VALIDATION OF SATELLITE RAINFALL ESTIMATES USING GAUGE RAINFALL OVER TANZANIA

BY

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Declaration

I hereby declare that this is my original work and has not been presented for a degree in any other University.

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Dedication

This work is dedicated to my lovely parents, Mr. and Mrs. Hamis Mohamed

Abstract

This study sought to investigate the relationship between the gauge and satellite based rainfall measurements over Tanzania based on gauge rainfall data spanning the period 1983 to 2012 from the Tanzania Meteorological Agency while the corresponding satellite based rainfall estimates were retrieved from the African Rainfall Climatology Project of the Climate Prediction Centre. Data quality control, time series analysis (graphical and spectral), correlation and error analysis techniques (Root Mean Square Error and Nash Sutcliffe coefficient) were used.

Graphical analysis indicated similar patterns of gauge and satellite estimates whose trend was increasing over all stations. The periodogram indicated that rainfall records from satellite and gauge stations were comparable with dominant period of approximately two years. Correlation analysis showed that ground and satellite based rainfall over Tanzania were positively correlated with the correlation coefficient ranging between 0.4 in Sumbawanga and 0.82 in Mtwara and significant at 95% and 99% confidence level over coastal stations. The dominant frequency indicated that rainfall patterns had a periodicity of two years over Tanzania. The RMSE showed that satellite derived rainfall estimates positively deviated from the gauge rainfall while positive values of the efficiency score showed that there was good skill except in Bukoba, Dodoma, Mbeya, Mwanza, Pemba and Sumbawanga stations.

The study showed that satellite derived rainfall estimates from the African Rainfall Climatology version 2 was comparable to gauge rainfall data. Implied that satellite derived rainfall estimates could be used a great degree of skill in place of the gauge rainfall data. However, satellite derived rainfall estimates were noted to overestimate gauge rainfall; the error analysis indicated that these data sets were highly comparable as indicated by positive values in most of the locations. Therefore, the study recommends that the National Meteorological and Hydrological Centres (NMHS's) to consider the use of satellite data in regions where the spatial network of stations is highly sparse.

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Acronyms

AMSU - Advanced Microwave Sensor Unit

ARC 2 - African Rainfall Climatology version 2

AVHRR - Advanced Very High Resolution Radiometer

EAMD - East Africa Meteorological Department

EUMETSAT – European Organization for the Exploitation of Meteorological Satellite

GMSRA - Multispectral Rainfall Algorithm

GOES - Geostationary Operational Environmental Satellite

GOS - Global Observing System

IR - Infrared

ITCZ - Inter-Tropical Convergence Zone

MW - microwave

NASA - National Aeronautical and Space Administration

NASDA - National Space Development Agency

NWP - Numerical weather predication

PMW - Passive Microwave

RMSE - Root-Mean Square Error

SPEs - Satellite Precipitation Estimates

SSM/I - Special Sensor Microwave Image-

SW - South west

TIR - Thermal Infrared

TMA - Tanzania Meteorological Agency

TMI - Tropical microwave imager

TRAP - Tropical Rainfall Potential

TRMM -Tropical Rainfall Measuring Mission

VIS - visible

WMO - World Meteorological Organization

WWW - World Weather Watch

CHAPTER ONE

1.0 Introduction

The economies and livelihoods of the countries in East Africa are weather dependent, whose variation affects related economic activities (Centella et al., 1999) such as Agriculture, Transport, Communication and Industrialization. For example, In Tanzania, where agriculture is mainly rain-fed, rainfall remains one of the most significant weather parameters (Javanmard et al., 2010). Inadequate rainfall can mean crop failure and famine while too much rainfall can lead to devastating floods and thus makes its monitoring at both space and time scales very important. However, measurement of rainfall still poses a challenge due to its great spatial variability and the fact that a large proportion of rainfall occurs over inaccessible areas.

Historically, the areal estimation of rainfall has been accomplished by use of rain gauges distributed over particular catchments (WMO, 1996). The rain gauge is a relatively simple instrument which samples the rain by capturing rain drops continuously over a fixed time interval. Rainfall amount is specified as the depth (mm) to which a flat horizontal impermeable surface would have been covered if no water were lost by run-off, evaporation or percolation. Rain gauges are known to give direct measurement of rain accumulation. However, they are limited to land regions and islands (Ebert and McBride, 2000 and Levizzani et al. 2007).

Recognizing the practical limitations of rain gauges, scientists have increasingly turned to remote sensing as a possible means for quantifying and providing precipitation estimates on near real-time and monthly timescales for climate studies, numerical weather prediction (NWP) data assimilation, now-casting and flash flood warning, tropical rainfall potential, and water resources monitoring (WMO, 1996). Notably, remote sensing will continue as a supplement to, rather than a replacement for, more traditional methods of rainfall assessment.

Similar to any observational data, investigating their accuracy and limitations is crucial by verifying the satellite estimates against independent data from rain gauges and radars (Levizzani et al. 2007). This will address issues such as rainfall occurrence, amount and distribution at all temporal scales for a number of applications in meteorology, climatology, hydrology and environmental sciences. Therefore, the study sought to investigate the relationship between the observed and satellite based estimates of rainfall over Tanzania

1.1 Problem statement

Conventional rain gauge network is currently used to give rainfall observations at a daily time scale. However, the gauge network is inadequate both in terms of spatial and temporal coverage (Grimes et al., 2003). Furthermore, a large proportion of tropical rainfall occurs over inaccessible areas limiting distribution of rain gauges over particular catchments such as land and islands (WMO, 1996). According to the World Meteorological Organization (WMO) (1996), a representative gauge density is one gauge every 15 km^2, a condition rarely met by Tanzania Meteorological Agency (TMA) and other hydro-meteorological services. Inadequate gauge network coupled with inadequate maintenance of rainfall gauge measuring instruments, human error and inaccessible areas such as mountainous locations has resulted to existence of gaps in precipitation measurements as most events are not recorded.

With the advent of remote sensing technology, numerous satellites are being used to provide rainfall estimates at improved spatial and temporal scale and support ground based rainfall network in monitoring and measuring rainfall.

1.2 Hypothesis

In this study, the hypothesis was stated that satellite derived rainfall estimates from the African rainfall Climatology of Climate Prediction Centre are not comparable to gauge rainfall over Tanzania.

1.3 Objectives of the study

The main objective of this study was to assess the accuracy of satellite derived rainfall estimates in measuring rainfall over Tanzania. The specific objectives included;

1. To determine the temporal variability rainfall over Tanzania both gauge rainfall and satellite rainfall
2. To determine the relationship between satellite rainfall and Gauge rainfall over Tanzania.
3. To investigate the relationship between the gauge and satellite based rainfall measurements over Tanzania.

1.4 Justification

Recognizing the practical limitations of rain gauges has resulted to the use of satellite remote sensing as a possible means of quantifying rainfall such as visible and infrared techniques which derive qualitative or quantitative estimates of rainfall from satellite imagery. This is achieved through indirect relationships between energy reflected by clouds (or cloud brightness temperatures) and measured precipitation.

Inadequate gauge network coupled with inadequate maintenance of rainfall gauge measuring instruments, human error and inaccessible areas such as mountainous locations has resulted to existence of gaps in precipitation measurements as most events are not recorded necessitates a means to improve on the available data available from the gauge rainfall network. Satellite-based rainfall estimation will therefore be needed to address issues such as rainfall occurrence, amount and distribution at all temporal scales for a number of applications in meteorology, climatology, hydrology and environmental sciences. Moreover, it will provide more information necessary in the management of water resources and flood forecasting.

In order to use these rainfall estimates appropriately it is essential to know of their accuracy and expected error characteristics. This is done by calibrating the satellite precipitation estimates against “ground truth” from rain gauge and/or radar observations, but time and space scales have to be matched

1.4 Area of Study

1.4.1 Tanzania

Tanzania lies at latitude 1°S and 12°S and longitudes 29°E and 40°E as shown in Figure 1. It is located between the great East African lakes which include Lake Victoria in the north, Lake Tanganyika to the west and Lake Nyasa to the south. The Indian Ocean lies to the East. The country includes Africa’s highest point Mount Kilimanjaro, 5950 m above sea level) and lowest part (the floor of Lake Tanganyika, 358 m below sea level). However, most of Tanzania, except the eastern coastline lies above 200 m above mean sea level.

1.4.2 Climatology of Tanzania

Being in an equatorial zone, climate of Tanzania is influenced by synoptic scale circulations e.g. the convergent of low level winds in the Inter-tropical Convergence Zone (ITCZ) surface locations. However, synoptic scale circulations cannot explain the overall variability of rainfall over Tanzania. Superimposed on the synoptic scale circulations patterns are meso-scale systems induced by nearness to large water bodies such as the lakes and Oceans as well as topographical features.

Over northern part of Tanzania rainfall is bimodal occurring during the seasons of March-April-May and October-November-December with peaks in April of about 220mm and November of 150mm (Basalirwa, 1999). Regions close to Lake Victoria receive relatively more rainfall than those away from the gigantic lake due to the abundance of moisture generated through the land/lake breeze.

Northern parts also suffer the double maxima due to the ITCZ explaining the bimodality nature of rainfall to the north. Oven central Tanzania, rains begin in late October and continue until early May with seasonal rainfall maxima of less than 150mm occurring in December/January. Only negligible amount of rainfall is recorded between June and October. This is attributed to the low elevation of the area lying 1000-500 m above the Mean Sea Level. Thus, rainfall within the central parts of Tanzania is influenced solely by the north-south movement of the ITCZ.

Over the South Western parts of Tanzania, the seasonal rainfall distribution is such that there is only one rainfall season occurring between the months of October and May. The peak however is recorded during the month of April with a mean in excess of 600mm which is almost 5 times the amount received in the central parts of the country. This is attributed to the fact that the region lies on a topographic notch of about 3000m above mean sea level to the north of L. Tanganyika which can be said to play a major role in rainfall enhancement from the lake breeze effects coupled with orographic lifting. The peak of rainfall during April in this region is said to be as a result of the north-south movement of the ITCZ.

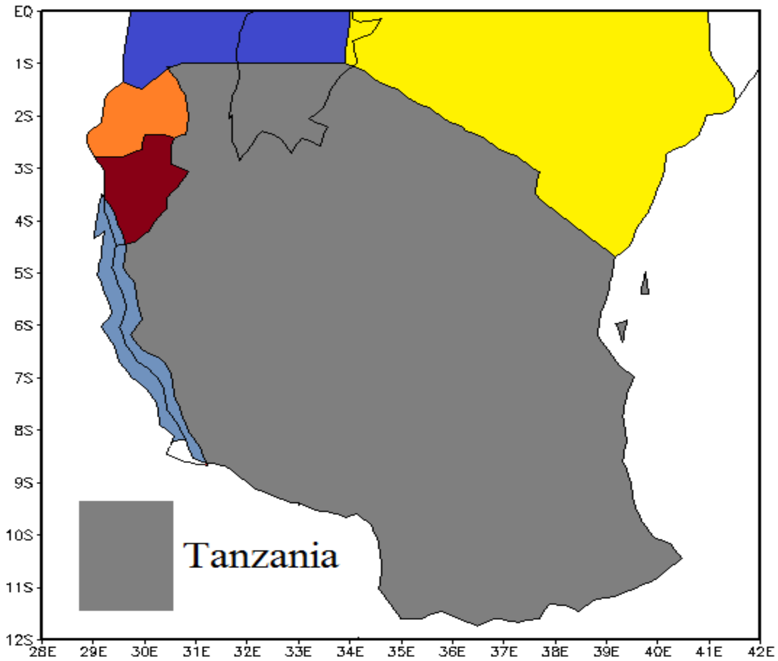

Figure 1: Map of Tanzania

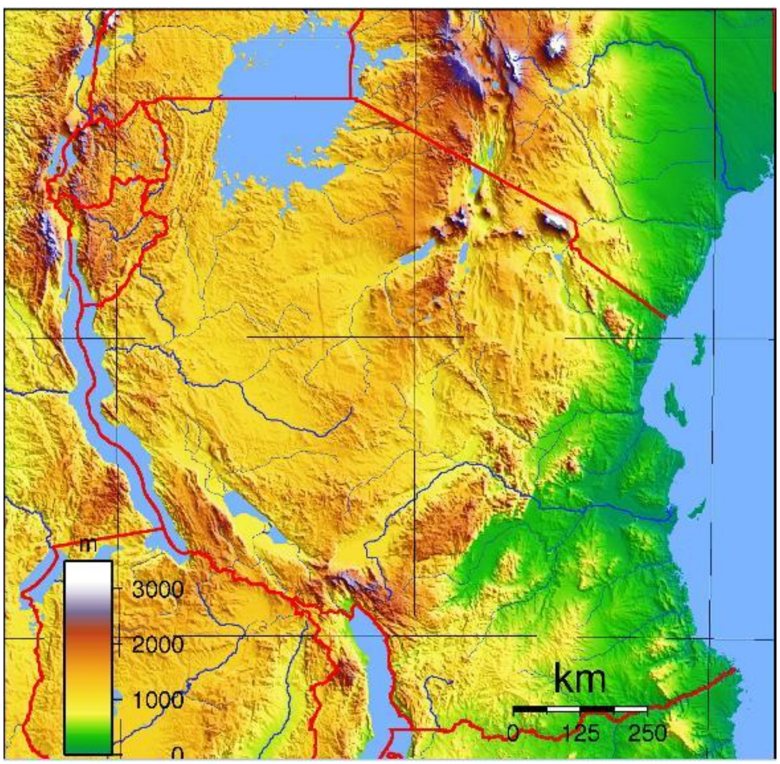

Figure 2: Topography of Tanzania (Source: Mapsof.net)

CHAPTER TWO

2.0 Literature review

This chapter provides a review of previous studies on rainfall measurements and satellite calibration.

2.1 Rainfall Measurements

There are many operational meteorological satellites that can be used for monitoring the weather over different parts of the globe. The satellites have different spatial and temporal resolutions and provide a stream of invaluable data in support of operational meteorology and many other disciplines. In recent years, the applications of these satellites have grown far beyond the dreams of those who designed and operated the systems. One of the applications of weather satellites is the monitoring of precipitation. Several satellite precipitation algorithms have been developed to estimate rainfall from visible, thermal infrared (TIR) and microwave radiation using satellite imagery (Barrett, 1970).

The measurement of rainfall by rain gauges is fraught with some problems, but those relatively simple instruments will long continue to provide the data against which rainfall assessments by other means must be adjusted. Satellites measure an integral of space at a point in time. Visible and infrared techniques derive qualitative or quantitative estimates of rainfall from satellite imagery through indirect relationships between energy reflected by clouds (or cloud brightness temperatures) and measured precipitation. A number of methods have been developed and tested during the past 20 years with a measured degree of success (WMO, 1996).

2.2 Background on Meteorological Satellites

Meteorological satellites measure radiation coming from the earth and its atmosphere. This radiation may be reflected solar radiation i.e. by the surface, clouds, water vapour and aerosols, or it may be terrestrial radiation emitted by the earth’s surface, atmosphere and clouds. The earth’s atmospheric gases are affected differently by different wavelengths of radiation. Meteorological satellites have been designed to take advantage of these responses to observe different aspects of the earth and its atmosphere (Harries, 2000).

A major problem facing the calibration of satellite estimates with validation data is the matching of the datasets both temporally and spatially. Errors noted by Kidd et al.(2003) include systematic errors due to satellite–ground misregistration that lead to a significant drop in statistical accuracy. Temporally coincident data are rarely achieved and several minutes' leeway between the two datasets is often required. This can lead to displacement in position and changes in the spatial form of the precipitation. Finally, physical differences between satellite retrievals and validation retrievals exist and it is not realistic to assume that the satellite measurements will replicate those of the validation data precisely. These include resolution differences, viewing angles, and response to hydrometeors, and the characteristics of rainfall also need to be recognized (Joyce et al., 2004).

The radiometer is the instrument used to measure the intensity of the radiant energy received in a specific wavelength band. When the radiometer collects a certain amount of energy it registers a count, which is proportional to the intensity of the radiation received. The relationship between radiation and counts is established by the radiometer's calibration. The area viewed by the radiometer is called a footprint and its total radiation is assigned to a pixel centred at the middle of the footprint. In order to build an image of earth of a reasonable size, a scanning system is employed to physically change the direction in which the radiometer is pointing. A complete image is built up when all the pixels in the image have been assigned a value by the radiometer (Rao et al., 1990).

There are two kinds of meteorological satellites, geostationary and polar-orbiting. Geostationary meteorological satellites orbit the equator at the same rate the earth spins and hence they remain at nearly an altitude of about 36000 km above one point on the equator. This position allows continuous monitoring of a specific region. Geostationary meteorological satellites are also important because they use a "real time" data system, meaning that the satellites transmit images to the receiving system on the ground as soon as the sensor takes the picture (Schmetz et al. 2002).

Successive cloud photographs from these satellites can be put into a time-lapse movie sequence to show the cloud movement, dissipation, or development associated with weather fronts and storms. This information is a great help in forecasting the progress of large weather systems. The observation area of a geostationary satellite is limited within its field of view, and the information of its imagery is useful in the area between 70^{o}N and 70^{o}S (EUMETSAT, 1998). The main advantages of geostationary satellites are that they observe the earth from a fixed position above the equator and they can be used to monitor the change of meteorological phenomena including cloud motion of tropical cyclones and/or depressions at short time intervals.

Polar-orbiting satellites closely parallel the earth's meridional lines. These satellites pass over the north and south Polar Regions on each revolution. As the earth rotates to the east beneath the satellite, each pass monitors an area to the west of the previous pass. Eventually, the satellite covers the entire globe. Polar-orbiting satellites have the advantage of photographing clouds directly beneath them (EUMETSAT, 1998). Thus, they provide sharp pictures in polar regions, where photographs from a geostationary meteorological satellite are distorted because of the low angle at which the satellite "sees" this region. In any period of 24 hours each polar satellite can view the entire planet, once during daylight and once at night (Schmetz et al., 2002). Polar orbiters also circle the earth at a much lower altitude (about 850 km) than geostationary meteorological satellites and provide detailed photographic information about objects, such as violent storms and cloud systems (Ahrens, 2000). The polar satellites carry a much wider variety of instrumentation than the geostationary satellites and can observe the planet in far more details, but less frequency.

The whole globe can be effectively observed by the good/dense combination of observing system composed of both geostationary and polar orbiting meteorological satellites. The combination of the geostationary, polar orbiting and Tropical Rainfall Measuring Mission meteorological satellites makes up the space segment of the Global Observing System (GOS) under the World Weather Watch (WWW) program promoted by the World Meteorological Organization (WMO) (EUMETSAT, 1998)

Advances in satellite-based remote sensing have enabled scientists to develop precipitation estimates having near-global coverage, thereby providing data for regions where ground-based networks are sparse or unavailable (Sorooshian et al., 2000). However, this advantage is offset by the indirect nature of the satellite observables (e.g., cloud-top reflectance or thermal radiance) which have then to be related to surface precipitation amount (Petty and Krajewski, 1996). In general, satellite-based precipitation estimation algorithms use information from two primary sources. The visible (VIS) and infrared (IR) channels from geosynchronous satellites are used to establish a relationship between cloud-top conditions and rainfall rates at the base of the cloud. This relationship can be developed at relatively high spatial (4 km x 4 km) and temporal resolution (30 minutes).

The first imaging sensors aboard meteorological satellites measured radiation in the VIS band (0.4 – 0.7 µm). VIS imagery generally offers the highest spatial resolution and provides a view of the earth that closely matches our senses (Stanley and Thomas, 1995). Land, clouds, and ocean are easily discernible. The obvious limitation to VIS data is that they are available only from the sunlit portion of the earth, as effectively data is lost during night time.

The IR channels are most often between 1 and 30 µm. The most common IR band for meteorological satellites is in the 10 – 12.5 µm window, in which the atmosphere is relatively transparent to radiation upwelling from the earth surface. When the word infrared is used alone to describe an image, it is nearly always in the 10 – 12.5 µm window rather than in another portion of the electromagnetic spectrum. IR radiation is related to the temperature of the emitting body and because of that the troposphere generally cools with night and it helps to interpret the atmospheric processes occurring within the scene. An important characteristic of the IR channels is their ability to provide images at night. This provides continuous coverage of cloud evolution over a full 24 – hour period (Stanley and Thomas, 1995).

Microwave is an electromagnetic radiation having wavelengths between approximately 1 x 10^3 µm and 1 x 10^6 µm (corresponding to 0.3 and 300-GHz frequency) bounded on the short wavelengths side by far infrared and on the long wavelength side by very high frequency radio waves. Passive systems operating at these wavelengths are sometimes called passive microwave systems. The microwave (MW) channels from low-orbiting satellite are used to more directly infer precipitation rates by penetrating the cloud, but a low-orbiting satellite can retrieve only one or two samples per day from one area. Microwave radiation is sensitive to an array of surface and atmospheric parameters, including precipitation, cloud water, water vapour, water droplets phase, soil moisture, surface temperature, atmospheric temperature and ocean surface wind speed. The relative strengths and weaknesses of various sources (Yilmaz et al., 2005) have been exploited in the development of algorithms that combine and make the best use of each source.

2.3 Satellite-based Rainfall Estimation Methods

The development of visible (VIS) and infrared (IR) techniques has a long history and relies upon the relationship between cloud top characteristics and the rainfall falling from the cloud. Although this relationship can be somewhat tenuous many techniques have been developed. One of them is the geostationary operational environmental satellite (GOES) precipitation index (GPI) (Arkin and Meisner, 1987). The technique relies upon the fraction of cloud colder than 235K in the IR with a fixed rain rate. This method provides a useful benchmark by which to assess other algorithms.

Complex algorithms have been developed with varying degrees of success. Recent techniques have included the operational GOES IR rainfall estimation technique, or auto-estimator (Vicente et al., 1998, 2001) and the GOES multispectral rainfall algorithm (GMSRA) (Ba and Gruber, 2001). The auto-estimator utilizes data from the GOES 10.7 µm channel through a regression against radar to generate rainfall estimates, while the GMSRA uses all five channels from the GOES instrument. Information provided by the growth rate of clouds and the spatial gradients is used to discriminate between rain clouds and non-raining cirrus clouds, with the GMSRA incorporating cloud-top particle information.

According to Ba and Gruber (2001), correlations between the surface data and the auto-estimator were slightly less than that of the GPI but substantial improvements are seen in the bias and root-mean square error (RMSE). Similar improvements were seen with the GMSRA not only in the RMSE and bias, but also the correlation (Vicente et al., 1998; Ba and Gruber, 2001).

Visible and infrared techniques are grouped together because they share a common characteristic: the radiation does not penetrate through the cloud. VIS and IR techniques estimate precipitation falling from the bottom of the cloud based on radiation coming from the top and/ or the side of the cloud, depending on viewing geometry. According to Stanley and Thomas (1995), VIS and IR precipitation estimation schemes are necessarily indirect; a cloud’s brightness or equivalent blackness temperature may be related to the rain falling from it, but the raindrops themselves are not directly sensed.

Early research using data from polar-orbiting satellites (prior to the era of geostationary satellites) pursued a wide range of avenues, including relating 3-hour precipitation probability to IR window brightness temperatures (Lethbridge, 1967), estimating daily rainfall from visible (Follansbee, 1973) and IR (Follansbee and Oliver, 1975) data, and estimating monthly rainfall based on charts of cloud type and coverage constructed from polar-orbiting satellite overpasses (Barrett, 1970).

The advent of geostationary satellites made VIS/IR-based satellite precipitation estimates (SPEs) useful for operational evaluation of extreme-precipitation events, because the time interval involved (15 minutes at present) is much more compatible with the time scale of these events than the time interval between the overpasses of a polar-orbiting satellite (Scofield and Kuligowski, 2003). This dramatic increase in the availability of IR and VIS imagery was accompanied by a similarly dramatic increase in the number of techniques for retrieving precipitation estimates from these data such as the so-called Griffith–Woodley technique (Griffith et al., 1978); the GOES precipitation index (Arkin and Meisner, 1987), and the convective–stratiform technique (Adler and Negri, 1988).

Satellite passive microwave (PMW) data provide a direct method for rainfall estimation through the emission-based retrieval of atmospheric liquid water over ocean or scattering-based retrieval of precipitation ice above the freezing level over land or ocean. Unfortunately the passive microwave techniques have poorer spatial resolution due to longer wavelengths than IR techniques (Visser et al., 2004) and low temporal resolution for they are usually flown on polar orbiters. Therefore, it is not useful for short-term precipitation estimations, unless combined with geostationary IR or other orbiting data.

Despite the time limitations of observations from polar-orbiting satellites, Ferraro et al. (2000) have demonstrated that microwave-based SPEs are useful for meso-scale storm analysis and forecasting. However, the most useful application appears to be in using microwave SPEs in conjunction with GOES data. TRMM also offers an opportunity to investigate the use of multiple instruments in conjunction for SPE, because the TRMM satellite carries not only the TRMM microwave imager (TMI) but also precipitation radar, VIS and IR sensors, and a lightning detector. Microwave SPEs have also proven to be useful as a basis for short-term forecasts of precipitation from tropical systems making landfall (Visser et al., 2004). The original technique, developed for GOES data by Spayd and Scofield (1984), has evolved into an automated tropical rainfall potential (TRaP) technique that combines SSM/I, advanced microwave sensor unit (AMSU), and TMI based estimates of rainfall with storm-track forecasts to produce forecasts of 24-hour precipitation prior to landfall (Ferraro et al., 2002).

The tropical rainfall measuring mission (TRMM) is a joint National Aeronautical and Space Administration (NASA) and National Space Development Agency of Japan (NASDA) mission designed to measure tropical rainfall and its diurnal variability on a monthly time scale and in area of $105km^2$(Visser et al., 2004). The precipitation weather radar provides three-dimensional structure of rainfall, particularly of the vertical distribution; quantitative rainfall measurements over land as well as over ocean and improvements in the overall TRMM precipitation retrieval accuracy by combined use of active (PR) and passive (TMI) and VIRS sensor data. The VIRS is a five-channel imaging spectral radiometer with bands in the wavelength range from 0.63 - 12 µm, and is similar to the advanced very high resolution radiometer (AVHRR) instrument (Visser et al., 2004).

Miller et al. (2001) developed a technique that generates rainfall from IR and PMW data using a linear brightness temperature (Tb) to rain-rate relationship. The common problem with the IR–PMW techniques has been the choice of the calibration domain. Many techniques, such as Adler et al. (1993) and Xu et al. (1999), use temporal domains spanning entire months to provide robust calibrations. However, while the monthly calibrations will reflect the climatological variations in the IR–PMW relationship they do not respond to the sub-monthly changes in the relationships. Instantaneous calibrations based upon coincident IR–PMW values have been utilized by Miller et al. (2001) and Turk et al. (2000), and have the advantage of responding to changes in the calibration over short-term periods.

CHAPTER THREE

3.0 Data and Methods

3.1 Data

In this study, two types of datasets were used. These included Ground based and Satellite derived rainfall data.

3.1.1 Gauge Rainfall data

Ground based monthly rainfall data from 21 synoptic stations distributed across the country was sought from Tanzania Meteorological Agency. The stations and locations of the rainfall stations are summarized in table 1. The dataset covered the period 1983 -2012. The figure 3 shows the spatial distribution of the rainfall stations across Tanzania used for the study.

Table 1: Synoptic stations to be adopted for the study

No.	Station	Latitude	Longitude	No.	Station	Latitude	Longitude
1	Ashusha	3.37°S	36.68°E	12	Mtwara	10.27ºS	40.18°E
2	Bukoba	1.33°S	31.82°E	13	Musoma	1.50ºS	33.80ºE
3	Dar es salaam	6.82°S	39.23°E	14	Mwanza	2.75°S	32.75°E
4	Dodoma	6.19°S	35.74°E	15	Pemba	5.22ºS	39.73ºE
5	Iringa	7.77°S	35.69°E	16	Singida	5.5°S	34.5°E
6	Kibaha	6.77ºS	38.92°E	17	Songea	10°S	37°E
7	Kigoma	4.88°S	29.63°E	18	Sumbawanga	7.97ºS	31.62ºE
8	Mahenge	8.41°S	36.43°E	19	Tabora	5.01°S	32.48°E
9	Mbeya	8.9°S	33.45°E	20	Tanga Airport	5.08ºS	39.07ºE
10	Morogoro	6.82°S	37.67°E	21	Zanzibar	6.13°S	39.32°E
11	Moshi	3.35ºS	37.33ºE				

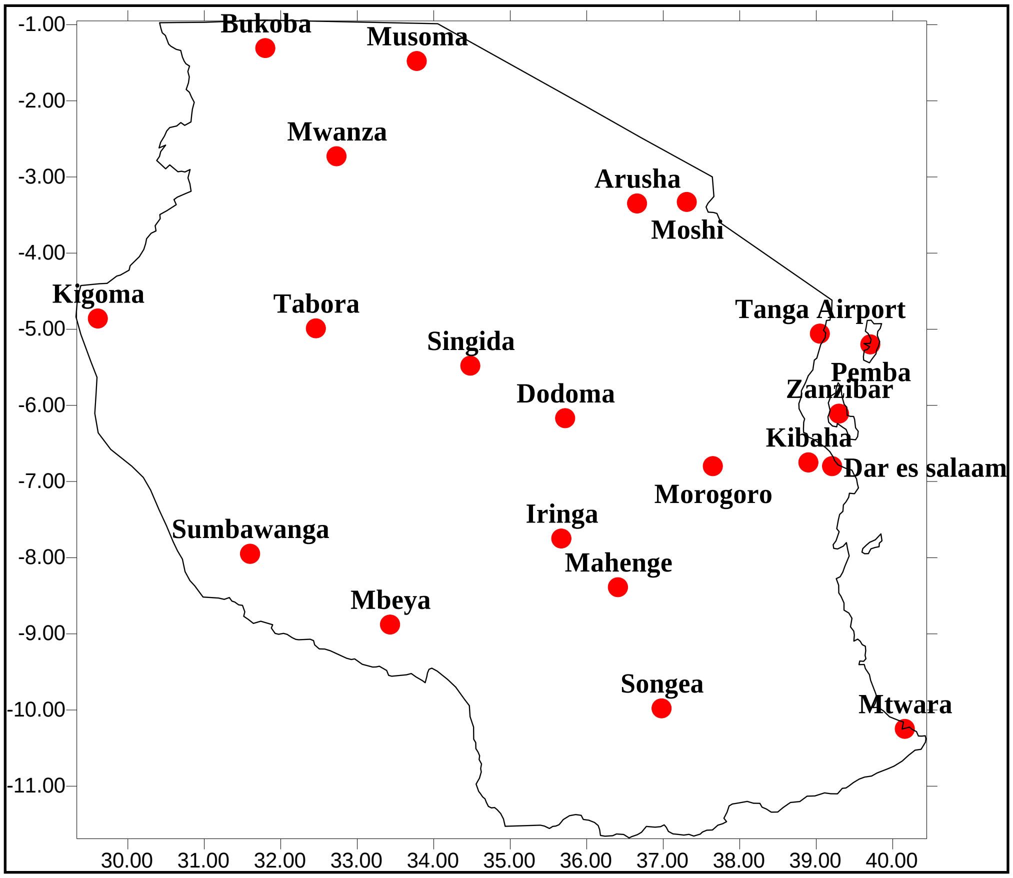

Figure 3: Distribution of selected synoptic stations across Tanzania

3.1.2 Satellite data

Satellite derived data was retrieved from the African Rainfall Climatology version 2 (ARC2), a gridded precipitation estimates with a spatial resolution of 0.1˚ by 0.1˚ (Novella et al., 2013). The satellite data retrieved covered the period between 1983 and 2012 corresponding to the period with available gauge rainfall data.

3.2 Methodology

Data quality control was done through estimation of missing data and homogeneity test. The different methods used to achieve the objectives of the study included spectral and correlation analysis. Skill evaluation methods included Root Mean Square Error, Bias and Efficiency Scores (Dinka et al., 2007) were also used.

3.2.1 Data Quality Control

The consistency of gauge rainfall data was tested using single mass curve method while the missing data were estimated using the arithmetic mean method.

3.2.1.1 Estimation of Missing Data

Various methods of estimating missing meteorological data are available. The type of method depends on whether the missing data are temporal or spatial data. Temporal resolution is good for annual, monthly, daily and hourly depends on the length or amount of missing records. In some cases, certain methods (e.g. methods based on time series analysis) can only be applied on the available record length. Apart from normal ratio, inverse distance method, correlation and regression methods can be used. In this analysis, arithmetic mean method was used. It involves replacing the missing data with the average or the mean for a given station as shown in Equation 1.

$$X_m = \left(\frac{\bar{X}}{\bar{Y}}\right) Y_m \qquad 1$$

In Equation 1, X_m is the missing records at station X, $\bar{X}$ is the long term mean for the station with the missing data in ceratin year and month, $\bar{Y}$ is the long term mean of the station with complete data and Y_m is the corresponding records of the station Y having complete data.

3.2.1.2 Data Homogeneity

Reliable data which are free from artificial trends or changes are important in any research. Data reliability was checked by applying homogeneity test which involved comparison of data from one station to its surrounding stations. Single mass curve and moving average plots was used in this research to test for homogeneity. The linearity of the plots indicated homogeneity of the data, otherwise heterogeneity was be depicted by non-linear plots.

3.2.2 Time series Analysis

Graphical and spectral analysis was used in this study.

3.2.2.1 Graphical Analysis

Graphical analysis was used to compare rainfall from ground and satellite based rainfall estimates over selected stations in Tanzania. This method involved plotting gauge and satellite based measurements against time. This method is simple and provides quick visual observation at a given time.

3.2.2.2 Spectral Analysis

The main aim of spectral analysis is to decompose a complex time series with cyclical components into a few underlying sinusoidal (sine and cosine) functions of particular wavelengths and eventually detecting periodic or quasi-periodic fluctuations in the time series. In detecting cyclic variations in a time series, a variance function known as the spectral density function F (e) is used.

Fourier transform is a mathematical function that can be used for mapping a time series from the time domain into the frequency domain for spectral analysis. In effect, Fourier transform decomposes a waveform or a function into sinusoids of different frequencies which sum to the original waveform. It identifies or distinguishes different frequency sinusoids and their respective amplitudes

For any datasets, spectral analysis is achieved through autocovariance function given by Equation 2;

$$\gamma(k) = \int_{0}^{\pi} \cos(\omega k)\, dF(\omega) \qquad 2$$

Equation (2) is called the spectral representation of the autocovariance function and $\gamma(k)$ is the autocovarience coefficient, $F(\omega)$ is called the spectral distribution function and k denotes time units. A periodogram, a plot of spectral density with dominant frequencies was used in this study to determine the consistencies/inconsistencies in the dominant frequencies in the two data sets adopted.

3.2.3 Correlation Analysis

In this study, spatial variability was assessed based on the correlation coefficients between gauge and satellite rainfall data aimed at identifying regions where satellite rainfall estimates were highly comparable to ground based data. Correlation measures the degree of association between two variables. The higher the correlation, the more one variable explains the variability in the other variable (Wilks, 1995). Positive correlation implies that when one quantity increases, the other one increases and vice-versa. If it's negative, it implies that when one quantity increases, the other decreases and vice-versa. The significance of the strength of the correlation is tested using the student t-test. Product moment correlation coefficient was computed between the satellite based and the gauge based precipitation data using Equation 3. Spatial correlation maps were generated for all the months of the year.

$$r_{xy} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad 3$$

In Equation (3), r_{xy} is the correlation coefficient, n is the sample size, xi and yi are the variables being correlated and $(\bar{x}), (\bar{y})$ are the mean values of variables of satellite and gauge based data respectively.

The resulting correlation was tested using the student t-test at 95% and 99% confidence level using equation 4

$$t_{n-2} = r\sqrt{\frac{n-2}{1-r^2}} \qquad 4$$

3.2.4 Error Analysis Techniques

Error analysis was used to assess the accuracy of satellite derived rainfall data based on the gauge measurements using Root Mean Square Error and Nash-Sutcliffe Methods as discussed in the sub sequent sections.

3.2.4.1 Root-Mean-Square-Error

Root Mean Square Error (RMSE) is a frequently used measure of the differences between values predicted by a model and the actual observations. A lower value of RMSE indicates better fit. RMSE is a good measure of how accurately the model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction. RMSE is computed as shown in equation 5;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(s_i - g_i)^2} \qquad 5$$

Where n is the total number of observation, s_i is the satellite data and g_i is the observed value.

3.2.4.2 Nash-Sutcliffe coefficient (E)

The Nash-Sutcliffe model efficiency coefficient (E) also known as the efficiency score shows the skill of the estimates relative to a reference (in this case the gauge mean). It varies from minus infinity to one, one being the perfect skill. Negative values mean that the observed mean is a better estimate; zero implies that the observed mean is as good as the estimate, and positive values show good skill. The Efficiency Score is given in Equation 6

$$Eff = 1 - \frac{\sum_{i=1}^{n}(s_i - g_i)^2}{\sum_{i=1}^{n}(g_i - \bar{g})^2} \qquad 6$$

In Equation (6), s_i is the satellite data and g_i is the observed value

3.2.4.3 Bias

Bias is a systematic deviation from a true value. It cannot be reduced by increasing the sample size. It is also known as the difference between an estimator's expectations and the true value of the parameter being estimated. It is given by Equation 7;

$$Bias = \frac{\sum_{i=1}^{n} s_i}{\sum_{i=1}^{n} g_i} \qquad 7$$

In Equation (7), s_i is the satellite data and g_i is the observed value

CHAPTER FOUR

4.0 Results and discussions

This section presents the results generated from the study. They include results from time series analysis where cyclic trends were investigated, linear correlation and evaluation of skill techniques.

4.1 Data quality control

Most observed rainfall data were noted to have missing values which were all less than 10 in each station. Therefore, estimation of missing values was done using arithmetic mean method. Single mass curve was then used to test for homogeneity of observed rainfall records as shown in Figures 4 to Figures 7.

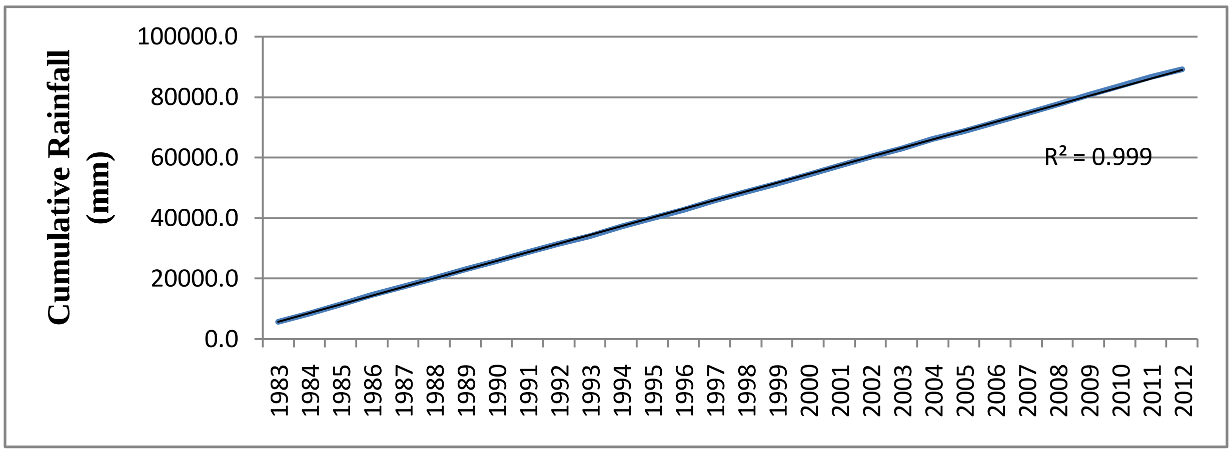

Figure 4: single mass curve of cumulated gauge rainfall over Sumbawanga

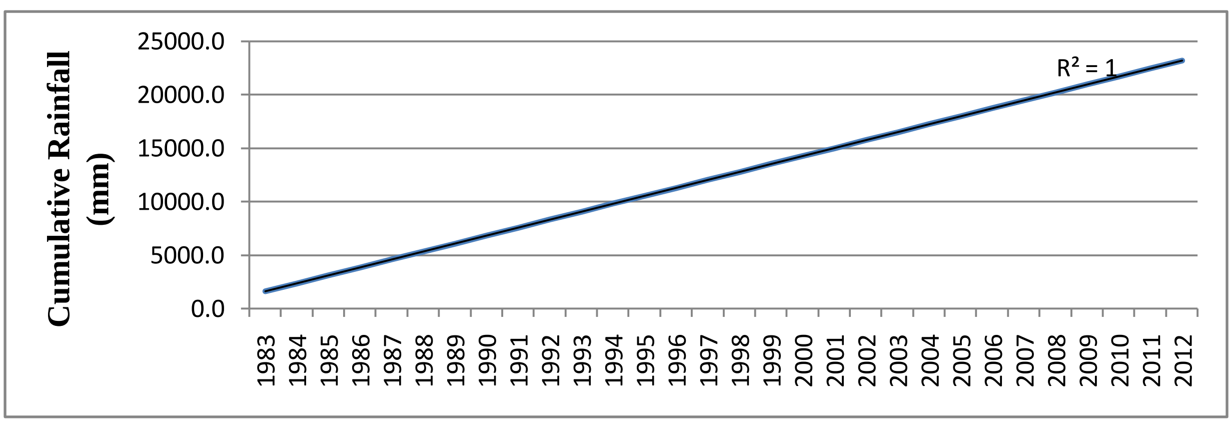

Figure 5: single mass curve of cumulated gauge rainfall over Mbeya

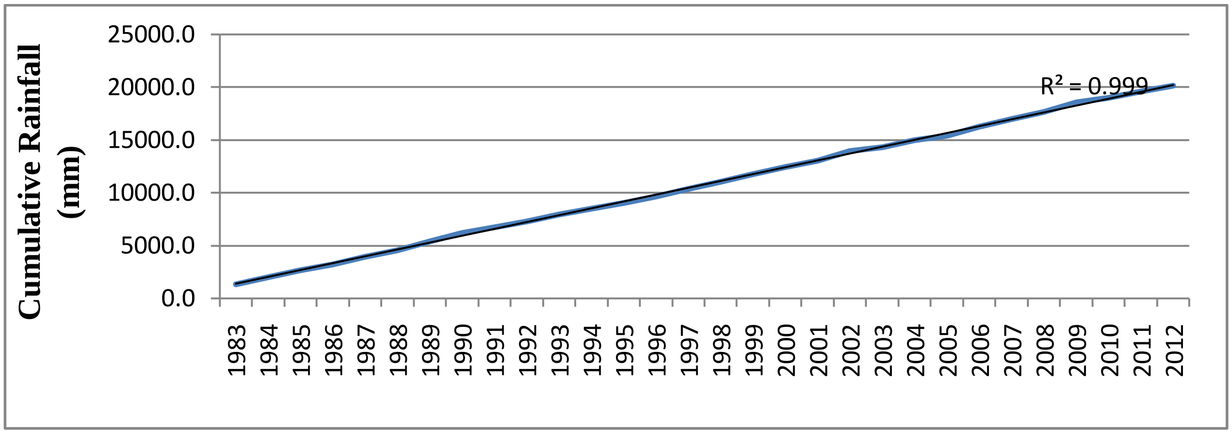

Figure 6: Single mass curve of cumulated gauge rainfall over Dodoma

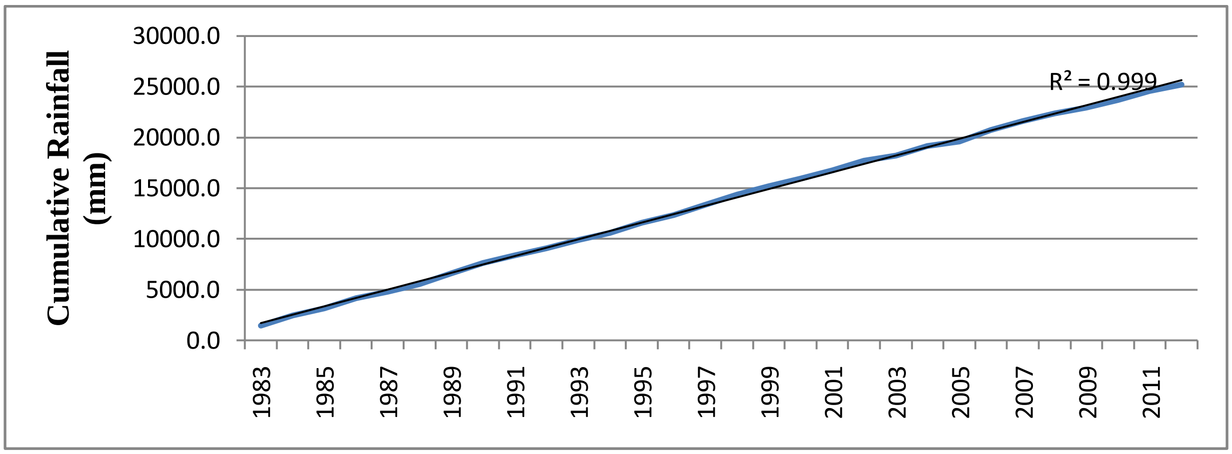

Figure 7: Single mass curve of cumulated gauge rainfall over Morogoro

Linear graphs of single mass curves of cumulated rainfall displayed straight lines in all stations used in the study. Furthermore, the coefficient of determination (R^2) was above 0.9 in all Gauge stations, an indication that more than 99% of gauge rainfall values fitted the linear regression line. Therefore, the data was considered valid and consistent over these stations and thus homogeneous and good for further analysis.

4.2 Temporal and spatial variability of Rainfall over Tanzania

Time series and correlation analysis was used to investigate the temporal and spatial variability of ground and satellite based rainfall estimates.

4.2.1 **Temporal variability of rainfall over Tanzania**

Time series analysis comprised of graphical and spectral analysis

4.2.1.1 Graphical Analysis

Graphical analysis was used to investigate the annual variability of rainfall for both the ground and satellite based rainfall in Tanzania and presented in Figure 8 for selected stations.

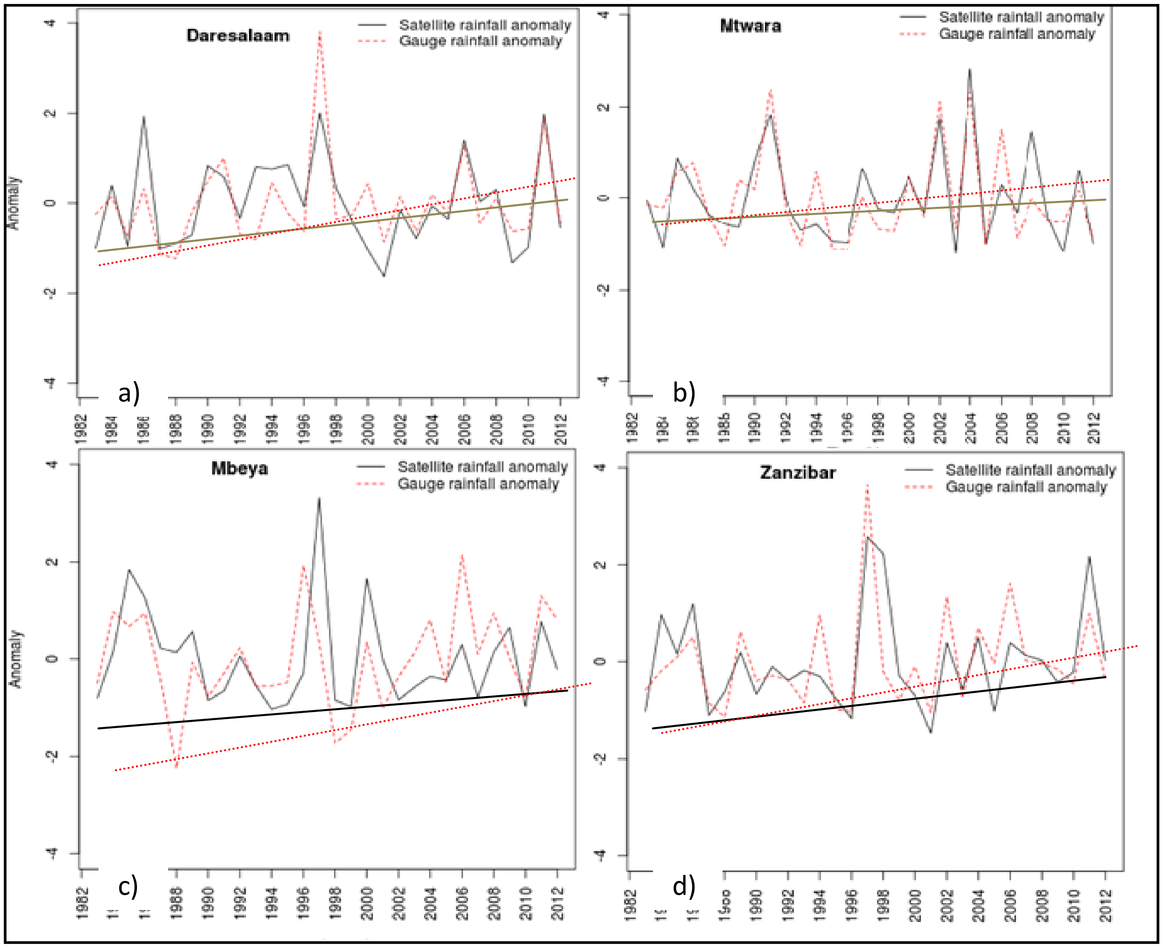

Figure 8: Annual variability of rainfall over a) Dar es Salaam, b) Mtwara c) Mbeya and Zanzibar Stations

The figure 8 shows that the two data sets had similar patterns with slightly differences. Moreover, all stations indicated an increasing trend in annual rainfall. This could be attributed to fact that satellite measurement, are gridded and thus averaged compared to gauge rainfall which are measured at a point.

4.2.1.2 Spectral Analysis

Spectral analysis was aimed at understanding whether both data sets would show the same patterns in mimicking particular systems and unearth underlying patterns. Plots of periodogram are presented in Figure 9 and Figure 10. The dominant frequency and periods were then computed as shown in table 2.

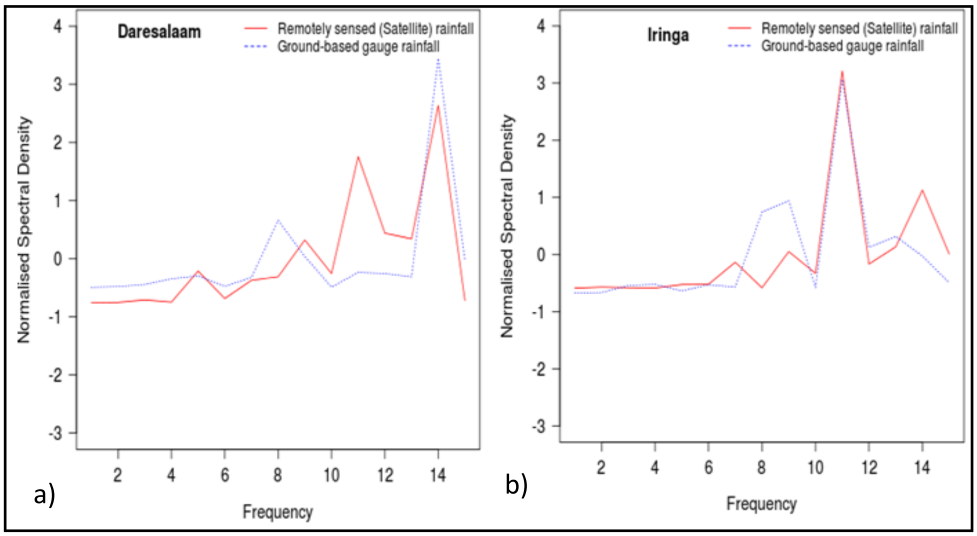

Figure 9: Periodogram for a) Dar es Salaam and b) Iringa Stations

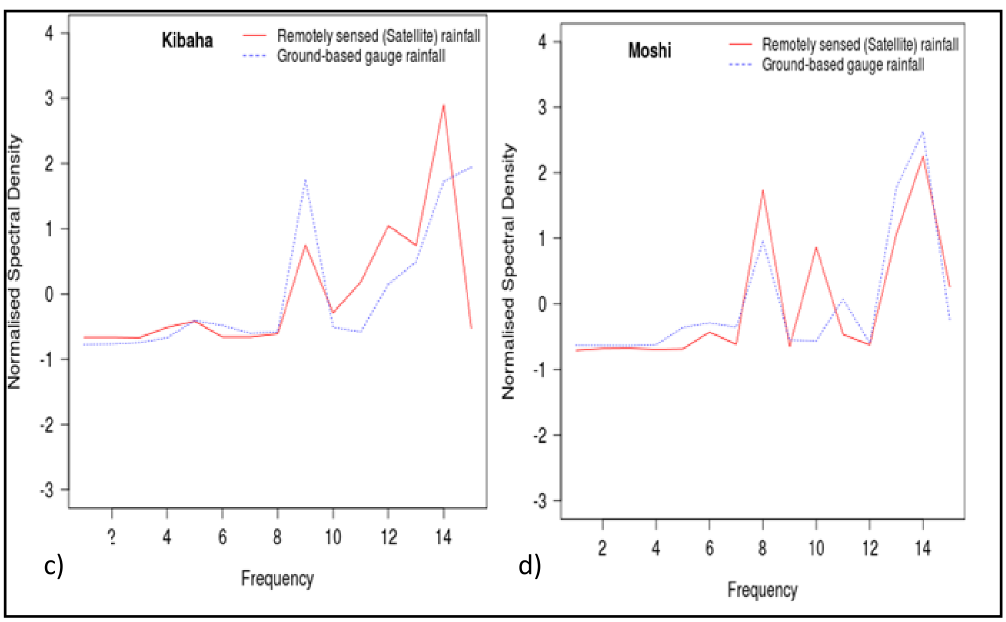

Figure 10: Periodogram for a) Kibaha b) Moshi Stations in Tanzania

Table 2: Periodogram table showing dominant frequency and their periods

No.	**Stations**	**Frequency**	**Period (Years)**	**No.**	**Stations**	**Frequency**	**Period (Years)**
1	Arusha	0.32	3.11	12	Mtwara	0.5	2
2	Bukoba	0.46	2.15	13	Musoma	0.43	2.33
3	Daresalaam	0.46	2.15	14	Mwanza	0.43	2.33
4	Dodoma	0.39	2.55	15	Pemba	0.46	2.15
5	Iringa	0.36	2.8	16	Singida	0.5	2
6	Kibaha	0.5	2	17	Songea	0.5	2
7	Kigoma	0.43	2.33	18	Sumbawanga	0.36	2.8
8	mahenge	0.43	2.33	19	Tabora	0.5	2
9	Mbeya	0.36	2.8	20	Tanga_airport	0.43	2.33
10	Morogoro	0.46	2.15	21	Zanzibar	0.46	2.15
11	Moshi	0.46	2.15				

In the figures 9 and 10, plots of normalized spectral density and against frequency indicated that rainfall records from satellite and gauge stations were comparable over Tanzania. Based on the periodogram, table 2 showed that the dominant frequency for the selected stations ranged between 0.32 in Arusha station to and 0.5 in Mtwara, Kibaha, Singida, Songea and Tabora. These frequencies were noted to have a period approximately two years.

4.2.2 **Correlation between Satellite rainfall and Gauge rainfall over Tanzania**

Correlation analysis was used to investigate the relationship between ground and satellite based rainfall estimates from all station in Tanzania as shown in table 3. These correlation coefficients are plotted as shown in Figure 11

Table 3: Correlation analysis of Ground and satellite based rainfall over Tanzania

No.	Station	Cor.Coeff	P-value	No.	Station	Cor.Coeff	P-value
1	Arusha	0.643	0.00	12	Mtwara	0.817	0.00
2	Bukoba	0.341	0.07	13	Musoma	0.59	0.00
3	Daresalaam	0.727	0.00	14	Mwanza	0.427	0.02
4	Dodoma	0.453	0.01	15	Pemba	0.402	0.03
5	Iringa	0.531	0.00	16	Singida	0.526	0.00
6	Kibaha	0.606	0.00	17	Songea	0.535	0.00
7	Kigoma	0.557	0.00	18	Sumbawanga	0.4	0.03
8	mahenge	0.504	0.00	19	Tabora	0.53	0.00
9	Mbeya	0.387	0.03	20	Tanga_airport	0.753	0.00
10	Morogoro	0.631	0.00	21	Zanzibar	0.695	0.00
11	Moshi	0.75	0.00				

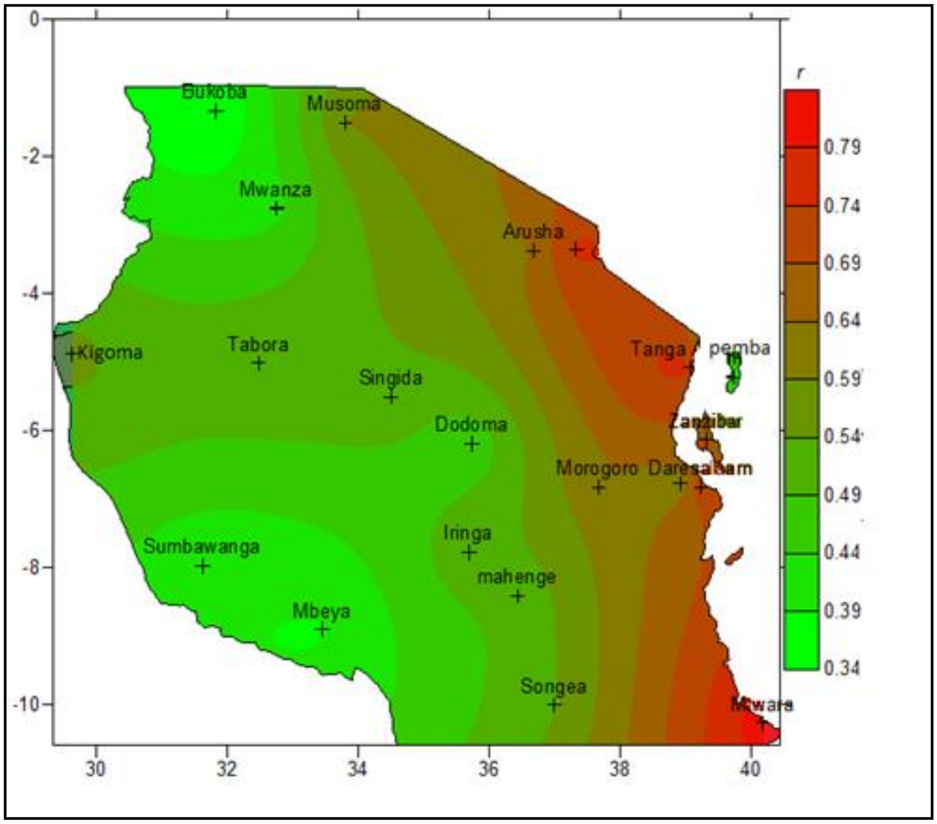

Figure 11: Comparison of correlation coefficient over Tanzania

Correlation analysis showed that ground and satellite based rainfall over Tanzania were positively correlated. The correlation coefficient ranged between 0.4 in Sumbawanga and 0.82 in

Mtwara. The test of significance using the student t test at 95% confidence level showed that all stations except Bukoba had p-values less than alpha (0.05) were statistically significant. At 99% confidence level, most stations were significantly correlated except Bukoba, Dodoma, Mbeya, Pemba, Sumbawanga and Mwanza had p-values greater than or equal to alpha (0.01). Spatial comparison of these correlation coefficients indicated that rainfall stations close to the Indian Ocean displayed a high correlation compared to stations located further inlands.

4.2.3 **Evaluation of Skill of satellite derived rainfall estimates**

Evaluation of skill was carried out between the 2 datasets based on the Root Mean Square Error, Efficiency score and Bias and the results tabulated as shown in table 4.

Table 4: Evaluation of Skill

No	Station	RMSE	Efficiency score	Bias	No.	Station	RMSE	Efficiency score	Bias
1	Arusha	0.99	0.29	10	12	Mtwara	0.71	0.63	-0.5
2	Bukoba	1.35	-0.32	0.96	13	Musoma	1.06	0.18	-0.2
3	Dar es Salaam	0.87	0.45	1.07	14	Mwanza	1.26	-0.15	-0.1
4	Dodoma	1.23	-0.09	0.06	15	Pemba	1.29	-0.2	-3.3
5	Iringa	1.14	0.06	0.38	16	Singida	1.14	0.05	0.1
6	Kibaha	1.04	0.21	-0.09	17	Songea	1.13	0.07	1.3
7	Kigoma	1.11	0.11	-0.17	18	Sumbawanga	1.29	-0.2	-0.2
8	mahenge	1.17	0.01	0.38	19	Tabora	1.14	0.06	-0.1
9	Mbeya	1.3	-0.23	-0.03	20	Tanga_airport	0.83	0.51	-14.2
10	Morogoro	1.01	0.26	2.72	21	Zanzibar	0.92	0.39	2.3
11	Moshi	0.83	0.5	-0.99					

Based on the RMSE, deviations or residuals were noted to be positive and ranged between 0.71 and 1.35 over all stations (table 4), an indication that satellite derived rainfall estimates overestimated the observed rainfall over Tanzania.

Based on the Nash –Sutcliffe Coefficient, the study noted that satellite derived rainfall estimates had positive values and thus showed good skill except Bukoba, Dodoma, Mbeya, Mwanza, Pemba and Sumbawanga which had negative values of the efficiency score.

In the table 4, the numbers of positive and negative values of the Bias were randomly distributed across the country. However, the absolute values of Bias were all less than 3.3 except Arusha and Tanga Airport Station which were 10 and 14.2 respectively.

CHAPTER FIVE

5.0 Summary, Conclusions And Recommendations

This section gives the summary, conclusion and recommendations based on the results of the study.

5.1 Summary

Inadequate gauge network coupled with inadequate maintenance of rainfall gauge measuring instruments, human error and inaccessible areas such as mountainous locations has resulted to existence of gaps in precipitation measurements as most events are not recorded necessitates a means to improve on the available data available from the gauge rainfall network. Therefore, this study sought to investigate the relationship between the gauge and satellite based rainfall measurements over Tanzania through determination of space time variability of gauge and satellite derived rainfall estimates and assessment of its accuracy over Tanzania

Gauge rainfall data for a period 1983 -2012 was sought from the Tanzania Meteorological Agency while the corresponding satellite based rainfall estimates were retrieved from the African Rainfall Climatology Project of the Climate Prediction Centre. Data quality control involved estimation of missing data using arithmetic mean method and homogeneity test based on the single mass curve. Temporal variability was achieved through time series analysis which included graphical and spectral analysis. Spatial variability was based on comparison of stations correlation coefficient to ascertain the spatial correlations and presence of any significance relationship between gauge and satellite based rainfall. The accuracy of satellite derived rainfall estimates was done through error analysis techniques which included the Root Mean Square Error, Bias and Nash –Sutcliffe coefficient.

The study noted that less than 10% of data were missing and thus used the arithmetic mean method to fill the missing data. The linear graphs of single mass curves of cumulated rainfall displayed straight lines in all stations with the coefficient of determination (R^2) values all above 0.9 in all Gauge stations, an indication that more than 99% of gauge rainfall values fitted the linear regression line. This implied that the data set was valid, consistent and thus good for further use.

Graphical analysis to compare the temporal variation of gauge and satellite data showed similar patterns with slight difference which implied an existence of a positive or negative lag in the two data sets with an increasing rainfall Pattern. Moreover, plots of normalized spectral density and against frequency indicated that rainfall records from satellite and gauge stations were also comparable over Tanzania with the frequency ranging between 0.32 in Arusha station to and 0.5 in Mtwara, Kibaha, Singida, Songea and Tabora and dominant period of approximately two years.

Correlation analysis showed that ground and satellite based rainfall over Tanzania were positively correlated with the correlation coefficient ranging between 0.4 in Sumbawanga and 0.82 in Mtwara with significance test at 95% confidence level showed that all stations except Bukoba were statistically significant while all stations except Bukoba, Dodoma, Mbeya, Pemba, Sumbawanga and Mwanza were significantly correlated at 99% confidence level. Most stations close to the Indian Ocean displayed a high correlation compared to stations located further inlands.

The RMSE showed that satellite derived rainfall estimates positively deviated from the gauge rainfall, an indication that it overestimated the observed rainfall over Tanzania. Moreover, positive values of the efficiency score showed that there was good skill except in Bukoba, Dodoma, Mbeya, Mwanza, Pemba and Sumbawanga stations which had negative values of the efficiency score. Based on the Bias method, the study found equal number of positive and negative values over the Tanzania.

5.2 Conclusions

The overall objective of this study to investigate the relationship between the gauge and satellite based rainfall measurements were achieved through statistical analysis of gauge and satellite rainfall data sets for stations in Tanzania.

The temporal variability of rainfall from both the gauge and satellite rainfall estimates showed an increasing trend in rainfall over Tanzania while spatial variability was noted to indicate that the eastern Tanzania regions located close to the Indian Ocean received higher amounts of rainfall and decreased inlands. The dominant frequency indicated that rainfall patterns had a periodicity of two years over Tanzania. The coastal areas near the Indian Ocean were noted to have significant correlation between gauge and satellite derived rainfall and positive RMSE. Although satellite derived rainfall estimates were noted to overestimate gauge rainfall, the error analysis indicated that these data sets were highly comparable as indicated by positive values in most of the locations.

Therefore, the study hypothesis stating that satellite derived rainfall estimates from the African rainfall Climatology are not comparable to gauge rainfall over Tanzania was rejected and the alternative hypothesis accepted. This implied that satellite derived rainfall estimates could be used a great degree of skill in place of the gauge rainfall data especially in mountainous regions where mounting of the ground based instruments is highly compromised by the terrain features. Moreover, this data can be used to fill up gaps for gauge-based rainfall data which is suspect and inhomogeneous.

5.3 Recommendations

This study recommends that the National Meteorological and Hydrological Centres (NMHS's) to consider the use of satellite data in regions where the spatial network of stations is highly sparse and where mounting of such instruments is practically impossible due to physical features which might provide installations of instruments a challenge. Furthermore, studies should be carried out to understand the reasons why over the Lake regions and other areas closer to large water bodies are difficult to monitor from the satellite as far as rainfall measurement and calibration is concerned.

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GOD (ALMIGHTY) BLESSES YOU ALL!!!

References

Adler, R. F., and A. J. Negri, 1988: A satellite infrared technique to estimate tropical convective and stratiform rainfall. J. Climate Appl. Meteor., 27, 30 – 51.

Adler, R. F., P. R. Keehn, and I. M. Hakkarinen, 1993: Estimation of monthly rainfall over Japan and surrounding waters from a combination of low-orbit microwave and geosynchronous IR data. J. Appl. Meteor., 32, 335 – 356.

Alusa A, and Mushi M, 1973: A study of the onset, duration and cessation of the rains in East Africa Proceedings of the fifth specialist Meeting on Applied Meteorology in East Africa, Nairobi, Kenya, 133-140

Arkin, P. A., and B. N. Meisner, 1987: The relationship between largescale convective rainfall and cold cloud over the Western Hemisphere during 1982–84. Mon. Wea. Rev., 115, 51 – 74

Barrett, E. C., 1970: The estimation of monthly rainfall from satellite data. Mon. Wea. Rev., 98, 322 – 327.

BasaIirwa, C.P.K.,Odiyo, O J., Mngodo, R.J. and Mpeta, E J.,1999: The clirnatological regions of Tanzania based on the rainfall characteristics, Int.J. Climatol., 19, 69-80

Ba, M. B., and A. Gruber, 2001: GOES Multispectral Rainfall Algorithm (GMSRA). J. Appl. Meteor., 40, 1500 – 1514

Centella, A., Gutiérrez, T., Limia, M. and Rivero, J. R., 1999: Climate change scenarios for impact assessment in Cuba Institute of Meteorology, Apartado 17032, CP 11700 Habana 17, Cuba

Dinku T, P. Ceccato , E. Grover-Kopec , M. Lemma , S. J. Connor & C. F. Ropelewski 2007: Validation of satellite rainfall products over East Africa's complex topography, International Journal of Remote Sensing, 28:7, 1503-1526

EAMD, 1963: The weather of East Africa, Part 1; General, Pamphlet Series No.8, EAMD, Nairobi

Ebert, E. E., A. P. Arkin, R. J. Allam, G. E. Holpin, and A. Gruber, 1996: Results from the GPCP algorithm inter comparison program. Bull. Amer. Meteor. Soc., 77, 2875 – 2887.

EUMETSAT, 1998: Directory of Meteorological Satellites Applications. Coordination Group for Meteorological Satellites (CGMS), EUM BR 08

Ferraro, R. R., N. Weng, Grody, and L. Zhao, 2000: Precipitation characteristics over land from the NOAA-15 AMSU sensor. Geophys. Res. Lett., 27, 2669 – 2672.

Ferraro, R. R., P. Pellegrino, S. Kusselson, M. Turk, and S. Kidder, 2002: Validation of SSM/I and AMSU-derived tropical rainfall potential (TraP) during the 2001 Atlantic hurricane season. NOAA Tech. Rep. NESDIS 105, 43

Follansbee, W. A., 1973: Estimation of average daily rainfall from satellite cloud photographs. NOAA Tech. Memo. NESS 44, 39

Follansbee, W. A., and V. J. Oliver, 1975: A comparison of infrared imagery and video pictures in the estimation ofdaily rainfall from satellite data. NOAA Tech. Memo. NESS 62, 14

Griffiths, J.F. 1972: Eastern Africa, *Climates of Africa*, World Survey of Climatology, Vol. 10, Elsevier, 604 pp

Griffith, C. G., W. L. Woodley, P. G. Grube, D. W. Martin, J. Stout, and D. N. Sikdar, 1978: Rain estimates from geosynchronous satellite imagery: Visible and infrared studies. Mon. Wea. Rev., 106, 1153 – 1171.

Grimes, D. I. F., and M. Diop, 2003: Satellite-based rainfall estimation for river flow forecasting in Africa. I: Rainfall estimates and hydrological forecasts. Hydrol. Sci. J., 48, 567–584.

Harries, J. E. 2000: The Geostationary Earth radiation Energy experiment: Status and Science. Proceedings of the 2000 EUMETSAT Meteorological Satellite Data User's Conference,

Javanmard, S., Yatagai, A., Nodzu, M. I., BodaghJamali, J., and Kawamoto, H, 2010: Comparing high-resolution gridded precipitation data with satellite rainfall estimates of TRMM_3B42 over Iran, Adv. Geosci., 25, 119-125

Joyce, R. J., J. E Janowiak, P.A Arkin, and P Xie, 2004: CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. J. Hydrometeor., 5, 487 – 503.

Kidd, C., D. R. Kniveton, M. C. Todd, and T. J. Bellerby, 2003: Satellite rainfall estimation using combined passive microwave and infrared algorithms. J. Hydrometeor (AMS), 4(6), 1088 – 1104.

Kuligowski, R. J., 2002: A self-calibrating real-time GOES rainfall algorithm for short-term rainfall estimates. J. Hydrometeor., 3, 112–130.

Lethbridge, M., 1967: Precipitation probability and satellite radiation data. Mon. Wea. Rev., 95, 487 – 490.

Levizzani, V., Bauer, P. and Turk, F. J. 2007: Measuring precipitation from space: EURAINSAT and the future, Vol. 28. Berlin: Springer-Verlag, pp. 722

Miller, S. W., P. A. Arkin, and R. Joyce, 2001: A combined microwave/infrared rain rate algorithm. Inte. J. Remote Sens., 22, 3285 – 3307.

Novella, Nicholas S., Wassila M. Thiaw, 2013: African Rainfall Climatology Version 2 for Famine Early Warning Systems. J. Appl. Meteor. Climatol., 52, 588–606.doi:http://dx.doi.org/10.1175/JAMC-D-11-0238.1

Nyenzi, B.S. 1992: An analysis of the inter-annual variability of rainfall over East Africa, *J. Afr. Met. Soc.* (*SMA*), 1, 57–79.

Ogallo,L. J., Janiowiak, J. E., and Halpert,M.S., 1988: Teleconneclions between seasonal rainfall over east Africa and global sea surface temperature anomalies. J. Meteorol. Soc., Japan, 6: 807-821.

Okoola, R.E., 1999: A diagnostic study of the East African monsoon circulation during the northern Hemisphere spring season. Int. J. Climate, 19: 143-168.

Petty, G., and W. F. Krajewisk, 1996: Satellite estimation of precipitation over land: Hydrol. Sci. J., 41, 433 – 451.

Rao, P. K., S. J. Holmes, R. K. Anderson, J. S. Winston, and P. E. Lehr, 1990: Weather Satellites: System, Data, and Environmental Applications. American Meteorological Society, Boston.

Schmetz, J. P. Pili, S. Tjemkes, D. Just, J. Kerkmann, S. Rota, and A. Ratier, 2002: An Introduction to Meteosat Second Generation (MSG). Bull Amer. Meteor. Soc., 83, 977 – 992.

Sorooshian, S., K. L. Hsu, X. Gao, H. V. Gupta, B. Imam, and D. Braithwaite, 2000: Evaluation of PERSIANN system satellite-based estimates of tropical rain. Bull. Amer. Meteor. Soc., 81, 2035 – 2046.

Spayd, L. E., and R. A. Scofield, 1984: A tropical cyclone precipitation estimation technique using geostationary satellite data. NOAA Tech. Memo. NESDIS 5, 36

Stanley, Q. K., and H. V. Thomas, 1995: Satellite Meteorology. An Introduction United Kingdom. Academic Press

Turk, F. J., J. Hawkins, E. A. Smith, F. S. Marzano, A. Mugnai, and V. Levizzani, 2000: Combining SSM/I TRMM and infrared geostationary satellite data in a near- real time fashion for rapid precipitation updates: Advantages and limitations. Proc. 2000

Vicente, G. A., R. A. Scofield, W. P. Menzel, 1998: The operational GOES infrared rainfall estimation technique. Bull. Amer. Meteor. Soc., 79, 1883 – 1898.

Vicente, G. A., J. C. Davenport, and R. A. Scofield, 2001: The role of orographic and parallax correction on real time high resolution satellite rainrate distribution. Inte. J. Remote Sens., 23, 221 – 230.

Visser, P. J. M, D. Dicks, I. T. H. Deyzel, and G. G. S. Pegram, 2004: Radar and Satellite Products. Spatial Interpolation and Mapping of Rainfall (SIMAR), WRC report No.1152/1/04

WMO, 1996: Guide to Meteorological Instruments and Methods of Observations. Sixth Edition. WMO No.8.

Xu, L., X. Gao, S. Sorooshian, P. A. Arkin, and B. Imam, 1999: A microwave infrared threshold technique to improve the GOES precipitation index. J. Appl. Meteor., 38, 569 – 579.

Yilmaz, K. K., T. S. Hogue, H. Hsu, S Sorooshian, H. V. Gupta, and T. Wagener, 2005: Intercomparison of rain gauge, radar, and satellite-based precipitation estimates with emphasis on hydrologic forecasting. J. Hydrometeor. (AMS), 6(4), 497 – 517.

Wilks, D. S., 1995: Statistical methods in the atmospheric sciences: Academic press, pp 45-50, 399-402.

http://mapsof.net/map/tanzania-physical