

Evaluation and Comparison of Satellite and GCM Rainfall Estimates for the Mara River Basin, Kenya/Tanzania

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Abstract Water resources and climate change studies in data-scarce regions of the world are increasingly employing satellite rainfall estimates (RFEs) and rainfall outputs from general circulations models (GCMs). The reliability of these data sources is seldom verified with observed data prior to application. This chapter outlines the application of simple evaluation techniques to assess the potential of RFE and GCMs outputs as a potential rainfall information sources in the Mara River basin (MRB), Kenya/Tanzania. Results of the assessment show that proper care is required in comparing/mixing of results from studies using different RFE in the MRB. In general, RFE and GCMs are promising sources of information, but refining the estimates with a much improved algorithms is essential.

Keywords Climate change, GCM, Mara River, RFE, Satellite rainfall, Water resources

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1 Introduction

Water resources planning and management is inevitably the foundation of sustainable development plan. Limitation of observed data stands out among the wide spectrum and variety of challenges in water resources development and management facing the developing regions of the world. The feasible threshold towards which water utilization could be pushed is crucial information to ensure sustainable development. In these regions, water resources data and information are either absent or limited in time and location. With the advent and progress of remote data collection and development of complex earth system models, satellite rainfall estimates (RFEs) and rainfall outputs from general circulations models (GCMs) are becoming readily available for end-users offsetting the limitations posed by data scarcity. A number of algorithms and mathematical approaches have been developed to model rainfall process with varying complexity in representations of the natural process, theoretical concepts and assumptions, temporal and spatial scale, computational efficiency, data requirement, etc. Their application ranges from simple daily rainfall estimation/forecast to simulation of complex hydrologic processes that supplement decision.

The use of satellite RFE requires proper verification as the remote sensing approaches usually combine different factors that determine the information sought for. Remote sensing information also depends on number of variables considered in the measurement and estimation process. For example, precipitation is highly influenced by topography and concentration of aerosols at a particular time and prediction of precipitation from cloud temperature may not provide complete picture of rainfall event. The daily RFE distributed by USAID and Famine Early Warning Systems Network (FEWS NET) (<http://www.fews.net>) program is one of the widely used satellite estimate in Africa and other developing regions of the world. We have used this estimate to explore easy-to-use techniques in evaluation of the performance of similar estimates in water resources assessment.

GCMs are increasingly used to simulate past and future climate scenarios [1]. GCMs outputs have become part and parcel of hydrological systems study due to the fact that water resources planning and development requires resilience to anticipated future climate conditions [1–3]. Among the variables driving climate change, rainfall and temperature are used more often as input to hydrologic models. The amount of rainfall and its occurrence determines the gross volume of available resource while temperature is usually considered as direct signal of the evapotranspiration in the area. Performance of GCMs in tropical regions, especially Africa, is relatively less investigated. GCMs outputs enable long-term climate simulation of past-climate and assessment of future climate scenarios in Mara River basin (MRB) [4–7].

As shown in Fig. 1, the transboundary MRB is part and prototype of the Nile River Basin between Kenya and Tanzania. The basin is one of such basins with limited observations of climate and hydrological data. On top of the regional scarcity, the number of functional rain gages in the basin has sharply decreased since 1990. Due to the lack of sufficient rainfall data, recent studies in the basin

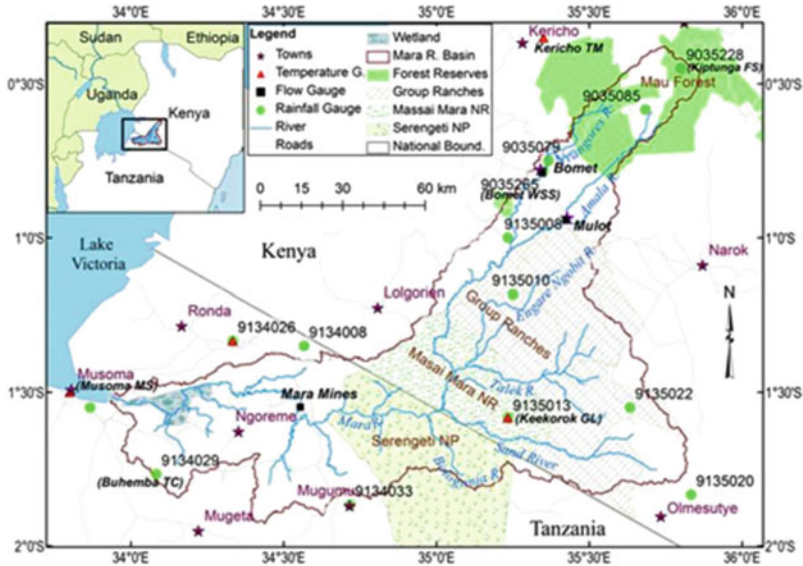


Fig. 1 The Mara River basin location map with major land use types and distribution of monitoring stations [13]

used satellite estimates and GCMs outputs to investigate the hydrological processes and water resources assessment of the basin [7–10]. For example, Soil and Water Assessment Tool (SWAT) was applied on the Nyangores and Amala tributaries of the upper Mara River to assess the impact of land use change using gage rainfall records and satellite RFE from 2002 to 2006 [11, 12].

GCMs are designed for climate simulation at global scale representing major earth systems and regional climate. For data scarce regions, GCMs may prove valuable in simulating past climate condition. Since regional/local hydrologic systems are considerably affected by local physiographic condition, the spatial resolution of GCMs has been a major limitation to direct application [14]. Moreover, hydrologic systems response is highly dependent on surface properties that respond at slower rate compared to atmospheric phenomena. For instance, MRB covers an area of $2^\circ \times 2^\circ$ while the best atmospheric resolution of GCMs with daily atmospheric output in the basin was $1^\circ \times 1.2^\circ$ Latitude and Longitude. Downscaling techniques are commonly used to bridge the spatial disparity of GCMs output and finer scale data required for water resources assessment [15, 16].

Two major classes of downscaling methods, dynamic and statistical, are widely used to cope with the scale problem and extract usable information from GCMs. Wilby et al. [14] suggested that hydrologic impact assessment need to start with direct use of coarse GCM output followed by comparative analysis of the improvements achieved by downscaling procedures. Wilby and Wigley [15] summarized the advantages and disadvantages of these two downscaling techniques. Regional climate models (RCMs) perform dynamic downscaling by

nesting and constraining a GCM with local boundary condition of specific region improving the hundreds of kilometers spatial scale to tens of kilometers. However, RCMs are not readily available in the developing regions of the world. Moreover, the need of point climate data in hydrologic assessment requires statistical downscaling on GCM and RCM. The choice of GCMs rainfall output faces two challenges at the very start: what climate model to pick and which downscaling method to apply [16, 17]. Statistical downscaling utilizes statistical properties to build relationship between coarse scale GCM output and the local climate and physiographic variables [14]. The delta and direct statistical downscaling methods [18] were applied in this study. Each downscaling method has certain advantages and disadvantages, and the selection depends on a number of factors such as intended use, resolution of the GCM, size of the study area, and availability of observed data [19].

The increasing variety of RFE, though offers flexibility, is becoming a challenge for users and decision makers. Their performance also varies on the basis of the intended purpose of use, conceptual framework, and assumptions of development. Besides, use of different sources of information to address a specific or similar problem may obstruct dissemination and comparison of findings among researchers to understand the whole system. The reliability of these data sources is seldom verified with observed data. Prior evaluation of estimates may help to utilize the strength of estimates to the best advantage of the project being undertaken and to recognize the limitations as well. Therefore, users need to have a certain preestablished set of criteria to choose a RFE that best represent and able to achieve the objectives of the intended task.

The objective of this chapter is to outline and illustrate simple procedures used to evaluate the potential of RFE and GCMs outputs as an alternative rainfall data sources in the MRB. The procedures outlined in this chapter can be used to assist in understanding the past and planning future water resources development in other watersheds of similar challenge.

2 Study Area

The Mara River flows from the Mau Escarpment in Kenya through Mara-Serengeti protected areas of Kenya and Tanzania and empties to Lake Victoria. The Mara River drains 13, 750 km² combined area of south western Kenya and northwestern Tanzania over a stretch of 395 km length (Fig. 1). The highest elevation of the basin is 3,062 m above mean sea level (amsl) at the upstream edge and the lowest is 1,138 m amsl at the downstream flood plain. The two perennial tributaries, Nyangores and Amala Rivers, flow through sections of mixed small- and large-scale agricultural farms and the Mau Forest Reserve, and merge to form the Mara River. The River then joins three ephemeral tributaries Engare Ngobit River, Talek River, and Sand River inside the Massai Mara National Reserve (MMNR) before crossing the Kenya-Tanzania national border. The river then runs through the

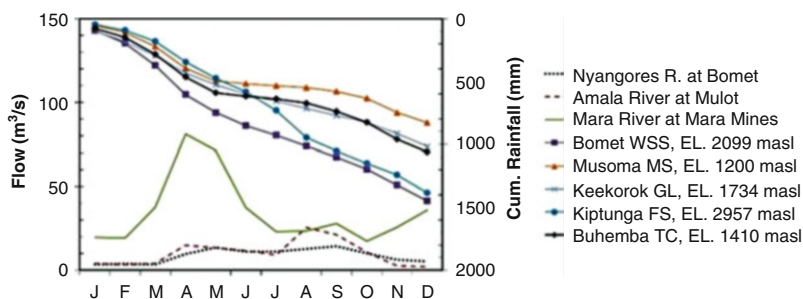


Fig. 2 Average cumulative rainfall and average monthly river flow at selected stations in the MRB (1961–1990) [22]

northern part of Serengeti National Park (SNP) on the Tanzanian side. The SNP is listed as a UNESCO World Heritage site attributed to the unique biannual wild beast migration and pristine biodiversity of the Mara-Serengeti ecosystem. After crossing the SNP, the Mara River joins the last remaining major tributary, Bologonja River, on Tanzanian side and runs through flood plains to Lake Victoria [20].

The social structure and livelihood in MRB is highly dependent on the quantity and quality of the flow in the Mara River and its tributaries. Small-scale agriculture is the largest economic activity engaging 62% of the population over 28% of the available arable land followed by livestock husbandry [21]. Other economic activities in the MRB include large-scale farming, tourism, gold mining, fisheries, logging, and charcoal burning. Major land use types in the MRB are dense forest, bushland, grassland, group ranches, agricultural lands, urban area, and wetland [9, 22].

MRB has bimodal rainfall (Fig. 2) driven by the migration of Inter-Tropical Convergence Zone (ITCZ). The southward migration of the ITCZ causes the short rains in October to December and the returning northward causes the long rains in March to May. The migration of ITCZ is sensitive to variations in Indian Ocean sea surface temperatures that vary from year to year influencing the onset, duration, and intensity of rainfalls in the MRB as well as episodes of El Nino southern Oscillation and La Nina. The annual rainfall decreases with altitude ranging from 1,000 to 1,750 mm in the upper reaches, 900–1,000 mm in the middle, and 300–850 mm at the lower reaches of the river (Fig. 2). Due to orographic effect, windward (Western) side of the basin gets higher rainfall compared to its leeward (Eastern) side. For example, eastern station #9035022 at recorded 660 mm while western station #9035079 recorded 1,440 mm of average annual rainfall. The spatial variation in annual rainfall in the basin indicates orographic effect at the higher altitudes with significant variability across the basin. Amala, Nyangores, and Mara Mines flow gage stations have relatively longer records. The average annual flows at Amala and Nyangores Rivers are 8.1 and 8.5 m^3/s with a standard deviation of 12.4 and 6.5 m^3/s , respectively. The average annual flow at the Mara Mine station is 24 m^3/s with a standard deviation of 22.8 m^3/s .

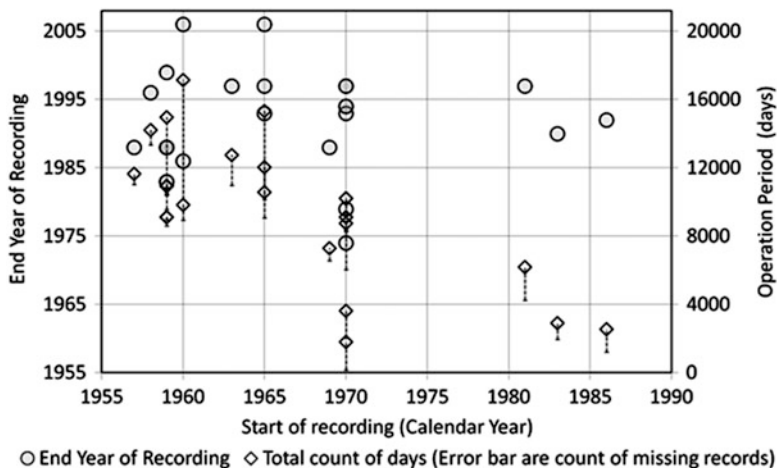


Fig. 3 Start and end year of rainfall recording period for stations in and around the MRB. The end year only corresponds to the availability of data not actual termination of the station

3 Data Set and Methods

3.1 Data Set

The historical observed climate data sets for the MRB were obtained from Kenya Meteorological Department and Tanzanian Meteorological Agency. Twenty rainfall gaging stations were used to represent the spatial variability of rainfall inside and around the basin (Fig. 1). Evaluation of the sufficiency of record length and quality discussed in this chapter was based on the data requirement of the SWAT applied to simulate the rainfall runoff processes [22] and study of uncertainties and impact of climate change [6] in the MRB. Operation period and continuity of observed daily rainfall data were assessed from 1955 to 2006 to see the need to augment/replace the available rainfall data with alternative sources (Fig. 3). These stations were further screened to 13 stations based on their length of record and proximity to the basin. The structure of SWAT version applied for this study takes the closest station to the center of each subbasin cutting down the number of stations needed for simulation to eight. Nine of the 20 rain gage stations are in the MRB and four of the nine were reported to have data after 1994 and only two stations (Bomet WSS and Kiptunga FS) had daily records after 2004.

To assess the possibility of using satellite RFE over the MRB and extend simulation of the rainfall-runoff process beyond 1995, a comparative analysis of RFE and rain gage data sets was done over the intersecting time period. Since RFE were available in 10 days interval from June 1995 to 2000 [23] and the observed rainfall had missing daily records, the monthly total of the two stations in the MRB was compared with the corresponding RFE.

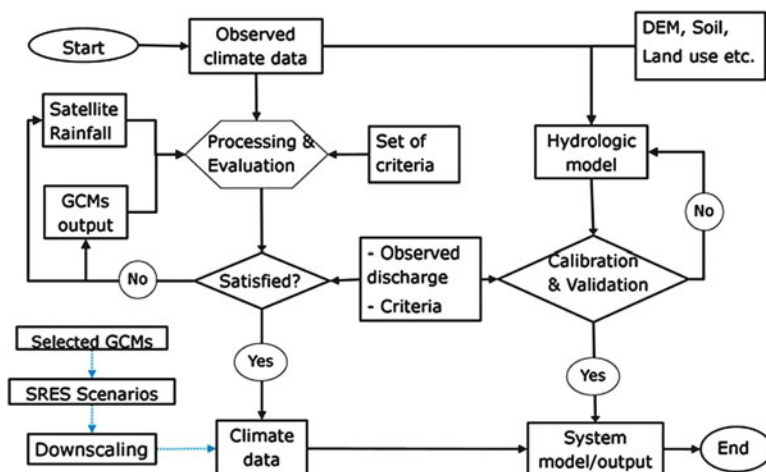


Fig. 4 Evaluation and comparison scheme for satellite rainfall and GCMs rainfall estimates

3.2 Methods

This study has combined two components (Fig. 4). The first component involved assessment of satellite-based RFE and past observed rainfall of the MRB. The second component investigated performance of GCMs in capturing the rainfall process in the MRB. The later component also uses simple statistical downscaling techniques to assess the potential improvement in the performance of raw GCMs outputs.

3.2.1 Satellite Rainfall Estimates

The performance of RFEs may vary with respect to the specific objective(s), the input information used in estimation process, the theoretical basis and validity of assumptions made, the availability and easiness of estimates for water resources applications. The following additional set of criteria were used to select the RFE used in this chapter (Fig. 4): (1) flexibility to various hydrological analysis; (2) convenience and cost to obtain; (3) documentation and user support; (4) previous experience of the estimate's performance, implementation and extent; and (5) capability and limitations in representing the observed rainfall.

The selected RFE was also checked for the following useful features necessary for hydrological modeling and water resources assessment in the MRB: (1) scale, both temporal and spatial; (2) availability of computer software and hardware and skills to use the estimate; (3) simplicity and ease of use, implementation and operation; (4) additional data requirement, resolution with respect to time and record horizon; and (5) presence of additional utilities for input data preparation and output display and interpretation, etc.

The RFE from FEWS NET is a satellite-based RFE database available since June 1995 that combines cloud temperature data from METEOSAT, Global Telecommunication system (GTS) rain gage reports, and other weather inputs. Detailed description on the evolution of RFE is given by Herman et al. [23] and Xie and Arkin [24]. The first algorithm (RFE 1.0) was used from 1998 to 2000, whereas RFE 2.0 developed by Xie and Arkin [24] has been operational since January 2001. RFE 1.0 [23] utilizes cloud top temperature from METEOSAT 5 satellite, GTS rain gage data, model analyses of wind and relative humidity, and orography for the computation of estimates of accumulated rainfall for 10-day period. RFE 2.0 was an improvement over RFE 1.0 including METEOSAT 7, Special Sensor Microwave/Imager (SSM/I) aboard Defense Meteorological Satellite Program Satellites and The Advanced Microwave Sounding Unit on board of NOAA satellites. Free daily RFE grids are available in 0.1° resolution (<http://earlywarning.usgs.gov/fews/africa/index.php>) for continental Africa and other developing regions of the world.

3.2.2 Global Circulation Models: Selection and Downscaling

Evaluation of GCMs as alternative rainfall information source begins by producing a guideline of model selection and categorical division according to common attributes. The GCMs output used in this chapter were prepared to investigate the impact and uncertainties of climate change on the hydrology of the MRB [6]. A set of six criteria were used to select representative GCMs for the MRB [6]: (1) availability of daily RFE [25]; (2) positive correlation coefficient of monthly average observed and GCM output; (3) mixture of GCMs that overestimate, underestimate, and closer to the average annual observed data in the base period; (4) large or intermediate 30 years average annual range as compared to the range of the observed; (5) heterogeneity of model source such as country or sponsor institution; and (6) ability to capture the observed seasonal variability of average monthly data.

The period 1961–1990 is used as control period for the evaluation of GCMs rainfall outputs as recommended by World Meteorological Organization in assessment of climate model performance. Sixteen GCMs with daily simulation outputs of rainfall and maximum and minimum surface temperature were identified [25] (Table 1). Area average monthly rainfall (mm) of stations falling within a grid cell was used to assess cell-wise performance of GCMs to reproduce observed climate pattern over the control period (1961–1990).

The GCMs were first evaluated based on their performance in tracing back the past climate. Annual rainfall data were evaluated and the trend was examined with respect to outputs of GCM. On the basis of analysis of the raw GCM output and observed data, selected GCMs were downscaled using delta and scaling methods [Eqs. (1) and (2)] [6, 18, 19], respectively.

Table 1 List of GCMs used for this impact study with daily mean atmospheric data availability and at least one currently available output for A1B, A2, and B1 SRES scenario [4, 6, 25]

Originating group (country)	GCM	Latitude° × Longitude°
Bjerknes Centre for Climate Research (Norway)	BCCR-BCM2.0	2.8 × 2.8
National Center for Atmospheric Research (USA)	NCAR-CCSM3	1.4 × 1.4
	NCAR-PCM	2.8 × 2.8
Canadian Centre for Climate Modeling and Analysis (Canada)	CGCM3.1(T47)	2.8 × 2.8
Météo-France/Centre National de Recherches Météorologiques (France)	CNRM-CM3	2.8 × 2.8
Commonwealth Scientific and Industrial Research Organization (Australia)	CSIRO-MK3.0	1.9 × 1.9
	CSIRO-MK3.5	1.9 × 1.9
Max Planck Institute for Meteorology (Germany)	ECHAM5/MPI-OM	1.9 × 1.9
US Department of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory (USA)	GFDL-CM2.0	2 × 2.5
	GFDL-CM2.1	2 × 2.5
NASA/Goddard Institute for Space Studies (USA)	GISS-ER	3.9 × 5
Institute for Numerical Mathematics (Russia)	INM-CM3.0	4 × 5
Institut Pierre Simon Laplace (France)	IPSL-CM4	2.5 × 3.75
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC) (Japan)	MIROC3.2 (Med)	2.8 × 2.8
Meteorological Research Institute (Japan)	MRI-CGCM2.3.2	2.8 × 2.8
Hadley Centre for Climate Prediction and Research/Met Office (UK)	UKMO-HadCM3	2.5 × 3.75

$$\text{Delta method : } P_{\text{delta,daily}} = P_{\text{Observed,daily}} \times \left(\frac{\bar{P}_{\text{eval}}}{\bar{P}_{\text{control}}} \right)_{\text{monthly}} \quad (1)$$

$$\text{Scaling method : } P_{\text{Scaling,daily}} = P_{\text{eval,daily}} \times \left(\frac{\bar{P}_{\text{Observed}}}{\bar{P}_{\text{control}}} \right)_{\text{monthly}} \quad (2)$$

where P is rainfall, observed is the observed time series, control is the GCM output of the control period, and eval is the period GCM output were evaluated.

The delta method assumes stationarity in rainfall due to the relative correction factor being applied on the control period observed rainfall. It maintains the number of rainy days and suppresses the daily climate variability of the GCM output. When the evaluation period coincides with the control period, the delta method reproduces the observed daily rainfall. The scaling method, on the other hand, adjusts daily GCM output by long-term average monthly observed and control period GCM output data. The scaling method may produce a new frequency as well as amount of rainfall for the control period. Comparatively, the scaling method offers better flexibility in frequency of climate events but has the limitation of propagating model structural error over the period of analysis. Both methods were

used in this study so as to get a comprehensive insight to their applicability simulate past rainfall events of the MRB.

Two representative gage stations from the upper Bomet Water Supply Station (BWSS) and lower reach Buhemba Training Center (BTC) were considered to assess the performance of GCMs and downscaling techniques. Based on the comparative results of downscaled climate data, results were input to SWAT model to evaluate the hydrologic response of MRB to the various GCM outputs.

3.2.3 Analysis and Evaluation of Rainfall Estimates

Evaluation of RFE was first conducted based on statistical relationship between the estimates and the observed rainfall. Acceptable graphical comparison of daily, monthly or annual rainfall time series was followed by quantitative evaluation of RFE with respect to the observed quantity, trend, and variability (and seasonality). Descriptive statistical parameters (mean, standard deviation, range, etc.) and the correlation between the GCMs outputs and observed rainfall were used as primary indicators of performance of GCMs rainfall outputs. Daily RFE are becoming more common, though monthly water balance is more practical in water resources applications. Annual comparisons would help to suppress seasonal/monthly variability between observed and estimated rainfall, but helps to evaluate the quality of the estimate in capturing the annual water balance in the basin. Trend analysis helps to filter outliers in the observed rainfall and check if estimates are able to reproduce such characteristic features. However, a thorough investigation is necessary to ensure whether such deviations are inherent to the model structure or techniques used in generating/estimating the estimate.

Performance of the estimates was assessed through objective functions [Eqs. (3)–(7)] that minimize the distance and optimize the variability between observed event and model result. Mean relative error, MRE [Eq. (5)], was used to evaluate measurement unit independent bias of the model output. It computes the deviation from the observed and reports the expected error per unit of simulation output. A second objective function that optimizes the coefficient of determination, R^2 [Eq. (7)] to evaluate whether the simulations had optimally reproduced observed variability [26, 27] of the rainfall process while minimizing the overall deviation.

$$\text{Mean relative error (MRE)} = \frac{1}{n} \sum_{i=1}^n \frac{|O_i - S_i|}{O_i} \quad (3)$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - S_i)^2} \quad (4)$$

$$\text{Correlation coefficient, } r = \frac{\sum_{i=1}^n (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2}}; \quad r \in [-1, 1] \quad (5)$$

$$\text{Coefficient of determination, } R^2 = \frac{[\sum_{i=1}^n (O_i - \bar{O})(S_i - \bar{S})]^2}{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2}; \quad R^2 \in [0, 1] \quad (6)$$

$$\text{Objective function, } \text{Obj}F(O, S) = \begin{cases} \text{minimize} \left(\sum_{j=1}^k \text{RMSE}(O, S), \text{MRE}(O, S) \right) \\ \text{Optimize} \left(\sum_{j=1}^k R^2(O, S) \right) \end{cases} \quad (7)$$

where O is observed rainfall, S is estimated rainfall, j is the time step, and k is the total number of events.

4 Results and Discussion

4.1 Satellite Rainfall Estimates

More than 11 years (July 1995–December 2006) of monthly rainfall at BWSS and Kiptunga Forest Station (KFS) were compared with point (grid-cell) value and area-average satellite RFE (RFE) over Nyangores and Amala subbasins of MRB (Fig. 5a). Overall, RFEs were higher than observed rainfall in all six pairs of comparison. Over the period of comparison, the observed and RFE (mean, standard deviation) rainfall at KFS were (97.7 mm, 65.4 mm) and (164.1 mm, 108.5 mm), respectively (Fig. 5b). For BWSS, the mean and standard deviation rainfall for the observed and RFE results were (128.4 mm, 83.8 mm) and (183.2 mm, 128.2 mm), respectively (Fig. 5c). On the basis of the results, RFE has not only a consistent overestimation of more than 40% but also inconsistent skill in reproducing rainfall variability ($0.25 \leq R^2 \leq 0.70$) observed in gage data (Fig. 5d, e) [22].

The best statistics among the six paired comparison was obtained from BWSS vs. Amala subbasin. The mean and standard deviation of subbasin averages of the RFE were higher in the same order as the point sampled RFE values as compared to the observed monthly rainfall depth. The R^2 estimate for KFS vs. Amala subbasin was 0.2. When KFS was regressed with the average of Nyangores and Amala subbasins, R^2 values of 0.44 and 0.55 were obtained, respectively. The result might suggest that BWSS would better represent rainfall over the two adjacent subbasins as compared to the KFS at the northern tip of the Amala subbasin. On the contrary, the orographic effect of relatively higher elevation (Fig. 2) might be responsible for the difference observed in the analysis.

The relatively low performance at KFS could be due to the number of missing rain gage data or the reduced performance of RFE to capture local orographic rainfall. Given the uncertainties in both RFE and gage data, the analysis showed that RFE repeats the trend of gage data as claimed by Mango et al. [7]. Since only

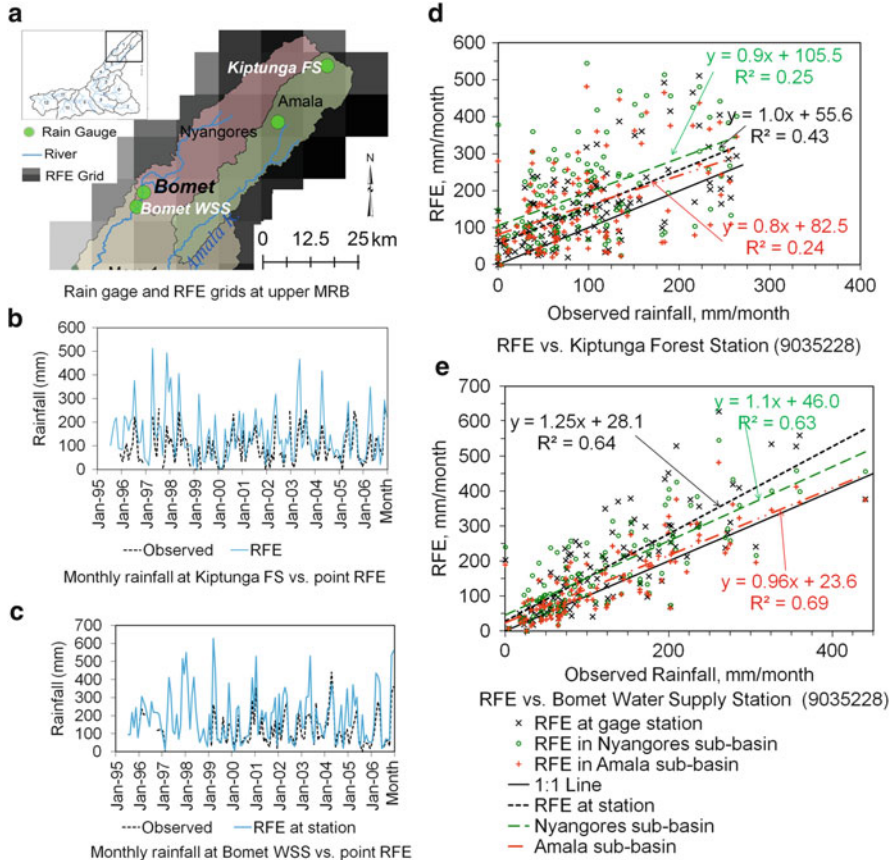


Fig. 5 Monthly RFE values versus observed rain gauge records for the upper MRB from July 1995 to December 2006. RFE values were extracted from RFE grids corresponding to the locations of rain gage, and averaged over Nyangores and Amala subbasin area. Linear trend lines were fitted [22]

two stations were considered, the results are diagnostic to the potential use of RFE as an alternative rainfall data in hydrologic analysis [28]. Accordingly, comparing (extending) hydrological simulation results that use rainfall input from rain gage and RFE may compromise the otherwise meaningful output of independent outputs.

4.2 GCMs Rainfall Outputs

Sixteen GCMs with daily outputs of atmospheric data (rainfall, maximum and minimum temperature) were considered (Table 1). Observed monthly rainfall data over the control period (1961–1990) was used to assess the capability of these GCMs in reproducing past climate of the MRB (Fig. 6a). Nine of the 16

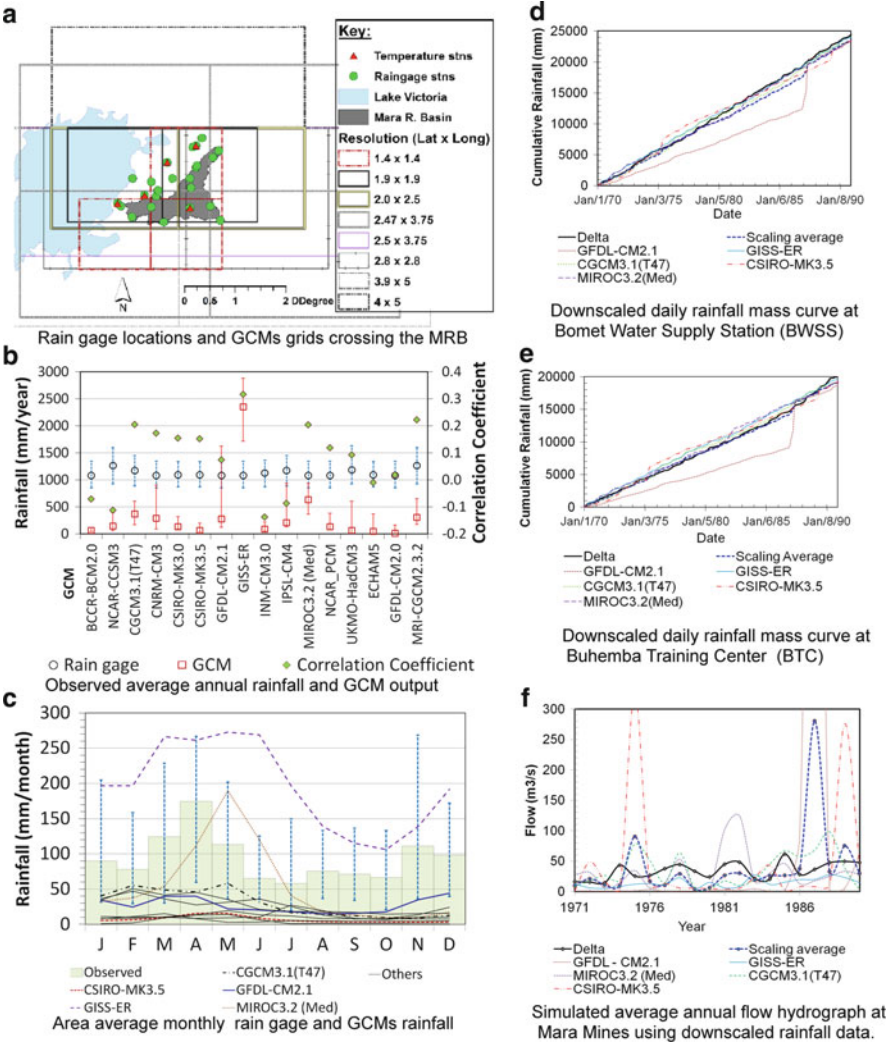


Fig. 6 (a) Area-average gage and GCM output rainfall from 1961 to 1990, (b) and (c) are based on raw outputs from 16 GCMs. Error bars correspond to minimum and maximum for observed (*dash*) and GCM output (*solid*) from 1961 to 1990 [4, 25]. (d–f) are based on downscaled daily rainfall from five selected GCMs over 20 years (1970–1990). Scaling average is the average of analysis result of five GCMs output

models were positively correlated with the monthly observed, but the correlation coefficients are all below 0.5 (Fig. 6b). The average annual RFE of the GCMs also indicated a significant underestimation of the observed average annual rainfall (Fig. 6b) of 30 years control period. Only GISS-ER had considerably overestimated rainfall (200%) with the highest correlation coefficient. The average annual rainfall

from GCMs fell below the 30 years minimum of the observed except for GISS-ER and MIROC3.2 (Med). On the basis of the observed monthly (seasonal) variability, none of the models were able to simulate the rainfall pattern of the MRB (Fig. 6c). The overall skill of the GCMs in capturing the MRB rainfall was found to suggest statistical downscaling based on the observed data to better represent the climate of the river basin.

On the basis of prior established set of criteria, five GCMs [GCM3.1 (T47), CSIRO-MK3.5, GFDL-CM2.1, GISS-ER, and MIROC 3.2 (Med)] were selected for statistical downscaling and further hydrological evaluation. The scaling and delta downscaling methods were applied on selected GCMs output over the 21 years (1970–1990) rainfall output. Results showed that performance varies with the GCM and downscaling technique suggesting the choice of particular GCM and downscaling over the other may depend on the purpose that the rainfall information is required for (Fig. 6c–e). On the basis of the current GCMs output in MRB, the RFE are less reliable with poor skill to simulate the MRB rainfall driven by migration of ITCZ, but they offer a longer time span of data to the past and future.

The delta downscaling method preserved the historical daily rainfall over the period of analysis. The scaling method, on the other hand, produced new set rainfall characteristics such as the number of rainy days, quantity, and sequence of rainfall events (Fig. 6d, e). Accordingly, the runoff response using different GCMs outputs and downscaling method produces different hydrographs (Fig. 6f).

The daily rainfall mass curves prepared over 21 years for the observed (delta) and scaling method reflect on the characteristics of the GCMs performance at the two stations, upstream and downstream of the Mara River. The mass curve from the scaling method at BWSS showed overestimation of the daily rainfall in the 1970s and underestimation afterwards, whereas at Buhemba Training Center (BTC) the scaling method overestimated for the most part of the 21 years daily estimation. GFDL-CM2.1 has significantly deviated from the other models in estimating the daily rainfall until 1987 and jumped in just a few days to match with the steady curve of the other four GCMs. This pattern may suggest either model error or simulation of global climate perturbation by the particular GCM. However, such attributes may not fully serve to generate realistic RFE of the past unless verified by historical observation.

Selected GCMs outputs downscaled and input to the SWAT model to compare the extent that downscaling methods will influence the rainfall runoff process in the MRB. On the basis of the average annual hydrographs (Fig. 6f) the scaling method had produced unique hydrograph for each of the five GCMs considered. The average of the five hydrographs was plotted along with the hydrograph from the observed (delta) rainfall. The peak annual flows correspond to the jumps observed in the rainfall mass curves (Fig. 6d, e). The results suggest that rainfall data generated using the scaling method may not represent the past climate condition but can shade light on how the basin would have responded, had those rainfall events occurred. Hence, the flow hydrographs can be used simply as a potential realization in the ensemble of probable rainfall events for water resources planning purposes.

5 Conclusions

Scarcity and inconsistency of observed rainfall data has been a major limitation in water resources study. Alternative rainfall data sources are being used to circumvent the challenge with limited verification of the techniques employed or reliability of the estimates. Satellite RFE and general circulation models (GCMs) are becoming the source of rainfall information in the developing regions of the world. This chapter outlined basic evaluation and comparison techniques applied to verify the reliability of RFE (from FEWS-NET) and selected GCMs outputs as an alternative rainfall data sources in the MRB.

RFEs are appealing to users due to the continuity in time, spatial coverage and suitability of gridded data to standard GIS processing tools in water resources. Compared to observed rainfall, RFE values were generally higher (>40%) than gage rainfall and displayed nonuniform skill in reproducing monthly rainfall variability and amount. Despite the limitations observed in the two stations, RFE has a promising potential to supplement the existing observed rainfall data for regions that lack sufficient and reliable amount of observed data for the intended purpose.

The GCMs are designed to simulate global climate and may be used as a tool for learning about the rainfall pattern of particular place. The performance of the GCMs varies with the GCM and downscaling technique suggesting the choice of particular GCM and downscaling over the other may depend on the purpose that the rainfall information is required for. On the basis of the current GCMs output considered for the MRB, the RFE are less reliable with poor skill to capture the migration of ITCZ, but they offer a longer time span to generate rainfall information in the past (and future). Comparison of the delta and statistical downscaling methods applied on the daily rainfall outputs of selected GCMs have improved the quality of rainfall information extracted from GCMs. Since hydrological response of a watershed at a particular time depends not only on the amount, duration, and frequency of rainfall but also on the antecedent rainfall event; the delta method can recapture the past and be useful to fill data gaps in the past. The scaling method, on the other hand, alters the characteristics of daily rainfall events in the past that may require careful consideration to use as alternative data source for sensitive water resource applications.

On the basis of the hydrological assessment using rain gage data, RFE and GCMs output in the MRB, comparison of results from studies using different rainfall data input may potentially result in different pictures of the water resources of the basin. Since few stations were considered in the analysis, the findings are hardly conclusive rather diagnostic that further investigation is necessary to exploit the potential of RFE and GCMs as alternative data sources. These sources of rainfall information may supplement watersheds/stations with insufficient amount of observed data. The evaluation methods can also be applied to other climate data as well as watersheds of similar data challenge as the MRB. Finally, the current advances in remote sensing and evolution of GCMs is continuously improving quality and availability of reliable rainfall as well as other climate data.

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