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COMPARING THE ACCURACY OF CHIRP AND TAMSAT IN ASSESSING RAINFALL OVER RWANDA

by

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DECLARATION

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CERTIFICATION

This is to certify that the master's dissertation titled "**Comparing the Accuracy of CHIRP and TAMSAT in Assessing Rainfall Over Rwanda**" was completed by **Venuste MUGENZI** as part of the requirements for the Master's Degree in Atmospheric and Climate Science at the University of Rwanda, College of Science and Technology.

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DEDICATION

The author dedicates their dissertation to their wife, Fortunée UWUJINEMA, and their children, expressing gratitude for their prayers, support, and encouragement throughout the author's period of study. This dedication acknowledges the significant role of their family in the author's academic journey and highlights their love and appreciation for their spouse and children.

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ABSTRACT

This research study compares the accuracy of two prominent satellite-based rainfall products, CHIRP and TAMSAT, in assessing rainfall over Rwanda from 2011 to 2022. Using historical data and rigorous preprocessing techniques, the study determines that CHIRP provides more reliable estimates of rainfall for the region during this period. Ground-based observations validate CHIRP's accuracy, and statistical analysis identifies trends and biases. The findings support policymakers and stakeholders in water resource management, agriculture, and disaster preparedness, aiding in climate change adaptation efforts. Additionally, the research contributes valuable insights into satellite-based rainfall products' strengths and limitations, benefiting similar studies in other regions. Overall, CHIRP emerges as the preferred product for accurate rainfall assessments in Rwanda, contributing to climate science advancement and resilience-building efforts in the country.

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LIST OF SYMBOLS AND ACRONYMS

CHIRP/S: Climate Hazards Group Infrared Precipitation with Station data

CRU: Climate Research Unit

ENACTS: Enhancing National Climate Services

GPCC: Global Precipitation Climatology Center

IPCC: Inter-Governmental Panel on Climate Change

ITCZ: Inter-Tropical Convergence Zone

TRMM: Tropical Rainfall Measuring Mission

WMO: World Meteorological Organization

TAMSAT: Tropical Applications of Meteorology using Satellite data and ground based Observations

CCD: Cold Cloud Duration

CORR: Correlation

RMSE: Root Mean Square Error

NSE: Nash-Sutcliffe Efficiency

IOA: Index of Agreement

BIAS: Bias

NOAA: National Oceanic and Atmospheric Administration

CFSv2: Climate Forecast System, version 2

OBS: Ground observation

MAM: March April May seasonal

OND: October November December seasonal

CHAPTER ONE: INTRODUCTION

1.1 Background of study

Rainfall assessment is crucial for various sectors, including agriculture, water resource management, and disaster preparedness. In Rwanda, a landlocked country located in East Africa, rainfall plays a vital role in supporting its predominantly agrarian economy and sustaining ecosystems. Accurate and timely information on rainfall patterns is essential for effective planning, resource allocation, and decision-making to ensure food security and water availability[1].

Traditional rain gauge measurements have been the primary method for collecting rainfall data. However, these measurements are limited in spatial coverage and may not capture the full extent of rainfall variations across the country. In recent years, remote sensing technologies have emerged as promising tools for monitoring and assessing rainfall over large areas.[2]

Two such remote sensing methods used for rainfall estimation are the Climate Hazards Group InfraRed Precipitation with Stations (CHIRP) and the TAMSAT (Tropical Applications of Meteorology using SATellite data and ground-based observations) rainfall products. Both methods utilize satellite-based observations in combination with ground-based data to estimate rainfall amounts over a given region. [3]

CHIRP is a widely used rainfall estimation tool developed by the Climate Hazards Group at the University of California, Santa Barbara. It employs infrared data from geostationary satellites and combines them with rain gauge data to produce high-resolution rainfall estimates on a global scale. CHIRP is known for its long-term records and relatively high accuracy in various regions worldwide.[4]

On the other hand, TAMSAT is a rainfall estimation system developed specifically for the tropics. It was designed to provide accurate and timely rainfall information for decision-making in agriculture and food security. TAMSAT combines satellite observations with ground-based meteorological data and uses a statistical algorithm to estimate rainfall over regions in Africa, including Rwanda.[5]

Despite the importance of rainfall estimation for Rwanda's socio-economic development, limited studies have directly compared the accuracy and performance of CHIRP and

TAMSAT within the country's context. Understanding the strengths and weaknesses of these two methods is essential for improving rainfall monitoring and forecasting systems in Rwanda.[6]

The proposed research aims to bridge this gap by conducting a comprehensive comparison of the accuracy of CHIRP and TAMSAT in assessing rainfall over Rwanda. The study will use historical rainfall data from both methods and compare them with ground-based rain gauge measurements to validate their estimates. Evaluation of spatial temporal resolution, data availability and sensitivity to rainfall intensity in assessing factors affecting hydrological processes. [7]

The findings of this research will have practical implications for Rwanda's meteorological agencies, policymakers, and stakeholders involved in agriculture and water resource management. The study's results will contribute to enhancing the accuracy and reliability of rainfall data, leading to more effective decision-making processes for climate-resilient development in Rwanda.

This research topic addresses an essential aspect of Rwanda's development, focusing on improving the accuracy of rainfall assessment using remote sensing methods. By comparing the performance of CHIRP and TAMSAT, the study seeks to contribute valuable insights into optimizing rainfall monitoring and forecasting systems, ultimately benefiting various sectors and supporting sustainable development in the country.

1.2 The statement of problem and justification

The accuracy of rainfall estimates from different sources can vary, leading to potential discrepancies in decision-making processes and resource allocation for agricultural and water management sectors. The use of inconsistent or unreliable rainfall data may result in misinformed policies and actions. Thus, it is essential to evaluate the performance of rainfall estimation products, particularly CHIRP and TAMSAT, in the context of Rwanda to identify the most accurate and suitable data source for the region. [1]

Rainfall assessment is of utmost importance for various sectors, including agriculture, water resource management, and disaster preparedness, especially in regions prone to weather variability, such as Rwanda. Accurate rainfall data is crucial for informed decision-making and effective planning. The Climate Hazards Group InfraRed Precipitation with Station data (CHIRP) and the TAMSAT (Tropical Applications of Meteorology using SATellite data and ground-based observations) are two widely used datasets for rainfall estimation. However, there is a need to compare their accuracy in the specific context of Rwanda to identify which dataset better suits the country's unique meteorological conditions. [8]

Across Rwanda, the rain gauge network is extremely sparse and it often takes many months before rain gauge records are accessible to the wider community. However, rainfall information is very critical to predict yields and inform food security early warning system of the country. TAMSAT provides a gridded daily rainfall map at a resolution of 4 km and this gives around 1,646 pixels for Rwanda. Since Rwanda has not such distribution of rain gauge, the use of TAMSAT data can be of high importance. TAMSAT rainfall estimates can be used in different areas of the country. This study attempt to provide information on the reliability of spaciotemporal satellite rainfall data to alleviate the scarcity of rainfall data in Rwanda.[1]

1.3 Objectives

The main objective of this research is evaluating the performance and accuracy of CHIRP and TAMSAT for measuring rainfall in Rwanda with observations at 5 synoptic stations Rwanda.

The specific objectives include:

- Collecting and analyzing historical rainfall data from CHIRP and TAMSAT datasets for Rwanda over a specific period (2011-2022).
- Validating the rainfall data from both datasets against ground-based observations from weather stations across Rwanda.
- Assessing the spatial and temporal variability of rainfall estimates provided by CHIRP and TAMSAT in Rwanda.
- Identifying the strengths and weaknesses of each dataset in capturing extreme rainfall events, seasonal patterns, and inter-annual variability.
- Examining the impact of elevation and topography on the accuracy of rainfall estimates from both datasets in the mountainous terrain of Rwanda.

This research has provided information on rainfall estimates in Rwanda in order to determine which satellite dataset is effective in measuring rainfall estimates between the CHIRP and TAMSAT datasets.

1.4 Hypothesis of the Study

It is hypothesized that either CHIRP or TAMSAT will exhibit superior accuracy in rainfall estimation over Rwanda. The research aims to identify the product that provides more reliable and consistent rainfall estimates, contributing to better-informed decision-making in various sectors dependent on accurate rainfall data.

1.5 Study area

The research be conducted in Rwanda, a landlocked country in East Africa known for its varied topography and climate. Rwanda experiences distinct dry and rainy seasons, with significant spatial variations in rainfall distribution due to its mountainous landscape. The study area covers the entire country, including urban and rural regions, with a focus on rainfall variability across different elevations and geographical locations. The research involves the use of historical rainfall data from both CHIRP and TAMSAT datasets for Rwanda. Additionally, ground-based rainfall observations from various meteorological stations across the country will be utilized for validation purposes. Satellite remote sensing data, geographical information systems (GIS), and statistical analysis be employed to achieve the research object.

CHAPTER TWO: LITERATURE REVIEW

The literature review begins by highlighting existing research on remote sensing-based rainfall estimation products like CHIRP and TAMSAT, noting their varying performance across different regions globally. While CHIRP has shown superiority in certain areas due to its infrared-based approach, TAMSAT has demonstrated strength in tropical regions thanks to its specialized algorithms. However, there's a lack of studies directly comparing the accuracy of these products over Rwanda, with only limited regional comparisons available. [4]

Moving into the climatology of Rwanda, the review provides an overview of the country's geographical and climatic characteristics, divided into three main altitude-based zones: highlands in the west and north, a central plateau, and lower elevations in the east. The rainfall patterns, influenced by factors like the Inter-Tropical Convergence Zone (ITCZ) and local topography, result in two main rainy seasons and two dry seasons throughout the year. [9]

The literature further delves into the data collection process, outlining the sources and selection criteria for observational rainfall stations in Rwanda. Five stations were chosen based on data availability and completeness, ensuring reliable data for analysis. Additionally, the development of the ENACTS gridded rainfall dataset, aimed at enhancing climate data availability, is discussed, detailing the methodology and resolution of the dataset. [4, 10, 11]

The review then explores the satellite data used in the study, focusing on the CHIRP/S and TAMSAT rainfall estimation methods. CHIRP/S combines various data sources to provide precipitation estimates globally, while TAMSAT utilizes thermal-infrared images and historical rain-gauge observations for rainfall estimation in tropical regions like Africa. The differences between the two methods, including calibration approaches and time series homogeneity, are highlighted. Overall, the literature review provides a comprehensive overview of existing research on rainfall estimation products, Rwanda's climatology, data collection methods, and satellite rainfall estimation techniques. It sets the stage for the proposed research by identifying gaps in knowledge and laying the foundation for the comparative analysis of CHIRP and TAMSAT's accuracy in Rwanda.[12]

2.1 Climatology of Rwanda

Rwanda is a landlocked country located in East Africa, situated between latitudes 1° and 3° South and longitudes 28° and 31° East. Its geography is characterized by a diverse landscape, including highlands, savannas, and lakes. The country shares borders with Uganda to the north, Tanzania to the east, Burundi to the south, and the Democratic Republic of the Congo to the west. Climatically, Rwanda falls within the tropical zone, but due to its varying elevations, the climate exhibits distinct regional differences.[13] The country can be divided into three main climatic zones based on altitude:

The western and northern parts of Rwanda are characterized by highlands and mountainous terrain. This region includes the capital city, Kigali, and the Volcanoes National Park. The altitude in this zone ranges from approximately 1,500 to 4,500 meters (4,900 to 14,800 feet) above sea level. As a result, temperatures in the highland zone are relatively cooler than in other parts of the country. The average temperatures in Kigali, for example, range from 12°C to 27°C (54°F to 81°F) throughout the year.[14]

The central part of Rwanda consists of a plateau with an average elevation of around 1,500 to 2,000 meters (4,900 to 6,600 feet) above sea level. The central plateau includes areas such as Butare, the country's second-largest city, and is characterized by a milder climate compared to the highlands. Temperatures here are generally higher than in the highland zone but still moderate. Average temperatures in Butare range from 14°C to 28°C (57°F to 82°F).[14,15]

The eastern part of Rwanda is characterized by lower elevations, including areas around Akagera National Park. The altitude in this region varies from approximately 950 to 1,450 meters (3,100 to 4,760 feet) above sea level. The eastern lowlands experience a warmer climate compared to the highlands and central plateau. Average temperatures in this region range from 16°C to 32°C (61°F to 90°F). [13, 14, 15]

Rainfall patterns in Rwanda are influenced by several factors, including the Inter-Tropical Convergence Zone (ITCZ), local topography, and nearby bodies of water like Lake Kivu and Lake Victoria. The country experiences two main rainy seasons and two dry seasons:

The long rainy season typically occurs from March to May. During this period, the ITCZ shifts southwards, bringing moist air masses and rainfall to Rwanda. This is the primary rainy season, and rainfall amounts can be significant, especially in the western highlands. The short rainy season occurs from October to December. During this time, the ITCZ shifts northwards, and Rwanda experiences a second, relatively less intense rainy season.[16]

The two dry seasons fall between January and February and between June and September. These periods are characterized by reduced rainfall and are essential for agricultural planning and activities.[16]

Rwanda's climatology is influenced by its diverse topography, altitude variation, and regional climate phenomena. Understanding these climatic factors is crucial for sustainable development planning, agricultural practices, water resource management, and climate adaptation strategies in the country.[16]

2.2 Station Rainfall data

The research collected rainfall data from five observational stations in Rwanda through the Rwanda Meteorology Agency (METEO Rwanda). The data included daily, monthly mean, seasonal rainfall, and average rainfall of annual measurements. The study period covered various durations depending on the available data for each station, but the target period ranged from 2011 to 2022.[11]

The selection of the observational rainfall stations was based on data availability, ensuring that the chosen stations had no missing gaps exceeding 10% for their study period. This criterion aimed to ensure the reliability and completeness of the data used in the analysis. Table 1 presented the details of the selected rain gauge stations, including their climatology history, study period, and the percentage of data gaps. These details provided an overview of the data quality and completeness for each station.[17]

Table 1 and Figure 1 displayed the geographical locations of the selected rain gauge stations in Rwanda. The map visualization helped to understand the spatial distribution of the stations across the country.

Overall, the study collected rainfall data from five observational stations in Rwanda, covering the period from 2011 to 2022. The selected stations had minimal missing data, ensuring the data's reliability for further analysis and comparison of rainfall estimation methods like CHIRP and TAMSAT.

Table 1:Weather Stations

No	STATION	Province	Longitude	Latitude	Elevation
1	Byimana	South	29.71	-2.16	1750m
2	Byumba	North	30.05	-1.6	2235m
3	Gitega	Kigali	30.06	-1.96	1522m
4	Nyagatare	East	30.31	-1.28	1377m
5	Rubengera	West	29.41	-2.07	1700m

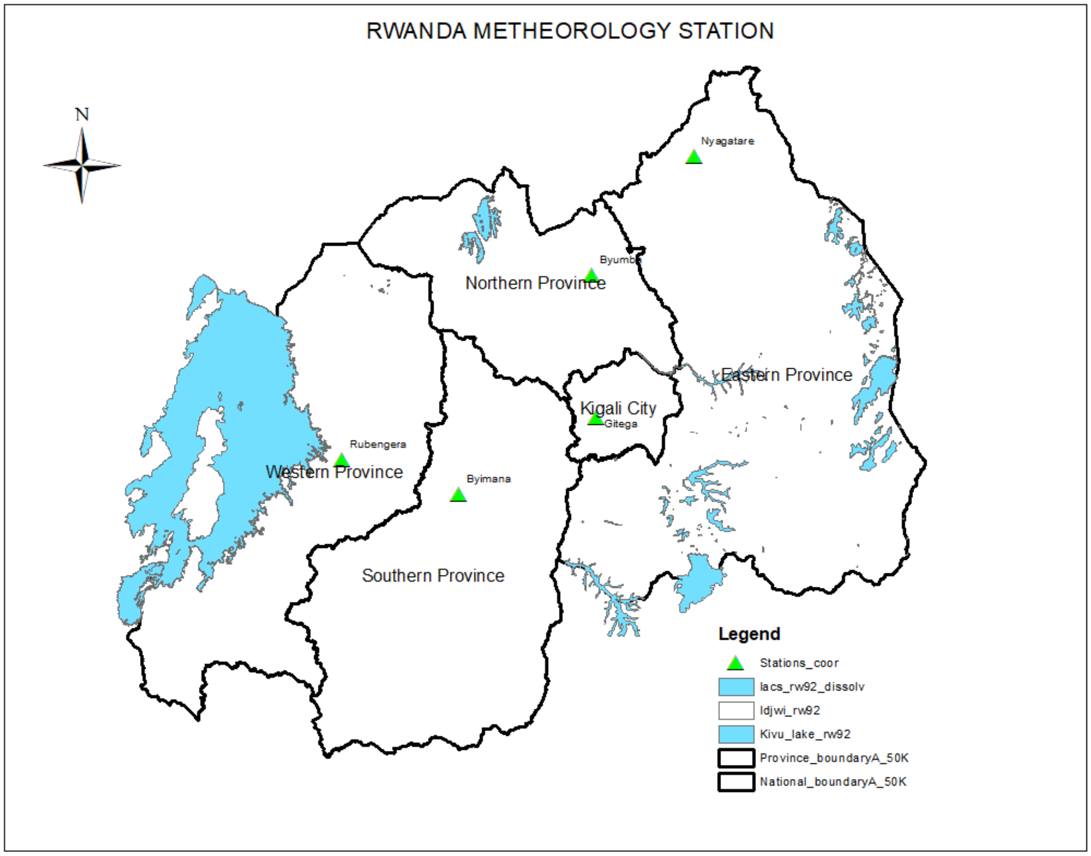

Figure 1: Rwanda Meteorology Station

2.3 SATELLITE DATA

2.3.1 CHIRP/S

The CHIRP/S (Climate Hazards group InfraRed Precipitation with Station data) dataset is a product that combines various data sources to provide high-resolution precipitation estimates on a global scale. The algorithm involves several steps to derive unbiased precipitation fields, taking advantage of satellite observations, in situ rain-gauge measurements, and climatology data.[18, 19]

The algorithm involves a multi-step process that includes deriving TIR precipitation estimates from satellite observations, converting these estimates to percentage anomalies, and multiplying them by the CHPclim to produce unbiased precipitation fields. The product, known as CHIRP, is a time series that goes back to 1981 at a spatial resolution of 0.05° latitude/longitude.

To fill missing TIR data from the early 1980s, the algorithm uses unbiased data from the atmospheric model rainfall fields from the National Oceanic and Atmospheric Administration (NOAA) Climate Forecast System, version 2 (CFSv2).

To adjust CHIRP using station observations, the algorithm estimates the correlation between precipitation for each pixel and nearby stations. The correlation values are used to calculate bias ratios, which are then combined into a single correction factor. These correction factors are multiplied by CHIRP values to create an adjusted-CHIRP, which is then combined with the original CHIRP to create the final CHIRPS product.

The CHIRPS product is available in both pentad (5-day) and monthly time scales. The algorithm merges station data with CHIRP at these time scales, with the pentads later rescaled to ensure the sum of pentads in a calendar month equals the monthly values. There are two versions of CHIRPS produced operationally, a preliminary version with fewer station data and a final version with more station data.

Regarding homogeneity of the time series, CHIRP is expected to be more consistent than CHIRPS. The ingestion of varying numbers of stations over the years may lead to inhomogeneity in the CHIRPS time series. However, the use of weighted bias ratios in calculating CHIRPS helps minimize the effect of varying station availability. The CHIRP product may also have some inhomogeneity due to missing satellite slots in the early 1980s.

2.3.2 TAMSAT

The TAMSAT (Tropical Applications of Meteorology using SATellite data and ground-based observations) rainfall estimates are developed at the University of Reading in the UK. This approach relies on the premise that lower temperatures of tropical storm cloud tops suggest the presence of rain-producing clouds, as determined from thermal-infrared images from Meteosat. The algorithm measures the duration for which a satellite pixel stays below a specified temperature threshold (cold cloud duration) over a set period, typically 10 days, to generate accumulated CCD fields over time. It is based on the assumption of a linear correlation between CCD and rainfall amounts.[20]

TAMSAT utilizes historical rain-gauge data to calibrate the cold cloud duration (CCD) and develop climatological calibration parameters that vary seasonally and spatially, but remain consistent from year to year. These calibration maps are then applied to the thermal-infrared data from 1983 onward, allowing for the creation of an updated rainfall time series. This method helps maintain temporal consistency in the rainfall estimates.[21]

The TAMSAT method is particularly effective for Africa because it employs local calibration using rain-gauge data from various regions across the continent. This localized approach takes into account factors like orography and proximity to lakes and coastlines, resulting in a clear relationship between rainfall and cold cloud duration (CCD) in areas with adequate gauge records.

TAMSAT provides rainfall estimates on daily, pentadal (in the latest version), and dekadal timescales, delivering updates within a few days after each period. The latest iteration, TAMSAT3, features several enhancements over TAMSAT2. It focuses on pentadal estimates, employs detailed calibration fields derived from interpolated point data rather than broad calibration zones, calibrates CCD against average gauge rainfall to minimize dry bias, and adjusts rainfall calibration coefficients using CHPclim pentadal fields to enhance geographical accuracy and reduce mean bias.[22]

TAMSAT3 and CHIRP (Climate Hazards group InfraRed Precipitation with Station data) share some similarities, but they also have notable differences. Both products utilize calibration and generate pentadal estimates; however, TAMSAT employs a varying temperature threshold to distinguish between rain and no-rain, whereas CHIRP relies on a fixed threshold. Moreover, TAMSAT's data collection begins in 1983, while CHIRP's starts in 1981. TAMSAT opted not to begin in 1981 due to numerous missing satellite images, while CHIRP compensates for these gaps using climate model estimates. This discrepancy could affect the consistency of the CHIRP time series for the years 1981 and 1982.[22]

CHAPTER THREE: DATA AND METHODOLOGY

3.1 DATA

This study daily rain gauge data from 2011 to 2022, provided by the National Meteorological Agency of Rwanda. Stations with significant missing data were excluded from the analysis. The study covered various locations across the country. From the available daily data, researchers derived monthly average, Seasonal (March-May), Seasonal (October-December), and annual average rainfall data. [23, 24]

The datasets rainfall from satellite will be collected data are CHIRP and TAMSAT datasets. However, due to the scarcity of gauge stations and also the best resolution of both satellite-based as well as reanalysis data sets, the nearest neighbor-interpolated gridded data from the satellite/model grids to the location of a weather station (grids around the station) were compared with a single-point gauge station. The five regions selected for validation in this study are far apart, have much elevation difference and experience different climate conditions.[21, 25, 26, 27]

The well-known Kriging interpolation method has been applied to estimate the monthly mean rainfall, seasonal mean rainfall, and annual mean rainfall for the locations lacking gauge observations.[27, 28]

3.2 Methods

In this study, several common skills assessment methods will be employed to evaluate the statistical performance. These methods include the Index of Agreement (IA), Pearson's correlation coefficients (r), Root Mean Square Error (RMSE), Nash and Sutcliffe efficiency (NSE), and BIAS. These metrics will be used to assess the accuracy and reliability of the models or analyses applied in the study. While a detailed explanation of these methods is available elsewhere, they serve as valuable tools for evaluating the performance of statistical models and their predictions in this particular research.[23, 25, 29, 30, 31, 32]

Index of Agreement (IA)

The Index of Agreement (IA) is a performance evaluation metric used to assess the accuracy of simulation or model predictions. It is a dimensionless index that ranges from 0 to 1. A value closer to 1 indicates a better agreement between the simulated values and the observed data, suggesting a more accurate prediction. On the other hand, a value closer to 0 indicates a weaker agreement, implying a less accurate simulation or model prediction. [33]

$$IA = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(|y_i - \overline{x}| + |x_i - \overline{x}|)^2} \quad (1)$$

Nash and Sutcliffe efficiency (NSE)

The Nash and Sutcliffe efficiency (NSE) is a performance evaluation metric commonly assess the accuracy of model predictions compared to observed data. The NSE ranges from negative infinity to 1, with a value of 1 indicating a perfect match between the simulation and observed data. Values between 0 and 1 indicate acceptable model performance, with higher values indicating better agreement with the observed data. When the NSE is negative, it suggests that the simulation performs worse than simply using the mean value of the observed data. It is defined as the ratio of the mean square error of the simulation to the variance of the observed data. The NSE ranges from negative infinity to 1, with a value of 1 indicating a perfect match between the simulation and observed data. Values between 0 and 1 indicate acceptable model performance, with higher values indicating better agreement with the observed data. When the NSE is negative, it suggests that the simulation performs worse than simply using the mean value of the data. The NSE provides a quantitative measure of the overall deviation of the simulation from the observed data, with values closer to 1 indicating better satellite dataset performance and values below 0 suggesting poorer performance compared to a simple mean value prediction. [34]

$$NSE = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad (2)$$

Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) is a performance evaluation metric used to measure the absolute mean difference between two datasets, such as satellite products and corresponding rain gauge observations. It quantifies the average magnitude of errors between the predicted values (satellite products) and the actual observed values (rain gauge observations). A lower RMSE value indicates a smaller average difference between the datasets and signifies better performance of the satellite products or model. In other words, an RMSE value close to 0 suggests that the satellite data aligns well with the gauge observations, indicating accurate predictions or model performance.[35]

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad (3)$$

Pearson's correlation coefficients (r)

Pearson's correlation coefficient (r) is a statistical metric used to measure the strength and direction of the linear relationship between two datasets, such as satellite and rain gauge data. The value of r ranges from -1 to 1. A correlation coefficient of -1 indicates a perfect negative linear correlation, meaning that as one dataset increases, the other decreases in a perfectly linear fashion. A correlation coefficient of 1 indicates a perfect positive linear correlation, meaning that as one dataset increases, the other also increases in a perfectly linear fashion.

If the correlation coefficient is close to -1 or 1, it indicates a strong linear relationship between the satellite and rain gauge data, with one dataset being a reliable predictor of the other. On the other hand, if the correlation coefficient is close to 0, it suggests a weak or no linear relationship between the datasets, meaning that they are not strongly associated in a linear manner. In summary, Pearson's correlation coefficient (r) provides valuable information about the strength and direction of the linear relationship between the satellite and rain gauge observations.[35]

$$r = \frac{\sum_{i=1}^{n} y_i x_i - n\bar{x}\bar{y}}{\sqrt{\sum_{i=1}^{n} y_i^2 - n\bar{y}^2}\sqrt{\sum_{i=1}^{n} x_i^2 - n\bar{x}^2}} \quad (4)$$

BIAS

The BIAS (Bias) is a performance evaluation metric used to measure the difference between satellite or model products and gauge observations. It quantifies whether the satellite or model tends to underestimate or overestimate the observed data. BIAS values close to 1 indicate that the satellite or model products exhibit the best performance, meaning that their predictions closely match the gauge observations. If the BIAS is less than 1, it suggests underestimation, indicating that the satellite or model consistently predicts values lower than the observed data. Conversely, if the BIAS is greater than 1, it indicates overestimation, meaning that the satellite or model consistently predicts values higher than the observed data.

The BIAS provides a measure of the systematic errors in the satellite or model products compared to the gauge observations. A BIAS value close to 1 signifies accurate predictions, while values less than or greater than 1 indicate a tendency to under or overestimate the observed data, respectively.[36]

$$BIAS = \frac{\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} x_i} \tag{5}$$

Where yi is satellite data and xi is rain gauge data (station data)

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 MONTHLY AVERAGE RAINFALL

The TAMSAT and CHIRP are the two satellite-based products selected for this study. Both products have the best resolution and cover the study region for an extended period.

The results from table 2 and figure (2 and 3) of comparing the accuracy of CHIRP and TAMSAT in assessing rainfall over Rwanda, based on the coefficients of correlation, BIAS, RMSE, and Nash and Sutcliffe efficiency (NSE) at different weather stations, can be summarized as follows:

CHIRP generally shows higher correlation coefficients compared to TAMSAT at most of the weather stations in Rwanda. This indicates that CHIRP's rainfall estimates are more closely related to the observed rainfall data than TAMSAT's estimates.[37]

BIAS measures the average difference between estimated and observed rainfall. Both CHIRP and TAMSAT tend to have positive BIAS values at all stations, suggesting that, on average, they tend to overestimate rainfall. However, the magnitude of the overestimation varies between the two methods and across stations.

RMSE represents the root mean square error between estimated and observed rainfall. CHIRP generally exhibits lower RMSE values compared to TAMSAT at most stations, indicating that CHIRP's estimates are closer to the observed data than TAMSAT's estimates.

Nash and Sutcliffe Efficiency (NSE) assesses the relative magnitude of errors compared to the variability in the observed data. CHIRP generally shows higher NSE values compared to TAMSAT at most stations, indicating that CHIRP's estimates are more efficient in capturing the observed rainfall variability.[37]

In summary, the results consistently suggest that CHIRP performs better than TAMSAT in estimating rainfall accuracy in Rwanda, as it shows higher correlation coefficients, lower RMSE values, and higher NSE values at most weather stations. However, it's important to interpret these results with caution and consider other factors such as data availability, spatial distribution, and temporal coverage, as well as the specific requirements of the applications for which rainfall estimates are being used.

Table 2: Performances result for the monthly average rainfall estimates between Rain gauge and CHIRP, TAMSAT

		CHIRP			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.903	0.952	0.948	0.984	0.801
BIAS	0.877	0.897	0.88	1.079	0.831
RMSE	25.234	20.502	21.597	10.042	32.15
NSE	0.733	0.866	0.844	0.923	0.406
IOA	0.935	0.966	0.954	0.983	0.852
		TAMSAT			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.706	0.813	0.809	0.904	0.888
BIAS	0.835	0.886	0.936	1.244	0.921
RMSE	41.377	35.313	32.929	28.725	24.744
NSE	0.282	0.604	0.638	0.372	0.648
IOA	0.81	0.883	0.888	0.89	0.926

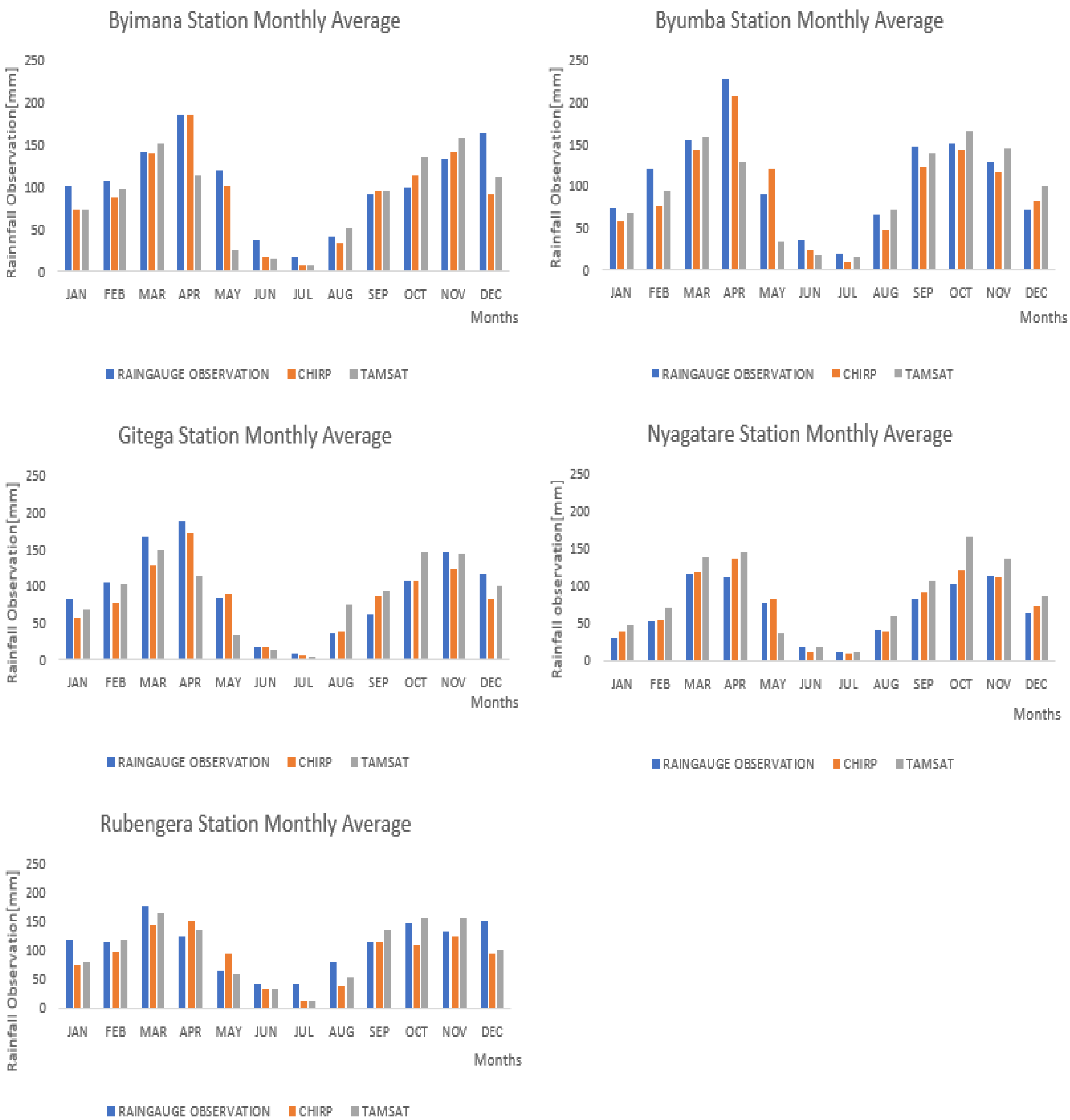

Figure 2: **Performances result for the monthly average rainfall estimates between Rain gauge and CHIRP, TAMSAT**

The application of the well-established Kriging interpolation method for estimating monthly average rainfall involves a systematic process that incorporates spatial autocorrelation and variogram modeling. This approach proves especially beneficial in regions with limited meteorological stations.

The results indicate that CHIRP demonstrates higher accuracy compared to TAMSAT in estimating monthly average rainfall over Rwanda. Specifically, when compared to ground observations, CHIRP exhibits a higher correlation coefficient and lower root mean square error (RMSE) than TAMSAT. The Kriging interpolation method further confirms the superiority of CHIRP over TAMSAT, with CHIRP consistently producing estimates closer to ground observation values.

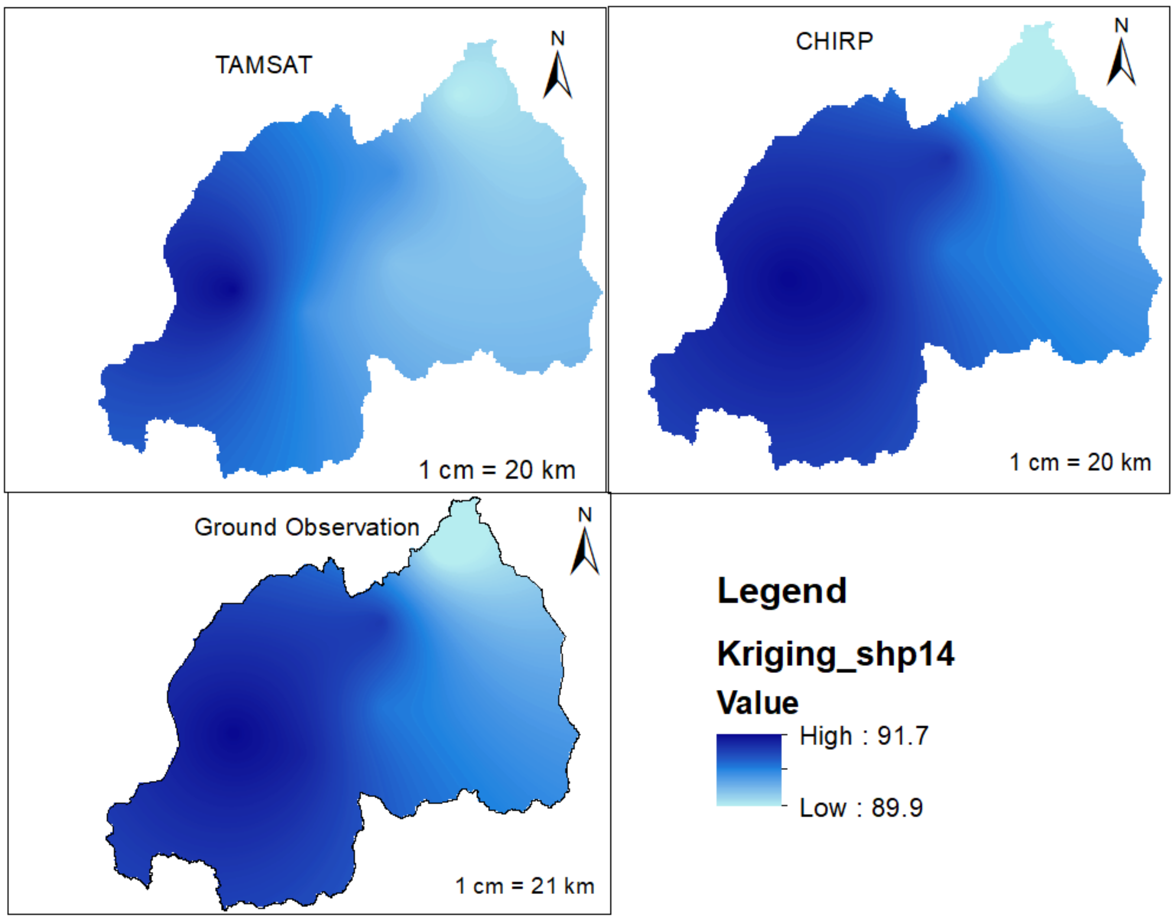

Figure 3: Monthly average rainfall distribution kriging interpolation

The result from figure 3, the higher accuracy of CHIRP over TAMSAT in rainfall estimation can be attributed to several factors. Firstly, CHIRP utilizes infrared satellite data in combination with ground observations, potentially enhancing its accuracy compared to TAMSAT, which relies solely on satellite data. Additionally, differences in algorithmic approaches and spatial resolution between the two datasets may contribute to variations in accuracy. The statement emphasizes that CHIRP is more effective than ground observations for estimating rainfall in Rwanda. This reliability is important, as accurate rainfall data is essential for numerous socio-economic activities in the country.[38]

4.2 Seasonal rainfall

Seasonal rainfall is the total amount of rainfall received during specific seasons in a year. In Rwanda, there are two main seasons: the long season (March to May) and the shorty rainy season (October to December).[39]

The study calculated a total rainfall for each season using CHIRP and TAMSAT rainfall data. The findings indicated that CHIRP and TAMSAT generally captured Rwanda's rainfall patterns.

However, discrepancies between the two products were noted in certain years or seasons.

Accuracy varied across Rwanda's regions due to factors like terrain, gauge density, and satellite-based rainfall estimation performance.[4]

Based on the results in table 3 and figure 4 you provided for the coefficients of correlation, BIAS, RMSE, Nash and Sutcliffe efficiency (NSE), and Index of Agreement (IOA) at various weather stations in Rwanda, let's discuss the performance of two estimation methods:

The coefficients of correlation vary across stations, with both CHIRP and TAMSAT showing a mix of moderate to strong correlations. TAMSAT generally exhibits higher correlation coefficients compared to CHIRP at most weather station.

Both CHIRP and TAMSAT tend to have positive BIAS values at all stations, indicating a tendency to overestimate the actual observed rainfall. The magnitudes of BIAS values at different stations.

The RMSE values for both CHIRP and TAMSAT vary across stations. In most cases, TAMSAT has higher RMSE values compared to CHIRP, indicating that TAMSAT's estimates have larger errors compared to the observed data.

The NSE values for both CHIRP and TAMSAT show a mix of positive and negative values across stations. Negative NSE values suggest that the method have poor efficiency in capturing the observed variability. Same stations show slightly positive NSE values, indicating better performance in capturing the observed patterns.

The IOA values indicate the agreement between estimated and observed data, with higher values indicating better agreement. CHIRP generally shows higher IOA values compared to TAMSAT at most weather stations, suggesting that CHIRP's estimates have better agreement with observed data.

Overall, the results are more mixed compared to the previous scenario. TAMSAT shows higher correlation coefficients and mixed performance in terms of BIAS, RMSE, NSE, and IOA across different weather stations. CHIRP, on the hand, demonstrates better performance in terms of IOA at most stations, indicating its better agreement with observed data.

Table 3: Performances result for the Seasonal rainfall (March to May) estimates between Rain gauge and CHIRP, TAMSAT

		CHIRP			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.444	0.531	0.205	0.369	0.621
BIAS	0.954	0.998	0.884	1.097	1.065
RMSE	157.252	101.281	162.723	116.328	96.436
NSE	0.183	-0.257	-0.361	-0.341	0.331
IOA	0.581	0.74	0.541	0.562	0.665
		TAMSAT			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.792	0.624	0.624	0.534	0.742
BIAS	0.652	0.684	0.68	1.046	0.983
RMSE	196.799	168.871	178.104	91.839	85.094
NSE	-0.28	-2.493	-0.63	0.164	0.479
IOA	0.605	0.547	0.581	0.713	0.861

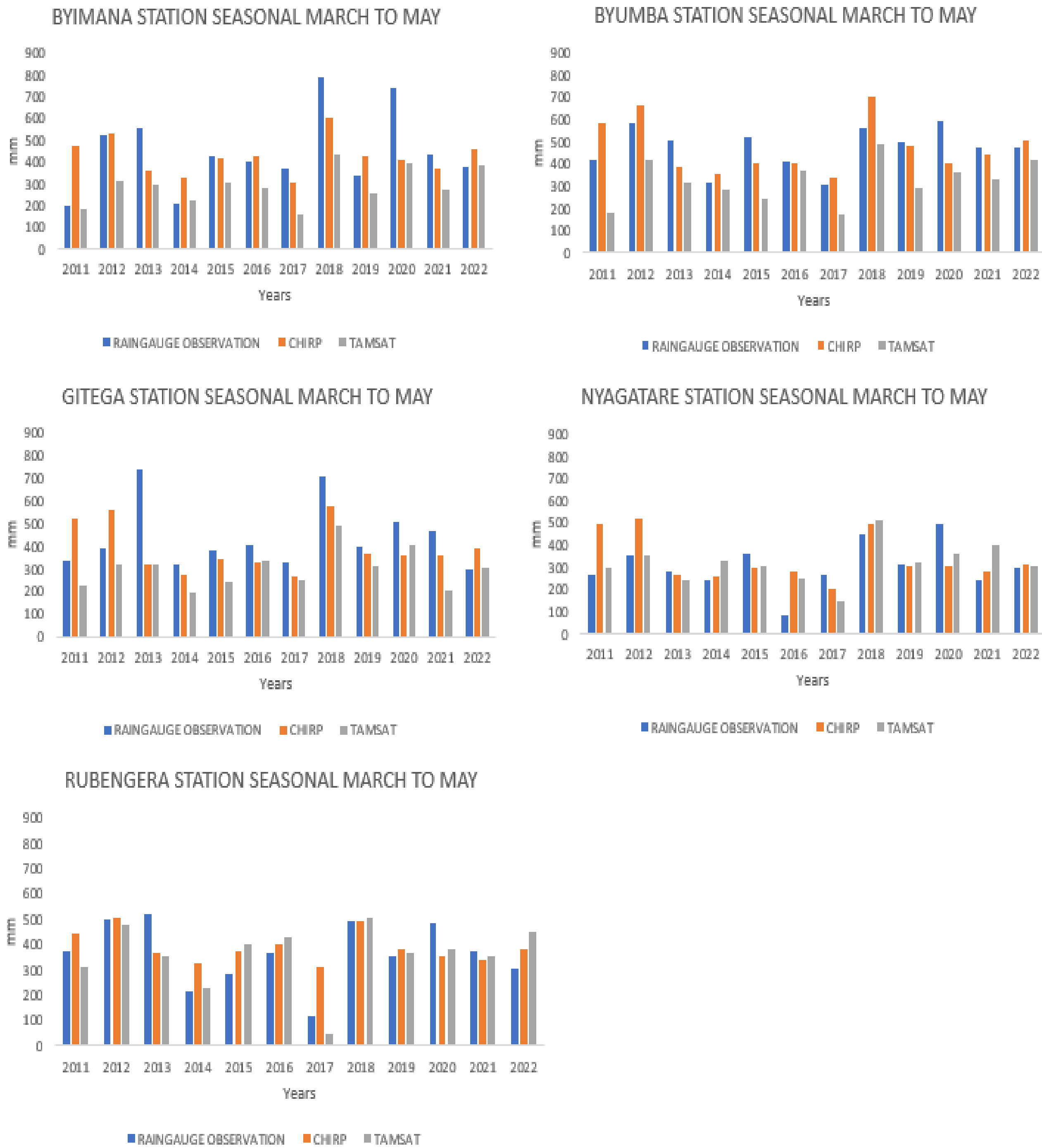

Figure 4: **Performances result for the Seasonal rainfall (March to May) estimates between Rain gauge and CHIRP, TAMSAT**

The result from figure 5, the kriging interpolation of seasonal measures for March to May (MAM), with ground observations ranging from high 471.931 to low 305.203, was compared against CHIRP and TAMST datasets. Both CHIRP and TAMST provided high and low measure estimates, with high values at 470.815 and low values at 334.701.

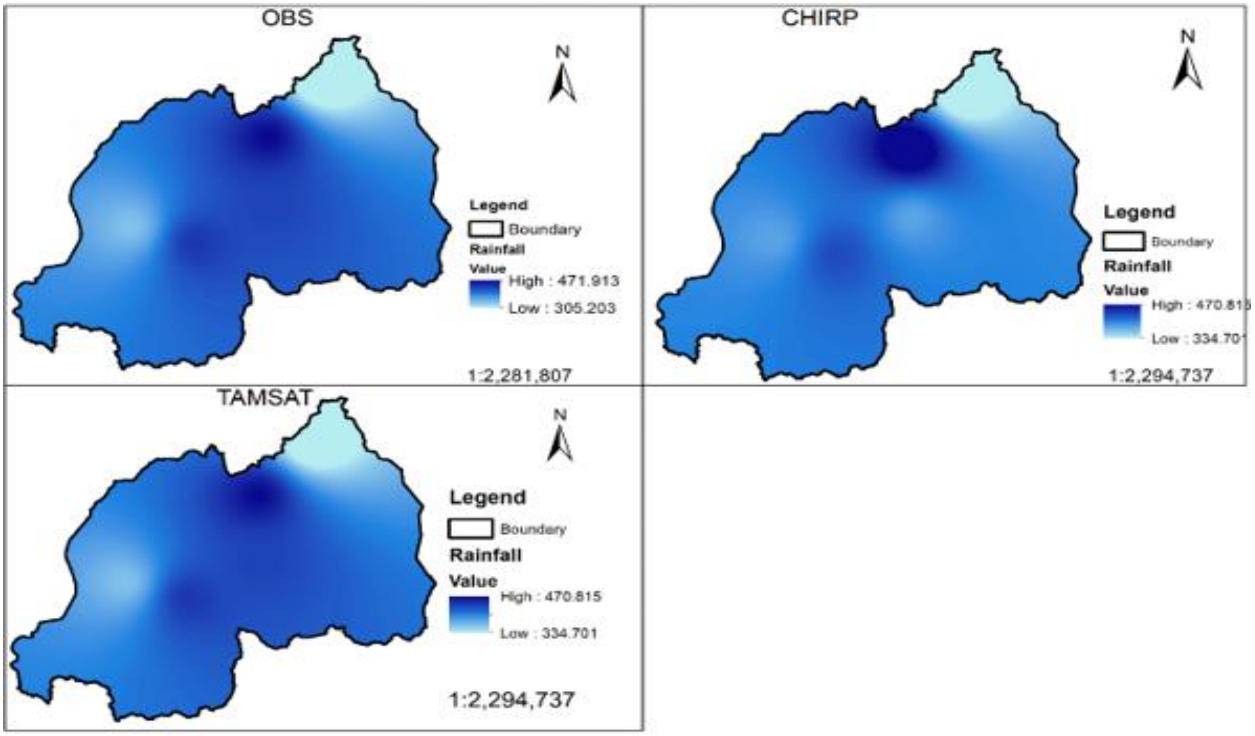

Figure 5: Rainfall distribution in March to May Season Kriging interpolation

Based on Table 4 and figure 6, the results you provided for the coefficients of correlation, BIAS, RMSE, Nash and Sutcliffe efficiency (NSE), and Index of Agreement (IOA) for CHIRP and TAMSAT at various weather stations in Rwanda, specifically for the seasonal (October to December) climatology, let's discuss the performance of the two rainfall estimation methods:

The coefficients of correlation vary across stations and methods. In some cases, CHIRP shows lower correlation coefficients compared to TAMSAT, indicating a weaker relationship between CHIRP's estimates and the observed rainfall data.

Both CHIRP and TAMSAT tend to have positive BIAS values at all stations, suggesting a tendency to overestimate the actual observed rainfall. The BIAS values for both methods are close in most cases, with small differences between them.

The RMSE values for both CHIRP and TAMSAT show variations across stations. In some cases, TAMSAT has lower RMSE values than CHIRP, indicating that TAMSAT's estimates have smaller errors compared to the observed data.

The NSE values for both methods vary across stations, showing a mix of positive and negative values. Negative NSE values suggest that the methods have limitations in capturing the observed rainfall variability during the specified time frame.

The IOA values indicate the agreement between estimated and observed data. TAMSAT generally shows higher IOA values compared to CHIRP at most weather stations, suggesting that TAMSAT's estimates have better agreement with the observed data during this seasonal period.

Overall, the results from this specific seasonal climatology period are mixed. TAMSAT shows better performance in terms of IOA at most stations, suggesting better agreement with the observed data during October to December. However, CHIRP and TAMSAT exhibit similar BIAS values, and the performance differences are not as consistent across stations as seen in previous scenarios.

Table 4: Performances result for the Seasonal rainfall (October to December) estimates between Rain gauge and CHIRP, TAMSAT

		CHIRP			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.288	0.315	0.232	0.419	0.007
BIAS	0.863	0.965	0.777	0.985	0.758
RMSE	156.47	101.2	152.862	144.068	157.195
NSE	-0.084	-0.322	-0.54	-3.087	-1.342
IOA	0.293	0.51	0.295	0.684	0.473
		TAMSAT			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.764	0.213	0.578	0.528	0.087
BIAS	0.979	1.121	0.941	1.164	0.935
RMSE	113.873	112.502	102.024	118.171	129.627
NSE	0.468	-0.634	0.277	-1.536	-0.52
IOA	0.41	0.92	0.413	0.893	0.612

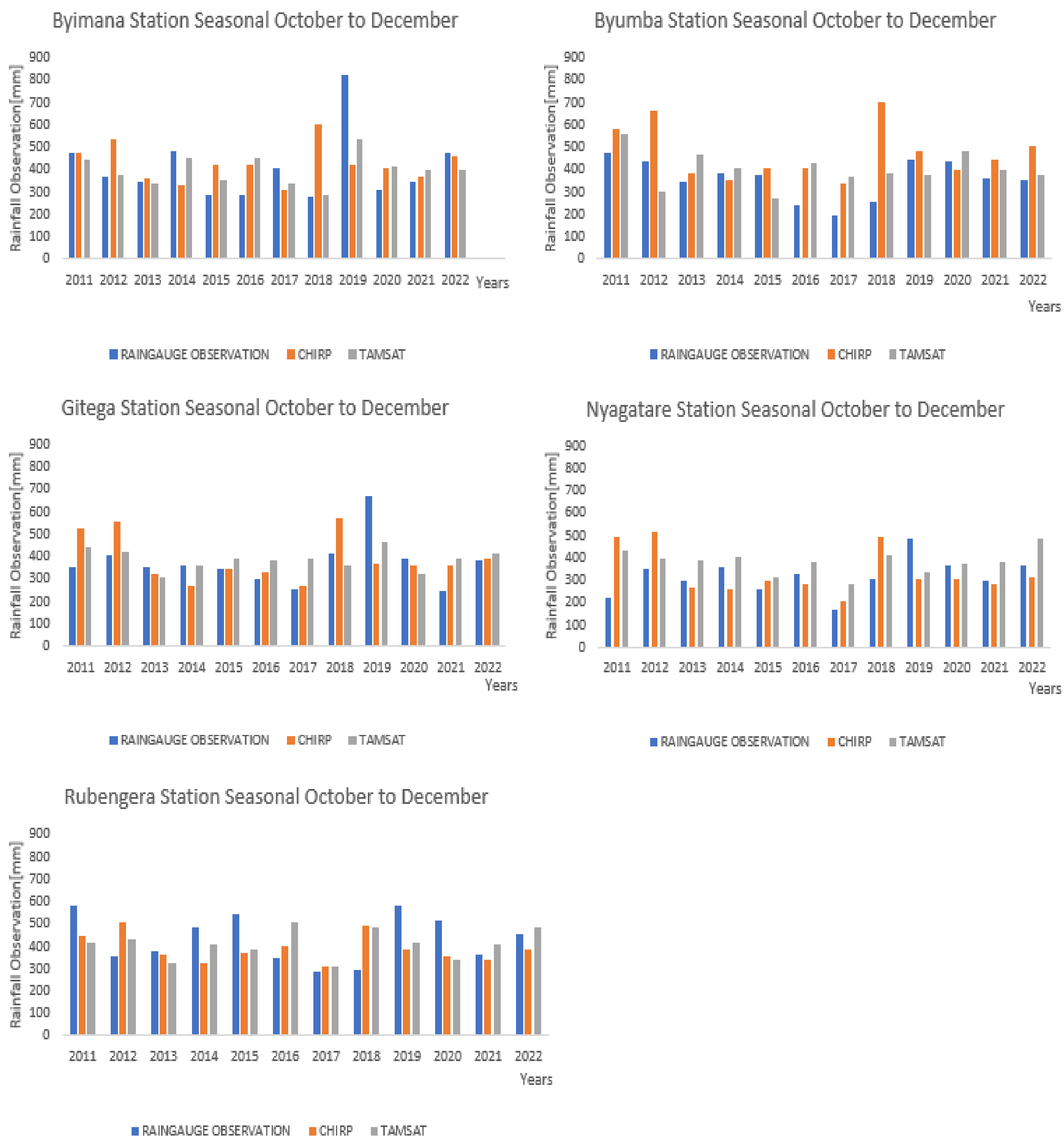

Figure 6: Performances result for the Seasonal rainfall (October to December) estimates between Rain gauge and CHIRP, TAMSAT

The result from figure 7, the kriging interpolation of seasonal rainfall measures for September to December (SOND), based on ground observations ranging from a high of 544.659 to a low of 363.159, was compared against CHIRP and TAMST datasets. CHIRP provided high and low measure estimates of 465.314 and 397.499, respectively, while TAMST estimates were 537.94 for high and 477.283 for low measures.

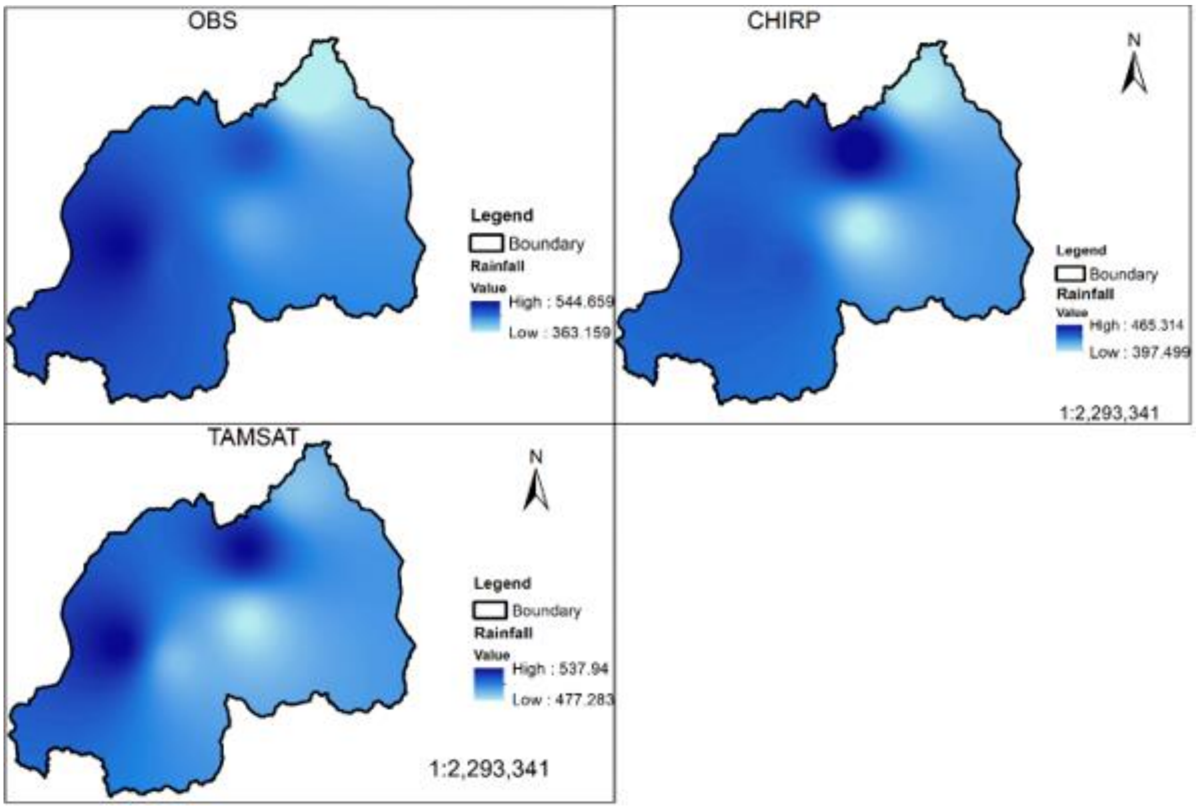

Figure 7: Rainfall distribution in October to December (OND) Seasonal kriging interpolation

4.3 Annual Rainfall

Based on table 5 and figure 8, the results you provided for the coefficients of correlation, BIAS, RMSE, Nash and Sutcliffe efficiency (NSE), and Index of Agreement (IOA) for CHIRP and TAMSAT at various weather stations in Rwanda, particularly using the annual rainfall climatology, let's discuss the performance of the two rainfall estimation methods:

The coefficients of correlation vary across stations and methods. Both CHIRP and TAMSAT show a mix of weak to moderate correlation coefficients. In some cases, TAMSAT has slightly higher correlation coefficients compared to CHIRP.

Both CHIRP and TAMSAT tend to have positive BIAS values at all stations, indicating a general tendency to overestimate the actual observed rainfall. The BIAS values for both methods are relatively close in most cases, with only slight variations between them.

The RMSE values for both CHIRP and TAMSAT vary across stations. TAMSAT sometimes exhibits slightly lower RMSE values compared to CHIRP, suggesting that TAMSAT's estimates have slightly smaller errors compared to the observed data.

The NSE values for both methods are mostly negative across stations, indicating challenges in capturing the observed rainfall variability. The NSE values are generally low, which means that neither CHIRP nor TAMSAT are capturing the observed patterns well using this metric.

The IOA values indicate that the agreement between estimated and observed data is relatively low for both CHIRP and TAMSAT at most stations. The IOA values are generally moderate, suggesting that there is room for improvement in terms of agreement between the estimates and observations.

Overall, the results from the annual rainfall climatology show that both CHIRP and TAMSAT have limitations in accurately estimating rainfall across different weather stations in Rwanda. The methods tend to overestimate rainfall, and their performance in terms of correlation, RMSE, NSE, and IOA is relatively modest.

Table 5: Performances result for the Annual rainfall estimates between Rain gauge and CHIRP, TAMSAT

		CHIRP			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.268	0.579	0.209	0.211	0.331
BIAS	0.877	0.897	0.88	1.079	0.848
RMSE	271.763	256.591	376.054	305.34	275.513
NSE	-0.839	-0.26	-1.984	-0.897	-1.406
IOA	0.54	0.719	0.319	0.405	0.473
		TAMSAT			
STATION	BYIMANA	BYUMBA	GITEGA	NYAGATARE	RUBENGERA
LON	29.71	30.05	30.06	30.31	29.41
STATS/LAT	-2.16	-1.59	-1.96	-1.28	-2.07
CORR	0.537	0.633	0.132	0.508	0.393
BIAS	0.827	0.875	0.939	1.217	0.924
RMSE	278.673	249.713	288.334	275.352	257.818
NSE	-0.776	-0.094	-0.624	-0.418	-0.939
IOA	0.41	0.92	0.413	0.893	0.612

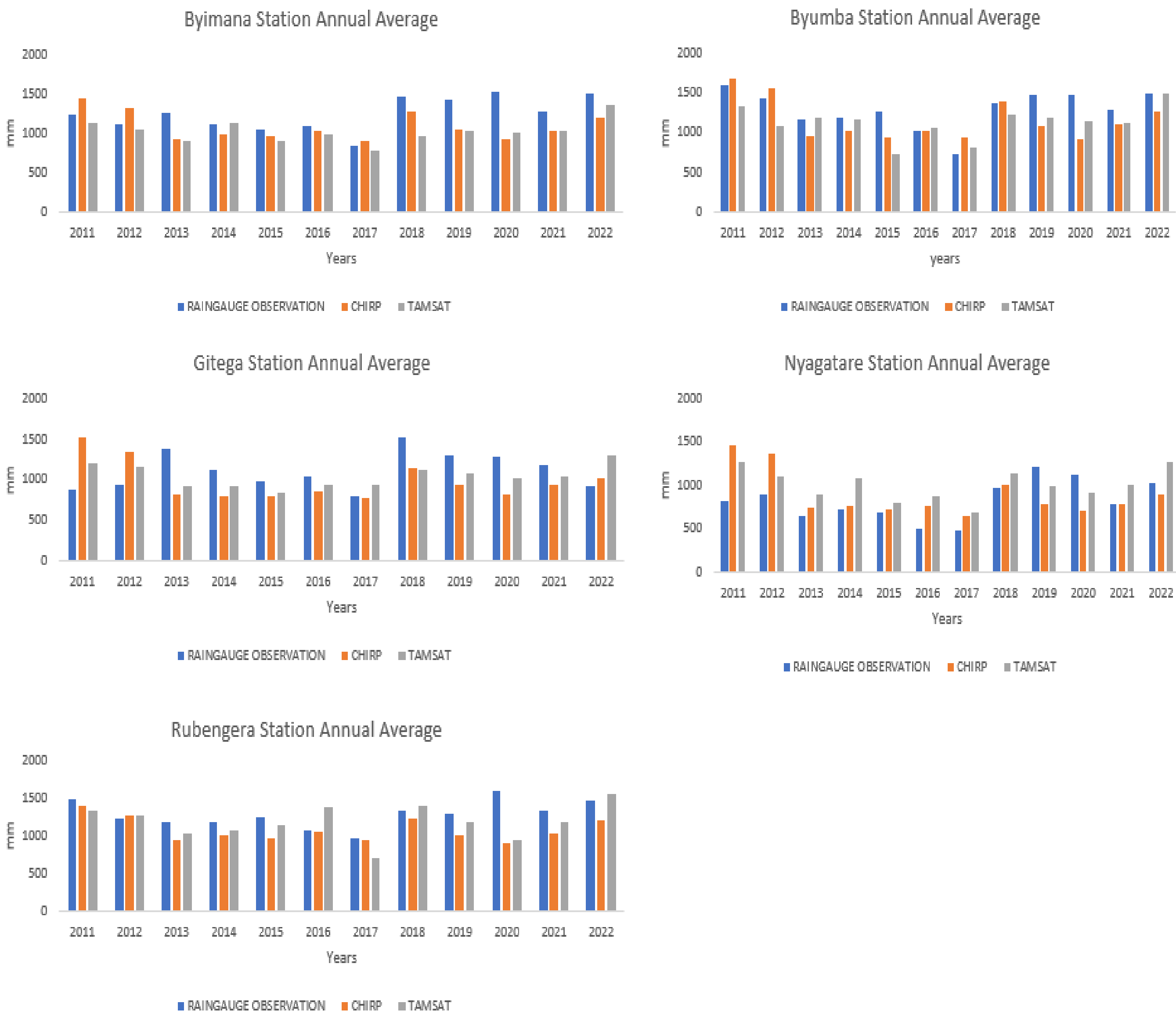

Figure 8: Performances result for the Annual rainfall estimates between Rain gauge and CHIRP, TAMSAT

The result from figure 9, the kriging interpolation of annual rainfall distribution, utilizing ground observations ranging from a high of 1285.46 to a low of 882.256, was compared against CHIRP and TAMST datasets. CHIRP provided high and low measure estimates of 1152.77 and 887.042, respectively, while TAMST estimates were 1182.43 for high and 1005.28 for low measures.

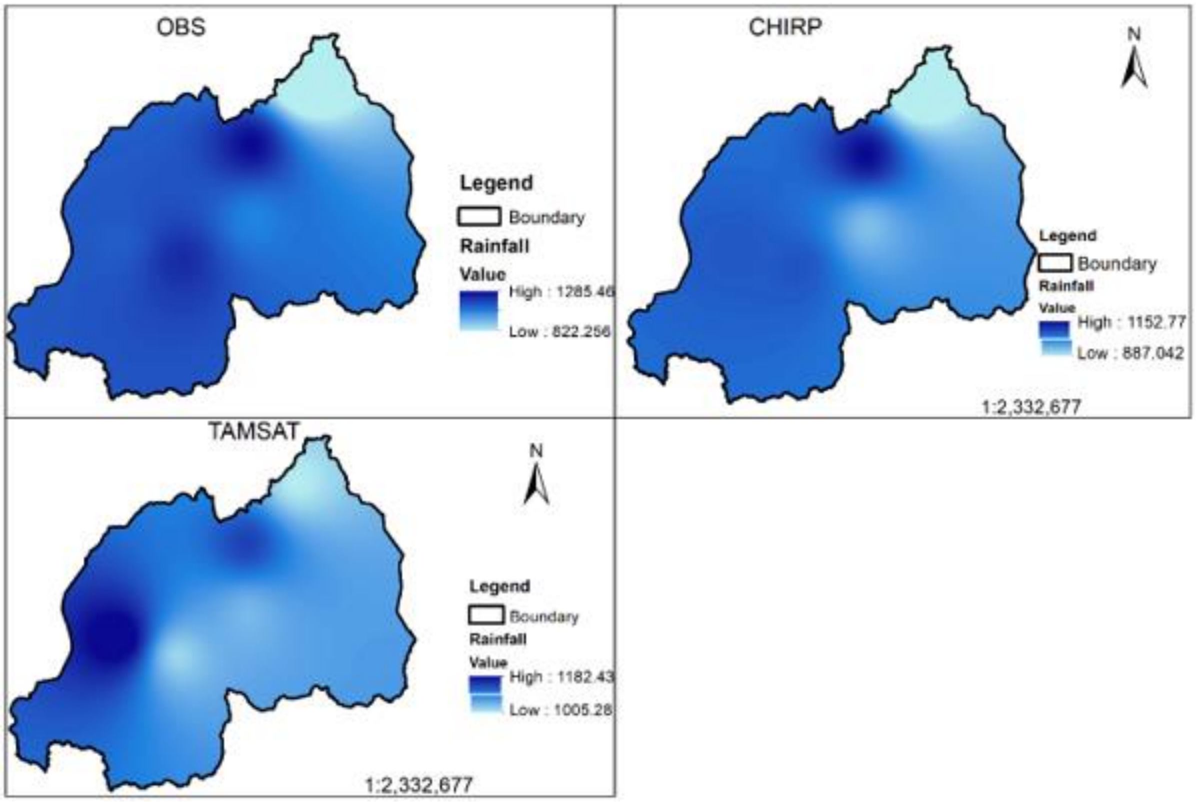

Figure 9: Annual rainfall distribution kriging interpolation

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

After conducting a comprehensive evaluation of CHIRP (Climate Hazards Group Infrared Precipitation) and TAMSAT (Tropical Applications of Meteorology using SATellite data and ground-based observations) rainfall products in assessing rainfall over Rwanda, several key findings have been observed.

Both CHIRP and TAMSAT products showed the ability to capture the temporal pattern of rainfall in Rwanda, with reasonable accuracy. However, certain differences were identified in their performance. CHIRP demonstrated consistent accuracy in estimating rainfall in most regions of Rwanda, displaying minimal biases during the rainy season. On the other hand, TAMSAT exhibited some challenges in accurately estimating rainfall, particularly during heavy rainfall events and in regions with complex topography.

During the validation process, it was observed that both CHIRP and TAMSAT products had some deviations from ground observations. These discrepancies might be attributed to factors such as gauge density, interpolation methods, and inherent limitations of satellite-based rainfall estimates. Nonetheless, despite these discrepancies, both products provided valuable and complementary information that can be utilized for various applications, including agricultural planning, water resource management, and disaster preparedness.

5.2 RECOMMENDATION

Based on the findings of this research, the following recommendations are proposed to improve the accuracy and usability of CHIRP and TAMSAT rainfall products for Rwanda:

Improve Gauge Density: Enhancing the density and distribution of rain gauges across Rwanda will significantly contribute to the accuracy of ground-based rainfall observations. Additional gauge data will help in better calibrating and validating satellite-based rainfall products, thereby reducing uncertainties in their estimates.

Enhanced Spatial Resolution: Efforts should be made to enhance the spatial resolution of both CHIRP and TAMSAT products, especially in regions with complex terrain. High-resolution data will enable more precise rainfall estimates and address the challenges associated with capturing localized rainfall patterns.

Satellite Data Fusion: Investigate the possibility of combining different satellite data sources and rainfall products to create more accurate and reliable rainfall estimates for Rwanda. Data fusion techniques can leverage the strengths of individual products and minimize their weaknesses.

Local Calibration and Validation: Conducting local calibration and validation exercises specific to different regions in Rwanda can improve the accuracy of rainfall estimates. Different regions may exhibit unique rainfall characteristics, and region-specific calibrations can enhance the performance of rainfall products at a local scale.

Public Outreach and Capacity Building: Enhance public awareness among stakeholders, including farmers, water resource managers, and disaster response agencies, about the strengths and limitations of CHIRP and TAMSAT products. Capacity building workshops and training sessions can empower users to make informed decisions based on satellite-based rainfall information.

Continuous Product Improvement: Encourage the research and development of both CHIRP and TAMSAT products to continually enhance their accuracy and reliability. Collaboration between meteorological agencies, research institutions, and international organizations can facilitate product improvement through the incorporation of new data and methodologies.

By implementing these recommendations, Rwanda can benefit from more accurate and reliable rainfall information, leading to improved decision-making in various sectors, ultimately contributing to the country's sustainable development and resilience to climate variability and change.

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ANNEX

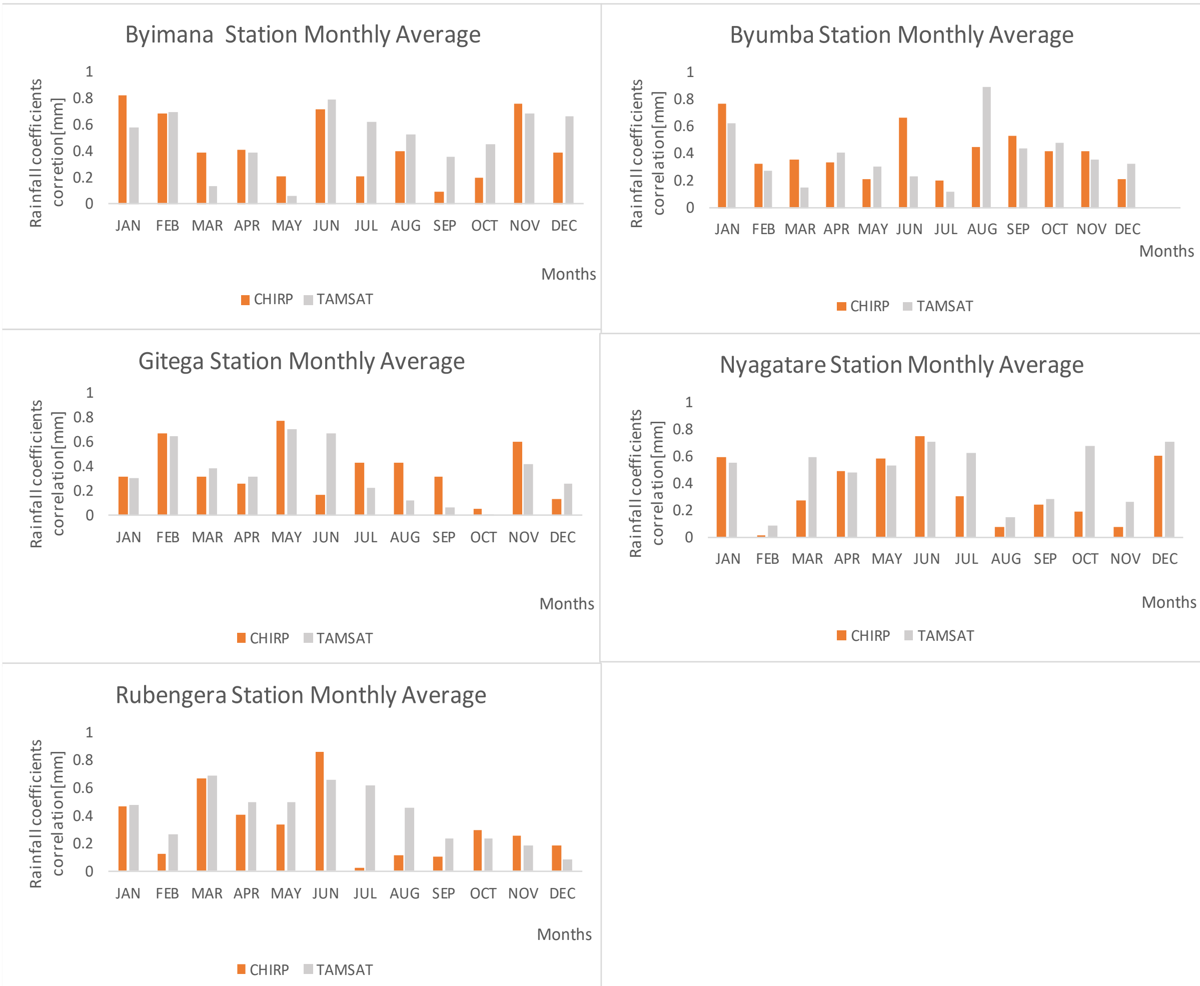

Figure 10: Monthly average Rainfall coefficients correlation

Figure 11: Monthly average RSME

Figure 12: Monthly average rainfall NSE

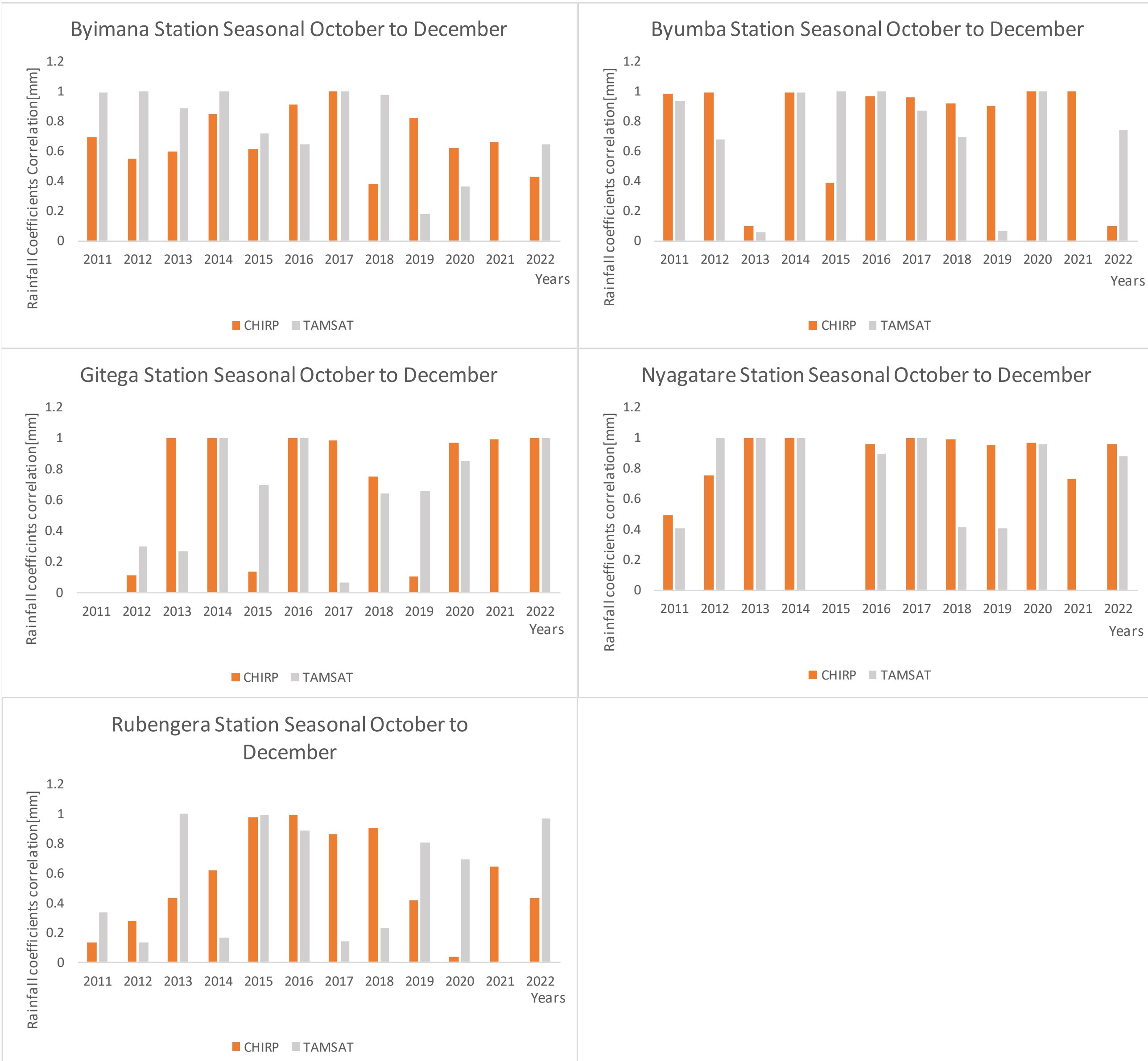

Figure 13: Seasonal Rainfall coefficients correlation October to December (OND)

Figure 14: Seasonal Rainfall BIAS October to December (OND)