

Simulated Impacts of Climate Change on Surface Water Yields over the Sondu Basin in Kenya

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Abstract

Potential impacts of climate change on surface water yields over the Sondu River basin in the western region of Kenya were analysed using the Soil and Water Assessment Tool (SWAT) model with climate input data obtained from the fourth generation coupled Ocean-Atmosphere European Community Hamburg Model (ECHAM4) using the Providing Regional Climates for Impacts Studies (PRECIS) model. Daily time step regional climate scenarios at a spatial grid resolution of 0.44° over the Eastern Africa region were matched to the Sondu river basin and used to calibrate and validate the SWAT model. Analysis of historical and projected rainfall over the basin strongly indicated that the climate of the area will significantly change with wetter climates being experienced by 2030 and beyond. Projected monthly rainfall distribution shows increasing trends in the relatively dry DJF and SON seasons while showing decreasing trends in the relatively wet MAM and JJA seasons. Potential changes in water yields resulting from climate change were computed by comparing simulated yields under climate change scenarios with those simulated under baseline conditions.

There was evidence of substantial increases in water yields ranging between 88% and 110% of the

baseline yields by 2030 and 2050 respectively. Although simulated water yields are subject to further verification from observed values, this study has provided useful information about potential changes in water yields as a result of climate change over the Sondu River basin and in similar basins in this region

Keywords: Simulated Impacts; Climate Change; Water Yields; Sondu Basin; Kenya

1. Introduction

During the twentieth century, freshwater became increasingly limited because of the ever-increasing demand resulting from the rapid growth in population, unsustainable use, and increasing incidences of pollution due to emissions from anthropogenic activities. It is expected that climate change will have an impact on surface water yields over the Sondu River basin but the extent is not well understood. Climate change has created problems to water supply, human health and loss of biodiversity (IPCC, 2007). Most studies have concluded that besides being the most vulnerable, Africa is the continent least equipped to handle the impacts of climate change (Lubini and Adamowsky, 2013). The importance of water in agriculture, domestic use, power generation and industry calls for effective and sustainable water resources management. To achieve this, it is important to assess the potential impacts of climate change on the hydrological processes at the watershed level using hydrological models.

The goal of this study was to evaluate the impacts of climate change on surface water yields from the Sondu River basin in the western region of Kenya using the Soil and Water Assessment Tool (SWAT) hydrological model with climate data observed from the basin and those derived from the fourth generation coupled Ocean-Atmosphere European Community Hamburg Model (ECHAM4) using the Providing Regional Climates for Impacts Studies (PRECIS) regional climate modelling system.

2. Literature review

2.1 Previous Studies on Climate Change

In their review on the studies of climate change done on the African watersheds, Lubini and Adamowski (2013) have demonstrated that apart from Tyson's (1991) early research, relatively little work has emerged on future climate change scenarios focused on the African continent. Tyson (1991) constructed climate change scenarios for Southern Africa using results from the first generation of General Circulation Model (GCM) equilibrium experiments. Hulme (1994) later presented a method for creating regional climate change scenarios combining GCM results with the IPCC emission scenarios and demonstrated the application of the method in the African continent.

Hulme *et al.* (1996) went further and took a more focused approach to the use of GCM experiments in describing the 2050 consequences of three future climate change scenarios for the Southern African Development Community (SADC). They selected three different GCM experiments spanning the range of precipitation changes predicted by the GCM for the SADC region, allowing for the assessment of potential impacts and implications of climate change on agriculture, hydrology and health among others.

However, considerable uncertainty remains regarding the large scale precipitation changes simulated by GCMs for Africa. Based on such models, Joubert and Hewitson (1997) came to the conclusion that precipitation would generally increase over much of the African continent by the year 2050 by as much as 15% over 1961-1990 means in the Sahel region (Lubini and Adamowski, 2013).

It is clear from the foregoing that very little work on the impacts of climate change on hydrology has been done for the eastern part of the continent of Africa. This study simulates the impacts of climate change on surface water yields at the watershed level over the Sondu River Basin in Kenya.

2.2 The Soil and Water Assessment Tool

The Soil and Water Assessment Tool (SWAT) (Arnold *et al.* 1998) is a public domain physically-based continuous watershed scale hydrologic model that operates on a daily time-step designed to predict the impacts of changes of input variables, such as climate and land use/cover on water quantity and quality, *inter alia*, in a catchment area. The model simulates a watershed by first delineating and dividing it into multiple sub-basins which are further subdivided into homogenous Hydrological Response Units (HRUs). The HRUs are the smallest homogeneous units of the watershed created by overlaying unique digitised land use, soil properties and slope characteristics maps of the watershed. SWAT model performs hydrological computations at the HRU level from daily rainfall using the modified United States Department of Agriculture (USDA) Soil Conservation Service (SCS) Runoff Number (CN) or the Green-Ampt infiltration method and then sums it up to the sub basin level before routing it to the watershed outlet (Golmohammadi *et al.* 2014; Khanal and Parajuli, 2013).

Model calibration (bettering the parameterisation to reduce the model prediction uncertainty) and validation (demonstrating the capability of a given site specific model to replicate observations) is normally done following three key steps: The selection of a portion of observed data; running the model at different values of known input parameters and comparing the results with observed data until fit to observation is good; and applying the model with calibrated parameters to the remaining portion of the observed data. The model input parameters are adjusted through relaxation techniques during the second step (Arnold *et al.*, 2012; Krause *et al.*, 2005).

A number of researchers have demonstrated the ability of the SWAT model to replicate hydrologic loads at a variety of spatial scales on an annual and monthly basis (Gassman *et al.*, 2007; Schuol *et al.*, 2008). The model has been applied successfully in at least five river basins in Kenya that include Sondu (Jayakrishnan *et al.*, 2005), Tana (Jacobs *et al.*, 2007), Nzoia (Githui, *et al.*, 2009) and Mara (Mango *et al.*, 2011).

3. Methodology

3.1 The study area – Sondu River Basin

Sondu River basin was selected for this study in view of its economic, social, and environmental importance in the western part of Kenya. Agriculture is the mainstay of the people in this basin while the Sondu-Miriu Hydropower station derives its flow from Sondu River; the main river that drains the basin.

The dominant land use activities in the basin include agriculture and forestry accounting for about 64% and 27% respectively of the total basin area.

The landform of the basin consists of low plains near the lakeshore rising eastwards to volcanic plateaus with dissected margins in the middle parts and rugged terrain with deep gorges and V-shaped valleys in the upper eastern parts (JICA, 2013). Land elevation in the basin varies from about 1134 m at the lakeshore to 2900 m above sea level at the summit of Londiani Mountains with an average elevation of 2039 m. The slope of the watershed also varies highly with steeper slopes in the mountains and relatively flatter slopes near the lake.

Elevation and slope play significant roles in watershed hydrology. The slope of the land affects the volume and timing of runoff. The average slope of each individual HRU was calculated by the ArcSWAT interface during the SWAT model setup process (Neitsch *et al.* 2011).

Rainfall in the basin follows a trimodal pattern with the main rainfall season coming in the months of March-April-May (MAM) followed by June-July-August (JJA), and the short rains in September-October-November (SON). The mean monthly rainfall ranges from about 60 mm in January to about 284 mm in May while the mean annual rainfall exceeds 1500 mm, the threshold for a tropical wet type of climate (Ahrens, 2009).

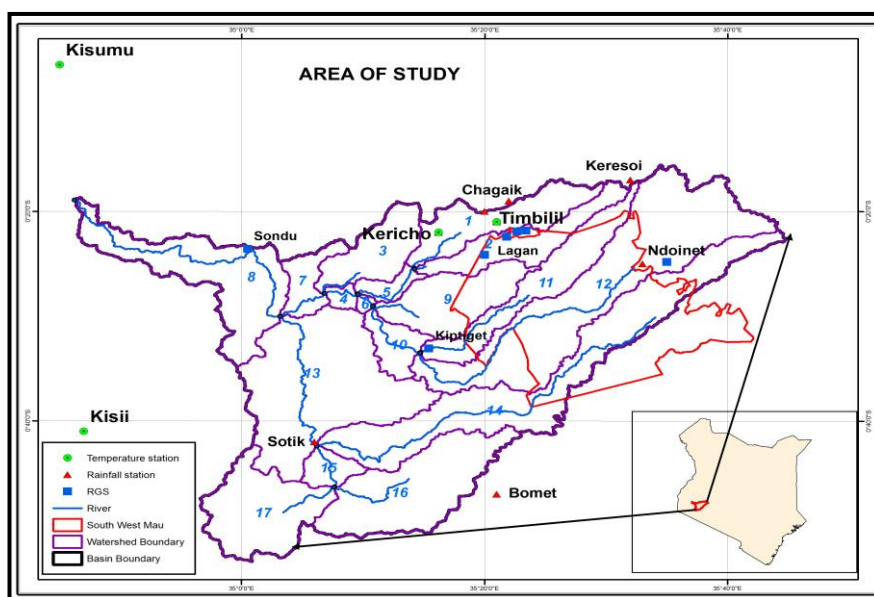


Figure 1: Sondu River basin; its location in Kenya and the river, rainfall and temperature gauging stations networks

Figure 1 shows the basin is located within latitudes 00°23'S and 01°10'S and longitudes 34°46'E and 35°45'E and covers an area of about 3500 km². Sondu River is approximately 173 km long and drains into Lake Victoria at a mean annual rate of about 1.37 BCM/yr (WRMA, 2009).

3.2 Regional Climate Scenario Modelling

Downscaled GCM outputs have been used in hydrological studies to translate projected climate scenarios into hydrological responses (Akhtar *et al.*, 2009). In this study, PRECIS regional climate modelling system was used to downscale the coarse global climate scenarios from ECHAM4, following the IPCC

(2000) special report on emissions scenarios (SRES) A2, to 0.5° grid resolution for eastern Africa where the model domain was set up with a horizontal resolution of 50 km spanning latitudes 12°S to 18°N and longitudes 22°E to 52°E (Wilson *et al.*, 2009; Jones *et al.*, 2004). The study focussed on climate change based on the future global climate scenarios simulated using the A2 emissions scenario which assumes that efforts to reduce global emissions this century will be relatively ineffective (Lumsden *et al.*, 2009).

Regional scenarios of daily time series of rainfall and temperature for the periods 1961-1990 (baseline), 1991-2020 (present and immediate future), and 2021-2050 (intermediate future) were developed. Changes between the projected rainfall and temperature (1991-2020 and 2021-2050) and the baseline values (1961-1990) were evaluated to determine the possible climate change in the region. In order to represent the regional climate scenarios at the watershed scale, three 0.5° grid squares that cover most of the Sondu basin were used to extract time series of daily rainfall and temperature using the coordinates of at least one existing rain gauge station within the grid square.

3.3 SWAT Data Preparation

The input data requirements for the SWAT model fall into three main categories: spatial datasets that include the Shuttle Radar Topography Mission Digital Elevation Model (SRTM-DEM), land use/land cover (LULC) and soil properties digital maps; climate data that include long term mean monthly precipitation, probabilities of a wet day following a dry day (PR_W1) and a wet day following a wet day (PR_W2) in a month and the average number of days of precipitation in a month; and weather data that include time series of daily precipitation, maximum and minimum temperature, wind speed, solar radiation and relative humidity (Winchel *et al.*, 2010).

The SRTM-DEM used in this study was a 3 arc-second (approximately 90 m) medium resolution elevation data resampled using cubic convolution interpolation and was used to automatically delineate the watershed boundary, define stream networks, identify gage outlets, and to generate percent slope values over the watershed (Khanal and Parajuli, 2013; Neitsch *et al.* 2011). The LULC maps of the Sondu Basin were generated from a series of four LANDSAT imageries from Multispectral Scanner System (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper (ETM), and Enhanced Thematic Mapper Plus (ETM+) sensors aboard the National Aeronautical and Space Administration (NASA) LANDSAT satellites. The four processed LANDSAT imageries were obtained from the Department of Resource Survey and Remote Sensing (DRSRS) in Kenya. Soil data, obtained in digital map format from the Kenya Soil and Terrain (KENSOTER) database compiled by the Kenya Soil Survey (KSS) in conjunction with the International Soil Reference and Information Centre (ISRIC) according to the Soil and Terrain (SOTER) methodology, were used to generate the requisite soil layers for the model.

Climate data were used in the weather generator stations to fill in gaps in the daily time series weather data that were used to simulate flows from the basin. Figure 1 shows the weather stations located inside and outside the Sondu basin that were used in this study. These stations had daily and monthly rainfall and temperature (minimum and maximum) data. Climate change data were extracted from the PRECIS regional climate modelling system.

Using these input data, SWAT model was used to simulate the terrestrial phase of the hydrologic cycle

based on the water balance equation (Equation 1).

$$SW_t = SW_o + \sum_{i=1}^t (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad (1)$$

Where SW_t is the final soil water content, SW_o is the initial soil water content on day i , t is the time in days, R_{day} is the amount of rainfall on day i , Q_{surf} is the amount of surface runoff on day i , E_a is the amount of evapotranspiration on day i , W_{seep} is the amount of water entering the vadoze zone from the soil profile on day i , and Q_{gw} is the amount of groundwater flow on day i .

3.4 Model Skill Assessment (Model Calibration and Validation)

The SWAT model was calibrated and validated against observed monthly water yields obtained from Kiptiget gauging station for the periods 1982-1987 and 1988- 1990 respectively. The fit-to-observations calibration criterion was adopted in this study on account of its objectivity and affordability (Moriasi *et al*, 2007).

The model performance was evaluated by comparing the model-simulated and observed surface water yields using four commonly used test statistics in hydrological studies: Coefficient of Determination (R^2), Nash–Sutcliffe Efficiency (NSE) index, Percentage Bias (PBIAS), and the Ratio of Root-Mean-Square Error to the Standard Deviation of Observations (RSR) (Moriasi *et al*, 2007). Calibration process was performed manually by continuously adjusting seven of the most sensitive model input parameters obtained from model sensitivity analyses (Winchel *et al*, 2010), until simulation results of $R^2 \geq 0.5$ and $NSE \geq 0.5$, both of which indicate good model performance, were obtained (Parajuli *et al*, 2009).

The R^2 (Equation 2) is a value that indicates the consistency with which model-simulated versus observed values follow a best fit line (Parajuli *et al*, 2009; Muthama *et al*, 2008) and ranges from 0 to 1. Values of R^2 close to zero indicate poor model performance while a value of 1 indicates a perfect fit between model-simulated and observed values. Parajuli *et al*, (2009) have recommended that values of R^2 of at least 0.5 indicate good model performance. The main limitation of R^2 is that it only describes how much of the observed variance is explained by the model simulation and it can therefore not be used alone to evaluate model performance.

$$R^2 = 1 - \frac{SS_E}{SS_T} \quad (2)$$

In Equation (2), SS_E is the sum of squared errors of estimates and SS_T is the total sum of squares of the original values.

The NSE (Equation 3) is a normalised index whose values range between $-\infty$ (poor model performance) and 1 (perfect model performance) and measures how well the plot of the observed versus model-simulated values fit the 1:1 line. Values of NSE between 0 and 1 are considered acceptable while those less than 0 are considered unacceptable (Moriasi *et al*, 2007). Accordingly, $0.5 \leq NSE \leq 0.74$

signifies good model performance, $0.75 \leq NSE \leq 0.89$ signifies very good model performance, and $0.9 \leq NSE \leq 1.0$ signifies excellent model performance (Parajuli *et al*, 2009).

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \tag{3}$$

In Equation (3) O_i is the observed discharge series, P_i is the predicted discharge series, \bar{O} is the mean of the observed discharge series, and n is the total number of observations.

The *PBIAS* (Equation 4) is the percentage deviation of simulated from observed values. It measures the average tendency of the model-simulated values to be larger or smaller than the corresponding observed values (Moriassi *et al*, 2007). The optimal value of *PBIAS* is 0, indicating perfect model performance. Positive and negative values of *PBIAS* indicate model bias towards underestimation and overestimation respectively.

$$PBIAS = \left(\frac{\sum_{i=1}^n O_i - P_i}{\sum_{i=1}^n O_i} \right) \times 100 \tag{4}$$

In Equation (4), O_i is the observed discharge series and P_i is the simulated discharge series. Values of *PBIAS* falling within $\pm 16\% \leq PBIAS \leq \pm 25\%$ denote good model performance, those within $\pm 11\% \leq PBIAS \leq \pm 15\%$ denote very good model performance, and those within $PBIAS < \pm 10\%$ denote excellent model performance (Parajuli *et al*, 2009).

The *RSR* (Equation 5) was used to evaluate the accuracy of the model simulation. *RSR* values range from the optimal value of 0 (for a perfect model simulation) to large positive values.

$$RSR = \sqrt{\frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}} \tag{5}$$

In Equation 5, O_i is the observed discharge series, P_i is the simulated discharge series, and \bar{O} is the mean observed discharge series. Values of *RSR* falling within $0.6 \leq RSR \leq 0.7$ denote satisfactory model performance, those within $0.5 \leq RSR \leq 0.6$ denote good model performance those within $0.3 \leq RSR \leq 0.5$ denote very good model performance while those within $0.0 \leq RSR \leq 0.25$ denote excellent model performance (Moriassi *et al*, 2007).

3.5 Impacts of Climate Change on Surface Water Yields

The impacts of climate change on surface water yields from the Sondu River basin were assessed by simulating water yields under different climate scenarios keeping the LULC unchanged. Surface water

yields were simulated under the 1970s baseline climate and projected climates in 2010s and 2030s. The impacts of climate change on surface water yields were then evaluated as the percentage difference between the projected and the baseline water yields (Equation 6). Any changes in the simulated water yields were attributed to climate change.

$$I = \left(\frac{W_C - W_B}{W_B} \right) \times 100 \tag{6}$$

In Equation 6, W_C is the surface water yields under changed climate scenarios, W_B is the water yields under the baseline climate scenario.

4.0 Results and Discussions

The results of the analyses of projected rainfall, model calibration and validation, and model simulation and projections are presented and discussed in this section.

4.1 Projected Rainfall in 2010s and 2030s

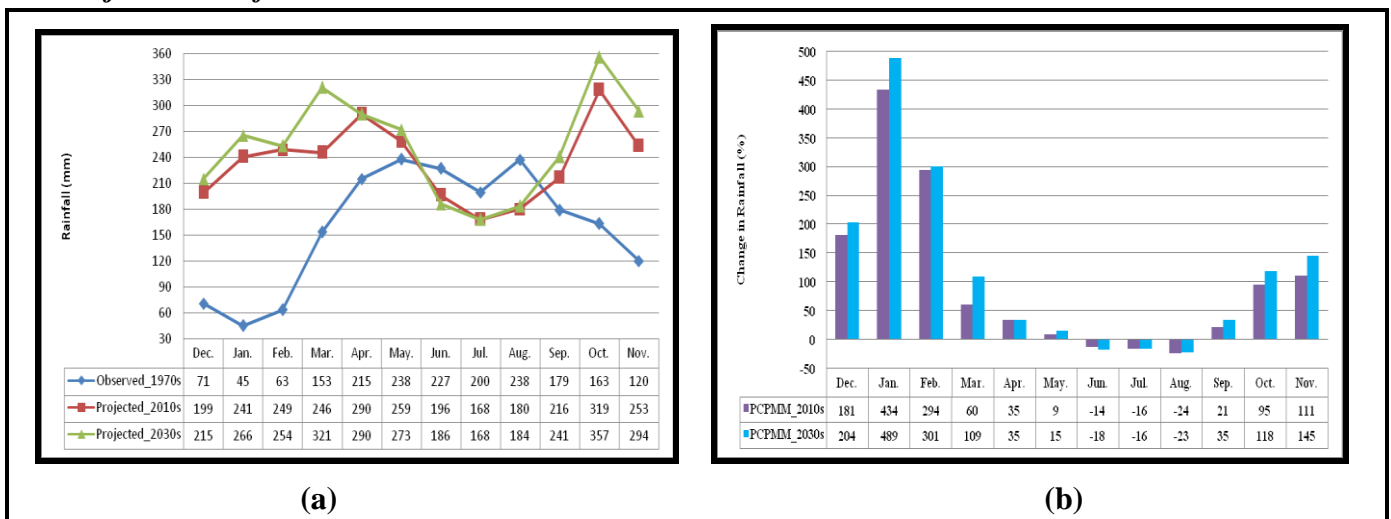


Figure 2: Projected (a) Mean monthly rainfall scenarios (PCPMM), and (b) Percentage change in PCPMM from the baseline values at Kericho Meteorological Station

Figure 2 shows the baseline and projected monthly rainfall scenarios together with projected changes in 2010s and 2030s. It was noted that there will be increases in monthly rainfall ranging between 9% and 489% over the baseline values between September and May inclusive. Between June and August inclusive rainfall values are projected to fall by between 14% and 24% of the baseline values. The unusually high projected rainfall in the otherwise relatively dry seasons (DJF and SON) is expected to improve water yields from the basin but is also likely to cause an increase in flooding incidents if not well managed. These results agree with those of Githui *et al*, (2009) for Nzoia basin which is also within the larger Lake Vitoria basin.

4.2 SWAT Model Calibration and Validation

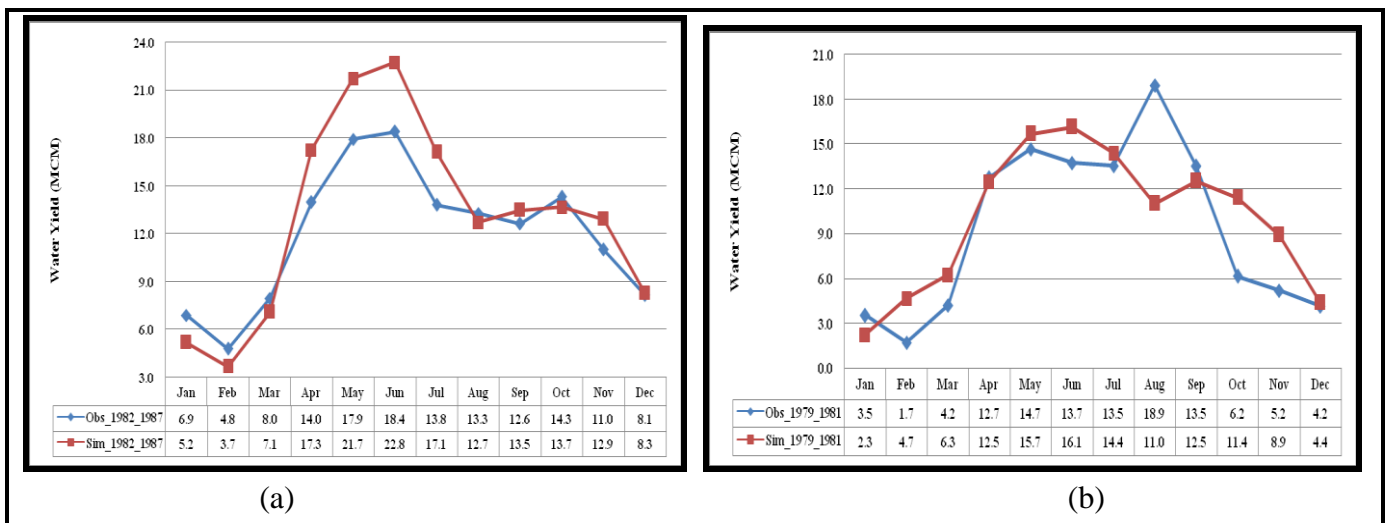


Figure 3: Hydrographs of observed and SWAT model-simulated mean monthly water yields (MCM) during (a) calibration and (b) validation at Kiptiget RGS

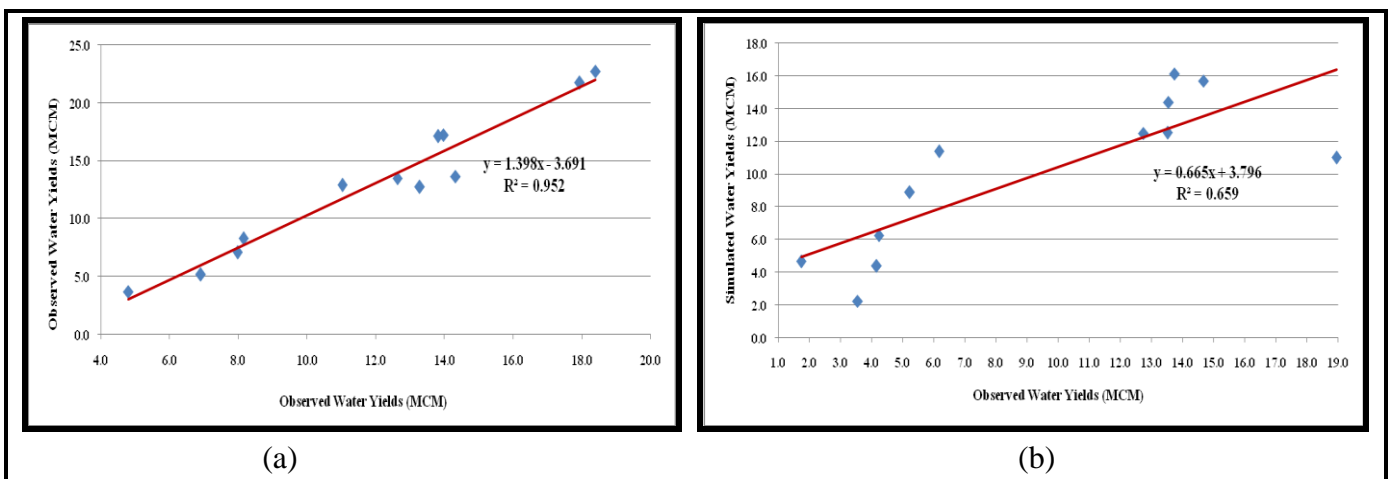


Figure 4: Regression of mean monthly SWAT model-simulated on observed water yields (MCM) during (a) calibration and (b) validation periods at Kiptiget RGS

Figure 3 shows a comparison of hydrographs of simulated and observed mean monthly water yields while Figure 4 shows regression of simulated mean monthly water yields on corresponding observed values averaged over the calibration (1982-1987) and validation (1988-1990) periods respectively, at Kiptiget RGS. During calibration (Figure 3a) the model captures the monthly distribution of water yields from the catchment quite well but overestimates between April and July. During validation (Figure 3b) the monthly distribution of water yields is fairly well captured but the model generally overestimates the water yields in all the months except August.

Monthly simulated water yields were found to be consistent with the corresponding observed values during calibration and validation periods. The R² value of 0.66 during validation period indicates good model performance in the basin. Based on these results the model is recommended for use in predicting monthly water yields in the basin.

Table 1: SWAT Model performance statistics for the average monthly water yields during calibration and validation periods

Period	Observed (MCM/yr)		Simulated (MCM/yr)		Evaluation Statistics			
	Mean	Stdev	Mean	Stdev	R ²	PBIAS	NSE	RSR
Calibration (1982-1987)	11.9	7.4	13.0	9.4	0.95	-9	0.6	0.6
Validation (1988-1990)	9.4	7.0	10.0	6.9	0.7	-7	0.5	0.7

Table 1 shows a summary of results of the model performance statistics. Columns 2 and 3 show observed and simulated mean values and standard deviations respectively, of annual water yields during calibration and validation periods. Column 4 shows the model performance statistics for mean monthly water yields during calibration and validation periods. These results indicate that: there was good correlation between model-simulated and observed mean monthly water yields as shown by the values of R² (0.7) and NSE (0.5) during validation; there was excellent match between the model-simulated and observed water yields as shown by the PBIAS value (-7%) during validation, and the model-simulated water yields were fairly accurate as shown by the RSR value (0.7) during validation. The PBIAS value of -7% indicates that the model tends to slightly over estimate monthly water yields from the watershed but this is within the limits of very good model performance as recommended by Moriasi *et al*, (2007) and Parajuli *et al*, (2009).

According to the classification of Parajuli *et al*, (2009), this study has shown that SWAT model performed with good to very good correlation and agreement when model simulations are compared with observed values. This was shown by the high values of R² and NSE (≥ 0.5) and the low values of PBIAS (≤ ± 10%) and RSR (≤ 0.7) which show that the model was able to simulate monthly water yields with minimum error and limited bias.

4.2.1 SWAT Model Simulations and Projections

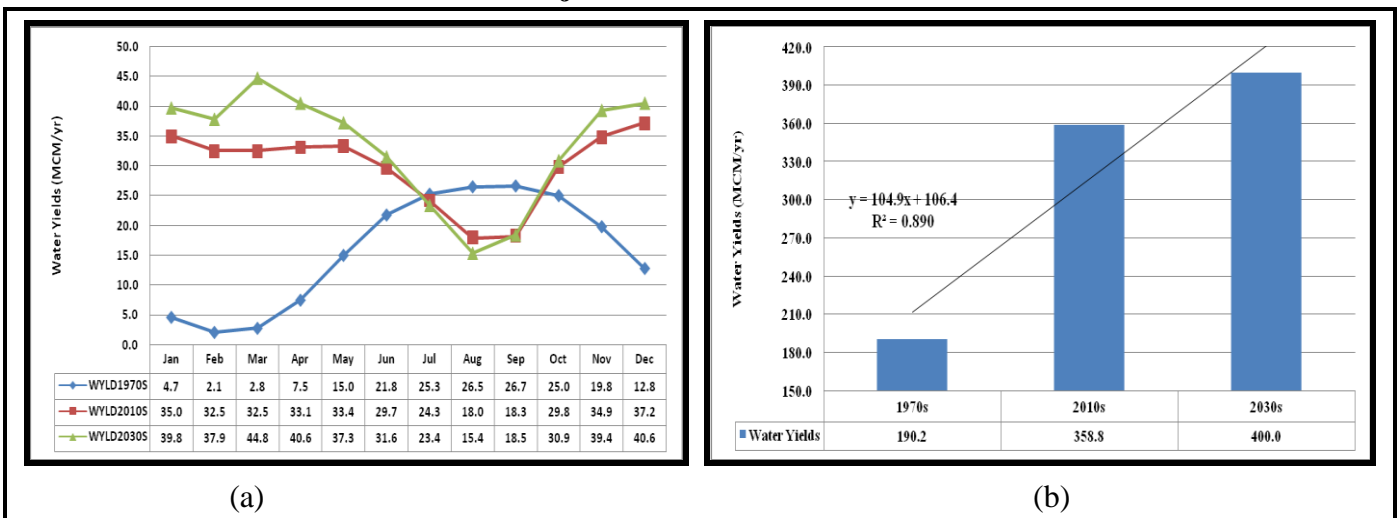


Figure 5: Baseline and SRES A2 scenario projected mean monthly (a) and annual water yields (b) at Kiptiget RGS

Figure 5 shows a comparison of the baseline (1961-1990) and projected (1991-2030, 2021-2050) values for 30-year average monthly and annual water yields at Kiptiget RGS. Figure 5a shows increasing trends in mean monthly water yields between October and June but decreasing trends between July and September. The months currently experiencing relatively low water yields (December-March) are expected to experience relatively higher water yields while those currently experiencing relatively high water yields (August and September) are expected to experience relatively lower water yields under this scenario. On the other hand, from the 1970s through 2010s to 2030s, the mean annual water yields averaged over the thirty-year periods are expected to increase at a rate of about 105 MCM every 30 years under this scenario (Figure 5b).

5. Conclusion

The study has demonstrated a changing climate in the Sondu basin and the surrounding areas between 1961 and 2050, with some seasons becoming wetter and others drier than the baseline conditions. Monthly rainfall patterns are projected to shift with the relatively drier seasons becoming relatively wetter and the relatively wetter seasons becoming relatively drier. This is expected to bring about a redistribution of seasonal water yields with the currently relatively dry seasons yielding more and the currently wet seasons yielding less water compared to the baseline period. An increase in water yields with climate change was observed which is in tandem with the results of an earlier study in Nzoia basin (Githui *et al*, 2009).

Even though the model-simulated water yields under the baseline and climate change scenarios are subject to further verification using observed data, this study has provided useful information about the potential patterns of water yields from Sondu and other similar watersheds that may result from climate change. This study will therefore contribute to the scientific community's understanding of the impacts of climate change on water resources over Lake Victoria basin in general and Sondu River basin in particular. Further, as a result of this study, a great amount of Hydrometeorological data in and around the area of study spanning the period 1961-2050 has been acquired. This forms a significant contribution to researchers wishing to advance the science of Hydrometeorology and climate change. Results of this study could also be used to provide information to inform policy in the strategic planning and management of water resources in this area as set out in the Kenya National water Master Plan 2030 in various sectors such as agriculture, hydropower and water supply.

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provided observed stream flow data, Kenya Soil Survey (KSS) who provided soil data, and Kenya Forest Service (KFS) who offered use of their facilities during the field trip.

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