Available online at http://www.journalcra.com

International Journal of Current Research
Vol. 12, Issue, 07, pp.12796-12803, July, 2020

DOI: https://doi.org/10.24941/ijcr.39267.07.2020

ISSN: 0975-833X

INTERNATIONAL JOURNAL
OF CURRENT RESEARCH

RESEARCH ARTICLE

COMPARISON OF TRMM3B42 V7 DERIVED SATELLITE RAINFALL WITH TWO RAIN GAUGE DATA FOR YEARS 2000 - 2012, KILIFI, KENYA

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ARTICLE INFO

Article History:
Received 07th April, 2020
Received in revised form
25th May, 2020
Accepted 27th June, 2020
Published online 30th July, 2020

Key Words:
Kilifi; Kenya Coast; TRMM3B42v7; validation; Rainfall detrending

ABSTRACT

The study presents the results of rainfall data comparisons from three sources, namely the Kilifi Plantation Limited (KPL), Pwani University (PU) and Tropical Rainfall Measuring Mission's (TRMM), TRMM3B42v7 satellite derived rainfall. The study aims at evaluating the ability of TRMM data to substitute local rain guage data as a sub-daily input parameter due to its finer temporal resolution. The study is motivated by the need to know the characteristics of sub-daily rainfall that would be useful in groundwater artificial recharge studies. The study's methodology of comparing trend, seasonality and remainder of the rainfall data indicates that after removal of trend and seasonality in the rainfall data, the remainder signals' cross correlation function between the datasets have a range of difference that may be accounted for by rainfall variability. The value for TRMM3B42v7/KPL is 0.43, for TRMM3B42v7/PU it is 0.48 and for PU/KPL is 0.49. This is further evidence of variability of rainfall in Kilifi as the cross correlation function of local ground gauges are not much different when compared with and to the satellite data-set. These Comparisons of similarities made on TRMM3b42v7 satellite derived rainfall against two local rain-gauges at a distance of 5 km apart from each other, was for data from 2000 – 2011. Out of the 4017 rainfall data events, 1801 are coincident (wet days) in at least one of the three rainfall data-sets. Kolmogorov-Smirnoff (KS) test that was used on the coincident rainfall events and had a p value of less than 0.05 for the two tailed test. Further cross correlation was done on the rainfall, which was decomposed for more analysis. The similarities obtained from the correlation of the decomposed trend, seasonality and remainder of the three datasets indicate that TRMM3B42v7 data can be used as a data input to model for the hydrological studies in the envisaged artificial aquifer recharge. This study also reveals the strengths and limitations of using the satellite derived rainfall product. The correlation of Kilifi rainfall data-sets with TRMM3B42v7 can be regarded as good when the cross correlation function between the ground gauges are noted to be in similar range to their correlation with TRMM3B42v7 data. This is despite close distance between the rain gauges.

Citation: ***Collins O. Owuor, Mwakio Tole and Bernards Okeyo.* 2020.** "Comparison of TRMM3B42 v7 Derived Satellite Rainfall with two rain gauge data for years 2000 - 2012, Kilifi, Kenya..", *International Journal of Current Research*, 12, (07), 12796-12803.

INTRODUCTION

The use of satellite derived rainfall for hydrological studies requires that it is validated and compared to local rain guages. The comparison can be done in a number of ways. The intensity, amount and time of rain-events can be compared on a skill score methods similar to studies by Tufa Dinku *et al.* (2018); Ochoa *et al.* (2014); T Dinku *et al.* (2007) and many more authors. The rmse of the correlation between rainfall data has been used to infer similarity of rainfall time series similar to validation studies by Khan, Koch, and Chinchilla (2018); Scheel *et al.* (2011); Gourley *et al.* (2011) and many other authors.

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Other statistical requirements before the data, and can be used is correction of the biases that may arise from instrumental sources and conversion algorithms. Due to its finer temporal and sometimes spatial resolution Satellite derived rainfall products are more desirable datasets to use in some studies and therefore requires that they be validated and compared with available coarse scale local rain gauge data. Comparison of rainfall from different sources, (whether the source is radar, satellite or ground rain gauges), requires techniques that can deal with the non-linear, non-stationary and randomness in the nature of rainfall. Methods to obtain spatially and temporally fine scale data from coarse daily rainfall data include the application of dissaggregation techniques on the observed data and also the use of validated satellite derived rainfall data.

The latter are produced by algorithms that link the cloud microphysical phenomenon to measured signals of satellites. The utility of satellite derived rain products in hydrological studies can be known after validation with local rainfall gauges having adequate data coverage. Numerous validation and comparison studies for TRMM rainfall products against local gauges in different climatological environments (Michot *et al*. 2018; Quirino *et al*. 2017; Hong *et al*. 2018) have been carried out showing different levels of skill scores and having both positive and negative biases (Cohen Liechti *et al*. 2012; Ochoa *et al*. 2014; Jiang *et al.* 2016;). Reasons given for the lack of agreement between local gauges and the satellite have been attributed to algorithm inadequacy (Lo Conti *et al*. 2014; Petty and Krajewski 1996), instrument limitations (Tufa Dinku, Connor, and Ceccato 2011; Clarke *et al*. 2011) and difficulty in representation of cloud microphysics (Vali 1997; Michaelides 2019). These shortcomings in derived rainfall products are noted to have challenges in reflecting gauge data and therefore validation studies must be carried out before the derived rainfall product can be used in hydrological studies (Venkata Lakshmi Kumar *et al*. 2019). Different metrics have been used to validate rainfall data, most include statistical measures of dispersion and correlation between the validated rainfall and gauge rainfall.

In checking the accuracy (validation) of the satellite derived rainfall against the local rainfall gauges the metrics must be first be interrogated for their overall goal in showing similarity. Similarity can be defined by fidelity to amplitude, frequency and phase comparisons of time series data. Local variability of rainfall has been reported alongside low temporal resolution as challenges in the use of rainfall data for analysis in hydrological studies. The justification for obtaining temporally fine scaled rainfall data are numerous and has given by many authors in disaggregation studies (Koutsoyiannis 2003; Segond *et al*. 2007; Güntner *et al*. 2010; Breinl and Di Baldassarre 2019). Notable reasons include high rainfall intensities over short periods that frequently have a significant effects on peak flows and flood frequency curves. An example of requirement of fine temporal scale temporal rainfall data would include recharging an aquifer from rainfall harvested rainfall. The required rainfall data cannot be provided by daily rainguage measurements, similar to design problems observed in of urban storm drainages. A similar need is in sizing of drains and sinks in other hydrological studies where runoff from surfaces requires data at finer than daily temporal measurements. e.g. rainfall intensities over short periods frequently have a significant effect on peak flows and flood frequency curves (Hingray and Ben Haha 2005; Segond *et al*. 2007; Hannes Müller *et al*. 2017). It is therefore important that rainfall data should be capable of capturing intensities and frequences at a finer scale. Disaggregation has been used in many hydrological investigations with, cascading the rainfall based on some justified statistical criteria. Disaggregation methods usually require external temporal rainfall pattern (Hingray and Ben Haha 2005) for more valid outcomes. Disaggregation of coarse data to the required level can also obtain better temporal and spatial resolution,however it is necessary to know the phenomenon behavior at the disaggregated scale, to allow for improved disaggregation results (Sivakumar 2001; Koutsoyiannis 2003; Hannes Müller *et al*. 2017; H. Müller and Haberlandt 2018).

TRMM3B42v7: The Tropical Rainfall Measuring Mission (TRMM) is a joint mission between NASA and the Japan Aerospace Exploration Agency (JAXA) designed to monitor and study tropical rainfall. (NASA and JAXA 2001). The TRMM 3B42V7 product time series has a 3-hour temporal resolution and a 0.25 degree spatial resolution (Goddard Earth Sciences Data and Information Services Center (GES DISC) 2011).The origins and characteristics of TRMM have been summarized in (Seyyedi *et al*. 2014).

Measures of comparison: Most statistical methods assume normality, and are based on the assumption that the data follows a normal distribution or a Gaussian distribution (Ghasemi and Zahediasl 2012) and will have limited ability in comparisons of rainfall time series which have a non Gaussian distribution. Comparisons/similarity of rainfall data that are purely qualitative may be enough for some applications, when quantitative approaches are limited. Quantitative comparisons of two or more data signals have challenges because the metrics used differ widely from author to author depending on the intended application of the rainfall product and ground data available.

Examples of some common measures and metrics include the use of Mean Squared Error (MSE), which is a measure of how close a fitted line is to data points. Root Mean Squared Error (RMSE) is also commonly used and is just the square root of the mean square error. Other measures include Mean Absolute Error (MAE), which is a measure of difference between two continuous variables. Efficiency Indices such as Kling Gupta- (KGE) and Nash-Sutcliffe NSE index are efficiency criteria that are used to see how well an observed data is predicted by another data set (Krause, Boyle, and Bäse 2005; Moriasi *et al*. 2007; Gupta *et al*. 2009). The Kolmogorov-Smirnov test (KS-test) tries to determine if two data-sets differ significantly. The KS-test has the advantage of making no assumption about the distribution of data. The Kolmogorov–Smirnov test is a nonparametric goodness-of-fit test and is used to determine weather two distributions differ, or whether an underlying probability distribution differs from a hypothesized distribution. ("Kolmogorov–Smirnov Test" 2008). It is a good comparitor of the shape of two distributions. The test hypothesizes that the two samples were drawn from the same distribution. Dynamic Time Warping (Shou, Mamoulis, and Cheung 2005; Fu 2011) and Spectral similarities (Morse and Patel 2007; Ma *et al.* 2016) can also be used to measure similarity of two time series. In addition to these methods dynamical characteristics of time series is can be made from entropy. Entropy has been referred to as quantified uncertainty with a tendency to achieve a maximal value (Koutsoyiannis 2014). Sample entropy (SE), Permutation entropy (PE) and a new method, termed dispersion entropy (DE) have been previously used in the assessment of dynamical characteristics of time series. DE has been used above PE and SE (Rostaghi and Azami 2016). According to Phung *et al*. (2014) Shannon entropy can be used to reflects how well a data-set can predict the behavior of another data-set, inferring, that higher entropy indicates more complex or chaotic systems, and is thus less predictable. The Kullback–Leibler divergence in entropy has been explained as a method of comparing differences between two probability distributions and a measure how much information is lost when one distribution is used to approximate another one. (Cheng *et al.* 2017) has summarized the most used measures of comparison in hydrological studies.

Decomposition of data: Seasonal Decomposition of Time Series by Loess ("locally-weighted scatterplot smoothing") uses local regression to separate trend and seasonality in data. The seasonal decomposition of time series based on loess, "STL", is a filtering procedure for decomposing a time series into trend, seasonal, and remainder components. (Cleveland *et al*. 1990). Rainfall time series is here considered as a time series signal that can be decomposed to trend, seasonality and remainder components (Figure 2).

Bias corrections: Bias corrections are widely applied in satellite observations to correct biases that may arise from numerous sources that include a combination of instrumental effects, systematic errors in the radiative transfer model, or the bias of the forecast models applied (Dee 2004). To remove these biases in order to minimize the differences in observational data and satellite data many methods exist that include variational bias schemes (Fertig *et al*. 2009; Milan and Haimberger 2015).

Data and Methods: In order to obtain finer temporal data than those that are currently generated by available rain gauges, TRMM3B42v7, the satellite derived rainfall, was downloaded, for the years 2000-2013. Kilifi Plantation rainfall data set comprised of the years 2000 – 2011 with 2008 data missing. Pwani university available rainfall data was for the year 2000 – 2012. The TRMM data was compared to two local rain-gauge datasets. Both graphical and non parametric statistical methods were used for the investigation. Entropy values were also obtained to indicate degree of complexity and regularity of the rainfall time series.

Rainfall data: The three rainfall datasets Kilifi Plantation (KPL), Pwani University(PU) and Satellite data (TRMM3B42v7) were obtained. The latter was downloaded from GIOVANNI, (Geospatial Interactive Online Visualization ANd aNalysis Infrastructure). https://disc.gsfc.nasa.gov/ datasets/TRMM_3B42_7/summary). This is a NASA/JAXA data-set, with a 3 hourly temporal resolution and a spatial resolution 0.25 degree x 0.25 degree. The TRMM3B42v7 dataset is a satellite derived rainfall product that is obtained from algorithms as and are calibrated with rain gauge measurements (Tropical Rainfall Measuring Mission (TRMM) 2011).

METHODS

The TRMM3B42v7 data set was accumulated to daily values from the 3 hourly downloaded rainfall time series with observations made from 00:00 UTC to 21:00 UTC. All the three data sets were plotted together using their daily rainfall from 2000 – 2012 despite KPL missing 2008 rainfall data to make qualitative observations, (Figure 1). The three data sets were statistically evaluated using metrics of distance, namely RMSE and MAE and entropy (Table 2). It was noted that the three data-set time series did not have a stationary mean and required non-normally distributed data statistical methods for comparison. Catogorised correlations were also carried out in the three data sets to gain insight on the nature of rainfall at different intensities. The results are indicated in Decomposition of Rainfall data sets.

After the initial plots of the three data sets that showed observations with similarities in trends and seasonality, see (Figure 2). The data was decomposed to trend, seasonality and residual components. The former two, which were observed to show high correlations, were removed to allow the correlation of the residual component. The results can be found in Figure 4. The decomposition of the daily time series was carried out for the years 2000 -2007 that was unbroken and common to all the datasets. This was done using open source STL package by Cleveland *et al*. (1990).

RESULTS

The preliminary statistics for rainfall data-set events (2000 - 2012) are tabulated in table 2.

Quantile Statistics: The number of coincident rainfall events for all the rainfall data sets were 219, while between KPL and TRMM3B42v7 was 291 and Pwani university and TRMM3B42V7 was 392, compared to 557 between ground gauges of KPL and Pwani University. There were also 1801 wet rainfall events that were recorded in either of the three data sets, i.e 2216 (4017 – 1801), non wet rain days of the 4017 recorded rainfall data, spanning 2000 to 2011 with 2008 data missing (Due to missing KPL 2008 rainfall data). The unbroken rainfall time series of the data was up to the end of 2007. This was used in comparative analysis of the rainfall time series.

Correlation Functions (CCF): The 0.95 confidence levels (horizontal black dotted line in figure 4(d) and figure 5) have been calculated from the formula qnorm ((1 – conf level)/2)/sqrt (number of data rows). The summary (table 2) on statistical parameters indicate a better agreement between KPL and TRMM3B42v7 data-set on all comparison measures between the data-sets. Of the 4017 data events 1801 events had rain reported in one of the three data sets and the KS statistics for the latter have been included. The two sample Kolmogorov-Smirnofft est is used to test whether two samples come from the same distribution. The p-value for the KS-D statistic is much less than the significance level of 0.05 or 0.01 and therefore indicating that the underlying distribution are dissimilar for the datasets, with the highest similarity found between KPL and TRMM3B42v7. With a D statistic of 0.14, one rejects the null hypothesis that the two samples were drawn from the same distribution if the p-value is less than the chosen significance level . The Shannon entropy measures the information content of data or as a measure of uncertainty and shows the highest value for KPL and the lowest for TRMM data-set. Meanwhile the Kullback-Leibler (KL) divergence is a measure of how different a probability distribution Y is with respect to some initial one X, showing that the largest divergence is between PU and TRMM while the smallest between KPL and PU.

DISCUSSION

The cross correlations are strongest for Kilifi Plantation and TRMM3B42v7 data for all the categories of rain with weakest correlation being between Kilifi Plantation and Pwani University for all categories of rain except for rainfall between 30 mm and 50 mm. Several reasons can be advanced on the low correlation between Pwani University and Kilifi Plantation that are only 5 km apart, and the stronger correlation of TRMM3B42v7 with Kilifi plantation data. These may include differences in the gauge types between KPL and PU along with TRMM3B42v7 instrument and algorithm limitation. The random nature of rainfall at different categories in this area is observed in all the three data-sets.

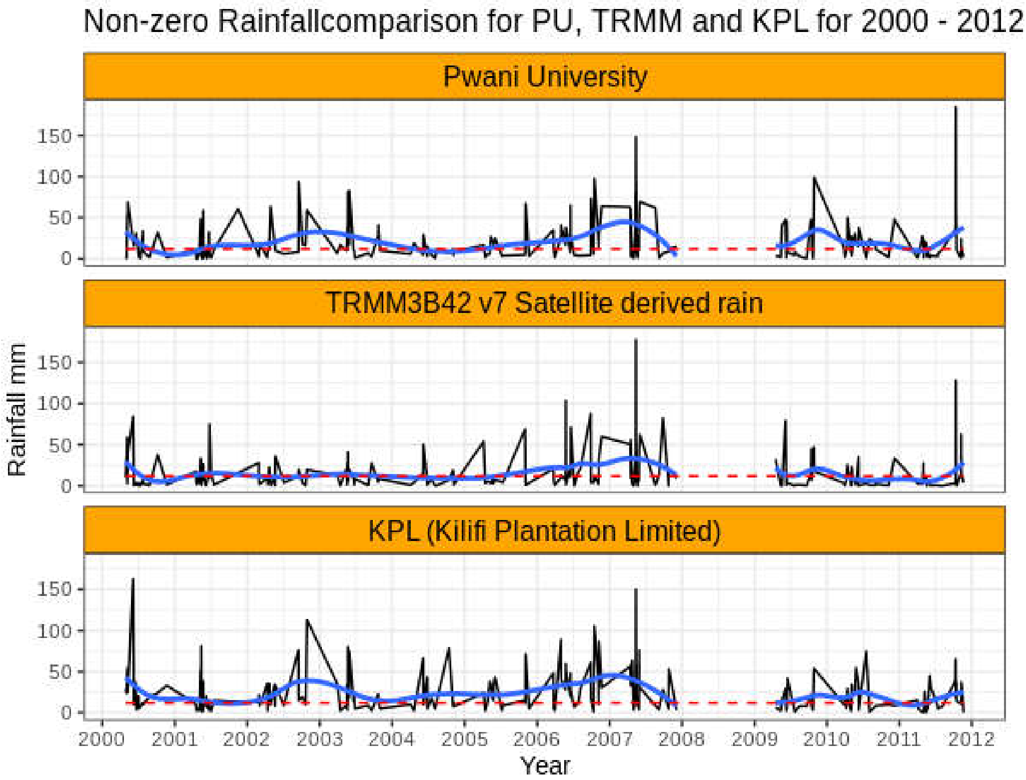

Figure 1. Rainfall data for Pwani University, TRMM and KPL (smoothing line in blue) and median line in dashed red

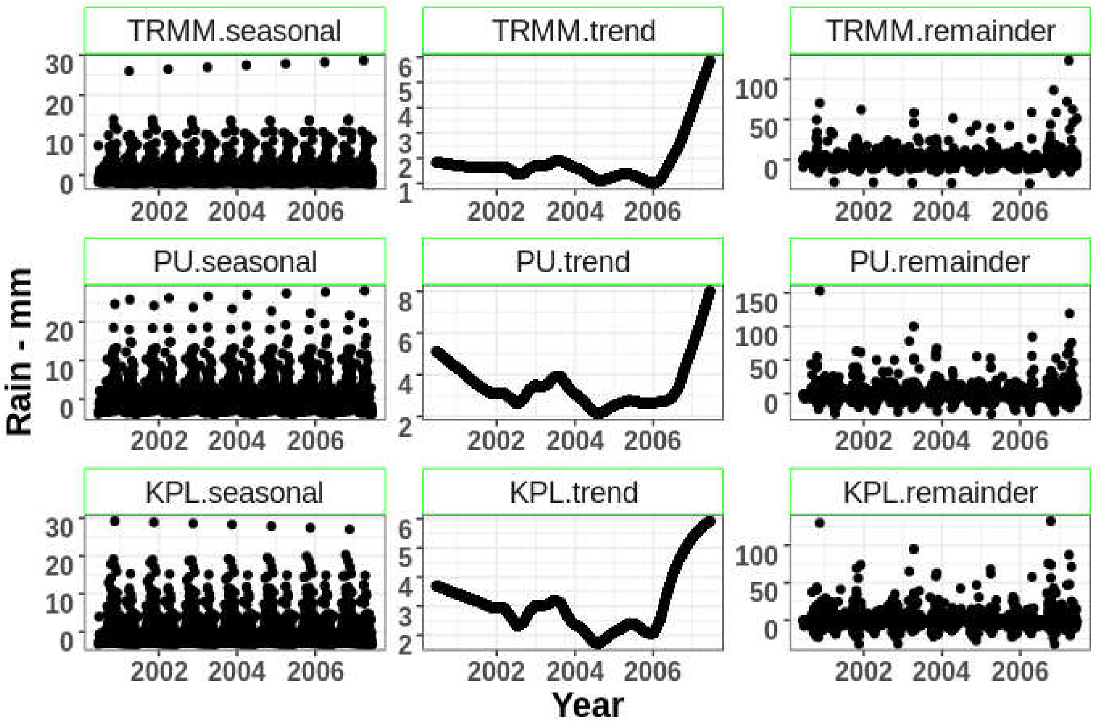

Figure 1. Rainfall decomposition

Table 1: Quantile statistical values

	Pwani University Rainfall (mm)	KPL rainfall (mm)	TRMM3B42v7 derived rainfall (mm)
Min.	0	0	0
1st Qu.	0.02	0	0
Median	2	0	0
Mean	7.823	6.497	3.964
3rd Qu.	8	6.604	2.34
Max.	184.5	162.56	177.69
No of recorded rain days	1378	763	681

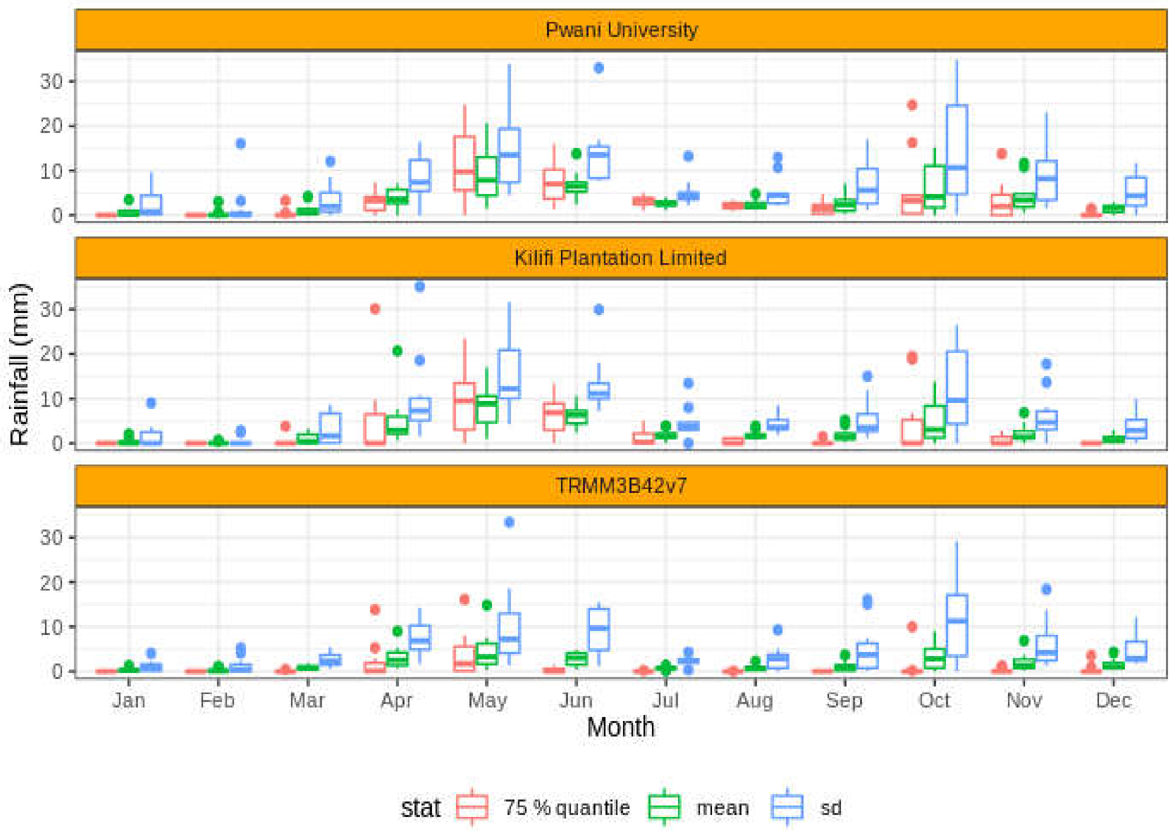

Figure 2: 75% quantile, mean and Standard deviation values compared for PU, KPL and TRMM3B42v7 data

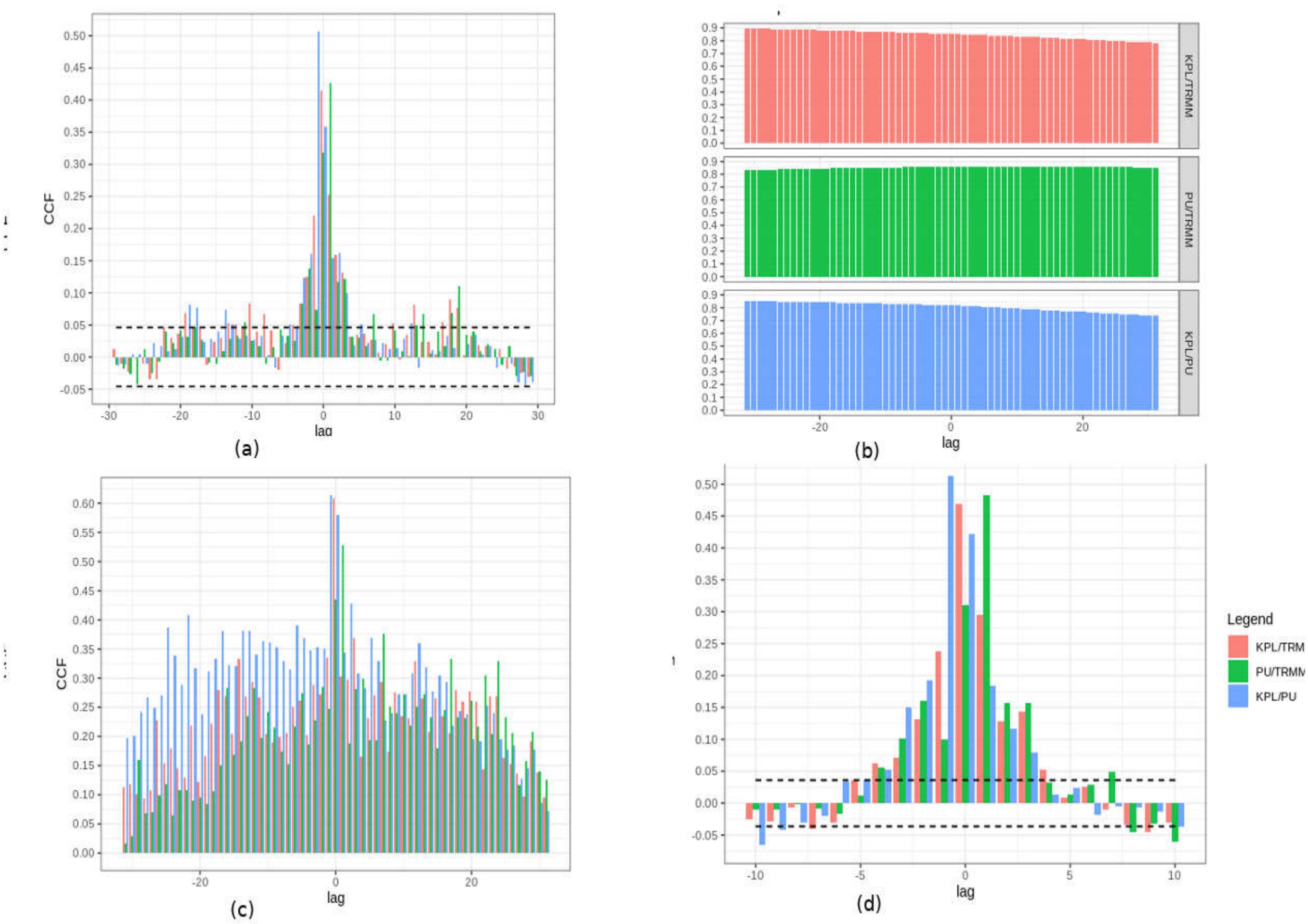

Figure 3. (a) CCF of undecomposed Rainfall Data, (b) Decomposed Trend CCF, (c) Decomposed Seasonality CCF (d) Decomposed Residual CCF

Table 2: Statistics on rainfall events of the rainfall data sets

Statistic	KPL/TRMM		PU/TRMM		KPL/PU	
	All (4017) coincident rainfall data	All (1801) rainfall data with at-least a rain event recording in one of the three datasets	All (4017) coincident rainfall data	All (1801) rainfall data with at-least a rain event recording in one of the three datasets	All (4017) coincident rainfall data	All (1801) rainfall data with at-least a rain event recording in one of the three datasets
MSE	96.97	216.29	129.61	289.09	134.00	298.89
RMSE	9.85	14.71	11.38	17.00	11.58	17.29
MAE	3.14	7.01	3.80	8.48	3.78	8.44
R2	0.21	0.17	0.14	0.10	0.18	0.13
KS-D statistic	-------------	0.14	-------------	0.41	-------------	0.34
KS-P statistic	-------------	4.441e-16	-------------	< 2.2e-16	-------------	< 2.2e-16
Shannon Entropy	-------------	6.12 (KPL)	-------------	5.70 (TRMM)	-------------	6.39 (PU)
K.L divergence	-------------	4.473187	-------------	5.312002	-------------	4.192385

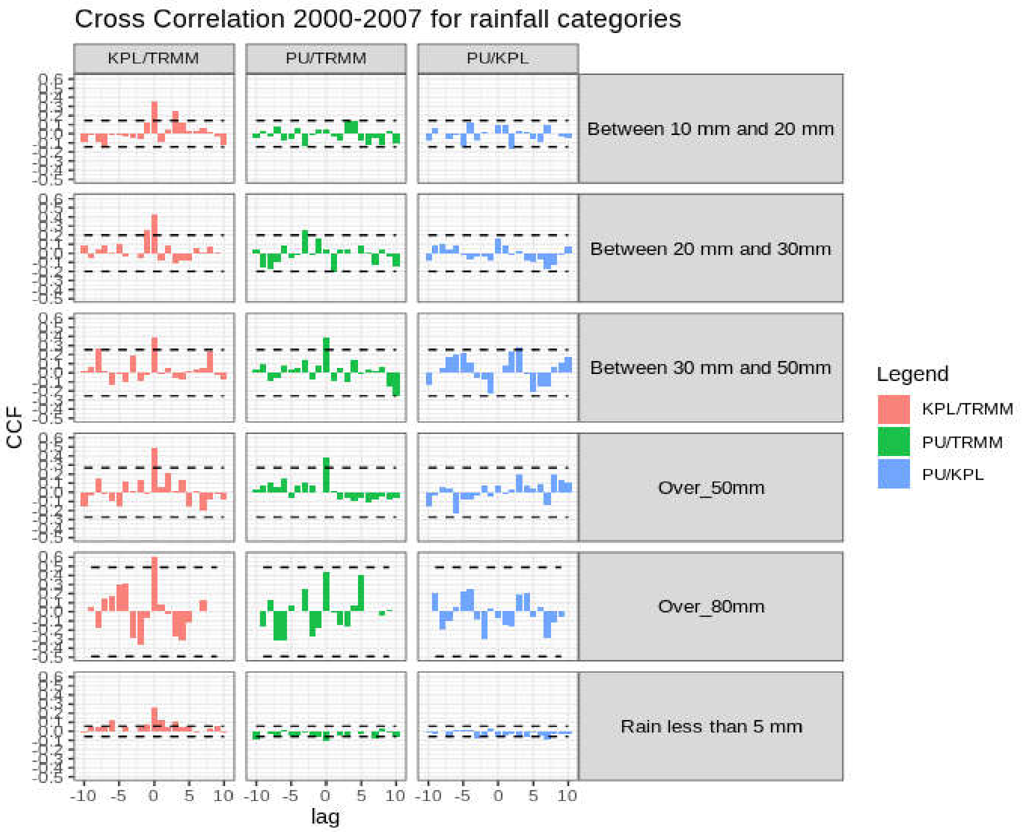

Figure 5. Categorized rainfall cross correlations at 0.95 confidence level (black dashed line)

Considering that low correlations exist in raingauges less than 5 Km apart compared to their correlation with TRMM3B42v7, it is conceivable use can be made of TRMM3B42v7 data with finer temporal resolution to represent rainfall input at a finer temporal scale. The categorised cross correlations indicate that KPL and TRMM3B42v7 are more correlated at all catogories compared to both PU/TRMM and PU/KPL. When decomposed rainfall data is compared by removal of trends and seasonality for the three data sets, the remainders are noted to be similar. This similarity is considered adequate and after correction for bias the TRMM3B42v7 is considered to represent rainfall in the study area at hourly temporal resolution. As the satellite data is over both PU and KPL if its sensitivity is great, it should have more instances of rainfall events. The limit of rainfall detection in TRMM is less than 7 mm/hr and and rainfall from shallow clouds (Behrangi *et al*. 2014).

While descriptive statistics may rule out close relationship between the data sets, the CCF of their residual components after decomposition, show closeness in values and indicates that variability even between ground gauges only 5 Km apart has similar range when compared to the TRMM3B42v7 rainfall data. The correlation between the two rain gauges are expected to be much higher than either with TRMM3B42 v7 data. Seasonal correlation of rainfall data may point out at instruments varying seasonal characteristics and natural changing weather charateristics. The choice of whether to use disaggregated rainfall from coarse gauge data or to find appropriate satellite derived rainfall product would depend on available data characteristics e.g. a priori information on rainfall distribution at the fine time scale and number of daily rain gauges within the study area. Apriori information of rainfall characteristics at finer subdaily values are difficult to obtain for study area. The low values of p statistic in the KS test for the whole data-set indicated that the samples did not come from the same distribution, However other comparison measures like trend and seasonality in decomposition showed high correlation, which justifies the use of TRMM3B42v7 data in hydrological studies that require sub-daily rainfall data.

Conclusion

One of the outcomes of the study is the observation low correlation in rainfall between the datasets, with slightly higher correlation of the ground gauges, which are only 5 Km apart.
It is inferred that the nature of rainfall in the area shows more randomness with small amounts of less than 5mm and improves with higher categories of rainfall. Correlation is expected to improve with amounts of rain fall as higher amounts are likely to be indicated all three data-sets. Despite having more coincident rainfall events than both TRMM3B42v7 as well as KPL, the Pwani University data has less correlation with both data-sets in the gross rainfall correlation. This may be attributed to the data quality, seasonality and trend aspects of the data. When seasonality and trend are removed, the decomposed remainder correlation show decreasing order of correlations from KPL/PU, followed by KPL/TRMM and finally PU/TRMM. It is also noted that KPL/TRMM are more correlated compared to PU/TRMM. Considering that the rainfall time series come from the same process then it is conceivable that after removal of trend and seasonality, which are highly correlated in the time series, then the remainders exhibit correlations within similar ranges. The conclusion is that despite low correlations observed in the data-sets (< 0.4) the Kilifi's rainfall has random nature and variability of rainfall even within small areas is a fact that may apply to other areas. This observation adequately represents the rainfall phenomenon in Kilifi and can therefore be used in hydrological endeavours that require sub-daily data input.

Disaggregation of coarse precipitation gauge data: Despite not having fine temporal rainfall data in the sub daily range for the ground rain-gauges, the validation of derived satellite rainfall can allow its use in hydrological endeavours that require data with finer temporal resolution. This should be compared with other disaggregation methods applied on coarse rain-gauge products to produce sub-daily rainfall from the daily gauge readings.

Acknowledgements

We wish thank Pwani University and Kilifi Plantation Ltd for rainfall data-sets that made this study possible

Conflict of Interest Statement: The authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, the authors certify that this material or similar material has not been submitted to or published in any other publication. The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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