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Validation of remotely sensed rainfall over major climatic regions in Northeast Tanzania

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ABSTRACT

Increase in population has resulted in pressure for more land and water use for food security in Northeast Tanzania. This calls for proper understanding of spatial-temporal variations of quality and quantity of water to ensure sustainable management. The number of hydro-meteorological stations such as rainfall stations and flow measuring stations has not increased and even the functioning of the existing ones is deteriorating. Satellite rainfall estimates (SRE) are being used widely in place of gauge observations or to supplement gauge observations. However, rigorous validation is necessary to have some level of confidence in using the satellite products for different applications. This paper discusses the results of application of SRE over a data scarce tropical complex region in Northeast Tanzania. We selected river catchments found in two different climatological zones: the inland region mountains (i.e. Kikuletwa and Ruvu basins) and the coastal region mountains (i.e. Mkomazi, Luengera and Zigi basins), characterized by semi arid, sub-humid to humid tropical climate. Thus, the validation sites were ideal for testing the different SRE products. In this study, we evaluated two gauge corrected high resolution SRE products which combine both infrared and passive-microwave estimates; the National Oceanographic and Atmospheric Administration Climate Prediction Center (NOAA-CPC) African Rainfall Estimation (RFE2) and the Tropical Rainfall Measuring Mission product 3B42 (TRMM-3B42) using station network.

The accuracy of the products was evaluated through a comparison with available gauge data. The comparison was made on pair-wise (point to pixel) and sub-basin level with the reproduction of rainfall volume, rainfall intensity and consistency of rain and no-rain days. The SRE products performed reasonably well over both regions in detecting the occurrence of rainfall. The underestimation was mainly ascribed to topology and the coastal effect. Whereas, the overestimation was mainly ascribed to evaporation of rainfall in the dry atmosphere under the cloud base. Local calibration of satellite-derived rainfall estimates and merging of satellite estimates with locally available rain-gauge observations are some of the approaches that could be employed to alleviate these problems. Although, the products did not show strong correlation to the observed rainfall over the complex tropical mountainous catchments considered, they have high potential to augment gauge observations in data sparse basins.

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1. Introduction

Climate related hazards such as droughts and floods are increasing in Tanzania (URT, 2012), all of which have serious water resources implications. There is therefore a need to strengthen the tools which can be used to shed more light on what is happening both at spatial-temporal scale in terms of water quantity and even quality.

Hydrological models may be used to forecast what will happen under different scenarios of land use/cover and precipitation but the applicability is largely limited by lack of data especially in developing countries. Satellite remote sensing now has the potential to provide extensive coverage of key variables such as precipitation (Smith et al., 1996; Sturdevant-Rees et al., 2001), soil moisture (Sano et al., 1998) and flooding extent (Townsend and Foster, 2002), as well as parameters such as vegetation cover (Nemani et al., 1993), vegetation change (Nemani et al., 1996) and surface imperviousness (Slonecker et al., 2001) that are important inputs to modern hydrological models. The range and extent of these inputs would have been impractical to obtain through traditional, terrestrial, data collection techniques (Entekhabi et al., 1999).

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The spatial variability of rainfall is often identified as the major source of error in investigations of rainfall–runoff processes and hydrological modeling (O'Loughlin et al., 1996; Syed et al., 2003). However, in Tanzania the extent of the ground-based rainfall network is not adequate to capture all the spatial rainfall variability. Many data collection programs have been abandoned for socio-economic or political reasons, resulting in both spatial and temporal gaps in valuable data time series. Remote sensing offers extremely valuable opportunities to not only fill the gaps, but also to extend the point measurements into spatio-temporal estimates of rainfall. The retrieval of rain rate from satellite data is one of the major research fields in satellite meteorology at the moment and different research groups are trying to co-ordinate those efforts on an international basis. Many of those satellite rainfall estimate (SRE) products are freely available through the internet but in many parts of Africa, there has been very little validation work (see Laurent et al., 1998; Grimes et al., 1999; Nicholson et al., 2003a,b; Thorne et al., 2001; Ali et al., 2005; Hughes, 2006; Dinku et al., 2007, 2008).

In the present study, two SRE products: the National Oceanographic and Atmospheric Administration Climate Prediction Center (NOAA-CPC) African rainfall estimation (RFE2) and the Tropical Rainfall Measuring Mission product 3B42 (TRMM-3B42) are applied and validated over the major climatic regions in Northeast Tanzania. It is essential to quantify direct use of these products in flood forecasting and hydrological modeling.

2. Study area

Northeast Tanzania comprises three administrative regions of Tanga, Kilimanjaro and Arusha, which fall within three hydrological basins: the large Pangani, medium Umba and small Zigi (Fig. 1). The Pangani River Basin covers an area of about 43,600 km^2 extending from the northern mountains of Kilimanjaro and Meru through the central Maasai Steppes and Usambara Mountains to the Indian Ocean. The surface water resources of Pangani are further subdivided by the *Nyumba ya Mungu* Reservoir into two main systems, the *upstream* and *downstream* water resource systems. The upstream system comprises the eastern Ruvu river, which drains the area between Mount Kilimanjaro and the North Pare Mountains, and the western Kikuletwa river, which drains the areas around Mount Kilimanjaro and Mount Meru. The downstream system comprises the Mkomazi river, which drains the South Pare Mountains and the Luengera river which drains the catchment area between the western and eastern Usambara Mountains. The rivers draining mountains in the coastal region (Umba, Sigi, Luengera, Mkomazi and Lower Pangani) exhibit different multi-year pattern of variability from that of rivers draining the northern inland region mountains (Kikuletwa, Ruvu and Upper Pangani).

The high altitude slopes above the forest line on Mt. Meru and Mt. Kilimanjaro have an Afro-Alpine climate and receive in excess of 2500 mm of rainfall per year. The middle slopes of these mountains, and the Pare and Usambara Mountains are characterized by a humid to sub-humid tropical climate. Forest reserves, grasslands and bushlands cover the mountain slopes and no agricultural activities are entertained within reserve areas. Mean annual rainfall increases in a southerly direction along the mountain range, and varies from about 650 mm/year in the North and South Pare Mountains, to 800 mm/year in the Western Usambara Mountains, and 2000 mm/year in the Eastern Usambara Mountains. The lower Mkomazi catchment and the lower Pangani catchment have a sub-humid to semi-arid climate. These areas are not forested although they have a high agricultural potential. Cash crops such as tea and some coffee growing is practiced. The central and western parts of the Basin have a semi-arid to arid climate. Rainfall varies between 300 and 600 mm/year. The area is covered in dry woodlands and thorn bushveld, and has marginal agricultural potential (mainly sisal). From these areas, five catchments were selected to be used in the comparison of satellite and terrestrial precipitation estimates; Kikuletwa (6765 km^2), Ruvu (6065 km^2), Mkomazi (3902 km^2), Luengera (1310 km^2) and Zigi (1068 km^2) (Fig. 1).

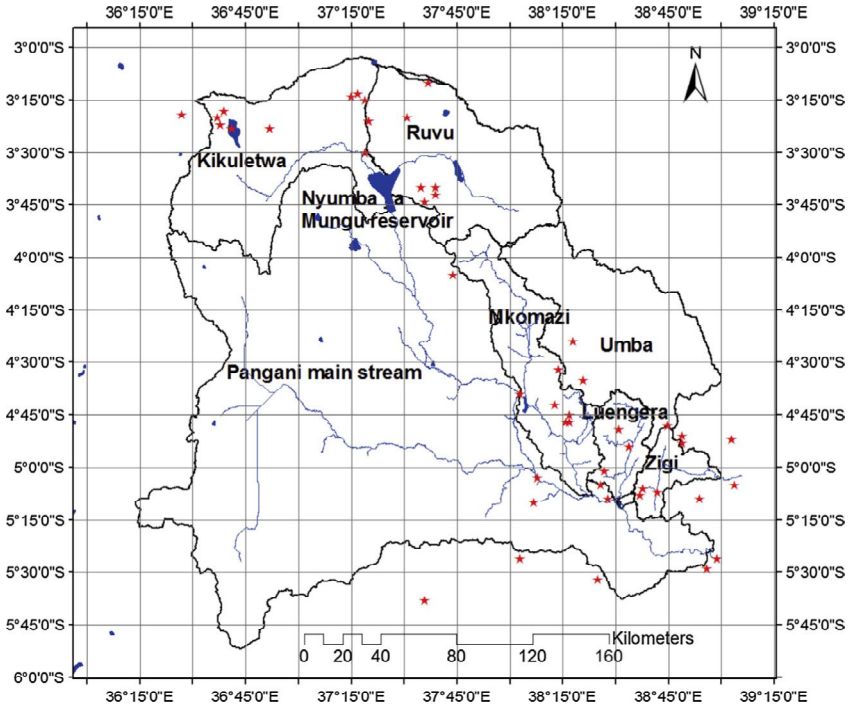


Fig. 1. Location and hydro-meteorological network of the basins in Northeast Tanzania with a 0.25° × 0.25° grid overlay.

3. Materials and methods

3.1. Gauge rainfall data

A total of 68 daily gauge precipitation records were collected and analyzed. Only 43 stations were selected based on data quality (Table 1). Data were provided by the University of Dar es Salaam (UDSM) – Department of Water Resources Engineering, Pangani Basin Office (PBO) and the Hydrology section of the Ministry of Water (MoW) in Tanzania. We used rainfall station available within and around the study catchments. Most of the stations had records overlapping the available satellite products time series in the period 1998 until 2010, with the exception of the Pangani main stream and Umba sub-basins whose meteorological stations were extremely sparse, with missing records greater than 30%. We therefore did not include those catchments in our analysis. The records were checked for gaps and quality control has been performed based on visual comparisons between neighboring stations and double mass curve analyses. A total of 10, 7, 11, 5 and 10 rainfall gauge stations were selected for analysis in Kikuletwa, Ruvu, Mkomazi, Luengera and Zigi respectively. Most of the stations contained missing data less than 15%. But we did not include any missing data in analysis at daily time steps. For the monthly rainfall accumulation, up to 5 days of missing data were accepted according to WMO standards (WMO, 1989).

3.2. Satellite rainfall estimates

The retrieval of rain rate from satellite data is one of the major research fields in satellite meteorology and many of those satellite rainfall estimate (SRE) products are freely available through the internet (Table 2). In this study, two satellite rainfall products are compared over the five validation sites. The reasons for selecting these products were (1) They are the simplest to access (via internet links) and process into readily usable information, (2) They are gauge corrected and (3) They have high spatial and temporal resolutions.

The first product is provided by the operational mission that the National Oceanic and Atmosphere Administration Climate Prediction Center (NOAA/CPC) launched for the Famine Early Warning Systems (FEWS) to assist in drought monitoring activities over Africa. Since January 2001, the African rainfall estimation version 2.0 (REF2) has been in use and has significantly increased the accuracy of the rainfall estimates compared to the previous version (Xie and Arkin, 1996). The dataset is based on merged information from several sources: daily Global Telecommunication System (GTS) rain gauge data, Advanced Microwave Sounding (AMSU) microwave satellite precipitation estimates, Special Sensor Microwave/Imager (SSM/I) satellite rainfall estimates and Geostationary Operational Environmental Satellite Precipitation Index (GPI) cloud top Infrared (IR) temperature precipitation estimates. The data has a

Table 1
Inventory of used rainfall stations in Northeast Tanzania.

Station code	Station name	Lat (°S)	Long (°E)	Elevation (m.a.s.l)	Period of data	Missing data (%)
9336001	ARUSHA AGRIC OFFICE	−3.38	36.68	1372.0	1998–2009	13.9
9336033	ARUSHA MET STATION	−3.37	36.63	1387.0	1998–2010	3.2
9336031	ARUSHA TPRI	−3.33	36.62	1432.0	1998–2007	13.5
9337005	KIBOSHO MISSION	−3.25	37.32	1478.0	1998–2010	23.3
9337021	LYAMUNGU	−3.23	37.25	1250.0	1998–2010	1.3
9336014	MONDULI ESTATE	−3.32	36.45	1585.0	1998–2010	2.6
9336000	OLMOTONYI FOREST	−3.30	36.65	1609.0	1998–2010	23.4
9337121	OSAKI FOREST STATION	−3.22	37.28	1524.0	1998–2010	7.8
9336035	TENGERU MET STATION	−3.38	36.87	1280.0	1998–2010	5.7
9337028	TPC LANGASANI	−3.50	37.32	701.0	1998–2009	17.8
9337045	KILEMA CHINI	−3.33	37.52	1219.0	2002–2010	5.6
9337132	HURUMA CONVET	−3.17	37.62	1300.0	1999–2010	20.5
9337033	KISANGARA SISAL ESTATE	−3.73	37.60	945.0	1998–2010	25.0
9337075	LOMWE SEC SCHOOL	−3.70	37.65	1371.0	1998–2006	15.0
9337004	MOSHI MET	−3.35	37.33	813.0	1998–2010	0.0
9337146	MWANGA AGRIC	−3.67	37.58	999.0	1998–2010	13.7
9337067	SHIGATI PR. SCHOOL	−3.67	37.65	1341.0	1998–2006	24.1
9438003	LUSHOTO AGRIC. OFFICE	−4.78	38.28	1396.0	1998–2010	4.5
9438019	MAZINDE FACTORY	−4.70	38.22	439.0	1998–2010	12.2
9438013	MAGAMBA FOREST STATION	−4.75	38.28	1676.0	2001–2010	9.2
9538076	NGOMENI	−5.05	38.13	184.0	2004–2010	18.7
9437003	SAME MET STATION	−4.08	37.73	860.0	1998–2010	0.0
9438049	SHAGAYU FOREST ESTATE	−4.53	38.23	1981.0	1998–2010	12.3
9438009	BUIKO HYDROMET STATION	−4.65	38.05	534.0	1998–2008	0.0
9438075	MNAZI WATER MASTER PLAN	−4.40	38.30	510.0	1998–2008	5.5
9538078	MZERI RANCH	−5.17	38.12	540.0	1998–2006	8.1
9438076	LUSHOTO HYDROMET	−4.78	38.27	1400.0	1998–2008	0.0
9438068	MLALO PRIMARY SCHOOL	−4.58	38.35	457.0	1998–2008	0.8
9538004	AMBANGULU TEA ESTATE	−5.08	38.43	1219.0	1998–2010	7.0
9538002	DINDIRA ESTATE	−5.02	38.45	1067.0	1998–2010	18.7
9538040	KOROGWE MAJI	−5.15	38.47	259.0	1998–2010	7.1
9438074	MAGOMA	−4.90	38.57	350.0	1998–2009	14.1
9438023	MAZUMBAI ESTATE	−4.82	38.52	1524.0	1998–2010	26.3
9538003	AMANI MALARIA UNIT	−5.10	38.63	911.0	1998–2010	9.6
9438060	KIGONGONI PR. SCHOOL	−4.80	38.75	999.0	1998–2010	16.7
9438033	LUGONGONGO SISAL ESTATE	−4.88	38.82	183.0	1999–2010	10.7
9538041	LUNGUZA FOREST	−5.12	38.70	168.0	1998–2010	17.9
9538067	MARIKITANDA	−5.13	38.62	999.0	2002–2010	17.6
9538011	MLINGANO AGROMET	−5.15	38.90	183.0	1998–2008	26.5
9438054	MWELE SISAL ESTATE	−4.85	38.82	999.0	1998–2008	21.2
9539015	TANGA MET	−5.08	39.07	49.0	1998–2010	0.0
9439063	MAZOLA KILIFI PR SCHOOL	−4.87	39.05	62.0	1998–2008	8.5
9538053	LANCONI SISAL ESTATE	−5.02	38.80	121.0	1998–2010	3.0

Table 2
Freely available global satellite rainfall estimate products.

Dataset name	Spatial resolution	Temporal resolution	Data existence	Data provider	Reference
MPE	Original pixel	15-min	2002-present	EUMESAT	Heinemann et al. (2002)
GSMaP MVK	0.1° × 0.1°	1 h	2003–2006	JAXA	Okamoto et al. (2007)
GSMaP MWR	0.25° × 0.25°	1 h	1998–2006	JAXA	Okamoto et al. (2007)
GSMaP TMI	0.25° × 0.25°	1 h	1998–2006	JAXA	Okamoto et al. (2007)
GSMaP NRT	0.1° × 0.1°	1 h	2007–2010	JAXA	Kubota et al. (2007)
CMORPH	0.07° × 0.07°	30-min	2002-present	NOAA-CPC	Joyce et al. (2004)
NRLB	0.25° × 0.25°	3-hourly	2003–2006	US-NRL	Turk et al. (1999)
PERSIANN	0.25° × 0.25°	3-hourly	2000–2006	University of Arizona	Hsu et al. (1997)
TRMM-3B42	0.25° × 0.25°	3-hourly	1998–present	NASA	Huffman et al. (2003)
TRMM-3B42RT	0.25° × 0.25°	3-hourly	2002-present	NASA	Huffman et al. (2003)
TRMM-3B43	0.25° × 0.25°	Monthly	1998-present	NASA	Huffman et al. (2003)
RFE	0.1° × 0.1°	Daily	2000-Present	NOAA-CPC	Herman et al. (1997)
ARC	0.1° × 0.1°	Daily	1995-Present	NOAA-CPC	Love et al. (2004)
GPCP-1DD	1.0° × 1.0°	Daily	1996-Present		Huffman et al. (2001)
TAMSAT	0.05° × 0.05°	10-daily	1996-Present	University of Reading	Grimes et al. (1999), Thorne et al. (2001)
GPCP	2.5° × 2.5°	Monthly	1979–2007		Huffman et al. (1997), Adler et al. (2003)
CMAP	2.5° × 2.5°	Monthly	1979–2006	NOAA-CPC	Xie and Arkin (1997)

temporal resolution of 1 day and spatial resolution of 0.1° and covers regions between 40°N–40°S and 20°W–55°E.

The second product is produced by the tropical rainfall measuring mission (TRMM) project at the National Aeronautics and Space Administration (NASA). The NASA's TRMM 3B42 product is produced since 1998 in four stages:

- Microwave estimates of precipitation (SSM/I, AMSU and Advanced Microwave Scanning Radiometer) are calibrated and combined
- Geostationary thermal IR estimates are created using the calibrated microwave precipitation
- Microwave and IR estimates are combined
- The 3B42 estimates are scaled to match the monthly rain gauge analyses used in the 3B43 product (Huffman et al., 2007).

The gridded estimates are on a 3-hour temporal resolution and a 0.25° spatial resolution and cover regions between 50°S and 50°N latitude.

In the Pangani River upstream system, a total of 10 TRMM and 55 RFE grids covered the majority of Kikulewa basin and a total of 8 TRMM and 50 RFE grids covered the whole of the Ruvu basin. Whereas, in the downstream system, 6 TRMM and 9 RFE2 grid squares covered the Mkomazi basin and a total of 2 TRMM and 4 RFE2 grid squares covered the Luengera basin. In Zigi, a total of 3 TRMM and 9 RFE grids squares covered the majority of the basin (Figs. 1, 2, 3 and 4)

3.3. Methods of comparison

To investigate the accuracy of the remote sensing products, comparisons were performed between rainfall that has been measured on the ground, and the SRE product. The comparison was based on both pair-wise (point to pixel) and sub-basin levels. Areal-average rainfall over the catchments was produced from point rainfall values observed within and around the study area. This was done using the Thiessen (nearest-neighbor) approach (Thiessen, 1911). The Thiessen polygons were created with the ArealRain extension in ArcView (Petras, 2001). Catchment average rainfall estimates for the satellite based time series for the same period of records have been produced from each satellite product by averaging all the pixels of that product that lie within the catchment of interest. The two time series of catchment average rainfall have been compared by means of statistical criteria (Eqs. (1)–(4), time series plots and double mass curve analysis. The time series plots and statistical tests are made on daily and monthly basis to establish how well the products perform with increasing averaging time. The precision of the satellite products is evaluated by the Pearson's correlation coefficient (CC), mean error (ME), root-mean-square error (RMSE), Mean Absolue Error (MAE) and bias:

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N}(S_i - G_i) \tag{1}$$

Range: minus infinity to infinity. Perfect score: 0

$$\mathrm{BIAS} = \frac{\frac{1}{N}\sum_{i=1}^{N} S_i}{\frac{1}{N}\sum_{i=1}^{N} G_i} \tag{2}$$

Range: minus infinity to infinity. Perfect score: 1

$$\mathrm{MAE} = \frac{\frac{1}{N}\sum_{i=1}^{N}|S_i - G_i|}{G_i^-} \tag{3}$$

Range: 0 to infinity. Perfect score: 0

$$\mathrm{RMSE} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - G_i)^2}}{G_i^-} \tag{4}$$

Range: 0 to infinity. Perfect score: 0.

The ability of each of the products to detect rainfall is evaluated by the Probability of Detection (POD), False Alarm Ratio (FAR), Critical Success Index (CSI), Equitable Threat Score (ETS), Hanssen and Kuipers Discriminate (HK) and Heidke Skill Score (HSS) indices, Eqs. (5)–(11). All are based on a contingency table (Table 3), where A, B, C, and D represent hits (i.e. *event forecast to occur, and did occur*), false alarms (i.e. *event forecast to occur, but did not occur*), misses (i.e. *event forecast not to occur, but did occur*), and correct negatives (i.e. *event forecast not to occur, and did not occur*), respectively.

$$\mathrm{POD} = \frac{A}{A+C} \tag{5}$$

$$\mathrm{FAR} = \frac{B}{A+B} \tag{6}$$

$$\mathrm{CSI} = \frac{A}{A+B+C} \tag{7}$$

$$\mathrm{ETS} = \frac{A - \mathrm{Ar}}{A+B+C-\mathrm{Ar}} \tag{8}$$

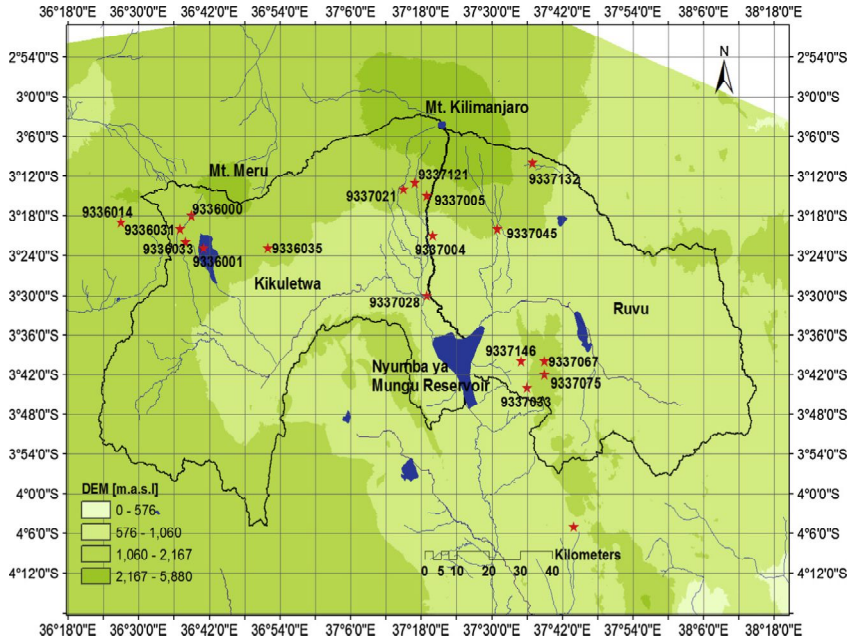


Fig. 2. Pangani river upstream sub-basins showing rain gauges and the channel network with a 0.1° × 0.1° grid overlay.

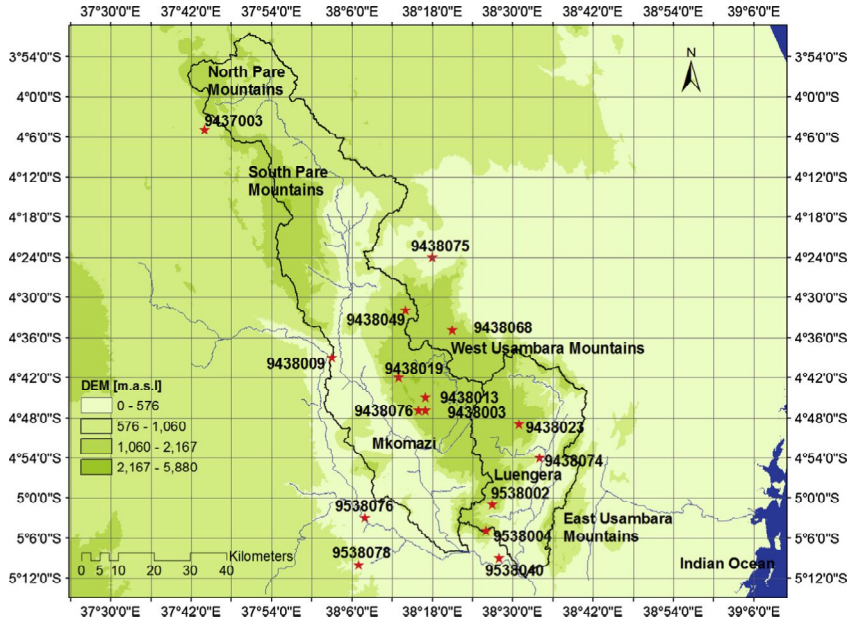


Fig. 3. Pangani river downstream sub-basins showing rain gauges and the channel network with a 0.1° × 0.1° grid overlay.

Where Ar stands for hits that could occur by chance, and is given by

$$\mathrm{Ar} = \frac{(A+C).(A+B)}{N} \tag{9}$$

$$\mathrm{HK} = \frac{A}{A+C} - \frac{B}{B+D} \tag{10}$$

$$\mathrm{HSS} = \frac{2\cdot(A\cdot D - B\cdot C)}{(A+C)\cdot(C+D)+(A+B)\cdot(B+D)} \tag{11}$$

Correlation coefficient, ME, BIAS, MAE and RMSE are point-by-pixel comparison statistics used to evaluate the performance of the satellite products in estimating the amount of the rainfall. The POD, FAR, CSI, ETS, HK, and HSS are categorical validation statistics used to assess rain-detection capabilities. POD, FAR, and CSI are affected by the climatology of the study region (Dinku et al., 2008). Thus, these statistics might not be useful for comparing rain-detection accuracy over two different climatic regions. On the other hand, ETS, HK, and HSS are not affected as much by the wetness or dryness of the different regions (Dinku et al., 2008). POD assesses how good the satellite estimates are in detecting the occurrence of rainfall; FAR measures how often the satellite

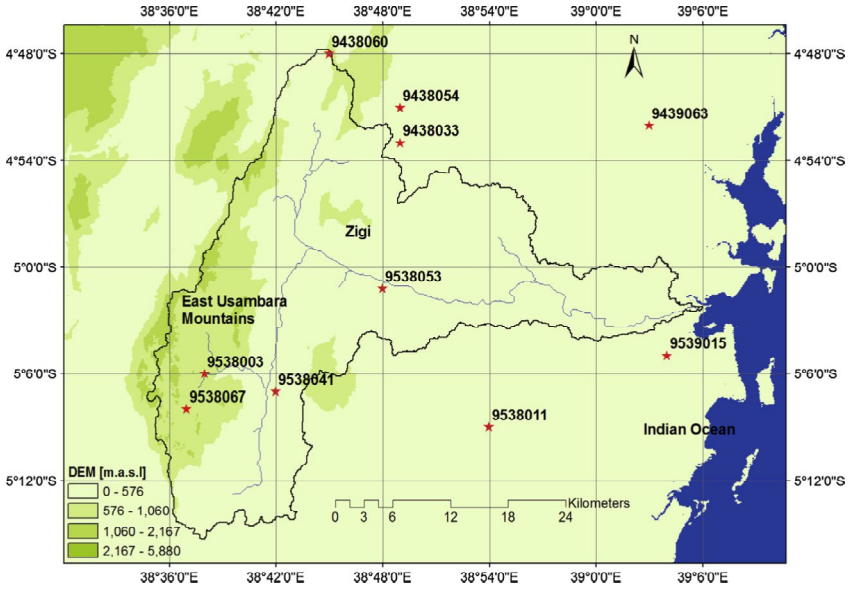


Fig. 4. Zigi river basin showing rain gauges and the channel network with a 0.1° × 0.1° grid overlay.

Table 3
Contingency table for comparing gauge area-averages and satellite rainfall estimates. The rainfall threshold used is 0.5 mm.

	Gauge ⩾ threshold	Gauge < threshold
Satellite ⩾ threshold	A	B
Satellite < threshold	C	D

products detect rainfall when there is actually no rainfall; CSI measures the fraction of gauge and/or satellite events that were correctly predicted; ETS evaluates how well the satellite rain events correspond to the gauge events; HK shows how well the satellite estimates discriminate between rain and no-rain events, and HSS measures the accuracy of the estimates accounting for matches due to random chance (see http://www.bom.gov.au/bmrc/wefor/staff/eee/verif/verif_web_page.html for more).

4. Results and discussion

4.1. Pangani river upstream sub-basins

The point to pixel comparison, carried out for daily and monthly time steps on TRMM 0.25° and RFE 0.1°'s grids (Table 4) shows that both products exhibit a relatively poor performance at a daily time step; correlation coefficients are low, and MAE values are high. However, as the time step increases to monthly, the performance of the estimates improves (higher correlation coefficients and lower MAE and RMSE). This is consistent with the results already published in terms of the effect of time step (e.g. Liechti et al., 2012). Both products did not show significant bias. This, of course, is related to the fact that TRMM-3B42 and RFE2 incorporate ground observations. Because of this low bias, similar statistic results were obtained for both products with TRMM-3B42 being slightly better than RFE2. The differences may be ascribed to fixed temperature thresholds and fixed rain rates used to compute IR estimates in the RFE2 algorithm (Liechti et al., 2012). In the TRMM-3B42 algorithm, the PM estimates are also used to calibrate the TIR brightness temperatures and as a result, both the temperature thresholds and the rain rate may vary from one location to the other (Dinku et al., 2011). The poor performance of the SRE products is partly attributed to complex topography of the region and the associated orographic rain process. Topography poses a challenge to satellite rainfall estimation from either IR or PM sensors (Dinku et al., 2008). IR algorithms use cloud-top temperature thresholds that are too cold for the orographic cloud which leads to an underestimation of orographic rains. PM algorithms are based mainly on scattering by ice aloft, which may lead to underestimation of surface rain. Both products significantly underestimate precipitation in the Kikuletwa basin, while TRMM-3B42 slightly overestimates and RFE2 slightly underestimates precipitation in Ruvu basin (Fig. 5(a) and (b)). The differences may be because most of the rain gauges in Kikuletwa are located in the humid regions either close to Mt. Meru in the west or Mt. Kilimajaro in the east, thus catching significant amounts of local orographic precipitation. For example, lower correlation coefficient values (0.26 and 0.48 for RFE2 and 0.41 and 0.52 for TRMM-3B42

Table 4
Statistics for the point to pixel comparison over each catchment.

Measure	Product	Kikuletwa		Ruvu		Mkomazi		Luengera		Zigi	
		Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly	Daily	Monthly
CC	RFEV2	0.23	0.50	0.23	0.64	0.18	0.52	0.21	0.47	0.29	0.58
	TRMM	0.20	0.65	0.26	0.76	0.27	0.70	0.31	0.75	0.32	0.73
ME	RFEV2	−1.74	−52.59	−1.71	−48.98	−0.76	−18.45	−1.82	−57.48	−1.73	−36.11
	TRMM	−1.11	−35.15	−1.27	−38.68	−0.39	−10.42	−1.28	−38.78	−1.08	−39.49
BIAS	RFEV2	0.45	0.45	0.46	0.49	0.78	0.76	0.51	0.49	0.48	0.72
	TRMM	0.65	0.62	0.60	0.61	0.94	0.91	0.68	0.69	0.70	0.67
MAE	RFEV2	1.12	0.73	1.13	0.67	1.33	0.64	1.15	0.72	1.10	0.77
	TRMM	1.21	0.63	1.18	0.57	1.40	0.58	1.16	0.55	1.23	0.54
RMSE	RFEV2	3.68	1.21	3.96	1.12	5.55	0.98	3.32	1.06	3.34	1.08
	TRMM	3.70	1.00	3.91	0.96	5.14	0.85	3.33	0.79	3.71	0.77

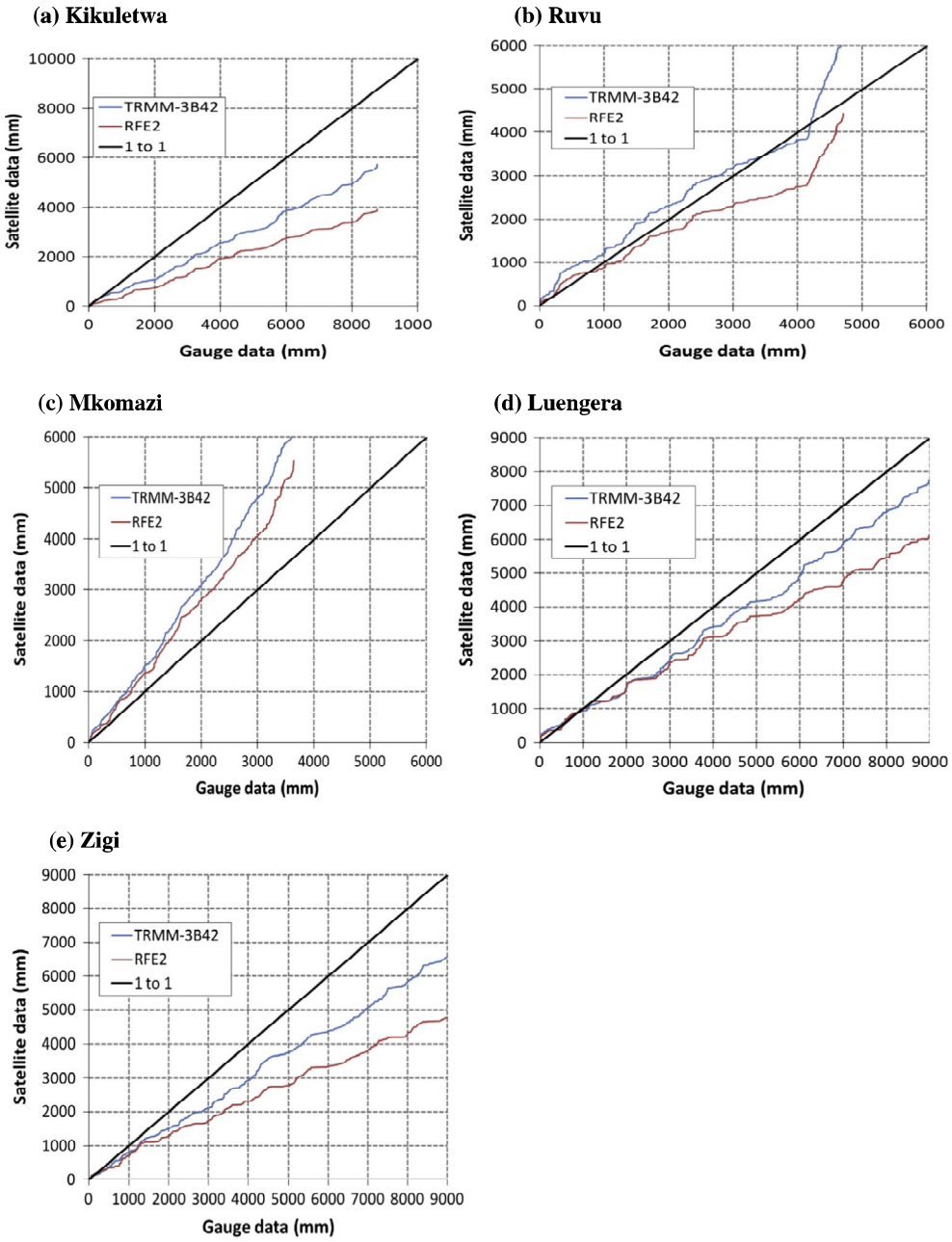


Fig. 5. Double mass curves showing the accumulated amount of rainfall of the observations against satellite rainfall estimate products in the study basins.

for monthly time steps) were observed in gauges 9337121 (Osaki forest) and 9336000 (Olmotonyi forest) respectively. However, in the Ruvu basin, higher correlation coefficient values (0.81 and 0.74 for RFE2 and 0.75 and 0.86 for TRMM-3B42 for the monthly time step) were observed in gauges 9337067 (Shigati primary school) and 9337075 (Lomwe secondary school) respectively. These gauges are also located in mountainous region suggesting that the effect of topography is more complex, as it includes factors other than elevation, for instance slope, orientation of the slope with respect to wind direction at a given time, and geographical location of the slopes (Dinku et al., 2008). The other reason may be due to an inadequate rain gauge network, which can produce inaccurate estimates of rain in the gauge analysis. Since the satellite estimates are adjusted by the gauge analysis, this implies that the satellite estimates may be better than the blended gauge and satellite product (McCollum et al., 2000). The other reason may be due to different rain processes for different regions, suggesting that a single calibration may not be adequate for use everywhere (McCollum et al., 2000; Dinku et al., 2011; Arias-Hidalgo et al., 2013). The overall performance of the satellite rainfall products in detecting the occurrence of rainfall was found to be reasonably good for both sites, with better results in Ruvu (Table 5). It is also evident TRMM-3B42 performed better than RFE2 in terms of rain detection. Fig. 6 show time series comparisons for monthly sub-basin average rainfall.

4.2. Pangani river downstream sub-basins

Mkomazi basin has a relatively dry climate and statistics show the opposite of what has been observed in the upstream sub-basins. Fig. 5c showed the huge overestimation of rainfall amount by all the products, with RFE2 slightly better than TRMM-3B42. The first possible explanation is that convective clouds forming under dry conditions generally have cloud bases considerably higher

Table 5
Skill scores for each investigated rainfall product and over each catchment.

Measure	Product	Kikuletwa	Ruvu	Mkomazi	Luengera	Zigi
POD	RFEV2	0.43	0.62	0.61	0.39	0.38
	TRMM	0.53	0.66	0.65	0.48	0.49
FAR	RFEV2	0.19	0.42	0.34	0.28	0.15
	TRMM	0.30	0.48	0.30	0.37	0.25
CSI	RFEV2	0.39	0.43	0.46	0.34	0.35
	TRMM	0.43	0.41	0.51	0.38	0.42
ETS	RFEV2	0.22	0.31	0.33	0.18	0.20
	TRMM	0.21	0.24	0.37	0.18	0.22
HK	RFEV2	0.35	0.48	0.49	0.29	0.32
	TRMM	0.34	0.42	0.53	0.30	0.36
HSS	RFEV2	0.36	0.47	0.50	0.31	0.33
	TRMM	0.35	0.39	0.54	0.31	0.36

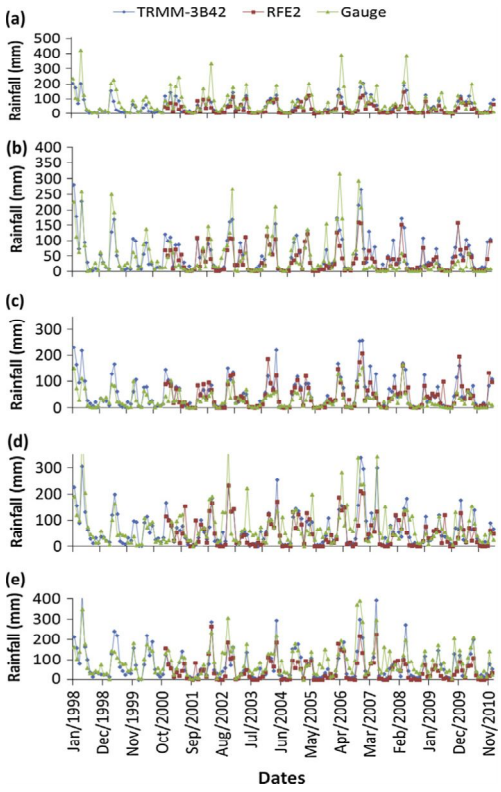


Fig. 6. Time series comparisons for monthly sub-basin average rainfall in (a) Kikuletwa, (b) Ruvu, (c) Mkomazi, (d) Luengera and (e) Zigi.

than those of clouds forming in moist environments leading to an increase in the evaporation rate of the falling rain and therefore less precipitation reaching the ground (McCollum et al., 2000). The second possibility, which is specific to PM algorithms, is that dry/desert surfaces could be confused with rain signatures (e.g. Wang et al. 2009). And the third possible explanation is that there may not be enough rain gauges in the area to provide accurate estimates of rainfall for comparisons with satellite estimates as seen from previous Kikuletwa and Ruvu basins. For the rainfall-detection skills (Table 5), surprisingly, both products performed better in this site. However, there could be uncertainty due to the fact that most gauges were located only at the lower mountainous part of the basin. SRE products have been shown to exhibit better rainfall-detection skills in mountainous regions as compared to dry regions (Dinku et al., 2011).

The other basin, Luengera, is relatively smaller and located between the coastal mountains, East and West Usambara. The results show almost the same trend as in Kikuletwa basin, with the underestimation relatively better (Tables 4 and 5, Figs. 5 and 6). The ocean influence is unlikely to be the cause of the underestimation, due to its remoteness. The relatively even distribution of gauges might have contributed to better performance. This emphasizes the importance of evenly distributed ground observations to represent the spatial variations caused by topographic influences.

4.3. Zigi basin

From Table 4, we may conclude that satellite products are able to represent the temporal variability and again TRMM-3B42 compares best with the ground observations. The skill scores (Table 5) show that TRMM-3B42 again gives the best performances although the false alarm rates are slightly better for REF2. Fig. 5e show significant underestimation of rainfall amount by all the products in the Zigi basin, with TRMM-3B42 slightly better than RFE2. This underestimation is ascribed to the warm-rain process associated with the orography of the region and greater proximity of the ocean. This is consistent with already published results (eg Herman et al. 1997; Dinku et al., 2007; Novella and Thiaw, 2013).

5. Conclusions

We have reported the validation results of satellite derived rainfall estimates through a comparison with available rain gauge data for a number of complex tropical catchments in Tanzania. It has been shown that both TRMM-3B42 and RFE2 substantially reproduce the large scale temporal variation in rainfall, particularly at monthly time intervals suitable for water resources management, and that TRMM-3B42 is better than RFE2. However, both underestimate the rainfall for most catchments, but overestimate for the Mkomazi catchment. The overestimation was mainly ascribed to evaporation of rainfall in the dry atmosphere under the cloud base. The underestimation was mainly ascribed to topology and the coastal effect. These results confirm the high importance of local calibration for satellite rainfall products using the available rain-gauge observations over different climatic regions. Another approach to improving satellite rainfall products is merging satellite estimates and gauge observations. Finally, our study area represent very complex climate regime in Tanzania and the results are encouraging enough to suggest that further detailed investigations are justified. Future research will focus on validation of high resolution satellite rainfall, error corrections and their application in distributed hydrological modeling.

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