ISSN No:-2456-2165

Validation of the Climate Hazards Group Infrared Precipitation with Station Data (CHIRPS) Satellite Rainfall Estimates in Different Seasons of the Year and in Different Geographic Locations Over Malawi

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Abstract:- Satellite-based rainfall estimates offer a valuable alternative for rainfall data collection, particularly in developing countries like Malawi, which face challenges due to limited ground gauge station networks. However, these estimates often exhibit biases and systematic errors, necessitating validation against ground station data. The Climate Hazards Group Infrared Precipitation with Station Data (CHIRPS) v2 is one such product that has demonstrated promising performance worldwide and is accessible in Malawi.

In this study, we evaluated CHIRPS monthly rainfall estimates from January 1981 to December 2021 against ground station data from twenty locations in Malawi. Our assessment considered CHIRPS' performance in different seasons (wet and dry) and geographic regions (high altitude, medium altitude, low altitude, and the lakeshore). We used both continuous (Coefficient of Correlation (R), Percent Bias (PBias), and unbiased Root Mean Square Error (ubRMSE)) and categorical scores (Probability of Detection (POD), False Alarm Ratio (FAR), and Threat Score (TS)) for evaluation.

Our results revealed that CHIRPS outperformed during the wet season in comparison to the dry season, considering both continuous and categorical scores. In terms of geographic locations, CHIRPS exhibited the highest R in the mid-altitude areas during both wet and dry seasons, while low altitude areas had the poorest performance. Additionally, CHIRPS displayed low bias in the mid and low altitude areas during the wet season, with poor performance observed at high altitudes and the lakeshore. In the dry season, mid-altitude areas maintained a good R performance. CHIRPS showed the least error in high altitude areas in both seasons in terms of ubRMSE. Furthermore, all locations achieved a good POD of at least 0.957 during the wet season, while the lakeshore had the highest mean POD of 0.369 during the dry season. All regions exhibited a good FAR during the wet season, with high altitudes performing well in the dry season (mean FAR of 0.250). The Lakeshore reported the highest mean TS of 0.932, while high altitudes had the lowest (mean TS of 0.887).

In conclusion, CHIRPS demonstrates superior performance in Malawi during the wet season compared to the dry season. Geographically, there is no single station that excels in all assessments; however, mid-altitude areas consistently perform better in most evaluations. Thus, CHIRPS can be a valuable resource for water management and agricultural operations in Malawi.

Keywords:- *CHIRPS Dataset; Rainfall Analysis; Seasonal Variability; Geographic Locations; Performance Metrics; Malawi; Satellite-based Estimates; Precipitation Estimation.*

I. INTRODUCTION

Rainfall is one of the most important weather parameters and one of the key elements of the hydrological cycle. Rainfall variability in its rate, amount, and distribution substantially determine the earth's ecosystem, water cycle and climate [1]. Rainfed agriculture is practised on 80% of the world's agricultural area and generates 60–70% of the world's staple food [2]. As such having reliable and accurate rainfall data is very crucial in planning agricultural and related engineering activities to ensure maximum efficiency and production.

Malawi is a landlocked country in southern Africa with a population of about of 18 million. Over 80% of the population depends on rainfed Agriculture and Agriculture accounts for 30% of Malawi's Gross Domestic Product (GDP) and is important to the livelihoods of more than 90% of the population [3]. Apparently, rainfall measurements are done through gauge stations that are distributed across the nation. The climate change and meteorological services department of the Malawi government has provided useful information but is fraught with major challenges in the delivery of meteorological services which include: few and poorly distributed functional observational stations, shortage of trained personnel, vandalism of equipment, weak telecommunication support systems, and inadequate data processing and information dissemination facilities [4]. In the recent years Malawi has been experiencing persistent drought and hunger due to erratic rainfall pattern because of climate change. The variation in precipitation influences the harvest which in turn determines how food secure that year will be for the households [5]. Further to that, adequate knowledge of the starting dates and period of dry spells has a considerable importance in rainfed agriculture, irrigation planning and various decision making processes [6]. In view of this, having reliable data on rainfall for planning and development of irrigated agriculture has been key interventions of the Malawi government to avert the status quo.

Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS) is a satellite-based tool that provides 35+ years global precipitation dataset with data ranging from 1981. At present, satellite rainfall products, such as the CHIRPS products, have become an alternative source of rainfall data for regions where rain gauge stations are sparse. CHIRPS products perform significantly better than other satellite tool such as ARC2 and TAMSAT3 with higher skill, low or no bias, and lower random errors at monthly and annual time scales [7]. Malawi, with sparse distribution of the stations and complex terrain, some areas might base their decisions on the data obtained from CHIRPS. However, use of invalidated data for planning purposes would result into poor and unresponsive decisions being made. As much as satellites can be used for sensing large regions with a high temporal and spatial resolution, satellite retrieval approaches are prone to biases and systematic errors as a result satellite-based rainfall estimates must be validated against rain gauge data in order to assess their uncertainties before being used [8]. Apparently, very few studies have been carried out to validate CHIRPS rainfall estimates in Malawi. The purpose of this study was to evaluate the quality of the CHIRPS rainfall estimates in Malawi. The evaluation considered different seasons of the year (wet and dry season) and geographic location which is classified as High altitude, Mid altitude, Low altitude and the Lakeshore [9].

II. MATERIALS AND METHODS

A. Study Area

The study was conducted in Malawi. Malawi is a country in southern Africa that covers a total area of 118,484 km^2. Lake Malawi, accounts for more than 20% of the country's total area, and the country is bordered with Mozambique to the south, south-east and south-west, Tanzania to the north and north-east and Zambia to the west and north-west [10]. The coordinate of Malawi's northernmost point is 09°22' S, Malawi's most southern point is positioned at a latitudinal coordinate of 17°07' S, in the very East, Malawi extends as far as a longitude of 35°55' E and longitude of 32°40' E is the most western point of Malawi.

The hydrology of Malawi is composed of lakes, rivers in addition to the vast groundwater resources. Topography and location play major roles in the annual rainfall distribution in Malawi and the country's topography is highly variable, dominated by the Great Rift Valley including lake Malawi [11]. The East African Lift Valley and spans approximately 9° – 14° S and sits at an elevation of 474 m [12]. The rift valley is located between the rift shoulder or rift mountains [13] and is surrounded by high terrain [14] such that most escarpments are located along the Lakeshore.

B. Data Collection and Sources

➢ *Ground Station Data*

Monthly rainfall data for a period of Fourty years from 1981 to 2021 of twenty rain stations were obtained from the Department of Climate Change and Meteorological Services. The rain stations included; Chitipa, Karonga, Chikangawa, Mzuzu, Dowa, Chinthechi, Mzimba, Mwimba, Nkhotakota, Chitedze, Lifuwu, Dedza, Monkey-Bay, Chileka Airport, Namwera, Ngabu, Nchalo, Nsanje, Chikwawa and Makhanga. The stations were strategically sampled to represent each of the four classifications of interests. Each classification had five stations as follows;

Table 1 Selected Stations that were Samples for the Study

Lake Shore	High Altitude	Mid Altitude	Low Altitude
Karonga MS	Chikangawa Forest	Chileka Airport	Nsanje MS
Chinthechi AO	Mzimba MS	Namwera AO	Nchalo Illovo
Monkey-Bay MS	Dowa AO	Chitedze MS	Ngabu MS
Nkhotakota MS	Dedza MS	Mwimba College	Chikwawa MS
Lifuwu AO	Chitipa MS	Mzuzu MS	Makhanga MS

➢ *CHIRPS Data*

CHIRPS rainfall estimates were obtained from the UCSB-Climate Hazards Group (CHG) webpage (https://www.chc.ucsb.edu/data accessed on the February 24, 2023). The data was at a monthly time scale at spatial resolution of 0.10º (equivalent to 124km^2) at monthly time step starting January 1981 to December 2021.

C. Methods and Techniques

The CHIRPS rainfall estimates were extracted to generate a paired rainfall data from January 1981 to December, 2021 with the gauge station data. QGIS software was used to extract the CHIRPS estimates. QGIS was chosen because it is an open-source software but with various analysis tools making it suitable for the study. Monthly rainfall values of the selected stations were extracted using point-pixel method. A proximity criterion was used to determine the centroid of the pixel closest to the rain gauge, subsequently, the registration period of the rain gauge was extracted [15].

➢ *Test Statistics*

Intercomparison of the rainfall data from both rain stations and CHIRPS was carried out in order to evaluate the performance of CHIRPS. The comparison was done at monthly time scales with common temporal coverage. A number of metrics of pixel-to-station basis were carried out. Both continuous and categorical score were made.

- *Continuous Scores*

The Pearson's correlation coefficient (R), unbiased root mean square error (ubRMSE), and percentage bias (PBIAS) were used as continuous scores. R measures the degree of association or linear relationship strength between estimations and observations, while ubRMSE and PBIAS scores measure how the value of estimates differs from the observed values [16]. A positive PBIAS indicates an overestimation of values by a model while negative values indicate underestimation. For drought monitoring, it is important not to overestimate rainfall amounts or rainfall events and for flood forecasting underestimations need to be avoided [17].

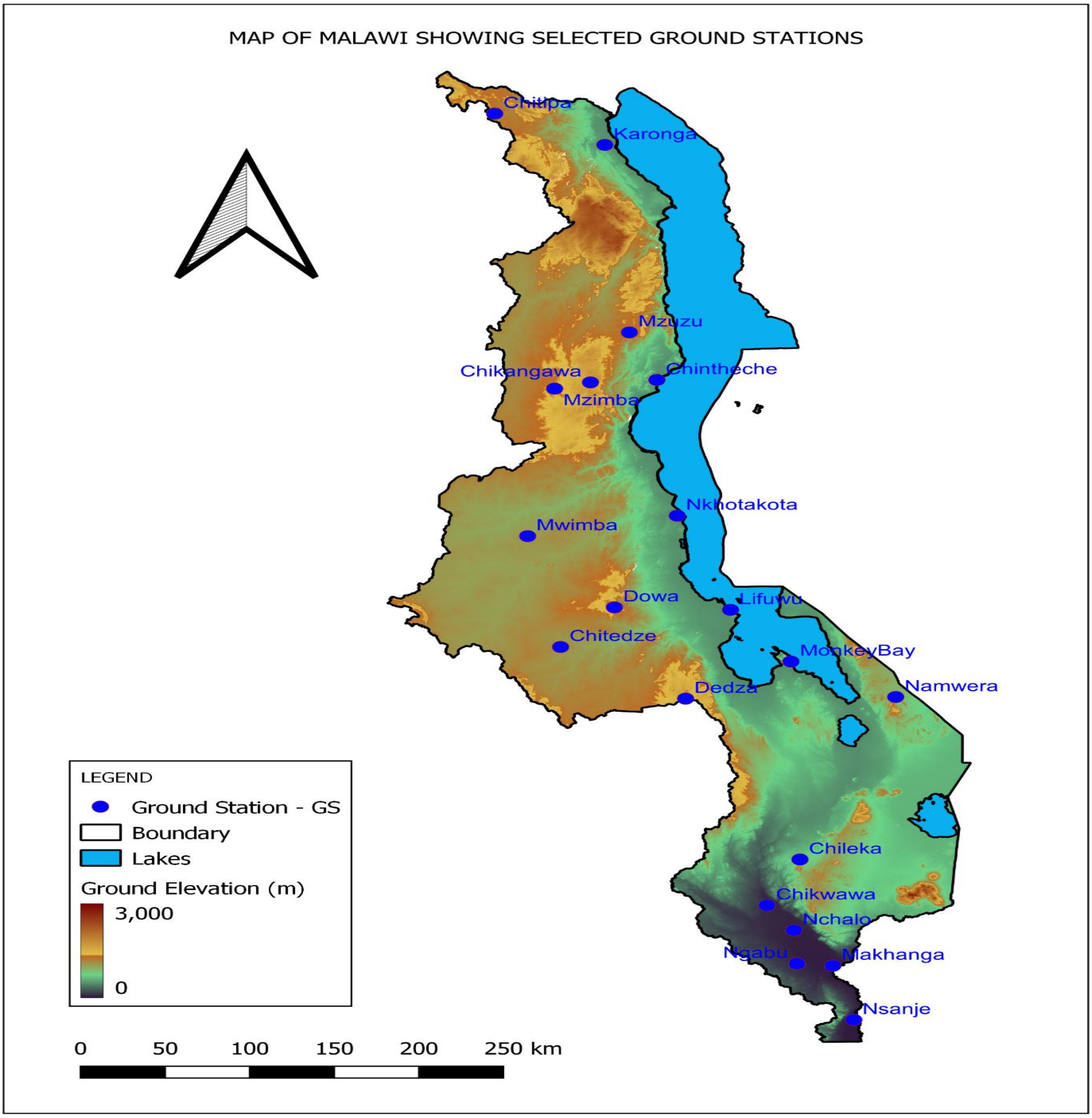

Fig 1 Selected Stations that were Sampled for the Study

Table 2 Formulas of Continuous Scores. G, Gauge-based Rainfall Measurement (mm/day); S, CHIRPS based Rainfall Estimate (mm/day); G and S, average for G and S, Respectively (mm/day); N, Number of Data Pairs.

Name	Formula	Range	Perfect Score
Pearson's Correlation Coefficient	$R = \left(\sum(G-\bar{G})(S-\bar{S})\right)/(\sqrt{\sum(G-\bar{G})^2}\sqrt{\sum(S-\bar{S})^2})$	[-1,1]	1
Root Mean Square (RMSE)	$RMSE = \sqrt{\frac{1}{N}(S-G)^2}$	[0,∞)	0
Percentage Bias	$B = \frac{100\sum(S-G)}{N}$	(-∞,∞)	0
Unbiased Root Mean Square (ubRMSE)	$ubRMSE = \sqrt{RMSE^2 - \left(\frac{B}{100}\right)^2}$	[0,∞)	0

(Source: [18])

- *Categorical Scores*

Probability of Detection (POD), False Alarm Ration (FAR) and Threat score (TS) were used as categorical scores. The Probability of Detection (POD) and False Alarm Ratio (FAR) respectively indicate what fraction of the observed events was correctly forecast and what fraction of the predicted events did not occur, and Threat Score (TS) evaluates how well the satellite rain events correspond to the gauge events, accounting for hits due to chance [17]. The computations were done in all the categories of the study of context which are altitude and season of the year.

➢ *Data Analysis*

The data was analysed using two statistical packages; Microsoft Excel and R. R was used mainly for the calculations and statistical analysis. However, for graphical presentation and flexibility, Microsoft excel was used.

Table 3 Contingency Table for Categorical Score Estimation: H is the Number of Hits, F is the Number of False Alarms, M is the Number of Misses and N is the Number of Correct Negatives. 30mm/Month is the Threshold.

	Gauge ≥ threshold	Gauge < Threshold
CHIRPS ≥ Threshold	H	F
CHIRPS < Threshold	M	N

(Source: [18])

Table 4 Formulas of Categorical Scores

Name	Formula	Range	Perfect Score
Probability of Detection	$POD = \frac{H}{H+M}$	[0,1]	1
False Alarm Ratio	$FAR = \frac{F}{H+F}$	[0,1]	0
Threat Score	$TS = \frac{H}{H+F+M}$	[0,1]	1

(Source: [18])

III. RESULTS AND DISCUSSION

A. *Chirps Performance in Different Seasons*

On continuous scores CHIRPS has shown to have better results during the wet season than the dry season in terms of Pearson's coefficient correlation (R) and percentage bias (PBIAS). However, Chirps produces better results during the dry season in terms of unbiased Root Mean Square Error (ubRMSE).

➢ *Continuous Scores*

- *Pearson's Correlation Coefficient, R*

During the wet season CHIRPS has a higher mean R compared to dry season in all the four geographical locations: Lakeshore, High altitude, Mid altitude and the Low altitude. Further to this is that the correlation is always positive in all scenarios.

Considering independent gauge stations, the wet season has a mean R and median R of 0.736 and 0.764 respectively while the dry season has mean R and median R of 0.460 and 0 .488 respectively.

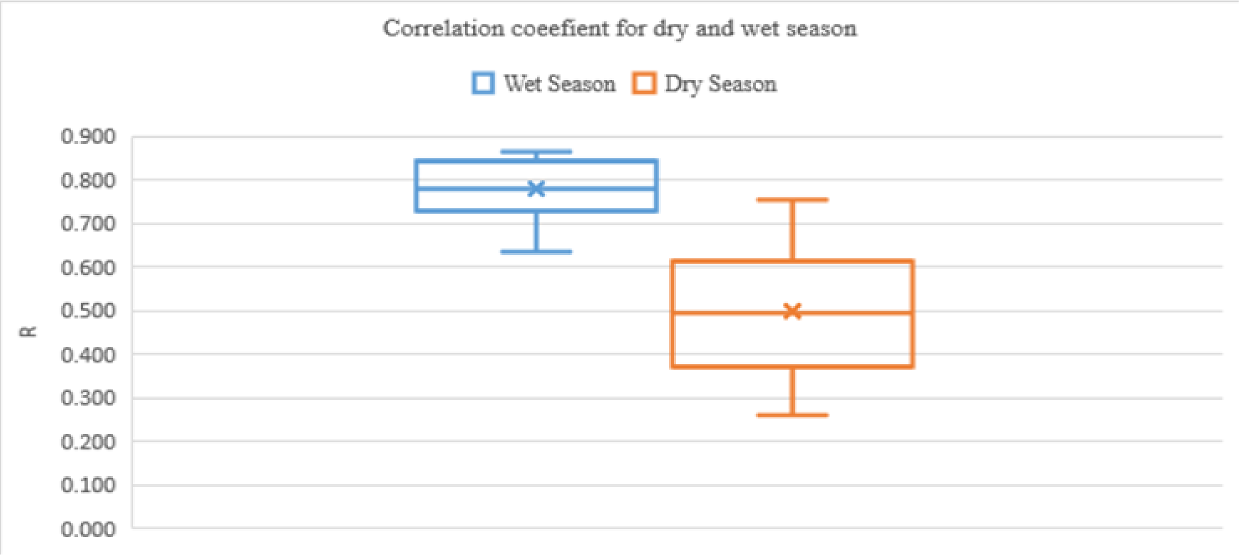

Fig 2 Whisker Plot for Correlation Coefficient During the Dry and Wet Season

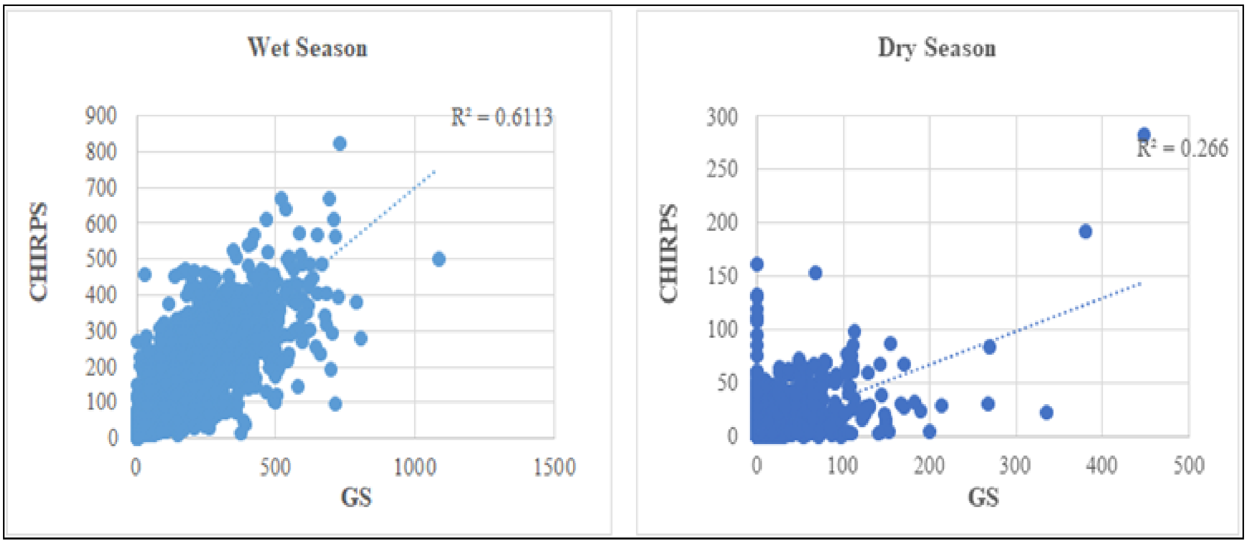

Fig 3 Graphs of Correlation Coefficients during the Dry and Wet Season

For the entire wet season and dry season, the correlation coefficients are 0.781 (thus square root of 0.6113) and 0.516 (thus square root of 0.232) respectively. In both scenarios, there is a significant correlation between ground station and CHIRPS estimates; ($r>0.739$, $p<2.2e-16$) and ($r>0.452$, $p<2.2e-16$) for wet season and dry season respectively at 99% confidence interval.

Malawi experiences rainfall events of both convective, frontal and orographic origin; the peak wet months of December – January are dominated by rainfall of convective origin while the onset (November) and end (April) is dominated by precipitation of frontal origin [19]. A very strong correlation during the wet season is attributed to higher temperature and moisture content in the atmosphere as a result of convective lifting mechanisms present which are amenable to the CCD algorithm of CHIRPS [20]. A combination of convective processes over land and adjacent water bodies (e.g. Lake Malawi and rivers) and rain shadow effects are major influences of intense rainfall in the region [21]. Lack of precipitation of convective during the dry season in Malawi results to low correlation.

Similar findings were also found by several studies; North-Eastern Brazil [18], Iran [20] and Upper Blue Nile Basin, Ethiopia [1].

- *Percentage Bias (Pbias)*

During the wet season, CHIPRS performs better in terms of percent bias compared to the dry season. In wet season CHIPRS produces a mean percent bias of -0.3% and 8% during the dry season. This entails that CHIPRPs overestimates the precipitation events during the dry season and very slightly underestimates the precipitation events during the wet season. This result is consistent with the findings of Paredes-Trejo et al. and Nogueira et al. who found that CHIRPS tends to overestimate low and underestimate high rainfall values in NEB [18]. For lower rainfall amounts CHIRPS tends to overestimate the gauge observations, while for heavy rainfall amounts it underestimates them [20].

Table 5 Mean PBIAS for Different Locations

Area	PBIAS	
	Wet Season	Dry Season
High Altitude	9.3	18
Mid Altitude	-1.8	-20.8
Low Altitude (Lower Shire)	-0.1	34.6
Lakeshore	-8.4	2.8
Mean	-0.3	8.0

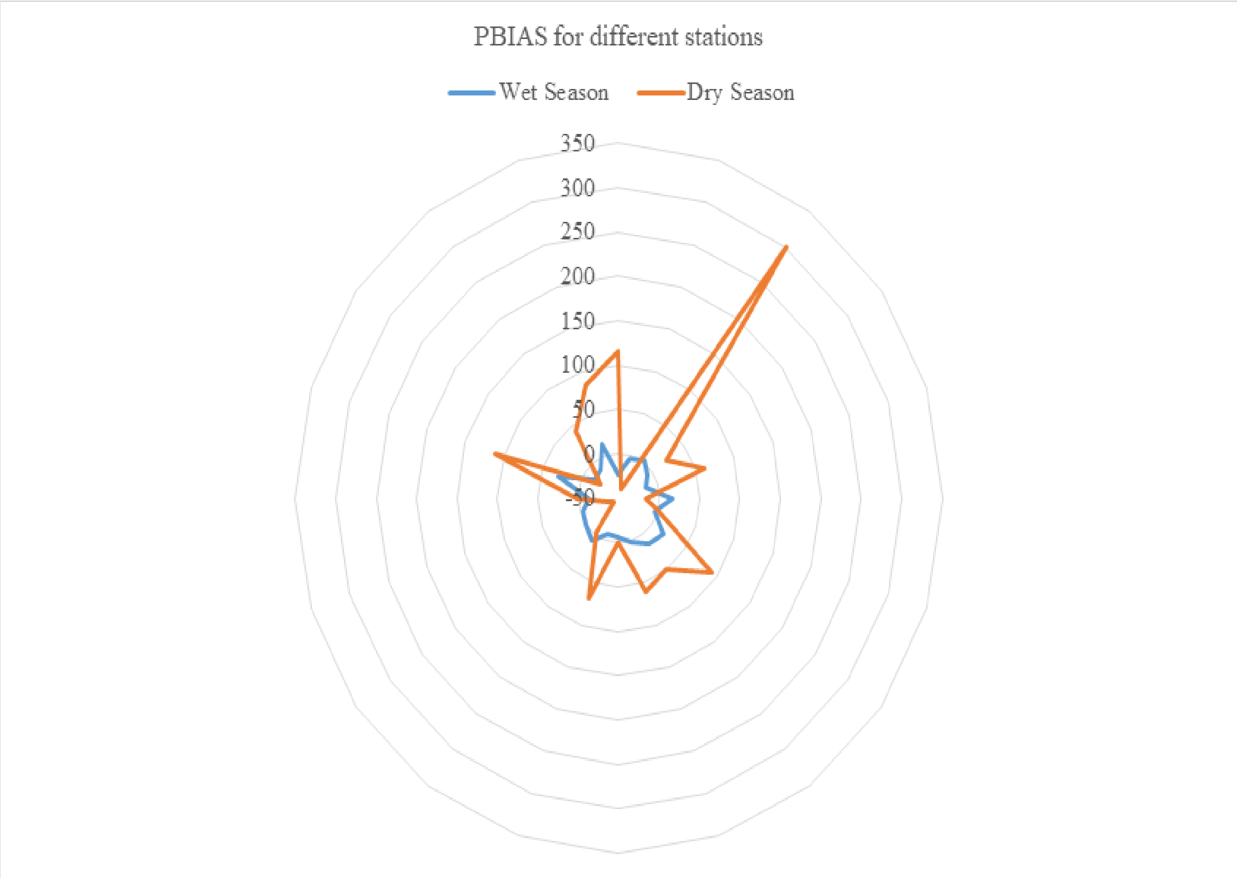

Fig 4 PBIAS for Dry Season and Wet Season

From the graph above, there is so much variation and inconsistence in the PBIAS during dry season compared to the wet season. The wet season has PBIAS standard deviation of 13.12% while the dry season has a PBIAS standard deviation of 79.459%.

Dry season is characterised by less moisture in the atmosphere in Malawi. Therefore, the degradation of the performance under extreme droughts may be attributed to the evaporation processes of raindrops in the dry atmosphere before reaching the surface [22] hence leading to higher PBIAS values during the dry season. This is called sub-cloud evaporation.

- *Unbiased Root Mean Square Error, Ubrmse*

Primarily, ubRMSE gives more weight to high rainfall events [23]. Consequently, CHIRPS may seem to perform better in terms of ubRMSE during the dry season since they are low rainfall events. In this case, during the wet season CHIRPS gave a mean ubRMSE of 74.8mm/month while during the wet season it gave a mean ubRMSE of 17.4mm/month. Without any exception, in all locations, wet season gives a huge error compared to the dry season.

Table 6 Mean ubRMSE for Different Geographic Locations

Area	ubRMSE (mm/month)	
	Wet Season	Dry Season
High Altitude	67.7	8.6
Mid Altitude	63.8	16.6
Low Altitude	73.0	20.7
Lakeshore	94.8	23.5
Mean	74.8	17.4

The wet season has high rainfall events compared to the dry season. Over 90 % of Malawi's total annual rainfall occurs between November and April [24]. The wet season received a mean of 154.8mm/month while the dry season received as average of 7.7mm/month during the period between 1981 to 2020. It is therefore anticipated that the ubRMSE would be likely be lower during the dry season and higher during the wet season.

Furthermore, the mean ubRMSE is lower during the dry season, is it higher than the mean seasonal precipitation (17.4mm/month > 7.7mm/month), this indicates that there is a very high variability between the estimated values and the observed values hence CHIRPS is performing poorly during the dry season. To the contrary, mean ubRMSE is lower than the mean seasonal precipitation (74.8mm/month < 154.8mm/month), this indicate that CHIRPS is generally better during the wet season.

➢ *Categorical Scores in Dry and Wet Season*

- *Probability of Detection, POD*

The wet season has a high percentage of detection than the dry season. Specifically, the wet season has a mean and median POD of 0.963 and 0.969 respectively while the dry season has a mean and median POD of 0.237 and 0.252 respectively.

In dry season, the POD is slightly negatively skewed. With POD close to one during the wet season and POD close to zero during the dry season, it means the CHIRPS performs better during the wet season and poor during the dry season.

Table 7 Mean POD for Different Geographic Locations

Area	**POD**	
	Wet Season	**Dry Season**
High Altitude	0.975	0.069
Mid Altitude	0.958	0.352
Low Altitude	0.962	0.376
Lakeshore	0.983	0.259
Mean	0.969	0.264

Fig 5 Whisker Plot of POD for Different Geographic Locations

- *False Alarm Ratio, FAR*

For FAR the wet season has a mean of 0.080 and a median of 0.077. Lakeshore has least FAR of 0.050 and the Low altitude has the highest FAR of 0.118. The dry season has a mean FAR of 0.587 and a median FAR of 0.593, Mid altitude has lowest FAR of 0.448 and High altitude has the highest FAR of 0.714.

Table 8 Mean FAR for Different Geographic Location

Area	**FAR**	
	Wet Season	**Dry Season**
High Altitude	0.078	0.714
Mid Altitude	0.075	0.448
Low Altitude	0.118	0.617
Lakeshore	0.050	0.569
Mean	0.080	0.587

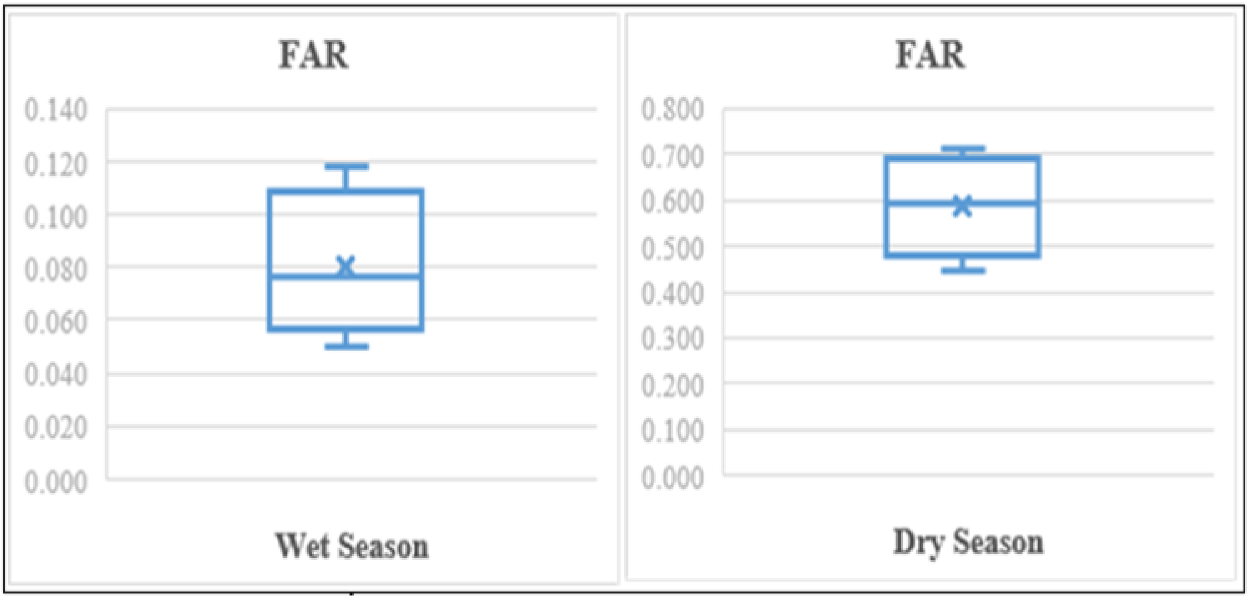

Fig 6 FAR for Different Geographic Location

During the dry season, the FAR is negatively skewed while during the wet season it is positively skewed. The wet season has FAR, both mean and median, close to zero while the dry season has FAR, both mean and median, far from zero. This implies that in terms of FAR, the CHIRPS performs better during the wet season.

- *Threat Score, TS*

The wet season has a mean and median TS of 0.882 and 0876 respectively while the dry season has a mean and median TS of 0.166 and 0.186 respectively. During the wet season, the Lakeshore and Mid altitude has the highest and lowest TS respectively while during the dry season Low altitude and the High altitude has the highest and lowest TS respectively.

Table 9 TS for Different Geographic Location

Area	**TS**	
	Wet Season	**Dry Season**
High Altltude	0.901	0.059
Mid Altitude	0.889	0.274
Low Altitude	0.852	0.234
Lakeshore	0.934	0.193
	0.894	0.190
	0.895	0.214

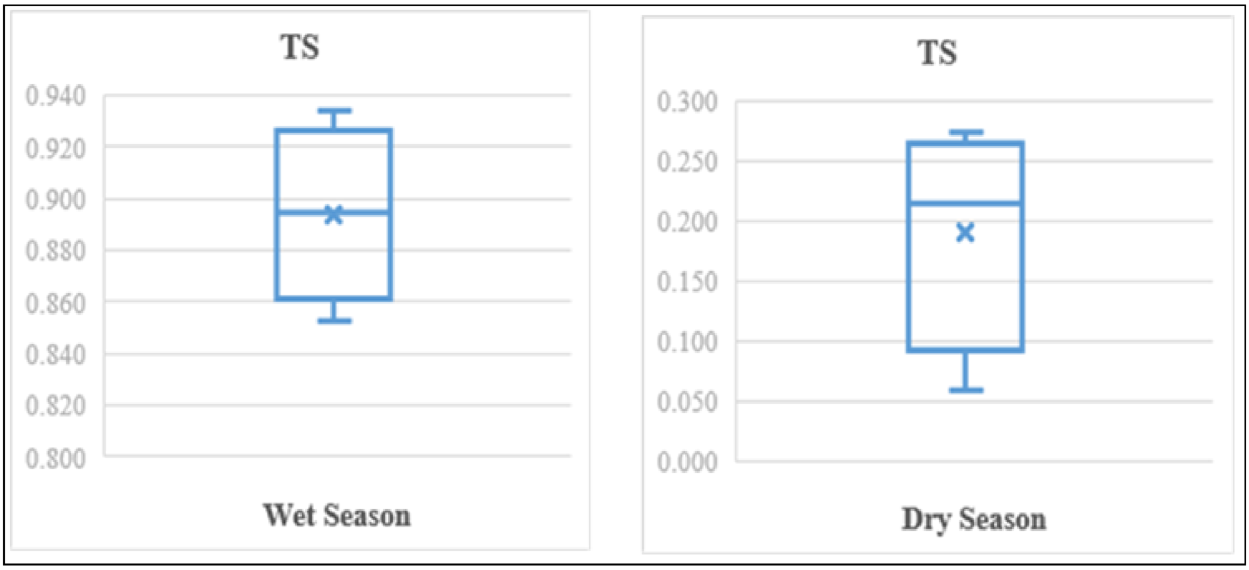

Fig 7 TS for Different Geographic Location

The TS during the wet season is negatively skewed while in the dry season it is positively skewed. With TS of close to one during the wet season and close to zero during the dry season, this implies that CHIRPS performs better during the wet season compared to the dry season in terms of TS.

From the three categorical scores; POD, FAR and TS, it has shown that CHIRPS performs better during the wet season and performs poorly during the poorly during the dry season.

Firstly this is due to sub-cloud evaporation during the dry season where the CHIRPS is able to detect some precipitation in the atmosphere but the moisture evaporates back into the atmosphere before reaching the ground hence not registered by the gauge stations. This reduces the hits between the CHIRPS estimates and Gauge recordings, and it also increases the false alarms.

B. Chirps Performance in Different Geographic Locations: High Altitude, Mid Latitude, Low Altitude and Lakeshore

➢ *Continuous Scores in Different Geographic Locations*

- *Pearson's correlation coefficient, R*

During the wet season, mid altitude areas have the highest correlation coefficient of 0.795, followed by Lakeshore areas at 0.787 and High-altitude areas at 0.785. Low altitude area has the lowest correlation coefficient of 0.731.

During the dry season, Mid altitude has the highest mean correlation coefficient of 0.575, followed by Lakeshore area at 0.545 and High-altitude areas at 0.429. Low altitude area has the lowest mean correlation coefficient of 0.408.

Table 10 Mean R for Different Geographic Location

Area	R^2			R	
	Wet Season	**Dry Season**		**Wet Season**	**Dry Season**
High Altitude	0.616	0.184		0.785	0.429
Mid Altitude	0.632	0.330		0.795	0.575
Low Altitude	0.534	0.167		0.731	0.408
Lakeshore	0.619	0.297		0.787	0.545

In both locations, there is a significant correlation at between ground station and CHIRPS estimates. This shows that CHIRPS performs much better with a very strong correlation in mid altitude areas in Malawi and has the least performance in Low altitude areas in both dry season and wet season.

The mid altitude areas are dominated by plains [25] that make it easier for CHIPRS to produce better results than the rest of the areas in terms of correlation [26]. While the low altitude areas, which is the lower shire valley (Chikwawa and Nsanje districts) is a semi-arid area [27]. As such CHIRPS has been reported to produce low results in semi-arid areas due to sub-cloud evaporation.

The results from the High altitude and the Lakeshore are likely affected by the complex terrain and prevalence of warm-top stratiform cloud systems along the coastal region which have been found to affect its performance [28].

- *PBIAS*

The mid altitude and the low altitude perform better in terms of PBIAS during the wet season; CHIRPS slightly overestimates precipitation by a mean of 1.2% in low altitude areas and slightly underestimates precipitation in the mid altitude areas by a mean of 1.6%. While in the High altitude and Lakeshore, CHIRPS overestimates precipitation by a mean of 9.08% and underestimates by a mean of 8.68% respectively.

The lower values in the Low altitude and Mid altitude locations are likely to the fact that the two are dominated with plains with no complex terrains which is not the case with high the altitude area and the lake shore.

Table 11 Mean PBIAS for Different Geographical Locations

Area	Wet Season	Dry Season
High Altitude	9.08	37.46
Mid Altitude	-1.6	-2.72
Low Altitude	1.2	43.0
Lake Shore	-8.68	92.2

Being mountainous and with some escarpments along the lakeshore there is some precipitation of orographic origin along the lake shore due to the moisture contribution from the lake, such precipitation is registered by the ground stations but not picked by CHIRPS as it very amenable to precipitation of convective origin hence underestimates the precipitation. CHIRPS has limitations in reproducing the orographic rainfall due to the adoption of a fixed IRP CCD threshold value (i.e., 235 K), leading to classify warm orographic clouds as nonprecipitating [7].

The same process also occurs in the high-altitude areas where there is orographic lifting mechanisms of the air, however, the air does not have sufficient moisture to result into rainfall resulting into sub cloud evaporation hence overestimating precipitation.

During the dry season, all the region except the mid altitude region there is overestimation of precipitation with Lake shore region being the highest at a mean 92.2%. The sub-cloud evaporation plays an important role in the overestimation of rainfall occurrence over different semiarid and arid regions in the world [18]. Generally, during the dry season characterised by less moist air and high temperature there are more occurrences of sub cloud evaporation across Malawi hence likely to cause rainfall overestimation by CHIRPS.

Further to this, CHIRPS also exhibits poorer performance over those stations near the coast than the ones located in inland regions due to prevalence of warm-top stratiform cloud systems along the coastal region, conditions which CHIRPS may not detect rainfall because the cloud tops tend to have a value warmer than the IRP CCD threshold value [18].

Dry season in Malawi is also dominated by poor vegetative cover which may lead to high reflectance of the earth surface in the near-infrared wavelengths. This may affect the affect the CHIRPS algorithm hence leading to some overestimates registered.

- *Unbiased Root Mean Square Error, ubRMSE*

In terms of ubRMSE, High altitude has the least error in both the wet season and the dry season, 66mm/month and 8mm/month respectively. The least performance is registered in the Lakeshore area and the Low altitude area during the wet season and the dry season respectively.

Table 12 Mean ubRMSE for Different Geographical Locations

Area	Wet Season	Dry Season
High Altitude	66	8
Mid Altitude	81	17
Low Altitude	73	27
Lakeshore	93	18

The findings are very in line with other research outputs which found the RMSE tends have a maximum value of 100mm in comparison of monthly rainfall of CHIRPS satellite-based and ground-based rainfall estimates [1, 29, 30].

This implies that while there is a systematic overestimation, the CHIRPS estimates are closer to gauge station data in High altitude and much different in the Lakeshore during the wet season.

The Low altitude and most parts of the Lakeshore are all classified as semi-arid [27], however, during the dry season in the Low altitude the air has very little moisture while in the Lakeshore the air has some moisture contribution from the lake. This makes the Low altitude to experience more sub cloud evaporation hence contributing to the huge ubRMSE in the Low altitude compared to the other three regions during the dry season.

- *Categorical Scores In Different Geographic Locations*

Table 13 Mean of Categorical Scores

Location	POD		FAR		TS	
	Wet Season	Dry Season	Wet Season	Dry Season	Wet Season	Dry Season
Lakeshore	0.982	0.357	0.053	0.470	0.932	0.177
High Altitude	0.970	0.000	0.088	0.250	0.887	0.000
Mid Altitude	0.957	0.289	0.076	0.375	0.888	0.235
Low Altitude	0.962	0.369	0.116	0.558	0.852	0.232

- *Probability of Detection, POD*

All the four geographical location have very strong POD during the wet season. Lakeshore has the highest POD for 0.982 during the wet season, followed by the High-altitude areas and the Low altitude at 0.970 and 0.962 respectively. Mid altitude has the least POD of 0.957.

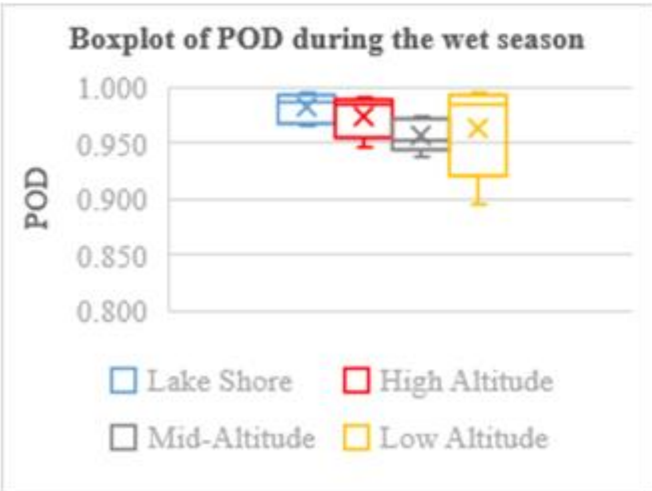

Fig 8 POD of Different Geographical Location

While all the four stations are demonstrating a very strong POD, there is a wide range in the low altitude area during the wet season. This is likely due to the fact that the low altitude area, also known as the lower shire, is a semi-arid (with highest temperatures in Malawi) and persistently a drought-stricken region. Probably, there is a lot more sub-cloud evaporation during the wet season in other stations under extreme droughts in the dry atmosphere compared to the other three regions.

During the dry season the POD is generally weaker for all the regions. The lakeshore, the mid altitude and the low altitude have a POD of 0.357, 0.289 and 0.369 respectively. However, the High altitude has the poorest POD of 0. Since the high altitude are characterised with mountainous and complex terrain with very low temperatures and orographic clouds, this might be the reason why CHIRPS fails to sufficiently detect precipitation events during the dry season since it mostly has precipitation of orographic origin which falls under the threshold of this study.

- *False Alarm Ratio, FAR*

During the wet season, all the four regions have weak FAR, ranging from 0.053 to 0.116, indicating a good performance. Highest FAR of 0.116 for the low altitude is likely due to the same sub-cloud evaporation where CHIRPS detect rainfall events which did not occur. On the other, while both the low altitude and some parts of the lakeshore might be semi-arid in nature, there is some moisture contribution from the lake that makes cloud formation in the lake show to be sufficient to result into precipitation hence reducing the FAR, 0.053, making it the least.

With already observed poor performance during the dry season, the low altitude and the lake shore have higher FAR values of 0.558 and 0.470 respectively compared to high altitude and mid altitude that register FAR values of 0.250 and 0.375. To begin with, both low altitude and the lakeshore are semi-arid regions with higher temperatures, however, the air in the low altitude has less moisture compared to lakeshore. For this reason, most cloud detected in the low altitude do not result into precipitation on the ground. However, in lakeshore region some cloud detected may have moisture enough to result into precipitation on the ground hence reducing false alarms.

On the other hand, the mid altitude are sub-humid and the high altitude are sub-humid to humid in some parts. Therefore, the two regions experience medium to low temperatures making the sub-cloud evaporation much less than the low altitude and lakeshore, subsequently resulting to lower FAR values with the high altitude being the least at 0.250.

- *Threat Score, TS*

All the four regions have a strong mean threat score ranging from 0.852 to 0.932 during the wet season with lakeshore being the highest and low altitude the lowest. High altitude and the mid altitude have threat scores of 0.888 and 0.887 respectively. Being a fraction of hits and all CHIRPS based events, a higher threat score indicates a good performance in general as already observed.

However, the highest performance in the lakeshore areas might be due to local meteorological factors such as lake breeze effects and orographic effects since almost the entire lakeshore region is characterised by such a cliff on one side. On the other hand, sub-cloud evaporation might greatly contribute to the relatively low threat score in the low altitude region.

In dry season, high altitude region has a threat score of 0, probably due to the mountainous and complex terrain just like it is with POD. The lakeshore, mid altitude and the low altitude have the mean TS of 0.177, 0.235 and 0.232 respectively. The mid altitude and the low altitude are all plain hence a relatively higher performance during dry season. Their difference might come due difference in climate since the low altitude is semi-arid while the mid altitude is semi-humid resulting into more sub cloud evaporation in the low altitude. Whilst the lake shore is of a similar climate with the low altitude, it might receive some more precipitation due to local meteorological factors such as lake breezes and some if orographic origin that may not be detected by the CHIRPS hence a lower value of threat score compared to the low altitude region.

IV. CONCLUSION AND RECOMMENDATION

A. Conclusion

The performance CHIRPS monthly rainfall data against gauge station monthly rainfall data across Malawi from 1981 to 2021 was evaluated. Data from twenty stations was sourced from the Malawi's Department of Climate Change and Meteorological Services. CHIRPS data was sourced from the CHIRPS website and retrieved through point-to-pixel method using the QGIS software.

Two major performance evaluation were done; performance in different seasons, that's wet season and the dry season, and performance in different geographical location across the country; Low altitude, Mid altitude, High altitude and Lakeshore regions. Five stations were selected from each of the four geographical locations across the country. Continuous and Categorical scores were used for the performance evaluation. The continuous scores were Pearson's Correlation Coefficient (R), unbiased Root Mean Square Error (ubRMSE) and Percent Bias (PBIAS). The categorical scores were Probability of Detection (POD), False Alarm Ratio (FAR) and Threat Score (TS).

Regarding the continuous scores and seasonal performance, it was found that CHIRPS performs better during the wet season in terms of correlation and PBIAS. In all seasons there was significant correlation, however, the wet season has a correlation of 0.753 while the dry season has a correlation of 0.481. The wet season had a mean PBIAS of -0.3% while the dry season had a mean PBIAS of 8.0%. This implies that CHIRPS underestimates precipitation during the wet season and overestimates precipitation during the dry season. In terms of ubRMSE, CHIPRS has a huge error in wet season and a smaller error in the dry season, 74.8mm/month and 17.4mm/moth. However, it should be noted that while the dry season registered a lower error, it is bigger than the mean monthly precipitation while it is inverse for the wet season. This implies that the CHIPRS also performs better in the wet season regardless the huge error reported.

In term of categorical scores and seasonal performance, wet season has a mean POD, FAR and TS of 0.969, 0.077 and 0.895 respectively while the dry season has mean POD of 0.264, 0.593 and 0.190 respectively. This implies that in terms of categorical scores, CHIRPS performs better during the wet season. CHIRPS can detect the rainfall events better in wet season than the dry season, it has less false alarms in wet season than the dry season and it has less threat in the wet season than the dry season.

When the performance was evaluated based on geographical locations, in terms of continuous scores it was found that the mid-altitude areas performed better in terms of correlation during both the wet season and the dry season with R of 0.795 and 0.575 respectively. The least performance was observed in the low altitude are which registered R of 0.731 and 0.408 respectively. Regarding PBIAS during wet season, both low altitude and mid altitude performed better with low values of 1.2% and -1.6% respectively while high altitude and the lakeshore areas registered high values of 9.08% and -8.68% respectively. The results also indicate that in the low altitude and the lakeshore CHIRPS underestimated the rainfall events while in the high altitude and the mid altitude CHIRPS overestimated the rainfall events. During the dry season, in the mid altitude CHIRPS performed much better with a PBIAS of -2.72 while three areas; high altitude, low altitude and the lakeshore registered a PBIAS of 37.46%, 43.0% and 92.2% respectively. In terms of ubRMSE, CHIRPS performed better in the high-altitude area with the least error of 66mm/month and 8mm/month during the wet season and dry season respectively. However, the worst performances were registered lakeshore with an error of 93mm/month during the wet season and the low altitude with an error of 27mm/month during the dry season.

In terms of categorical scores, in the lakeshore CHIRPS had the highest mean POD of 0.982 and the least was in the mid altitude with mean POD of 0.957 during the wet season. During the dry season, CHIRPS reported the least mean POD of 0 while the highest mean POD was registered in the lakeshore of a 0.369. Regarding FAR, during the wet season, CHIPRS reported the best results of 0.053 in the lakeshore while the worst result of 0.116 was reported in the Low altitude. However, in the dry season, the best FAR result of 0.250 was reported in the high altitude but the low altitude maintained a worst result of 0.558. Finally, CHIPRS maintained best result of TS in the lakeshore during the wet season of 0.932 while the worst result of 0.887 was reported in the high altitude. In dry season, the best result of 0.235 was reported in the mid altitude and the worst result of 0 was reported in the high altitude. Generally, in terms of the categorical scores, during the wet season, CHIRPS always reported the best results in the lakeshore. In the dry season the best performance alternates between the low altitude and the mid altitude but not the high altitude.

B. Recommendations

From the study, the following recommendations have been drawn:

- Since CHIRPS performs better during the wet season than the dry season in Malawi, it can be used for various agriculture water resources and engineering activities during the wet season.
- Considering its performance in different geographical locations, during the wet season CHIRPS may be applied as follows.
- In low and mid altitude, during the wet season CHIRPS may be used for drought monitoring and flood forecasting since it has PBIAS of close to 0, -1.6 and 1.2 respectively.
- In High altitude areas, with PBIAS of 9.08, it should be avoided to use CHIRPS for drought monitoring due to the overestimation.
- In the Lakeshore with PBIAS of -8.68, it should be avoided to use CHIRPS for flood forecasting due to the underestimation.
- It is not advisable to use CHIRPS during the dry season in Malawi.

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