THE UNIVERSITY OF TEXAS ATAUSTIN

Climate Change Impacts on the Water Resources

An overview of global Impacts and techniques to assess at local scale

Literature Review

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Abstract

This document presents an overview over global impacts on hydrology and water resources as consequence of climate changes. Likewise, in order to evaluate these impacts at local scale, main downscaling techniques and some applications are reviewed. At the global scale, precipitation will increase in some regions such as part of tropics and high latitudes and decreases in lower and mid latitudes. Runoff depends of the changes in precipitation; in this sense, it is noted a reduction in central American and Europe. Risks of droughts are projected for sub tropical, low and mid latitudes and floods for tropical and highs latitudes. Changes in groundwater recharge, soils moisture and evaporation are also reviewed. Likewise, some results from GCMs, climate change will affect directly on the water resources systems, indicating that in next 50 years will increase the water stress on land areas. On the other hand, statistical and dynamical methods are discussed. Statistical downscaling is classified in stochastic weather generators, regression models, and weather pattern approach. Dynamic downscaling develops and uses a regional climate model (RCM) with the course GCM data used as boundary conditions. Both techniques show great skill to perform the downscaling data. Finally, this paper presents a general procedure to incorporate the climate change impacts on hydrological and water resources models.

1. Introduction

Climate variability has relevant importance on the hydrology and water resources availability in the world. Changes in temperature and precipitation patterns as consequence of the increase in concentrations of greenhouse gases may affect the hydrology process, availability of water resources, and water use for agriculture, population, mining industry, aquatic life in rivers and lakes, and hydropower. Climate changes will accelerate the global hydrological cycle, with increase in the surface temperature, changes in precipitation patterns, and evapotranspiration rate. The spatial change in amount, intensity and frequency of the precipitation will affect the magnitude and frequency of stream flows; consequently, it increases the intensity of floods and droughts, with substantial impacts on the water resources at local and regional levels. Global climate simulations indicate that precipitation will decrease in lower and mid latitudes and increase in high latitudes (IPCC, 2008). Results show that rainfall will decrease in Caribbean regions, sub tropical western coasts, part of North American (Mexico), and over the Mediterranean. Evaporation, soils moisture content, groundwater recharge will also affected by climate changes. Drought conditions are projected in summer for sub tropics, low and mid latitudes. Some results show that for warmer climate the drought increases from 1% to 30 % in 2100. On the other hand, global impacts on the water resources show that freshwater for different uses will be affected.

According to IPCC, a notable reduction of the water resources service is projected where the runoff decrease, and also the projection of water stress for 2050 s indicates a increase in range of 62-76 % of the global land areas. On the other hand, to assess these impacts at the local scales, downscaling techniques need be applied. In that context, Statistical and dynamical methods are used in hydrologic and water resources studies. Statistical downscaling allows relates the large scale climate from GCMs with the historical (local) scale variables. This method is classified in regression models, stochastic weather generation, and weather pattern approach (Wilby, 1997). Dynamic method uses complex algorithms to describe the atmospheric process and whose goal is to extract the local weather data from large scale GCM. Based on several studies, both methodologies have performed efficiently; however, the dynamic downscaling is a method more sophisticated that requires of large amount of computational resources.

2. Climate Impacts on the Hydrology and Water Resources

2.1 Impacts on the hydrology cycle

The main components of hydrology cycle are the precipitation, evaporation, runoff, groundwater, and soil moisture, and it is liked with changes in atmospheric temperature and radiation balance. According to IPCC (2008), *precipitation* pattern over 20th century has shown important spatial variability; which has decreased from 10^{o} S to 30^{o} N latitude and increased in high northern latitudes since 1970. In addition to this, precipitation increased around 2% between 0 ^{o}S to 55 ^{o}S and from 7 to 12 % from areas located between 30 ^{o}N to 85 ^{o}N (IPCC, 2001).

On the other hand, for the 21st century, simulations with climate models indicate a increase in the globally evaporation, water vapor, and precipitation, indicating that precipitation will decrease in the lower and mid latitudes regions while it increases in high latitudes and part of tropics (IPCC, 2008). Figure 1 shows the mean change in precipitation of fifteen climate models for the scenario A1B (from December to February: DJF and from June to August: JJA). It is noted that precipitation decreases over several sub tropical areas and mid latitudes (for summer) while for tropical oceans and in some monsoon regimens such as South Asian monsoon summer the precipitation increases. The global annual mean precipitation change (in percentage) for the period 2080 – 2099, for the SRES A1B scenario, is presented in figure 2 (from IPCC, 2008). Important decrease of up 20% will occur on the Caribbean regions, sub tropical western coasts in most countries, and over the Mediterranean. For instance, all Central American, Mexico and south USA will be affected by a significant reduction in precipitation. Increase in annual precipitation in more than 20 % will occur high latitudes such as in Northern part of central Asia, Eastern Africa, and the Equatorial Pacific Ocean. Changes in *soil moisture* depend basically of the precipitation and evaporation which may be affected by changes in the land use; therefore its spatial variation is a little different from the changes in precipitation. Projections indicate that the annual mean soil moisture content increases up around 15 % in some regions where the precipitation is increased, East Africa, and central Asia (figure 2b) while it decreases in sub tropical and Mediterranean zone. Changes in stream flows in rivers depend fundamentally of the change in the volume and time precipitation, and some cases of the snow melting. Figure 2c shows the change in *global runoff* under A1B scenario. Runoff is clearly reduced in Central American, part of Mexico, and Europe; however it is increased in high latitude rivers.

Additionally, in figure 2d is shown the global evaporation. It is noted that annual evaporation increases over most oceans (surface temperature increase). At the global scale, mean evaporation changes balance global precipitation but it is different at local scale due to changes at the atmospheric transport of water vapor (IPCC, 2001).

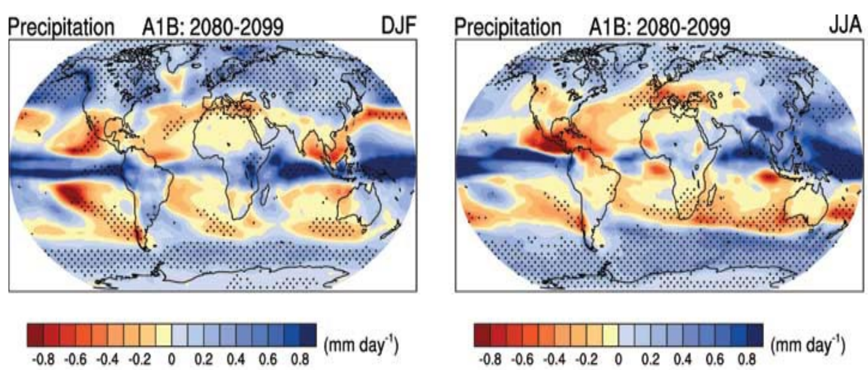

Figure 1. **"**15-model mean changes in precipitation (unit: mm/day) for DJF (left) and JJA (right). Changes are given for the SRES A1B scenario, for the period 2080–2099 relative to 1980–1999. Stippling denotes areas where the magnitude of the multi-model ensemble mean exceeds the inter-model standard deviation". (IPCC, 2008). DJF (December, January, and February), and JJA (June, July, and August).

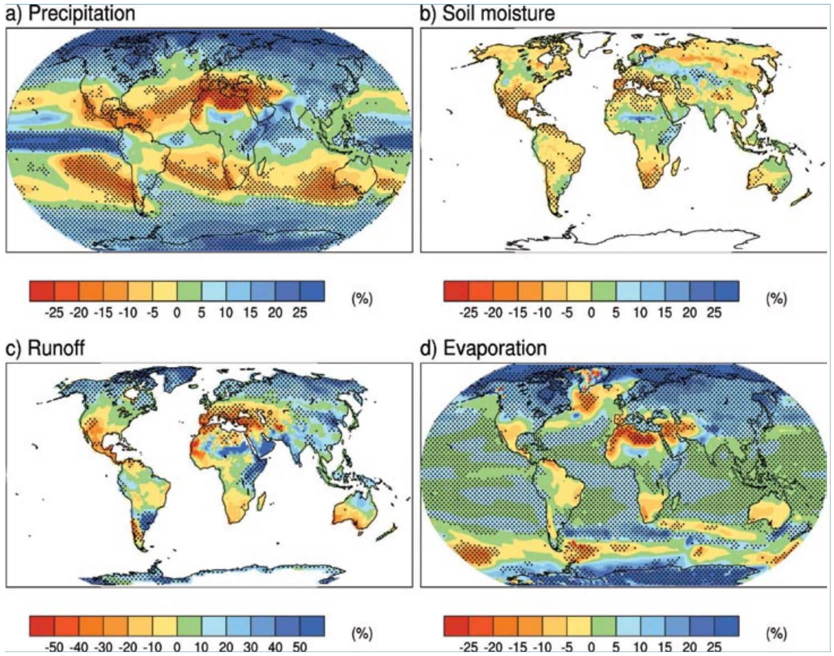

Figure 2. 15-model mean changes in (a) precipitation (%), (b) soil moisture content (%), (c) runoff (%), and (d) evaporation (%). To indicate consistency of sign of change, regions are stippled where at least 80% of models agree on the sign of the mean change. Changes are annual means for the scenario SRES A1B for the period 2080–2099 relative to 1980–1999. Soil moisture and runoff changes are shown at land points with valid data from at least ten models.(IPCC, 2008)

Evapotranspiration is projected to increase in almost everywhere due to the water holding capacity of the atmosphere increases with higher temperatures. Climate change also affects the groundwater recharge rate which is the most important source of water in many places of the world. Some results reported by IPCC (2008) through a global hydrological model applied with four climate change scenarios (the ECHAM4 and HadCM3 GCMs with the SRES A2 and B2 emissions scenarios), the groundwater recharge decreased by more than 70 % for the South West Africa and North-Eastern Brazil. Groundwater recharge has a direct influence on the base flow of rivers, when the water table depth and groundwater decrease, the base flow is reduced fundamentally in dry seasons. In addition to this, the Near East, western USA, northern China, and Siberia are zones where the groundwater recharge is estimated to increase by more than 30% by the 2050s; consequently the water table will increase and it will affect agriculture areas located in the lower basins by soil salinisation.

In some regions is projected to increase the risks of droughts and flooding due to the increase of the intensity and variability of the precipitation for the 21st century. Dry periods are projected for mid continental zones in summer (sub tropics, low and mid latitudes), with marked risk of droughts in these regions. Likewise, extreme rainfall is projected to increase in tropical and high latitudes regions that experiment increases of the mean precipitation. For instance, results from 15 AOGCM runs for the future warmer climate show that the extreme drought increases from 1% at the current day land area to 30 % in 2100 for the A2 emission scenario (IPCC, 2008).

2.2 Impacts on the Water Resources Management

As it was discussed in the section above about the potential effect of climate change on the precipitation, stream flows, groundwater recharge components which would affect directly over the water resources availability in regions above all in those under climate stresses. This situation even more complicated if the characteristics and policies of water resources management systems are not adequate to mitigate these changes. Water for agriculture, population, hydropower, water pollution control, mining industry, etc, are depending on the hydrological cycle. In this sense, climate change affects the management and operation of existing water infrastructure such reservoirs, structural flood defense, channels, dams, irrigation systems, and hydropower plants. Irrigation methods and water management practices also will be affected. Likewise, in many places in the world, the main water resources for agriculture and urban uses come from base flows in rivers and groundwater (for dry periods) which will be affected due to the changes in the recharge groundwater (effect on aquifers in long term). Changes in runoff and water availability influence over it. In addition to this, increase in melting snow in some regions like the Andes in South America contribute in the short time to increase the runoff and in the long term to reduce the snow area; consequently a reduction of water availability understanding that some places, it is the main source of water use. On the other hand, raising sea level increases the possibility of sea intrusion into coast aquifers affecting the groundwater use due to the high salinity concentrations.

In global terms, water demand will grow in the next decades due to the population growth and regionally, substantial changes in irrigation water demand are expected as results of climate change (IPCC, 2008). In general, negative effects of climate changes on water resources systems would complicate the impacts on the changing economic activity, water quality, increase population, land use change and urbanization. According to IPCC (2008), in the 2050s "the area of the land subject to increasing water stress due to climate change is projected to be more than double than with decreasing stress". A clear reduction of the water resources services is shown in zones where the runoff is projected to decrease and the others where the rainfall increases, increased total water supply are projected. However, probably this benefit can be reduced by the negative effects of higher variability of the precipitation and seasonal runoff in water supply, food risks, and water quality. Table 1 presents the impact of the population growth and climate change on the people living in water stressed river projected for 2050 for two scenarios emissions A2 and B2. It can be noted the number of people living in water stresses river basins would increase notably, being more marked this projection for the emission scenario A2. The projection of water stress for 2050s indicates that it increases over 62 -76 % of the global land area (IPCC, 2008). Theses estimations were made from several climate models.

Table 1: Impact of population growth and climate change on the number of people living in water-stressed river basins (per capita renewable water resources less than 1,000 m3/yr) around 2050. IPCC, 2008

	Estimated population in water-stressed river basins in the year 2050 (billions)	
	Arnell (2004)	**Alcamo et al. (2007)**
1995: Baseline	1.4	1.6
2050: A2 emissions scenario	4.4–5.7	6.4–6.9
2050: B2 emission scenario	2.8–4.0	4.9–5.2

Estimates are based on emissions scenarios for several climate model runs.

Figure 3 shows the future climate change impacts for freshwater elaborated by IPCC on the base of different studies about climate change impacts on water resources in the world. It should be noted that stream flows decrease and the demand will not be satisfied after 2020 in Central America and Mexico; the results indicates a reduction of the stream flows around 25 % for these regions. North and south Africa, Europe show the same trend.

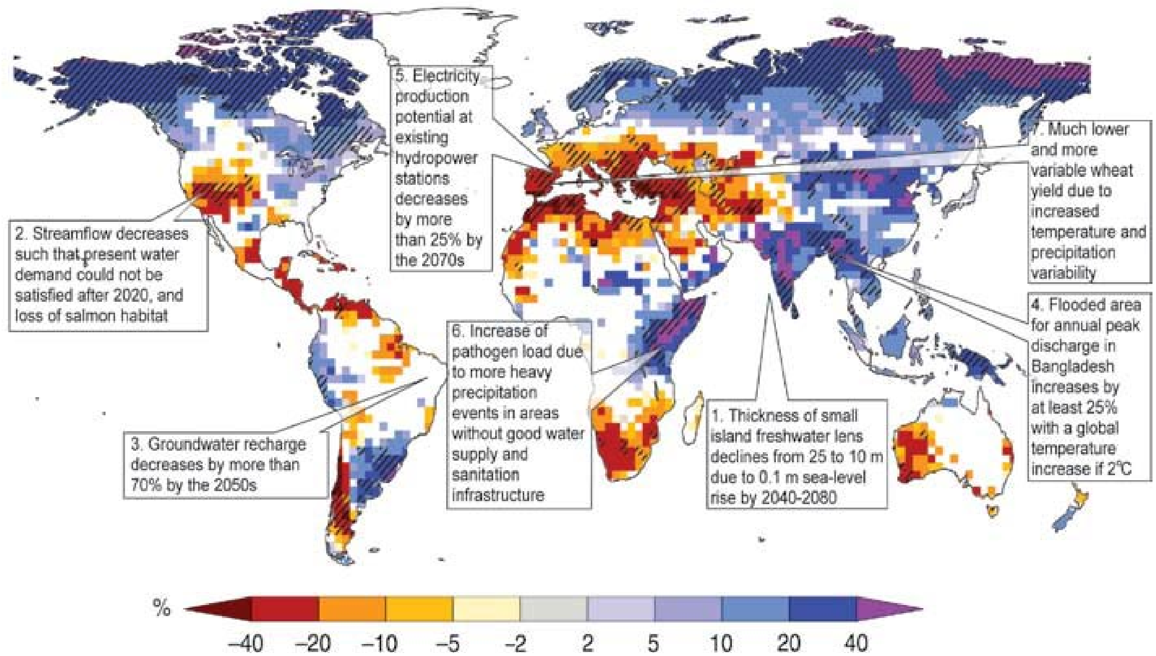

Figure 3. Future climate change impacts on the freshwater which threaten the sustainable development of the affected regions. 1: Bobba et al. (2000), 2: Barnett et al. (2004), 3: Döll and Flörke (2005), 4: Mirza et al. (2003), 5: Lehner et al. (2005), 6: Kistemann et al. (2002), 7: Porter and Semenov (2005). Background map, see Figure 2.10: Ensemble mean change in annual runoff (%) between present (1980–1999) and 2090–2099 for the SRES A1B emissions scenario (based on Milly et al., 2005). Areas with blue (red) colors indicate the increase (decrease) of annual runoff. (IPCC, 2008)

Another interesting aspect is related with glaciers and snow cover which are projected to decrease due to increase of the surface temperature. Consequently reducing the water availability during dry periods in regions contributed by the melting snow water from mountain ranges where currently one-sixth of the world's population is located. Water quality will be another problem in the future. Higher water temperatures and extreme events of the precipitation are projected to affect the water quality and increase many form of water pollution. Oxygen concentrations would be reduced due to the increase of the water temperature (IPCC, 2008). As it is noted there will have multiples climate impacts in the future on the hydrology and water resources. Here only the most important issues have been mentioned.

Finally, to face these impacts in the future, period of transition and adaptation must be designed in order to guarantee the water supply fundamentally for drought periods. Strategies need be developed and applied according to the reality of each water resources system. These strategies should be focused to improve the water use efficiency through the modernization of hydraulic infrastructures, development of water markets, water conservation plans, change the crop patterns with less water consumption (reduce the demand), change irrigation methods, build structural flood defenses, improvement of the water management policies, in some case increase the storage capacity of the reservoirs, etc. Additionally, many places with stresses water, generally in poor countries; there is a deficit of storage structures such as reservoirs and dams that does difficult to face the climate change impacts at current conditions. In this sense, it is necessary to build storage systems that allow mitigating these effects within of framework of integrated water resources management and environmental protection.

As it was mentioned, the changes described above are at global scale. At the local scale, several studies about changes in precipitation, runoff, and soil moisture using different emission scenarios have been carried in the many basins. However, it is necessary to indicate that to estimate climate impacts on the water resources at local scale, the global data from GCMs need be downscaled. Two techniques have commonly been used: Statistical and dynamic methods which are described in the next section.

3. Downscaling from Global Climate Models

Global Climate Models provides weather data at global scale and their use directly in local scale applications is restricted due to their coarse spatial and temporal resolution. In that sense, for assess the change impact of the climatology parameters such as temperature and precipitation on hydrology and water resources systems, the outputs of GCMs need be downscaled. Downscaling can be defined as a technique that allows increases the resolution of the Global Climate Models (GCMs regional scale) to obtain local scale surface weather for several applications. There are two very known methods: Statistical and dynamic downscaling. Both methods have been developed and implemented for different researchers.

3.1 Statistical Downscaling

The statistical downscaling is based on statistical relationship between the large scale climate parameters (GCMs) and the local scale meteorological variables such as temperature and precipitation. According to Wilby and Wigley (1997), this method can be classified in regression models, stochastic weather generators, and weather pattern based approach. Linear or nonlinear relationship between sub grid –local scale parameters and low resolution predictor variable from GCMs is frequently performed in the regression methods. On the other hand, the stochastic generators produce a large synthetic time series of weather data for a location based on the statistical of statistical historical variables. The model of SGWGs used by several researchers for climate impact studies is referred to Richardson (1981) who developed a stochastic technique to generate daily precipitation, temperature, and radiation solar. Using Markov chain – exponential model, daily precipitation was estimated independently modeling the occurrence through two states wet and dry days and the other variables are generated using a multivariate stochastic model with daily means and standard deviations conditioned to wet or dry days. The Richardson-type generator has been used very successfully in several applications in hydrology, agriculture and environmental management (IPCC, 2008).

Downscaling methods with weather pattern approaches are based generally on statistic relating area average meteorological data to a determined weather classification scheme. These involve canonical correlations analysis, neural networks, correlation based on pattern recognition techniques (Wilby and Wigley, 1997).

Another classification of statistical downscaling for GCM simulation is shown by Chong-Yu (1999). There, statistical methods can be found such as the *downscaling with surface variable* which involves empirical relationship between local weather scale parameters and large –scale surface variables, *the perfect prognosis method* that involves the analysis of free atmospheric and surface data in order to develop the statistical relationship between large and local scale. In addition to this, *the model output statistic method* is mentioned. It indicates that free atmospheric variables used to develop statistical relationship are taken from General climate Model (GCM) output.

3.2 Dynamic Downscaling

This method is referred to fine spatial-scale atmospheric models, which use complex algorithms to describe atmospheric process embed within the General Climate Model (GCM) outputs. The objective of this method is to extract the local –scale weather data from large scale GCM information. For this end, it develops and uses Limited –Area –Models (LAM) or Regional Climate Models (RCM) with the coarse GCM data used as boundary conditions. According to Castro and Pielke (2005), downscaling from LAM can be classified into four types:

1. LAM forced by three boundary conditions: Initial conditions, lateral boundary conditions from a numerical weather prediction GCM or global reanalysis at regular time intervals, and by bottom boundary conditions.
2. No initial atmospheric conditions for the LAM; however, results continue depending of the lateral boundary conditions from numerical weather predictions of GCM and the bottom boundary conditions.
3. Specified surface boundary conditions force to GCM which provides lateral boundary conditions.
4. Lateral boundary conditions from completely coupled earth system global climate model in which the atmosphere –ocean –biosphere and cryosphere are interactive.

This technique has been applied for some researchers in order to find weather parameters and fluxes (high resolution) such as precipitation, temperature, radiation, etc, with positives results however; it requires a huge amount of computational resources and takes long time for the simulations. It due to the high resolution sub grids that it need to simulate and the complete climate equations are also used. A general procedure of downscaling from CGMs is shown in the figure below:

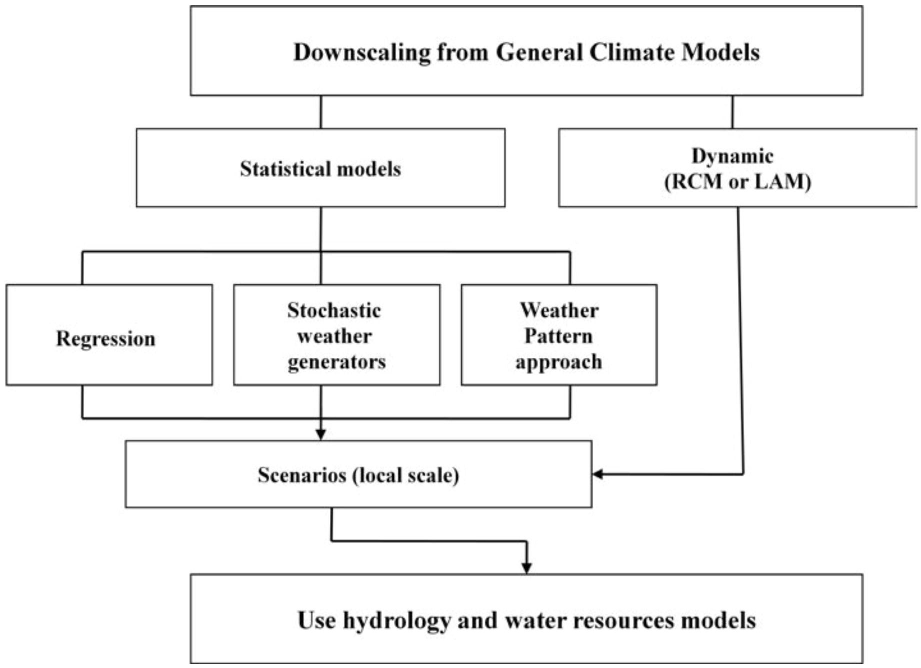

Figure 4. Scheme for downscaling data from GCMs

3.3 Applications of downscaling methods

In this part, a summary of some downscaling applications in climate change impacts on hydrology and water resources are presented in order to illustrate the performance of some methods.

Yates et al. (2003) developed a technique for generating regional climate scenarios. It uses the nearest –neighbor algorithm based on the nonparametric stochastic water generator in order to generate synthetic climate series as well as a set of climate scenarios that may be used in the assess of climate change impact on the water resources management. In summary the methodology described in this application follows the steps:

The k-nn algorithm.

To apply this model, historical daily weather data is supposed to be available in the *r* stations for *N* years. Considering that the number of variable studied is 3 (p =3): Precipitation (PPT), temperature maxima (TMX), and minimum temperature (TMN). Likewise, the vector of weather variables for day t and station j can be denoted by X_t^j, where j = 1, …..k, and t = 1, …T. T is the total days of the observed time series. The weather vector can be expanded of following form:

$$X_t^j = x_{i,t}^j = x_{1,t}^j, x_{2,t}^j, \ldots\ldots, x_{p,t}^j \qquad \text{, where i = 1,….p}$$

The algorithm steps are:

1. The regional means of the *p* variables across of *k* weather stations to a day *t* can be computed as follow:

   $\bar{x}_{i,t} = \frac{1}{k}\sum_{j=1}^{r} x_{i,t}^j$ Where $\bar{x}_{i,j}^j$ is the mean value of the weather variable *i* for station *j*, or more specifically:

   $$\bar{x}_t = \begin{bmatrix} \overline{PPT_t} \\ \overline{TMX_t} \\ \overline{TMN_t} \end{bmatrix}$$

   Where

   $$\overline{PPT_t} = \frac{1}{k}\sum_{j=1}^{r} PPT_{j,t} \quad , \overline{TMA_t} = \frac{1}{k}\sum_{j=1}^{r} TMA_{j,t} \quad \text{, and } \overline{TMI_t} = \frac{1}{k}\sum_{j=1}^{r} TMI_{j,t}$$

   $\overline{PPT_t}$ is the mean precipitation, $\overline{TMX_t}$ is the mean maxima temperature, and $\overline{TMN_t}$ is the mean minimum temperature which is calculated for day t from all m stations.

2. Select a temporal window of width w centered on day t. All days within the temporal window are considered as potential candidates for day t+1. For instance, in this study Yates (2003) used a temporal Window of 14 days which means that if the current day t is January 10, the temporal window of days consists of all day between January 03 and January 17 for all N years but excluding day t (January 10). Consequently, the potential neighbors for day t is determined by s = (w+1)*N -1 days.

3. For each day of potential neighbors computes mean vectors across *r* stations. For this end, the equations given in the step1 are used.

4. Compute the covariance matrix, Cov_t for day *t*, using the data block sxp.

5. The weather on the first day *t* (e.g. January) comprising all *p* variables at *r* stations is randomly chosen from set of all January 1 values of the historic record of N years; which means that all January 1 are candidate days with the same probability of selection. This is the feature vector F_t^i that constitutes the stochastically generated weather for day *t* of year *i* given for each station. The algorithm continues with the next day, *t*+1.

6. Mahalanobis distances d_i are computed between mean vector of the current day's weather, $\overline{x}_i$ and the mean vector $\overline{x}_i$ for day i where i = 1,…..s . Then the distance can be computed through the following expression:

$$d_i = \sqrt{(\overline{x}_t - \overline{x}_i)^T Cov_t^{-1} (\overline{x}_t - \overline{x}_i)}$$

Where T is the transpose of the vector , i =1, ……s, and Cov_t^{-1} is the inverse of the covariance matrix.

The distances are sorted in order ascending and the first K nearest neighbors are retained.

7. In this study, a heuristic method for choosing K was used, where $K = \sqrt{s}$. The first K-nearest neighbors is determined to be retained for resampling out of the total *s*.

8. A probability metric with weight function which assigns weights to each of the K-nearest neighbors is compute by the following expression:

$$w_j = \frac{1/j}{\sum_{i=1}^{K} 1/i}$$

A high weight is assigned to the neighbor with smallest distance while the least weight is assigned the largest distance. Likewise, the cumulative probability can be estimated as:

$$p_j = \sum_{i=1}^{j} w_i$$

9. Estimate, using the cumulative probability metric p_j, the nearest neighbor of the current day (t+1). First, generate a random number, $z \subset (0,1)$, for a $p_1 < z < p_k$ the day j (t+1), to the distance d_j, is selected for which z is closest to p_j. On the other hand, if $z \leq P_k$, then t+1 day corresponding to distance d_k is selected. If $z \geq p_1$, the day t+1 corresponding to distance d_1 is selected. Finally, the steps 6 through 9 are repeated to generate as many days of synthetic data are required for the simulation.

In addition, to generate subsets of years for each week, a temporal probabilistic resampling scheme was introduced in this study. The *K-nn algorithm* model was used to simulate daily precipitation, maximum and minimum temperature at stations located in the Rocky Mountains region and the central Midwest of the United States (Figure 5). Statistics analysis such as correlation between variables, means, standard deviations, etc were carried out in order to assess the performance of the model. In order to illustrate part of the results obtained in this study, the figure 6 is presented. It shows the variation of the total precipitation over time series of 100 years in which it is noted that the changes for April and May were the biggest with decreasing of the precipitation in last decades of time series studied (90-100 mm first decades to 50-60 mm last decades) . January and June present the smallest decline in the last decades for whole the simulation period. On the other hand, in the same figure (on the right), the behavior of the daily average temperature (weighted average of minimum and maximum temperature) can be seen. It is clearly observed that in the long term the temperature increases for April and May in the range of +2.7 °C and +3°C over all time period. Finally, it is shown that this technique simulates the weather sequences at different stations, with a good performance in reproduce the spatial and temporal statistics and a successful generation of climate change scenarios through the strategies used to adapt the K-nn (strategic resampling).

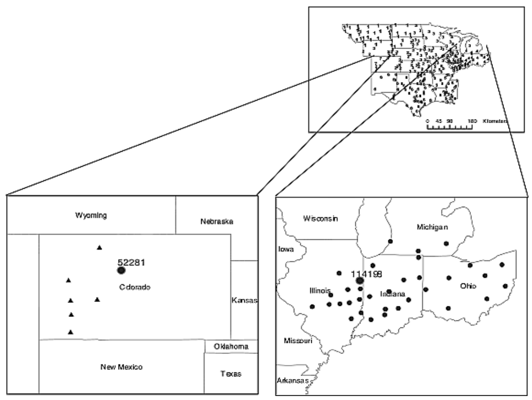

Figure 5. Study area and two focus regions with their weather stations used to apply the algorithm. 114198 in region 4 and 52281 in region 7 stations were used to illustrate the results. Yates et al (2003).

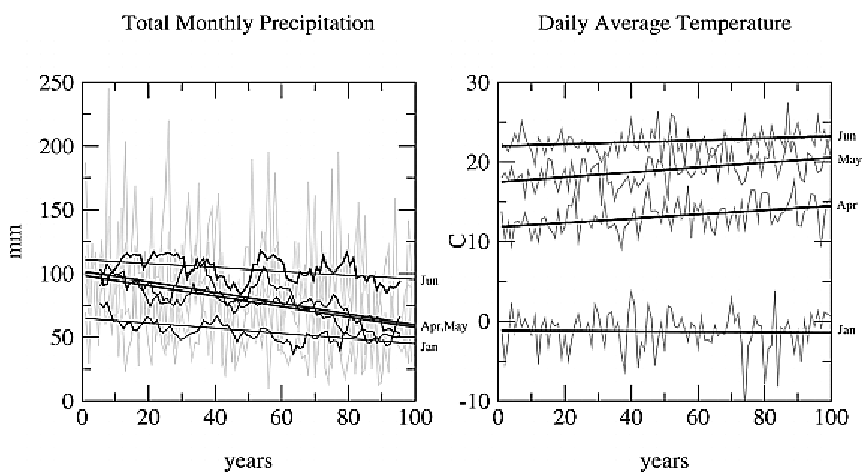

Figure 6. Total monthly precipitation for 100 years times for warmer-drier spring scenarios (left). Regional averaged time series (shaded lines), the 10-year moving averages (solids lines), and the linear trends for January, April, May, and June are shown with straight lines. Daily average temperature for the indicated months is shown in the right graph, with regionally averaged time series and the linear trend for the 100 years. Yates et al (2003).

Ghosh and Mujumdar (2006) generated future climate scenarios for rainfall by statistical downscaling over state Orissa located on the east coast of India. In this study, the method developed is based on a linear regression model to compute the precipitation using Global Climate Model (GCM) outputs. Mean sea- level pressure and geo potential height of this GCM were used as variables to regression. On the other hand, the Coupled Global Climate Model (CGCM2) developed by the Canadian Center was used in this research. The IPCC-IS92a scenario is considered in the model for which the variation of green-house gases forcing belongs to the historical data from 1900 to 1990, with a rate increase of 1 % per year which is considered to continue until 2100. First, the methodology consists in performing a statistical procedure called Principal Component Analysis (PCA) in order to reduce the dimensionality of the variables considered. It allows to indentify the multidimensional variables and to transfer to a group of uncorrelated variables, those correlated. Likewise, the fuzzy clustering method was used to classify the main variables indentified by PCA, and for the regression analysis, the fuzzy cluster membership values were used, indicating that the regression models were modified for a seasonal/periodic component different for months. Additionally, for future rainfall scenario, the method assumes that the regression relationship will not change in the future time. On the other hand, to carry out the regression analysis, monthly rainfall data from 1950 to 2003 was used. The projections estimated for the future rainfall based on IPCC-IS92a scenario indicate that is probably the increase of extreme hydrological events in Orissa in future such as is shown in figure 7 and 8. For instance, it is noted that for wet periods the precipitation increases on the time series period considered while for dry period the precipitation decreases considerably. Also, it is suggested that the methodology developed in this study can be used to simulate precipitation at regional scale and therefore also can be used for assessing climate change impacts.

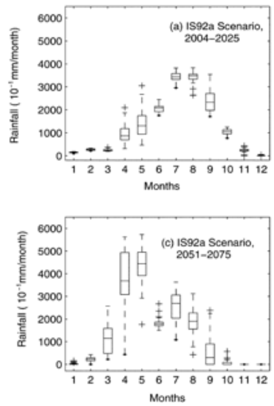

Figure 7. Box-plot for monthly predicted rainfall. Ghosh(2006).

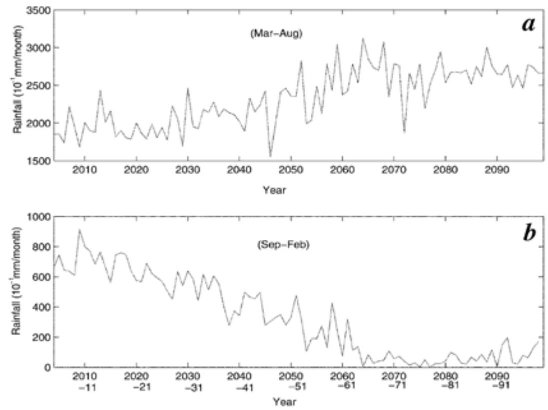

Figure 8. Predicted rainfall for wet (***a***) and dry (***b***) periods

On the other hand, the reality of many places in the world is the lack of weather stations with historical records and other cases, it is limited, resulting difficult the application of the downscaling methods from GCMs. However, several statistical methods have been applied for some researchers to generate time series data for precipitation and temperature fundamentally, so that it is possible to apply future climate scenarios and to assess the climate change impacts in a specific region. A conditional generation method (CGM) based was applied to generate monthly precipitation time series for the upper Blues Nile Basin in Ethiopia (Kim and Kaluarachchi, 2008). The method consists in determining the conditional occurrence probability of a given event. The joint probability density should be uniformly distributed if the probability of occurrence of given variable at current month is independent of event of previous months. The CGM was validated comparing with others statistical method such inverse transformation of the cumulative density function and autoregressive processes (stochastic method first –order Markov process). Furthermore, in this study, a time series of 100 years of six GCMs were used to evaluate the change in precipitation for which only the emission scenario A2 was selected. The main characteristics of this scenario is that it is used for mid to high range of emission, with high CO_2 concentrations, increase of the global population and energy consumption (IPCC, 2001). From GCMs, a percent change of monthly precipitation for each grid was estimated.

These changes were spatially downscaled to the weather stations considered in this study; for this end, the triangular cubic interpolation method was used. In general, the results in this research showed the conditional generation method reproduced reliable historical precipitation being even more accurate than other methods applied which means that the historical spatial correlation at stations can be conserved by CGM used. On the other hand, changes in the precipitation were estimated for upper Nile basin indicating variations of 47 % in dry, 5% in wet, and 6 % in mild seasons. Figure 9 shows the changes of precipitation (in percentage) in the area study estimated for the six GCMs.

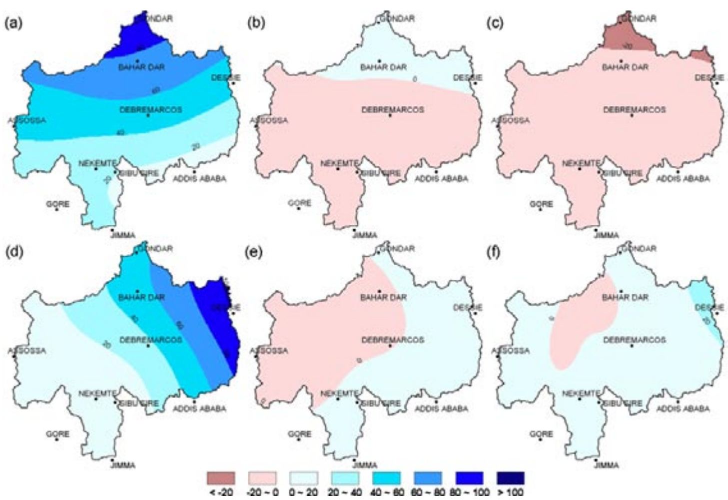

Figure 9. Spatial Distribution of annual precipitation changes (%) by the 2050s for Six GCMs: (a) CCSR, (b) CGCM, (c) CSIRO, (d) ECHAM, (e) GFDL, and (f) HADCM. (Kim and Kaluarachchi, 20008)

It is also necessary to indicate that in chapter 10 of IPCC (2001) can be found a description and evaluation of statistical and dynamical downscaling from GCMs. Likewise, some comparisons both techniques have been carried out. For instance, Murphy (1999) compared a statistical downscaling based on regression against two dynamical downscaling techniques (RCM) over Europe. Monthly mean precipitation and surface temperature anomalies were downscaled using predictor sets. The results showed that the dynamical model estimated better the precipitation for winter time while the statistical model was better to estimate the summertime temperature. Both techniques showed important approximations; however, because of sophisticated dynamical technique, it showed a better accuracy over the statistical method. Wilby et al. (2000) evaluated hydrology response for the Animas River basin in Colorado, USA to statistical and dynamic downscaling output for which daily precipitation and surface temperature were simulated. In this study, the results indicate that both techniques showed a good performance for hydrological modeling and these had greater skill than the course resolution data used to drive the downscaling (raw NCEP output). In addition, for hydrological applications, the statistical downscaling has the advantage of require few parameter and simple computations and the dynamical model provides better estimates water balance than the raw and corrected reanalysis output.

In general, all comparative studies described above showed that both methods have similar skills. However, "the results may represent a further validation of the performance of RCMs, due to that the statistical downscaling is based on observed relationships between predictands and predictors" (IPCC, 2001).

4. Hydrology and Water Resources Modeling

Once, the GCMs data is downscaled, hydrology and water resources models are used in order to assess the climate change impacts at local scale. The general procedure to evaluate climate change impacts on the water resources are presented below:

- Precipitation, temperature, and solar radiation are extracted at the grid nodes from a long time period of General Circulation Model simulations.
- A downscaling method is used to relate the regional GCM output to the surface variables at the river basin scale.

- Using meteorological data and observed stream flows, a Hydrological model is calibrated and validated, and it is forced with downscaled GCM scenarios to produce stream flows sequences for different climates GCM scenarios.
- With the stream flow sequences produced, a water resource simulation model is used to assess the climate scenarios and their impact on hydrology and the water resources system
- Finally, evaluate some water management policies in order to mitigate the impacts on water resources system.

There are several hydrological and water resources models. For instance, the Hydrologic Modeling System (HEC – HMS) developed by the Hydrologic Engineering Center from US Army Corps Engineers. This model is designed to simulate the precipitation and runoff processes in the watershed systems. HMS computes the runoff by calculating the water volume that is infiltrated, intercepted, stored, evaporated, or transpired and subtracting it from the precipitation (US Army Corps, 2000). HEC-HMS includes several mathematical models which are appropriated under different conditions and environments. In figure below is presented a basin model in HMS for a particular sub basin in the north Mexico. This model allows assessing the climates impact on the hydrology of river basins.

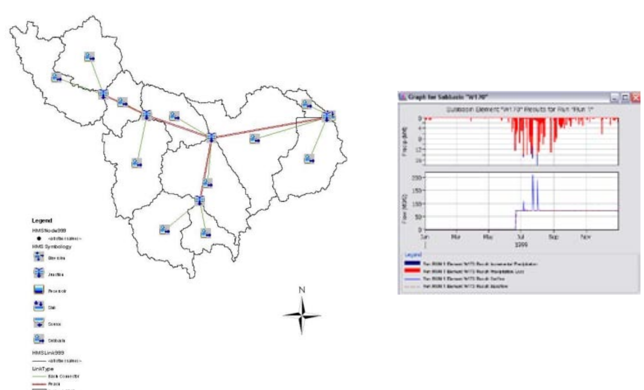

Figure 10. HMS model for the Boquilla sub basin. Conchos River basin

On the other hand, Water Evaluation and planning System (WEAP) is an integrated water resources model that simulates an entire water resources system that includes water demands, groundwater, hydrology, water supply, water quality, and evaluate water management policies. It has a hydrological module which is spatially continuous with areas configured as a set sub-catchments that cover the entire river basin under study, considering them to be a complete network such as rivers, reservoirs, channels, aquifers, demand points, etc. Likewise, this module includes three methods to simulate catchment processes such as evapotranspiration, runoff, infiltration, as a dynamic integrated rainfall-runoff model including various components of hydrologic cycle.

For hydrological modeling purposes in WEAP, the soil moisture method can be performed. Essentially the model considers the movement of water through the soil composed for two simple layers o reservoirs. This model can be applied to several climatic conditions for which the capacity of layers as well as the water movement between them need be adjusted (Environmental Institute of Stockholm, 2007). The one dimensional mathematical expression used in this model is following:

$$Rd_j \frac{dz_{1,j}}{dt} = P_e(t) - PET(t)k_{c,j}(t)\left(\frac{5z_{1,j} - 2z_{1,j}^2}{3}\right) - P_e(t)z_{1,j}^{RRF_j} - f_j k_{s,j} z_{1,j}^2 - (1 - f_j)k_{s,j} z_{1,j}^2$$

Where $z_{1,j}$ =[1,0] is the relative storage represented as a percentage of the total effective storage of the root zone water capacity, Rd_j in mm for land cover fraction , P_e is the effective precipitation in mm which includes snowmelt, PET(t) is the Penman-Montieth reference potential evapotranspiration, $k_{c,j}$ is the crop coefficient for each fractional land cover. $P_e(t)z_{1,j}^{RRF_j}$ is the surface runoff, where RRF_j is the Runoff Resistance Factor that depend of the land cover. Higher values of this factor result in a high evaporation the basin; therefore, less surface runoff. $f_j k_{s,j} z_{1,j}^2$ is the interflow of the first layer where f_j is a partitioning coefficient related to the land cover type , soil, and topography that divides in both in vertically and horizontally flows, $k_{s,j}$ is the hydraulic conductivity of saturated root zone in mm/time. The last term $(1-f_f)k_{s,j}z_{1,j}^2$ is the deep percolation.

Now this model is being applied to assess the climate change impacts on the water resources in the Rio Bravo basin, specifically in the Conchos River. Figure 11 shows some results of the performance of the model. Temperature, precipitation, wind velocity, and relative humidity were the inputs.

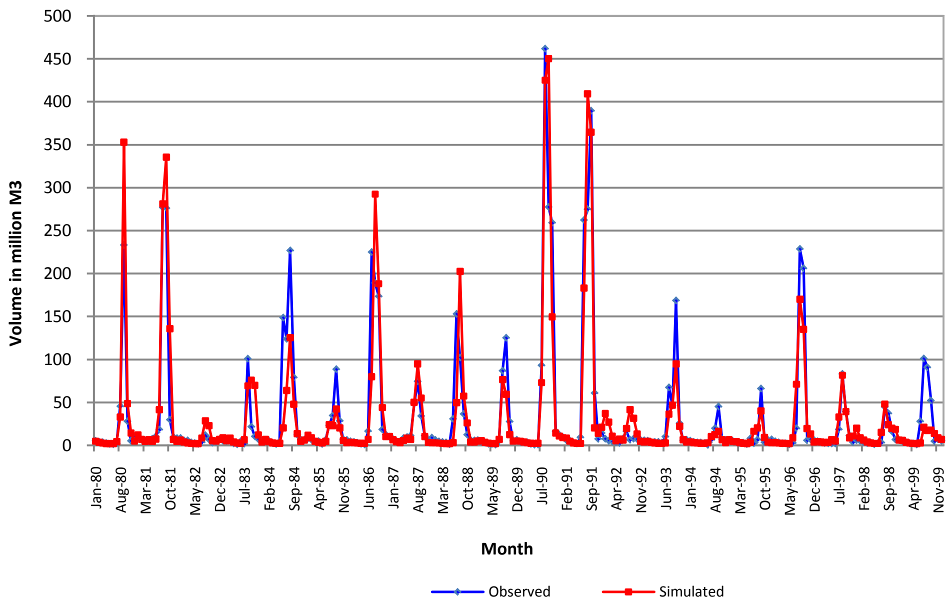

Figure 11. Observed and simulated runoff for a control station in the Conchos river basin. Period 20 years.

5. Conclusions

Based on the literature review, as consequence of climate changes, precipitation will decline in lower and middle latitudes and it increases in some regions such as in the part of tropics and high latitudes (simulated for 2080-2099 relative to 1980-1999). Soil moisture content decreases in sub tropical and Mediterranean region. Runoff depends of the changes in precipitation; in this sense, it is clearly reduced in central American and Europe and increases in high latitudes.

Moreover, the annual evaporation increases over most oceans. Few indicators exists about the change of groundwater recharge; however, in some studies evaluated, the groundwater recharge will decrease considerably in the South West Africa and North-Eastern Brazil. Another interesting aspect is the increase of risks of droughts and floods for sub tropical, low and mid latitudes, and tropical and highs latitudes regions respectively.

Climate change will affect directly the water resources systems as is shown with results described from GCMs models at global scale. Management and operation of hydraulic infrastructures, irrigation methods, and water management practices will be affected. According to IPCC, the area of land subject to increase of water stress due to climate change will be more than double than those with decreasing stress.

On the other hand, for using the GCMs weather data to assess climate change impacts at local scale is necessary and fundamental to downscale the global data. Statistical and dynamical downscaling was reviewed. Statistical downscaling such as stochastic weather generators and regression models has been used by several studies. Dynamic downscaling develops and uses a regional climate model (RCM) with the course GCM data used as boundary conditions. According to several studies, both techniques showed great skill to carry out the downscaling task; however, dynamic downscaling requires of huge amount of computational resources and take long time for the simulations.

Finally, the hydrology and water resources models are tools very important to evaluate climate change impacts in the future at local scale. Many of them use mathematical models to represent the behavior the runoff, groundwater, and climatic parameters.

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