Analysis of rainfall variability and trends for better climate risk management in the major agro-ecological zones in Tanzania

Working Paper No. 363

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Contact us
CCAFS Program Management Unit, Wageningen University & Research, Lumen building, Droevendaalsesteeg 3a, 6708 PB Wageningen, the Netherlands. Email: ccafs@cgiar.org

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Abstract

Managing climate risk in agriculture requires a proper understanding of climatic conditions, regional and global climatic drivers, as well as major agricultural activities at the particular location of interest. Critical analyses of variability and trends in the historical climatic conditions are crucial in designing and implementing action plans to improve resilience and reduce the risks of exposure to harsh climatic conditions. However, in Tanzania, less is known about the variability and trends in the recent climatological conditions. The current study examined variability and trends in rainfall of major agro-ecological zones in Tanzania (1^o - 12^oS, 21^o - 41^oE) using station data from seven locations i.e. Hombolo, Igeri, Ilonga, Naliendele, Mlingano, Tumbi, and Ukiliguru which had records from 1981 to 2020 and two locations i.e. Dodoma and Tanga having records from 1958 to 2020. The variability in annual rainfall was high in Hombolo and Tanga locations (CV ≥ 28%) and low in Igeri (CV = 16%). The OND season showed the highest variability in rainfall (34% to 61%) as compared to the MAM (26% to 36%) and DJFMA (20% to 31%) seasons. We found increasing and decreasing trends in the number of rainy days in Ukiliguru and Tanga respectively, and a decreasing trend in the MAM rainfall in Mlingano. The trends in other locations were statistically insignificant. We assessed the forecast skills of seasonal rainfall forecasts issued by the Tanzania Meteorological Authority (TMA) and IGAD (Intergovernmental Authority on Development) Climate Prediction and Application Center (ICPAC). We found TMA forecasts had higher skills compared to ICPAC forecasts, however, our assessment was limited to MAM and OND seasons due to the unavailability of seasonal forecasts of the DJFMA season issued by ICPAC. Moreover, we showed that Integration of SCF with SSTa increases the reliability of the SCF to 80% at many locations which present an opportunity for better utilization of the SCF in agricultural decision making and better management of climate risks.

Keywords

Climate risk, Climate variability, Sea Surface Temperature Anomalies, El Nino Southern Oscillation, Indian Ocean Dipole, Seasonal climate forecast.

About the authors

Jacob E. Joseph, Research officer, International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Tanzania. Contact: j.emanuel@cgiar.org

Karuturi Purna Chandra Rao, Honorary Fellow, Innovations Systems for the Drylands, ICRISAT, Hyderabad. Contact: k.p.rao@cgiar.org

Amos Robert Ngwira, Systems Agronomist and Modeler, International Crops Research Institute for the Semi-Arid Tropics, CRISAT - Kenya (Regional hub ESA). Contact: a.ngwira@cgiar.org

Elirehema Swai, Research Agronomist and Soil Scientist, Tanzanian Agricultural Research Insititute (TARI) Makutupora, Dodoma. Contact: eyswai29@gmail.com

Reimund P Rötter, Chair Tropical Plant Production and Agricultural Systems Modelling (TROPAGS) and Dean of Research, Agricultural Faculty, University of Göttingen, Germany. Contact: reimund.roetter@uni-goettingen.de

Anthony M. Whitbread, Global Research Program Director, Innovation Systems for the DrylandsResilent Farm and Food Systems, ICRISAT, Tanzania. Contact: a.whitbread@cgiar.org

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Contents

Acronyms

CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
CWR	Crop water requirements
ENSO	El Niño Southern Oscillation
ICPAC	IGAD Climate Prediction and Applications Centre
IGAD	Intergovernmental Authority on Development
IOD	Indian Ocean Dipole
SCF	Seasonal Climate Forecast
TMA	Tanzania Meteorological Authority
WMO	World Meteorological Organization

1. Background

The dynamics of the Earth's physical climate system, i.e. the atmosphere, oceans, cryosphere, and land surface, are drivers of the Spatio-temporal variability of the global climate. Global atmospheric and oceanic circulations are among the factors that contribute to fluctuations in weather variables such as temperature, atmospheric pressure, and rainfall. For example, MacLeod, et al. (2019) used the atmospheric relaxation technique in coupled seasonal climate hindcast experiments to study seasonal rainfall variability in East Africa. They found the northwest Indian Ocean lower troposphere to be among the key drivers of inter-annual variability of March and April rainfall in East Africa. Endris et al. (2018) found the projected changes in the intensity and frequency of El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) will significantly impact both the amount and distribution of seasonal rainfall in East Africa.

Increased variability in the hydrological cycles and extreme events in many parts of the globe are vivid examples of global climate change and climate variability (Merabtene et al., 2016). At a country level, a proper understanding of such kind of variability is crucial for better climate risk management in various sectors such as agriculture, transport, and energy. Similar to other sectors, climate risk management in agriculture is impossible without adequate knowledge of climatic conditions—acquired through critical analyses of variability and trends in the historical climatic conditions—, regional and global climatic drivers, as well as major agricultural activities at the particular location of interest. This is among the reason why the provision of climate information services is crucial in agricultural risk management. Evidence from previous studies (Dayamba et al., 2018; Meybeck et al., 2012; Mittal & Hariharan, 2018; van Huysen et al., 2018) highlights the importance of climate information services in agricultural risk management to minimize the impacts of climate variability, improve the sustainability of agricultural systems, and productivity of agricultural activities.

In Tanzania, several studies have been conducted to analyze the variability and trends in rainfall and temperature patterns over the country. Insights from recent studies show increasing trends in maximum and minimum temperature and insignificant trends in annual and seasonal rainfall. Moreover, the evidence of high intra-seasonal and inter-seasonal variability in rainfall, increase in extreme weather events such as drought and flood were presented in those studies (Borhara et al., 2020; Gebrechorkos et al., 2018, 2020; Nicholson, 2017; Nyembo et al., 2020). The aforementioned anomalies were associated with reduced livestock production; higher livestock morbidity and mortality; crop damage due to heavy rainfall, flooding, and waterlogging; increased pest and disease which all increase agricultural production risk in Tanzania (Kangalawe et al., 2016; Lugendo et al., 2017; Mkonda & He, 2018).

Existing studies are limited to climate change and variability analyses rather than providing detailed analyses on the magnitude of the risks associated with such variabilities and the possible ways to minimize such risks. The present study used historical rainfall records from major agro-ecological zones in Tanzania to provide comprehensive analyses, oriented to crop production requirements, to quantify the production risks, and identify ways in which the risks can be minimized. A practical example of climate risk reduction is provided using the seasonal climate forecast. We investigated the level to which sea surface temperature anomalies in Indian and Pacific Oceans can explain the variability in seasonal rainfall. Moreover, we suggested further areas to explore which can be integrated into agricultural activities by small-holder farmers in Tanzania to minimize production risks associated with climate change and climate variability.

2. Methodology

2.1 Study location and dataset

The present study selected 9 locations distributed across major agro-ecological zones in Tanzania located between latitude 1^{o} to 12^{o} S and longitude 21^{o} to 41^{o} E (Figure 1). The elevation of the study locations ranges from 120m (Naliendele) to 2249m (Igeri). Ilonga, Dodoma, and Hombolo represent the agro-ecological zone of central

Tanzania while Tumbi and Ukiliguru represent the western and lake zone agro-ecologies respectively. Tanga and Mlingano represent the north-coast agro-ecology. Naliendele and Igeri represent the south-western highland and southern coast agro-ecological zones respectively.

The study used a combination of station data from Tanzania Meteorological Authority (TMA) and gridded data from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS). Rainfall data from 1958 to 2016 for Dodoma and Tanga locations were obtained from station data with CHIRPS rainfall data used for the period 2017 to 2020 which was unavailable. For the other locations—Hombolo, Igeri, Ilonga, Mlingano, Naliendele, and Ukiliguru, observed rainfall data from 1981 to 2020 was available. The sea surface temperature anomalies data over the Pacific Ocean—the NINO3.4 regions (5oN - 5oS, 170oW-120oW)—were obtained from the National Oceanic and Atmospheric Administration (NOAA). The SSTa from the Indian Ocean i.e 90°E-100°E, 28°S-18°S and 90°E-110°E, 10°S- 0°S regions were obtained from ECMWF SEAS5. Except for Ilonga, Dodoma, and Tanga, other locations had 1 to 4 months in different years with missing records which were substituted by the climatological daily mean.

We obtained historical seasonal forecast data from TMA and IGAD Climate Prediction and Applications Centre (ICPAC is a regional climate center accredited by the WMO that provides climate services to 11 East African Countries). For the long rainy season (March-May (MAM)) season the forecasts were from 2009 to 2019 except 2014 which was missing and for the short rainy season (October – December (OND)) the forecast was from 2007 to 2018 except 2009 which was missing.

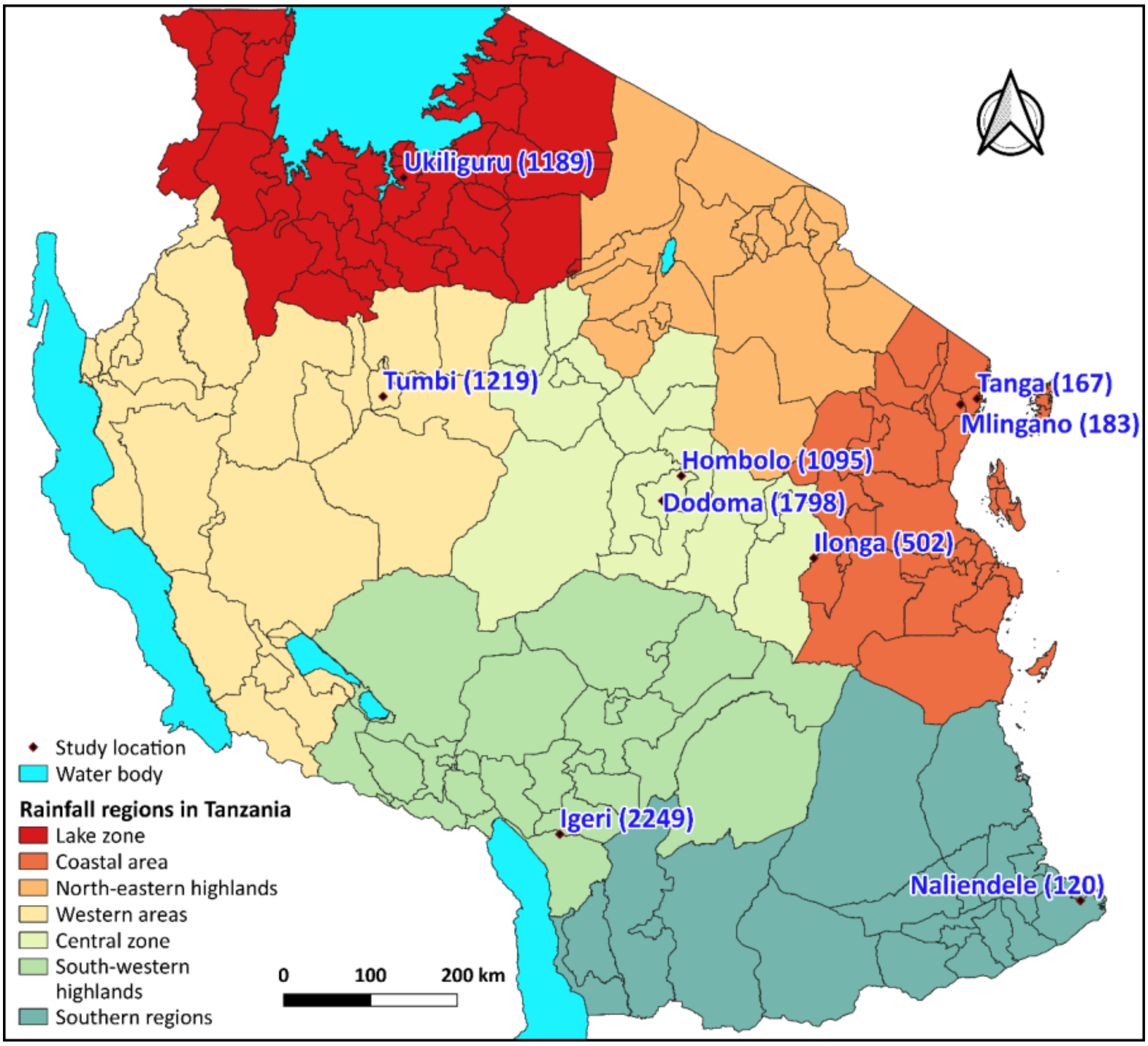


Figure 1: **The map of the study area showing locations in different rainfall zones and their respective elevation in meters.**

2.2 Seasonal rainfall trends and variability

Statistical analyses were conducted to understand the distribution and variability of annual, seasonal, and monthly rainfall in the study locations. We used average to characterize temporal variability and coefficient of variation (CV) to measure the amount of dispersion in the annual and seasonal rainfall amounts. Analysis of variance (ANOVA) was used to test for significant differences in means of various groups of seasonal rainfall, and rainfall predictors such as sea surface temperature anomalies. Trends in seasonal and annual rainfall were computed using the Mann-Kendall test. The Mann-Kendall test is a non-parametric test that determines whether a monotonic time series data has an increasing or decreasing trend. It does not require a series to be normally distributed or linear. It tests the hypotheses (i)

Null hypothesis: there is no trend in the time series (ii) Alternative hypothesis: there is either a decreasing or increasing trend in the time series (Gocic & Trajkovic, 2013). The Mann-Kendall test has been proven for its suitability to detect increasing and decreasing trends in climate and environmental data (Alemu & Dioha, 2020). The same test was also used to determine trends in the number of rainy days—a rainy day defined as a day that receives at least 1 mm rain-(WMO, 2010).

The seasons were classified to below-normal, and above-normal according to the amount of rainfall they received relative to maize and sorghum crop water requirement (CWR). Maize and sorghum water requirements for the locations in the current study were calculated using a novel empirical method proposed by FAO (*Crop water needs*, n.d.). We found an average of 450 and 350 mm to be the minimum water requirement for maize and sorghum respectively in the study locations. We used the computed values as thresholds to get two definitions of above-normal and below-normal season i.e. a value greater than the calculated CWR was classified as above-normal and less than the calculated CWR was classified as below-normal.

2.3 Predicting seasonal rainfall variability in the MAM, OND, and DJFMA seasons

Variations in seasonal rainfall intensity and frequency are largely associated with sea surface temperature patterns around the globe. The impact of sea surface temperature anomalies on the atmosphere persists throughout the season due to their slow evolution. This makes the SSTa a good predictor of seasonal rainfall variabilities. Various statistical methods such as linear regression, canonical correlation analysis, and principal component analysis are used to predict seasonal rainfall variability (Parker and Diop-Kane, 2017). The current study used SSTa as predictors in the following multiple regression equation to estimate the amount of rainfall in the MAM, OND, and DJFMA seasons:

$$RF = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

Whereby

$RF =$ Seasonal rainfall of a particular season i.e MAM, OND, or DJFMA

$\beta =$ Regression coefficients

$X =$ SSTa of a particular month (January to November)

$\varepsilon =$ Model error

The month X_n is the value of SSTa a month before the start of the season for instance for MAM, OND, and DJFMA seasons X_n were the SSTa in January, August, and October respectively. We computed the differences between SSTa in the 90°E-100°E, 28°S-18°S and 90°E-110°E, 10°S- 0°S regions and used the values in the linear regression model to predict seasonal rainfall variabilities. The choice of the aforementioned regions is due to the observed correlation between SSTa over the regions and coupled convectively equatorial waves such as Equatorial Rossby wave, Kelvin wave, and Mixed Rossby-gravity wave (Keshav and Landu, 2020; Subudhi and Landu, 2019) which all influence the variability in seasonal rainfall, especially in a local scale.

The predicted rainfall amounts were then compared with the observed rainfall to determine the level to which the model characterizes the seasonal rainfall i.e. the accuracy of the predicted rainfall to capture the above-normal and below-normal seasons. The performance is presented in the results section.

2.4 Reliability of Seasonal Climate Forecast (SCF)

To understand the predictability of seasonal rainfall amounts and assess the potential role they can play in managing climate risks, we examined the reliability of the seasonal forecasts issued by TMA and ICPAC as well as the predicted seasonal rainfall using the SSTa of the above described Indian Ocean region in the linear regression model. The observed rainfall amounts were classified as below-normal (BN) and above-normal (AN) as described in the previous section. A hit was defined as an AN or BN forecast which matched the observed rainfall group (AN or BN) among the forecasts which were AN or BN respectively. Otherwise, a forecast was termed as a miss. We computed the number of hits and misses forecasts and calculated the accuracy (hit rate) of the forecast using the following equation:

$$Accuracy\ of\ AN(BN) forecast\ = \frac{Number\ of\ Hits\ in\ AN(BN) forecast}{Number\ of\ AN(BN) forecasts} \times 100\%$$

Based on the accuracy of the forecast calculated using the above equation, the skills of the seasonal rainfall forecasts were evaluated.

3. Results

3.1 Rainfall distribution, trends, and variability

Annual and seasonal rainfall variability

The average annual and seasonal rainfall amounts show significant variation among the locations (Table 1). The western highlands, and western agro-ecological zones represented by Igeri, and Tumbi respectively received the highest amount of annual rainfall—above 1500 mm—followed by the coastal areas (both north and south coastal zones) represented by Mlingano, Tanga, and Naliendele which received over 1100 mm per year. In the lake zone and the central part of the country, the average annual rainfall was less than 1100 mm. The variability in annual rainfall was highest in Hombolo, Ilonga, and Tanga locations—both CV > 25%—, and lowest in Igeri (CV = 16%). Other locations have CV values ranging from 17% to 23%. The number of rainy days was at least 100 annually in Igeri, Mlingano, Tanga, and Ukiliguru (Table 1). However, the variability in the number of rainy days was very high in Mlingano (CV = 50%) and Ukiliguru (CV=36%) and a bit lower (CV < 20%) in Igeri and Tanga.

Table 1: Annual and seasonal rainfall amounts and associated coefficient of variation (CV) in the study locations. Figures in parenthesis indicate the number of rainy days and their CV.

Location	Annual Rainfall (mm)		MAM Rainfall (mm)		OND Rainfall (mm)		DJFMA Rainfall (mm)	
	Mean	CV%	Mean	CV%	Mean	CV%	Mean	CV%
Dodoma	598 (43)	20(21)	-	-	-	-	**563(40)**	**31(20)**
Hombolo	623(54)	29(43)	-	-	-	-	**571(48)**	**30(48)**
Igeri	2681(142)	16(18)	-	-	-	-	**2343(110)**	**14(13)**
Ilonga	1067(82)	26(21)	-	-	-	-	**796(54)**	**29(22)**
Naliendele	1118(82)	23(20)	-	-	-	-	**934(61)**	**22(16)**
Tumbi	1880(92)	18(35)	-	-	-	-	**1521(68)**	**20(31)**
Mlingano	1129(125)	21(50)	**473(43)**	**29(42)**	**391(37)**	**53(62)**	**-**	**-**
Tanga	1332(101)	28(17)	**641(35)**	**36(20)**	**363(26)**	**61(31)**	**-**	**-**
Ukiliguru	858(110)	17(36)	**323(37)**	**26(38)**	**315(40)**	**34(45)**	-	-

Similar to annual rainfall, Igeri and Tumbi received the highest amount of rainfall (> 1500 mm) in the DJFMA season. The aforementioned locations received over 1000 mm in 80% of the seasons in the study period (1981 to 2020). Three locations in the central zone i.e. Dodoma, Hombolo, and Ilonga, and one in the southern coast part of Tanzania received less than 1000 mm per season on average. Compared to Dodoma which receives at least 400 mm in only 2 out of 5 seasons, Hombolo, Ilonga, and Naliendele receive the same in almost all seasons during the DJFMA rainy season (Figure 2). The central zone locations showed the highest variability (CV >25% (Table 1) as compared to other locations with a similar rainfall regime in the study areas. Igeri had the highest number of rainy days (110) on average compared to other locations. Except in Dodoma and Hombolo, other locations had at least 50 rainy days per season. Variability in the number of rainy days was higher in Hombolo (CV = 48%) compared to other locations (Table 1).

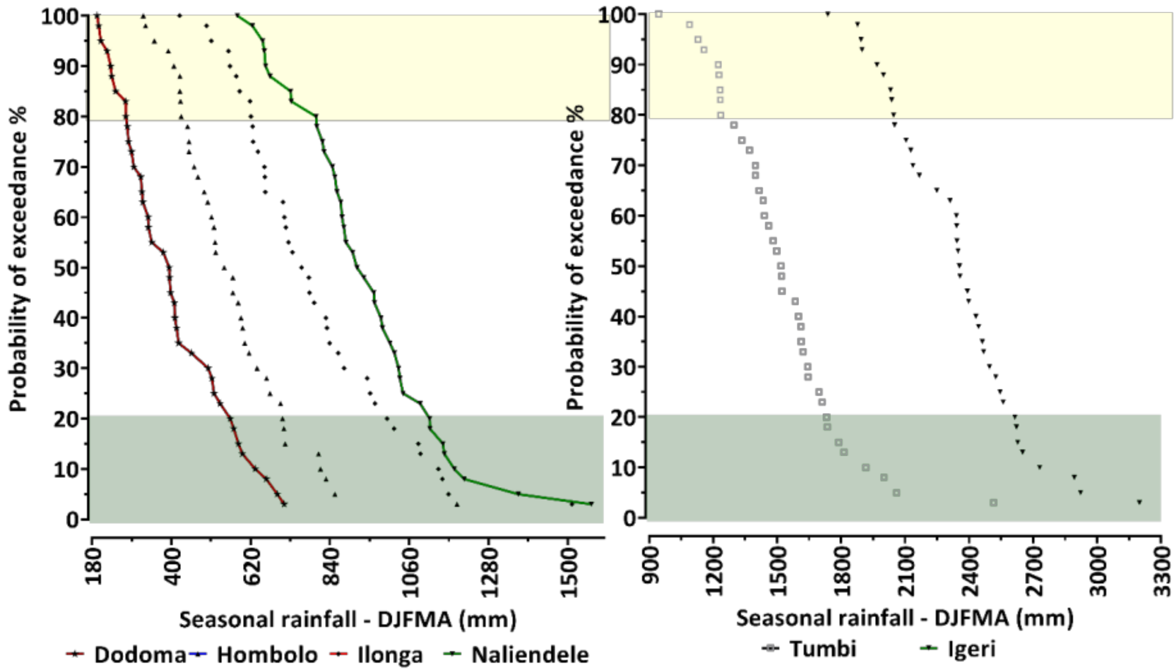


Figure 2: **The seasonal rainfall probability of exceedance chart for the locations with unimodal rainfall regime i.e. *Msimu* (DJFMA) season**

In the locations with bimodal rainfall regime i.e. long rain season (*Masika*: MAM season) and short rain season, the amount of rainfall and the number of rainy days were slightly higher with less variability in the MAM season compared to OND season. Tanga and Mlingano received 350 mm in 80% of the MAM seasons in the study period (1981 – 2020) while Ukiliguru received at least 350 mm in only 30% of the MAM seasons. In the OND season, the same locations received at least 350 mm of rainfall in less than 60% of the seasons (Figure 3). The overall variability in seasonal rainfall was significantly high during the short rain season (*Vuli* –OND season) and varied from 31% to 62% compared to that during the long rain season (*Masika*-MAM)—varied from 20% to 42%.

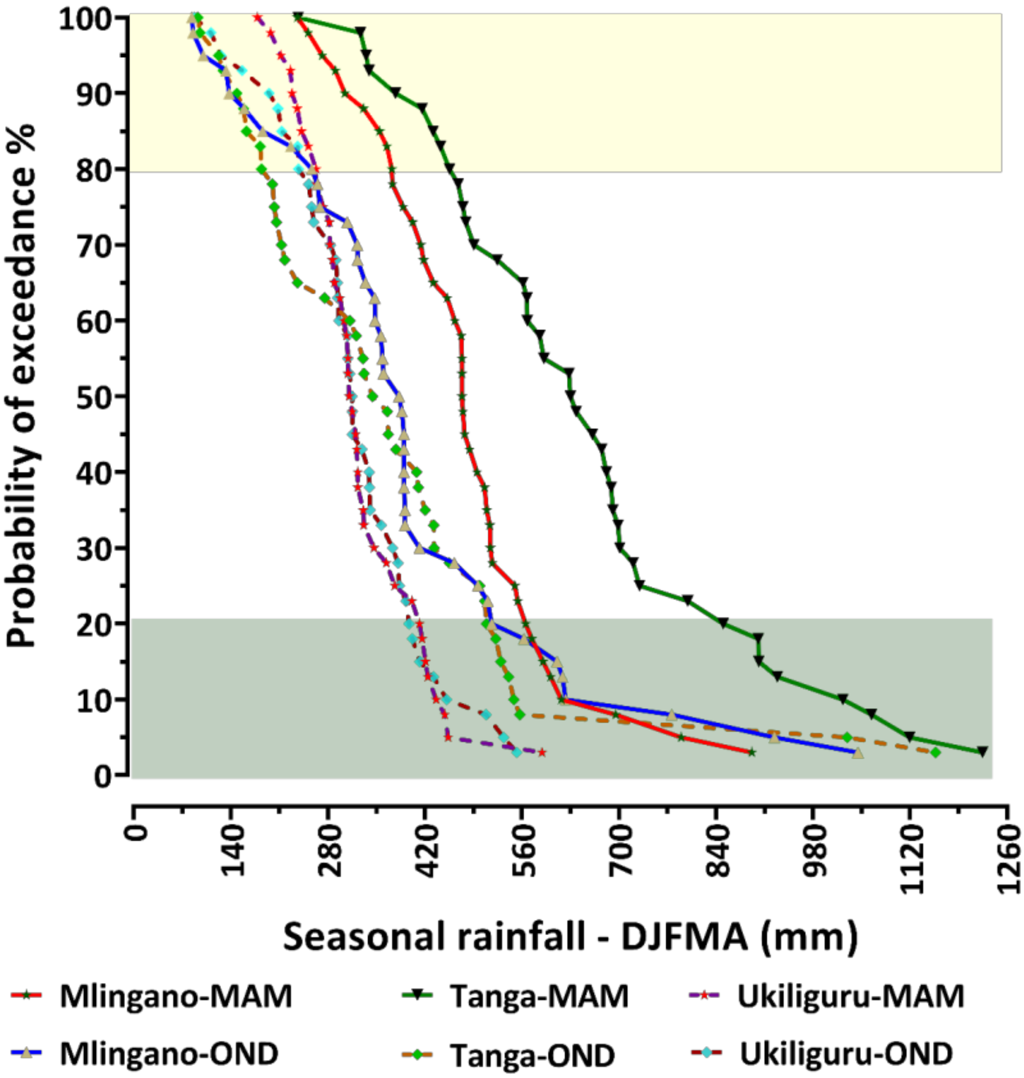


Figure 3: **The seasonal rainfall probability of exceedance chart for the locations with bimodal rainfall regime i.e. long rain (MAM) and short rain (OND) seasons**

Annual and seasonal rainfall trends

The long-term trends in the annual and seasonal rainfall were examined using the Mann-Kendall statistical test. We found insignificant increasing and decreasing trends in annual rainfall amount in all locations. However, increasing and decreasing trends in the number of rainy days in Ukiliguru and Tanga respectively, and a decreasing trend in the amount of rainfall in the MAM season in Mlingano were found to be significant (Table 2).

Table 2: Mann-Kendall statistic for annual and seasonal rainfall and annual rainy days in the study locations. (* and + are significant trends at 99% and 90% confidence intervals respectively).

Location	Annual		Seasonal rainfall		
	RF Amount	Rainy days	MAM	OND	DJFMA
Dodoma	0.45	0.04	0.13	0.99	0.71
Hombolo	0.50	0.45	0.45	0.48	0.15
Igeri	0.34	-1.09	-0.56	-0.41	-0.27
Ilonga	-0.43	-0.97	0.52	-0.55	-0.29
Naliendele	-0.19	-0.84	0.17	-0.99	-0.10
Tumbi	-0.56	-0.87	-0.47	-0.38	-1.03
Mlingano	-0.96	0.68	-1.86+	0.58	-1.07
Tanga	-0.15	-3.97*	-0.19	0.59	-0.92
Ukiliguru	-0.50	1.91+	-1.37	0.12	-0.93

Monthly rainfall variability and distribution

The average monthly rainfall and number of rainy days per month showed both spatial and temporal variation. In the central, south-western highland, and the south-coast agro-ecologies, the wettest months were December, March, and April except for Dodoma and Hombolo for which January was the wettest month in the year (Figure C1 (a – f) in Appendices). The highest monthly rainfall of 575 mm was recorded in Igeri in March and the minimum monthly rainfall was observed in Dodoma (50 mm) in April. The variation in the amount of rainfall and the number of rainy days during the non-growing period months was very high with a CV>100% in all locations. During the growing season, December (CV≥42%) and April (CV≥37%) showed higher variation compared to January, February, and March. The central zone and the south-coast zone locations showed higher variability in both rainfall and number of rainy days (CV > 37%) as compared to the south-western highland and the western zone locations (Figure C1 (a – f) in the Appendices).

Figure 4 represents the probabilities of dry <100 mm), wet (100-200 mm), and very wet (>200 mm) months in the study locations with DJFMA rainy season. As expected, the chance of getting less than 100 mm per month is very high in the months outside the rainy season or non-crop growing period in all locations. The same decreased during the growing period from December to April. Within the growing period, the central and south-coast locations (Dodoma, Hombolo, Ilonga, and Naliendele) have a higher chance (≥ 40% in most months) of getting less than 100 mm per month compared to Igeri and Tumbi. Igeri and Tumbi locations showed a very low probability (< 10%) of getting less than 100 mm per month and a high probability of getting > 200 mm per month during the growing period. Thus, In the DJFMA season, our analysis revealed the central and southern coast locations receive less rainfall with high variation during the growing period as compared to the western and south-west highland locations which receive a higher amount of rainfall and showed less variability in monthly rainfall during the growing period.

In the locations with bimodal rainfall regimes (Figure C1 (g – i) in the Appendices), the wettest months were April and May in the MAM season and November and December in the OND season. Ukiliguru (lake zone) received a low amount of rainfall ranging from 4 mm in July to 141 mm in April with higher variation ranging from 39% in the wettest month to 175% in the driest month. January and February were the driest months with fewer rainy days (< 6 per month) and the highest variability (CV ≥ 105%) in both Mlingano and Tanga locations.

Except in Ukiliguru, the probability of getting at least 100 mm per month is ≥ 80% in April and May, the wettest months of the MAM season. The probabilities are lower, about 70% in November and 40% in December, the wettest months of the OND season in Mlingano and Tanga (Figure 5). The probability of getting at least 100 mm per month in Ukiliguru is about 80% in April, 70% in May and December, and is 60% in November. The probability of getting a very wet month with more than 200 mm rainfall is about 60% in April and May in Tanga while the same is less than 30% in Mlingano and Ukiliguru.

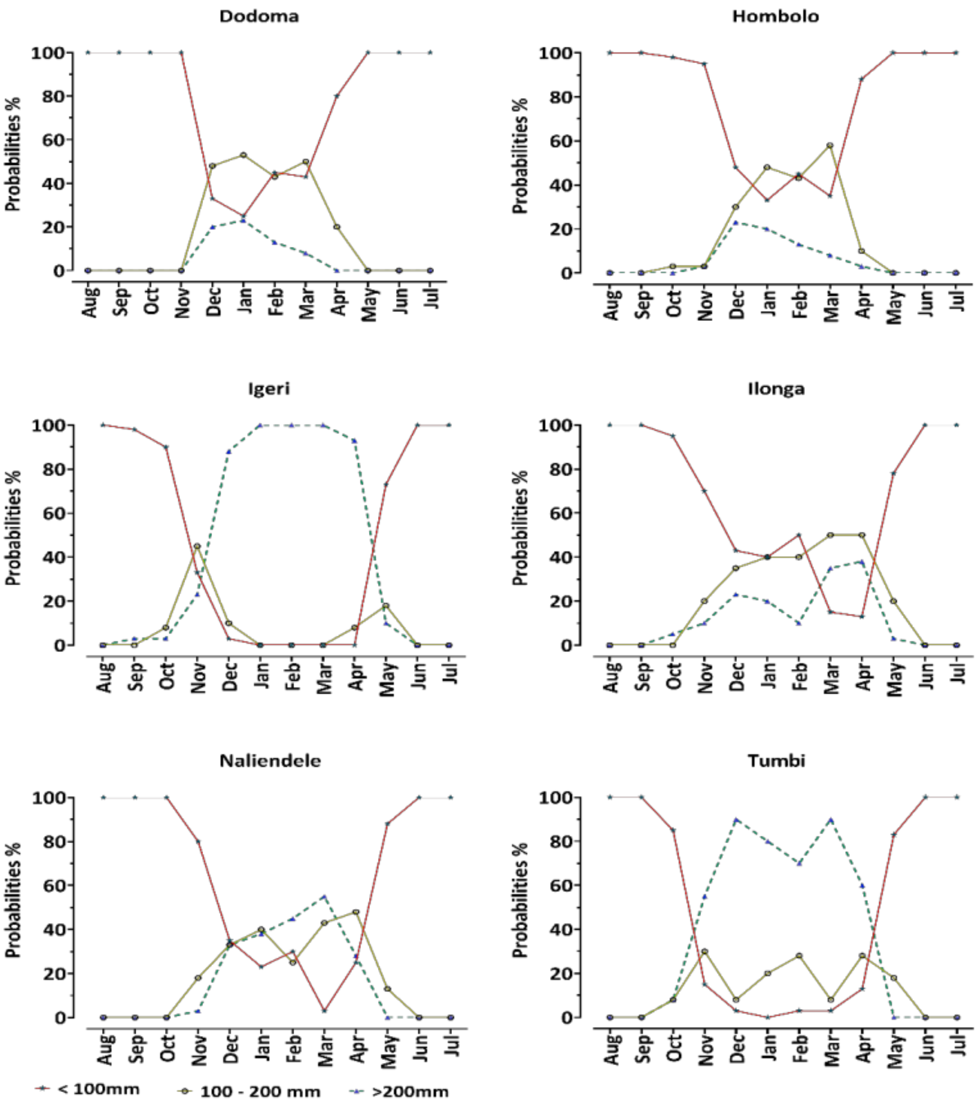
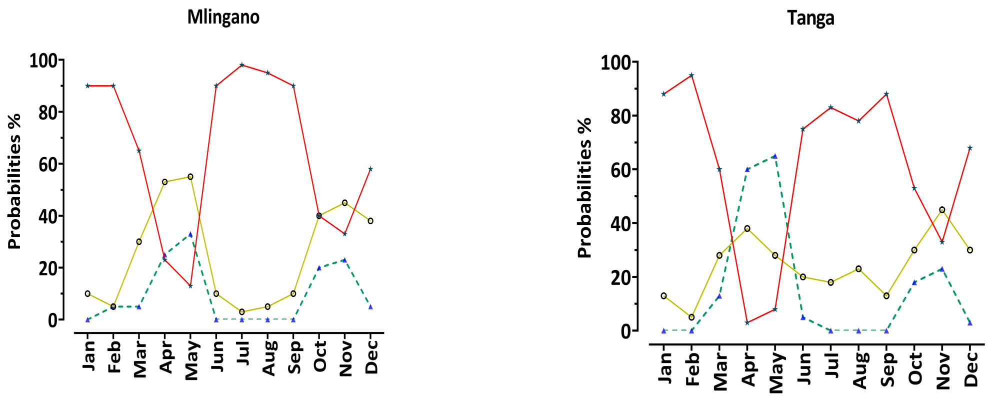


Figure 4: The probabilities of getting dry (< 100 mm), wet (100 - 200 mm), and very wet (> 200 mm) months in the location with a unimodal rainfall regime.



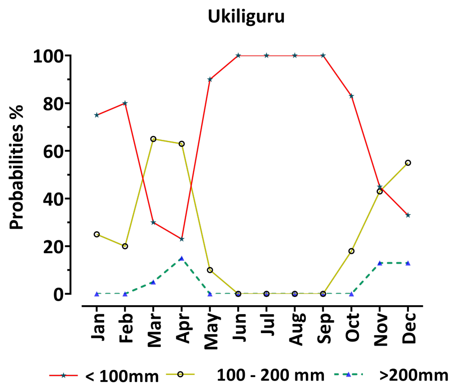


Figure 5: The probabilities of getting dry (< 100 mm), wet (100 - 200 mm), and very wet (≥ 200 mm) months in the locations with a bimodal rainfall regime

3.2 Reliability and skills of the Seasonal Climate Forecast (SCF) in the study area

Seasonal Climate Forecast in the MAM (*long rain*) and OND (*short rain*) Season.

We examined the reliability of seasonal rainfall forecasts provided by TMA (local seasonal forecast) and ICPAC (regional seasonal forecast). ICPAC seasonal forecast is a consensus forecast that is negotiated by participating national meteorological agencies and is presented as a coarse-scale map showing the probability as "below-normal," "normal" or "above-normal" categories. The TMA forecast is a downscaled version of the same. The predictions from the two forecast sources i.e. TMA and ICPAC matched in some years and mismatched in the others. Figures A1 and A2 (Appendix A) show how the matching and mismatching were distributed among the years in the MAM and OND seasons. The mismatch was higher in Tanga (73%) and lower in Mlingano (19%) both in the OND season. It is interesting to note that both locations fall in the same agro-ecological zone and are spatially very close. The mismatch in all three locations i.e. Ukiliguru, Mlingano, and Tanga is about 60% of the seasons. Adding SSTa phases as an additional criterion to the seasonal forecasts (SFC) tends to reduce the mismatch in the two datasets from 30 – 50 % (Figure A2).

The available skill in the forecasts from the two sources for the MAM season was further evaluated for its usefulness in farm-level decision-making. Forecasts for 10 years from 2009 to 2019, except 2014 which was missing, and for 11 years from 2007 to 2018, except 2009 which was missing in the case of the OND season were used. The seasons were classified as below-normal or above-normal by using two threshold values that are based on crop water requirements as described in the methodology section. The two thresholds were used for performance comparison and to establish the usefulness of the forecast skills in selecting crops with different water requirements as a way to minimize the risks of exposure to uncertainties created by climate variability. Table 3 provides the details of the performance of the two sources of forecast used in the present study.

An unpaired t-test revealed a statistically insignificant difference ($t(10) = 0.4622$, $p = 0.6538$) in the prediction of AN seasons between TMA and ICPAC forecasts. However, there are differences in the forecast reliability across the seasons and the locations. ICPAC had higher accuracy in predicting the MAM above-normal seasons in Tanga while TMA predicted with higher accuracy the MAM above-normal seasons in Mlingano (Table 3). The performance of TMA and ICPAC in Ukiliguru for the MAM season slightly differed. In the OND seasons, ICPAC predicted with higher accuracy the BN seasons in all locations as compared to TMA. The accuracy has not improved when the threshold was reduced to 350 mm.

Table 3: Skill assessment of seasonal rainfall forecasts issued by TMA and ICPAC (values in parenthesis) for MAM and OND seasons using two different thresholds that are based on the seasonal crop water requirements of maize and sorghum crops.

			AN>450 mm, BN<450 mm				AN>350 mm, BN<350 mm			
Season	**Location**	**RF**	**OBS**	**FC**	**Hits**	**Rate(%)**	**OBS**	**FC**	**Hits**	**Rate(%)**
MAM	**Ukiliguru***	**AN**	7	8(4)	6(3)	**75(75)**				
		BN	3	2(6)	1(2)	**50(33)**				
	Mlingano	**AN**	4	5(4)	3(2)	**60(50)**	5	5(4)	4(3)	**80(75)**
		BN	6	5(6)	4(4)	**80(67)**	5	5(6)	4(4)	**80(67)**
	Tanga	**AN**	7	5(4)	3(4)	**60(100)**	8	5(4)	3(4)	**60(100)**
		BN	3	5(6)	1(3)	**20(50)**	2	5(6)	0(2)	**0(33)**
OND	**Ukiliguru***	**AN**	6	6(7)	5(6)	**83(86)**				
		BN	5	5(4)	4(4)	**80(100)**				
	Mlingano	**AN**	2	6(7)	2(2)	**33(29)**	8	6(7)	4(5)	**67(71)**
		BN	9	5(4)	5(4)	**100(100)**	3	5(4)	1(1)	**20(25)**
	Tanga	**AN**	3	6(7)	2(3)	**33(43)**	5	6(7)	3(4)	**50(57)**
		BN	8	5(4)	4(4)	**80(100)**	6	5(4)	3(3)	**60(75)**

*Note: *The average rainfall for Ukiliguru is less than 350 mm for both MAM and OND seasons. The threshold was reduced to 300 mm instead of 350 mm.*

The warm and cold phases of the IOD and NINO3.4 regions were added to make an additional criterion to predict a seasonal type i.e. AN/BN seasons. In both regions i.e. IOD and NINO3.4, the warm phases were associated with increased and the cold phases with decreased rainfall intensity and frequency. The phases were computed one month before the start of the rainy season using the previous three-month average SSTAa. Accordingly, November to January average SSTa for MAM season, June to August SSTa for OND season, and August to October SSTa for DJFMA season were used. The phases were identified as warm if 3 months' average SSTa>0^{o}C and cold if 3 months' average SSTa<0^{o}C. The season was classified as AN only when it was forecasted either by TMA or ICPAC to be AN and the SSTa phase was warm otherwise it was classified as BN. The Tables below show the performance of the forecasts after additional of SSTa criteria.

The addition of warm and cold phases of the SSTa in the IOD and NINO3.4 regions significantly changed the skills of both the TMA and ICPAC seasonal forecast. IOD SSTa phases increased the accuracy of predicting the AN seasons by 10% in both TMA and ICPAC seasonal forecasts, however, the prediction of BN seasons in both forecasts insignificantly changed (Table 4).

Table 4: Assessment of skill of seasonal rainfall forecasts issued by TMA and ICPAC—in parenthesis—in the MAM and OND seasons using seasonal crop water requirements of maize and sorghum during warm and cold phases in the IOD.

			AN>450 mm, BN<450 mm				AN>350 mm, BN<350 mm			
Season	**Location**	**RF**	**OBS**	**FC**	**Hits**	**Rate(%)**	**OBS**	**FC**	**Hits**	**Rate(%)**
MAM	Ukiliguru*	AN	7	5(3)	3(2)	**60(67)**				
		BN	3	5(7)	1(2)	**20(29)**				
	Mlingano	AN	4	4(3)	3(2)	**75(67)**	5	4(3)	4(3)	**100(100)**
		BN	6	6(7)	5(5)	**83(71)**	5	6(7)	5(5)	**83(71)**
	Tanga	AN	7	4(3)	3(3)	**75(100)**	8	4(3)	3(3)	**75(100)**
		BN	3	6(7)	2(3)	**33(43)**	2	6(7)	1(2)	**17(29)**
OND	Ukiliguru*	AN	6	4(5)	4(5)	**100(100)**				
		BN	5	6(5)	5(5)	**83(100)**				
	Mlingano	AN	2	4(5)	2(2)	**50(40)**	8	4(5)	3(4)	**75(80)**
		BN	9	6(5)	6(5)	**100(100)**	3	6(5)	2(2)	**33(40)**
	Tanga	AN	3	4(5)	2(3)	**50(60)**	5	4(5)	2(3)	**50(60)**
		BN	8	6(5)	5(5)	**83(100)**	6	6(5)	4(4)	**67(80)**

The NINO3.4 SSTa phases increased significantly the prediction accuracy of the MAM above-normal seasons in Mlingano and Tanga and decreased the accuracy of predicting the below-normal seasons in TMA (8% decrease) and ICPAC (13% decrease) seasonal forecasts (Table 5). The change of a threshold from 450 mm to 350 mm improved slightly the accuracy of the forecasts before and after the addition of the SSTa phases. The prediction of both AN and BN seasons slightly increase in Mlingano by changing the threshold from 450 mm to 350 mm especially in the OND seasons while in Tanga the accuracy of predicting OND below-normal seasons significantly decrease with the change of threshold from 450 mm to 350 mm.

Table 5: Seasonal forecast skills assessment of seasonal rainfall forecasts issued by TMA and ICPAC—in parenthesis—in the MAM and OND seasons using seasonal crop water requirements of maize and sorghum during warm and cold phases in the NINO3.4 regions.

Season	Location	AN>450 mm, BN<450 mm					AN>350 mm, BN<350 mm			
		RF	OBS	FC	Hits	Rate(%)	OBS	FC	Hits	Rate(%)
MAM	Ukiliguru*	AN	7	4(3)	3(2)	**75(67)**				
		BN	3	6(7)	2(2)	**33(29)**				
	Mlingano	AN	4	2(3)	2(2)	**100(67)**	5	2(3)	2(2)	**100(67)**
		BN	6	8(7)	6(5)	**75(71)**	5	8(7)	5(4)	**63(57)**
	Tanga	AN	7	2(3)	2(3)	**100(100)**	8	2(3)	2(3)	**100(100)**
		BN	3	8(7)	3(3)	**38(43)**	2	8(7)	2(2)	**25(29)**
OND	Ukiliguru*	AN	6	3(4)	2(3)	**67(75)**				
		BN	5	7(6)	4(4)	**57(67)**				
	Mlingano	AN	2	3(4)	1(1)	**33(25)**	8	3(4)	1(2)	**33(50)**
		BN	9	7(6)	6(5)	**86(83)**	3	7(6)	1(1)	**14(17)**
	Tanga	AN	3	3(4)	1(2)	**33(50)**	5	3(4)	1(2)	**33(50)**
		BN	8	7(6)	5(5)	**71(83)**	6	7(6)	4(4)	**57(67)**

Seasonal Climate Forecast in the DJFMA (*Msimu*) Season

The central, western, and southern part of Tanzania's seasonal rainfall starts in December and continues to April the following year—DJFMA(*Msimu*) season. Six locations in the current study i.e. Dodoma, Hombolo, Igeri, Ilonga, Tumbi, and Naliendele, belong to the aforementioned categories. We assessed the reliability of the seasonal forecast issued by TMA in the aforementioned locations from the

2007/2008 season to the 2019/2020 season (the 2018/2019 season was missing). However, we could not compare the forecast skills with ICPAC seasonal forecasts as in the previous section due to the unavailability of data—ICPAC issues their seasonal forecasts in MAM, JJAS, and OND seasons only. Moreover, Igeri and Tumbi were excluded from the analysis because their minimum seasonal rainfall was above the thresholds used in the present study. Table 6 shows the details of the performance.

The DJFMA forecast showed very low accuracy except in Naliendeli in which the prediction skills of the AN seasons were good. The change of the threshold from 450 mm to 350 mm improved the prediction of the AN seasons in Hombolo, Ilonga, and Naliendeli and insignificantly affected the prediction accuracy of BN seasons in all locations (Table 6).

Table 6: Skill assessment of seasonal rainfall forecasts issued by TMA for the DJFMA season using two different thresholds that are based on the seasonal crop water requirements of maize and sorghum crops.

			AN>450 mm, BN<450 mm				AN>350 mm, BN<350 mm			
Season	**Location**	**RF**	**OBS**	**FC**	**Hits**	**Rate(%)**	**OBS**	**FC**	**Hits**	**Rate(%)**
DJFMA	Dodoma	AN	5	8	2	25	5	8	2	25
		BN	7	4	1	25	7	4	1	25
	Hombolo	AN	3	8	0	0	8	8	4	50
		BN	9	4	1	25	4	4	0	0
	Ilonga	AN	3	8	0	0	7	8	4	50
		BN	9	4	1	25	5	4	1	25
	Naliendele	AN	11	8	7	88	12	8	8	100
		BN	1	4	0	0	0	4	0	0

The forecast skills of the BN seasons were increased during the SSTa warm and cold phases of the IOD and NINO3.4 regions when 450 mm was used as a threshold while the same decreased when the threshold was changed to 350 mm. The AN prediction skills during the warm and cold phases of SSTa increased in 350 mm threshold and slightly increased in 450 mm threshold (Table 7).

Table 7: Assessment of seasonal rainfall forecast skills issued by TMA in the DJFMA seasons during warm and cold phases in the IOD and NINO3.4(in parenthesis) regions.

			AN>450 mm, BN<450 mm				AN>350 mm, BN<350 mm			
Season	**Location**	**RF**	**OBS**	**FC**	**Hits**	**Rate(%)**	**OBS**	**FC**	**Hits**	**Rate(%)**
DJFMA	Dodoma	AN	5	5(5)	2(2)	40(40)	5	5(5)	2(2)	40(40)
		BN	7	7(7)	4(2)	57(57)	7	7(7)	4(2)	57(57)
	Hombolo	AN	3	5(5)	0(0)	0(0)	8	5(5)	3(3)	60(60)
		BN	9	7(7)	4(4)	57(57)	4	7(7)	2(2)	29(29)
	Ilonga	AN	3	5(5)	0(1)	0(0)	7	5(5)	3(2)	60(40)
		BN	9	7(7)	4(4)	57(57)	5	7(7)	3(2)	43(29)
	Naliendele	AN	11	5(5)	4(4)	80(80)	12	5(5)	5(5)	100(100)
		BN	1	7(7)	0(0)	0(0)	0	7(7)	0(0)	0(0)

Seasonal rainfall prediction using Sea Surface Temperature anomalies in a regression model

Using the SSTa in the 90°E-100°E, 28°S-18°S, and 90°E-110°E, 10°S- 0°S regions as predictors of the MAM, OND, and DJFMA rainfall we created a linear regression model to predict seasonal rainfall in the study area. The details of the model are described in the methodology section. The accuracy of the model in different locations is presented below using the R^2 values in Figure 6. The model had higher accuracy in all seasons in the central zone i.e. Dodoma, Hombolo, and Ilonga, and the lowest accuracy(less than 40%) was observed in Mlingano in MAM and OND. Other locations showed fair good accuracy (> 40%) in their growing period.

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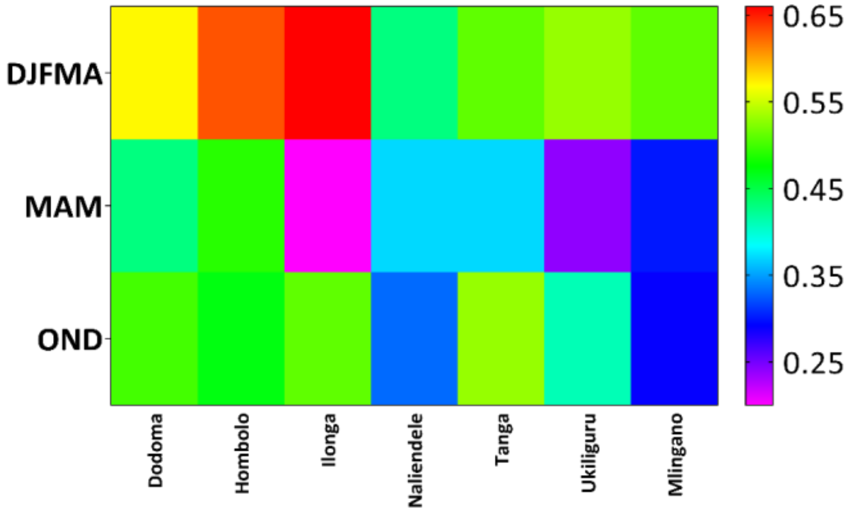

Figure 6: Model accuracy (R^2) in predicting the DJFMA, MAM, and OND rainfall in different locations

Performance of the model in predicting the MAM (*long rain*) and OND (*short rain*) rainfall

Table 8 represents the performance of the regression model in predicting the MAM and OND rainfall. On average the accuracy of predicting the AN seasons is 76% and 84% when the first and the second thresholds were used respectively. Similarly, the model predicted the BN seasons with accuracies of 75% and 63% when the first and the second thresholds were used respectively.

In the MAM season, the accuracy was at least 70% in both AN and BN seasons (7 out of 10 predicted seasons were correct) except in Mlingano in which the accuracy of predicting the BN seasons was 63%. Moreover, the model predicted the below-normal OND seasons with fairly good accuracy(67%) in Mlingano and the above-normal MAM seasons in Tanga (60%). Changing the threshold from 450 mm to 350 mm slightly improved the accuracy in AN seasons but decreased the accuracy in BN seasons prediction(Table 8).

Table 8: Performance of Indian Ocean SSTa in predicting the MAM (1982 -2020, except 2017 and 2018) and OND (1982 – 2020, except 2017) seasonal rainfall

			AN>450 mm, BN<450 mm				AN>350 mm, BN<350 mm			
Season	**Location**	**RF**	**OBS**	**FC**	**Hits**	**Rate(%)**	**OBS**	**FC**	**Hits**	**Rate(%)**
MAM	Ukiliguru*	AN	22	27	20	**74**				
		BN	15	10	8	**80**				
	Mlingano	AN	22	21	16	**76**	31	36	30	**83**
		BN	15	16	10	**63**	6	1	0	**0**
	Tanga	AN	29	34	28	**82**	31	34	31	**91**
		BN	8	3	2	**67**	4	1	1	**100**
OND	Ukiliguru*	AN	22	22	18	**82**				
		BN	16	16	12	**75**				
	Mlingano	AN	23	24	20	**83**	32	35	31	**89**
		BN	15	14	11	**79**	6	3	2	**67**
	Tanga	AN	10	10	6	**60**	17	19	14	**74**
		BN	28	28	24	**86**	21	19	16	**84**

Performance of the model in predicting the DJFMA rainfall

The overall performance of the model in predicting the DJFMA rainfall is good in both AN and BN seasons. The average accuracy in predicting the AN seasons is 72% and 79% when the first and the second threshold values were used respectively whereas the BN seasons were predicted with an average accuracy of 79% and 85% when the first and the second threshold values were used respectively. Therefore, in 7 out of 10 years the model predicted accurately the AN seasons while in 8 out of 10 years the model predicted accurately the BN seasons.

The model performed poorly in predicting AN and BN seasons (less than 70% accuracy) in Dodoma and Naliendele respectively as compared to other locations.

Table 9: Performance of Indian Ocean SSTa in predicting the DJFMA seasonal rainfall from 1982/83 to 2019/20 (2017/18 season was missing)

			AN>450 mm, BN<450 mm				AN>350 mm, BN<350 mm			
Season	**Location**	**RF**	**OBS**	**FC**	**Hits**	**Rate(%)**	**OBS**	**FC**	**Hits**	**Rate(%)**
DJFMA	Dodoma	AN	13	12	8	**67**	20	25	17	**68**
		BN	24	25	20	**80**	17	12	9	**79**
	Hombolo	AN	9	10	7	**70**	20	24	18	**75**
		BN	28	27	25	**93**	17	13	11	**85**
	Ilonga	AN	10	11	8	**73**	21	21	17	**81**
		BN	27	26	24	**92**	16	16	12	**75**
	Naliendele	AN	28	33	26	**79**	33	36	33	**92**
		BN	9	4	2	**50**	4	1	1	**100**

Comparison of the performance of the regression model, TMA, and ICPAC forecast skills

On average the regression model created in this study to predict seasonal rainfall using the SSTa in the Indian Ocean as predictors performed well in both AN and BN predictions compared to TMA and ICPAC forecasts especially in the DJFMA season (Figure 7). The probability of detecting the AN and BN seasons by the model was at least 70% and 50% respectively while TMA and ICPAC had lower probabilities (< 50%) in some locations (Figure 7). Moreover, using the SSTa as predictors enabled the model to cover a bigger number of years than the TMA and ICPAC seasonal forecast which had a lot of missing years.

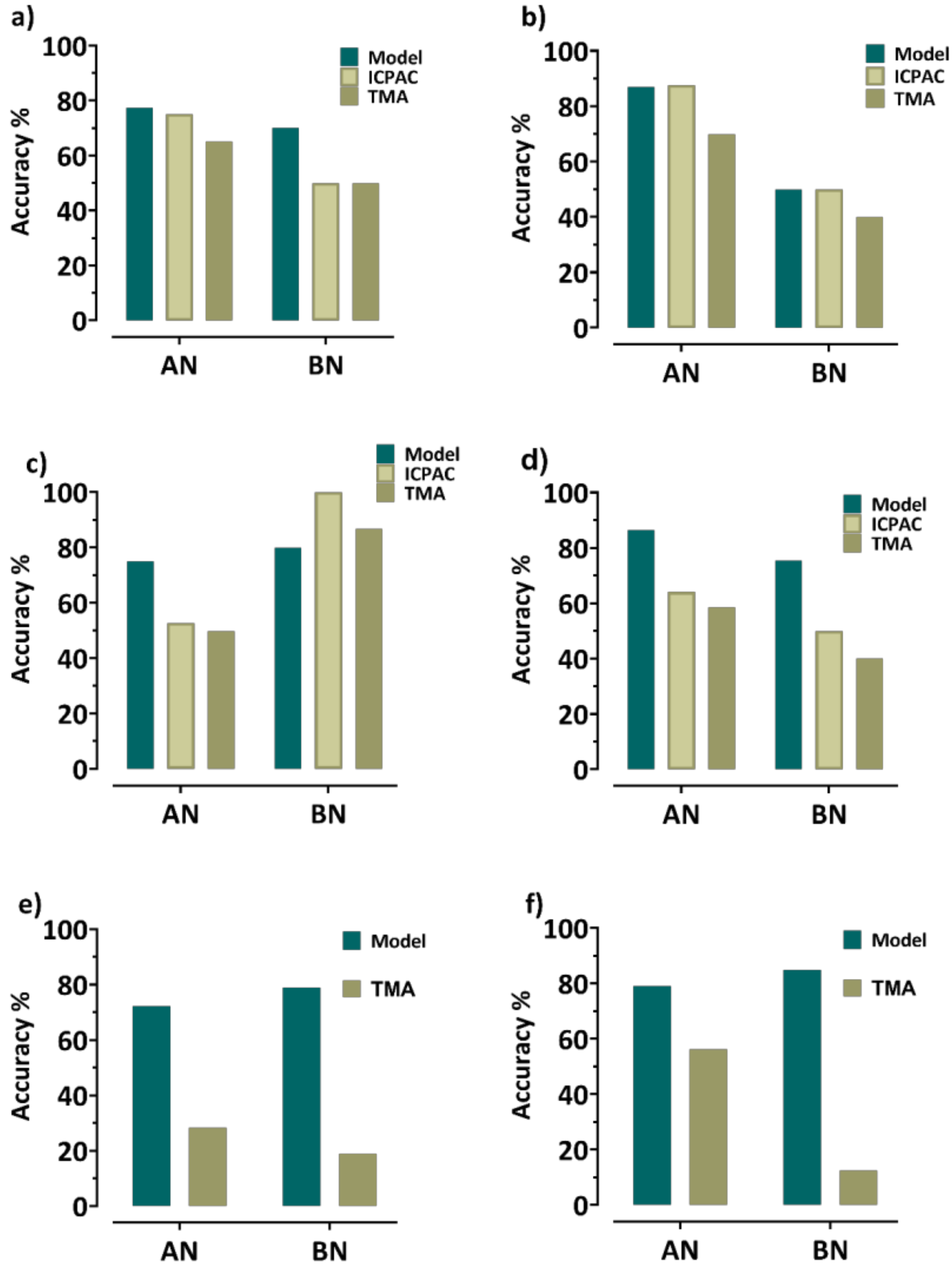

Figure 7: Comparison of performance of the regression model, ICPAC, and TMA forecasts in predicting the AN and BN seasons*. a, c* and *e* are MAM, OND, and DJFMA seasons when 450 mm threshold was used, and *b, d,* and *f* are MAM, OND, and DJFMA seasons when 350 mm threshold was used.

4. Discussion

Rainfall trends and variability

Analysis of trends and variability in annual, seasonal, and monthly rainfall in the study locations revealed significant Spatio-temporal variation of Tanzania rainfall patterns in both amount and frequency (Borhara et al., 2020). The difference between the amount and frequency of rainfall in dry and wet areas is large. For example, the northeast locations i.e. Tanga and Mlingano received about 1000 mm higher than the central zone locations i.e. Dodoma, Hombolo, and Ilonga annually. Likewise, the number of rainy days at Tanga and Mlingano were at least 20 days more than in central zones locations (Table 1). Such differences in rainfall distribution among the locations are associated with distance from water bodies, topographical differences, and other factors such as vegetation which influence the magnitude of coast influence and other atmospheric circulation effects (Borhara et al., 2020). Similar to annual rainfall, seasonal rainfall has also shown high variation among the locations and between the seasons at the same location. The short rain season (OND) received lower rainfall and showed higher variation with CVs ranging from 34% to 61% compared to the long rain season(MAM) during which the CV ranged between 26% and 36%. In the unimodal rainfall regions, the CV of seasonal rainfall (DJFMA) varied from 20% to 31% which is lower as compared to that observed in the bimodal rainfall regions. In general, variability has increased with decreasing seasonal rainfall.

The probability of receiving 450 mm or higher amount of rainfall as required for growing water-sensitive crops such as maize has also shown high variability from one location to another depending on the rainfall regime of the location. For example, in the DJFMA season, Dodoma had the lowest probability (40%) of receiving at least 450 mm of rain per season as compared to other locations with similar rainfall regimes (Figure 2). Moreover, there is a relatively higher probability (20-40%) of getting less than 100 mm rain per month during the five-month crop growing period from December to April in Dodoma and Hombolo as compared to other locations with similar rainfall regimes (Figure 4). Locations with a bimodal rainfall regime also showed variation in the amount of rainfall received per season and monthly during the growing period. The MAM season was wetter compared to the OND season. Tanga and Mlingano had an 80% probability of receiving at least 350 mm in the MAM season whereas the probability significantly decreased in the OND season for the same locations and in both MAM and OND seasons in Ukiliguru. This kind of variation in the environment leads to production uncertainties and constrains agricultural production under rainfed conditions (Leweri et al., 2021; Silungwe et al., 2019). Hence, adaptation to variable climatic conditions is an important first step in making rainfed agriculture more productive and profitable. Adaptation measures are required both in pre-season planning and in tactical management during the season to minimize risks, optimize crop productivity and improve the sustainably of resource base in these areas. The analysis has indicated that the risk of growing crops with water requirements having greater than 450 mm is very high at Dodoma, Hombolo, Ilonga, and Naliendele compared to Igeri and Tumbi among the locations having unimodal rainfall regimes and at all locations during both MAM and OND seasons in the environment characterized by bimodal rainfall regimes.

Climate risk reduction using seasonal climate forecast.

Several studies have indicated that a significant reduction in the risk of exposure to climate uncertainties can be achieved with the integration of seasonal climate forecast (SCF) information in farm-level decision-making (Hansen et al., 2011). SCF, though less reliable than the short and medium-range weather forecasts, are reported to have sufficient skill to indicate the probability of getting or not getting average rainfall during the forthcoming season. This is an important piece of information with the potential to help in planning pre-season farm operations such as selection of crops to be grown, allocation of land to various crops, and the estimation of the potential level of crop performance or profitability based on the amount of rainfall that is required to meet the minimum water requirement of various crops in a season (Meybeck et al., 2012).

We evaluated the skills of the regional and local SCF issued by ICPAC and TMA respectively in different rainfall seasons for their potential usefulness to serve as a basis in pre-season planning activities. In addition, a linear regression model to predict seasonal rainfall in the study area using sea surface temperature anomalies (SSTa) over the Indian Ocean as predictors was also developed and evaluated for its potential application in planning operations. Our analysis has shown higher forecast skills in SCF issued by TMA than those issued by ICPAC but there are differences between the locations and seasons. For example, in the MAM season, TMA prediction's accuracy of AN and BN seasons is higher(Table 6) in Ukiliguru and Mlingano as compared to that by ICPAC. However, ICPAC seasonal forecast had better skills than TMA in predicting the BN seasons in Tanga. In the OND season, the BN seasons were predicted more accurately as compared to AN seasons by both ICPAC and TMA. The SSTa predictors in the created linear regression model showed higher accuracy—in most locations the accuracy was found to be ≥70%—in characterizing the AN and BN seasons (Table 9 and 10). This brings the reliability of SCF to the level that farmers expect them to be. In general, farmers expect the SCFs to have 80% or higher reliability for use in farm-level decision-making (Rao et al., 2011). The overall performance of the regression model is higher compared to ICPAC and TMA forecasts because the SSTa predictors cover a large number of seasons compared to ICPAC and TMA. Moreover, the SSTa have proved to be more reliable predictors of seasonal rainfall variabilities due to their slow evolution and persistence for longer periods and because of their high predictability with greater accuracy (Parker & Diop-Kane, 2017).

In rain-fed systems farmers make climate-sensitive decisions such as selection of crops and varieties, planting dates, planting density, and input use to adopt during the growing period. In the absence of reliable information about the forthcoming season, such decisions are mainly driven by farmers' expectations or perceptions of how the season is going to be (Guido et al., 2020; Nyasimi et al., 2017), the fact that makes seasonal climate forecast with the good skill to be critical input in planning farm operations. The uncertainties or lower skill in seasonal climate forecast provided by various institutions leads to a lack of trust in the information provided and makes farmers rely on the indigenous knowledge—whose skill and usefulness in planning and managing farm activities are unknown (Tsounis & Vlachvei, 2018). Under these conditions, assessing the potentials and limitations of seasonal climate forecasts is extremely important. Past studies on evaluating the SCF were focused on either ex-ante assessment of potential benefits (Thornton, 2006) or ex-post impact assessment (Msangi et al., 2006) to establish the potential role SCF play in improving the management of agricultural systems. Here, we used a different approach to evaluate the SCF. The method is based on the end-user requirements for making decisions. Farmers are more interested to know to what extent they can base their decisions on SCF. The present study revealed the level to which the seasonal climate forecasts can be reliable. In general, the skills of available forecasts from ICPAC and TMA are falling short of the end-user requirement. The end-user expects a positive outcome from forecast-based decisions 80% of the time or four out of five times. This condition was met only with a certain type of season and in some locations. However, the study revealed that there are opportunities to improve the forecast skill by taking into consideration the SSTa conditions in IOD and NINO3.4 regions. Such improvement in the skill presents an opportunity for better integration of the SCF in agricultural decision-making and better management of climate risks. Further improvement of the SCF in their reliability and enhancement of communication of climate information to smallholder farmers will help the farmers make informed decisions and use the available resources more efficiently. We have also revealed the usefulness of simple techniques of seasonal forecasts such as linear regression in predicting the seasonal climate variabilities in a month lead time. The insights emerging from this analysis will inform efforts to promote the use of probabilistic climate information with the right level of confidence and caution.

5. Conclusions

Our study establishes that the complex dynamics of rainfall patterns in Tanzania are difficult to predict at a seasonal scale with high levels of reliability that meet the expectations of farmers and other end users. However, it is possible to improve the reliability of the seasonal climate forecasts by taking into consideration the SSTa and other phenomena and also by using better downscaling techniques. Integration of SCF with SSTa has increased the reliability of SCF to 80% at many locations which is also the level of reliability that farmers expect. Therefore, further improvement of the forecast skills, meaningful communication of climate information to smallholder farmers, and skillful integration of seasonal climate forecast with farm-level decision making could be among the effective strategies for climate risk management in Tanzania.

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Appendices

Appendix A: TMA and ICPAC Seasonal Climate Forecast

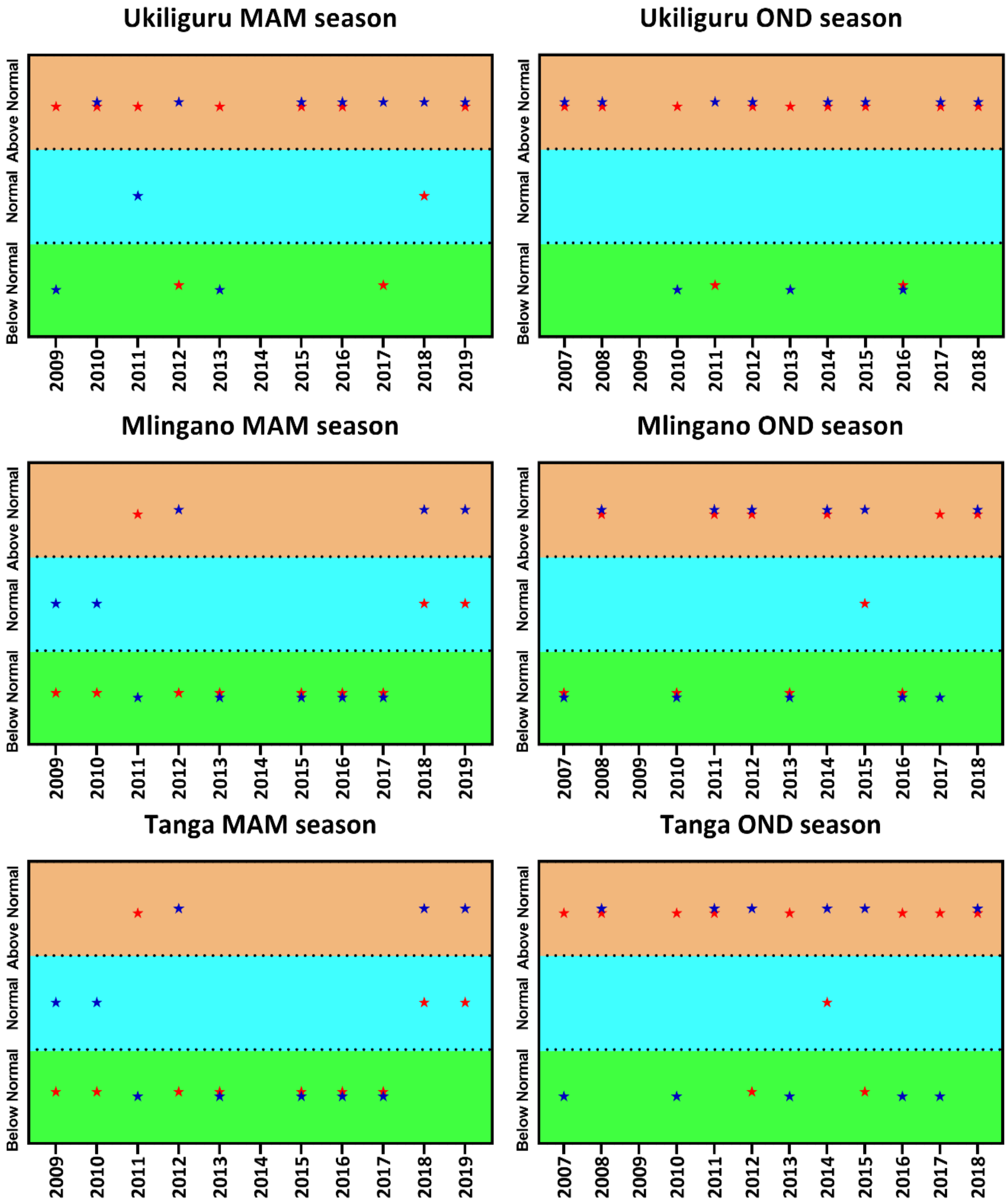


Figure A1: A comparison of seasonal rainfall forecasts issued by TMA (★) and ICPAC(★) for the MAM and OND seasons in the study area.

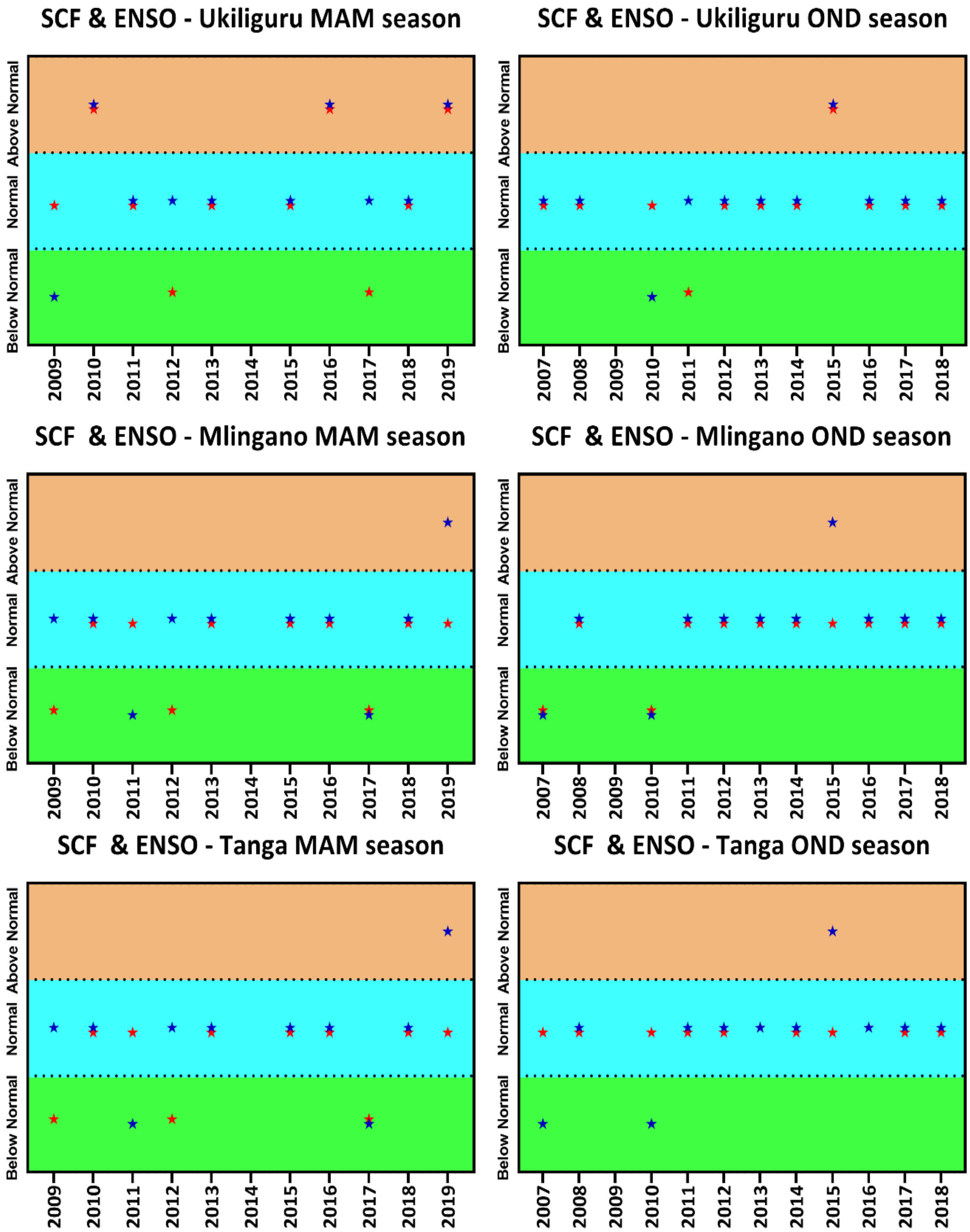
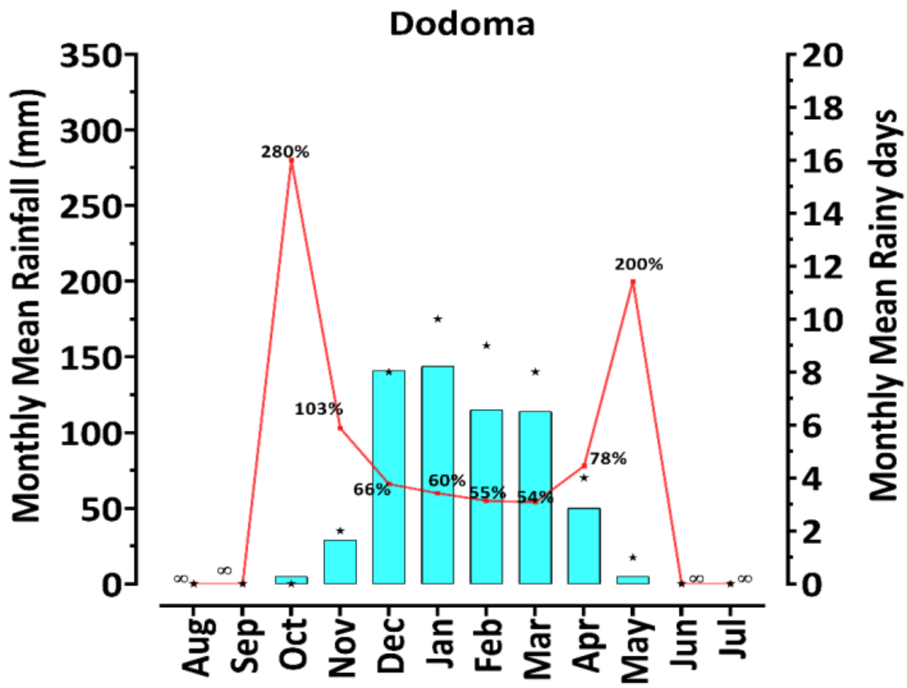


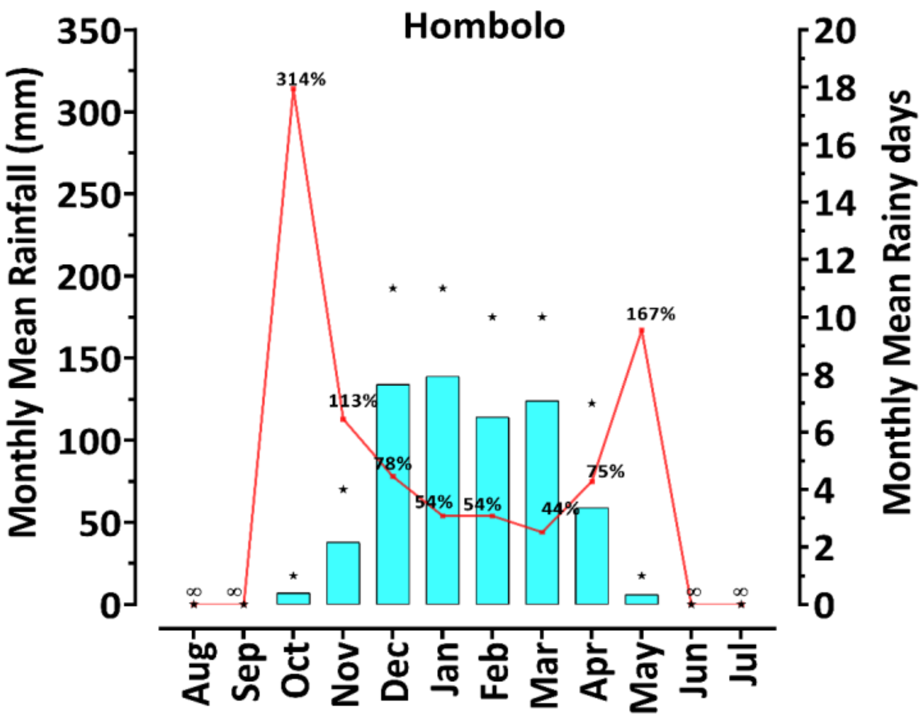
Figure A2: A comparison of seasonal rainfall forecasts issued by TMA (★) and ICPAC (★) for the MAM and OND seasons including ENSO signals/SSTa phases as additional criteria in the study area.

Appendix B: Monthly rainfall distribution

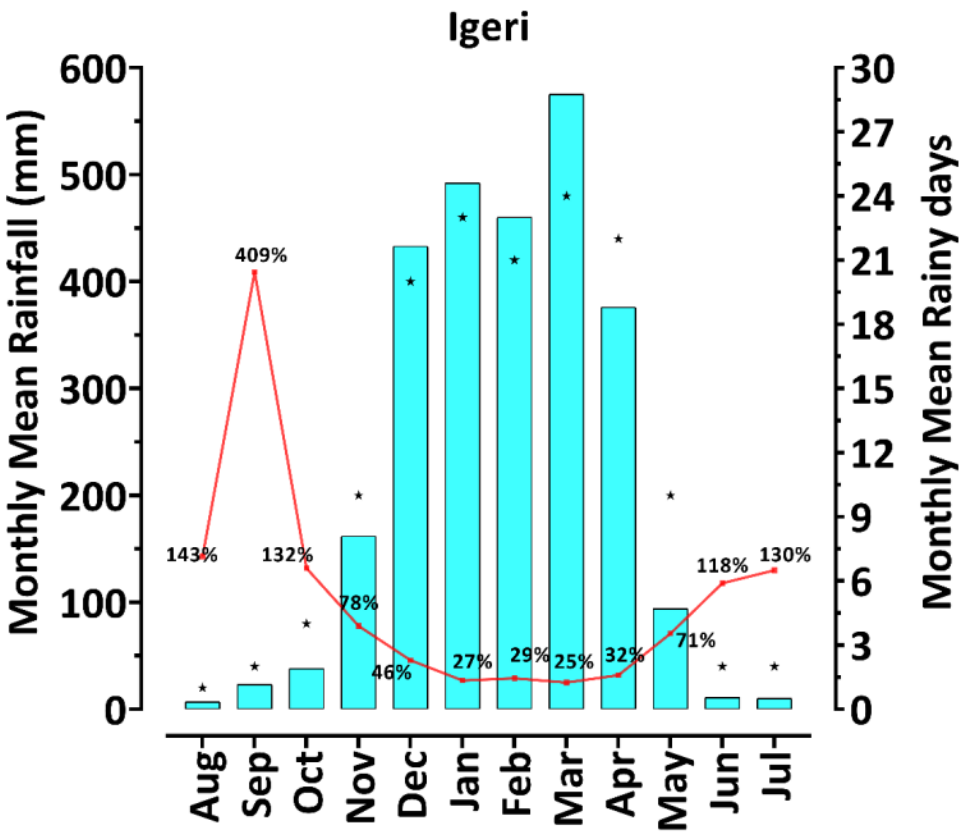
a)



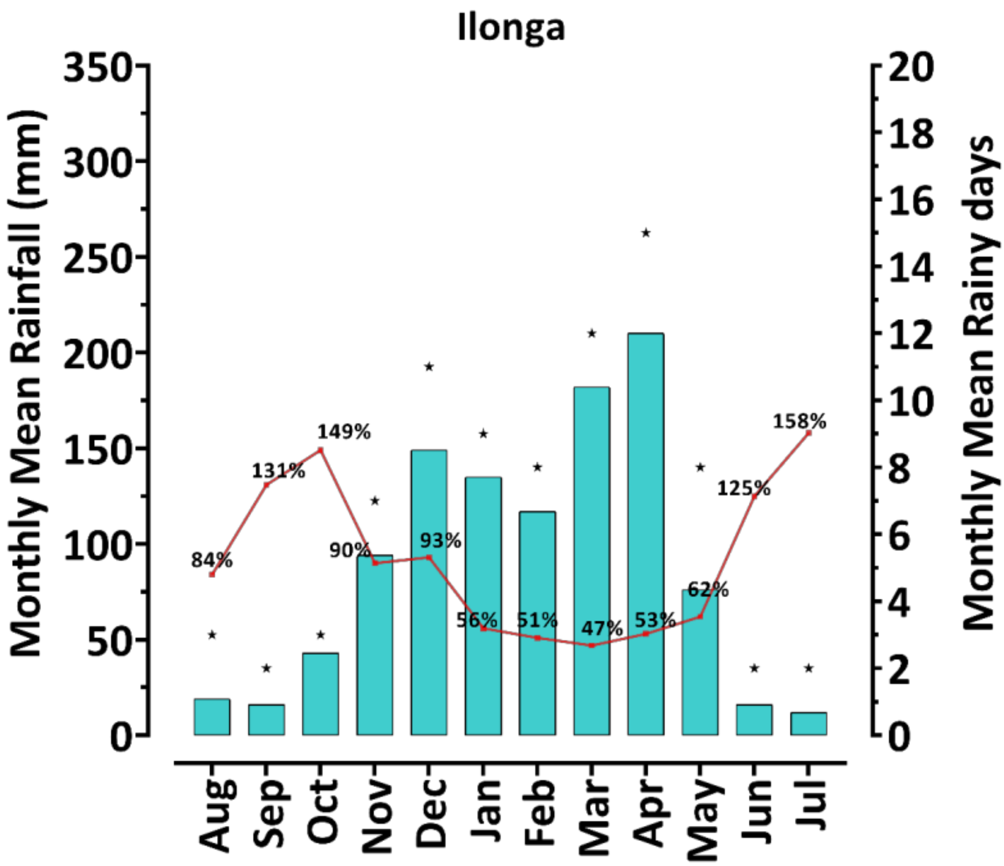
b)



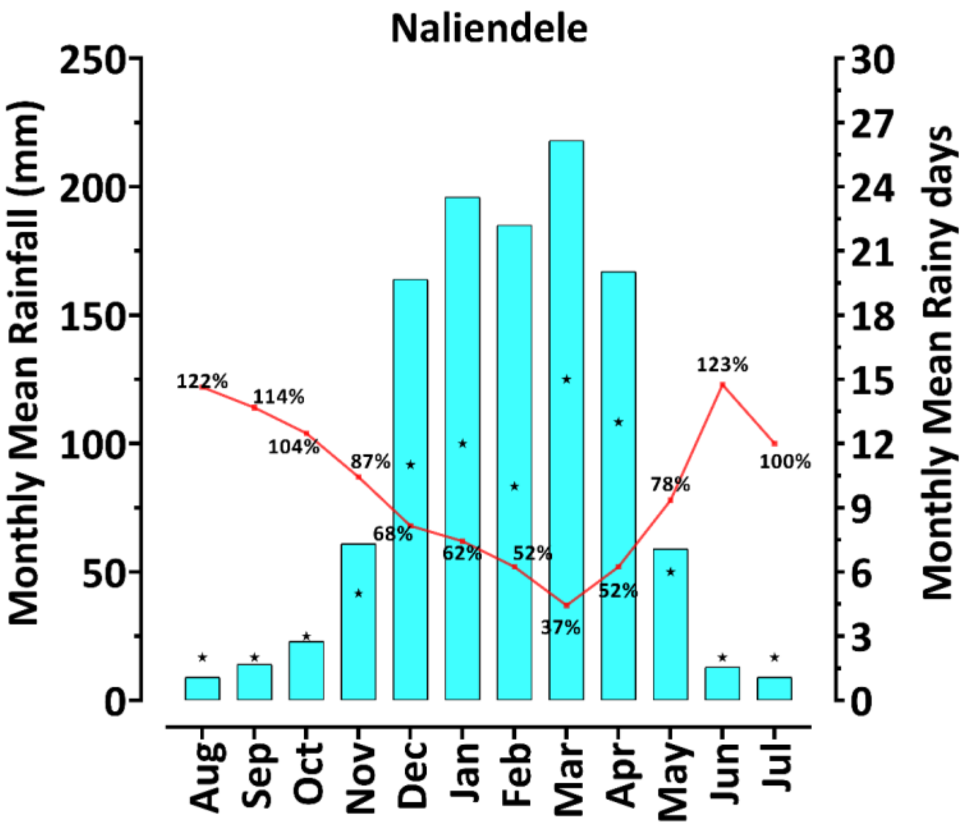
c)


Igeri
Monthly Mean Rainfall (mm)
Monthly Mean Rainy days
0
100
200
300
400
500
600
0
3
6
9
12
15
18
21
24
27
30
409%
143%
132%
78%
46%
27%
29%
25%
32%
71%
118%
130%
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul

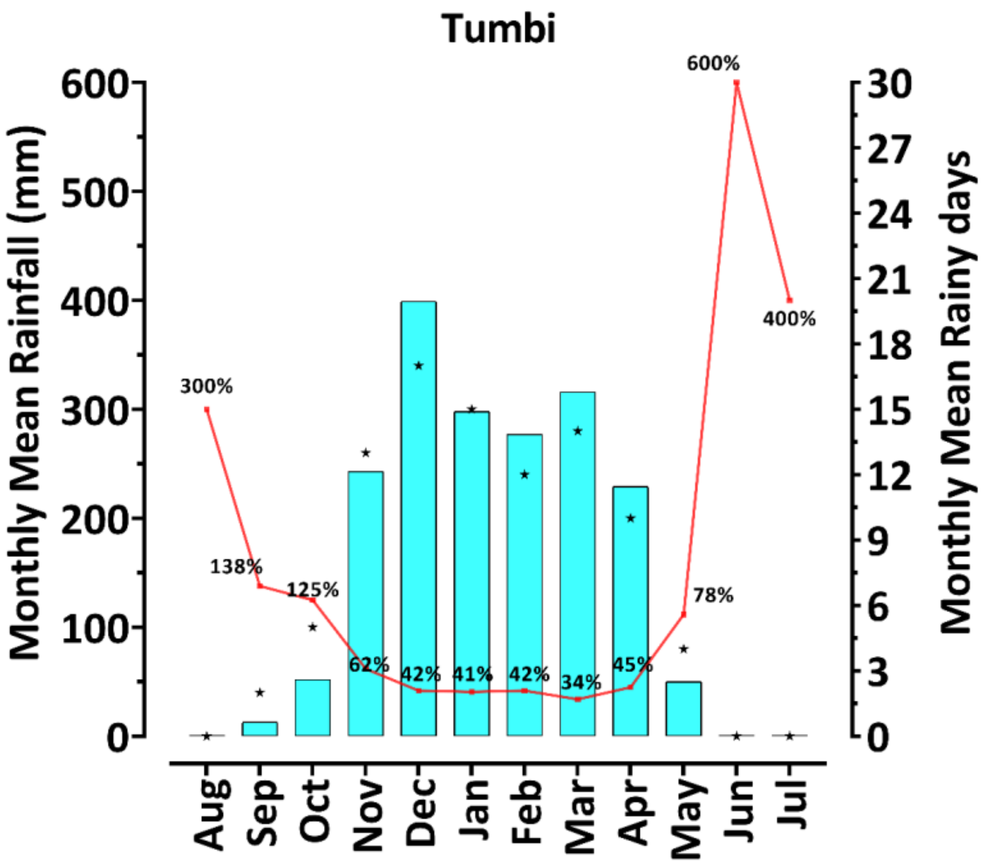
d)


Ilonga
Monthly Mean Rainfall (mm)
Monthly Mean Rainy days
0
50
100
150
200
250
300
350
0
2
4
6
8
10
12
14
16
18
20
84%
131%
149%
90%
93%
56%
51%
47%
53%
62%
125%
158%
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul

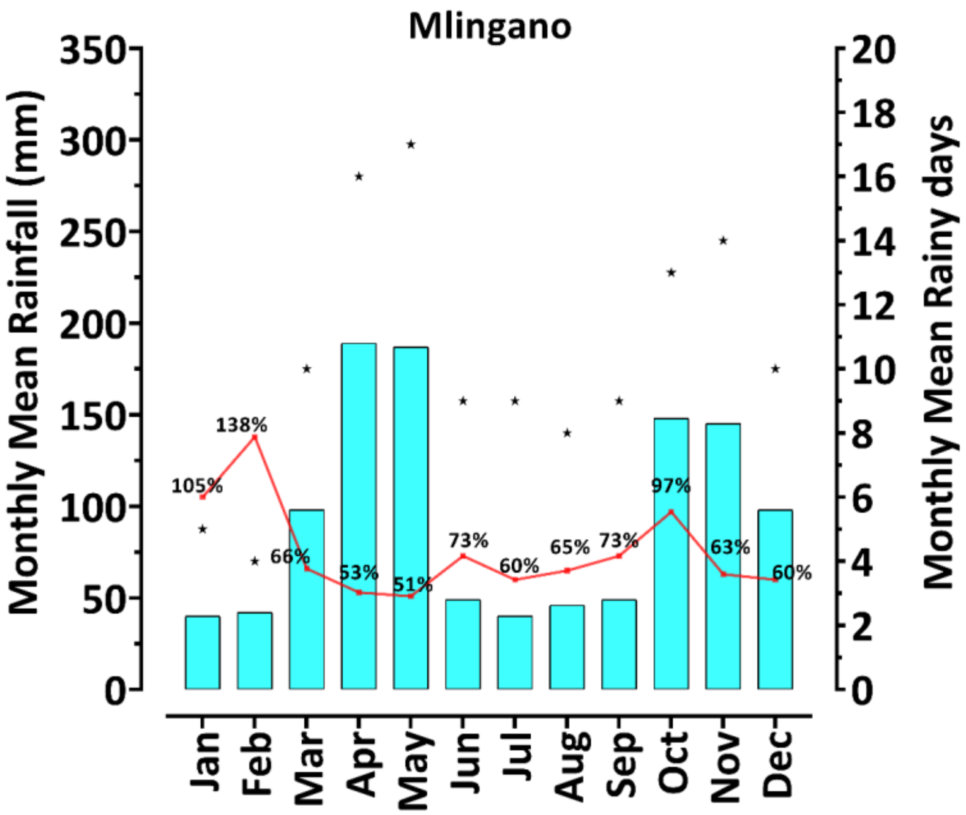
e)


Naliendele
Monthly Mean Rainfall (mm)
Monthly Mean Rainy days
250
200
150
100
50
0
30
27
24
21
18
15
12
9
6
3
0
122%
114%
104%
87%
68%
62%
52%
37%
52%
78%
123%
100%
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul

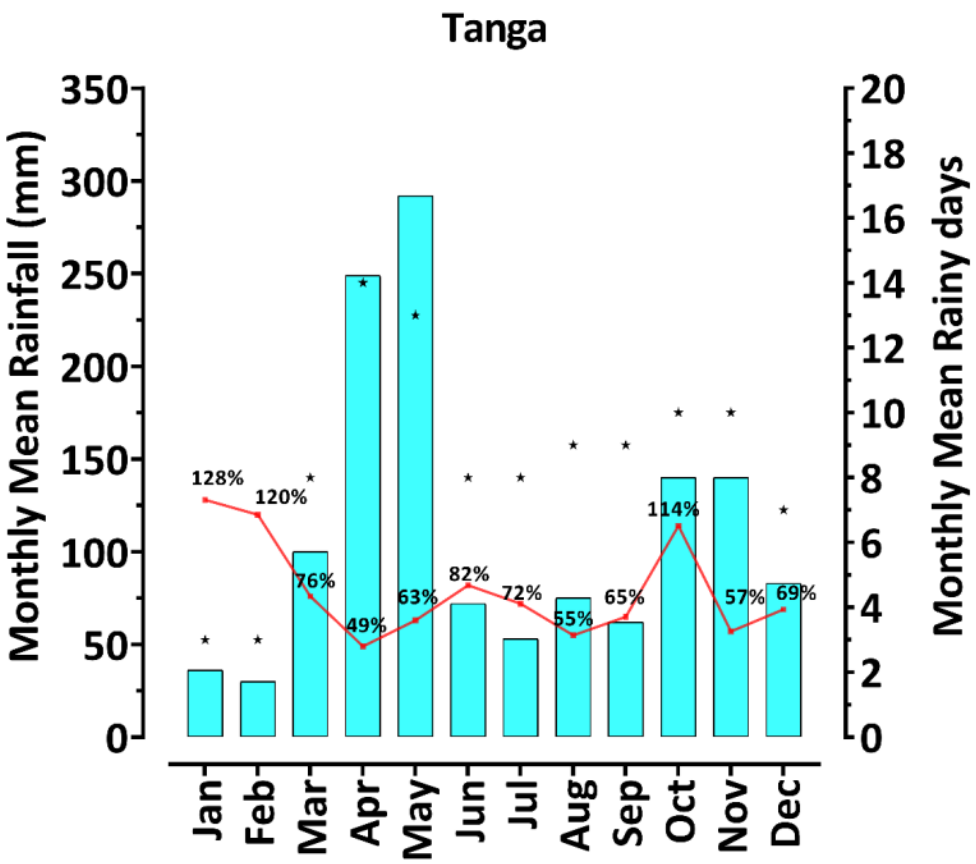
f)


Tumbi
Monthly Mean Rainfall (mm)
Monthly Mean Rainy days
600
500
400
300
200
100
0
30
27
24
21
18
15
12
9
6
3
0
300%
138%
125%
62%
42%
41%
42%
34%
45%
78%
600%
400%
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul

g)


Mlingano
Monthly Mean Rainfall (mm)
Monthly Mean Rainy days
350
300
250
200
150
100
50
0
20
18
16
14
12
10
8
6
4
2
0
105%
138%
66%
53%
51%
73%
60%
65%
73%
97%
63%
60%
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

h)


Tanga
Monthly Mean Rainfall (mm)
Monthly Mean Rainy days
350
300
250
200
150
100
50
0
20
18
16
14
12
10
8
6
4
2
0
128%
120%
76%
49%
63%
82%
72%
55%
65%
114%
57%
69%
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

i)

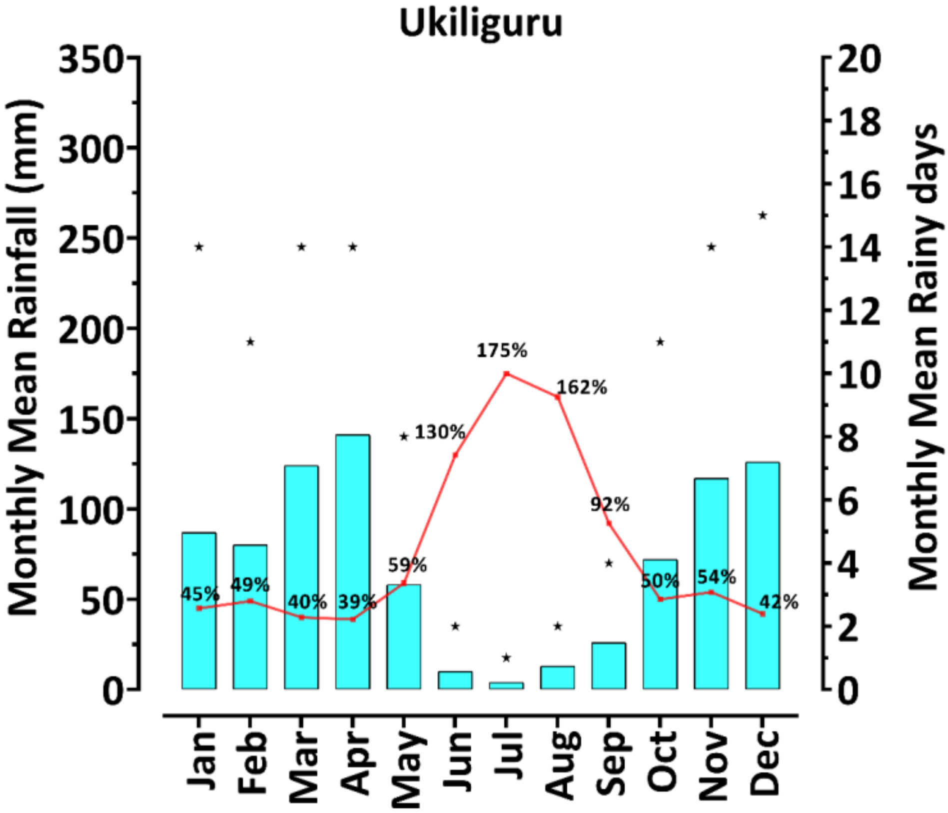


Figure C1: Monthly rainfall (bars) and the number of rainy days' (stars) distribution in the locations in the study area. The red curve represents the monthly coefficient of variation

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