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# Quantitative Assessment of Water Security Using a Hydrological Modeling Framework

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QUANTITATIVE ASSESSMENT OF WATER SECURITY USING A  
HYDROLOGICAL MODELING FRAMEWORK

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A Thesis  
Presented to  
the Graduate School of  
Clemson University

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In Partial Fulfillment  
of the Requirements for the Degree  
Doctor of Philosophy  
Civil Engineering

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by  
Anoop Valiyaveetil  
August 2017

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## ABSTRACT

Water scarcity and drought are major threats to water security. Quantifying and defining boundaries between these threats are necessary to properly assess water security of a region. A comprehensive assessment of water security in terms of water scarcity, water vulnerability and drought can address water policy issues related to hydrological conditions and their interactions with societal and ecosystem functioning. Therefore, study of water security can provide useful information to multiple stakeholders.

The overarching goal of this thesis is to improve water security in river basins around the world. To demonstrate our proposed methods, we selected Savannah River Basin (SRB) as a case study. In addition to water security assessment of SRB, we also explored the combined as well as individual roles of climate, anthropogenic (e.g., urbanization, agriculture, water demand) and ecological elements on various aspects of water security. Realizing the importance of water security impacts on society and ecosystem, the following objectives are formulated:

- 1) To investigate the blue and green water security of Savannah River Basin by applying the water footprint concept.
- 2) To quantify the influence of climate variability and land use change on streamflow, ecosystem services, and water scarcity.
- 3) To assess the climate, catchment, and morphological variables control over hydrological drought of a river basin.

To summarize, the results obtained from **first objective** shows that our proposed modeling framework can be applied to investigate spatio-temporal pattern of blue and

green water footprints as well as water security at a county scale for SRB, thereby locating the emerging hot spots within the river basin. The results obtained from **second objective** indicate that the land use change and climate variability have a key influence (either concomitant or independent) in altering the blue (green) water and related water security over the basin. The results based on **third objective** demonstrate that in addition to climate variables, catchment and morphological properties significantly control short, medium and long-term duration of hydrological droughts in SRB. An integrated modeling framework was developed to achieve these objectives and additional findings are explained in detail through the following chapters.

## **DEDICATION**

To my family & my friends.

## **ACKNOWLEDGMENTS**

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## **CHAPTER ONE**

### **INTRODUCTION TO WATER FOOTPRINT AND WATER SECURITY**

#### **1. Water footprint concept**

Water plays a vital role in functioning of ecological, industrial and agricultural systems. As a result, efficient management of water resources are important to sustain food production, energy sector as well as activities related to human water consumption (Vorosmarty et al., 2000; Molden et al., 2007; Mishra and Singh, 2010; Mishra et al., 2015). However, it is to be noted that, water consumption for both natural and human activities varies not only among sectors but also with location and time. For instance, water usage for total crop production in USA is significantly higher than the water usage for total crop production in China (Mekonnen and Hoekstra, 2011). Also, the water usage of different irrigation practices (rain-fed, micro irrigation) considerably influences the total water consumption (Mekonnen and Hoekstra, 2011). Therefore, we can say that water consumption varies in a three dimensional structure (i.e., process-type, space and time). The water footprint (WF) concept was developed by Hoekstra and Hung (2002), a conception based on carbon footprint (Wiedmann and Minx, 2008). The concept was initiated to develop suitable indicators to evaluate human consumption of fresh water resources.

WF can be calculated for almost any product (Chapagain and Hoekstra, 2007; Dourte and Fraisse, 2012), human being (Hoekstra, 2009), as well as ecosystem services (Karabulut et al., 2016) and river basins (Veettil and Mishra, 2016; Rodrigues et al., 2014). Among them, issues related WF at a river basin scale are particularly relevant in

21<sup>st</sup> century, due to the ongoing environmental transformations of widespread human-induced water pollution, transformation of landscapes and climate change impact on the water provisioning service of a river ecosystem. On the top of these issues, an exponential increase in the population and related transboundary conflicts in river basins (Gleick, 1998; Stahl, 2005) causes further strain on water security of a river basin. Therefore, there is an immediate need to understand the water footprint concepts and then further apply these concepts to study the spatio-temporal dynamics of water security of a river basin. Broadly speaking, the goal of assessing water footprints is to analyze how human activities or specific products relate to issues of water security, and to see how activities and products can become more sustainable from a water perspective. Therefore, in this thesis (chapter two) we developed a hydrological modeling framework for quantifying the water security of a river basin through WF concept. The study is extended (chapter three) for evaluating the impact of land use change and climate variability on water security by applying the concept of WF. The classification of WF and its applications are briefly applied in the following sections.

## **2. Classification of water footprints**

Conceptually, the water footprint is classified into blue, green and grey water use, which are discussed in the following section (Figure 1).

### **2.1 Blue water footprint**

The flow of water through streams, rivers, aquifers (i.e., ground water) which can be stored in lakes, wetlands and manmade structures (e.g., reservoirs) are categorized as blue water. These are directly available for human use (Falkenmark and Rockström, 2006;

Rockström et al., 2009; Rodrigues et al., 2014; Veetil and Mishra). Normally blue water flow or internal renewable water resources (Schuol et al., 2008a) can be calculated from total water yield and water storage in deep aquifer (Abbaspour et al., 2015a; Schuol et al., 2008b). The blue water footprint is the water used for human consumptions from the blue water resources, such as, (i) domestic water (ii) industrial use (iii) water use for mining and (v) water use for thermo-electric power generation. The components of agricultural water use are (i) irrigation water (ii) water supply for livestock and (iii) water supply for aquaculture. Blue water scarcity in basin is the ratio of blue water footprint and available blue water in a particular sub-watershed area during a specific period time (day, month or year).

Blue water consumption by protecting the natural fresh water ecosystem is a crucial part of water resource management. The presumptive standard for environmental flow protection developed by Richter et al. (2012) is an appropriate or best method for assessing the availability of blue water by satisfying the environmental flow requirement (Hoekstra et al., 2012). According to presumptive standard, extraction of available water (river flow) above 20 percent will cause ecosystem degradation and environmental inequality. Different eco-hydrological techniques are available for estimating Environmental Flow Requirement (EFR) but the recent studies (Hoekstra et al., 2012, Rodrigues et al., 2014) showed the presumptive method can be more reasonable in blue water scarcity analysis.

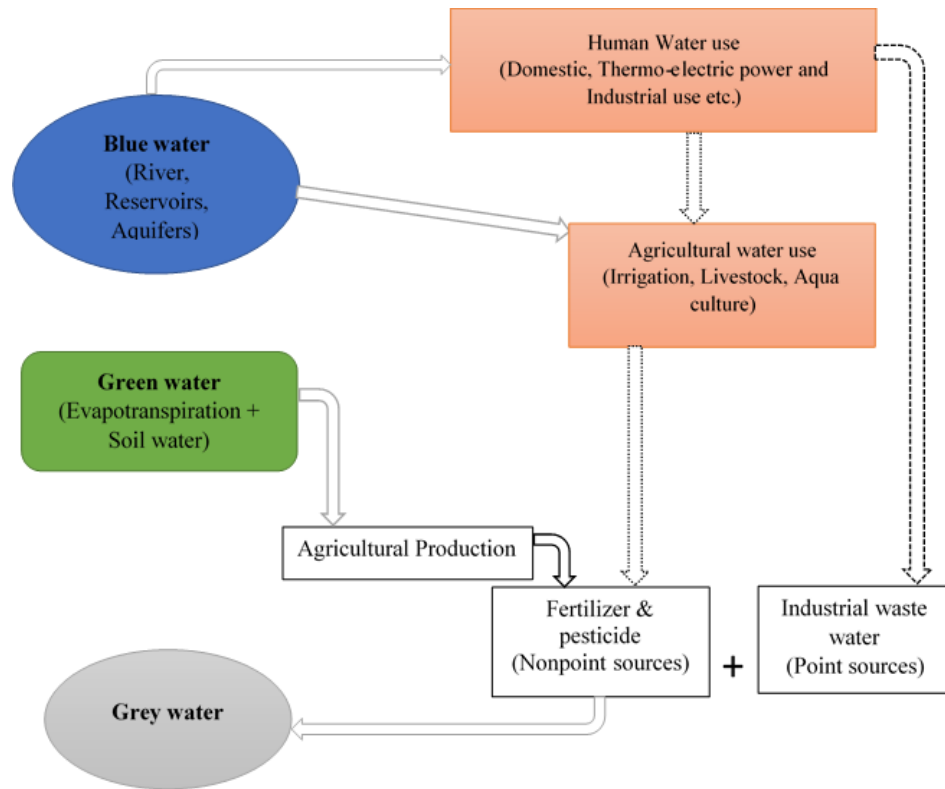
## **2.2 Green water footprint**

The portion of precipitation available in unsaturated layer of soil and canopies of vegetation, which flow back to the atmosphere as evapotranspiration is termed as green water (Falkenmark and Rockström, 2006; Rockström et al., 2009; Rodrigues et al., 2014). It can be differentiated into two components, (i) green water resource (storage), which is soil water content and (ii) green water flow, which is the actual evapotranspiration (Hoekstra et al., 2012; Falkenmark and Rockström, 2006; Schuol et al., 2008b). Overall green water is an important factor for an essential part of food production and return of agricultural economic growth to the region. Green water footprint is the amount of green water consumed during the production process of agriculture and forest products. The evaluation of green water scarcity has greater importance for meeting the agricultural water requirement in a controlled irrigation and other management practices (Calder, 2007), it can be expressed as the ratio of green water footprint to the availability of green water (GW-available) and it indicates the influence of human activities for green water use in a specific geographic location with respect to the time (Rodrigues et al., 2014).

## **2.3 Grey water footprint**

Grey water represents the amount of water (fresh water) required to dilute the concentration of nutrients/chemicals such that the stream reaches its natural (original) nutrient concentration (Hoekstra et al., 2012; Mekonnen and Hoekstra, 2011; Wu et al., 2012; Liu et al, 2012). In other words, grey water serves as a proxy for estimating the level of water pollution. Further, grey water can be used to investigate water quality standard of available water with respect to different pollutants like nitrogen phosphorus;

potassium and lime (Humbird et al., 2011). Some studies states that grey water is fictional or a theoretical concept (Chenoweth et al., 2014), and it is difficult to measure the volume of water needed to assimilate as well as difficulties in acquiring accurate measurement of background pollutant concentration of streams.



**Fig. 1.** Conceptual diagram of water footprint systems based on different application.

### 3. Necessity of water footprint concept in changing environment

The world is going through a rapid change in socio-environmental sector by incrementing the negative impact on natural resources and its future sustainability. The population growth leads to a tremendous need of food and energy (Hejazi et al., 2014) and the urbanization culture is expanding to every corner of globe (Molden et al., 2007). The

following section provides an overview of necessity of water footprint applications in a changing environment.

### **3.1 Water scarcity issues**

Water scarcity is a global crisis and typically experienced in densely populated area, intensive agricultural areas and arid regions including central Asia, North Africa, middle east, Indian sub-continent and eastern China (Rijsberman, 2006, Vörösmarty et al., 2010). The water scarcity can be addressed by quantifying spatio-temporal distribution of water resources as well as demand that is necessary for human consumption and environmental sustainability. Vörösmarty et al. (2010) reported the global threat to human water security and biodiversity by focusing on the rivers, which is the major source of renewable blue water. The areas with dense population and intense cultivation showed an accentuating risk to water scarcity and environment. At the same time, non-accessible areas of north and tropical zone indicated minimum risk of water security. The excessive loading of pollutants to the water body (Schleich et al., 1996) is another important factor that threatens water security. Measuring the water quality and addressing its impact on the water security is still a major issue. Evaluation of grey water indices for nutrient discharging zones can indicate degree of water quality degradation of a stream. Therefore, the expansion of water quality measurement gauges in the global river network is one of the important steps to achieve this goal (Mishra and Coulibaly, 2010).

According to the world's science and policy (Baumert et al., 2005), greenhouse gasses directly increases the stress on terrestrial water system and the consequence of water scarcity leads to eradication of aqua system and extinction of species, water spread

diseases, conflicts between water sharing nations/states (Gleick, 1998). Long term water planning and technological investments (e.g., massive infrastructure) are critical for sustainable and improved human water security (Gleick, 2003, Vörösmarty et al., 2010).

Oki and Kane (2006) addressed that the total blue water abstraction for human use is 3800 km<sup>3</sup>/yr and majority of them is derived from the streamflow, however, the quantity of water flowing from land surface to sea is about 45,500 km<sup>3</sup>/yr. The amount of water conserved through artificial structures is almost double of total human water abstraction. The green water contribution, which is considered as a useful resource for community (especially for agricultural sector), is estimated to be more than 20,000 km<sup>3</sup>/yr. But the unevenness in spatio-temporal distribution of blue and green water is one of the major reasons for human water insecurity. Based on monthly water scarcity analysis (Hoekstra et al., 2012), it was observed that most of the river basin around the world is going through low, moderate or significant blue water scarcity for at least one month of a given year. The water scarcity assessment needs an integrated modeling framework by incorporating a hydrologic model. Such a conceptual framework can inform water availability and water demand information for stakeholders to develop appropriate policies for improving water management in a changing environment.

### **3.2 Examples of conflicting water demand**

*Water-food-energy (WEF) nexus:* - Quantifying the interaction between water, energy, food and understanding the system behavior (failure) can improve the water management in a region. However, due to lack of policy and institutional infrastructure, the global water footprint of food production and energy production likely to increase. The

examples for energy perspective include biofuel production, hydro-power generation, desalination and irrigation water supply (Bazilian et al., 2011). Energy is required to distribute water, produce food crops, waste water treatment and transportation of agricultural goods.

Vanhan, (2014) evaluated the link between water footprint and different components of WEF nexus. The process of energy generation is more related with the blue water resources and green water contribute more towards the agriculture and food production. By improving the soil moisture capacity (green water resources) of an area is an excellent practice for reducing the opportunity cost of blue water distribution, specifically in the rain-fed agriculture regions. The concentration of fertilizer use in agricultural food production sector is increasing in developing countries (FAO, 2011), and it will increase the grey water requirement of the stream, especially for downstream users. The better productivity of water and its link between energy and food can be addressed by incorporating the blue, green and grey water component in water resource planning and policy making.

*Changes in agricultural water availability:* - Agriculture is the predominant user of fresh water (Gleick, 2003; Shiklomanov, 2000). Rost et al. (2008) interpreted the blue and green water consumption of agricultural crops in a global scale. The study shows that the land use land cover pattern change augmented the evapotranspiration rate by 1.9% in irrigated regions. They also suggest irrigation efficiency can be improved by reducing the runoff, soil evaporation, drainage. It causes the improvement of green water storage in the soil. The inefficient irrigation practice make 30% global loss of irrigation water (Bos,



1985) and which directly affect the blue water resources and indirectly to the energy usage. The supply of irrigation water to the agriculture land is further scale down by the influence of drought in all the continents (Mishra et al., 2015; Dai, 2001; Mishra et al., 2010). Hence the net irrigation requirement varies from crop to crop, the quantification of drought induced water scarcity of an agricultural land is a complex assignment. Green water consumption dominates over blue water consumption in global crop production (Rost et al., 2008; Mekonnen and Hoekstra, 2011). Majority of global food production (60 – 70%) is from the rain-fed agriculture in the form of green water storage (Falkenmark and Rockström, 2004). The blue water resource is only consumed when the green water storage is less than crop water requirement. Salt water intrusion (in coastal agriculture) due to exploitation of ground water storage (blue water component) is another concern which is deteriorating the global water supply to the crop field (Abarca et al., 2006, Goswami and Clement, 2007, Mantoglou, 2003, Sethi et al., 2002). The application of blue water through micro irrigation techniques, for example, drip and sprinkler irrigation, is an adequate way of blue water consumption during dry season for reducing the disorder in plant water relationship.

### **3.3 Quantifying virtual water trade**

The concept of water footprint (Hoekstra and Hung, 2002) represents the human consumption of fresh water resources, and how it will affect the water scarcity of a region. The concept of virtual water initially proposed by Allen (1993) can be used to quantify the volume of water consumed during the whole process of product development (Hoekstra and Hung, 2002). The water footprint is quantitatively identical to virtual water

content of a particular product (Zhang et al., 2012), but water footprint can also be applicable at a consumer level as well as it can generate indices for water use (for example, agriculture, food and other industrial products). The direct export of water for commodity production is possible only through gravity system (Oki and Kanae, 2006; Lenzen, 2009). Therefore, the states/countries/continents which have limited water resources can solve their water scarcity issues up to an extent by importing the goods (with intense virtual water content) from water abundant region. The water - rich nation can accelerate their economic growth by the trading of virtual water to the water deficit nations and the practice will improve the international link between the nations economically and politically (Hoekstra and Hung, 2002). There is a significant increase (from 1986 to 2008) in blue and green water consumption due to the growth of food commodity trade between the nations (Dalin et al., 2012; Konar et al. 2012). The analysis of virtual water business is entirely complex due to the network is extremely dynamic and the formation of link changes spatially and temporally. Therefore, there is scope for network based model development that can evaluate the networks and links between the nation's virtual water trades.

### **3.4 Growing anthropogenic impact on blue water**

The amount of fresh water accessible to the global population is a marginal fraction of world's total water (Oki and Kanae, 2006), which is referred as blue water resources. The global population is multiplying more rapidly (Hanasaki et al., 2006; Nilsson et al., 2005; Pokhrel et al., 2012; Vorosmarty et al., 2000), and it has tremendous pressure on blue water resources through depleting surface and ground water storages. Anthropogenic

factors, for example, increase in land use and land cover change further alters the spatio-temporal patterns of hydrologic fluxes (e.g., evapotranspiration, runoff, and ground water flow) (Costa et al., 2003; Sahin and Hall, 1996). Sectoral water demand continues to grow, for example, the consumptive use of agricultural sector is about 85% (Gleick, 2003), which has a significant influence on the normal flow in Major River networks. The construction of water storage structures (for example, dams, and aqueducts) had a direct influence on blue water resources management (Gleick, 2003). The making of massive structures caused unequal partitioning of blue water in between the Transboundary River sharing nations/States. That is leading to several international or state conflicts (Sathl, 2005). In addition, it also created changes in sea water level (Oki and Kane, 2006).

### **3.5 Low flow influence on grey water footprint**

The concentration of nutrients/pollutants in stream networks are expected to increase with anthropogenic activities and related changes in the land use and cover (Bouraoui et al., 2002). The low flow in streams occurs seasonally as well as during drought events (Smakhtin, 2001). During the low flow period, the pollution from point and non-point sources hinders the availability of clean water for downstream users. Also, the low flow regime is characterized by high stream temperatures causing low dilution of nutrients and subsequently changing the  $p^H$  level and dissolved oxygen content (Sprague, 2005). Finally, it will lead to the upsurge of grey water content in the streamflow. In agriculture, the grey water footprint can be reduced by constraining the application of chemical fertilizers and pesticides in the crop land to minimize their impact on water quality in the

water system through run-off from the field or by leaching. The concentration of nutrients in streams varies also with the season. For example, during the dry season nutrients in stream elevates due to intensive irrigation (Verhoeven et al., 2006). Other studies have indicated that the precipitation over an agricultural watershed has strong control on leaching of fertilizers and manure to the stream network (Sigleo and Frick, 2003).

Water Pollution Level (WPL) is another appropriate indicator for addressing the impact of pollutant in streams (Hoekstra et al., 2012). It is quantified as the ratio of grey water to river discharge (Wu et al., 2012). As evident from the WPL definition, the higher the value of WPL higher is the water pollution. Therefore, calculating WPL during low flow period can inform the farmers to understand the impact of fertilizers and manure application in a river ecosystem. However, the grey water footprint concept is considered as least meaningful of three water forms as it is a theoretical concept rather than an actual measured volume (Morrison et al., 2010). The water experts and policymakers consider that it is extremely difficult to determine how much freshwater will be polluted due to the flow of nutrients flow from point and nonpoint sources (Nazer et al., 2008).

### **3.6 Model based applications**

Several modeling approaches are proposed to quantify the blue and green water footprints (Veettil and Mishra, 2016). The decision support tool of CROPWAT (Allen et al., 1998), AquaCrop model (Heng et al., 2009) and the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) are commonly used to estimate the blue, green and grey water resources at a basin scale as well as for individual crop. For example, Abbaspour et al. (2015) estimated the green and blue water for the continental Europe; Schuol et al. (2008)

and Zang et al. (2012) used SWAT model for evaluating the blue and green water availability in Africa and Heihe River Basin (north east China) respectively. Rodrigues et al. (2014) developed a framework to quantify blue and green water in a catchment located at Sao Paulo, Brazil. For individual crops, the water balance model CROPWAT (Allen et al., 1998) is commonly used for analyzing WF (Chapagain and Hoekstra, 2011; Chapagain and Hoekstra, 2007; Gerbens-Leenes et al., 2009a; Kongboon and Sampattagul, 2012; Mekonnen and Hoekstra, 2011a). EPIC model (Williamsetal, 1989; Williams, 1995) is another efficient crop model that can be used for quantifying the green water footprint.

In CROPWAT, the green water and blue water footprint can be separately estimated based on the source of evapotranspiration (Crop Water Use) during the crop growth period (Hoekstra et al., 2012). Other models used for crop WF calculation that are dependent on water budget equation are PolyCrop (Nana et al., 2014), Decision Support System for Agrotechnology Transfert – Cropping System Model, (DSSAT-CSM; Dalla Marta et al., 2012), and Lund-Potsdam-Jena managed Land (LPJmL; Rost et al., 2008).

#### **4. Applications in different sectors**

The application of water footprint concept is applied in multiple sectors (e.g. food production, energy projects, and industry). Most of these studies have focused on water footprint accounting based on the methodologies applied to calculate water footprints for individual products/process. In this section, an overview of the application of water footprint concept in food production, biofuel production, and some other sectors including industry, mining, and energy production is provided.

#### **4.1 Food production sector**

Water footprint of food crops are analyzed in several literatures (Hoekstra et al., 2011; Mekonnen and Hoekstra, 2011; Rost et al., 2008). The estimated amount of total water for 126 agricultural crops (Mekonnen and Hoekstra, 2011) showed that the global water footprint related to crop production was 7404 billion cubic meters per year comprising of 78% green, 12% blue, and 10% grey water footprint. The global average water footprint for wheat found to be 1827 m<sup>3</sup>/ton, which consists of green water footprint (1277 m<sup>3</sup>/ton) blue water footprint (342 m<sup>3</sup>/ ton) and grey water footprint (207 m<sup>3</sup>/ton). The water footprints of crops also vary significantly from region to region (Chapagain and Hoekstra, 2011). Agricultural crops often cultivated in coarse land likely to use irrigation water, which will have higher average blue water footprints than crops that are largely cultivated in rain-fed land (Vanham and Bidoglio, 2013). Rainfed agriculture is the major user of green water in agricultural sector, but the amount of green water exploited in irrigated crop land is insignificant in a global scale. The water footprint application based on a disaggregation (blue, green and grey water footprint) approach are maize (Nana et al., 2014), cotton (Chapagain et al., 2006), and tomato (Chapagain and Orr, 2009). The water footprint of varieties of crops is provided in the Table 1.

The water footprint for animal products is greater than crop products with an equivalent nutritional value (Mekonnen and Hoekstra, 2012). The estimated water footprint for beef and milk products found to be the highest among the food products. But the revised water footprint approach formulated by Ridoutt et al (2012) by excluding green water provides different results. According to the revised water footprint concept,

the life stock grown in non-arable land has no contribution in water footprint, and hence is not a threat to water security. However, the water footprint concept which considers relative scarcity in each catchment strongly recommends the addition of green water footprint (Hoekstra and Mekonnen, 2012) and this concept make more environmental relevance in water footprint calculations. Therefore, the global animal production based on three components (blue, green, and grey) of water footprint concept requires about 2422 Gm<sup>3</sup> of water per year. In that 87.2% belongs to green, 6.2% belongs to blue, and 6.6% belongs to grey water footprint. One third of this volume is for the beef cattle sector and another 19% for the dairy cattle sector.

#### **4.2 Bioenergy production sector**

Greenhouse gas emission is one of the most significant contributor to the climate change since the mid of 20<sup>th</sup> century and the majority of them coming from energy and transportation sector (Mint et al., 2011). Many researchers highlighted that the use of biofuel will significantly reduce greenhouse gas emission (Gerbens-Leenes and Hoekstra, 2008; Kongboon and Sampattagul, 2012). The U.S department of energy aims to provide 16% of electricity through biofuel production (Gerbens-Leenes et al., 2012) by 2020. Therefore the water footprint and related water security analysis due to the biofuel production is necessary for understanding the pressure on water resources (Dalla Marta et al., 2012; De Gorter and Tsur, 2010; Fargione et al., 2008; Dominguez-Faus et al., 2009). Generally, the sources of biomass for energy are food crops, energy crops and organic wastes (Minnesma and Hisschemöller, 2003). However, several other studies suggested

that biofuels made from few food crops can contribute more greenhouse gases than the fossil fuels.

The water footprint for biofuel production varies between crops depending upon the climate, topography, type of crop, and crop yield (Dalla Marta et al., 2012). For example, Biodiesel has the largest water footprint (Gerbens-Leenes and Hoekstra, 2008), which is generally produced from coconut, groundnut, and cotton. Additionally, the water footprint of sugar cane and cassava varies considerably with respect to the region, climate and agricultural production system and on average water footprint of sugarcane is less than that of cassava (Kongboon and Sampattagul, 2012). A comparison between water footprints per unit energy of biomass with water footprint of oil, coal and gas (Gerbens-leens et al.,2009) shows that the water footprint of energy from biomass is 70 – 400 times greater than the same quantity of energy from the above mentioned primary energy carriers. Therefore, the higher energy use in combination with an increasing contribution of energy from biomass will result in competition for water consumption with food production. The application of WF concept in bioenergy sector is listed in Table 2.

### **4.3 Application in other sectors**

Addressing water footprint of any product or a geographic location can provide a sustainable water management solution. Many countries performed water footprint analysis at national level, for example, Hoekstra et al. (2008), Bulsink et al. (2010), Liu and Savenije (2008), and Verma et al. (2009). A comprehensive water footprint assessment of humanity is only possible through the comparative analysis based on all the water usage sector such as, agricultural production, industrial production, domestic



water supply, electricity production, and public use. International virtual water flows related to trade in agricultural and industrial commodities can be considered as part of human water footprint. Table 3 shows some important sectorial application of water footprint on humanity.

**Table 1.** Application of water footprint in food production sector

<b>Field of application</b>	<b>Authors</b>	<b>Major contribution</b>
Crops and crop derived products	(Mekonnen and Hoekstra, 2011)	Water footprint of 126 crops and 200 crop products in a global scale is quantified with CROPWAT model.
Wheat	(Mekonnen and Hoekstra, 2010a)	The global assessment of wheat water footprint was 1830 m <sup>3</sup> /ton, the analysis was based on a high resolution grid-dynamic model.
Animals and Animal products	(Mekonnen and Hoekstra, 2010b)	The blue, green, grey water footprint of animals and animal product showed a maximum in beef cattle and in cow milk production. The calculated water footprint of animal product was greater than water footprint of crop products for the same volume.
Agricultural consumption	(Rost et al., 2008)	The dynamic global vegetation and water balance model (LPJ) is used for estimating the global crop water consumption.
Cotton	(Chapagain et al., 2006)	The worldwide consumption of cotton products consumes 256 Gm <sup>3</sup> of water per year, with a maximum water footprint of blue water.
Rice (Global Scale)	(Chapagain and Hoekstra, 2011)	The global water footprint of rice production is 784 km <sup>3</sup> /year, with maximum green water consumption.
Spanish tomatoes	(Chapagain and Orr, 2009)	Water footprint analysis is applied to a local level, for the horticulture industry, based on the tomato consumption. The result showed that green water consumption is 71 Mm <sup>3</sup> /yr and 7 Mm <sup>3</sup> /yr of nitrate grey water.
Coffee and Tea	(Chapagain and Hoekstra, 2007)	Evaluated the global water foot print of tea and coffee consumption in Dutch society, the calculation is based on water requirement in the major countries which is exporting the product.
Maize	(Nana et al., 2014)	PolyCrop- multiyear daily crop model is used for calculating the water use according to the simulated growth of maize.

**Table 2.** Application of water footprint in bioenergy sector

Bioenergy	(Gerbens-Leenes et al., 2009b)	The study analyzed the water footprint of bioenergy from the crops, including Jatropha, which is having maximum bioenergy production.
Biomass	(Gerbens-Leenes et al., 2009a)	The water footprint of primary energy carriers derived from biomass in different countries are evaluated and estimated water footprint of bioenergy was much larger than fossil energy.
Biofuel	(Wu et al., 2012)	The spatial variation of water footprint of stover ethanol production is estimated based on standardized water footprint methodology combined with hydrologic modeling.
US transportation fuels	(Scown et al., 2011)	Explained the potential change in water footprint due to the increased production of biofuel and electricity. The study proved production of ethanol and petroleum fuels already made impact in aquifer storage due to over pumping.
Bioethanol	(Dalla Marta et al., 2012)	Examined the relation between the pressure on water resources due to the production of biofuel and how it is affected by climate variability.
Bioethanol	(Chiu and Wu, 2012)	Analyzed county level water footprint of bioethanol from corn grain, stover, and wheat straw in the United States.
Sugarcane and Cassava	(Kongboon and Sampattagul, 2012)	The water footprint of both crops varies considerably with respect to the region, climate and agricultural production system.
Sweeteners and Bioethanol	(Gerbens-Leenes and Hoekstra, 2012)	Evaluated the WF of sweeteners and bioethanol from the crop sugarcane, sugar beet and maize.

**Table 3.** Application of water footprint in other sectors

Copper production	(Peña and Huijbregts, 2014)	The study from Northern Chile on extraction and production of high grade copper found that sea water use will reduce the blue water footprint by 62% in Copper mines.
Electricity	(Mekonnen and Hoekstra, 2011c)	The water evaporated from 35 reservoir for producing electricity was equivalent to the 10% of global blue water footprint of crop production.
Business	(Gerbens-Leenes and Hoekstra, 2008)	Formed an accounting method for Business Water Footprint that helps to identify all the questions related to water footprint in business performance.
Platinum mine	(Haggard et al., 2013)	WaterMiner tool (program) is used for calculating the WF of platinum mines in South Africa.

### **5. Difference between water scarcity and drought**

The water security may be defined as the capacity of a water resource system to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods. Water scarcity, water vulnerability, drought, aridity, and water quality are the major stress on water security of a region. In this thesis, we focused on the water scarcity, water vulnerability and drought. Generally, drought and water scarcity are interwoven in nature and this can lead to confusion in water security assessment (Van Loon and Van Lanen, 2013). Therefore, crafting a boundary between water security, water vulnerability and drought is vital for proper policy decisions. Water scarcity refers to long-term water imbalances in supply (Environmental Flow Requirement) and demand (water footprint) of water (EU, 2007). Generally, the practice that leads to water scarcity is the over exploitation of water during the higher demand than the water availability. Therefore, by incorporating human activities in a hydrological system can improve water scarcity assessment of a region (Van Loon and Van Lanen, 2013).

Drought can be triggered due to natural deficit of water caused by low precipitation and high evapotranspiration. Drought is monitored and quantified based on the intensity, duration, severity and spatial extent by using several indices (Dai, 2011; Mishra and Singh, 2010). Palmer Drought Severity Index introduced by Palmer (1965) was the first index to quantify severity, duration and intensity of droughts. It is built upon a water balance model utilizing the precipitation and temperature information of a region. Later several indices like Crop Moisture Index (CMI; Palmer 1968), Surface Water Supply Index (SWSI; Shafer and Dezman, 1982), Standardized precipitation index (SPI; McKee et al., 1993), Soil Moisture Drought Index (SMDI; Hollinger et al., 1993), Reclamation Drought Index (RDI; Weghorst, 1996), Vegetation Condition Index (VCI; Liu and Kogan, 1996) were introduced to study various aspects of drought impacts. However, all these indices do not explicitly consider direct streamflow in their calculations. Therefore, we used standardized runoff index (SRI) (Shukla and Wood, 2008) in our hydrological drought analysis. In chapter four we analyzed the influence of climate, catchment and morphological variables on water availability (hydrological drought) of Savannah River Basin.

## **6. Limitations of hydrologic modeling framework**

The hydrological models have become increasingly sophisticated, in line with developments in fast computing using large amounts of data. Hydrological model can be used for evaluating the anthropogenic influence and climate change impact on water resources and as well as climate change impact assessment. The major uncertainties in generating streamflow using a hydrological model are (a) errors in the input data used for

model development, (b) bias in the model parameters, and (c) errors in the datasets used for model evaluation (observed streamflow data) (Butts et al., 2004). The practices to quantify the uncertainties in the form of probability distributions evolve high degree of nonlinearity and complex interactions with in the hydrological modeling framework (Rodrigues et al., 2014). Therefore, robust approaches are necessary for water policy decisions under uncertainty.

All specific studies presented in each chapter are related to the water security evaluation of Savannah River Basin (SRB), a transboundary river basin located at southeastern United States. Here, the variables (e.g., water yield, groundwater, and streamflow) associated with the water security are quantified using Soil and Water Assessment tool (SWAT) developed by United States Department of Agriculture (Arnold et al., 1998). The uncertainties associated with the input data and the model parameter ranges are quantified by using SWAT-CUP software (Abbaspour et al., 2004). However, there is possibility for model uncertainty and it can be further improved by calibrating the baseflow component, better representation of human interventions (e.g., reservoir operation, irrigation water use), and simulating low flow during the drought period.

## **7. Overall research objectives**

The overall aim of this research is to evaluate the water security of Savannah River Basin by quantifying water scarcity and drought. Three specific research objectives have been identified, each of which has a number of sub-objectives:

**Objective 1:- To quantify water security by using blue and green water footprint concepts** (Chapter one).

*Objective 1.1:* To investigate the spatio-temporal distribution of blue and green water for counties located in the Savannah River Basin.

*Objective 1.2:* To quantify the water security for each county in terms of water scarcity and vulnerability.

**Objective 2:- To quantify the influence of climate variability and land use change on streamflow, ecosystem services, and water scarcity** (Chapter two).

*Objective 2.1:* To quantify the land use change and climate variability impact over hydrological stream network.

*Objective 2.2:* To evaluate the influence of land use change and climate variability in controlling the ecosystem provisioning service of the basin.

*Objective 2.3:* To quantify the potential influence of land use change and climate variability in altering the water scarcity through water footprint concept.

**Objective 3:- To assess the climate, catchment, and morphological variables control over hydrological drought of a river basin** (Chapter three).

*Objective 3.1:* To investigate the influence of (either individually or combined) of climate, catchment and morphometric variables responsible for triggering hydrological drought for SRB.

*Objective 3.2:* To identify threshold limits for the climate, catchment and morphological variables by using decision tree approach.

## **8. Thesis organization**

This contains five chapters with the main objectives of research presented in **chapter two to five**. The chapter two is published in journal of hydrology (Veettil and Mishra, 2016). Here, we discussed about the spatio-temporal variability of blue and green water over a river basin. The spatial variation in water security is also evaluated in the chapter two. Chapter three discuss about the influence of land use change and climate variability on streamflow, blue (green) water and water scarcity. Chapter four illustrates the relation between hydrological drought and climate, catchment and morphological variables. **Chapter five** discusses conclusions and recommendations. The text, figures and tables in this thesis are modified in line with the University guidelines.

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## CHAPTER TWO

### WATER SECURITY ASSESSMENT USING BLUE AND GREEN WATER FOOTPRINT CONCEPTS

#### 1. Introduction

Availability of fresh water resources for human consumption is under threat due to changing climate, limited water supply and growing water demand (Mishra and Singh, 2010; Vorosmarty et al., 2000). The major source of surface water supply is often complicated due to uncertainty associated with spatio-temporal distribution of rainfall as well as multi-year droughts (Oki and Kanae, 2006). The drought and related socioeconomic impact (Rajsekhar et al., 2015) are expected to increase in future, which will further increase the complexity in fresh water availability as well as its distribution among different stakeholders. The demand for water is continue to grow due to growing population, industrialization, agriculture, domestic use and energy production (Vörösmarty and Sahagian, 2000; Lumia et al., 2005; Srinivasan et al., 2013). It is anticipated that by 2025 about 1.8 billion people will likely to witness absolute water scarcity (WWAP, 2012; WWDR, 2015). Similarly the percentage of water consumption for energy and agriculture production will increase drastically by 2035 (IEA, 2012). Therefore, quantification of water availability and its vulnerability will play a critical role in defining and implementing sustainable water management in a changing environment. For example, Padowski and Jawitz (2012) provided a quantitative assessment of national urban water availability and vulnerability for 225 U.S. cities by incorporating renewable water flows as well as water stored using regulated infrastructure systems.

Addressing water security by classifying fresh water resources into blue, green and grey water (Schneider, 2013) is an appropriate method for water resources management. Blue water is defined as water flowing through surface and subsurface medium (i.e., ground water) which are stored in lakes, aquifers and manmade structures, that can be directly used for human consumption (Falkenmark and Rockström, 2006; Falkenmark and Rockström, 2010; Rockström et al., 2009, Rodrigues et al., 2014; Hoekstra et al., 2011). The water stored in unsaturated soil layer and vegetation canopy is classified as green water (Falkenmark and Rockström, 2006; Rockström et al., 2009; Rodrigues et al., 2014). Therefore, evaluating the blue and green water consumption for human activities is crucial for water resources planning.

Water Footprint (WF) concept (Hoekstra and Hung, 2002; Hoekstra et al., 2011) can establish the link between the depletion of water resources and increase in population. Blue water footprint ( $BW_{\text{footprint}}$ ) is the human water consumption from blue water resources and it can be quantified based on the volume of surface and groundwater consumed as a result of the production of a good or service (e.g., domestic, industrial, power production, irrigation etc.) (Hoekstra et al., 2011; Rodrigues et al., 2014). Green water footprint ( $GW_{\text{footprint}}$ ) refers to the consumption of green water resources, for example evapotranspiration from agriculture and forest area (Hoekstra et al., 2011; Rodrigues et al., 2014). Further water security (water scarcity and vulnerability) can be quantified as a ratio of water consumed to water available (Rodrigues et al., 2014) and it is considered to be a globally accepted metric (Hoekstra et al., 2011; Rodrigues et al., 2014) to characterize and map the geographic hotspots for water stress region. The blue

water footprint is directly related to human water consumption but the green water footprint is indirectly influenced by the human activities (e.g., agriculture). Therefore, blue and green water footprint are related to human water consumption. The spatio-temporal analysis of water footprint reflects the spatial distribution of potential linkage between climatic factors (i.e., water supply) and anthropogenic factors (i.e., water demand) and how do they evolve with time. Therefore, this information is particularly useful: (a) for quantifying water related scarcity and vulnerability, (b) it will help the decision makers to understand the current status of water availability, sustainable utilization and the importance of water resources protection of an area, and (c) to reveal the spatially varying pattern of geographic hotspot.

According to Hoekstra and Mekonnen (2012), WF can be relevant to environmental sustainability metric by addition of green water consumption in the analysis. Liu et al. (2009) estimated that nearly 80% of green water footprint are associated with global agriculture production, which includes wheat (Mekonnen and Hoekstra, 2010a), animal products (Mekonnen and Hoekstra, 2010b; Mekonnen and Hoekstra, 2012), cotton (Chapagain et al., 2006) and bioenergy (Gerbens-Leenes et al., 2009). Excessive utilization of blue water from stream can damage stream ecosystem, therefore Environmental Flow Requirement (EFR) concept needs to be applied for maintaining a healthy river system (Honrado et al., 2013). Presumptive standard method (Richter, 2010; Richter et al., 2012) can be useful for EFR analysis as well as for estimating the availability of blue water in a stream. According to presumptive standard, extraction of stream flow greater than 20 percent likely to cause degradation in ecological

health and environmental balance. Various methods are developed for calculating EFR (Tharme, 2003; Hoekstra et al., 2011; Rodrigues et al., 2014) as well as to perform water security analysis.

There are number of approaches proposed to investigate the blue and green water footprints. The decision support tool CROPWAT (Allen et al., 1998), AquaCrop model (Heng et al., 2009) and the process based Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) are popular models commonly used to quantify blue and green water resources. For example, Abbaspour et al. (2015) estimated the green and blue water for the continental Europe. Schuol et al. (2008b) and Zang et al. (2012) used SWAT model for evaluating the blue and green water availability in Africa and Heihe River Basin (north east China) respectively. Rodrigues et al. (2014) developed a framework to quantify blue and green water in a catchment located at Sao Paulo, Brazil.

Due to the changing pattern in climate variables and sectorial water demands, it is desirable to study the spatio-temporal variability of water footprints (security) indicators in a river basin for formulating water management practices. However, there are limited studies that investigated (Zang et al., 2012; Rost et al., 2008) spatio-temporal pattern of water footprints indicator with potential application to water resources management. The specific objectives of our study are: (a) to investigate the spatio-temporal distribution of blue and green water for counties located in the Savannah River Basin, and (b) to quantify the water security for each county in terms of water scarcity and vulnerability. The results from this study will be useful to understand the spatio-temporal pattern of water distribution in a river basin that is necessary for formulating best water



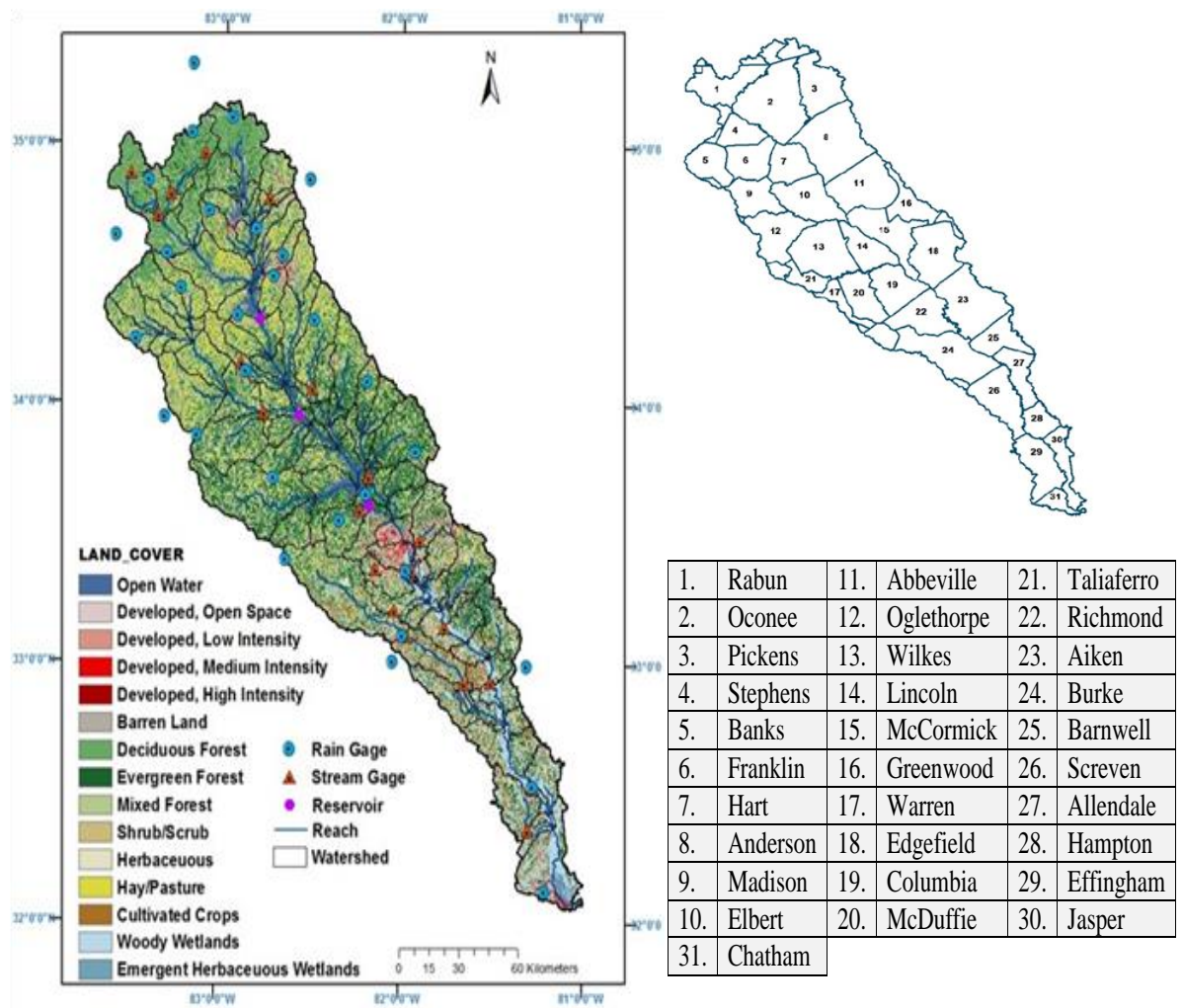
management practice and to improve water resources sustainability. Additionally, there were no prior studies conducted in Savannah River Basin.

## **2. Study area and Data**

Savannah River Basin (SRB) is a transboundary river basin located in south-east Atlantic region of USA. It has drainage area of 27171 km<sup>2</sup>, out of which 11875 km<sup>2</sup> is located in the South Carolina and 14965 km<sup>2</sup> in Georgia and the remaining portion is located in the state of North Carolina (SCDHEC, 2010). The land cover of SRB consists of forest (69%), agriculture (22%) and urban/developed (7%) areas. According to Georgia department of natural resources, the percentage of irrigated agricultural land in SRB has increased by 1.8 % between 1984 and 1995. During the recent decade, SRB is going through a periodic water shortage due to a combination of drought and growing water consumption for domestic, industrial and agricultural sectors (Sun et al., 2008). The available water resources in SRB are used for domestic use (more than 1.5 million people), energy (hydro power generation, nuclear plants etc.), industrial and agricultural water uses (SCDHEC, 2010). According to Environment Georgia (a citizen based environmental advocacy project of Environment America), Savannah River is considered as the third most polluted river in the country, which further complicates the allocation of water resources for different sectors.

The basin is composed of nine USGS 8-digit HUCs (Hydrologic Unit Codes) (03060101 to 03060109) and 31 counties (Figure 1). The SRB which serves three different states (North Carolina, South Carolina and Georgia) is also likely to be affected by trans-boundary disputes; climate and land use change as well as growing water

demands. During the last decade, the SRB was severely affected by extreme droughts that began in early 2006, which in turn dropped reservoir levels (Knaak et al., 2011; Roehl et al., 2015) faster than any previous drought on record. This situation is only likely to worsen because the water is shared by three states and each state is witnessing an increase in water scarcity issues.



**Fig. 1.** Savannah River Basin and its land use pattern, stream network and location of gaging stations (Left). Spatial location of counties in the Savannah River Basin (Right).

## 2.1. Data

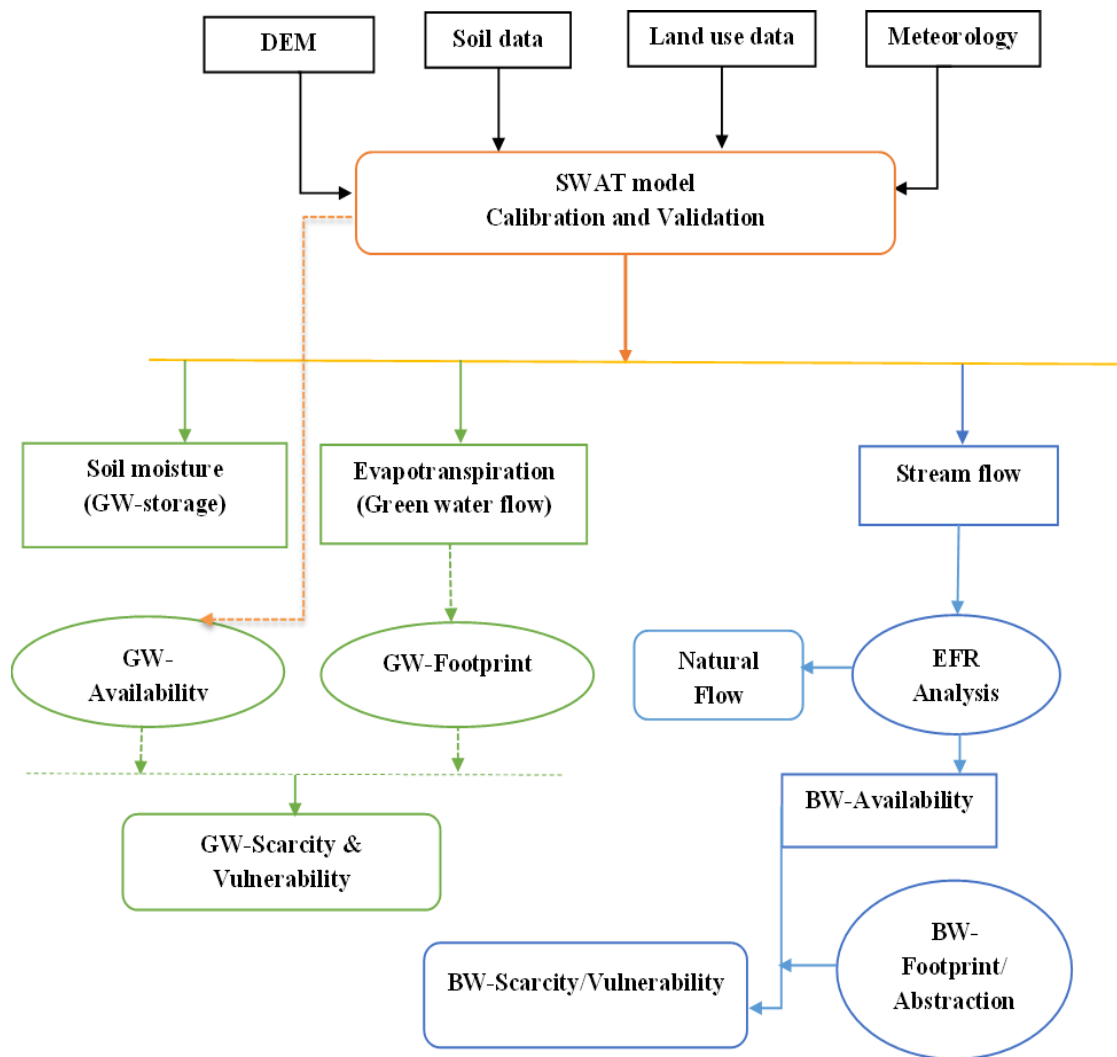
The list of data sets used in this study and their sources are provided in Table 1. The digital elevation model (DEM) was obtained from National elevation data set at a resolution of 30m to delineate the study area and to estimate the topographic features. The land use and soil data were used for generating the HRUs (Hydrologic Response Units). The meteorological (precipitation and temperature) and stream flow data for 1990 to 2013 were collected from National Climatic Data Centre (NCDC) and United States Geological Survey (USGS) respectively. The reservoir outflow data collected from Savannah District Water Management (US Army Corps of Engineers) was incorporated in SWAT model development.

**Table 1.** Data used (inputs) for SWAT model development.

Data Used	Description	Resolution	Source
Land use map	The Crop Data Layer produced using Landsat imagery during 2013	30 × 30	United State Department of Agriculture (USDA)
Topography and Hydrograph	Digital Elevation Model from National Elevation Data set (NED, NAD 83)	30 × 30	National Elevation Dataset, USGS
Soils	The SSURGO data base provides the most detailed level of information, helpful for county level analysis	1:12,000 to 1:63,360	United State Department of Agriculture (USDA)
Meteorological Data	The daily Precipitation, maximum and minimum air temperature	Daily (mm)	National Climatic Data Centre (NCDC)
Stream flow gages	River Discharge	Daily and monthly mean (m <sup>3</sup> /s)	United States Geological Survey (USGS)
Reservoir data	Outflow and dimension	Daily and monthly	U.S. Army Corps of Engineers

### 3. Methodology

The integrated modeling framework applied for generating blue and green water as well as to quantify water security in a river basin is provided in Figure. 2. The following section provides a brief overview of individual components provided in the modeling framework.



**Fig. 2.** Modeling framework for water security assessment using blue and green water footprints.

### **3.1. Hydrologic modeling**

We used Soil and Water Assessment Tool (SWAT) developed by United States Department of Agriculture (USDA) for simulating the blue and green water resource components. The SWAT is a process based, semi-distributed basin scale model (Arnold et al., 1998; Neitsch et al., 2004) and it operates at a daily time step. The model has the advantage to study water quantity (stream flow), water quality (sediment load and nutrients flow) and crop growth in different landscapes and management practices. The model has been widely applied in different sectors (water quantity, quality and crop management) (Faramazi et al., 2009) and it can be applied to a small catchment as well as to a large river basin (Chu et al., 2004; Cibin et al., 2012; Gassman et al., 2007; Giri et al., 2014). The SWAT model is recently applied to quantify the blue and green water indicators in different part of the world, for example northeast China (Zang et al., 2012), Africa (Schuol et al., 2008b), Continental Europe (Abbaspour et al., 2015) and Brazil (Rodrigues et al., 2014).

Digital Elevation Model (DEM) is used in SWAT model to delineate a river basin. The delineated river basin is divided into sub-basins, which are further divided in to unique land use/soil/slope units called Hydrologic Response Units (HRUs). The delineation of HRUs are performed by super imposing the soil, land use and slope map. Five classes of slopes used for HRU delineation are 0-2.5%, 2.5-5%, 5-10%, 10-40% and above 40%. The number of HRUs is controlled by adjusting the threshold (Her et al., 2015) of land use (3%), soil (10%) and slope (16%), which resulted in 1408 HRUs distributed over 104

sub-basins. We used SUFI2 algorithm for evaluating the model performance, and the explanation is given in section 3.2.

Water balance is the driving force which controls all the process in SWAT. Surface runoff occurs whenever the amount of water on the land surface exceeds the rate of infiltration. Here, surface runoff is calculated by SCS curve number (CN) method and variable storage method is used for routing the runoff from sub-basin through river network and to the main basin outlet. The preprocessing of the SWAT model input was accomplished in ArcGIS 10.2.2 version of ESRI.

### **3.2. Model evaluation and uncertainty analysis – SUFI2 algorithm**

The model was calibrated and evaluated against the observed stream flow data (source: USGS) located in the Savannah River Basin. We used SUFI2 optimization algorithm developed by Abbaspour et al. (2005) for parameter estimation and sensitivity analysis. The primary objective of calibration is to identify the sensitive parameters in the watershed that controls the runoff. The sensitivity analysis was performed using the in-built global sensitivity option of SUFI2 algorithm, where the statistical significance of a parameter is estimated based on t-stat and p-value. Each model consists of uncertainty in predictions due to the uncertainty associated with input data and model parameters. SUFI2 algorithm can narrow down the range of uncertainty by identifying a range of parameters that reduce overall uncertainty in the output. The model output is quantified by 95% prediction uncertainty (95PPU) calculated at 2.5% and 97.5%. The performance of SWAT model was evaluated by using the goodness-of-fit criteria, such as, coefficient of determination ( $R^2$ ), Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliff, 1970), R- and

P-factor. R-factor is the ratio of average thickness of 95PPU band to standard deviation of observed data, whereas P-factor is the percentage of observed data enclosed in 95PPU (Abbaspour et al., 2007). The maximum value of P-factor is 1, which means 100% of observed data is bracketed by the 95PPU. The lower value of the R-factor indicates better model performance. The overall time period used in our analysis is: 1990 – 2013. The first three years (1990-1992) were used as warm-up period to alleviate the effects of unknown initial conditions and subsequently this time period is excluded from the analysis. We divided the discharge data set in to two periods 1993 – 2005 (calibration period) and 2006 – 2013 (validation period). The model calibration and validation results and most sensitive parameters for SWAT model are explained in section 4.1.

### **3.3. Blue and green water calculation**

The blue water is calculated by applying modeling framework (Fig. 2) by combining both water yield (WYLD) and ground water storage. Water yield is the amount of water leaving the HRU and entering the main channel. Ground water storage is the difference between total amount of water recharge to aquifers (GW\_RCHG) and the amount of water from aquifer that contributes to the main channel flow (GW\_W) (Rodrigues et al., 2014). Green water is divided in to green water flow (evapotranspiration) and green water storage (soil water content) (Schuol et al., 2008a). Green water is estimated as the sum of evapotranspiration (ET) and soil water content (SW) (Abbaspour et al., 2015; Schuol et al., 2008b; Falkenmark and Rockström, 2006). In section 4 we analyzed the coefficient of variation (CV) of blue and green water based on the 21 years of simulation period. We used Sen's Slope method (Sen, 1968), which is the median of all pairwise slope in the

data set, for estimating the annual trend of blue and green water for counties located in SRB.

### **3.4. Quantification of green water security**

Green water security ( $GW_{security}$ ) can provide information on management of fresh water resources (Rockstrom, 2001).  $GW_{security}$  is evaluated in terms of green water scarcity and green water vulnerability.

#### **3.4.1. Green water scarcity**

Green water scarcity ( $GW_{scarcity}$ ) in a catchment is calculated as the ratio between green water footprints ( $GW_{footprint}$ ) to green water availability ( $GW_{availability}$ ) (Hoekstra et al., 2011). Here  $GW_{footprint}$  is estimated as the actual evapotranspiration, which is calculated by using Hargreaves method (Hargreaves et al., 1985) and it can be obtained from HRU output of the SWAT model (Winchell et al., 2013). The SWAT HRU output also provides the initial soil water ( $SW_i$ ) content (Winchell et al., 2013), which is the difference between root zone soil moisture and wilting point (DeLiberty and Legates, 2003; Rodrigues et al., 2014). Wilting point is the minimum soil moisture content that is no longer available for crop (plant) sustainability. Therefore, the  $SW$  represents the amount of soil moisture available for the sustaining crop growth, therefore in this study  $SW$  is considered as  $GW_{availability}$  (Rodrigues et al., 2014). The  $GW_{scarcity}$  for a county is estimated by using equation (1),

$$GW_{scarcity(x,t)} = GW_{footprint(x,t)} / GW_{availability(x,t)} \quad (1)$$



Where,  $GW_{availability(x,t)}$  is the amount of initial soil water content (which is considered as available green water) in county 'x' during the period 't'.  $GW_{footprint(x,t)}$  is the green water consumed from a county 'x' during time 't'.

### **3.4.2. Green water vulnerability**

Green water vulnerability ( $GW_{vulnerability}$ ) is calculated as the ratio between green water footprint to the historical low (30th percentile) green water availability.  $GW_{vulnerability}$  is calculated by using equation (2),

$$GW_{vulnerability(x,t)} = GW_{footprint(x,t)} / GW_{availability(P30)(x,t)} \quad (2)$$

where  $GW_{availability(P30)(x,t)}$  is the historical low green water availability, expressed as the 30<sup>th</sup> percentile (i.e.,  $GW_{availability}$  exceeded 70% of the time) of available green water volume in a county.

### **3.5. Quantification of blue water security**

Blue water security ( $BW_{security}$ ) is evaluated using water scarcity and water vulnerability indicators. Blue water scarcity ( $BW_{scarcity}$ ) is defined as the ratio of blue water footprint ( $BW_{footprint}$ ) to the blue water availability ( $BW_{availability}$ ).

#### **3.5.1. Blue water scarcity**

Where,  $BW_{footprint}$  refers to the consumptive use of water based on the difference between water withdrawal (abstraction) and returned flow (Hoekstra et al., 2011).

Returned flow is defined as the part of the flow that is not consumptively used and likely to return to its primary source or to the same catchment area. The county level sectorial water demand data (e.g., human water use and agricultural use) are obtained from United State Geological Survey (USGS). The human water use includes domestic, public, thermo-electric, industrial, mining and commercial water use, whereas, the agricultural water use consists of irrigation, livestock and aquaculture water use. We used this information to calculate the consumptive use of fresh water for human and agricultural water use (Carr et al., 1990; Fanning and Trent 2009; Shaffer 2008 and Solley et al., 1998). For human water use, the water footprint of domestic, industrial and mining sector showed maximum of 20% of total water withdrawal. For agricultural water use, the water footprint of irrigation is 85% of total withdrawal. The estimated consumptive use of fresh water in SRB is as shown in Figure. 3.

$BW_{availability}$  is the limited amount of water which can be abstracted without affecting the ecology of stream. Here  $BW_{availability}$  is calculated (Hoekstra et al. 2011) based on the equation (3) and finally  $BW_{availability}$  is converted to the yearly scale for evaluating the  $BW_{security}$  over the counties located in the SRB. (The  $BW_{availability}$  is calculated by considering the amount of stream flow (river flow) which is available for the consumptive use (Hoekstra et al., 2011), it does not include aquifer storage).

$$BW_{availability(x,t)} = Q_{(x,t)} - EFR_{(x,t)} \quad (3)$$

where ‘x’ represent a county with respect to time ‘t’. EFR is the environmental flow requirement (m<sup>3</sup>/s) and Q is the corresponding monthly stream flow (m<sup>3</sup>/s). To develop a practical method for quantifying the optimum water usage from available resource is often challenging in water resourcing planning. To overcome this limitation, the presumptive standard method (equation 4) is used in this study and according to this method 20% of the flow can be considered appropriate for withdrawal purpose (Richter, 2010; Richter et al., 2012),

$$EFR(p)_{(x,t)} = 0.8Q_{\text{mean}(x,t)} \quad (4)$$

where  $EFR(p)_{(x,t)}$  is the EFR according to presumptive standard for county ‘x’ at time period ‘t’. Finally,  $BW_{\text{scarcity}}$  is calculated according to the equation (5),

$$BW_{\text{scarcity}} = BW_{\text{footprint}(x,t)} / BW_{\text{availability}} \quad (5)$$

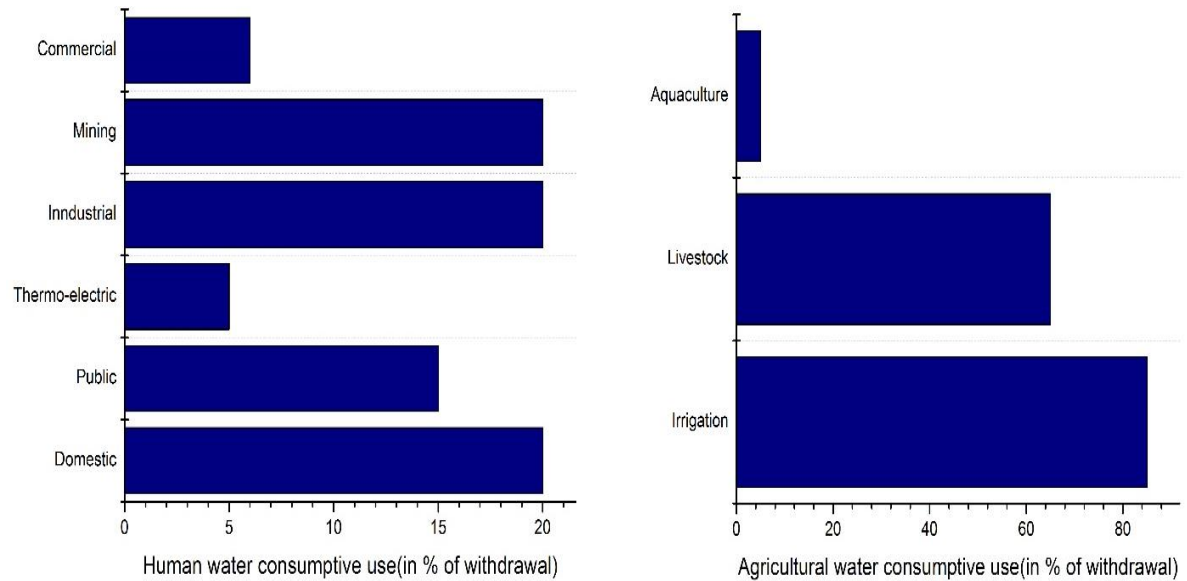
$BW_{\text{footprint}}(x, t)$  represents the consumptive use of water (Fig. 3) by human and agricultural sector in county ‘x’ during time period ‘t’.

### **3.5.2. Blue water vulnerability**

Blue water vulnerability ( $BW_{\text{vulnerability}}$ ) can provide useful information about water use during low flow or drought conditions (Padowski and Jawitz, 2012; Rodrigues et al., 2014). It is defined as the ratio of blue water abstraction to the historical minimum flow conditions (Rodrigues et al, 2014). The  $BW_{\text{vulnerability}}$  is estimated based on the equation (6).

$$BW_{\text{vulnerability}}(x,t) = BW_{\text{abstraction}} / BW_{\text{availability}}(P30)(x,t) \quad (6)$$

Where,  $BW_{\text{availability}}(P30)$  indicates the historical low availability of blue water that is exceeded 70% of the time, and is represented as 30<sup>th</sup> percentile of calculated blue water availability in a county.  $BW_{\text{vulnerability}}$  more than 100% indicates that the particular county is environmentally vulnerable or is an ecological hotspot, where the availability of water for human use is below minimum during the low flow conditions.



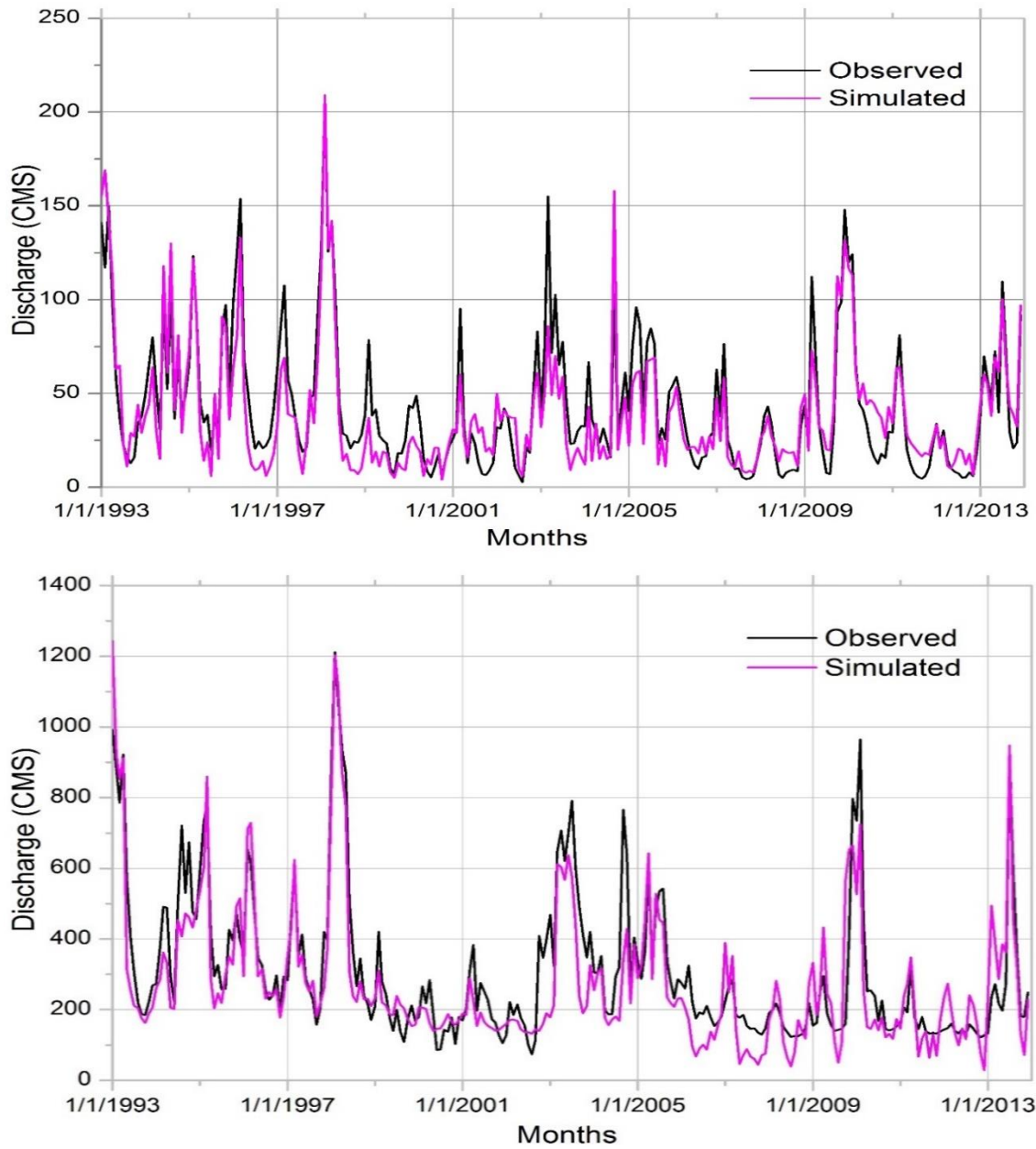
**Fig. 3.** Consumptive water use for human and agricultural sector in SRB.

## **4. Results and Discussions**

### **4.1. SWAT model development**

The calibration and validation of the SWAT model was performed with SUFI2 algorithm at 6 gaging stations located in upper, middle and lower part of the SRB. The location (latitude/longitude) of these six gaging stations are: 34°48'05"/82°44'55", 34°04'17"/82°30'03", 33°58'27"/82°46'12", 32°31'41"/81°16'08", 33°22'25"/81°56'35", 32°56'20"/81°30'10". The peak flow was calibrated by adjusting the sensitive parameters including CN2.mgt (curve number), SOL\_AWC.Sol (Available water capacity of the soil layer) and ESCO.bsn (Soil evaporation compensation factor). We used baseflow separator program (Arnold et al., 1995; Arnold and Allen, 1999) to determine the ground water parameter 'baseflow recession constant' (ALPHA\_BF.gw). Other parameters used for adjusting the baseflow are v\_GW\_DELAY.gw (Groundwater delay time) and r\_GW\_REVAP.gw (Groundwater revap. coefficient).

Overall 17 hydrologic parameters were evaluated during model calibration stage, and the SUFI2 algorithm was applied to determine most sensitive parameters as well as to determine their uncertainty range and 10 parameters are identified as most sensitive based on t-stat and p-value (table 2). The goodness of fit statistics (R<sup>2</sup>, NSE, P-factor and R-factor) were calculated between SWAT based flow and observed flow (Table 3) and showed for four hydrologic stations located in the SRB. The time series plot between SWAT based flow and observed flow at USGS stream gauging stations 02192000 and 021985000 are shown in Figure 4.



**Fig. 4.** Time series plot between modeled (SWAT) and observed (USGS) stream flow at gauging stations 02192000 and 021985000 at monthly time scale.

The goodness of fit statistics indicates a reasonable agreement between observed and modeled streamflow. Based on the graphical interpretation, the performance of SWAT for simulating lowflow is comparable to previous studies (Zhang et al., 2015; Setegn et al., 2010). However, the higher deviation was observed during 2006-2009 and during this time the SRB witnessed a historically severe drought (Knaak et al., 2011), which may be the reason for comparatively higher deviation between observed (i.e., USGS) and model flow (i.e., SWAT output). The SWAT model may not perform best for simulating low flows and specifically during drought, which was also highlighted by Zhang et al (2015) and Setegn et al (2010).

**Table 2.** Most sensitive parameters used for the SWAT model development.

<b>Sensitive Parameters</b>	<b>Explanation</b>	<b>Calibrated range</b>
r_CN2.mgt	Curve number	-0.2 to 0.3
r_SOL_AWC.Sol	Available water capacity of the soil	-0.2 to 2
v_ALPHA_BF.gw	Baseflow recession constant	0.4 to 0.9
v_GW_DELAY.gw	Groundwater delay time (days)	30 to 450
r_GW_REVAP.gw	Groundwater revap. coefficient	0.02 to 0.2
r_HRU_SLP.hru	Average slope steepness (m/m)	-0.5 to 1
r_SLSUBBSN.hru	Average slope length (m)	-0.5 to 1
r_EPCO.bsn	Plant uptake compensation factor	0 to 0.7
r_ESCO.bsn	Soil evaporation compensation factor	0 to 0.4
v_CH_N2.rte	Manning's n value	0.01 to 0.4

**Table 3.** Goodness of fit statistics between modeled and observed (i.e., USGS)

USGS flow station	Station ID	Calibration period				Validation period			
		R <sup>2</sup>	NSE	R-factor	P-factor	R <sup>2</sup>	NSE	R-factor	P-factor
Broad River near Bell	02192000	0.88	0.87	0.89	0.81	0.81	0.77	0.57	0.71
Savannah River near Clyo	02198500	0.85	0.76	0.89	0.82	0.64	0.58	0.58	0.51
Savannah River at Augusta	02197000	0.54	0.45	0.86	0.66	0.55	0.42	0.89	0.53
Savannah River at Burtons Ferry Br Nr Millhaven	02197500	0.62	0.62	0.84	0.76	0.55	0.38	0.76	0.63

#### **4.2. Spatial and temporal analysis of blue and green water**

The spatio-temporal changes of blue and green water play an important role in water resource planning and management (Zuo et al., 2015). Hydrological components: Evapotranspiration (ET), Soil Water (SW), Water yield (WYLD), Ground water Recharge (GW\_RCHG) and Ground water contribution to stream (GW\_Q) obtained from the well calibrated SWAT model was used for calculating blue and green water at monthly and annual time scales. The mean annual blue water, green water flow and green water storage based on the simulated period (1993-2013) for counties located in SRB are shown in Figure 5. The spatial distribution of blue water was found to be influenced by the rainfall pattern. The maximum precipitation was observed in upstream of the basin and the annual blue water flow was found to be high in Rabun County located in upper SRB, where the amount of average blue water observed to be 1291 mm per year.



The Sen's Slope analysis showed a marginal increasing trend for blue water in Rabun County (Fig. 6a). The minimum annual blue water was observed in central area of SRB (e.g., Lincoln and Columbia County located in Georgia), with less than 400 mm of blue water per year. These counties witnessed decreasing trend of blue water (Fig. 6b). The percentage change in blue water was evaluated and it was observed that both Rabun and Pickens County witnessed an increase of 64% and 70% respectively. The percentage change in blue water for the counties located in middle part of SRB was less than five percent. The annual precipitation has a decreasing pattern from upstream to downstream, which plays an important role in controlling the spatial distribution of blue water resources based on their similarity in spatial distribution.

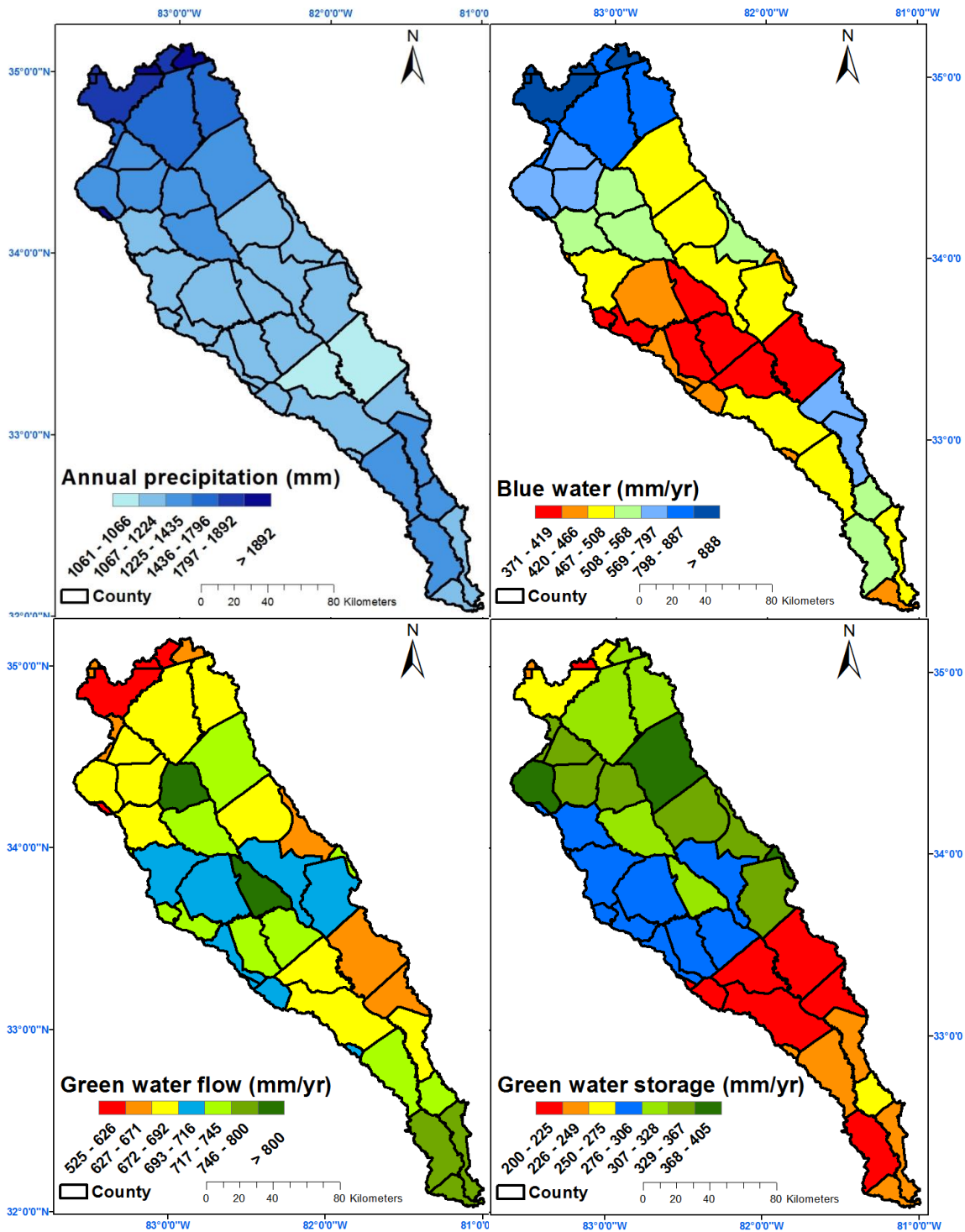
The spatial distribution of mean annual green water flow seems to have less variability in comparison to spatial distribution of blue water in most of the counties located in SRB (Fig.5b). The maximum green water flow was observed in Hart and Lincoln County with an average of more than 800 mm per year. The evaporation from reservoir may be a possible reason for higher amount of green water flow in both counties. The land use is likely to play an important role as the 75% of the farm land of SRB is hay and pasture, therefore the evapotranspiration from pasture cultivation likely to have a strong influence in controlling the green water flow throughout the basin. The cultivation of corn, soybean and wheat are significant in Hart County and these crops likely to influence green water flow and the similar findings were discussed in Rost et al. (2008). The Sen's Slope indicates a decreasing trend in green water flow for all the counties in SRB. For example, the Sen Slope estimate of green water flow for the

counties located in upper SRB (Hart County) and central SRB (Lincoln County) indicates a decreasing trend (Fig. 7). The spatial distribution of green water flow was found to be minimum in Rabun County located in the upper part of the SRB.

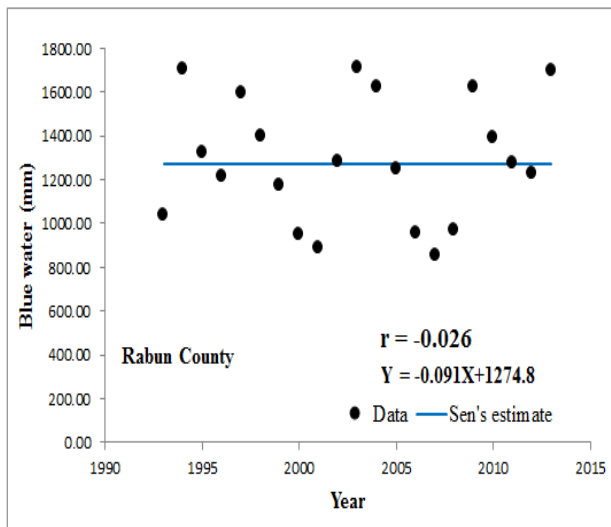
The mean annual green water storage showed a variation from 200 mm to 400 mm throughout the SRB and its annual variability is comparatively small in comparison to blue and green water flow. The maximum green water storage was observed in Anderson and Edgefield County of South Carolina and Banks County of Georgia. A decreasing trend in green water storage was noticed in most of the counties, for example, the Sen's slope for counties located in upper SRB (Anderson County) and lower SRB (Richmond County) indicates a decreasing trend (Figure 8).

The coefficient of variation (CV) of blue water, green water flow and green water storage for the counties is presented in Fig. 9. The higher CV was observed for blue water and lower CV was observed for green water flow. The blue water (internal water resources) calculated by FAO for USA (national scale) is 2180 km<sup>3</sup>/yr (AQUASTAT, 2013), however our study highlights the spatio-temporal variability of blue and green water within SRB. The overall result indicates that, blue water varies between 24 – 68% of rainfall (maximum in Rabun County, average rainfall is 1892 mm per year), green water flow varies between 32 – 70% of precipitation (maximum in Lincoln County, average rainfall 1143 mm per year), and the green water storage varies between 13 – 34% (maximum in Anderson County, average rainfall 1228 mm per year). The results are acceptable for humid subtropical region (Schuol et al., 2008b and Rost et al., 2008).

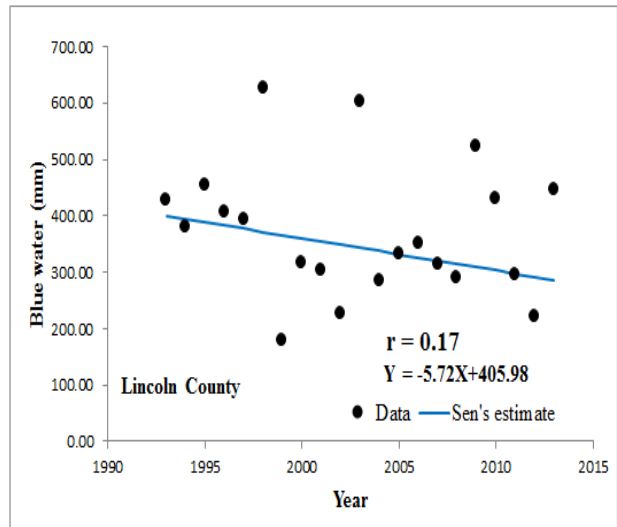
The distribution of average blue water and green water flow at monthly time scale from selected counties located in upper, middle and lower part of SRB are shown in Figure 10. Even though the maximum rainfall in SRB occurs during June -September, the maximum blue water was observed in December -March (Fig. 10). This indicates a time lag between maximum rainfall and blue water. This may be due to higher amount of evapotranspiration in the basin reduces the peak discharge. The higher rainfall and minimum temperature during January to March may be the reason for higher amount of blue water flow in March. The green water flows found to be maximum during June to August, and it may be due to higher temperature and rainfall pattern during this period.



**Fig. 5.** Spatial distribution of annual precipitation, mean annual blue water, green water flow and green water storage over the counties located in Savannah River Basin.

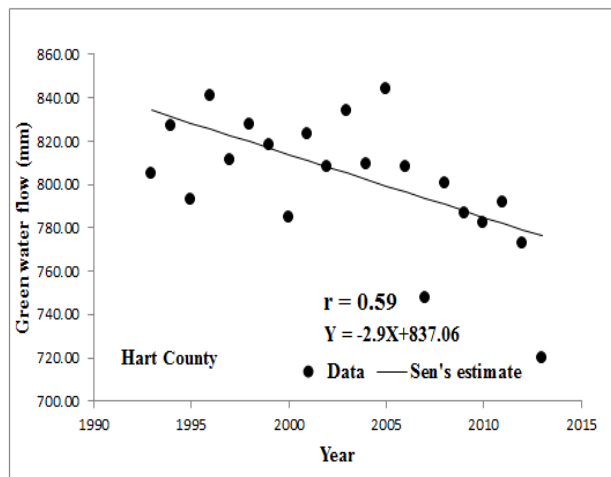


a

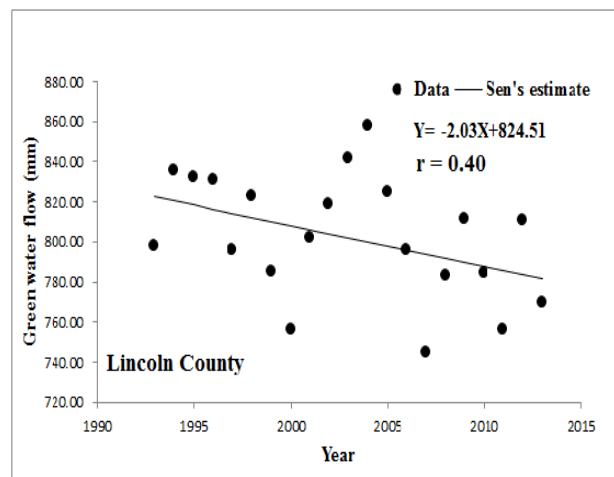


b

**Fig. 6.** Linear trend of annual blue water for (a) Rabun County, and (b) Lincoln County located at upper and middle Savannah River Basin respectively

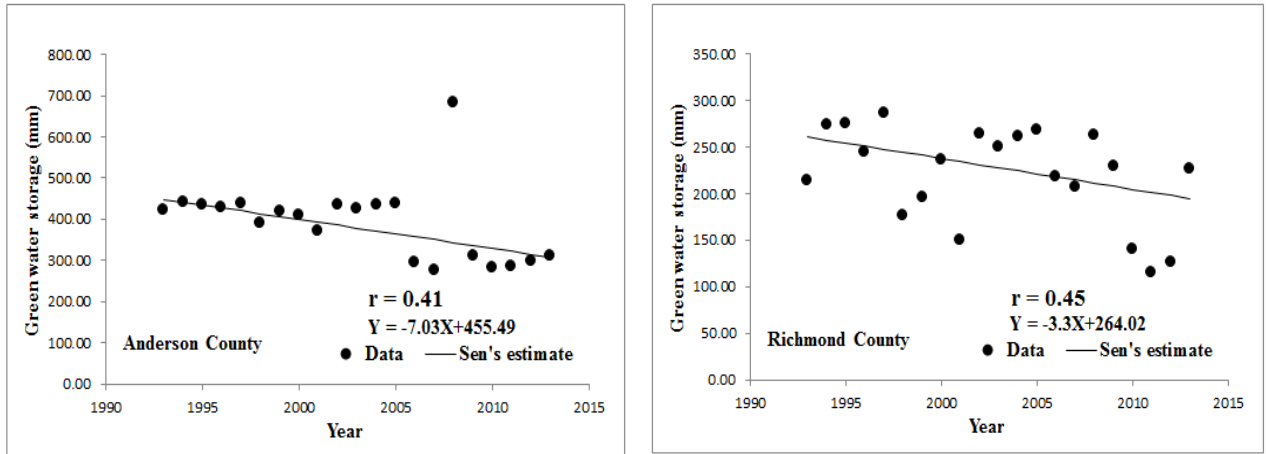


a



b

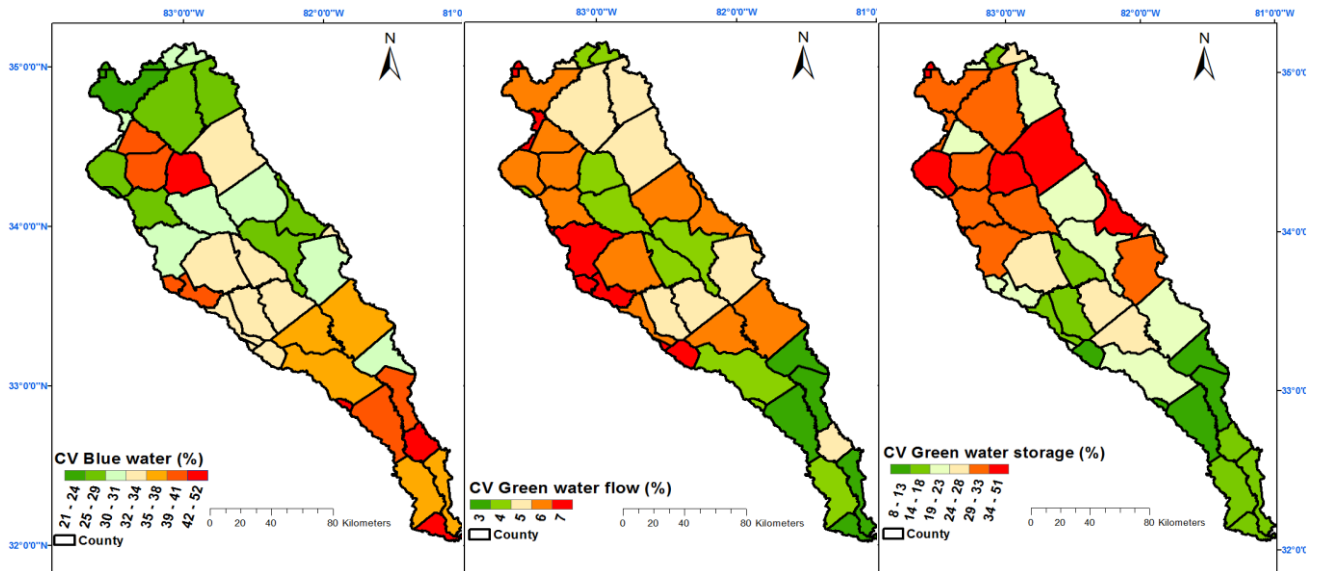
**Fig. 7.** Linear trend of annual green water flow for (a) Hart County, and (b) Lincoln County located at upper and middle Savannah River Basin respectively



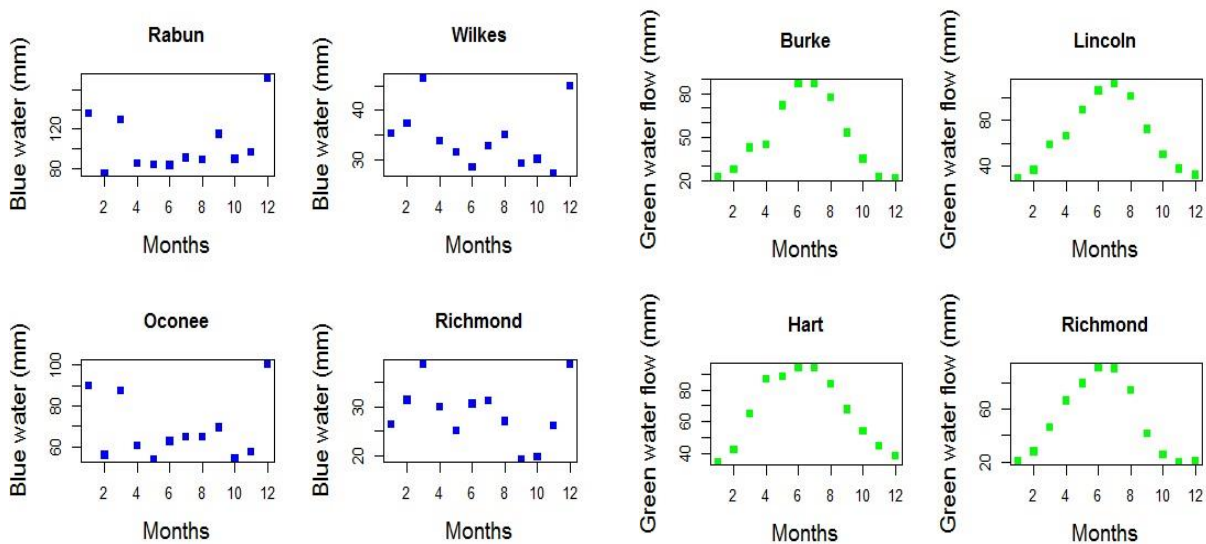
a

b

**Fig. 8.** Linear trend of annual green water storage for (a) Anderson County, and (b) Richmond County located at upper and lower Savannah River Basin respectively.



**Fig. 9.** Coefficient of Variation (CV) of blue water, green water flow and green water storage for the counties located in Savannah River Basin.

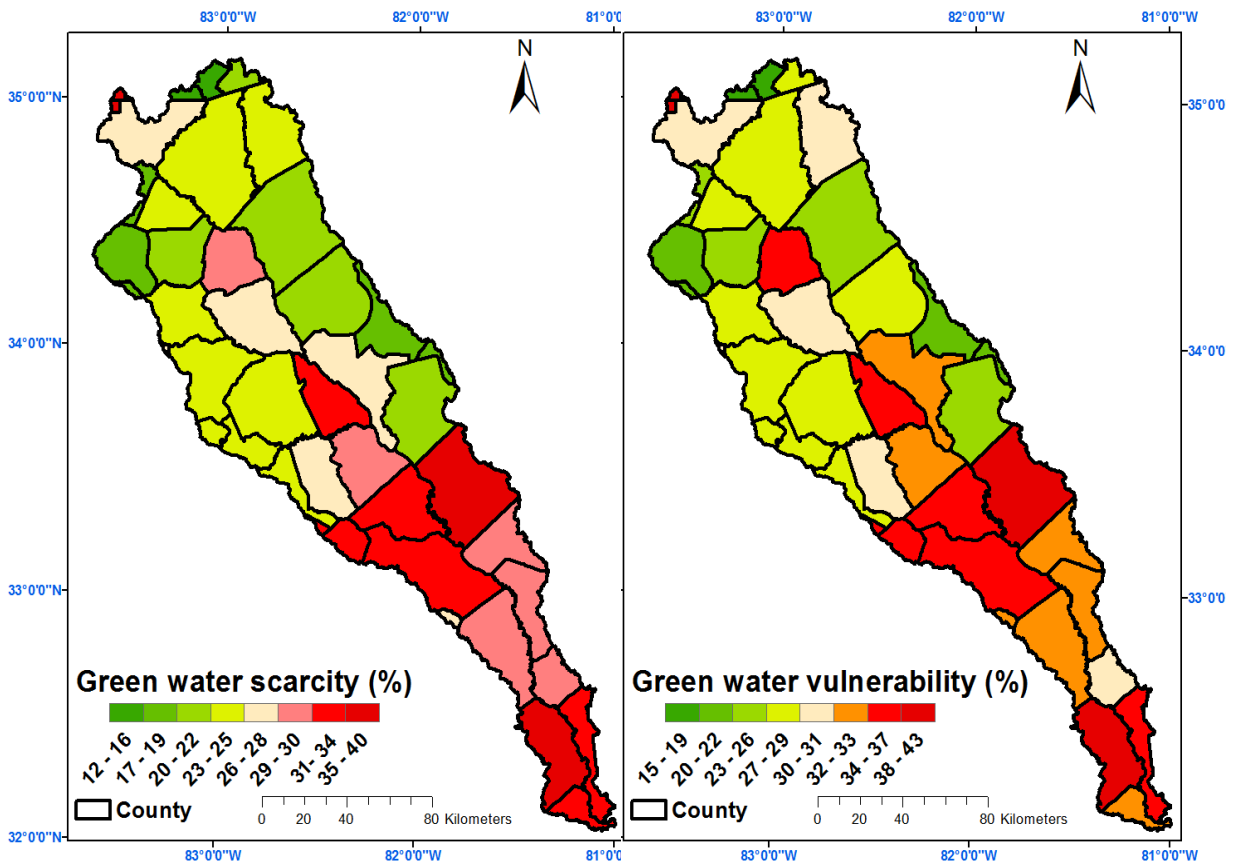


**Fig. 10.** Variation of mean monthly blue water and green water flow for selected counties located in Savannah River Basin during simulated period (1993-2013).

#### 4.2. Quantification of green water security

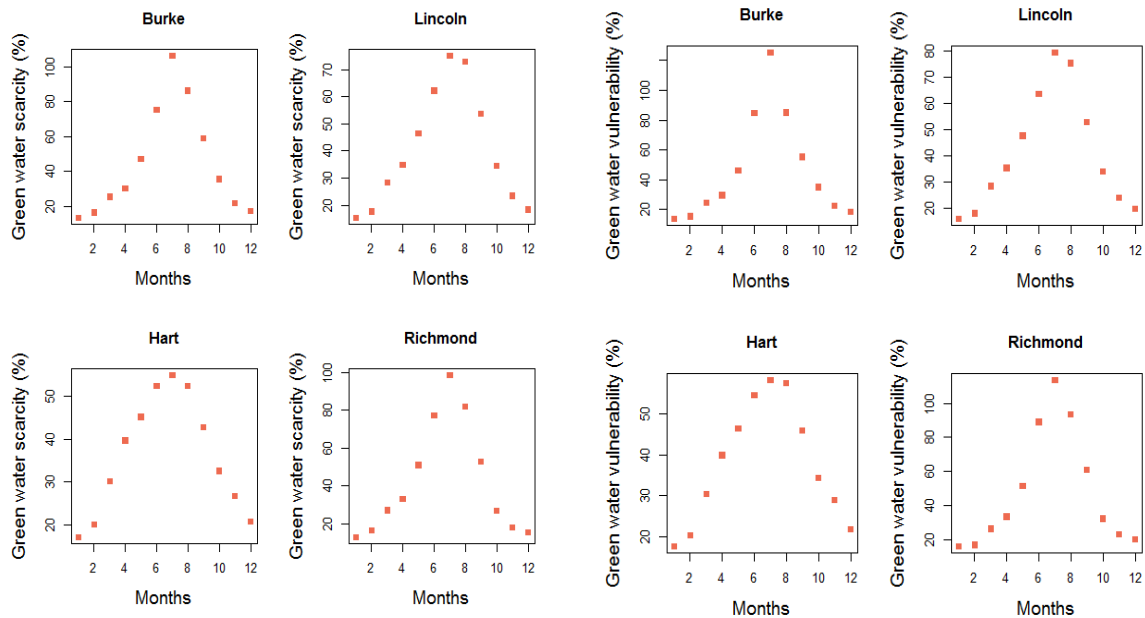
The computation of  $GW_{security}$  was performed in terms of  $GW_{scarcity}$  and  $GW_{vulnerability}$  at an annual scale and monthly scale. The percentage change in mean annual  $GW_{scarcity}$  and  $GW_{vulnerability}$  is represented in Figure 11. The maximum  $GW_{scarcity}$  was observed in Lincoln County located in middle part of SRB and the counties at lower part of SRB. The  $GW_{scarcity}$  for upper Savannah region was minimum (e.g., Anderson County), but Hart County showed a higher value due to the intense crop production and evaporation from Hartwell reservoir. The  $GW_{vulnerability}$  result followed the similar pattern to  $GW_{scarcity}$  in most of the counties. The change in average annual  $GW_{scarcity}$  and  $GW_{vulnerability}$  was less than 50%, so the green water shortage may not

be a serious problem in SRB. However, based on the seasonal analysis it was observed that majority of the counties are becoming environmental hotspots during summer (May – July) and the beginning of fall (August – December) season, as a result of crop growth and high evapotranspiration during this period (Fig. 12). The monthly and seasonal scale assessment of GW-security can be beneficial for agricultural planning (i.e., cultivation and harvesting) of a particular crop as well as possibility in crop rotation during summer to improve water sustainability in SRB.



**Fig. 11.** Spatial distribution of the average annual GW-scarcity and GW-vulnerability for counties located in Savannah River Basin.





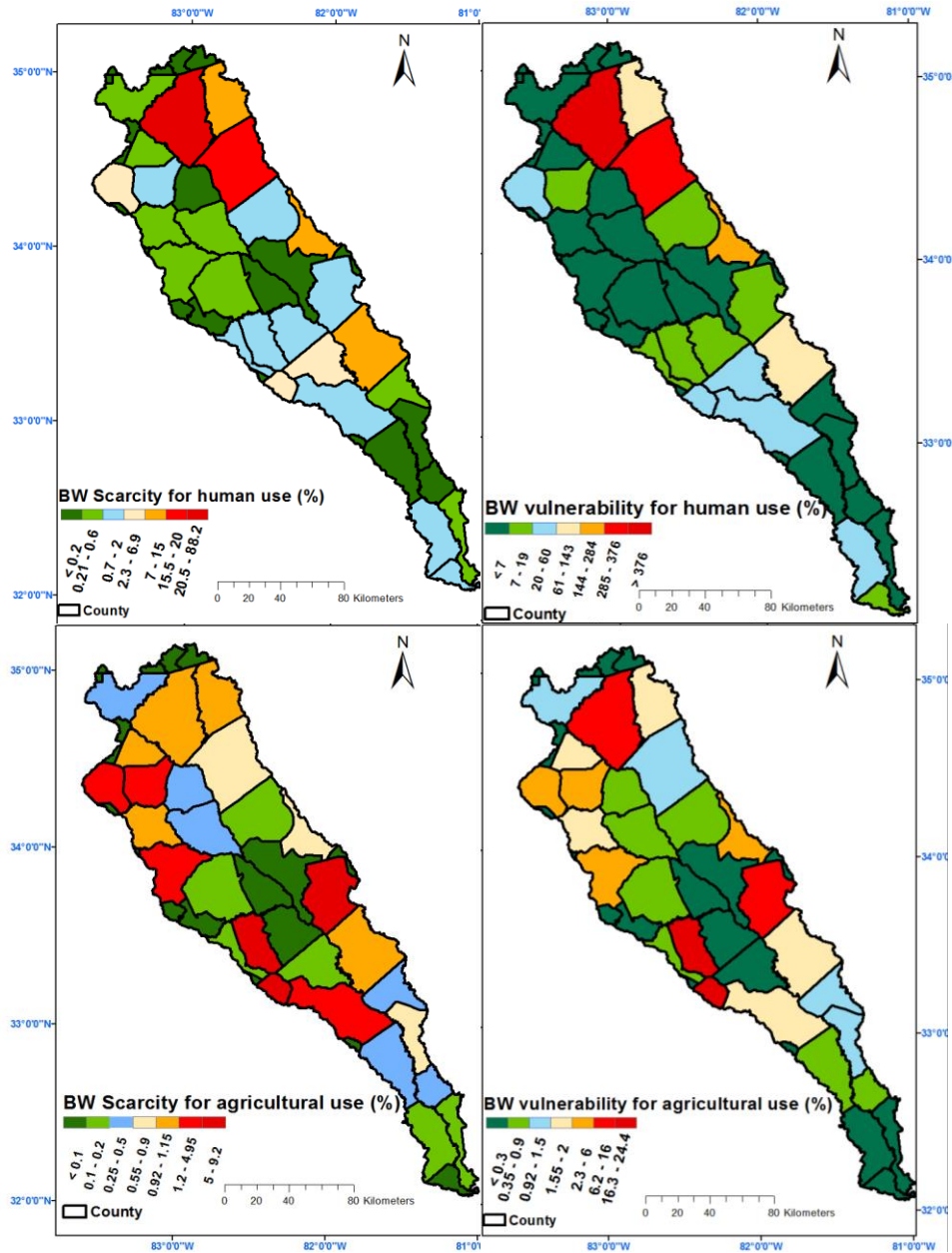
**Fig. 12.** Distribution of average monthly variation of GW-scarcity and GW-vulnerability for selected counties in the Savannah River Basin.

#### 4.2. Quantification of blue water security

The spatial and temporal variation of  $BW_{security}$  was analyzed by evaluating the  $BW_{scarcity}$  and  $BW_{vulnerability}$ . The consumptive use of blue water is calculated based on the water use data available from USGS at a county level for the years 1995, 2000, 2005 and 2010. For example, the spatial variation of  $BW_{scarcity}$  and  $BW_{vulnerability}$  (for the year 2010) for human and agricultural water use are shown in Figure 13. The maximum  $BW_{scarcity}$  was observed in Oconee County, which consumes maximum amount of water due to the active nuclear power sector. According to Duke Energy (the largest electric

power holding company in USA), the nuclear power station located in Oconee County is capable for producing 2.6 million KW for supplying 1.9 million homes. According to the USGS, the thermo-electric plant located in lower SRB region withdraws most of its water supply from the Atlantic Ocean, therefore the blue water scarcity is comparatively low in these energy producing counties located in the lower stream area. The  $BW_{\text{vulnerability}}$  for human water usage indicates Oconee and Anderson County are ecological hotspots ( $BW_{\text{vulnerability}}$  greater than 100%). This blue water shortage may thus become a serious issue in upper SRB due to the increase in water consumption in energy sector.

The maximum  $BW_{\text{scarcity}}$  for agricultural water use in the SRB was nine percent for McDuffie County located at Georgia. The maximum agricultural  $BW_{\text{vulnerability}}$  was 24% for counties located in middle SRB region (e.g., Edgefield and McDuffie County). Overall the  $BW_{\text{scarcity}}$  and  $BW_{\text{vulnerability}}$  for agricultural water usage remain below 25%. However, maximum water was withdrawn for irrigation purpose for agricultural sector, which is likely to increase the possibility of  $BW_{\text{scarcity}}$  and  $BW_{\text{vulnerability}}$  in the region. Therefore, the possibility of irrigating the land with desalinated water (Assouline et al., 2015) or by utilizing the returned flow has potential in decreasing the agricultural  $BW_{\text{scarcity}}$  and vulnerability, and there by improving the water security.



**Fig. 13.** Spatial distribution of BW-scarcity and BW-vulnerability (during 2010) based on human and agricultural water use.

## 5. Conclusion

We applied a hydrological modeling framework for evaluating the spatio-temporal variability of Blue and Green water and to quantify the water security in Savannah River Basin. The modeling framework incorporates both climatic and anthropogenic factors to quantify water security in the Savannah River Basin. Our proposed modeling framework can be applied to investigate and improve water security for other river basins in different parts of the world; however, there is room for further improvement, for example: (i) the performance of hydrologic modeling (e.g., SWAT) for simulating low flow can be further improved, specifically during drought periods, (ii) better quantification of groundwater contribution to baseflow, (iii) improvement in calculation of anthropogenic water demands for improving water security (Mishra and Singh, 2010), and (iv) better representation of human interventions (e.g., reservoir operation, irrigation water use) within hydrologic modeling framework to improve quantification of hydrologic fluxes necessary for Blue and Green water assessment. Over all, the proposed modeling framework found to be useful for quantifying status of the water security and to identify ‘hot spot regions’ within the watershed. The following conclusions are drawn from this study:

(a) Climatic factors control spatio-temporal distributions of blue water. For example, blue water for counties located in the upper part of SRB is comparatively higher, which may be associated with the higher amount of precipitation in upper part of SRB and it decreases towards lower part of SRB. In general, the increasing (decreasing) trend of blue water was observed in areas where the blue water is comparatively high (low).

(b) Green water flow is influenced by the intense agriculture and water bodies (e.g., reservoir). A higher amount of green water flow was observed in counties which has the influence of intense agriculture and reservoir. The higher amount of green water storage was observed in the Anderson and Edgefield County during the assessment period. In general, a decreasing trend of green water flow and green water storage was observed in most of the counties located at SRB.

(c) There is a time lag between the maximum rainfall during June-September and the maximum blue water in December- March. This may be due to higher amount of evapotranspiration which reduces the peak discharge and ground water flow responsible for contributing to peak discharge. The higher rainfall and minimum temperature during January to March may be responsible for higher amount of blue water flow in March. The green water flows were maximum during June to August. It is because of higher temperature and rainfall pattern during this period.

(d) Analysis of green water scarcity and vulnerability indicates that counties are safe for practicing rain-fed agriculture during spring and fall. Our findings suggest that blue water scarcity is enormously upsetting the ecological balance in upper part of river basin, particularly in Oconee County of South Carolina. Both Oconee and Anderson County are identified as ecological hotspots, where the BW-vulnerability is more than 100%.

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## CHAPTER THREE

### INFLUENCE OF CLIMATE AND ANTHROPOGENIC VARIABLES ON WATER SECURITY AND ECOSYSTEM SERVICES

#### 1. Introduction

Land use and climate variables are likely to alter hydrologic process within a river ecosystem (Nijssen et al., 2001; Oki and Kane, 2006; Li et al., 2009; Mishra and Singh, 2010; Chawla and Mujumdar, 2015) and related ecosystem services, especially during the 21<sup>st</sup> century (Teshager et al., 2016; Ostberg et al., 2015; Howells et al., 2013). The unevenness in the Spatio-temporal distribution of rainfall over a period of time further complicates regional water resources availability (Mishra et al., 2015). For example, a year of uneven distribution or lack (excessive) of rainfall can create a significant effect on local crop yields, livestock and aquaculture production. Therefore, it is important to appraise the water use in the agricultural sectors to meet the compounding challenges on fresh water resources (Wu et al., 2010; Cao et al., 2014). Several methodologies/indices have been developed for addressing the water security of a region (e.g. Falkenmark, 1989; Gleick, 1996; Ohlsson, 2000; Chavez and Alipaz; 2007). The water security indices based on the water footprint concept are important tools to improve water resources management (Hoekstra et al., 2011; Veetil and Mishra, 2016). This approach can inform broad aspect of policies from environmental, social and economic perspectives.

Water footprint (WF) (Hoekstra and Hung, 2002; Hoekstra et al., 2011) indicators can quantify the amount of water consumed in a specific river basin or from an aquifer at

a local or regional scale. Blue water footprint is the human water consumption from blue water resources (Veetil and Mishra, 2016; Hoekstra, 2011) and can be quantified based on the volume of surface and groundwater consumed as a result of the production of goods or services [e.g., domestic, industrial, power production and irrigation] (Veetil and Mishra, 2016; Falkenmark and Rockström, 2006; Falkenmark and Rockström, 2010; Rockström et al., 2009, Rodrigues et al., 2014; Hoekstra et al., 2011). Green water footprint (GWfootprint) refers to the consumption of green water resources (Veetil and Mishra, 2016; Hoekstra et al., 2011; Rodrigues et al., 2014), for example, evapotranspiration from agriculture and forest area. The green water footprint is relevant to agricultural, biofuel and forestry products. The applications of water footprint concept are rapidly increasing in various sectors (Hoekstra et al., 2011). The applications can be categorized into regional to global ecosystem for different sectors including food products (e.g., Mekonnen and Hoekstra, 2011a; Mekonnen and Hoekstra, 2010a; Mekonnen and Hoekstra, 2010b; Rost et al., 2008; Jackson et al., 2015; Yoo et al., 2014; Chapagain and Hoekstra, 2007), biofuel products (e.g., Gerbens-Leenes et al., 2009b; Gerbens-Leenes et al., 2009a; Wu et al., 2012; Scown et al., 2011; Dalla Marta et al., 2012; Chiu and Wu, 2012; Kongboon and Sampattagul, 2012) and other commercial products (e.g., copper [Peña and Huijbregts, 2014], electricity [Mekonnen and Hoekstra, 2011c], platinum mine [Haggard et al., 2013], paper [Van Oel and Hoekstra, 2010]). Water footprint approaches are currently applied for water security analysis (Veetil and Mishra, 2016) as well as for ecosystem services (Galli et al., 2012; Karabulut et al., 2016).



Ecosystem services (ES) can be defined as the benefits that are derived from the ecosystem by the society (TEEB-2005; Karabut et al., 2016; Egoh, 2012; Nelson et al., 2009). The ES play an important role in formulating environmental and water resources related policy making (MA, 2005). The major ES include provisioning of water, food, soil productivity, and use of natural areas for recreation purposes (Egoh, 2012). The ecosystem provides services to the livelihood of more than a billion people around the world and contributes to an overall economy of about \$125 to 145 trillion per year (Karabut et al., 2016). The theory of ES is clearly defined and classified into four groups [Daily, 1997]: (a) provisioning service (e.g., water, food), (b) regulating service (e.g., climate, air and soil quality, carbon sequestration, erosion prevention), (c) supporting service (e.g., habitats for species and maintenance of genetic diversity) and (d) cultural service (e.g., recreation, tourism, and inspiration). The process and quantification of ES are challenging and, they require better integration of anthropogenic (e.g., society impact) and natural components (e.g., water availability). Researchers have already developed and applied modelling tools for understanding the importance and economic value (by using economic models) of ES to the society (Bagstad et al., 2013; Naidoo and Ricketts, 2006; Anderson et al., 2009). The examples for modeling tools developed for quantifying ES (Costanza et al., 1997; Chan et al., 2006; Bagstad et al., 2013) are MIMES (Multi-scale Integrated Model of Ecosystem Services), ARIES (Artificial Intelligence for Ecosystem Services), InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) and SWAT (Soil and Water Assessment Tool). The availability of water at a geographic location in terms of both quantity and quality is the most important service

provided by the ecosystem and one of the valuable commodity in food production (TEEB, 2010).

Anthropogenic factors, such as, increase in population and water consumption (Hanasaki et al., 2006; Nilsson et al., 2005; Pokhrel et al., 2012; Vorosmarty et al., 2000) are likely to tremendously impact blue water resources through altering seasonal flow regime and depleting groundwater storages. Whereas, land use and land cover change (LULC) can upset the water balance by changing the segregation of precipitation, i.e. by altering the quantity of evapotranspiration, runoff and groundwater flow (Costa et al., 2003; Sahin and Hall, 1996). For example, the agricultural sector has a consumptive use of about 85% to 90% (Gleick, 2003; Shiklomanov, 2000), which often reduces the normal flow in several river networks (Rosegrant et al., 2002). It is also recognized that land use change has substantial influence over water quality by altering the concentration of nutrients (Stonestrom et al., 2009; Schlesinger et al., 2006) and sediment budget (Valentin et al., 2008). This suggests anthropogenic factors potentially influence the water footprint indicators as well as water security and ecosystem services. As these substantiations are crucial for land use planning and water resources management, the quantification of land use change and climate variability on streamflow, ecosystem services, and related water scarcity can expose the current state of a river basin's ecological health. The development of hydrologic models which account for the spatio-temporal watershed characteristics can contribute an important role in quantifying the seasonal water availability (He and Hogue, 2012; Costa et al., 2003).

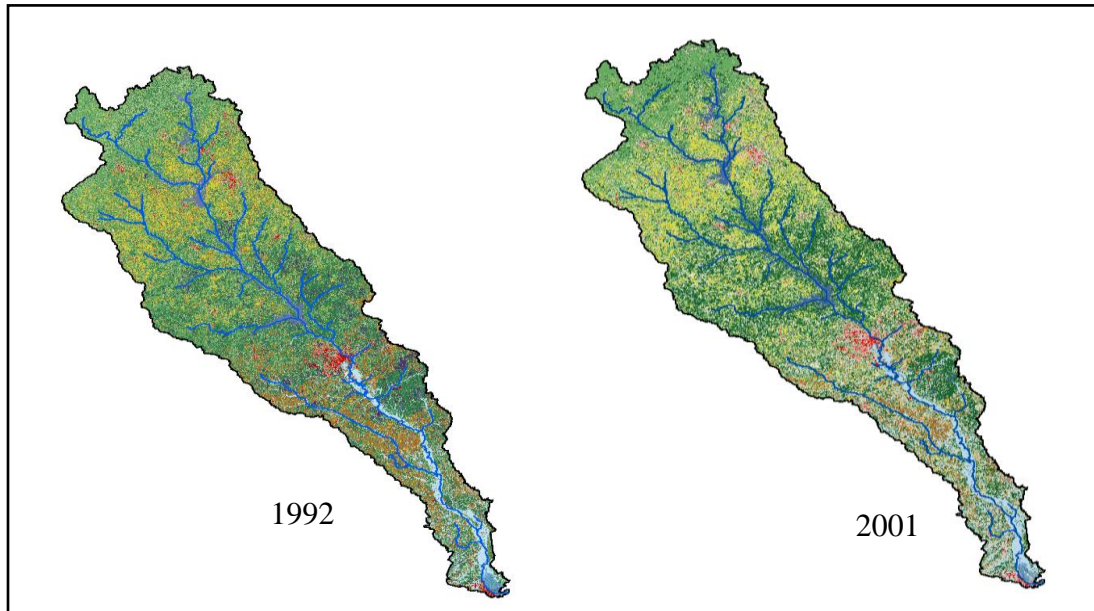
Although the influence of anthropogenic activities (e.g., land use change) on hydrologic cycle, climate and energy budget are extensively studied by applying potential modeling approaches (McColl and Aggett, 2007; Wijesekara et al., 2012; Choi and Deal, 2008), the possible influence of land use change and climate variability on blue (green) water footprints as well as ecosystem services in the context of water security (scarcity) are limited. This study is important in order to identify potential influence of human activities on water footprint indicators leading to failure in water provisioning in ecosystem services. It also evaluates the sustainability of water provisioning services to satisfy the major food production sectors of the counties located in the Savannah River ecosystem. The objective of this work is therefore to quantify the individual and combined impact of land use change and climate variability on the water resources and related water scarcity of the Savannah River Basin. The specific objectives for this work are; i) to quantify the land use change and climate variability impact over hydrological stream network, ii) to evaluate the influence of land use change and climate variability in controlling the ecosystem provisioning service of the basin, and iii) to quantify the potential influence of land use change and climate variability in altering the blue (green) water scarcity through water footprint concept.

## **2. Study area and Data**

Savannah River Basin (SRB) has a drainage area of 27,171 km<sup>2</sup>, out of which 11,875 km<sup>2</sup> is located in South Carolina, 14,965 km<sup>2</sup> in Georgia and the remaining portion belongs to the state of North Carolina of USA (SCDHEC, 2010). The major impoundments in the basin are Hartwell Lake, Richard B Russel Lake and J. Strom Thurmond Lake. The

climate of SRB is characterized by mild winters and hot summers in the lower portions and cold winters and mild summers in the upper basin area. The annual precipitation ranges from 1000mm to 2050mm. A dry weather typically occurs between midsummers to fall (SCDHEC, 2010). The geographical location of SRB and the counties located within SRB are shown Chapter 2, Figure 2. Forestry sector constitutes a significant part of the economy in the SRB, with 2.4 million acres of forest used for commercial purpose (SCDHEC, 2010). The irrigated agriculture land in the SRB increased by 1.8% from 1984 to 1995 and the majority of the irrigation water is used from surface water resources (Veettil and Mishra, 2016). The agriculture in the SRB includes livestock, crop production and a minor percentage of aquaculture production. Almost 75% of the farm land is hay/pasture cultivation with the remaining 25% including row crops. According to the Nature Conservancy of Georgia (DATE) (a nonprofit organization) the SRB ecology has abundant diversity of life, which includes more than 75 species of rare plants and animals.

The percentage change in the land use and land cover pattern from 1992 to 2001 for the SRB was analyzed by using the classified images of National Land Cover Dataset (NLCD). The major land use sector in the SRB includes forest and farm lands which constitutes about 77% of total basin area. The percentage change (Figure 1) analysis in land use/land cover (LULC) from 1992 to 2001 indicates that the total forest cover decreased by 20.5% and the developed area which includes construction land, residential area and commercial area increased by 247%. There is a marginal increase in open water body, whereas, the farm land decreased by 21%.



Land use	Forest ■	Agriculture ■	Water body ■	Pasture ■	Development ■
1992 Area (km <sup>2</sup> )	17538	4884	845	2007	691
2001 Area (km <sup>2</sup> )	13932	3849	870	3071	2403
% Change in area	-20.5	-21.0	+3.0	+53	+247.0

**Fig. 1.** The major changes developed in the land use land cover (LULC) of Savannah River Basin from 1992 to 2001.

### 2.1. Data

The digital elevation model (DEM) was obtained from National elevation data set at a resolution of 30m to delineate the study area and to estimate the topographic features. The land use data used for simulating the stream flow are obtained from national Land Cover Dataset for the years 1992 and 2001. The soil data is downloaded from SSURGO data base. The meteorological (precipitation and temperature) and stream flow data for

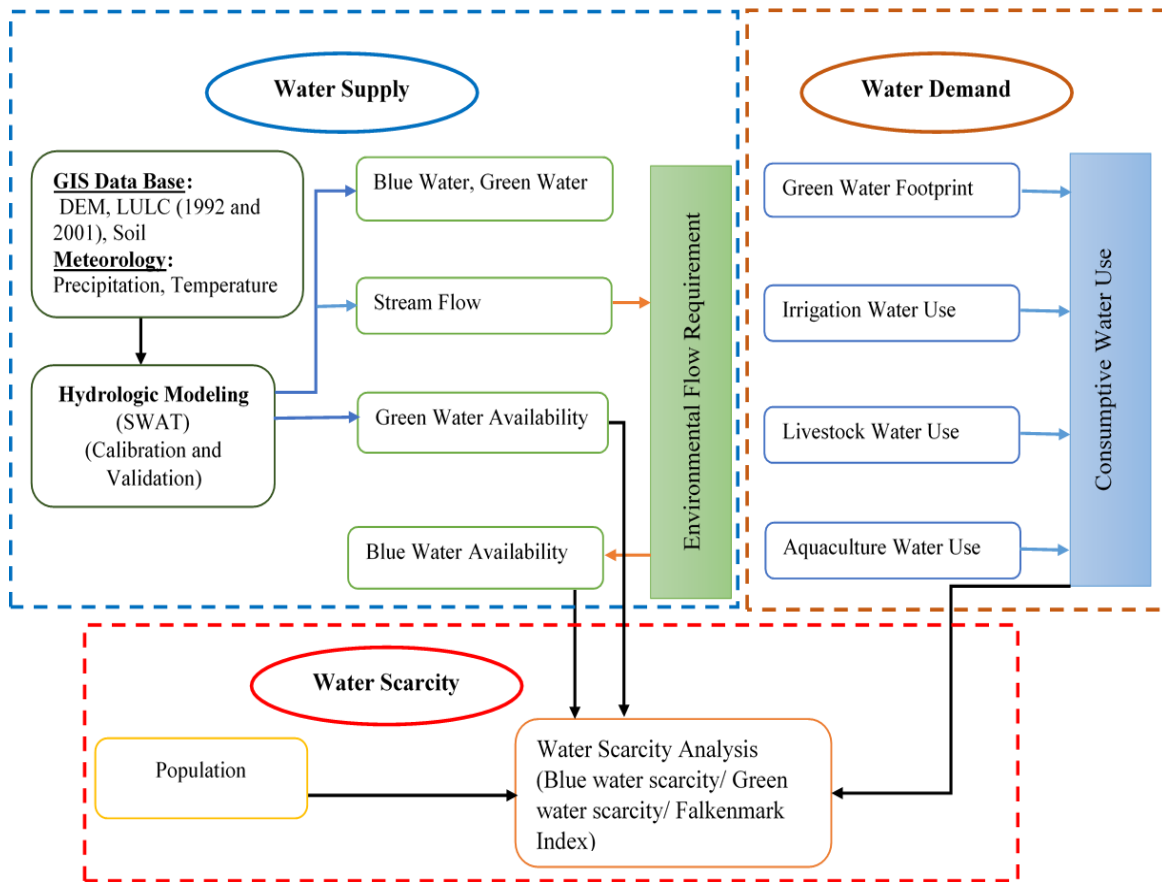
1990 to 2013 were collected from National Climatic Data Centre (NCDC) and United States Geological Survey (USGS) respectively. The reservoir outflow data collected from Savannah District Water Management (US Army Corps of Engineers) was incorporated in SWAT model development. The water use data in each county for irrigation, livestock and aquaculture are also collected from USGS. The list of data sets used in this study and their sources are provided in Chapter two, Table 1.

### **3.Method**

The hydrological modeling framework applied for assessing the land use change impact on water scarcity and corresponding ecosystem services is provided in figure 2. The following sections provide an overview of individual components incorporated in the conceptual modeling framework.

#### **3.1.Hydrological model set-up**

The Soil and Water Assessment Tool (SWAT) developed by the United States Department of Agriculture (USDA) (Arnold et al., 1998; Neitsch et al., 2004) is used for simulating the hydrological fluxes of SRB. The SWAT model is widely used around the world for studying water quantity (stream flow), water quality (sediment load and nutrients flow) and crop growth in different landscapes and management practices (Faramazi et al., 2009). SWAT is a process based, semi-distributed basin scale model (Arnold et al., 1998; Neitsch et al., 2004) and it operates at a daily time step. The SWAT model is useful for quantifying blue and green water resources from a catchment scale to continental scale (Veettil and Mishra, 2016; Zang et al., 2012; Schuol et al., 2008b; Abbaspour et al., 2015).



**Fig. 2.** The model framework applied for quantifying the influence of land use change and climatic variability on ecosystem services and related water scarcity over Savannah River ecosystem.

The Digital Elevation Model (DEM) is the basic component of SWAT model development, which delineate the basin with respect to the topography. The delineated river basin is divided into sub-basins, which are further divided in to unique land use/soil/slope units called Hydrologic Response Units (HRUs). Two SWAT models were developed by incorporating the land use of 1992 and 2001. Five classes of slopes used for

HRU delineation were 0-2.5%, 2.5-5%, 5-10%, 10-40% and above 40%. The number of HRUs were controlled by adjusting the threshold (Her et al., 2015) of land use (6%), soil (12%) and slope (20%), which resulted 1464 HRUs in 1992 land use models and 1412 HRUs in 2001 land use models distributed over 105 sub-basins. Three large reservoirs (Hartwell, Thurmond and Russel reservoirs) were included in the SRB model for reducing the uncertainty associated with hydrological parameter estimation. The SWAT hydrological parameters were calibrated and validated by using the Sequential Uncertainty Fitting ver. 2 (Abbaspour et al., 2005). The model was simulated and evaluated against the USGS (observed) stream flow data located in the Savannah River Basin. The developed SWAT models were simulated by using the parameters that were calibrated for the previous study (Chapter two, Veettil and Mishra, 2016), where the result of model simulation from 1990 to 2013 for SRB were consistently performed during the calibration and validation phase. For example the USGS station located at lower SRB (Savannah River near Clyo, USGS 02198500) showed a coefficient of determination ( $R^2$ ) of 0.85, Nash-Sutcliffe Efficiency (NSE) of 0.76, R-factor of 0.89 and P-factor of 0.82 during the calibration period (1992 - 2005). During the validation period (2006 -2013)  $R^2$  was 0.64, NSE was 0.58, R-factor was 0.58 and P-factor was 0.51. The parameterization and goodness of fit criteria adopted in the SRB model is explained in (Chapter two).

### **3.2. Quantifying the influence of land use change and climate variability**

The effects of land use change and climate variability were quantified by analyzing the four scenarios as shown in the Table 1. The hydrologic variables simulated from SWAT



model outputs were compared for quantifying the effect of the two factors including land use change and climate variability based on the four scenarios (SRB1, SRB2, SRB3, and SRB4). Initially, only one factor at a time was changed while keeping the other factor as constant. Subsequently, the analysis was extended for verifying the concomitant influence (i.e. analysis of both factors at a given time).

The blue water was estimated as the combination of both water yield (WYLD) and ground water storage of SWAT HRU output. Water yield is the amount of water leaving the HRU and entering the main channel. Ground water storage is the difference between total amount of water recharge to aquifers (GW\_RCHG) and the amount of water from aquifer that contributes to the main channel flow (GW\_W) (Veetil & Mishra, 2016; Rodrigues et al., 2014). Green water is estimated as the sum of evapotranspiration (ET) and soil water content (SW) (Veetil and Mishra, 2016; Rodrigues et al., 2014; Abbaspour et al., 2015; Schuol et al., 2008).

**Table 1:** Different scenarios analyzed in the study

<b>Scenarios</b>	<b>Land use</b>	<b>Climate variables</b>
SRB1	1992	1990 – 2000
SRB2	2001	2001 – 2013
SRB3	1992	2001 – 2013
SRB4	2001	1990 - 2000

### 3.3. Evaluation of blue and green water availability

Blue water availability ( $BW_{availability}$ ) is the amount of water that can be abstracted without affecting ecology of a stream. The over exploitation of blue water from a stream can potentially damage the river ecosystem. The concept of Environmental Flow Requirement (EFR) can be an appropriate method for maintaining a healthy ecosystem (Honrado et al., 2013). The presumptive standard method suggested by Ritcher (2010, 2012) is used for EFR analysis in SRB. According to this method, extraction of more than 20% of water from a stream will likely cause ecological degradation and this amount can be considered as available blue water which can be used for water provisioning services (Veettiland Mishra, 2016; Rodrigues et al., 2014). The following equations (1 & 2) are used to calculate EFR and blue water availability.

$$EFR(p)_{(x,t)} = 0.8Q_{mean(x,t)} \quad (1)$$

where  $EFR(p)_{(x,t)}$  is the EFR according to presumptive standard for county 'x' at time period 't'.

$$BW_{availability(x,t)} = Q_{(x,t)} - EFR_{(x,t)} \quad (2)$$

where 'x' represent a county with respect to time 't'.  $EFR$  is the environmental flow requirement ( $m^3/s$ ) and  $Q$  is the corresponding monthly stream flow ( $m^3/s$ ).

The green water availability ( $GW_{availability}$ ) is the amount of soil moisture (SW) available for the sustaining crop growth. In this modeling framework, the initial soil water ( $SW_i$ ) from the SWAT HRU output (Winchell et al., 2013) is considered as the

available green water to the plants (Veettil and Mishra, 2016; Rodrigues et al., 2014). The  $SW_i$  is the difference between the root-zone soil moisture and wilting point, where the wilting point is defined as the minimum soil moisture available for the plant sustainability. This water content is available to the plants for consumptive use (DeLiberty and Legates, 2003; Rodrigues et al., 2014).

### 3.4. Evaluation of freshwater provision indicator

The fresh water provision index (FPI) is measured based on quantitative amount of fresh water (stream flow) and EFR (Logsdon and Chaubey, 2013; Rodrigues et al., 2014). The FPI can provide information related to the variation in EFR due to the drought, low flow etc. The FPI is calculated by using equation 3.

$$FPI_{(x,t)} = \frac{Q_{avg(x,t)} / EFR_{(x,t)}}{(Q_{avg(x,t)} / EFR_{(x,t)}) + q_t / m_t} \quad (3)$$

where  $FPI_{(x,t)}$  is the freshwater provision index for a county during time  $t$ ;  $Q_{avg(x,t)}$  and  $EFR_{(x,t)}$  are the average flow and Environmental Flow Requirement for a county  $x$  and during time  $t$ ;  $q_t$  is the number of times the average flow is less than  $EFR$  and  $m_t$  is the total number of years considered.

### 3.5. Evaluation of water scarcity indicators

Three water scarcity indicators were selected: a) Blue water scarcity, b) Green water scarcity, and c) Falkenmark indicators. Blue and green water scarcity are quantified based on the water footprint concept. The blue water footprint ( $BW_{footprint}$ ) denotes the

consumptive use (i.e. the difference between water abstracted for a particular use and the remaining flow returned to the same watershed (Veettil and Mishra, 2016; Hoekstra et al., 2011; Rodrigues et al., 2014)). The United State Geological Survey (USGS) provides county level sectorial water use data at an interval of 5 years period. We collected water use data separately for irrigation, livestock and aquaculture water use and found the consumptive use (Carr et al., 1990; Fanning and Trent 2009; Shaffer 2008 and Solley et al., 1998). The consumptive water use of irrigation, livestock and aquaculture water use are estimated as 85%, 65% and 5% (as shown in figure 3, chapter two) of total water abstraction (Veettil and Mishra, 2016). The blue water scarcity ( $BW_{scarcity}$ ) is finally calculated as a ratio of  $BW_{footprint}$  to the available blue water using equation 4.

$$BW_{scarcity} = BW_{footprint(x,t)} / BW_{availability} \quad (4)$$

where 'x' represent a county with respect to time 't'. EFR is the environmental flow requirement ( $m^3/s$ ) and  $Q$  is the corresponding monthly stream flow ( $m^3/s$ ).

Green water scarcity ( $GW_{scarcity}$ ) is estimated as the ratio between green water footprints ( $GW_{footprint}$ ) to the green water availability ( $GW_{availability}$ ).  $GW_{footprint}$  is estimated as the evapotranspiration which is calculated by using Hargreaves method (Hargreaves et al., 1985) available in the SWAT model. In our analysis, we evaluated  $GW_{scarcity}$  for the two land use change scenarios (1992 & 2001).

$$GW_{scarcity(x,t)} = GW_{footprint(x,t)} / GW_{availability(x,t)} \quad (5)$$

Where,  $GW_{availability}(x,t)$  is the amount of initial soil water content (which is considered as available green water) in county 'x' during the period 't'.  $GW_{footprint}(x,t)$  is the green water consumed from a county 'x' during time 't'.

### **3.4.1. Falkenmark Index**

Falkenmark (FLK) (Falkenmark, 1989) index is one of the most widely used indicators to measure the stress on water resources (Rijsberman, 2006), which is defined as the fraction of blue water availability to the total population. According to FLK indicator, when the per capita water availability is less than  $1700\text{m}^3$  per year, the area is under water stress. If the per capita water availability is less than  $1000\text{m}^3$  per year the area is under water scarcity and if it is less than  $500\text{m}^3$  per year the area is classified as absolute water scarcity. Thus the FLK indicator is a clear indication of human health and water economy (Falkenmark, 1989; UN-WBCSD, 2006).

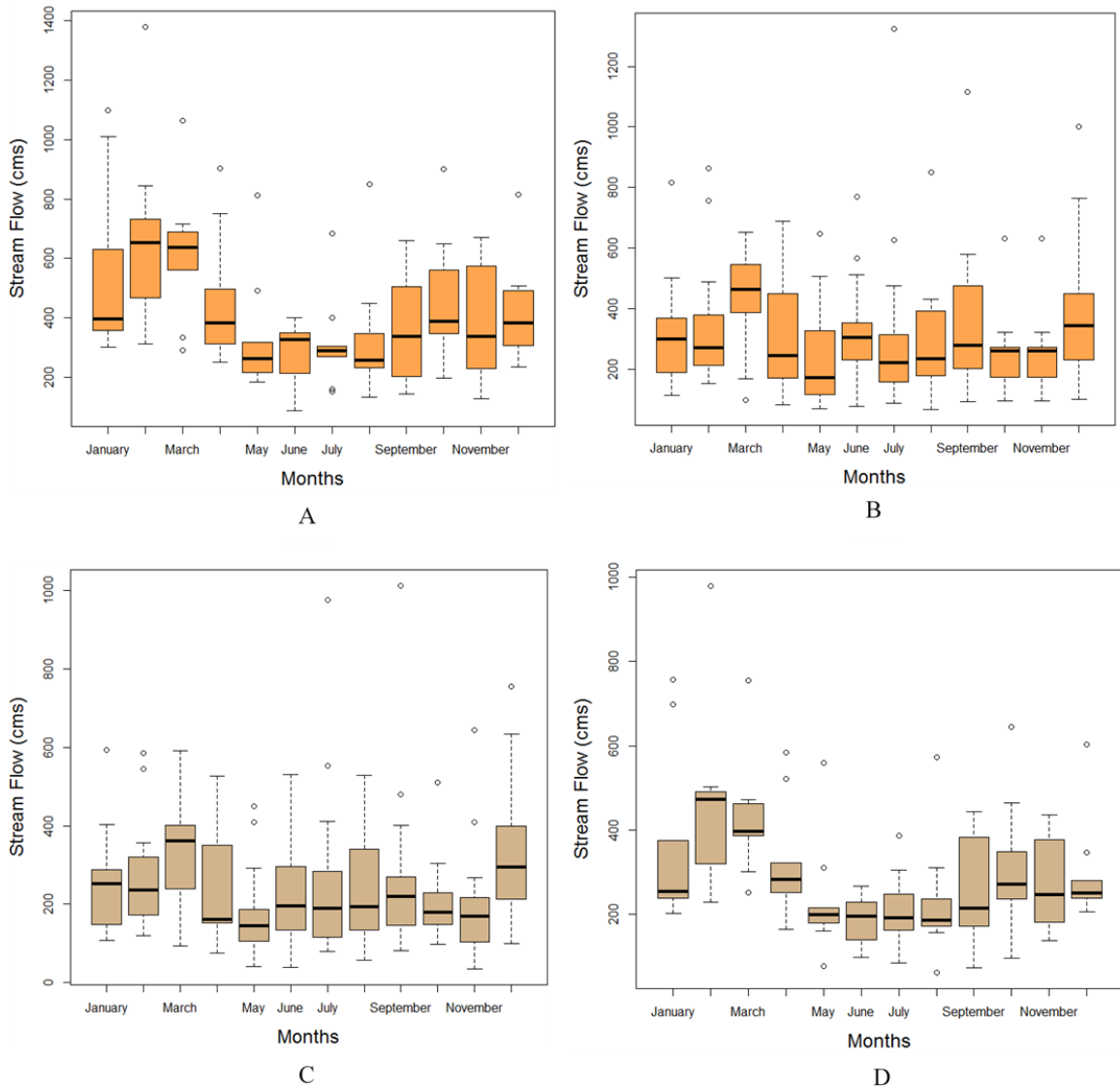
## **4. Results and Discussions**

### **4.1. Influence of climate variability and land use change on streamflow**

Streamflow simulated from four scenarios (SRB1, SRB2, SRB3, and SRB4) are compared for quantifying the effect of land use change and climate variability. The change in mean monthly runoff due to the individual and combined scenarios is shown in figure 3. The dissimilarity in streamflow pattern due to the land use change is shown in figure 3A (land use: 1992) and figure 3D (land use: 2001). The land use change from 1992 to 2001 (i.e., comparing SRB4 with SRB1) has resulted into a significant reduction in simulated monthly streamflow for all the months. For example, the streamflow in

January is reduced from 400 cubic meter per second (cms) to less than 300cms. Overall, the land use change resulted in a total streamflow reduction (percentage change) of 31%. The variation in streamflow can be explained by considering the increase in pasture land. The percentage increase in pasture land is 53%. The pasture land increases the amount of evapotranspiration and decreases the water yield (Zhang et al., 2016). This may be a possible reason for decrease in streamflow of the Savannah River Basin.

The climate variability caused a remarkable reduction in streamflow (Figure 3A and figure 3C). The climate variables accounted for a streamflow percentage reduction of 41% in the basin. The relative contribution of land use change and climate variables can be analyzed from Figure 3A and Figure 3B. This scenario led to a consistent reduction in surface runoff. For example, the streamflow during January is decreased by 80cms. The above result clarifies that the climate variability and land use change decreased the runoff generation in the SRB. It also suggests that climate variability plays a prominent role than land use change in impacting the streamflow generation capacity of the Savannah River Basin.



**Fig. 3.** Difference in monthly stream flow due to the effect of land use change and climate variability based on different scenarios: A) Stream flow generation from SRB1, B) Stream flow generation from SRB2, C) Stream flow generation from SRB3, D) Stream flow generation from SRB4.

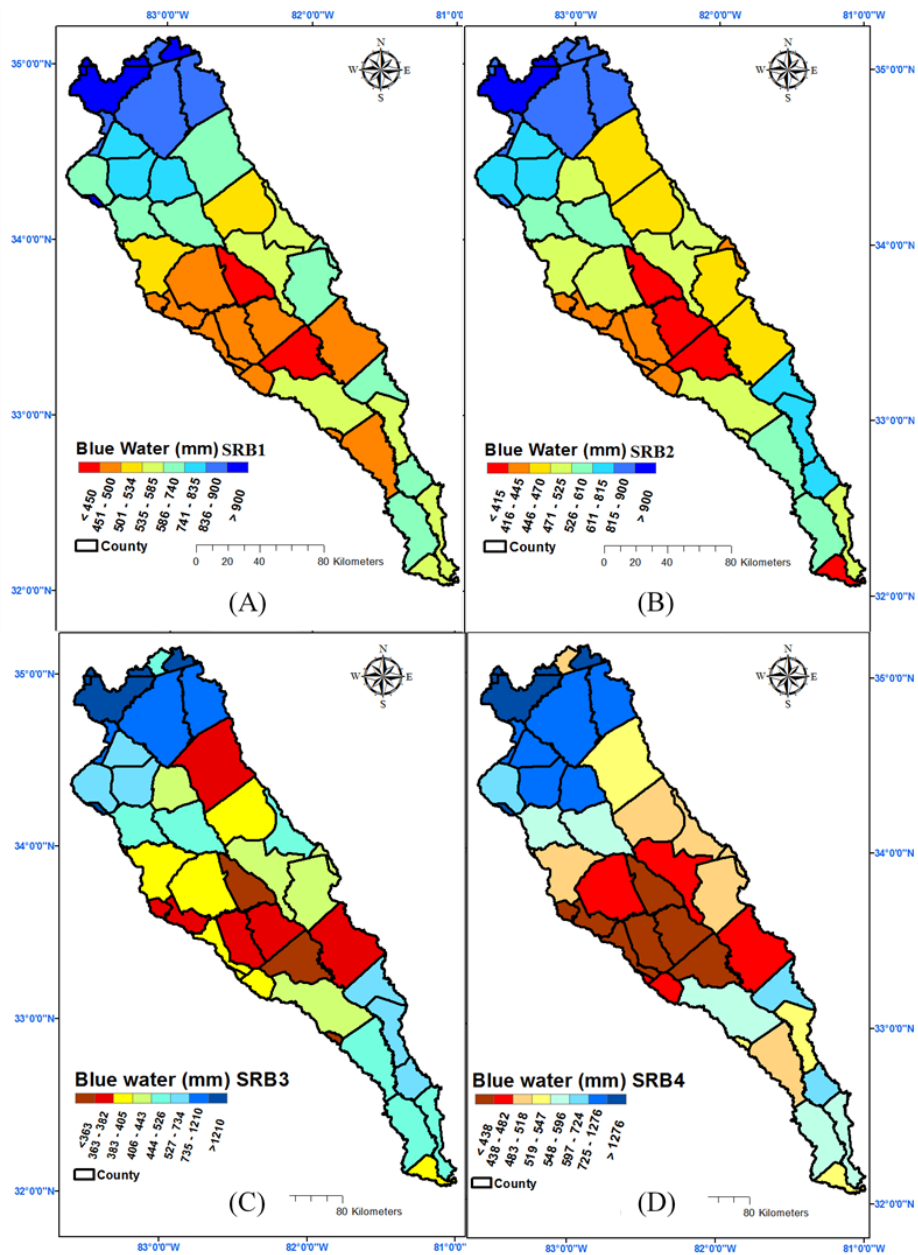
#### **4.2. Influence of land use change and climate variability on blue and green water**

The influence of land use change and climate variability on spatio-temporal variations of blue and green water resources are evaluated based on the hydrologic fluxes (e.g., water yield, soil water, and evapotranspiration) obtained from the SWAT model (Veetil and Mishra, 2016; Rodrigues et al., 2014) based on different scenarios (SRB1, SRB2, SRB3, and SRB4). The spatio-temporal distribution of blue and green water are influenced by the spatial pattern of precipitation and land use pattern. These results indicated that in most of the counties there exists a significant reduction of blue water due to the influence of land use change and climate variability. The maximum blue water was observed in Rabun County in all the scenarios where the annual rainfall availability was comparatively greater than other counties from 1992 to 2013. The observed amount of blue water was nearly consistent for the four scenarios in the county. The land use component which affects the amount of blue water is forest cover that is directly proportional to the amount of rainfall they receive. In Rabun County the average rainfall from 1992 – 2000 was 1800 mm/year and the average rainfall from 2001 – 2013 was 1900 mm/year, however, the forested area in the county was decreased from 96% to 88%. This can be a possible reason for equalizing the amount of blue water in Rabun County during the scenarios analyzed. The influence of land use change on blue water for each county is explained by analyzing SRB1 and SRB4 scenarios (figure 4A and figure 4D). The minimum blue water was observed in Lincoln County, Richmond County and Columbia County which are located in central part of SRB. These counties also showed a reasonable decrease in blue water quantity due to the land use change impact. For



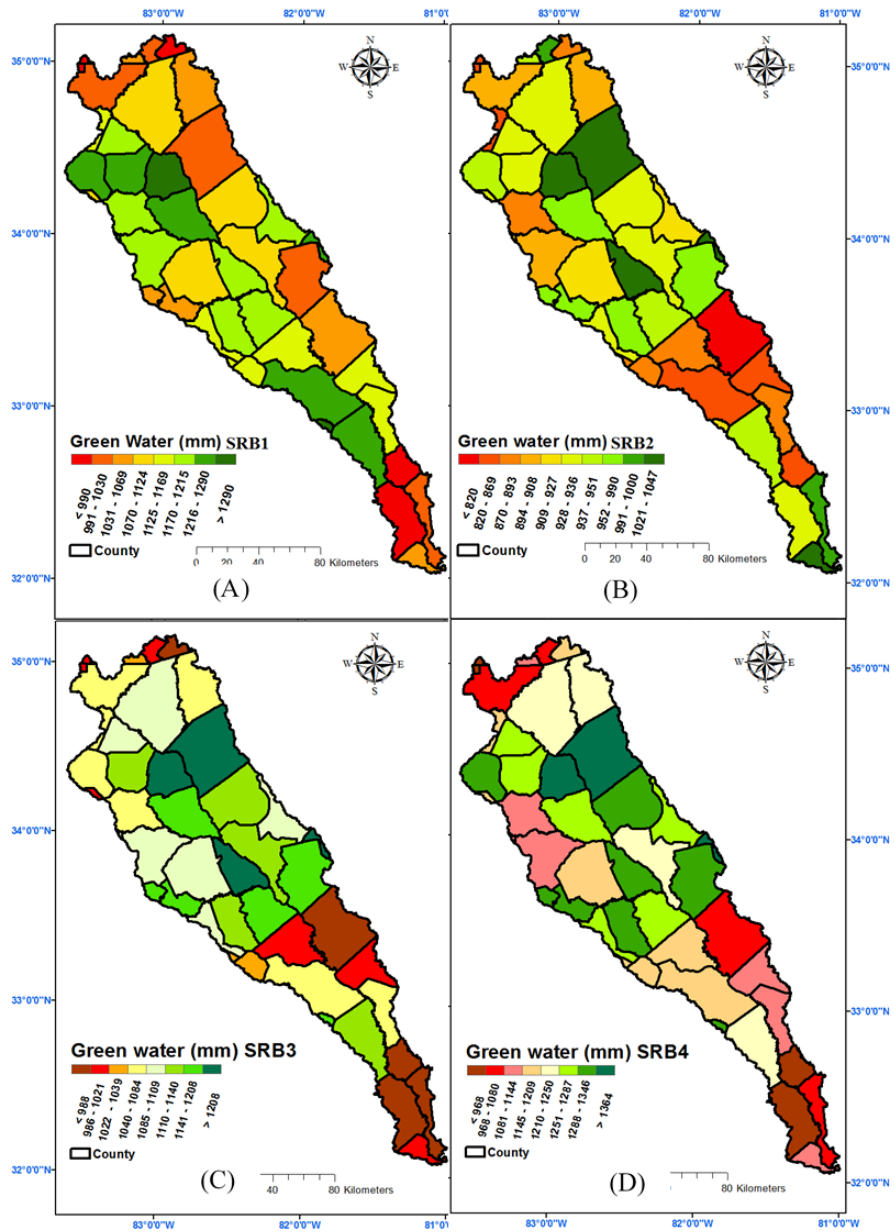
example, the blue water at Lincoln County showed a 10% decrease. The forest cover decreased in Lincoln County (from 67% to 53%), Richmond County (from 45% to 31%), and Columbia County (from 70% to 55%) and could be a possible reason in reduction of blue water. The built-up area in Richmond County almost doubled during the time period (from 15% to 29%) which is likely to be another reason for decrease in the blue water in the county, hence the water yield is affected by the urbanization (Karabut et al., 2016). The maximum reduction in blue water due to the contribution of land use change was observed in McCormick County located in central SRB, where the forest cover was reduced from 78% to 70%.

Hart County, located in the upper SRB experienced maximum reduction (338mm) in blue water flow due to the impact of climate variability (comparing SRB1 (Figure 4A) and SRB3 (Figure 4c)). Annual rainfall availability was identified as the major cause in substantial reduction of blue water in the county. Franklin and Anderson County also showed a large reduction in blue water resources. All the counties excluding Allendale County showed an increase in blue water flow due to the climate variability. The combined effect of climate variables and land use change (comparing SRB1 and SRB2) also caused a reduction in blue water flow in all the counties of the basin. Hart County showed maximum reduction in blue water flow, where the forest cover reduced from 45% to 35% and built-up area increased from 1.7% to 10%. The spatio-temporal changes in blue water resources in counties located in the SRB due to the different scenarios are shown in figure 4.

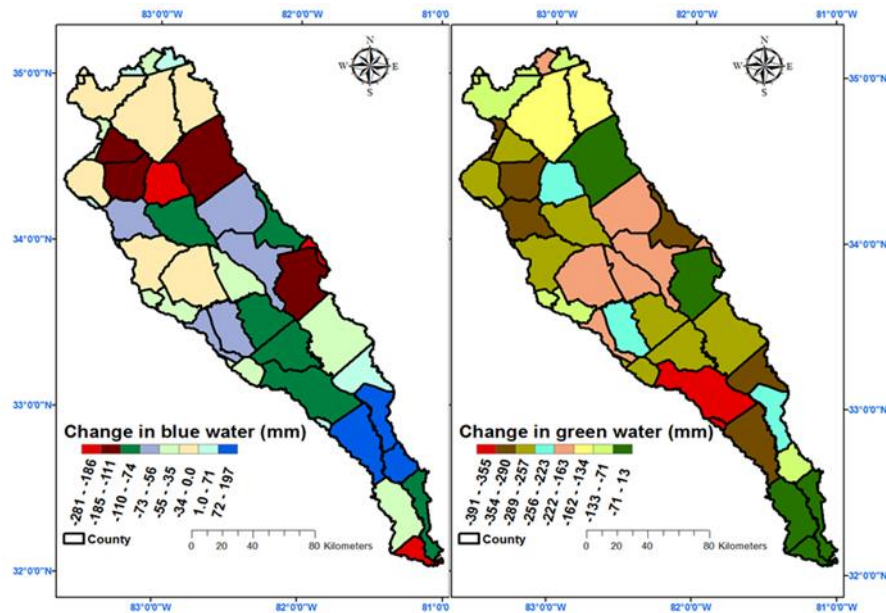


**Fig. 4.** Spatial distribution of blue water for each scenarios analyzed. A) Blue water from SRB1, B) SRB2, C) SRB3, and D) SRB4.

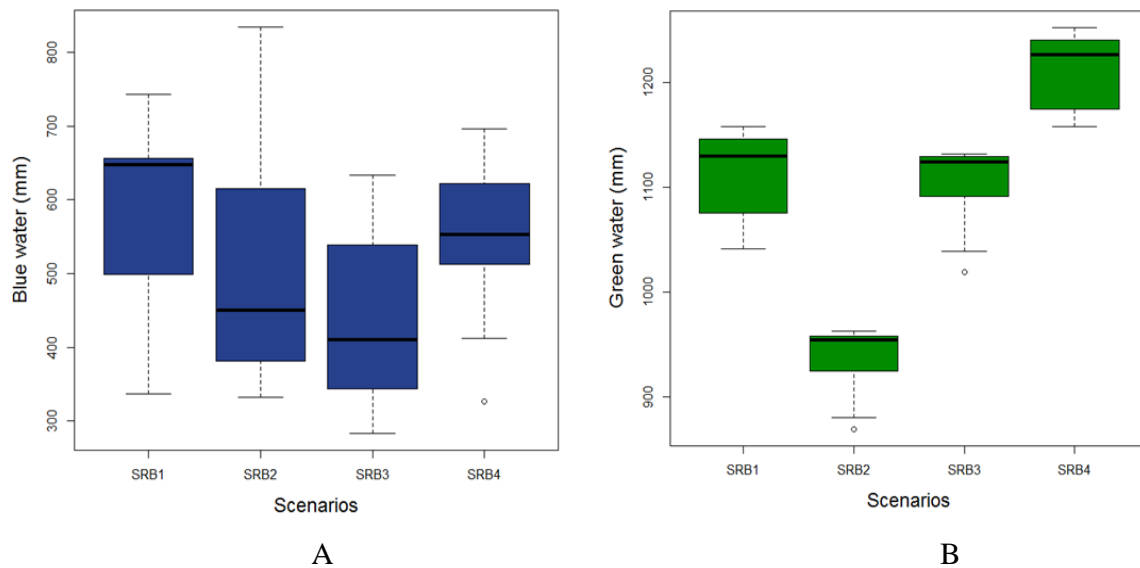
Representing total water resources in an ecosystem only based on blue water component is not appropriate in water management and related policy making (Hoekstra et al., 2011). Therefore, the amount of green water in the basin was also investigated. Green water has a crucial role in sustaining ecosystem services, particularly in rain-fed farming practice. Figure 5A and figure 5D shows the spatial distribution of green water due to the influence of land use change. Most of the counties showed significant increase in green water as a result of change in land use. Anderson County located in Upper SRB showed maximum increase in green water. The pasture land in the county increased from 21% to 26%. The grass land also increased from one percent to nine percent. This can be considered as a possible reason for accelerating the green water amount in the county. The analysis also indicated that green water in most of the counties located in upper SRB had a significant growth (e.g. Pickens, Oconee, Rabun and Hall). All these counties also showed a significant increase in pasture land and grass land. Burke County located in middle SRB showed highest declination in green water due to the land use change. It was interesting to observe that the influence of climate variability on green water was conflicting towards the impact of land use change. The green water in most of the counties decreased as a result of climate variables. Figure 5A and figure 5C shows the spatial distribution of green water due to the influence of climate variables.



**Fig. 5.** Spatial distribution of green water for each scenarios analyzed A) Green water from SRB1, B) SRB2, C) SRB3, and D) SRB4.



**Fig. 6.** Difference in blue water and green water for counties located at Savannah River basin due to the combined impact of land use change and climate variability (Here the values shown are SRB2 – SRB1).



**Fig. 7.** The boxplot showing the annual A) blue water and B) green water in whole Savannah River Basin based on the four scenarios.

Most of the counties showed a significant decrease in green water amount due to combined impacts of both land use change and climate variability (by comparing Figure 5A and Figure 5C). The maximum green water diminution was observed in Burke County, which is located in lower SRB. Agricultural land in Burke County was reduced from 33% to 21%. Agricultural land has relatively higher availability of saturated soil water content (Karabut et al., 2016; Hoekstra et al., 2011), which may influence the green water reduction in the county. The annual average precipitation also decreased in this county. Overall, analysis showed that land use change has an important role in controlling green water of SRB. Therefore, the percentage change in pasture cultivation and other agricultural crops in SRB highly influenced the green water distribution of each county.

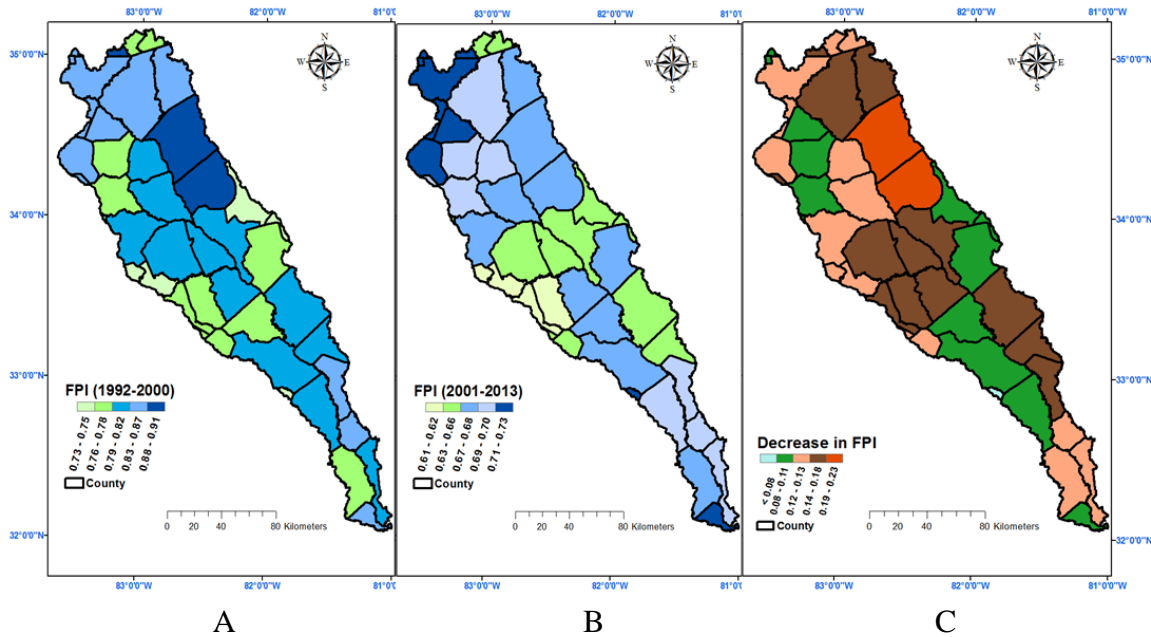
The difference in blue water and green water due to the joint impact of land use change and climate variability are shown in Figure 6. The boxplot shown in the figure 7A illustrates the variation in annual average of blue water of whole Savannah River Basin due to the influence of four scenarios incorporated in the study. The median (50th percentile) of blue water amount is reduced from 620 mm to 550mm due to the land use change (by comparing SRB1 and SRB4) and it declined to 410mm because of the climate variability (by comparing SRB1 and SRB3). The blue water flow decreased to 430mm due to the combined effect of climate variability and land use change during 1990 – 2013 (by comparing SRB1 and SRB2). The discussions on the different scenarios indicate that climate variability and land use change has significant control over blue water (Zhao et

al., 2016). Moreover, the impact of climate variability has relatively higher influences over the blue water over the SRB.

The boxplot shown in the Figure 7B illustrates the variation in annual green water for the SRB based on the different scenarios used in the study. The median (50th percentile) of the green water amount is reduced from 1130 mm to 960 mm for the SRB due to the combined influence of land use change and climate variability. It also shows the land use change has dominant control over the green water of the basin. The analysis of green water in a geographic location is critical for agricultural planning hence the usage of blue water (irrigation water) and can be reduced by identifying the area is proper for rain-fed agriculture (Abbaspour et al., 2015).

#### **4.3. Combined impact of land use change and climate variability on Freshwater Provision Indicator**

The combined influence of climate variability and land use change on the EFR levels for each county is evaluated by the freshwater provision indicator (FPI). FPI will be equal to one if water provisioning service meets the ecosystem conditions; otherwise FPI will be less than one. Our analysis showed that FPI for the SRB is less than one during the period of analysis. The value is further decreased as a result of control of both factors. Anderson County located at upper SRB showed maximum reduction in FPI. FPI of each county for the scenarios SRB1 and SRB2 and corresponding decrease in FPI due to the influence of both of these factors are shown in figure 8.



**Fig. 8.** The freshwater provision indicator for counties located at Savannah River basin for the scenarios A) SRB1, B) SRB2, and C) Decrease in FPI due to the combined impact of both the factors.

#### 4.4. Combined impact of land use change and climate variability on blue water scarcity

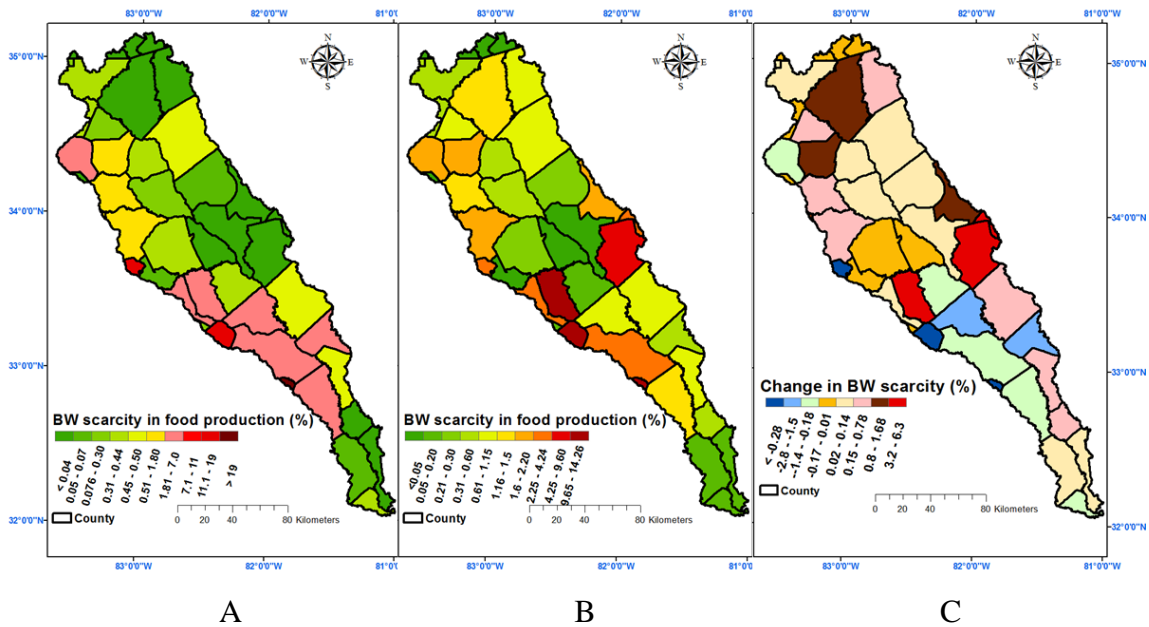
Blue water scarcity ( $BW_{scarcity}$ ) associated with the water provisioning service of the food production sector (irrigation, livestock and aquaculture) is quantified by considering the blue water footprint and blue water availability in a county. The blue water availability is calculated as the difference between total streamflow and EFR (Ritcher, 2010). It indicated that most of the counties experienced a significant reduction in blue water availability due to the combined impact of land use change and climate variability.



Majority of the counties showed an increase in blue water scarcity due to the combined influence of climate variability and land use change. The result indicated that McDuffie and Edgefield County located in the central SRB is most affected by the  $BW_{scarcity}$  (of food production) due to both factors. In McDuffie County the  $BW_{scarcity}$  increased by 6.5% and in Edgefield County it was about five percent (figure 9). The  $BW_{scarcity}$  for food production in several counties only showed a slight variation during the analysis. A reasonable change in  $BW_{scarcity}$  was also observed in the counties located in the central part of SRB. Anderson County and Hart County located in the upper SRB also indicated comparatively large variation in blue water scarcity. The irrigation water footprint is the major water consumption sector of food production in the counties located in SRB. Therefore, an increment in irrigation water consumption and relatively less availability of blue water due to the influence of land use change and climate variability may lead counties to higher water scarcity. The  $BW_{scarcity}$  for both the land use period and change in  $BW_{scarcity}$  during the analysis are shown in figure 9.

#### **4.5. Combined impact of land use change and climate variability on green water scarcity**

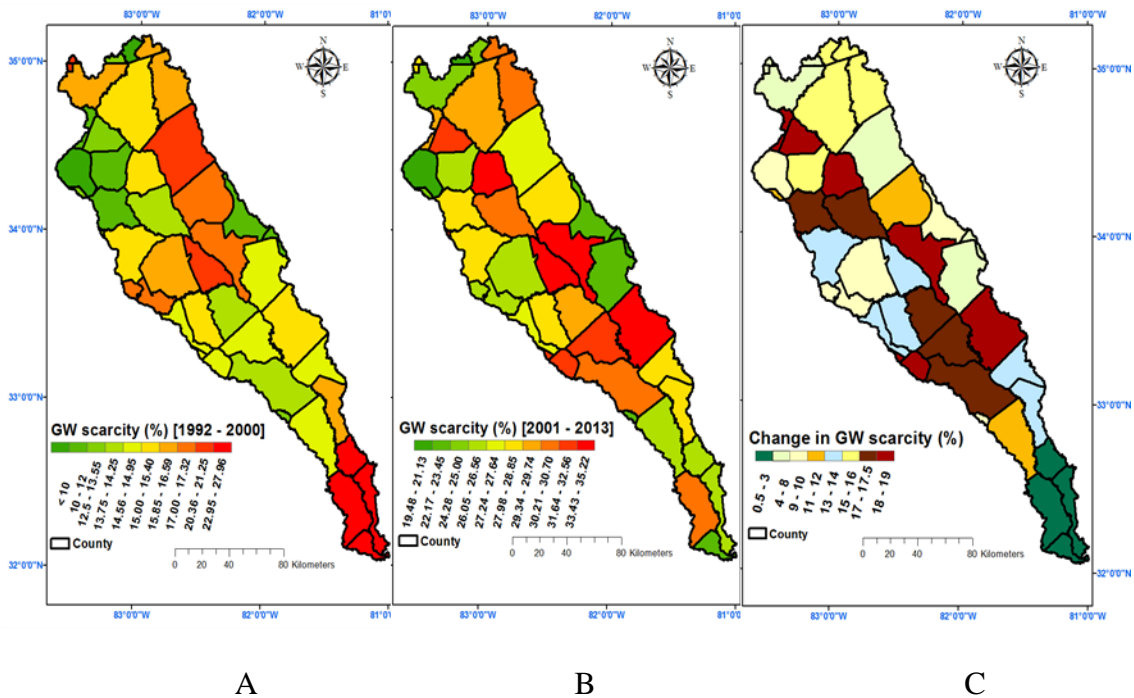
$GW_{scarcity}$  is quantified as a fraction of green water footprint to the green water availability. The Green water availability is quantified as the initial soil water content from the SWAT model HRU output.



**Fig. 9.** Blue water scarcity for counties located at Savannah River basin for the scenarios A) SRB1, B) SRB2, and C) Difference in blue water due to the combined impact of both the factors (SRB2 – SRB1).

We observed a significant reduction in green water availability in all counties located in SRB due to the combined effect of land use change and climate variability. The counties located in upper SRB showed a substantial reduction of green water availability during the period. Burke County which has major agriculture production in SRB also indicated a large reduction in green water availability mainly due to the shrinkage of cropland.

The results indicated that the  $GW_{\text{scarcity}}$  for all the counties located in SRB is significantly increased due to the impact of land use change and climate variability. Stephens (located in upper SRB) County and Hart County (located at upper SRB) showed maximum increase in  $GW_{\text{scarcity}}$  (Figure 10). Both the counties showed 19% rise in  $GW_{\text{scarcity}}$ . Minimum increase in  $GW_{\text{scarcity}}$  was observed in Anderson County.



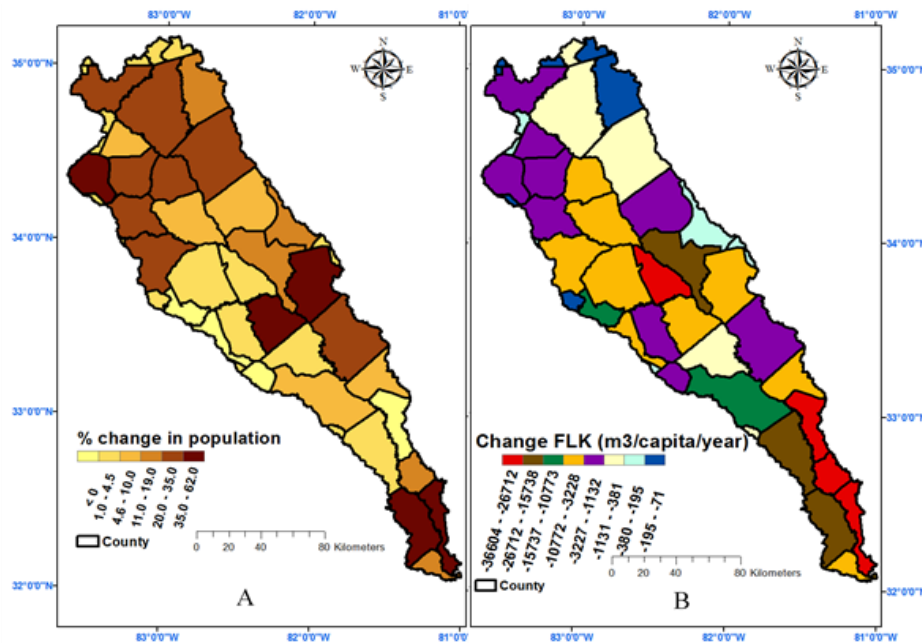
**Fig. 10.** Green water scarcity for counties located at Savannah River basin for the scenarios A) SRB1, B) SRB2, and C) Difference in green water due to the combined impact of both the factors (SRB2 – SRB1).

#### 4.6. Combined Influence of land use change and climate variability on FLK indicator

Population growth and land use pattern change are closely related. Communities that grow rapidly may cause increase in built-up area as well as industrial sectors, thereby affecting ecological sustainability.. In this study, the percentage change in population of each county located at SRB was evaluated. In most counties, human settlement increased from 1995 to 2010 (figure 11A). The maximum population increase was observed in Richmond County located in the central part of SRB, where the built-up area increased from 15.3% to 29.4% and the forest area decreased from 45% to 31%. Higher percent

increase in population (Figure 11A) was observed in Effingham (63%), Columbia (58%) and Edgefield (51%) counties as well as built-up area.

The FLK indicator is calculated as a fraction of blue water availability to population for each county in SRB. None of the counties indicated absolute water scarcity (i.e., per capita water availability is less than 500m<sup>3</sup>/year) during the assessment period, but results indicated that fresh water availability per person is decreased. The minimum amount of per capita water was observed in counties located in upper SRB (e.g., Pickens and Anderson County) and the higher amount was observed in counties located in lower SRB. The counties located in lower SRB and Lincoln County (central SRB) showed a substantial decrease in FLK index. The change in FLK index is shown in figure 11B.



**Fig. 11.** A) The percentage change in population of counties located at SRB, and B) the change in FLK indicator due to the combined influence.

The spatial mapping of ecosystem services can quantify supply (where the water resources are available) and demand (where the water resources are consumed) of water in an ecosystem (Naidoo et al., 2008; Karevia, 2011). This study evaluated the water scarcity in food production by analyzing the water usage and related water footprint in the agricultural sector based on crop irrigation, livestock production and aquaculture practice. Evaluating the impact of land use change in water provisioning services can improve the future aspect of water policy making (Polasky et al., 2011). For example, increasing blue water abstraction for agricultural production from the upstream of the basin may affect the agricultural production in the lower basin. It can be addressed through proper spatial mapping of ecosystem service of the basin. The green water scarcity evaluation of a geographic location can help to identify the possibility of rain-fed agriculture in a catchment, which will reduce the blue water abstraction for irrigation usage. In addition to blue and green water scarcity our analysis indicated that the combination of high population density with climate variability and land use change may increase water scarcity in the SRB.

## **5. Conclusion**

In this study, an integrated hydrological modeling framework for evaluating the influence of land use change and climate variability on ecosystem services and related water scarcity over the Savannah River Basin was developed. The process based hydrological model, SWAT was used to assess the separate and joint impacts of both these factors. Result from the modeling framework indicated a significant impact of land use change and climate variability will likely affect water scarcity in the region. During 1992 – 2001,

the total forest cover in the basin decreased by 20.5% and the built-up area which includes construction land, residential area and commercial area has grown by 247% and the farm land has declined by 21%. The following conclusions can be drawn based on this study:

- a) Stream flow is influenced by land use change (forest cover and agricultural land) and climate variability. Climate variability plays a prominent role compared to land use change in reducing the potential streamflow generation capacity in the Savannah River Basin.
- b) Land use change and climate variability likely will reduce blue water in the SRB. Climate variability seems to have a strong control on blue water over the basin. As a result of combined influence of land use change and climate variability, blue water is reduced by 200mm. The impact of land use change and climate variability varies between counties located in the basin. Hart County showed the maximum reduction in blue water due to the combined influence of both factors.
- c) Green water is also impacted by land use change and climate variability. In contrast to the blue water, land use change plays an important role in controlling green water. Land use change lead to augmentation in the green water of the basin. The influence of land use change over the basin is more identifiable in Anderson County located in upper Savannah River Basin.
- d) The combined analysis of climate variability and land use change showed that Fresh Water Provision (FPI) of the SRB is less than one during the period of analysis. The value is further decreased as a result of combined influence of both

- factors. Pickens County located in upper SRB showed maximum reduction of FPI compared to other counties.
- e) A reasonable change (increase) in blue water scarcity for food production is observed in most counties due to the combined influence of land use change and climate variability. The maximum increase in blue water scarcity was observed in McDuffie and Edgefield County located in the central Savannah River Basin.
  - f) The combined influence of land use change and climate variability further intensified the green water scarcity in the basin. Stephens County and Hart County (located in upper SRB) showed maximum rise in green water scarcity.

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## CHAPTER FOUR

### ASSESSMENT OF HYDRO-CLIMATIC AND CATCHMENT CONTROL ON HYDROLOGICAL DROUGHT

#### 1. Introduction

A prolonged drought has a significant impact on the socio-economic, environmental and ecological systems that affects millions of people in the world each year (Domeisen, 1995; Carolwicz, 1996; Wilhite, 2000; Dai, 2011). Drought is recognized as the most hazardous natural disaster based on several key indicators, such as, degree of severity, the duration of the event, areal extent, loss of life and economic loss (Bryant, 1991; Mishra and Singh, 2010). Several studies highlighted the impact of drought on multiple sectors, for example, annual economic loss estimated to be \$ 6-8 billion in the United States (Wilhite,2000), mortality and conflicts (Garcia-Herra, 2010; Hsiang, 2013), ecology (Choat et al., 2012), and agriculture (Mishra et al., 2015) etc. Drought has a significant impact on water resources planning and management (Rajsekhar et al., 2015; Mishra and Singh, 2011) and affects water quantity (Lund, 1995) and water quality (Van and Zwolsman, 2008) of surface and ground water (Mishra and Singh, 2010).

Drought quantification plays an important role in water resources planning and management. The definition of drought varies widely and can be defined in many ways (Mishra and Singh, 2010). For example, long term (extended) deficiency in precipitation (WMO, 1986); the percentage of years when crops fail from the lack of moisture (FAO, 2002); and a significant deviation from the normal hydrologic conditions of an area (Palmer, 1965). Drought is monitored and quantified through different indices based on



intensity, duration, severity and spatial extent of a drought event (Dai, 2011; Mishra and Singh, 2010). In recent decades, several indices have been developed for quantifying drought events (Mishra and Singh, 2010; Mishra et al., 2015; Rajsekhar et al., 2015). Palmer Drought Severity Index (PDSI; Palmer 1965), Crop Moisture Index (CMI; Palmer 1968), and standardized precipitation index (SPI; McKee et al., 1993) are a few examples of commonly used indices. Indices used for categorizing (mild, medium and severe) hydrological droughts are based on threshold level (e.g. Variable threshold (Beyene et al., 2014)) or standardized indices (e.g. SRI (Standardized Runoff Index), SSI (Standardized Streamflow Index)). Here we applied Standardized Runoff Index (SRI) developed by Shukla and Wood (2008). It is based on the concept employed for SPI. SRI is formulated based on the standardization of river flow, which estimates the periodic (e.g., 1-month, 6-months, 12-months) loss in streamflow. Reviews on drought indices also suggest that representing the propagation of drought only based on meteorological (precipitation) data may result in inaccurate prediction of drought process in a catchment (Van Lanen et al, 2013; Van Loon, 2015).

The long term and short term (but severe) droughts are anticipated to increase in the United States due to the influence of climate change (Sheffield et al., 2012). For instance, in 2002 more than 50% of the North American continent was effected by moderate to severe drought condition (Lawrimore and Stephens, 2003; and Cook et al., 2007). The southeast United States experienced a significant period of drought during 1965 – 1971, 1980 – 1982, 1985 – 1988, 1998 – 2002 (USGS, 2002; Weaver, 2005) and 2006 – 2009 (Veettil and Mishra, 2016). Water rights also intensified in the Southeastern

states due to the frequent droughts (Billah and Goodall, 2011). The Savannah River Basin, which shares boundary between South Carolina, Georgia and North Carolina Sates is experiencing an increased water demand, and changes in hydrologic variability (Veettil and Mishra, 2006). This will likely to intensify water disputes among these states during future drought events.

Hydrological drought has a direct impact on multiple stakeholders, For example, drinking water abstraction, irrigation, electricity generation, recreation etc. (Tallaksen et al., 2014; Sheffield and Wood, 2012; Van Vliet et al., 2012). In addition, hydrological drought indicators can be used to monitor the water supply, scarcity and dispute based on the water supply and demand at a given time. Key information about hydrological drought is necessary for better assessment of water resources rather than meteorological drought (Van Lanen et al., 2012).

Several studies have been conducted to evaluate past, present and future drought impact from a catchment scale to the continental scale (Mishra and Desai, 2005; Andreadis et al., 2005; Mishra and Deasi, 2006; Shukla and Wood, 2008; Van Huijgevoort et al., 2012; Van Loon and Laaha, 2015). These analyses are performed by deriving the indices from time series simulated from hydrologic/land surface models or from observed data. However, hydrologic drought assessment in a catchment scale is difficult with observed streamflow data due to the lack of monitoring in each catchment. In a water resources management point of view, the duration and severity analysis of a hydrological drought is essential. For example, the duration of hydrological drought is predominantly crucial for lives in an aquatic ecosystem (Humphries and Baldwin, 2003)

and understanding the severity is more important for abstraction of water from a stream for different purposes (e.g. hydropower production, mining, domestic use etc.). Hydrological drought occurs when the surface flow (river flow) and lakes or reservoirs levels decline below long term mean (van Lanen et al., 2012; Van Loon, 2015). It can be also termed as streamflow drought (Clausen and Pearson, 1995). Similar to the other categories of drought, the anomalies in atmospheric processes initiates the hydrologic drought.

The propagation of hydrological drought is not only related to the characteristics of climate (e.g., transmission of meteorological drought. Peters et al., 2006) but also to the catchment properties (Mishra and Singh, 2010; Van Loon 2015) and morphology of stream network (Bond, 2008). It was also observed that catchment characteristics influence the hydrological drought over a geographic area (Peters et al., 2006; Tallaksen et al., 2009). For example, a decrease in soil moisture storage in a catchment causes depletion in the amount of water contribution to the aquifer system and stream network. This causes gradual drying of ground water discharge (base flow) and tapering of stream flow (Huntington and Niswonger, 2012). Finally, it will lead to hydrological drought. Additional catchment characters which can make an impact on hydrological drought are land use type (area of forest, agriculture, and pastureland), elevation, soil type etc. The catchment characteristics influence the propagation of drought, which varies in fast and slow responding catchments. For example, in Savannah River Basin availability of rainfall in the winter is comparatively less. This may lead to a lack of recharge during winter. It may turn to an important catchment variable in triggering hydrological drought

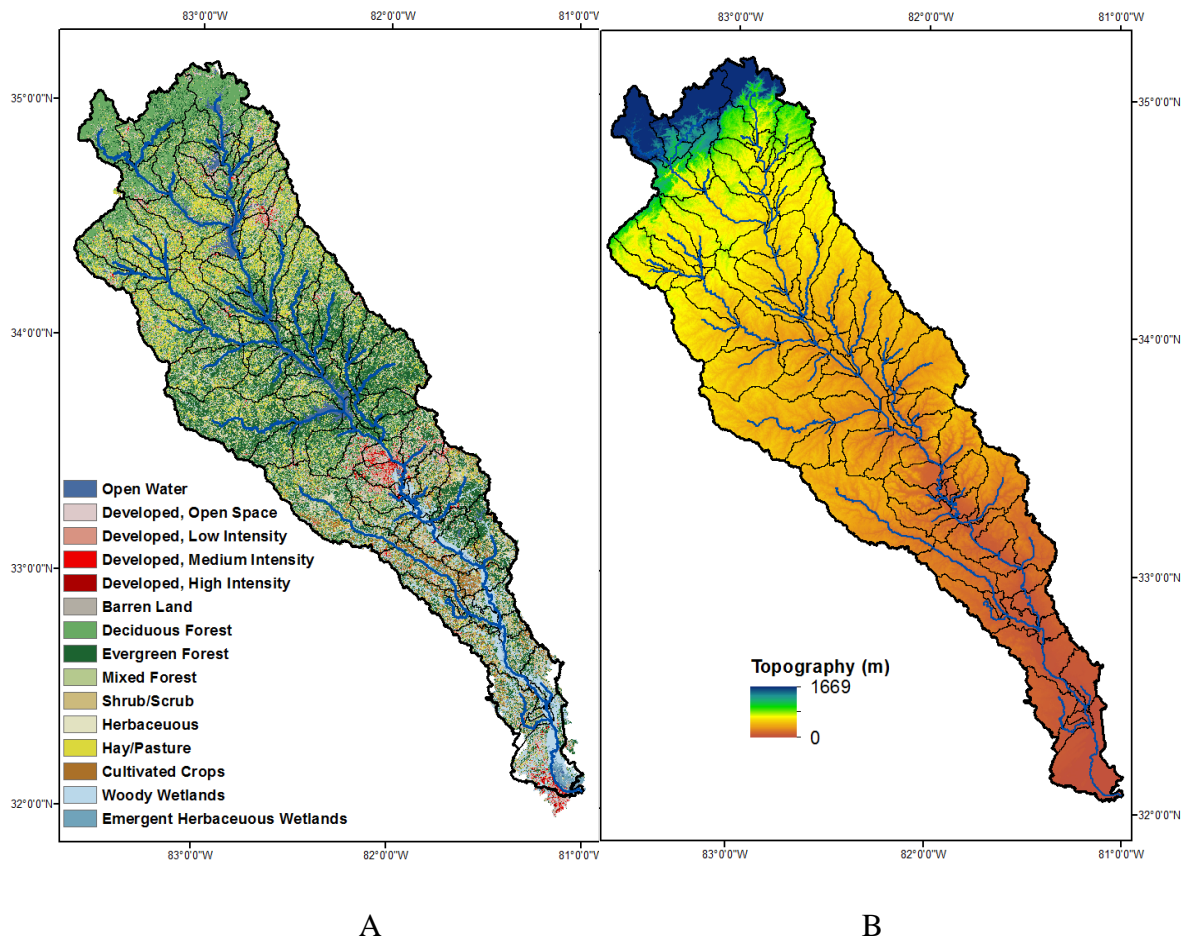
during the summer for slow responding catchments. Examples for morphological variables which control the hydrological drought includes stream order, circularity ratio, and drainage density.

Although droughts are defined based on the deviation of hydro-climatic variables from long term average, several questions or either partly answered or remain unanswered: a) what are the variables that contributes to the evolution (propagation) of the drought event, (b) which variables are more important, and (c) how to identify variable thresholds that likely trigger a drought event? This study attempts to answer these questions with a focus on hydrological drought. In the present study, we focused on the potential influence of climate, catchment and morphological variables to quantify hydrological drought for the Savannah River Basin located which is located in a humid subtropical climate. Evaluating the influence of climate and catchment variables in controlling the hydrological drought is an emerging area in drought hydrology (e.g. Van Loon and Laaha, 2015; Peters et al., 2006; Tallaksen et al., 2009). There is no prior analysis on the impact of morphological variables on hydrological drought. This study investigated the influence (either individually or combined) of climate, catchment and morphometric variables responsible for triggering hydrological drought (based on SRI1, SRI6, and SRI12) at Savannah River Basin. The streamflow output from each sub-catchment is derived from the hydrologic SWAT (Soil and Water Assessment Tool) model for the basin (Veettil and Mishra, 2016). In the second phase of our analysis, we calculated threshold limits for the climate, catchment and morphological variables by using decision tree approach. This threshold limit can provide useful information for

decision makers to assess the short, medium and long - term hydrological drought at the Savannah River Basin.

## **2. Study area**

The Savannah River Basin (SRB), which has a drainage area of 27,171 km<sup>2</sup>, located in the state of South Carolina (11,875 km<sup>2</sup>), Georgia (14,965 km<sup>2</sup>) and North Carolina (331 km<sup>2</sup>) of Southeastern USA (SCDHEC, 2010; Veettil and Mishra, 2016). The maximum elevation of the basin is 1670m (figure 1). The major land use and land cover of the basin are forest (60%), agriculture (14%), development (10%) and open water (4%). The climate and physical characteristics of SRB are as follows. The annual precipitation over the basin ranges from 1000mm to 2050mm. The mean annual temperature of the basin is 18<sup>0</sup>C (SCDHEC, 2010). The climate of SRB is characterized by mild winters and hot summers in the lower portions and cold winters and mild summers in the upper basin area. The SRB comprises parts of the Blue Ridge, Piedmont and Coastal Plain physiographic provinces, which spread throughout the southeastern United States. The northernmost part of the SRB (approximately 1%) is within the Blue Ridge Province, where the headwaters arise. Stream velocity is quite fast in Blue Ridge province because of the steep terrain. The SRB topography varies widely across the watershed, ranging from nearly level to very steep, with soils being shallow to very deep, from excessively drained to very poorly drained, and from sandy to clayey. The major reservoirs in the basin are Hartwell Lake, Richard B Russel Lake, and J. Strom Thurmond Lake, which are controlled by the US Army Corps of Engineers. The SRB and its major land use classes are shown in figure 1A.



**Fig.1.** A) Land use and land cover map of Savannah River Basin, B) topography of the basin.

### 2.1. Data

Digital elevation model (DEM) was obtained from National Elevation data set at a resolution of 30m to delineate the study area and to estimate the topographic features. The land use data used for simulating the stream flow were obtained from National Land Cover Dataset for the year 2011. The soil data was downloaded from SSURGO database. The meteorological (precipitation and temperature) and stream flow data for 1990 to 2013 were collected from National Climatic Data Center (NCDC) and United States

Geological Survey (USGS) respectively. The reservoir outflow data collected from Savannah District Water Management (US Army Corps of Engineers) was incorporated in SWAT model development. The datasets used for developing the hydrological model are listed in Table 1.

**Table 1:** Data and source for SWAT model development

<b>Data Used</b>	<b>Description</b>	<b>Resolution</b>	<b>Source</b>
Land use map	The Crop Data Layer produced using Landsat imagery during 2013	30 × 30	United State Department of Agriculture (USDA)
Topography and Hydrograph	Digital Elevation Model from National Elevation Data set (NED, NAD 83)	30 × 30	National Elevation Dataset, USGS
Soils	The SSURGO data base provides the most detailed level of information, helpful for county level analysis	1:12,000 to 1:63,360	United State Department of Agriculture (USDA)
Meteorological Data	The daily Precipitation, maximum and minimum air temperature	Daily (mm)	National Climatic Data Centre (NCDC)
Stream flow gages	River Discharge	Daily and monthly mean (m <sup>3</sup> /s)	United States Geological Survey (USGS)
Reservoir data	Outflow and dimension	Daily and monthly	U.S. Army Corps of Engineers

The climate, catchment and morphological variables for SRB considered in this study are listed in Table 2. The climate variables (Table 2A) include annual average precipitation, evapotranspiration, and number of wet and dry spells. Catchment variables (Table 2B) are area, and land use classes. Morphometric variables (Table 3C) are stream order, drainage density, relief, relief ratio, form factor, circularity ratio, elongation ratio

and length of overland flow. The equations adopted for calculating the morphological variables are also provided in Table 3C. The SWAT model developed for simulating the streamflow of catchments located at the SRB is explained in section 3.

**Table 2A:** Climate variables

<b>Name</b>	<b>Climate variable definition</b>	<b>Unit</b>
A.PCP	Annual average precipitation	mm
A.ET	Annual average evapotranspiration	mm
Wet Spell	Number of months with precipitation more than average monthly precipitation	-
Dry Spell	Number of months with precipitation less than average monthly precipitation	-

### **3. Methodology**

The modeling framework developed for quantifying the significant variables which have impact on the hydrological drought and its threshold to control the hydrologic drought duration/severity is shown in figure 2. The following sections present an outline of specific components incorporated in the conceptual modeling framework.

#### **3.1. Hydrologic Modeling description**

The hydrological parameters in the SRB catchments are simulated by using Soil and Water Assessment Tool (SWAT, Arnold et al., 1995; Arnold et al., 1998). The modeling of SRB is a challenging task hence it involves many uncertainties (e.g., meteorological data, streamflow data etc.). In this region, contribution or loss of water towards nuclear power generation, irrigation and other water consumption purpose (SCDHEC, 2010) are high.



**Table 2B: Catchment variables**

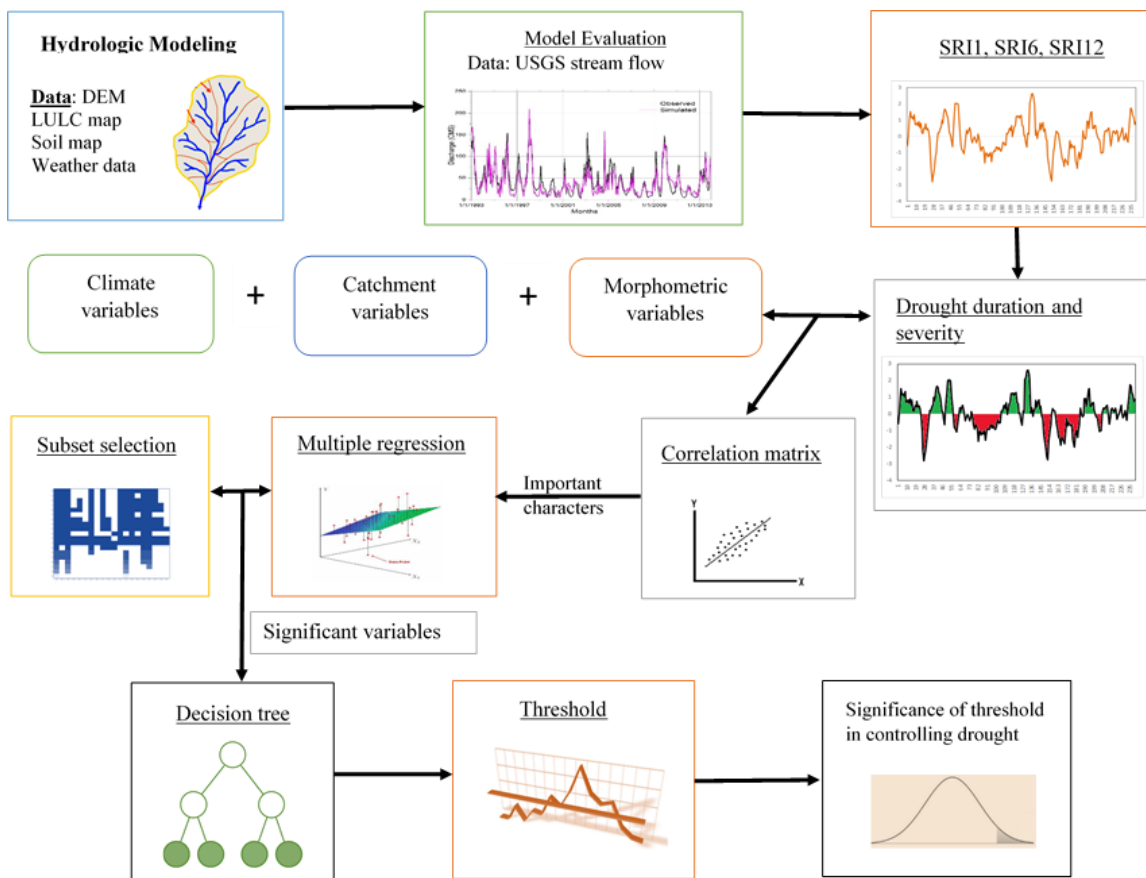
<b>Name</b>	<b>Catchment variable definition</b>	<b>Unit</b>
Area	Area of the catchment	m <sup>2</sup>
Slop	Slope of catchment	%
Length	Longest flow path of stream in a catchment	m
Width	Width of stream in a catchment	m
Depth	Depth of stream in a catchment	m
Elev	Elevation of the sub-basin	m
ElevMin	Min elevation in the sub-basin	m
ElevMax	Max elevation in the sub-basin	m
O. Water	Percentage of open water area in a catchment	%
D. Area	Percentage of developed area in a catchment	%
Barren	Percentage of barren land in a catchment	%
Forest	Percentage of forest area in a catchment	%
W.Land	Percentage of wetland in a catchment	%
Pasture	Percentage of pasture in a catchment	%
loamy	Percentage of loamy soil in a catchment	%
clayey	Percentage of clayey soil in a catchment	%
Sandy	Percentage of sandy soil in a catchment	%

**Table 2C: Morphological variables**

<b>Name</b>	<b>Morphometric variable definition</b>	<b>Unit</b>
Drainage Density (DD)	Ratio of stream length to Area of the basin	-
Stream order (S.Order)	Hierarchical ranking of streams	-
Relief (R)	Difference between maximum and minimum elevation	m
Relief ratio (RR)	Ratio of relief of a catchment to basin length	-
Form factor (FF)	Ratio of area of a catchment to square of the basin length.	-
Circularity ratio (CR)	Calculated as $4 \cdot \pi \cdot A / P^2$ . Where $\pi = 3.14$ and P is the square of the perimeter.	-
Elongation ratio (ER)	$ER = 2 / \text{Basin length}$	-
Length of overland land flow (LF)	$LF = 1 / D * 2$	-

These factors make the model development more complicated. Veetil and Mishra (2016) developed the SWAT model for SRB. The same model was used for evaluating the hydrological drought in the each catchment located at SRB. In this section a brief description of the SWAT model and its performance in streamflow generation at SRB catchments is described.

SWAT is a process based, semi-distributed basin scale model (Arnold et al., 1998; Neitsch et al., 2004) and it operates based on the daily series of meteorological input. The model can be used for simulating evapotranspiration, plant growth, infiltration, percolation, runoff and nutrient loads, and erosion (Neitsch et al., 2011; Faramazi et al., 2009) from a small catchment scale to a continental scale (Chu et al., 2004; Cibirin et al., 2012; Gassman et al., 165 2007; Giri et al., 2014). The SWAT model has been tested in different sectors (e.g., agricultural water management, water scarcity, water quality management etc.) and discussed extensively in the literature (Gassman et al., 2007). More recently SWAT modeling has been applied in drought management sector (Wu et al., 2007; Zhang et al., 2007; Bucak et al., 2017; Kamali et al., 2015). SWAT models the local water balance through four storage volumes: snow, soil profile (0–2 m), shallow aquifer (2–20 m) and deep aquifer (> 20 m). The soil water balance equation is the basis of SWAT modeling algorithm. Surface runoff is estimated by a Soil Conservation Service-Curve Number (SCS-CN) equation using daily precipitation data and soil hydrologic group, land use and land cover characteristics and antecedent soil moisture. A more detailed description of the model is given by Neitsch et al. (2005). In this study; ArcSWAT 2012 with ArcGIS (ESRI-version 10.2.2) was used.



**Fig. 2.** The modeling framework applied for quantifying the significant variable and its threshold.

Digital Elevation Models (DEMs) are the basic input data for Hydrologic SWAT modeling, and DEM uncertainty has major importance in a hydrologic model development (Thieken et al., 1999; Gertner et al., 2002; Chaplot, 2005). The delineation of the watershed is performed based on the topographic data stored in the DEM pixel cells (Figure 1B). In SRB model, we used National Elevation Set (NED) data of 30m resolution (USGS, 2009). The delineated river basin is divided into sub-basins. These sub-basins are further divided into Hydrologic Response Units (HRUs). The hydrological

response units are created based on unique land use, soil and slope data provided to the model. The final SRB model resulted in 1408 HRUs distributed over 104 sub-basins.

The Soil and Water Assessment Tool Calibration and Uncertainty Analysis Program (SWAT-CUP) developed by Abbaspour et al (2005), was employed for calibrating the developed model. Calibration of river discharge rates was executed using the Sequential Uncertainty Fitting (SUFI-2) procedure as described by Abbaspour et al. (2007), implemented in SWAT-CUP. The model was simulated and evaluated against the USGS (observed) stream flow data located in the Savannah River Basin. For example, the USGS station located at lower SRB (Savannah River near Clyo, USGS 02198500) showed a coefficient of determination ( $R^2$ ) of 0.85, Nash-Sutcliffe Efficiency (NSE) of 0.76, R-factor of 0.89 and P-factor of 0.82 during the calibration period (1992 - 2005). During the validation period (2006 -2013)  $R^2$  was 0.64, NSE was 0.58, R-factor was 0.58 and P-factor was 0.51. The parameterization and goodness of fit criteria adopted in the SRB model are explained in Veetil and Mishra (2016). The comparison of SWAT simulated flow and observed flow (USGS) are provided in chapter 2.

### **3.2. Hydrological drought identification**

Standardized Runoff Index (SRI) (Shukla and Wood, 2008) was used for calculating the drought duration and severity for SRB. The process for calculating the SRI is explained in the following steps: (a) The monthly series of stream flow data was extracted from the SWAT model; (b) Long-term streamflow record was fitted to a suitable probability distribution. The Gamma distribution was identified as a suitable distribution for the sub-catchment streamflow in SRB. Several prior studies selected Gamma distribution in

drought studies (Lloyd-Hughes and Saunders, 2002; Sönmez et al., 2005); (c) The gamma distribution was used for estimating the cumulative probability of runoff for a desired period of accumulation. (d) The cumulative probability was then converted to standard normal deviate with mean zero and unit standard deviation. This dimensionless standardized value (Z-value) was used for classifying the catchment as dry or wet for a particular period of time. Table 3 shows the classification of hydrological drought according to SRI (Z-value). Our study considered the SRI value less than '-1' (i.e. from moderate drought to extreme drought). Subsequently, the duration and severity of moderate to extreme drought of each catchment at the SRB was evaluated. The SRI analysis is performed for short-term drought (accumulation period of 1 month, SRI1); medium term drought (accumulation period of 6 months, SRI6); and long-term drought (accumulation period of 12 months, SRI12). The duration of a drought period is estimated by counting the total number of consecutive months that the SRI value is less than the threshold (i.e. -1) and the corresponding Z-value is considered as the severity of that drought event. The average drought duration and were calculated with respect to the total number of drought events that occurred in each sub-catchment of SRB from 1993 to 2013.

### **3.3. Potential influence of climate, catchment and morphological variables on hydrological droughts.**

The relationship between hydrological drought characteristics (duration and severity) with respect to climate, catchment and morphological variables by using linear and non-linear techniques was analyzed.

**Table 3:** Classification of Drought category for the SRI

<b>SRI Values</b>	<b>Drought Category</b>
0 to -0.99	Mild drought
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
< -2.00	Extreme drought

### **3.3.1. Selection of variables**

A preliminary analysis using correlation matrix was first conducted to evaluate the possible relationship among different variables and drought characteristics. It is possible that collinearity may exist between different variables used in the study and this multicollinearity may lead to wrong estimation of significant variables during regression analysis. Therefore, we estimated multicollinearity by plotting correlation matrix among the variables. The candidate variables were selected using two criteria: (1) the variables which are more correlated with drought features, and 2) which are not collinear with the other variables. In the second phase of evaluation, the association between climate, catchment and morphometric variables and drought features were carried out by using multilinear regression and automatic stepwise selection (backward selection) method. Primarily, the multi regression technique was applied to climate, catchment and morphologic variables individually, for evaluating their key role in drought generation. The subset selection method for identifying a subset of variables from climate, catchment and morphometric variable space was used. These selected variables are believed to be

more related to the hydrological drought response. The best model from automatic stepwise selection was selected by Akaike Information Criterion (AIC) (Akaike, 1974).

### **3.3.2. Identifying the threshold with decision tree approach**

The threshold of each variable in generating the hydrologic drought was estimated by using non-linear regression tree approach. The regression tree algorithm involves the stratification of predictor space (climate, catchment and morphometric variables) to a number of simple regions, based on drought characteristics (Breiman et al., 1984; James et al., 2013). In order to predict a given observation, this approach normally uses the mean or mode of the training observations in the region to which it belongs. The set of splitting rules applied to divide the predictor space was represented as a tree. Therefore, these types of approaches are known as decision tree methods. Decision tree approaches are simple to use and easy to interpret. They are considered one of the best methods in supervised learning techniques (James et al., 2013).

In this study, the concept of regression tree using statistical package ‘party’ (Hothorn et al., 2016) available in R software was applied. This statistical analysis package ensures the right sized tree is grown by automatic pruning and performing cross validation. The final tree provides the threshold and significance of a variable to control the hydrologic drought in the river basin. The input variables to the decision tree are selected from the automatic stepwise regression model, which showed higher significance in estimating the output response. The output tree divides data into a number of classes (or series of nodes) and each represents response variables in the form of a

boxplot. The threshold level of input variables and range of output response are explained in section 4.

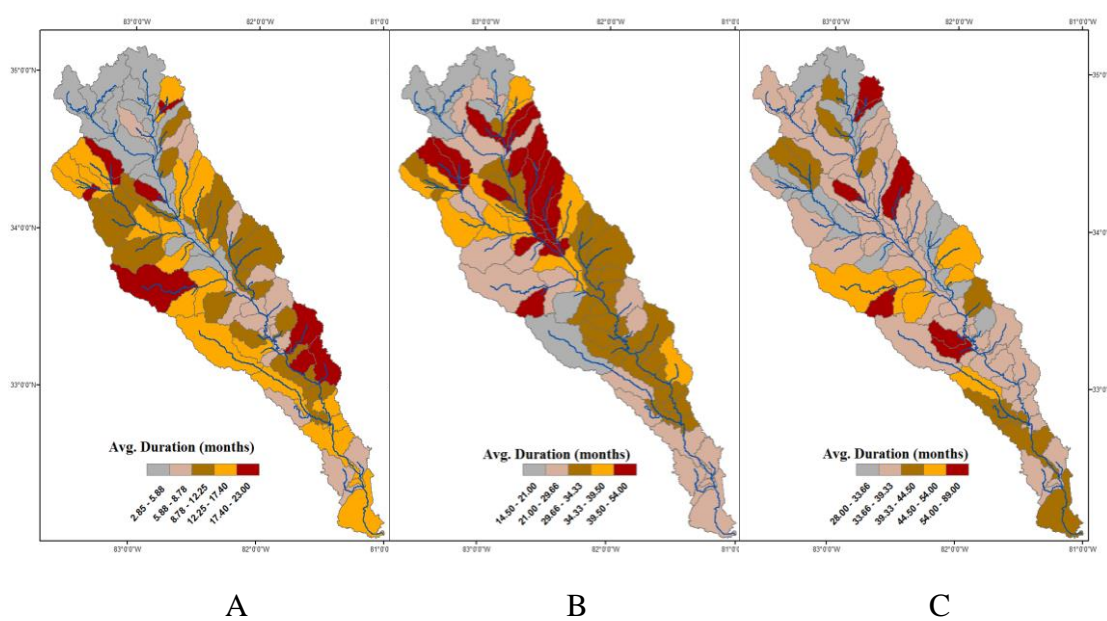
## **4. Results and discussions**

### **4.1. Hydrological drought analysis**

The SRI (SRI1, SRI6, and SRI12) was calculated for the 104 catchments located in SRB, and their spatial drought characteristics (duration and severity) are provided in figure 3. It can be seen that the distribution of drought severity varies in space and by increasing temporal resolutions of SRI. In this section, the term duration indicates the average duration of drought in a catchment and severity indicates the average severity of drought in a catchment. The hydrologic drought duration and severity showed strong correlation (figure 3). The catchments located in the upper SRB showed less duration and severity in all three types of drought. Based on SRI6, more catchments witness higher drought duration while comparing with SRI1 and SRI12 indices. The maximum duration of drought in SRI1, SRI6 and SRI12 was found to be 23, 54 and 89 months respectively. Based on SRI6, higher drought duration seems to be observed in the catchments located in the state of South Carolina in comparison to the state of Georgia. The number of hydrological drought events varies between 4 and 27 based on SRI1 index. Patterns of hydrological drought in some catchments can be identified by comparing annual average precipitation (figure 5A), land use pattern (figure 1A) and elevation map (figure 1B). For example, the annual precipitation was comparatively high in catchments located in the upper SRB and had a higher forest cover. Therefore, the droughts in catchments for this part of the river basin have the lowest duration, and similar observations made elsewhere

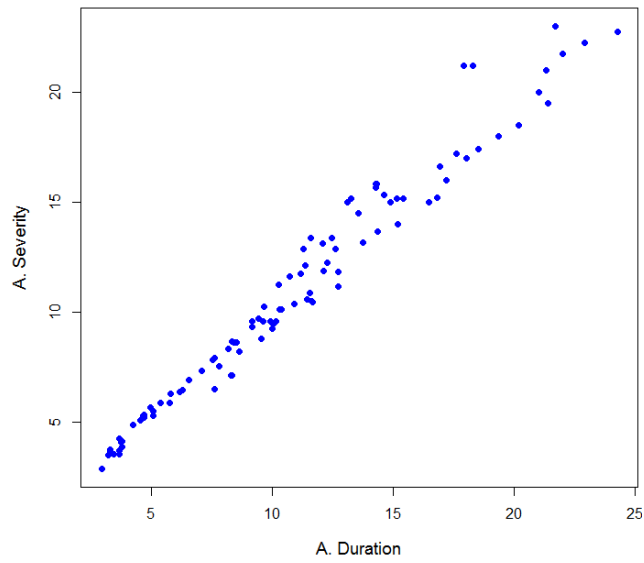


(Tran et al., 2015; Beyene et al., 2014). Higher drought durations were observed in the catchments located away from the mainstream network. The distribution of baseflow index (BFI) and stream order (S.Order) are shown in figure 5B and figure 5C respectively.

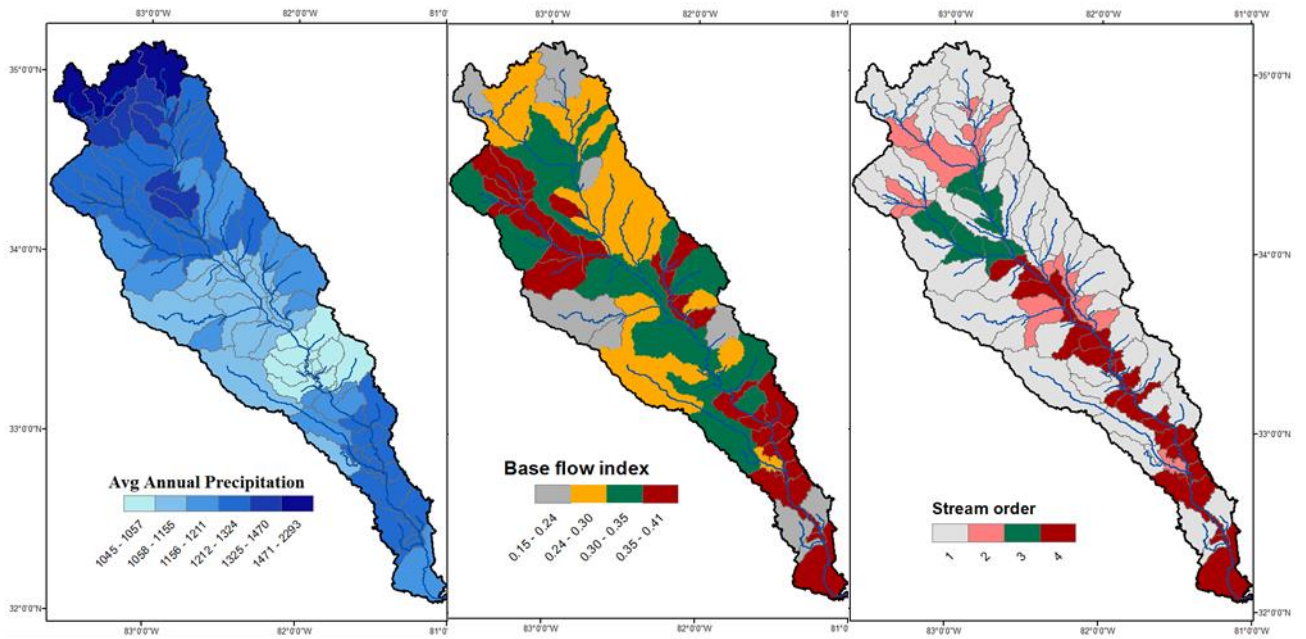


**Fig. 3.** Average drought duration of A) SRI1, B) SRI6 and C) SRI12 drought

The relationship between hydrological drought duration and its governing factors are implemented through various statistical analysis. The study did not take into account all the variables shown in Table 2 because some were substitutable (i.e. one variable is correlated with the response in the same way with another variable). For example, the association of variables related to elevation (MaxElev, Elev, MinElev) was obvious and average elevation (Elev) for further analysis. Simultaneously, linear correlation between all variables using the correlation matrix were evaluated.



**Fig. 4.** Correlation between average hydrological drought duration and average hydrological drought severity.



**Fig. 5.** A) Average annual precipitation, B) Base flow index and Stream order of each catchment located at the Savannah River Basin.

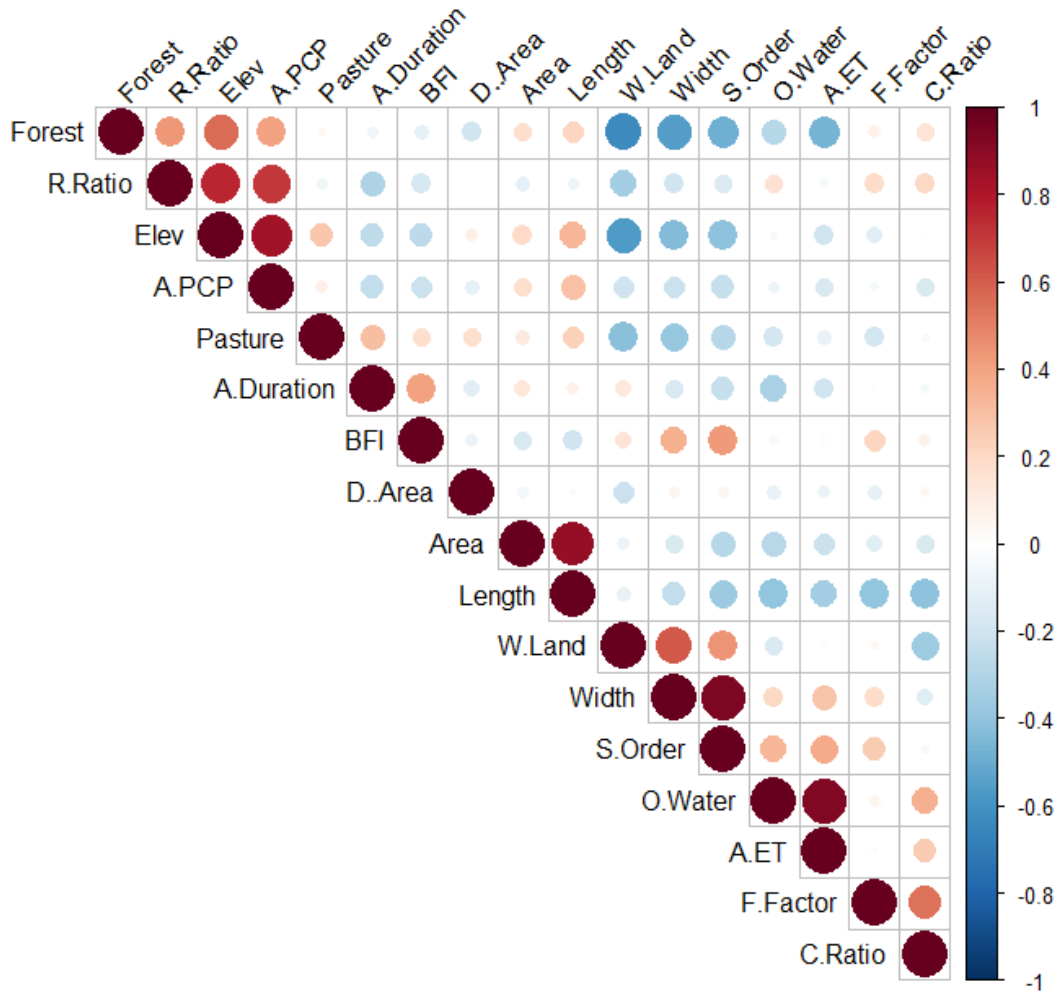
Finally, a list of variables which are least multi-collinear in nature and had a strong role in controlling the hydrological drought duration and severity were selected. The capacity of variables for generating drought is further analyzed with multiple linear regression and decision tree approaches in the following sections.

The association between most of the variables used in the study is shown as a correlation matrix (figure 6) based on the Pearson correlation (Helsel and Hirsch, 1991). Examples for variables which showed a negative association with SRI1 are A.PCP and S.Order. The variables that showed a positive association in the analysis are BFI, pasture, and wetland etc. The important variables which showed high correlation with drought characteristics are A.PCP, BFI, S.Order, pasture (%) and area of the catchment. The relationship of these important variables with the duration based on SRI1 and SRI6 are shown in figure 7 and figure 8.

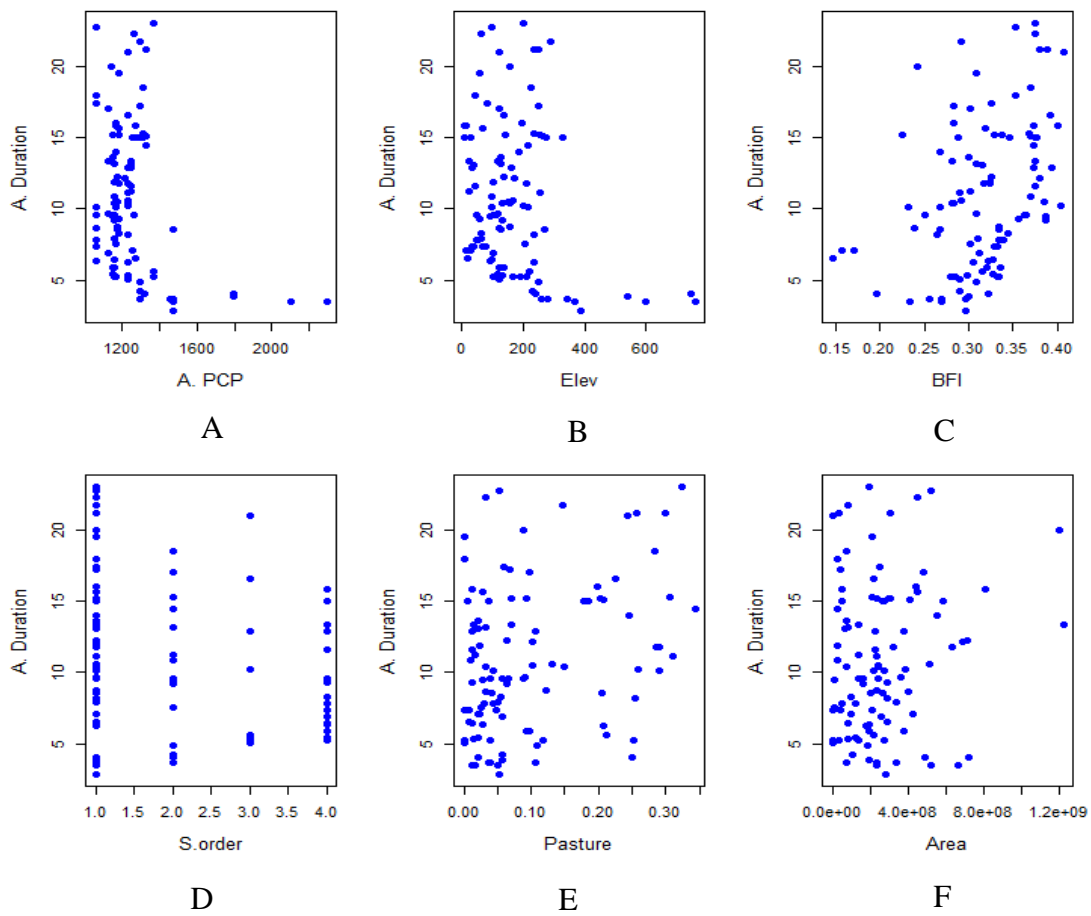
#### **4.2. Identifying impact of climate, catchment and morphological variables**

The selection of major variables which has significant association over the hydrological drought of Savannah River Basin was explained in the previous section. Overall the SRI's are classified as short term (i.e., SRI1), medium term (i.e., SRI6) and long term (SRI12). Similar classifications are made in previous studies (e.g., Mishra and Singh, 2005 and Belayneh, 2012). Belayneh (2012) performed similar classification on meteorological drought based on the Standardized Precipitation Index (SPI). Primarily, the association between climate, catchment, and morphological variables separately on controlling the short, medium and long - term hydrological drought by using multi-linear regression technique was examined. These models were named climate model, catchment

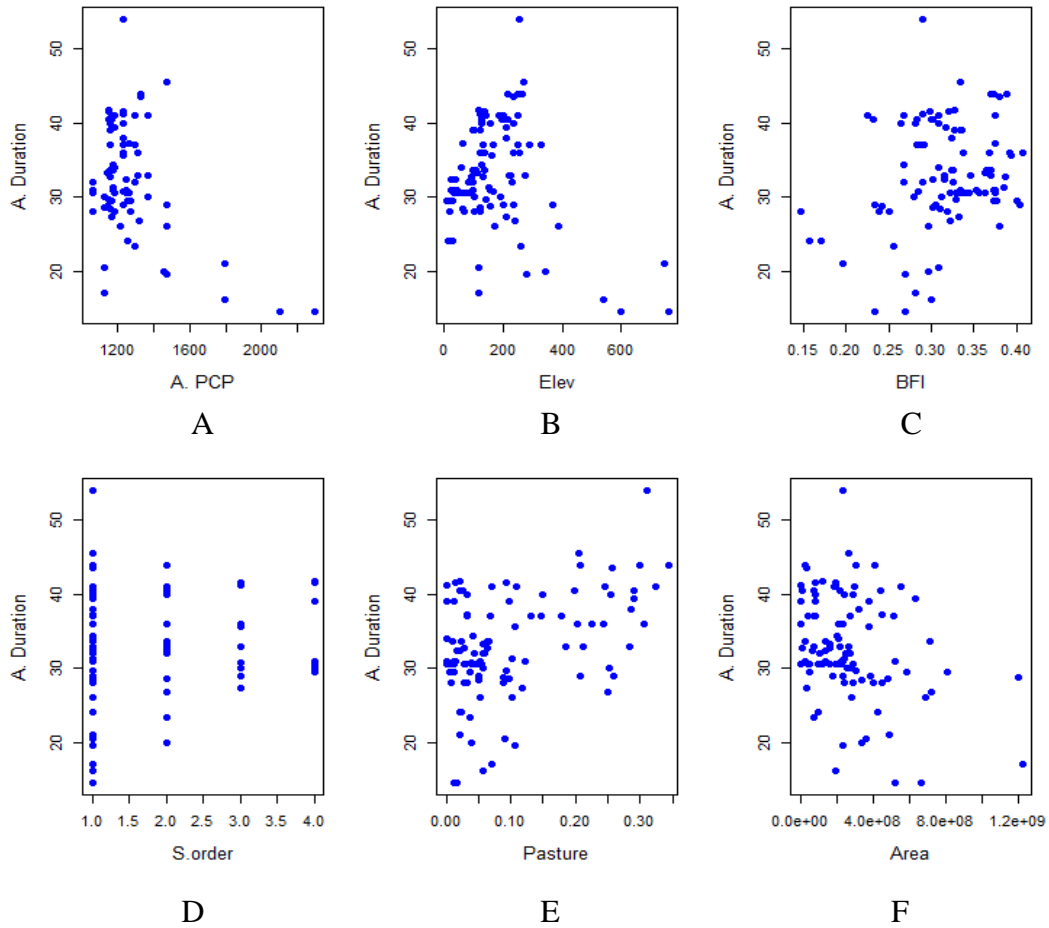
model, and morphological model as shown in table 4, table 5 and table 6. (Significance codes given in the tables: 0 ‘\*\*\*\*’ 0.001 ‘\*\*\*’ 0.01 ‘\*’ 0.05 ‘.’)



**Fig. 6.** The Pearson correlation between the variables for short term accumulation drought.



**Fig. 7.** Relation between SRII average drought duration and A) annual average precipitation, B) elevation of catchment, C) baseflow flow index, D) stream order, E) percentage of pasture in a catchment and F) area of catchments.



**Fig. 8.** Relation between SRI6 average drought duration and A) annual average precipitation, B) elevation of catchment, C) baseflow flow index, D) stream order, E) percentage of pasture in a catchment and F) area of catchments.

**Table 4:** Linear regression of climate variables with SRI1 and SRI6 drought (Climate model)

Drought class	Variable	p-value	R <sup>2</sup>
SRI 1	A.PCP	0.00283 (**)	0.12
	A.ET	0.01049 (*)	
SRI 6	A.PCP	0.000377 (***)	0.15

**Table 5:** Linear regression of catchment variables with SRI1 and SRI6 drought (catchment model)

Drought class	Variable	p-value	R <sup>2</sup>
SRI1	Area	0.00336 **	0.49
	Elevation	0.028494 *	
	Width	1.63e-07 ***	
	Pasture	0.007718 **	
	Wetland	0.000249 ***	
	BFI	5.03e-07 ***	
SRI6	Area	0.001687 **	0.47
	Elevation	1.57e-06 ***	
	Pasture	9.74e-06 ***	
	Wetland	0.000359 ***	

#### 4.2.1. Impact of variables on Short – term drought

Various studies have proved the significant role of climate variables in justifying the hydrological drought over a river basin (Wang et al., 2015; Sheffield and Wood, 2012). This study indicates that A.PCP and A.ET plays an important role for predicting the SRI1 drought characteristics (Table 4). Therefore, precipitation below normal (average) has strong control for the drought characteristics. Additionally, the combination of lower

precipitation with higher evapotranspiration can increase the impact of drought over an area. Decreased moisture availability or increased temperature in the atmosphere may lead to an increase in actual evapotranspiration. This situation led to an additional loss of water stored in soil layer, water bodies and result in hydrological drought. The climate variables which showed high significance (p-value less than 0.05), in the climate model were able to explain 12% ( $R^2$ , the coefficient of determination) of variability in SRI1 drought duration. The significant variables selected along with their  $R^2$  and the level of significance are also shown in Table 4. The result of the climate model explains the necessity of additional variables (i.e., catchment and morphological variables) in quantifying the hydrological drought characteristics. The catchment variables which showed high significance in predicting the duration of short – term drought were Area, elevation, width, pasture, wetland and BFI (table 5). The catchment model was able to explain 49% variability with SRI-1 drought characteristics. The important morphological variables were S.Order and R.Ratio with a coefficient of determination of 0.18 (Table 6).

**Table 6:** Linear regression of morphological variables with SRI1 and SRI6 drought (Morphological model)

<b>Drought class</b>	<b>Variable</b>	<b>p-value</b>	<b>R<sup>2</sup></b>
SRI1	S.Order	0.002463 **	0.18
	RR	0.000306 ***	
SRI6	RR	0.000497 ***	0.16
	CR	0.002526 **	

The selected variables based on the Pearson correlation matrix were added to stepwise regression analysis and significant input variables were selected according to the decrease in Akaike Information Criterion (AIC). By integrating climate, catchment and



morphological variables, the combined model was able to predict 58% of short-term drought duration (Table 7). S.Order, BFI, and A.PCP were the most significant variables in predicting SRII drought. The BFI cannot be defined as a catchment character but it has a strong role in controlling the storage capacity and response time of a catchment (Van Loon and Laaha, 2015). It also replicates the geological characteristics of a catchment (Bloomfield et al., 2009; Hidsal et al., 2004). The BFI showed a positive correlation with the SRII drought. A similar trend is also observed in Van Loon and Laaha (2015); Tallaksen and Van Lanen, (2004); Barker et al., (2015). During drought, the major flow in the stream network is contributed by ground water discharge (base flow). Therefore, the BFI has a strong role in controlling the hydrological drought. Moreover, the contribution of base flow for a long term in the catchments denote higher duration of drought in the catchments. This may be a possible reason for the positive association of SRII drought to the BFI. Although, a complex relationship exists between drought characteristics and variables, the results indicate the linear models can be applied to exemplify the monotonic relationship between the hydrologic drought features and drought generating variables. However, this study incorporated non-linear models for exploring the non-linear relationship between the variables and hydrological drought.

First or second order streams are the most drought affected spatial units in a stream network (Cowx et al., 1984; Hakala and Hartman, 2004). This study also suggested an inverse correlation of S.Order with short - term drought duration. The maximum S.Order in this study was four (Figure 5C) and the higher order streams were observed in the mainstream channel network. Therefore, the drought events of higher

duration are typically located in the catchments far from the mainstream network. The land use pattern, such as, wetland (%) and pasture (%) had a positive control for drought events based on SRI1 index.

**Table 7:** Combined linear regression model based on BWS

Drought class	Variable	p-value	R <sup>2</sup>
SRI1	Area	0.00168 **	0.58
	Length	0.00433 **	
	Pasture	0.00302 **	
	Wetland	0.00033 ***	
	BFI	3.01e-09 ***	
	A.PCP	0.00965 **	
	S.Order	1.39e-10 ***	
	C.Ratio	0.08345 (.)	
SRI6	Area	2.84e-05 ***	0.50
	Width	0.025673 *	
	Pasture	2.69e-08 ***	
	Wetland	0.000108 ***	
	Elevation	5.77e-07 ***	
	S.Order	0.039544 *	

It was observed that wetland showed a positive correlation with hydrological drought. Catchments with a larger area of wetland were more susceptible to hydrologic drought. Similarly, pasture land in each catchment also revealed a positive correlation with hydrological drought based on linear regression analysis. Therefore, pasture lands had a major role in controlling the hydrological drought at the SRB. It is important to note that 75% of the agricultural land is pasture for SRB.

Catchment area, the length of stream network in catchment and circularity ratio are the other variables that had significant control on hydrologic drought duration. Finally, S. Order, BFI, A.PCP, and wetland were the four major governing factors which

control the short - term hydrological drought in Savannah River basin. Here, the BFI, wetland and pasture land can relate to the catchment characteristics which indicate the catchment storage.

#### **4.2.2. Impact of variables on medium and long – term drought**

Similar analysis was used to evaluate the control of climate, catchment and morphometric variables on medium - term (SRI6) and long - term (SRI12) drought. Annual average precipitation (i.e., A.PCP) was the only climate variable which had a significant role on SRI6 drought duration (Table 4).A.PCP showed a comparatively higher significance than SRI1 climate model. Multiple regression analysis of catchment variables with SRI6 drought showed that elevation is the most important variable in predicting medium term drought duration. The land use patterns including pasture and wetland also showed a significant control on medium – term drought duration (Table 5). The combined model developed based on backward Stepwise Selection outputs was able to predict 50% variability in medium - term drought duration (Table 7).

The combined BWS model showed that climate variables do not have an important role in predicting the duration of drought derived based on SRI6 index. The percentage of pasture land was identified as one of the major control governing of medium – term drought. The pasture land had a major role in governing the surface detention or storage capacity. This type of vegetation also affects soil surface micro-topography. Pasture land showed a positive correlation with the duration of medium – term drought. This scenario may be due to the influence of higher evapotranspiration in the grassed land or may be due to the control of pasture land on soil water (Gutiérrez et

al., 2014). After pasture land, the next highest correlation was observed between medium – term drought duration (based on SPI 6) and the elevation of the catchments. Maximum precipitation occurs at the upstream of the SRB where the elevation is high. S.Order seems to be the only morphometric variable that is influencing the SRI6 drought.

Based on linear analysis, there was no clear relationship observed between climate variables and long – term drought derived based on SPI12. The width of stream and S.Order were the significant variables in the combined BWS model analysis. But the correlation between SRI12 drought with catchment and morphometric variables were relatively less in comparison with the short and medium – term drought. Based on the linear regression models, the drought characteristics (duration and severity) can be better quantified (predicted) using a combination of climate, catchment, and morphological variables.

#### **4.3. Identification of variable threshold in controlling the hydrological drought**

Non-linear regression tree analysis (decision tree) was implemented to identify the critical threshold of climate, catchment and morphological variables that triggers hydrological drought. First, the relevant variables were selected based on the correlation and linear regression methods discussed in previous section. Then, the decision tree approach was used to identify the thresholds associated with relevant variables.

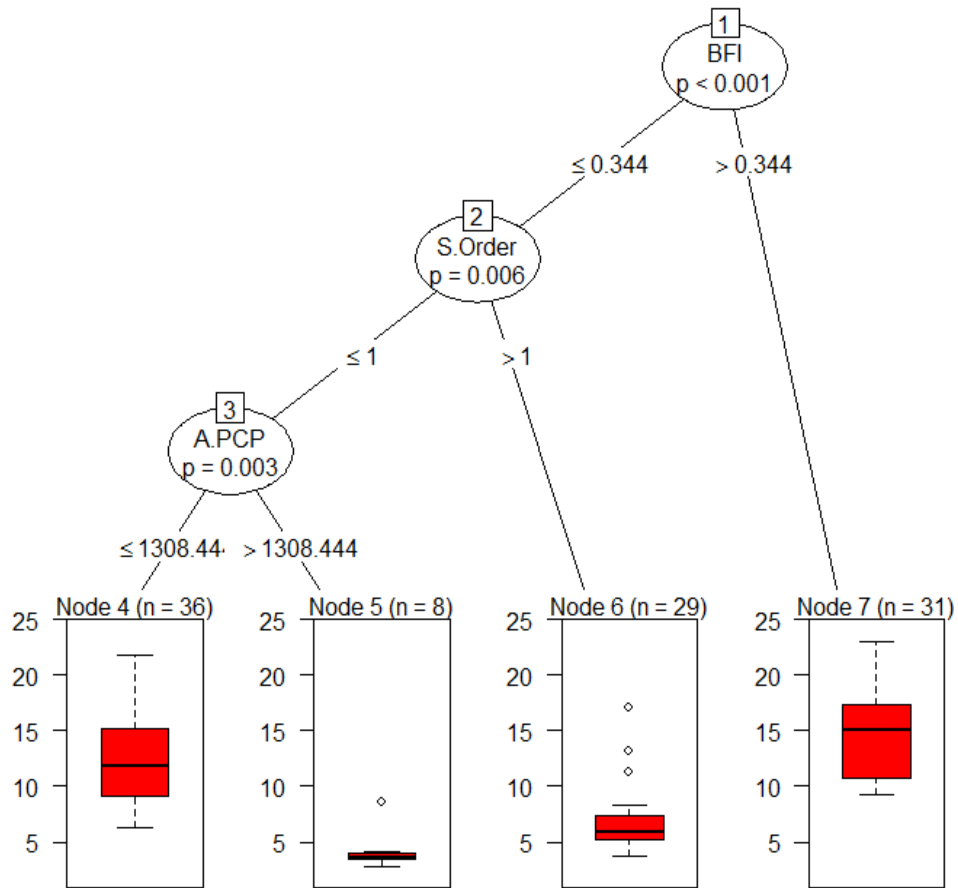
The standard output from the decision tree analysis by using ‘party’ package is shown in Figure 9 to 12. The decision tree figures outline the process of estimating the threshold of variables and the range of response (drought duration) in the form of a box plot. Figure 9 represents the decision tree output of short - term drought. The node ‘1’

divides the whole data sets into two groups based on the BFI, which is the most significant variable in the decision tree. It was observed that, if BFI is equal to or less than 0.344 ( $\leq 0.344$ ), there is further splits leading to the growth of branches towards the left of the growing tree or else to the right branch. Here  $p < 0.001$ , represents the significance of the correlation between the split based on BFI and response variable (drought duration). The node '2' split into two branches based on the S.Order ( $p = 0.006$ ). If the S.Order is  $\leq 1$  the branches are assigned to the left. The node '2' leads to the node '3', where the partitioning is carried out based on the A.PCP. Here the precipitation threshold is 1308.44mm.

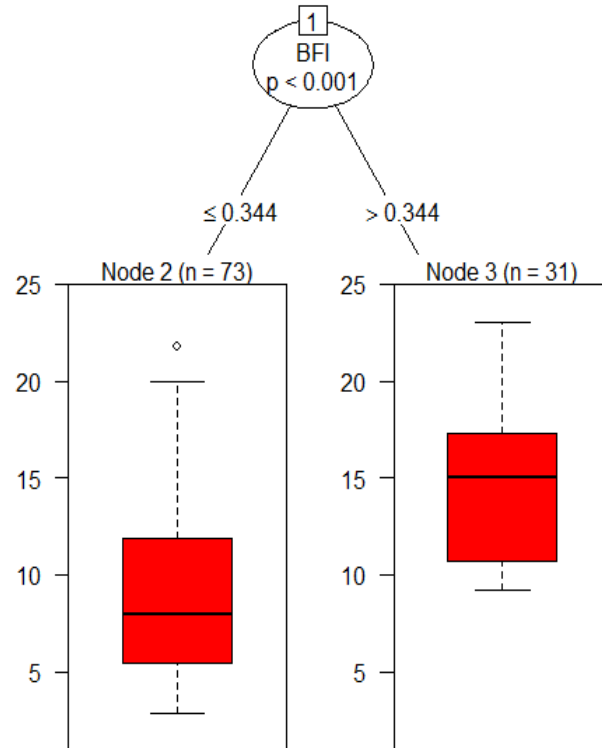
Using this decision tree concept, the critical threshold of BFI, S.Order, and A.PCP are identified evaluating their response on drought characteristics. If the BFI is  $\leq 0.344$ , S.Order is  $\leq 1$  and A.PCP is  $\leq 1308.44$ mm the duration of short - term hydrological drought will vary from 6 months to 22 months and the median (50th percentile, solid line within the boxplot) of drought duration is 12 months. Here  $n = 36$  represents a particular subgroup which consists of 36 catchment out of 104 catchments. When the A.PCP is more than 1308.44mm the average duration of SRI drought will range from 2 to 4.5 months. The right branch of the node '2' explains that when S. Order  $> 1$  and BFI of  $\leq 0.344$ , this will lead to an average drought duration of 5.5 months (median) at the SRB.

The average precipitation in the SRB is 1240mm per year. Our analysis indicates that most of the sub-catchments receive an average annual precipitation less than the threshold 1308.44mm. This may be a possible reason for increasing the average drought duration more than 5 months. The right branch of node '1' is only based on the BFI. As

already discussed, BFI has a positive correlation with the SRI1 drought. Since, BFI has maximum correlation with the SRI1 drought, a decision tree generated using BFI.

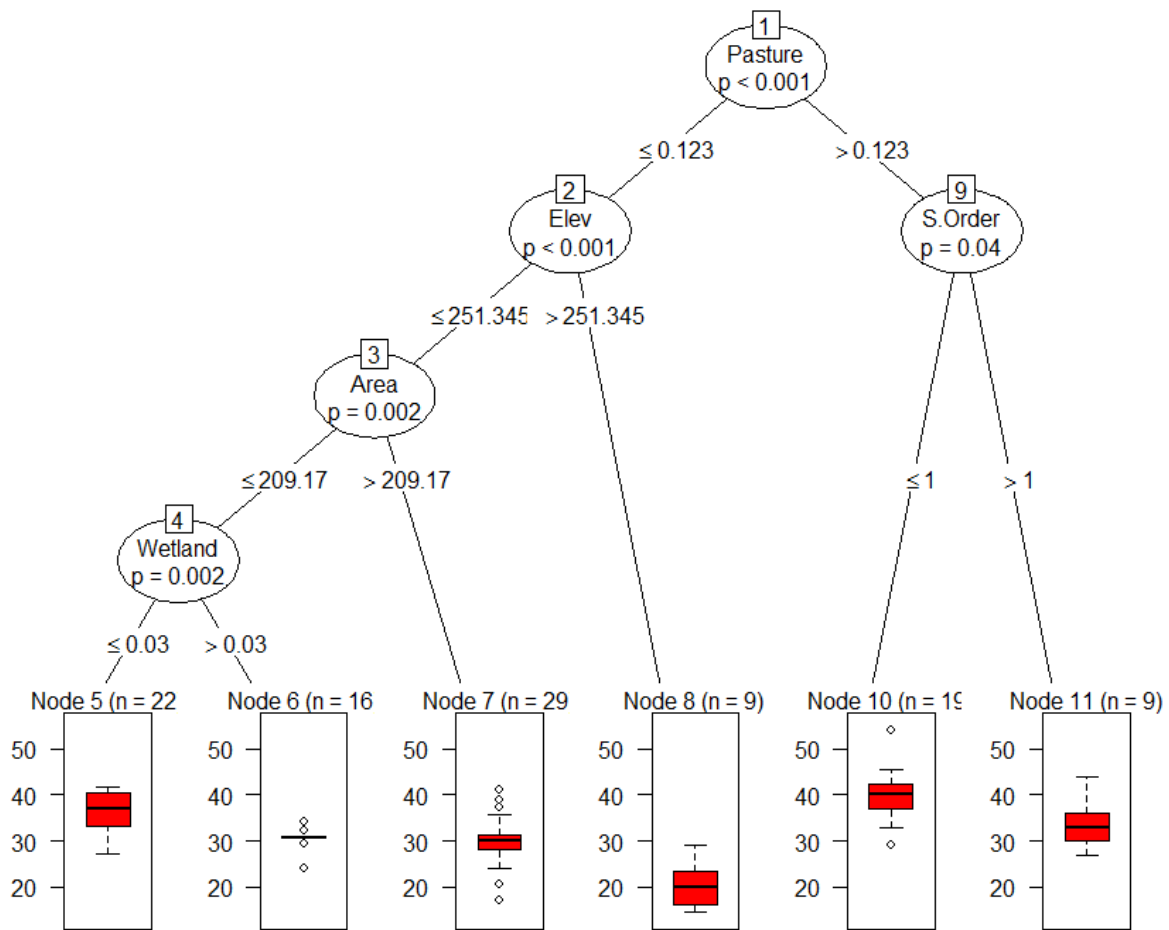


**Fig. 9.** Decision tree showing the threshold of climate, catchment and morphological variables.



**Fig. 10.** Decision tree developed for short – term drought duration using Baseflow Index (BFI)

Figure 11 shows the decision tree for medium-term drought derived based on SPI6. The figure consists of many nodes as well as thresholds associated with variables which can control the particular class of drought. It was found that catchment and morphological variables controls the SRI6 drought duration. The land use variable ‘pasture’ showed maximum influence. Therefore, first split of the tree was based on this variable with a threshold of 12.3%. The resulting box plot in the node ‘5’ can be explained as follows. For a catchment with an area  $\leq 20.9\text{km}^2$ , elevation  $\leq 251.345\text{m}$  and with a pasture/hay cultivation  $\leq 12.3\%$  and a wetland area of  $\leq 3\%$  likely to experience a drought period of 38 months (median).



**Fig. 11.** Decision tree showing the threshold of catchment and morphological variables.

The average elevation of SRB is observed as 165m and if the elevation is more than 251m the duration of drought seems to be reduced. The decision tree further illustrates the role of land use variables in controlling the SRI6 drought. It was observed that S.Order can be the most significant morphological variable in this analysis. The long-term accumulation drought was also analyzed through decision tree approach (Figure 12). S.Order and Width of channels were the important variables, which have potential governance over the drought duration based on SRI12. By examining the anatomy of a decision tree, it is possible to identify different combinations of climate,



catchment and morphological characters that will lead a particular catchment to hydrological drought.

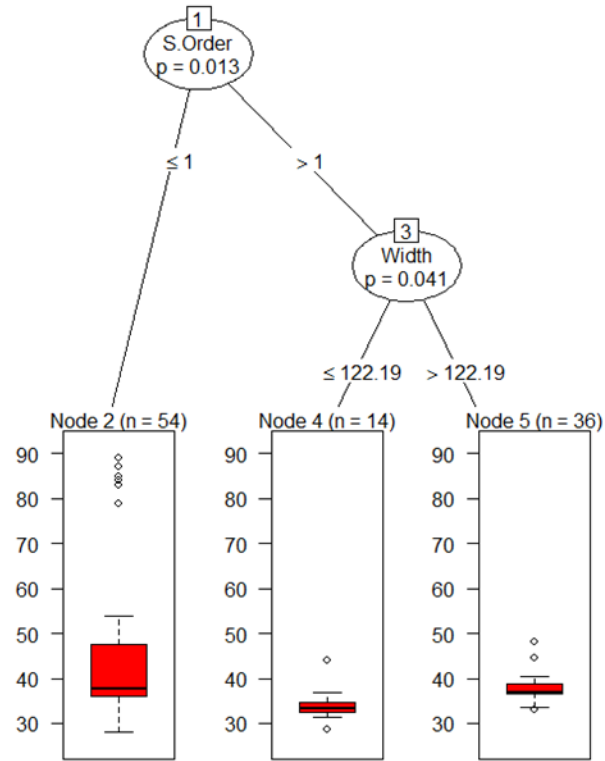


Fig. 12. Decision tree showing the threshold of catchment and morphological variables.

## 5. Conclusion

A statistical modelling framework to quantify the potential influence of climate, catchment and morphological variables for generating short, medium and long-term duration drought was developed. In this study, the hydrological drought characteristics (duration and severity) were generated by using a SWAT hydrologic model. The proposed framework was capable of identifying significant variables and their associated threshold levels that controls the duration of the hydrological drought of a river basin. The study can be also extended for an ungauged basin, where the availability of

hydrological data is insufficient. In the proposed framework, streamflow for each sub-catchment in the Savannah River Basin is simulated by using Soil and Water Assessment Tool (SWAT) and the hydrological drought is quantified based on Standardized Runoff Index. The following conclusions are set forth from this analysis.

a) The linear models developed based only on climate variables may not be capable of predicting the duration of hydrological drought in the Savannah River Basin. The performance of linear models significantly improved by combined climate, catchment and morphological variables and were better to explain the variability in hydrological drought duration.

b) The short – term drought duration analysis was conducted using SRI1. It was observed that climate (e.g., A.PCP), catchment (e.g., BFI) and morphological (e.g., S. Order) variables are significant in predicting the SRI1 drought duration, but catchment and morphometric control on short – term drought over the SRB were dominant.

c) The medium – term drought duration derived based on SRI6 showed higher correlation with catchment variables including Pasture, Wetland, Area, and Elevation. The backward Stepwise Selection model could not identify any climate variables which was sensitive in controlling the medium – term drought over the SRB. In this study we used annual precipitation as climate variable, which has influence on SRI1 drought duration. Annual precipitation did not show its influence on SRI6 and SRI12 in our analysis, however more analysis is required to quantify the potential influence of precipitation derived based on moving window of various length.

d) Stream order was identified as the only variable which had significant control over short, medium and long – term duration drought.

e) A comparatively large number of climate, catchment and morphological variables using decision tree approach were explored in order to identify their threshold for possible controls on the hydrological drought. For example, if the storage variable BFI is greater than 0.344 the short – term hydrological drought will likely continue for 15 months in the basin. This information helps stakeholders assess the variety of crops which can be cultivated in a catchment with respect to the drought tolerance.

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## CHAPTER FIVE

### CONCLUSIONS AND RECOMMENDATIONS

The demand for water has increased substantially in many parts of the world due to increase in water use by multiple sectors, such as, agriculture, domestic, industrial, mining, and thermo-electric power generation sector. The water scarcity challenge is further compounded by uneven distribution in fresh water supplies (e.g., rainfall and snowfall), climate variability and anthropogenic activities (e.g., land use change). Therefore, quantifying water scarcity and drought will improve water security of a region. The specific objectives that we focused on our research are:

- 1) To investigate the blue and green water security of Savannah River Basin by applying the water footprint concept.
- 2) To quantify the influence of climate variability and land use change on streamflow, ecosystem services, and water scarcity.
- 3) To assess the climate, catchment, and morphological variables control over hydrological drought of a river basin.

Based on the above study, the following conclusions can be drawn from this study:

- 1) Climatic factors control spatio-temporal distributions of blue water. For example, blue water for counties located in the upper part of SRB is comparatively higher, which may be associated with the higher amount of precipitation in upper part of SRB and it decreases towards lower part of SRB.
- 2) Analysis of green water scarcity and vulnerability indicates that counties are safe for practicing rain-fed agriculture during spring and fall. Our findings suggest that

- blue water scarcity is enormously upsetting the ecological balance in upper part of river basin, particularly in Oconee County of South Carolina. Both Oconee and Anderson County are identified as ecological hotspots, where the BW-vulnerability is more than 100%.
- 3) The land use change and climate variability cause reduction in blue water. Climate variability indicated a strong control on blue water over the basin. As a result of joint effects of land use change and climate variability, the blue water is reduced by 200mm. Spatially the impact of land use change and climate variability vary with counties located in the basin. Hart County showed the maximum reduction in blue water due to the combined influence of both the factors.
  - 4) A reasonable change (decrease) in blue water scarcity (in food production) is observed in most of the counties due to the joint influence of land use change and climate variability. The maximum rise of blue water scarcity was observed in McDuffie and Edgefield County located at the central Savannah River Basin.
  - 5) The linear models developed based only on climate variables may not be capable for predicting the duration of hydrological drought in the Savannah River Basin. The performance of linear models significantly improved by combined climate, catchment and morphological variables as well as it better explain the variability in hydrological drought duration.
  - 6) We explored a comparatively large number of climate, catchment and morphological variables by decision tree approach in order to identify their

threshold for possible control over the hydrological drought. For example, if the storage variable BFI is greater than 0.344 the short – term hydrological drought will likely to continue for 15 months in the basin. This information helps the stake holders to assess the variety of crops which can be cultivated in a catchment with respect to the drought tolerance.

The overall results in this study indicate that the proposed modeling framework is capable for quantifying the water security of a river basin. By accurately evaluating and predicting water scarcity and droughts the decision makers can improve efficient water management plans and proactive mitigation to minimize social, environmental and economic impacts significantly.

*Recommendations for future study:* In recent years, promising research is taking place, which examines the possibility for using big data concepts accesses water security in space and time. Investigating the water quality in a catchment scale is necessary in evaluating the ecological health of a river basin. Also, it is essential for comprehensive analysis of water security. But the lack of harmonized water quality data limits the grey water footprint analysis in the water security modeling framework. Therefore, the integration of multiple data sources with the local based indicator (related to water quality and quantity) overcome the limited information related to the water quality and water quantity (streamflow, blue water, and green water).

Better quantification of groundwater contribution to baseflow, improvement in calculation of anthropogenic water demands can improve water security, and better representation of human interventions (e.g., reservoir operation, irrigation water use) with in

hydrologic modeling framework can improve quantification of hydrologic fluxes necessary for Blue water, Green water and hydrological drought assessment.