ABSTRACT

TOUMA, DANIELLE ELIE. A Quantitative Framework for Assessing the Effects of Climate and Land-use Change on Streamflow. (Under the direction of Dr. Ranji Ranjithan, Dr. E. Downey Brill and Dr. Sankar Arumugam.)

The objective of this research was to develop and test a framework that can be used to assess the effects of climate and land-use change on the stream ecology in a basin. The current method of analyzing extreme events of streamflow is insufficient in non-stationary environments. Although tools and models are available for this assessment, no systematic approach is established. The proposed framework outlines and integrates the key steps and necessary procedures to assess the changes in streamflows. Precipitation and temperature data from four General Circulation Models (GCMs) and land cover data from a land-use model were coupled with a hydrologic model to simulate daily flows. The GCM monthly precipitation and temperature data were preprocessed using a downscaling method to achieve data on a refined spatial scale and a k-Nearest Neighbor algorithm was used to temporally disaggregate the data to a daily scale. The housing density data from the EPA Integrated Climate and Land-use Scenarios (ICLUS HD) were reclassified to be compatible with the USGS National Land Cover Database. The Soil and Water Assessment Tool (SWAT) was used to process the land-use and climate data in the basin. The flow values were used to estimate several Indicators of Hydrologic Alteration (IHA) which were then assessed for the amount of changes using the Range of Variability Approach (RVA). The hydrologic alterations are evaluated based on flows in a pre-development period and post-development period. To assess the changes under reduced scenario uncertainties and realistic planning time frames, the post-development period flows were scenario simulated for 2011-2040, while the pre-development period flows were simulated using the observed conditions between 1981-2010.

The North East Cape Fear River basin was used to illustrate the framework. The SWAT model was calibrated to an $R^2$ of 0.69 for the daily streamflow. The A2 and B1 scenarios from the Fourth Assessment Report from the Intergovernmental Panel for Climate Change were used in the framework to drive the climate and land-use changes in the post-development period. The basin is expected to experience 3.4 – 10.8% increase in mean

precipitation, 0.35 – 1.10 °C increase in mean temperature based on four different types of GCMs. Urban development is expected to increase by 14 – 17% between the pre-development period and the post-development period which is representative of the A2 and B1 scenarios. The mean flows increased by 1.6-19.6% under climate change simulations but do not change more that 0.01% under land-use change simulations. Changes in mean flows and some mean monthly flows under climate change conditions were statistically significant to a 95% level for all GCMs and both the A2 and B1 scenarios but were not significant under land-use change conditions. The combination of both land-use and climate change provided the same alterations as climate change alone. The IHA parameters showed alterations in the annual minimum and maximum daily means and mean monthly flows for all GCMs under climate change for both scenarios, even when the mean changes were not shown to be statistically significant. Flows simulated under land-use change, however, showed no hydrologic alteration. Overall, the climate change for the A2 scenario showed the most alteration in the basin. There was a wide variation among the simulations under the different GCM data sets that leads to uncertainty in the flows. The framework was found to streamline the tools and methods used in modeling the streamflow in the basin under climate and land-use change conditions and enable systematic assessments of their affects on ecological flow alterations. Further investigation into the uncertainty in the flows is needed, while other preprocessing tools such as multi-model combinations can be integrated into the framework to potentially improve it.

# A Quantitative Framework for Assessing the Effects of Climate and Land-use Change on Streamflow

by
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## DEDICATION

This thesis is dedicated to my parents and sister.

You are everything to me.

# BIOGRAPHY

Danielle's life is in sets of six. She was born in Statesville, NC on August 5, 1986 and immediately moved to Saudi Arabia with her parents and big sister. They lived there until Danielle was six and then moved to the United Arab Emirates where they lived for the next six years. The next six years of her life was spent in Cyprus where she became interested in rivers and hydrographs from her Geography class. She chose to study Civil Engineering at North Carolina State University and after receiving her B.S. degree, decided to continue into her M.S. degree in Water Resources and Environmental Engineering which coincidentally made it another six in NC. Other than hydrology and statistics, Danielle has a passion for traveling and non-profit work. Where will Danielle's next six years take her?

## ACKNOWLEDGEMENTS

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## 1. Introduction

The hydrology in a watershed can be impacted by changes in land-use and climate. These changes can ultimately affect the ecology by altering the flows in the channel. Assessments of these effects have been studied for at least two decades, and a large number of hydrologic, climate and land-use models have been developed. National datasets have also been established ranging from observed hydroclimatic time series to future scenarios of the climate that are provided by the Intergovernmental Panel for Climate Change (IPCC). The common practice related to development in watersheds, however, continues to focus on analyzing the peak flow of extreme events and minimum flows. This has been criticized as being insufficient in a non-stationary environment and for ecological purposes (Poff et al., 1997).

Studies in the past have assessed streamflow changes in the watershed due to either climate change, land-use change, or both, but there is no established approach to study these changes systematically. Basins have been studied using different methodologies, resulting in different types of results. Praskievicz and Chang (2009) summarize multiple studies that have assessed the changes in streamflow due to climate or land-use change. Consideration of uncertainties includes scenario uncertainty, model uncertainty and variability in the associated physical (e.g., atmospheric and hydrological) systems (Hawkins and Sutton, 2009; Praskievicz and Chang, 2009).

A systematic approach is needed to combine the models and data sets to support a comprehensive assessment of the impacts on ecological flows arising from land-use alterations and climate change. The Indicators of Hydrologic Alterations (IHA) parameters use statistics of the daily flows to assess the ecology relevant changes (Richter, 1996). These parameters encompass all characteristics of the daily flow regime including the magnitude of the flow, the duration and timing of flow events, the frequency and duration of high and low pulses and the rate and frequency of flow changes. The classifications of the parameters are linked to certain aspects of the ecology of the river basin. For instance, the magnitudes of monthly flows influence the habitat availability for aquatic organisms and the reliability of water supplies for terrestrial animals, while the timing of extreme annual conditions is linked to the life cycle of organisms as well as their reproduction needs. Some other flow parameters represent nutrient and organic matter availability and drought stress on plants. The IHA parameters also capture common hydrologic characteristics of the flow regime that are studied for other applications such as reservoir management and water treatment (Richter, 1996). These parameters can be used to establish a systematic approach within a quantitative framework to assess the effects of climate and land-use change scenarios on streamflow and associated ecological impacts.

This paper describes a framework for analyzing the impacts of climate change and land-use change on ecological flow alterations in a basin. First, the climate and land-use changes that are being assessed are described, including their temporal and spatial scales. Then, the models used in the framework as well as the available data sets are presented. Subsequently, the study applies the framework to assess a basin in North Carolina that has been experiencing rapid development. Then the results from the analyses are presented, with a discussion of the impacts of climate and land-use changes in altering ecological flows. Finally, concluding remarks and observations about the framework are presented.

## 2. Problem definition

This paper provides a framework for assessing the role of  climate and land-use changes in altering the ecological flow in a basin. Future changes in the climate and land-use are uncertain since they depend on the economy, politics and demography of the globe. As the lead-time increases, future projections deviate further from the present and more assumptions are made, and become more uncertain. Therefore, it is important to consider different projections as characterized by the storylines developed by the Intergovernmental Panel for Climate Change (IPCC) to assess the changes in a basin. Storylines A2 and B1 are considered here. Further details on the A2 and B1 (Table 2.1) storylines can be found in the IPCC Fourth Assessment Report (AR4) (IPCC, 2007).

*Table 2.1: Descriptions of the A2 and B1 storylines from IPCC AR4.*

| **A2** | **B1** |
|---|---|
| Differentiated world | Convergent world |
| Regionally oriented economy with a lowest per capita growth out of all scenarios | Service and information based economy with a higher per capita growth than A2 but not the highest |
| Continuously increasing population | Population peaks at 2050 then declines |
| Self-reliant governments preserve local identities | Global governments provide solutions to economic, social and environmental sustainability |
| Slowest and most fragmented technological development out of all scenarios | Clean and resource efficient technologies |

To make these storylines more relevant and meaningful, they have been converted to scenarios that project the changes in populations, GDP, land development, emissions and other parameters related to growth (Figure 2.1). The scenarios can then be explicitly incorporated to drive the emissions in general circulation models (GCMs) and the associated land development in land-use models. Using this information, assessments can be made about other aspects of the physical environment, including the hydrological and ecological impacts in the basin.

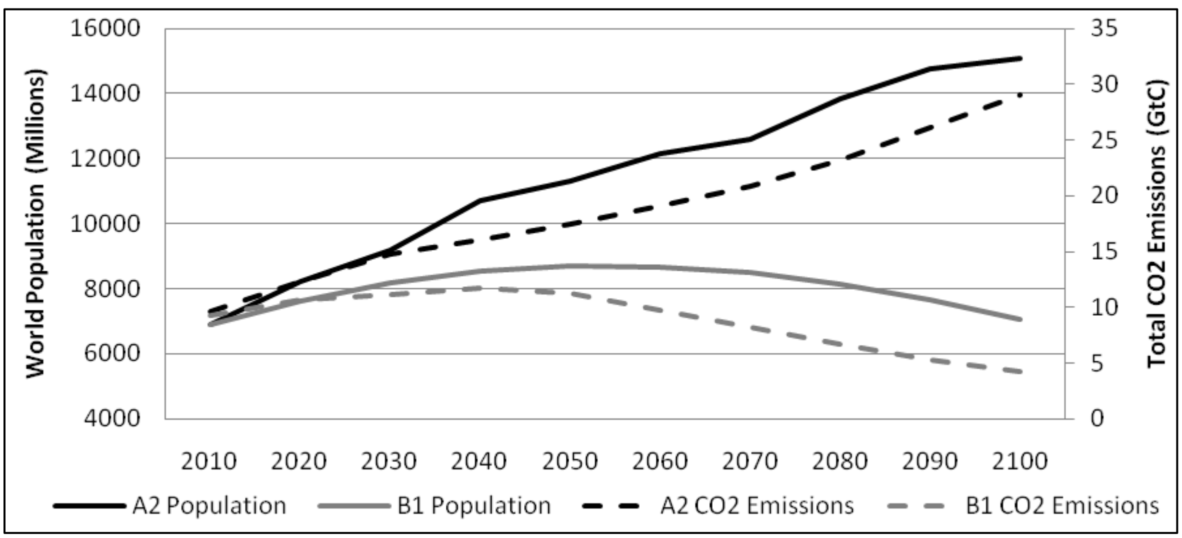



*Figure 2.1: Emissions and population projections for the A2 and B1 storylines (SRES, 2000).*

Based on the projected temperatures under different scenarios, it has been shown that the uncertainties in the scenarios are significantly less in the nearer future (30 years) than in the later years (100 years) (Hawkins and Sutton, 2009). Engineering and planning decisions typically take place in this time frame. Having a more reliable and realistic assessment for the next 30 years is more helpful and needed than a vague vision for the next 100 years. Therefore, the analysis presented is illustrated using a near-term (30 years) consideration, even though it could be used over other desired time scales.

Data from GCMs and the Environmental Protection Agency (EPA) Integrated Climate and Land-Use Scenarios (ICLUS HD) (US EPA, 2009) for the A2 and B1 storylines are combined with a hydrologic watershed model. Using demographic population projections consistent with the storylines as an input, the ICLUS HD model assigns new housing densities across the landscape (US EPA, 2009). Because the available climatic data are not spatially or temporally compatible with the hydrologic model, several preprocessing steps are used in the framework. This includes spatio-temporal downscaling of climatic data so that it can be utilized as daily input into the watershed model, and conversion from housing density classes into National Land Cover Data set classes to correctly model the hydrologic processes. By matching the climate and land-use data to the spatio-temporal resolution of the watershed model, changes in the streamflows can then be assessed using flow regime alteration indicators represented by the IHA parameters and other statistical measures.

## 3. Methodology

Figure 3.1 shows the key steps used in the framework to assess the effects of land-use change and climate change on hydrologic flow alterations. Each major step is described below.

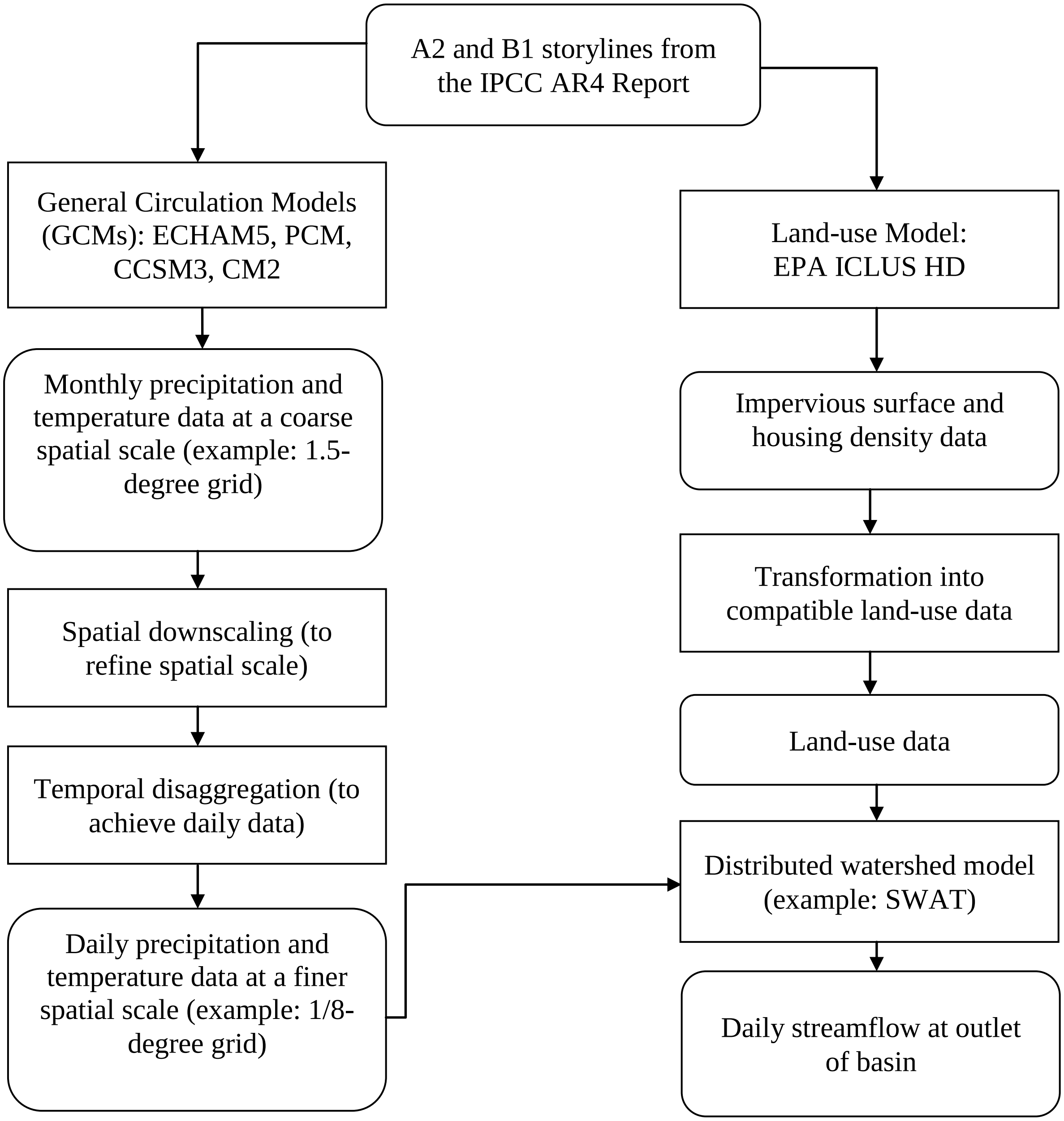



*Figure 3.1: Structure of the framework used for assessing the impact of climate change and land-use change on ecological flows.*

## 3.1. Climate data

Sixteen GCM model simulations for the A2 and B1 scenarios are available from the IPCC database for the years 2010-2100. The models chosen in this study are ECHAM 5 (Jungclaus et al., 2006) by the Max Planck Institute for Meteorology, CM2.0 (Delworth et al., 2005) by the Geophysical Fluid Dynamic Laboratory, NOAA, and the PCM (Washington et al., 2000) and CCSM3 (Collins et al., 2006) by the National Center for Atmospheric Research. These models have been used often for impact studies in the US and are generally accepted in the climate and hydrological modeling communities. Projections from these GCMs, primarily precipitation and temperature, are available at a monthly time scale over a larger spatial resolution.

#### 3.1.1. Spatial downscaling

The spatial scale of the climate data, which is in a 1.5-degree grid, has large biases in certain geographic areas, especially in coastal or mountainous regions (Wood et al., 2002). To overcome this issue, regional climate models can be used, but they are computationally intensive. Therefore, spatial downscaling using statistical techniques was used in the framework to obtain the climate data in a 1/8-degree grid scale. Spatial downscaling requires observed data for both 1/8-degree and 1.5-degree scales. Additionally, GCM-simulated climate data for the observed period is needed. The observed data on a daily scale is available from the Surface Water Modeling group at the University of Washington for the US (Maurer et al., 2002). The GCM's historical predictions are also available from the IPCC database.

The spatial downscaling technique is a two-step procedure that includes bias correction and downscaling methods. This procedure was established by the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project (CMIP3) (Wood et al., 2002; Maurer et al., 2007). The first step of the method removes any bias that the GCM included in the 21$^{st}$ century monthly climate data set by using the 20$^{th}$ century monthly climate simulation by the GCM and the observed monthly climate data set for the set of 1.5-degree grid points in question. By using a quantile mapping technique on these data sets, any tendency to over or under predict the 21$^{st}$ century climate was removed. The second spatial downscaling step established a ratio between the 1/8-degree observed data for each month and the corresponding 1.5-degree observed data for each grid point. Using this ratio, the 1.5-degree GCM data for that month were then downscaled to a 1/8-degree grid. The WCRP

CMIP3 maintains a database for the sixteen climate models with downscaled datasets of monthly precipitation and temperature at a 1/8-degree grid for the US. These datasets were used in the research reported here.

### 3.1.2. Temporal disaggregation

For the purpose of simulating the hydrologic model at a daily scale, temporal disaggregation was applied to obtain daily precipitation and temperature data from the GCMs' monthly data. A *k*-nearest-neighbor algorithm (*k*-NN) was used to temporally disaggregate the downscaled monthly climate data (Cover and Hart, 1967). This disaggregation method was used in the studies reported by both Wood et al. (2002) and Salathe (2004). This method uses past daily observations to create the structure of the daily temperature and precipitation data based on the future monthly values, assuming that the daily structure is similar. Also, each month was disaggregated using the values for the same month from the historic data. For example, to disaggregate the monthly precipitation value for January 2015, only January historic data were used. This approach preserves the seasonality with the associated climate data. The closest neighbor was used to disaggregate precipitation to preserve the number of zero-rain days. The observed and future monthly time series of the grid points in the basin were spatially averaged. Then, for each spatially averaged future month, a nearest neighbor month was chosen from the spatially averaged observed data. Then, this nearest neighbor month was used to disaggregate all the grid points in the future month. The daily precipitation values from the nearest neighbor month were divided by the total precipitation of that month to obtain daily fractions. Each daily fraction was then applied to the future monthly value to obtain daily time series of precipitation under different scenarios.

For disaggregating temperature, ten neighbors were used since there is no constraint with zero flow days as there is in precipitation. Using ten neighbors reduces the variance in the disaggregated data. The monthly values for the future data were compared with the monthly values of the observed data to obtain the first ten neighbors. Then, each of the neighbors was resampled by giving different weights using the Epanechnikov kernel (Equation 3.1).

$$w(k) = \frac{3}{4}\,(1 - k^2) \tag{3.1}$$

where w(k) is the weight of the $k^{th}$ neighbor.

The minimum and maximum temperatures for each day of the future month were obtained by using a weighted average of the observed minimum and maximum temperatures in the neighboring months.

## 3.2. Land-use data

Land-use data for the framework (Figure 3.1) were obtained from two sources: the current land-use data were obtained from the 2001 USGS National Land Cover Database (NLCD 2001) (USGS, 2008) and the land-use model projections for housing density scenarios were obtained from EPA's ICLUS HD (US EPA, 2009). The ICLUS HD scenarios are available on a decadal scale for the $21^{st}$ century on a one-hectare scale for all of the US. The land-use models are also available as ArcGIS toolboxes in which the parameters can be modified to specify different scenarios.

There is incompatibility between the NLCD 2001 and ICLUS HD datasets due to the different land-use classifications. The ICLUS HD categories are rural, exurban, urban/suburban, commercial/industrial and undevelopable (Table 3.1), while the NLCD 2001 development categories fall into low intensity development, medium intensity development and high intensity development (Table 3.2). The EPA study did not find a direct relationship between ICLUS HD categories and the NLCD 2001 classes. They tested, however, a linear relationship between the impervious surfaces and the housing density definitions but found a poor fit.

*Table 3.1: EPA ICLUS HD categories' definitions.*

| Housing density category | EPA definition (lots/acre) |
|---|---|
| Rural | >16.18 ha per housing unit (<0.03) |
| Exurban | 0.68-16.18 ha per housing unit (0.03-0.60) |
| Urban/Suburban | < 0.68 ha per housing unit (>0.6) |
| Commercial/Industrial | > 25% urban/built up areas |

*Table 3.2 USGS NLCD 2001 class definitions.*

| NLCD 2001 class | Definition | SCS curve number description |
|---|---|---|
| Developed, Low intensity | Single family housing units | 1 lot/acre |
| Developed, Medium intensity | Single family housing units | 2-4 lots/acre |
| Developed, High intensity | Apartment complexes, row houses | 8 lots/acre |
| Industrial | Infrastructure, highly developed | 80% impervious |

By doing an assessment of the relationship between the lot/acre measure in the ICLUS HD definition and the SCS curve number descriptions of the NLCD 2001 class, all the “developed” NLCD 2001 classes were found to fit the definition of the Urban/Suburban EPA category. Therefore, the growth in the Urban/Suburban category was applied equally to the NLCD developed classes, and the growth in the Commercial/Industrial category was applied to the industrial NLCD 2001 class. Even though this simplifies the relationship, it captures the average development that occurs in the basin.

Additionally, the ICLUS HD project output does not specify the changes by the land-use categories, but by urban density changes. Thus, an assumption must be made about the other land-uses in the basin. Possible sources of information to improve these assumptions include local or regional planning documents.

## 3.3. Hydrologic watershed model

As shown in the framework (Figure 3.1), the land-use and climate data are given as input to the watershed model to simulate the streamflow data at the outlet of the basin. The Soil and Water Assessment Tool (SWAT) was used in this research. The driving force of the model is the water balance in the watershed, taking into account the climate, the topography, soil and land-use in the watershed. The SWAT model splits the basin into several subbasins, which are then split into hydrologic response units (HRUs) that have their unique land-use, soil type and slope specifications. HRUs are not allocated spatially in the subbasin, but are computational units that are used to calculate mass balances for the subbasin. Using the HRUs, the land phase of the hydrologic cycles is processed to determine the amount of water as well as nutrient and sediment loadings to the subbasin channel. The routing phase of the hydrologic cycle then moves the water through the channel network in the watershed to the basin outlet (Neitsch et al., 2005). Land-use can be allocated on a subbasin-specific scale, which is acceptable for smaller watersheds.

The SWAT model is available in ESRI ArcMap, which is part of the ArcGIS Desktop package, through an interface developed by Blackland Research Center in the Texas Agricultural Experiment Center (Winchell at al., 2010). The ArcSWAT interface within ESRI ArcMAP analyzes the topography and allows for an outlet to be chosen within the basin for automatic watershed delineation. The topography is represented by the Digital Elevation Model (DEM), which was obtained from the USGS Seamless Server (USGS, 2004). Additionally, soil data were retrieved from the National Resources Conservation Service (NRCS) (Soil Survey Staff, 2010), which is part of the Department of Agriculture. These are raster datasets with the DEM being on a refined 1/3-degree scale.

## 3.4. Assessment of flows

The output of the framework is the time series of daily flows at the outlet of the basin (Figure 3.1), which was then processed using statistical methods to assess changes in the flow regime. The comparison was made between two periods: a “pre-development” period that represents the conditions prior to any significant changes that may affect the hydrology in the basin, and a “post-development” period that represents some changed conditions in the basin. In this research, the pre-development period was set to be the past thirty years (1981 – 2011) and the post-development period was set to be the next thirty years (2011 – 2040).

For the pre-development period data, the model was run using the NLCD 2001 land-use cover set, and the flow was simulated using the observed gridded precipitation and temperature data. The post-development period was based on seven combinations, in which the climate and land-use change data for different scenarios was used (Table 3.3). These combinations are realistic possibilities for the future and are useful in separating the land-use change effects from the climate change effects. The model was run continuously from 1980-2040, and the land-use for 2020 and 2030 was updated accordingly for Combinations 2, 3, 5 and 7. To assess the changes between the two periods using a statistical approach, significance testing of the changes in mean, standard deviation and trends of streamflow was conducted.

*Table 3.3: Combinations for the post-development period flows.*

| Combination | Climate change | Land-use change |
|---|---|---|
| **1** | Same as pre-development period | Same as pre-development period |
| **2** | Same as pre-development period | A2 scenario |
| **3** | Same as pre-development period | B1 scenario |
| **4** | A2 scenario | Same as pre-development period |
| **5** | A2 scenario | A2 scenario |
| **6** | B1 scenario | Same as pre-development period |
| **7** | B1 scenario | B1 scenario |

### 3.4.1. Statistical approach

Significance tests are used to verify whether any change between the pre-development period and post-development period is a sampling error or a meaningful change. The two-sample *t*-test was used to test whether the differences in the mean flow values are statistically significant:

$$t = \frac{\bar{x}-\bar{y}}{S_p\sqrt{\frac{1}{n}+\frac{1}{m}}}\ is\ either \begin{cases} \leq & -t_{\alpha/2,n+m-2} \\ \geq & t_{\alpha/2,n+m-2} \end{cases} \tag{3.2}$$

where the pooled variance, $S_p^2$ is defined as

$$S_p^2 = \frac{(n-1)S_X^2+(m-1)S_Y^2}{n+m-2} \tag{3.3}$$

where $\bar{x}$ is the mean of the variable in the pre-development period, $\bar{y}$ is the mean of the variable in the post-development period, $S_X^2$ is the variance of the variable in the pre-development period, $S_Y^2$ is the variance of the variable in the post-development period, n number of data points in the pre-development period, m is the number of data points in the post-development period, and $t_{\alpha/2,df}$ is the percentile of the t-distribution for α level of significance and df degrees of freedom (Larsen and Marx, 2006).

The *F*-test was then used to evaluate the significance of a given change in the variance of streamflow data. Whether there is a change in the mean or not, a change in the annual variance may denote an alteration in the flow regime between the pre- and post-development periods. For the variance to be significantly different,

$$\frac{S_Y^2}{S_X^2}\ is\ either \begin{cases} \leq \quad F_{\alpha/2,m-1,n-1} \\ \geq F_{1-\alpha/2,m-1,n-1} \end{cases}, \qquad (3.4)$$

where $F_{\alpha/2,m,n}$ is the percentile of the F-distribution for α level of significance with m and n degrees of freedom (Larsen and Marx, 2006).

A trend could also be present in the flow, indicating that the flows are consistently increasing or decreasing due to land development. To test for the significance of a trend, a linear regression equation, y = bt + c, was created. The predictor, t, is time, the predictand, y, is the annual precipitation, temperature or streamflow, and b describes the trend of the variable in time. To show its significance at an α level, a derivation of the t-statistic was used (Larsen and Marx, 2006).

$$\frac{\sqrt{n-2}\,b\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}}{\sqrt{n\sigma^2}}\ is\ either \begin{cases} \leq \ -t_{\alpha/2,n+m-2} \\ \geq \quad t_{\alpha/2,n+m-2} \end{cases}, \qquad (3.5)$$

where $\sigma^2$ is the variance of the data.

### 3.4.2. Ecological flow alterations analysis

The IHA parameters (Table 3.4) can be analyzed by comparing the flow regime in the pre-development period with that in the post-development period. The IHA parameters are classified into five groups based on their potential effect on the ecology. To assess the relative change in each parameter value, the Range of Variability Approach (RVA) was used (Richter, 1997). The range of variability for each IHA parameter was first obtained by determining the 33rd and 67th percentiles of the flows in the pre-development period. These values define three (high, middle and low) categories in which approximately a third of the data points lie (Figure 3.2). The same distribution is expected to occur in the post-development period flows if the natural variability in the flow is expected to be similar.

*Table 3.4: Summary of IHA parameters as classified into five groups.*

| IHA parameter group | Hydrological parameters |
|---|---|
| Group 1: Magnitude of monthly water conditions | Mean or median value for each calendar month |
| Group 2: Magnitude and duration of annual extreme water conditions | Annual minima 1-day means<br>Annual maxima 1-day means<br>Annual minima 3-day means<br>Annual maxima 3-day means<br>Annual minima 7-day means<br>Annual maxima 7-day means<br>Annual minima 30-day means<br>Annual maxima 30-day means<br>Annual minima 90-day means<br>Annual maxima 90-day means<br>Number of zero-flow days<br>Base flow index (7-day minimum flow/mean flow for year) |
| Group 3: Timing of annual extreme water conditions | Julian date of each annual 1-day maximum<br>Julian data of each annual 1-day minimum |
| Group 4: Frequency and duration of high and low pulses | Number of high pulses each year<br>Number of low pulses each year<br>Mean or median duration of high pulses within each year (days)<br>Mean or median duration of low pulses within each year (days) |
| Group 5: Rate and frequency of water condition changes | Rise rate (mean or median of all positive differences between consecutive daily values)<br>Fall rates (mean or median of all negative difference between consecutive daily values)<br>Number of hydrologic reversals |

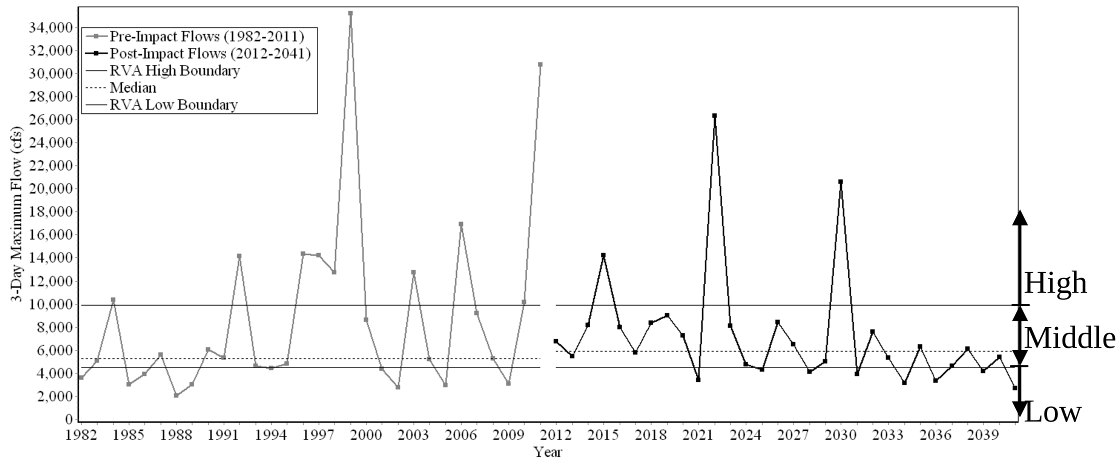



*Figure 3.2: 3-Day Maximum analysis for an example set of pre-development period and post-development period flows.*

To obtain the total alteration in the variability in all parameter values, the sum of mis-hits approach was used (Table 3.5) (Pierpont, 2008). This approach sums the absolute difference between the pre-development period and the post-development period data points in each category over all the parameters of importance. This approach helps to gain insight into the magnitude of the total change in the parameter values but it does not distinguish the changes by categories or the direction of changes. Thus, an "alteration ratio" was defined to represent the change in relation to the pre-development conditions in each category (Table 3.5 and Figure 3.3). For each parameter, a ratio value of 1 for a category indicates that there is no change in the number of occurrences in that category, while a ratio greater than 1 indicates an increase in the occurrences in that category and vice versa. While this representation of changes in the flow enables assessment of the direction of change as well as the degree of change for each parameter, it is not suitable for an aggregate indicator, which is captured by the number of mis-hits.

*Table 3.5: Sum of mis-hits and alteration ratio calculations for the example in Figure 3.2.*

| Category | Pre-development | Post-development | Alteration Ratio | Mis-hits |
|---|---|---|---|---|
| **High** | 10 | 3 | 0.3 | 7 |
| **Middle** | 10 | 19 | 1.9 | 9 |
| **Low** | 10 | 8 | 0.8 | 2 |
| | | | | **Sum** = 18 |

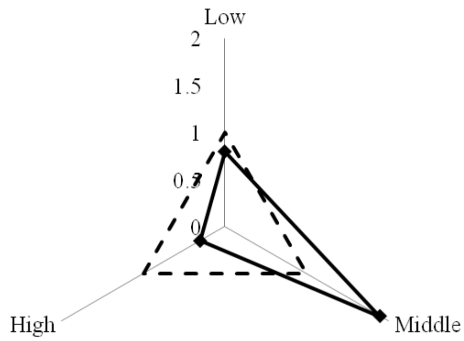



*Figure 3.3: Graphical representation of alteration ratio. Dashed triangle shows the no-alteration case while solid line shows the alteration ratios for the 3-Day Maximum Flow parameter illustrated in the example in Figure 3.2.*

## 4. Illustrative example

### 4.1. Basin description

The framework was applied to the North East Cape Fear (NECF) Basin (Figure 4.1) to study the effects of land-use and climate change on the ecological flows. This basin is part of the Cape Fear watershed in North Carolina, and it has eight different soil types with fourteen different land-use types where agricultural row crops dominate (Table 4.1). USGS gauge 02108000, located at the outlet of the basin, provides a relatively long period of record dating back to the 1960's. This outlet includes drainage from 23 subbasins covering a total area of 668 square miles (Figure 4.2). The NECF Basin also has no large reservoirs on its main channel, which helps void the need for considering potential changes in the flow due to man-made storage.

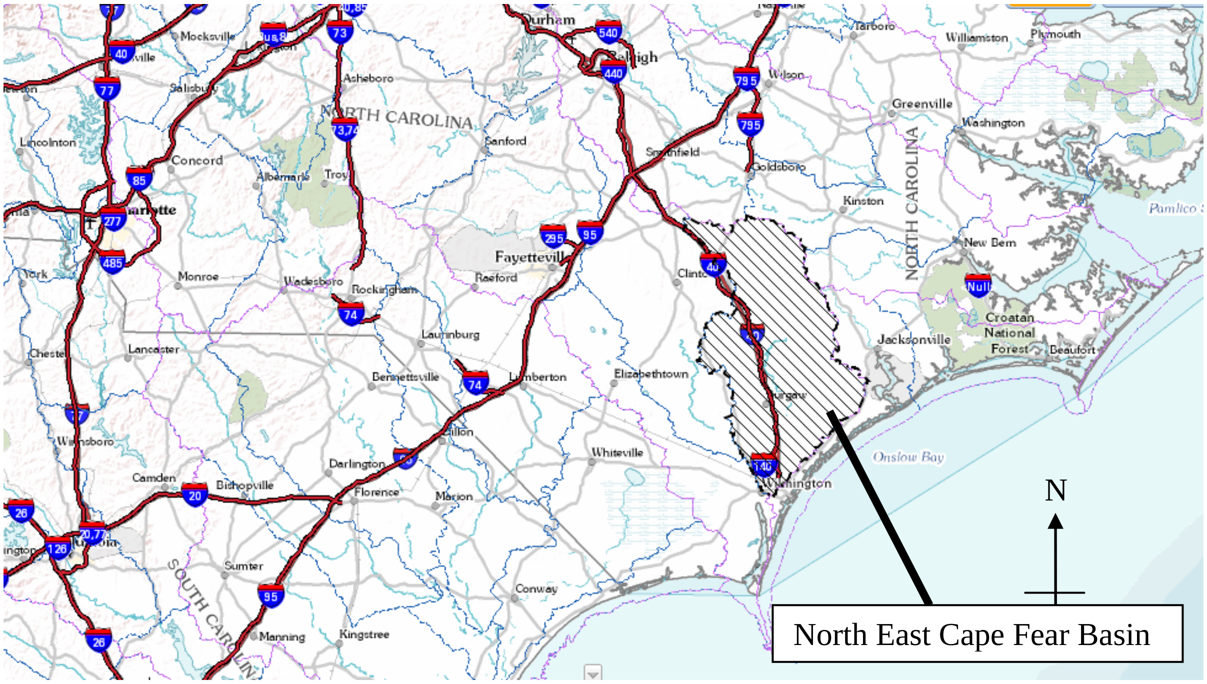


*Figure 4.1: Location of NECF River Basin in NC.*

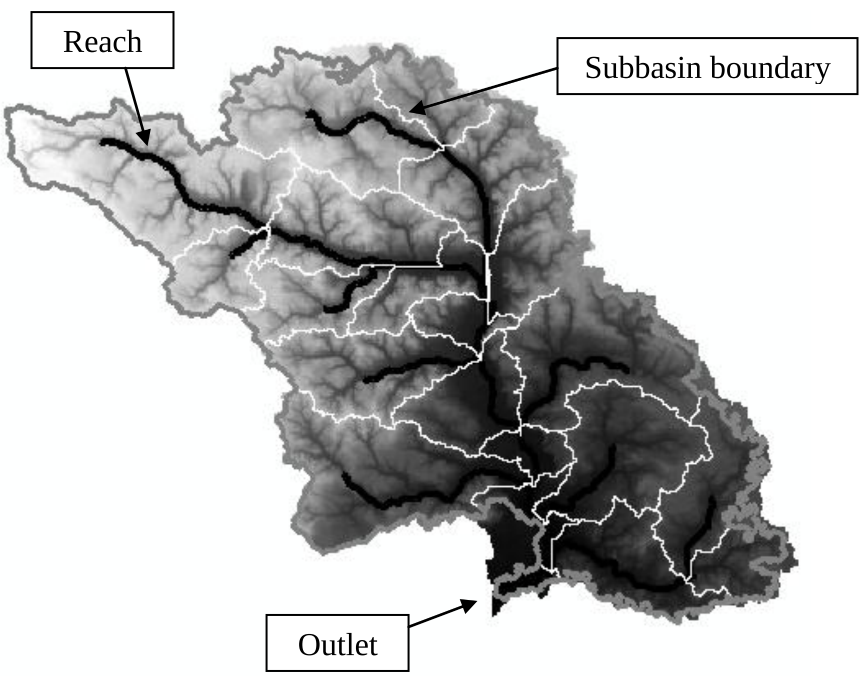
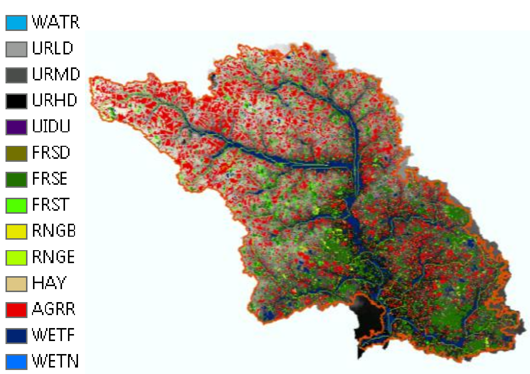


*Figure 4.2: DEM of the delineated watershed with 23 subbasins, main and tributary reaches and the longest path of flow for each subbasin, calculated by ArcSWAT. The outlet is located on the southern boundary of the basin.*

The DEM and land-use data were downloaded from the USGS Seamless Server and the soil cover from NRCS (Figures 4.3 a and b). The basin has a relatively low percentage (4.07%) of developed urban area (Table 4.1), but that area is expected to grow in the future decades, as evidenced by the high population growth (in the period 1990-2000) of the two main counties, Pender and Duplin, in the basin with 42% and 23% growth rates, respectively.

a)




b)

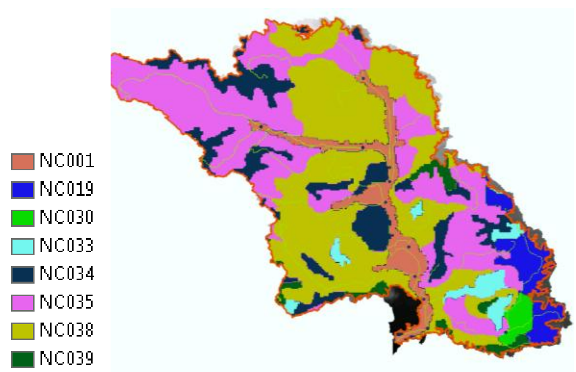



*Figure 4.3: Land-use data (a) from NLCD 2001 data and soil data (b) from NRCS for the NECF Basin.*

*Table 4.1: NCLD 2001 Land-use/Land Cover categories in the basin with the corresponding percentage of basin area covered.*

| **NCLD 2001 Land-use/Land Cover (abbreviation in legend for Figure 4.3)** | **Percentage of Basin Area (%)** |
|---|---|
| Water (WATR) | 0.18 |
| Residential – Low Density (URLD) | 3.28 |
| Residential – Medium Density (URMD) | 0.68 |
| Residential – High Density (URHD) | 0.09 |
| Industrial (UIDU) | 0.02 |
| Forest – Deciduous (FRSD) | 3.17 |
| Forest – Evergreen (FRSE) | 17.32 |
| Forest – Mixed (FRST) | 6.13 |
| Range – Brush (RNGB) | 5.50 |
| Range – Grasses (RNGE) | 8.66 |
| Hay (HAY) | 0.99 |
| Agricultural Land – Row Crops (AGRR) | 36.60 |
| Wetlands – Forested (WETF) | 16.68 |
| Wetlands – Non-Forested (WETN) | 0.50 |

As the simulated climate data for the coastal basin are more likely to exhibit a bias than those for inland basins, a higher level of spatial refinement of the climate data was needed. Gridded observed daily temperature and precipitation data are available on a 1/8-degree scale, which were used to simulate the flow in the pre-development period and to disaggregate the precipitation for the post-development period (Figure 4.4). The seasonality of the climate is in phase, with the highest temperatures coinciding with the greatest amounts of precipitation. This results in the monthly streamflows being greatest in the winter when precipitations rates are relatively high and temperatures are low. Further, the basin experiences low flows during the spring months due to higher temperatures and lower precipitation.

a) b)

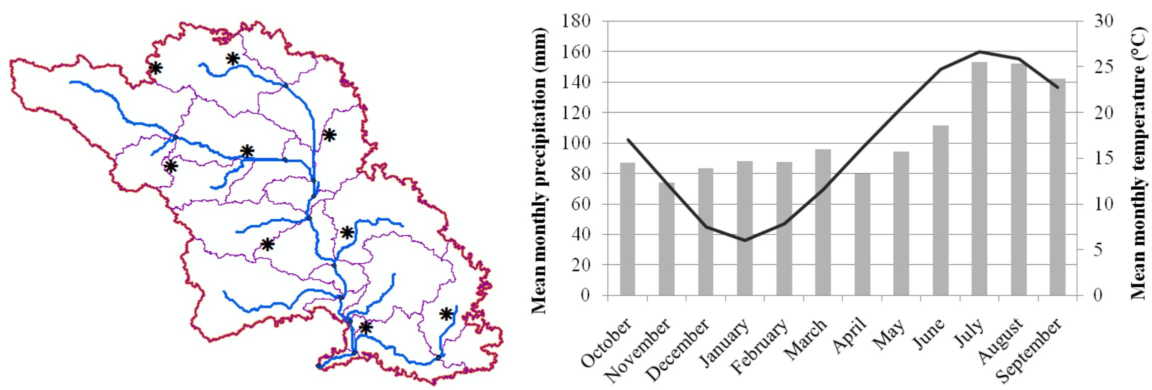



*Figure 4.4:a) Nine grid points of precipitation and temperature data used for simulating the flows in the NECF basin, and b) spatially averaged 1980-2010 mean monthly precipitation and temperature values for the NECF basin.*

## 4.2. Calibration of the SWAT model for the NECF basin

After calibration, the SWAT model performance for the NECF basin was evaluated using the R-squared values and Pearson's correlation coefficient between the simulated and observed daily, monthly and annual flows for 1981-2005 (Table 4.2 and Figure 4.5). Previous studies using SWAT as well as unofficial discussions among users have reported that similar calibration performance levels are acceptable. Even though the SWAT model consistently predicted higher flows than observed flows for the basin (Figure 4.6 a and b), the simulated flows vary reasonably well with the observed flows over different time scales (Table 4.2). Though the SWAT model over predicts the observed flows, assessing the alterations in the flows will be only minimally impacted since it is reasonable to expect the marginal bias to be similar over the pre-development and post-development periods.

*Table 4.2: Statistics of SWAT model calibration using 1981-2005 observations at the NECF outlet.*

| Timescale | R-squared value | Correlation coefficient |
|---|---|---|
| **Daily** | 0.69 | 0.83 |
| **Monthly** | 0.81 | 0.90 |
| **Annual** | 0.77 | 0.88 |

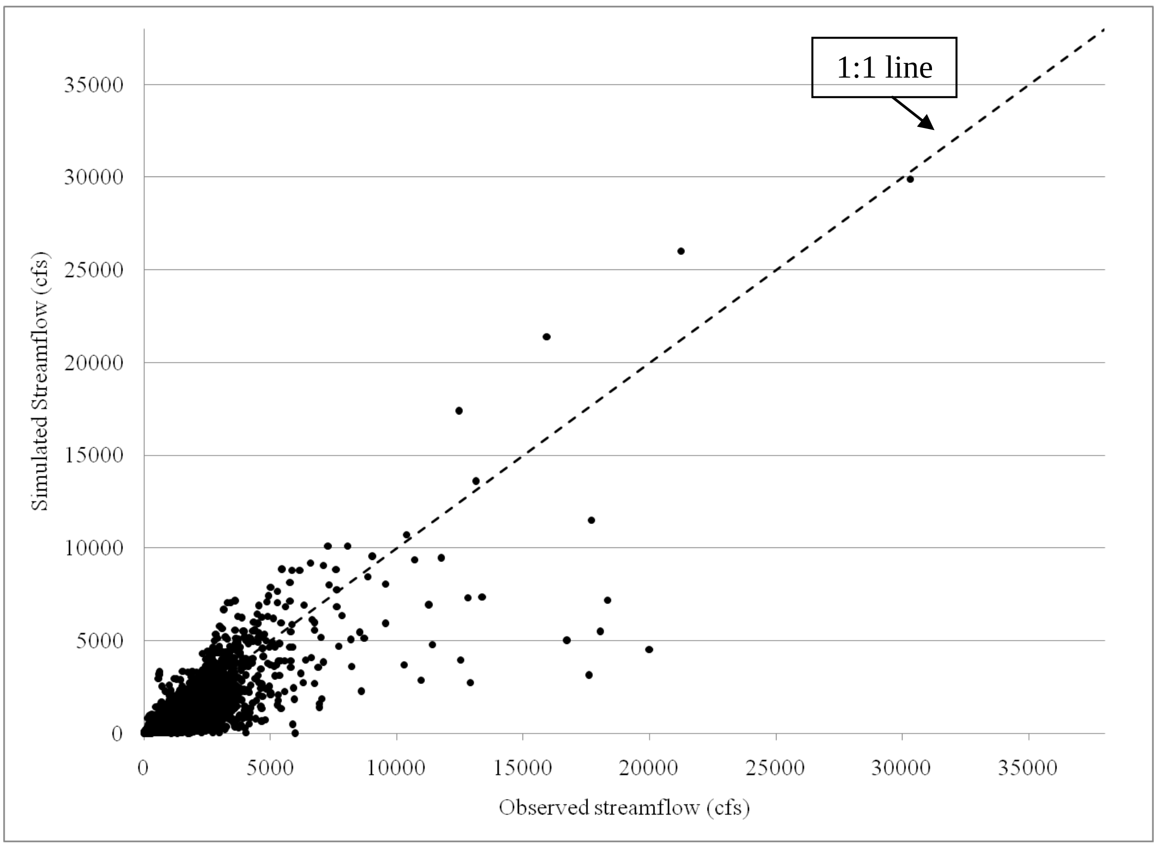



*Figure 4.5: Scatter-plot of the simulated and observed daily flows for 1981-2005.*

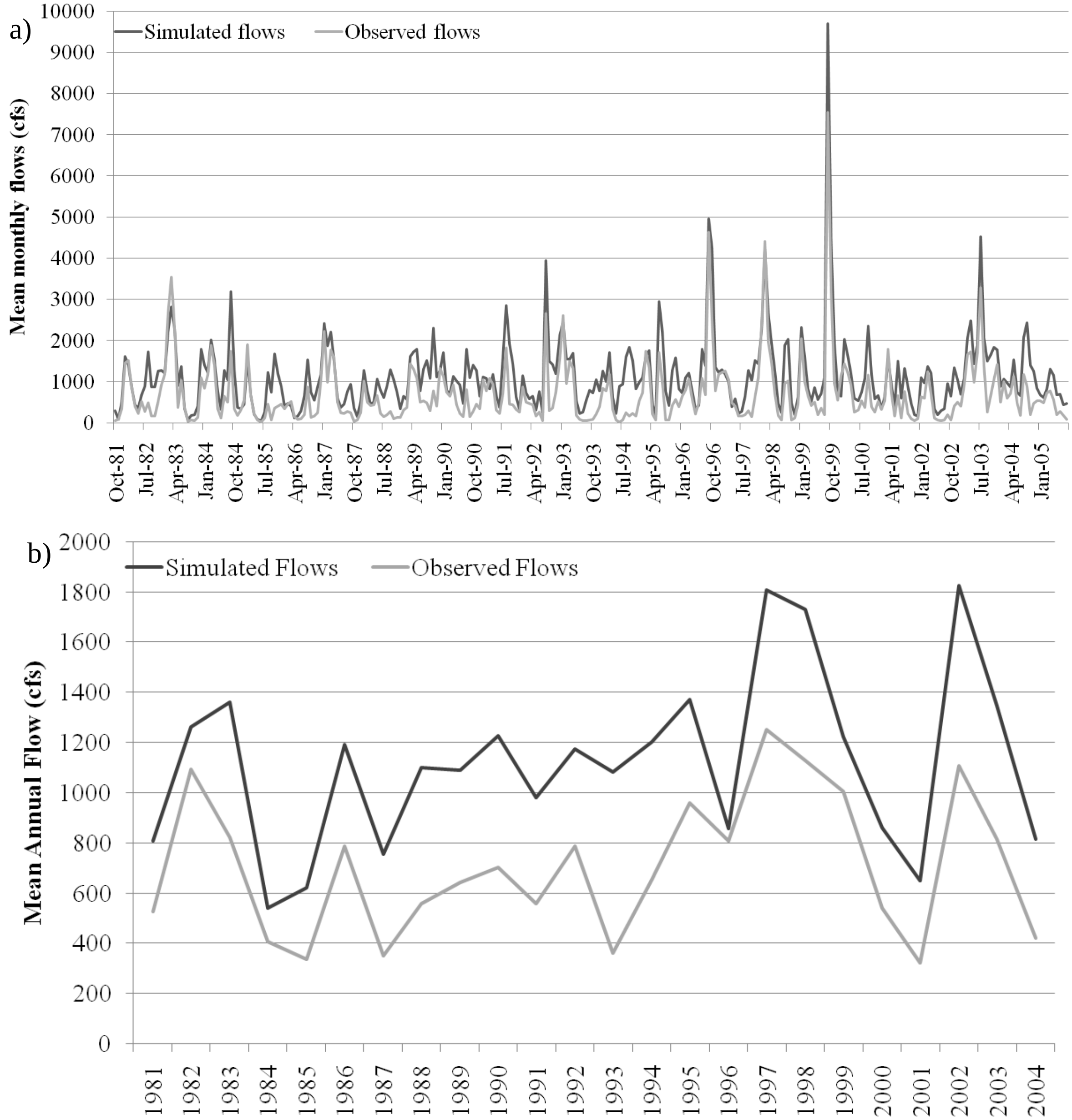



*Figure 4.6: (a) Mean monthly simulated and observed flows, and (b) mean annual simulated and observed flows for 1981-2005 in the NECF basin.*

## 4.3. Future climate and land-use change in the NECF River Basin

### 4.3.1. Projected climate change in the NECF River Basin

The climate data for the basin from the four GCMs that had been spatially downscaled were tested using significance tests described in Section 3.4. Significant changes in the climate data are expected to result in significant changes in the simulated flows. Using the t-test for significance testing, the pre-development period and post-development period mean values were compared for both A2 and B1 scenarios for all GCMs, while the pre-development period and post-development period standard deviations were tested using the F-test. Overall, the mean annual precipitation exhibited significant changes only in two GCMs for the A2 scenario and one GCM for the B1 scenario (Table 4.3).

*Table 4.3: Mean annual precipitation in the basin for the A2 and B1 scenarios. Values that are significantly different than the pre-development period values are indicated by an asterisk.*

| | A2 Scenario | | B1 Scenario | |
|---|---|---|---|---|
| **GCM** | **Mean Annual Precipitation Average (mm)** | **Mean Annual Standard Deviation (mm)** | **Mean Annual Precipitation Average (mm)** | **Mean Annual Standard Deviation (mm)** |
| **Pre-development period** | 1252 | 185 | 1252 | 185 |
| **ECHAM5** | 1372* | 198 | 1365 | 348* |
| **PCM** | 1295 | 213 | 1274 | 214 |
| **CCSM3** | 1352 | 231 | 1399* | 241 |
| **CM2** | 1388* | 246 | 1349 | 231 |

When the monthly means were assessed separately from each other using the t-test, significant changes were seen, however, in the A2 scenario using all GCMs (Figure 4.7). Except for the ECHAM simulation, the significant changes were in February, July and August precipitations. Therefore, these months are expected to show a significant change in the simulated streamflow for the A2 scenario. This implies that the models indicate pronounced seasonality, with high precipitation months receiving increased rainfall and low precipitation months receiving decreased rainfall, resulting in statistically significant change in the mean annual precipitation.

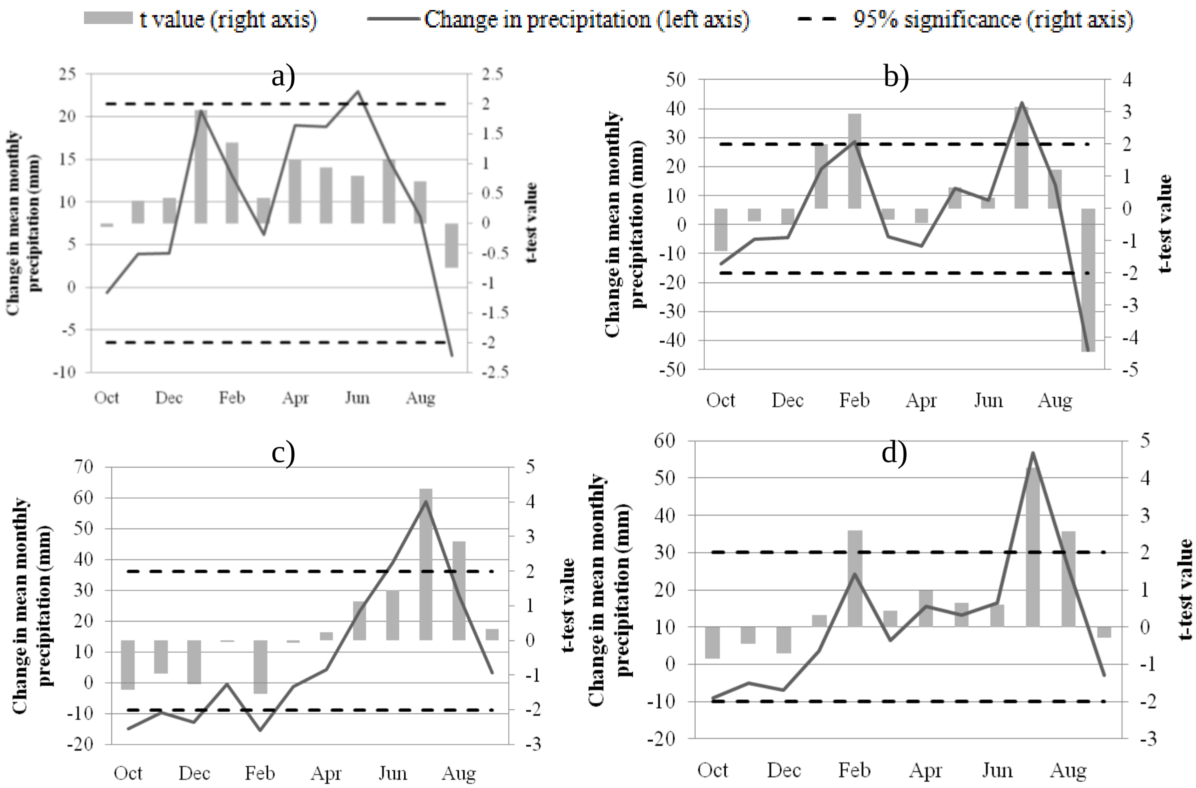



*Figure 4.7: Changes in the monthly means of the precipitation for the A2 scenario using (a) ECHAM, (b)PCM, (c) CCSM and (d) CM2 data. The t-values are shown for each month with the significant changes showing t-values above the upper or below the lower significance levels.*

Unlike in the A2 scenario, the ECHAM model in the B1 scenario had the most number of months with significant changes in the precipitation between pre-development period and post-development period (Figure 4.8a). The PCM, CCSM and CM2 models showed significant increases in the July precipitation values, while a significant decrease was associated with the ECHAM model (Figure 4.8). Additionally, ECHAM and PCM models showed a significant decrease in precipitation in August, but the CCSM and CM2 models showed a significant increase. The variations in the precipitation changes over all the GCMs show the need to use more than one GCM in the framework to overcome the uncertainties among them.

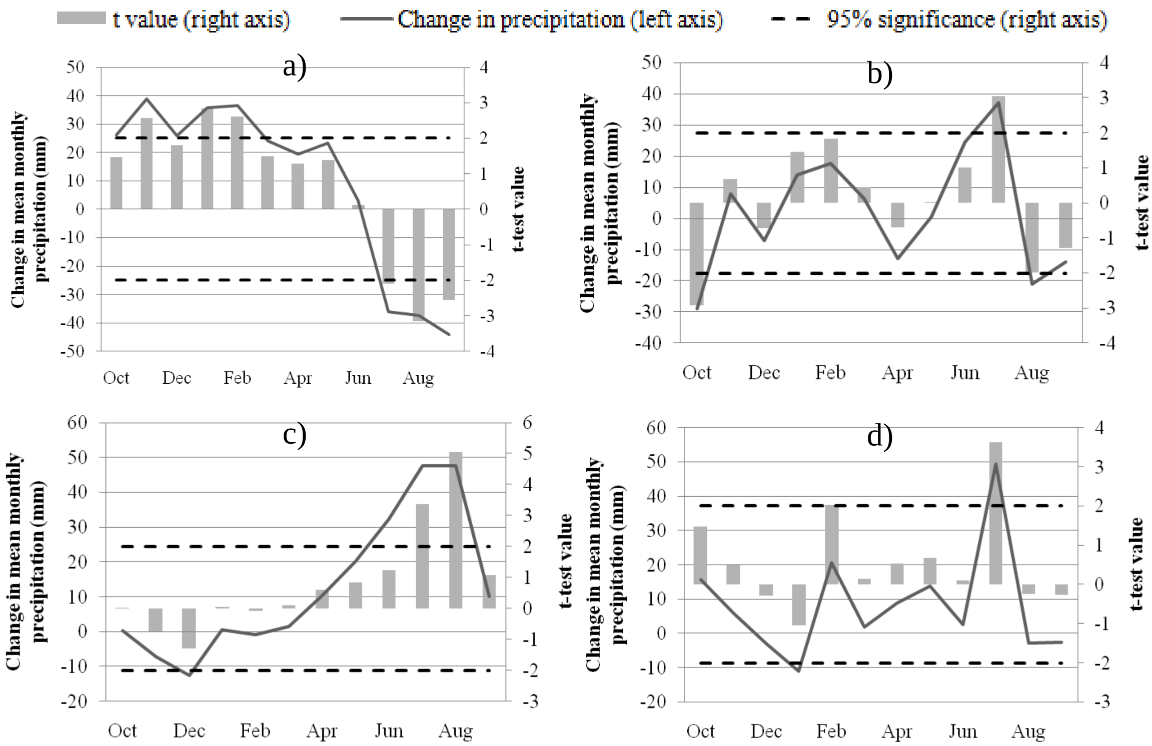



*Figure 4.8: Changes in the monthly means of the precipitation for the B1 scenario using (a) ECHAM, (b)PCM, (c) CCSM and (d) CM2 data. The t-values are shown for each month with the significant changes showing t-values above the upper or below the lower significance levels.*

Based on the t-test and F-test at a 95% significance level, the temperature changes for all GCMs and both scenarios showed no significant changes in the 30-year mean and standard deviation (Table 4.4). Additionally, the trends (not shown here) in both the combined periods and the separate periods were insignificant at a 95% significance level. There were numerous significant monthly changes, however, in the temperature (Figures 4.9 and 4.10). Whether the changes were significant or not in the climate data, the hydrologic aspects of the basin may have been sensitive to the changes and may have resulted in different levels of alteration. Also, the land-use changes may have amplified or subdued the impact of these climate change effects on the basin.

*Table 4.4: Statistical properties of the temperature for the basin for the A2 and B1 scenarios*

| | A2 Scenario | | B1 Scenario | |
|---|---|---|---|---|
| **GCM** | **Mean (°C)** | **Annual Standard Deviation (°C)** | **Mean (°C)** | **Annual Standard Deviation (°C)** |
| **Pre-development period** | 16.53 | 0.678 | 16.53 | 0.678 |
| **ECHAM5** | 17.24 | 0.841 | 17.24 | 0.852 |
| **PCM** | 16.88 | 0.560 | 17.17 | 0.486 |
| **CCSM3** | 17.43 | 0.533 | 17.63 | 0.668 |
| **CM2** | 17.26 | 0.773 | 17.25 | 0.666 |

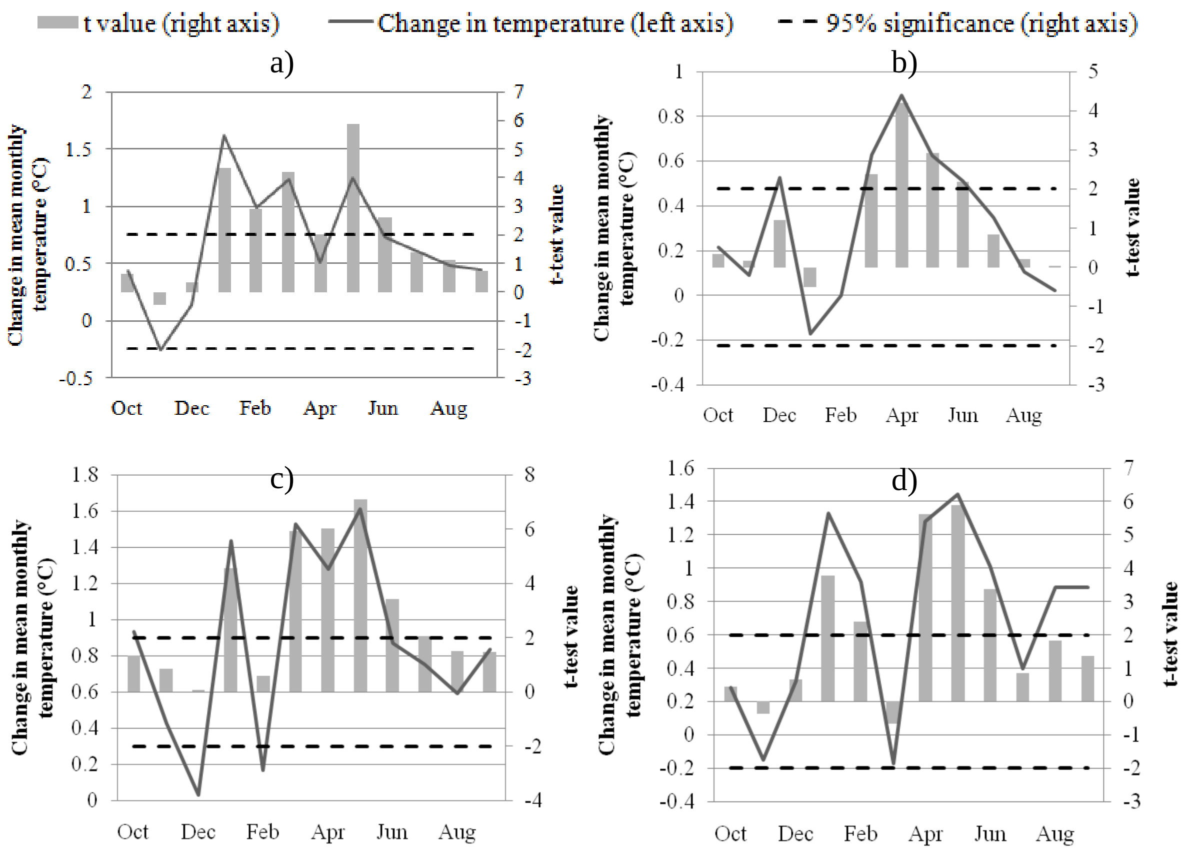



*Figure 4.9: Changes in the monthly means of the temperature for the A2 scenario using (a) ECHAM, (b)PCM, (c) CCSM and (d) CM2 data. The t-values are shown for each month with the significant changes showing t-values above the upper or below the lower significance levels.*

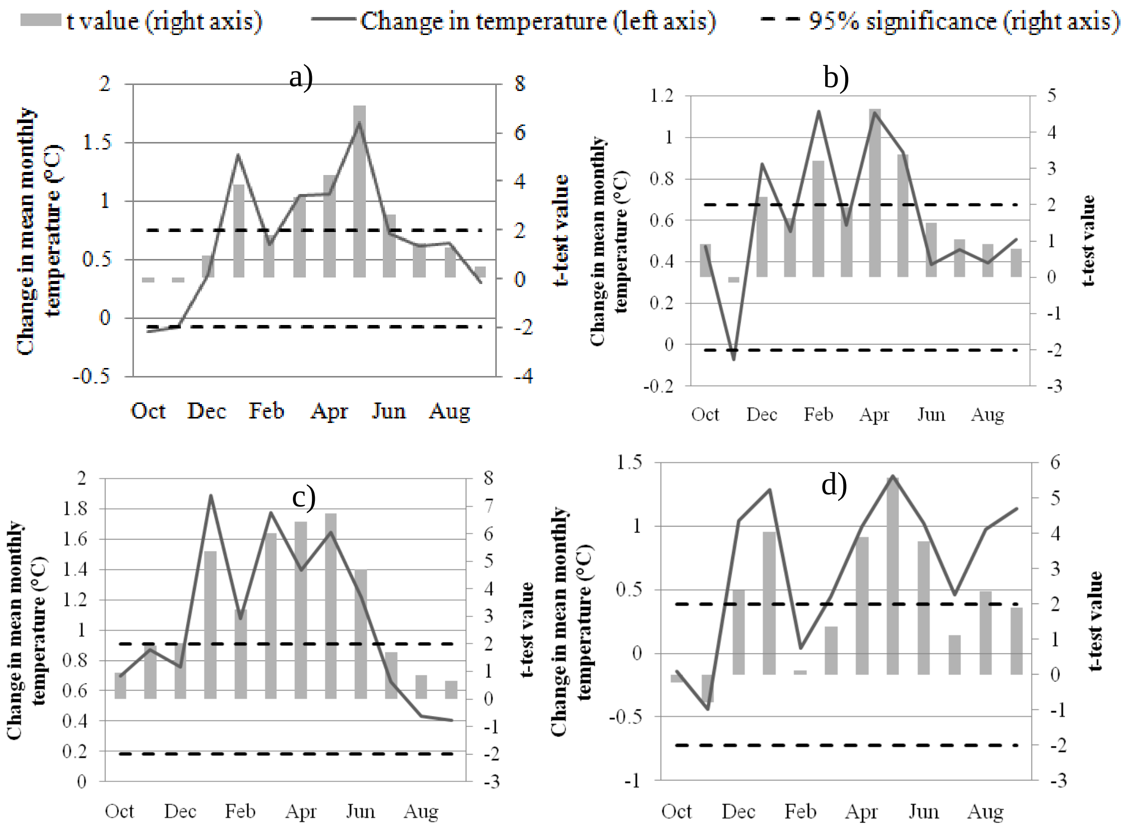



*Figure 4.10: Changes in the monthly means of the temperature for the B1 scenario using (a) ECHAM, (b)PCM, (c) CCSM and (d) CM2 data. The t-values are shown for each month with the significant changes showing t-values above the upper or below the lower significance levels.*

### 4.3.2. Future land-use changes in the NECF River Basin

After having assessed the observed land-use changes in the basin, it was evident that, due to the nature of the basin and the ICLUS HD model, the basin is expected to experience a maximum of only 1% urban growth between 2010 and 2040. Even though this is realistic due to the high level of agricultural activities and presence of wetlands, the future urbanization changes are too low to be assessed. Also, the recent growth rates discussed in Section 4.1 suggest that the basin is expected to grow at a higher rate. Therefore the spatial average of urbanization changes over the US in the ICLUS HD data was applied to this basin (Table 4.5).

The A2 scenario showed more aggressive growth in the Urban/Suburban land-use categories while the Commercial/Industrial land-use categories in the B1 scenario grew at a much faster rate. Based on these values, the projected urban areas for both A2 and B1 scenarios are somewhat similar in 2020, but show more variation in 2030 with a greater degree of urbanization in the A2 scenario (Figure 4.11). The future urbanization was introduced by converting range land (RNGE), which is well distributed across the basin and it is not linked to economic activities. Thus, existing urban areas were expanded but no new urban areas were created.

*Table 4.5: Average growth over the continental US in the Urban/Suburban and Commercial/Industrial categories for the two scenarios.*

| | **A2 Scenario** | | **B1 Scenario** | |
|---|---|---|---|---|
| | Urban/Suburban | Commercial/Industrial | Urban/Suburban | Commercial/Industrial |
| **2020** | 9.0% | 7.7% | 8.6% | 9.8% |
| **2030** | 7.3% | 7.5% | 5.2% | 8.2% |

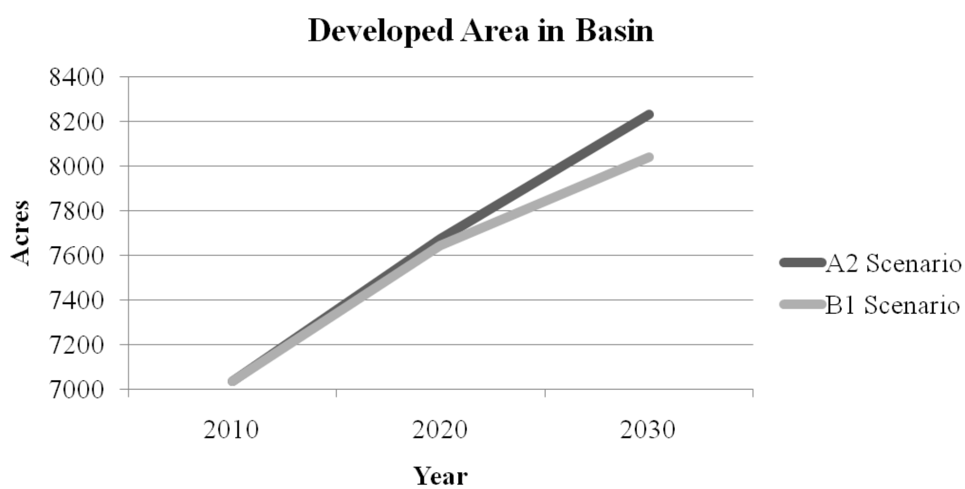
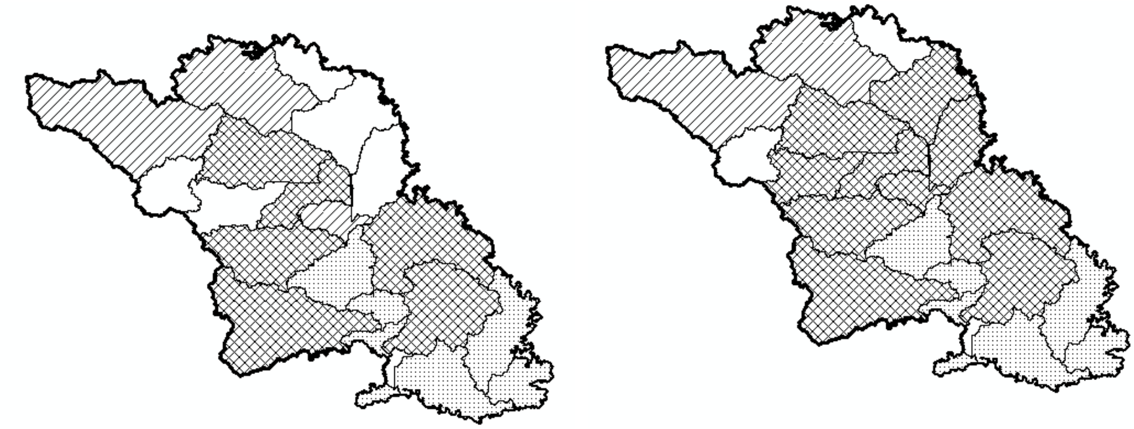



*Figure 4.11: Projected developed area in the basin for 2020 and 2030 for the A2 and B1 scenarios.*

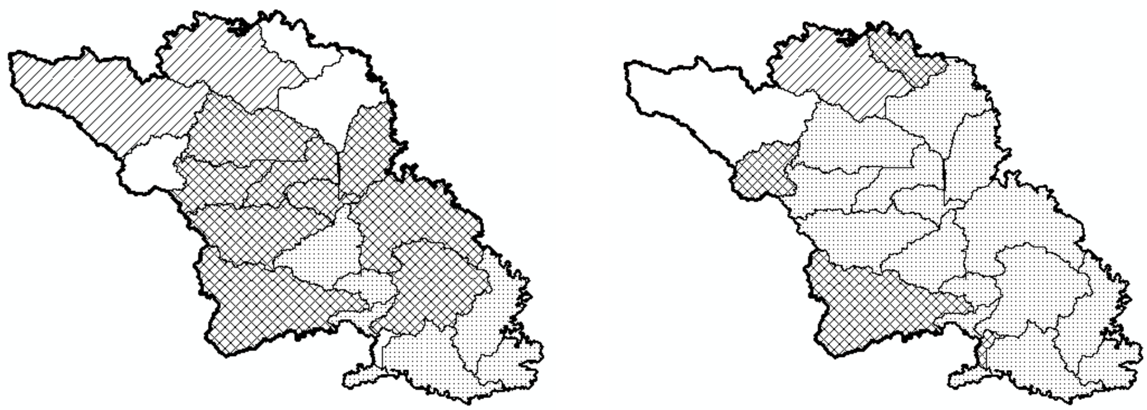
Since the subbasins of the watershed have different urban areas currently, they were altered at different rates (Figures 4.12 and 4.13). Due to the absence of high density developed category and industrial category, the increases in these categories were almost zero and were not included. The A2 scenario showed subbasins with greater changes in the urban category, especially in 2030, than the B1 scenario (Figure 4.12). For the B1 scenario, the percentage changes decreased between 2020 and 2030, and were not as large as for the A2 scenario (Figure 4.13).



| 2020 | URLD[1] | URMD | RNGE |
|---|---|---|---|
| | 7 | 3 | -10 |
| | 4 | 1 | -5 |
| | 3 | 1 | -4 |
| | 2 | 0 | -2 |

| 2030 | URLD | URMD | RNGE |
|---|---|---|---|
| | 7 | 3 | -10 |
| | 4 | 1 | -5 |
| | 3 | 1 | -4 |
| | 2 | 0 | -2 |

*Figure 4.12: Percentage changes in the land-use categories in 2020 and 2030 for the different subbasins in the watershed for the A2 scenario that were implemented.*
[1] *URLD: Developed, low density, URMD: Developed, medium density, RNGE: Range land.*



| 2020 | URLD[1] | URMD | RNGE |
|---|---|---|---|
| | 7 | 2 | -9 |
| | 4 | 1 | -5 |
| | 3 | 1 | -4 |
| | 2 | 0 | -2 |

| 2030 | URLD | URMD | RNGE |
|---|---|---|---|
| | 5 | 2 | -7 |
| | 4 | 1 | -5 |
| | 3 | 1 | -4 |
| | 2 | 0 | -2 |

*Figure 4.13: Percentage changes in the land-use categories in 2020 and 2030 for the different subbasins in the watershed for the B1 scenario that were implemented.*
*[1] URLD: Developed, low density, URMD: Developed, medium density, RNGE: Range land.*

# 5. Results and discussion

## 5.1. Results from the illustrative example

### 5.1.1. Statistical analysis of flows

The SWAT model was run for 60 years (1981-2040) with the pre-development period (1981-2010) using the observed climate for all grid points and the post-development period (2011-2040) using downscaled and disaggregated data (as described in Section 3.1) from the ECHAM, PCM, CCSM and CM2 climate models. Separate simulations were conducted using each GCM's climate data and the flow was analyzed at the outlet to the basin (Figure 4.2).

While the climate data showed a lack of significant changes for some of the GCMs, the t-test (Equation 3.2) showed that all the simulated mean daily streamflow values exhibited increases at a 95% significance level for both A2 and B1 scenarios (Table 5.1). On a daily level, the standard deviations were also significantly different; however, this result may have been due to the high number of degrees of freedom in the F-test calculation (Equation 3.4).

These results for the mean and standard deviation show the sensitivity of the hydrological processes to the changes in climate.

*Table 5.1: Statistical analysis of the mean daily flow values for the A2and B1 scenario for four GCMs under climate change alone.*

| | **A2 Scenario** | | **B1 Scenario** | |
|---|---|---|---|---|
| **GCM** | **Mean (cfs)** | **Standard deviation (cfs)** | **Mean (cfs)** | **Standard deviation (cfs)** |
| **Pre-development period** | 1242 | 1399 | 1242 | 1399 |
| **ECHAM** | 1445 | 1334 | 1447 | 1392 |
| **PCM** | 1313 | 957 | 1263 | 906 |
| **CCSM** | 1415 | 1329 | 1476 | 1277 |
| **CM2** | 1486 | 1410 | 1380 | 1148 |

Flow duration curves (FDCs) could also be used to analyze the “flashiness” of a basin as well as the behavior of the low flows (Dingman 2008) (Figure 5.1). All FDCs for the A2 scenario (results for only the CCSM model are shown in Figure 5.1) showed an increase in the frequency of the lower magnitude flows. This result could be due to the disaggregation scheme, which is limited in capturing the extremes. This observation indicates that the increasing mean daily flows may be due to higher values of low flows. Additionally, the B1 scenario showed similar post-development period FDCs for each GCM simulation (the results for only the CCSM model are shown in Figure 5.2). There were increasing flows for all the exceedance probabilities in the FDCs for all GCMs except for the PCM model simulation that shows decreasing flows for low exceedance probabilities. Therefore, the relatively small increase in the mean daily flow for the B1 scenario using the PCM model may have been due to subdued peak flows (Table 5.1).

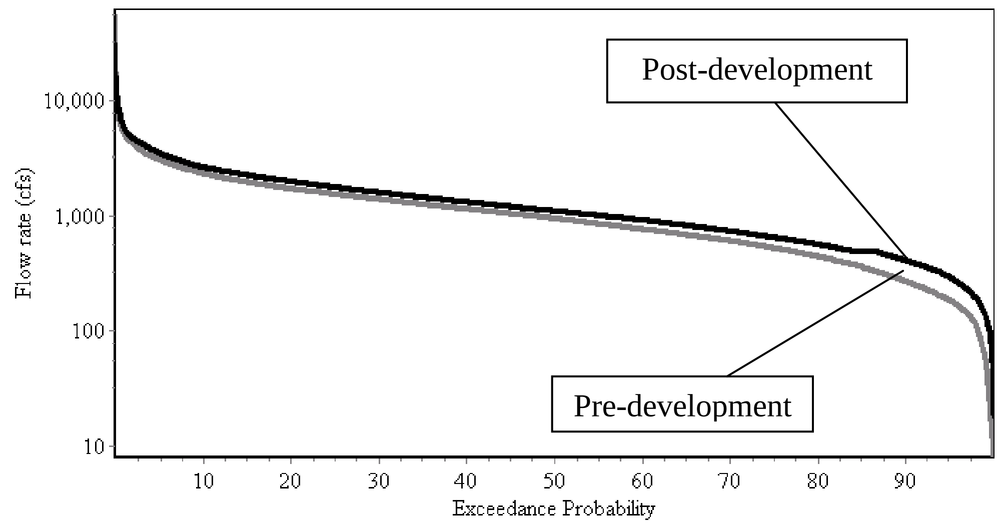



*Figure 5.1: Flow duration curves for climate change under the A2 scenario using the CCSM climate model for the mean annual flows.*

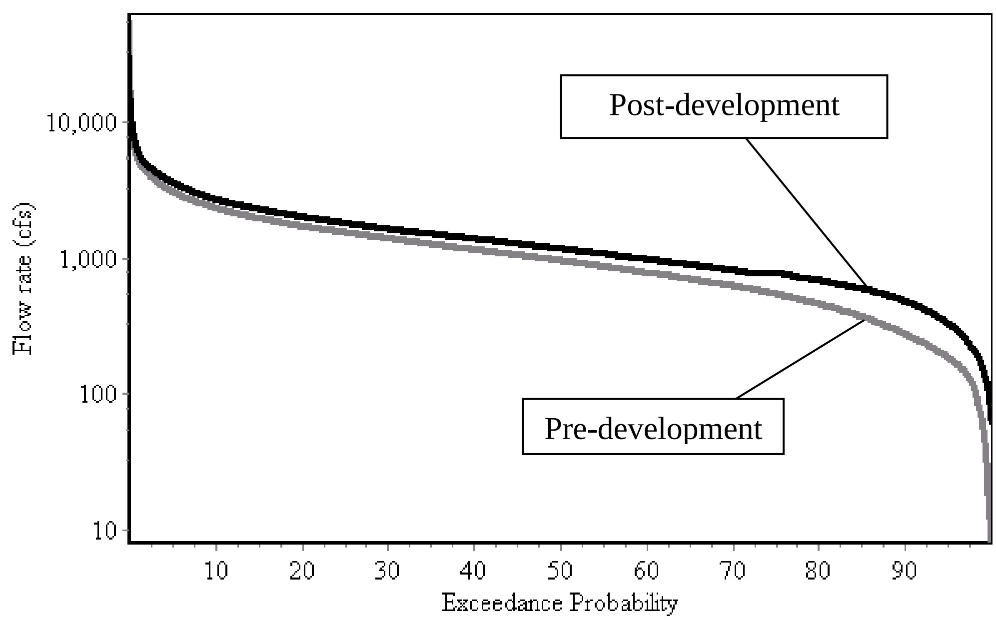



*Figure 5.2: Flow duration curves for climate change under the B1 scenario using the CCSM climate model for the mean annual flows.*

The t-test was conducted on the mean monthly flow values to check for the significance of the changes in the mean flow at a 95% confidence level. Significant changes in the monthly flow values occurred in the same months for both scenarios for each GCM. This indicates that the scenarios are somewhat similar in the near-term since they are dependent on the initial conditions rather than the scenario-relevant factors. Results from the PCM, CCSM, and CM2 models show that the largest increases in mean monthly flows occur in the summer months (results for only the CCSM model for A2 and B1 scenarios are shown in Figure 5.3), while the ECHAM model shows that the most significant increases occur in the winter months. This can be associated with the monthly changes in the precipitation in the basin (Figures 4.7 and 4.8) where the same months show significant increases for each model. For each GCM, the A2 scenario shows an equal or greater number of months with significant changes in the streamflow as the B1 scenario.

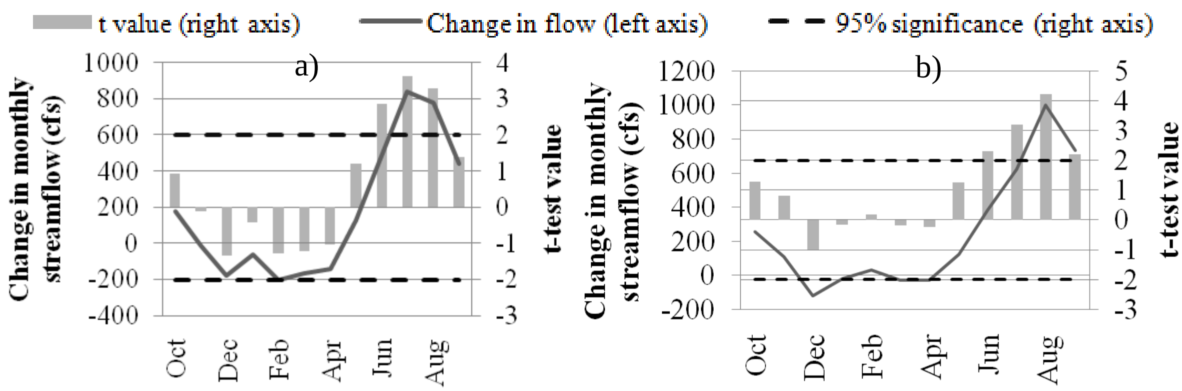



*Figure 5.3: Changes in mean monthly flows from pre-period to post-period for the CCSM simulation with the t-test value shown in bars for the (a) A2 scenario and the (b) B1 scenario. The change in flow is only significant when the t-test value is greater than the positive 95% significant t-value or less than the negative significant t-value.*

The land-use changes in the basin were implemented using the pre-development period (observed) climate data to isolate the flow alterations due to climate change effects from those due to the land-use changes. When the resulting flows were compared to the pre-development period flows corresponding to the current land-use data, no significant changes were observed based on the t-test for the mean and the F-test for the standard deviation. The FDCs for both scenarios also remained unaltered. The impact land-use change has on flow is still an irresolute issue (Praskievicz and Chang, 2000). In some modeling studies, climate change was found to have a greater effect on streamflow than land-use change (Chen et al., 2005; Herron et al., 2002) while the contrary was found in other studies (Chang, 2003; Davis Todd et al., 2007). The former was observed to be the case for this study where the combined effects of climate change and land-use change on flow were similar to those due to climate change only. The rates of urban growth estimated using the ICLUS HD land-use model for the A2 and B1 scenarios were too low to show any significant alterations. Additionally, retrospective studies have shown that the relative size of the basin influences the effect that urbanization has on the hydrologic cycle (Nirupama and Simonovic, 2007; Wang, 2006).

#### 5.1.2. Ecological assessment of flows

The statistical analysis of the flows described above shows how significant the changes are in the flow but is insufficient to assess the impacts on the ecology of the basin. The IHA parameters that provide a simple but more comprehensive assessment of the changes in the flows were used to study the changes in flow regimes reflected not only by the magnitude, but also by duration, frequency, and variability of flow.

The FDC curves assessed in Section 5.1.1 identified the increases in the low flows over all the GCMs and scenarios. These changes were assessed in a more comprehensive manner by analyzing the minimum flow parameters in Group 2 of the IHA parameters (Table 3.4). The changes in flows between the pre-development and post-development conditions for the A2 and B1 scenarios were similar, reflected by the increase in occurrences in the high category (upper third percentile) for the minimum flows (Figure 5.5). The A2 scenario showed greater reductions of occurrences in the low category, while the B1 scenario showed greater reductions of occurrences in the middle category. While only the CCSM simulations-based results are shown in Figure 5.5, the other GCM flow simulations showed similar results, consistent with the observations from the analysis conducted with the FDCs.

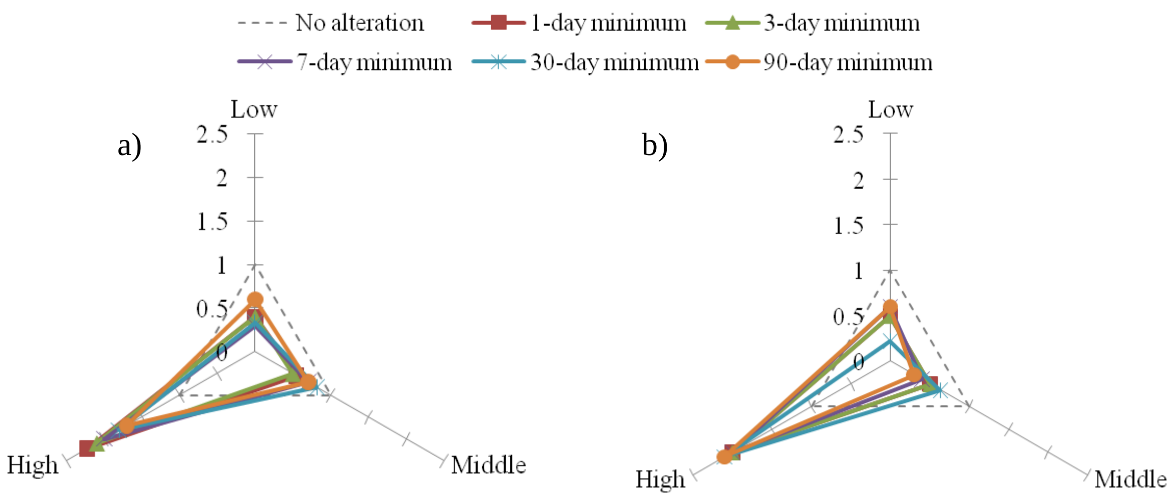



*Figure 5.4: Hydrologic alteration ratios for the minimum flow (IHA Group 2) parameters estimated using the CCSM-based flow simulations for (a) the A2 scenario and (b) the B1 scenario.*

The maximum flow parameters showed larger differences among the GCM model simulations for the A2 scenario than for the B1 scenario. The ECHAM and PCM simulations showed much greater alterations in flows than those simulated by CCSM and CM2, which showed almost no alterations. Figure 5.5 shows the comparison between ECHAM and CCSM results. Overall, the effects on the maximum flow (IHA Group 1) parameters showed smaller effects compared to those for the minimum flow (IHA Group 2) parameters, as well as showed a tendency for increasing occurrences in the middle category. The GCM simulations for the B1 scenario showed lower alterations in the maximum flow (IHA Group 1) parameters than for the A2 scenario, with increases in the occurrences in the middle and low flow categories. The results for the CCSM simulations are shown in Figure 5.6.

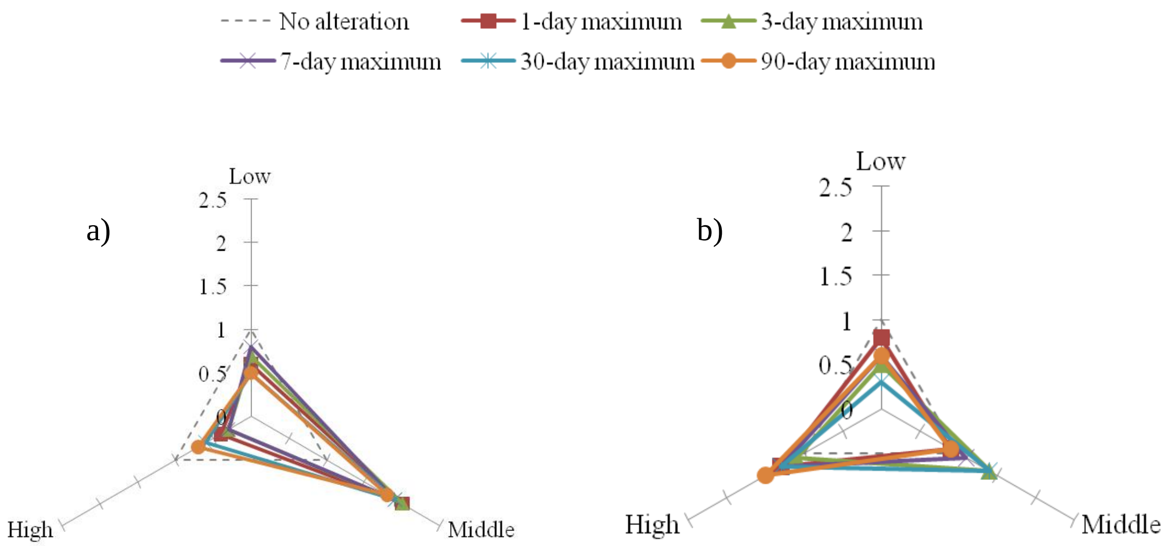



*Figure 5.5: Hydrologic alteration ratios for the maximum flow (IHA Group 2) parameters estimated using the (a) ECHAM-based flow simulations for the A2 scenario and (b) using the CCSM-based flow simulations for the A2 scenario.*

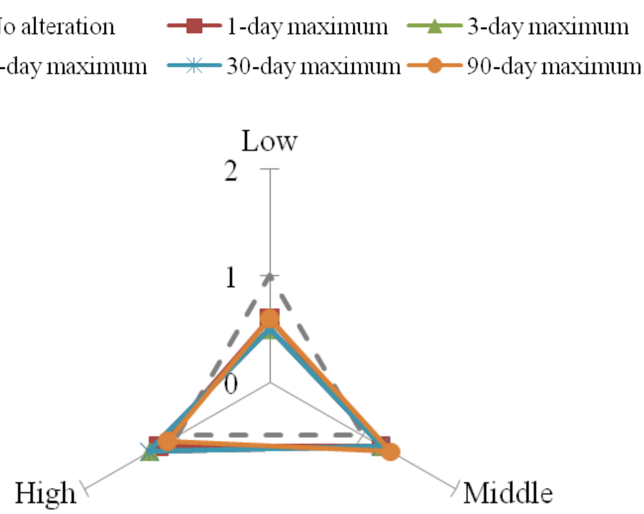



*Figure 5.6: Hydrologic alteration ratios for the maximum flow (IHA Group 2) parameters estimated using the CCSM-based flow simulations for the B1scenario.*

Even though the statistical analysis of the monthly mean flows (Section 5.1.1) show that the changes in monthly flows were only significant in certain months, the IHA Group 1 parameters (Table 3.4) show that all months have alterations with some months showing more than others. The greatest alterations occurred in the same months where significant changes were seen, but high alterations also occurred where significant changes were not seen. For example, the CCSM simulation of flows for the A2 scenario showed no significant changes in the monthly mean for September (Figure 5.3a); however, the IHA alteration ratios showed a large change in the high category (Figure 5.7). The same was seen for the B1 scenario where the alteration ratio in the high category for October was large (Figure 5.8), but there were no significant changes in the mean flows for that month (Figure 5.3b). These observations show the need to assess the changes in the flows using multiple parameters and methods to correctly analyze the potential effects on ecological flow regimes in the basin.

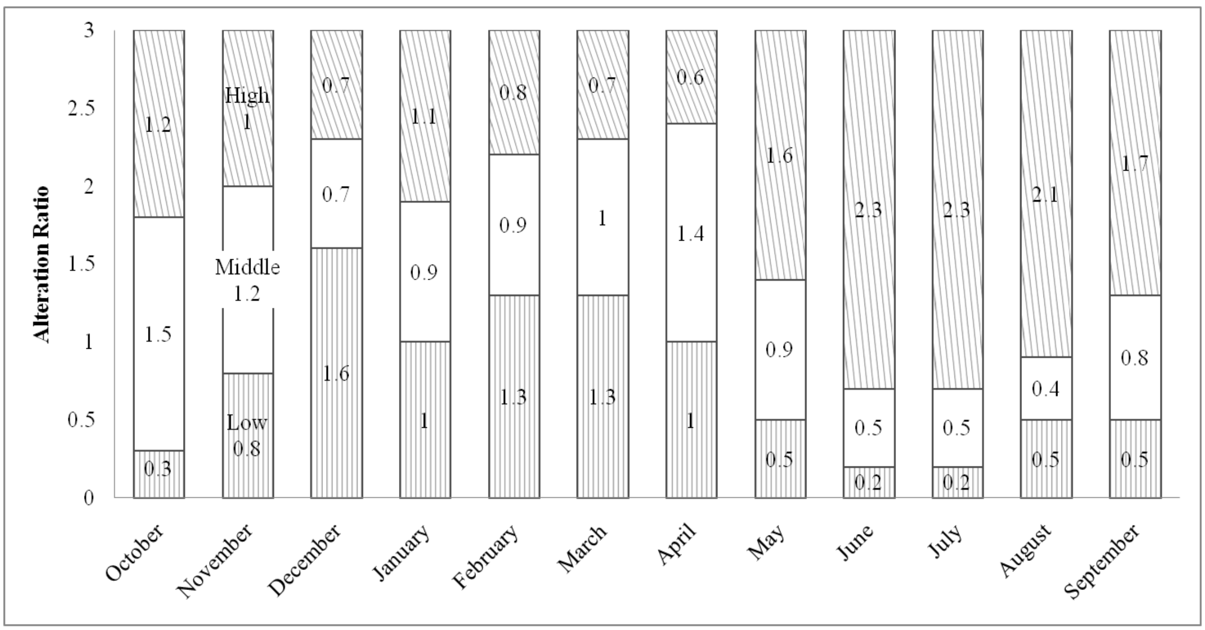



*Figure 5.7: Group 1 of IHA parameters' alteration ratios for the CCSM simulation for the A2 scenario.*

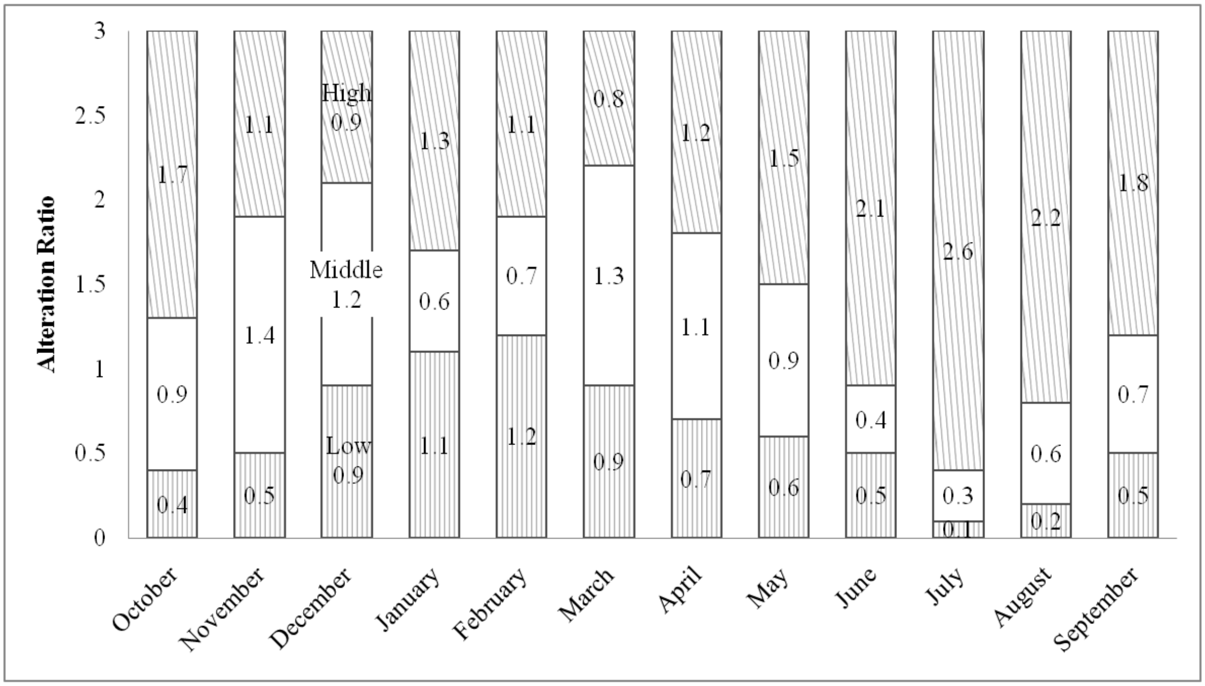



*Figure 5.8: Group 1 of IHA parameters' alteration ratios for the CCSM simulation for the B1 scenario.*

Alternatively, there were no alterations in the IHA parameters in Group 1 (Figures 5.9 and 5.10) and Group 2 (Figures 5.11 and 5.12) when the flows were simulated under land-use change alone for both A2 and B1 scenarios. In these cases, the statistical analyses also showed a lack of significant changes in the mean annual flows and their standard deviations (less than 0.01% change). The size of the basin or the low levels of initial urban development may have accounted for the lack of any effects that could be captured using statistical analysis or the IHA parameters. When the land-use and climate change effects were combined, no increased effects were observed compared to the results from climate change alone.

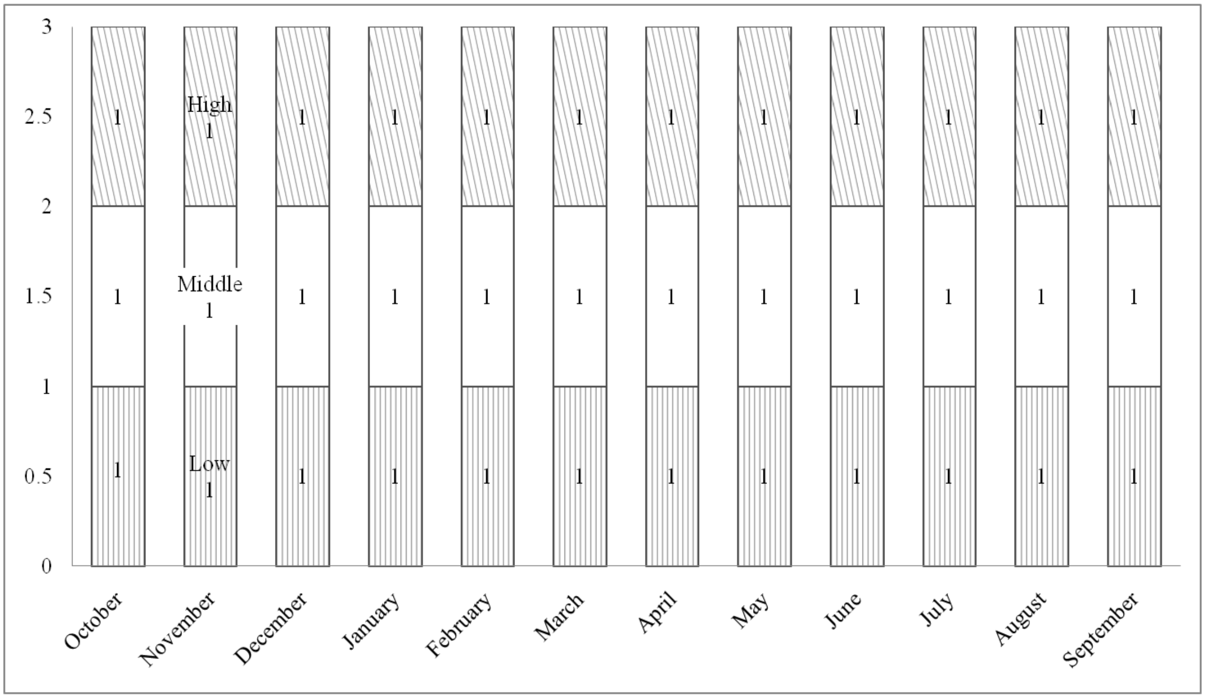



*Figure 5.9: Mean monthly flows (IHA Group 1) alteration ratios for the A2 scenario for land-use change alone.*

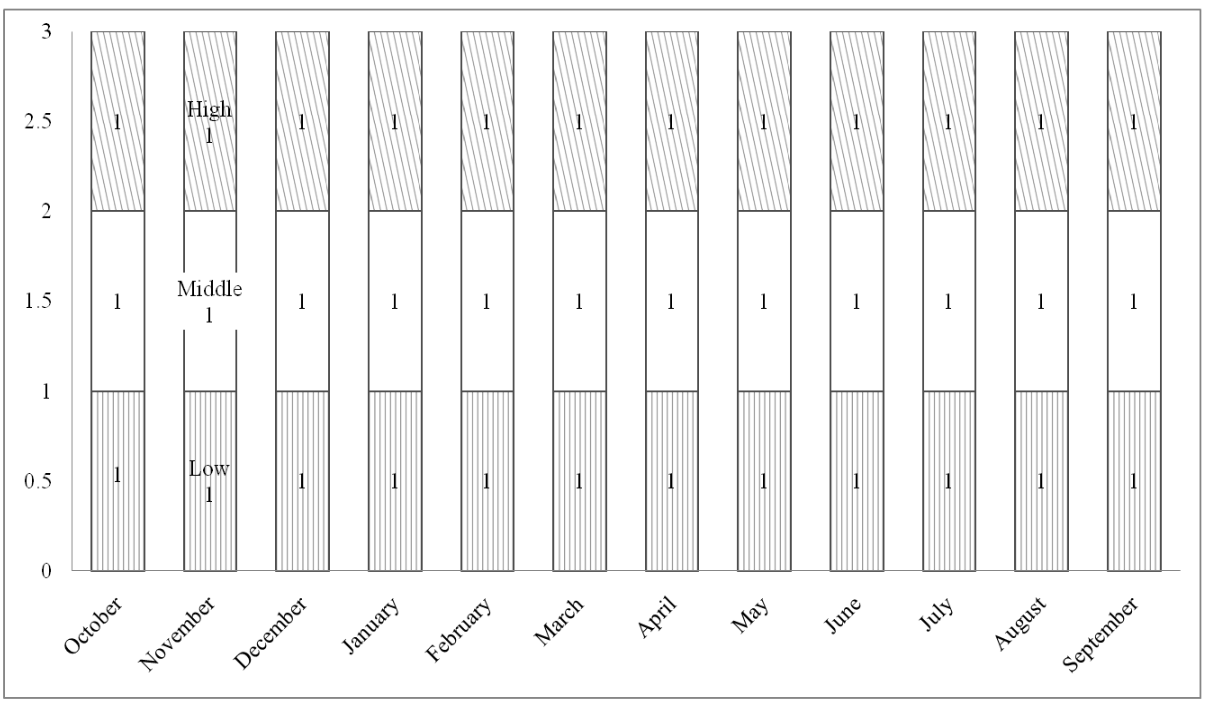



*Figure 5.10: Mean monthly flows (IHA Group 1) alteration ratios for the B1 scenario for land-use change alone.*

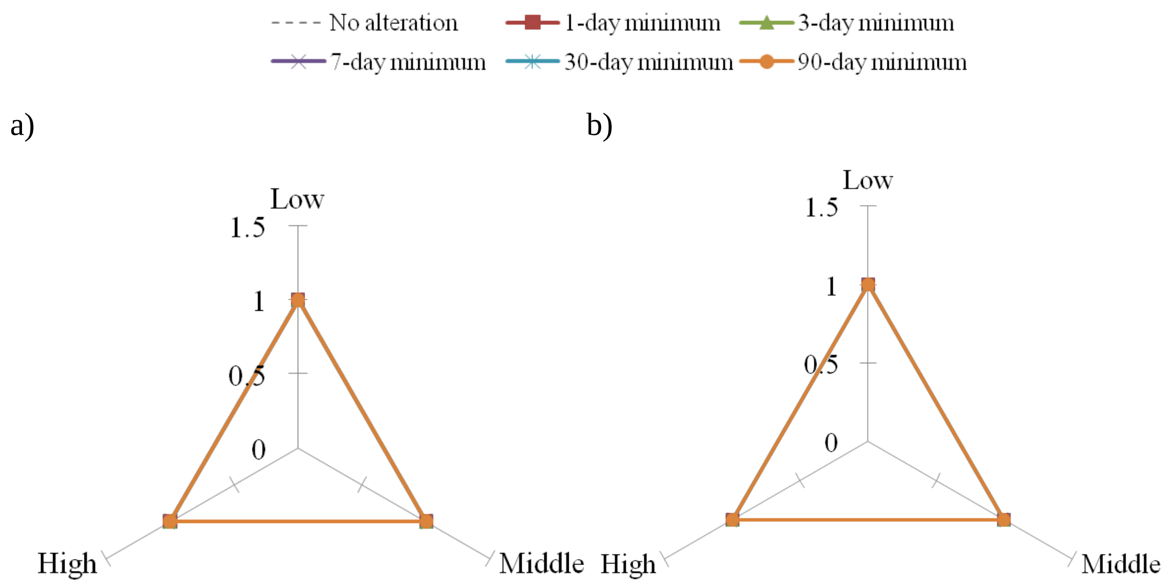



*Figure 5.11: Annual minimum flows (IHA Group 2) alteration ratio for (a) A2 and (b) B1 scenarios for land-use change alone.*

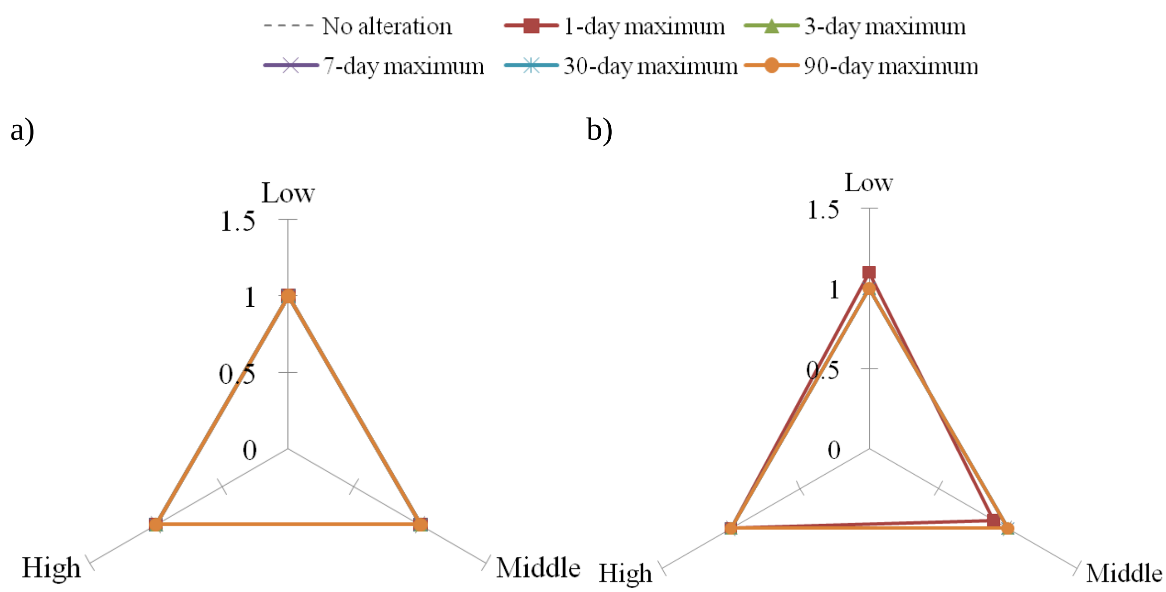



*Figure 5.12: Annual maximum flows (IHA Group 2) alteration ratio for (a) A2 and (b) B1 scenarios for land-use change alone.*

### 5.1.3. General observations from the illustrative application

The illustrative application shows how a comprehensive assessment of climate and land-use change effects on flows in a basin can be conducted systematically using the framework. For the selected basin and for the scenarios considered, the effects on the flows from climate change were much larger than the land-use change effects. The climate change under the A2 scenario showed greater effects, confirmed by using the sum of mis-hits approach described in Section 3.4.2. The mis-hits were summed over all the parameters in an IHA group (Table 3.4) to achieve the total sum of mis-hits. The A2 scenario was observed to have the most effect on the first two groups of the IHA parameters (Figure 5.13) over all the GCMs. Also, the different GCM simulations showed varying results for the sum of mis-hits for the IHA parameters (Figure 5.14) as well as for the mean increases in flows (Table 5.1) for both scenarios. These results confirm the need to use multiple climate data sources for the same scenario to achieve an overall assessment of the effects on the streamflow.

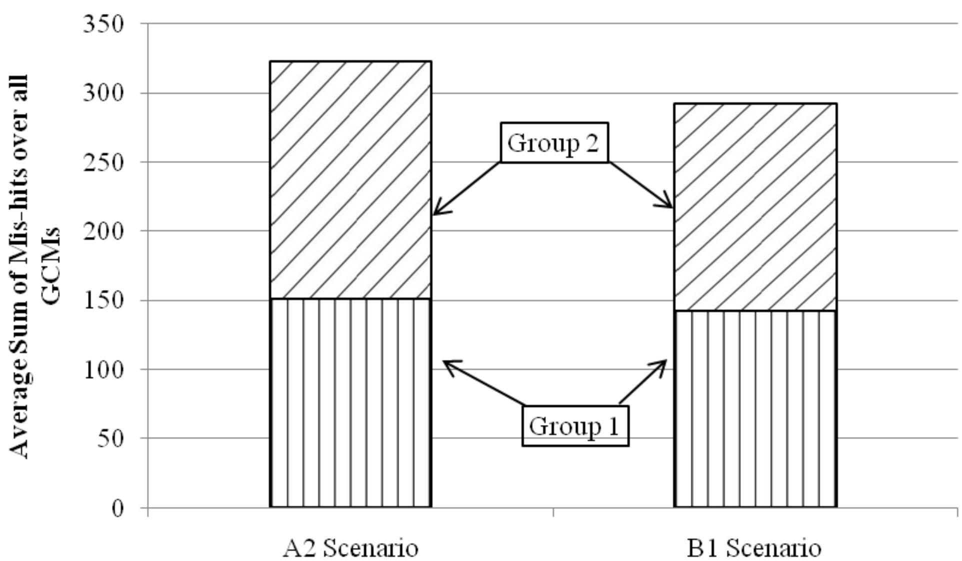



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*Figure 5.13: Average sum of mis-hits over all GCM flow simulations for Group 1 and Group 2 of the IHA parameters.*

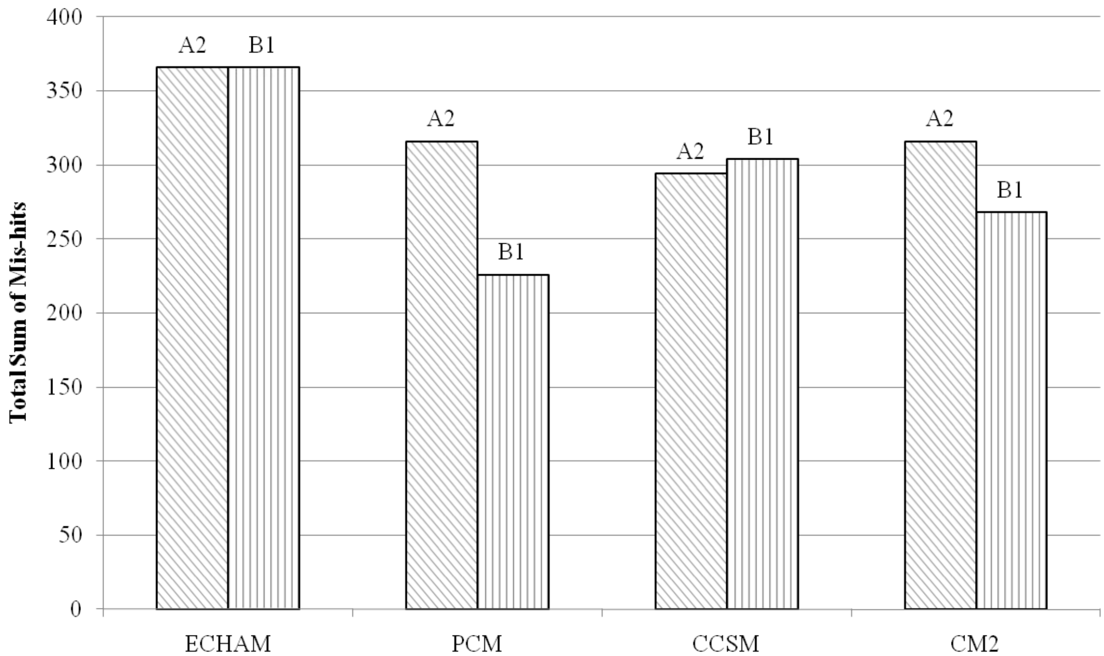


*Figure 5.14: Total sum of mis-hits for Group 1 and Group 2 of IHA parameters for the A2 and B1scnearios for all GCM flow simulations.*

The illustrative application also highlights the need to use multiple parameters to assess the alterations in flow. Many statistically insignificant changes showed high alteration ratios in the IHA parameters, especially in the monthly flows. This result confirms the need to assess the variability in the flow regime, as well as the changes in the mean.

## 5.2.Discussion of framework

The illustrative application demonstrated how the different steps of the proposed framework, including the associated model applications and data analyses, can be implemented to assess quantitatively the effects of climate and land-use change on the flows in a basin. The climate change and land-use change under the scenarios were implemented separately and in combinations to simulate the flows in the basin. A comparative assessment of the effects on flow was performed, and the differences among the flow simulations of different GCMs were analyzed.

The preprocessing of the global climate data through the spatial downscaling step helped reduce the bias in the precipitation and temperature predictions. This step is less effective for the near-term predictions (2010-2039), where the bias-correction step altered the change in mean annual precipitation and temperature by only a small percentage (Figure 5.15). On the other hand the bias-correction and spatial downscaling steps caused the precipitation and temperature changes to be greatly different than the raw GCM data for the 2040-2069 and 2070-2099 time periods. Additionally, the mean change in precipitation was greater than that for the mean change in temperature over all years.

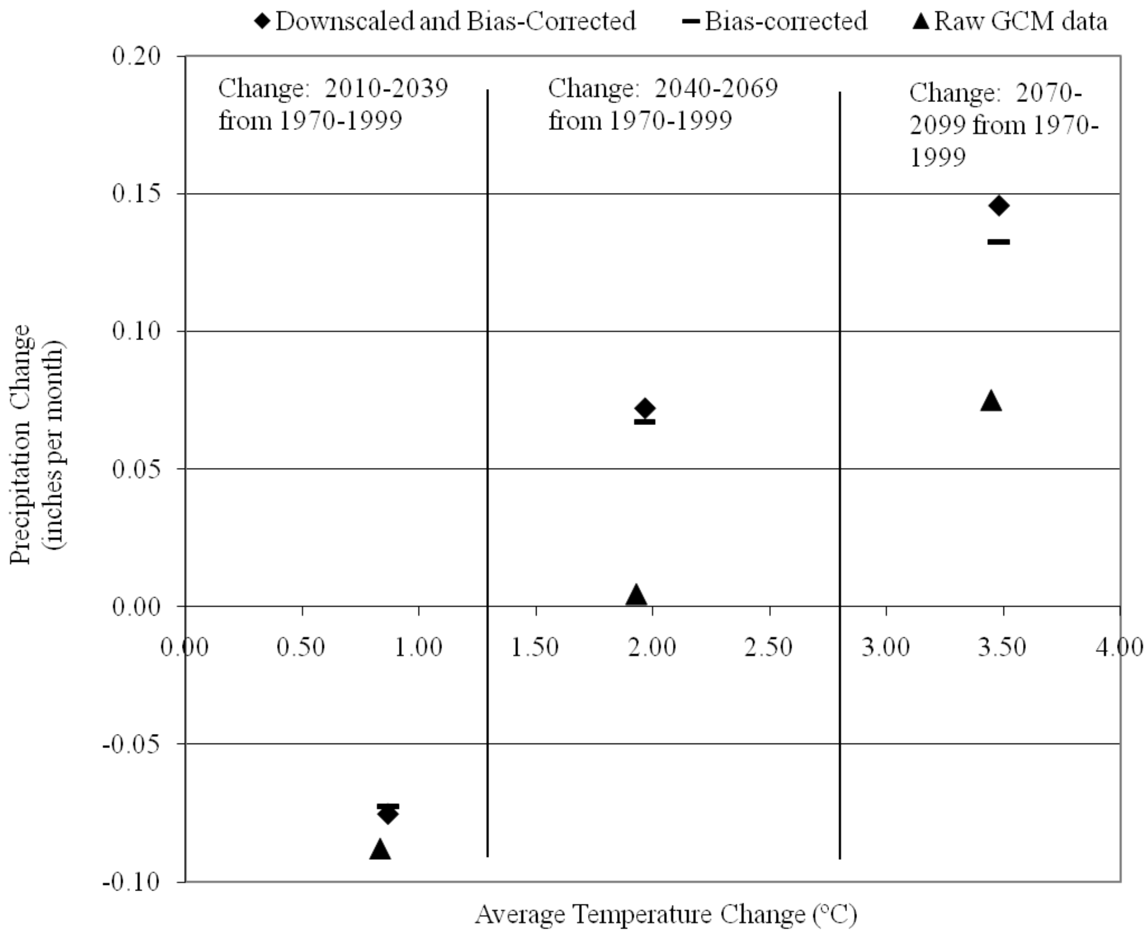


*Figure 5.15: Mean annual changes of precipitation and temperature between 1970-1999 and 2010-2039, 2040-2069 and 2070-2099 for raw GCM data, bias-corrected data and downscaled data for the CCSM model for the NECF basin.*

The temporal disaggregation step of the climate data sets allowed the flows to be simulated on a daily basis. Alternatively, the monthly streamflows can be simulated using the hydrologic model and then disaggregated using the k-NN algorithm. Temporal disaggregation of streamflow is a widely studied area, and many parametric and non-parametric methods are established to do so (Prairie et al., 2007).

The ICLUS HD model chosen for illustrating the framework is compatible with the IPCC AR4 scenarios studied. The housing density classifications, however, caused inaccurate assumptions to be applied to the basin, such as the urban development densities and their respective curve numbers. Additionally, assumptions about losses in certain land-use types may not be accurate. Thus, if the aim of the research is to find a general assessment of the land-use change effects under the scenarios on the basin, the ICLUS HD model and the assumptions made in the framework are sufficient. On the other hand, if more specific study is needed of the development in the basin, a more precise relationship between the NLCD 2001 and the ICLUS HD is required, or a different land-use model that has land-use outputs with NLCD 2001 classifications can be used.

There are spatial limits to the scope of the framework. Spatial downscaling at a more refined scale than a 1/8-degree grid is not possible using the proposed technique since the most refined observed climate data available is at this spatial scale. Also, due to the spatial extent of the mass balance calculations of the SWAT model, land-use can only be allocated at a subbasin scale, and the flow values can be only determined at the outlet of each subbasin. Therefore, the framework is suitable for basin-wide assessment, and more spatially refined data sets would be needed to perform assessments at a finer spatial scale.

## 6. Concluding remarks

This research provides a framework that combines analytical tools, models and data to assess the effects of climate and land-use change under different scenarios on the flows in a basin. The primary purpose of this framework is to allow researchers, planners and decision-makers to employ a systematic approach to estimate the ecological flow alterations in a basin and to assess the effects of different conditions by which the basin is affected. The framework was demonstrated by applying it to answer research questions about the effects of land-use and climate change on the streamflow. This study implemented and tested the necessary steps in the framework to process data and model climate change as well as land development under different scenarios. This helped identify the strengths and weaknesses of the framework. The framework is able to use existing tools and methods that represent different spatial and temporal scales, and use different data types to complete an assessment of flow in a basin considering climate change effects. On the other hand, improvements to land-use models and the housing density data transformation could be beneficial. Also, incorporation of Best Management Practices (BMPs) for stormwater management in the framework would enhance its applicability in watershed assessment and management.

The variation among the GCM simulations under the same scenarios prompts the need for uncertainty analysis in the framework. Hawkins and Sutton (2009) have provided a methodology to decompose the uncertainty in GCM temperature predictions for the next century into model uncertainty, scenario uncertainty and internal variability. This approach has been adapted to streamflow predictions to find the uncertainty contributed by the GCM predictions of temperature and precipitation. Preliminary results show that the greatest source of uncertainty in the flow stems from the uncertainty in GCM-generated precipitation values. These preliminary results also show that the scenario uncertainty in near-term or decadal predictions is relatively small. This is a common finding among GCM prediction studies where the predictions are shown to be more dependent on the initial conditions and interannual oscillations (ENSO, PDO) than on the scenario (Meehl et al., 2009). Also, uncertainty analysis could be conducted on the IHA parameter values to get a finer assessment of the effects on the basin.

A potential addition to the framework is to incorporate the ability to use multi-model combinations for obtaining the GCM predictions, and similarly for basin flow simulations.

Mutli-model combination of predictions for each scenario would generate an ensemble of time-series that uses the “best” information from each of the models and is expected to improve the predictions (Wiegel at al., 2008). When using multi-model combinations, the data is based on, for example, the GCMs’ performance in simulating the observed data. This would eliminate the need to assess simulations from multiple GCMs. By having an ensemble that is created by using the uncertainty in the streamflow data, the variability in the data could still be captured.

While the current version of the framework supports primarily simulation and assessment abilities, it can be extended to consider explicitly watershed development decisions, such as ecologically sound land development plans and flow mitigation using BMP placements. Coupling these enhanced abilities with optimization search techniques, the framework could be used to search for efficient watershed development strategies, especially considering anticipated changes in the regional and local climate. This allows engineers to plan development under predicted changes in the hydrologic cycle and not under current conditions that are assumed based on historical information. Also, the framework can provide a relationship between the land-use and climate change effects, which could allow certain land-use allocation to mitigate or negate the alterations that are expected to occur in the basin because of climate change.

Overall, this study enables and promotes the necessary quantitative assessments of stream flow alterations due to influencing factors such as climate change and land development. The continuously growing global population promotes inevitable anthropogenic changes in basins. Not only could streamflow change affect the ecology, but it could also affect hydropower operations, reservoir management and water supply systems. By knowing the long-term effects of changes in a basin, adaptation and mitigation processes can begin so that the ecology and water resources systems can be properly planned, managed and protected.

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