USE OF DOWNSCALED TROPICAL RAINFALL MEASURING MISSION DATA FOR METEOROLOGICAL DROUGHT MONITORING: CASE STUDY OF NARUMORU CATCHMENT

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ABSTRACT

Remotely sensed satellite rainfall data has gained popularity in the recent past, been especially attractive to ungauged catchments or poorly gauged catchments. Tropical Rainfall Measuring Mission (TRMM) data is considered to be most accurate of the satellite derived rainfall data and with the best spatial resolution at 250 x 250 grid. For purposes of hydrological modelling in small catchments, this data is usually downscaled to 1km x 1km grid to bring it closer to point measurement rain gauge data. This study evaluates whether downscaling of TRMM improves its meteorological drought monitoring capacity. TRMM was downscaled from the original 250 x 250 resolution (Approximately 28km x28km) to 1km x 1km resolution based on the relationship between Normalised Difference Vegetation Index (NDVI) and precipitation. Standardized Precipitation Index (SPI) was computed at 3, 6, 9, 12, and 24 month aggregation periods using the downscaled TRMM data (TRMM1km), TRMM at original resolution (TRMM28km) and observed rain gauge data. Analysis of Variance (ANOVA), t-test and data visualization methods were used to determine the similarity of the SPIs from the three datasets. Similarly, correlation analysis was done to determine dependency and modelling capability of the datasets.TRMM1km derived SPI was found to have lower correlation with the (correlation coefficients ranging from 0.34 to 0.42 for the different aggregation periods) rain gauge derived SPI as compared to TRMM28km derived SPI which had correlation coefficients ranging from 0.57 to 0.66. From analysis of variance, there was no significant difference between the SPI computed from TRMM and from that computed from rain gauge data. Additionally SPI visualization indicated similar drought patterns were identified by both TRMM and rain gauge computed SPIs. Therefore it was concluded that TRMM data, whether downscaled or at original resolution are useful for meteorological drought monitoring in Narumoro catchment.

KEYWORDS – *TRMM, Artificial Neural Networks, Meteorological droughts, remote sensing*

I. INTRODUCTION

Droughts affects more people on earth than any other natural disaster [1]. Droughts are defined as deficit below what is normal in surface water, groundwater, precipitation among others components of the water cycle resulting into hydrological, groundwater and meteorological droughts respectively [2]. Droughts in the meteorological and / or in hydrological sense ultimately results into some economic and / or social loss resulting into social-economic drought. Due to their huge impact on the society, droughts are constantly monitored using various indices including SPI (Standardized Precipitation Index), Palmers Drought Severity Index (PDSI) [3] just to mention a few. To effectively monitor droughts, reliable precipitation records in adequate temporal spatial resolutions are required. In most developing countries, a network of rain gauges that will provide the required coverage is largely missing or inadequate. Remotely sensed rainfall data can provide the required spatial and temporal coverage but as noted by [4], it is important to establish the accuracy of satellite precipitation data with the ground based observations since they are estimates and not direct observation of precipitation. [5] Also underscores the importance of verifying the usefulness and the quality of satellite derived precipitation due to their importance in filling in the limitation of traditional rain gauge data especially in the developing countries.

Drought monitoring is usually done by means of various drought indices, the Standardized Precipitation Index (SPI) is one the more popular index and has been recommended by the World Meteorological Organization (WMO) for drought monitoring all over the world and has found widespread application. Drought identification is based on taking a drought period to be a consecutives time interval where SPI is less than -1. SPI is computed by fitting a probability distribution on aggregated monthly precipitation series and by computing the corresponding non-exceedence probabilities and standard normal quantiles [6].

As mentioned, satellite data provides coverage for large spatial extent and large temporal resolution including real-time coverage. However the spatial coverage is often too coarse for work in localised / small catchments. TRMM data used in this research has a spatial resolution of 25^0 x 25^0 which is not comparable to point measurements by rain gauge. To compare or validate the satellite data it is important to have the data in resolution that is comparable to point measurements that are obtained from rain gauge data hence downscaling is required. Several studies have been done employing various methodologies for downscaling TRMM; [7] Used Digital Elevation Model from SRTM (Shuttle Radar Topography Mission) and SPOT VEGETATION to downscale TRMM in Qaidam Basin and they reported coefficient of determination r^2 ranging from 0.72 to 0.96 for the annual precipitation at six different rain gauge stations after validating the downscaled TRMM with the rain gauge data .In their study at the Iberian Peninsula, [8] used SPOT VEGETATION NDVI to downscale TRMM and they reported ”significant improvements in correlation, bias, and root mean square error for average annual precipitation over the whole period, for a dry year (2005), and a wet year”.

There is no extensive study done to evaluate the use of TRMM data in drought monitoring in Kenya and in small catchments, this study seeks to find out if TRMM data is suitable for drought monitoring in small catchments. Monitoring droughts in small catchments is important especially in water resources allocation. This is especially critical in Arid and Semi-Arid Lands in which Narumoro catchment is located.

This paper is organized into five sections: 1) Introduction where a background to the study is presented, 2) Study area where the case study area (Narumoro River catchment is described), 3) Methods section where the various methodologies and data used in the study is described, 4) Results and discussion section where the study’s results are presented and discussed, 5) Conclusions and recommendations of the study are presented in the conclusion and recommendation section 6) Finally the references used in the study are presented in this section, 7) at the very end is a short profile of the authors.

II. STUDY AREA

The study area is Narumoro river catchment. This catchment lies at the North Western slopes of Mt. Kenya. The river originates from the peak of Mount Kenya and is tributary to the Ewaso Ngiro River [9]. The catchment area utilized for this study is defined from the River Gauging Station (RGS) 5BC02, giving a catchment area of about 96 Km2 [10]. Within this area, only one rain gauge is available, the Narumoro Gate Station which is located within the Mount Kenya forest. From the 1971-2010 rainfall record, Narumoro station receives a rainfall monthly mean of 92 mm with most of the rainfall been received in MAM (March, April and May) and OND (October, November, and December) seasons.

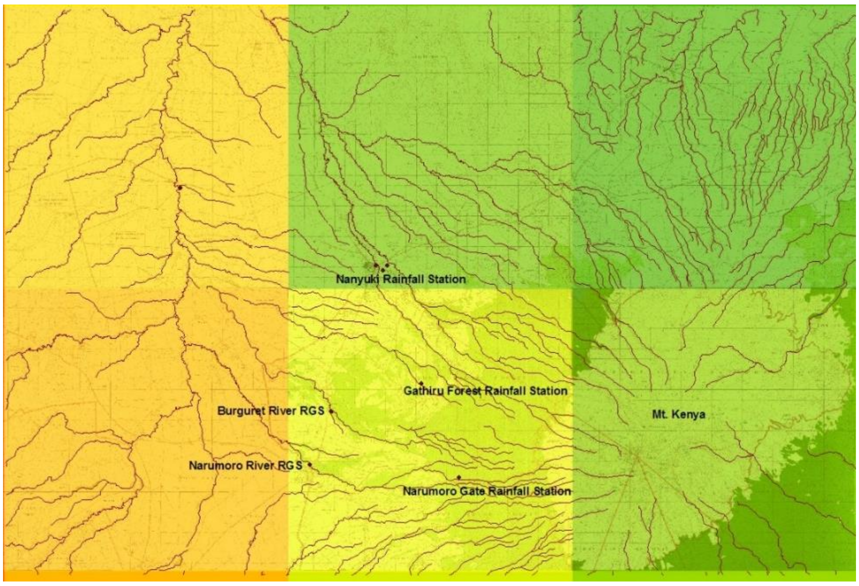


Figure 1: Location of the stations used in the Research. The brightly coloured patterns demarcate the TRMM 25^0 x 25^0Pixels

III. METHODS

The study focus is the utility of using satellite observed rainfall data for meteorological drought monitoring. The data collected consisted of the Tropical Rainfall Measuring Mission (TRMM 3B43 v.7) [11], [12] rainfall data, the SPOT VEGETATION (SPOT VGT data) for period 2000 – 2013, and Ground measured rain gauge data was also collected form Narumoro Gate Rainfall station.

3.1. Tropical Rainfall Measuring Mission

"The Tropical Rainfall Monitoring Mission (TRMM) is a joint project between NASA and the Japanese space agency, JAXA. TRMM was launched on November 27th, 1997. The primary TRMM instruments are the Precipitation Radar (PR) (the first and only rain radar in space)and the TRMM Microwave Imager (TMI), a multi-channel passive microwave radiometer, which complements the PR by providing total hydrometeor (liquid and ice) content within precipitating systems. The Visible Infrared Scanner (VIRS) is used to provide the cloud context of the precipitation and is used to connect microwave precipitation information to infrared-based precipitation estimates from geosynchronous satellites. TRMM processing algorithms combine information from these instruments and provide the finest scale(0.25°×0.25°) precipitation estimate currently available from space" [8]. Tropical Rainfall Measuring Mission is one of satellite derived precipitation estimates that has good spatial temporal resolution suitable for large scale precipitation / drought monitoring .

TRMM is distributed in form of netCDF files free of charge from NASA's website [13] In their study to evaluate the difference between rain gauge and TRMM data in Xinjiang catchment, [5] reported good correlation between the satellite estimates and the observed data, they further noted that daily TRMM values are ill fitted for estimating rainfall extremes and that monthly TRMM values can be used to simulate stream flows. It should also be noted that Rain gauge data are also known to be erroneous, [14] citing a world meteorological organisation article stated that rain gauge values could have up to 30% difference with the actual rainfall. Similarly, TRMM data suffers from errors which can be associated with non-detection, false detection and bias hence the need to calibrate and ground truth the satellite estimates [14] which is a challenge considering the potential errors in rain gauge measurements. In spite of the shortcomings, TRMM data have found wide application in hydrology and drought studies especially those involving large spatial areas.

3.2. Spot Vegetation 10-Day Composite NDVI

The 10 day synthesis is a 1km resolution product providing 10-day MVC NDVI [15], this data is obtained off the SPOT 4 and SPOT 5 satellite whose mission started in 1998. The SPOT VEGETATION

(VGT) products are available in the three types: a)Primary products (P), extracted from a single image segment, b) Daily (S1) or ten-day (S10) syntheses; these are mosaics of acquired image segments, respectively for 24h periods and for the last 10 days, and c) Vegetation indices (NDVI) calculated from daily or ten-day syntheses. The data (the S products) is distributed free of charge from the Vito website [16] in form of images, NDVI is computed from the pixel values in the image by using the following relationship:

$$NDVI = (RAW*0.004) - 0.1 \qquad (1)$$

Where *RAW* is the pixel value. There is a relationship between the SPOT VEGETATION (SPOT VGT) NDVI values a proxy for vegetation and precipitation [7], it is this relationship that is utilized in downscaling of TRMM to 1km resolution.

3.3. Meteorological Data

Data sets containing daily rainfall records for stations Narumoro Gate and Nanyuki MOW were collected from the Water Resources Management Authority (WRMA). The data starting from year 2000 up to 2011 was utilized for this study.

3.4. Downscaling of TRMM

Downscaling of the TRMM from $TRMM_{28km}$to $TRMM_{1km}$was done in accordance to the following procedure: SPOT VGT image resolution was degraded from 1km x 1km grid to 28km x 28km grid to match the resolution of TRMM image. The resulting SPOT VGT image is referred to as $VGT_{25.}$ A regression model was developed between VGT_{25} and TRMM by plotting TRMM against VGT_{25} and getting the best curve fitting the model. A polynomial relationship was found to be the best fit model based on R squared, the order of the polynomial model was varied from one to three and the best model was adopted for the downscaling. This regression was done for every month of the data set since the regression models varies across the different months due to influence of rainfall amounts and other seasonal factors. The typical polynomial models adopted are

$TRMM_{25} = aNDVI^3{}_{25} + bNDVI^2{}_{25} + cNDVI_{25} + d$ ---- 3^{rd} *order* (2)

$TRMM_{25} = aNDVI^2{}_{25} + bNDVI_{25} + c$ ---- 2^{nd} *order* (3)

$TRMM_{25} = aNDVI_{25} + b$ ---- 1^{st} *order* (4)

Where: $TRMM_{25}$ is TRMM at 25^0 x 25^0 grid, NDVI25 is NDVI computed from the SPOT VGT_{25} image, and *a, b, c, d* are the model factors determined by regression analysis. The model obtained is applied to the original NDVI image at 1km to obtain downscaled TRMM at 1km (P_n), and for every 28km pixel the average value P_{25} of the P_n is found. The two values are used to derive a weighting factor that is used to calculate TRMM at 1km ($TRMM_{1km}$) using the relation:

$$TRMM_{1km} = \frac{P_n}{P_{25}} * TRMM_{25} \qquad (5)$$

This process ensures that the average precipitation of the TRMM grid is preserved in the downscaled image.

3.5. Standardized Precipitation Index (SPI)

Standardized Precipitation Index (SPI) is used to monitor the development of meteorological droughts. It has been recommended by the World Meteorological Organization for use in drought monitoring. SPI was computed for 3, 6, 9, 12, and 24 month's aggregation period for $TRMM_{25}$, $TRMM_{1km}$ and original Rain gauge data to get SPI3, SPI6, SPI9, SPI12, and SPI24 respectively. Correlation coefficients between the SPIs so calculated were determined. TRMM values used were derived from the pixel within which the coordinates of the subject rain gauge is located.

IV. RESULTS AND DISCUSSION

4.1.Comparison of TRMM and Rain gauge data at Narumoro Gate Rainfall Station

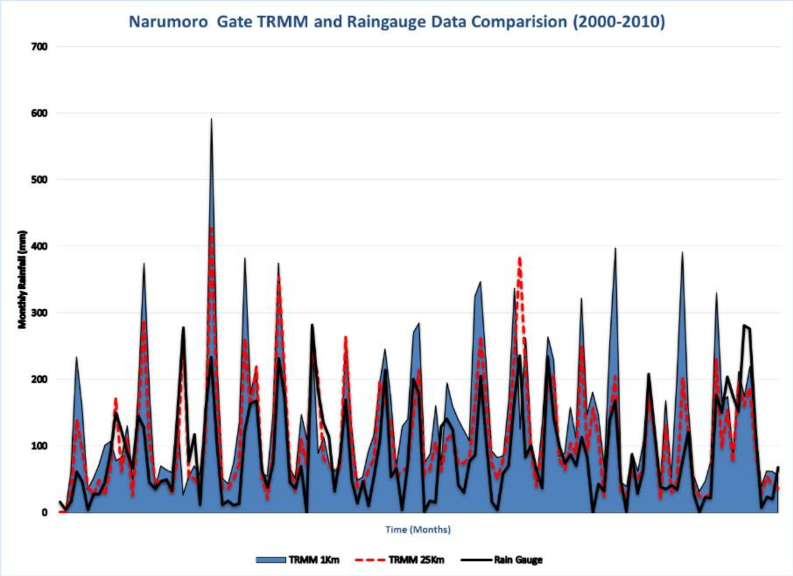


Figure 2: Comparison of TRMM and Rain gauge Data at Narumoro Gate Station, TRMM over estimates the Rain gauge observed rainfall.

Figure 2 shows that both TRMM1km and TRMM_{28km} over estimates the observed rainfall with TRMM_{1km} showing more rainfall than TRMM_{28km}. This observation is to be expected noting that the Narumoro gate station is located within the Mt. Kenya forest whereas most of the TRMM pixel it belongs to is semi-arid. By downscaling TRMM to 1km grid, the satellite estimates are more realistic and comparable to the situation on the ground. It can also be noted that all the three data sets displays a similar pattern indicating further that the TRMM data is able to capture the precipitation pattern. Table 1 shows that TRMM_{28km} is more correlated to rain gauge data that TRMM_{1km} is at Narumoro catchment.

Table 1: Correlation Coefficients of TRMM data and Rain Gauge Data

	TRMM 28km	TRMM 1Km	Rain Gauge
TRMM 1Km	0.83	1.00	
Rain Gauge	0.76	0.58	1.00

Drought Identification

Droughts were identified by computing SPI for TRMM_{1km}, Rain gauge data and TRMM_{28km}, The SPI values were plotted together in a comparison charts for visualization. The SPI comparison charts are presented in the following figures. In regard to SPI3 as seen in Figure 3, it is noted that the pattern of the SPI is similar for both TRMM and Rain gauge derived SPIs meaning that the suppression of precipitation is been picked by both the TRMM and rain gauge data. In cases of no-detection of droughts by TRMM, the corresponding SPI is mainly below 1 (SPI -1 to 1 is classified as near normal). TRMM_{28km} derived SPIs seems to follow the rain gauge derived SPIs better than TRMM_{1km}. the number of droughts identified generally increases from SPI3 – SPI24 in the case of TRMM_{1km}. Figure 4 shows the close match in SPI pattern as computed from TRMM_{1km} and those from rain gauge data. TRMM_{28km} does not follow the pattern quite closely but it does retain the general pattern. There are only one case of non-detection and false detection of drought by TRMM_{1km}, even with these cases the SPI classification is the same for both TRMM_{1km} and rain gauge data i.e. near normal. Figure 5 shows at 9 month aggregation, TRMM_{1km} detects droughts with a slight earlier onset time as compared to rain gauge data. This earlier onset if proven to be consistent, can be quite useful in drought early warning. This finding is consistent with correlation analysis which shows stronger dependence relationship between TRMM_{1km} and rain gauge derived SPI at SPI9 and SPI12 with correlation coefficients of 0.37 and 0.42 respectively (see Figure 9) .

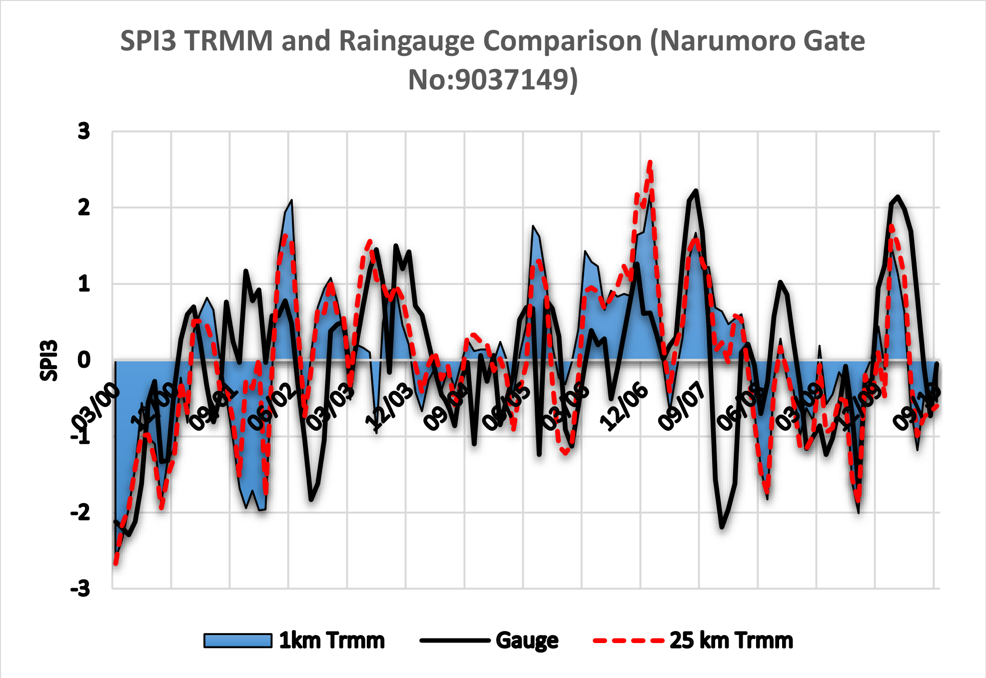
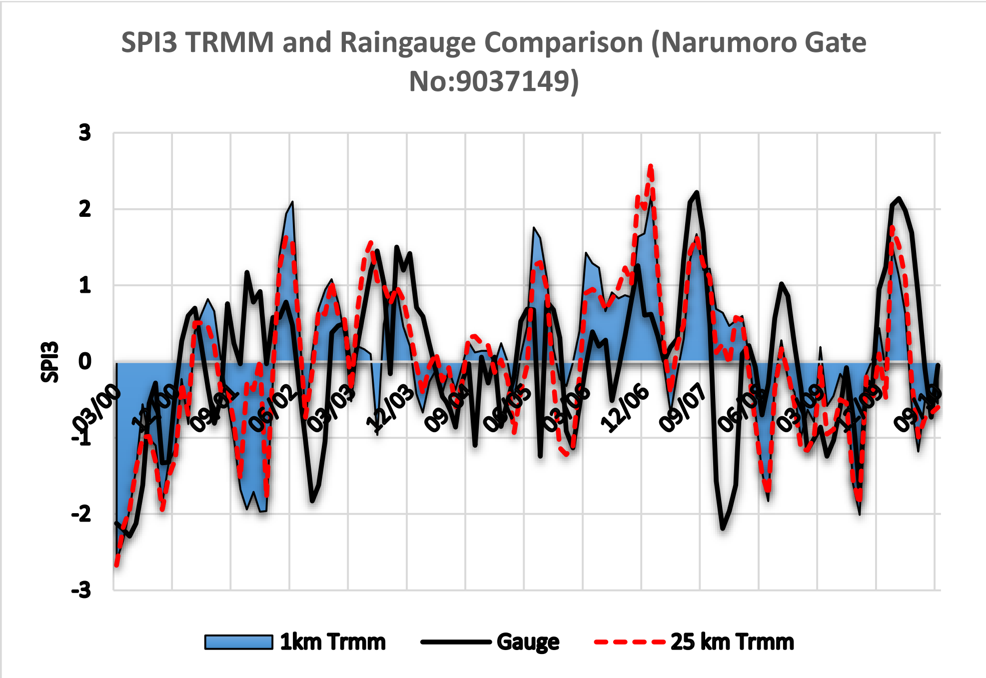


Figure 3: SPI3 derived from TRMM and Rain gauge Data for Narumoro Gate Station. TRMM1km SPI & TRMM28km pattern closely match, Rain gauge SPI follows a similar pattern though it picks more low points than both of the TRMM SPIs.



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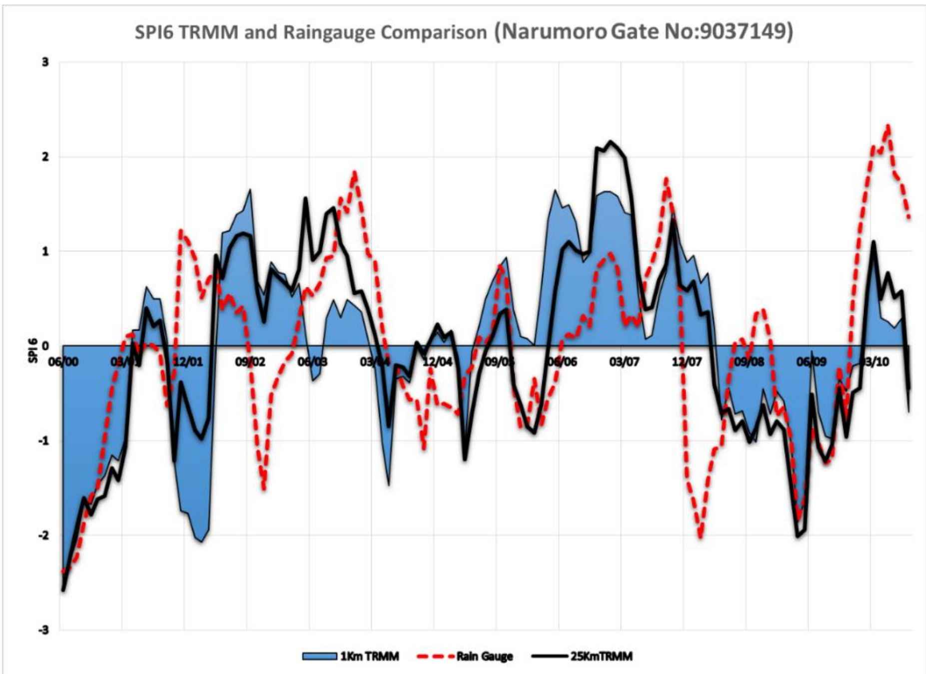

Figure 4: SPI6 derived from TRMM and Rain gauge data: there is a more similarity in the pattern of TRMM1km and rain gauge SPI than was in SPI3. TRMM SPI6 shape similarity with the rest is worsening. There is no case of non-detection by TRMM1km and only one case of false detect.

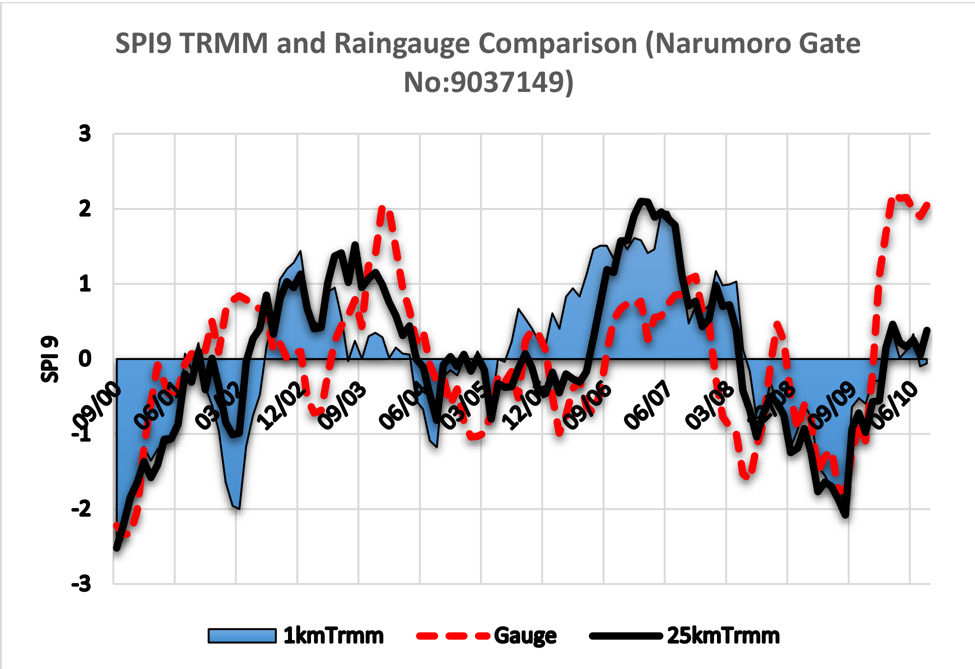

Figure 5: SPI9 from TRMM and Rain gauge Data: TRMM28km is largely out of pattern with the rain gauge and TRMM1km. There is a case of non-detection by TRMM1km showing drought recovery earlier than the rain gauge data does

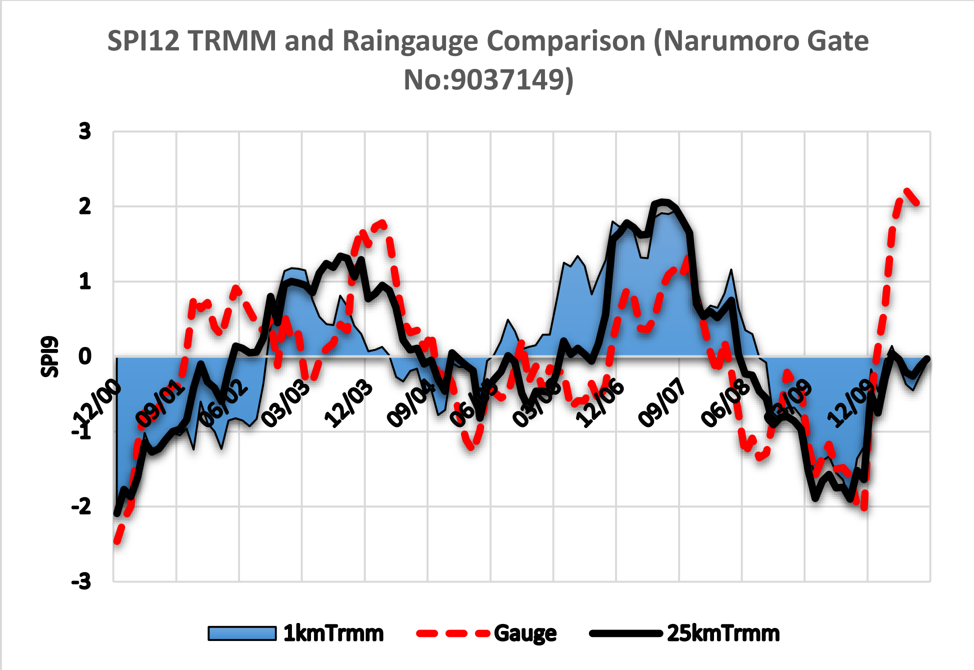

Figure 6: SPI12 from TRMM and Rain gauge data: TRMM28km SPI closely follows rain gauge TRMM in detecting onset and ending of drought periods though the magnitudes of the detected droughts varies. There is similarity in the drought patterns as detected by TRMM1km and those detected by rain gauge data.

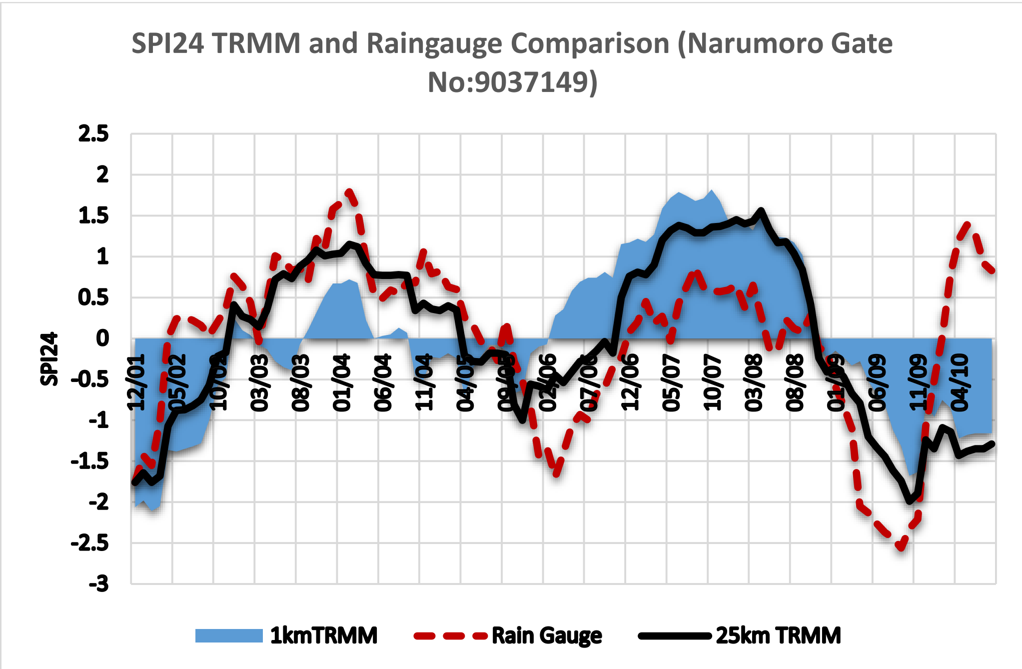

Figure 7: SPI24 computed from TRMM and Rain gauge data. The number of false detect by TRMM1km is higher than in other aggregations. TRMM25 has a better pattern with rain gauge SPI than in all other aggregations.

Figure 5 and Figure 6 shows very similar drought patterns to those shown by the rain gauge data, for the same aggregation period the correlation coefficients with the rain gauge data is higher than for all other aggregation periods as can be seen in Figure 9. The p-values from the t-test and ANOVA as seen Figure 8 decreases from SPI3 to SPI6, however it can be noted that the decrease in p-values from SPI6 and SPI12 is very minimal which can be explained by the close matching of the drought patterns identified by $TRMM_{1km}$ and rain gauge data.

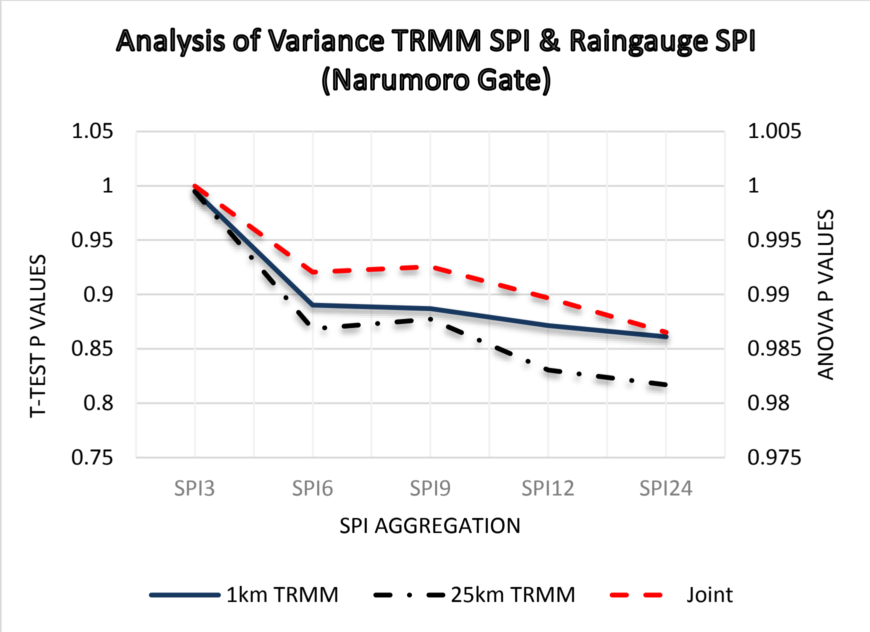

Figure 8: Analysis of variance shows that the probability of the SPI means derived from all sources are similar. The similarity decreases with the increase in SPI aggregation period. On average this would mean that droughts identified through the data sets are similar.

Table 2 and Table 3 shows drought class identification for the study area, the identified drought periods are very similar across the different drought classes and along the various aggregation period.

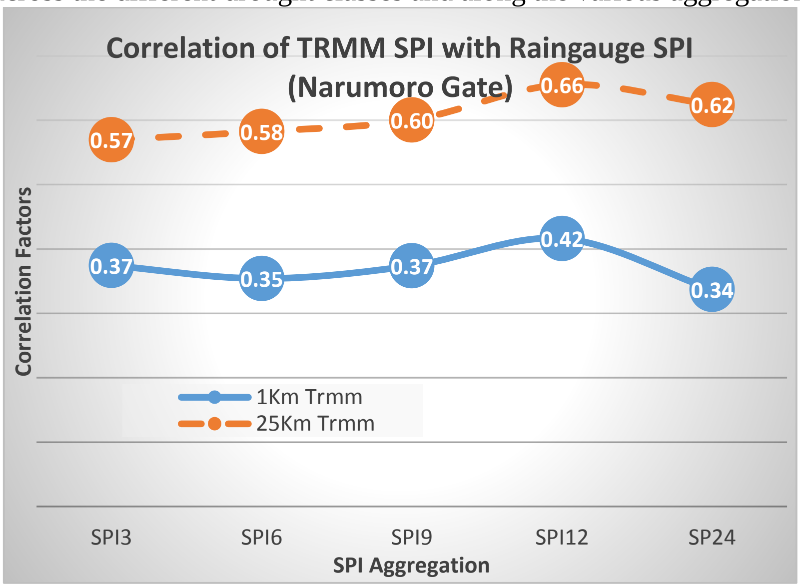

Figure 9: Correlation Analysis of the SPI Values showing that TRMM28km is correlated to Rain gauge SPI.

Table 2: Drought Class Identification for Narumoro Gate Station using SPI3 and SPI6. Note the near match in the droughts periods identified

	SPI3			SPI6		
	TRMM$_{1km}$	**Gauge**	**TRMM$_{28km}$**	**TRMM$_{1km}$**	**Gauge**	**TRMM$_{28km}$**
Extremely Dry	3	5	2	5	4	3
Severely Dry	9	7	8	7	7	6
Moderately Dry	9	11	9	11	10	11
Near Normal	41	39	48	32	41	40
Total	**62**	**62**	**67**	**55**	**62**	**60**

Table 3: Drought Class Identification for Narumoro Gate Station using SPI9, SPI12 and SP24. Note the near match in the droughts periods identified

	SPI9			SPI12			SPI24		
	$TRMM_{1km}$	Gauge	$TRMM_{28km}$	$TRMM_{1km}$	Gauge	$TRMM_{28km}$	$TRMM_{1km}$	Gauge	$TRMM_{28km}$
Extremely Dry	3	4	3	1	4	1	3	8	0
Severely Dry	8	8	7	7	4	12	3	3	8
Moderately Dry	10	8	9	14	11	5	13	9	15
Near Normal	37	43	42	42	45	47	55	36	46
Total	**58**	**63**	**61**	**64**	**64**	**65**	**74**	**56**	**69**

V. CONCLUSIONS AND RECOMMENDATIONS

The following comments and conclusions can be made on the results: 1) both the original and downscaled TRMM are capable of picking up the drought pattern as identified by SPI, 2) From the analysis of variance and the t-test as seen in Figure 8, there is no significant difference between means of SPIs from both TRMM and rain gauge data. This confirms that the TRMM data can be used to define droughts in study area, 3) based on figure 3 -7, it is noted that the onset and cessation of the drought events as indicated by the different SPIs is similar. Cases of non-detection or false detection by TRMM are few and in most of these incidences, Rain gauge data derived SPI are between +1 and -1 which basically belongs to the same drought class (Near Normal), 4) Downscaled TRMM SPI is more similar to the rain gauge SPI than is non-downscaled TRMM as indicated by the p-values of the t-test. These similarity decreases from SPI3 to SPI24 which SPI24 having the least similarity indicating drought monitoring using TRMM data is best done at aggregation periods of less than 9 months (see Figure 8). TRMM can be used to monitor meteorological droughts in Narumoro catchment. Downscaling the TRMM to 1 km appears to improve these capability. It is recommended that more studies to be done on the downscaling process to improve the similarity of TRMM and rain gauge data and how to use the TRMM in ungauged catchments.

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