Hydrological Response of a Catchment to Climate Change in the Upper Beles River Basin, Upper Blue Nile, Ethiopia

Girma Yimer [1], Andreja Jonoski [2] and Ann Van Griensven [2]

[1]Research fellow , UNESCO-IHE Institute for Water Education, Department of Hydroinformatics and Knowledge Management, 2601 DA Delft ,The Netherlands (corresponding author), E-mail: girmayimer@yahoo.com
[2] Senior Lecturer, UNESCO-IHE Institute for Water Education, Department of Hydroinformatics and Knowledge Management, 2601 DA Delft ,The Netherlands

Abstract
A Statistical downscaling model was developed and validated using large-scale predictor variables derived from the National Centre for Environmental Prediction (NCEP) reanalysis data and observed station data that was achieved in order to establish a statistical relationship between large-scale NCEP reanalysis predictor variables and locally observed meteorological variables. The relationship obtained was then used to generate the possible future scenarios of meteorological variables such as temperature and precipitation using large-scale predictor variables obtained from the Global Climate Model, HadCM3 (Hadley Centre Coupled Model version3) outputs. The downscaled meteorological variables corresponding to global emissions scenario (A2a) were then used as input to the HEC-HMS hydrological model calibrated and validated with observed station data to simulate the corresponding future streamflow changes in the Beles River.

Hydrological impact assessment over the basin showed a projected decrease in annual runoff in the future. Most of this decrease in flow is also found to be in the summer season (main rainy season of the area).

***Key Words**:* Climate Change, Downscaling; SDSM, HEC-HMS; Streamflow

1. INTRODUCTION

Global Climate models (GCMs) are the best tools to estimate future global climate changes resulting from the continuous increase of greenhouse gas concentration in the atmospheres (Busuioc et al., 2001; Dibike and Coulibaly, 2005). However, due to their coarse spatial resolution, the outputs from these models may not be used directly in impact studies. Hydrological models, for instance, deal with small or sub catchment scale processes whereas GCMs simulate planetary scale and parameterize many regional and smaller-scale processes. Therefore, downscaling techniques emerged as a mean to relate the scale mismatch between the GCMs results and the increasingly small scales required by impact community (Dibike and Coulibaly, 2005; Wilby and Wigley, 1999). The two main approaches used for deriving local or regional scales information from the global climate scenarios generated by GCMs are dynamic downscaling which involves a nested regional climate model (RCM) and statistical downscaling techniques which employs a statistical relationship between the large scale climatic state and the local variations derived from historical data. A diverse range of statistical downscaling techniques are available where each method lies, generally, in one of the three categories, namely regression_(transfer function) methods , stochastic weather generators and weather classification schemes (Wilby et al., 2004). Among the widely applied statistical downscaling techniques is the universally multiple linear regression models called Statistical Down-Scaling Model (SDSM). This technique is used in this study and is briefly reviewed for clarity and discussions.

2. STATISTICAL DOWNSCALING METHODS OVERVIEW

Statistical downscaling methods involve developing quantitative relationships between large-scale atmospheric variables (predictors) and local scale surface variables (predictand) through the transfer functions (Wilby et al., 2004). The most common form has a predictand as a function of the predictors. The two frequently used terms in statistical downscaling are defined as follows as used in many publications.

The predictor is the input data used in statistical models, typically a large scale variable describing the circulation regime over a region. The predictor is also known as ’independent variable’, or simply as the ’input variable’, usually written as

Predictand = f (predictors)

The predictand is the output data, typically the small-scale variable representing the temperature or rainfall at a weather/climate station. The predictand, is also known as ’dependent variable’, ’response variable’, ’responding variable’, or simply as the ’output’

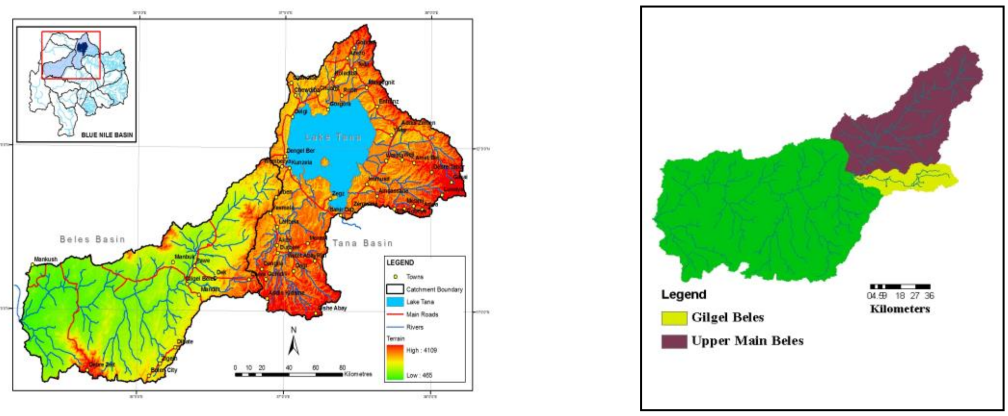
Statistical downscaling is computationally inexpensive, and thus can be easily applied to the output of different GCM experiments (Wilby and Dawson, 2007). Additionally, it can be used to provide local information, which could be most needed in many climate change impact applications. According to Wilby and Wigley (1999), the following three implicit assumptions are involved in the statistical downscaling:

- predictors are variables of relevance and are realistically modeled by the GCMs
- the employed predictors fully represent the climate change signal
- these observed empirical relationships are valid also under altered climate change conditions

3. STUDY AREA AND DATA USED

Beles sub-basin of the Upper Blue Nile was chosen to be investigated in this study. This is because the basin is sought to be one of the potential future development areas where currently, some water resources development projects like TanaBeles Multipurpose hydropower project through inter basin water transfer from Lake Tana and Upper Beles Irrigation projects are in progress. Therefore assessing the impact of climate change will give an insight upon which appropriate decisions about water resources development can be made in the future

The main stem of the Beles River originates on the face of the escarpment across the division to the west of the south-western portion of Tana Lake. It then flows in a westerly direction and enters into the Blue Nile just before it crosses the Ethiopia-Sudan frontier. It is the only major right bank tributary of Blue Nile. The Beles basin covers an area of about 14,000 km2 and geographically it extends from 10o 56’ to 12o N latitude and 35o12’ to 370 E longitude. The basin has two gauged sub-catchments namely upper-main Beles and Giligile Beles that have sizes of 3474 km2 and 675 km2, respectively. In particular, the focus of this study is Upper Beles sub-basin (figure 1). Three meteorological stations in the vicinity of the Upper Beles sub-basin namely Pawe, Dangila and Bhardar are used in the downscaling experiments. For Bhardar station, 30 years of daily data (1961-1990) were used for the downscaling experiment. For the other two stations, 15 years (1987-2001) daily precipitation, daily maximum and minimum temperature records have been used as predictands as they exhibit shorter records. Also, large-scale reanalysis was executed to daily data sets of the National Center for Environmental Prediction (NCEP) for the same period. These were used as predictors.



(a) *(b)*

Figure 1: Tana and Beles Basin Map: (a) Tana-Beles basin, (b) Upper Beles sub-basins

4. STATISTICAL DOWNSCALING MODEL

Statistical Downscaling Model (SDSM) is a hybrid of multiple linear regression and stochastic downscaling model developed by Rob Wilby and Christian Dawson (Harpham and Wilby, 2005; Wilby and Dawson, 2007). It is a freely available decision support tool for assessing local climate change impact using a robust statistical downscaling technique.[7] In SDSM downscaling, a multiple linear regression model is developed between a selected large-scale predictor variables and local scale predictands such as temperature and precipitation. And the parameters of the regression equation are estimated using an ordinary Least Squares algorithm. Precipitation is modeled as a conditional process in which the local precipitation amount is correlated with the occurrence of wet days. As the distribution of precipitation is skewed, a forth root transformation is applied to the original series to convert it to the normal distribution, and then used in the regression analysis. Minimum and maximum temperatures are modeled as unconditional process, where a direct link is assumed between the large scale predictors and local scale predictand.

4.1 Predictor Variables

Predictor data files for SDSM were obtained from the Canadian Institute for climate studies (CICS) website.[8] The predictor variables for HadCM3 were provided on a grid box by grid box basis of size 2.5° latitude and 3.75° longitude. The watershed area of Beles basin lies in two grid boxes 10° latitude and 37.5° longitude and 12.5° latitude and 37.5° longitude (Figure 2). Table 1 shows large- scale atmospheric variables derived from the grid boxes

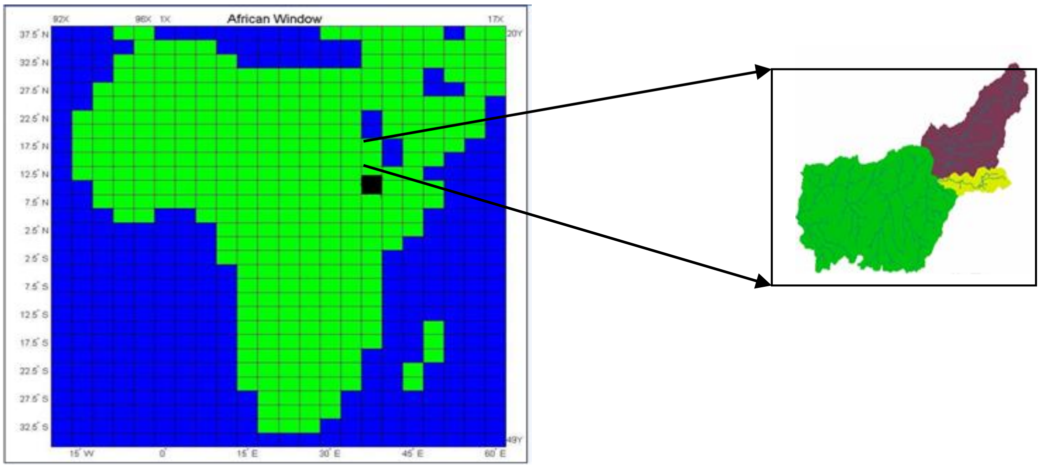


Figure 2: African continent windows with 2.50 latitude x 3.75o longitude from which grid of study area selected shown in black square box

[7] https://co-public.lboro.ac.uk/cocwd/SDSM/index.html

[8] http://www.cics.uvic.ca/scenarios/sdsm/select.cgi

Table 1 Large-scale atmospheric variables from the NCEP reanalysis and HadCM3 simulation output that are used as potential inputs to the multiple linear regression model.

No.	*Predictors*	*description*	*No.*	*predictors*	*description*
1	mslpaf	men sea level pressure	14	P5_ zhaf	500hpa divergence
2	p_faf	surface air flow strength	15	p8_faf	850hpa airflow strength
3	p_uaf	surface zonal velocity	16	p8_uaf	850hpa zonal velocity
4	p_vaf	surface meridian velocity	17	p8_vaf	850 hpa meriodinal velocity
5	p_zaf	surface vorticity	18	p8_zaf	850 hpa vorticity
6	p_thaf	surface wind direction	19	p850af	850hpa geo-potential height
7	p_zhaf	surface divergence	20	p8thaf	850hpa wind direction
8	p5_faf	500hpa air flow strength	21	p8zhaf	850 hpa divergence
9	p5_uaf	500pa zonal velocity	22	r500af	relative humidity at 500 hpa
10	p5_vaf	500hp meriodinal velocity	23	r850af	relative humidity at 850 hpa
11	p5_zaf	500hpa voritcity	24	rhumaf	near surface relative humidity
12	p500af	500hpa geo-potential height	25	shumaf	surface specific humidity
13	p5thaf	500hpa wind direction	26	tempaf	mean temperature at 2 m

All predictors were normalized with respect to the 1961-1990 mean and standard deviation, except the wind direction.
(Source:http://www.cccsn.ca/Help_and_Contact/Predictors_Help-e.html, accessed on April 24, 2009)

4.2 Choice of Predictor Variables

The choice of predictor variable(s) is one of the most challenging stages in the development of any statistical downscaling model. This is attributed to the fact that decision largely determines the character of the downscaled scenario. The decision process is also complicated due to the fact that the explanatory power of individual predictor variables varies spatially and temporally (Hessami *et al.*, 2007; Wilby and Dawson, 2007). In SDSM, the selection of the most relevant predictor variables was carried out through linear correlation analysis, partial correlation analysis and scatter plots between the predictors and the predictand variables. Large-scale predictor variables representing the current climate conditions, derived from the NCEP reanalysis data sets, were used to investigate the percentage of variance explained by each predictand-predictor pairs. Table 2 shows the selected predictor variables for the stations in the downscaling experiments.

Table 2 Large-scale climate predictors for computing surface meteorological variables at different stations with SDSM model

Predictors No.		2	3	4	5	9	12	17	22	23	26
Station	***Predictand***										
pawe	***precipitation***				X	X				X	
	Max Temp	X						X			X
	Min Temp		X		X		X				
Bhardar	***precipitation***			X					X		X
	Max Temp					X	X		X	X	X
	Min Temp						X		X		X
Dangila	***precipitation***					X			X		

Definition of the variables corresponding to each predictor number is the same as in Table1

4.3 SDSM Model Calibration and Validation

Model calibration was carried out based on the selected predictor variables that were derived from the NCEP data set. Model calibration in this case was to find the coefficients of the multiple linear regression equation parameters that relate the large scale atmospheric variables derived from NCEP and local scale variables. The temporal resolution of the downscaling model for precipitation downscaling was specified as seasonal for Pawe station and monthly for Dangila and Bhardr stations. Seasonal model could be used in situations where data are too sparse, at the monthly level, for model calibrations. For example, in a low incidences of precipitation in semi arid area (Wilby and Dawson, 2007), is a typical case for Pawe station.

For Bhardar station, from the 30 years of data, representing the current climate condition, the first 15 years of data (1961-1975) were considered during calibrating the regression model while the remaining 15 years (1976-1990) were used to validate the model, where as for Pawe and Dangila station, the 15 years of data, representing the current climate condition, the first 10 years of data (1987-1996) were considered during calibrating the regression models while the remaining 5 years of data (1997-2001) were used to validate the model. Some of the SDSM setup parameters for event threshold, bias correction and variance inflation were adjusted during calibration to obtain a good statistical agreement between the observed and simulated climate variables. During the calibration of precipitation, downscaling models, in addition to the mean daily precipitation, monthly average dry and wet-spell lengths were used as performance criteria. Figure 3 & 4 shows the performance of the model during validation period. The graph shows a good agreement between the observed and simulated mean daily precipitation and average wet spell lengths for all months of the year except August, whereas the observed and simulated mean daily maximum and minimum temperature showed good agreement for all months of the year. Unlike temperature, precipitation is a conditional process that dependents on other intermediate process like occurrence of humidity, cloud cover, and /or wet-days. For that reason, it is identified by many researchers as one of the most problematic variable in downscaling.

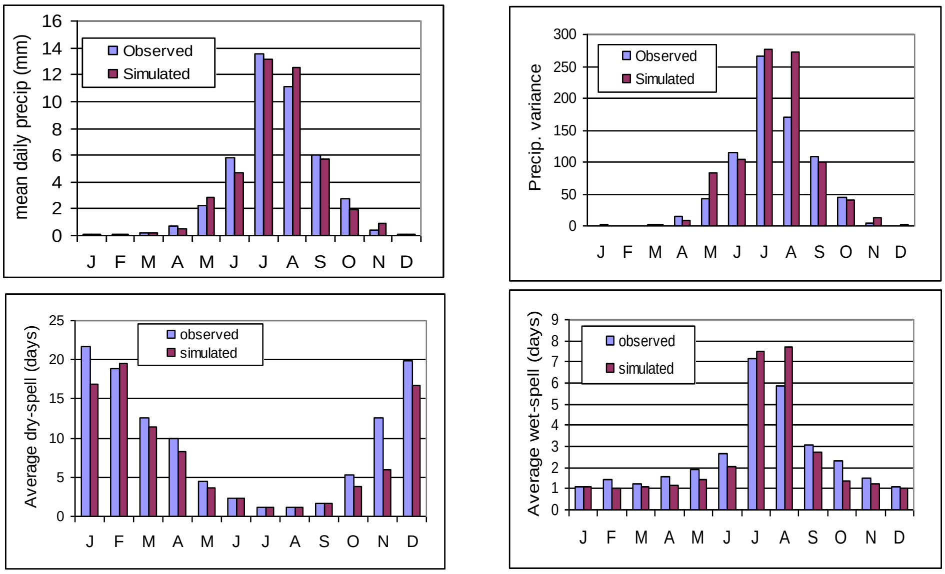


Figure 3: Validation result of SDSM model downscaling (1976-1990) of daily precipitation at Bhardar station

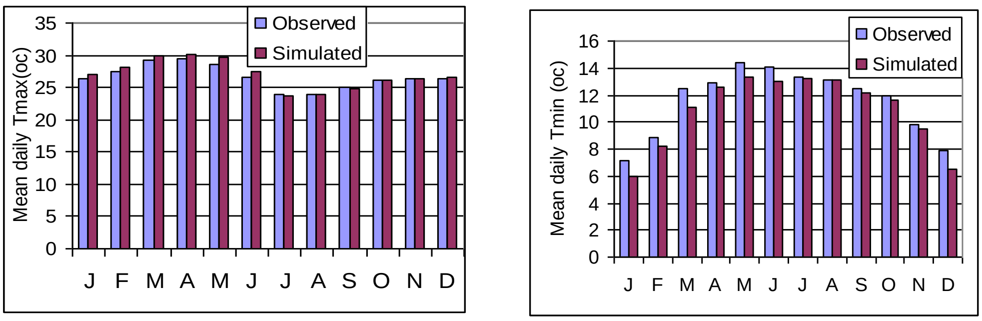


Figure 4: Validation results of SDSM model downscaling (1976-1990) of daily maximum and minimum temperature at Bhardar station

4.4 Downscaling with SDSM

After calibrating the SDSM model, using observed data and large-scale predictors originating from NCEP reanalysis, the same empirical relationship with predictors, supplied by GCMs, were tuned to downscale the future climate change scenario simulated by GCMs. 20 ensembles of synthetic daily time series were generated for A2a SERS emission scenarios for the period of 139 years (2061-2099). The ensemble mean of the 20 ensemble members for the period 2050s (2040-2069) were used for impact analysis using Hydrological model, for this case HEC-HMS.
Figures 5& 6 shows the general trend in the mean daily precipitation and the mean daily maximum and minimum temperature at Bhardar station corresponding to future climate change scenarios downscaled with SDSM. Form these figures, it could be seen that the precipitation decreased, during the rainy season, and a general increasing trend is evident for both minimum and maximum temperature through out the seasons. The average increase in minimum and maximum temperature between the current climate and that of 2050 s will be about 2.5 ºC and 2.3 ºC , respectively.

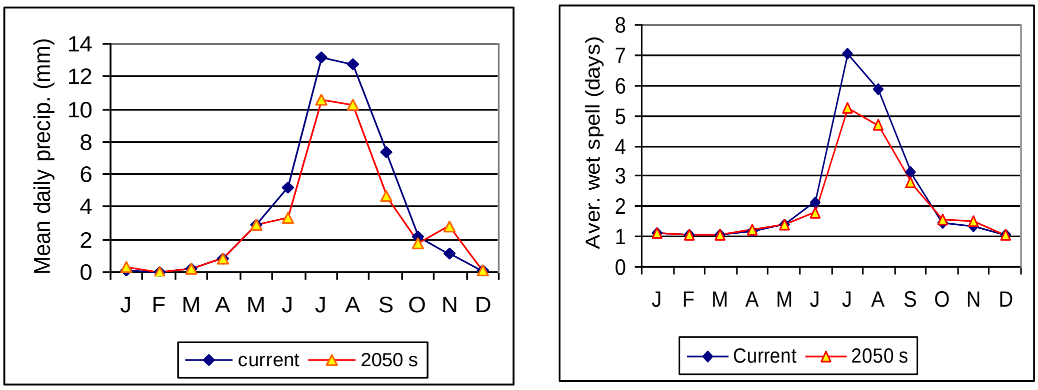


Figure 5: General trend in the mean daily precipitation at Bhardar corresponding to climate change scenario downscaled with SDSM

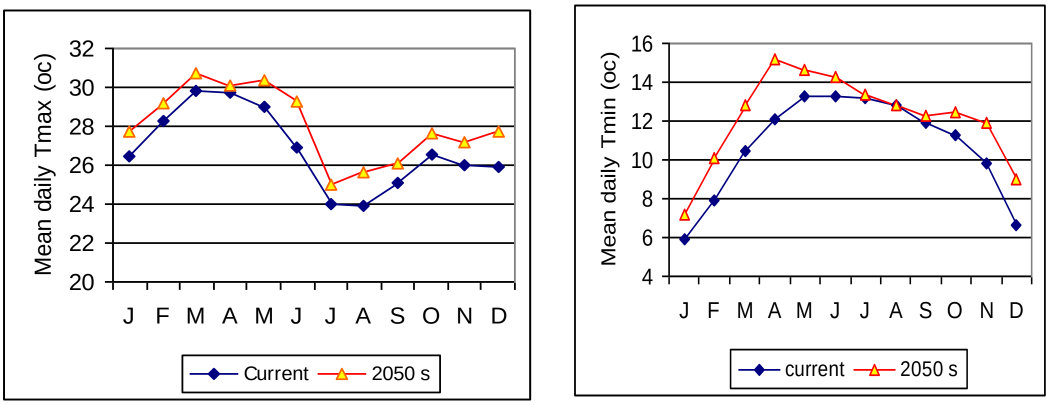


Figure 6: General trend in mean daily maximum & minimum temperature at Bhardar corresponding to climate change scenario downscaled with SDSM

5. HYDROLOGIC MODEL DESCRIPTION

HEC-HMS which is a comprehensive hydrologic model, developed by Hydrologic Engineering Centre (HEC) of United States Army Corps of Engineers (USACE), was used in this study. HEC-HMS is designed to simulate the precipitation-runoff processes of dendritic watershed systems. It is also designed to be applicable in a wide range of geographic areas for solving the widest possible range of problems. This includes large river basin water supply, and flood hydrology, and small urban or natural watershed runoff (HEC, 2006).

The current version of HEC-HMS (3.1.0) is a highly flexible package. It includes different methods to simulate infiltration losses, transforming excess precipitation, base-flow estimation and channel routing.

For this particular study, continuous soil moisture accounting for (SMA) model, Clark's unit hydrograph, Muskingum and linear reservoir methods were used. SMA method allows for a long-term continuous simulation of hydrologic processes that change over time in a watershed. This could be achieved by simulating the movement of precipitation through storage volumes that represent canopy interception, surface depressions, the soil profile and two groundwater layers. Computational components of this algorithm also include evapotranspiration (ET), surface runoff, and groundwater flow (HEC, 2006). Conceptually, the HMS SMA algorithm divides the potential path of rainfall onto a watershed into 5 layers, Figure 7. Besides precipitation the only other input to SMA algorithm is potential evapotranspiartion rate. Clark unit hydrograph technique, used to transform the excess rainfall to direct runoff, has 2 important parameters, namely time of concentration and storage coefficient which is needed to be determined through the calibration process.

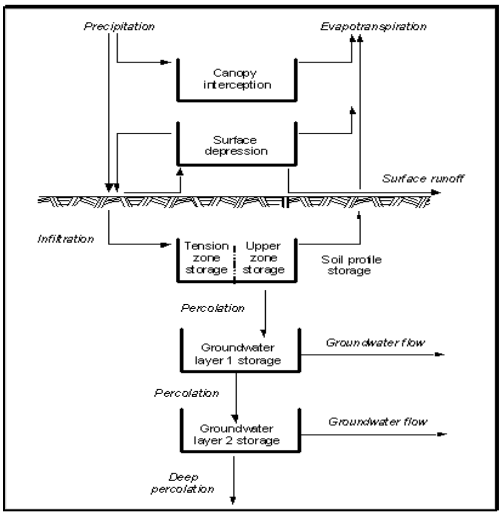


Figure 7: Conceptual schematic of the continuous soil moisture accounting algorithm (Bennett, 1998) (source HEC-HMS Technical manual)

5.1. HEC-HMS Model Setup

HEC-HMS Model setup consists of 4 main model components: basin model, meteorologic model, control specifications and input data (time series, paired data and gridded data).

The Basin model for instance, contains the hydrologic element and their connectivity that represents the movement of water through the drainage system (HEC, 2006). HEC-GeoHMS, an Arc view extension developed by the U.S. Army Corps of Engineers (USACE) was employed to create the basin model background map file and to delineate the sub catchments from the Digital Elevation Model (DEM). DEM was downloaded from the Consortium for Spatial Information (CGIAR_CSI)[9], which provides the NASA Shuttle Radar Topographic Mission (SRTM) 90 m x 90 m resolution Digital Elevation Data for the entire world.

The sub basin physical characteristics such as longest flow lengths, centeroidal flow length and slopes derived from DEM were used for estimating the hydrologic parameters. Longest flow path information, for example, was used for estimating time of concentration

The background maps provide a spatial context for the hydrologic elements composing basin model. They are commonly used for showing the boundaries of a watershed or the location of streams. Terrain

[9] . http://www.ambiotek.com/srtm

pre-processing, Basin processing and HMS model support are the main functionalities of HEC-GeoHMS. In the terrain pre-processing DEM derived from SRTM is used as input and a series of steps consisting of computing the flow direction, flow accumulation, stream definition, stream delineation, watershed delineation, and watershed aggregation were performed step by step to derive the drainage networks. The basin processing step gives capability of merging, editing and subdividing of basins and rivers whereas the HMS model support produces a number of hydrologic inputs that are used directly in HMS. Figure 8 shows the Upper main Beles sub-basins used in the modeling.

The meteorologic component is also the first computational element by means of which precipitation input is spatially and temporally distributed over the river basin. The spatio-temporal precipitation distribution is accomplished by the gauge weight method. The Thiessen polygon technique was used to determine the gauge weights. The Meteorologic model uses monthly evapotranspiartion as input for continuous hydrological simulation which is the case for this model. For this particular study, potential evapotranspiartion computations were carried out using FAO Penman-Monteith method. FAO Penman-Monteith Method is recommended as a sole standard method for the definition and computation of the reference evapotranpspiartion (ETo) (Allen *et al.*, 1990). It requires radiation, minimum and maximum temperatures, air humidity, and wind speed as input.

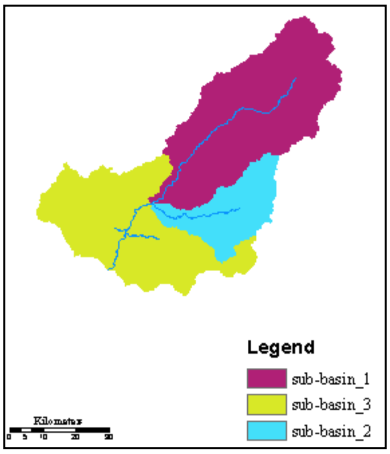


Figure 8: The three small sub-basins of Upper Main Beles

5.2. Calibration and Validation

HMS has the capabilities to process automated calibration in order to minimize a specific objective function, such as sum of the absolute error, sum of the squared error, percent error in peak, and peak-weighted root mean square error. Therefore, automated calibration in conjunction with manual calibration was used to determine a practical range of the parameter values preserving the hydrograph shape and minimum error in volumes. Flow calibration was carried out over the period of `1994-1998 and model validation was carried out over the period of 1999-2001. The whole 12 parameters, needed for the SMA, were taken into consideration in the simulation. The maximum infiltration rate and the maximum soil depth, as well as, the percolation rates and groundwater components had significant influence on the simulated flow discharges. The remaining parameters were adjusted to match the simulated and observed volumes and hydrograph shape. The coefficient of determination (R^2) and Nash-Sutcliffe simulation efficiency (E) were used as evaluation criteria. The coefficient of determination (R^2) during calibration and validation were found to be 0.63 and 0.73, respectively. Nash-Sutcliffe simulation efficiency (E) was found to be 0.62 during calibration and 0.72 during validation (Figure 9). In general, the validation results showed that the model performance is reasonably good in simulating flows for periods outside of the calibration period.

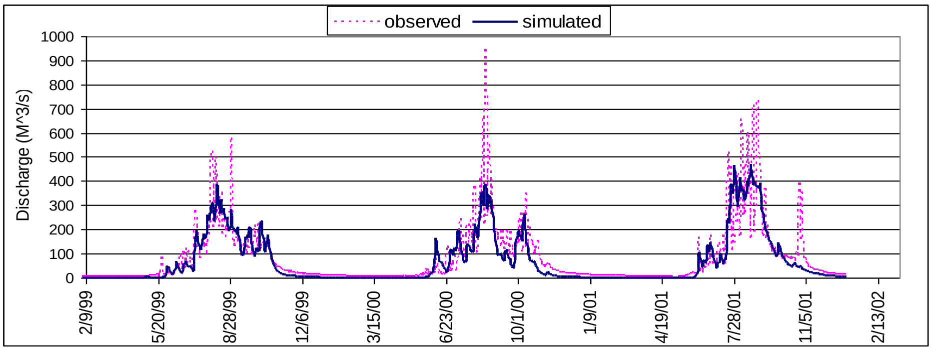


Figure 9: Validation result of Simulated and observed flow hydrographs

5.3. Model Simulation Corresponding to Future Climate Change Scenarios

The ultimate goal of downscaling is to generate an estimate of meteorological variables corresponding to a given scenario of future climate so that these meteorological variables will be used as a basis for hydrological impact assessments. Therefore, after calibrating the hydrological model with the historical data, the next step was to simulate flows corresponding to future climate conditions by using the downscaled precipitation and temperature data for emission scenario used in the downscaling experiment (A2a). This might help in identifying any specific trend in the mean flows in the Beles River corresponding to future time horizon considered in this study.

The future simulation (2050 s) was carried out with the downscaled precipitation and temperature data. Fig 10 shows the change in simulated average monthly mean flows of Beles River corresponding to the downscaled precipitation and temperature data of the current(1961-2001) and future(2040-2069) 2050s climate. The simulation results showed an average mean flow reduction in the summer. SDSM downscaling data resulted in a decrease in the mean annual flow by 5.7 % during the period between the present and the future (2050).

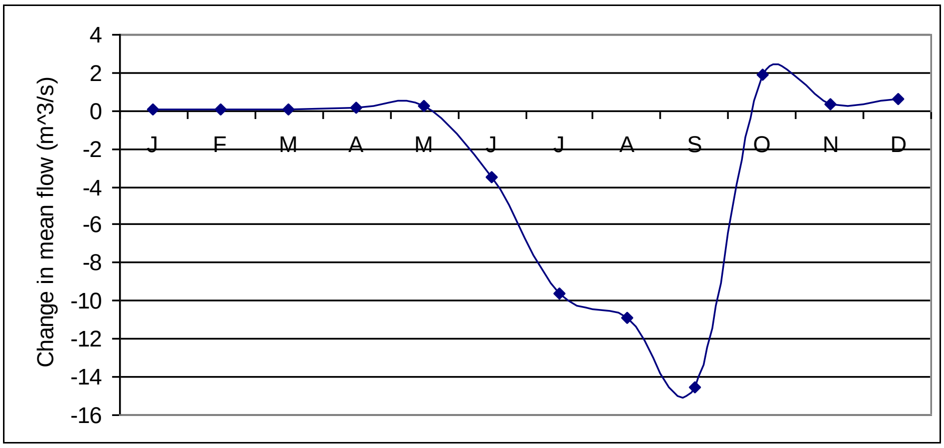


Figure 10: Comparison of simulated change in the average monthly mean flows in Beles River corresponding to the downscaled precipitation and temperature data of the present (1961-2001) and future (2040-2069)

6. CONCLUSION

A number of studies were conducted on the Nile River. However, few studies investigated the impact of climate change on Upper Blue Nile River Basin (Ethiopia). Apparent was, also, that there is no literature published at sub-basin levels. All studies focused on the whole basin. But the water resource planning and managements were carried out at the sub- basin levels. The use of watershed, as the basic planning unit, did not allow the integration of water uses only, but it was also important in managing the relationship between quantity and quality, upstream and downstream water interests.

The results of the downscaling model indicated an increasing trend in both minimum and maximum temperature in the future. The average increase in the minimum and maximum temperature is about 2.5 °C and 2.3 °C, respectively. The IPCC finding, based on the results from several GCM model output, indicated that warming across Africa ranges from 2 °C (low scenario) to 5 °C (high scenario). Hence the result obtained in this case agrees with the IPCC findings. The result of downscaled Precipitation indicated a reduction in precipitation in the main rainy season which accounts the major share of the annual runoff of the area. The streamflow change corresponding to the downscaled precipitation and temperature showed a decrease in the mean annual flow of 5.7 %, during the period between the present and the future (2050s). The downscaling, in this study, is performed by using one GCM model output (HadCM3) only.

Previous studies showed that data taken from different GCMs could differ significantly. Therefore, the methods described in this paper could be used to provide an indication to the likely impact of climate change in the Beles sub basin Upper Blue Nile. Consequently, care should be taken in interpreting the results for further impacts assessments.

7. LIST OF SYMBOLS /ACRONYMS

A2a	Medium-high Emissions Scenario
CICS	Canadian Institute for Climate Studies
DEM	Digital Elevation Model
ETo	Reference Evapotranpspiartion
GCM	General Circulation Model
HadCM3	Hadley Centre Coupled Model version3
HEC- HMS	Hydrologic Engineering Center-Hydrologic Modeling System
NCEP	National Center for Environmental Prediction
SDSM	Statistical Downscaling Model
SMA	Soil Moisture Accounting
SRES-	Special Report on Emission Scenarios
SRTM	Shuttle Radar Topographic Mission
USACE	U.S. Army Corps of Engineers

8. ACKNOWLEDGEMENT

This study was made possible through a scholarship grant from the Water Resources Planning and Management project, Nile Basin Initiative. The author would like to thank the Canadian climate research data distribution centre for providing GCM data and Ethiopian meteorological agency and Ministry of Water Resources for providing station data. The author would also like to thank Yonas Berhan Dibike for his valuable support through e-mail contacts.

9. REFERENCES

1. Allen, R. G., Pereira, L. S., Raes, D., and Smith, M. (1990) *FAO Irrigation and Drainage Paper, NO.56, Crop Evaoptranspiartion(guidelines for computing crop water requirements)*.
2. Busuioc, A., Chen, D., and Hellstrom, C. (2001) Performance of Statistical downscaling Models in GCM validation and regional climate change estimates: application for swedish precipitation. *International Journal of Climatology*.
3. Dibike, Y. B., and Coulibaly, P. (2005) Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. *Journal of Hydrology (Amsterdam)*, **307**(1/4), 145-163.
4. Harpham, c., and Wilby, R. L. (2005) Multi-site downscaling of heavy daily precipiation occurrence and amounts. *Journal of hydrology*.
5. HEC (2006) *Hydrological Modeling system (HEC-HMS) User's Manual , US Army corps of Engineers*

6. Hessami, M., Gachon, P., ourda, T. B. M. J., and St-Hilaire, A. (2007) Automated regression-based statistical downscaling tool. *Environmental Modeling and Software , Science Direct*.

7. Wilby, R., Charles, S., Zorita, E., Timbl, B., Whetton, P., and Means, L. (2004) *Guildlines for use of Climate Scenrios Developed from Statistical Downscaling Methods*.
8. Wilby, R. L., and Dawson, C. W. (2007) *SDSM 4.2 — A decision support tool for the assessment of regional climate change impacts,User Manual*
9. Wilby, R. L., and Wigley, T. M. L. (1999) Precipiation Predictors for Downscaling: Observed and General Circulation Model Relationships. International Journal of Climatology