APPLICATION OF REMOTELY SENSED RAINFALL DATA IN RAINFALL-RUNOFF MODELLING. A CASE OF PANGANI RIVER BASIN, TANZANIA

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ABSTRACT

Rainfall runoff modelling in a river basin is vital for number of hydrologic application including water resources assessment. However, rainfall data from sparse gauging stations are usually inadequate for modelling which is a major concern in Tanzania. This study presents the results of comparison of Tropical Rainfall Measuring Mission (TRMM) satellite rainfall products at daily and monthly time-steps with ground stations rainfall data; and explores the possibility of using satellite rainfall data for rainfall runoff modelling in Pangani River Basin, Tanzania. Statistical analysis was carried out to find the correlation between the ground stations data and TRMM estimates. It was found that TRMM estimates at monthly scale compare reasonably well with ground stations data. Time series comparison was also done at daily and annual time scales. Monthly and annual time series compared well with coefficient of determination of 0.68 and 0.70, respectively. It was also found that areal rainfall comparison in the northern parts of the study area had poor results compared to the rest of areas. On the other hand, rainfall runoff modelling with ground stations data alone and TRMM data set alone was carried out using five Real-Time River Flow Forecasting System models and then outputs combined by Models Outputs Combination Techniques. The results showed that ground stations data performed better during calibration period with coefficient of efficiency of 76.7%, 81.7% and 89.1% for Simple Average Method, Weight Average Method and Neural Network Method respectively. Simulation results using TRMM data were 59.8%, 73.5% and 76.8%. It can therefore be concluded that TRMM data are adequate and promising in hydrological modelling.

Keywords: *Remotely Sensed Rainfall Data, rainfall-runoff modelling.*

1. INTRODUCTION

The network of ground-based rainfall observations have always been relatively sparse in most of developing countries. Currently in Tanzania there are about 2043 ground stations in 945,087 km^2, the density of stations is very low in most of the country's river basins. The situation is not improving and the density of the network is increasingly declining. The amount of missing data is increasing and the reliability of some of the data is becoming increasingly suspect. Part of the reason for this trend is the lack of commitment to funding hydro-meteorological gauging networks because of more pressing economic and social issues. However, economic and social development depends, to a certain extent, on the availability of sound water resources information. The quality, availability and coverage of rain gauge data are particular obstacles to effective water resource planning in Africa as well as most developing countries (Hughes, 2006). Precipitation is among the most important forcing data for hydrological models (Xue *et al*., 2013). The successful modelling depends not only on the model structure and the time scale associated, but also on the accuracy of rainfall as the main input and also the spatial distribution of the rain gauge stations. Ground observation of rainfall has been considered the most reliable input for hydrological models. Yet, uncertainties are very much dependent on spatio-temporal resolution of rainfall. At the same time, it is both economically and practically impossible to greatly increase the number of rain gages for estimating the spatial rainfall (Taesombat and Sriwongsitanon, 2009). Alternatively, the incorporation of satellite-based and weather radar based (He et al., 2011) rainfall estimates in hydrological modelling has the potential to improve our capability to reduce uncertainty in rainfall inputs (Sawunyama and Hughes, 2008). Such data are especially valuable in developing countries or remote locations, where conventional rain gauge data are sparse or of bad quality (Hughes, 2006). Furthermore, the near-real-time availability of the satellite-based data products such as Tropical Rainfall Measuring Mission (TRMM) makes them suitable for modelling applications where water resources management is crucial and data gathering and quality assurance are cumbersome (Stisen and Sandholt, 2010).

The Tropical Rainfall Measuring Mission (TRMM) is a joint project between the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploratory Agency (JAXA) launched in November 1997 with the specific objectives of studying and monitoring the tropical rainfall (Rozante *et al*., 2010). It can provide precipitation products with high temporal (3 hours) and reasonably high spatial resolution (0.25^o x 0.25^o). As its name indicates, the TRMM mission covers only the tropical zone, i.e. between the latitudes 50^o N and 50^o S.

Therefore, the objectives of the study are designed to (1) evaluate and compare the temporal characteristics of daily, monthly and annual TRMM rainfall with that of the rain gauge data Pangani river basin. By doing so, different statistical measures are calculated and the correlations of the TRMM rainfall with rain gauge data at daily, monthly and annual time scales are investigated; and (2) cross compare the performance of the TRMM rainfall and rain gauge data in rainfall-runoff modelling for the basin.

2. DESCRIPTION OF THE STUDY AREA

The Pangani River Basin covers an area of about 43,650 km^2, mostly in Tanzania with approximately 5% in Kenya. It is located in the north eastern part of Tanzania between Latitudes 02º 55’s to 05º 40’s and Longitude 36º 20’E to 39º 02’E (Figure 1). The main tributaries of the Pangani are the Kikuletwa and the Ruvu, which join at Nyumba ya Mungu, a reservoir of some 140 km^2, the Mkomazi further downstream below the Nyumba ya Mungu Reservoir, and the Luengera before the Pangani reaches the Hale Hydropower plant. The effluent of the reservoir is known as the Pangani River, which flows for 432 km before emptying into the Indian Ocean.

The climate of the Pangani River Basin is generally classified as semi-arid to Savannah type but is somewhat modified along the coast and in the mountain areas (Sadiki *et al*., 1999).Temperatures are generally high throughout the year, with the lowest temperatures (14-18^{o}C) occurring in July-August and the highest (32-35^{o}C) in January/February. Rainfall distribution in the basin is bimodal with the highest rainfall between March and May. Highland areas such as the slopes of Mounts Meru and Kilimanjaro, as well as areas in the Usambara and Pare Mountains, receive between 1,200 and 2,000 mm of rainfall annually.

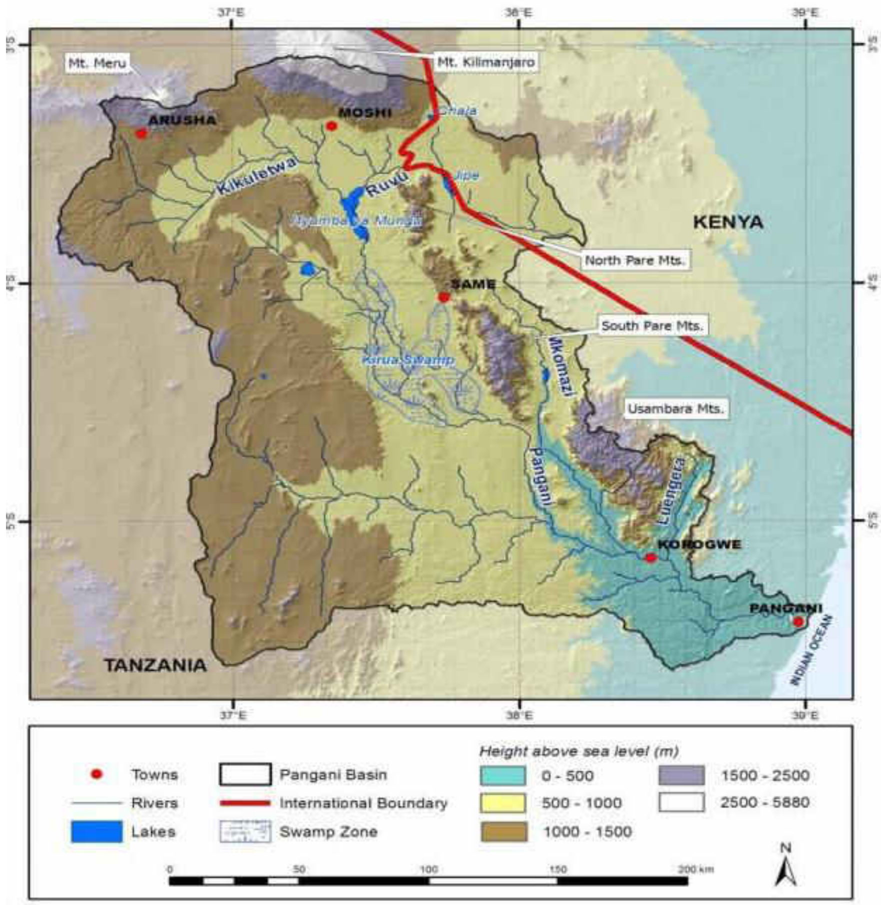


Figure 1: Geographical Location of Pangani River Basin; Source: PBWO/IUCN, 2008

3. METHODOLOGY

3.1 Data availability and analysis

The data used in this study were hydro-meteorological data including rainfall, evaporation, discharge and satellite data (TRMM 3B42). The daily rainfall data were obtained at Pangani Basin Water office. The basin has over 150 standard rain gauges; unfortunately most of gauges have missing or completely no data. For the purpose of this study i.e. comparing TRMM and gauges rainfall data, gauges with data from 1998 – 2008 (Table 1 and Figure 2) were selected take into account that TRMM satellite was launched on November 27, 1997 and data are available from January, 1998 to date. Evaporation and Discharge data were also obtained at Pangani Basin Water office. Gauge and TRMM data were compared based on availability of data; dates with missing data from gauges rainfall were excluded as well as that of TRMM. The data were sourced from TRMM Online Visualization and Analysis System (2008). The interface allows users to visualize and analyze global and regional rainfall. Accumulated rainfall or rain rate data are available for the period of 1998 to date for all TRMM data products, with a spatial resolution varying from 0.25° × 0.25° to 5.0° × 5.0 °. In this study data used were daily and monthly TRMM estimate.

Missing data for daily discharge were filled using the daily seasonal mean values. Similar procedure was used for rainfall and evaporation data. Comparison of TRMM estimates and rain gauges was done in four stages, first statistical analysis of TRMM and rain gauges rainfall was done for each station, also mean seasonal time series comparison was performed. The study area was divided in 5 main catchments and comparison of areal rainfall for rain gauges data and TRMM estimates was done for each catchment. Finally rainfall runoff modelling for both ground and satellite measured data was done and results were compared.

Table 1: List of rain gauge stations used in the study

SN	Station Name	Stn IDs	Altitude (m)	Lat	Long	Catchment	Available data	%Missing
1	Buiko Met RF	9438043	533	-4.65	38.05	Mkomazi	1998-2008	0.7
2	Maji Korogwe	9538040	259	-5.15	38.47		1998-2008	0.8
3	Magamba	9438013	1676	-4.75	38.28		1998-2004	27.5
4	Tia DAM	9437010	1676	-4.23	37.95		1998-2003	25
5	Lushoto Agric.	9438003	1396	-4.78	38.28		1998-2008	4.6
6	Handeni Agr.	9538007	677	-5.43	38.03	Pangani	1998-2006	7.5
7	Kilindi Pr.	9537005	520	-5.63	37.6		1998-2005	13.9
8	Mazola Kilifi Pr.	9439063	62	-4.87	39.05		1998-2008	10.7
9	Songe	9537009	1150	-5.58	37.28		1998-2005	24.4
10	Naururu	9437016	660	-4.07	37.53		1998-2008	20.3
11	Mswaki Pr.Sch	9537010	724	-5.47	37.77		1998-2005	18.7
12	Mzeri Ranch	9538078	540	-5.17	38.12		1998-2006	15.8
13	Kwedibola	9538077	340	-5.53	38.42		2000-2008	13.9
14	KIA Met Stn	9337115	891	-3.42	37.07	Kikuletwa	1998-2004	13
15	Kibong'oto hospital	9337078	1249	-3.2	37.12		1998-2003	9.8
16	Kibosho-M	9337005	1478	-3.25	37.32		1998-2005	5.1
17	Lyamungo Met.	9337021	1250	-3.23	37.25		1998-2002	1.4
18	Osaki Forest	9337121	1524	-3.22	37.28		1998-2004	7.2
19	Uru West RF	9337116	1585	-3.23	37.35		1998-2006	38
20	Tengeru Met.	9336035	1280	-3.38	36.87		1998-2003	0
21	Magoma	9438016	381	-4.87	38.58	Luengera	1998-2008	3
22	Moshi Airport	9337004	813	-3.35	37.33	Ruvu	1998-2009	0.97
23	Nafco Kahe	9337144	750	-3.52	37.43		1998-2002	0
24	Himo Sisal Est.	9337031	960	-3.38	37.55		1998-2007	8.5
25	WD ID Moshi	9337091	840	-3.35	37.33		1998-2002	11.7
26	Kilema Forest	9337120	1828	-3.25	37.45		2000-2002	40

3.2 Comparison of TRMM and ground measured data

TRMM data sets and rain-gauge data at daily and monthly time-step were compared with some known statistical analysis. Simple statistics such as coefficient of determination (R^2) is used. R^2 has been used successfully in other comparative studies of this type (Hughes, 2006); and is defined as follows:

$$R^2 = \frac{\sum\left(\hat{Y} - \bar{Y}\right)^2}{\sum\left(Y_i - \bar{Y}\right)^2} \tag{1}$$

$\bar{Y}$ = Average value of the dependent variable
Y_i = Observed values of the dependent variable
$\hat{Y}$ = Predicted value of Y for the given X_i value

Statistical measures like Mean Error (ME) and Root Mean Square Error (RMSE) were also used. Mean absolute error (MAE) is also included as it is deemed a more appropriate measure for comparison (Willmott *et al*., 2005). A model which systematically over- or under-predicts all the time will still result in good R^2 values close to 1.0 even if all predictions were wrong. If R^2 is used for model validation it therefore is advisable to take into account additional information which can cope with that problem. Such information is provided by the gradient ***b*** and the intercept **a** of the regression on which R^2 is based. For a good agreement the intercept ***a*** should be close to zero which means that an observed runoff of zero would also result in a prediction near zero and the gradient ***b*** should be close to one.

The Root Mean Square Error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. According to Boyle *et al.* (2000), optimizing RMSE during model calibration may give small error variance but at the expense of significant model bias.

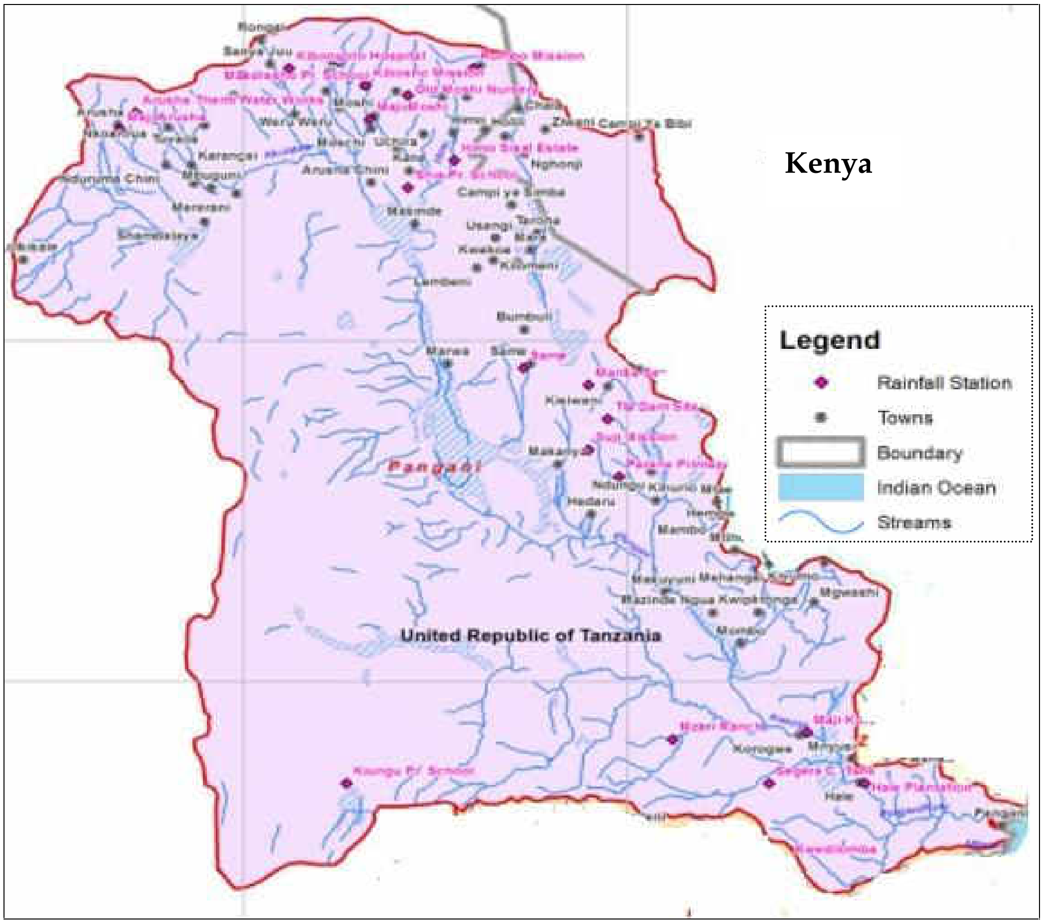


Figure 2: Location of the rainfall station in Pangani river basin

3.2 Rainfall-Runoff modelling

In this study 5 models were used i.e. Simple Linear Model - Non Parametric (SLM – NP), Linear Perturbation Model - Non Parametric (LPM-NP), Linearly Varying Gain Factor Model (LVGFM), Artificial Neural Network (ANN) Model, and the conceptual Soil Moisture Accounting and Routing (SMAR) Model. Models output Combination Techniques (MOCT) was also applied using all three methods i.e., Simple Average Method (SAM), the Weighted Average Method (WAM), and the Artificial Neural Network Method (NNM). The results for both gauges rainfall data and TRMM estimates were compared. For the calibration of the model, observed data from 1DD1 gauging station were used.

3.2.1 Simple Linear Model-Non Parametric (SLM -NP)

The intrinsic hypothesis of the SLM, introduced by Nash and Foley (1982), is the assumption of a linear time-invariant relationship between the total rainfall R_i and the total discharge Q_i. In its discrete non-parametric form, the SLM-NP, including the forecast error term e_i, is expressed by the convolution summation relation (Kachroo *et al.*, 1992),

$$Q_i = \sum_{j=1}^{m} R_{i-j+1} h'_j + e_i = G \sum_{j=1}^{m} R_{i-j+1} B_j + e_i \qquad (4)$$

With, $\sum_{j=1}^{m} B_j = 1$

Where Q_i and R_i are the discharge and rainfall respectively at the i-th time-step, h'_j is the *j-th* discrete pulse response ordinate or weight, *m* is the memory length of the system and G is the gain factor. This can be viewed as a multiple linear regression model of the observed discharge on the previous observed rainfall values and hence estimates of the unit pulse response ordinates can be obtained directly by the method of ordinary least squares (OLS) (Nash and Foley, 1982; Kachroo and Liang, 1992).

3.2.2 Linear Perturbation Model-Non Parametric (LPM-NP)

In the LPM, originally introduced in the context of rainfall-runoff modelling by Nash and Barsi (1983), it is assumed that, during a year in which the rainfall is identical to its seasonal expectation, the corresponding discharge hydrograph is also identical to its seasonal expectation. However, in all other years, when the rainfall and the discharge values depart from their respective seasonal expectations, these departures series are assumed to be related by a linear time-invariant system. The relation between the departures/perturbation series of the LPM, incorporating an output error term e_i, may be represented algebraically by the convolution summation equation

$$Q'_i = \sum_{j=1}^{m} R'_{i-j+1} h'_j + e_i \quad (5)$$

Where R'_i and Q'_i are the rainfall departures and the corresponding discharge departures from their seasonal expectations, respectively.

3.2.3 Artificial Neural Network (ANN) Model

The "*multi-layer feed-forward network"* type of artificial neural network, used in this study, consists of an input layer, an output layer and only one *"hidden"* layer located between the input and the output layers. Each neuron of a particular layer has connection pathways to all the neurons in the following adjacent layer, but none to those of its own layer or to those of the previous layer (if any), i.e. nodes within a layer are not inter-connected.

3.3 Calibration and validation of the models

Daily rainfall (ground observed and TRMM estimate) and discharge records for the period starting January 1, 1998 up to December 31, 2002 were used for calibration and validation of the models. The data was split in two periods for calibration and verification; from January 1, 1998 to December 31, 2000 for calibration and from January 1, 2001 to December 31, 2002 for verification. Models performances were evaluated by visual comparison of the simulated and observed flows plots as well as scatter plots of residuals. Numerical efficiency criteria were also used. The numerical efficiency criteria used in this study were four i.e. the Coefficient of determination, R^2 , the Index of Agreement, IoA, the Index of volumetric fit (*IVF*), and the Relative error of the peak (*RE*).

4. RESULTS AND DISCUSSIONS

4.1 Comparison between ground measured and TRMM rainfall data

The results for the comparison between TRMM and ground measured rainfall data are summarized in Table 2. It was found that the monthly rainfall shows much more agreement than the daily rainfall.

Out of 26 stations compared with TRMM data, the maximum R^2 was 0.13 and 0.74 for daily and monthly time-steps respectively. The values of R^2 for all 26 stations are considerably larger than those of daily temporal resolution with average of 0.06 and 0.44 for daily and monthly time-steps respectively. The scatterplots for some selected stations for the monthly rainfall data are as shown in Figures 3a-d. The average daily and monthly Mean Error (ME) for all the 26 stations of the study area were 0.71 mm/day and 20.04 mm/month respectively. It is clear that in majority of stations TRMM data set under estimate actual rainfall. Also average ground measured rainfall and TRMM data set reveal that TRMM underestimates in both daily and monthly scales. However, for seven (7) stations out of twenty six (26), TRMM 3B42 over-estimates actual rainfall based on gauge measurement. These stations are located in the low lying areas of the basin with elevation between 62 m and 750 m above mean sea level.

Another statistical indicator, Mean Absolute Error (MAE) was used to quantify the absolute difference between the TRMM estimates and gauge data. For daily rainfall, the least error is 1.83 mm found at Naururu gauging station with an elevation of 660m above mean sea level and the highest error is 6.20 mm found at Uru West gauging station with elevation of 1585 m above mean sea level. MAE for monthly data shows minimum value of 19.42 mm at KIA Met station with an elevation of 891 m above mean sea level and maximum value of 112.26 mm at Osaki Forest station with an elevation of 1524 m above mean sea level. The average daily and monthly MAE from all the 26 stations in the basin is 3.54 mm and 49.80 mm respectively. Also Root mean square (RMSE) was calculated to quantify the absolute difference between the two data sets. For all the stations, minimum difference for daily rainfall is 2.78 mm found at Handeni Agric station with an elevation of 677 m above mean sea level and the highest difference is 14.50 mm found at Osaki Forest station with an elevation of 1524 m above mean sea level. RMSE for monthly data shows a minimum value of 29.90 mm at KIA Met station and maximum value of 183.6 mm again at Osaki Forest station. The average daily and monthly RMSE from all the 26 stations of the basin was 9.57mm and 79.72mm, respectively. Hence it is clear that the difference between TRMM 3B42 and rain gauge data is influenced by local factors such as topography.

The results for the comparison between areal rainfall and TRMM data, which aimed at determining the effect of local factors such as elevation and spatial variability of rainfall is presented in Figures 4a-e. The statistics show that for Luengera, Mkomazi and Pangani mainstream there was better fit between ground measured rainfall and TRMM estimates than that of Kikuletwa and Ruvu catchments. This may be influenced by elevation and spatial variability of rainfall. Kikuletwa and Ruvu catchments are in the highlands as compared to Luengera, Mkomazi and Pangani mainstream.

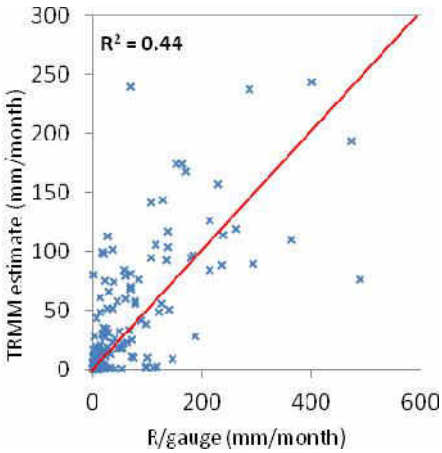
Similar results have been reported by different authors, for example the publications whose case studies deal with oceanic environments or flat areas (e.g. Amazon Basin) report very good match between the data from rain-gauges mounted on buoys and the TRMM data (Adler *et al*., 2000; Bowman, 2005). In studies on locations with higher altitudes and particularly in the foothills of mountainous regions (e.g the Andes), there were notorious differences between the two sources of data (Tian and Peters-Lidard, 2010). In this regard, under the orographic effect TRMM might show lower values than the gauge rainfall (Dinku *et al*., 2010).

Table 2: Daily and monthly statistics of ground measured and TRMM rainfall data

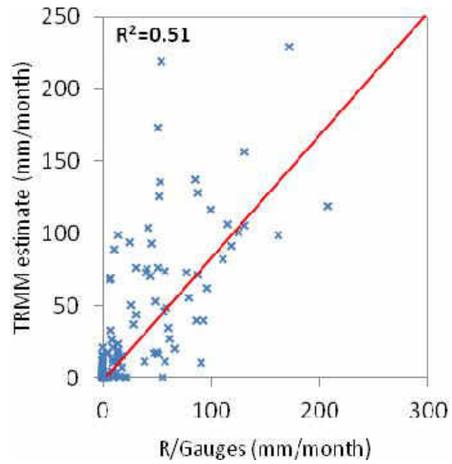
Station Name	Daily Temporal Resolution						Monthly Temporal Resolution					
	Mean [Gauge]	**Mean** [TRMM]	R^2	**ME** [mm/day]	**MAE** [mm/day]	**RMSE** [mm/day]	**Mean** [Gauge]	**Mean** [TRMM]	R^2	**ME** [mm/month]	**MAE** [mm/month]	**RMSE** [mm/month]
Buiko Met	1.15	2.12	0.07	-0.98	2.47	7.72	34.89	64.73	0.15	-29.84	39.71	59.85
Handeni	2.14	1.99	0.07	0.15	2.92	2.78	65.83	61.80	0.66	4.03	27.72	41.82
Himo Sisal	2.08	1.90	0.08	0.17	2.95	8.44	63.03	57.74	0.55	5.15	32.31	48.67
KIA Met Stn	1.46	1.39	0.11	0.07	2.01	6.69	44.32	42.35	0.74	1.81	19.42	29.90
Kibong'oto	3.92	1.71	0.02	2.22	4.65	12.66	119.70	52.80	0.15	66.90	94.79	164.71
Kibosho	4.27	2.07	0.03	2.21	5.25	13.27	124.67	60.29	0.27	63.71	92.48	152.01
Kilema	5.03	2.58	0.08	2.45	5.41	10.71	153.05	78.51	0.15	74.54	94.09	128.35
Kilindi Pr.	3.11	2.13	0.05	0.98	3.89	9.76	94.21	64.42	0.37	26.02	50.31	83.65
Kwedibola	2.42	2.47	0.05	-0.05	3.57	11.03	73.56	75.16	0.54	-1.43	37.60	57.98
Lancon	3.03	2.32	0.11	0.70	3.66	10.18	91.38	69.82	0.56	21.56	41.96	60.58
Lushoto	2.68	2.06	0.07	0.62	3.38	8.43	81.54	62.73	0.52	18.81	39.03	54.29
Lyamungo	4.12	2.63	0.05	1.47	5.04	11.61	123.71	79.25	0.23	44.46	93.22	154.29
Magamba	2.74	1.94	0.13	0.79	3.23	8.90	80.74	58.86	0.56	17.80	32.01	44.93
Magoma	2.33	2.22	0.12	0.10	3.09	8.63	70.71	67.21	0.60	3.51	35.17	47.85
Maji	2.80	2.31	0.09	0.49	3.52	9.64	85.16	70.03	0.56	15.13	43.30	57.90
Mazola Kilifi	2.17	2.40	0.00	-0.23	4.04	12.78	65.92	72.99	0.03	-6.41	65.82	104.07
Mlalo	3.55	2.06	0.04	1.49	4.25	12.84	105.52	62.48	0.51	42.39	59.48	109.14
Mnazi	1.24	1.95	0.00	-0.71	2.60	7.92	38.80	58.46	0.40	-18.59	34.36	57.75
Moshi	2.15	1.43	0.07	0.71	2.62	8.61	65.42	43.03	0.44	22.23	38.97	70.37
Mswaki	2.33	2.21	0.09	0.12	3.12	9.07	70.94	67.21	0.74	3.72	28.34	40.54
Mzeri Ranch	1.87	1.94	0.12	-0.08	2.76	7.75	56.51	59.46	0.48	-2.71	31.73	48.03
Nafco Kahe	0.89	1.53	0.05	-0.65	1.94	6.25	27.04	46.71	0.45	-19.68	29.68	47.48
Naururu	1.22	1.38	0.09	-0.17	1.83	6.32	30.90	35.19	0.51	-4.10	20.25	33.62
Osaki Forest	5.12	1.98	0.02	3.15	5.85	14.50	154.77	62.04	0.21	91.56	112.26	183.65
Songe	1.59	1.57	0.10	0.02	2.09	6.54	47.41	46.89	0.67	0.52	22.22	33.61
Tengeru	2.72	1.29	0.08	1.44	3.01	8.78	82.92	39.11	0.68	43.81	49.42	77.32
Tia DAM	2.17	1.78	0.01	0.39	3.37	10.60	70.16	53.98	0.39	16.18	45.74	77.09
Uru West RF	5.33	2.55	0.03	2.78	6.20	14.33	161.78	77.44	0.14	55.40	80.59	153.18
WD ID	2.96	2.14	0.06	0.81	3.81	10.79	89.97	65.20	0.46	24.77	52.33	89.12
Average Over the entire Basin	2.71	2.00	0.06	0.71	3.54	9.57	81.88	60.55	0.44	20.04	49.80	79.72

4.2 Rainfall-runoff modelling

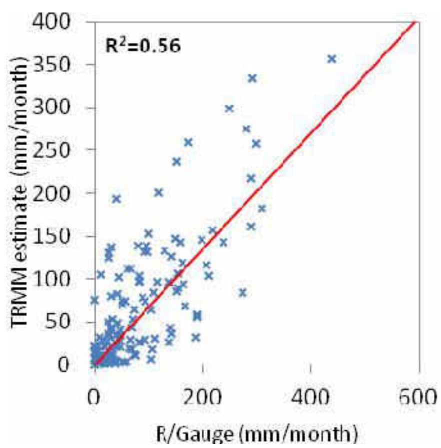
The performance of LPM-NP and ANNM for both ground measured rainfall and TRMM in calibration period was good (Tables 3 & 4). However with SMAR conceptual model which is intended to reflect soil moisture condition, SLM-NP which is very simplified model of input – output transformation process and that of LVGFM which is an improvement of SLM (NP), was not good for TRMM but for ground measured rainfall it was fairly well. The simulated discharge obtained by combination of models show significant improvement for both TRMM and ground measured rainfall (Figures 5&6). The flow duration curve (Figure 7) between the observed flow at 1DD1 gauging station and the simulated flow shows the good agreement. However, the simulated flows based on TRMM data set underestimates low flows.



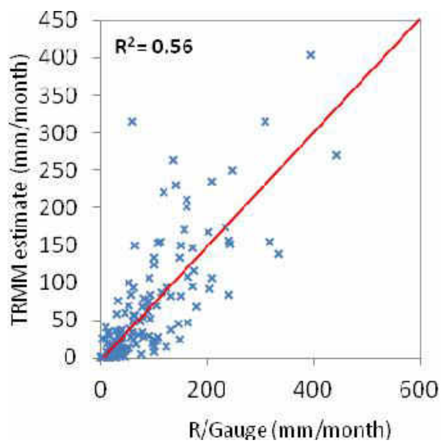
a) Moshi airport (09337004)



b) Naururu (09437016)

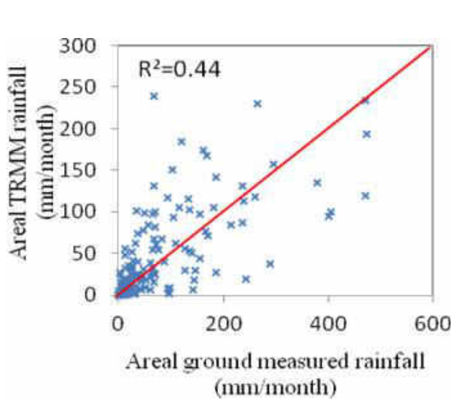


c) Maji Korogwe (09538040)

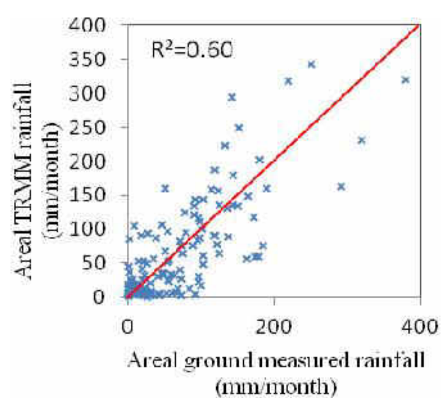


d) Lancon (09538053)

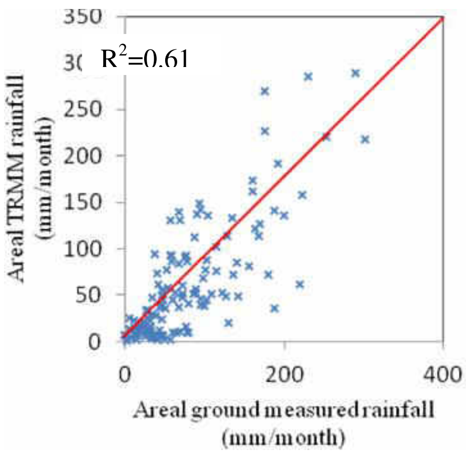
Figure 3a-d: Scatter plots of Monthly TRMM and ground measured rainfall (mm/month) for some selected Stations.

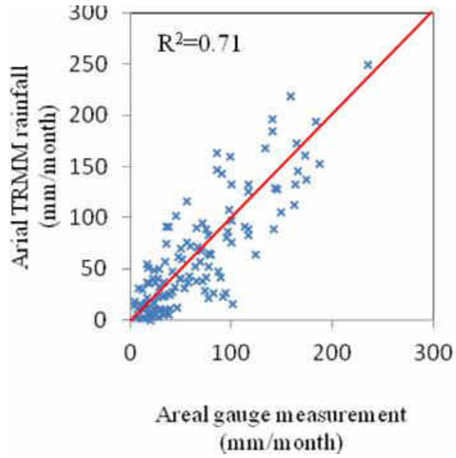


a) Kikuletwa

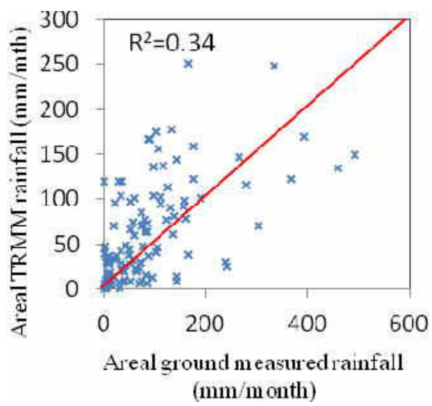


b) Luengera





c) Mkomazi **d) Pangani river**



e) Ruvu

Figure 4a-e: Scatter plots of monthly TRMM and ground measured areal rainfall (mm/month) for the main sub-catchments

Table 3: Model calibration and verification results for Kikuletwa subcatchment (1DD1) using ground measured rainfall data

Model		Calibration				Verification			
		R^2	*IoA*	*IVF*	*RE*	*R^2*	*IoA*	*IVF*	*RE*
Simulation Mode									
SLM (NP)		0.59	0.91	0.89	0.23	0.18	0.83	0.97	0.22
LPM (NP)		0.78	0.94	1.00	0.17	0.33	0.83	1.00	0.34
LVGFM		0.46	0.89	0.82	0.18	0.28	0.82	0.85	0.29
ANNM		0.80	0.94	1.00	0.14	0.17	0.79	1.06	0.21
SMAR		0.43	0.82	0.94	0.50	0.49	0.79	1.00	0.45
MOCTs	SAM	0.77	0.94	0.93	0.14	0.38	0.85	0.97	0.30
	WAM	0.82	0.95	0.99	0.02	0.27	0.82	1.04	0.00
	NNM	0.89	0.97	1.00	0.02	0.28	0.81	1.03	0.06

Table 4: Model calibration and verification results for Kikuletwa subcatchment (1DD1) using TRMM data

Model		Calibration				Verification			
		R^2	*IoA*	*IVF*	*RE*	R^2	*IoA*	*IVF*	*RE*
SLM (NP)		0.24	0.78	1.00	0.39	0.03	0.58	1.10	0.57
LPM (NP)		0.63	0.89	1.00	0.34	0.37	0.73	0.82	0.55
LVGFM		0.21	0.78	1.01	0.35	0.00	0.58	1.10	0.54
ANNM		0.73	0.92	0.99	0.00	0.42	0.73	0.83	0.47
MOCTs	SAM	0.60	0.88	1.00	0.31	0.36	0.69	0.96	0.53
	WAM	0.74	0.92	1.00	0.02	0.43	0.73	0.85	0.46
	NNM	0.77	0.93	1.00	0.04	0.45	0.74	0.86	0.43

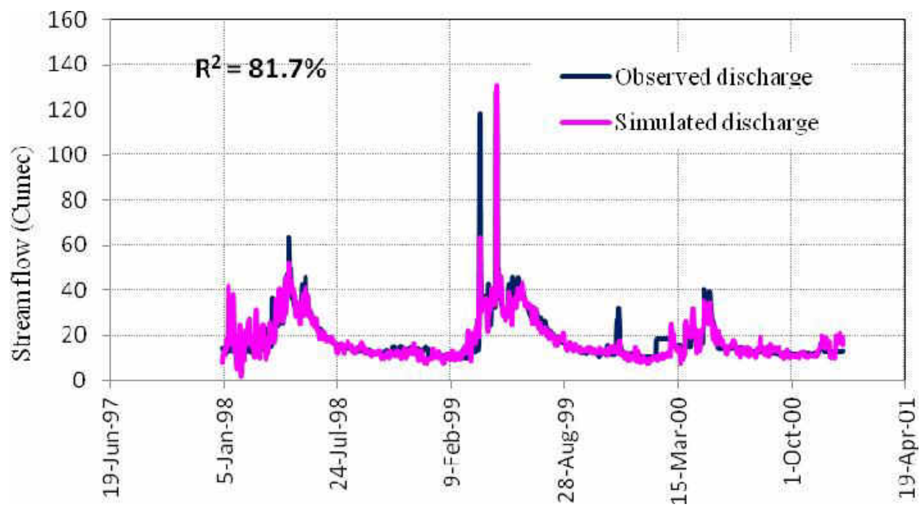


Figure 5: Observed and Simulated discharge MOCT (WAM) using ground measured rainfall – Calibration Period

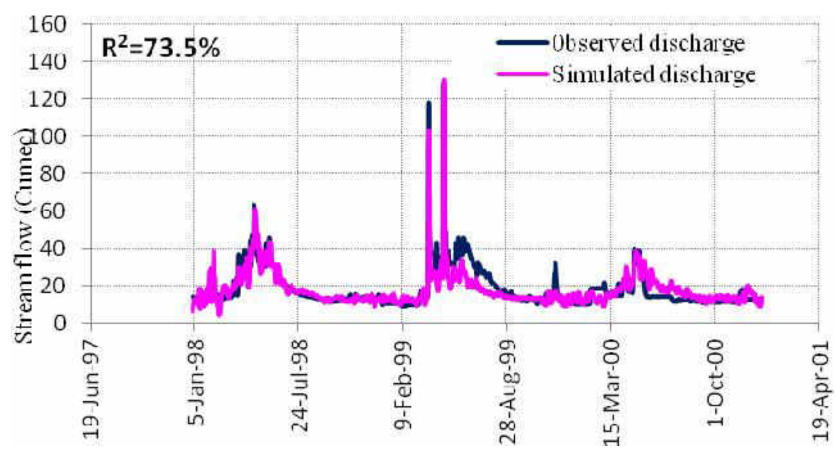


Figure 6: Observed and Simulated discharge MOCT (WAM) using TRMM – Calibration Period

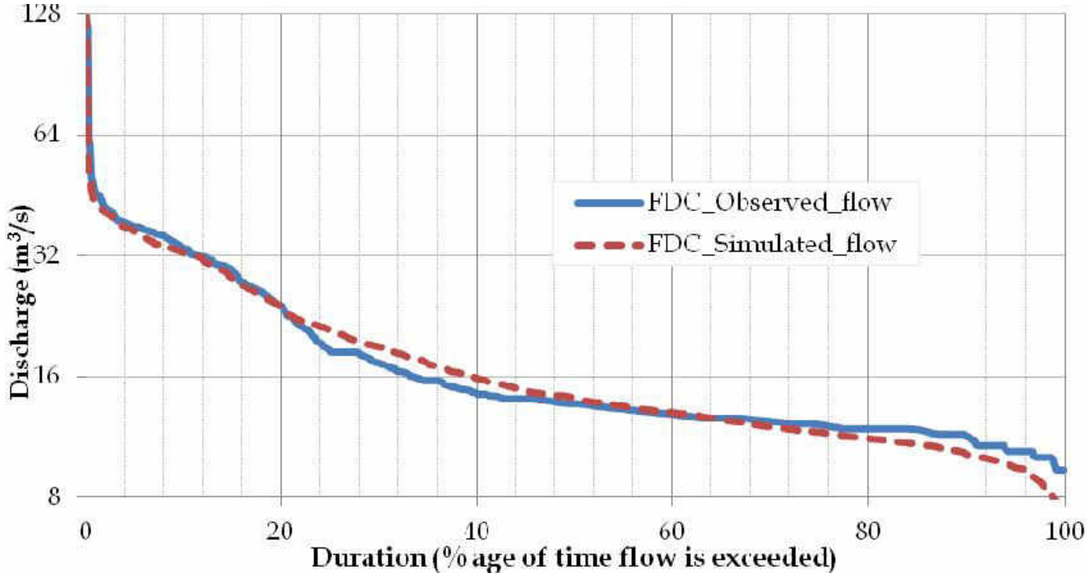


Figure 7: Flow duration curve for the observed and simulated flows

5. CONCLUSIONS

Comparison of gauges data and TRMM estimate at basin and subcatchments level was successfully evaluated using different statistical measures at different spatial – temporal resolution. From the results, it was clear that ground measured rainfall and TRMM data estimates compare fairly well at monthly scale than daily. The northern part of the study area i.e. Kikuletwa and Ruvu, TRMM estimates had poor performance than the rest of areas. This may be due to the influence of topography. Rainfall-runoff modelling using ground measured rainfall data had fairly better results than TRMM estimates for most of numerical efficiency criteria used, however TRMM estimates results were fairly good. It can be concluded that TRMM data at monthly time-step have good potential for useful application to hydrological modelling in the data scarce regions.

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