2016

Hydrologic Modeling Scenarios in a South Carolina Piedmont Drainage Basin

Parker Douglas Leslie
University of South Carolina

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by

Parker Douglas Leslie

Bachelor of Science
University of South Carolina, 2013

Submitted in Partial Fulfillment of the Requirements

For the Degree of Master of Science in

Geography

College of Arts and Sciences

University of South Carolina

2016

Accepted by:

L. Allan James, Director of Thesis

John Kupfer, Reader

Kirstin Dow, Reader

Lacy Ford, Senior Vice Provost and Dean of Graduate Studies

Acknowledgements

I would like to thank my advisor Dr. Allan James. His thoughtfulness, patience, and encouragement proved crucial in writing this thesis and throughout my time in graduate school. He is responsible for my deep interest in geography and has influenced me to think critically at all points in the research process (as well as in life). I would also like to extend thanks to the others on my committee for their aid over the past two years. Summer research opportunities provided by Dr. John Kupfer allowed me to continue researching over the summer and experience the Congaree National Park like few others have. Dr. Kirstin Dow proved crucial to the research questions and design of the methods and I am incredibly thankful for her support. Chris Kaase was a doctoral student who I spent time researching and studying with during my time in the department. I am beyond grateful I had him as a resource to keep me motivated and I deeply respect him.

My family provided invaluable support and allowed me to pursue my goals. Without their love and understanding this would not have been possible. Dad, Mom, Seth, and Levi I love you all and am blessed to have you in my life.

Abstract

Changing land cover can drastically alter the hydrologic processes of a drainage basin. At the same time, the hydrologic processes that occur are governed by weather and climate of the region. The Southeastern United States, and more specifically the Piedmont region of South Carolina, is experiencing significant changes to the landscape and highly variable weather and climate conditions. Few modern hydrologic studies that investigate the impact from these dynamic variables on streamflow and the water balance within the region have taken place and further study is warranted because of the drastic change likely to occur. One objective of this thesis is to determine how increased low-density development alters streamflow and the water balance within a drainage basin characteristic to the Piedmont. The other objective is to test how streamflow and the water balance differ among two extreme weather periods and a period of moderate weather. The Arc SWAT model, and a land-use land-cover update module built within the model, were used to create scenarios for each research objective and non-parametric ANOVA tests were used to compare modeled simulations. The Arc SWAT model simulation assessments show that varying periods of extreme weather cause more significant changes to streamflow than the subtle changes in rural land cover within the region. Surprisingly, the Arc SWAT simulations of development resulted in decreased runoff. This resulted from assigning lower curve numbers to rural

development within the model than for Hay or Rangeland conditions. The model did not simulate medium-density, or high-density, development that occurs in urban areas. Caution is advised when extrapolating the hydrologic response simulated in this study to urban or sub-urban environments within the Piedmont because of the vast generalization in land-use updates that occurred.

Table of Contents

Acknowledgments....................iii

Abstract....................iv

List of Tables....................ix

List of Figures....................xii

List of Abbreviations....................xiv

Chapter I: Literature Review and Research Questions....................1

I.I: Literature Overview and Objectives....................1

I.II: Weather, Climate, and Streamflow....................3

I.III: Changes and Impacts from LULC....................11

I.IV: Arc SWAT Modeling....................16

I.V: Research Questions....................23

I.VI: Study Area....................24

Chapter II: Arc SWAT Model and Input Data Descriptions....................28

II.I: Description of Arc SWAT Model....................28

II.II: Data Description 31

Chapter III: Methods 39

III.I: Detecting Periods of Extreme and Moderate Weather Conditions 39

III.II: LULC and LULC Change Scenarios 41

III.III: Lup.dat Module 43

III.IV: Extreme Weather Periods (EWP) and LULC Change Scenarios 44

III.V: Data Pre-processing 46

III.VI: Statistical Methods 48

III.VII: Modeling Processes 53

III.VIII: Calibration and Validation 55

III.IX: Post-Calibration LULC Updates 58

Chapter IV: Results 66

IV.I: Uncertainty, Calibration, and Validation Outcomes 66

IV.II: Modeled Output 69

IV.III: Statistical Testing of Output 71

IV.IV: Analysis of Water Budget Changes 74

Chapter V: Discussion 90

V.I: Impacts of Extreme Weather Conditions on Hydrology................................ 90

V.II: Impacts of LULC Change on Streamflow 96

V.III: Critical Interpretations of Results and Modeling 101

Chapter VI: Conclusion.. 108

Works Cited.. 112

Appendix A: Descriptions, Model Output, and Maps 120

List of Tables

Table 2.1: NLCD of BRDB 35

Table 3.1: Index Monthly Threshold Counts 60

Table 3.2: Annual Sums of Standardized Index Records 3-Year Totals 60

Table 3.3: lup.dat Impacted Sub-Basins 60

Table 3.4: LULC Scenarios Areas 61

Table 3.5: Percent Drainage Basin LULC 63

Table 3.6: Duration Streamflow Setup 63

Table 3.7: Monthly Streamflow Setup 63

Table 3.8: Sub-basin Streamflow Setup 64

Table 4.1: Calibration/Validation Results 80

Table 4.2: Calibrated Model Parameters 81

Table 4.3: Kruskal-Wallis Results 82

Table 4.4: Duration Test Results 82

Table 4.5: Monthly Test Results 83

Table 4.6: Difference in Streamflow 83

Table 4.7: Scenario Average Hydrologic Variables 84

Table 5.1: Surface Runoff Totals by Sub-basin 104

Table 5.2: Sub-basin Median Runoff by Scenario 104

Table 5.3: Sub-basin Specific Changes in Runoff 105

Table A.1: Formatting descriptions for scenario abbreviations 120

Table A.2: Average streamflow values for the 6 Scenarios (units $m^3\ s^{-1}$)........ 121

Table A.3: Average streamflow values for specific months (units $m^3\ s^{-1}$) 122

Table A.4: Average streamflow values for all sub-basins (units $m^3\ s^{-1}$)........ 122

Table A.5: Sub-basin Streamflow Contribution and Water Balance for BM Scenario.... 123

Table A.6: Sub-basin Streamflow Contribution and Water Balance for BW Scenario ... 123

Table A.7: Sub-basin Streamflow Contribution and Water Balance for BD Scenario..... 124

Table A.8: Sub-basin Streamflow Contribution and Water Balance for DM Scenario ... 124

Table A.9: Sub-basin Streamflow Contribution and Water Balance for DW Scenario ... 125

Table A.10: Sub-basin Streamflow Contribution and Water Balance for DD Scenario .. 125

Table A.11: Water Balance Parameters for the BRDB for all scenarios........ 126

Table A.12: Percent Change in Water Balance parameters between weather periods. 126

Table A.13: Percent change in Water Balance parameters with LULC change 126

List of Figures

Figure 1.1: Bush River Drainage Basin over Aerial Imagery 27

Figure 2.1: Bush River DEM 36

Figure 2.2: NLCD 2001 37

Figure 2.3: Rainfall and Stream Flow Record for Bush River 38

Figure 3.1: Record of SPI and PDSI of the Bush River Drainage Basin 64

Figure 3.2: Lup.dat Module 65

Figure 4.1: Calibration Accuracy and Uncertainty Ranges 85

Figure 4.2: Validation Accuracy and Uncertainty Ranges 85

Figure 4.3 (A): Scenario Streamflow Distributions: Duration 86

Figure 4.3 (B): Scenario Streamflow Distributions: Monthly 87

Figure 4.3 (C): Scenario Streamflow Distributions: Sub-basin 88

Figure 4.4: Scenario Monthly Average Streamflow 88

Figure 4.5: Simulated Scenario Monthly Streamflow 89

Figure 5.1: Average Monthly CN Values and Ranges 106

Figure 5.2: Sub-Basin Surface Runoff Distributions 106

Figure 5.3: Changes in Sub-basin Runoff between Scenarios.. 107

Figure A.1: Ratio of surface runoff between the BD and BM scenarios 127

Figure A.2: Ratio of surface runoff between the BW and BM scenarios....................... 127

Figure A.3: Ratio of surface runoff between the DM and BM scenarios....................... 128

Figure A.4: Ratio of surface runoff between the DW and BM scenarios 128

Figure A.5: Ratio of surface runoff between the DD and BM scenarios 129

Figure A.6: Ratio of surface runoff between the BD and BW scenarios........................ 129

Figure A.7: Ratio of surface runoff between the DM and BW scenarios 130

Figure A.8: Ratio of surface runoff between the DW and BW scenarios 130

Figure A.9: Ratio of surface runoff between the DD and BW scenarios 131

Figure A.10: Ratio of surface runoff between the DM and BD scenarios 131

Figure A.11: Ratio of surface runoff between the DW and BD scenarios 132

Figure A.12: Ratio of surface runoff between the DD and BD scenarios 132

Figure A.13: Ratio of surface runoff between the DW and DM scenarios 133

Figure A.14: Ratio of surface runoff between the DD and DM scenarios 133

Figure A.15: Ratio of surface runoff between the DD and DW scenarios 134

List of Abbreviations

ANOVA .... Analysis of Variance

BRDB.. Bush River Drainage Basin

LULC ....Land Use Land Cover

NLCD.. National Land Cover Dataset

PDSI .... Palmer Drought Severity Index

PSC ....Piedmont of South Carolina

SEUS .... Southeastern United States

SPI..Standardized Precipitation Index

SWAT..Soil and Water Assessment Tool

Chapter I: Literature Review and Research Questions

I.I: Literature Overview and Objectives

The main objective of this literature review is to show that monotonic trend detection methods vary widely from study-to-study, yet climate variability (inter-annual to multi-decadal) is more widely recognized and explained across the literature. Hydrologic processes are governed by numerous variables, with precipitation driving the entire cycle. Basic rainfall-runoff models, while simple and easy to implement, do not account for all of the various processes that can impact runoff and streamflow such as evapotranspiration, land-use and land-cover (LULC) changes, or changes in groundwater. That being said, it is imperative to take into account the past and present states of physical and climatological factors that can impact water resources and be aware of projected changes and trends in these variables.

While general trends in climatologic variables (i.e.; precipitation, temperature, and evapotranspiration) have been studied throughout the Southeastern United States (SEUS), uncertainty exists in the dominant trends and magnitudes of variability (Groisman et al., 2004; Seager et al., 2009). Changes in the physical landscape (e.g.; increasing development, reforestation, deforestation, and silviculture) have also been documented (Costanza *et al.*, 2010; Griffith *et al.*, 2003; Terando *et al.*, 2014), but these studies vary across a range of spatial scales and time periods. Observed data of these variables, whether physical or climatological, often have reoccurring errors that need to be corrected and assessed for accuracy (Misra and Michael, 2013).

Hydrologic modeling has made great advances in recent decades. Hydrologic models can be used to assess scenario impacts to streamflow (Chattopadhyay and Jha, 2014; Guo et al., 2008; Li et al., 2012). The conditions of the landscape and variability and trends in climate inputs need to be assessed to note how specific combinations of input variables can affect modeled output. Regional comparisons allow scientists to understand how cumulative changes vary throughout the physical landscape and over time. While many hydrologic models exist, the Arc SWAT model was selected for this thesis due to the fact it is an extension to Arc Map GIS software, many current studies use this model when evaluating water resource issues, and the large community and user support for it. Arc SWAT is a physically-based, semi-distributed, continuous-time model that was developed for primarily agricultural and forested drainage basins (Arnold et al., 2012).

This literature review is broken into sections to address the issues associated with major variables affecting hydrologic processes. It covers analyses of individual variables (e.g.; changes in precipitation), as well as studies applying the Arc SWAT model to quantify impacts of changing physical and climatic conditions on water resources. It also covers the current scientific literature on how changes in LULC, weather, and climate variability can impact streamflow in a South Carolina Piedmont drainage basin. This review indicates recent advances and regional research needs.

I.II: Weather, Climate, and Streamflow

Weather and climate in the SEUS and the Piedmont of South Carolina (PSC) is generally quite variable due to several factors including latitude, longitude, topography, proximity to large water bodies and seasonality (Kunkel *et al.*, 2013; Powell and Keim, 2014). As a consequence, streamflow also varies. The SEUS encompasses a vast region stretching from Washington D.C. to portions of the Coastal Plains of the Gulf of Mexico (Rose, 2009; Wang *et al.,* 2014). Physiographic regions within the SEUS have drastically different weather and climate conditions, such as the PSC. The Piedmont physiographic region is located along the eastern foothills of the Appalachian Mountains between the Coastal Plains and the Blue Ridge Mountains. The PSC is located in what is commonly known as the 'warming hole' (Kunkel *et al.*, 2013; Schwartz *et al.*, 2009). Recent research shows that slight warming within the SEUS has been steadily occurring since the 1970s yet these almost global trends in warming during the 20th century are not showing up in observed weather records of the region (Kunkel et al., 2013). Long-term warming or cooling can affect precipitation totals and at a finer temporal scale can lead to changes in monthly variability.

I.II.I: Precipitation

Precipitation is the driving force of the hydrologic cycle. Precipitation can recharge groundwater, restore surface water resources, and generate runoff. Average annual precipitation totals in the Piedmont physiographic region of South Carolina range from 1143 – 1270 mm (South Carolina State Climatology Office and SCDNR, 2015).

Patterns of total precipitation within South Carolina strongly relate to elevation and proximity to moisture sources, which are major forcing factors (Changnon, 1994). Inter-annual variations in precipitation depend on seasonal weather patterns that result in relatively wet or dry conditions in different portions of the state (Changnon, 1994). Some literature and data concerned with changes in precipitation in the PSC exist, although most of the relevant literature focuses on the regional scale (SEUS). Yet local findings can be discerned from results and discussion within the literature. Localized findings (i.e.; where the study area was just the PSC) should be compared to these larger patterns in precipitation at a regional scale.

Trends in precipitation are important to document because they could help in prediction of changing precipitation totals. Annual and seasonal trends have been documented across the SEUS, as well as in the Piedmont of South Carolina (Kunkel *et al.*, 2013; Mizzell *et al*., 2014; Powell and Keim, 2015; Rose, 2009). However, only a handful of stations demonstrate a trend (out of the many used in the studies). This inconsistency may depend on the different types of datasets that were used for each study and the time period of the data and the specific methods used to detect a trend (e.g.; linear regression or Mann-Kendall). The region shows increasing amounts of precipitation over the past century in some respects, but the trend has not been statistically significant at an annual scale (Kunkel *et al.*, 2013; Rose, 2009). However, statistically significant decreasing (increasing) precipitation trends through time have been shown in summer (fall) (Kunkel *et al.*, 2013; Mizzell *et al.*, 2014). Mizzell *et al.* (2014) found these trends to be uniform across the state, covering all physiographic regions. Martino et al. (2013)

found that within the PSC very few precipitation records displayed annual increasing or decreasing trends, yet all but one location demonstrated a significant positive trend in the number or rainy days. However, the findings of Powell and Keim (2015) contradict the Martino et al. (2013) study even though they used the same dataset (USHCN). This disparity may have been due to the different thresholds set for ‘rainy day’ criteria between the articles. Within South Carolina, increasing and decreasing trends in precipitation are spatially diverse and no clear consistent increasing or decreasing trend can be determined at the annual scale.

Extreme amounts of precipitation falling within a single day or over two consecutive days strongly influences runoff. Statistically significant precipitation trends have been detected for extreme amounts of precipitation within the region (Changnon, 1994; Konrad, 1997; Powell and Keim, 2015; Wang *et al.*, 2014). Changes in extreme amounts of daily precipitation may indicate a long-term trend or merely a period when storm intensification is occurring over a region. The SEUS is experiencing an overall increase in heavy precipitation days, yet few are statistically significant and those significant increases are generally in the Coastal Plain along the Gulf Coast (Powell and Keim, 2015; Wang et al., 2014).

While it is unclear if there is a monotonic increasing/decreasing precipitation trend in the SEUS and the PSC, variability in monthly and annual precipitation records have been observed for the region. Annual variability in precipitation totals in the region often reflect an increase or decrease in precipitation in a season. The region also experiences annual variability due to severe droughts (e.g.; mid-1950s and 1998 – 2002) and periods of persistent above-average precipitation at many weather stations (e.g.; early 1960s and again in the early 1970s) (Patterson et al., 2013). Patterson et al. (2012) found that from 1970 – 2005, May precipitation is the most variable, ranging from 0 – 8 cm below the long-term monthly averages, while the months from June to September experience moderate variability, and the months from January to April show the least amount of variability. The same study conducted monthly trend detection, splitting the record into different periods (1934 – 2005, 1934 – 1969, and 1970 – 2005) yet found little agreement between magnitude and direction of trend or the number of stations in the SEUS and PSC experiencing trends within the same months.

Most of the regional variation in precipitation can be attributed to high-frequency variations in climate caused by oceanic oscillations (AMO, ENSO, PDO) bringing increased moisture to the region for a short period of time (Misra *et al.*, 2013). Describing the influence of each oceanic oscillation on precipitation totals in the SEUS and PSC is outside the scope of this literature review, yet they are a dominant cause of precipitation variability in the region. Downscaled climate models show the SEUS and the PSC have experienced frequent episodes of drier and wetter conditions (Misra *et al.*, 2013; Peterson *et al*., 2013). In summary, these highly variable episodes can affect the detection of long-term trends and could be the reason that very few locations in the SEUS and PSC experienced significant increasing or decreasing trends in precipitation over longer periods of time.

I.II.II: Temperature

Much like the patterns observed with precipitation, temperature is also variable within the region. Temperature trends and variability are important because they can influence evapotranspiration and exacerbate the impacts related to drought conditions (Brown, 2014). The mean annual maximum temperature for the PSC is approximately 23.3 °C and the mean annual minimum temperature is approximately 10 °C (SCDNR and South Carolina State Climatology Office, 2015). Temperature ranges within the region are highly dependent on proximity to sources of moisture and specific elevation gradients, much like precipitation.

Recall that many researchers have observed a temperature 'warming hole' in the SEUS. The SEUS is one of the few places in the world that has not experienced increasing temperature trends over the 20th century (Kunkel et al., 2013). However, some trends do exist in daily temperature ranges and seasonal average temperature ranges. At the regional scale, decreasing diurnal temperature ranges and warmer night-time temperatures are some of the widespread trends occurring in the observed weather record (Misra et al., 2012; Misra et al., 2013; Powell and Keim, 2015). Some have hypothesized that the significant decrease in diurnal temperature range could be associated with intensive irrigation, a common practice in the agricultural portions of the SEUS and PSC, where areas that regularly irrigate tend to have slightly reduced daily temperatures and increased evening temperatures because of the increased heat capacity from regularly wetted soils (Misra et al., 2012). Indeed, local forcing factors (i.e.; urban heat island, irrigation, forests, and water bodies) can influence variations in daily temperature (Chen et al., 2012). Within the PSC, there has been a significant increase in warm nights (annual count when minimum temperature above 24 °C) and a significant decrease in cold nights (annual count when minimum temperature below 0 °C) (Powell and Keim, 2015). Warmer nights and days are projected for the region by the mid-21st century with noticeable increases in the PSC (Carter et al., 2014). Mizzell et al. (2014) found that maximum temperatures from 1901 – 2010 in the PSC increased in spring (3.5 – 4.5 °F) and winter (3.5 – 4.5 °F). This differs from the findings of Carbone and Burdett (1995) for the SEUS as a whole from 1910 – 1987 that winter maximum and minimum temperatures were decreasing (1.06 °C temperature maximum and 1.63 °C temperature minimum). Furthermore, uncertainty of these trends is only increased because both articles used the same dataset.

Similar to precipitation records, temperatures within the region have been highly variable through time. The region has experienced many extreme hot and cold periods within the observed record. Generally, cooling in the region was persistent throughout the 1960s and 1970s. Records also indicate that in the early-to-mid 20th century there were periods of extreme heat in the region as well as periods of extreme heat in the past 20 years (Patterson et al., 2013; Peterson et al., 2013). Shorter-term (seasonal) variations in temperature are common in the region and strongly related to oceanic oscillations. Stefanova et al. (2013) found that winter diurnal temperature ranges were smaller in positive phases of ENSO because of increased cloud cover over the PSC. The temperature gradient from the coast to the Appalachian Mountains along the eastern coast of the SEUS has been shown to increase or decrease depending on the phase of the AMO (Ortegren et al., 2011). This implies that seasonal temperature trends and variability can vary drastically with the spatial and temporal scales of the study. Furthermore, the literature indicates that temperatures across the SEUS didn't experience continuous annual warming trends, yet seasonal variations are evident.

I.II.III: Streamflow

Although changes in precipitation and temperature can be observed from weather observations, it is important to understand how streamflow has responded to increased variability over the past century. Streamflow variability is used to quantify hydrologic droughts (or the absence of them), which have a strong governing role on water resources in the region (Patterson et al., 2013). Most of the SEUS and the PSC receive their water resources from surface water and reservoirs that are fed by rivers and smaller tributaries. Identifying changes within streamflow records could indicate if reservoirs are receiving more or less incoming streamflow. Within the PSC numerous power generating facilities depend upon surface waters for operation (e.g.; Lake Murray Hydroelectric Dam and V.C. Summer Nuclear Reactor 1).

Trends in streamflow within the region have been observed over the past century (Lins and Slack, 2005; McCabe and Wolock, 2002). Within the SEUS, streamflow has generally experienced decreasing trends in low-flow observations with increasing trends in median and high flows (Lins and Slack, 2005). Patterson et al. (2012) found that in the mid-20th century, 5 gages in the PSC experienced general increasing trends (between 3.1 – 8 cm annual runoff depth), yet out of five stream gages chosen for the study only one was statistically significant. The same study found that for the latter half of the 20th century all stations within the PSC experienced significant declines ranging from 16.1 – 35 cm in runoff depth (Patterson et al., 2012). Again, slight differences between findings of the studies are due to how different authors define the SEUS and PSC. Patterson et al. (2012) clearly delineated the PSC within the SEUS, whereas Lins and Slack (2005) defined the SEUS from Mississippi to the southern portions of Virginia. However, both studies report regional streamflow is lowest in September and highest in March.

Variability of streamflow in the SEUS with respect to specific months, and trends in specific months, was generally overlooked by most studies. Patterson et al. (2012) investigated monthly variability in SEUS streamflow records and found that most summer months across the entire record (1934 – 2005) had significant decreases in streamflow with most in the mid-20th century. They also found that streamflow declined for months of generally high streamflow in the PSC (January – April) with an average total runoff decrease of approximately 1.5 cm. Various authors found streamflow variability in the SEUS correlated to specific phases of oceanic oscillations (Almanaseer and Sankarasubramanian, 2012; Tootle et al., 2005).

I.II.IV: Synopsis: Weather in the SEUS and PSC

Although some trends in precipitation, temperature, and streamflow occur within the observed records, those observations were influenced by frequent extreme changes in weather. This indicates that hydrologists and water resource managers should be more concerned with the highly variable weather in the SEUS and the PSC due to the lack of significant increases or decreases in precipitation, temperature, and streamflow over longer periods (i.e.; multiple decades). Specifically, few studies of the PSC relate to seasonal and annual changes in precipitation, temperature, and streamflow and many of the findings come from research with a much larger geographic scope. This often means that only a few weather stations and streamflow gauges were used from within the region and many of the findings are generalizations.

Climatic data do not show monotonic gradual trends in precipitation, temperature, and streamflow in the SEUS region. A usual justification for this in the literature is that the SEUS is susceptible to changes in weather and climate brought about by high frequency oceanic oscillations (i.e.; ENSO) that can be coupled with less frequent oceanic oscillations (i.e.; AMO), which when compounded, can raise the variability of extreme weather and climate conditions (Patterson et al., 2012; Patterson et al., 2013). This variability attributes to uncertainty in weather and climate conditions for long-term planning, which pose challenges to water resource policy and decision making in the SEUS and the PSC.

I.III: <u>Changes and Impacts from LULC:</u>

This section reviews historic LULC conditions and dominant patterns of LULC change within the SEUS and specifically within the PSC. While weather and climate have a strong influence on hydrology and water resources, the physical conditions of the landscape can be just as important in influencing the generation of runoff, rates of evapotranspiration, and sub-surface flows. Trends in LULC change may also explain water resources changes over time. The following sub-sections investigate changes to the physical landscape at different spatial and temporal scales, specific types of change, and how these changes can impact local and regional weather, climate, and water resources.

I.III.I: Historical LULC in the SEUS and PSC:

The landscape of this region has been altered by people for thousands of years, but widespread intensive agriculture dominated the landscape after the time of European settlement (Napton et al., 2010). Relatively benign land-use practices were commonplace in the PSC until after the Civil War. Around the end of the Civil War, however, intensive agriculture lowered the productivity of the soil (Fox et al., 2007). It was no longer economically feasible to produce cotton (the cash crop in the region at the time), much of the top soil had been eroded away, and the hilly landscape became accentuated with gullies which proved too difficult to continue growing any crop (Napton et al., 2010). These factors in turn led to rural populations migrating towards cities for jobs and much cropland in the region being left fallow. Throughout much of the first half of the 20th century, reforestation was a dominant process with the SEUS and the PSC (Fox et al., 2007; Napton et al., 2010; Revels, 2003).

During the middle of the 20th century, the migration to cities continued, and some abandoned croplands were beginning to be used again. However, the major change was not a continuation of traditional agricultural practices but a widespread introduction of silviculture to the region (Fox et al., 2007). Harvesting timber provided the means to make an income from exhausted marginal lands. It wasn't economically feasible to grow cotton on the depleted soils, but southern pines could be grown with a much better economic return. Innovations in forestry from research institutes and national forests, like Sumter National Forest, in the PSC were the result of a combined effort to determine the best ways to grow loblolly pine (*Pinus taeda*) and slash pine (*Pinus elliottii*) in the region (Fox et al., 2007). Changes to LULC in the first half of the 20th century influenced the types of LULC changes in the recent past. Most changes continued to occur on marginal lands (i.e.; abandoned agricultural fields).

I.III.II: Recent Trends in LULC in the Region

Increases in development, reforestation, and declines in cropland all occurred at different rates of change over different spatial and temporal scales. Most historical LULC studies focus on the past 50 years but remark on previous LULC conditions in the first half of the 20th century. The spatial resolution of studies (e.g.; PSC or SEUS) determines the dominant types of LULC change and the associated forces driving change. Across the SEUS and PSC population growth has been notably increasing. Terando et al. (2014) noted that over 77 million people now live in the SEUS, which experienced one of the greatest growth rates of any area in the United States over the past half century (approximately 60% increase). The region is a desirable place to live because of economic growth with international companies such as BMW, Fleur, and Michelin all operating within the PSC (Napton et al., 2010; Terando et al., 2014). Population growth helps explain the increasing development of the region. While some development is occurring in urban areas, most development in the SEUS and PSC is occurring in exurban areas. Recent growth projections predict that exurban and urban areas in the region from 2009 to 2060 will increase from 90,700 km^2 to 216,900 km^2 with that the largest loss to urbanization from grasslands (9% - 17%) and forests (7% - 12%) (Terando et al., 2014).

When compared to other ecoregions in the SEUS (i.e.; Middle Atlantic Coastal Plains, Blue Ridge, and Southeastern Coastal Plains) the Piedmont has experienced moderate growth. The total change in land area from 1973 – 2000 in the Piedmont was 14.5%, which was the third highest out of the 7 ecoregions in the SEUS (Brown et al., 2005). Most of the change occurred recently (1992 – 2000) with 6.8% of land within the Piedmont ecoregion experiencing a change in LULC conditions. Compared to most other regions of the SEUS, the PSC experienced some of the greatest increases in developed areas and the largest decreases in forested areas. Developed land area in the Piedmont ecoregion increased from 11.9% in 1973 to 16.4% in 2000 (Brown et al., 2005; Napton et al., 2010). On the other hand, forested cover in the full southeastern Piedmont ecoregion decreased from 59.8% of land cover in 1973 to 55.1% in 2000 (Brown et al., 2005). Agricultural land cover and forest use in the region also decreased during that period. Similar trends in LULC were observed from 1972 – 2000 with an increasing trend in the number of forest patches in the Piedmont ecoregion although the trend wasn't statistically significant (p-value = 0.057) (Griffith et al., 2003). Brown et al. (2005) observed changes in rural areas of the Piedmont ecoregion and found that the dominant types of LULC from 1973 -2000 were clear-cutting and forest regeneration. At a finer scale than ecoregions, silviculture is evident and being practiced in rural parts of South Carolina on private and public lands (e.g.; Sumter National Forest and Francis Marion National Forest). In spite of substantial late-20th century LULC changes, the most dominant LULC type in South Carolina remains forested areas that cover approximately 67% of the land with noticeably higher concentrations in the Piedmont region than in other parts of the state (SCFC, 2010).

I.III.III: Impacts from LULC Changes and Hydroclimatology on Runoff

Feedbacks among vegetation, precipitation, and temperature play a vital role in the availability of water resources and changes in LULC impact streamflow. Literature pertaining to effects that reforestation and urbanization have on streamflow are summarized as follows. Climate and vegetation feedbacks have been widely studied and a general understanding of feedbacks in specific regions of the United States can be discerned. For example, decreased precipitation over a region may cause closure of stomatal openings of vegetation which, in turn, lowers rates of evapotranspiration (Notaro et al., 2006). Numerous studies have investigated the impacts forests have on the local and regional environment with an emphasis on feedbacks to precipitation, temperature, and evapotranspiration. Lu et al. (2003) used a set of 23 climate and physical environment variables (e.g.; mean annual precipitation, mean annual temperature, estimated evapotranspiration from various methods, percent of a LULC type of a drainage basin, etc.) to build a logistic regression model to determine rates of actual evapotranspiration within the SEUS and PSC. The regression analysis found that actual evapotranspiration in and around the PSC averaged 796 mm/year. The study also found that only using latitude, elevation, long-term mean annual rainfall, and percent forest-cover variables yielded an R^2 of 0.817 for logistic regressions. Chen et al. (2012) modeled reforestation in the SEUS by converting 25% of grasslands to forested lands. The authors found that increased forest cover augmented precipitation by 18% in summer and decreased winter precipitation by 30%. The same study found that reforestation didn't lead to a significant increase or decrease in precipitation or temperature yet noted a significant increase in evapotranspiration. Reforestation can also lead to increased surface roughness, lower albedo, and increase convective cloud cover (Chen et al., 2012). These studies are important because, while records of observed precipitation and temperature exist from many stations in the SEUS and PSC, rates of evapotranspiration aren't regularly recorded and analyses such as these give insight into how vegetation can impact multiple climate variables.

Streamflow responses to weather events are strongly related to the dominant LULC conditions in a drainage basin. Drainage basins that are predominantly developed (urban or exurban) have distinctly different streamflow responses to storms than forested drainage basins. Increased impervious surface cover results in increased surface runoff, reduced infiltration and groundwater recharge, and higher peaks in streamflow (Julian and Gardner, 2014).

I.IV: Arc SWAT Modeling

Many different models can be used to quantify hydrologic processes. The decision of what model to use comes down to whether the model can realistically simulate processes in a given environment and at what spatial scale the model is designed to work. Water models range in focus from quantifying urban water quality on smaller basins (SWMM), the water balance of larger basins such as HUC 8s (HSPF-BASINS), to water quantity in forested drainage basins (SWAT). Since most watersheds in the SEUS and the PSC are predominantly covered by agricultural and forested LULC, the Arc SWAT model was used in this study because it has been proven efficient in quantifying water balances in similar drainage basins in the region (Chattopadhyay and Jha, 2014; Kim et al., 2014). The literature reviewed in this section focuses on Arc SWAT modeling applications not only within the SEUS but also in drainage basins with similar LULC conditions and those regions with similar weather and climate (i.e.; temperate and sub-humid). Arc SWAT model applications to changes in water quantity from either LULC changes or specific periods of weather and climate are also briefly summarized.

I.IV.I: LULC Change Impact on Arc SWAT Models

The review in the previous sub-section highlighted influences from LULC on hydrology. Factors such as area of a drainage basin covered by a specific LULC condition play dominant roles in the hydrologic process. Yet, LULC conditions are not static and changes to them should be accounted for when modeling water resources. The landscape of the SEUS and the PSC is constantly being repurposed for new uses (e.g.; development or silviculture) and these changes have impacted hydrologic processes within the region. The Arc SWAT model has the capability to simulate LULC changes and can be used to quantify the associated changes in streamflow (Pai and Saraswat, 2011).

Multiple studies using the Arc SWAT model have found that when simulating streamflow over a LULC dataset that has more (or less) vegetation cover than baseline conditions, there is a general decrease (or increase) in streamflow. Li et al. (2009) noted that deforestation in a temperate drainage basin in China resulted in a 9.6% increase in average-annual simulated runoff depth when compared to baseline conditions. Guo et al. (2008) examined how reforestation on previously agricultural plots (23.3% of basin area) resulted in a 3.2% decrease in annual basin discharge. The same study found that simulating clear-cutting of all forested lands (74.2% of the drainage basin area) resulted in a 21.9% increase in annual basin discharge when compared to baseline values. A model application in the Piedmont of North Carolina on a drainage basin that experienced reforestation over the latter half of the 20th century found that average February – April groundwater contributions increased runoff depth by 25mm when compared to less forested conditions (Kim et al., 2014). Impacts to streamflow related to decreases in pasture land and cropland have also been simulated by modelers. Schilling et al. (2014) found that switches from mostly cropland and pastureland to strictly grassland resulted in less runoff generation because of increased infiltration.

Most studies report results and discussions in terms of impacts related to increases or decreases specific to forest cover, developed area, and agricultural area. While other LULC conditions increase or decrease over time, they were generally not as significant as changes relating to forest, developed, and agricultural lands. These studies are relevant to water resources analysis in the SEUS and PSC because the region has experienced many of the same changes in LULC conditions as most drainage basins in these studies.

I.IV.II: Impacts from Altering Weather and Climate in Arc SWAT Scenarios

Weather and climate variability has been projected to impact most of the world's water resources in the near-future (Kunkel et al., 2013). However, there isn't one universally agreed upon projection. Diverse scenarios result in different changes to weather and climate (i.e.; increasing CO_2 concentrations, temperature increases, precipitation increases). Hydrologic modeling can be used to assess the impacts to water resources from changes in weather and climate. Model applications are summarized as follows.

Not all studies take the same approach to quantify changes caused by weather and climate. The literature is generally divided into studies that investigate long-term trends (using either annual or monthly data), and other modeling applications that focus on periods that are markedly drier or wetter than average. To be clear, this thesis does not attempt to detect long-term trends in precipitation, temperature, or streamflow records. Regional insight into weather, climate, and streamflow was gained, however, from those studies that did choose to apply trend-detection methods. Almost all studies provide results and discussions of monthly simulated output, which allows comparisons to be made of monthly changes across different study areas. Model projecting to produce relatively long simulations was the predominant method used by studies, although hindcasting was also used.

The Arc SWAT model has been applied in similar drainage basins in the Piedmont of North Carolina using different approaches to climate change and LULC scenarios. Chattopadhyay and Jha (2014) modeled streamflow response from projected climate variability (IPCC scenarios), whereas Kim et al. (2014) hindcasted simulations and conducted a trend-detection analysis. Chattopadhyay and Jha (2014) found that the different climate projections produced noticeable water yield variability in the middle of the 21st century ranging from 179 – 674 mm. They also found that late winter and all spring months experienced increases in water yields up to 74%. These spring-time projections are in contrast to the findings of the Kim et al. (2014) study in a nearby drainage basin, which found some of the most significant decreasing trends in streamflow during the spring months. The decreasing trends in spring were the strongest magnitude out of all months (all significant at the p = 0.001 level and with a regression line slope ranging from -0.3 to -0.58). Although these two studies are geographically close to one another the temporal scope of the studies have little overlap. Chattopadhyay and Jha (2014) observed water yields from 1990 – 2069, whereas Kim et al. (2014) examined streamflow from 1920 – 2000. The Chattopadhyay and Jha (2014) article further investigated variability between climate scenarios by comparing changes in percentile streamflow (10th and 99th percentiles). The climate scenario that produced the greatest decreases (increases) in the 99th (10th) percentile was the RCM3-GFDL (downscaled climate model developed by the NARCCAP), the other 3 climate scenarios indicated less variability for the drainage basin during the middle of the 21st century.

Only a small portion of the relevant literature, on LULC and climate modeling, was specific to the SEUS and PSC and the objectives of this thesis. Most studies with a similar focus did occur in temperate environments and impacts from extreme weather and climate scenarios could be discerned. All of them were located in the eastern portions of Asia (Guo et al., 2008; Kim et al., 2013; Li et al., 2009; Li et al., 2012; Ma et al., 2009). Guo et al. (2008) examined differences in streamflow under wet, dry, and normal weather conditions simulated over baseline LULC conditions. In spite of noticeable seasonal variation, the most drastic changes were at the annual scale for which the wet period produced approximately 120% more streamflow than the normal period. The dry period produced a 40% decrease in streamflow as compared to normal weather streamflow (Guo et al., 2008). Seasonal impacts were opposite of one another under wet and dry weather conditions. Streamflow during the dry period experienced the most noticeable departures from normal streamflow from January to March (approximately 70%), whereas streamflow during the wet period experienced the greatest departure from normal streamflow from October to December (approximately 225%). Li et al. (2012) conducted a similar study in Taoerhe River drainage basin in China. This study selected three years that were characteristic of an extremely wet year (1990), an extremely dry year (2001), and a year with moderate conditions (1970). When they compared the simulated runoff from the moderate year to the extremely wet year, there was a 161.9% increase in runoff. Simulated runoff from the dry year was 75.5% less than for the moderate year (Li et al., 2012).

Another study that examined annual and inter-annual changes to streamflow from weather and climate change was Kim et al. (2013), who simulated two climate scenarios (RCP 4.5 and RCP 8.5) in the Hoeya River Basin, Korea. They found that, compared to baseline streamflow, the greatest increases in streamflow were during the spring (15 – 35% for RCP 4.5 and 29-64% for RCP 8.5) and winter months (31 – 50% for RCP 4.5 and 28 – 59% for RCP 8.5), which were also the seasons with the highest variability. They found that climate-scenario simulated streamflow in the autumn and summer decreased compared to baseline streamflow.

I.IV.III: Gaps in Recent Literature and Potential for Hydrologic Scenario Testing

The Arc SWAT model has been successfully used to quantify changes to streamflow under different LULC, weather, and climate scenarios, yet no such simulations have been applied to drainage basins in the PSC. This region has many largely undeveloped drainage basins that are projected to experience major growth in the near future. Most of the relevant modeling literature also examined changes in long-term streamflow averages and sought to detect increasing or decreasing trends. Because there exists little agreement with respect to trend detection, with respect to precipitation, temperature, and streamflow in the region it would be wise to assess the effects of streamflow over specific periods of extreme weather.

Guo et al. (2008) and Li et al. (2012) investigated the impacts to streamflow caused by periods of extreme weather and LULC change. However, neither article's justification for the extreme weather periods were lucid. Guo et al. (2008) stated that the dry and wet periods relate to modes within the region and didn't provide specific years. Li et al. (2009) averaged the annual climate conditions and chose a single year for each period. This is an over-simplification of the problem because their models only simulated one year. More understanding is needed of how streamflow is affected during an extended period of anomalous years rather than one specific year. Understanding the impact on streamflow of a group of anomalous years with above or below average precipitation—instead of a single year—would be more valuable to those that work with water resources because it provides insight into how streamflow is impacted from a persistent weather condition. Likewise, when evaluating impacts of extreme weather at the decadal scale it is unlikely that every year in a decade is characteristic of the extreme conditions (e.g.; a single extremely wet year following and preceding droughts). More attention should be given to quantifying the impacts of a period of extreme weather and the duration of those events on hydrology.

I.V: Research Questions

Previous research from various fields indicates that impacts from changing weather, climate, and LULC can drastically change streamflow, yet little is known of these impacts to streamflow in the PSC. The objective of this research is to calibrate an Arc SWAT model for the Bush River drainage basin and use it to simulate a set of scenarios. The scenarios will take into account different combinations of LULC and periods of extreme weather. The following research questions will then be addressed.

i. Can the Arc SWAT model accurately simulate streamflow in the PSC?

ii. Are changes in streamflow in the Bush River drainage basin influenced more by changes between periods of extreme weather or by increased development and decreased vegetated cover (LULC)?

iii. How does the water balance of the drainage basin change between scenarios? Specifically, what is the change in monthly rates of runoff, infiltration, evapotranspiration, and water yields and what parts of the water budget are affected (ET, runoff, groundwater, etc.)?

Multiple hypotheses can be postulated from these research questions. One hypothesis is that streamflow will generally increase with wetter conditions under all LULC because precipitation is the key component of the hydrologic cycle. Another hypothesis is that the water budget will show distinct differences between weather periods. Relating to impacts from LULC, one hypothesis is that increasing developed area within the model will increase surface runoff, decrease infiltration, and alter the characteristics of the hydrograph (compared against baseline conditions). A hypothesis centered on calibration of a hydrologic model is that using similar modeling parameters from research with a similar climate and physical landscape will produce similar results. While there are differences in methods and scale, there should not be any drastic differences in objective functions between these simulations and similar research.

I.VI: Study Area

The Bush River Drainage Basin (BRDB) is located in Newberry County and the eastern portions of Laurens County in the South Carolina Piedmont (Figure 1.1). The

BRDB has a drainage area of 297 km^2 at the USGS gage near where it drains to Lake Murray (area derived by ArcHydro). The BRDB is located in a rural region of the state outside of most major urban areas (~ 61 km northwest of Columbia and ~ 90 km southeast of Greenville) yet it is experiencing growth. It is primarily covered by forests, agriculture, rangeland, ponds, and wetlands in the lower portions of the catchment. The town of Newberry and the southeastern portion of Clinton are contained within the BRDB. The Sumter National Forest is adjacent to the BRDB along its northern drainage divide. One of South Carolina's major transportation corridors, Interstate 26, runs along the northern portion of the drainage divide. The watershed is predominantly composed of clay-rich soils and metamorphic rock. LiDAR data show the topography consists of rolling hills with many rills and gullies (James et al., 2007). The shape of the watershed is fairly linear and the drainage pattern is not distinctly dendritic as most other drainage basins in the region.

The history of land use in the BRDB, including cultivation of crops and small settlements, extends back to the 18th century (Revels, 2003). In the early-to-mid 1800s a majority of the land was used to grow cotton, and planting and harvesting were not well managed. This led to widespread soil exhaustion because of the extensive monoculture and erosive practices (Revels, 2003). Aerial photographs of Newberry County from the middle to the end of the 20th century show agricultural practices are still widely practiced in the BRDB. The most evident changes in LULC in the basin are emergent successional forests, slight increases in urbanization, and the loss of agriculture land, which are common trends in the Southeast (Castanza *et al.,* 2010).

The BRDB is a prime location to conduct hydrologic modeling because it drains to a major water resource in the region, has experienced constant changes in LULC conditions, and investigations in this drainage basin could serve as an analog to predict water resources in many other similar drainage basins in the region. Bush Rriver drains to Lake Murray which has been a resource for generating electricity since 1930. Modeling this watershed could increase understanding of how climatic variability and changes in the landscape affect water resources in the PSC and SEUS.

Tables and Figures:

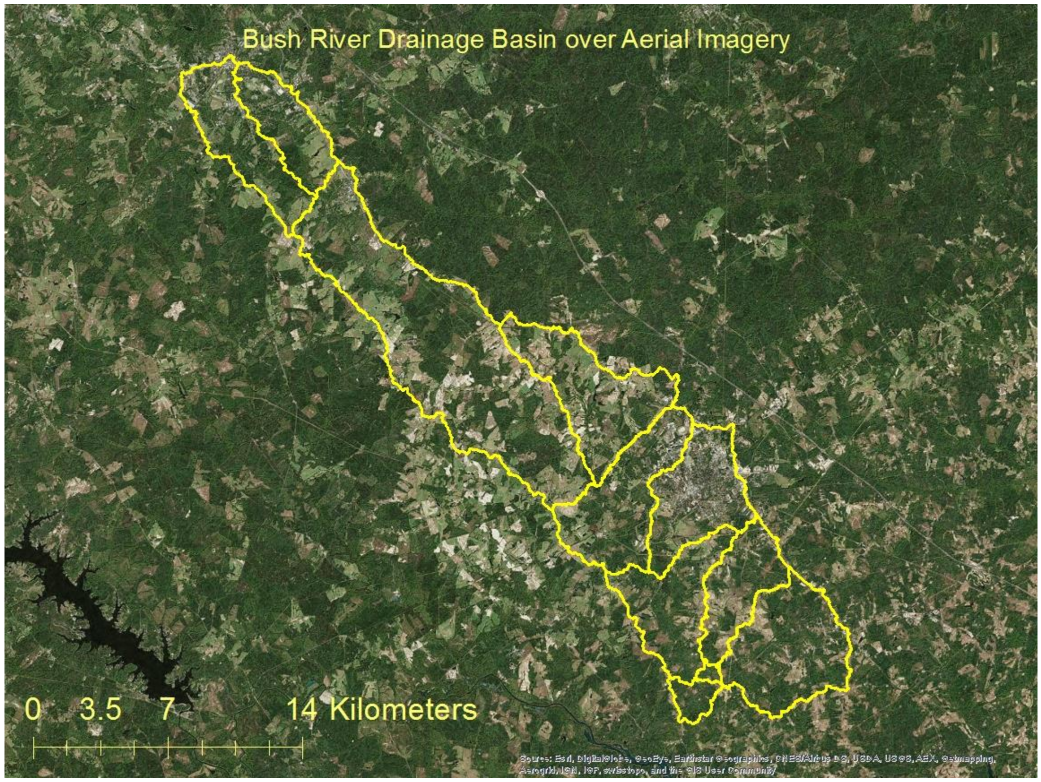

Figure 1.1: Bush River delineated drainage basin overlaying aerial imagery.

Chapter II: Arc SWAT Model and Input Data Descriptions

II.I: Description of Arc SWAT Model

Arc SWAT, an ArcGIS (©ESRI Corporation) application of SWAT, is one of the most widely used tools that modelers use to simulate hydrologic processes (Chu *et al.*, 2004; Gassman *et al.,* 2007). The SWAT model is continuous in time, semi-distributed in space, and a process-based river-basin model that evaluates the effects of alternative management decisions on water resources (Arnold *et al.*, 2012). The model is fairly robust in terms of the number of parameters (e.g.: streamflow, runoff, pollutant yields, climate variables, etc.) that can be modeled, but the number of parameters that are actually needed for accurate simulations depends on which processes within a drainage basin are being modeled. Arc SWAT subdivides the drainage basin into sub-basins (Arc Hydro) that are further subdivided into Hydrologic Response Units (HRUs). HRUs are created immediately after sub-basin delineation in the model. HRUs are characterized by unique combinations of soil properties, topography, and LULC conditions. Thresholds can be set to a given area of a sub-basin, or a percentage of a sub-basin covered by a specific input, to establish the number and size of HRUs in a model. HRUs are the smallest parcel of land that hydrologic and hydraulic processes can be on simulated in the model.

The model has the capability to simulate hydrologic and hydraulic processes such as surface runoff, base flow, lateral flow, and streamflow velocity (Neitsch *et al.*, 2005). This allows modelers to investigate specific components of the water balance. Neitsch *et al.* (2005) note that hydrologic and hydraulic processes can be split into two components. The first component of the water balance is comprised of processes that occur above the surface. Surface processes are important because overland flow can rapidly transport sediments, nutrients, and chemicals into a water body. The water balance equation is given by Neitsch *et al.* (2005) as follows:

$$SW_t = SW_0 + \sum_{i=1}^{n}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \qquad \text{(Eq. 2.1)}$$

where, SW_t is final soil water content (mm), SW_0 is initial soil water content on day *i* (mm), *t* is time (days for monthly model runs), R_{day} is precipitation on day *i*, Q_{surf} is surface runoff on day *i*, E_a is evapotranspiration on day *i*, w_{seep} is water entering the vadose zone from the soil profile on day *i*, and Q_{gw} is return flow to the surface on day *i*. The vadose zone is the unsaturated zone between the bottom of the soil profile and the top of the aquifer (Neitsch *et al.*, 2005), so flow from the vadose zone to groundwater is percolation of water recharging the aquifers. Equation 1 may be rearranged to solve for surface runoff or groundwater fluxes. Because SW_0 is carried forward each day, Equation 1 shows that potential runoff and groundwater flow are dependent on antecedent moisture conditions and may vary from day-to-day. The land-phase module of SWAT accounts for, and influences, other processes such as evapotranspiration, canopy storage, ponding, and management practices (Neitsch *et al.*, 2005). Erosion is accounted for as well in the surface component and is computed by the Modified Universal Soil Loss Equation (MUSLE) (Mukandan et al, 2010).

The second phase of the hydrologic cycle in the model is the routing phase (Neitsch *et al.,* 2005). This component deals with how water, and organic and inorganic matter are transferred through the channels of a drainage basin. Routing methods vary for flood, sediment, nutrient, and chemical materials. Streamflow routing is computed by the storage coefficient method or the Muskingum routing method (Neitsch *et al.*, 2005). Sediments are transported by the Bagnold equation which depends on peak channel velocity and channel morphology. Nutrients and chemical transportation equations vary because specific types can dissolve in water or adsorb onto sediment and travel at different rates. The QUAL2E module is used to account for this phenomenon. This thesis does not examine sediment transport.

Arc SWAT has the ability to predict water availability under future climate projections and has been used to model streamflow, sediment yields, and pesticide impacts on water quality (Arnold *et al.,* 2012; Srinivasan et al., 2010). This thesis models monthly streamflow. The SWAT model is widely used because of the incorporation of various computational methods, the possibility to expand or limit the number of parameters used, and the capability to build in accuracy assessments (SWAT Check). The Arc SWAT program (Version 2012 for ArcMap Version 10.2) was downloaded from swat.tamu.edu, a website established by Arc SWAT developers. The website also has extension programs (SWAT-CUP) that aid in calibration of Arc SWAT, a literature database, and instructional videos on how to initialize and run the model.

II.II: Data Description

The Arc SWAT model requires topographic data, geologic data, LULC information, and climate data to model physical processes. Observed streamflow data is also necessary to calibrate and validate the model to realistic values. The types of input data used in this thesis and their properties are listed and described as follows.

II.II.I: Topographic Data

High spatial resolution, 3.0-m (10-ft) grid cell, DEM data were obtained from http://www.dnr.sc.gov/GIS/lidarstatus.html for Newberry and Laurens Counties, South Carolina (Figure 2.1). The LiDAR data were flown during January in 2008 for both counties. The elevation in the BRDB ranges from 110 – 211 meters above mean sea level. The drainage basin is fairly linear compared to most other drainage basins in the region.

II.II.II: Soils Data

SSURGO soils data were used for the soils input data for the model. Newberry and Laurens County SSURGO data were obtained from the USDA Web Soil Survey (websoilsurvey.sc.egov.usda.gov/App/WebSoilSuvey.aspx). These data contain information as to the soil composition, the number and thickness of layers for each soil type, and the hydraulic conductivity for each soil type and layer. The dominant soil types within the BRDB are Cecil loams which cover approximately 25.2% of the drainage basin. Hydric soils, which can be used to delineate wetlands, are not widespread in the BRDB and are usually found near channels or in small depressions. High resolution soils data are invaluable to modeling because this allows for finer, more unique, combinations of HRUs.

II.II.III: LULC Data

Land cover and management practices effect the amount of runoff a surface can generate. The LULC dataset used for this model was the National Land Cover Dataset (NLCD) for the year 2001, which was obtained from http://www.mrlc.gov/nlcd01_data.php. This dataset was chosen over other available datasets because it represents LULC conditions roughly half way through the available streamflow record (1990 – present) and the look-up tables are built into the model. Figure 2.2 and Table 2.1 show the spatial distribution of LULC throughout the BRDB and the area (km^2) covered by each LULC type. The dominant land use in the basin is agriculture with a mosaic of coniferous, deciduous, and mixed forest types. The total forest area is 125.8 km^2 (app. 42.2%) with evergreen forest being the most predominant of all forest types (69.7 km^2). Small patches of rangeland and abandoned agricultural fields, classified as herbaceous lands (6.38 km^2) are also evident. Table 2.1 shows that most of the lands are classified as hay/pasture (94.4 km^2). Developed lands cover 45.8 km^2 (~ 15.4%) of the drainage basin, yet most development is low density with only the most intense development being located in the city centers or small business districts of Newberry and Clinton. Wetlands account for 2.55% of drainage basin area.

II.II.IV: Weather Data

Weather data were obtained from the NOAA National Climatic Data Center (ncdc.coaa.gov/cdc-web/datatools/findstation). Four weather stations were used for modeling climate variables, one in Newberry and the other three just outside the boundaries of the BRDB in the towns of Clinton, Little Mountain, and Laurens. All of these stations have over a century of observations, yet only the observations from 1 January 1950 to 31 December 2013 were collected. Data were collected back to 1950 because the Arc SWAT model requires a warm-up period before calibration of at least 10 years for groundwater flows to stabilize to near-realistic levels. Although the model can take inputs for precipitation, temperature, relative humidity, solar radiation, and wind speed, only precipitation and temperature were available for all stations. However, studies have achieved satisfactory results just using these two types of observed weather data (need ref).

II.II.V: Streamflow Data

Mean daily streamflow data were obtained from the USGS National Water Information System. The outlet of the drainage basin is just downstream of a USGS stream gage (02167582 Bush River near Prosperity, SC), which has 24 years of daily streamflow data (maximum, minimum, and average) from 27 February 1990 to 16 September 2014 (time of data retrieval, gage was still operating at the time of writing). However, modeling constraints only allow use of the observations from January 1st to December 31st so only the years of complete record were used (1991 – 2013). These observed flows were compared against flow simulations to calibrate and validate the streamflow output produced by the model. A long-term hydrograph for the duration of the monitoring period shows the 23-year period of record (Figure 2.3). The median discharge for the period was 1.08 m^3/s (38.1 cfs) while the mean observed discharge was 2.55 m^3/s. The modal daily flow was 0.040 m^3/s while the maximum daily observed discharge was 123 m^3/s. Exploratory analysis of the data revealed the asymmetry of streamflow frequencies. A multitude of flows were experienced under relatively low-flow conditions (< median discharge) while several outliers throughout the observation period were an order of magnitude greater than the median discharge.

Tables and Figures:

Table 2.1: NLCD LULC type and area in square kilometers of drainage basin.

Table 2.1: NLCD of BRDB

LULC Type	2001 LULC Area (sq. km)
Open Water	1.52
Developed, Open Space	25.86
Developed, Low Intensity	13.68
Developed, Medium Intensity	3.03
Developed, High Intensity	1.09
Barren Land	3.46
Deciduous Forest	53.20
Evergreen Forest	70.02
Mixed Forest	2.88
Shrub/Scrub	1.36
Herbaceuous	18.98
Hay/Pasture	94.63
Cultivated Crops	0.54
Woody Wetlands	7.59

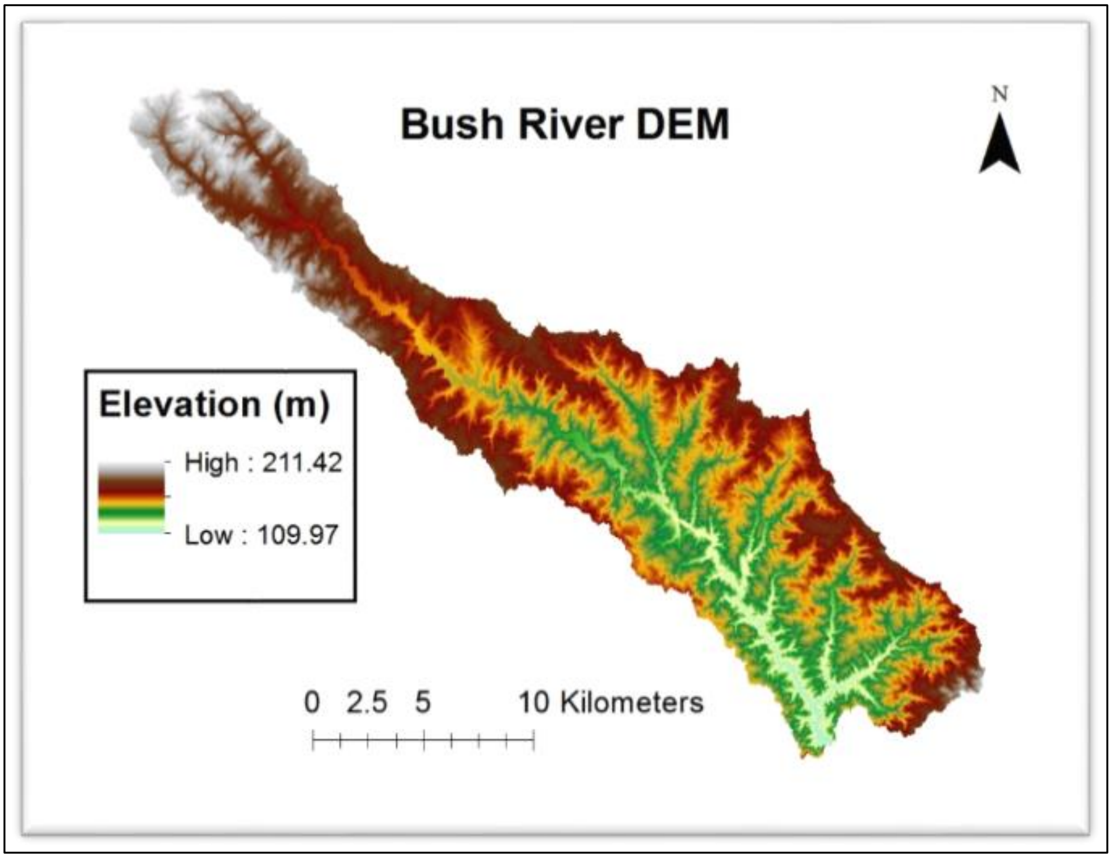

Figure 2.1: DEM of the Bush River Drainage Basin. Note the fairly linear shape of the basin.

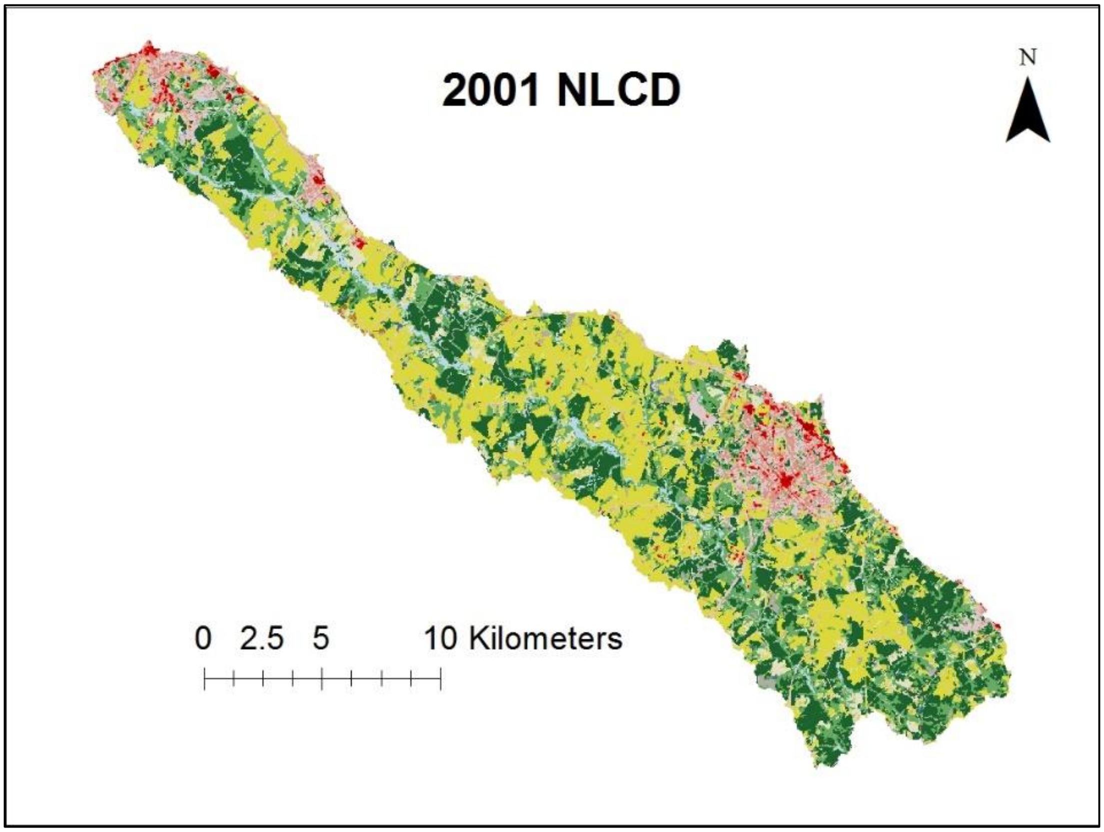

Figure 2.2: NLCD 2001 LULC for Bush River Drainage Basin.

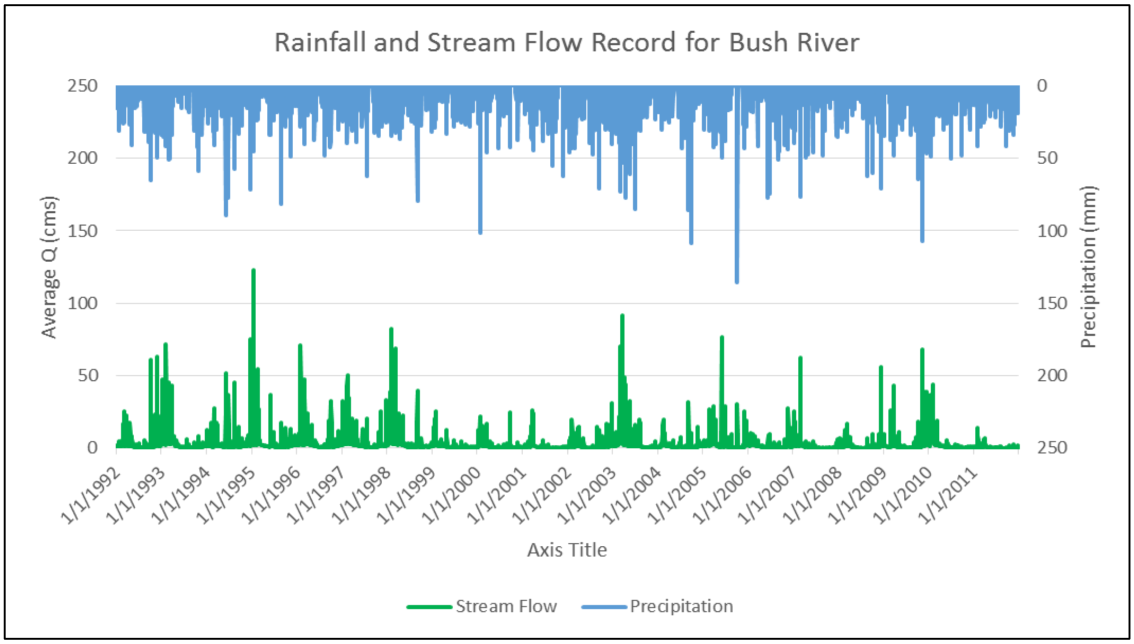

Figure 2.3: Streamflow record for the Bush River Drainage Basin with available precipitation data.

Chapter III: Methods

III.I: Detecting Periods of Extreme and Moderate Weather Conditions

One period of drought, moderate weather, and markedly wet conditions were identified by observing county-level monthly Standardized Precipitation (SPI), Palmer Drought Severity (PDSI), and average temperature indices. Monthly SPI and PDSI values for Newberry County were collected from drought.dnr.sc.gov. These records generally extended from the early 1950s through the middle 2000s. Calculated monthly values were normalized with respect to that specific month for the entire record. The inter-annual variability in indices scores was accounted for by counting the number of months a specific index was above or below a threshold. For example, the threshold for drought or extremely wet conditions for a month was one standard deviation below or above normal for the PDSI record, respectively. SPI values were counted if they were above or below 1 or -1 to detect wet or dry periods, respectively, as defined by Guttman (1999). Baseline conditions were determined as periods when the number of months with mean monthly PDSI values were within +/- 0.25 standard deviations from the long-term monthly mean and had SPI monthly counts close to the mean.

After the threshold for each index was applied, a moving three-year sum of the months above or below a certain index was computed. This procedure identified specific three year periods that were consistently drier or wetter than average, and identified a period of moderate weather conditions in terms of both the PDSI and the SPI. The three-year sums for each index were then ranked and the three periods with the most extreme drought, most moderate conditions, and greatest amount of precipitation were noted. The drought period identified was from 1999 – 2001, which was the period for the most severe drought in South Carolina's recent history (with regard to the PDSI and SPI records) (Carbone and Dow, 2005). Magnitudes of the selected weather scenarios do not match in terms of severity (dry or wet), but the durations are similar. The ranked three-year sums of the weather periods show all of the potential three year periods that were consistently wet or dry. A three year period with the most months experiencing above normal precipitation was from 1971 – 1973. The period of moderate weather conditions with respect to multiple indices was from 1967 - 1969. Monthly threshold criteria and three years sums are given below in Table 3.1, which shows extreme variability on a monthly scale and Table 3.2, which shows index extremes. SPI and PDSI records of the Bush River Drainage Basin are illustrated in Figure 3.1.

Table 3.1 gives insight into the need to use multiple indices to detect extreme dry periods and extreme wet periods. The difference between the two indices are that the PDSI is based on precipitation, evapotranspiration, and soil moisture, whereas the SPI is based solely on precipitation (Guttman, 1999). The SPI was used to detect wet and dry periods, while the PDSI was used to verify the severity of the two drought periods.

Primarily, the PDSI was used to prove that the drought condition (1999 – 2001) was the most severe on record. The baseline period (1967 – 1969) experienced the most months with near-average conditions in terms of the two indices.

Table 3.2 makes the differentiation between periods lucid. The previous table showed the number of months above a threshold, whereas Table 3.2 focuses on the 3-year index sums by adding all monthly values for each weather period. While Table 3.1 shows that most periods had nearly similar PSI extreme threshold values, Table 3.2 shows that the weather periods were markedly different. In particular, the wet and moderate weather periods may have appeared similar from the monthly threshold values of Table 3.1, but appear to have been extremely different when grouped in terms of years.

The objective of this analysis was to use multiple weather and climate indices (SPI and PDSI) to determine periods where weather conditions were markedly different from one another in terms of abundance or lack of precipitation. Periods of extreme weather had to be discerned in order to model and quantify impacts to streamflow and the water balance from a highly variable climate. Using a combined-indices approach allowed for in-depth analysis and quantification of extremely wet and dry periods throughout the record.

III.II: LULC and LULC Change Scenarios

Evaluating the differences between extreme weather periods streamflow and water yields provides information about water resources of the drainage basin during droughts and wet periods. However, LULC also has been shown to alter streamflow in a drainage basin and affect local climate. An increased low-density development scenario was created for the model to simulate potential changes to LULC conditions in the BRDB. This is one of the dominant types of LULC change in the PSC and within rural basins such as the BRDB. This type of change is also the most likely to occur with projected growth of the region (Coastanza et al., 2010; Napton et al., 2010; Oliver and Thomas, 2014; Terando et al., 2014).

The hypothetical scenario simulated specific changes of two initial LULC conditions to one new LULC condition. Previous studies predict that agricultural lands and abandoned fields are the most likely to change to developed lands (Napton et al., 2010). They show that abandoned agricultural fields are largely put back to use, and that the gradual decline in agriculture is likely to force some, but not all, of these lands to be developed. Much of the agricultural land and abandoned fields in the basin are classified as rangeland and herbaceous lands (RNGE) and livestock grazing, hay, and seed crop lands (HAY). The updated LULC scenario, therefore, changed all of the RNGE and half of the HAY to low-density development (URLD). This scenario was used to estimate the changes likely to be caused by widespread development, and to test the assumption that LULC change in the form of development would alter streamflow simulations when compared to baseline conditions. While not derived from any future projection of the exact amount of predicted LULC change, these scenarios should be viewed as significant changes to landscape of the BRDB.

Changes in LULC were simulated by activating the land-use update module within the model. This module is used to select a baseline LULC condition currently within the model and convert it to a new LULC condition. A visualization of how the updated LULC scenario was input into the module is given in Figure 3.2. Note how 60% of HAY is being converted to FRSE and the remaining 40% stays as HAY. The values in the percent column within the land-use update module must add up to 100%, so the remainder of the initial LULC must always be included. Land-use updates only occur in sub-basins where both the initial and target LULC condition exist. This implies that the amount of increasing development isn't the same across the drainage basin. The model also requires the target LULC (in this case URLD) to pre-exist within the drainage basin. Likewise, if a sub-basin had URLD but no RNGE or HAY lands present at baseline conditions, then the module would not alter the sub-basin. This analysis tests hypothetical percentage changes in specific LULC conditions and not equal amounts of LULC area changes in each sub-basin. However, total amounts of LULC area change were accounted for and their effects will be addressed in the interpretation of model output. Table 3.3 indicates which sub-basins were affected by specific land-use updates, and updated areas for each LULC condition for each scenario are given in Tables 3.4 and 3.5.

III.III: Lup.dat Module

The land-use update module is not applied to the raw LULC input data but to the constructed HRUs. In this analysis, the HRU threshold definition for all inputs (i.e.; LULC conditions, soils, and slope) was set at 5%. Thus, no less than 5% of a sub-basin's area could be covered by a unique combination of physical data inputs. If LULC conditions within a sub-basin do not cover a total of at least 5% of the area with similar slope and soil conditions, physical processes will not be simulated for those conditions. This 5% threshold was based on the objectives of the study, spatial distribution of LULC conditions in the basin, and processing times. A threshold definition of 0% would attempt to include all possible LULC conditions, yet this would greatly increase the time of processing and likelihood of simulation failures. Setting thresholds at a low value (e.g., 5%) is a compromise that allows efficient computations with only a slight abstraction.

III.IV: Extreme Weather Periods (EWP) and LULC Change Scenarios

A variation of a well-documented method was used to quantify the specific impacts of drought and wet periods and LULC change on streamflow (Li et al., 2009). Six scenarios with unique extreme weather periods (EWP) and LULC combinations were created to estimate impacts on streamflow from changing conditions. Streamflow was simulated on a calibrated model under baseline conditions over the three EWPs. After the baseline calibrations, the land-use module (lup.dat) was updated and streamflow was simulated for the three EWPs again. The 6 scenarios should reveal the impacts on streamflow due to changing physical conditions of the drainage basin, as well as the impacts on streamflow due to different weather periods. The first three scenarios utilize baseline LULC conditions under varying extreme 3-year periods. These scenarios actually occurred and simulations are based on direct observations. The following three scenarios employ changes in LULC under the same three weather periods. All six are explicitly listed as follows:

Group I Observed Scenarios:

1. Moderate Period (1967 – 1969) weather inputs and Baseline LULC
2. Wet Period (1971 – 1973) weather inputs and Baseline LULC
3. Drought Period (1999 – 2001) weather inputs and Baseline LULC

Group II Modified LULC Scenarios:

4. Moderate Period (1967 – 1969) weather inputs and Developed LULC
5. Wet Period (1971 – 1973) weather inputs and Developed LULC
6. Drought Period (1999 – 2001) weather inputs and Developed LULC

Scenario 1 simulates processes using precipitation and temperature inputs from the moderate period (1967 – 1969) over baseline LULC conditions. Scenarios 2 and 3 were derived from the same model run which meant that simulated streamflow and water balance information from the wet (1971 – 1973) and dry (1999 – 2001) periods were extracted. Output from these simulated scenarios were compared to Scenario 1 to discern the impacts on streamflow from extremely dry and wet periods. Specifically, comparing Scenario 1 to Scenario 2 measures impacts to streamflow due to a change from moderate to extremely wet weather conditions over a three-year period. Comparing Scenario 3 to Scenario 1 measures the runoff impacts of droughts as compared to moderate weather conditions. Finally, comparing Scenario 3 to Scenario 2 measures how streamflow differs between extremely dry and extremely wet periods.

The same methodology of comparing simulated streamflow from moderate weather conditions to simulated streamflow from extremely wet and dry periods was applied to a model run with updated LULC conditions. Scenarios 4 – 6 (Group II Scenarios) mimic the first three weather conditions applied to updated LULC conditions to simulate intensive development throughout the BRDB. Scenarios with the same weather conditions; e.g., scenarios 2 and 5, were compared against one another to measure the impacts on streamflow related to changing land-use conditions within the drainage basin. Scenarios 1 and 4 are moderate weather scenarios, Scenarios 2 and 5 are extremely wet scenarios, and Scenarios 3 and 6 are the extreme drought scenarios. Comparisons between these pairs examined differences in average annual and monthly streamflow values, precipitation differences, and changes in water balances from scenario-to-scenario. Comparisons were not limited to the same LULC conditions or the same weather conditions. Unrelated scenarios (i.e.; Scenario 1 to Scenario 5) were also compared with non-parametric significance testing to assess the affects from cumulative impacts to streamflow. The objective in comparing the 6 scenarios was to identify differences between unique combinations of inputs and seeking to use these differences to explain variations in water yields under the specific conditions.

III.V: Data Pre-processing

Model input data comes from many sources and in many formats. For example, the required geospatial data may come in a variety of projections and weather data may be incomplete. Prior to simulating physically based processes, pre-processing must be done to format the geospatial data into a uniform projection, append observed records, and detect potential errors within the input data. The BRDB was not located entirely in one county so LiDAR DEM data from Laurens County and Newberry County had to be mosaicked to obtain a single DEM that contained the entire BRDB. The DEM was also resampled from 3 to 10 meters to allow faster processing. A DEM with 10-meter spatial resolution is still much finer than the 30-meter DEMs typically used in most Arc SWAT models. Arc Hydro, the tool that is used to calculate sinks, flow accumulation, and delineate streams in the model had the potential to falsely delineate streams at finer scales of spatial resolution and resampling to 10 meters allowed for better accuracy in mapping streams (Lin *et al*., 2010). At finer spatial resolutions the local geomorphology has a greater influence on hydraulics and hydrology.

The soils data for Laurens and Newberry County also had to be combined by merging and re-projecting the shape files to match the projection of the DEM data. The projection that was used for all geospatial data in the study was the NAD 1983 HARN State Plane FIPS 3900 (Meters). The NLCD 2001 was re-projected to this projection as well. The observed weather data were checked for days of missing and erroneous observations. Days with a missing observation for precipitation, maximum temperature, or minimum temperature were assigned an average value computed from the nearest stations that didn't have a missing observation that day. Erroneous records that were detected within the climate dataset were corrected so they would not impact simulations. Most errors were from observations that were an order of magnitude greater than the previous day or nearby weather stations. The handful of erroneous precipitation records that were identified coincided with some of the most extreme winter storms in South Carolina's recent history. The issue was apparently that the accumulation height of snow was not converted to precipitation totals using a snow-to-liquid ratio. Snow-to-liquid ratio was converted by using values from Baxter et al. (2004). The errors caused by inaccurate snow accumulations would likely be minor because snow rarely falls in the region. Streamflow data that were obtained from the USGS had previously been corrected for errors and potential missing values by the USGS, so the only pre-processing that was done was to convert from cubic feet per second to cubic meters per second.

III.VI: Statistical Methods

After the calibrated models were run, the outputs were extracted from the reach files (output.rch). This file contains the simulated streamflow for all sub-basins for the entire period of simulation excluding the warm-up period (1951 – 1953). Simulated streamflow values from the three time periods of the weather scenarios (Moderate, Extremely Wet, and Extremely Dry) were extracted from the calibrated original and model with updated LULC conditions. Each of the 6 scenarios produced 36 monthly streamflow observations, one for each month of the 3-year period. The objective of the statistical analysis was to test each of the 36 monthly streamflow sets for significant differences between the 6 scenarios. The testing framework is shown in Table 3.7, which denotes the observations from each scenario and how they were set up for significance testing. The actual simulated values are given in the Results and Discussion section.

Statistical testing was applied to the entire duration of streamflow (36 months) for each scenario to make comparisons without regard to specific temporal or spatial differences. Analysis of variance (ANOVA) and pairwise significance testing were carried out to determine if there were differences in streamflow between the various scenarios. However, it was imperative to determine whether parametric or non-parametric statistical tests were appropriate for this analysis. Previous observations have revealed that the distribution of streamflow is generally non-normal (Lins and Slack, 1999). Therefore, the Kruskal-Wallis non-parametric ANOVA test was applied to the simulated output to determine if there were significant differences in streamflow between the 6 scenarios. While corrections can be made to the data to allow for parametric testing of the data (i.e.; log-normalizing the data), preliminary analysis found that parametric statistical tests were too conservative and yielded no scenarios with significantly different streamflow.

Assessing the distribution of the data is not the only way to determine which test to use, nor does it satisfy the assumptions that apply to a test. An assumption for significance testing is that the data must be independent. However, this assumption is very rarely met in hydrology due to autocorrelations (Bruce and Clark, 1966). Streamflow from one day will usually affect streamflow the next day (Herschy, 2008). Although ways exist to deal with autocorrelation they are complex and tend to dampen out the trend signal. At a daily scale, autocorrelation in streamflow may be clearly evident, yet as the temporal resolution is decreased (i.e.; using longer time scales), it is likely to diminish in strength (Bruce and Clark, 1966). While it will still exist, using monthly instead of daily data could reduce the impact of autocorrelation. Some autocorrelation issues remain, such as seasonality, which are difficult to eliminate. Yet seasonal patterns may be diminished during periods of extreme weather. ANOVA can be carried out on monthly streamflow data on time periods where seasonality does not have a strong impact on streamflow (Bruce and Clark, 1966). The moderate time period would be the most susceptible to seasonality and this is recognized when interpreting the outcome of ANOVA analysis and pairwise testing with this category of simulations. It is imperative to state that no methods to correct for potential autocorrelation within the data were taken due to the complexities of such analyses. Due to the nature of the data it was assumed to be autocorrelated.

The Kruskal-Wallis non-parametric ANOVA test was used to test if streamflow differed significantly between scenarios. The Kruskal-Wallis test may detect differences between groups but it does not identify which groups are different from one another. This method introduced two cases:

1) At least one scenario existed where simulated streamflow was significantly different from the other scenarios, or

2) No scenario produced simulated streamflow significantly different from any other scenario.

The method employed by this thesis was to test to see if the first case was satisfied, and if so, then apply ad-hoc pairwise Mann-Whitney significance testing between two specific groups. The total number of paired post-hoc tests is 15 (possible permutations of pairs of 6 scenarios). The relatively large number of pairs to be tested for significance against one another presented a difficulty in that some paired test outcomes could be significant by chance alone (Bland and Altman, 1995; illustrated examples by Adbi, 2010). Therefore, the Holm-Bonferroni correction was made to each paired significance test, following the formula given by Adbi (2010):

$$p\text{Bonferroni}, {}_{i/C} = (C - i + 1) * p \qquad \text{(Eq. 3.1)}$$

where pBonferroni, $_{i/C}$ is the adjusted significance level, C is the number of pairwise tests computed, i is the sequential p-value ranks of the Mann-Whitney tests ordered from smallest to largest, and p is the original level of significance. In any case when pBonferroni, $_{i/C}$ is greater than 1.00 the value is then truncated to 1.00. Values for this formula are C = 15 and p = 0.05 for this study. If case 2 was satisfied; no significant differences in streamflow were produced between the six scenarios, no further pairwise testing of the groups would be needed.

Additional month-specific and spatial-specific significance tests were run to focus on specific monthly averages in streamflow within a scenario and average streamflow within a specific sub-basin within a scenario. The monthly and spatially specific tests are given in Table 3.8 and Table 3.9.

As with the 3-year tests, non-parametric testing between monthly or sub-basin groups was used because of non-normal distributions within scenario simulations and the drastically reduced number of observations (12 for months and 11 for sub-basins). The Kruskal-Wallis non-parametric test was used to test for significantly different streamflow between all 6 scenarios. As with the 3-year tests, results may fall into one of two categories: (1) cases exist with at least one scenario where the specific months (sub-basins) streamflow were significantly different from any other scenario, or (2) no scenarios are significantly different from any of the others. The method employed by this thesis was to test to see if a scenario had a significantly different streamflow and, if so, conduct a post-hoc pairwise comparison using Mann-Whitney pair-wise tests with the post-hoc Holm-Bonferroni method to account for erroneous Type I errors. Conversely, if the Kruskal-Wallis test found no significant difference between scenarios, no Mann-Whitney testing would be conducted and the analysis would be complete.

Significant differences between simulated streamflow based on monthly and sub-basin differences can be related to changes in weather inputs and LULC. Therefore, sub-basin specific LULC data and weather period descriptive statistics were used to describe and interpret significant differences. These processes could potentially be cumulative or specific impacts. For example, scenarios with the same LULC but differences in weather inputs would be specific changes, whereas those that had different LULC inputs and different weather conditions would be cumulative impacts. The timing of extreme precipitation, duration of drought, and location of LULC change within sub-basin across the scenarios were systematically examined as potential indicators of what may have caused changes to streamflow.

III.VII: Modeling Processes

Arc SWAT modeling was carried out by loading the pre-processed data in a step-by-step manner to delineate the drainage basin, delineate streams, create HRUs, and add observed weather data to be used by the model. The first step was to start a new SWAT project and load the DEM. The model incorporates the Arc Hydro tool to delineate streams based on accumulation thresholds. The default value for stream accumulation was used because this generated sub-basins that were large enough to be unique in LULC composition (i.e.; predominantly forested, developed, cultivated, etc.). This is also important because the size of the sub-basins influence the size of HRUs created from spatial thresholds (i.e.; 5% of the sub-basin having this LULC classification). The location of the stream gage was designated as the outlet for the drainage basin. The delineated Bush River drainage basin (BRDB) contains 11 sub-basins.

After the BRDB was delineated, both the sets of processed LULC and soils data were added to the model. These data were used by the SWAT model to construct hydrologic response units (HRUs) that are unique combinations of slope, soil type, and LULC within a sub-basin (Gassman *et al.*, 2007). Runoff was generated from the HRUs using the USDA NRCS Curve Number method, which is commonly used in modeling applications and has been proven successful at simulating runoff (Pilgrim and Cordroy, 1993). This method calculates runoff based on LULC type and antecedent moisture conditions. Another reason for using this method over the Green-Ampt method, another commonly used method to calculate runoff, was that the observed precipitation data were recorded at a daily time-step and not sub-daily. Green-Ampt works on a finer temporal scale so it was not applied to the study.

As described in Section II of this chapter thresholds were set at 5% to limit the number of HRUs delimited based on the percent of land covered by a specific combination of physical properties. To express hydrologic processes accurately within a sub-basin, low thresholds were established for a less generalized representation of each sub-basin. Higher HRU delimiting thresholds overlook very small yet unique physical conditions. Lower HRU delimiting thresholds theoretically increase representation of specific physical conditions within the sub-basin, yet can greatly increase the time it takes to calibrate a model and perform uncertainty analysis. Thresholds were selected as 5% of the land covering the sub-basin for all HRU inputs (slope, soil type, and LULC). Low thresholds were advantageous to conduct LULC change analysis because small scale changes were more likely to be within threshold values and simulate runoff processes on the changed surface.

After the HRUs were delimited, weather station locations and observed data were loaded into the model. Weather data (described in Chapter 2, Section II.IV)for all stations were edited to start on 1 January 1951 and end on 31 December 2013, a time period spanning all Extreme Weather Periods (EWPs). The only parameters that were input into the model were precipitation and temperature. While Arc SWAT can use weather inputs such as wind, solar radiation, and evaporation, the model has been shown to successfully model streamflow and water yields with only precipitation and temperature inputs (Arnold et al., 2012). The simulated weather parameters were based on nearby weather stations used to make the model's weather generator. The Penman-Monteith method was applied to calculate evapotranspiration (ET) using the SWAT weather generator. This approach was chosen because the SWAT weather generator (which can simulate daily weather data for days with no recorded observations) is located in Newberry and was assumed to provide accurate simulations for the ET method.

Model simulations were run from 1 January 1951 to 31 December 2013. This also meant there was quite a long warm-up period until the observed streamflow record started (1992), so some of the groundwater parameters, generally the most difficult to model, had enough time to self-regulate and fluctuate to near-realistic ranges (Mukandan *et al.*, 2010). Simulated output in the reach (.rch), sub-basin (.sub), and HRU (.hru) file types was saved for further examination.

III.VIII: Calibration and Validation

The Arc SWAT model simulates streamflow, yet—as with all hydrologic simulations—initial output from the model seldom matches observed streamflow. Parameters within the model that govern various processes (groundwater transfer, evapotranspiration, generation of runoff, etc.) can be adjusted and more realistic streamflow simulations can be obtained. Although a program within the model can check parameter ranges and the water balance (SWAT Check), it is a manual method for calibration and uncertainty analysis which is time-consuming. SWAT Check was used but it was done only to assess the accuracy of the simulated water balance after calibrated values were input back into the model.

SWAT CUP is an open-source calibration and validation program that is capable of performing a multitude of calibration and uncertainty procedures (Abbaspour *et al.*, 2007). The calibration/uncertainty analysis used on the model was the Sequential Uncertainty Fitting version 2 algorithm (SUFI-2). This semi-automatic method selects a subset of parameters from the model to adjust in order to improve the match between simulated and observed streamflow. Choosing meaningful parameters was the first step in performing the SUFI-2 calibration/uncertainty analysis. While the software has the potential to use many parameters in the calibration, a parsimonious approach is to use a few meaningful parameters that are best understood by the modeler and are important to the specific objectives of the study. For example, this thesis is not concerned with water quality or establishing TMDL for the BRDB, so nutrient parameters were not included in the calibration/uncertainty analysis. One method for initially selecting calibration/uncertainty parameters was to identify parameters that were used in successful analyses of modeling efforts in similar drainage basins. Ideally, these models were located within South Carolina, Georgia, or North Carolina, or within the Piedmont physiographic region. Another method for selecting parameters for calibration/uncertainty was to identify which parameters were the least understood, yet have a great impact on runoff in the resulting calibrated model. Generally, groundwater parameters (.gw) are commonly included in calibration/uncertainty analysis because they vary from region-to-region and groundwater observations are limited.

Groundwater parameters govern sub-surface flow, return flow, and percolation to the shallow aquifer, so they are an essential element of the water budget.

The parameters chosen for calibration/uncertainty are given in the Results section (with acceptable parameter ranges and calibrated values). Once the parameters were selected, parameter ranges that were realistic to the study area were set and iterations consisting of 1500 simulations were carried out. This produced 1500 time series of streamflow in the BRDB all with slightly different parameter values. Objective methods were used to quantitatively evaluate how accurately the simulations match the observed streamflow record and to indicate whether a round of calibrations produced a simulation with realistic results. The Nash-Sutcliffe Efficiency (NSE) is commonly used to quantify simulation accuracy (Van Liew *et al.*, 2007):

$$NSE = 1 - \left(\frac{\sum_{k=1}^{n}(Qkobs - Qksim)}{\sum_{k=1}^{n}(Qkobs - Qmean)}\right)^2 \qquad \text{(Eq. 3.2)}$$

where Q_{kobs} is the kth observation, Q_{ksim} is the kth simulated response, and Q_{mean} is the long-term mean of the observed parameter being evaluated (Moriasi *et al.,* 2007; Van Liew *et al.,* 2007). The observed and simulated streamflows in this case represent mean monthly average flow rates for the BRDB. The NSE ranges from negative infinity up to 1.0, which represents a perfect fit between the model and observations. NSE values above 0.75 (for stream flow) are generally considered acceptable (Van Liew *et al.,* 2007). Using the NSE to compare simulations with observed data helps determine when to readjust input parameters or if the current inputs are suitable for modeling.

After satisfactory values were obtained for the objective functions and calibrated parameters were within realistic ranges for the calibration period (1992 – 2001), the same calibrated parameter ranges were used for the validation period of the model (2002 – 2013) and the process was repeated for an iteration of 1500 simulations. After the validation process, updates to the .gw, .hru, .sol, and .mgt files in the model were made by direct changes to parameters within the Arc SWAT 2012 interface or query updates in the model Microsoft Access Database files. This allowed for accurate, as well as realistic, parameters and a model that could sufficiently simulate streamflow if there were weather input data available.

III.IX: Post-Calibration LULC Updates

Land-use update procedures were carried out by updating LULC in the lup.dat file at the HRU-scale, which was far easier than re-running the model for an entirely different LULC dataset (NLCD 2011). This procedure not only avoids having to do another calibration/uncertainty analysis, it also means that comparisons between the two different land-use scenarios are based on runoff and streamflow differences from the same HRUs. Indeed, if the model were run with an entirely new LULC dataset, the amount and spatial distribution of HRUs would change. The two model runs could still be compared but they wouldn't be comparisons controlled for LULC because the spatial distribution of HRUs would also change. The land-use update module (lup.dat) operates by quantifying HRU change from the initial LULC type to the later LULC type and the percent change in HRU area within a sub-basin (Pai and Saraswat, 2011). This conserves the number and spatial distribution of the HRUs. After the HRUs are updated, the model was run with no further calibration/uncertainty analysis and simulated streamflow output from the updated and calibrated original model was compared between the two.

Tables and Figures:

Table 3.1: Total Months above or below Index Thresholds.

Table 3.1: Index Monthly Threshold Counts

Scenario	SPI > 1	SPI < -1	PDSI > 1	PDSI < -1	SPI +/- 0.25	PDSI +/- 1
Moderate	3	2	9	0	3	27
Wet	5	2	22	0	2	14
Drought	2	7	0	20	2	16

Table 3.2: Annual Sums of Standardized Index Records 3-Year Totals.

Table 3.2: Annual Sums of Standardized Index Records 3-Year Totals

Scenario	SPI	PDSI
Moderate (1967 - 1969)	0.54	1.06
Wet (1971 - 1973)	3.44	1.94
Drought (1999 - 2001)	-4.26	-4.45

Table 3.3: Sub-basins affected by updating two initial LULC conditions (HAY and RNGE) to hypothetical urbanizing LULC conditions (URLD).

Table 3.3: lup.dat Impacted Sub-Basins

Initial	Target	Sub-basins affected
HAY	URLD	1 - 6, 8, 9
RNGE	URLD	3, 6, 8, 9

Table 3.4: Approximate percent LULC area in each sub-basin under baseline and updated LULC. Percentage of sub-basin area is given in the Baseline and Lup.dat columns

Table 3.4: LULC Scenarios Areas

Sub-basin	LULC	Baseline	Lup.dat Scenario
Sub-basin 1	FRSD	25.11	25.11
	FRSE	18.74	18.74
	HAY	25.18	11.37
	URLD	18.65	32.47
	URMD	12.31	12.31
Sub-basin 2	FRSD	21.39	21.39
	FRSE	20.78	20.78
	HAY	31.60	12.64
	URLD	15.27	34.24
	URMD	10.96	10.96
Sub-basin 3	FRSD	17.24	17.24
	FRSE	24.43	24.43
	HAY	44.05	22.13
	RNGE	8.46	5.09
	URLD	5.81	31.11
Sub-basin 4	FRSD	16.75	16.75
	FRSE	19.78	19.78
	HAY	55.19	24.14
	URLD	8.28	39.33
Sub-basin 5	FRSD	13.36	13.36
	FRSE	13.71	13.71
	HAY	19.87	10.28
	URLD	28.20	37.79
	URMD	24.86	24.86
Sub-basin 6	FRSD	19.72	19.72
	FRSE	26.22	26.22
	HAY	31.33	15.35
	RNGE	5.60	2.93
	URLD	9.73	28.38
	URMD	7.40	7.40

Sub-basin 7	FRSD	20.35	20.35
	FRSE	29.80	29.80
	HAY	40.26	40.26
	RNGE	9.58	9.58
Sub-basin 8	FRSD	23.78	23.78
	FRSE	42.32	42.32
	HAY	19.43	8.51
	RNGE	7.41	4.03
	URLD	7.06	21.37
Sub-basin 9	FRSD	26.20	26.20
	FRSE	29.68	29.68
	HAY	29.17	13.08
	RNGE	9.47	5.09
	URLD	5.48	25.96
Sub-basin 10	FRSD	43.49	43.49
	FRSE	20.52	20.52
	HAY	11.69	11.69
	RNGE	24.30	24.30
Sub-basin 11	FRSD	25.67	25.67
	FRSE	56.74	56.74
	HAY	8.48	8.48
	RNGE	9.11	9.11

Table 3.5: Approximate percent change in HRU area for the entire drainage basin under baseline and updated scenarios. Total area for each LULC condition are given for baseline conditions and both updated LULC scenarios.

Table 3.5: Percent Drainage Basin LULC

LULC Condition	Baseline	Development
FRSD	23.01	23.01
FRSE	27.52	27.52
HAY	28.75	16.17
RNGE	6.72	5.47
URLD	8.95	22.79
URMD	5.05	5.05

Table 3.6: Simulated streamflow values for all scenarios. Q (cms) signifies the simulated streamflow in cubic meters per second.

Table 3.6: Duration Streamflow Setup

Obs.	Scen. 1	Scen. 2	Scen. 3	Scen. 4	Scen. 5	Scen. 6
Obs. 1	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
Obs. 2	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
…	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
Obs. 36	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)

Table 3.7: Monthly Differences between Scenarios based on Months.

Table 3.7: Monthly Streamflow Setup

	Scen. 1	Scen. 2	Scen. 3	Scen. 4	Scen. 5	Scen. 6
January	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
...	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
December	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)

Table .3.8: Spatial Differences between Scenarios based on the Sub-basins.

Table 3.8: Sub-basin Streamflow Setup

	Scen. 1	Scen. 2	Scen. 3	Scen. 4	Scen. 5	Scen. 6
Sub-basin 1	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
…	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)
Sub-basin 11	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)	Q (cms)

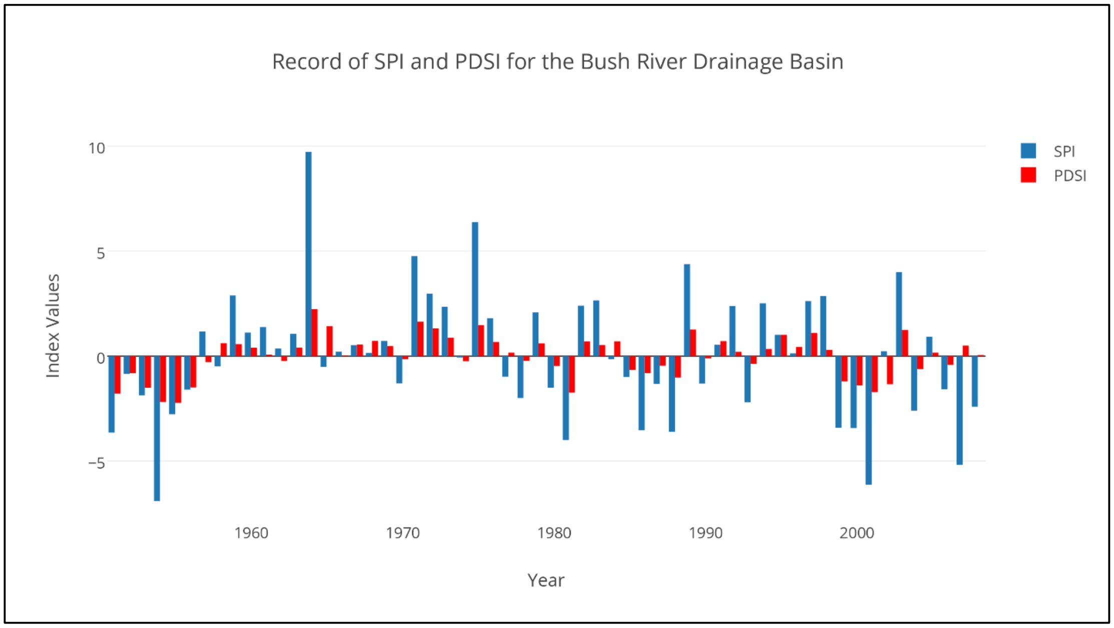

Figure 3.1: SPI and PDSI records for Newberry County, the county containing most of the Bush River Drainage Basin. Annual sums of monthly index values can be used to indicate which years had most months experiencing above/below average conditions.

Lup.dat Module

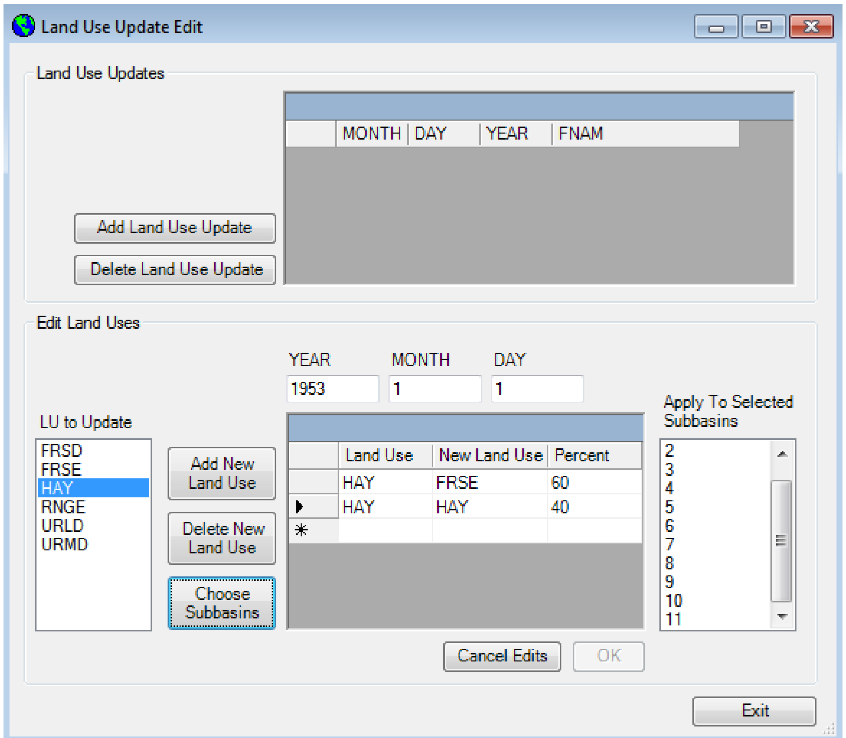

Figure 3.2: SWAT land-use update module interface. In this example, the land use to update is HAY and the projected change is for 60% of all HAY HRUs to be simulated as evergreen forest (FRSE).

Chapter IV: Results

This chapter presents the results of calibration and validation of the model and the modeled output. These results are followed by discussion of the impacts of weather conditions and LULC changes on the simulated monthly runoff for the basin. Finally, the chapter concludes with a discussion and evaluation of the overall analysis and results.

IV.I: Uncertainty, Calibration, and Validation Outcomes

Calibration and uncertainty analysis results were computed as SWAT-CUP objective function values for the calibration period (1992 – 2001) as described in Chapter III. The objective functions quantify the ability of the model to replicate observed streamflow conditions (Table 4.1). The objective function values for the calibration period were NSE = 0.78, r^2 = 0.80, and the simulation percent bias (PBIAS) = 5.2%. A visualization of the calibration results is given in Figure 4.1. All of the selected objective function values fall within ranges that are widely considered good among hydrologic modelers (Moriasi et al., 2007). The objective function values indicate above average accuracy in simulating realistic streamflow with only a slight bias of simulated values greater than observed streamflow. The NSE value of 0.78 indicates that the model predicted streamflow values better than using the average of all observed values (Moriasi et al., 2007). r^2 = 0.80 expresses how little error there was in the model's ability to describe streamflow variance in the simulations (Van Liew et al., 2003). The p-factor measures the percent of observations that are bracketed by the 95 percent prediction uncertainty (95ppu). That means a p value of 0.71 indicates that 71% of observed values fall within the 95% confidence interval. This p value is relatively close to the desired (perfect) value of 1.0, which would represent 100% of observations. Conversely, the r-factor value (0.66) was greater than the desired (perfect) value of 0, which may indicate that the final parameter ranges were not as precise as they could have been. The r-factor describes the thickness of the uncertainty range (Arnold et al, 2012). While most (71%) of the simulated streamflow values were within the 95ppu, the uncertainty range was still relatively large (r=0.66), which may be improved upon with greater knowledge of parameter ranges for the region. A majority of the simulations were within realistic ranges for streamflow and the objective functions reflect this fact as well. The slightly positive bias (PBIAS = 5.2%) may also be due to the use of simulated parameter inputs during a drought within the end of the calibration period. Objective function values during the validation period (2002 – 2013) are also given in Table 4.1. The validated NSE = 0.80 and r^2 = 0.83 were within the range of good objective function values, and the PBIAS improved to a lower value of 1.3%. This represents even less bias in the simulation of streamflow throughout the validation period, which can be observed in Figure 4.2. Table 4.1 also reveals that the p-factor remained the same for the validation period (0.71), whereas the r-factor slightly increased to 0.67. Again, all of the objective function values are considered good for the validation period. Considering objective function values from both calibration and validation periods, the model does a good job at replicating observed streamflow data within a Piedmont drainage basin.

Errors in calibration and validation can sometimes be attributed to overly wet conditions or drought conditions (Abbaspour et al., 2007). Both of these conditions occurred during the calibration and validation time periods with a severe drought in the late 1990s and early 2000s, followed by an extremely wet year in 2003. However, both calibration and validation periods need to have variability, with respect to weather, to be able to accurately simulate streamflow during varying weather conditions (Arnold *et al.*, 2012). A relatively long warm-up period (from 1953 to 1991) provided ample time to allow a wide fluctuation of processes (e.g., groundwater percolation and soil moisture) within realistic values.

Adjusted parameter values are given in Table 4.2, which includes the fitted parameter values that were used to calibrate the model and brief descriptions of the selected parameters. Theoretic parameter values (realistic minimum and maximum values) are included that represent the range of realistic input data for this region. The fitted values were determined from the SUFI-2 calibration/uncertainty analysis. The calibrated parameters from Table 4.2 were imported back into the original Arc SWAT model and a complete simulation (1953 – 2013) was carried out at a monthly time-step. The model LULC was updated using the lup.dat module and the same calibrated parameters were used. The updated model was run for the same period on a monthly time-step

Even after being adjusted, all calibrated parameter values were within realistic ranges. The SCS curve number (CN.mgt) parameter adjustment ranges from application to application and the value that was obtained was within a realistic parameter range. The ALPHA_BF.gw factor agrees with Purdue University's WHAT tool to estimate percent of the year in which baseflow sustains streamflow. The groundwater (GW_DELAY.gw) factor was within realistic ranges and related well to values from Santhi et al. (2007). Soil parameters were applied to all soil horizons. It is possible to parameterize using just the top layer of soil or individually calibrate each soil layer. All soil layers were selected for simplicity. SOL_AWC indicates the water in the soil available for plant uptake and SOL_K indicates the hydraulic conductivity of the soil. Calibrated values indicate that the available water for plant uptake was increased from default values and the hydraulic conductivity of all soil layers was also increased from default values. These calibrated parameters were accepted because of the water demand that a drainage basin predominantly covered in vegetation required and most of the soils in the Piedmont region are rich in clay which impedes the transfer of water through the soil horizons. The soil evaporation compensation factor (ESCO.hru) was adjusted based on Mukandan et al. (2010).

IV.II: Modeled Output

The highest simulated streamflows occurred during the late winter and early spring months across the 3 weather conditions, and this period also experienced the highest variability in streamflow (Figure 4.3 & Figure 4.4). The summer and autumn months experienced the lowest average streamflow values. Seasonal streamflow patterns are evident regardless of extreme weather conditions, suggesting one hypothesis was incorrect that extreme weather periods could suppress seasonal streamflow patterns in the PSC. The larger variance for late winter and early spring is to be expected due to the greater magnitude of flows. Hydrographs for the 3-year weather conditions under baseline LULC conditions (Figure 4.4) are nearly identical to those simulated with developed LULC conditions, which are not shown. It is evident that even within a specific weather condition there existed variability (e.g.; the occasional wet (dry) month in the dry (wet) period). However, the hydrographs of each weather period exhibit distinct traits. The hydrograph of the dry period is unique from the other weather periods in that there were protracted periods of low streamflow. Conversely, there appeared to be protracted periods of higher streamflow during the wet period with increased month-to-month variability in streamflow. The moderate weather period's hydrograph reveals that there were no long-term periods of characteristically low or high streamflow and less drastic streamflow variability.

Modeled streamflow output from contrasting weather condition scenarios were significantly different and produced the greatest changes in median streamflow which agrees with many of the recent studies that focus on quantifying changes to streamflow caused by extreme weather conditions (Chattopadhyay and Jha, 2014; Guo et al., 2008; Kim et al., 2013, Li et al., 2013; Li et al., 2009). Results indicated that changes to streamflow resulting from increased development were not significant. The percent change in median streamflow and in the overall water balance were minimal. Again, similar findings have been observed by previous studies (Guo et al., 2008; Kim et al., 2013; Li et al., 2013; Li et al., 2009; Zhu and Li, 2015). However, the conditions under which these studies were conducted all varied with scale, magnitude, and the type of LULC change.

Simulated streamflow for all EWPs under both the original and updated LULC conditions are given in Appendix Table Results.2 - 4. Appendix Table Results.2 - 4 shows how the original model, with more rangeland and cultivated land cover and less low-density development, produced less streamflow than the updated model which accounted for increased low density development in the region. These formatted values were used for ANOVA and pairwise testing to determine statistically significant differences between the scenarios simulated streamflow.

IV.III: Statistical Testing of Output

Kruskal-Wallis tests—non-parametric ANOVA—were conducted on three sets of the input data created from model output (Appendix Table Results.2 – 4), The data were grouped to test for significant differences in simulated streamflow between scenarios for (1) their entire durations (all 36 months in a scenario), (2) at a finer temporal scale (specific months), and (3) at a finer spatial scale (sub-basins). The test results include Chi-Squared values, degrees of freedom (5 for all test groups), and the p-value (Table 4.3). A p-value less than 0.05 meant a simulated streamflow scenario was statistically different from one of the other scenarios. The p-values were significant for the duration group and the monthly group. The lack of significant difference with the spatial group represents a lack of difference in streamflow attributable to changes in the physical characteristics of the sub-basin. Figures 4.3 (A – C) show the distribution of samples within each scenario for each formatted table.

After the Kruskal-Wallis test was computed for all three formatted groups, pair-wise comparisons were carried out using the Mann-Whitney test for all 15 possible pairs of scenarios for the duration group and the month-specific group. Abbreviations used in this and subsequent discussions are defined in Appendix Table A.1. Mann-Whitney tests for the spatial group were not performed because the Kruskal-Wallis test indicated that no two scenarios simulated significantly different streamflow at the sub-basin scale.

The pair-wise test results for the duration group indicate that out of the 15 scenarios 12 are significantly ($p < 0.05$) different (Table 4.5). The only three that were not significantly different were the paired scenarios from the same weather period in which only LULC changed (e.g., Baseline Moderate (BM) to Developed Moderate (DM)). This indicates that changes in streamflow caused by conversion of abandoned and agricultural lands to low-density development were relatively small. The post-hoc Bonferroni correction was applied for a more conservative estimate of significance levels to determine significant differences in streamflow between scenarios. The Bonferroni correction indicated only 4 of the 15 paired scenarios had significant differences in streamflow (Table 4.5). These 4 paired scenarios were the Baseline Wet (BW) to Baseline Dry (BD), Baseline Wet to Developed Dry (DD), Developed Wet (DW) to Baseline Dry, and Developed Wet to Developed Dry. None of the moderate weather scenarios were significantly different from any of the other scenarios. These results indicate that only extreme weather scenarios, comparing a wet scenario to a dry scenario, produced statistically significant differences in streamflow.

Pair-wise significance testing performed on the month-specific grouped streamflow indicates that only 4 of the 15 paired scenarios had statistically different streamflow (Table 4.6). These were the same 4 scenarios that were significantly different after the Bonferroni correction from the duration group pair-wise testing. However, after the Bonferroni correction was implemented on the month-specific group not a single pair of scenarios exhibited significantly different values for streamflow (Table 4.6). This could have been expected because the data were aggregated from 36 specific months to 12 months that were each averaged from 3 values. In summary, median streamflow was less sensitive to changes in land cover than changes in weather and climate.

The smallest changes in median streamflow between scenarios for the duration group were associated with substantial increases in low-density development rather than changes in weather periods (Table 4.7). For example, using the moderate weather scenario under baseline land-use conditions and changing only land use by increasing low-density development, the baseline median streamflow was 0.14 $m^3 s^{-1}$ less than the developed scenario's median streamflow. This represents a 5.53% increase in median streamflow from the Baseline Moderate to the Developed Moderate scenario. In contrast, under baseline LULC conditions, changing the weather from moderate conditions to wet conditions resulted in a 2.61 $m^3 s^{-1}$ (102%) increase in streamflow. When the moderate weather period is compared to the extremely dry weather conditions there was a 1.5 m^3 s^{-1} (57.9%) decrease in median streamflow. Similar responses in median streamflow were obtained under developed LULC conditions when the weather periods were shifted. For example, median streamflow from the Developed Moderate period to the Developed Wet period increased by 2.49 m^3 s^{-1} (91.2%), and median streamflow decreased by 1.68 m^3 s^{-1} (61.7%) with a shift from the Developed Moderate scenario to the Developed Dry scenario.

IV.IV: Analysis of Water Budget Changes

One of the advantages of spatially-distributed simulation modeling is that individual pathways and repositories of water can be tracked using a water budget. These results are divided into changes due to weather extremes versus those due to changes in LULC. Water budgets for each scenario produced by the model give insight into the processes and components of the water balance contributing to streamflow for each scenario (Appendix: Tables A1 – A9). All scenarios indicate that lateral flow contributed the least to simulated streamflow. Runoff and groundwater flow contribute substantially more to streamflow than lateral flow with groundwater flow contributing the most throughout all 6 scenarios. In the most basic sense, the water yield is computed as the difference between precipitation and ET:

$$WY = P - ET \qquad \text{(Eq. 4.1)}$$

Model documentation states that water yield (streamflow leaving the sub-basin or basin) is calculated by the following equation (Neitsch et al., 2005):

$$WY = SURQ + LATQ + GWQ - Abstractions \qquad \text{(Eq. 4.2)}$$

Where *WY* is water in the sub-basins or basin contributing to streamflow (mm), *SURQ* is surface runoff contribution to streamflow (mm), *LATQ* is lateral flow contribution to streamflow (mm), *GWQ* is groundwater contribution to streamflow (mm), and *Abstractions* is the combination of transmission losses of water through the channel to the shallow and deep aquifers, ponding throughout the sub-basins, and infiltration (mm). It is important to note that abstractions are not given and must be manually calculated using the following corollary equation:

$$Abstractions = WY - SURQ - LATQ - GWQ \qquad \text{(Eq. 4.3)}$$

Overall, abstractions only accounted for 2-3% of the water budget when compared to surface runoff, lateral flow, and groundwater contributions to streamflow for any given scenario. In the BRDB the entire water yield was measured at the outlet.

IV.IV.I: Water Budget Changes Due to Weather Extremes

Differences in water balance parameters between scenarios were noticeable. Regardless of LULC condition within the BRDB soil moisture was shown to be greatest for the wet period, least for the drought period, and the moderate weather period had soil moisture conditions similar to the wet period. Only having one year separate the moderate and wet weather periods may have been why the amount of soil moisture between the two periods was similar. Soil moisture is a key indicator of drought and is a common metric used to define drought (e.g.: PDSI takes into account soil moisture) (Carbone and Dow, 2005). Calculated PDSI values for the drainage basin were used in establishing the weather periods of the thesis and this was evident from the simulated soil moisture differences between scenarios. Greater amounts of soil moisture could have influenced the increase in the total amount of evapotranspiration (Zhang and Schilling, 2006). The moderate and wet weather conditions both had higher soil moisture and higher total amounts of actual evapotranspiration. The highest amounts of actual evapotranspiration occurred during the moderate period.

Differences in soil moisture between the 3 weather periods was also shown to substantially influence hydrologic processes. An abundance of soil moisture can greatly decrease infiltration and increase runoff generation (Penna et al., 2011). The wet and moderate periods had similar amounts of soil moisture with less than a 1% difference between the two scenarios (Table 4.7 and Table A.13). However, the wet period had more precipitation than the moderate period and had a slightly higher soil moisture content, which resulted in a 30% increase in total surface runoff between the Baseline Moderate and Baseline Wet scenarios, and a 31% increase in total surface runoff between the Developed Moderate and Developed Wet scenarios. This demonstrates the sensitivity of runoff to soil moisture in this environment. Surface runoff from the moderate to wet weather conditions increased about the same regardless of the LULC conditions. There was a 42% decrease in surface runoff from the Baseline Moderate to Baseline Dry scenarios and a 43% decrease from the Developed Moderate to Developed Dry scenarios. Again the reduction in the average runoff was about the same when comparing different weather periods with the same LULC conditions. These findings relate to those of other studies that investigated how the amount of runoff can decrease during droughts (Dracup et al., 1980; Shukla and Wood, 2008). These studies both found that less runoff is generated when persistent deficits in precipitation and soil moisture exist. Soils that have lower amounts of moisture content would allow for more infiltration to occur.

When accounting for the total precipitation that occurred during a weather period, the relative amount of precipitation that was evaporated and transpired was greatest during the drought period. ET accounted for approximately 67% of precipitation during the moderate period, 58% during the wet period, and 76% during the driest period. These values were effectively the same for both LULC scenarios. Rates of actual evapotranspiration are effected not only by soil moisture but by solar radiation, wind, temperature, and humidity (Notaro et al., 2006). The simulated solar radiation was greater during the drought period when compared to the moderate period, and least during the wet period. While this finding from the modeled output is intuitive and supports the hypothesis, the output was simulated by the weather generator and should be checked with nearby observed solar radiation data if it existed.

IV.IV.II: Water Budget Changes Due to LULC Development

Differences in the water yield to streamflow for scenarios with the same weather conditions but different LULC (e.g., Baseline Moderate to Developed Moderate) were all minor with all differences between any two LULC change scenarios being less than 1%. However, changes to components of the water balance are noticeable when comparing values between the scenarios with baseline LULC to those with increased low-density development. All scenarios with increased development experienced lower contributions from surface runoff and greater contributions to streamflow from lateral flow and groundwater. Specifically, surface runoff decreased from Baseline Moderate to Developed Moderate by 7%, from Baseline Wet to Developed Wet by 6%, and from Baseline Dry to Developed Dry by 9%. These changes are all greater than the changes in scenario water yield. Conversely, lateral flow increased by 2% from Baseline Moderate to Developed Moderate, from Baseline Wet to Developed Wet, and from Baseline Dry to Developed Dry. Groundwater flows also increased between development scenarios with similar weather conditions but different LULC conditions. Groundwater flows increased from Baseline Moderate to Developed Moderate by 7%, Baseline Wet to Developed Wet by 4%, and from Baseline Dry to Developed Dry by 8%. When comparing scenarios with similar weather periods but contrasting LULC conditions percolation was greater for the scenarios with increased low-density development.

The water balance tables for each scenario (Appendix Table A.1-6) indicate that increasing low-density development across the drainage basin will result in decreased surface runoff, greater lateral flow and groundwater contribution to streamflow, and more percolation of water to the deep aquifer. Specifically, surface runoff decreased from Baseline Moderate to Developed Moderate by 7%, from Baseline Wet to Developed Wet by 6%, and from Baseline Dry to Developed Dry by 9%. Conversely, lateral flow increased by 2% from baseline to developed LULC conditions over all EWP. Groundwater flows increased from Baseline Moderate to Developed Moderate by 7%, Baseline Wet to Developed Wet by 4%, and from Baseline Dry to Developed Dry by 8%.

The table shows that there were not large changes in ET, the water yield, or soil moisture when simulating over different LULC conditions. Percolation experienced increases from baseline due to developed conditions.

Tables and Figures:

Table 4.1: Calibration and Validation objective function results.

Table 4.1: Calibration/Validation Results

Phase	r^2	NSE	PBIAS	p-factor	r-factor
Calibration	0.80	0.78	5.2	0.71	0.66
Validation	0.85	0.80	1.3	0.71	0.67

Table 4.2: Parameters and their ranges for Calibration and Validation of the model.

Table 4.2: Calibrated Model Parameters

Parameter Name	Description	Min. Value	Max. Value	Fitted Value
R__CN2.mgt	Curve Number	0.02	0.15	0.088
V__ALPHA_BF.gw	Baseflow Contribution (Days/Year)	0.5	0.54	0.535
V__GW_DELAY.gw	Groundwater Delay (Days)	0	52	31.174
V__GWQMN.gw	Depth of Shallow Aquifer for Return Flow (mm)	0	14	11.571
V__GW_REVAP.gw	Groundwater "Revap" Coefficient	0.06	0.19	0.140
V__ESCO.hru	Soil Evaporation Compensation Factor	0.5	0.85	0.637
R__SOL_AWC(..).sol	Soil Available Water Content (mm H20/mm soil)	0.01	0.15	0.080
R__SOL_K(..).sol	Saturated Hydrualic Conductivity (mm/hr)	0.1	0.2	0.186

Table 4.3: Kruskal-Wallis test results for all comparisons. Level of significance $p < 0.05$.

Table 4.3: Kruskal-Wallis Results

Grouping Method	Kruksal-Wallis Chi-Squared Value	p-value
Duration	29.86	1.57E-05
Spatial	7.677	0.175
Monthly	14.41	0.0132

Table 4.4: Bonferroni-corrected Mann-Whitney significance values for 36-month duration groups.

Table 4.4: Duration Test Results

Paired Scenarios	Original p-value	Bonferroni Corrected p-values
DW-BD	0.0002	0.003
BW-BD	0.0002427	0.0033978
BW-DD	0.0002427	0.0031551
DW-DD	0.0003417	0.0041004
BM-DW	0.02261	Not Significant
BM-BW	0.02475	Not Significant
DM-DW	0.02706	Not Significant
DM-BW	0.02955	Not Significant
DM-BD	0.03132	Not Significant
BM-BD	0.03318	Not Significant
DM-DD	0.03614	Not Significant
BM-DD	0.04043	Not Significant
BM-DM	0.942	Not Significant
BW-DW	0.9777	Not Significant
BD-DD	0.982	Not Significant

Table 4.5: Bonferroni-corrected Mann-Whitney results for temporal (monthly) groups.

Table 4.5: Monthly Test Results

Paired Scenarios	Original p-value	Bonferroni Corrected p-values
DW-BD	0.008293	Not Significant
BW-BD	0.008293	Not Significant
BW-DD	0.008293	Not Significant
DW-DD	0.008293	Not Significant
BM-BW	0.1432	Not Significant
BM-DW	0.16	Not Significant
DM-BW	0.16	Not Significant
DM-DW	0.1782	Not Significant
DM-BD	0.1978	Not Significant
BM-BD	0.1978	Not Significant
DM-DD	0.2189	Not Significant
BM-DD	0.2189	Not Significant
BM-DM	0.9081	Not Significant
BW-DW	0.9323	Not Significant
BD-DD	0.9323	Not Significant

Table 4.6: Differences in median streamflow between scenarios. (A) Difference in median values given in cubic meters per second (row scenario minus column scenario). (B) Percent difference between scenarios. Note the smallest changes were between different LULC conditions within the same period of EWP.

Table 4.6 A: Difference in Median Streamflow

Scenario	BM	DM	BW	DW	BD	DD
BM	-	-0.14	-2.61	-2.63	1.50	1.54
DM		-	-2.47	-2.49	1.64	1.68
BW			-	-0.02	4.11	4.15
DW				-	4.13	4.17
BD					-	0.04
DD						-

Table 4.6 B: Percent Difference in Median Streamflow

Scenario	BM	DM	BW	DW	BD	DD
BM	-	5.53	101.08	101.82	-57.91	-59.56
DM		-	90.54	91.24	-60.12	-61.68
BW			-	0.37	-79.07	-79.89
DW				-	-79.15	-79.96
BD					-	-3.91
DD						-

Table 4.7: Average annual water quantity values for each Scenario. All values given in millimeters.

Table 4.7: Scenario Average Hydrologic Variables

Scenarios	Precipitation	SURQ	LATQ	GWQ	Percolate	SW	ET	PET	WY
BM	1194.95	162.77	27.98	182.92	196.66	253.06	791.96	1000.23	383.08
BW	1361.09	212.23	34.5	316.69	333.64	253.35	781.17	984.55	579.85
BD	981.43	93.24	23.13	140.47	143.85	195.13	735.39	978.45	264.62
DM	1194.91	151.2	28.47	195.69	209.55	253.63	791.24	1000.2	385.45
DW	1361.05	198.43	35.1	329.41	347.65	254.12	780.06	984.52	580.03
DD	981.4	84.67	23.5	151.04	155.26	198.93	731.21	978.42	267.53

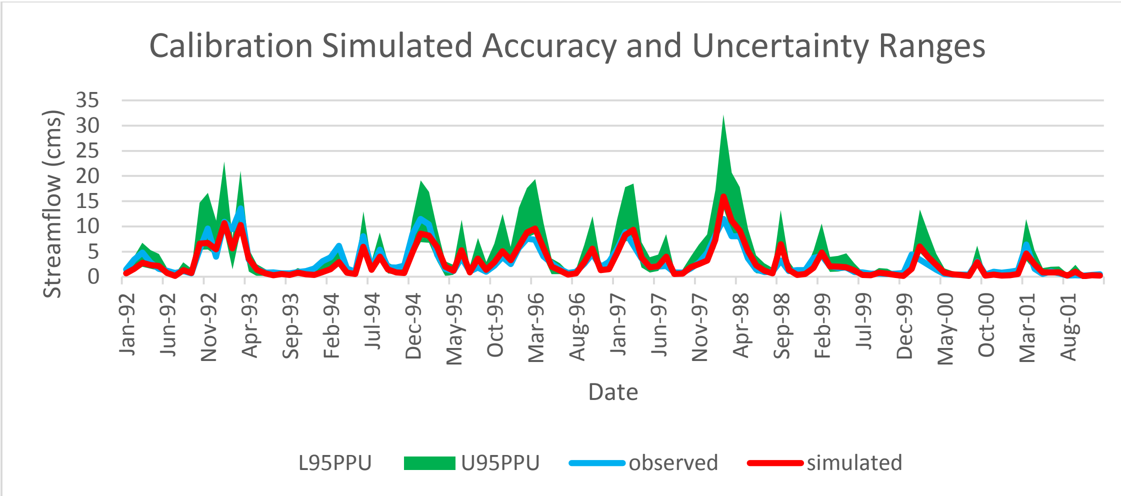

Figure 4.1: Simulated results for the calibration time period (1992 – 2001). The period experiences fairly moderate weather conditions through most of the early portions of the record. On the other hand, the latter portions of the calibration period was during one of the most severe droughts on record. The green band indicates the range of all simulated values for the calibration period. The red line indicates the best simulation

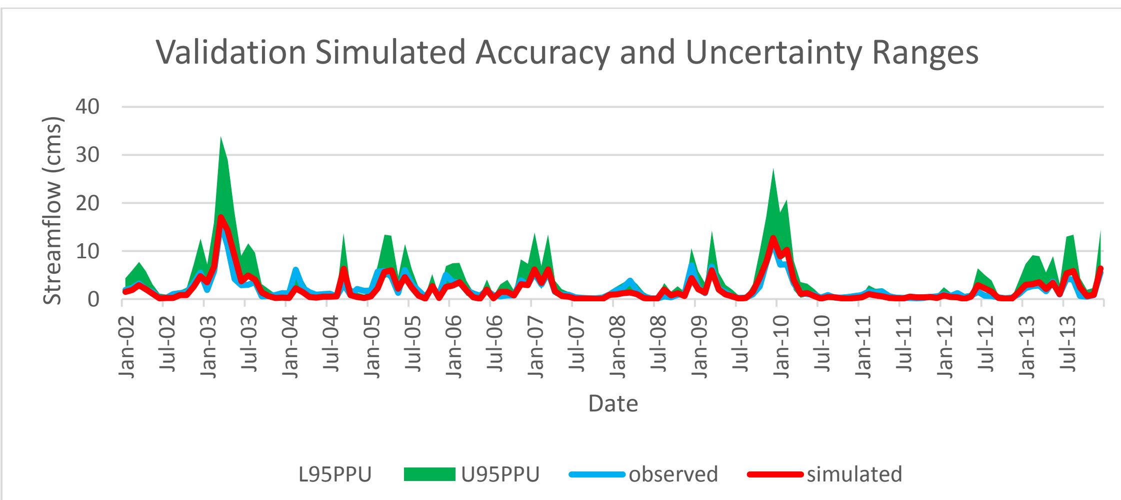

Figure 4.2: Simulated results for the validation period (2002 – 2013). There were many years characteristic of drought within the validation period. However, there existed some extremely wet years during the period. The green band indicates the range of all simulated values during the validation period. The red line indicates the best simulation.

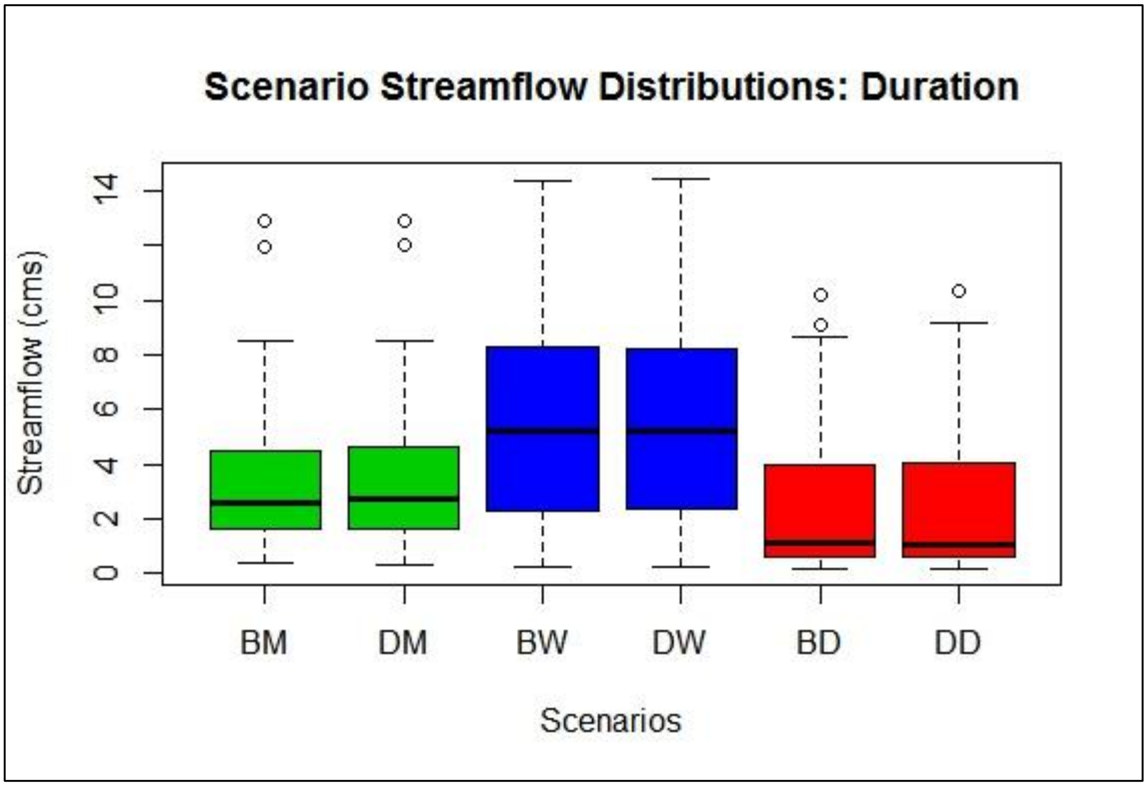

Figure 4.3 (A): Boxplots for the 6 Scenarios by duration (36 months per scenario). Boxplots are grouped by color for easier indication. Green boxplots indicate the moderate weather conditions, blue boxplots indicate extremely wet weather conditions, and red boxplots indicate extremely dry weather conditions. The same two letter scenario formatting was applied.

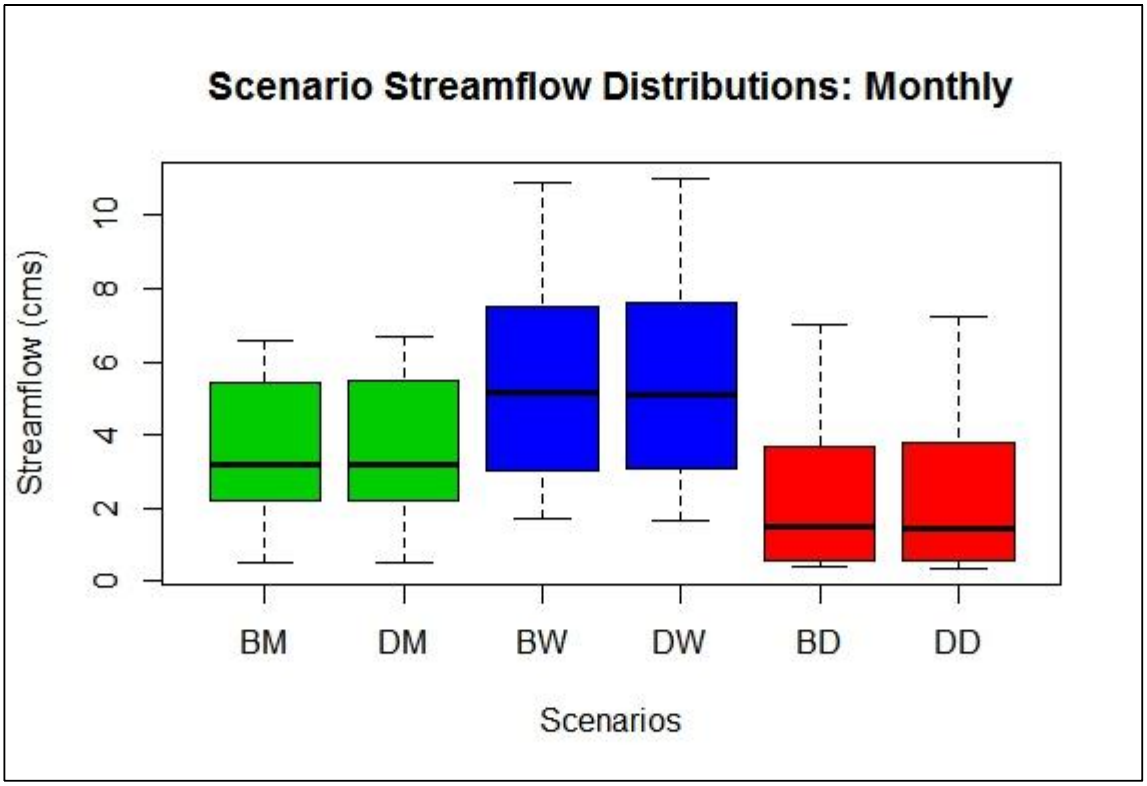

Figure 4.3 (B): Boxplots visualizing streamflow distribution for all monthly averages within a scenario.

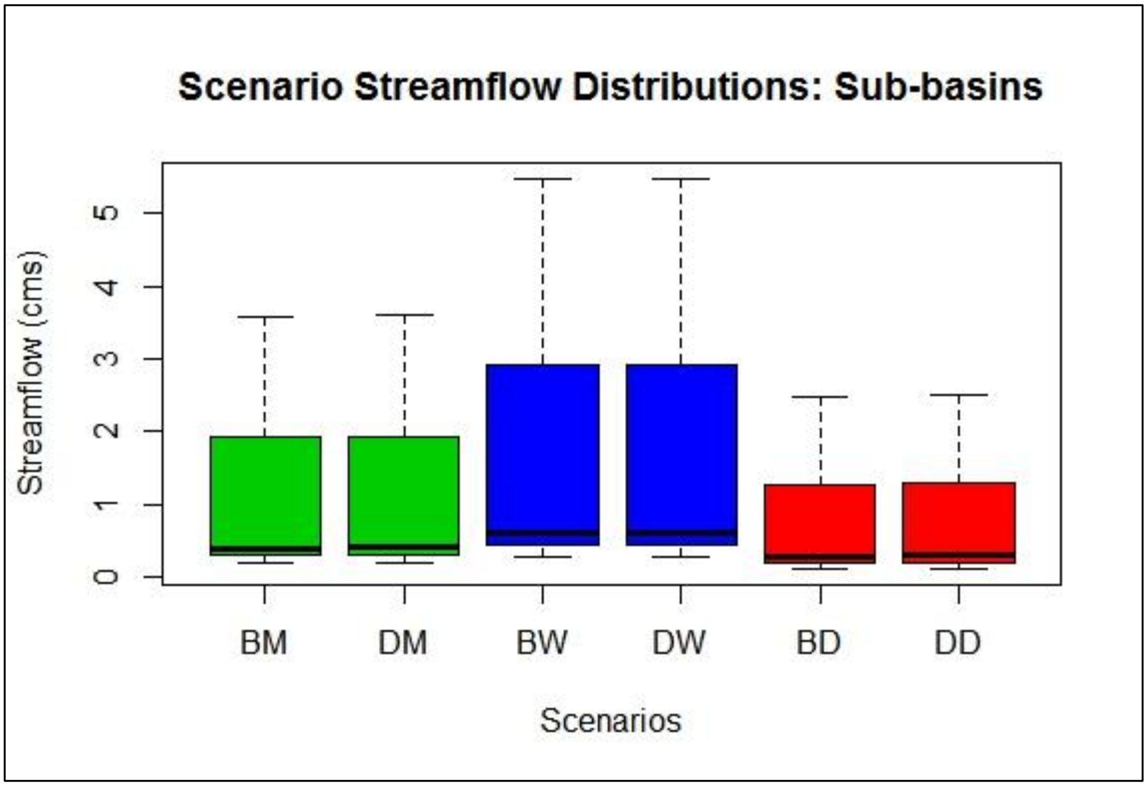

Figure 4.3 (C): Boxplots indicating the distribution from the average sub-basin streamflow for all scenarios. Formatting from Figure Result.1 was applied to this figure as well.

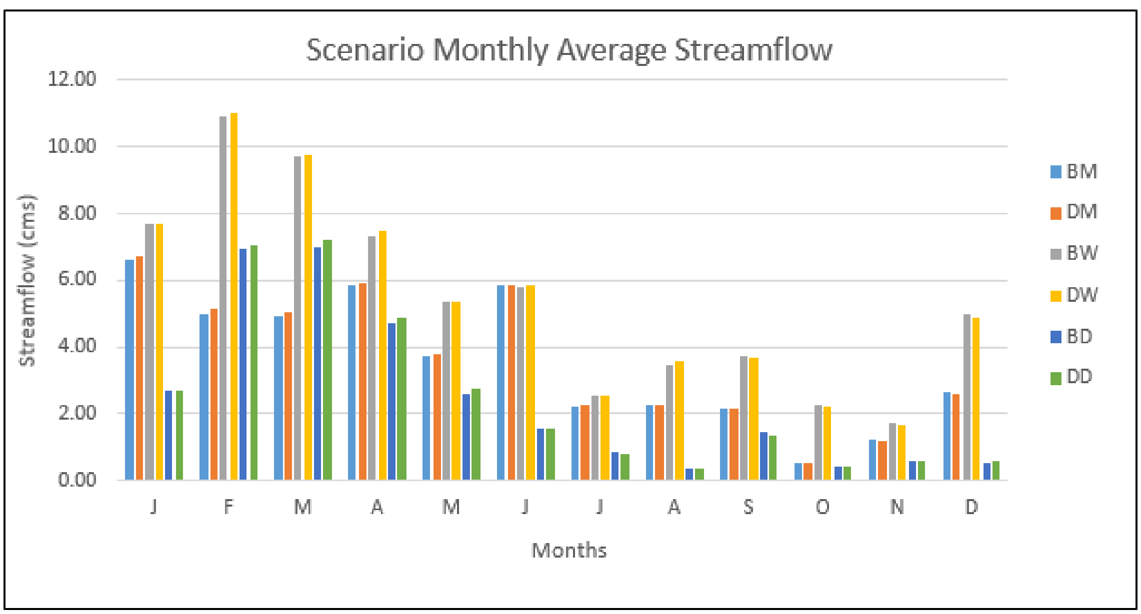

Figure 4.4: Simulated streamflow for all months from all six scenarios.

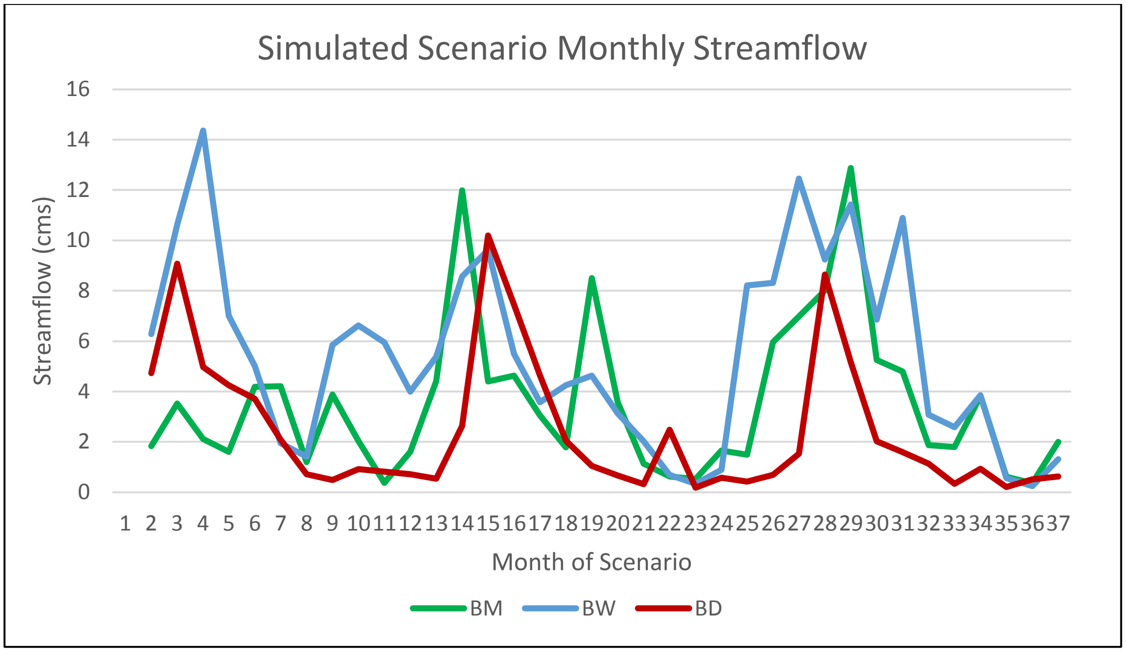

Figure 4.5: Hydrographs for the 3 EWP (Baseline LULC conditions).

Chapter V: Discussion

Overall, the model was able to answer the research questions by accurately simulating streamflow and runoff over various weather periods and over different physical land-use conditions. The findings described in the previous section compare well with recent literature regarding scenario testing using the Arc SWAT hydrologic model. In addition, model outcomes conform closely with expected results as expressed by the hypotheses. The model was shown to be well calibrated and all calibrated parameters were within realistic ranges. However, a degree of uncertainty remained that is explained in further detail within this section. The objectives of this section are to (1) discuss the findings previous studies and hydrologic theory, (2) to address uncertainty of the findings, and (3) to offer suggestions on how future research could improve hydrologic understanding of this region.

V.I: <u>Impacts of Extreme Weather Conditions on Hydrology</u>

V.I.I: <u>Responses of Hydrologic Processes to EWP</u>

Aside from the comparisons of runoff generation and streamflow to other modeling applications, the modeled streamflow and water balance results from this study reveal specific responses that relate well to hydrologic theory. The model indicates how characteristically dry or wet periods are likely to influence specific hydrologic processes generating streamflow within the landscape. Precipitation is obviously the driving force of the hydrologic cycle and distinct changes in duration, frequency, and intensity can cause noticeable changes in hydrologic processes such as soil moisture, groundwater percolation, and water yields. Soil moisture, total and relative amounts of ET, and surface runoff all changed systematically between the weather scenarios. During periods of consistently above-average precipitation, soil moisture increases, which eventually reduces infiltration and increases surface runoff. Evapotranspiration has the potential to increase from increased soil moisture, yet it is also dependent on climate variables such as temperature, solar radiation, and humidity. Lastly, groundwater recharge is likely to be greater during periods of increased precipitation that occur over saturated soils. Conversely, periods of extremely dry conditions in the drainage basin experienced less soil moisture, less contribution to groundwater recharge, and less runoff compared to moderate conditions. Evapotranspiration accounted for a larger proportion of the water balance (~ 75%) during drought conditions and was markedly higher than during the moderate and wet weather periods. The model successfully simulated the impacts to streamflow and the water balance that were characteristic of the defined weather periods. This sufficiently answers the hypothesis postulated in Chapter 1 that the model could accurately simulate hydrologic processes over varying extreme weather conditions. These results relate to relevant modeling literature and hydrologic theory.

V.I.II: Relevance of Extreme Weather Studies to Climate Change Studies

Modeling applications such as these are important, not only because the work in this thesis provided simulated streamflow from historic weather observations but because they provide information on the characteristics of streamflow and the water budget across a range of weather and climate conditions that a drainage basin will experience. In addition to providing information on basin response to periods of extreme weather, this type of study is ideal for regions with highly variable weather and climate. Across the United States, most areas are experiencing significant trends in precipitation and temperature at a longer temporal scale. This generally implies that the increases or decreases in climate variables are persistent with some year-to-year fluctuation. The SEUS is an exception that has been noted to have little evidence supporting long-term annual trends in climate variables (i.e.; precipitation, temperature, etc.) when compared to other regions of the United States. While climate change is an issue that has received immense attention, studies investigating climate variability and its impact on the environment haven't garnered as much attention. Small-scale studies such as this thesis provide detailed water resources information on the hydrologic response to areas with frequent periods of extreme weather.

The statistical methods of this modeling application are simpler than studies that conduct trend detection on climatic variables and streamflow. Normalizing observed weather records and counting the number of months in a year above a threshold (wet/dry) and applying a moving window is a fairly simple procedure. Conducting the Kruskal-Wallis test, Mann-Whitney test, and the Bonferroni correction are also relatively straightforward procedures. Long-term time series are ideal for trend detection, yet some complex computations must be performed on the time series (i.e.; pre-whitening) before analysis of data can begin. The simplified methods used in this thesis do not imply that the results are less accurate, or less reliable, compared to findings from studies incorporating trend detection. The methods used in this thesis applied a conservative correction to account for erroneously significant initial testing results. The relevance of investigating extreme weather periods is that they can be compared to moderate weather periods, as well as the opposite extreme (wet/dry), and quantify how weather and climate variability impact streamflow.

V.I.III: Comparisons with Other Studies

Previous investigations of differences in streamflow caused by varying weather conditions did not use the exact same methods as this study (i.e.; the use of non-parametric ANOVA and pair-wise testing). Nevertheless, similarities are noteworthy between the findings from this thesis and those of other studies investigating the differences in streamflow caused by different weather conditions. Recall that the highest simulated streamflow values were during the winter and early spring and the lowest values were during the summer and early autumn months. These results match those of other modeling applications as well as hydroclimatological and streamflow studies within the Piedmont physiographic region and hydrologic theory (Chattopadhyay and Jha, 2014; Groisman et al., 2001; Kim et al., 2014; Lins and Slack, 1999).

Few applications of the model have been implemented within the Piedmont physiographic region or watersheds in the United States with similar climates. Modeling applications that investigated similar issues were primarily located in the eastern portions of Asia. Impacts on streamflow from different weather conditions from these Asian studies were summarized in Chapter One and are compared here to similar findings from this thesis. Li et al. (2009) conducted LULC change and weather scenarios and found when comparing baseline runoff depth from a scenario with drier weather conditions and similar LULC inputs there was approximately 95% less runoff depth generated. Li et al. (2012) found that when comparing an average weather year to a wet weather year runoff increased by 161.9%, and decreased by 75.5% when comparing an average weather year to a dry weather year. Likewise, Guo et al. (2008) found that streamflow increased by 120% from an average weather year to a wet weather year, and decreased around 40% when comparing streamflow from a dry weather year to an average weather year. Scenario testing in the BRDB indicated that there was approximately 57 – 62% decrease in median streamflow from the moderate weather conditions to the extremely dry weather conditions, and approximately 90 – 100% increase in median streamflow when comparing moderate weather conditions to extremely wet weather conditions (Table 4.6). The impacts to streamflow caused by periods of extreme weather within this modeling application are similar to the findings of previous studies using the same model. The percent change in median streamflow from moderate to dry weather conditions was within the range of similar studies. However, the percent change in median streamflow from the moderate to wet weather conditions in this study weren't as high as those from similar studies. A possible explanation for this finding could be because the year/s defined as wet year/s in similar studies could have experienced much more precipitation compared to the wet weather years of this thesis.

The modeling approach used in this thesis was fairly specific, yet moderate, wet, and dry periods were defined differently than other studies due to the different observed precipitation records between each drainage basin. While this thesis established thresholds to quantify periods of moderate, wet, and dry weather, other relevant studies compared streamflow from the single wettest and driest years on record to streamflow from a year that was closest to the average amount of precipitation. The multi-year approach of this thesis provided a more robust characterization of persistent weather conditions. This relates to another challenge of comparing results between studies of runoff generation and streamflow. Most other studies used varying temporal scales of analysis. Studies that emphasized differences in streamflow from the single wettest year to the single driest year are not directly comparable with a study such as this that investigated differences during the drier and wetter periods (in some cases halves) of a climate record. These comparisons reveal a range of streamflow values over various weather conditions and how they change at various temporal resolutions (e.g.; year, period of years, decades).

V.II: Impacts of LULC Change on Streamflow

The modeling results indicated that there was no significant difference in streamflow attributed to changes in LULC within the BRDB at the basin or sub-basin scale. However, changes in water balance parameters between paired scenarios with the same weather conditions but different LULC conditions experienced distinct changes.

V.II.I: Discussion of Low-Density Developments Impact on the Water Budget

The water yield from all HRUs to streamflow was shown to increase slightly from baseline conditions to increased low-density development conditions. Contrary to theories of urban hydrology that postulate increased surface water and decreased infiltration to groundwater, however, surface runoff decreased with development and was compensated for by increased groundwater and lateral flow contributions to streamflow. Sub-basin surface runoff totals for the 6 scenarios and 11 sub basins are given in Table 5.1, which shows that sub-basins 7, 10, and 11 did not experience changing surface runoff totals. Although these sub-basins did have agricultural lands and abandoned lands, no low-density development previously existed within these sub-basins, so the lup.dat module could not activate the LULC condition increase (Pai and Saraswat, 2011). This was a severe limitation of the modeling application but the simplest and most efficient way to implement LULC change within the model. Regardless, even with 3 of the 11 sub-basins not experiencing any LULC change, the median total surface runoff decreased when low-density development increased within the basin. Median total surface runoff decreased from Baseline Moderate to Developed Moderate by 7%, from Baseline Wet to Developed Wet by 6%, and from Baseline Dry to Developed Dry by 9% (Table 5.2).

Differences in the amount of runoff produced were greatest when comparing the driest conditions with different LULC scenarios and least when comparing the wettest conditions with different LULC. During drier conditions simulated soil moistures were less saturated and thus infiltration would be higher during these periods because of less antecedent moisture in the soils. Runoff is generated quickly from impervious and saturated surfaces because less infiltration occurs on these surfaces. The moderate and wet periods had higher and similar amounts of soil moisture, so infiltration was less and the introduction of less permeable surfaces during these periods wouldn't create as great an increase in surface runoff as introducing less permeable surfaces during a period with less saturated soils (Putnam, 1972).

The spatial patterns of LULC and surface runoff change in sub-basins were investigated on a case-by-case basis. Sub-basins with the most noticeable decreases in total surface runoff were sub-basins 2, 3, and 4 (Table 5.1 and Table 5.3). These sub-basins were all predominantly covered by agricultural lands with some pre-existing low-density development. Total surface runoff decreased from Baseline Moderate to Developed Moderate in sub-basin 2 by 9.7%, in sub-basin 3 by 8.6%, and in sub-basin 4 by 19.4%. A similar analysis comparing the runoff generated in these sub-basins from Baseline Wet to Developed Wet and from Baseline Dry to Developed Dry resulted in similar conclusions. The greatest decrease in total surface runoff (30.4%) was in sub-basin 4 from Baseline Dry to Developed Dry. Again, this was the sub-basin with the greatest increase in low-density development. Visualization of sub-basin changes in runoff between scenarios are given in Figure 5.3 and in the Appendix by Figure A.1-15.

V.II.II: Why Simulated Surface Runoff Decreased

Increases in developed land are generally expected to lead to increased surface runoff due to decreased infiltration and ET. An examination of how streamflow was calculated as a function of Soil Conservation Service curve numbers (CN) for each LULC type reveals why surface runoff decreased with low-density development in the simulations. First, RNGE (rangeland) and HAY (agriculture) are assumed by the model to be similar in composition to URLD (low-density development) with grasses, shrubs, and trees present. Note that the monthly CN values for all LULC conditions in the model are computed as a function of LULC, antecedent moisture, and other factors that change seasonally (Figure 5.1). Agriculture and low-density development have similar CN values that decrease in summer months, yet the rangeland CN is noticeably higher and doesn't experience the usual summertime decrease. The LULC update resulted in the conversion of Rangeland to URLD, which resulted in decreased CNs, especially during summer months when Rangeland CNs remain high whereas developed CNs are much lower (Figure 5.1). Groundwater contributes greatly to streamflow within the BRDB and reducing the ability of precipitation to infiltrate could cause the overall water yield to decrease. When the lup.dat module activated the LULC change scenario, half of the agricultural rangelands and all of the abandoned agricultural lands were converted to low-density development in all but 3 sub-basins.

Another issue with the selected method for implementing LULC change was that the spatial patterns of simulated change didn't accurately simulate the change where it would be most likely to occur (i.e.; near roads, urban areas, and areas with favorable topography for development). Growth of developed areas usually emanates outward from developed areas, not just on land in cultivation or barren lands. Proximity to population centers is a major factor in LULC change within the SEUS and more detailed HRU updates could account for this change. However, this approach would be extremely time-consuming accounting for the thousands of HRUs in some simulations. Furthermore, this basin does not have stream gages within each sub-basin to provide streamflow data for calibrating simulations at the sub-basin scale.

Recall the curve number values for the low-density developed LULC classification were actually lower than the rangeland and cultivated land LULC classifications. In general, increases in development are taken as increasing impervious areas. What the model actually did, however, was alter the curve numbers of the RNGE and HAY LULC classification HRUs to reflect large parcels of land covered primarily by grass with very little impervious cover. When sparsely vegetated RNGE and HAY HRUs were updated to low-density development (URLD), the model simulated hydrologic and hydraulic processes and a drainage basin with drastically increased grass cover. In many cases, where clay soils were converted to low-density development, increased imperviousness would result in little increase to the CN.

V.II.III: Comparisons with Other Studies

A few similar modeling applications have been conducted within the PSC and SEUS and, together with additional modeling applications with similar physical conditions in Asia, those results are comparable to the results of this thesis. Kim et al. (2014), Wang et al. (2014), and Zhu and Li (2015) all conducted modeling applications investigating LULC change effects on streamflow in the SEUS. Kim et al. (2014) emphasized impacts of reforestation on streamflow, whereas Wang et al. (2014) emphasized how varying degrees of development can impact streamflow. Kim et al. (2014) found that prolonged reforestation (1920s – 2000s) led to decreasing monthly streamflow trends, especially from February to April. The Wang et al. (2014) study in the SEUS found that changing LULC to more urban conditions resulted in only a 2.1 – 3.5% increase in average daily streamflow depending on the magnitude of urbanization in the drainage basin. Zhu and Li (2015) found that increasing urban development and impacts to streamflow varied with scale. At the scale of the entire basin streamflow increased by approximately 3% as urbanization increased. However, when taking into account the spatial variation of the drainage basin, areas around cities that experienced rapid development experienced approximately 10% increase in streamflow (Zhu and Li, 2015). While their methods were different than those of this thesis, the study found that increases in developed lands led to increased streamflow within the Piedmont physiographic region.

Similar results were obtained in this simulation of monthly average streamflow in the BRDB. Increases in low-density development generally resulted in modest increases in streamflow. However, the streamflow increases were relatively minor compared to those caused by varying weather conditions and were insignificant by Kruskal-Wallis ANOVA and Mann-Whitney pair-wise tests. However, the modest gains in streamflow, both in this and other studies, seems quite conservative compared to theories of urban runoff and they result from increased groundwater rather than surface runoff. This discrepancy is discussed in the following sub-sections.

V.III: Critical Interpretations of Results and Modeling

V.III.I: Interpretations of Statistical Results

Bonferroni corrections were intended to reduce the amount of findings that were significant by chance alone. However, 15 pair-wise scenarios may have been too few for the correction to be necessary and beneficial. Therefore, the significance tests should be considered to be a conservative measure of confidence in the difference tests. Tests that were significantly different by these metrics stood up to rigorous testing. On the other hand, tests that were not shown to be significant after the corrections should not be misinterpreted as proof that no differences existed. Although those pairs cannot be shown to be different at a high level of statistical confidence, they should not be dismissed completely. After the post-hoc corrections were accounted for, only 4 of the 15 scenarios in the duration test were significantly different and no scenarios were significantly different when streamflow values were aggregated on a monthly scale. The post-hoc corrections revealed that drastically different weather periods (specifically comparing wet periods to dry periods) do produce significant differences in streamflow.

V.III.II: Water Budget

Minor inconsistencies existed within the water budget of the model. Model output documentation recommended using only a few output parameters to develop a water budget (Neitsch et al., 2005). While simple, it introduced the most uncertainty when synthesizing the modeled output. Abstractions were not given and had to be calculated from simulated sub-basin output. As mentioned earlier, abstractions only accounted for 2-3% of the water budget using the given equation. However when incorporating more variables that are traditionally used to create a water budget (e.g.; precipitation, evapotranspiration, and change in water storage of the soils) this small error still persisted. For example, a simple water budget equation of P = ET + WY yielded small errors as well (0-2%). There was great uncertainty when describing groundwater parameter output because few other modeling applications focus their discussion on this issue and generally little data exists to validate groundwater processes within the model. While streamflow and the water budget were assumed acceptable after model calibration and validation, it is apparent that further research into parameter calibration (specifically groundwater parameters) within the SEUS and PSC with the SWAT model is warranted.

V.III.III: Sources of Error

Error existed in multiple components of the model and were primarily the result of uncertainty. Errors within the weather data were in some cases evident whereas some were not noticed and propagated throughout the model. A weather generator also had to be used for some periods when no weather information existed. While the streamflow data that was used for the model was corrected by the USGS, simulated streamflow that was generated from erroneous or synthesized weather observations could have impacted model calibration and validation. Parameter ranges for the model were formed from the parameter ranges of other studies. These parameters were not calibrated specifically to the PSC so some uncertainty existed but caution was taken to not have unrealistic parameter ranges. Propagated errors from parameter uncertainty could have resulted in changes in the curve number which could have effected surface runoff generation and infiltration of water to the shallow and deep aquifer. This would in turn impact the water budget. Smaller parameter ranges could be developed for the PSC but this would require more research and experience with the model. In short, there are many sources of error when modeling and while they cannot always be determined and solved they must be kept in mind.

Tables and Figures:

Table 5.1: Simulated total surface runoff generated in each sub-basin by each scenario (mm).

Table 5.1: Surface Runoff Totals by Sub-basin

Sub-basin	BM	BW	BD	DM	DW	DD
1	484.04	636.87	321.83	455.69	603.41	299.39
2	453.51	601.15	300.17	413.51	554.60	269.37
3	485.70	632.39	267.27	447.08	585.02	239.02
4	448.97	593.85	230.00	375.98	506.71	176.41
5	589.04	749.61	379.92	565.30	722.36	363.13
6	515.00	673.39	293.68	490.73	642.24	275.62
7	394.78	525.17	204.66	394.78	525.17	204.66
8	553.90	715.55	319.10	545.08	706.22	310.08
9	403.85	528.08	211.99	380.91	500.21	194.20
10	551.15	718.73	300.87	551.15	718.72	300.87
11	405.24	539.85	207.32	405.24	539.85	207.32

Table 5.2: Median Total Sub-basin Runoff for all 6 Scenarios.

Table 5.2: Sub-basin Median Runoff by Scenario

Scenario	Median RO
BM	484.04
BW	632.39
BD	293.68
DM	447.08
DW	585.02
DD	269.37

Table 5.3: Comparison of Sub-basin Runoff Ratios by Sub-basin between scenarios.

Table 5.3: Sub-basin Specific Changes in Runoff

	Scenarios														
Sub-basin	BW:BM	BD:BM	DM:BM	DW:BM	DD:BM	BD:BW	DM:BW	DW:BW	DD:BW	DM:BD	DW:BD	DD:BD	DW:DM	DD:DM	DD:DW
1	1.32	0.66	0.94	1.25	0.62	0.51	0.72	0.95	0.47	1.42	1.87	0.93	1.32	0.66	0.50
2	1.33	0.66	0.91	1.22	0.59	0.50	0.69	0.92	0.45	1.38	1.85	0.90	1.34	0.65	0.49
3	1.30	0.55	0.92	1.20	0.49	0.42	0.71	0.93	0.38	1.67	2.19	0.89	1.31	0.53	0.41
4	1.32	0.51	0.84	1.13	0.39	0.39	0.63	0.85	0.30	1.63	2.20	0.77	1.35	0.47	0.35
5	1.27	0.64	0.96	1.23	0.62	0.51	0.75	0.96	0.48	1.49	1.90	0.96	1.28	0.64	0.50
6	1.31	0.57	0.95	1.25	0.54	0.44	0.73	0.95	0.41	1.67	2.19	0.94	1.31	0.56	0.43
7	1.33	0.52	1.00	1.33	0.52	0.39	0.75	1.00	0.39	1.93	2.57	1.00	1.33	0.52	0.39
8	1.29	0.58	0.98	1.28	0.56	0.45	0.76	0.99	0.43	1.71	2.21	0.97	1.30	0.57	0.44
9	1.31	0.52	0.94	1.24	0.48	0.40	0.72	0.95	0.37	1.80	2.36	0.92	1.31	0.51	0.39
10	1.30	0.55	1.00	1.30	0.55	0.42	0.77	1.00	0.42	1.83	2.39	1.00	1.30	0.55	0.42
11	1.33	0.51	1.00	1.33	0.51	0.38	0.75	1.00	0.38	1.95	2.60	1.00	1.33	0.51	0.38

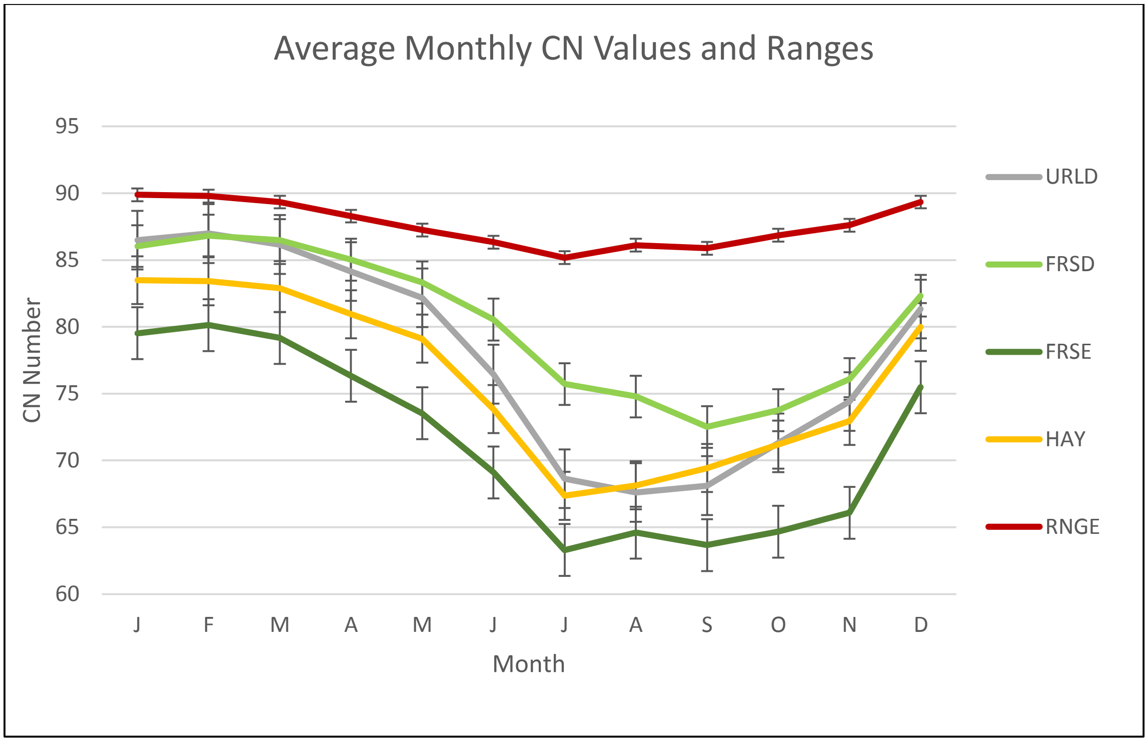

Figure 5.1: Monthly CN average values and variability for LULC conditions in the BRDB.

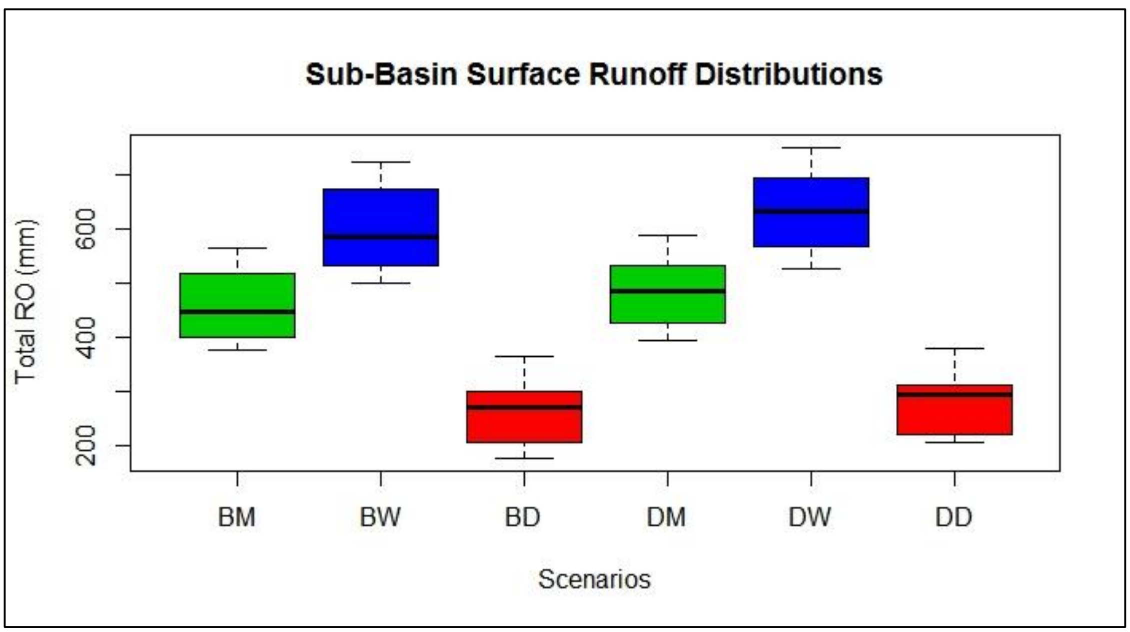

Figure 5.2: Distribution of sub-basin total surface runoff between scenarios.

Changes in Sub-basin Runoff between Scenarios

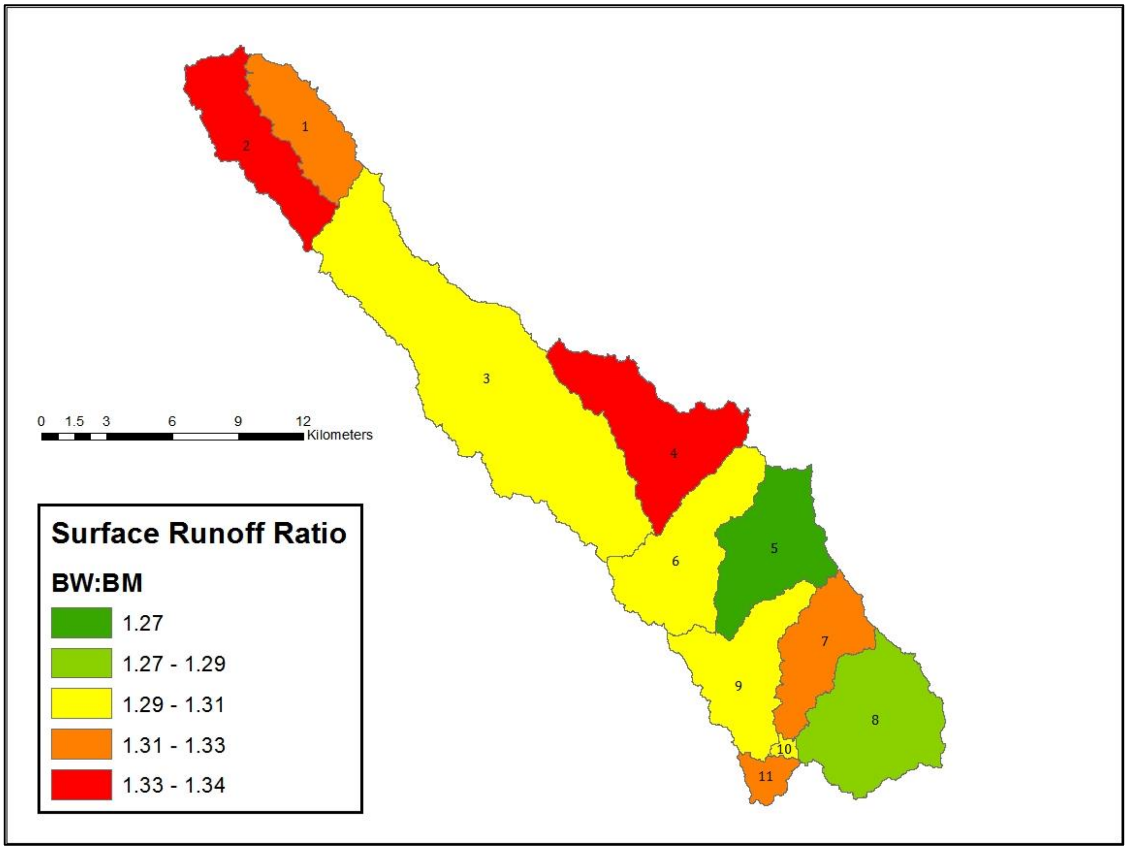

Figure 5.3: Change in sub-basin surface runoff between two scenarios (BW and BM). Similar figures for all possible pairs of scenarios are given in the Appendix section.

Chapter VI: Conclusion

This thesis investigated how changes in extreme weather periods and increases in low-density development impact streamflow in a South Carolina Piedmont drainage basin. Weather and climate variability of the SEUS generally suppressed trends in precipitation and streamflow that were occurring in most other areas of the United States. Therefore, one facet of this research was focused on periods of extreme weather to capture the total range of streamflow over highly variable weather and climate conditions. LULC change research shows that specific to the Piedmont physiographic region, low-density development is increasing because of a desirable environment, increasing industry and business sectors, and an affordable cost of living. This increase in developed area often occurs on recently abandoned agricultural fields or parcels of land that aren't being used. Modeling incorporated these potential changes to the landscape and how they affected the hydrologic process.

Methods involved quantifying periods of extremely wet, extremely dry, and moderate weather conditions by establishing thresholds in observed SPI and PDSI indices and counting months above, below, or in between index thresholds. The Arc SWAT hydrologic model with the applied land-use update module (lup.dat) was calibrated to simulate increased low-density development occurring on abandoned agricultural land. This specific method of modeling allowed for an investigation into the differences in scenario streamflow by using non-parametric ANOVA (Kruskal-Wallis) and pair-wise (Mann-Whitney) testing with post-hoc corrections (Bonferroni) on data that were not corrected for autocorrelation.

Significant differences in streamflow existed between periods of extreme weather (wet to dry) and the magnitude of increased surface runoff was subtle and varied in each sub-basin with respect to increased low-density development. Bonferroni corrected pair-wise testing revealed that only 4 scenario pairs had significantly different streamflow values for the 36 months in each weather period. These were the Baseline Wet to Baseline Dry, Baseline Wet to Developed Dry, Developed Wet to Developed Dry, and Developed Wet to Baseline Dry paired scenarios. These were the 4 pairs that all were comparing the streamflow values from the extremely dry to the extremely wet weather periods. Before the Bonferroni corrections were calculated, the 3 scenarios with the largest p-values from the Mann-Whitney test were the Baseline Moderate to Developed Moderate, Baseline Wet to Developed Wet, and Baseline Dry to Developed Dry scenarios. This indicates that the least significant change to streamflow occurred when just accounting for changes in land-use and keeping weather conditions constant. Comparison of streamflow between scenarios with the same weather period and different LULC scenarios, and vice-versa, exhibited similar changes to findings from relevant literature/modeling applications. Analysis of the water balance between scenarios with different LULC conditions but similar weather conditions revealed that increasing the amount of low-density development decreased surface runoff and increased lateral and groundwater flow contributions to streamflow.

No modeling applications that account for changes in LULC, specifically to the anticipated increases in low-density development, have been applied to the PSC. That is alarming because the region is expected to dramatically grow within the near future. Low-density development increases that were modeled resulted in decreased runoff and increased sub-surface flows in response to low-density development. This result is contrary to conventional concepts of urban hydrology but this can be contributed to how the lup.dat module works within the model. The study area was a rural drainage basin that had intensive agricultural use, forested cover, some low-density development, and sparse pockets of abandoned land. Growth in the region radiates out from two small urban centers and transportation corridors. However, the simulated LULC change was a relatively uniform change from rangeland and agricultural land to low-density development. This offers insight into the potential changes to streamflow and surface runoff if only low-density developments were to occur within drainage basins with similar physical characteristics to the BRDB. Future work could project changes around a larger metropolitan area, such as a modeling application of the drainage basin that contains the city of Greenville. Using similar methods and accounting for changes in coniferous tree cover would surely alter the water balance and streamflow and would be worthwhile to investigate in drainage basins that silviculture is projected to increase or decrease.

This thesis focused on the most extreme wet and dry periods of weather compared to a representative moderate condition. Future modeling applications could model specific positive and negative phases of oceanic oscillations and investigate their impacts to the water balance in the SEUS and the PSC. Drainage basins could potentially have more stream gages on sub-basins which would allow for model calibration at the outlet and at interior locations within the watershed. Another likelihood is that other drainage basins in the PSC could have more observations from weather stations and include more variables (e.g.: humidity, wind, and evapotranspiration records). More complete datasets aid in the calibration and validation of a hydrologic model.

Few studies have investigated the impacts from highly variable periods of weather and instead focus on detecting trends. This thesis detailed how variations from moderate weather periods can alter streamflow and the water balance. Significant changes were determined at 3 year periods which characterize the range of weather variability, and their impact to the water balance, within the PSC. This research strongly relates to water resources, environmental science, GIS modeling, and planning and development research within the SEUS. Findings could clearly support future investigations into the environmental impacts of increasing development in South Carolina Piedmont drainage basins.

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Appendix A: Descriptions, Model Output, and Maps

Table A.1: Formatting descriptions for scenario abbreviations.

Scenario Abbreviations			
First Letter	Meaning	Second Letter	Meaning
B	Baseline LULC	M	Moderate
D	Increased Development	W	Extremely Wet
		D	Extremely Dry

Table A.2: Average streamflow values for the 6 Scenarios (units $m^3 s^{-1}$).

Date	BM	DM	BW	DW	BD	DD
1	1.838	1.968	6.274	6.296	4.727	4.679
2	3.518	3.736	10.63	10.79	9.074	9.18
3	2.117	2.311	14.36	14.43	4.968	5.101
4	1.608	1.647	7.005	7.191	4.25	4.252
5	4.18	4.163	5.021	5.11	3.711	3.891
6	4.213	4.262	1.943	2.026	2.086	2.077
7	1.191	1.228	1.417	1.374	0.714	0.701
8	3.876	3.929	5.845	5.971	0.481	0.451
9	2.038	2.127	6.624	6.411	0.921	0.835
10	0.367	0.398	5.955	5.744	0.818	0.796
11	1.609	1.527	3.987	3.939	0.709	0.702
12	4.414	4.477	5.375	5.324	0.539	0.565
13	11.98	12.04	8.568	8.527	2.634	2.697
14	4.404	4.541	9.616	9.691	10.19	10.35
15	4.623	4.7	5.489	5.579	7.448	7.618
16	3.053	3.145	3.574	3.723	4.646	4.83
17	1.785	1.806	4.243	4.197	2.051	2.195
18	8.509	8.48	4.632	4.608	1.041	1.038
19	3.576	3.601	3.129	3.088	0.664	0.613
20	1.13	1.136	2.022	2.116	0.318	0.281
21	0.623	0.599	0.686	0.674	2.482	2.397
22	0.524	0.475	0.327	0.322	0.185	0.21
23	1.649	1.626	0.886	0.76	0.575	0.511
24	1.493	1.577	8.206	8.008	0.427	0.455
25	5.96	6.104	8.312	8.349	0.689	0.722
26	6.974	7.117	12.46	12.54	1.532	1.66
27	8.006	8.104	9.244	9.235	8.639	8.922
28	12.87	12.93	11.42	11.59	5.163	5.486
29	5.256	5.353	6.852	6.822	2.025	2.133
30	4.797	4.776	10.89	10.92	1.592	1.562
31	1.871	1.916	3.081	3.189	1.135	1.053
32	1.79	1.74	2.578	2.55	0.331	0.32
33	3.824	3.685	3.852	3.881	0.925	0.837
34	0.608	0.627	0.563	0.565	0.205	0.185
35	0.361	0.344	0.24	0.242	0.517	0.5
36	1.999	1.762	1.307	1.296	0.631	0.648

Table A.3: Average streamflow values for specific months (units m^3 s^{-1}).

Month	BM	DM	BW	DW	BD	DD
January	6.593	6.704	7.718	7.724	2.683	2.699
February	4.965	5.131	10.902	11.007	6.932	7.063
March	4.915	5.038	9.698	9.748	7.018	7.214
April	5.844	5.907	7.333	7.501	4.686	4.856
May	3.740	3.774	5.372	5.376	2.596	2.740
June	5.840	5.839	5.822	5.851	1.573	1.559
July	2.213	2.248	2.542	2.550	0.838	0.789
August	2.265	2.268	3.482	3.546	0.376	0.351
September	2.162	2.137	3.721	3.655	1.443	1.356
October	0.500	0.500	2.282	2.210	0.403	0.397
November	1.206	1.166	1.704	1.647	0.600	0.571
December	2.635	2.605	4.963	4.876	0.532	0.556

Table A.4: Average streamflow values for all sub-basins (units m^3 s^{-1}).

Sub-basin	BM	DM	BW	DW	BD	DD
1	0.215	0.217	0.293	0.292	0.123	0.124
2	0.289	0.292	0.391	0.390	0.162	0.163
3	1.574	1.597	2.372	2.378	1.036	1.058
4	0.349	0.347	0.569	0.566	0.240	0.240
5	0.362	0.361	0.518	0.517	0.280	0.279
6	2.265	2.290	3.474	3.479	1.520	1.548
7	0.213	0.213	0.332	0.332	0.152	0.152
8	0.403	0.408	0.610	0.614	0.293	0.298
9	2.900	2.931	4.429	4.438	1.988	2.022
10	0.628	0.633	0.960	0.964	0.454	0.459
11	3.573	3.610	5.461	5.474	2.473	2.513

Table A.5: Sub-basin Streamflow Contribution and Water Balance for BM Scenario.

Sub-basin	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
1	3410.71	484.04	92.42	580.66	7251.46	2284.07	2913.09	1188.05	581.24
2	3410.71	453.51	88.94	615.49	7389.91	2281.92	2913.33	1190.72	615.79
3	3611.70	485.70	63.86	541.44	7923.80	2411.26	3014.10	1118.66	592.60
4	3611.70	448.97	77.18	488.09	8318.40	2472.62	3013.58	1039.26	532.75
5	3611.70	589.04	56.69	679.80	5217.70	2205.40	3014.29	1360.19	730.20
6	3611.70	515.00	73.02	517.77	7334.81	2399.46	3013.75	1132.27	562.23
7	3611.70	394.78	91.19	599.24	7951.28	2418.37	3014.92	1115.97	649.30
8	3611.70	553.90	121.63	467.77	6535.44	2377.29	3016.01	1167.27	506.07
9	3611.70	403.85	106.13	559.11	8376.69	2421.98	3014.10	1097.65	612.05
10	3611.70	551.15	278.11	381.05	7833.17	2306.15	3013.17	1229.95	408.38
11	3611.70	405.24	261.85	411.29	7833.33	2424.63	3013.87	1099.57	443.56

Table A.6: Sub-basin Streamflow Contribution and Water Balance for BW Scenario.

Sub-basin	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
1	3821.50	636.87	108.11	821.03	7334.65	2243.33	2903.13	1609.39	858.30
2	3821.48	601.15	105.05	856.44	7453.97	2242.83	2903.37	1607.94	896.10
3	4124.04	632.39	81.31	980.74	8331.57	2377.03	2961.29	1745.30	1033.14
4	4123.68	593.85	94.71	946.22	8776.30	2432.90	2960.78	1683.79	996.36
5	4123.70	749.61	71.10	1059.51	5483.66	2182.90	2961.50	1935.67	1122.39
6	4123.95	673.39	90.04	937.16	7806.90	2368.43	2960.97	1749.26	988.47
7	4123.72	525.17	112.86	1040.09	8352.24	2380.90	2962.13	1732.02	1099.32
8	4124.07	715.55	147.70	850.44	6982.00	2361.99	2963.21	1757.75	895.87
9	4123.99	528.08	133.14	1020.81	8775.18	2384.36	2961.33	1734.93	1074.96
10	4123.70	718.73	335.62	737.09	8540.96	2281.51	2960.42	1829.66	777.98
11	4123.70	539.85	318.70	807.21	8483.09	2399.45	2961.12	1707.52	851.97

Table A.7: Sub-basin Streamflow Contribution and Water Balance for BD Scenario.

Sub-basin	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
1	2947.40	321.83	74.35	271.48	6761.01	2197.13	2946.07	682.71	296.57
2	2947.39	300.17	70.32	286.04	6900.75	2203.61	2946.31	672.32	313.16
3	2943.94	267.27	53.21	438.36	6820.30	2239.54	2933.55	783.14	443.52
4	2943.69	230.00	64.60	392.55	6947.68	2318.43	2933.03	708.89	402.26
5	2943.70	379.92	47.35	582.45	4629.15	1954.52	2933.69	1042.14	592.80
6	2943.88	293.68	60.80	427.63	6317.90	2213.64	2933.17	805.84	435.80
7	2943.71	204.66	75.68	484.75	6921.97	2225.26	2934.28	791.77	495.29
8	2943.96	319.10	101.08	400.26	5691.94	2175.13	2935.33	842.53	410.07
9	2943.91	211.99	88.07	435.95	7147.92	2265.89	2933.48	760.29	439.96
10	2943.70	300.87	230.00	322.55	7020.92	2136.89	2932.55	871.17	334.81
11	2943.70	207.32	213.06	331.54	6692.91	2254.36	2933.23	770.29	343.38

Table A.8: Sub-basin Streamflow Contribution and Water Balance for DM Scenario.

Sub-basin	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
1	3410.71	455.69	93.55	613.25	7315.05	2277.00	2913.09	1195.19	611.66
2	3410.71	413.51	91.02	662.68	7481.05	2270.62	2913.34	1202.55	659.29
3	3611.70	447.08	65.95	593.61	8024.48	2401.87	3013.85	1137.05	645.72
4	3611.70	375.98	79.44	548.26	8406.20	2486.27	3013.60	1031.86	595.45
5	3611.70	565.30	57.39	697.88	5233.42	2210.90	3014.29	1356.19	749.00
6	3611.70	490.73	73.26	555.95	7426.52	2390.39	3013.57	1148.42	601.45
7	3611.70	394.78	91.19	599.24	7951.25	2418.37	3014.90	1115.96	649.30
8	3611.70	545.08	122.18	489.31	6593.14	2367.27	3015.74	1181.69	528.15
9	3611.70	380.91	107.88	606.63	8470.49	2403.47	3013.89	1126.47	658.88
10	3611.70	551.15	278.11	381.05	7833.15	2306.15	3013.16	1229.95	408.38
11	3611.70	405.24	261.85	411.29	7833.32	2424.63	3013.87	1099.57	443.56

Table A.9: Sub-basin Streamflow Contribution and Water Balance for DW Scenario.

Sub-basin	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
1	3821.50	603.41	109.13	845.91	7362.85	2245.35	2903.14	1603.25	885.69
2	3821.50	554.60	106.89	891.80	7497.74	2243.38	2903.38	1600.60	935.60
3	4123.70	585.02	83.94	1031.45	8399.32	2364.78	2961.05	1753.89	1089.26
4	4123.70	506.71	97.72	1015.84	8829.10	2441.17	2960.80	1672.84	1071.63
5	4123.70	722.36	72.03	1081.25	5495.18	2185.41	2961.50	1932.20	1146.13
6	4123.70	642.24	90.43	974.27	7865.94	2357.42	2960.79	1757.52	1029.57
7	4123.70	525.17	112.86	1040.08	8352.20	2380.89	2962.12	1732.02	1099.32
8	4123.70	706.22	148.34	869.64	7028.26	2348.93	2962.95	1769.27	917.26
9	4123.70	500.21	135.20	1061.92	8846.28	2362.99	2961.12	1752.38	1121.69
10	4123.70	718.72	335.62	737.10	8540.94	2281.50	2960.42	1829.66	777.98
11	4123.70	539.85	318.70	807.21	8483.09	2399.45	2961.11	1707.52	851.97

Table A.10: Sub-basin Streamflow Contribution and Water Balance for DD Scenario.

Sub-basin	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
1	2947.4	299.393	75.11	294.857	6826.79	2195.578	2946.073	685.551	322.425
2	2947.4	269.369	71.677	319.557	6999.506	2199.805	2946.319	678.02	350.288
3	2943.7	239.023	54.77	483.289	7035.077	2211.607	2933.309	803.696	491.964
4	2943.7	176.406	66.397	442.425	7079.685	2311.863	2933.049	709.599	455.688
5	2943.7	363.132	47.878	596.216	4657.872	1955.196	2933.692	1040.353	607.364
6	2943.7	275.622	60.938	461.952	6490.079	2189.872	2932.994	824.028	472.395
7	2943.7	204.655	75.676	484.75	6921.941	2225.248	2934.268	791.764	495.287
8	2943.7	310.08	101.619	420.754	5805.934	2158.434	2935.069	855.608	431.813
9	2943.7	194.197	89.383	477.159	7376.298	2230.923	2933.275	787.151	484.918
10	2943.7	300.869	230.005	322.545	7020.893	2136.883	2932.548	871.171	334.808
11	2943.7	207.315	213.062	331.535	6692.915	2254.357	2933.227	770.29	343.384

Table A.11: Water Balance Parameters for the BRDB for all scenarios.

Scenario	Precipitation	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
BM	3575.16	485.22	84.01	547.59	7484.87	2379.46	3000.75	1144.99	588.86
BW	4068.67	633.18	103.62	950.11	7854.69	2346.96	2953.70	1736.33	1000.85
BD	2944.45	277.71	69.44	419.91	6510.40	2210.24	2935.39	790.33	429.98
DM	3575.16	453.61	85.40	587.07	7560.15	2373.73	3000.61	1156.34	628.66
DW	4068.67	595.14	105.31	988.23	7903.77	2340.20	2953.56	1740.08	1042.96
DD	2944.45	254.01	70.48	453.11	6652.33	2193.62	2935.26	802.58	465.79

Table A.12: Percent change in water balance parameters between weather periods.

Scenario	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
BM to BW	0.30	0.23	0.74	0.05	-0.01	-0.02	0.52	0.70
BM to BD	-0.43	-0.17	-0.23	-0.13	-0.07	-0.02	-0.31	-0.27
DM to DW	0.31	0.23	0.68	0.05	-0.01	-0.02	0.50	0.66
DM to DD	-0.44	-0.17	-0.23	-0.12	-0.08	-0.02	-0.31	-0.26

Table A.13: Percent change in water balance parameters with LULC change.

Scenario	Surface Runoff	Lateral Flow	Groundwater Flow	Soil Moisture	ET	PET	Water Yield	Percolation
BM to DM	-0.07	0.02	0.07	0.01	0.00	0.00	0.01	0.07
BW to DW	-0.06	0.02	0.04	0.01	0.00	0.00	0.00	0.04
BD to DD	-0.09	0.02	0.08	0.02	-0.01	0.00	0.02	0.08

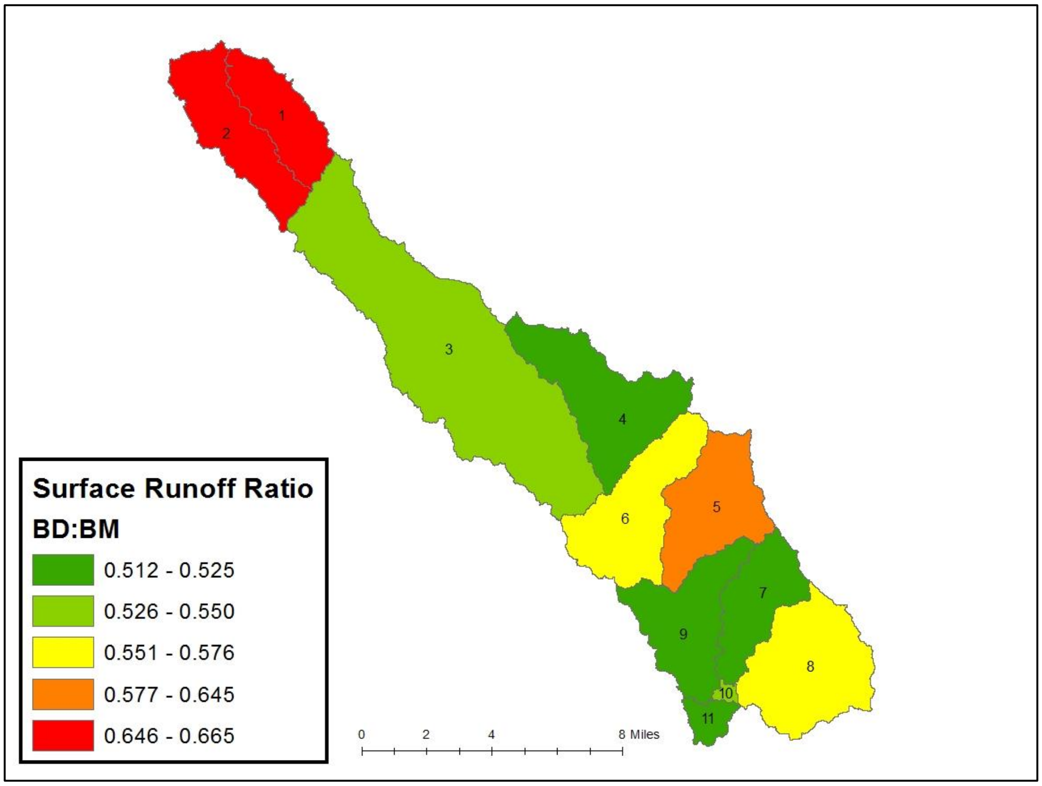

Figure A.1: Ratio of surface runoff between the BD and BM scenarios.

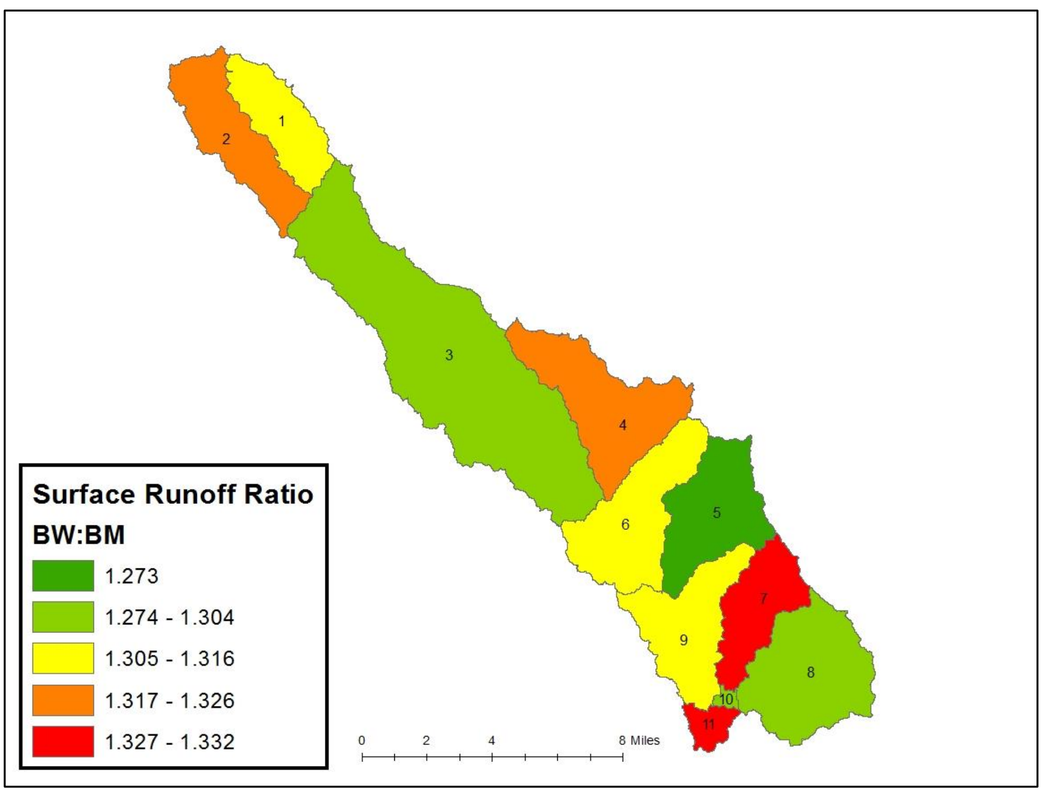

Figure A.2: Ratio of surface runoff between the BW and BM scenarios.

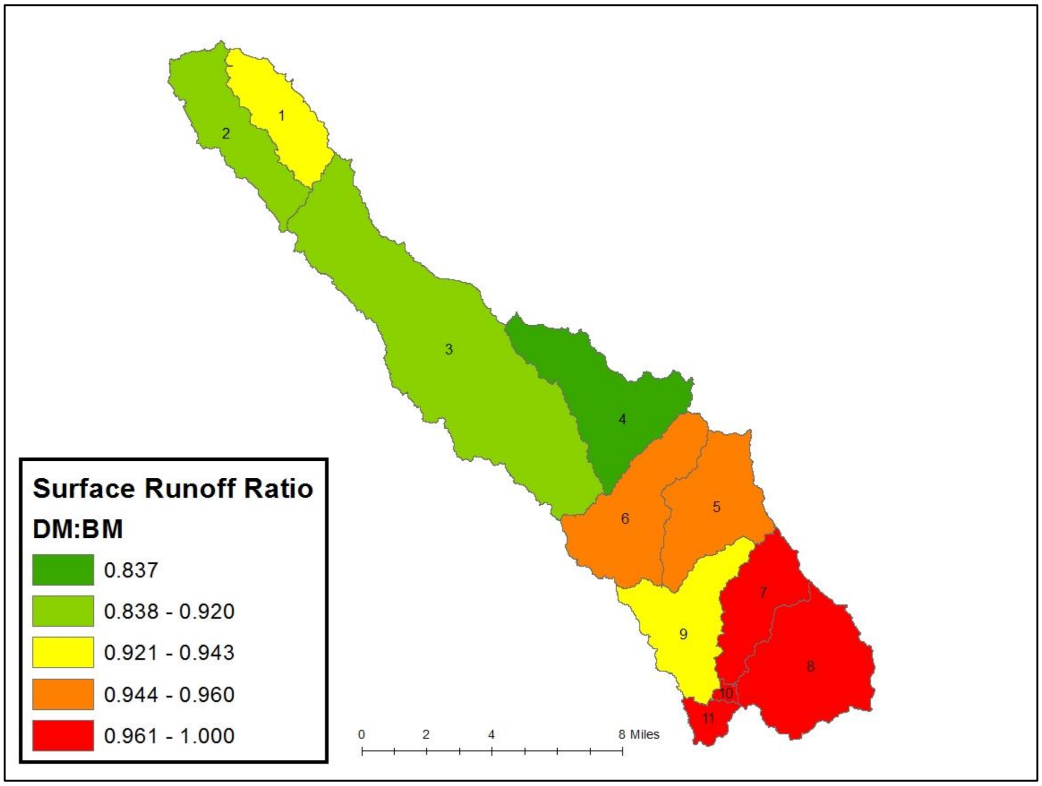

Figure A.3: Ratio of surface runoff between the DM and BM scenarios.

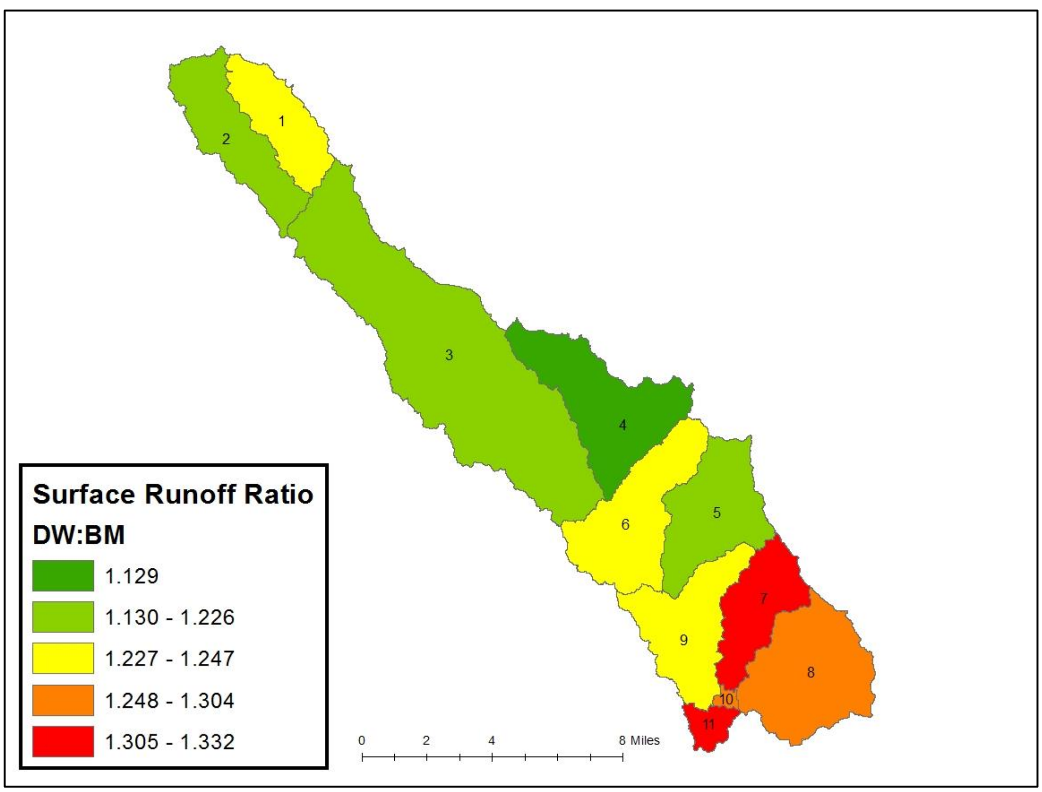

Figure A.4: Ratio of surface runoff between the DW and BM scenarios.

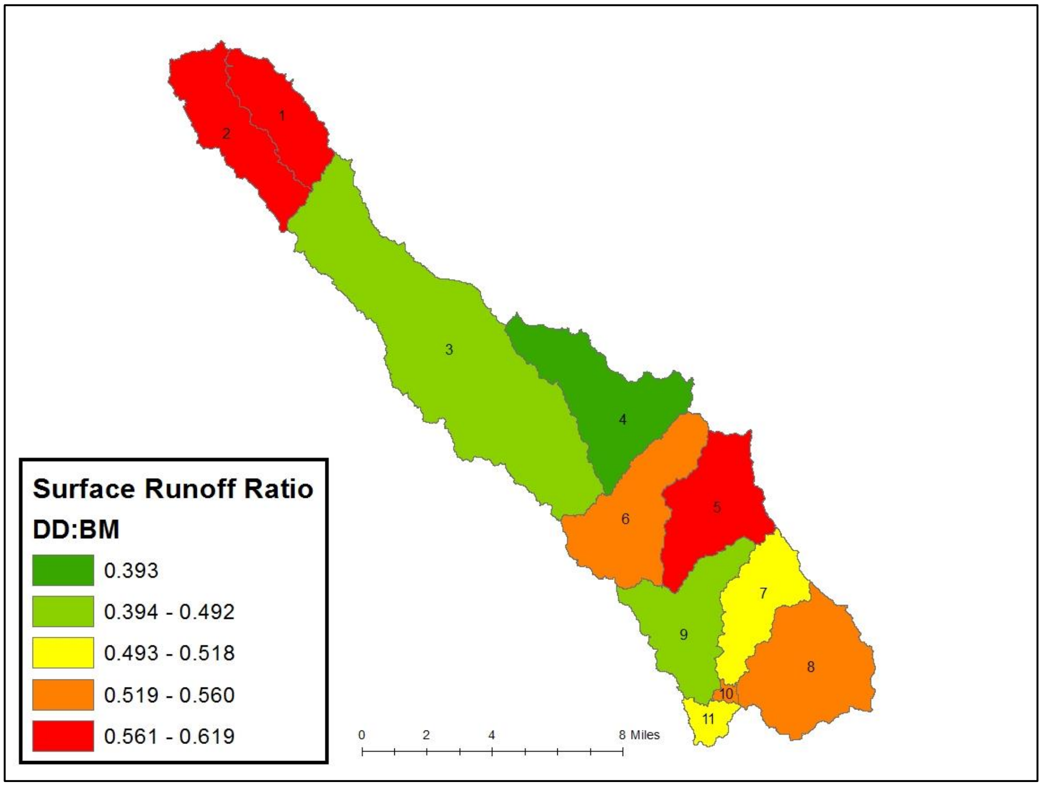

Figure A.5: Ratio of surface runoff between the DD and BM scenarios.

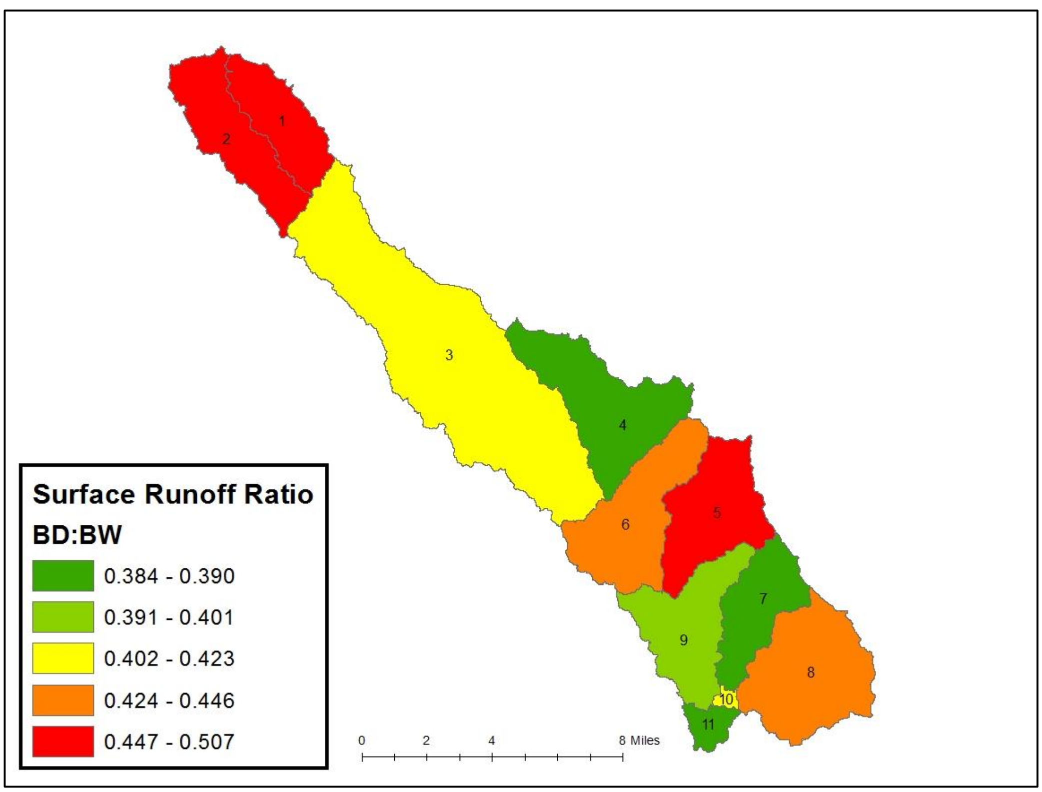

Figure A.6: Ratio of surface runoff between the BD and BW scenarios.

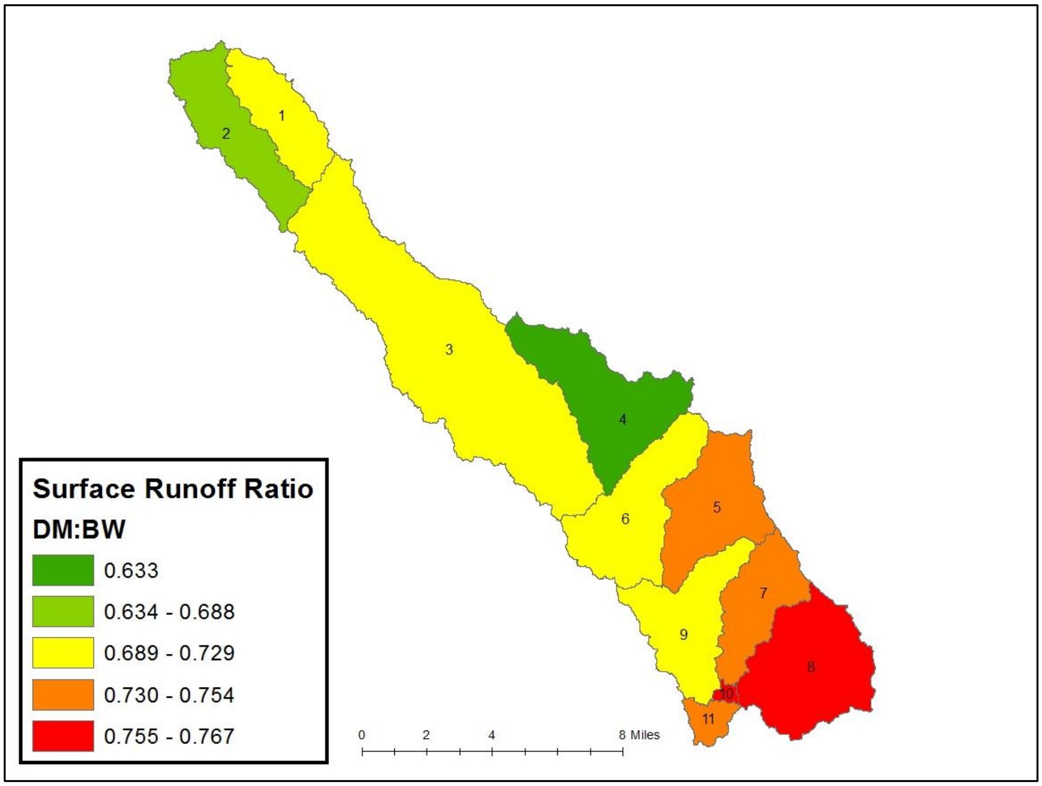

Figure A.7: Ratio of surface runoff between the DM and BW scenarios.

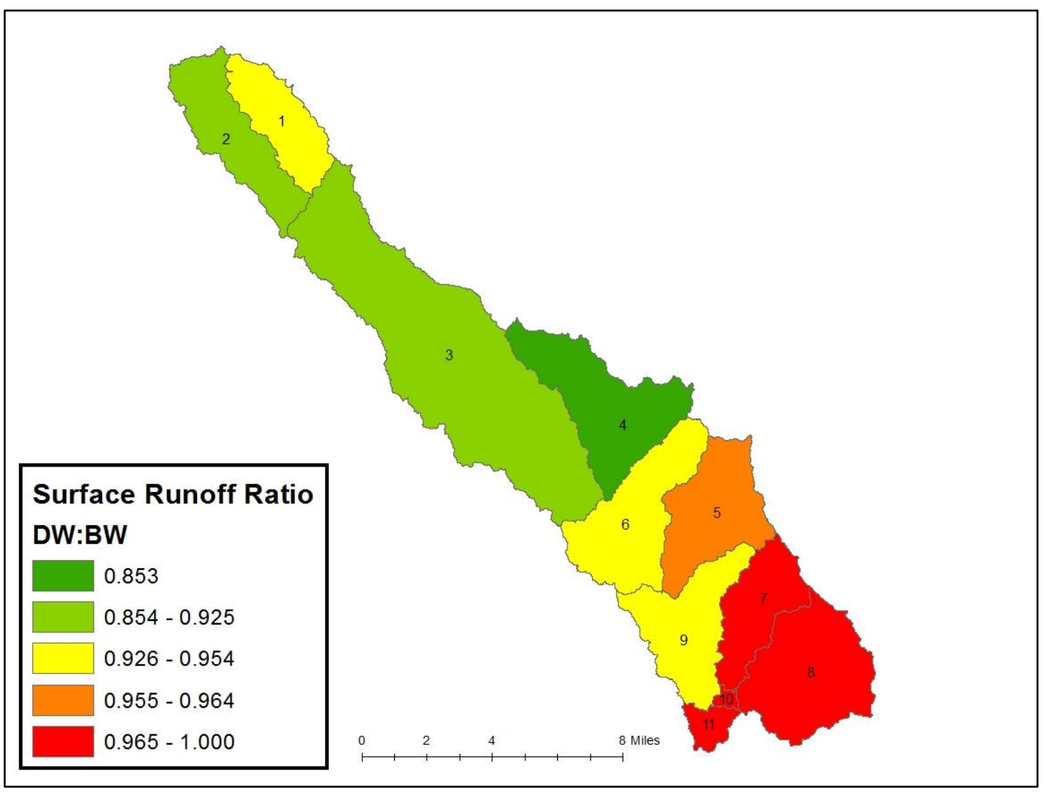

Figure A.8: Ratio of surface runoff between the DW and BW scenarios.

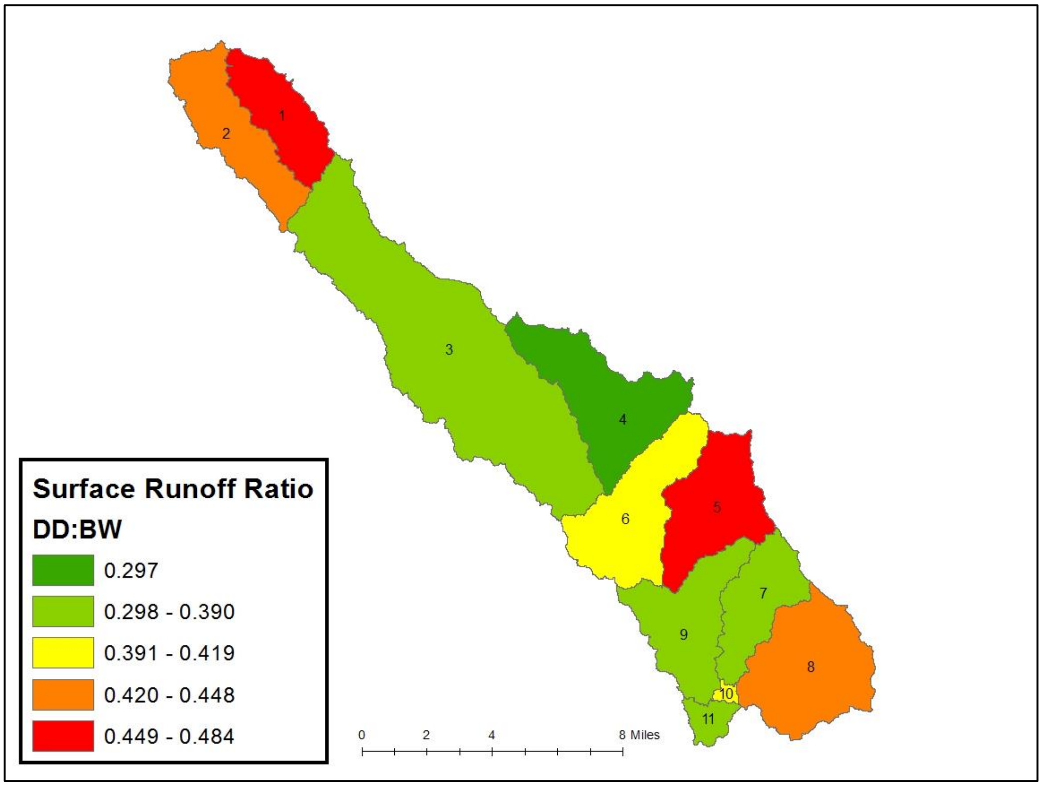

Figure A.9: Ratio of surface runoff between the DD and BW scenarios.

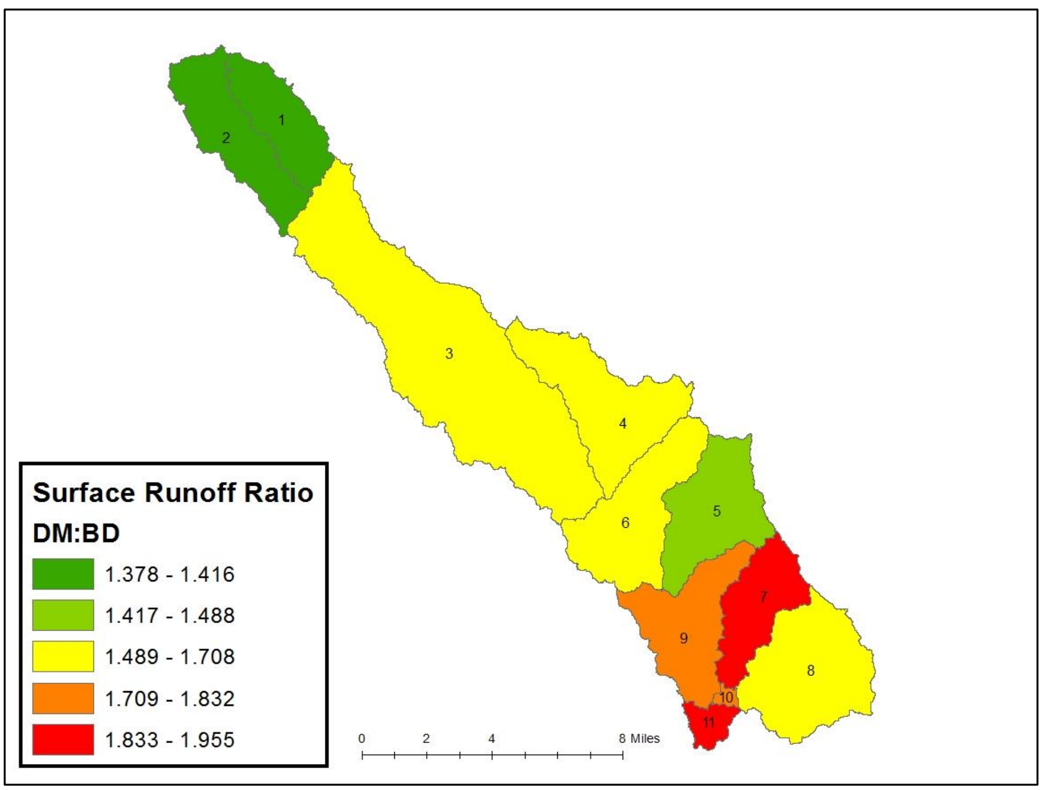

Figure A.10: Ratio of surface runoff between the DM and BD scenarios.

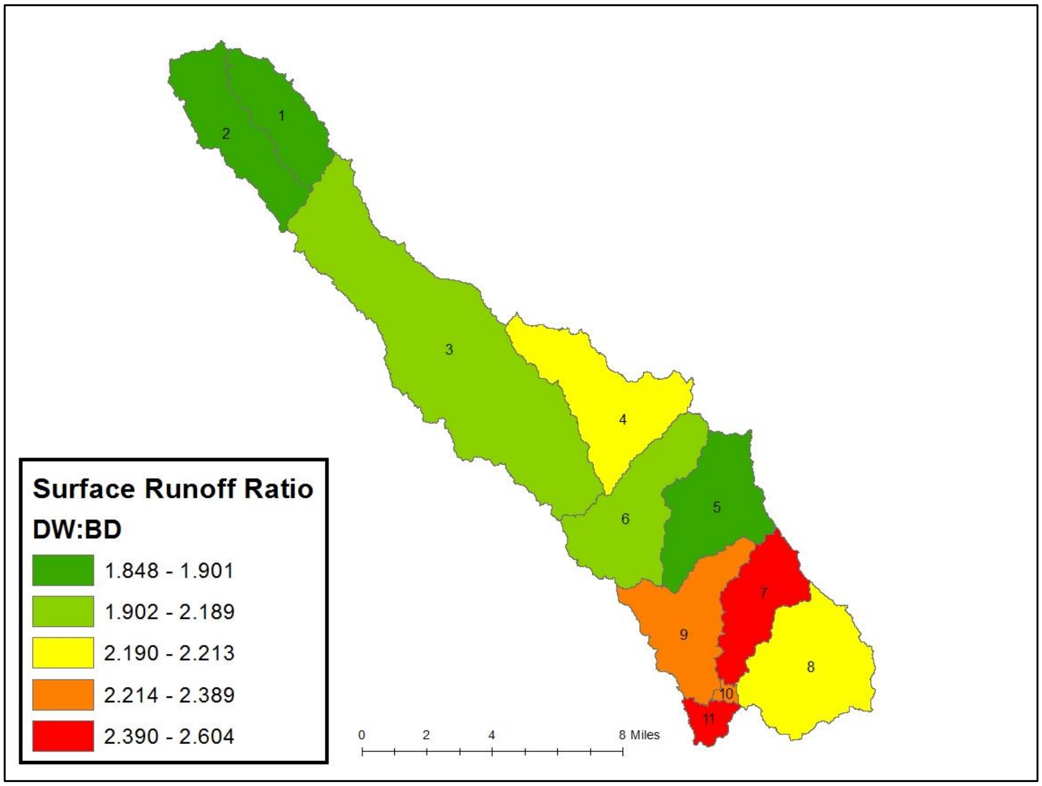

Figure A.11: Ratio of surface runoff between the DW and BD scenarios.

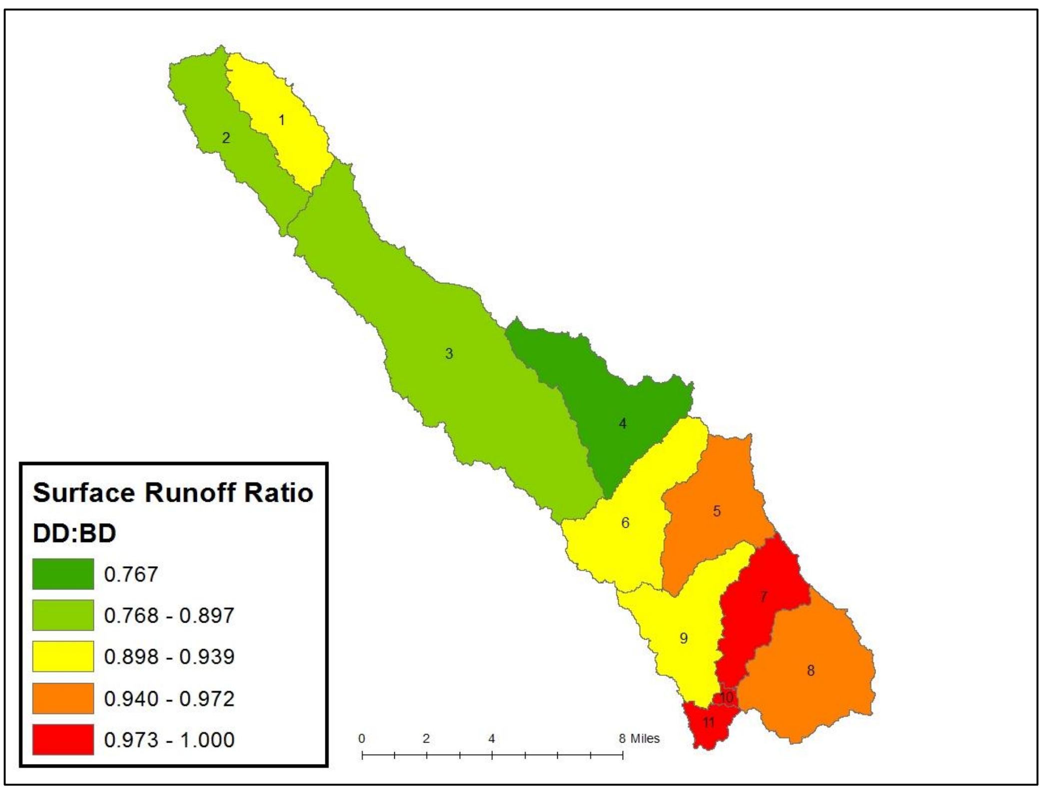

Figure A.12: Ratio of surface runoff between the DD and BD scenarios.

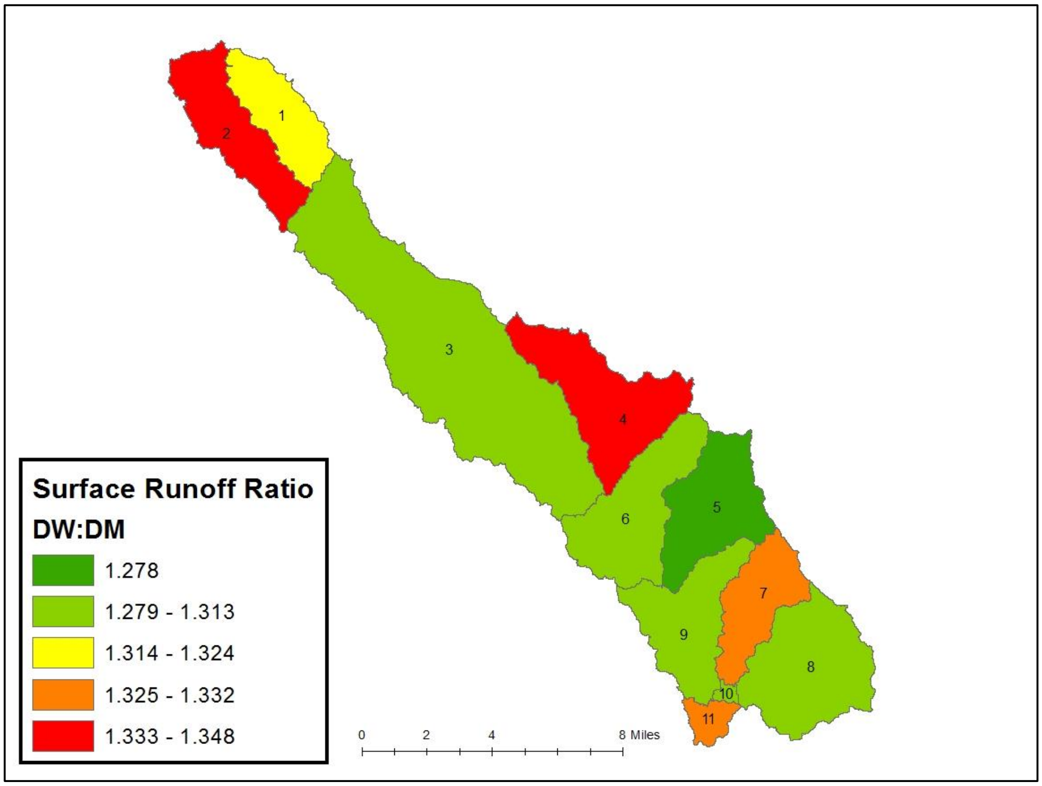

Figure A.13: Ratio of surface runoff between the DW and DM scenarios.

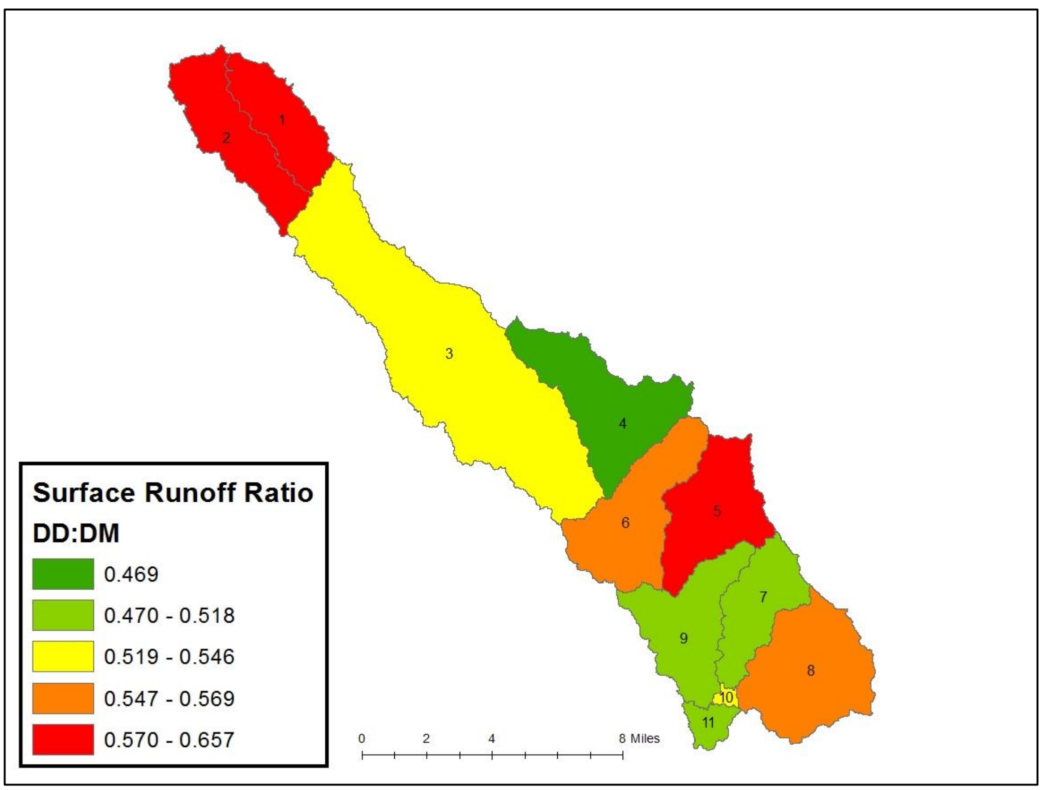

Figure A.14: Ratio of surface runoff between the DD and DM scenarios.

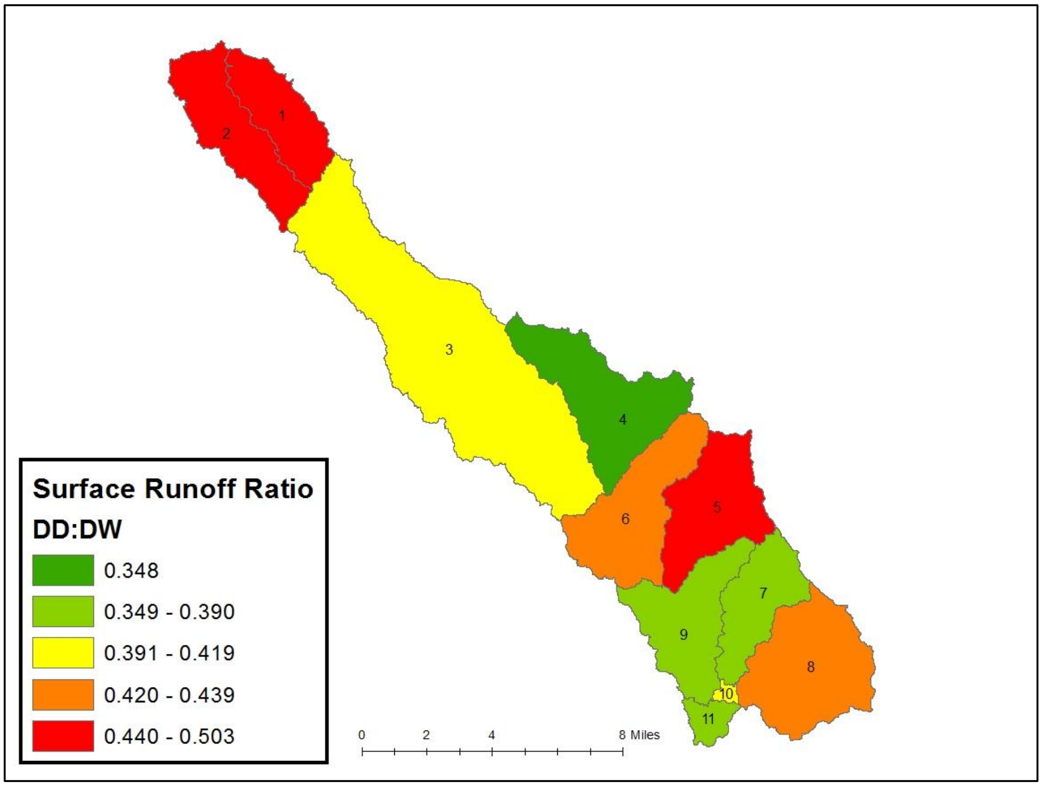

Figure A.15: Ratio of surface runoff between the DD and DW scenarios.