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Performance of bias corrected MPEG rainfall estimate for rainfall-runoff simulation in the upper Blue Nile Basin, Ethiopia

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ABSTRACT

In many developing countries and remote areas of important ecosystems, good quality precipitation data are neither available nor readily accessible. Satellite observations and processing algorithms are being extensively used to produce satellite rainfall products (SREs). Nevertheless, these products are prone to systematic errors and need extensive validation before to be usable for streamflow simulations. In this study, we investigated and corrected the bias of Multi-Sensor Precipitation Estimate–Geostationary (MPEG) data. The corrected MPEG dataset was used as input to a semi-distributed hydrological model Hydrologiska Byråns Vattenbalansavdelning (HBV) for simulation of discharge of the Gilgel Abay and Gumara watersheds in the Upper Blue Nile basin, Ethiopia. The result indicated that the MPEG satellite rainfall captured 81% and 78% of the gauged rainfall variability with a consistent bias of underestimating the gauged rainfall by 60%. A linear bias correction applied significantly reduced the bias while maintaining the coefficient of correlation. The simulated flow using bias corrected MPEG SRE resulted in a simulated flow comparable to the gauge rainfall for both watersheds. The study indicated the potential of MPEG SRE in water budget studies after applying a linear bias correction.

1. Introduction

Sustainable water resource management requires assessment of present hydrological conditions and impacts of potential developments and climate change on future streamflow. Such assessment is made using hydrologic models and often require considerable hydro-climatological data of sufficient spatial and temporal distribution (Wilk et al., 2006). Among the hydro-climatological data, rainfall plays an important role in the hydrologic cycle and is, therefore, one of the most sensitive model input parameter. In many developing countries and remote areas of important ecosystems, good quality precipitation data are neither available nor readily accessible. Moreover, the accuracy of rainfall data as a model input has been questioned in developing countries where ground rainfall observations are scarce (Fuka et al., 2013; Worqlul et al., 2014). Satellite observations and processing algorithms are being extensively used to produce satellite rainfall estimates (SREs). Satellite remote sensing has received increased attention in estimating precipitation (Aonashi et al., 2009; Barrett, 1989; Ebert and McBride, 2000; Ferriday, 1994; Hong, 2003; Huffman et al., 2007; Joyce et al., 2004; Kidd, 2001; Ochoa et al., 2014; Scofield and Kuligowski, 2003; Sorooshian et al., 2000). Very few of these studies have evaluated the satellite rainfall over Africa (Ali et al., 2005; Romilly and Gebremichael, 2011; Thorne et al., 2001; Worqlul et al., 2014). Freely available global satellite rainfall products include TRMM Multi-satellite Precipitation Analysis (TMPA; Huffman et al. 2007), Global Precipitation Climatology Project (GPCP) (GPCP, Huffman et al., 1997), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN, Sorooshian et al., 2000) and Multi-Sensor Precipitation Estimate–Geostationary (MPEG, EUMETSAT, 2008) are among others. Nevertheless, these products are prone to systematic errors and need extensive validation before use in streamflow simulations.

Satellite rainfall products use either the thermal infrared or the passive microwave channel portions of the electromagnetic spectrum, or a combination of both (Kurino, 1997; Tapiador et al.,

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2004). In the thermal infrared, rainfall is estimated using a cloud top temperature threshold to discriminate between rain-bearing and non-rain-bearing clouds; however, the threshold temperature can be too low for warm orographic precipitating clouds. The rainfall estimate made using passive microwave sensor relies on a strong relationship between the radiance received in the microwave channel and precipitation (Tian et al., 2007). Microwave sensors are available from polar orbiting satellites; this makes the observation frequency a couple of times a day. Rainfall estimates from microwave channel have a sampling error, especially for shorter rainfall (Kidd et al., 2003). Geostationary satellites that provides continuous coverage do not offer passive microwave measurements and are combined with the microwave measurements made from polar orbiting satellites.

Satellite rainfall products are affected typically by systematic and random error (Piani et al., 2010b; Teutschbein and Seibert, 2012b) and consists of under prediction, missing seasonal variation (Worqlul et al., 2014) and inconsistent prediction of dry days (Piani et al., 2010a). A systematic difference (bias) between satellite rainfall and gauged rainfall can be removed using gauged data. Bias correction may vary from simple additive correction (Berg et al., 2012) to a more complex histogram matching that can correct multiple moments of the distribution of a variable at a time (Haerter et al., 2011; Teutschbein and Seibert, 2012a).

Bias correction are often employed to correct precipitation scenarios of Global Climate Models (GCMs) and satellite rainfall estimates. Bias correction are proved to improve the raw SRE (Sharma et al., 2007; Piani et al., 2010; Habib et al., 2014; Teutschbein and Seibert, 2012). Habib et al. (2014) indicated that a linear bias correction applied on the Climate Prediction Center – MORPHing (CMORPH) SRE improved the CMORPH-driven runoff simulation. Vernimmen et al. (2012) also indicated that in Indonesia, a single empirical bias correction equation improved the performance of TMPA 3B42RT and recommended for real-time drought monitoring.

The objectives of this study is to assess the performance of MPEG (SRE) product to simulate streamflow in comparison to ground-based measurements. The MPEG SRE and rainfall from ground-based measurement were used as input to the HBV hydrological model to simulate streamflow in a watershed in the upper Blue Nile basin where a high quality longer time series hydro-climatic data is available. Part of the MPEG SRE was collected from Bahir Dar University's GEONETCast reception station established in collaboration with the University of Twente, Faculty ITC, the Netherlands and Tana Sub-Basin Organization (TaSBO), Bahir Dar, Ethiopia. In MPEG, rainfall is estimated by blending rainfall rates derived using a passive microwave channel from polar orbiting satellite and infrared channel from a geostationary satellite (Heinemann and Kerényi, 2003). The motivation for selecting the MPEG product over others rainfall products was the availability of the data at near-real-time (i.e. every 15 minutes). The HBV model was selected due to its proven performance in capturing observed streamflow of watersheds in the upper Blue Nile basin (Abdo et al., 2009; Uhlenbrook et al., 2010; Wale et al., 2009; Worqlul et al., 2015a).

2. Methodology

2.1. Study area description

The study was applied in two watersheds in the upper Blue Nile Basin: Gilgel Abay and Gumara watersheds. Gilgel Abay (10°56′–11°58′N and 36°44′–37°34′E) and Gumara (11°30′N–12°13′N and, 38°25′E–37°30′E) watersheds are located in the Tana sub-basin of the Blue Nile basin. Gilgel Abay starts with a small spring in the western part of the Ethiopian highland at elevation of 3,000 m and meanders 140 km before entering Lake Tana. Gumara watershed starts on one of the highest mountain in the country Mount Guna. The gauged area extracted from a 30 m resolution Shuttle Radar Topographic Mission (SRTM), Digital Elevation Model (DEM) is 1,650 km^2 for Gilgel Abay and 1,284 km^2 for Gumara. Fig. 1 indicates the drainage pattern and the monitoring stations of Gilgel Abay and Gumara watersheds.

The watersheds have a complex topography with significant elevation variation ranging from 1890 to 3530 m in Gilgel Abay and 1800 to 3710 m in Gumara. The slope varies between zero to 140% with an average value of 12% for Gilgel Abay and 17% for Gumara. The land use and soil map of the study watersheds were collected from the Ethiopian Ministry of Water, Irrigation and Electricity. Both watersheds are dominated by agricultural land. The dominant soils in Gilgel Abay are Luvisols and Alisols, covering approximately 56 and 40% of the watershed, respectively. Approximately 87% of Gumara watershed is dominated with Luvisols. Both Luvisols and Alisols have a higher clay content in the subsoil than in the topsoil (Michéli et al., 2006). Both watersheds have a largest surface irrigation potential compared to the sub-basins in the Lake Tana watershed (Worqlul et al., 2015b). Rainfall in the study area on average varies between 1300 and 2300 mm (1994–2013). The main rainfall season called "Kremt" in local language from May to September accounts for up to 80–90% of the annual rainfall.

2.2. Climate and discharge data

Meteorological and hydrological data for 2010–2013 were collected from the Ethiopian National Meteorological Agency (NMA) and Ethiopian Ministry of Water, Irrigation and Electricity (EMWIE), respectively. This time range was selected due to its coincidence with the MPEG data availability. Daily rainfall data were collected from six nearby stations: Dangila, Adet, Injibara, Bahir Dar, Debre Tabor and Mekane Yesus (Fig. 1). Minimum and maximum temperature, relative humidity, wind speed and daily sunshine hour were available from Dangila, Bahir Dara and Debre Tabor stations. The two rivers selected Gilgel Abay and Gumara have relatively quality data in the region. The average monthly flow of Gilgel Abay and Gumara rivers indicated a higher correlation coefficient of 0.96. However, Gilgel Abay annual average flow is approximately 1.6 times Gumara river flow. Since 2006 dry season flow of Gilgel Abay has shifted significantly but the wet season flow did not show a significant variation compared to 1980 to 2005 flow (Enku et al., 2014).

2.3. MPEG data

Multi-sensor precipitation estimate-geostationary (MPEG) is produced by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) meteorological product extraction facility (MPEF). MPEG was created by blending rain rates derived from Special Sensor Microwave/Imager (SSM/I) on board the US-DMSP satellite with brightness temperature from infrared channel of MTP-METEOSAT satellites (Heinemann and Kerényi, 2003). The data are freely available through the GEONETCast near real-time satellite-based data dissemination system (Wale et al., 2011; Worqlul et al., 2014). MPEG data is available at 3 km spatial resolution and 15-minute interval since 2010. The MPEG satellite rainfall estimate from MPEF was downloaded from the International Institute for Geo-Information Science and Earth Observation (ITC) ftp server and from Bahir Dar University GEONETCast reception station. For this study, daily MPEG rainfall estimate of Gilgel Abay and Gumara watersheds were constructed for the study period from 2010 to 2013.

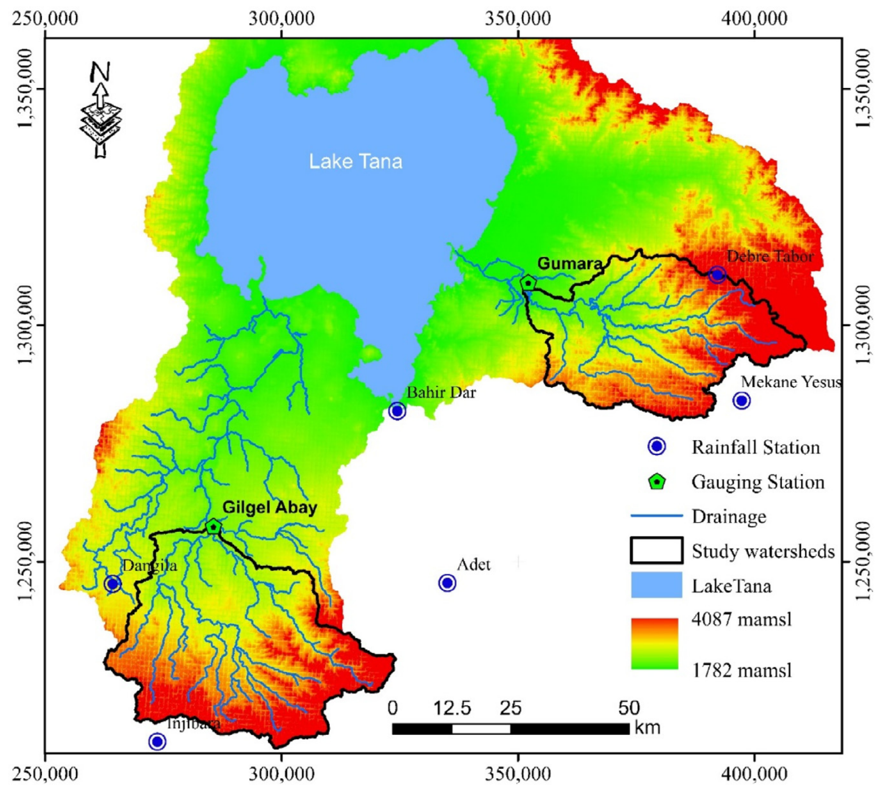

Fig. 1. Drainage pattern and monitoring station; digital elevation model as a background.

2.4. Methods

The MPEG SRE was used as forcing to a HBV semi-distributed hydrologic model to capture the observed flow of Gilgel Abay and Gumara watersheds. Three steps followed in this study are outlined below. First: the areal MPEG satellite rainfall estimate was compared to areal gauged rainfall data for 2010–2013. The comparison was done on monthly basis to determine how accurately the MPEG rainfall captures the pattern and volume of gauged rainfall. Second: the bias associated with the MPEG data was corrected using a linear monthly correction coefficient. The correction coefficient was adjusted until the volume of monthly MPEG SRE and gauged rainfall data match. A one year delay in the release of hydrological and meteorological data makes it practically difficult to establish a correction factor for a current year data. Therefore, to make use of the near-real-time MPEG data, the long-term average correction coefficients of the watersheds were developed instead.

The mean monthly gauge rainfall was calculated by aggregating the daily areal gauge rainfall. The point data was converted to areal rainfall using inverse distance interpolation (IDW). IDW assumes that the value of the unsampled is the weighted average of the sampled values within the neighborhood, and the weights are inversely related to the distance between the prediction location and the sampled location. Similarly, mean monthly areal MPEG data are calculated by aggregating the daily satellite grid rainfall products. Third: the gauged, original and bias corrected MPEG rainfall products were used in forcing HBV hydrologic model to reproduce observed flow of Gilgel Abay and Gumara through model parameter calibration. The model performance was evaluated using multiple objective functions. The performance of bias corrected MPEG SRE was also cross-validated by using as input to the gauged rainfall calibrated model. In this case, the calibrated model parameter sets obtained using the gauged rainfall data was used to simulate the observed flow of Gilgel Abay and Gumara watersheds forced with bias corrected MPEG rainfall.

2.4.1. Bias correction

Some of the errors associated with satellite rainfall are consistent under predictions, missing seasonal variation (Worqlul et al., 2014) and a low or higher number of dry days (Piani et al., 2010). Model parameter values obtained using biased SRE as forcing might not yield reliable estimate of watershed characteristics (Behrangi et al., 2011; Bitew et al., 2012). Therefore, understanding and correcting the bias associated within SRE is a necessity step. Bias correction may vary from simple additive correction (Berg et al., 2012) to a more complex histogram matching that can correct multiple moments of the distribution of a variable at a time (Haerter et al., 2011; Teutschbein and Seibert, 2012a). In this study, the bias of MPEG rainfall was corrected by applying a monthly multiplicative correction coefficients. The correction coefficients applied was to match the volume of monthly MPEG with the monthly gauged rainfall Eq. (1).

$$P_{\mathrm{CorrMPEG(i)}} = \mathrm{P}_{\mathrm{MPEG(i)}} * \frac{\overline{P_{(Obsmi)}}}{\overline{P_{MPEGmi}}} \tag{1}$$

where $P_{\mathrm{CorrMPEG(i)}}$ is the daily bias corrected MPEG rainfall, $\mathrm{P}_{\mathrm{MPEG(i)}}$ and $\overline{P_{MPEGmi}}$ are the daily and monthly average original MPEG rainfalls, respectively and, $\overline{P_{(Obsmi)}}$ is the monthly average gauge rainfall.

2.4.2. HBV model

The HBV hydrologic model (Lindström et al., 1997) is a conceptual semi-distributed rainfall-runoff model for streamflow simulation. The HBV model consists of subroutines for soil moisture accounting procedure, runoff generation and a simple routing procedure. The soil moisture accounting routine is based on three parameters: BETA, FC and LP (SMHI, 2006). BETA controls the contribution to the response function from each millimeter of rainfall.

FC is the maximum soil moisture storage. The limit for potential evaporation (LP) dictates a soil moisture value above which evaporation reaches its potential. The runoff generation routine transforms excess water from the soil moisture zone into runoff; this routine consists of an upper non-linear and a lower linear reservoir connected by percolation parameter (PERC). Khq and K4 are recession coefficients of the upper and lower reservoir, respectively. Alfa is the measure of non-linearity of the upper reservoir and it is used to fit the higher peaks into the observed hydrograph. A complete description of the model can be found in various literatures (Lindström et al., 1997; SMHI, 2006).

In HBV, the watershed is subdivided into sub-basins and further into different elevation and land use zones. The hydrological and climate input data for flow simulation includes: daily rainfall, temperature, observed flow and long-term average monthly potential evapotranspiration. Long-term potential evaporation was estimated by using the Penman-combination equation using data from Dangila station for Gilgel Abay and Bahir Dara and Debre Tabor were used for Gumara. A 30 m DEM was used to delineate watershed area draining to the gauging site of the watersheds and divide the watersheds into sub-basins and elevations zones.

2.4.3. Model calibration and validation

Prior to model calibration, the minimum and maximum model parameter space were determined from literature and based on our local knowledge. Optimized model parameters sets of Rientjes et al. (2011) and Wale et al. (2009) were used to initialize the models. For model calibration, the most sensitive model parameters listed in SMHI (2006) controlling the volume and shape of the hydrograph were selected. The initialised models were calibrated first for volume controlling parameters FC, LP, BETA and Khq followed by shape controlling parameters Alfa, K4 and PERC. The HBV model was calibrated for all rainfall products (gauge, original MPEG, and bias corrected MPEG) independently. Due to data limitation, a one-year data (i.e. 2013) was used to validate the calibrated model parameters.

2.4.4. Statistical analysis

The performance of the model was evaluated using multiple objective functions including percent bias (PBIAS), Nash-Sutcliffe Efficiency (NSE) and coefficient of determination (R-Square). PBIAS calculates the relative volume difference between simulated and observed volume. A negative value indicates over-prediction and a positive value indicates under-prediction of simulation. A PBIAS value of zero might not mean a perfect simulation since the distribution through time is not considered. NSE is the normalized statistic that describes the relative magnitude of residual variance compared to the observed flow variance. NSE indicates how well the plot between observed and simulated flow fits the 1:1 line (Moriasi et al., 2007). NSE value between 0.6 and 0.8 is considered fair to good and values greater than 0.8 are considered very good. R-Square evaluates the degree of linear association between observed and simulated flow, for a perfect fit the slope and intercept has to be checked.

$$\mathrm{PBIAS} = \frac{\sum(Q_{obs(i)} - Q_{MPEG(i)})}{\sum Q_{obs(i)}} * 100 \tag{2}$$

$$\mathrm{NSE} = 1 - \sum \frac{(Q_{obs(i)} - Q_{MPEG(i)})^2}{\sum\left(Q_{obs(i)} - \overline{Q_{Obs}}\right)^2} \tag{3}$$

$$R-\mathrm{square} = \left(\frac{n\sum_{i=1}^{n}(Q_{obs(i)}Q_{MPEG(i)}) - (\sum_{i=1}^{n}Q_{obs(i)})(\sum_{i=1}^{n}Q_{MPEG(i)})}{\sqrt{[n(\sum Q_{obs(i)}{}^2) - (\sum Q_{Obs(i)}{}^2)][n(\sum Q_{MPEG(i)}{}^2) - (\sum Q_{MPEG(i)})^2]}}\right)^2 \tag{4}$$

where PBIAS: Percent bias, $Q_{MPEG(i)}$: daily flow simulated by MPEG data, $Q_{Obs(i)}$: daily observed flow, NSE: Nash-Sutcliffe Efficiency, $\overline{Q_{Obs}}$: long-term average observed flow, R-square: coefficient of determination and n is number of data pairs.

3. Results and discussion

3.1. Comparison of observed areal rainfall with MPEG rainfall estimate

The areal average rainfall of gauged rainfall of Gilgel Abay and Gumara were estimated by inverse distance interpolation method. For MPEG data, the areal rainfall was determined by aggregating 15 minutes interval rainfall data to daily. Monthly gauged areal rainfall were well correlated with the MPEG satellite rainfall for

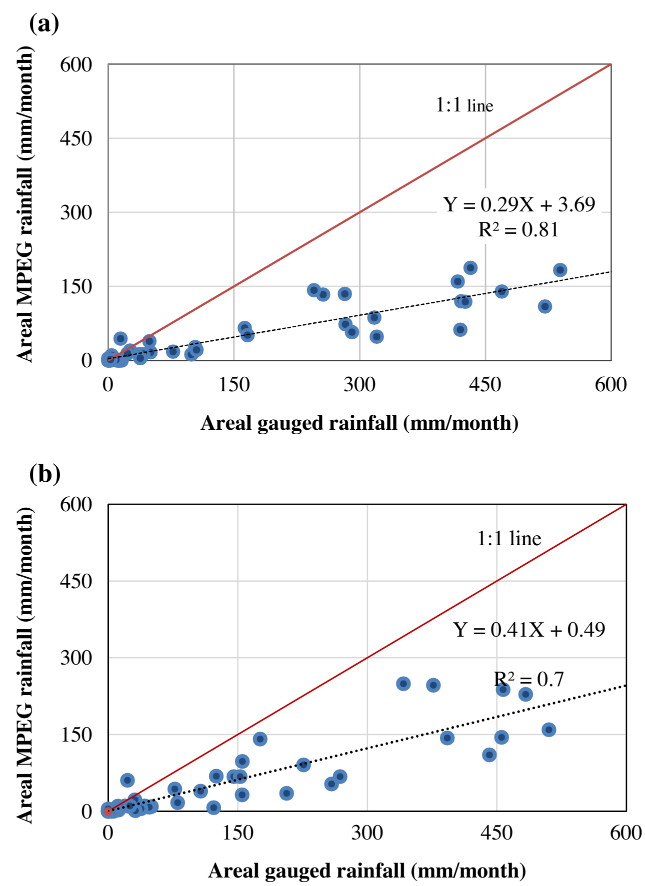

Fig. 2. Comparison of long-term monthly areal gauged rainfall and MPEG rainfall estimate for Gilgel Abay and Gumara basin 2010–2013. (a) Gilgel Abay and (b) Gumara River.

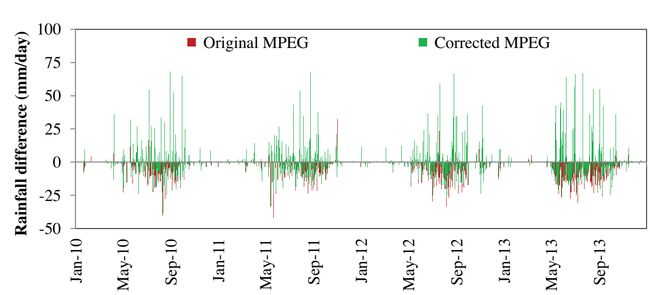

Fig. 3. Comparison of daily rainfall difference between original MPEG and corrected MPEG form observed gauged rainfall from (2010 to 2013).

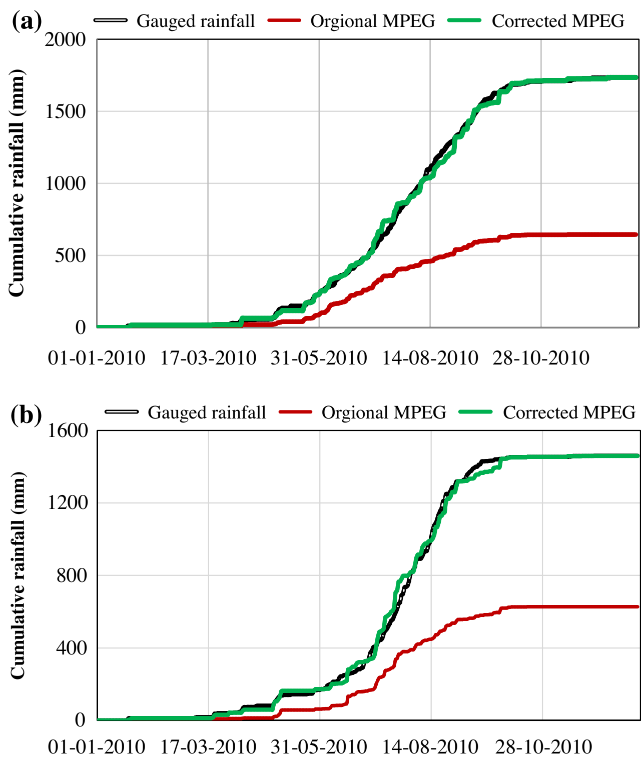

Fig. 4. Cumulative rainfall of gauged, original and bias corrected MPEG for year 2010. (a) Gilgel Abay and (b) Gumara River.

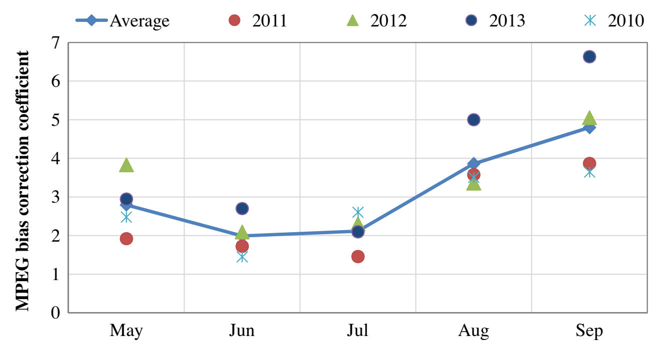

Fig. 5. Monthly MPEG bias correction coefficients and average bias correction coefficient of Gilgel Abay watershed for the study period.

both watersheds (correlation coefficient greater than 0.78 Fig. 2a and b), MPEG rainfall explained 81% and 78% of the ground rainfall variation of Gilgel Abay and Gumara watersheds, respectively. However, despite the good correlation with observed rainfall pattern, MPEG SRE underestimated the gauged rainfall of both watershed by about approximately 60%. Thus, the consistent bias with a high correlation, MPEG SRE can be adjusted using a linear bias correction coefficient.

3.2. Performance of bias corrected MPEG data

The MPEG data was corrected to match the monthly gauged rainfall amounts of gauged rainfall using a monthly correction coefficients. Fig. 3 shows the difference between original and bias

Table 1
Optimized HBV model parameter sets and their performance for gauged, original and bias corrected MPEG rainfall data for Gilgel Abay River.

HBV model parameters		Gauged rainfall	Original MPEG	Corrected MPEG
Upper reservoir outflow non-linearity (Alfa)		0.5	0.5	0.5
Soil moisture parameter (Beta)		1.0	1.0	1.0
Maximum soil moisture storage (mm, FC)		340	100	460
Recession coefficient of lower reservoir (K4)		0.08	0.07	0.10
Recession coefficient of upper reservoir (Khq)		0.18	0.01	0.08
Threshold for reduction of evaporation (LP)		0.70	0.90	0.80
Max. flow from upper to lower reservoir (mm, PERC)		6.0	6.0	6.0
Calibration period (2010–2012)	PBIAS (%)	8.5	70.0	5.9
	NSE	0.78	0.16	0.80
	R-square	0.84	0.60	0.82
Validation period (2013)	PBIAS (%)	5.2	65.3	4.0
	NSE	0.80	0.22	0.81
	R-square	0.85	0.68	0.86

Table 2
Optimized HBV model parameter sets and performance for gauged, original and bias corrected MPEG rainfall data for Gumara River.

HBV model parameters		Gauged rainfall	Original MPEG	Corrected MPEG
Upper reservoir outflow non-linearity (Alfa)		0.5	0.5	0.5
Soil moisture parameter (Beta)		0.5	0.5	0.5
Maximum soil moisture storage (mm, FC)		140	100	140
Recession coefficient of lower reservoir (K4)		0.04	0.1	0.05
Recession coefficient of upper reservoir (Khq)		0.06	0.08	0.05
Threshold for reduction of evaporation (LP)		0.99	0.99	0.99
Max. flow from upper to lower reservoir (mm, PERC)		1.8	1.5	1.5
Calibration period (2010 to 2012)	PBIAS (%)	9.5	69.4	8.2
	NSE	0.78	0.22	0.79
	R-square	0.79	0.70	0.83
Validation period (2013)	PBIAS (%)	14.3	74.5	15.2
	NSE	0.85	0.01	0.80
	R-square	0.87	0.65	0.81

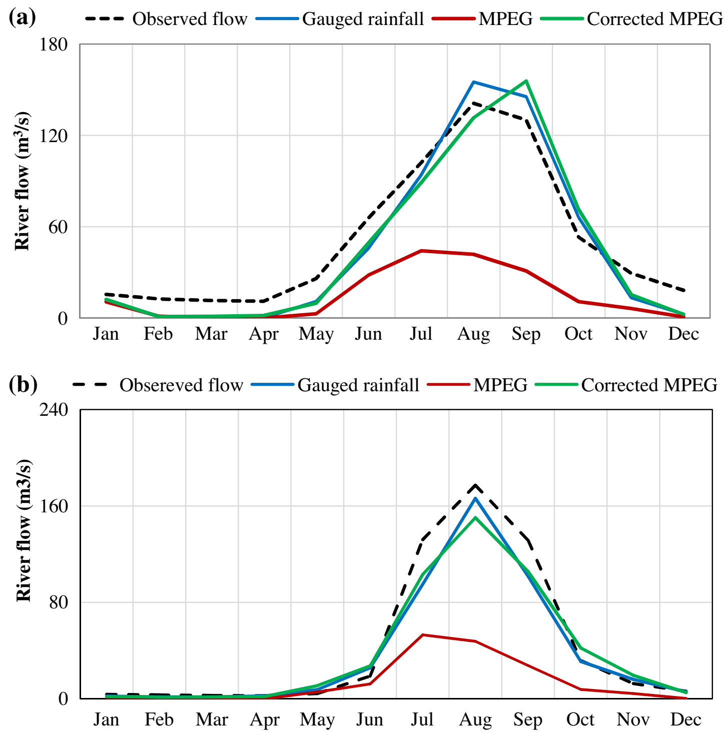

Fig. 6. Long-term monthly average flow of observed flow and HBV simulation by gauged rainfall, MPEG and bias corrected MPEG data (2010 to 2012). (a) Gilgel Abay and (b) Gumara River.

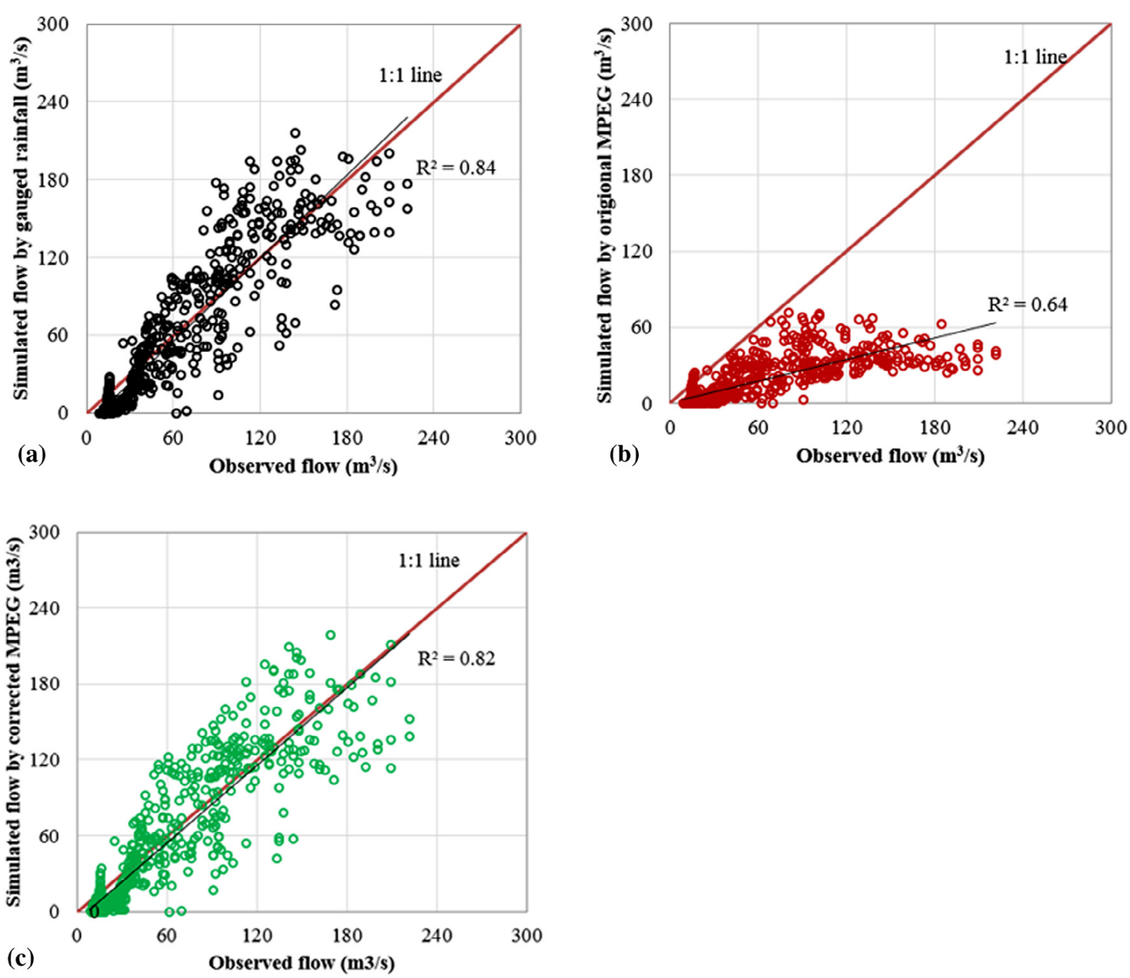

Fig. 7. Correlation between daily observed and simulated flow of Gilgel Abay for the calibration period using (a) gauged rainfall, (b) original MPEG, (c) bias-corrected MPEG.

corrected MPEG from the gauged rainfall data for Gilgel Abay (2010–2013). On a daily basis, throughout the study period, the original daily MPEG areal rainfall product was less than the gauged areal rainfall for more than 87% of the time (Fig. 3). After bias correction, approximately 63% of the daily events have a rainfall record less than the gauged record. The annual cumulative rainfall plot for 2010 (Fig. 4a and b), for both watersheds indicated that the bias corrected MPEG rainfall estimate predicts the cumulative gauged rainfall very well for both watersheds.

Fig. 5 shows the correction coefficients of the MPEG data on a monthly basis for the main rainfall season. The monthly mean bias correction coefficients of MPEG data compared over the study period indicated a similar value for the main rainy season from May to September, which accounts 80–90% of the annual rainfall. The monthly correction coefficients for the dry season have a significant variation as both satellite and gauged rainfall products have poor performance in capturing lower rainfall amounts (Berg et al., 2012; Toté et al., 2015). The line in Fig. 5 indicates the average values of the monthly average correction coefficients. The average values correction coefficients can be used to correct the near-real-time MPEG data for further use. This is especially useful in the Ethiopian context where gauged rainfall data usually takes up to a year or more to be available for commercial use due to delays in data entry, moving, and sharing procedures.

3.3. Discharge simulation with gauged rainfall, original MPEG, and bias corrected MPEG data

The HBV model was calibrated for gauge rainfall as well as original and bias-corrected MPEG SRE independently. Prior to calibration the parameter space minimum and maximum values were specified to represent the watershed conditions based on literature and local knowledge. HBV model was initialized with the optimal model parameter sets of Rientjes et al. (2011) and Wale et al. (2009). The initialized HBV model was further fine-tuned systematically by first calibrating the volume controlling parameters and then fine-tuning the shape controlling parameters. The shape controlling parameters influence the shape of the hydrograph by distributing the calculated discharge over time. The list of sensitive parameters controlling volume and shape of the hydrograph are tabulated in (Seibert and Vis, 2012; SMHI, 2006; Wale et al., 2009). In Tables 1 and 2, the optimized model parameter sets and model performance of Gilgel Abay and Gumara watersheds calibrated with gauged, original and bias corrected MPEG rainfall are tabulated.

The performance of the simulated flow using gauged and bias corrected MPEG SRE indicated a fair to good performance for both watersheds. In Gilgel Abay gauged and bias corrected MPEG indicated a NSH of 0.78 and 0.80, respectively, and a PBIAS of less than

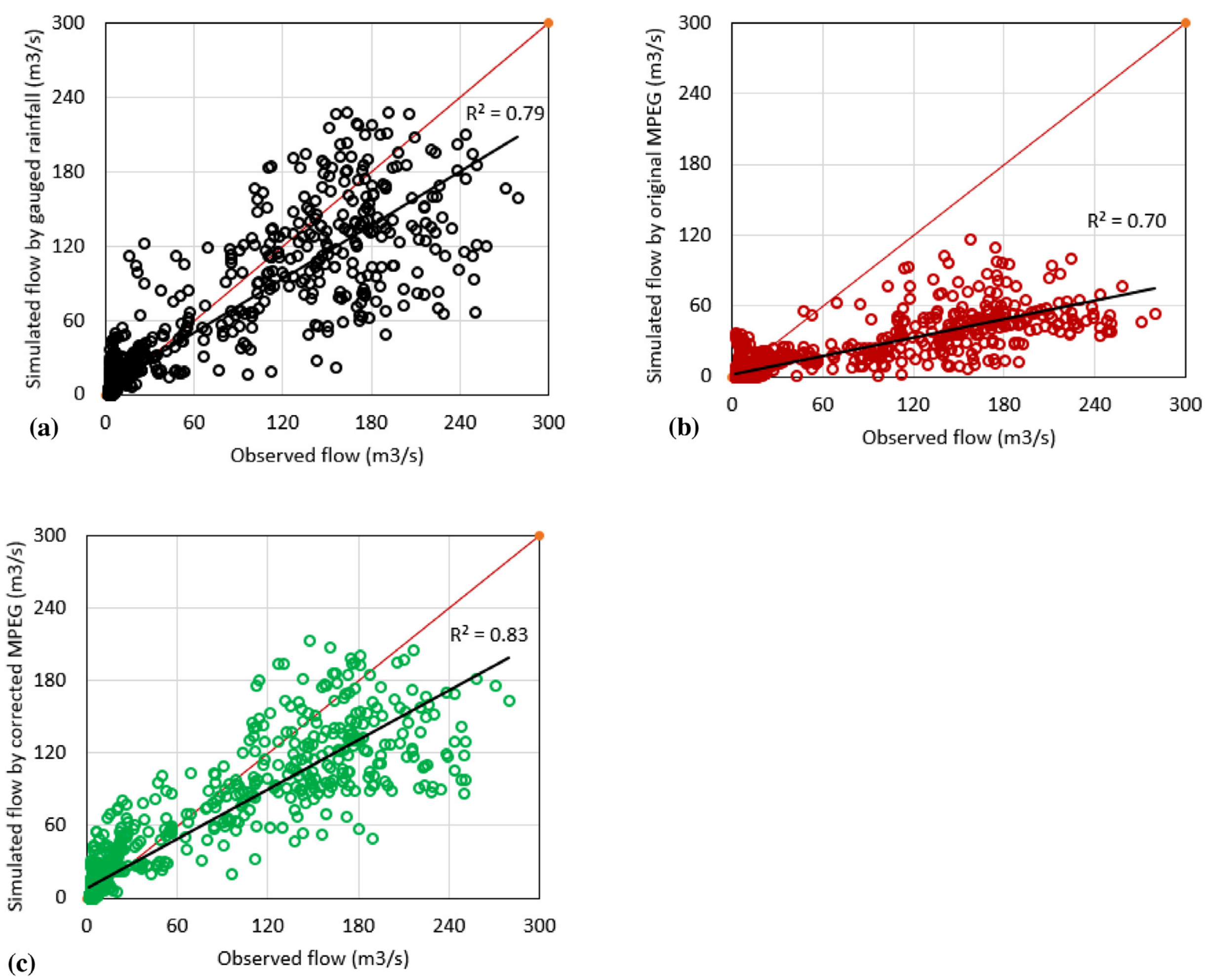

Fig. 8. Correlation between daily observed and simulated flow of Gumara watershed for the calibration period using (a) gauged rainfall, (b) original MPEG, (c) bias-corrected MPEG.

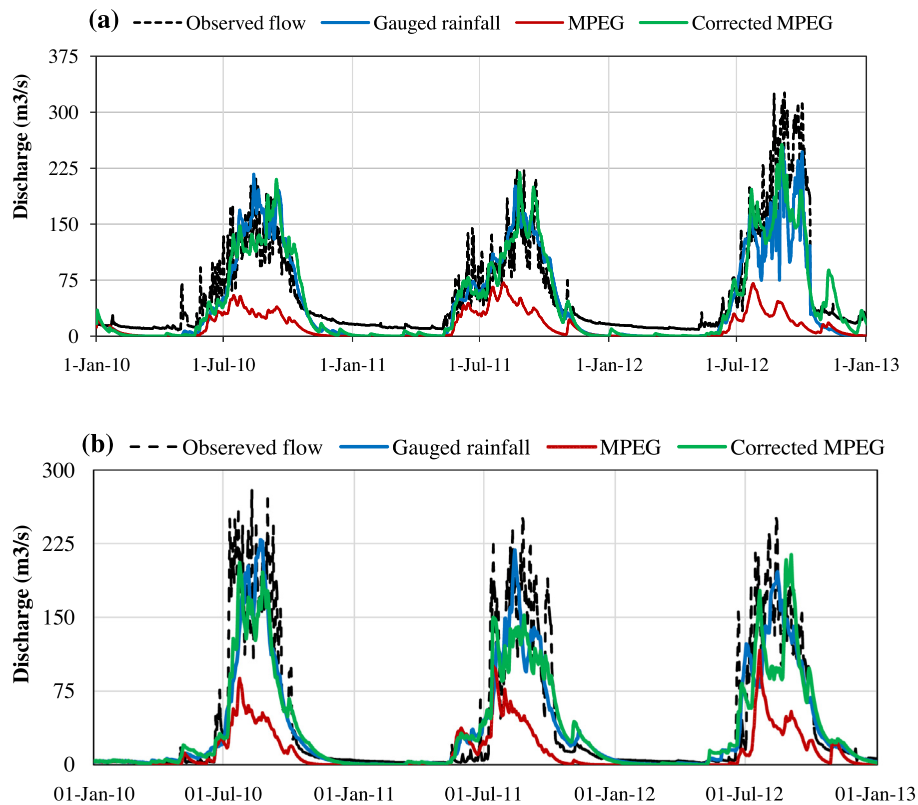

Fig. 9. Daily observed and simulated hydrograph using gauged rainfall, original and bias corrected MPEG for the calibration period. (a) Gilgel Abay and (b) Gumara River.

10% (Table 1, Fig. 6a, Figs. 7 and 8a). The gauged and bias corrected rainfall resulted in a comparable model performance in Gumara watershed with NSE of 0.78 and 0.79 (Table 2, Fig. 6b, Fig. 8a and b). Both watershed models validated for independent gauge and bias corrected rainfall indicated acceptable result with a minimum of 0.8 NSE. With a NSE of 0.16 and a 70% PBIAS for Gilgel Abay and NSE of 0.22 and PBIAS of 69.4% for Gumara watershed, the original MPEG SRE performance was poor in simulating the observed flow (Figs. 7b and 8b).

The fitted model parameter sets of gauged rainfall and corrected MPEG data were close except for FC and Khq for Gilgel Abay and in Gumara a minor difference was observed in PERC. The result of simple sensitivity analysis done by sequentially changing one model parameter value while keeping others at their optimal value indicated that FC and Khq were the most sensitive model parameters, and LP and BETA parameters were less sensitive, while the model parameters ALFA, K4 and PERC were the least sensitive.

Even though the percolation parameter (PERC), which links the upper and lower reservoir, was kept at the maximum value, the model did not capture the dry season flow of Gilgel Abay very well (Fig. 9a). Otherwise, the model has captured the rising and recession of the hydrograph of both watersheds for the gauged and bias corrected MPEG data. Although the effort made to get the rating curve data of Gilgel Abay at the EMWIE was not successful, we recommend a further examination of the dry season flow (October–May) after 2006 as it has increased significantly by 200% compared to the long-term average from 1980 to 2005. Fig. 9b shows the comparison daily simulated and observed flow of Gilgel Abay.

3.4. Cross-validation of bias corrected MPEG data

The calibrated model parameter sets obtained using the gauged rainfall data were used to validate the flow prediction performance of bias corrected MPEG data. Comparison of calibrated model parameters using gauged rainfall and bias corrected MPEG data are listed in Tables 1 and 2 for Gilgel Abay and Gumara, respectively. Except for the FC, Khq and Lp for Gilgel Abay and PERC for Gumara other parameters have identical values. The bias corrected MPEG dataset has a higher FC for Gilgel Abay watershed indicating a larger active soil layer that store water and emptied by evaporation, which is clearly attributed to the stronger effect of the linear multiplication correction coefficient which has a larger effect on the higher MPEG rainfall values. The bias correction has a higher scaling effect on the extreme precipitation events than the dry season rainfall (Berg et al., 2012; Leander and Buishand, 2007). Simulation of bias corrected MPEG rainfall estimate using gauged rainfall parameters perform well for both watersheds with NSE value of 0.74 and with acceptable PBIAS value of 8% for Gilgel Abay and NSE of 0.78 and PBIAS of 10% for Gumara watershed in capturing the observed flow (2010–2013).

4. Conclusions

Rainfall is a major input to hydrological models. Its spatial and temporal variability is prohibitively difficult to represent using traditional ground gauging stations. While SREs using various remote sensing techniques are freely available for use their potential to study hydrologic processes and/or assess water resources potential at watershed scale is not thoroughly explored. In this research we evaluated the rainfall volume estimation performance of MPEG rainfall products using in situ rainfall measurements. The performance of a HBV model forced using MPEG rainfall products is also used to evaluate the rainfall product performance in simulating the observed flow of two watersheds in the upper Blue Nile basin, Ethiopia. Our results indicated that MPEG SREs are prone to systematic error. Understanding and correcting the bias associated within should be a mandatory procedure in using them as forcing to a hydrological model.

The MPEG rainfall estimate compared with the gauged rainfall data indicated a higher correlation coefficient in capturing 81% and 78% of the gauged rainfall variation in Gilgel Abay and Gumara watersheds, respectively. However, in comparison to gauged rainfall measurements, MPEG SREs consistently under predicts rainfall volume by about 60%. The bias corrected MPEG data captured the volume on monthly basis while capturing 81% and 78% of the gauged rainfall variation for Gilgel Abay and Gumara, respectively. The performance of bias corrected MPEG data was validated by its predictive ability of the observed flow of Gilgel Abay and Gumara daily observed flow though model calibration. The result indicated that the performance of the MPEG data performed as good as the gauged rainfall simulation for both watersheds. The performance of bias corrected MPEG data validated with gauged rainfall model parameters has also performed well in capturing the observed flow of both watersheds. These hydrologic models performance indicates the potential of MPEG SRE in water budget studies after applying a linear bias correction. The long-term mean monthly MPEG rainfall correction coefficients estimated from 2010 to 2013 indicated a consistent value especially for the rainy season. The average of MPEG correction coefficients can be used to correct the bias of MPEG data where there is limited or no gauged rainfall data at near-real-time to predict floods in the Lake Tana sub-basin.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2017.01.058.

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