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DEPARTMENT OF METEOROLOGY

A new rainfall data set for AFRICA – Comparison of Different Rainfall Estimates over Southern Africa

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ABSTRACT

The study compares three precipitation products (GPCC, GPCP and TAMSAT) over southern Africa (10°E, 44°E and 10°S, 35°S) using monthly rainfall datasets during the period 1984-2010. GPCC dataset is global (regional) data generated from SYNOPS and CLIMAT data available from the GTS of WMO. GPCP and TAMSAT rainfall data is satellite derived rainfall estimates available over the region generated using different satellite rainfall estimation techniques from international centres of excellence. The study area was subdivided into smaller zones using the long mean spatial distribution of the rainfall over the region, topography and the mean weather controlling systems during the different seasons.

Several methods that include spatial plotting, descriptive statistics such as scatter plots and histograms, measures of variability that include the standard deviation and coefficient of variation, root mean square errors, differences and correlation, between the datasets using different time steps and selected locations within the region were used in the evaluation.

The evaluation showed that in general, all the rainfall estimation techniques agree in the spatial and temporal representation of the mean rainfall over the region with consistent bias. However, the relationship between TAMSAT and GPCP is especially very poor in winter near the Cape Town area. TAMSAT and GPCC show good agreement over the flat dry areas of Southern Africa.

The bias between the different methodologies was found to be low (≤ 10%) during the austral summer months than during winter where the bias surpass 70%. Correlation amongst the estimates is higher during summer and weaker during winter, while the root mean square error varies with rainfall amounts both spatially and temporally. Generally, TAMSAT estimates compares lower to both GPCC and GPCP rainfall estimates over the region.

Acknowledgements

I would like to express my sincere appreciation to all my supervisors, Prof Allan Richard P., Dr Black Emily and Dr Maidment Ross for their guidance, support and cooperation throughout my dissertation preparation. Special thank you to Dr. Maidment Ross who provided technical support in using the data analysis tools (R Software) and always willing to lend a hand.

Special recognition goes to the UK Met Office and the WMO who provided the financial support that enabled my study, I say "thank you so much". I also extend special thanks to the Government of the Kingdom of Swaziland, Swaziland Meteorological Services, for being supportive and allowing me time off to further my studies.

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Lastly, would like to extend special thank you to my family and friends for all the support they extended to me during my studies.

"PRAISE BE TO THE LORD, GOD BLESS US ALL"

LIST OF ACRONYMS

AMESD	AFRICA MONITORING OF ENVIRONMENT FOR SUSTAINABLE DEVELOPMENT
CCAFS	CLIMATE CHANGE AGRICULTURE FOOD SECURITY
CCD	COLD CLOUD DURATION
CLIMAT	WMO CODE FOR REPORTING MONTHLY METEOROLOGICAL PAREMETERS FROM LAND AND OCEAN STATIONS
CPC	CLIMATE PREDICTION CENTRE
ENSO SOI	EL NINO SOUTHERN OSCILLATION INDICES
EO	EARTH OBSERVATIONS
EUC	EUROPEAN UNION COMMUNITY
FOV	FIELD OF VIEW
GCOS	GLOBAL CLIMATE OBSERVATIONS SYSTEM
GEWEX	GLOBAL ENERGY AND WATER EXPERINMENT
GPCC	GLOBAL PRECIPITATION CLIMATOLOGY CENTRE
GPCP	GLOBAL CLIMATOLOGY PRECIPITATION PROJECT
GPS	GEOGRAPHIC POSITIONING SYSTEM
GTS	GLOBAL TELECOMMUNICATIONS SYSTEM
IODZM	INDIAN OCEAN DIPOLE / ZONAL MODE
IPCC	INTER GOVERNMENTAL PANEL ON CLIMATE CHANGE
ITCZ	INTER TROPICAL CONVERGENCE ZONE
JCR	JOINT RESEARCH COUNCIL
K	KELVIN (TEMPERATURE SCALE)
LDC	LEAST DEVELOPING COUNTRIES
MCC	MESOSCALE CONVECTIVE COMPLEXES
MFG /MSG	METEOSAT FIRST/SECOND GENERATION
MJO	MADDEN JULIAN OSCILLATION
NSI	NASH SUTCLIFFE INDEX

SADC RSAP & RIP	SOUTHERN AFRICA COMMUNITY REGIONAL STRATEGY PAPER AND REGIONAL INDICATOR PLAN
SAH	SOUTH ATLANTIC HIGH
SAFFG	SOUTHERN AFRICA FLASH FLOOD GUIDANCE
SST	SEA SURFACE TEMPERATURE
SYNOP	SURFACE SYNOPTIC OBSERVATIONS (WMO CODE)
TAMSAT	TROPICAL APPLICATIONS OF METEOROLOGICAL SATELLITES
TIR	THERMAL INFRA RED
UK	UNITED KINGDOM
UV	ULTRA VIOLET
WCRD	WORLD CLIMATE RESEARCH PROGRAMME
WMO	WORLD METEOROLOGICAL ORGANIZATON

Contents

1 INTRODUCTION

The successful application of weather and climate information to decision making and planning is dependent upon understanding this information which increases its economic value and its appropriate use. The economic value tends to increase with the quality, accuracy, timeliness, and location specificity and user-friendliness of the weather and climate information. Such an assertion is evident in a report "Weather Information for Development" (WIND, 2011) focussing on improving the livelihoods of small holder farms through the provision of improved weather and climate information in East Africa. The farmers stressed their need for better weather information to plan better farming throughout the year and enable effective use of resources such as in ploughing, planting, weeding and harvesting of crops, minimize risks and improve credit worthiness.

In southern Africa, which is composed mainly of least developed countries (LDC's) with about 45% of the population living with less than 1(one) $US a day according to Southern Africa Development Community Regional Strategy Paper and Regional Indication Plan March 2010 (SADC RSAP & RIP, 2010), over 95 % of the land used for food production is dependent on rain fed agriculture. The vegetation in this region consists of mainly annual plants which feed both domestic and wild animals many tourists from countries where these species do not exists, visit southern Africa to have a glimpse of them. Such plants closely follow the rainfall seasonality (Chikoore and Jury, 2010), germinating after the first rains, and unless affected by disease or die before maturity because of lack of water (rainfall), these plants will reach senescence after maturing of their fruits (which is also a function of temperature and light) to mark the end of the rainy season. This makes information on rainfall information indispensable both in space and time over the region for the ecosystem and economic growth at large.

The region is particularly very vulnerable to adverse effects of climatic change (Boko et al., 2007). The vulnerability of the sub-continent is exacerbated by its high level of dependency on natural and agricultural resources for fresh water including its low adaptive ability to changes because of multiple stresses such as the extreme poverty. Indeed other stresses such as environment degradation and uncertainties surrounding land transformation add salt to the injury. In addition, it is understood and established that future global warming may cause intensification of the hydrological cycle (Trenberth et al., 2007, Zahn and Allan, 2013) leading to changes in normal weather including frequencies of extreme events which calls for intensified planning for adaptation.

In recent decades, southern Africa experienced worst summer drought (1982/83 and 1991/92) associated with extreme El Nino events that caused severe fall in livestock and crop production which led to severe food shortage prompting the launch of a series of international humanitarian appeals aimed more fundamentally at averting the consequences of regional famine and widespread human suffering (Holloway, 2003). Such events are expected to be on the increase with global warming accelerating climate change (Meehl et al., 2007), and there is general consensus that agricultural production and food security in many countries and regions is likely to be severely compromised with projected reductions in yield in some countries reaching as much as 50% by 2020. This could further lead to falls in net crop revenues by as much as 90% by 2100, with small-scale farmers being the most affected.

Apart from agriculture, reports from other sectors show evidence of susceptibility of communities in the region to climate variability and change such as the report from the World Meteorological Organisation (WMO) Disaster Risk Reduction Programme (WMO DRRP) by the Centre for Epidemiology and Disasters for the period 1980–2007 (http://www.wmo.int/pages/prog/drr/). This report show that during the aforementioned period, 90% of the reported disasters were natural hazards related to weather and climate such as floods, drought, water-borne diseases and insect infestation. Figure 1.1 shows economic losses per decade and their associated causes which are indicated to have increased. Most of the losses are indicated to have resulted from hydro-meteorological natural hazards.

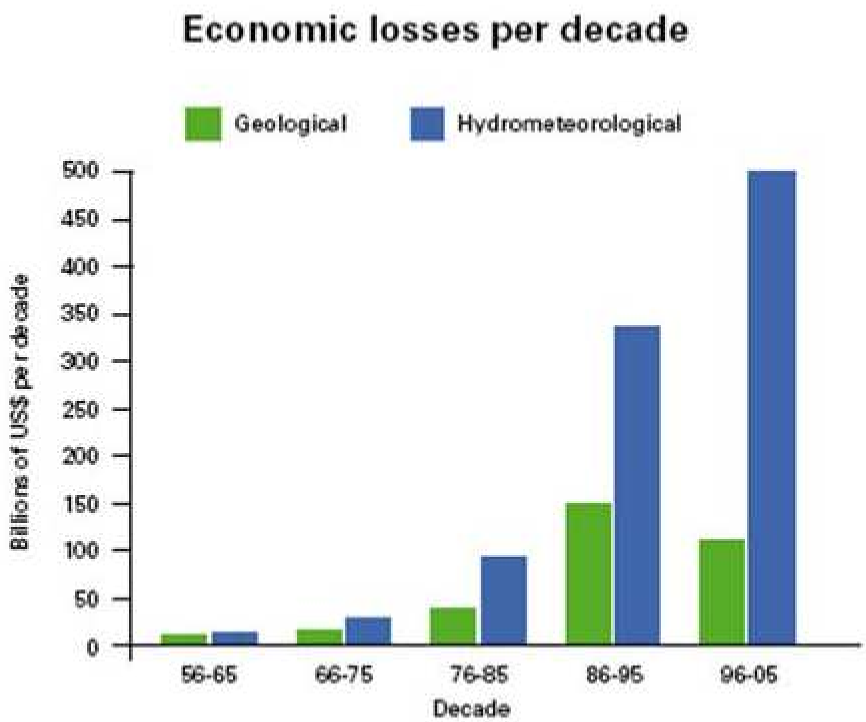


Figure 1.1: Decadal trends in natural hazards impacts over the last 50 years indicating a rise in economic losses associated with hydro-meteorological hazards (Golnaraghi et al., 2009)

In the year 2000, the worst floods occurred in Mozambique displacing and rendering multitudes of peoples homeless including 929 losses of lives which have been attributed to consequences of environmental change (Arnell, 2002). Resistance and resilience in communities and these sectors can be improved through availability of reliable and accurate climatic information. The availability of such information is helpful in the development of an early warning systems to mitigate effects of these disasters and unexpected shocks (Ogallo, 2010). The region information centres grapples with inconsistent and unreliable weather and climate information which compromise and hinders the provision of information for regional planning on climate change adaptation and disaster risk reduction to member states.

This dissertation project assesses TAMSAT satellite-derived rainfall dataset for Africa and compares it with two global community based rainfall datasets commonly used. It seeks to understand and evaluate the relative strengths and weaknesses of these rainfall products with the aim of providing quantitative information that may be necessary and useful for the product improvement and improve applicability. During the evaluation, links between rainfall estimates and subsequent climatic features will be investigated in order to identify deficiencies in the rainfall estimates in capturing the particular events with aim of providing feedback information for the improvement of the satellite estimation methods. Apart from providing information for improvements of the estimates, understanding the relative strengths and weaknesses of these estimates will provide useful information for the users of the information to derive full economic value from the information and apply the information appropriately.

The detailed motivation to this dissertation project is provided below together with the objectives of the study and details of study area. The rest of the sections in this document will be structured as follows; the second chapter provide information on the general weather and climate controlling systems over southern Africa. The third chapter provides literature on the surface rainfall measurement including satellite observations and different types of satellites in constellation. Chapter 4 provide details of the methodologies used to generate the different datasets used in the study including known uncertainties in the different methodologies and their understood sources. Chapter five provide the data analysis methodologies which are followed by results and analysis in chapter 6, before concluding and giving suggestions for the future in section 7.

1.1 MOTIVATION

Rainfall is the primary source of fresh water for consumption and to support vegetative growth and agriculture over southern Africa like in many in many parts of the world. This makes monitoring its distribution, amount and intensity essential for planning its full utilization, taking into consideration that the region is mainly semi arid. Apart from planning its utilization as input for agricultural produce, information on rainfall is useful for simulating the land-surface hydrologic processes, predicting drought and flood, monitoring the water resources state and supporting appropriate studies for the understanding of climate variability and change (Washington et al., 2006). Despite the importance of rainfall information and its usefulness to the community livelihoods, the southern Africa region is far from attaining an adequate level of monitoring of rainfall to meet the user needs both with the provision of quality information for socio economic growth and safety of life and property. This is partly due to the prevailing economic situation faced by most countries and other more demanding social hardships such as provision of primary health care services, primary education, and economic recessions (SADC RSAP & RIP 2010).

The current meteorological observing systems in the region fall short of meeting desired climate information needs as a result of the inadequate station network, instruments and system failure, lack of proper maintenance and calibration which is compounded by shortage of skilled staff and inefficient communication infrastructure for collecting and exchange of data. The African Climate Report (Washington et al., 2006) found the climate observing system for Africa in a rather worse state than in any other continent. Similar conclusions were made by (Sawunyama and Hughes, 2008) who observed a sharp decline of the active rain-gauge network over many developing countries including Africa and the available rainfall data unevenly distributed and most gauging stations located in towns and along roadsides. There is very little hope that the surface observations network will improve in the foreseeable future, considering the many economic situations in these countries. Evidence of the unreliable and unsatisfactory gauge observations in the region can be seen from the GPCC monitoring reports. Figure 1.2 provides an example of available gauge data from southern Africa at the GPCC monitoring centre for day selected randomly. A number of trials randomly selecting days were performed, with no improvement in the sampling. A vast area of the subcontinent shows unavailability of gauge reports which affect planning and providing advisories on rainfall and related operations.

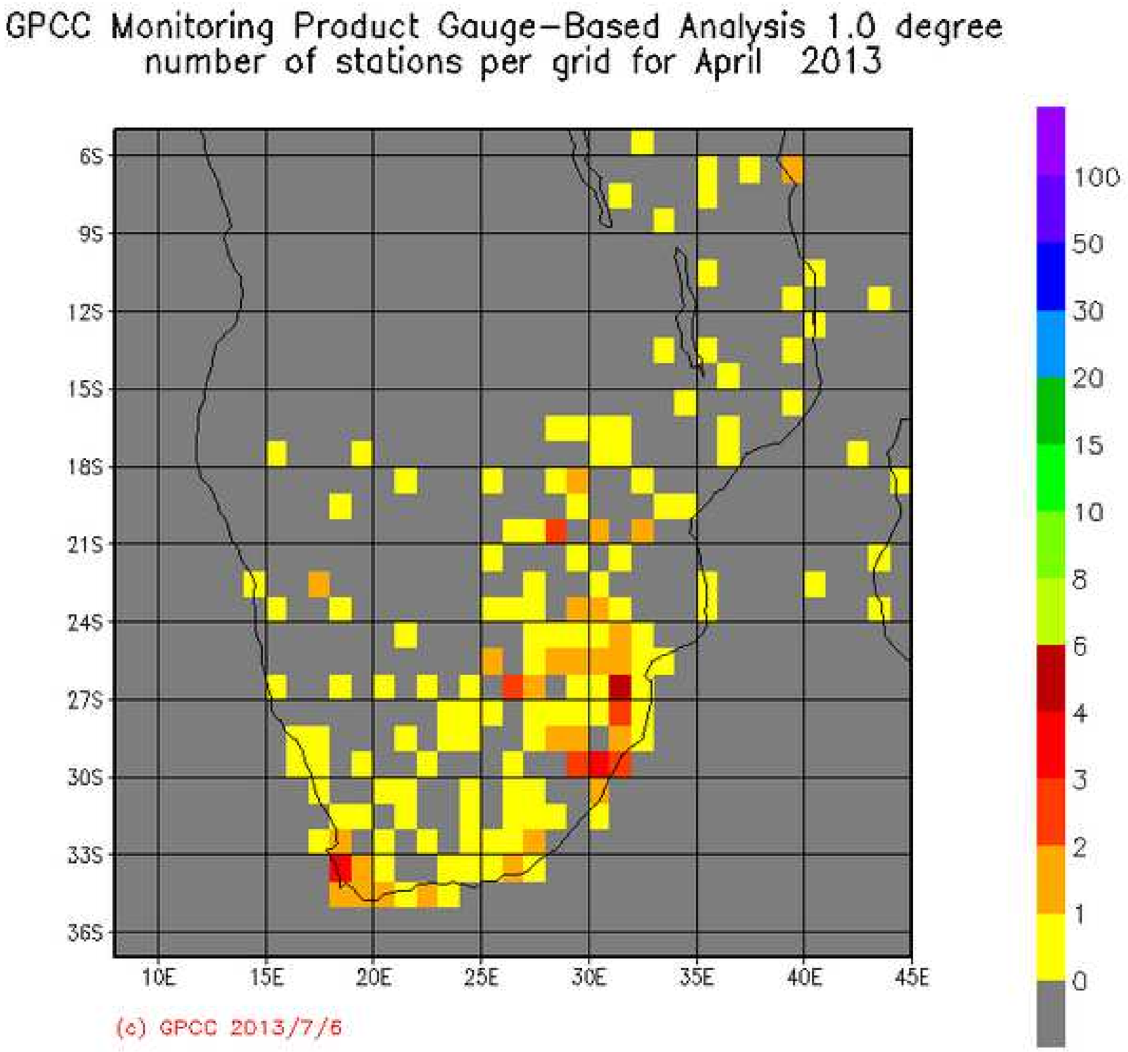


Figure 1.2: Map showing of number rain gauge network reports from southern Africa available in the GPCC monitoring

Through the advance in remote sensing technology and active participation of scientists from around the globe who seek to understand of the underlying key climate processes, (e.g. EUMETSAT, GEWEX, TAMSAT, and EU Joint Research Council JCR), and use of their scientific knowledge resulted in development of models that simulate the earth's climate system and derivation of rainfall from clouds using the remote sensing techniques. Given the sparse surface observation network, remote sensing techniques offer the only method of observing rainfall over all of Africa. This technology offers continuous observations in near-real time such as MSG observations that are currently updated every 15 minutes at a fine enough spatial resolution e.g. 0.0375° to be of use in a variety of applications. The satellite rainfall estimates have become increasingly available and accessible in near real time, their accuracy continuously improving as shown in a number of studies evaluating satellite rainfall estimates (e.g. Adler and Negri, 1988; Xie et al., 2003; Thorne et al., 2001; Bell and Kundu, 2003; Yilmaz, 2005; Roca et al., 2009; Maidment et al., 2012). The satellite rainfall estimates have become a viable data source for a wide range of applications, including studies on the physical climate system (Stephens and Kummerow, 2007), creating rainfall maps that are critical for the investigation of scientific issues such as hydrological regimes (Xie et al., 2003), (Yilmaz et al., 2005), delineating marginal lands and mapping flood prone areas, early warning and food security (Yilmaz et al., 2005), (Pierre et al., 2011).

The Tropical Applications of Meteorological using Satellite and ground based observations (TAMSAT) Group from the University of Reading, UK has been producing operational rainfall derived from METEOSAT thermal infra (TIR) images for northern Africa since 1988 and for southern Africa since 1993 (Thorne et al., 2001). These dekadal rainfall estimates for Africa have shown to perform well over most areas over Sub – Sahara Africa (Dinku et al., 2007, Jobard et al., 2011, Maidment et al., 2012) which gives confidence in the application of these estimates. The TAMSAT group recently developed two new methods based on TAMSAT decadal estimates to generate daily rainfall estimates for Africa spaning nearly 30 years (CCAFS, 2012 pdf). Creation of datasets from satellites enhances usefulness of precipitation data and provides an alternative method for providing timely, reliable and homogeneous records. Such data are of particular importance to overcoming other deficiencies such as the declining conventional operational rain gauges network over the continent.

The TAMSAT rainfall estimates have been made available to Southern Africa through the Africa Monitoring of Environment for Sustainable Development (AMESD) initiative that makes use of earth observations (EO) technologies and data set up operational environment and climate monitoring applications with funding from the European Union Community (EUC). This initiative aims at providing all African nations with the resources necessary to manage the environment effectively ensuring long term sustainability through full access to environmental data and products required to improve national and regional policy and decision making process. Proper application of the technology comes with understanding its strengths and weaknesses to be able to apply it effectively such as climate variability and change advisories. Currently remote sensing technology is the only available efficient means (Grimes et al., 1999) of ensuring adequacy of climate observing systems and is the only affordable way of monitoring environmental conditions over a large area in real-time.

Notwithstanding the advancement in the remote sensing technology and the fact that a large amount of work has been put into reducing discrepancies between satellite rainfall estimates and ground observations during the calibration processes (Dinku et al., 2007), the rainfall estimates still need to be validated against ground observations to increase the understanding of their quality and quantify the level of uncertainty for appropriate use and confidence in their different application. Understanding the discrepancies between the satellite rainfall estimates and observations is achieved through quantitatively evaluating these rainfall estimates and assessing their relative strengths and weaknesses (Thiemig et al., 2012). By comparing these sets of estimates and understanding the spread amongst them indirectly measures the effect of the different physical assumptions in the retrievals, impacts of different sampling strategies or limitations and effect of the various merger schemes. Assessing these estimates improves the confidence in their application and usefulness including increasing ability to assist other users with reliable information required for disaster mitigation through proper planning, poverty alleviation improved food security in the region.

1.2 OBJECTIVES

This study aims at contributing to the scientific base necessary for understanding and assessing the level of skill of the different satellite rainfall estimates by comparison with gridded rain gauge data over Africa with specific focus over Southern Africa region. The specific objectives are;

- Ascertain level of skill of rainfall estimates over Southern Africa for provision of high resolution gridded data sets for numerical model inputs, climate monitoring, detection and attribution
- Understand rainfall variability; detect trends, persistence and any cyclic variations in the rainfall with specific applications to agriculture and fresh water monitoring.
- Extended capabilities in monitoring extreme rainfall events and understanding how the rainfall has changed over time.

1.3 AREA OF STUDY

Figure 1.3 shows the area of focus for the study which is continental southern Africa bounded by 10°E, 44°E and 10°S, 35°S. Southern Africa climate varies spatially from arid in the west through semi arid and temperate areas in central zones with sub humid regions bordering the north and north eastern parts. This region is home to 16.7% of Africa continent population, and generally, it is understood that its climate is highly variable and complex e.g. (Thorne et al., 2001, de Coning and Poolman, 2011, Jury et al., 2007, Blamey and Reason, 2012). The region consists of highly varying topography ranging from mean sea level to about 3000 metres over the mountains and is bounded by the relatively warm Indian Ocean to the East and mild Atlantic Ocean to its West. Drought events over the region have been found to be on the increase in recent years (Rouault and Richard, 2005), and the region is widely recognised as one of the most vulnerable regions to climate variability and climate change as discussed in section 1 on a range of time scales because of low levels of adaptive capacity (particularly among rural communities), combined with a high dependence on rain-fed agriculture (IPCC, 2007).

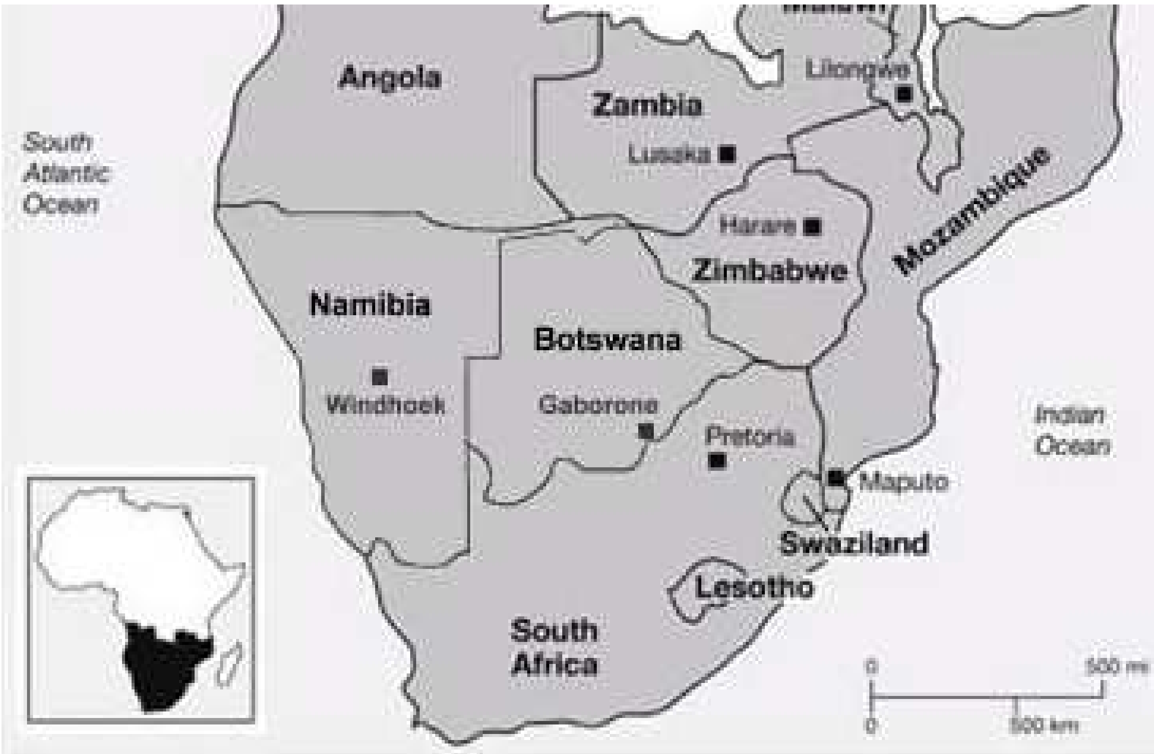


Figure 1.3: Map of Southern Africa and its surrounding oceans with countries found in the region

2 CLIMATE OVER SOUTHERN AFRICA

A larger part of Southern Africa and its adjacent Atlantic and Indian Oceans are located in the region of large – scale subsidence occurring between the Hadley and Ferrel cells of the Southern Hemisphere general circulation which accounts for its climate being generally arid to semi arid (Kidson and Newell, 1977). A combination of complex factors as shown in figure 2.1 that include the geographic location, variations in regional topography and sea surface temperatures, the tapering of the subcontinent result in subtropical southern Africa experiences considerable spatial and temporal variability in rainfall. At shorter temporal or synoptic time scales, the observed variability of rainfall can be linked to both tropical waves' dynamics and mid latitude air intrusion (Chikoore and Jury, 2010).

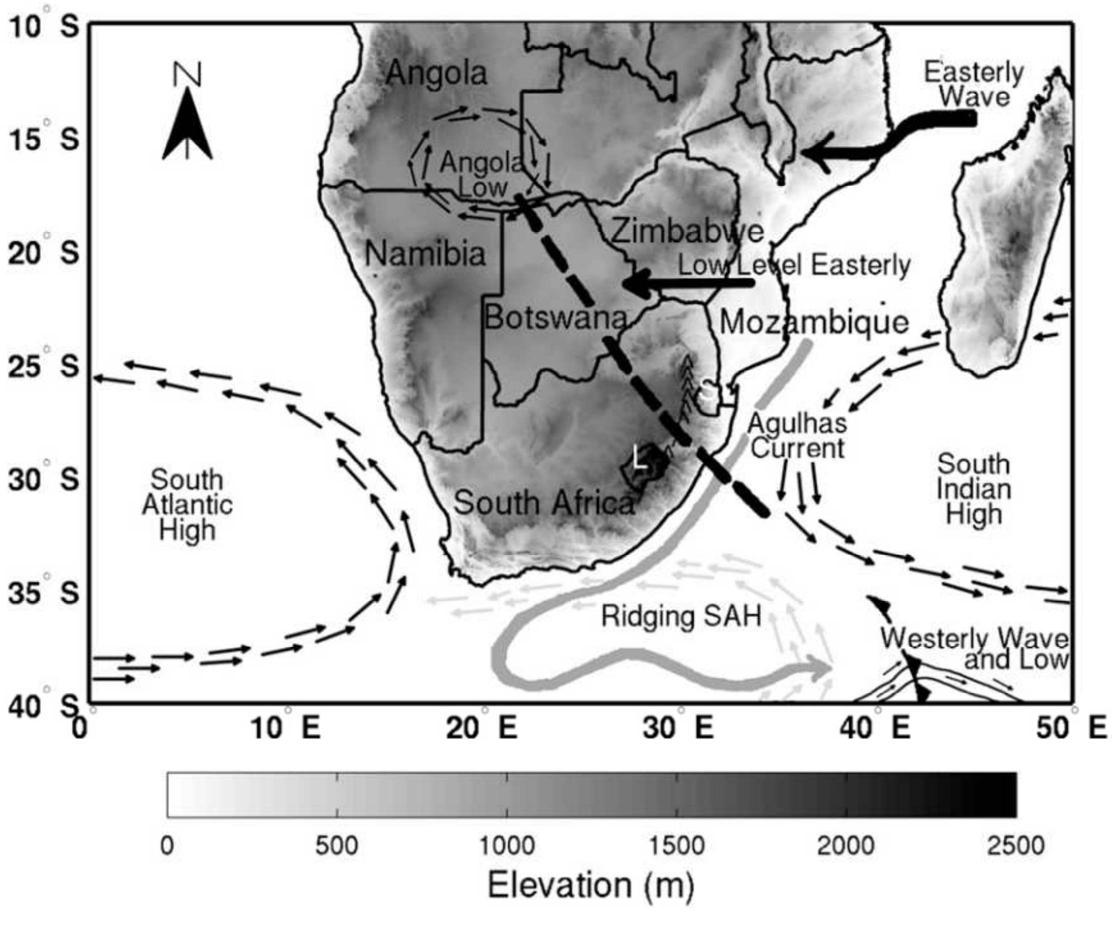


Figure 2.1: Map of the main weather and climate features over southern Africa during the austral summer. The broad dashed line lying diagonally across the sub continent represents mean position of convergence associated with convective bands during the period (Blamey and Reason, 2012).

Over this region, most of the rainfall occurs during the austral summer as shown in figure 2.2 in the form of convective thunderstorms associated with the seasonal mach (relative migration) of the Inter Tropical Convergence Zone (ITCZ) (Preston-Whyte and Tyson, 1988); (Lindesay and Bridgman, 1998).

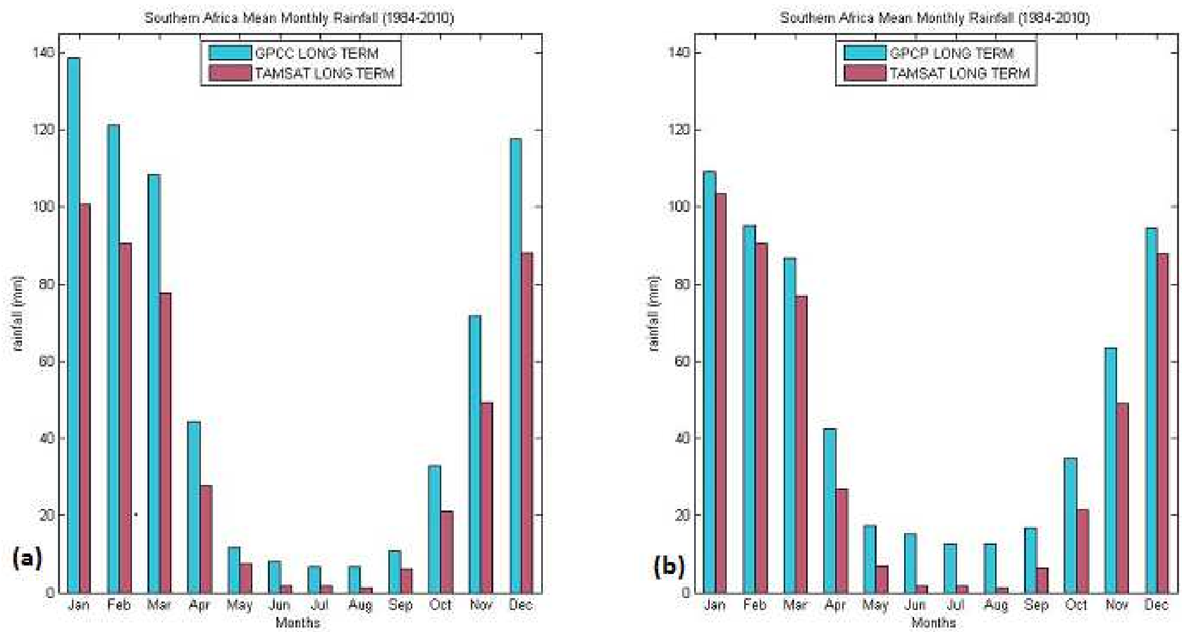


Figure 2.2: Mean annual rainfall distribution for the area bounded by 10°E, 44°E and 10°S, 35°S southern Africa) showing maximum rainfall between DJF when ITCZ has maximum extent to the southern hemisphere. Figure (a) graph of mean monthly GPCC and TAMSAT data at 0.5 degree grid scale; (b) mean monthly GPCP and TAMSAT data at 2.5 degree grid scale.

The ITCZ is a near equatorial trough in which tropical easterly flow from the north and south of the equator converge. During the southern hemisphere summer, the ITCZ lies south of the equator and has maximum southward displacement over south east Africa where it is displaced as much as 20°S (Lindesay and Vogel, 1990). During this period, the tropical temperate troughs have their maximum effect on the region with associated northwest – southeast cloud bands developing and dominating the summer rainfall. These meso-scale convective complexes (MCC) have been studied by (Blamey and Reason, 2012) who found that they tend to develop along the temperate tropical trough influencing rainfall over central Mozambique extending south to Swaziland. High precipitation totals have been associated with these systems which also occur over the neighbouring South West

Indian Ocean, particularly off the north east coast of South Africa. These contribute up to about 20% of the total summer rainfall (November – March) in parts of the eastern region of southern Africa.

Within the seasonal cycle there is alternating sequence of wet and dry spells which at times extend for more than a month with critical implications to rain fed agriculture (Tennant and Hewitson, 2002). The dry spells are associated with the development of an intense mid-troposphere anticyclone often referred to by the local meteorological community as the Botswana upper high pressure associated with the Kalahari desert which causes large scale subsidence over adjacent the sub continent. There also exist intra-seasonal cycles with fluctuations that have eastward moving areas of zonal winds, moisture convergence and surface pressure in the tropical zone that brings rain every 30 – 60 days associated with the Madden – Julian Oscillation (MJO) which studies have found to be prevalent mainly during wet years over southern Africa (Chikoore and Jury, 2010).

Over the western parts of the subcontinent, the ITCZ southward shift is not as pronounced as over the eastern parts of the region due to the relatively weak changes in the intensity of the Atlantic Ocean central pressure and strength (Reason et al., 2006). A pronounced seasonal difference in rainfall patterns exists in southern Africa that is related to the influence of the ITCZ and the annual cycle of the semi permanent anticyclones. The extreme south western parts of southern Africa receives much of rainfall during austral winter due to influence of mid latitude migratory weather patterns associated with cold fronts and ridging of high pressure behind causing influx of low level moisture inland.

The steep topography of the eastern escarpment, sub-tropical easterly flow, and contrasting warm Indian and cool Atlantic oceans, ensure sharp gradients in rainfall with semi arid conditions along the western boundary. The difference in heat capacities between land and water bodies maintains gradients of temperatures between the land and the ocean generating localised circulation. The rainfall is characterized by strong seasonal cycle with a well defined wet season (October – April) over most of the subcontinent (Reason et al., 2006).

2.1 OCEANS INFLUENCE

Recent studies have focussed on enhanced understanding of the links between the local oceans and their contributions in the evolution of the weather and climate over the region e.g. (Saji et al., 1999, Annamalai and Murtugudde, 2004, Cook et al., 2004, Song et al., 2008, Manatsa et al., 2012). There has been found the existence of an east – west mode of variability of the Indian Ocean Dipole / Zonal Mode (IODZM) that has influence on rainfall variability over parts of Southern Africa. The IODZM is described as the extreme sea surface cooling events that occur during the boreal autumn in the eastern tropical Indian Ocean that arises from coupled atmospheric feedbacks that result in an east – west sea surface temperature gradient along the tropical Indian Ocean (Saji et al., 1999). The positive phase of the IODZM is associated with the westward shift of convection over the eastern Indian Ocean resulting more rainfall over eastern southern Africa, thus the alternating warm (cool) sea surface temperatures to the east and cool (warm) sea surface temperature to the west result in wet(dry) spells. Over the western southern Africa on average, the Atlantic Ocean anticyclone shifts only about 6° latitude between seasons with significant semi-annual oscillation in position (Reason et al., 2006). The seasonal fluctuations in the anticyclone drive changes in the surface winds and hence SST's, particularly in the upwelling zones along the west coast of southern Africa such as along the Namibian coast during the winter months. These oceans act as sources of low level moisture and have high influence on the climate of Southern Africa both at synoptic and seasonal time scales.

2.2 El NINO SOUTHERN OSCILLATION INDEX (ENSO-SOI)

The El Nino Southern Oscillation Index (ENSO-SOI) is widely understood and accepted to be highly associated with the inter-annual rainfall variability over Southern Africa including patterns of tropical sea surface temperature (SST) and zonal overturning circulations e.g. (Richard et al., 2000, Ropelewski and Halpert, 1987, Ropelewski and Halpert, 1989, Reason and Rouault, 2002, Jury et al., 2002). ENSO, primarily a tropical Pacific phenomenon, is thought to influence southern Africa weather patterns through modulation of the local Walker circulation and SSTs in the neighbouring Indian and Atlantic Oceans; (Janowiak, 1988), (Fauchereau et al., 2009). Figure 2.3 show the general global conditions of moisture and temperature associated with warm El Nino episodes. During ENSO modes, parts of Southern Africa remain under warm and dry conditions such as was the case described in above that resulted in the worst drought that affected the region in recent times. The El Nino causes the south Indian Ocean convergence zone to be displaced and shifted north eastwards and positioned over the Indian Ocean, resulting in reduction of moisture convergence, uplift and instability that result in dry conditions prevailing over southern Africa. However, the relationship between rainfall over southern Africa in non linear (Mason and Goddard, 2001, Reason and Jagadheesha, 2005) as was shown by the 1997 El Nino phase which failed to produce the known results prompting further investigations into the El Nino characters and its relationship to the region precipitation (Mason and Goddard, 2001, Reason and Jagadheesha, 2005).

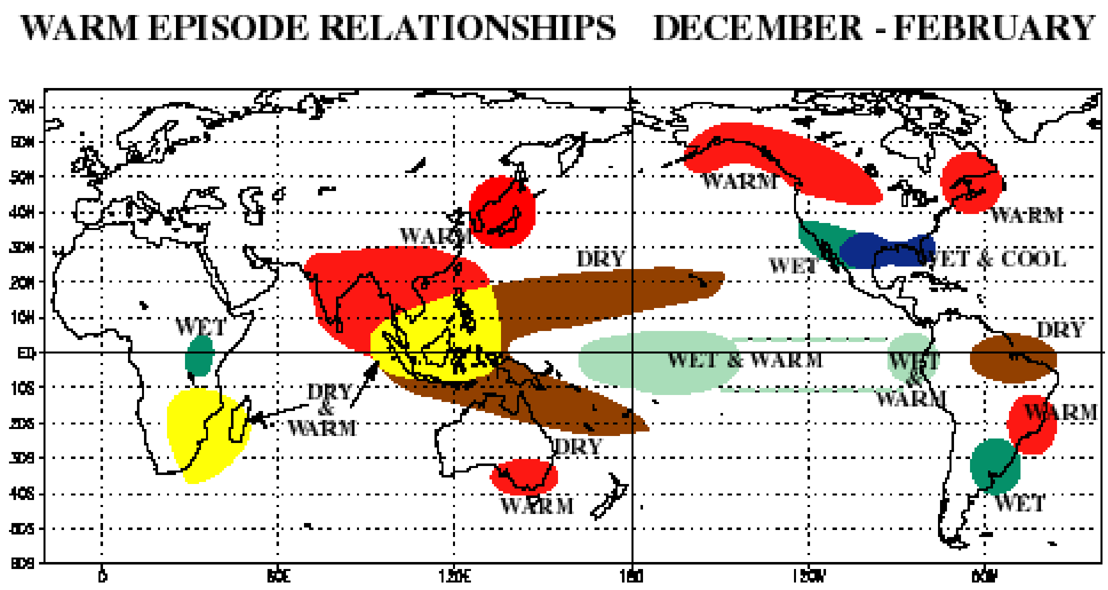


Figure 2.3: Warm and dry conditions in December - February prevail over Southern Africa during a warm El Nino Episode. During warm ENSO episodes the normal patterns of tropical precipitation and atmospheric circulation become disrupted. Source: NCDC NOAA

The reversal of the El Nino (La Nina) phase is associated with reversed conditions over the region, such that during these years the south Indian Ocean convergence zone tends to be located over the continent resulting in generally wet conditions over most parts of the sub-continent as shown in figure 2.4 which depict mean global conditions associated with La Nina.

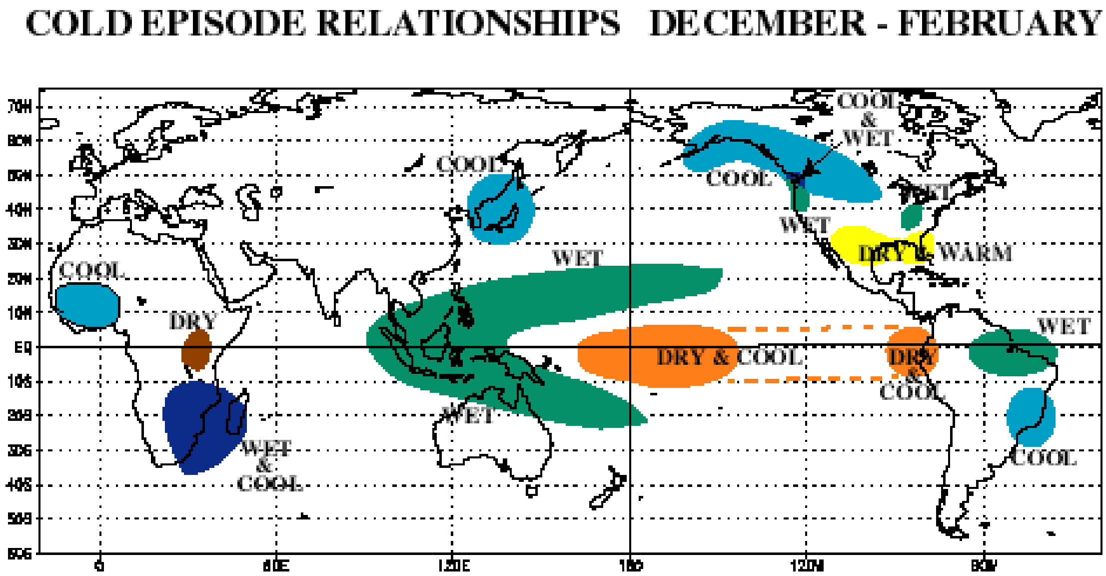


Figure 2.4: Map showing parts of Southern Africa covered by wet and cool conditions in December - February during La Nina episodes. During La Nina episodes the normal patterns of tropical precipitation and atmospheric circulations become disrupted. Source, http://www.ncdc.noaa.gov/

3 RAINFALL MEASUREMENTS AND ESTIMATION

Since rainfall is one of the most important parameters affecting human life its measurement has been pursued for a long time. As discussed in section 2, rainfall is variable both in space and in time making accurate measurements and representation difficult. Rainfall measured at a point is very different from over an area, hence spatial interpolation for inter comparison studies is required (e.g. Thorne et al. 2001, Ali et al., 2005, Pierre et al., 2011). Because of its importance to human life, man has developed different techniques for rainfall measurements ranging from planting gauging system on the ground to intercept the falling rain using a simple bucket with collecting funnel, storage and a measuring cylinder to sophisticated ground and space–borne using complex science and mathematical equations to provide information on rainfall both in space and in time (Adler et al., 2003). These different systems have their merits and limitations which are discussed in detail below.

3.1 RAIN GAUGES

Different rain gauge designs as shown in figure 3.1 below have evolved and existed over time in different regions and countries, and at times different designs exist and are used within country. These different designs however, can make comparisons of rainfall data very difficult especially where the information about the measurements is not provided to quantify the uncertainties related to these measurements (Arnell, 2002). The most common and simplest is a non recording cylindrical container of defined height with an orifice of a defined size that collects rainfall (Strangeways, 2007). The collected rainfall is emptied into an accompanying measuring cylinder for measurements usually at fixed time intervals.

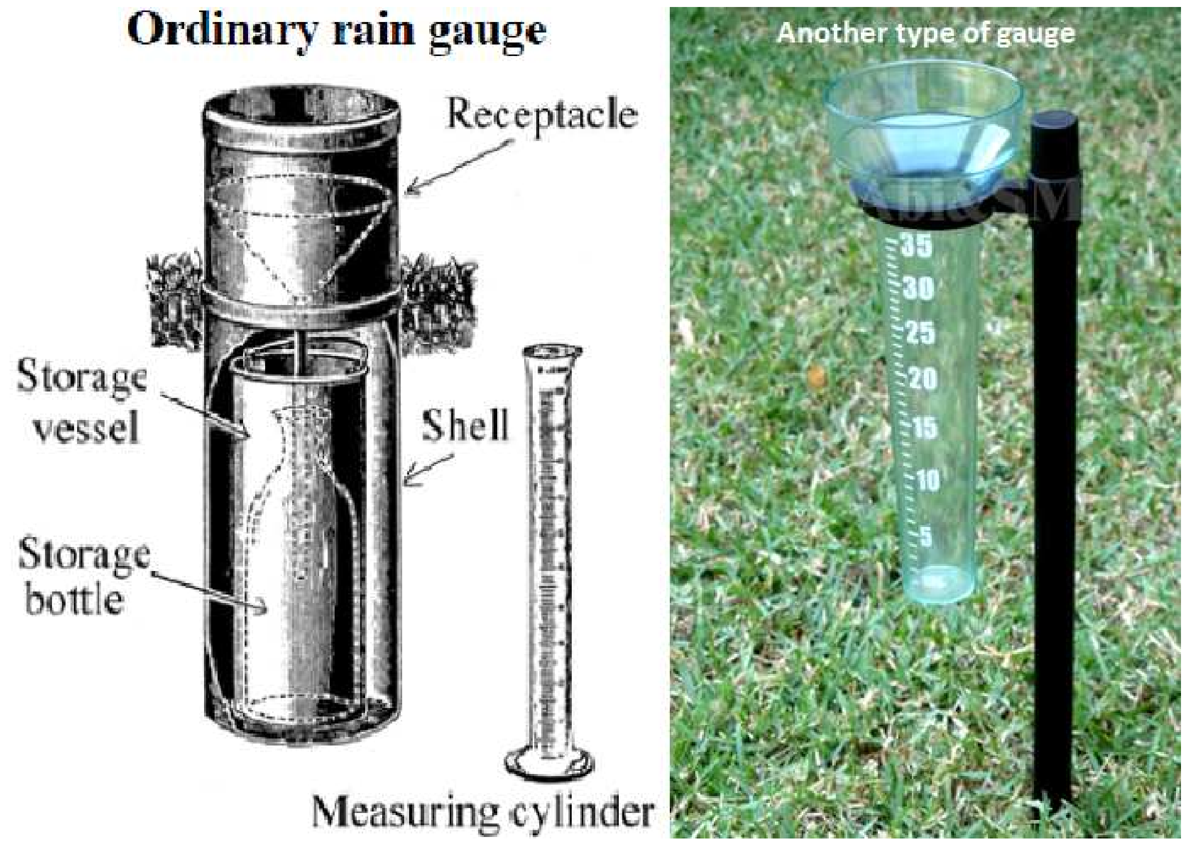


Figure 3.1: Images of different types of rain gauges available for rainfall measurements.

Other types of gauges include automatically recording systems which are either electronic or operating an analogue clock. The electronic gauges automatically record and store the measurements in a data logger and are capable of transmitting the observed data automatically at the required time. The analogue systems contain float and a chart wrapped around the drum and a pen arm in a dial clock normally wound once weekly for recording the amount of precipitation falling. The advantages of the automated rain gauge systems include being able to provide a continuous record of the precipitation event making it easy to trace intensities of the precipitation. However, these require higher expertise for maintenance compared to standard rain gauges and communication costs may prevent near real time of the observed data.

Standard rain gauges are the most affordable technology especially for developing countries because of their simplicity in design over time, thus long record of rainfall have been produced from them. Though they have been used over time, most of the rainfall record from standard rain gauges is susceptible to a number of errors (Habib et al., 2001) resulting from a number of varied reasons such as those related to installation and human error mainly due to incompetent observers taking the measurements. Even in gauges that are properly maintained, errors arise from both random and systematic components depending on the type of apparatus, the surrounding environment and the type of rainfall being measured. Aerodynamic effects are often the most common and can lead to underestimates of rainfall depending on the rate of the rainfall, wind speed, gauge type and exposure of the rain gauge. Apart from the errors associated with rain gauge measurements, rain gauges have a major disadvantage in aerial rainfall representation. Rain gauges measure precipitation falling within the diameter of the gauge (Huffman et al., 1995). Inferences to what may have fallen squares of kilometres around the gauge can only be made to the extent to what the gauge encounters is representative of what happened in the surrounding area.

However, gauge data provides the only means of verifying (ground truth) satellite derived rainfall data. But the distribution of the gauges (Ali et al., 2005) and how well these gauges agree amongst themselves (Rudolf et al. 1994) has an effect on the estimation errors of the satellite rainfall estimates. Greater variations in mean precipitation values amongst satellite estimates over the ocean were observed (Adler et al., (2011) compared to overland estimates where there is good gauge measurements and information.

3.2 SATELLITE OBSERVATIONS

Satellite are the only practicable means of observing rainfall continuously on a larger scale, but the remote sensing methods used in estimating rainfall from space borne instruments are inexact as explained below. Satellite observations of the earth's atmosphere are in the form of spectral radiance or irradiance arising as natural processes of emission and scattering of electromagnetic radiation by an object in the atmosphere or over a geographical area on the surface. The satellite measuring technique is based on the principle of black body laws of physics which in its simplicity relates emission and temperature. All objects emit electromagnetic radiation and the type of radiation they emit depends on their temperature as shown in figure 3.2a below. The hotter the object the more intense the radiation emitted and the greater the proportion of radiation emitted at shorter wavelengths. The surface of the Sun is at a temperature of about 6,000 °C and it emits predominantly in the visible region of the spectrum. The Earth has an average temperature of about 15 °C and emits mainly in the infra-red and microwave regions.

Given the inherent nature of the interactions between different bodies such as clouds and precipitation and the electromagnetic radiation, vary according to spectral region of interest (figure 3.2b), then it is expected that the information content in such observations also varies according to where in the spectral region the observations are performed.

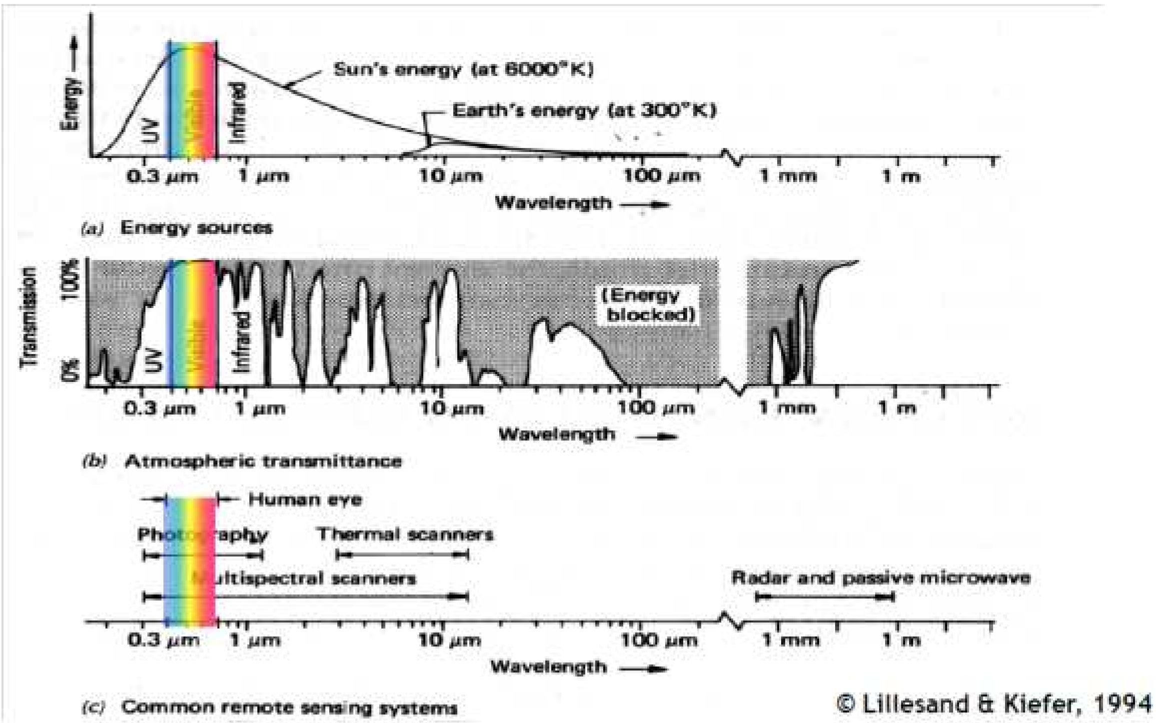


Figure 3.2: A diagram of the electromagnetic spectrum showing various properties across a range of wavelengths. (a) Show energy sources, (b) shows atmospheric windows (transmittance) and (c) indicates common remote sensing systems and wavelengths used. The main wavebands used in cloud measurements are highlighted in colour,

One class of approach for information retrieval relies on measurements of transmission where the attenuation of the defined source of radiation is used to determine some properties of clouds, while the other method utilizes the scattered radiation by clouds and precipitation (Lillesand et al., 2004).

3.3 TYPES OF SENSOR TECHNOLOGY

Different sensor technologies carried on board the different remote sensing platforms have evolved such as explained by Adler and Negri, (1988), Stephens and Kummerow, (2007), Yong et al., (2010), and used to acquire the information at these different wavelengths. The most common ones for meteorological applications are discussed below and include;

i) VISIBLE (VIS) SENSOR (0.4 – 0.7μm)

Visible sensors record the reflected light from the sun by the cloud tops, land and sea surface. Rainfall estimation depends on cloud optical depth, cloud phase, cloud particle sizes and distribution. This sensor type picks information from clouds using their different reflecting properties to the land and sea. However, visible sensor only provides information during daytime and the observations from this type of sensor only relate to characteristics of cloud tops, rather than the precipitation reaching the ground.

ii) INFRA–RED (IR) SENSORS (9 - 12μm)

This type of sensor records the emitted radiation by clouds, land or sea surface. As explained in section 3.2 above, infra red sensors utilize the part of the spectrum beyond the visible wavelength of light and the atmosphere transmission (atmospheric windows). The most used channel for rainfall estimation of the electromagnetic spectrum is IR 10.8μ. Similarly, IR sensor technology only relate to characteristics of cloud tops rather than the rainfall reaching the ground.

iii) PASSIVE MICROWAVE SENSORS (PMW)

The atmosphere optical window is not the only region of the electromagnetic spectrum that is used for meteorological and hydrological applications. Microwave sensors on board polar orbiting satellites commonly utilize the microwave (mw) wavelengths (~ 1cm) to exploit the atmosphere transparent window located at these wavelengths as shown in figure 3.2c of the spectrum and the fact that each height in the atmosphere is sensitive to a slightly different wavelength of radiation. Observations at microwave frequencies relate to the amount of water within the vertical column of the atmosphere being observed. At these wavelengths, clouds appear mostly transparent, thus the sensor can obtain information from underneath the cloud layer. These sensors are referred to as passive sensors since they measure the natural radiation emitted or scattered (re-directing) from the atmosphere beneath the sensor.

The remote sensing technology applied to rainfall estimation been in use for some time and ranging from relatively simple empirically derived and calibrated techniques such as the TAMSAT algorithm (Grimes et al., 1999), through to those that use complex atmospheric physics and radiative transfer equations. These have been applied to support of a variety of applications such as climate studies, input into agriculture, hydrological and weather forecasting. They have been useful in compensating for unreliable sparse and late reporting gauge stations especially in developing countries for early warning systems and decision making process e.g. (Arkin and Meisner, 1987, Adler and Negri, 1988, Kummerow et al., 2001).

3.4 TYPES OF SATELLITES

Different types of satellites are in existence and operated by different space agencies and different applications. For meteorological applications relevant to the study, two types of satellites will be discussed.

i) GEOSTATIONARY SATELLITES

A geostationary satellite has a geosynchronous orbit which implies that the satellite is always in the same position with respect to the rotating earth. The current generation of geostationary satellites orbit the earth at approximately 36,000 km along the equator (0°) at same period (24 hrs) with the rotating earth which makes the satellite appear stationary above the earth's surface. Figure 3.3(a) below illustrates a geostationary satellite in orbit relative to the rotating earth. The current operational geostationary satellites providing data for Africa and Europe is the METEOSAT Second Generation (MSG) which has evolved from first generation (MFG) and have in total provided satellite observations and subsequent meteorological products and information for over 30 years. Presently, the METEOSAT satellites make use of 12 spectral channels and have a spatial resolution of approximately 3 km at sub satellite point and produces full disk view of Africa and Europe every 15 minutes making it ideal for monitoring convective developments especially over Africa where the satellite has a good field of view (www.eumetsat.int). Geostationary satellites provide better information in the longer term due to its high temporal resolution.

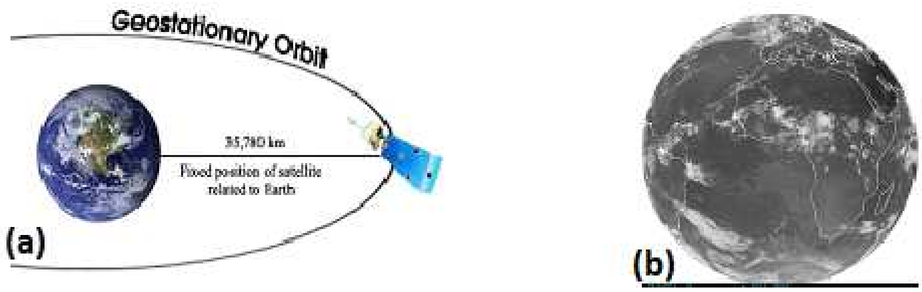


Figure 3.3: A model of a geostationary satellite in orbit. (b) Field of view of METEOSAT geostationary satellite on 2nd July 2013, 0600Z. Images source: www.eumetsat.int

Full utilization of satellite-based precipitation datasets is hindered by the uncertainty and reliability associated with the precipitation estimates. One disadvantage of IR/VIS rainfall estimation technique is that precipitation is inferred from clouds (Adler and Negri, 1988) which introduces further errors in the measurements and it is believed that the accuracy of such techniques cannot be readily transferable from one location to another location.

ii) POLAR ORBITING SATELLITES

Polar orbiting satellites are the family of satellites that orbit the earth at lower altitudes compared to the geostationary satellites at approximately 850km. They pass over the North Pole and South Pole on each revolution with each revolution taking about 90-100 minutes. This means that these satellites pass over every point on the earth's surface twice each day. Because of their low orbit, polar orbiting satellites provide much higher spatial resolution information than geostationary satellites. However, these cannot offer good information for short lived weather and climate events since they only sample a point on the earth's surface twice daily during their overpass carrying on board the passive microwave sensors.

Microwave rainfall retrieval are also affected by so-called beam-filling effect due to unresolved rainfall heterogeneity within sensor FOV, as well as having a non-linear relationship between brightness temperatures and high rainfall rate which can result in bias in estimated rainfall intensity (Curran, 1982) which may contributes to the error in accumulated rainfall estimates. Furthermore, the emissivity of the land surface at the microwave spectrum is higher and more variable in space and time than over the ocean, causing additional complexity of rainfall retrieval over semiarid regions of Africa. Bellerby and Sun, (2005) suggests that in general, passive microwave algorithms generally produce overestimates of rainfall. More information on polar orbiting satellites is available on, http://www.ospo.noaa.gov/

3.5 **WEATHER RADAR**

Other available technology for rainfall estimation especially in developed countries is the weather radar. Weather radar is also available in some aircrafts to provide information on hazardous weather during the aircraft in flight. The weather radar primary operating principle entails emitting of a beam or pulse of microwave or radio waves from the radar transmitter into the atmosphere. When the beam collides with an object on its path such as cloud droplets, solid or liquid rain drops such as hail stones, some of the energy bounces back to the radar receiver and redetected and processed in the processing unit and graphically displayed for interpretation.

Weather radar, provide a comprehensive picture of the rainfall pattern over an area and have high temporal resolution. One major non technical disadvantage with weather radar systems relates to their technical requirements related to installation, operations and maintenance costs which eliminate developing countries affording these systems. Over southern Africa, an operational radar network is found in South Africa which is useful in the South African Flash Flood Guidance (SAFFG) system (de Coning and Poolman, 2011) and supported by a fairly dense rain gauge network of about 1500 daily gauges. However, less rain gauge information is exchanged and made available to the GTS of WMO.

Apart from the non technical disadvantage, radars do not measure precipitation directly as discussed above. The conversion of the signal backscatter into rain rates is not exact and the surface affects radar accuracy, such as radar may fail to capture low level precipitation due to upward refraction of the radar beam (Morin et al., 2005) through the atmosphere leading to anomalous signals on the radar measurements.

4 RAINFALL ESTIMATION TECHNIQUES

This section discusses the different rainfall estimation techniques available for producing aerial rainfall relevant to the study and which the data used in this study was generated.

4.1 MEASUREMENTS AND ESTIMATION INTERCOMPARISON

Though satellite derived rainfall estimates have been available for use in Southern Africa, e.g. in Zambia, the Meteorological Service distribute 10-day rainfall estimates and related products for agriculture purposes (Thorne et al., 2001), minimal studies on these satellite rainfall estimates have been undertaken in southern Africa that provide information on their uncertainties, relative weaknesses and strengths unlike in other parts of the African continent such as northern Africa. Over northern Africa a number satellite rainfall estimates inter comparison studies have been undertaken e.g. (Herman et al., 1997, GRIMES and DIOP, 2003, Ali et al., 2005, Dinku et al., 2007, Roca et al., 2009, Roca et al., 2010, Jobard et al., 2011, Owolawi, 2011, Chadwick and Grimes, 2012, Maidment et al., 2012, Thiemig et al., 2012, Gosset et al., 2013).

Most of the studies are in general agreement that the influence of climate, location, rainfall types, season and topography and number of gauges within a grid box are important factors in the performance of satellite algorithm including the spectral range (IR or PMW) used in the measurements. A number of satellite rainfall estimates show the effect of the number of rain gauge measurements within each grid box in the bias error estimates including how the errors improve with increased density of gauge observations e.g. (Grimes et al., 1999, Thorne et al., 2001, Ali et al., 2005, Dinku et al., 2007, Maidment et al. 2012, Chadwick and Grimes, 2012). Adler et al., (2011) estimating climatological bias errors for GPCP argued that higher errors were found over the ocean than over land, and attributed lower bias error over the land to availability of gauge information over the land.

In an East Africa validation study, Dinku et al. (2007) found that satellite rainfall estimates did not compare well with in-situ rain gauge data in a study over regions of Ethiopia, attributing poor performance mainly to topography. Specifically, they noted that topography plays a significant role in satellite rainfall estimation due to an algorithm's inability to detect mountain enhanced rainfall. Similar observations were found by Romilly and Gebremichael, (2011) over northwest Ethiopia consisting of mainly highland topography and humid climate strongly influenced by the ITCZ.

Similarly, in the Climate Change, Agriculture and Food Security Technical Report, (CCAFS, 2012 pdf) suggests that the TAMSAT algorithm is more suited to the Sahel than East Africa as the occurrence of cold cloud at pixel scale over the Sahel is closely related to rainfall occurrence than it is over Central and East Africa where the cold cloud pixel is not always associated with rainfall.

In a study by Thorne et al (2001) over southern Africa which compared TAMSAT data, Climate Prediction Centre (CPC) and gauge data concluded that TAMSAT estimation technique of using varying calibration zones performs best over flat and arid regions and grossly under estimate rainfall over mountainous regions and areas with very few rain gauges available in real time. Other findings from inter-comparison studies show that in general, rainfall estimating techniques that include gauge data compare better e.g. (Dinku et al., 2007 and Jobard et al. 2011), or have less bias compared to the satellite only rainfall estimates.

However, these it should be noted that these limitations do not particularly imply that the satellite rainfall estimates cannot represent accurately ground rainfall, but provide an indication on the weaknesses and sources of uncertainty associated with the satellite rainfall estimation techniques. Although conclusions have been made about performance of different estimates and locations, more studies evaluating the performance of the different algorithms are necessary to enable the continuous improvements of the satellite rainfall estimates taking into consideration that they offer measurements even over remote areas particularly over southern Africa where fewer studies have been carried out.

Most of the studies carried out have considered daily and 10-day rainfall estimates for the inter-comparison but few have used monthly data and evaluated bias climatology in the rainfall estimates. It cannot be over emphasised that the most informative comparisons of satellite and rain gauge averages is one where enough averaging has been done to reduce the variability in the differences due to random sampling and retrieval error to a level where the residual bias is detectable at a certain desired level, hence this study is designed to consider monthly and annual scale of the bias. Bell and Kundu, (2003) in their study comparing satellite rainfall estimates and gauge data stated that mean differences between gauge and satellite data can be expected since each of the measurement technique include rain observations which the other does not include.

4.2 TAMSAT RAINFALL ESTIMATION

The TAMSAT methodology has been described in detail elsewhere e.g. (Milford et al., 1994, Thorne et al., 2001, GRIMES and DIOP, 2003) but here will give summary as background information for the study. This method of rainfall estimation utilizes the 10.8μm infra-red channel from the METEOSAT geostationary satellite and has data spanning more than 30 years. From this channel, the brightness temperature can be calculated. This methodology attempts to define a linear relationship between the numbers of hours for which a satellite pixel temperature is colder than a specified threshold temperature.

The TAMSAT rainfall estimation technique can be traced back to the work of (Arkin and Meisner, 1987) who used the idea of Cold Cloud Duration (CCD) to show that rainfall in the tropical Atlantic could be related to the fractional coverage of cloud with satellite-measured temperatures below 235K (-38 °C). The TAMSAT algorithm was initially developed for rainfall estimation over North Africa for agricultural purposes and predicting famine and floods.

The TAMSAT technique does not merge satellite data with current gauge observations, but uses historical data that is perceived to be invariant over long time periods to generate climatological calibrations. The TAMSAT methodology (Grimes et al., 1999) in its simplicity uses only geostationary IR data on board METEOSAT satellites and exclusively covers Africa (Thorne et al. 2001). The calibrations are carried out separately for each calendar month within empirically determined climatic zones. The methodology is perceived to the one of the simplest methods employed for remotely sensed rainfall which has better performance in rainfall estimation compared to more complicated methods such as those defined by Adler and Negri, (1988), Dinku et al., (2007), Chadwick and Grimes, (2012). The detailed basic assumptions inherent in the TAMSAT rainfall estimation method include as discussed by Grimes et al., (1999);

- Rainfall predominantly comes from convective clouds.
- Clouds only rain when their tops have reached a certain minimum height (threshold height)
- Cloud top height can be identified by its temperature on the thermal infra red (TIR) image referred to as T_t

Over a given location, the quantity of rainfall can be calculated from the length of time the cloud top has been above the threshold referred to as the cold cloud duration (CCD).

$$Rs = a_0 + a_1 \mathbf{D} + \mathbf{e} \qquad \textbf{... 4.1}$$

Where R_s is the rainfall over the pixel, D the cold cloud duration over the pixel and e the error with zero mean, $\mathbb{E}\{\boldsymbol{e}\} = 0$, and homogeneous variance {var} = σ^2. In practice T_t, a_0 and a_1 are calculated for each month for a number of empirically determined calibration zones. These zones are defined to be climatologically homogeneous areas with sufficient rain gauges to give a statistically reliable calibration. A further assumption is that the relationship between rainfall quantity and the cold cloud duration is linear provided there is adequate averaging of the data either in space or in time, then:

$$\boldsymbol{\hat{R}_s} = \boldsymbol{\hat{a}_0} + \boldsymbol{\hat{a}_1}\mathbf{D} \qquad \textbf{... 4.2}$$

Where, 'hat' indicates estimated parameters (Grimes et al., 1999). These above assumptions are explained schematically in the below figure;

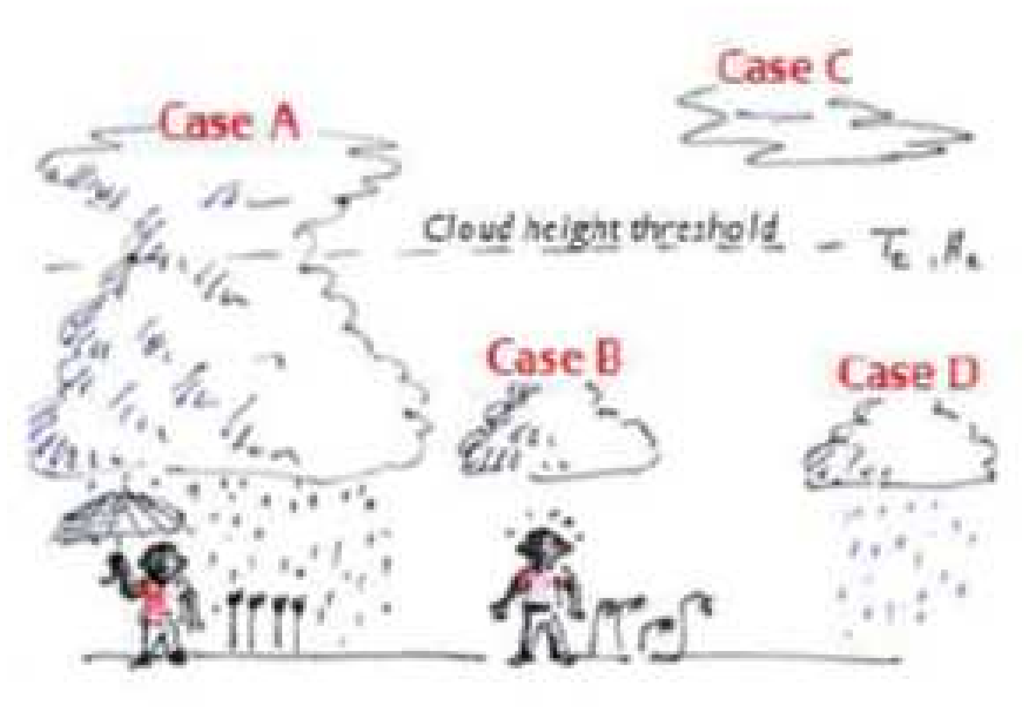


Figure 4.1: Schematic diagram of clouds with tops colder than threshold temperature T_t (dashed line) are assumed to be raining, while clouds with tops warmer than T_t are assumed not to be raining (Grimes et al., 1999).

From the discussions above, some limitations of the TAMSAT algorithm are evident as is shown by the schematic figure 4.1 above. These errors combined are associated with identification of cloudy scenes and identification of precipitation from cloudy scenes and non precipitating cloudy scenes. The problem of discriminating a cloud clear and cloud precipitating is represented in the above scheme, where small clouds generating precipitation without reaching the threshold temperature are missed or regarded as non precipitating clouds. Similarly high level non-precipitating cloud, when present, may sometimes be indistinguishable from convective cold cloud tops in TIR images, leading to overestimation of the rainy area.

4.3 GLOBAL PRECIPITATION CLIMATOLOGY CENTRE (GPCC)

GPCC is hosted by the German Weather Service and is Germany's contribution to the WCRP mandated by WMO Global Climate Observing System (GCOS) to provide global precipitation data sets for monitoring and research of the earth's climate system. The GPCC data are optimised for maximum spatial coverage and based on quality controlled rain gauge (Schneider et al., 2008) data that comes mainly from SYNOP and CLIMAT reports from 10000 - 45000 rain gauge stations worldwide available in the GPCC database, collected from the Global telecommunications System (GTS) of WMO. Additional data is also used but require more rigorous automatic and manual quality control procedures. The data set are based on station anomalies which are calculated with respect to GPCC global normal, gridded and superimposed on the gridded climatology before being released to users. This data is updated occasionally and is available from 1901 at 0.5° x 0.5°, 1.0° x 1.0° and 2.5° x 2.5° grid resolution.

Figure 1.2 shows an example of number of gauges from southern Africa on a particular day. As can be noted from this figure, there are large areas over much of southern Africa where there are little or no measurements of daily rainfall, notable over the north western and northern parts of the region. It is within such data void that satellite can provide vital information on precipitation and fill that gap.

The number of gauges available at the GPCC centre per grid box per time fluctuates due to a number of reasons. These include non availability of observations from station, station closure and relocation of gauging station which affects inter-comparison exercise as it contributes to the sampling (spatial) error in the gauge dataset. According to Roca et al., (2010), when the measurements errors make up to 50% of the variance on each series, the coefficient of correlation is reduced by roughly 50%.

4.4 GLOBAL PRECIPITATION CLIMATOLOGY PROJECT (GPCP)

The Global Precipitation Climatology Project (GPCP) was established to develop global long term precipitation records for the international community on behalf of World Meteorological Organization / World Climate Research Programme / Global Energy and Water Experiment (WMO/WCRP/GEWEX) since 1986. It is a component of the GEWEX global analysis of the energy and water cycle. The GPCP data sets are developed and maintained as an international activity with input data sets provided by several contributing scientific groups (Huffman et al., 2009). GPCP combine input data from multiple sources of satellites according to their availability and estimated accuracy to compute monthly precipitation data together with rain gauge data provided by the GPCC. It merges rainfall estimates taking advantage of over 6000 rain gauge data collected by the Global Precipitation Climatology Centre (GPCC) together with satellite infra red (IR) and passive micro wave (PMW) observations. The first version of the merged satellite and rain gauge data set was produced in 1979 and since then the precipitation data has been available in monthly and finer time scales. The final merged product is produced a few months after real time through the data inputs and products of a number of scientists and organizations (Adler et al., 2003). Such data are essential for varied applications such as quantifying the global water cycle, application in numerical modelling and climate related studies to permit a more complete understanding of the spatial and temporal patterns of global precipitation. Information on GPCP and GPCC available on: http://www.precip.gsfc.nasa.gov/gpcp_daily_comb.html

5 DATA AND METHODOLOGY

This section describes the data and methodologies employed in data analysis including different strategies applied in order to achieve the objectives of the study. One intention of the study is to quantitatively evaluate the differences between the three different rainfall estimates which are TAMSAT, GPCP and GPCC (gauge data) including assessing the dependence of relative bias on seasonality and geographic variations over southern Africa. Special interest will be on TAMSAT since it is also widely available to all meteorological services in Southern Africa through the MSG stations. The inter comparison focus on monthly, seasonal and annual scales using data from January 1984 – December 2010. This period was chosen based on all three datasets availability and completeness, especially TAMSAT data that is available from 1983 (1983 omitted since data unstable at beginning). The strategy entailed averaging the all datasets regionally and analysing the mean using different statistical techniques such as differences in the mean, variation of the mean and coefficient of variability.

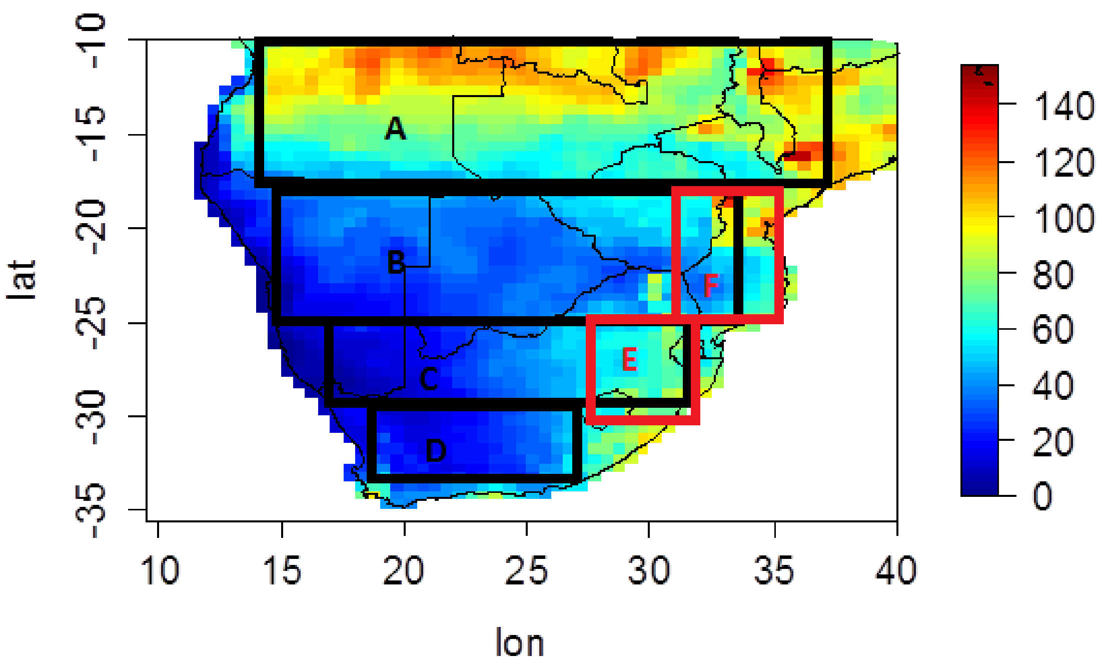


Figure 5.1: Map showing zones used to compare rainfall estimates based on mean rainfall distribution in mm (1984-2010) over southern Africa. A (10 - 16°S, 14-40°E); B (16-25°S, 15-32°E); C (25-29°S, 18-31.5°E); D (29-33.5°S, 18-26°E); E (24-29°S, 27-31.5°E); F (16-25°S, 30-35.5°E)

Having identified the mean patterns of the rainfall distribution over Southern Africa, the region was subdivided into smaller zones identified on basis of observed prominent mean features during preliminary analysis and taking into consideration the general climatic patterns over the region including mean topographic variations. The method used in selecting the homogeneous zones is similar to the one used for identifying calibration zones e.g. (Thorne et al., 2001) which depends on complexity of regions rainfall characteristics which was also applied over southern Africa. Other studies assessing satellite rainfall estimates such as Hong et al., (2007) and Hirpa et al., (2010), also recommend that evaluation studies must take into consideration the heterogeneity of the topography in addition to the specific region climatic characteristics.

Southern Africa, unlike other parts of Africa such as northern Africa which has generally invariant well defined fixed and documented climate zones cutting through across country boundaries, has not been able to demarcate regional fixed climatic zones. Over Southern Africa most studies on climate refer to weather patterns (Manatsa et al., 2012; Blamey and Reason, 2012). This could be attributed to the limited climate studies in the region besides the high spatial and temporal rainfall variability, including the heterogeneity of the topography.

However, fixed zones are disadvantageous in regions such as southern Africa (sub-tropics) with high rainfall variability where seasons with similar rainfall totals can have quite diverse rainfall characteristics since the fixed zones are based on annual rainfall totals and not rainfall generating patterns. This can be illustrated by for example when convective storms of the ITCZ are the main source of rain which from time to time does not arrive and retreat at the same time within the fixed climate zone resulting in bias in the long term.

5.1 DATA

Three different gridded monthly data 1984 – 2010 were used for this assessment as presented below. These data sets come in different grid resolution and it was necessary to re-grid the data to a common grid scale for qualitative assessment and comparison. Re-gridding is a process of interpolation from one grid resolution to a different resolution. It entails converting the coordinates of each pixel into latitude and longitude and calculating the mean of the variable of those pixel values falling within that grid box of a particular longitude and latitude. For the comparison between TAMSAT and GPCC data, the TAMSAT dataset was re-gridded to the GPCC 0.5° x 0.5° grid box and to evaluate relation between TAMSAT and GPCP data sets, the TAMSAT data re-gridded to the GPCP 2.5° x 2.5° grid boxes.

i) TAMSAT MONTHLY RAINFALL ESTIMATES

For this evaluation, the TAMSAT dataset which normally is at 0.0375° x 0.0375° grid boxes was re- gridded to 0.5° x 0.5° grid resolution for comparison with GPCC datasets by simple averaging over the appropriate number of pixels (Maidment et al., 2012) and to 2.5° x 2.5° grid boxes for comparison with GPCP data.

ii) GPCC MONTHLY RAINFALL DATA

The GPCC version 6.0 data at 0.5° x 0.5° gridded monthly gauge data from 1984 – 2010 is used in the evaluation as the reference data. GPCC is a mature product that has been widely applied on numerous precipitation related studies in similar fashion to GPCP such as Ali et al., (2005), Layberry et al., (2006), Liebmann et al.,(2012).

iii) GPCP MONTHLY RAINFALL DATA

Monthly GPCP version 2 data at 2.5° x 2.5 ° horizontal grid scale and calibrated in degree daily (1DD) estimates (Xie et al., 2003) from 1984 – 2010 was used in the evaluation. Similar to GPCC, this is a community based rainfall product which has been used in a number of regional to continental scales precipitation studies e.g. (Xie and Arkin, 1995; Hsu et al., 1997; Sorooshian et al., 2002; Huffman et al., 2001; Joyce et al., 2004; Huffman et al., 2007; Bergès et al., 2010).

The availability of these datasets overcome data bureaucracies related to in country data policies and promote data democracy, providing an efficient data service for regional and global scientific studies such as this current study.

5.2 UNCERTAITY RELATED TO DATA GENERATION

From discussions in chapter 4 it can be understood that whether measured directly by rain gauge or estimated by remote sensing technology, rainfall measurements, hence data contain uncertainty. The estimation of the errors in both the gauges and the satellite rainfall estimates can be a complex task which relates to the complexity of techniques in use for rainfall estimation and measurements.

Rain gauges offer the simplest and direct method of rainfall measurement, but may contain significant bias arising from poor spatial sampling, exposure of gauge and aerodynamic effects especially during events with high intermittency such as convection.

Remote sensed rainfall data involves indirect measurements and is inexact (Bell and Kundu, 2003), hence quantitative use of satellite rainfall estimates require information on accuracy of methodology. Rain rates vary remarkably with topography resulting in rainfall gradients which satellites may not be measure accurately as discussed above. This is especially an issue for polar orbiting satellite based products (i.e. those based on MW data), which only pass over Africa twice a day. Generally the uncertainty in the measurements between these systems can be grouped into two main types viewed by many studies such as Adler et al., (2011).

i) SAMPLING ERROR OR RANDOM ERROR

This type of error consists of random measurements errors due to sampling limitations and other related processes that also include variations in number of gauges especially for combined satellite and gauge rainfall estimation techniques. Random or sampling errors can be minimized by averaging over a large area and over longer time period to guarantee stability of the samples.

ii) SYSTEMATIC ERROR

The systematic errors results from uncertainty in the measurement and related sampling biases and the related algorithm. Uncertainties in satellite based rainfall estimates are due to uncertainties in the retrieval processes as well as different temporal and spatial sampling patterns of the observations systems. It has been suggested by other writers such as Adler et al., (2011), that no amount of averaging would eliminate systematic error and this usually forms part of the investigation in inter-comparison exercises as is the cases presently. For gauge data, one cause of systematic error could be gauge data continuously changing as gauging stations are set up while others close down.

It becomes clear from the above discussion that full utilization of satellite-based precipitation datasets may be hindered by the uncertainty and reliability associated with the precipitation estimates.

5.3 **METHODOLOGY**

Comparison of the different rainfall estimates was performed using map plots and different available statistical measures of describing datasets, dispersion amongst datasets, evaluating agreement relations since it is difficult to find one standard statistical measure with which to assess satellite rainfall estimation. For the purpose of these study, will use simply relational measure, the root mean square error (RMSE) and bias (b), mean absolute deviation and percentage difference (PDF). Each of these different statistics only offers particular information about the errors being evaluated hence the necessity to examine a number of statistical measures in combination for a comprehensive picture of the error and bias. These statistical indices have been extensively applied to evaluate relative accuracy of various rainfall estimation products in other studies e.g. (Yilmaz et al., 2005, Ali et al., 2005, Dinku et al., 2007, Adler et al., 2011, Jobard et al., 2011, Maidment et al., 2012). No further assumptions are applied when using these statistics that may introduce additional error.

Correlation co efficient (r) or relational measure is a single valued measure or degree of association between two variables using a linear measure. Mathematically, the correlation coefficient representation is as below, (symbols adopted relevant to the study)

Correlation Coefficient (r) = $$\frac{\sum_{i=1}^{n}\left(G_i-\bar{G}\right)\left(P_i-\bar{P}\right)}{\sqrt{\sum_{i=1}^{n}\left(G_i-\bar{G}\right)^2\sum_{i=1}^{n}\left(P_i-\bar{P}\right)^2}} \qquad \text{... 5.1}$$

P_i: i^{th} satellite derived rainfall estimate; **G_i**: i^{th} comparison data point. An over bar represents the time-mean.

The correlation coefficient can be explained as the ratio of the sample covariance of the two samples to the product of the two standard deviations (σ). The standard deviation explains the clustering around the mean or amount of spread of the dataset. Normally, for a leptokurtic bell shaped distribution, the standard deviation is small and relatively large for skewed distributions (Wilks, 2011).

Sample standard deviation σ = $$\sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(X_i-\mu\right)^2} \qquad \text{... 5.2}$$

Where N is the sample size, X_i being the sample at point i, and μ being the sample mean. Covariance describes the turbulence in the two variables while the standard deviation, which is defined by the square-root of the variance, measures the spread of the data about the mean which makes correlation to be sensitive to few outlier point pairs. The variance describes the average of the squared differences from the mean of the distribution. Correlation is bounded by, $-1 \leq \mathbf{R} \leq +1$, thus for R = -1, a perfect negative linear relationship exists between the variables, and if R = 1, a perfect positive relation exists which is represented in a scatter plot by all points falling in a straight line. Another property of the correlation coefficient is that R squared (R^2) explains the proportion of variance or variability of one of the two variables that is linearly accounted for or described by the other. The major weakness for correlation is that it does not account for bias which simple compares the average magnitudes between the estimates in a form of a ratio as discussed below.

Root mean squared error (RMSE) = $\sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(P_i - G_i\right)^2}$ **... 5.3**

The root mean squared error measures the average error magnitude. It should be noted that because RMSE make use of the differences between the two estimated values with one normally taken as reference, it gives more weight to larger error magnitude which results from the squaring of the errors.

Bias or relative bias will be used to measure the correspondence between the TAMSAT rainfall estimates and the GPCC and GPCP precipitation products. If one product is consistently below or above (wet/dry) it exhibits bias regardless of its relative accuracy or inaccuracy. One way of calculating bias or relative bias is use of equation 5.4 below. Bias can be represented by percentage(s).

Percentage difference (PDF) or Relative bias = $\sum_{i=1}^{n}\left(\frac{\left|P_i - G_i\right|}{G_i}\right)$ **... 5.4**

The relative bias itself is useful in evaluating systematic errors of the satellite derived rainfall estimates. Other available measures of bias which will be referred to from time to time in the analysis include mean error which simply scales the average difference between the rainfall estimates and observations, the mean absolute error which computes the average magnitude of the error. Apart from correlation which range between -1 and +1, ideal values for bias would be zero.

Additionally to the above discussed statistics, the Nash Sutcliffe Efficiency (NSI) index will be used to compare the TAMSAT rainfall estimates against GPCC and GPCP. This index determines the relative magnitude of the residual variance compared to the variance of the ground observations, hence provides an indication how well the plot of the observed estimation fits the bisector line (Thiemig et al., 2012).

NSI = 1 - $\left[\frac{\sum_{i=1}^{n}\left(P_i - G_i\right)^2}{\sum_{i=1}^{n}\left(G_i - \overline{G}\right)^2}\right]$ **... 5.5**

NSI can vary between $-\infty$ and 1 and is not influenced by bias. Higher values of this index (NSI =1) indicate better agreement between the simulated value and assumed reference or observed value which in this case will be rainfall estimates. For NSI = 0, the estimated values are as good as the observed mean, while for NSI < 0, indicates that the observed mean is a better predictor than the estimator (Ali et al., 2005). Since this skill score is composite of both linear association and bias, it is a better score to other individual skill scores as was observed (Jobard et al., 2011).

Examining these estimates will provide a clear insight into the physical assumptions in the product generation including impacts of the different strategies on the rainfall estimation over southern Africa. Thus it is hoped that will also go a long way in assisting the product developers with information required for appropriate action based on the provided evidence. Similarly, the information derived from the assessment would be helpful in applications and proper interpretation of the different rainfall products to the different users hence improving confidence and reliability of these products.

In general, the evaluation of these statistics is computed assuming an estimated reference value. Most rainfall estimates inter-comparison studies (e.g. Thorne et al. 2001, Adler et al., 2011, Chadwick and Grimes, 2012, Roca et al., 2009, Maidment et al., 2012) use gauge data as reference value and satellite rainfall product as the estimated value, hence this evaluation will use GPCC and GPCP as reference values and TAMSAT data as the estimated value.

Plotting, displaying and viewing the maps of the different rainfall estimates allow straightforward visualization and evaluation (Yilmaz et al., 2005) of each rainfall estimates which is essential in understanding and assessing the characteristics of each rainfall datasets.

6 RESULTS, DATA ANALYSIS AND DISCUSSIONS

This section presents and discusses the results of the analysis of rainfall estimates data analysed using the different data analysis methods described in section 4. With the study area limited to the evaluating the performance of rainfall products over continental southern Africa (figure 1.3), the GPCP oceanic data was masked out to ensure only overland rainfall data is included in the analysis. For the other products, as has been discussed earlier, only data over land were available. Because of the enormous volume of results, this section highlights the principle findings, and uses summary statistics to illustrate key points.

6.1 RAINFALL AMOUNTS

Part of the intentions of the study is to understand the characteristics of the systematic differences between the three datasets over the period 1984-2010. Hence it was necessary to establish the character of the distribution function that best fits these rainfall estimation datasets. Figure 6.1 shows the histograms of monthly rainfall amounts for each of the rainfall datasets averaged over the entire region of interest (refer Figure1.3). Bin sizes of 20mm were used for all the rainfall data sets to generate the histograms. A range of bin sizes were tested, but 20mm was found to provide a better visual representation. It should be noted however that the bin sizes do not affect the results and conclusions. All three datasets depict similar patterns of the rainfall distribution with evidence of differences in magnitude which can be easily seen from the histogram plots.

As might be expected, it is evident from these plots that the rainfall distribution over the region is highly skewed towards low rainfall amounts. From figure 6.1, it is apparent that although on average the region is dominated by very low rainfall because of the dominance of semi arid climate, there are certain periods (months) where parts of the region receives very high amounts of rainfall. From the histogram plots (figure 6.1a) it can be seen that that rainfall in excess of 1000mm/month is possible over parts of southern Africa. One possible explanation to these very high intensities in the datasets relates to parts (north east coastal areas) of the region occasionally being affected by tropical cyclones such as 1179mm in one month was recorded over Southern Mozambique area (zone F, Figure 5.1) in February 2000 which coincides with tropical cyclone Eline.

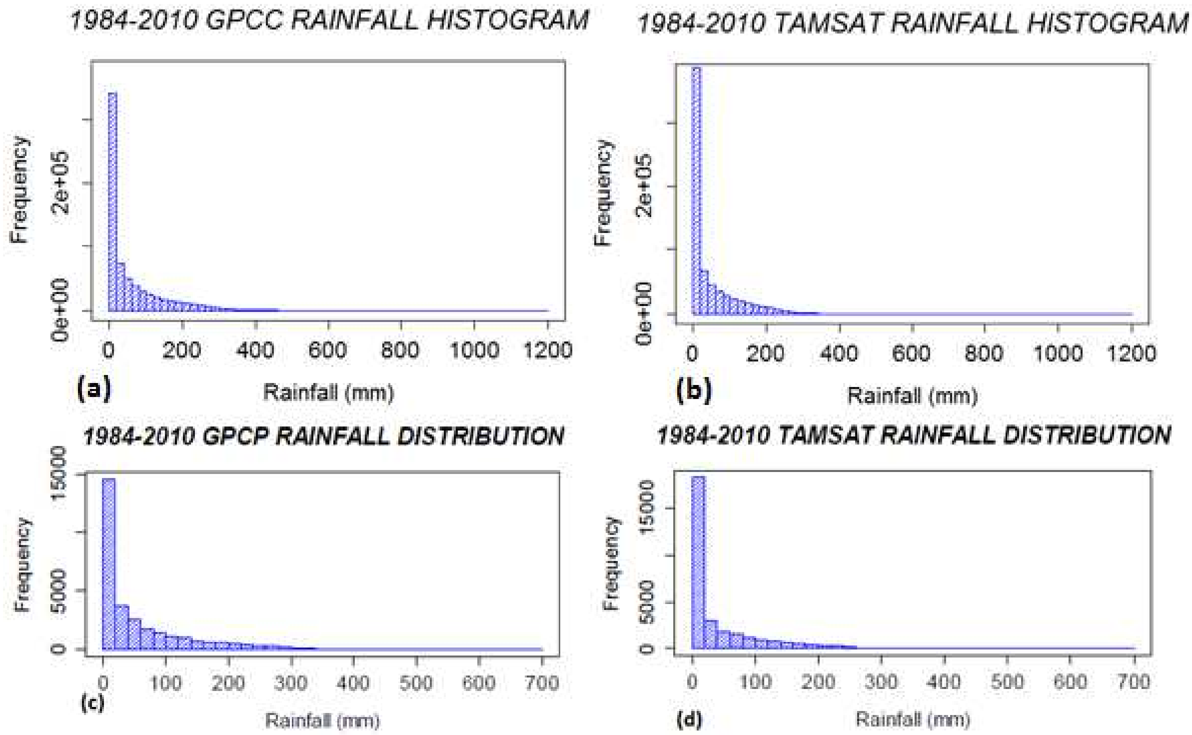


Figure 6.1: Histograms of the three rainfall estimates over southern Africa 10°S, 35°S and 10°E, 40°E. (Figure 6.1a and 6.1b are at 0.5° x 0.5° while 6.1c and 6.1d are at 2.5° x 2.5° grid boxes)

Apart from the evidence from figure 6.1, the box plots in figure 6.2 also confirm the skewness in these rainfall datasets. All the datasets show domination of outliers beyond the top whisker which supports the understanding of high variability of the climate of southern Africa as discussed in section 2 above, and in the published literature (Jury et al., 2007).

These datasets are composed of very low median values, 19 mm for GPCC, 11mm for TAMSAT at 0.5° grid scale, 26mm for GPCP and 9mm for TAMSAT at 2.5° grid scale while the upper extreme values for all datasets are approximately 200 mm. From the values presented above, TAMSAT estimates at the different grid scales are lower compared to the other two datasets. From the summary of the descriptive statistics, 25% of the rainfall lies between 0 - 3mm/month, and the mean ranges between approximately 40 – 55mm/month. Unlike the median, the mean is highly influenced by the occurrence of extreme rainfall events (large outliers) in the datasets.

One other remarkable observation was that 75% of the time the region receives approximately between 55–80mm/month, with extreme values range between approximately 550–1280 mm/month, which shows high variability in rainfall in time. The mean standard deviation for these datasets ranges between 25–35mm/month which compares to the average of the datasets showing the extent of variability in the rainfall estimates.

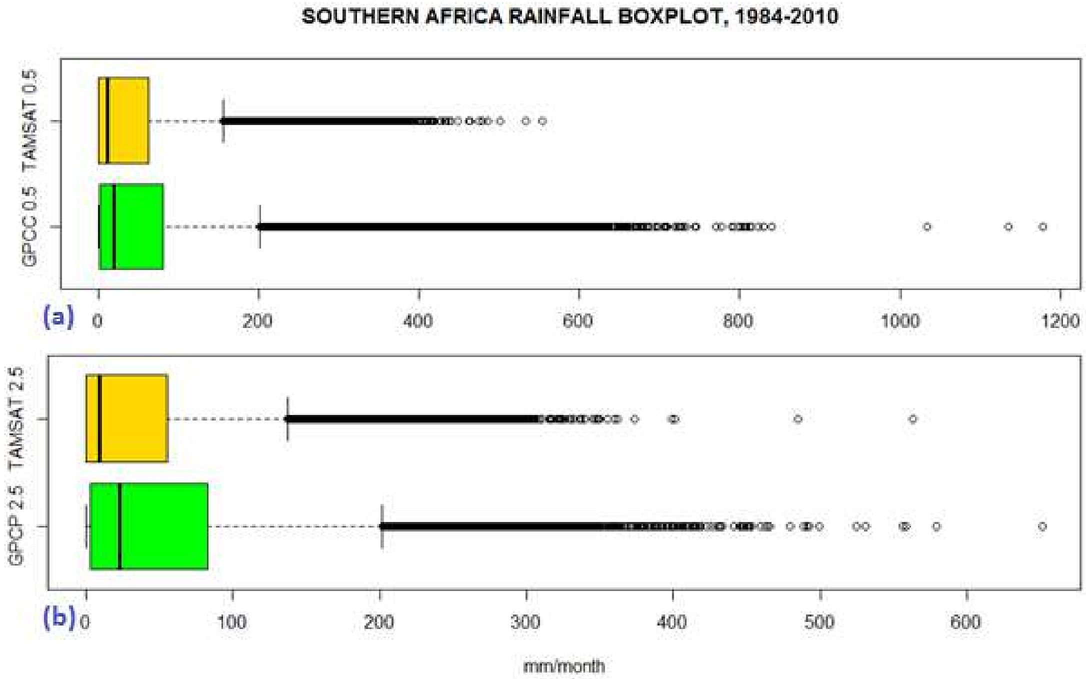


Figure 6.2: Diagram of box plots of the different rainfall estimation techniques during for period 1984-2010; (a) shows box plot of GPCC and TAMSAT rainfall estimates at 0.5° grid box, and (b) shows box plots of GPCP and TAMSAT rainfall estimates at 2.5° grid box

6.2 SPATIAL VARIATIONS

The large scale characteristics of the rainfall such as mean patterns, variability and seasonality were evaluated at regional scale to allow for the stability of the evaluation exercise as argued by Xie and Arkin, (1995) and at sub-regional scale to reveal details that were obscured by smoothing at the regional scale. Figure 6.3 shows the mean rainfall map of the rainfall estimates from 1948-2010 over southern

Africa. Similar to the above plots, the three datasets have high similarity on the distribution of rainfall over southern Africa and locating areas on high and low rainfall estimates. These rainfall products however differ in the representation of the magnitudes of the amounts of rainfall over the region. Figures 6.3a and 6.3b shows map produced using GPCC and TAMSAT rainfall product at 0.5° x 0.5° grid reference. Giving the benefit to GPCC as reference data (gauge data), these maps show evidence of TAMSAT rainfall estimates generally being lower compared to the GPCC rainfall products. Figures 6.3c and 6.3d represents GPCP and TAMSAT rainfall estimates at 2.5° x 2.5° grid reference. Similarly, there is evidence of TAMSAT rainfall estimates generally being lower than GPCP rainfall estimates.

These observed differences can be attributed to systematic difference in the algorithms employed by these systems, including sampling limitations, orbital errors and biases and other processes (see section 3) during data generation. In the GPCP analysis procedure for example, there are adjustments (minimizing bias error) made to satellite information using the GPCC gauge analysis over land and adjusting IR estimates over the ocean by relatively less frequent by passive microwave estimates (Adler et al., 2011). Though in the present case these datasets are in different grid scales, it can be observed the strong relaxation towards the GPCC data by the GPCP data showing that GPCP data are inevitably closer to GPCC than TAMSAT.

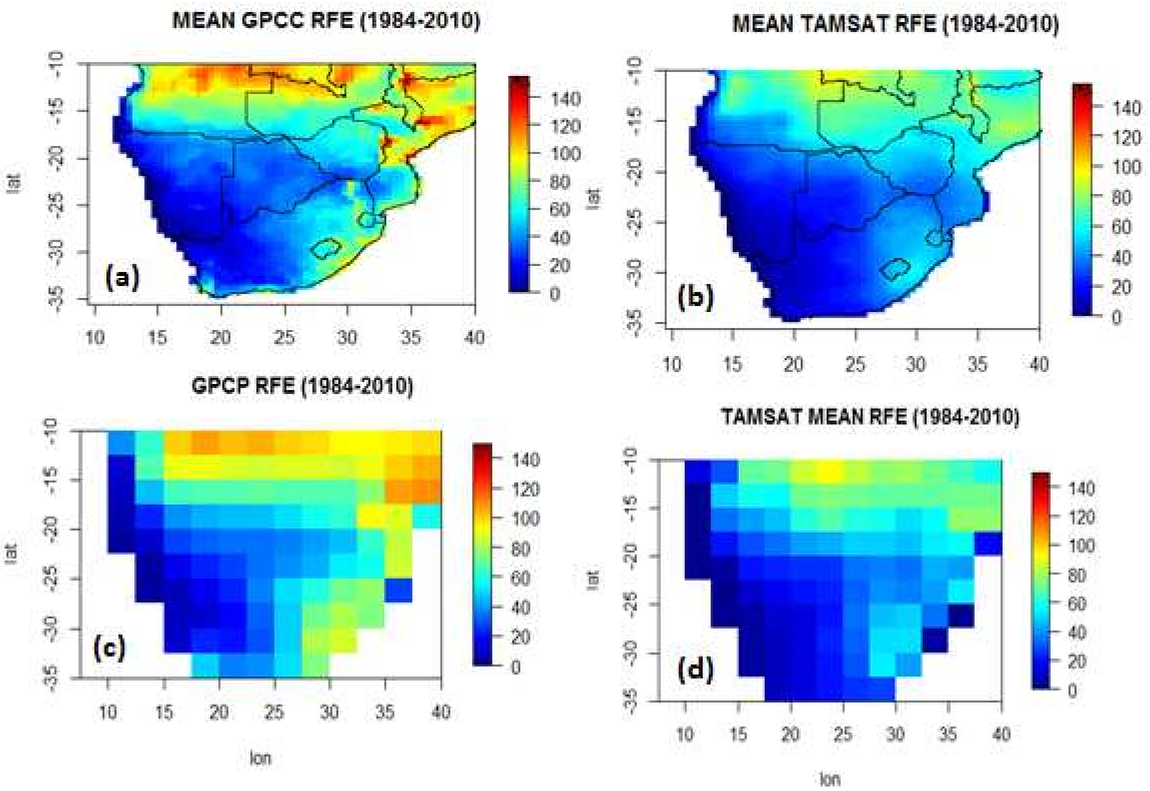


Figure 6.3: The 27- year climatology of southern Africa estimated rainfall: (a) GPCC mean at 0.5° grid scale; (b) TAMSAT mean at 0.5° grid scale; (c) GPCP mean at 2.5° grid scale and (d) TAMSAT mean at 2.5° grid scale.

Using these rainfall maps, zones of homogeneous rainfall can be identified and delineated with ease. Generally, the rainfall patterns show a decreasing tendency from equator southwards. The northern parts of the region falls more into the ITCZ region while moving southwards the region enters into the zone of large scale subsidence (Kidson and Newell, 1977) as discussed in section 2. Further to the south, the rainfall pattern show an increase from west to east in agreement with many literature covering precipitation distribution over Africa (southern Africa) e.g. (Xie et al., 2003, Huffman et al., 2009, Adler et al., 2011, Liebmann et al., 2012, Tennant and Hewitson, 2002, Washington and Preston, 2006, Jury et al. 2007). The eastern parts are influenced by the warm Mozambique currents and the high mountain range that are oriented parallel to the coastline forming a rain shadow over western southern Africa from moist easterlies.

Figure 6.4 shows the variations of the standard deviation **σ** of the rainfall estimates. The standard deviation of the rainfall products shows generally higher values of standard deviation over areas with generally higher mean rainfall. Since rainfall is non-Gaussian in nature (shown by the histograms of these datasets above) it is expected that high standard deviation should coincide with generally high mean rainfall. Higher values are found of the standard deviation are found over the north eastern parts of southern Africa (central south Mozambique) which occasionally is affected by tropical cyclones. Figures 6.4a and 6.4b represents GPCC and TAMSAT rainfall product at 0.5° x 0.5° grid reference and these maps show evidence of TAMSAT rainfall estimates generally lower compared to the GPCC rainfall products, which can be expected considering that the standard deviation is closely related to the mean of the distribution. Figures 6.4c and 6.4d represents GPCP and TAMSAT rainfall estimates at 2.5° x 2.5° grid reference and similarly there is evidence of TAMSAT rainfall estimates standard deviation being generally lower than for GPCP.

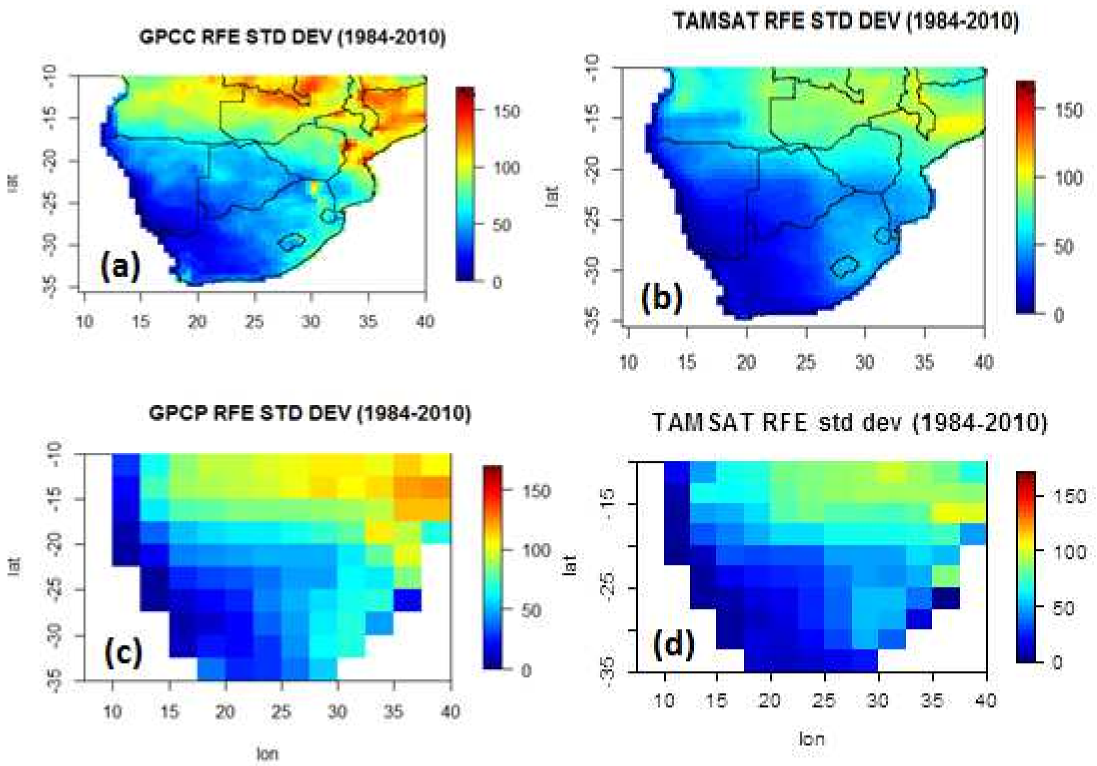


Figure 6.4: The 27–year standard deviation climatology of rainfall over southern Africa rainfall: (a) GPCC mean at 0.5° grid scale; (b) TAMSAT mean at 0.5° grid scale; (c) GPCP mean at 2.5° grid scale and (d) TAMSAT mean at 2.5° grid scale.

Figure 6.5 provides an estimation of rainfall variability over southern Africa using the coefficient of variation (CV) $=\frac{\sigma}{\mu}$, which is the ratio between the standard deviation (σ) and the mean (μ) of the dataset. From these maps (Figure 6.5) it can be observed that generally there is high variability over places with relatively low mean rainfall and vice versa. Over the northern parts and along the eastern escarpment areas of relatively high rainfall, the coefficient of variation ranges between ($0.5 \leq CV \leq \sim 1$) in all estimates compared to the central and western parts of the region. From the definition of the coefficient of variation, such an observation can be expected, indicating the bias related to this index. However, comparing TAMSAT and GPCC coefficient of variation shows that TAMSAT has fewer areas with high variability that GPCC. This could be attributed to the bias in TAMSAT representing extreme high values which is evident from the box plots (Figure 6.2). For TAMSAT and GPCP estimates however, there is an indication of greater variability in the TAMSAT estimates than GPCP, which could be attributed to the high number of low rainfall values in TAMSAT estimation as seen in the histogram plots (Figure 6.1c and d).

It should be noted however, that when the mean rainfall approaches zero, the relative error become meaningless hence the standard deviation become a better estimator. When the mean rainfall over an area is relatively large, the relative error become much more meaningful to use and interpret.

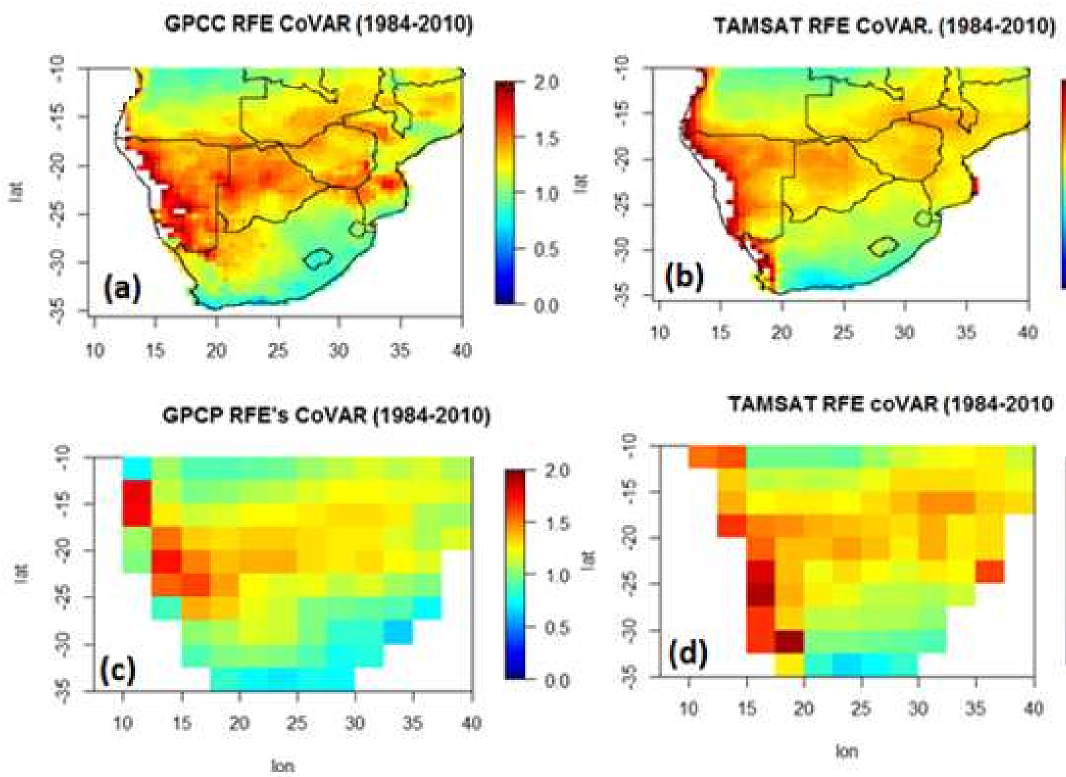


Figure 6.5: The 27–year coefficient of variation of rainfall over southern Africa rainfall: (a) GPCC mean at 0.5° grid scale; (b) TAMSAT mean at 0.5° grid scale; (c) GPCP mean at 2.5° grid scale and (d) TAMSAT mean at 2.5° grid scale.

6.3 TEMPORAL VARIABILITY

Scatter plots of monthly precipitation for GPCC/GPCP against TAMSAT can be used to compare monthly variations for the datasets, as discussed in section 5. Figure 6.6 shows the long term linear relationship between the datasets 1984-2010 and the contribution of the different seasons (April – March and Sept – Aug) representing dry and wet to the linear relationship. Generally, there is good correlation between the pairs of rainfall estimates as can be seen from the scatter plots and the high coefficient of determination (R^2). The fitted regression line closely matches the diagonal with a slight tilt away from TAMSAT estimates showing a dry bias by TAMSAT estimation compared to the two other rainfall products.

One remarkable observation from the scatter plots is the contribution of the different seasons to the linear relationship. It can be observed that different seasons contribute differently to the linear relationship. During the dry season (figure 6.6c and 6.6d), it can be observed the bias towards both GPCC and GPCP especially for relatively high values which is also evident during the wet season.

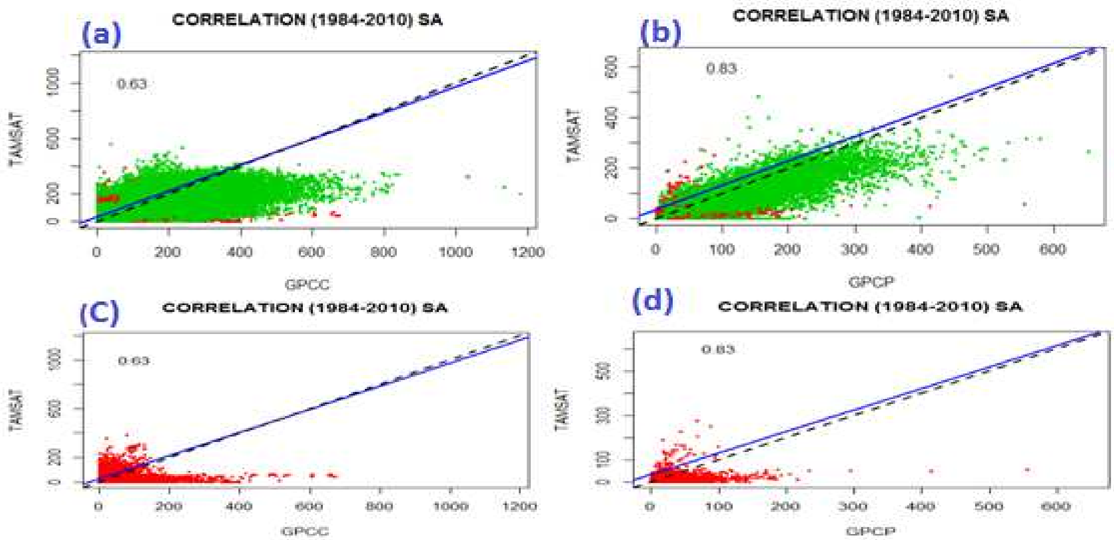


Figure 6.6: Scatter plots of monthly rainfall (1984-2010) over southern Africa. (i) Red: (April – September), (ii) Green: (October – March). Note the different scales. Figure 6.6c and 6.6d are extracted from figure 6.6a and 6.6b for added for clarity. They only reveal / emphasize the red dots (dry months) below green (wet season) in 6.6a and 6.6b.

The scatter plots reveal adequately the limitations/capabilities of the different methodologies in capturing very high values of precipitation as explained earlier. It should be noted the contribution of averaging over time and large space contribution to the observed generally high correlation amongst the estimates. The agreement between GPCP and TAMSAT is slightly higher compared to GPCC and TAMSAT estimation, which can be explained by both techniques use of IR technology, though GPCP also incorporate gauge information and PMW to enhance measurements performance which also increase bias between the two systems. This can be seen during the winter months (figure 6.6d) when GPCP is able to measure high values (values >400mm) which TAMSAT estimation is not able to detect. The month to month variation in the relationship between the estimates is presented in figure 6.7 confirming generally high R^2 values >0.4 between Oct – April and lower thereafter.

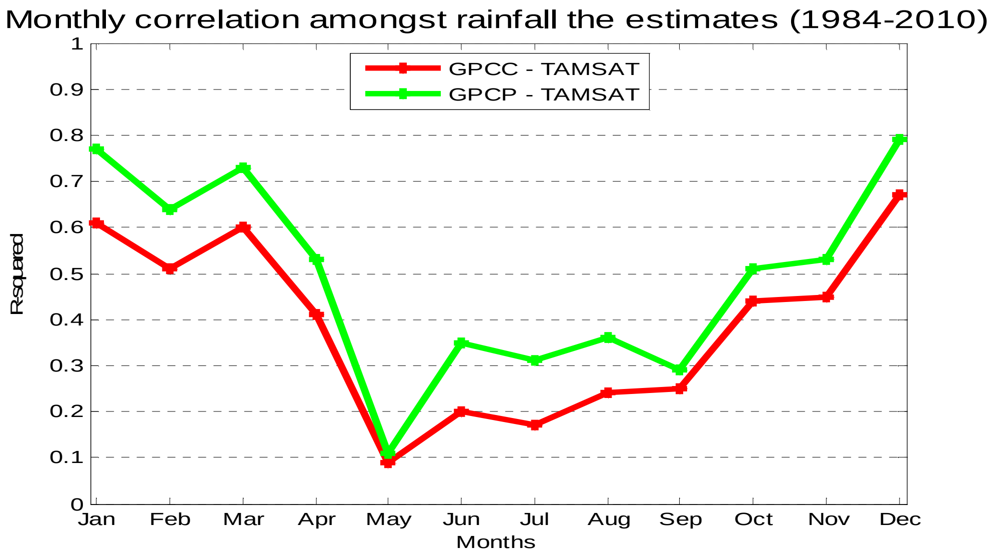


Figure 6.7: Diagram for coefficient of determination for the relationship of the different estimates (1984-2010)

6.4 MONTHLY AND SEASONAL VARIATIONS

Seasonal cycle analysis of the rainfall products over the region indicates all three rainfall products have generally similar mean annual cycles in the region. This was clear from figure 2.3, which showed average monthly rainfall over southern Africa during the period of study. Similarly to the observed mean seasonal rainfall variations, the statistics used to evaluate the differences in the estimation methods vary in time as shown in figure 6.7 and 6.8a. It can be observed from the plot of the RMSE (figure 6.8a) is generally higher during the wet season and lower during the austral winter. From the discussion in section 5, the observed variation in the RMSE is expected since RMSE is an absolute measure of error, and will thus be greater in months with high rainfall. Figure 6.8b shows the magnitude of the differences between the different estimates. The observed differences are larger between TAMSAT estimates and GPCC (gauge data) than they are between GPCP and TAMSAT estimates during the wet season. As an example, the mean difference between TAMSAT and GPCC is more than 35mm/month (figure 6.8b) during January compared to approximately 5mm/month during the same month between TAMSAT estimates and GPCP estimates.

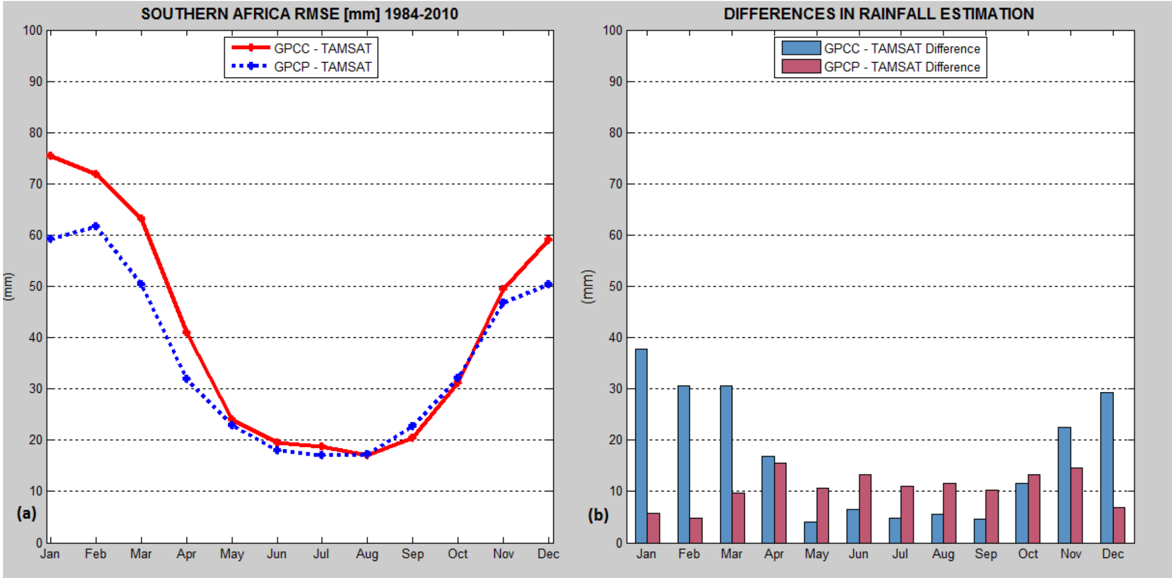


Figure 6.8: Diagrams of variations in the comparison statistics. (a) Variations in the root mean square error of the mean for the different data sets. (b) Mean absolute differences in the datasets.

During the dry season, it was observed that there are generally larger differences between the GPCP estimation and TAMSAT than there are during the wet months, with TAMSAT being closer to the GPCC values which can be linked to the contribution of the weather generating systems during the winter months and the limitations and or capabilities of the different rainfall estimation techniques. TAMSAT may be expected to estimate low rainfall during the austral winter. This is because, during the austral winter, the major prevailing weather patterns and contributing to rainfall (section 2) over much of southern Africa are the mid latitude weather systems (frontal system) having varying strengths of baroclinicity. This can result in convection or stratiform rainfall, characterised by warm clouds tops unlikely to give rise to a signal that can be detected by an IR sensor hence the lower estimation by the TAMSAT estimation technique (figure 4.1 TAMSAT methodology), which is based on CCD and convection.

Another remarkable observation relates to the low difference between the satellite-based rainfall estimates during the austral summer (GPCP and TAMSAT). During DJF, the relative difference between GPCP and TAMSAT estimates is minimal (< 10%) compared to the relative difference between GPCC and TAMSAT estimates which is approximately 25% during the same period. DJF falls at the peak of the peak of the austral summer and the main weather controlling system is the ITCZ, hence most rainfall occurring during that time is convective which both methodologies are able to detect in the IR channel. These observations are similar to results from other studies on comparing satellite rainfall estimates e.g. (Dinku et al., 2007, Maidment et al., 2012) purports that differences in satellite rainfall estimation methodologies depend on season and local climate. During the austral winter, the GPCP and TAMSAT estimates bias exceeds GPCC and TAMSAT estimates bias (figure 6.9a)

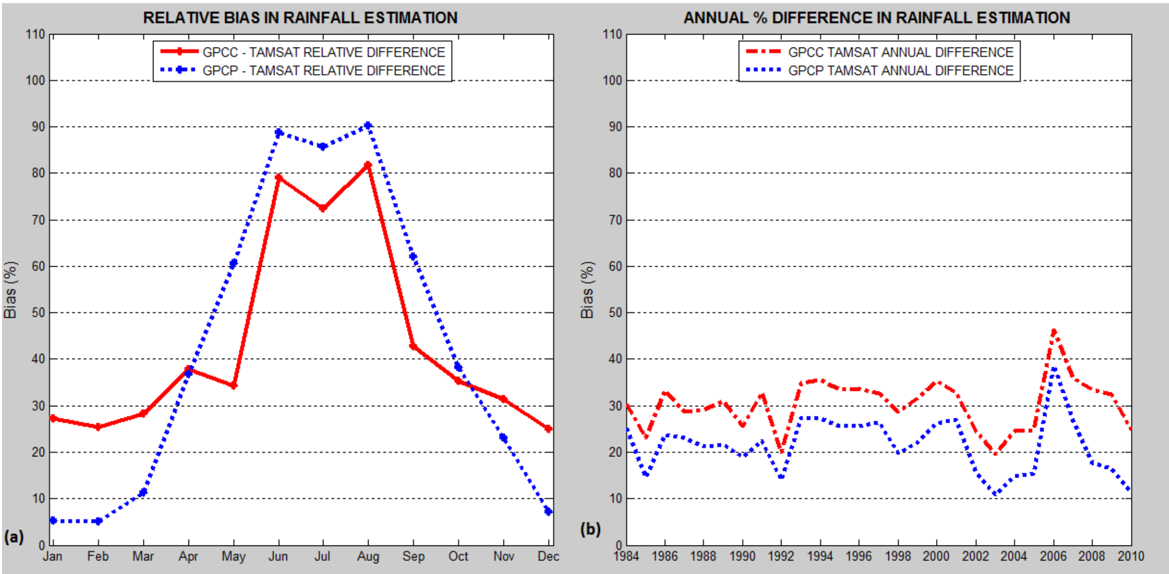


Figure 6.9: Mean monthly and annual variations in relative differences in rainfall estimation (1984-2010) over southern Africa

These datasets were further aggregated into seasonal sums (DJF, MAM, JJA and SON) to investigate the characteristics and tendencies of the observed bias errors in the other periods (monthly and annual). This revealed that apart from the annual climatology being less compared to the monthly climatology, the seasonal climatology of the errors is large compared to the annual climatology of errors as seen in figure 6.8 and 6.9. Similar to spatial averaging discussed above, temporal averaging over the annual cycle with compensating errors tends to result in lower error values.

Figure 6.10 shows part of the results obtained from seasonal analysis of these datasets. It can be observed from this figure that during the DJF season, there is generally low bias between the estimates (10 - 30%), though occasionally in some years MAM and SON also show very low bias. These low values can be attributed to the general contribution of convective systems, associated with the ITCZ during DJF season. Both algorithms making use of IR technology considers cloud top temperature hence has skill to detect convection than during winter (JJA).

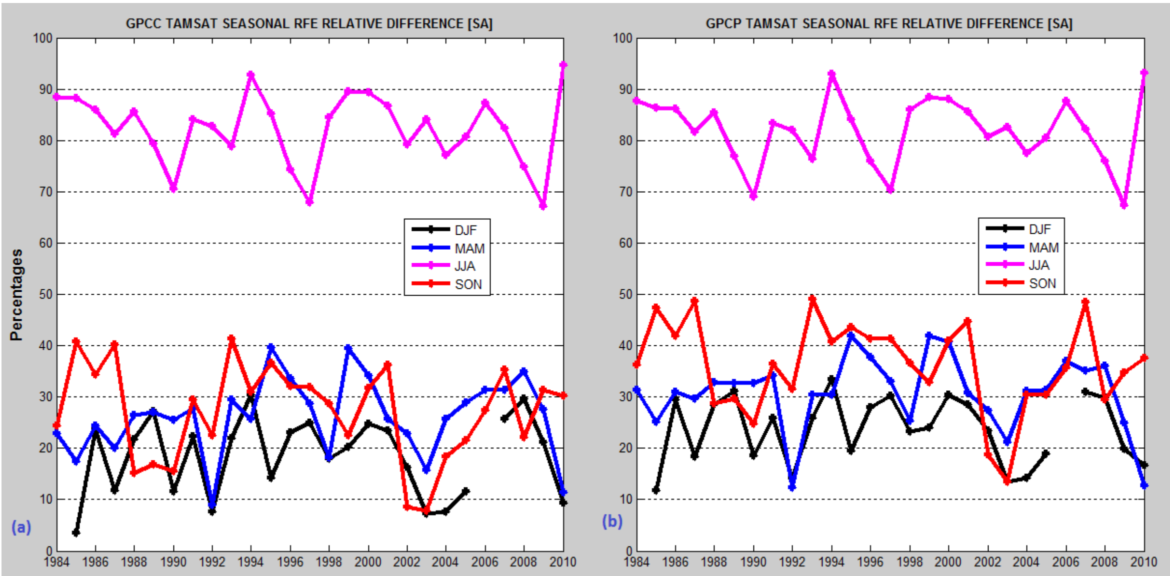


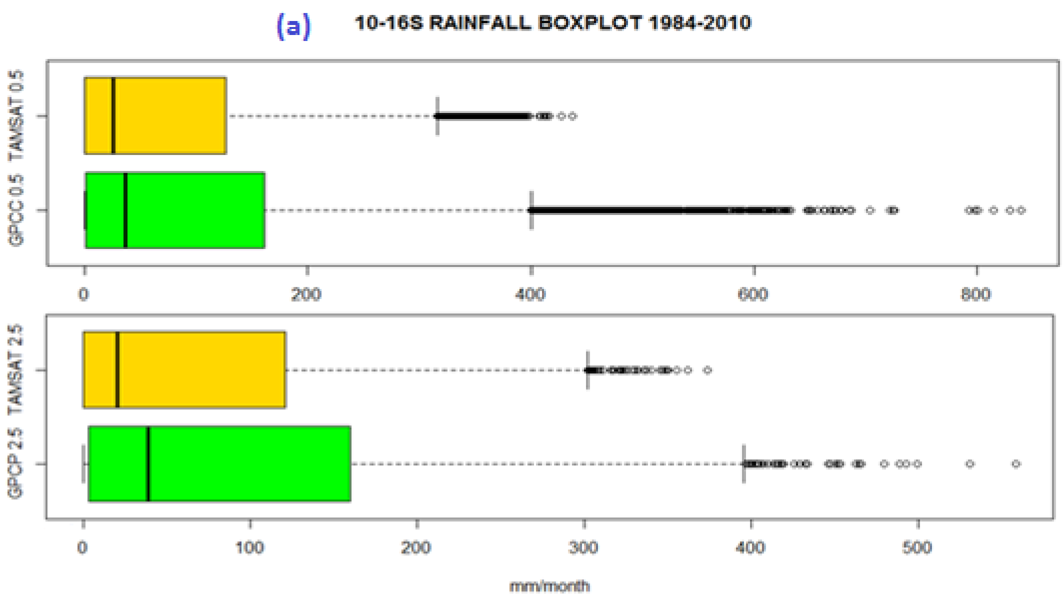
Figure 6.10: Diagram showing seasonal variations in bias (1948-2010). (a) Bias between GPCC and TAMSAT estimates, (b) bias between GPCP and TAMSAT estimates.

The high bias errors during the dry season can be attributed to the precipitation from shallower clouds which is difficult for both satellites techniques to detect as discussed above and also due to the tendency to over predict in the algorithm (bias correction) as suggested by Ali et al., (2005) and Layberry et al., (2006). One possible cause for the over prediction in the algorithm emanates from the inadequate or missing gauge information for quality control procedures employed during rainfall estimates calibration. Further analysis on the trends and tendencies in the different statistics was performed on the selected zones discussed below.

6.5 VARIATIONS IN SELECTED ZONES

Latitudinal variations of the differences in rainfall estimates over the region were further investigated and assessed from the selected zones as discussed earlier (Figure 5.1). Apart from demarcating and listing the zones in N-S orientation, additional zones over the escarpment (NE South Africa, including Swaziland area) and SSE Mozambique and East of Zimbabwe with occasional very high intensity precipitation from tropical cyclones were identified used to assess the differences in the rainfall estimates. In a similar fashion, data masking was applied to GPCP to remove oceanic observations and ensuring datasets are equal spatially.

The box plots (figure 6.11) of the precipitation in the selected zones, confirm earlier observation of rainfall deceasing north-south and east- west. It was observed that the rainfall is generally negatively skewed over the whole region. Using these zones it was it, the south east Mozambique was identified as the area (zone F) with the highest rainfall (1179mm/month) in the region during the period under consideration as discussed in 6.1 above. The box plots over these zones confirmed the general observations from the regional analysis including the estimates maintaining the consistent bias in rainfall magnitude representation. The consistent bias was observed in all the selected zones (figure 6.11)



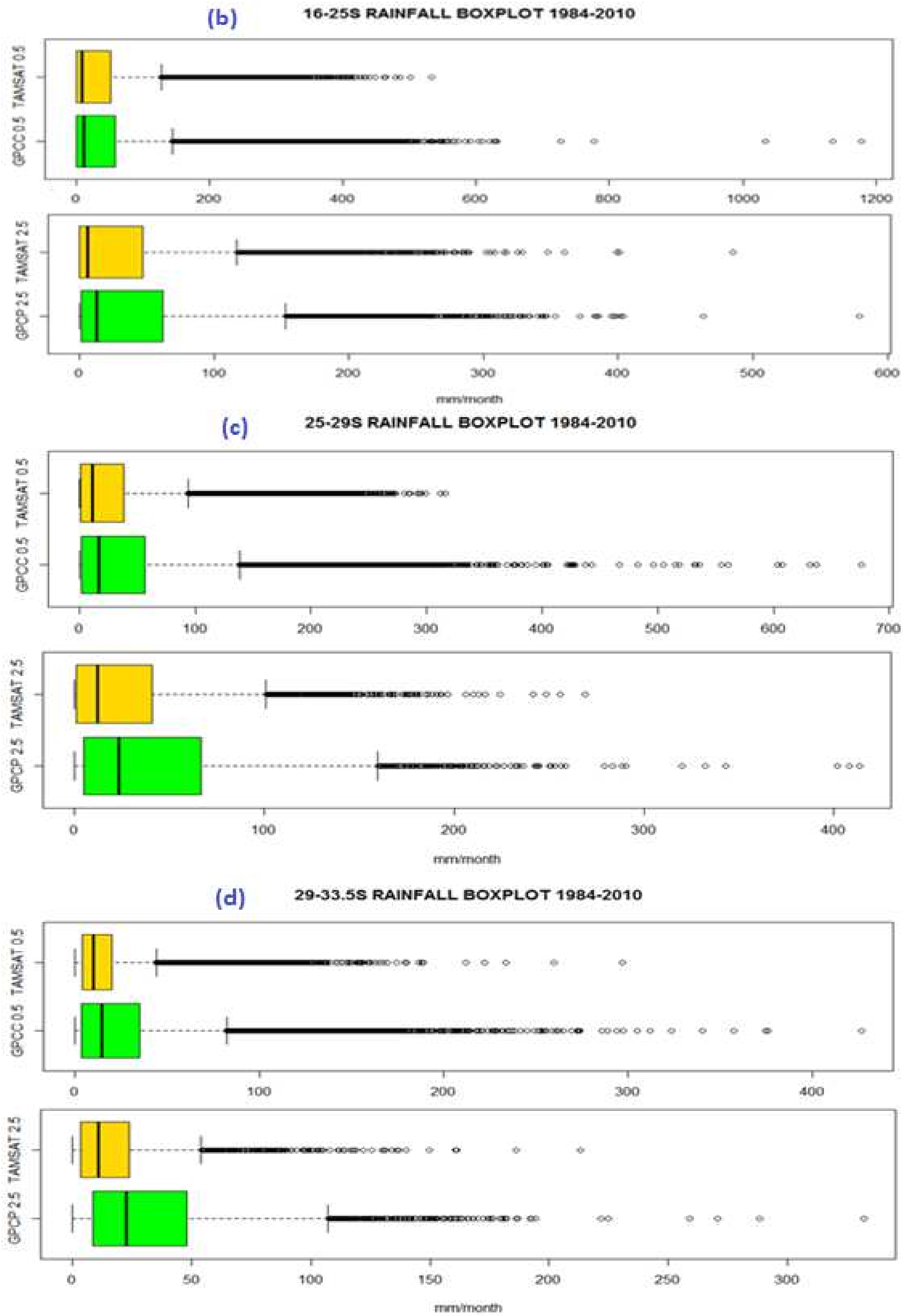


Figure 6.11: Diagram of box plots for different rainfall estimates over the selected zones. (a) Show box plot for the zone 10-16°S; (b) box plot for the zone 16-25°S, (c) for region 25-29°S and (d) represents region 29-33.5°S

Besides the strong seasonal variations in the associated differences (see previous sections), there exist geographic variations in the error estimates which can be observed from the summary statistics table 2 below. The geographic variations in the rainfall estimates were easily represented by the root mean square error amongst the estimates. The RMSE was found to be generally higher over areas with high rainfall and lower over areas of low rainfall including being high during the wet season as was observed earlier. Possible reasons were explained earlier 6.1 and 6.2 above. Zone A and F had the highest root mean square error above 80% and these zones generally have high rainfall since they are closer to the equator thus having great influence from tropical air mass. However zone A showed $R^2 = 0.3$ (amount of information found in the rainfall relationship) between GPCC and TAMSAT estimates. A number of factors can be thought of to contribute to the low R^2 value; hence low correlation. These include high rainfall variability indicated by existence of large extreme rainfall values that are not detected by TAMSAT algorithm (systematic bias). However, the possibility of the contribution of unavailability of gauge information (figure 1.2) over this region is also likely another factor to the low agreement between these datasets as discussed in section 5.

In general, high R^2 values were observed between the rainfall products during the summer months than during the dry season and the possible reason explained above. The highest values of $R^2 = 0.5$-0.6 corresponding to more than 50% of the variance explained are found in zones B, C and D which are generally dry arid areas with rainfall mainly from deep convection during summer. Low R^2 of 0.2 was also found between the rainfall estimates over the escarpment, which could be the result of the nature of the common precipitation associated with orographic enhancement and mid latitude weather systems influences. Similar results were obtained by Thorne et al., (2001) showing very little change or improvement on the TAMSAT methodology over this region since that study. During the austral summer months, deep convection only contributes about 28% of the total monthly rainfall (Blamey and Reason, 2012) over areas along the north east coast of south Africa, which include the escarpment.

Discrepancies between the rainfall estimates are higher over areas indicated to have no surface gauges information. Zone A has the highest bias (22%) during the austral summer compared to 8% bias over the escarpment which is depicted having a fairy dense network in figure 2. Systematic biases, amongst estimates can be reduced by including gauge rainfall observations in the rainfall estimation model, as those proposed by (Dybkjær, 2003), or a direct combination of the real-time rainfall network observations (Grimes et al., 1999). Zone A is located in the region with no gauges influencing concluding that the observed high bias over this zone is due to unavailability of gauge information.

Table 6.1 Summary table of validation statistics for the different indices used in the comparison for the different seasons (winter and summer). Highest value to desired score for each category is highlighted

	GPCC TAMSAT				GPCP TAMSAT			
Zone A	Bias	RMSE	R^2	NSI	Bias	RMSE	R^2	NSI
Summer	22.4	90.1	0.3	-2.4	23.0	70.7	0.5	-2.7
Winter	98.4	9.3	0.0	-4.5	98.7	8.9	0.0	-6.4
Zone B								
Summer	8.0	50.1	0.6	0.5	15.1	40.7	0.7	0.2
Winter	89.3	5.6	0.2	-0.6	89.8	5.9	0.2	-1.0
Zone C								
Summer	12.8	41.2	0.6	0.4	18.2	40.6	0.6	0.2
Winter	68.2	11.9	0.3	-0.0	76.9	14.5	0.4	-0.4
Zone D								
Summer	14.7	24.3	0.5	0.3	31.2	28.9	0.6	0.0
Winter	64.1	30.6	0.1	-1.0	69.7	41.6	0.2	-1.5
Escarpment								
Summer	8.5	54.1	0.2	0.2	11.5	47.7	0.4	0.2
Winter	80.8	16.4	0.3	-0.4	84.4	17.0	0.4	-0.6
Central Mozambique								
Summer	23.2	87.7	0.5	0.3	19.4	67.1	0.6	0.2
Winter	98.4	22.2	0.1	-2.1	97.9	18.9	0.1	-2.9

Finally, the Nash Sutcliffe Index (NSI) was also used to test the skill of the different estimates against each other. Generally, there was observed relatively good skill on TAMSAT estimates following GPCC rainfall estimates during the rainy season compared to the dry season similar to the other statistics. The closest agreement between TAMSAT estimates and GPCC was found in zone B and C which is also evident from the median values from box plots (figure 6.11b and c together with high R^2 (0.6) value. Similar to R^2, the lowest skill score during summer is found in zone A which is a possible confirmation of the effect of lack of gauge information on the performance of the inter comparison exercise. Investigating the differences in annual scales did not produce any significant different results from the monthly and seasonal scales.

An $R^2 \geq 0.4$ over the region was found between TAMSAT and GPCP estimates during the wet season. This indicates a good level of agreement in representing the observed precipitation patterns which could be attributed to the common IR sampling method and convection as discussed above. Besides both methodologies utilizing the cloud top temperature and presence of convection during summer, it should be noted that GPCP averages over a larger area (2.5° x 2.5° grid box) which would smoothen random variations hence improving bias errors compared to comparison between GPCC and TAMSAT (0.5 x 0.5° grid). Conversely, the observed high relationship in summer become poor during the dry season, due to differences in sampling methods capabilities or limitations and the representation of the general prevailing climate as discussed above. The other statistics follow similar patterns geographic and temporal patterns to the behaviour other measure between GPCC and TAMSAT though with different magnitudes.

7 DISCUSSIONS AND CONCLUSIONS

This chapter provides discussions from the analysis and concludes the study. The study provided a quantitative assessment of the characteristics, differences and similarities in the three rainfall datasets generated using different measurement and estimation techniques, to create an understanding of the characteristics, special attributes, strengths and weaknesses of the different methodologies rainfall in representation over southern Africa. A review of the main weather and climate controlling systems over southern Africa was included to provide background information on the mean patterns during the different seasons against which the different rainfall measurement techniques were to be evaluated. Also the different rainfall measurement methodologies were reviewed together with their known uncertainties forming the basis to understand the resulting biases, tendencies, trends and attributes from the data analysis.

Using descriptive statistical methodologies, the basic characteristics and probability distribution functions best describing the GPCC, GPCP and TAMSAT rainfall datasets were identified. The preliminary analysis revealed these datasets as highly skewed (negative), indicating the high variability in the rainfall over the region. The high variability in the rainfall was also confirmed by analysis of the mean and the standard deviation of these rainfall estimates over the region. It was observed that the standard deviation of the rainfall tracks or compares to the mean of the rainfall which can be used to infer strong spread hence variability. Similarly, the analysis of the coefficient of variability showed that areas with high variability coincide with regions of relatively low monthly mean rainfall similar to suggestions in similar studies, e.g. (Maidment et al., 2012).

The spatial analysis of the three datasets allowed identifying and selection of rainfall homogeneous zones, which demonstrate the usefulness of global and satellite derived rainfall in climate analysis. These identified climatic zones can be applied in future climate studies.

The characteristics of the different rainfall datasets were evaluated over the selected zones whose results proved that the estimates errors have both geographical and temporal variations. Geographically the errors between GPCC and TAMSAT estimates are higher (> 20%) to the northern parts of southern Africa where availability of gauge information is poor as shown in figure 1.2. However, the errors were generally minimal over the arid and generally flat regions (< 15%) of southern Africa particularly during the austral summer period, similar to observations made by (Thorne et al., 2001) in a TAMSAT comparison study over southern Africa. The root mean square error was found to be higher over regions with high rainfall such as > 80 mm over northern parts of southern Africa (Zone A) and relatively lower over geographic regions with less rainfall, e.g. less than 25mm over south western parts of southern Africa (zone D).

Seasonal variations amongst the bias errors were also identified exposing the capabilities or limitations of the different measurements techniques. The annual plot of the bias errors (figure 6.9b) indicate the bias errors becoming minimal coming closer towards end of period which could be an indication of improvements in the global and satellite rainfall estimation. This could be due to improved sensor technology together with improvements in the algorithm e.g. (GPCC V6). However these observed trend can only be confirmed in future validations.

Similar characteristics and observations of higher errors during the dry season where even the correlation can be said to break down between GPCP and TAMSAT rainfall estimates over certain geographical areas particularly over the extreme southern tip of southern Africa were realised. This shows the limitations of IR cloud top temperature based methodology during the cold season. The observed geographical variations in the error were attributed to the variations or intermittency of the weather systems and the topography, together with systematic bias of the different rainfall measurement techniques.

From the analysis and these discussions the characteristics of the different rainfall estimates in space and over time can be understood. These rainfall estimates generally compare well to each other especially during the summer season and over certain regions with distinct topographic and climatic features. The differences amongst the different methodologies are persistent and stable over time as shown in (figure 6.9b). As discussed above, it becomes apparent that the TAMSAT rainfall estimates are generally lower in representation of magnitude of rainfall amounts, but generally in agreement in terms of structure to GPCC and GPCP in estimating and representing the mean rainfall over much of southern Africa. Variations in errors highlight the deficiencies of satellite rainfall algorithms for estimating spatially and temporally variable rainfall. Considering the observed differences in the rainfall magnitude amongst the rainfall estimates, it would be desirable to understand the effect of these differences in other climate related studies.

(i) RECOMMENDATIONS

To improve on the effect of the systematic biases, near real time gauges or a direct combination of near real time rainfall observations should be included in the TAMSAT methodology, as those proposed by (Grimes et al., 1999). It is however worth noting that this suggestion will not be without challenges especially in regions where the gauge network is sparse. Augmentation of availability of gauge data can be possible through participation of local meteorological and hydrological services in regular validation e.g. (multiannual time scale) exercises which also assist improving understanding, applicability and visibility of satellite derived rainfall estimates. Understanding the operational accuracy requirements for satellite rainfall estimates would offer an additional incentive to the local national meteorological and hydrological services to invest on improving the local rain gauge networks and exchange available gauge data with the global centres.

Alternatively, a basic satellite rain gauge calibration network capable of automatic or self calibration can be established in partnership and collaboration with the local meteorological and hydrological services and the satellite data providers over idealised locations considering that the rain gauge network has been observed to be declining with little hope for improvements over Africa region. This can be extended and developed from existing data collecting platforms (DCP) technology with GPS capabilities.

(ii) LIMITATIONS

The study was limited to monthly rainfall data analysis, thus only monthly time scales and beyond were possible in the analysis. Noting the importance of rainfall over the region and the high reliance of agriculture production and water resources on rainfall, shorter time scales (dekad) of rainfall analysis have a wider application. The study confirmed that the rainfall over southern Africa is characterised by high spatial and temporal variability in nature which leads to high vulnerability when the rainfall departs from the expected or normal patterns.

GTS derived gauge data (GPCC) was utilised as reference data for the study, which is not easy to establish the exact number and location of the gauge source that went into the rainfall data generation. It is understood and was shown (figure 1.2) that the region suffers from uneven distribution of gauge network and uncertainty on rainfall estimates depends strongly on gauge network density as was discussed. A weak correlation between the TAMSAT and GPCC estimates was observed over zone A (figure 5.1) which apart from attributing this to systematic errors and random variability in the climate system provides reason for bias towards effects of lack of gauge information. The unavailability of gauge information within each grid box made it not possible geo referencing of the satellite derived estimates to ensure that all satellite pixel information on the data is positioned over the correct geographic location on the earth's surface. However, none of the observations showed obvious signs of misrepresentation of the rainfall over the region.

(iii) FUTURE WORK

Noting the results of the study, further studies are desirable to consider improving or optimising the accuracy of TAMSAT rainfall estimates by correcting for bias error using localised rain gauge measurements. From the consistency in the bias errors over time, it is likely to fit a model for bias correction or optimisation of the TAMSAT rainfall estimates.

Also noting that the satellite rainfall estimates represent the mean rainfall over the region with good skill, future work should consider also investigating characterization of inter and intra seasonal rainfall variability utilizing satellite derived rainfall estimates such as onset, cessation of rainfall and variability over the region.

As mentioned in the recommendations, other relevant studies to satellite rainfall estimates should consider optimal rainfall calibration network over Africa for satellite rainfall estimates optimization and bias correction.

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