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Modelling impact of climate change on catchment water balance, Kabompo River in Zambezi River Basin

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ABSTRACT

Study Region: The Kabompo River Basin (KRB) in Zambia is one of the 13 basins found in the Zambezi River Basin in Southern African region.

Study Focus: Global Climate Model (GCMs) projections have spatial resolution of up to several hundred kilometres, which may not be adequate for capturing local details mostly needed for impact assessment at local and regional scale. Downscaling techniques developed to improve the detail include; regional climate modelling and statistical techniques linking climate information at GCM resolution with that at local scale. This paper deals with evaluation and assessment of the impact of climate change on water balance for the KRB. In order to evaluate climate change impact, six bias–corrected and downscaled GCM outputs were acquired and used as inputs for hydrological modelling with the SWAT model to determine the impact under two future climate scenarios.

New Hydrological Insights for the Region: The results indicate that the future catchment water balance for KRB under RCP4.5 will have insignificant variation from the current catchment water balance as annual statistics show that rainfall will reduce by 1 % while water yield and runoff will increase by 5 % and 6 % respectively. Meanwhile under RCP8.5, annual statistics show that rainfall will increase by 19 % while water yield and runoff will increase by 40 % and 65 % respectively and resulting in a significant increase in catchment water balance.

1. Introduction

Global Climate Models (GCM) have often been used to simulate the present and future climates, and many scientists in the world have carried out studies of climate (Zhang et al., 2006; UNFCCC, 2001). GCMs generate projections of possible future changes over different periods with varying time scales, which have no exact previous historical climates (Liu et al., 2012). Simulations of the present day climate by GCMs are used to build confidence in the simulation of future climate by the models. However, such opportunities are much more limited in climate prediction than in weather prediction (Randall and Wood, 2012). These GCM projections may have spatial resolution of up to several hundred kilometres, which may not be adequate to be used for capturing the local detail needed for impact assessment at local and regional scale (IPCC, 2013; Murphy and Ro, 2006; Jones et al., 2004). Methods to improve this detail, also known as downscaling, have been developed and include dynamical downscaling (i.e. regional climate modelling) and statistical techniques linking climate information at GCM resolution with that at local level or point location (Randall and Wood, 2012; Jones et al., 2004).

Evaluation and assessment of the impact of climate change on water resources in the KRB was performed for the purposes of

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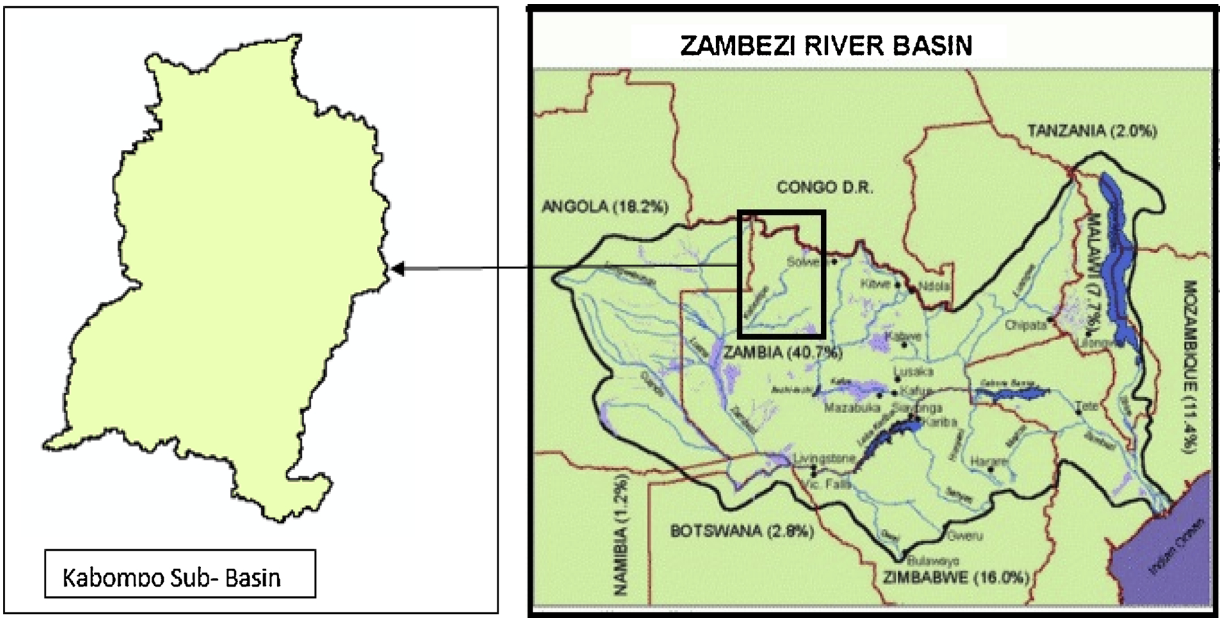

Fig. 1. Location of study area (Source:http://www.zambezira.org/media-centre/maps/zambezi-river-basin).

developing adaptation and mitigation strategies. In order to evaluate climate change impacts, six downscaled and bias corrected GCMs were acquired and used in modelling climate change under RCP4.5 and RCP8.5 climate scenarios. Therefore, this paper is focussed on evaluating climate change impacts on catchment water balance, more specifically rainfall, water yield and runoff variables for different time scales in the Kabompo River Basin (KRB).

1.1. Study area

The KRB is within the Zambezi River Basin (ZRB) located between 14^{O} 15″ 07.29′S, 23^{O} 08′ 27.44″ E and 17^{O} 36′ 17.21′S, 25^{O} 48′ 28.39″E. It is one of the 13 basins in the ZRB which has deep, well-drained Kalahari sands covering the entire region (Beilfuss, 2012).The basin has wooded savannahs as the predominant landuse and has Mean Annual Precipitation (MAP) of 1200 mm. Fig. 1 indicates the location of the study area in the ZRB of Southern Africa.

2. Materials and methods

2.1. Description of GCMs

The research utilised six GCMs obtained from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (Thrasher et al., 2015). The NEX-GDDP dataset is composed of downscaled and bias corrected global climate scenarios produced from the General Circulation Model (GCM) runs performed through the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). Furthermore, the selection of the six models was also based on how good they are in the study region, have different climate sensitivities, and hence provide a wide range of outcomes. They have been extensively used across the globe and have capabilities of producing reliable results (Burger et al., 2013; Abatzoglou and Brown, 2012). Utilising a couple of GCMs has advantages of reducing uncertainties in climate change projections (Sung and Chung, 2018; Abatzoglou and Brown, 2012). Table 1

Table 1
Summary of GCMS used in the study area.

GCM No	GCM Name	Developer	Resolution Lat x Lon degrees
1	ACCESS 1-0	Commonwealth Scientific and Industrial Research Organisation–Bureau of Meteorology, Australia	1.9 × 1.2
2	CNRM-CM5	Centre National de Recherches Météorologiques, Centre, France.	1.4 × 1.4
3	IPCL-CM5A-LR	Institute Pierre Simon Laplace, France	3.7 × 1.9
4	MIROC5	Centre for climate research system(The university of Tokyo), National Institute for Environmental Studies and Frontier Research Center for Global Change (JAMSTEC),Japan	1.4 × 1.4
5	MPI-ESM-MR	Max Planck Institute for Meteorology, Germany	1.9 × 1.9
6	MRI-CGCM3	Meteorological Research Institute, Japan	1.4 × 1.4

shows the summary of GCMs used in the study.

2.1.1. Prediction of changes in hydrology and water resources using GCMs

GCMs are one of the most widely used tools for modelling current and future climate scenarios for prediction (River et al., 2016; Liu et al., 2012; Wilby and Harris, 2006). Nevertheless, the scientific community have reached a consensus that GCM outputs should not be used directly as an input in hydrological models that are mostly used on spatial scales smaller than those of GCMs (Farzan et al., 2013).

In order to predict changes in hydrology and water resources, GCM outputs on a global scale require downscaling into the inputs of the hydrological model on a regional or local scale (River et al., 2016; Farzan et al., 2013). This is done to improve the accuracy of the results with reference to specific region or local scale. In view of the aforementioned, spatial downscaling and bias correction of GCM outputs are a requirement prior to their use in regional impact studies (Farzan et al., 2013). Downscaling GCM outputs is widely performed through dynamic and statistical methods. The six GCMs under analysis in this study were statistically downscaled and bias corrected for hydrological modelling at a regional scale.

2.2. GCMs data source

The six GCMs in Table 1 were composed of downscaled global climate scenarios produced from the General Circulation Model (GCM) runs performed through the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). The GCM runs were conducted over two (2) Representative Concentration Pathways (RCPs), namely RCP4.5 and RCP8.5 (Meinshausen et al., 2010). The CMIP5 GCM runs were produced to support the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). The datasets were chosen because they provide a set of global, high resolution, bias-corrected climate change projections that can be used to evaluate climate change impacts on processes that are sensitive to finer-scale climate gradients and the effects of local topography on climate conditions (Thrasher et al., 2015). Furthermore, availability of daily simulation for RCP4.5 and RCP8.5 representative concentration pathways scenarios was considered in selection process of GCMs. The RCP4.5 is a middle pathway scenario that correlates well with the recently released guidelines of lower greenhouse emission by the international community. It is therefore a good case sensitive scenario in light of the new guidelines. RCP 8.5 is a high emission scenario, which provides the possible highest impact on climate change. It is for the above mentioned reasons that RCP 4.5 and RCP 8.5 were selected to provide a possible complete range of impact. (Khan et al., 2018).

2.3. The GCMs projections

The six GCMs were obtained from 21 CMIP5 GCMs with 42 climate projections under RCP 4.5 and RCP 8.5 scenarios for the period 2006–2100 and the climate of the recent past experiment that was conducted from 1950 to 2005 for each model. Every climate projection was downscaled to a spatial resolution of 0.25deg x 0.25deg (about 25 km x 25 km) (Thrasher et al., 2015).The projections for climate change were based on six GCMs and the two RCPs baseline experiment for the period of 1975-2005. The baseline was found to be reasonably accurate in replicating the main climate effects in the KRB. The analysis of rainfall, water yield and runoff changes in the entire river basin was done at different time scales and an ensemble of six GCMs was used because of the huge benefits of depending on the many model outputs (Liu et al., 2012; River et al., 2016). Daily solar radiation, relative humidity and wind speed were generated with SWAT weather generator based on statistical information. SWAT model was used to simulate rainfall, water yield and runoff for Kabompo River Basin (KRB) which was delineated with an area of 72,078 km^2 and sub divided into 102 sub basins with 255 Hydrological Response Units (HRU). SWAT was then used to simulate three climate scenarios as follows: a baseline period with 31 years (1975–2005) and stochastically completed climate data; RCP4.5 2020–2050 period with GCMs climate change projections to modify baseline data and; RCP8.5 2020–2050 period with GCMs climate change projections to modify baseline data.

2.4. Hydrological modelling

The GCM output were statistically downscaled to the region and used as input data for hydrological modelling. Statistical downscaling is mostly used as a conduit for linking GCM outputs with hydrological models due to insignificant computing resources required and can incorporate observations into method. It is worth noting, that there is uncertainty in modelling impact of climate change on water resources which starts with socio economic story lines, future climate scenarios and actual impact modelling (Murphy and Ro, 2006). Hydrological models, therefore, provide the means for relating climate changes to water resources by simulating the hydrological processes in river basins. The most widely used hydrological model in simulating climate change effect is the Soil and Water Assessment Tool (SWAT) (Wang et al., 2012; Arnold et al., 2009). SWAT is a continuous watershed scale model that simulates major components of the hydrological processes on a daily time step (Neitsch et al., 2005). (Neitsch et al., 2005)

The SWAT model was firstly calibrated with 15 years (1982–1997) monthly flow data and validated with 8 years (1998–2005) monthly flow data. The model reached the objective function for Nash Sutcliff (NS) of 0.73 at calibration and 0.64 at validation while the coefficient of determination R^2 was 0.73 at calibration and 0.70 at validation. The model was further subjected to uncertainty analysis with Sequential Uncertainty Fitting version 2 (SUFI-2) where the P-factor was determined to be 0.75 during calibration and 0.73 during validation while the R-factor was determined to be 0.75 during calibration and 0.55 during validation and was therefore a very good result to be used for simulation of the GCM outputs.

In this study, land use and land cover were kept constant during SWAT simulations for future periods under RCP4.5 and RCP8.5, therefore climate change was the only factor influencing catchment water balance.

3. Results and discussion

3.1. Impact of climate change on catchment water balance

The results from six GCM projections that were simulated by SWAT model showed variations in increased and decreased water balance components in all the months under review for the Kabompo basin. The variation in water balance components were also in all the seasons except for June, July and August (JJA) season where no rainfall was simulated. However, the increases in rainfall, water yield and runoff were larger under RCP8.5 than the RCP4.5 scenarios. The highest rainfall increases were simulated by Access1-0 under RCP8.5 when compared with the remaining five (5) GCMs, whilst the same GCM also simulated the lowest rainfall under RCP4.5 amongst the six GCMs. This could be as a result of different responses of various GCMs to the same climate scenarios and therefore creates fundamental uncertainties in climate change projections (Li and Jin, 2017; Stone et al., 2003). The models have various baseline climates when compared and have different sensitivities to changes in emission scenarios (Carolina et al., 2003). The impact model (SWAT) was therefore analysed for sensitivity to the two RCPs representing the climate change at two various spatial scales that are physically related.

Hydrological model results are summarised for baseline period, 1975–2005, RCP4.5 2020–2050 and RCP8.5 2020–2050 future climate scenarios. The rainfall, water yield and runoff are investigated at monthly, seasonal and annual time scales. Water yield (WYLD) is the net amount of water that leaves the sub basin to contribute to stream flow (Stone et al., 2003). It is calculated by eq. No.1 as follows:

$$WYLD = Qsurf + Qgw + Qlat - Qloss \quad (1)$$

Runoff is the surface runoff simulated by SWAT model using the Soil conservation service (SCS) curve number method (Mohammad, 2016). Peak runoff indicates the erosive power of a storm and is many times used in the prediction of loss of sediments (Rostamian, 2010). Peak runoff rate is calculated in SWAT model using the modified rational method (Chow et al., 1988). The six GCM projections were simulated with SWAT model, their mean was calculated, and the results are shown in Fig. 2 as ensemble simulations.

The SWAT simulated ensemble and the mean for baseline rainfall and water yield in Fig. 2 shows minor variations and that the highest rainfall of 200 – 250 mm occurs in January and December with P_ISPL-CM5A-LR simulating the highest rainfall in January, exceeding the other five. The simulations also show that rainfall for February, March and April occurs in a decreasing order before finally ending in May, where there is insignificant rainfall. Fig. 2 further shows no simulation for rainfall in June and July but insignificant rainfall is simulated in August and September while for October, November and December rainfall is simulated in an increasing order.

The Water yield is a direct response to the rainfall in the basin and SWAT model simulates the highest water yield in January and December with 55 – 60 mm from the ensemble GCMs. The water yield decreases as rainfall reduces but maintains above 15 mm in May to September when there is either no rainfall or negligible. The Water yield rises again from October to December due to rainfall increase. In general, the SWAT simulated rainfall and water yield based on six GCMs shows a consensus with insignificant

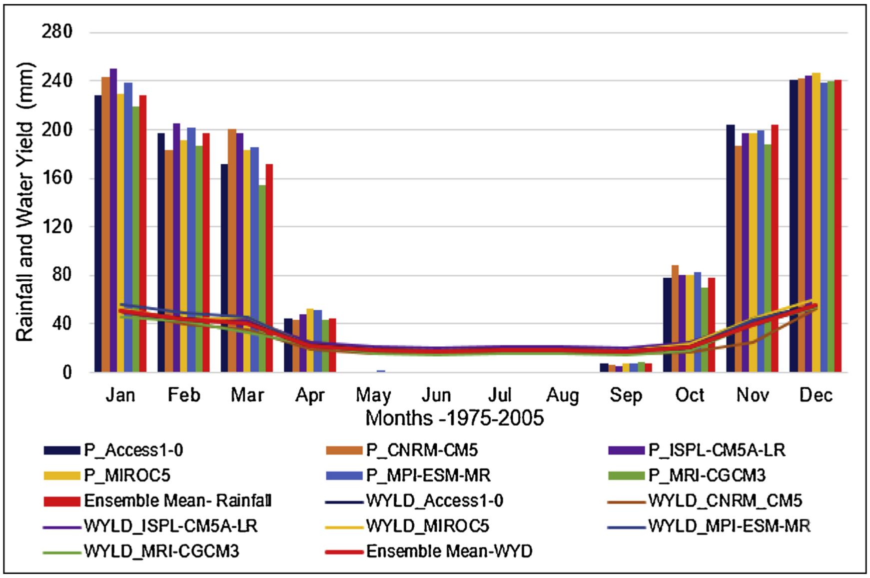

Fig. 2. Simulated ensemble and the mean for baseline rainfall and water yield.

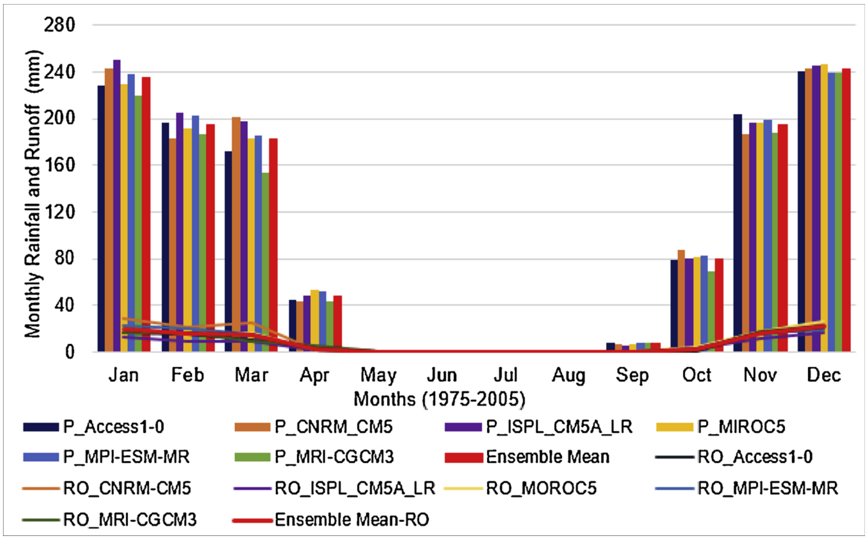

Fig. 3. Simulated ensemble and the mean for baseline rainfall and runoff.

uncertainties.

The ensemble runoff simulations and their calculated mean were also plotted with ensemble rainfall to further compare between the individual GCMs and analyse the impact and uncertainty and the results are shown on Fig. 3.

The SWAT simulated ensemble and the mean for baseline runoff in Fig. 3 shows minor variations in the rain season indicating uncertainty and differences in model skill. The ensemble runoff is slightly high in January, February, March, November and December when rainfall is also high and tend to decrease with decreasing rainfall occurring in April, September and October. The model simulates no runoff from May to end of August as must be the case since rainfall is also absent. The stream flow is composed of just base flow mainly coming from the water yield. Runoff also rises from September to December as a direct response to rainfall. The runoff simulated from CNRM-CM5 output gives the highest runoff of 29 mm in January while ISPL-CM5A-LR output gave the lowest runoff of 12 mm in the same period. In order to understand the baseline period better. Generally, SWAT simulated water yield based on six GCMs shows a consensus with insignificant uncertainties and variabilities.

Further comparisons were made between monthly rainfalls, actual evapotranspiration (ET) of the SWAT simulated GCM outputs, and the results are shown in Fig. 4.

The SWAT simulated ensemble and the mean for evapotranspiration (ET) in Fig. 4 shows no variations and that ET ranged from 87 – 74 mm for January to April, which is also the rain season, and temperatures are generally low. However, from April to June there is a sharp decrease due to the transitional period that ends spring season with rainfall in April and begins winter season (cold season) in June with the lowest temperatures recorded in the year. ET further decreases to zero or insignificant between June to September before rising gently to 81 mm in December, this may be attributed to the rise in temperature. The June, July and August (JJA) season

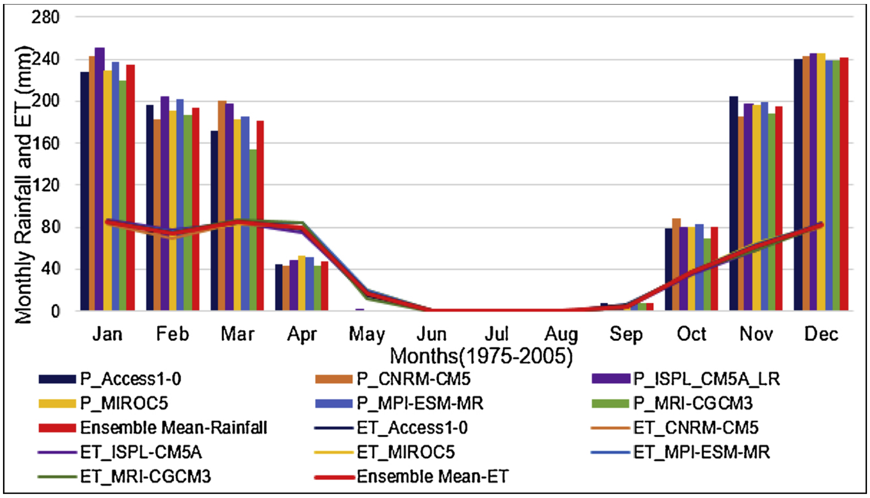

Fig. 4. Simulated ensemble and the mean for baseline rainfall and ET.

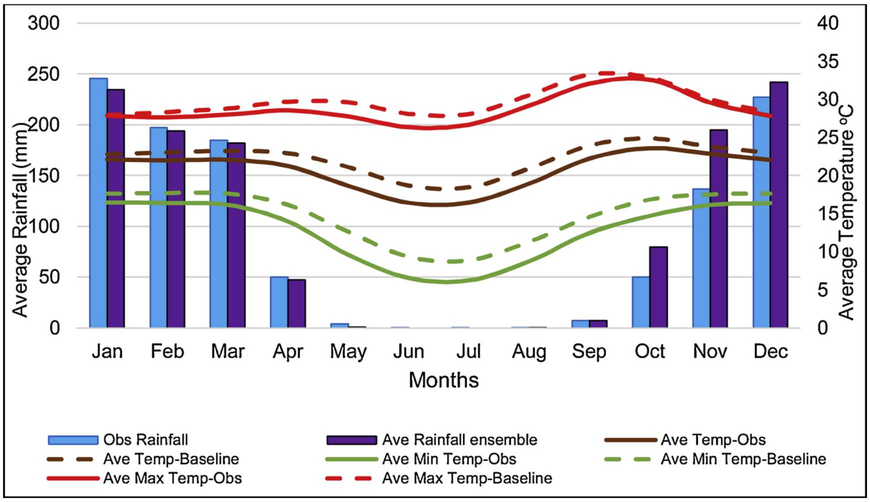

Fig. 5. Comparisons of temperature and rainfall for observed and baseline period.

is characterised with low temperatures as it is the winter season and temperatures begin to rise in September. In general, the SWAT, simulated ET based on six GCMs shows a consensus with insignificant uncertainties.

3.2. Comparisons of GCMs ensemble means and observed data

The GCM ensemble means were used to compare with observed data for the same historical period for validation. The focus was rainfall and temperature data obtained from Zambia Meteorological Department (ZMD), which was observed from five (5) weather stations in the KRB for the baseline period (1975–2005). Temperature was also plotted on the same graph to show the temporal variability across the basin. Fig. 5 indicates the graphical comparisons of GCM ensemble mean and observed climate variables.

Fig. 5 shows a good match between GCM ensemble means for baseline period and observed rainfall for the same period except for October and November where there is a notable mismatch. The baseline temperature is slightly over estimated when compared to the observed temperature for maximum, minimum and average temperatures. This could be attributed to inherent GCM uncertainties and the sparsely located ground weather stations. However, the baseline was still found to be suitable for determination of change factor for future temperatures because the regime is the same and the differences show some uncertainties coming from the wide coverage of ground observed weather stations and the inherent uncertainties in GCMs. Fig. 6 shows the location of the ground weather stations for observed stations.

The rainfall ensemble mean was further subjected to a trend analysis to determine its suitability for hydrological impact studies. A correlation efficiency was determined between the observed and the ensemble mean rainfall data sets. The results on Fig. 7 indicate a correlation efficiency of 96 %, which confirmed the reliability of the ensemble mean for use in hydrological impact studies.

The graph in Fig. 7 shows good correlation efficiency at 96 % and therefore gives confidence to use the ensemble mean as a baseline for climate change analysis.

3.3. Seasonal catchment water balance for baseline ensemble mean

The seasons for the KRB are defined to be December, January and February (DJF), March, April and May (MAM), June, July and August (JJA) and September, October and November (SON). Seasonal changes in catchment water balance are useful for planning of agricultural production, tourism, environmental flow concessions, water supply, industrial development and hydropower generation.

The baseline seasonal changes of the catchment water balance were plotted to show variability and Fig. 8 shows the results.

Fig. 8 shows the highest seasonal rainfall of 620 mm and the highest runoff of 58 mm recorded in DJF while the highest water yield of 256 mm was recorded in SON. The season of SON receives the second largest rainfall followed by MAM and lastly JJA when no rain is recorded. DJF shows the second highest water yield followed by MAM and the lowest is recorded in JJA. SON and MAM shows the 18 mm and 16 mm runoff respectively. While JJA has no rainfall and runoff but has considerable water yield. This is the baseline flow regime analysed for a period of 31 years (1975–2005).

3.4. Future changes in catchment water balance under RCP4.5

The GCM ensemble were analysed under the RCP4.5 2020–2050 to detect the change signal and quantify the magnitude of change with respect to catchment water balance components.The study focussed on rainfall and water yield with runoff. Runoff was separated to show its contribution in water yield and its relationship with rainfall. Different temporal scales were considered under RCP4.5 climate scenario including annual,monthly and seasonal across the basin. This was done to understand the occurences of the

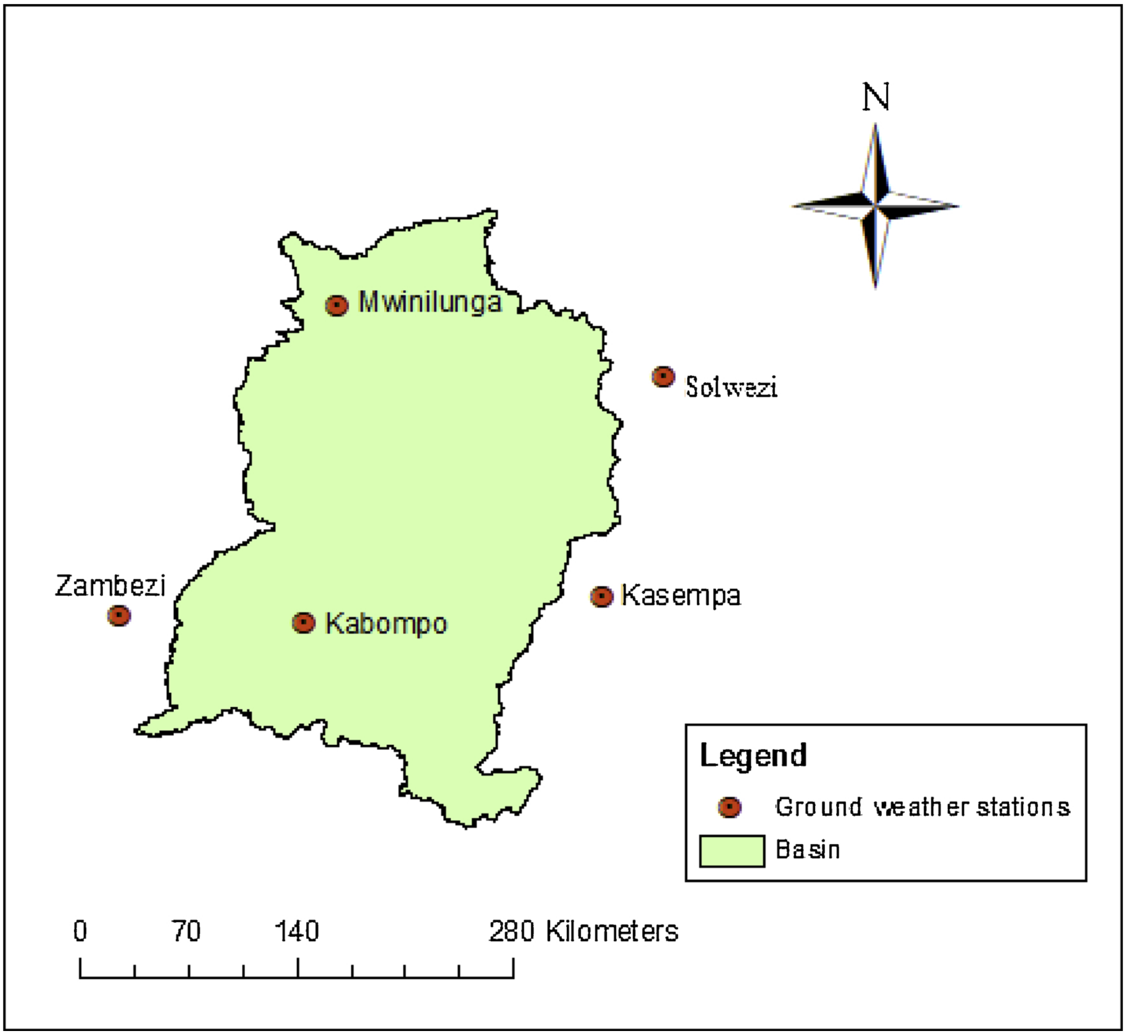

Fig. 6. Location of ground observed weather station.

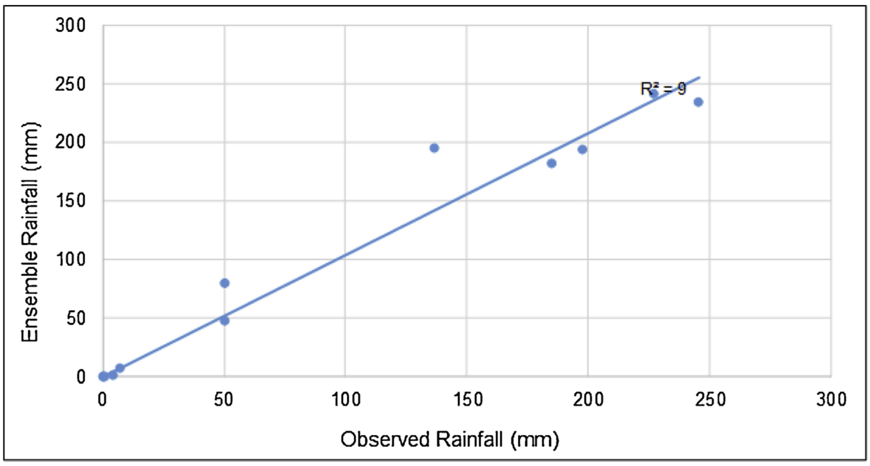

Fig. 7. Monthly observed Vs ensemble mean baseline rainfall.

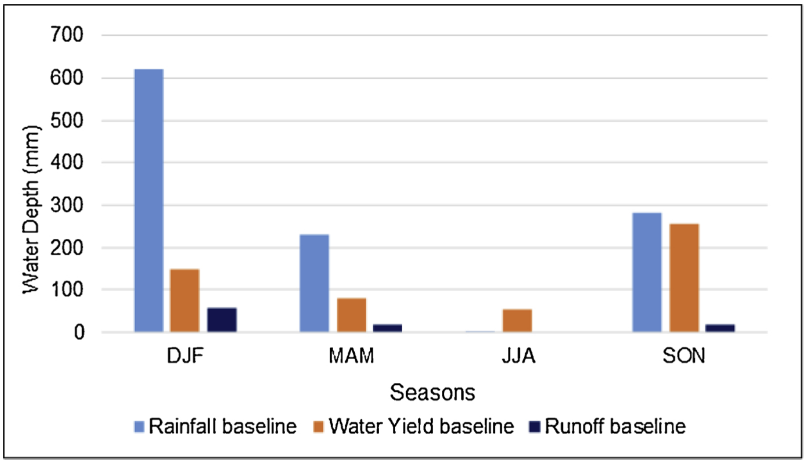

Fig. 8. Baseline seasonal water balance.

changes with their magnitude.

3.4.1. Monthly changes

Fig. 9 shows the individual GCM monthly changes in water balance as simulated by SWAT.

Fig. 9(a) and (f) shows a decrease of rainfall in all the months except for January where there is an moderate increase and May which has the highest increase among all GCMs in Figure (a) and April in Figure (f) while water yield of both Figures show a decrease for all the months. The highest decrease in rainfall of more than 50 % is shown in May under Fig. 9(e) and the highest runoff of more than 100 % is shown in April under the same figure. Fig. 9(d) predicts moderate increase in rainfall and water yield in all months except May, October and December while Fig. 9(e), (c), and (b) indicate moderate decreases and increases of rainfall and water yield. The results of GCM ensemble show uncertainty because various GCMs responded differently to external forcing, formulation of models and the process of downscaling.

One of the most widely used Change Factor Methodology in climate change impact studies (CFM) (Trzaska and Schnarr, 2014; Hamududu, 2012; Anandhi et al., 2011; Chen et al., 2011) was used to obtain an overview of the change for the entire basin by analysing GCM ensemble mean under RCP4.5 and the baseline ensemble mean. The results of the change under RCP4.5 are indicated on Fig. 10

The GCM ensemble mean in Fig. 10, indicate a slight increase in monthly rainfall for December, January, February and March while October and November show a significant decrease. The water yield and runoff when compared with a baseline ensemble also show a slight increase. The results clearly show that monthly rainfall, water yield and runoff has increased in December, January, February and March while rainfall decreased by 19 % and 4 % in October and November respectively. The highest rainfall increase of 3 % is predicted in January, followed by 2 % in February and December. The Highest monthly water yield is predicted to be 10 % and 8 % in March and January respectively and the highest and lowest runoff is predicted to be 13 % in December and −50 % in October respectively. There is a slight increase in water yield between April and September.

3.4.2. Seasonal changes

There are significant variations in water balance components based on seasons, which have also affected the catchment water balance. Fig. 11 shows the seasonal changes in rainfall, water yield and runoff.

Fig. 11 shows that rainfall in DJF will increase by 2 % across the basin while water yield will increase by 7 % and runoff by 11 %. Rainfall and water yield will increase in MAM by 1 % and 6 % respectively while runoff increases by 5 %. In JJA no rainfall and runoff is predicted while water yield is predicted to increase by 2 %. The SON season shows a rainfall decrease of 8 % while runoff also decreases by 5 % and water yield will slightly increase by 1 %. This decrease may lead to seasonal drought requiring major interventions. In general, the Figure shows insignificant changes in rainfall while keeping runoff with considerable changes.

3.4.3. Annual changes

The annual changes under RCP4.5 for the next period of 2020–2050 predict that rainfall will decrease by 1 %, while water yield and runoff will increase by 5 % and 6 % respectively. Table 2 show the results of the changes in ensemble mean.

The results under RCP4.5 predict that runoff in DJF will have a considerable increase of 11 % while the changes in the rest of the seasons in rainfall and other hydrological variables are generally insignificant throughout the period. The annual rainfall show insignificant reduction of 1 % and a small increase of 5 % in water yield while runoff increased by 6 %. The annual water balance components show that the RCP4.5 and baseline periods will have insignificant variations.

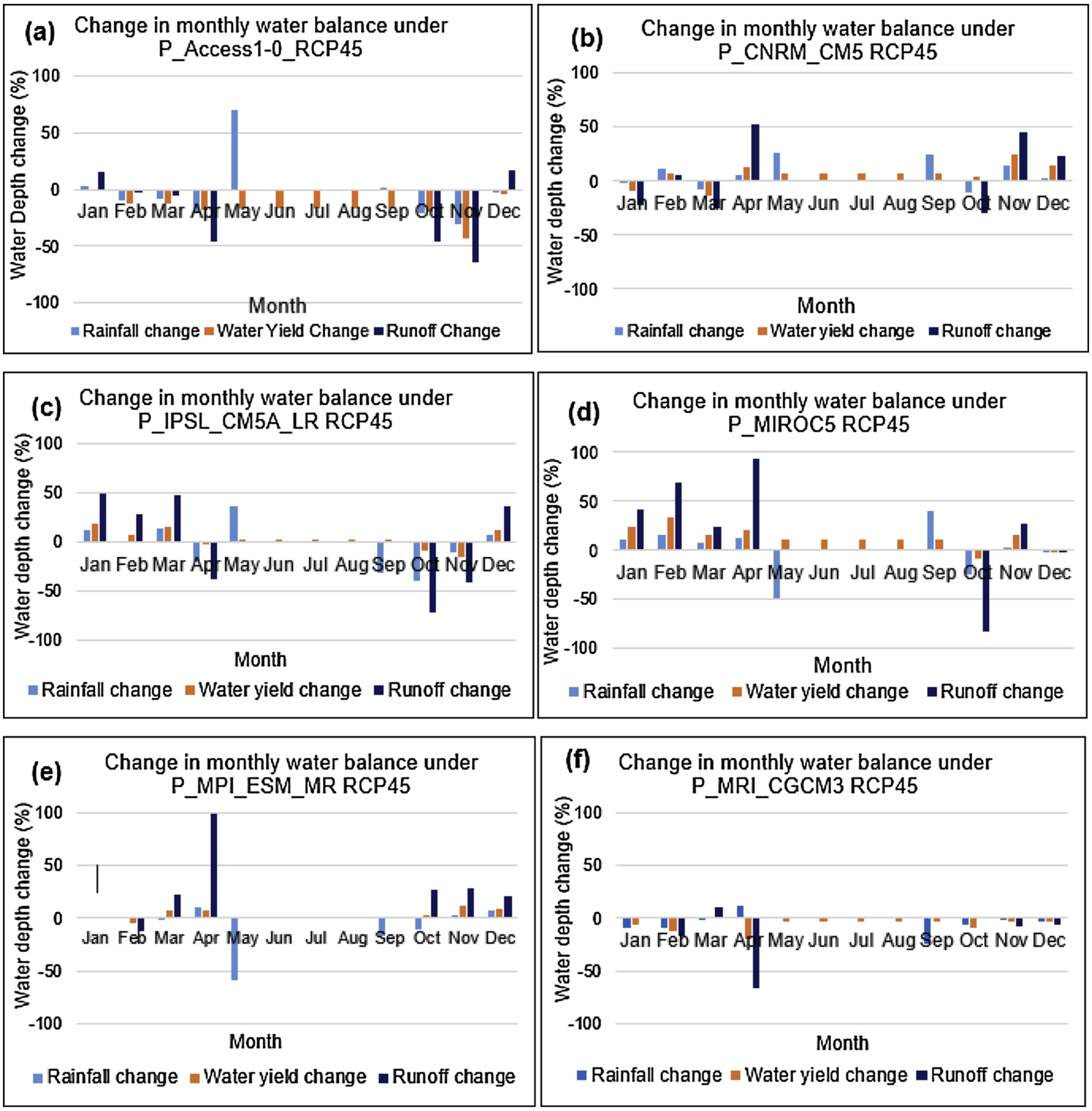

Fig. 9. Monthly changes in catchment water balance.

3.4.4. *Future changes in catchment water balance under RCP8.5*

The GCM ensemble was further analysed under the RCP8.5 2020–2050 to detect the change signal and quantify the magnitude of change with respect to water balance components. The SWAT simulations were considered under monthly,seasonal and annual time scales across the basin in order to analyse the variability of changes with their magnitude.

3.4.5. *Monthly changes*

Fig. 12 shows the monthly changes in water balance for individual GCMs as simulated by SWAT.

Fig. 12 (a) shows the P- Access1-0 with the highest increase in rainfall, water yield and runoff in January, February, March, November and December when compared with the other five GCMs. The increase in rainfall ranges from 3 to 180 % while Water yield and runoff it ranges from 83 to 534% and 153–1628 % respectively. The results show huge differences with the remaining five GCMs. Fig. 12 (b) indicates P-CNRM-CM5 with a decrease in rainfall, water yield and runoff for January and March while showing a moderate increase in the water balance components in February, November, December and April. The largest runoff increase of 416 % is predicted in October and the remaining months of May, June, July, August and September have insignificant rainfall, water yield with no runoff predictions.

Fig. 12 (c) shows P-IPSL-CM5A-LR with moderate increase in the water balance for January, February, March and December while October and November shows a decrease. The increase in rainfall and runoff ranges from 8 to 50% and 12–80 % respectively while water yield ranges from 4 to 31% while predicting the largest decrease in rainfall and runoff in October at 39 % and 99 %

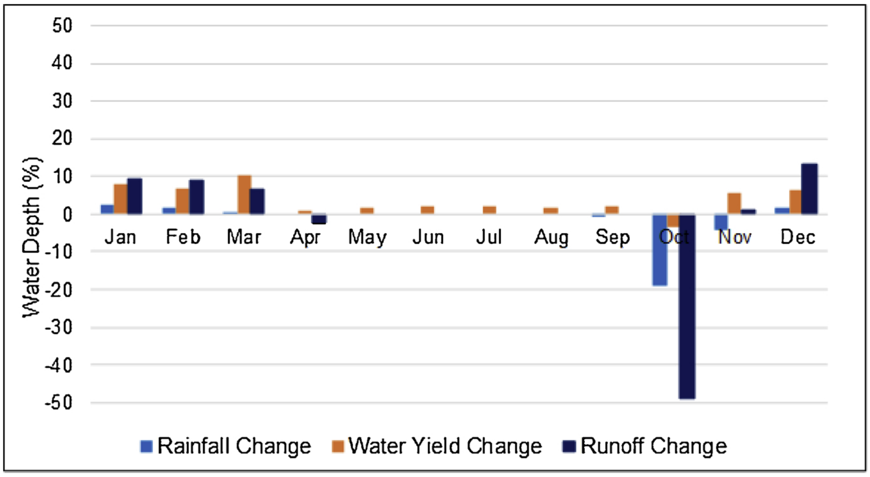

Fig. 10. Monthly average changes under RCP4.5 ensemble means.

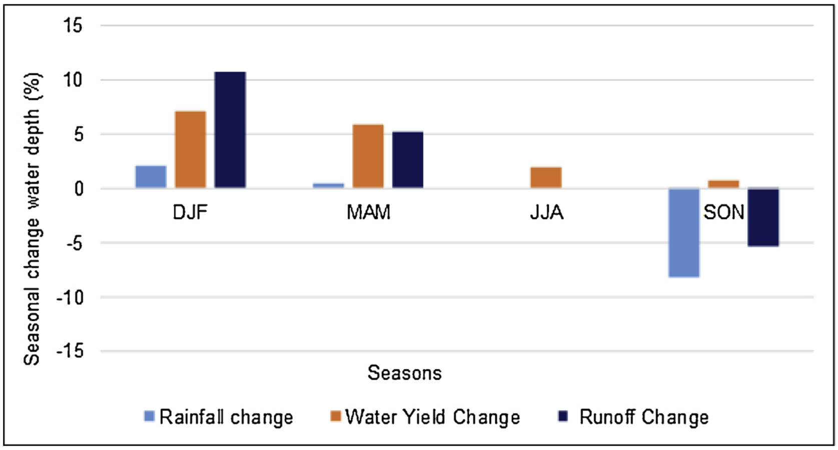

Fig. 11. Seasonal changes under RCP4.5 ensemble means.

Table 2
Annual changes under RCP4.5.

Water Balance	Future Annual	Baseline Annual	Change	Change
Component	Variable (mm)	Parameter (mm)	(mm)	%
Rainfall	1175	1184	−8.	−1
Water Yield	381	362	18	5
Runoff	99	93	6	6

respectively. There is a water yield increase of 10 % from May to September but without rainfall and runoff, perhaps due to a contribution of base flow. Fig. 12 (d) shows P-MIROC5 with a similar trend to 3.11 (c) where there is a moderate increase in water balance for the same months while April and October have a decrease. There is also a slight increase in water yield between May to August. Fig. 12(e) shows P-MPI-ESM-MR with March, September, October and November to have a decrease of 3–36 % in rainfall while January, February and April show an increase in rainfall, water yield and runoff. The figure also shows an increase in Water yield and runoff for March, November and December while also showing a notable decrease in water yield from May to September. Fig. 12(f) shows P-MRI-CGCM3 with a considerable decrease of rainfall in April, December, November and February in the order of 25 %, 16 %, 13 % and 7 %. The Figure also shows that January, March, September and October have also an increase in rainfall, water yield and runoff while May to August have a decrease in water yield and no rainfall and runoff is predicted.

There are considerable differences in GCM results, which can be attributed to uncertainty emanating from external forcing, downscaling and modelling processes. The results from GCM P-Access1-0 show significant increase in catchment water balance and far above the remaining five GCMs for the future period. There are also wide variations in the five GCMs and this could be due to uncertainties aforementioned. There is therefore no consensus in the six GCM results shown in Fig. 12.

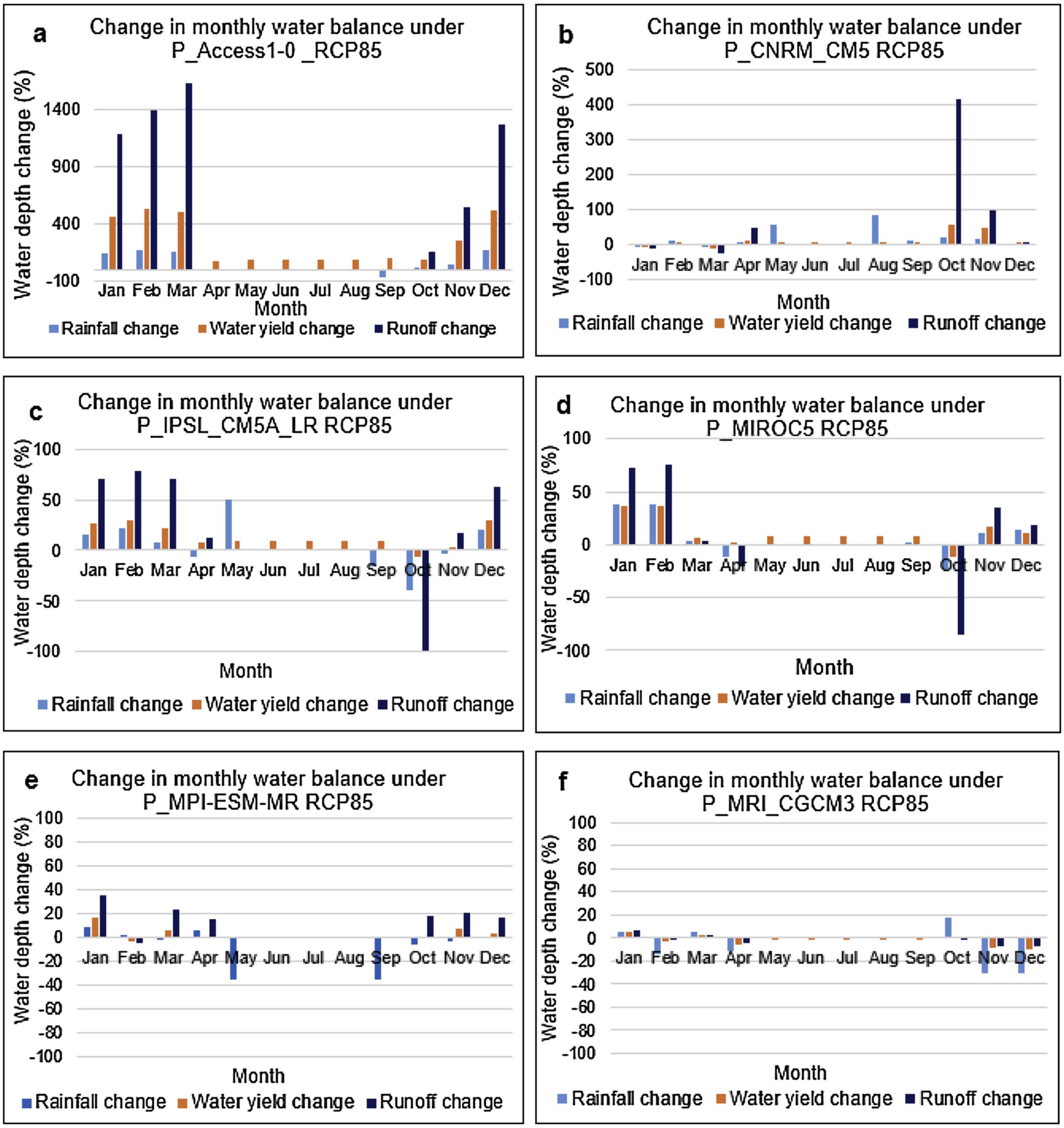

Fig. 12. Monthly changes under RCP8.5.

In order to obtain an overview of the change for the entire basin, further analysis was performed between the GCM ensemble mean under RCP8.5 and the baseline ensemble mean. The results of the change under RCP8.5 are indicated on Fig. 13

The results in Fig. 13 clearly show that monthly water balance will significantly increase in November, December, January, February and March. Rainfall and runoff will increase in the ranges of 9–39 % and 31–232 % respectively. Rainfall is expected to decrease in in October, September, May and April in the range of 1–13 %. The highest rainfall increase is 39 %, predicted in February, followed by 31 % in December and January, followed by 27 % predicted in March and lastly 9 % predicted in November. The Highest monthly water yield and runoff is predicted to be 106 % and 232 % in February respectively. The lowest decrease in runoff is predicted in April with 27 % while May, June, July, August and September are predicted with no runoff but 23–26 % increase in water yield.

3.4.6. Seasonal changes

The seasonal water balance varies from season to season. The DJF season is predicted to have the highest water balance followed by MAM, then SON and lastly JJA in that order. Fig. 14 shows the seasonal variability of water balance.

Fig. 14 shows a significant increase of runoff in DJF at 211 % while predicting 174 % rise in MAM and 105 % in SON with no

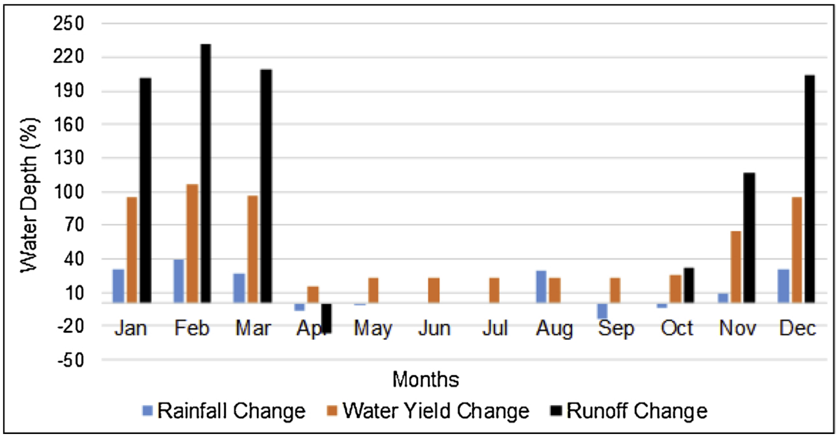

Fig. 13. Monthly changes under RCP8.5.

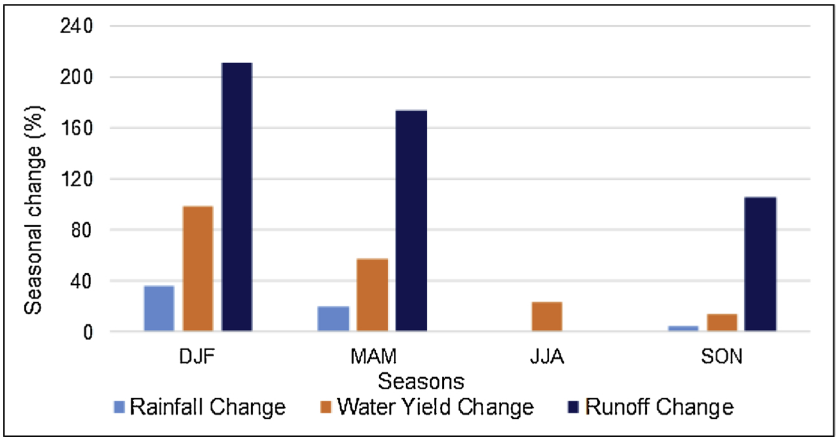

Fig. 14. Seasonal changes under RCP8.5.

runoff in JJA. The figure also shows 98 % increase in water yield for DJF followed by 58 % in MAM, 23 % in JJA and lastly 14 % in SON. The increase in rainfall is predicted to be 36 % in DJF followed 20 % in MAM and lastly 5 % in SON. The JJA season is predicted with no rain, as is the case with the current basin scenario.

3.4.7. Annual changes

The annual changes under RCP8.5 2020–2050 show that the annual water balance will increase in general. Rainfall will increase by 19.27 %, and water yield and runoff will increase by 40 % and 65 % respectively. Table 3 shows the annual changes.

The results under RCP8.5 predict a general increase in annual water balance. Annual rainfall and runoff will increase by 19 % and 65 % respectively while annual water yield will increase by 40 %. The general rise in annual water balance may culminate into excessive water availability and high storage of groundwater.

3.4.8. Analysis of future catchment water balance

Further analysis was performed to compare catchment water balance under RCP4.5 and RCP8.5. The results were plotted and shown in Fig. 15

The comparison of seasonal water balance in Fig. 15 shows no consensus of the two future climate scenarios. The water balance

Table 3
Annual changes under RCP8.5.

Water Balance	Future annual	Baseline annual	Change	Change
Component	Variable (mm)	Variable (mm)	(mm)	(%)
Rainfall	1466	1184	282	19
Water Yield	604	362	241	40
Runoff	264	93	171	65

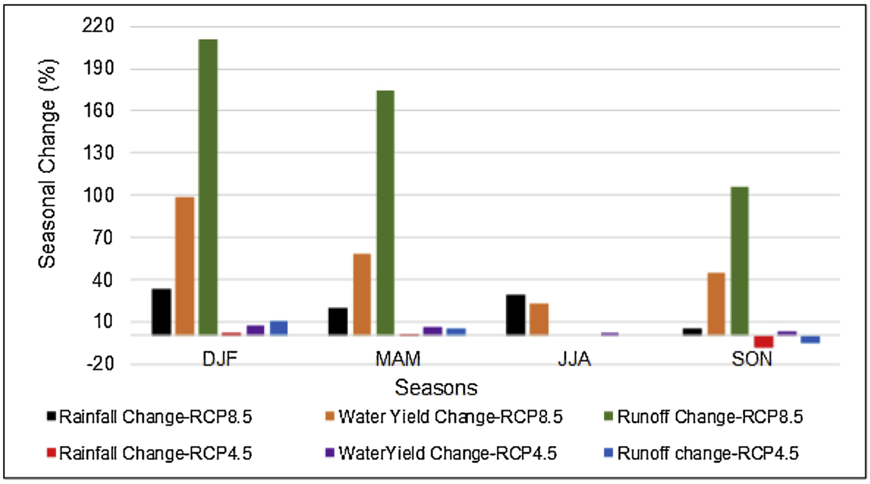

Fig. 15. Comparisons of future seasonal water balance.

Table 4
Annual changes.

Water balance component	RCP4.5 Annual Change	RCP8.5 Annual Change
	(%)	(%)
Rainfall	−1	19
Water Yield	5	40
Runoff	6	65

analysed under RCP8.5 is clearly much more than that of the RCP4.5. The seasonal rainfall change under RCP8.5 range from 5 %–35 % while RCP4.5 does not show any significant seasonal changes except for 8 % decrease in SON. The Figure also shows that the catchment water balance under RCP4.5 will have insignificant variations with the baseline catchment water balance. Another analysis was performed to compare and contrast the annual catchment water balance and the results are shown in Table 4.

Table 4 shows that the annual changes in water balance under RCP4.5 are insignificant and therefore unlikely to alter the current water balance. The changes under RCP8.5 are significant and most likely will increase the catchment water balance to unprecedented levels. Nevertheless, the scenario under RCP8.5 characterised with high uncertainty due to non-consensus of the SWAT simulated GCM projections results.

Therefore, in general the future is predicted with two scenarios, which can be summarised as the future catchment water balance without changes from the current status but with increased water demand and the future water balance with significant increase above the current status with excessive surplus.

4. Conclusion

The impact of climate change on catchment water balance based on GCMs is different and depends on temporal resolution and the climate scenarios.

The monthly changes under RCP4.5 indicate a slight increase in monthly rainfall for December, January, February and March while October and November show a significant decrease. The water yield and runoff when compared with a baseline also show a slight increase. The results clearly show that monthly rainfall, water yield and runoff has increased in December, January, February and March while rainfall decreased by 19 % and 4 % in October and November respectively. The highest rainfall increase of 3 % is predicted in January, followed by 2 % in February and December. The Highest monthly water yield is predicted to be 10 % and 8 % in March and January respectively and the highest and lowest runoff is predicted to be 13 % in December and 50 % in October respectively. There is a slight increase in water yield between April and September. The overall changes in monthly water balance are not significant under this scenario.

The monthly changes under RCP8.5 show that monthly water balance will significantly increase in November, December, January, February and March. Rainfall and runoff will increase in the ranges of 9–39 % and 31–232 % respectively. Rainfall is expected to decrease in in October, September, May and April in the range of 1–13 %. The highest rainfall increase is 39 %, predicted in February, followed by 31 % in December and January, followed by 27 % predicted in March and lastly 9 % predicted in November. The Highest monthly water yield and runoff is predicted to be 106 % and 232 % in February respectively. The lowest decrease in runoff is predicted in April with 27 % while May, June, July, August and September are predicted with no runoff but 23–26 % increase in water yield

The seasonal changes under RCP4.5 predicts 11 % seasonal runoff increase in DJF while the changes in the rest of the seasons in rainfall and water yield is generally insignificant throughout the period. The annual rainfall will reduce by 1 % while water yield and runoff will increase by 5 % and 6 % respectively. The individual GCM results show insignificant uncertainties and a good consensus.

The catchment water balance under this scenario will not deviate considerably from the baseline and therefore the major concern would be to enhance management of water resources because of the demand, which is likely to double by the end of the 31 year period for municipal water supply, environmental, industrial, agricultural, energy sector and mining sector. The evaluated impact under this scenario gives a status quo of water resources with the baseline period.

The seasonal changes under RCP8.5 scenario predicts significant increases in water balance that has a strong likelihood of increasing catchment water balance. The seasonal increases of runoff at 211 %, rainfall at 35 % may indicate occurrence of excessive catchment water balance.

The comparison of seasonal water balance under the two RCPs shows no consensus of the future climate scenarios. The water balance analysed under RCP8.5 is clearly much more than that of the RCP4.5. The seasonal rainfall change under RCP8.5 range from 5 %–35 % while RCP4.5 does not show any significant seasonal changes except for 8 % decrease in SON. The catchment water balance under RCP4.5 will have insignificant variations with the baseline catchment water balance.

Annual statistics under RCP8.5 show a significant increase of 65 %, 40 % and 19 % in runoff, water yield and rainfall respectively while under RCP4.5 there is an annual reduction in rainfall of 1 % and an increase in runoff and water yield of 6 % and 5 % respectively. Generally, RCP8.5 climate scenario shows high uncertainties of GCMs simulations than RCP4.5 climate scenario in the KRB. The variability of individual GCMs is also wide and shows no good consensus under RCP8.5 as compared with RCP4.5 results.

The six GCMs have demonstrated a rare skill in modelling climate change for KRB.

There is significant increase under RCP8.5 in catchment water balance at monthly, seasonal and annual time scales. The prediction may call for preparedness in disaster mitigation and adaptation, review of policies, review of designs of hydraulic structures, flood mapping and awareness campaign. Meanwhile under RCP4.5 the evaluated catchment water balance at monthly, seasonal and annual time scales may also call for integrated water resources management of available water resources against a growing water demand in the KRB.

Further research will be required for evaluation of the impact of climate change on streamflow, water quality, flood mapping of flood prone areas and rainfall intensity in order to inform the adaptation and mitigation strategies.

Declaration of Competing Interest

Authors declare no conflict of interest.

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