, and likely causes of these trends.

First, the influence of climate trends and LULC change on stream discharge in two North Carolina Piedmont watersheds over the 20th century was analyzed in Chapter 2. To simulate the effect of LULC on runoff, the Soil and Water Assessment Tool (SWAT) model is applied to study watersheds under two scenarios for long-term simulation (1926 – 2009): (1) no LULC conversion from agriculture, and (2) LULC similar to recent forest cover. The findings of this study are;

- During the time period of this study, 1920’s-2009, precipitation shows increasing trends whereas forest re-growth watersheds in the North Carolina Piedmont do not show corresponding increases in stream discharge.
- The re-growth of forests from abandoned farm land has offset increased precipitation, such that a return to prior climate conditions could leave significant freshwater vulnerability in the region.
Chapter 3 includes an evaluation and bias correction of General Circulation Model (GCM) nested Regional Climate Model (RCM) precipitation and temperature from the North American Regional Climate Change Assessment Program (NARCCAP). This is a required process for simulating both current watershed hydrology and future projected hydrologic behavior. Local intensity scaling method (Widmann et al., 2003) was applied to precipitation bias and daily maximum and minimum temperature bias were corrected by and Fourier function. The conclusions of this chapter are:

- Though there are pattern variations in NARCCAP models, fall precipitation tends to be significantly less than measured precipitation, and spring and winter precipitation are generally overestimated in NARCCAP.
- The degree of bias shows inter-model differences in NARCCAP temperature as well, but the general trend of error is cold bias. The daily maximum temperature cold bias tends to be maximized in winter season, with a range of 3.5 – 9.6°C, and minimized in summer or even warm biased with a couple of NARCCAP output by 5.0°C – 6.6°C.
- After applying bias correction methods, NARCCAP climate simulation outputs have a significant reduction of seasonal biases in precipitation and daily minimum and maximum temperature. Extreme events may not be adequately bias corrected by these methods, and it may be an important source of residual errors.
- SWAT results with both bias-uncorrected and corrected NARCCAP showed that SWAT with bias-uncorrected NARCCAP produced seasonally biased stream discharge. However, this bias pattern in simulated stream discharge is largely mitigated in SWAT with bias-corrected NARCCP. These results underline the need to evaluate and bias correct climate model output before being applied to future climate scenario hydrologic forecasts.
Finally, Chapter 4 focuses on future runoff change sensitivity under projected climate, increasing carbon dioxide (CO$_2$) and Landuse/Landcover (LULC) variability in the North Carolina Piedmont. In this study, increasing CO$_2$ from 330 to 600 ppm, bias corrected future climate scenarios from the North American Regional Climate Change Assessment Program (NARCCAP) and projected LULC by Spatially Explicit Regional Growth Model (SERGoM) from the spatial allocation model of Integrated Climate and Land Use Scenarios (ICLUS) by EPA are used to parameterize a hydrologic model, the Soil and Water Assessment Tool (SWAT). Analysis includes a factorial design of change factors to both de-convolve individual effects as well as estimating synergistic effects. The outcomes of this study are:

- In the North Carolina Piedmont, NARCCAP future scenarios (2041 – 2070) simulated future precipitation may be similar with current or have a small increase. The projected temperature is warmer than current conditions by 1 – 5°C, and July, August, and September show more temperature increase than other seasons in some NARCCAP outputs.

- ICLUS projections suggest some watersheds of the North Carolina Piedmont area would have a twofold increase in urban land compared to current landcover, but still contain significant amount of forest.

- Future warming results in increasing evapotranspiration (ET) especially in winter and spring while increasing CO$_2$ to 600 ppm mitigate ET increment. Projected Water Yield (WY) would show various changing patterns, with greater dependence on projected CO$_2$ and precipitation.

- In future climate only scenario (no change in LULC), the highest WY was produced by combining increasing CO$_2$ and future precipitation while future temperature alone produced the lowest WY.
When projected LULC is applied, future urban growth may cause decreased ET and increased WY because of the imperviousness increment. However, interaction between climate and LULC change can mitigate these effects. Most of the simulation scenarios projected WY similar or slightly lower than current WY on an annual basis due to the offsetting effects of increasing temperature and urbanization.

There are basic limitations of applying climate and LULC change scenarios to watershed management and planning because of the inherent uncertainties related with future projection. Therefore, we suggest that the results of this study can inform possible scenarios to support formulating flexible future watershed management and planning policy, rather than be used as a future prediction (Berke and Lyles, 2012). Each projection may be reasonable depending on how good the assumptions are. Therefore, it is important to evaluate which model seems most appropriate on the basis of observations. A robust monitoring design needs to be implemented to help managers adapt strategies based on updated evidence of which projections are being most closely experienced. This study adapted a set of climate change projections, which produce similar projected water yield change direction. However, including more climate and LULC change scenarios (i.e., climate model with SRES B storylines, which project environmentally sustainable development, and more integrated models of land system) to watershed hydrologic modeling would improve the skill of this study by reducing projection uncertainty.

Overall results from the three chapters suggest that water resources of the North Carolina Piedmont tends to be sensitive to the significant amount of forest cover in both past and future. In the past century, forest re-growth from abandoned agricultural area appears to have intensified hydrologic drought. In the future, projected CO₂ increment and temperature warming would change
forest phenologic characteristics to make ET and water balance pattern more complicated.

Increased urbanization has the potential to both increase annual WY, but it may also produce more frequent and lower low flow events. Some limitations of this study are common to many studies attempting to estimate future water resources trends. Vegetation development projection in this study may need improvement due to 1) the crop model restrictions in SWAT and 2) the lack of vegetation change consideration in the ICLUS SERGoM. More detailed vegetation projections may need to be included as one of the LULC changes in the North Carolina Piedmont for future water resources study. A more integrated model should include dynamic ecosystems that would provide direct feedback to hydroclimate change.
References


