Uncertainty of runoff projections under changing climate in Wami River sub-basin

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ABSTRACT

Study Region: The Wami River sub-basin is among the river sub-basins with a vital ecosystem in Tanzania. It comprises the Saadani National Park and it has the very great potential of irrigation and rain fed agriculture.

Study Focus: The objective of this study was to evaluate the uncertainty of future streamflow in respect of increasing water demands and uncertain projected climate inputs, General Circulation Models (GCMs). The water demands were projected to the year 2039 and GCM precipitation was selected as the changing climatic variable. The CMIP5-GCMs were evaluated for their skills and those with the minimum skill scores above 75% were downscaled and used in projection of scenario RCP 8.5 precipitation. Then uncertainties of RCP 8.5 precipitation were estimated using a fuzzy extension principle and finally used to simulate uncertainties of future runoff using a rainfall–runoff model, Soil and Water Assessment Tool (SWAT).

New Hydrological Insights for the Region: The results of projected streamflow shows that the baseline annual climatology flow (ACF) is 98 m³/s and for the future, the median ACF is projected to be 81 m³/s. At 100% uncertainty of skilled projections, the ACF from the sub-basin is projected to range between −47% and +36% from the baseline ACF. However, the midstream of the sub-basin shows reliable water availability for foreseen water uses expansion up to the year 2039.

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1. Introduction

Rigorous studies on climate change impact on streamflow in Tanzania were conducted in the Pangani basin (Notter et al., 2013), Ruvu River sub-basin (Mwandosya et al., 1998) and the Wami River sub-basin (Wambura, 2014). In the Pangani basin, Notter et al. (2013) studied climate change impact on streamflow using two individual GCMs representing the extremes of available IPCC predictions (i.e. the driest and wettest conditions). On the other hand in the Ruvu River sub-basin, Mwandosya et al. (1998) researched on the impact of climate change on streamflow using individual GCM showing the lowest Root Mean Squared Error (RMSE) in predicting the historical climate. In the Wami River sub-basin, Wambura (2014) studied the response of streamflow under changing climate using individual GCM showing the highest skill score in predicting the historical climate.

However, in the case of climate change, the use of the RMSE statistic (Mwandosya et al., 1998) for selection of GCMs does not compare corresponding dates and thus does not test GCMs’ season variability capability. Without testing GCMs’ spatial skill across the sub-basin, the reliability of the selected GCM in predictions cannot be guaranteed (Wambura, 2014). However, projections of future climate without uncertainty resulting from GCMs having similar performances in control period, but very different future predictions, compromises the credibility of a single GCM predictions (Nóbrega et al., 2011; Todd et al., 2011; Wambura, 2013). The point estimates are very uncertain because different GCMs often disagree, even in the direction of change on precipitation, although temperature can be relatively consistent between GCMs (Randall et al., 2007; Wambura, 2013). Therefore, there is a need to address the important issue of skilled GCM uncertainty using uncertainty bounds from several different skilled GCMs projections. Thus the technique (fuzzy set analysis) which includes all GCMs in estimating uncertainty at various levels from the median prediction of the downscaled GCMs is preferred.

Fuzzy set theory is a powerful tool for analysing the kind of uncertainty associated with a lack of information regarding a particular element of the problem at hand. In fuzzy set theory an element may have the degree of applicability, rather than simply being true or false. Another advantage of fuzzy set theory is that it allows for continuous values of membership between the full certainty and full uncertainty (Gonzalez et al., 1999). Since most of the GCMs project different future climate and there is a lack of information on which GCM is reliable, therefore fuzzy set analysis is the right approach in analysing that vagueness (Guyonnet et al., 2003; El-Baroudy and Simonovic, 2006; Wambura, 2013). The technique includes selected GCMs in estimating uncertainty at various levels of confidence. In a family of fuzzy set theory, the triangular fuzzy number (fuzzy extension principle) is one of the most common fuzzy number. It solves many practical and complex problems (Liang et al., 2005). The selection of fuzzy numbers seems not very essential because they have no significant difference in the performance (Chen et al., 2008). However, even with the use of fuzzy set analysis in constructing uncertainty of various GCMs, the resolution scale of GCMs still affects the representation of local climate, thus downscaling of GCMs to the point or region of interest is also preferred.

The GCMs have coarse resolution of about 1.3° × 2.7° latitude and longitude scale, therefore it is important to downscale them. There are many methods available for downscaling GCM projections to the specific region or study area of interest, for discriminating between mean changes and changes in climatic variability and for ensuring consistency between climate change scenarios. The common methods are dynamic downscaling, statistical downscaling and simple approaches like bias correction methods. Dynamic downscaling involves extraction of local scale information by developing limited area models or regional climate models with coarser resolution GCM data used as boundary conditions. But the demerit with this method is that the downscaling process requires computing facilities with very high computing efficiency (Wilby and Wigley, 1997). Statistical downscaling involves developing a quantitative relationship between large scale atmospheric variables and local surface variables. The local climate information is derived by determining a statistical model which relates large scale climatic variables to local climatic variables. Then the large scale output of a GCM simulation is fed into the statistical model to estimate the corresponding local climate characteristics. The simplest statistical downscaling technique is application of GCM-scale projections in the form of the delta method (Fowler et al., 2007). However, Fowler et al. (2007) argued that simple methods for downscaling GCMs projections are effective in simulating hydrological systems.
There is a need to address the important issue of GCM performance in predicting past climate before it is downscaled and entrusted to be used in future predictions. If a climate model can simulate an entire seasonal variability, this demonstrates a capability to simulate values that are currently rare and that may become more common in the future (Perkins et al., 2007). The hydrological models respond differently to perturbations of different climatic variables used in setting up the model. Therefore, the simple but useful application of hydrological models in simulating the climate change impact on streamflow is to use the climatic variables which readily affect the modelled runoff. The process of identifying the climatic variables which readily affect the hydrological modelled runoff is done by conducting the sensitivity analysis of the modelled runoff against various climate variables. This analysis reduces the number of climate variables, to be considered in the future runoff projections.

Therefore, the main objective of this study was to evaluate the uncertainty of future streamflow in respect of both increasing water demands and uncertain projected climate inputs. Firstly, we started with SWAT model setup and the streamflow naturalization using baseline water demands in the sub-basin. Secondly the model was calibrated and validated using the sub-basin outlet flows. Then the calibrated and validated model was used to assess the sensitivity of the modelled runoff against perturbations in temperature and precipitation. The sensitive climatic variable was then used in selecting the GCM climatic variable to be used in skill score test. The skilled scenario GCMs were downscaled to sub-catchments within the Wami River sub-basin. Then the skilled and downscaled GCMs were used in analysis of uncertainty in climate projections. Finally the uncertainty of skilled and downscaled GCMs climatic projections were applied in the hydrological model which was already conditioned with projected/future water demands; and the model was simulated to give out the corresponding uncertainties in projected runoff.

2. Materials and methods

2.1. Case study

The Wami River sub-basin is located between 5–7° S and 36–39° E, it extends from the semi-arid areas in central Tanzania to the humid inland swamps in East-central Tanzania to the Indian ocean. It encompasses an area of approximately 41,167 km². The sub-basin has three major catchments of Kinyasungwe, Mkondo and Wami (Fig. 1). The sub-basin has an average rainfall of 550–1000 mm per annum. There are two rainfall zones in the sub-basin, the Western and the Southwestern parts which fall within the uni-modal rainfall zone (i.e. wet period between December and April) and the Eastern and Northeastern parts of the sub-basin which fall within the bi-modal (two wet periods between October and December; and between March and May) rainfall zone. The mean annual temperature in the sub-basin ranges from 12 to 24 °C.

2.2. Data used

Data used for generating sub-basin characteristics (model parameters) were land cover (1:250,000 scale) from the FAO (2007); soil data (1:2,000,000 scale) from the FAO and ISRIC (2003); and the digital elevation model (DEM) of 90 m resolution from the SRTM (2007).

The sub-basin weather definition used daily rainfall and temperature data (1977–2010) from the Tanzania Meteorological Agency (TMA). To naturalize the streamflow in the sub-basin, we used the population data from the Tanzania National Bureau of Statistics (NBS) and water uses (domestic, livestock, irrigation and industrial water uses) from the Wami-Ruvu Basin Water Office (WRBWO). We also calibrated the sub-basin model using the observed flows (1977–2010) at 1G2-Mandera flow gauge (Wami catchment) from the WRBWO. The 1GD17-Godegode flow gauge (Kinyasungwe catchment) and the 1G1–Dakawa flow gauge (Mkondo catchment) were not used because they do not have reliable information for internal calibration of the model. The selection of GCMs and sub-basin future climate customization used control (1980–2009) and scenario RCP 8.5 (2010–2039) CMIP5-GCMs respectively downloaded from the Earth System Grid Federation (ESGF) portal (http://pcmdi9.llnl.gov/esgf-web-fe/).
2.3. Model setup and condition

SWAT was used in setting the hydrological model of the Wami River sub-basin. The sub-basin was divided into 45 sub-catchments which comprises of 530 hydrological response units (HRUs). However, due to computational resource constraints with regard to the size of the sub-basin, the number of HRUs was considered satisfactory. The land cover, soil and topography from the DEM were used to generate parameters for each of the 45 sub-catchments. The observed rainfall and temperature data were used to drive the current climate of the Wami River sub-basin. The domestic, livestock, irrigation and industrial water uses were distributed in each sub-catchment to naturalize the streamflows. Details on SWAT model are explained by Neitsch et al. (2005).

The 1G2-Mandera streamflow data between 1977 and 2010 with 37% missing data was used for calibration and validation. The periods from 1977 to 1990 and 1993 to 2010 were used for calibration and validation, respectively. The calibration was done using the SWAT Calibration and Uncertain Program (SWATCUP) because of its capability of calibrating the records with missing data. The procedure implemented in SWATCUP is the Generalized Likelihood Uncertainty Estimation (GLUE) method. The GLUE was used because its methodology determines the performance of the model focus on the parameter set, not on the individual parameters (Beven and Binley, 1992). The GLUE method can also handle the parameter interactions and non-linearity implicitly through the likelihood measure (Vazquez et al., 2009).

After calibration and validation, then the SWAT model was conditioned to year 2039 by introducing projected (2010–2039) domestic, livestock, irrigation and industrial water demands (Table 1) so that the model water demands corresponds with the climate simulation period. In this study land cover change was considered negligible, therefore projected simulations involved only water uses which impliedly relate to landuse changes.
2.4. Climate sensitivity and skill score test of GCMs

The sensitivity analysis of climatic variable in a rainfall–runoff model was then done to reduce the number of climatic variables using the sensitivity index (SI) method. The SI was calculated using Eq. (1) (Hoffman and Gardner, 1983).

\[ SI = \left| \frac{D_{\text{max}} - D_{\text{min}}}{D_{\text{max}}} \right| \]  

where \( D_{\text{min}} \) and \( D_{\text{max}} \) represent the minimum and maximum output values, respectively, resulting from varying the input over its entire range. Sensitivity analysis of the modelled runoff against temperature and precipitation was done using the streamflow at the 1G2-Mandera flow gauge.

In selection of skilled GCMs, the season lag skill score test (Eq. (2)) was used. This test measures the relative lag between the GCM precipitation and the observed precipitation. This is a very simple measure that provides a robust and comparable measure of the relative similarity between model and observed precipitation, using the seasonal variability curves (SVCs). It allows comparison across the entire SVCs. This metric calculates the cumulative minimum value of two curves of each monthly value, thereby measuring the common area between two SVCs. If a model simulates the observed SVC poorly, the skill score becomes close to zero with negligible overlap between the observed and modelled SVCs. But if a model simulates the observed conditions perfectly, the skill score equals one, which is the total sum of the monthly to annual ratios (MARs) of climatological precipitation. The MAR expresses the extent in which the monthly precipitation contributes to the annual precipitation in a given climatology. Generally, skill score is the summation of minimum MARs between climate model and measured precipitation (Eq. (2)).

\[ S_{\text{score} (k,r)} = \sum_{1}^{12} \min \left( \frac{\text{GCM}_{\text{baseline}(j,k,r)}}{\text{GCM}_{\text{MAPbaseline}(k,r)}}, \frac{\text{OBS}_{(j,k)}}{\text{OBS}_{\text{MAP}(k)}} \right) \]  

where \( S_{\text{score} (k,r)} \) is season skill score at sub-catchment, \( k \) for GCM, \( r \); \( \text{GCM}_{\text{baseline}(j,k,r)} \) is baseline monthly climatology precipitation in month, \( j \) at sub-catchment, \( k \) for GCM, \( r \); \( \text{OBS}_{(j,k)} \) is observed monthly climatology precipitation in month, \( j \) at sub-catchment, \( k \); \( \text{GCM}_{\text{MAPbaseline}(k,r)} \) is baseline mean annual climatology precipitation (ACP) at sub-catchment, \( k \) for GCM, \( r \); \( \text{OBS}_{\text{MAP}(k)} \) is observed mean ACP at sub-catchment, \( k \); the ratio of \( \text{GCM}_{\text{baseline}(j,k,r)} \) to \( \text{GCM}_{\text{MAPbaseline}(k,r)} \) and the ratio of \( \text{OBS}_{(j,k)} \) to \( \text{OBS}_{\text{MAP}(k)} \) are MARs of GCM and measured climatology precipitation, respectively.

In this study, 20 CMIP5-GCMs were tested for their skills in simulating the seasonal variability of precipitation in the control period (1980–2009) using Eq. (2). First, the GCMs and observed precipitation were interpolated into 45 sub-catchments using the inverse squared distance (ISD) method. Zhu and Jia (2004) explain in detail on the ISD method and its application in interpolation of climate variables. Secondly, the sub-catchments MARs of climate models and measured precipitation were used to obtain the sub-catchments skill scores. Then skill scores of GCMs were compared against a threshold. Perkins et al. (2007) selected best skilled GCMs using the threshold of 70%, but Wambura (2014) used 75% as the satisfactory threshold for selection of GCMs. In this study, the threshold of 75% was selected as the criteria for measuring the seasonal variability between the observed and the GCMs precipitation, because the curves of GCMs with skill score above 75% were comparable to the curves of the measured precipitation. The minimum, average and maximum sub-basin skill scores were obtained from the 45 sub-catchments skill scores.

The GCM scenario was selected before downscaling the skilled GCMs. Out of four RCPs, the RCP 8.5 was selected because it has the highest rising radiative forcing pathway leading to 8.5 W/m², the
underlying scenario drivers and resulting development pathways are based on the A2 scenario (CMIP3) detailed in Riahi et al. (2007).

2.5. Bias correction and uncertainty of climate projections

The skilled GCMs representing near-term scenario RCP 8.5 (2010–2039) were then bias corrected using the simple delta method (SDM). It is the most common bias correction method; the SDM is also called a linear delta method. In this study, the large grids of scenario GCM precipitation were interpolated to the 45 sub-catchments using the ISD method, then the ratios of mean statistics between the scenario projection and their baseline were applied to the observed data to obtain the bias corrected future precipitation. SDM for bias correction of GCM precipitation is expressed formally by Eq. (3) (Prudhomme et al., 2002).

\[
\text{PCP}_{\text{future}}(i,j,k,r) = \text{OBS}_{\text{past}}(i,j,k) \times \left( \frac{\text{GCM}_{\text{future}}(j,k,r)}{\text{GCM}_{\text{baseline}}(j,k,r)} \right)
\]

where, PCP_{\text{future}}(i,j,k,r) is the projected future precipitation on day, \(i\) in month, \(j\) at sub-catchment, \(k\) for GCM, \(r\); OBS_{\text{past}}(i,j,k) is the observed climatology precipitation on day, \(i\) in month, \(j\) at sub-catchment, \(k\); GCM_{\text{future}}(j,k,r) is the mean of future climatology precipitation in month, \(j\) at sub-catchment, \(k\) for GCM, \(r\) and GCM_{\text{baseline}}(j,k,r) is the mean of baseline climatology precipitation in month, \(j\) at sub-catchment, \(k\) for GCM, \(r\).

The uncertainty of skilled and bias corrected GCMs (6 GCMs) was then computed at various levels using the fuzzy extension principle (Eq. (4)). Fuzzy extension principle uses a horizontal line (fuzzy alpha-level cut) do describe the elements belonging to a particular certainty level from the membership function. The membership level may take any value between 0 and 1, with no membership at 0 and full membership at 1.

\[
\mu_A(x) = \begin{cases} 
0 & \text{if } x \leq a \\
\frac{x-a}{b-a} & \text{if } a \leq x \leq b \\
\frac{c-x}{c-b} & \text{if } b \leq x \leq c \\
0 & \text{if } x \geq c
\end{cases}
\]

(4)

The fuzzy alpha-level cut (\(\alpha\)-cut) is the certainty level which range from zero (uncertainty) to one (certainty) (Gonzalez et al., 1999). In mathematical terms, considering \(X\) as a universe set of \(x\) values (elements), and then \(A\) as a fuzzy subset of \(X\), in ordered pairs \(A\) is given by Eq. (5).

\[
A_\alpha = \{(x, \mu_A(x)); x \in X, \mu_A(x) \in [0, 1]\}
\]

(5)

where, \(\mu_A(x)\) is the grade of membership of \(x\) in the fuzzy subset \(A\) at a particular level of uncertainty, \(\alpha\)-cut.

In this study the \(\alpha\)-cut was assigned as 0%, 25%, 50% and 75%, therefore the corresponding uncertainty levels were 100%, 75%, 50% and 25%. The 100% uncertainty means that the user has confidence on wider bounds of the entire dataset of the skilled and bias corrected GCMs (6 GCMs) whereas the 75%, 50% and 25% shows that the user has confidence to the narrow bounds (subset) of the dataset. After computing the uncertainty bounds of precipitation, finally the uncertainty precipitation bounds were applied into the SWAT model for simulations of corresponding uncertainty runoff bounds. Since, the 1GD17-Godegode flow gauge is far upstream of 1G2-Mandera flow gauge (calibrated and validated), therefore only the streamflow at 1G1-Dakawa and 1G2-Mandera flow gauges were considered reliable.

3. Results and discussion

3.1. Model calibration and validation

The Nash–Sutcliffe coefficient (NSE) for calibration and validation were 69% and 76%, respectively. The model performance is considered satisfactory as NSE is greater than 60% as suggested by other
researchers (Saleh et al., 2000; Santhi et al., 2001; Benaman et al., 2005; Moriasi et al., 2007; Rossi et al., 2008).

Fig. 2 shows the time series comparison of simulated and observed daily flow at 1G2-Mandera flow gauge during the calibration and validation period. During the calibration period (Fig. 2), the model captures well the low flows and some peaks, although the highest flow peak was not well captured by the model. The scatter plot (Fig. 3a) of simulated flows against measured ones also shows that the model simulates well the low and average flows because most data are close to the reference line/identity line. You will see that the high flows are not well captured. However, the visual inspection of time series and the scatter plot of the simulated flow against the measured flow together with the statistical evaluation (NSE = 69%) in the calibration period was considered satisfactory.

During the validation period (Fig. 2), the time series of comparison between simulated flows and measured streamflows at the 1G2-Mandera flow gauge shows that the model is able to mimic the streamflows. Fig. 3b also shows that, the model captures almost the low, average and high flows.
because the simulated and measured flows fall close to the reference line. Therefore, time series observations and the scatter plot of the simulated against measured flows together with the statistical evaluation (NSE = 76%) of the model concludes that the model is also satisfactory in the validation period. It could be argued that the absence of high flow peaks in the validation period might be the reason for higher performance in comparison with the calibration period.

3.2. **Model sensitivity to temperature and precipitation changes**

The modelled runoff against perturbations in temperature and precipitation at 1G2-Mandera flow gauge show that, the SI does not vary linearly (Fig. 4). This is thought to be caused by the complexity of hydrological system. The magnitude of SI for both temperature and precipitation is higher in the negative axis than in the positive axis. However, precipitation changes in both positive and negative axes leads to higher SI(s) than in the case of the temperature changes (Fig. 4a and b). This means that in Wami River sub-basin, runoff is more sensitive to precipitation change than to temperature change.

In the negative axis, an increase in temperature change leads to decrease in SI (Fig. 2a). This is caused by the temperature change approaching zero value, thus the altered temperature approaches the baseline temperature. In the positive axis, the increase in temperature change causes an increase in the SI (Fig. 2b). In this case the altered temperature diverges positively away from the baseline temperature. This increase of SI in the positive axis is thought to be caused by more loss of water through evapotranspiration, thus consequently causing decrease in runoff. The resulted increase in evapotranspiration contributes to water that is lost and gets out of the model.

For precipitation, increases in precipitation in the negative axis leads to decrease in the SI (Fig. 4a). Like in the case of temperature, the altered precipitation also approaches the baseline precipitation. In the positive axis, the increase in precipitation leads to increase in the SI (Fig. 4b). This increase of SI in the positive axis is thought to be caused by an increase of the amount of rainfall, thus a consequent increase in the streamflow.

However, in this study the direction of change and comparative magnitudes were of more importance than the actual magnitudes of SI. This is because the analysis involved one at a time sensitivity analysis of the modelled runoff against perturbations in climatic variables. Therefore, the fluctuation of all other parameters in the hydrological model would have given different magnitudes.

3.3. **GCMs skill scores**

The minimum skill score of GCMs across the sub-basin shows that MPI-ESM-LR has the lowest minimum sub-basin skill score, whereas bcc-csm1-1, BNU-ESM, CanESM2, IPSL-CM5A-LR,
IPSL-CM5A-MR and MIROC5 have the minimum sub-basin skill scores above the threshold of 75% (Fig. 5). However, Fig. 5 also shows that some of the GCMs (ACCESS1-0 and HadGEM2-ES) have very high maximum skill scores, but their minimum skill scores across the sub-basin are below the threshold value. These GCMs show very high spatial uncertainty in representing the sub-basin historical climate. Out of 20 GCMs, only 6 GCMs met the minimum criteria of the 75% skill score (Fig. 5). These GCMs are bcc-csm1-1, BNU-ESM, CanESM2, IPSL-CM5A-LR, IPSL-CM5A-MR and MIROC5.

The pattern of skill scores of bcc-csm1-1 model (Fig. 6a) is almost similar to that of the BNU-ESM model (Fig. 6b). These two climate models show almost similar spatial uncertainty in prediction of historical precipitation of Wami River sub-basin. Fig. 6c shows that CanESM2 model has the highest spatial uncertainty in prediction of historical precipitation of the sub-basin. The IPSL-CM5A-LR model shows the skill scores which are more or less the same across the sub-basin (Fig. 6d); this is the climate model with the lowest spatial uncertainty in prediction. The IPSL-CM5A-MR model (Fig. 6e) and the MIROC5 model (Fig. 6f), like the CanESM2 model also show very high spatial uncertainty in prediction of historical precipitation of the sub-basin. Generally, Fig. 6 shows that, the spatial uncertainty of the GCMs skill scores across the sub-basin for the 6 GCMs is below 15%. Therefore, the 6 GCMs can be entrusted to simulate the scenario climate of the Wami River sub-basin.

Fig. 7 shows the maximum sub-basin SVCs of the 6 GCMs and the measured climatology precipitation from January to December. The bcc-csm1-1 model predicts slight delay in receding rainfall from May to June, but also it predicts the early start of the October–November–December (OND) rainfalls (Fig. 7a). The MARs of BNU-ESM precipitation (Fig. 7b) shows the presence of delay in the receding rainfall from May to June. Fig. 7c shows that, the CanESM2 model predicts a slight delay of the OND rainfalls. The IPSL-CM5A-LR model predicts a slight delay on the receding rainfall from May to July (Fig. 7d). The IPSL-CM5A-MR model (Fig. 6e) and the MIROC5 model (Fig. 7f) predict well the measured precipitation from September to March, but they show slight mismatch from March to August. Fig. 7a–f shows that, the 6 GCMs simulate well the measured climatology precipitation because the SVCs of both GCMs and measured climatology precipitation match.

### 3.4. Downscaled GCMs predictions

Fig. 8 shows the spatial distribution of projected (2010–2039) ACP changes of the 6 GCMs. The IPSL-CM5A-LR (Fig. 8d), IPSL-CM5A-MR (Fig. 8e) and MIROC5 (Fig. 8f) models predict very high decrease of ACP (driest future) across the sub-basin, whereas bcc-csm1-1 (Fig. 8a) shows slight decrease of ACP in the sub-basin. The BNU-ESM (Fig. 8b) model predicts both slight increase and decrease of ACP. The CanESM2 (Fig. 8c) model predicts the wettest future across the sub-basin. The 6 skilled GCMs projects different ACP changes across the sub-basin (Fig. 8).
Fig. 6. Skill scores of selected GCMs precipitation (1980–2009) across the sub-basin.
Fig. 7. Maximum sub-catchment skill scores of selected GCMs (1980–2009).

The average sub-basin climatology projections of the selected GCMs are very different (Fig. 9). Fig. 9 also shows that, almost all 6 GCMs projections show little changes from January to July, but the differences are high from September to November (Fig. 9). However, this change is not found in the actual projected precipitation because it occurs during the dry period (Fig. 10), thus considered as overestimation by GCMs. Figs. 8 and 9, also support the notion that, precipitation of different GCMs often disagree, even in the direction of change (Randall et al., 2007), therefore uncertainties associated with different skilled GCMs are very apparent in the projection of the scenario precipitation.
3.5. Precipitation uncertainty

Fig. 10 shows the uncertainty levels computed from the 6 skilled GCMs using the fuzzy extension principle. The uncertainty ranges are wide in November (Fig. 10), this is thought to be caused by shift in the beginning of wet season, OND rainfall. The sub-basin projected median
precipitation and baseline precipitation are very close (Fig. 10). The median ACP across the sub-basin is projected to change by -1% and at the worst case scenario (100% uncertainty), ACP is projected to change by -12% as the lower bound and +11% as the upper bound from the baseline ACP. Therefore, at 100% uncertainty the sub-basin ACP is projected to range between -12% and +11% of the sub-basin baseline ACP. Table 2, shows the sub-basin baseline (1980–2009) and projected (2010–2039)
median precipitation. The sub-basin projected median seasonal climatology precipitation and ACP shows that the December–January–February (DJF) season is projected to have an increase (+1%). The Jun–July–August (JJA) and September–October–November (SON) seasons are projected to have a decrease (−6%) whereas the MAM season is projected to have no change (0%). The sub-basin median ACP is also projected to show a decrease (−1%).

3.6. Runoff uncertainty

The baseline and projected climatology flow bounds (Fig. 11) have the same pattern of flow for the two catchments (Mkonda and Wami) in Wami River sub-basin. The baseline flow is within most of the upper and lower flow bounds (Fig. 11). However, the baseline touches the lower and mid of the 25% uncertainty bounds. The bounds are wider from January to June period and the median climatology flow in the catchment is projected to range between 2 m$^3$/s and 102 m$^3$/s. The lowest flow is projected in November and the highest in March. The stable flows at the catchment are suggested to have originated from groundwater discharge (base flow) which recharges during MAM heavy rains. The baseline ACF is 29 m$^3$/s and for the future, the median is projected to reach 32 m$^3$/s. However, this increase in flow is expected to encounter an increasing number of irrigation schemes at midstream.

![Flow Bounds at 1G1-Dakawa (Mkonda)](image)

**Fig. 11.** Average flow bounds at 1G1-Dakawa (Mkonda catchment).

![Flow Bounds at 1G2-Mandera (Wami)](image)

**Fig. 12.** Average flow bounds at 1G2-Mandera (Wami catchment).
Fig. 12 shows that, the baseline flow is within most of the upper and lower flow bounds. However, the baseline touches the 25%, 50% and 75% uncertainty bounds. The bounds are wider from January to May period. The climatology flow in the catchment is projected to range between 12 m$^3$/s and 253 m$^3$/s. The lowest flow is predicted in November and the highest in April. High flows in the catchment are suggested to have originated from groundwater discharge which recharge during MAM heavy rains. The baseline ACF is 98 m$^3$/s and for future, the median ACF is projected to be 81 m$^3$/s. At 100% uncertainty scenario, the lower bound of projected ACF shows flow change of −47% and upper bound shows flow change of +36% from the baseline ACF at 1G2-Mandera. This means that, at 100% uncertainty ACF is projected to range between −47% and +36% of the baseline ACF.

4. Conclusion

Projected water uses were estimated with consideration of the growing population and the projected agricultural (livestock and irrigation) and industrial demands. By the year 2039 the average water demand in the Wami River sub-basin is projected to increase by 19.7 m$^3$/s and the sub-basin median ACF is projected to range between −12% and +11% at 100% uncertainty whereas the baseline ACF is 884 mm. These two forcing factors lead to changes on runoff from the sub-basin and the ACF is projected to range between −47% and +36% at 100% uncertainty whereas the baseline ACF is 98 m$^3$/s. Either of the forcing factors lead to decrease in streamflow even if it could stand on its own, although water demand seems to exercise heavier impact. However, on the ground these two forcing factors act in a related manner in such a way that increase of water demand results from the increase in population, which in a kind the same population trigger the climate change due to increase in man-made emission of greenhouse gases.

The 1G1-Dakawa and 1G2-Mandera flow gauges show that for both baseline and predicted flows, the high flows are in the midstream of the sub-basin with reliable water availability for foreseen water uses like irrigation and industrial expansion up to the year 2039. However, management practices on water uses in the sub-basin are encouraged to be taken under the quantified uncertainty level. The water use is the only forcing factor which can be easily controlled at the sub-basin level. For the adaptation purposes the Wami River sub-basin management is advised to plan water uses which will not extend beyond the projected water demands. Nevertheless, researches on parameter uncertainty, model structure uncertainty and landcover/use change are encouraged for enhancing further understanding of water balance dynamics in Wami River sub-basin.

Conflict of interest

None.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ejrh.2015.05.013.

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