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Evaluation and Comparison of Remote Sensing Based Precipitation Products in Casamance basin, SENEGAL

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Declaration

I, AICHA MARIE AUGUSTINE NDECKY hereby declare that this thesis represents my personal work, realized to the best of my knowledge. I also declare that all information, material and results from other works presented here, have been fully cited and referenced in accordance with the academic rules and ethics.

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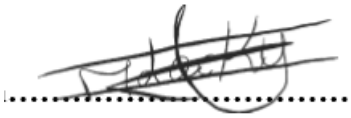

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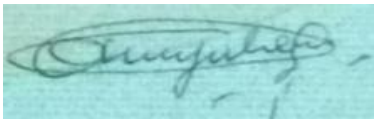
Certification

The undersigned certifies that they have read and hereby recommend for the acceptance by the Pan Africa University Institute of Water and Energy Sciences, a dissertation entitled "**Evaluation and Comparison of Remote Sensing Based Precipitation Products in Casamance basin, SENEGAL",** in fulfillment of the requirements for the Master degree in Water Engineering (WE).



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Dedication

I dedicate this work to my father Yves Ndecky and my mother Patricia Kantoussan who have always supported me unconditionally in all my projects,

To my sisters Rachelle Ndecky, Anilda Bacourine and my brothers Christophe Adams Ndecky, Michael Alex Ndecky, John Ismael Ndecky, Pascal Rudolph Amance Ndecky, Jean Claude Boris Ndecky, Stephane Anselme Ndecky who have always encouraged me to move forward and to be persevering to achieve my goals.

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Abbreviations and Acronyms

AMSL	Above Mean Sea Level
AMMA	African Monsoon Multidisciplinary Analyses
AMSR-E	Advanced Microwave Scanning Radiometer-Earth
AMSU-B	Advanced Microwave Sounding Unit-B
ARC 2	Africa Rainfall Estimate Climatology Version 2
BIAS	Relative Bias
BK	Block kriging
CC	Correlation Coefficient
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station Data
CMORPH	Climate Prediction Center's morphing technique
CPC	Climate Prediction Center
CSI	Critical Success Index
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
EPSAT	Estimation of Precipitation by Satellite
EROS	USGS Earth Resources Observation and Science Center
ESA	European Spatial Agency
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FAR	False Alarm Ratio
FBI	Frequency Bias Index
GIZ	Gesellschaft fur International Zusammenarbeit
GOES	Geostationary Operational Environmental Satellite
GPCP	Global Precipitation Climate Project
GPI	Precipitation index.
GSFC	Goddard Space Flight Center
GSMaP	Global Satellite Mapping of Precipitation
GTS	Global Telecommunications System

IDW	Inverse Distance Weighting
IR	Infrared
LAI	Leaf Area Index
MODIS	Moderate Resolution Imaging Spectroradiometer
NAP	National Adaptation Plan
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
OK	Ordinary kriging
PERSIANN-CDR	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record
PMW	Passive microwaves
PMW	Multi-pass microwave
POD	Probability of detection
PR	TRMM radar
RFE 2	African Rainfall Estimation Version 2
RMSE	Root Mean Square Error
SMI	Soil Water Index
SSM	Soil Surface Moisture
SSM/I	Special Sensor Microwave / Imager
TAMSAT	Tropical Applications in Meteorology using Satellite data
TARCAT	African Rainfall Climatology and Time-series
TIR	Thermal infrared
TMI	Microwave Imager
TMPA	Multi-satellite Precipitation Analysis Algorithm
TRMM	Tropical Rainfall Measuring Mission

Abstract

The role that rainfall can play in monitoring climate, floods and drought, but also in several socio-economic activities, namely agriculture and water resources management in Africa and especially in Senegal is very important. However, the availability and accessibility of these rainfall data are difficult due to the low number of functional rainfall station networks providing complete and reliable data, but also due to the high cost of these rainfall data. The use of remote sensing, through rainfall products, could be considered as an alternative to this problem. To be sure of obtaining complete and reliable data, evaluation and comparison studies of these satellite products are necessary to validate their effectiveness for efficient use in a given area. Our study is based on the evaluation and comparison of precipitation products derived from remote sensing in the Casamance basin, located in Southern Senegal. Under the influence of the Southern Sudanese climate, the basin covers an area of 20150 km^2 with relatively flat landforms and low altitudes. There are two types of seasons: the rainy season and the dry season. Four remote sensing derived rainfall products have been considered; ARC 2, RFE 2, CHIRPS-0.05 and TRMM-3B42RT. The evaluation of these rainfall products, over the Casamance basin, was carried out at four-time steps: daily, monthly, annual and seasonal using statistical equations, statistical tests and an assessment of the accuracy of the rainfall products on the spatial distribution of rainfall. The results obtained from the daily assessment showed a weak correlation between the estimated rainfall data from remote sensing derived rainfall products and the observed data from the rainfall stations. However, ARC 2 and CHIRPS presented the best correlation and comparatively lower, RMSE, MAE and BIAS results. Evaluation of estimated monthly rainfall from remote sensing derived rainfall products showed good performance of CHIRPS-0.05 with the best statistical results (r=0.90, RMSE=66.80, MAE=32.01 and BIAS=0.99). ARC 2 and RFE 2 also performed well with correlations 0.85 and 0.70, respectively. However, RFE 2 obtained a high RMSE, MAE and BIAS. TRMM-3B42RT performed worst with a negative correlation (-0.55). Despite the good results recorded by the rainfall products at the monthly time scale, low correlations ranging from 0.46 to -0.31 were obtained as results from the analysis of annual rainfall. The observed maximum rainfall amounts were underestimated by ARC 2, CHIRPS-0.05 and RFE 2. However, CHIRPS overestimated the average amount of observed rainfall. The tendency of CHIRPS to overestimate precipitation and of ARC 2 and RFE 2 to underestimate it was further demonstrated during the spatial assessment of precipitation. This analysis also showed that the difference in altitudes could affect the accuracy of remote sensing products in estimating precipitation. Seasonal changes also have an impact on remote sensing derived rainfall products estimates. Overall, the results obtained highlighted the good performance of CHIRPS-0.05 and ARC 2 rainfall products and the poor performance of TRMM-3B42RT product on all time scales at Casamance basin in Senegal. On the other hand, RFE 2 performed well only with monthly time scale and spatial rainfall assessments and poorly with daily and annual time scale assessments.

Résumé

Le rôle que peut jouer la pluviométrie dans la surveillance du climat, des inondations et de la sécheresse, mais aussi dans plusieurs activités socio-économiques, à savoir l'agriculture et la gestion des ressources en eau en Afrique et spécialement au Sénégal est très important. Cependant, la disponibilité et l'accessibilité à ces données de précipitation sont difficiles en raison du nombre faible de réseaux de stations pluviométriques fonctionnelles permettant d'obtenir des données complètes et fiables mais aussi du coût élevé de ces données de précipitations. L'utilisation de la télédétection à travers les produits de précipitations pourrait être considérer comme une alternative à ce problème. Pour avoir l'assurance de pouvoir obtenir des données complètes et fiables, des études d'évaluation et de comparaison de ces produits satellitaires sont nécessaires afin de valider leur efficacité pour une utilisation efficiente sur une zone donnée. Notre étude est basée sur l'évaluation et la comparaison de produits de précipitation dérivés de la télédétection sur le bassin de la Casamance. La zone d'étude est localisée au Sud du Sénégal. Sous l'influence du climat du Sud-Soudanien, le bassin couvre une superficie de 20150 km^2 avec des reliefs relativement plats et de faibles altitudes. Quatre produits d'estimation des précipitations ont été considérés ; ARC 2, RFE 2, CHIRPS-0,05 et TRMM-3B42RT. L'évaluation de ces produits sur le bassin de la Casamance a été effectuée à quatre pas de temps : journalier, mensuel, annuel et par saison utilisant des équations statistiques, des tests statistiques et une évaluation de la précision des produits d'estimation des précipitations sur la distribution spatiale des précipitations. Les résultats obtenus de l'évaluation journalière ont montré une faible corrélation entre les données pluviométriques estimées des produits de précipitations et les données observées des stations pluviométriques. Cependant, ARC 2 and CHIRPS ont présenté les meilleurs résultats de corrélation, RMSE, MAE et BIAS. L'évaluation des précipitations mensuelles estimées des produits satellitaires a mis en évidence la bonne performance de CHIRPS-0,05 avec les meilleurs résultats statistiques (r=0,90, RMSE=66,80, MAE=32.01 et BIAS=0,99). ARC 2 et RFE 2 ont eu aussi une bonne performance avec des corrélations 0,85 et 0,70 respectivement. Cependant, RFE 2 a obtenu un RMSE, un MAE et un BIAS élevés. TRMM-3B42RT a enregistré une corrélation négative (-0,55). Malgré les bons résultats enregistrés par les produits d'estimation des précipitations à l'échelle de temps mensuelle, de faibles corrélations allant de 0,46 à -0.31 ont été obtenues comme résultats à l'issu de l'analyse des précipitations annuelles. Les quantités maximales de précipitations observées ont été sous-estimées par ARC 2, CHIRPS-0.05 et RFE 2. Cependant, CHIRPS a surestimé la quantité moyenne des précipitations observées. La tendance de CHIRPS à surestimer les précipitations et d'ARC 2 et RFE 2 à les sous-estimer a été encore démontrée au cours de l'évaluation spatiale des précipitations. Cette analyse a aussi montré que la différence des altitudes pourrait avoir effet sur la précision des produits de télédétection à estimer les précipitations. Le changement des saisons a aussi un impact sur les estimations des produits de précipitation. Les résultats obtenus, dans l'ensemble, ont mis en évidence la bonne performance de CHIRPS-0,05 et d'ARC 2 et la mauvaise performance de TRMM-3B42RT à toutes les échelles de temps. Par contre, RFE 2 a eu une bonne performance qu'avec les évaluations à l'échelle de temps mensuel et à l'évaluation spatiale des précipitations et une mauvaise performance à l'échelle de temps quotidien et annuel.

1. INTRODUCTION

Assessing the occurrence of certain natural phenomena such as floods and drought requires the analysis of rainfall data (Labbe, 2016). Rainfall data are the basis to study on the return periods of an event which can be a period of drought or very heavy rainfall leading to flooding (Panthou, 2013). These phenomena have very important socio-economic impacts: displacement of the population, destruction of crops and infrastructure (Cabral, 2012), destruction of hydraulic infrastructure, increase in the rate of water-borne diseases, (Sene & Ozer, 2002; Panthou, 2013) etc. The adaptation of adequate preventive measures requires in-depth and detailed knowledge of the causes (floods, drought, etc.). This implies a study on the characteristics of precipitations in time and space. A better understanding of rainfall calls for a complete and up-to-date database of rainfall, which plays an important role in several fields, including the construction and management of hydraulic infrastructure (dams, sewerage pipes, etc.), land use planning, the study of river behaviour (hydrology), hydrogeology, agriculture, etc.

Unfortunately, precipitation is highly variable; its excess can cause floods while its deficits lead to drought, famine and the scarcity of water resources. Rainfall is one of the main factors regulating the rainwater harvesting in West Africa. It is one of the components of the global climate system. Its characterization is important for preventing water-related risks and predicting its fate in a changing climate (Vischel et al., 2015). Detailed information on rainfall pattern is required to manage natural hazards such as floods, landslides, debris flows, and drought by using rainfall models (Bâ et al., 2018).

Rainfall analysis in West Africa is most often carried out from data collected from rainfall stations. However, the availability and access to these data are often problematic (in terms of its availability (data scarcity) and quality (Bodian, 2014; Panthou, 2013). The alternative for addressing this lack of data availability is the application and use of remote sensing derived rainfall products. Advanced remote sensing sensors provide huge rainfall data around the globe at regular gridded format and at continuous time intervals ranging from 30 minutes interval to daily time steps. However, the use of such data requires first their evaluation (accuracy assessment) and comparison between different products based on the ground measured data in order to test their performance over a specific area. Few researches related to rainfall analysis has been done in Senegal; the assessment of wet and dry periods using remote sensing that was done by Fall et al. (2019). The team compared the

characteristics of wet and dry periods in Senegal using rainfall measurements from satellites, rain gauges and reanalysis data. The evaluation of the estimates for these different products indicated that periods of drought are mainly characterized by false starts and early cessation of the rainy season. The detection of the intensity of wet indicators by the same products revealed a significant contrast; which led to a large ambiguity in the assessment of the critical shortfall and overrun of rainfall (wet periods) on the intra-seasonal scale. The comparison of rainfall estimates by satellite products and reanalysed models on wet and dry periods led them to conclude that all these data sets used during the study are valid for the Senegalese territory and could be extended to the rest of West Africa (Fall et al., 2019).

Remote sensing is applied in several fields such as natural and water resource management, land use management (vegetation variability, agriculture), etc. Agriculture is one of Senegal's main economic sectors and therefore plays a major role in socio-economic life. Given that Senegal is characterized by two seasons (dry season and rainy season), the evaluation of the impact of these seasons on agriculture requires the study of rainfall, which leads to study the behaviour of the different seasons that prevail in Senegal, sometimes using remote sensing in case of non-availability of ground measured data (Bégué et al., 2016; Bacci et al., 2013). Remote sensing was used to study the impacts of intra-seasonal rainfall variability on vegetation in the Ferlo zone of Senegal. The study showed that of the two precipitation products used (TRMM-3B42 and RFE 2.0), RFE performed better than TRMM on the analysis of intra-seasonal rainfall variations with simulations. These simulations using Leaf Area Index (LAI) data from Moderate Resolution Imaging Spectroradiometer (MODIS) reproduce the dynamics of vegetation during the growth phase (Cissé, 2016).

These remote sensing derived rainfall products have been evaluated in several countries in Africa such as a satellite-based rainfall assessment and model re-analysis and over the Senegal River (Fall et al., 2019). The analysed products have shown a great similarity in their temporal frequencies and a seasonal spatial cohesion of accumulated rainfall with a high variability of intra-seasonal characteristics. The drought indicator that was highlighted most often marked a false start and an early end of the rainy season. However, it rarely occurs during the West African monsoon season (August - September). The assessment of wet indicators has given rise to great uncertainty (Fall et al., 2019).

Bâ et al. (2018) have analysed the PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record) rainfall assessment for the Bani River and Upper Senegal River basins for an evaluation of

hydrological modelling at the zone level where ground observations were not sufficient. As rainfall data are the main input data to the hydrological model CEQUEAU; the analysis of the rainfall estimates recorded by PERSIANN-CDR was carried out and the results showed good performance. PERSIANN-CDR data product can be used for rainfall simulation and thus serve as an input data source for hydrological modelling (simulation of river flow and runoff) and water resources management. The analysis of the performance of satellite rainfall products is necessary to identify and select the most suitable rainfall product for the application area and the region to be studied. It is in this context that a study carried out in Burkina Faso by Dembélé and Zwart (2016), on the evaluation and comparison of seven satellite rainfall products, had shown that the choice of a product depended on the indicated application and several other factors (a combination of data, size of the grid, time step) but also on the topographical and climatic characteristics of the study area; For example, in this study, the results had led to the conclusion that the rainfall products ARC, RFE and TARCAT could be used for drought monitoring, and PERSIANN, CHIRPS and TRMM could be used for daily flood monitoring in Burkina Faso. In the same context, the performance of CHIRPS compared with TAMSAT 3 and ARC 2 in the Blue Nile basin region of Ethiopia was evaluated. The evaluation was based on categorical, volumetric and continuous statistics. Thus, from the results obtained, Ayehu et al. (2018) highlighted the good performance of CHIRPS rainfall product for use in rainfall regime and variability analysis as well as other operational applications in the Upper Blue Nile Basin in Ethiopia.

1.1 Problem Statement

Precipitation is one of the most important factors in the hydrological cycle and plays a key role in the global energy system (Zen et al., 2018). It is an important input data for hydrological models to simulate the water balance components (Bâ et al., 2018).

The study of precipitation requires obtaining and updating data at the station level. However, in the developing world, data rainfall has several gaps. Also, the rainfall stations are scare and do not cover all the geographical area. Particularly in West Africa, not all measuring stations operate (silently) due to lack of continuous maintenance and monitoring. The lack of funding for the establishment of new stations or the renovation of old ones is also a major cause of this gap; Senegal is no exception. The rainfall data obtained at the gauging stations are considered as accurate (as they are measured directly). However, the rainfall gauging stations are not well distributed and there has been several data gaps and non-availability of

sufficient rainfall gauging stations in several basins in Africa. The advanced remote sensing technology is another fascinating method to determine the rainfall estimates indirectly without being on ground and without extra efforts, free of cost. There are several remote sensing derived rainfall products available. However, the accuracy of different products differs significantly for the area of interest and hence, before the application of remote sensing derived rainfall products, their accuracy needs to be evaluated and verified against the ground measured data and a inter comparison and selection of best rainfall product for the area of interest should be a pre requisite (Bâ et al., 2018).

1.2 Objectives And Research Questions

1.2.1 Main objective

The overall aim of this research is to evaluate and compare commonly used remote sensing derived precipitation products for the Casamance basin in Senegal.

1.2.2 Sub-objectives

- → Analyse the rainfall characteristics at Casamance basin.
- → Evaluate the performance of remote sensing derived rainfall products using ground measured data.
- → Comparison of different remote sensing derived rainfall products for the Casamance basin.
- → Evaluate the spatiotemporal variation of rainfall in Casamance basin.
- → Determine the more indicated and adequate remotely sensed rainfall product for Casamance basin.

1.2.3 Research questions

- ❖ What are the remote sensing derived rainfall products that are likely to be suitable for the Casamance basin?
- ❖ How do remote sensing derived rainfall products behave on different time scales?
- ❖ Which remote sensing derived rainfall product is more accurate for the study area?

1.3 Thesis Organization

The thesis is organized in seven chapters:

Chapter 1 is the section of general introduction.

Chapter 2 is the presentation and description of the study area including the geographical, climatic and topographical situations of the Casamance basin.

Chapter 3 is the literature review including the definition and principles of remote sensing, the basic operation of remote sensing, remote sensing techniques for rainfall measurement and the description of precipitation products based on remote sensing.

Chapter 4 is the methodology including criteria for selection of rainfall products and the brief description of statistical methods.

Chapter 5 is the section of results and discussion including the statistical analysis of observed rainfall, the daily rainfall assessment, the assessment of statistics for the detection of rainy and no rainy days, the monthly rainfall assessment, the annual rainfall assessment and the evaluation of spatial rainfall.

Chapter 6 is the general discussion.

Chapter 7 is the section of conclusion and recommendations.

2. CASE STUDY

2.1 Geographical Situation

Administratively, the southern Senegalese region is composed of three regions: Ziguinchor, Sédhiou and Kolda. Our study area Casamance basin is located in these three regions and extends over an area of about 20150 km^2, with a length of 270 km from west to east, and a width of 100 km from north to south (Dacosta, 1989; Faye et al., 2019). Casamance basin is subdivided into three parts according to the regions. The region of Ziguinchor belongs to lower Casamance, for the region of Sédhiou belongs to Middle Casamance and for the region of Kolda belongs to Upper Casamance. The Casamance basin is located between 12°20' and 13°21' north latitude and between 14°17' and 16°47' west longitude (Faye, 2018; Faye et al., 2019). To the north of the basin is the Gambia basin, to the south the Rio Cacheu and the east the Kayanga basin (Dacosta, 1989). Our study area Casamance basin and the spatial distribution of rainfall stations are shown in Figure 1.

Most economic activities in Casamance generally depend on the rainy season, as the majority of population belongs to rice farmers.

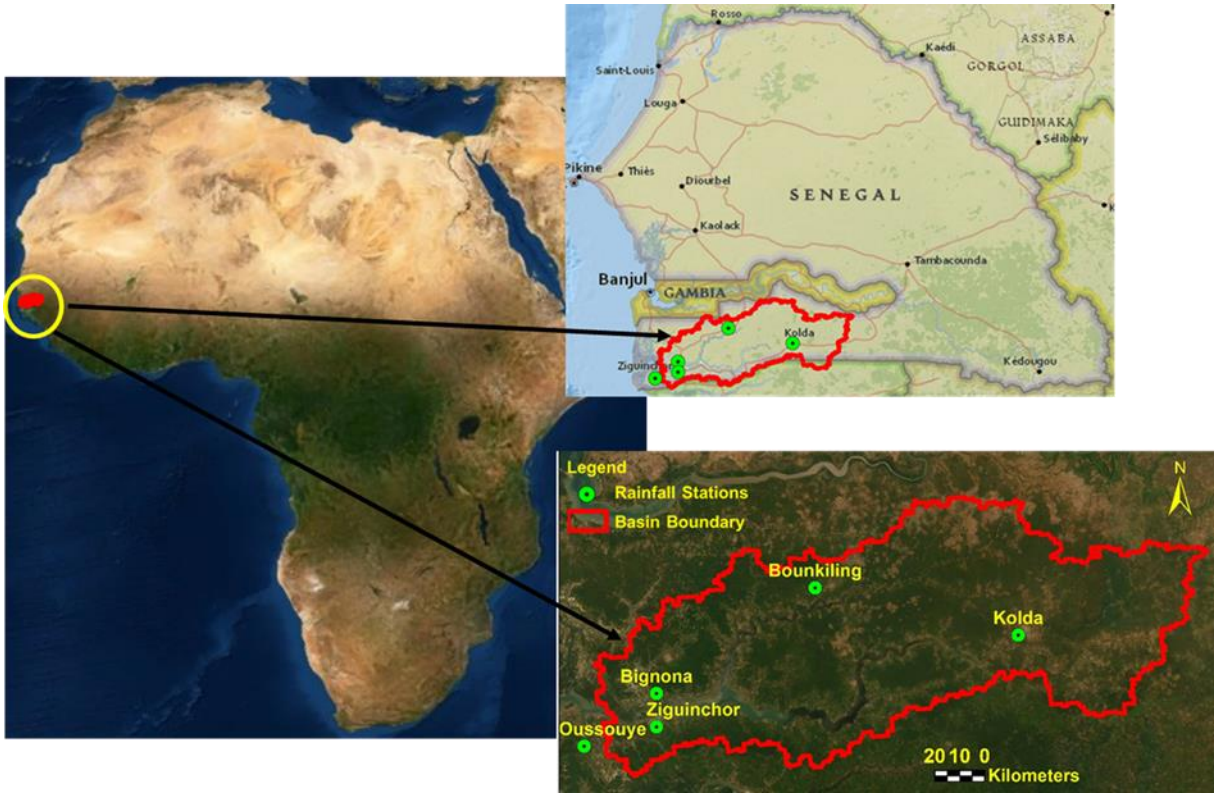


Figure 1: Location of rainfall stations and boundary of the Casamance basin.

2.2 Climatic Situation

The Casamance basin is subject to a coastal climate of southern Sudanese type covering a large part of Lower Casamance and a continental climate of southern Sudanese type covering Middle and Upper Casamance (Sané et al., 2007). Casamance as a whole is the wettest part of Senegal, with an average rainfall of more than 1000 mm per year (Faye et al., 2019).

It is characterized by a rainy season period, which generally begins in June and lasts 5 to 6 months (Faye & Sané, 2015).

The climatic situation of the region underwent two breaks in 1970 and 1995 corresponding respectively to a transition from a wet period (1960-1969) to a dry period (1970-1994), and a transition from the drought period to another wet period (1995-2010) according to a study carried out by (Faye, 2018) that is based on the analysis of trends in the regional distribution and intensity of rainfall in the Casamance basin. This analysis had shown that at the level of some parts of the basin the intensity of rainfall was increasingly strong and variable and had consequences on the river dynamics causing a strong progressive erosion. According to IDEE Casamance, (2015), rainfall in Casamance decreased from 1522 mm between 1918 and 1969 to 1141 mm between 1970 and 1992. This regression is one of the main causes of the degradation of the landscape and the impoverishment of biodiversity.

The intensity of rainfall in Casamance has increased on average by 1386 mm, which is almost the same amount as before 1970.

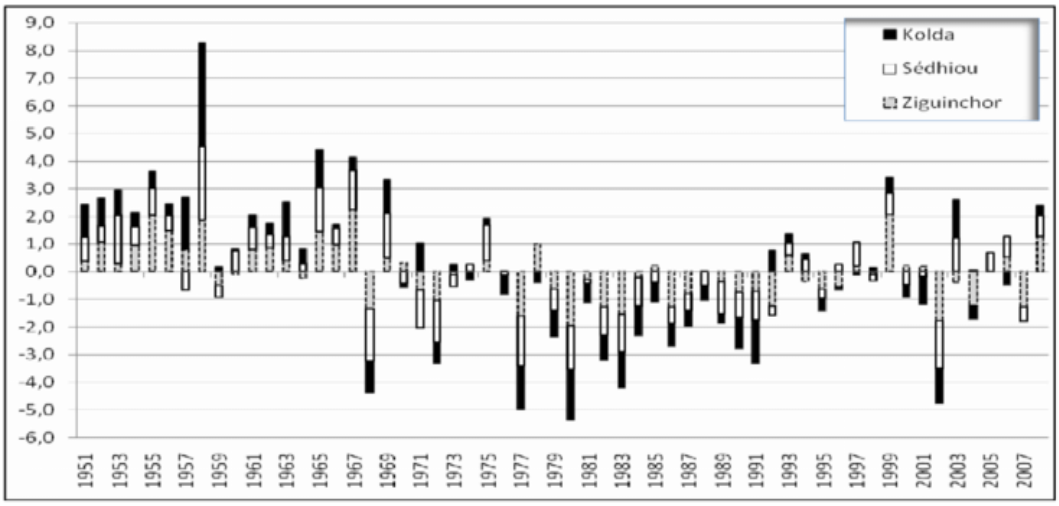


Figure 2: The evolution of rainfall in Casamance basin between 1951 and 2008 showing the two break periods (Source: Sané et al., 2010).

With an average temperature of 27°C, Casamance has a hot and humid climate (IDEE Casamance, 2015). Annual temperatures vary according to seasonal periods and the distance of the locality from the ocean. Average temperature is low in Lower Casamance due to permanent maritime influences and increase with distance from the sea. This explains the increase in temperatures in Middle and Upper Casamance, with the highest temperatures recorded in the Upper Casamance region (Sané et al., 2007).

There are two types of seasons (dry and rainy) as in the rest of Senegal and three types of winds blowing in this Casamance territory: Sea trade winds with low hygrometric power, the continental trade winds or harmattan, with almost no hygrometric power, a hot and dry wind that blows in the dry season and the monsoon which is responsible for the rain and which comes from the oceanic zone and arrives on the continent with high humidity (IDEE Casamance, 2015).

2.3 Topographical Situation

The Casamance basin is characterised by low landforms (Dacosta, 1989). The elevation ranges from 0 to 85m (above mean sea level (amsl)). The elevation between 68 and 85m is measured only at the extreme east of the basin. The majority of the basin has an elevation that varies between 34 and 68m (Figure 3).

The characterization of the relief divides the basin into two parts at the 16th meridian. At the level of the part where the terminal continental of 50 m of altitude is located, the maximum altitudes are from 51 m to 35 m between the region of Saré Boido Mali and Kolda. However, in the northern region of Kolda, a maximum altitude of 4 m is noted there. Altitudes between 43 m and 19 m are observed in the Pata Forest and at Diaw Ba. In the western part of the 16th meridian, the highest point is at 24 m elevation south of Ziguinchor (Dacosta, 1989). Seawater intrusion into the river waters is noted up to 200 km from its mouth due to the weakness of its slope (World Bank, 2004).

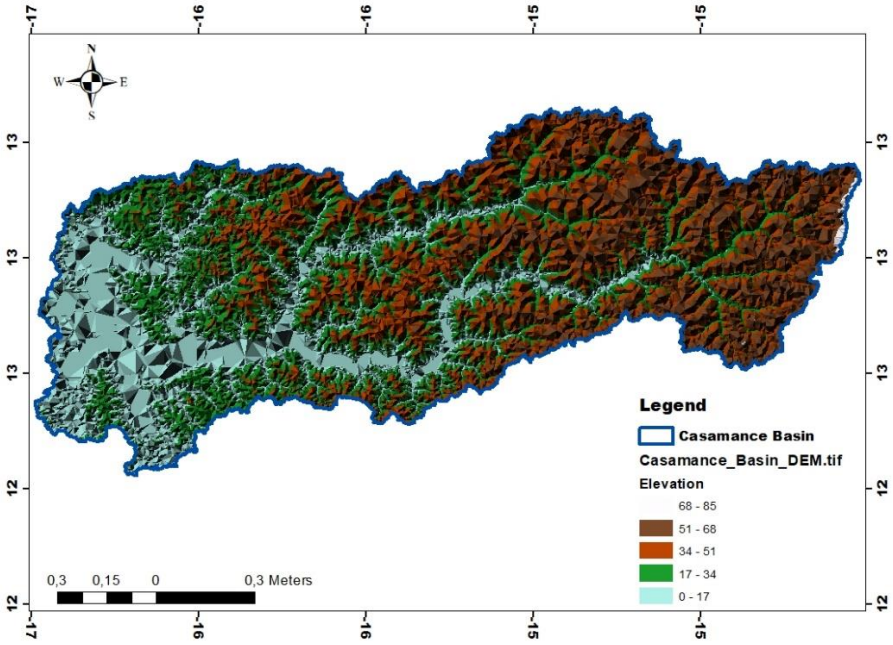


Figure 3**:** Variation of elevation in Casamance Basin.

The basin is characterised by a slope that varies between 0 and 89.996 m. Almost the entire territory of the basin has a slope of 89.996 m and the slope which is equal to 0 is measured mainly at the level of the watercourses (Figure 4). The analysis in Figure 4 shows that the Casamance basin is an area with relatively flat landforms.

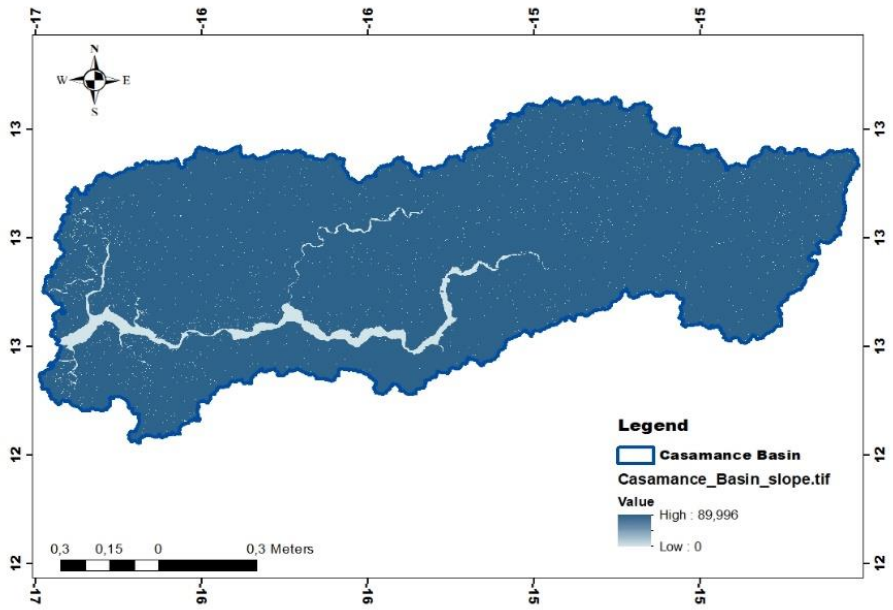


Figure 4: Variation of Slope in Casamance Basin.

3. LITERATURE REVIEW

The remote sensing is a promising technology and has been applied in several studies such as precipitations estimation, land use and land use change analysis, water & natural resource management, cartography, environment, agriculture, geology, oceans, disaster risk assessment, etc.

The history of remote sensing techniques can be classified into five main eras:

(1) Remote sensing originated in 1856 when a camera was first installed permanently onboard a balloon. World War I was the pioneering era, during which the possibilities of vertical aerial photography for mapping were explored. It was at the end of the 19th century that the fundamental laws of stereoscopy and photogrammetry were discovered (Rees, 2013).

(2) At the end of the 1950s, aerial photography became an operational tool for cartography, oil exploration and vegetation monitoring. There is a continuous evolution of aviation, cameras and emulsions (colour, black and white infrared, false colour infrared). Photo-interpretation methods are being specified and codified.

(3) From 1957 to 1972, the exploration of space had prepared for the advent of today's remote sensing. The launch of the first satellites, followed by manned spacecraft with cameras on board, revealed the importance of remote sensing from space. At the same time, imaging radiometers were developed and perfected, as were the first radars onboard aircraft. The first application of space-based remote sensing was operational with the ESSA series of meteorological satellites in the 1960s (Robin et al., 2005; Kergomard, 2014).

(4) The era of modern remote sensing was started from 1972 with the launch of the first satellite for remote sensing of Earth resources. The constant development of sensors and digital data processing methods is increasingly opening up the field of applications for remote sensing and making it an indispensable instrument for managing the planet and, increasingly, an economic tool (Robin et al., 2005; Kergomard, 2014).

(5) Since the 1970s, there has been a continuous development of remote sensing, marked in particular by:

the diversification of sensors using increasingly varied and specialised areas of the electromagnetic spectrum and the increase in the spatial resolution of these sensors. Sensors with the very high spectral resolution are today in common use in their airborne version and

are appearing onboard satellites in the visible and infrared radiation range. Indeed, in the 1990s several satellites were equipped with active sensors and radars especially (Robin et al., 2005; Kergomard, 2014).

3.1 Principles of Remote Sensing

Remote sensing is a functional tool for obtaining remote data such as images of a portion of the earth's surface at a given time that can be converted into rainfall data, climate data, environmental data, map data etc. These data are acquired with sensors (infrared, radar) installed on aerial or satellite rigs (satellites, aircraft, etc.). The sensors catch electromagnetic emissions or reflections coming from the earth. The use of remote sensing offers several advantages for the management of natural resources, such as the rapid acquisition of data, the easy updating of databases, a source of data for environmental modelling, the possibility of studying very large or difficult to access areas and the production of thematic maps (Bonnet et al., 2011).

3.2 Basic Operation of Remote Sensing

The operation of remote sensing is based on three fundamental elements which are the energy source, the target and the vector. The target can be a small or large area of the earth observed by a satellite. The energy source can be the sun or an electromagnetic wave transmitter (radar) placed on board an aircraft or satellite and aimed at the target. In some cases, the target becomes the energy source by emitting heat (stored and reflected solar energy (thermal infrared)) which is detected by sensors installed on the satellite. The vector is a remote sensing platform (satellite or aircraft) that measures, with the sensors installed, the amount of energy reflected or electromagnetic radiation. The measured amount of energy or electromagnetic radiation is transmitted by a transmitter to terrestrial receivers (receiving stations) in the form of images (satellite images). There are two forms of remote sensing: active and passive. Active remote sensing occurs when the satellite emits the electromagnetic wave and receives the echo of the wave back. Passive remote sensing is when the satellite only catches the reflected energy (source: www.cnes-csg.fr (Initiation à la télédétection)).

3.3 Remote Sensing Applications

3.3.1 Remote sensing and hydrology

Hydrology is the study of surface water, more specifically the water cycle, including groundwater. The observation of these exchanges can be ensured by several satellites which

are equipped with instruments that make it possible to monitor and study the different phases of the water cycle. It is almost impossible to directly assess the volumes of water and their variation in time and space. The most observed parts are soil moisture, the extent of snow, and open surface water (Biancamaria, S., & Kerr, Y., 2017).

In addition to these satellite missions, three products were noted for the assessment of surface waters.

- The European Spatial Agency (ESA) Global Water Bodies product detects average surface water bodies between 2005 and 2010.
- The Water Bodies product, distributed by Copernicus, detects minimum and maximum annual surface water coverage data as well as the seasonal evolution of surface water recorded between 1999 and 2014 based on SPOT-VGT and PROVA-V from 2014 onwards. The product allows differentiation between temporary and permanent surface waters and estimates seasonal water availability.
- The Water Point product, which allows the monitoring of surface water, is reserved for pastoral areas. Landsat and ASTER data provide access to water surface maps and SRTM data delineate catchment areas. The daily supply of water to these surfaces is estimated from data obtained from rainfall products (CHIRPS) and a climate model of evaporation.

The study of water surfaces aims at providing information to improve the satisfaction of the water needs of the populations (Bégué et al., 2016).

3.3.2 Remote sensing and soil moisture

Soil moisture is an important factor that strongly impacts agricultural production and surface hydrology. It is influenced by several factors such as topography, soil properties, precipitation, vegetation type, overall radiation or management practices. Remote sensing applied to soil moisture provides information on the exact water requirements of plants.

Soil Surface Moisture (SSM) represents the water in the top layer of the soil. Depending on the type of relief and soil type (properties and drainage capacity), soil surface moisture can change on very fine scales and is very spatially heterogeneous. Remote sensing (soil moisture products) applies to soil moisture with a low spatial resolution (~25 km). The low spatial resolution of these products is the main limitation of their use for agricultural applications.

The Soil Water Index (SMI) characterizes the amount of water contained in the first meter of soil and is mainly determined by infiltrated precipitation water. It allows the estimation of moisture in the root zone and varies between 0% (wilting point) and 100% (field capacity) (Bégué et al., 2016).

3.3.3 Remote sensing and agriculture

Remote sensing applied to agriculture makes it possible to determine, in a Spatio-temporal manner, cultivation practices, landscape units and variation in vegetation types (Bégué et al., 2016).

Vegetation monitoring developed in the 2000s with the arrival of satellite images with a metric definition (Ikonos, QuickBird) and global missions such as (MODIS, SPOT-VGT). A new era for vegetation monitoring will be ushered in with the launch of national satellite systems and the Sentinel satellite clusters, combined with other systems in the 2010s (Bégué et al., 2016).

In Africa, specifically in West Africa, remote sensing is difficult to apply in the field of agriculture because agricultural areas are represented by small plots with intra- and inter-plot variability. Indeed, the spatial variability of agricultural systems is strongly characterized by the presence of many trees or by the grouping of a variety of species in the same plot. It is often difficult to distinguish between natural vegetation and crops when it comes to long summer fallow crops and between natural vegetation and annual crops when it comes to short summer fallow crops (Bégué et al., 2016).

3.3.4 Precipitation estimation using remote sensing

In several African countries, the number of rainfall stations is low, almost non-existent, and the lack of reliable data causes many problems. The use of satellite images could be a particularly relevant tool for regions where rainfall data play an essential role in important activities in different fields representing at the same time political, social, environmental and economic issues such as agriculture, land use, study and management of water resources, the study of potential risks of natural disasters, etc. Meteorological satellites in orbit provide a general and permanent view of the entire Earth's planet over any underlying terrain. Satellites make it possible to detect precipitation and estimate its intensity at the same time. Precipitation products generally work with two sources of data: measurements taken with the thermal infrared from geostationary satellites and measurements taken with the radar

instrument from passing satellites. Data from rainfall stations can also be integrated into the algorithms for implementing the products. However, a wrong estimation of rainfall totals and/or rainfall distribution during the season can lead to error in its applications in different sectors, for example, in agriculture yield modelling, an error in rainfall estimates which serves as an input data ultimately leads to an over- or underestimation of agricultural yields (Bégué et al., 2016).

Many rainfall products (either remote sensing derived or interpolated rainfall estimates from gauge stations) are available over a period from 1901 to the present day with a spatial resolution ranging from 4 km to 200 km, and a temporal resolution ranging from 30 minutes to one month.

Rainfall products derived from remote sensing are used as in input data for hydrological modelling and serves as an early warning system to detect areas of drought or possible flood risks and thus identify the main causes of food security problems (e.g. FEWS NET or AGRHYMET) (Bégué et al., 2016).

3.3.5 Precipitation measurement methods

Precipitation measurements have always been carried out by ground-based station measurements (rain gauge) in different regions. However, with the evolution of technology another method has been established; remote sensing (infrared, radar). These precipitation measurements are used in several studies such as:

- The evaluation of the variability between rainfall and flow in a watershed, thus characterizing hydro-climatic changes, land use, hydrological modelling,
- Characterization of rainy seasons,
- The change in precipitation over a designated interval of years in a specific region,
- Climate change assessment,
- The flood and drought prevention study.

In Senegal, the first rainfall measurement network was installed in 1854 with the first station in Saint Louis. From 1854 to 2002, this network had 239 rainfall stations, including 14 synoptic stations. The spatial distribution of these stations is unbalanced (Dacosta et al., 2002).

The synoptic stations simultaneously provide measurements of climatic data (pressure, temperature, humidity, wind, insolation, precipitation) and visual observations (clouds,

meteorological phenomena). These synoptic stations make hourly to three-hourly measurements that are normally transmitted every three hours through the Global Data Transmission System (GTS) (Senegal National Science and Implementation Plan, 2004).

3.4 Remote Sensing Techniques for Rainfall Measurement

In many cases, countries without satisfactory and sufficient ground-based measurement networks, or even the means to develop them, have relied on remotely sensed data to understand better rainfall hazards (Dubreuil et al., 2004). Indeed, the use of satellite data for rainfall estimation has been growing steadily over the last twenty years. These experiments have led to the setting up of several international research programmes such as Global Precipitation Climate Project (GPCP) (Wilkerson, 1988), Climate Prediction Center (CPC) (Herman et al., 1997) using the Goes Precipitation Index, Estimation of Precipitation by Satellite (EPSAT) (Cadet & Guillot, 1991) which aimed at estimating rainfall over West Africa (Arnaud & Laurent, 1992), TAMSAT, Tropical Applications in Meteorology using Satellite data. The African Monsoon Study (AMMA) is one of the programmes that highlight the importance of having global data sets available for monitoring rainfall systems. Following some monitoring experiments using visible imagery, the use of infrared data and the use of microwave data are two methods being carried out for the study of rainfall by satellite. There is also the use of the combined method of the two types of data but also the use of the radar (Dubreuil et al., 2004).

3.4.1 Infrared (IR)

The Climate Prediction Centre (CPC) provides infrared (IR) data. These are images obtained from 5 geostationary satellites external to TRMM which are:

GOES-8, GOES-10, METEOSAT-7, METEOSAT-5 and GMS. Infrared data allow the determination of clouds temperature, i.e. any heated body emitting infrared radiation proportional to its temperature. The clouds that are likely to generate significant precipitation are high convective clouds aloft. However, cirrus clouds (clouds formed of ice crystals) can reach temperatures equal to those of cumulonimbus clouds (large convective clouds) without producing precipitation on the ground. This phenomenon causes significant errors that are processing by comparing two different infrared channels (Sarrand, 2011).

Thermal infrared was the first technique to be used: they generally based on the indirect relationship between the cloud top temperature and the intensity of the precipitation.

Algorithms made to determine the thick clouds that are responsible for convective rain at the surface. The determination based on the evaluation of the temperature of a cloud top, which, when cold, indicates the presence of a thick cloud. This method presents certain problems, such as overestimating rain clouds by integrating the cold, high cloud surfaces of cirrus clouds, or obscuring stratiform rain brought by clouds of more modest altitude.

Vegetation cover equated with a response to precipitation that cools the earth's surface. In this type of approach, the problems of cover heterogeneity and spatial variability of emissivity remain constraining.

The data acquired with the thermal infrared technique, are generally obtained with a temporal resolution of 30 minutes to 3 hours and with a spatial resolution varying from 3 to 5 kilometres depending on the sensors (Dubreuil et al., 2004).

3.4.2 Passive microwave

There is a direct relationship between measurements of radiation absorption, emission or scattering and the size and concentration of the cloud composition: water droplets and ice crystals. Microwaves are based on several algorithms. It is in this context that high-frequency scattering methods are like infrared methods, while low-frequency emission methods are more directly related to physical phenomena. At these wavelengths, Special Sensor Microwave / Imager (SSM/I) data are produced by Defense Meteorological Satellite Program (DMSP) satellites in low, polar and sun-synchronous orbits. These methods have drawbacks such as emissivity problems found on continental surfaces and their low space-time sampling. The main existing data sets for these methods are only available with a monthly temporal resolution and a spatial resolution of 1 to 2.5° (Dubreuil et al., 2004).

The microwave method includes two techniques: passive (wave reception) and active (wave emission)

The technique known as passive microwaves (PMW) is based only on the reception of naturally occurring waves, i.e. they are not emitted by the instruments.

The main advantage of passive microwaves is their low diffusion compared to visible waves. Regardless of the weather conditions, this type of wave passes through the cloud layers that allowing detection. However, at the coastal zone level, reliability becomes low because of the interface between the quite different emissivities of the maritime zone (homogeneous) and the continental zone (heterogeneous).

3.4.3 Radar

Radar technology is based on active microwaves and functions as both a transmitter and a receiver of a signal at the same time. This feature gives it the ability to receive a stronger signal than passive microwaves and therefore less noise. Water reflects a portion of the radar signal giving in this way to the radar the advantage of direct precipitation detection (unlike infrared).

The TRMM radar (called PR) is the first radar that has allowed the evaluation of precipitation distribution in 3D from space, over land and oceans. This functionality can alleviate some of the problems that land-based radars may face, such as fixed echoes and areas obscured by relief. The PR gives the thickness of the precipitation layer and information on the precipitation arriving on the ground. It has allowed the measurement of rainfall on land where passive microwaves are less effective. The PR is an electronically scanned radar with a spatial resolution of 250 m.

Table 1:Summary of remote sensing derived rainfall products.

Rainfall product	**Spatial resolution**	**Coverage**	**Temporal resolution**	**References**
TRMM-3B42RT	0,25 ° x 0,25 °	50°N to 50°S / 180°W to 180°E	3 hours, Daily	NASA, GES DISC (Goddard Earth Sciences Data and Information Services Center) (Braun et al., 2011)
CHIRPS-0.05	5 km (interpolated to 0,05°)	180°W to 180°E / 50°S to 50°N	Daily	http://chg.geog.ucsb.edu/data/chirps/
ARC version 2	10 km (interpolated to 0,1°)	20°W to 55°E / 40°S to 40°N	Daily	(Le Coz & van de Giesen, 2020)
RFE version 2	0.1° x 0.1°	Africa	Daily	(Le Coz & van de Giesen, 2020)

3.5 Description of Commonly Used Remote Sensing Derived Rainfall Products

3.5.1 The tropical rainfall measuring mission (TRMM)

In 1997, TRMM was put into operation. Indeed, this satellite mission was launched for the first time to measure precipitation. Later the Goddard Space Flight Center (GSFC) of the National Aeronautics and Space Administration (NASA) developed the multi-satellite precipitation analysis algorithm (TMPA). The TMPA designed the multi-pass microwave (PMW) data set, including the Microwave Imager (TMI), the Special Sensor Microwave Imager (SSM/I), Advanced Microwave Scanning Radiometer-Earth Observation System (AMSR-E), the Advanced Microwave Sounding Unit-B (AMSU-B) and IR data obtained from the international constellation of GEO satellites (Zeng et al, 2018). TRMM is available in different spatial and temporal resolutions, real-time and post-real-time versions with a spatial resolution of 0.25 and at hourly, daily and monthly temporal resolution versions.

The evaluation of the TRMM rainfall product in the China zone had shown that TRMM had performed very well with an accurate estimation of rainfall observed by rainfall stations on a daily scale in the north-western region of China (Yang & Luo, 2014) and Beijing (Huang et al., 2013). However, this same product has largely overestimated rainfall in the Laohahe high latitudes basin (China) (Yong et al., 2010) (Yong et al., 2012). Indeed, Curtis et al. (2007) reached the same result in eastern North Carolina in the United States by comparing TRMM with radar and rain gauge rainfall. The TRMM dataset was used by Asante et al. (2007) to develop and improve a flood early warning system in the Limpopo basin in South Africa. This flood prevention system for the Evros catchment in South-Eastern Europe used TRMM products (3B42 and 3B42RT) as a data source (Fotopoulos et al., 2010). TRMM underestimated the high rainfall observed in Burkina Faso and performed poorly (Dembélé & Zwart, 2016). However, it overestimated the high rainfall percentages in the Sahel zone (Dinku et al., 2015). In Benin and Niger, it was shown that the rainfall product could reproduce the diurnal cycle and the variability thereof (Pfeifroth et al., 2016).

There is a series of algorithms in TRMM 3B42 that can be used to transcribe the data obtained by the sensors into rainfall data. Like showed on the figure 5, the algorithms are naming by modules in 3 levels. The first digit of each name corresponds to each level (figure 5).

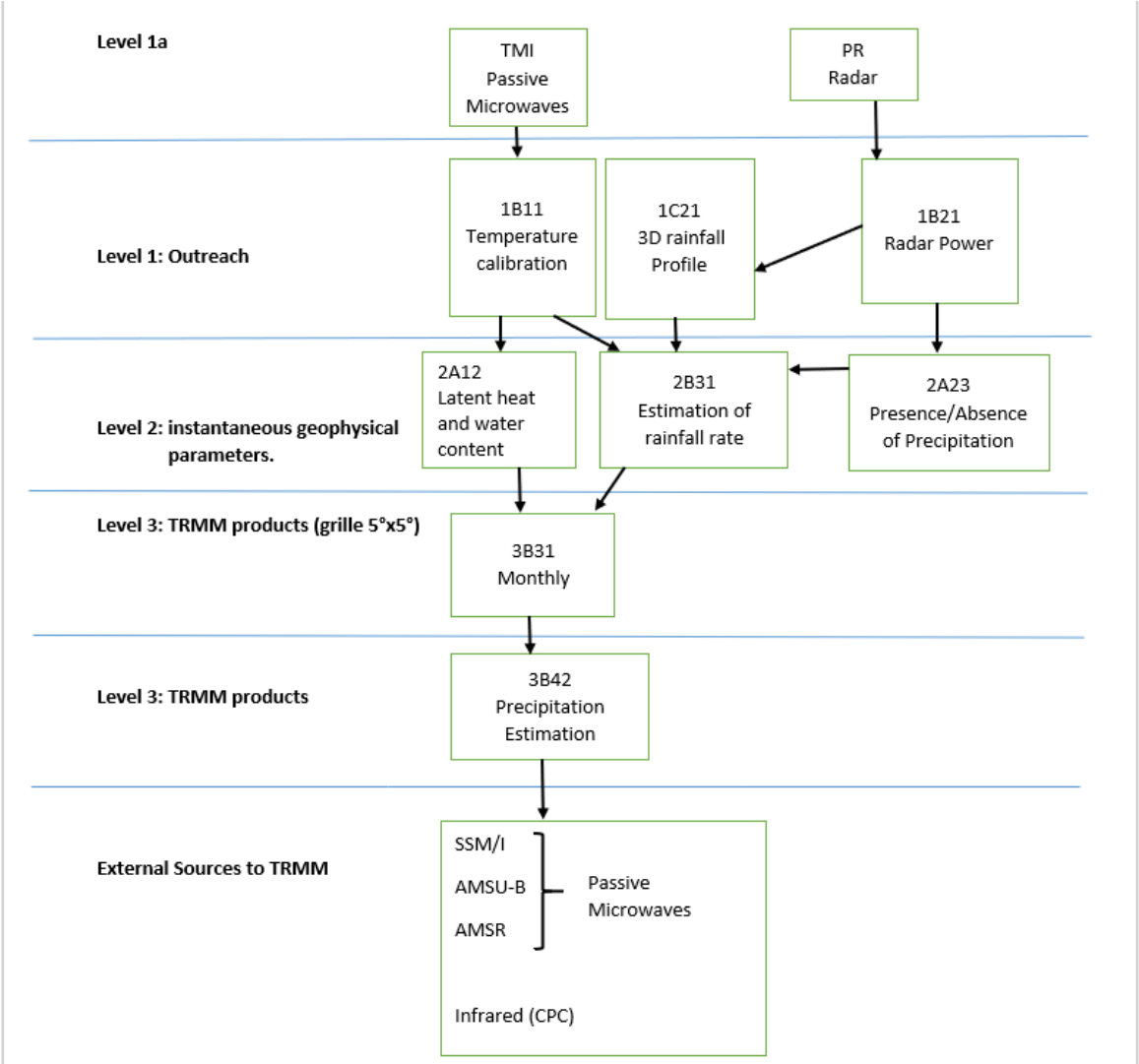


Figure 5: TRMM 3B42RT Product Algorithm (Sarrand, 2011).

3.5.2 Climate hazards group infrared precipitation with station data (CHIRPS)

The creation of CHIRPS with the help of scientists from the USGS Earth Resources Observation and Science Center (EROS) was aimed at preventing, in advance, the possibility of drought based on complete, reliable and up-to-date data. This was an essential means for USAID's Famine Early Warning Systems network to monitor drought periods. The first steps in the research were on assembling models to improve the resulting precipitation from a region with interpolation of station data. The development of high-resolution 0.05 gridded precipitation climatologies had required gridded precipitation estimates from NASA and NOAA. The use of these climatologies, applied to satellite precipitation fields, can eliminate systematic bias. This has always been an essential means in the production of the CHIRPS database.

The CHIRPS is a rainfall product implemented for the USAID Agency for the prevention of early famine. It is based on the techniques of some thermal infrared (TIR) rainfall products such as the National Oceanic and Atmospheric Administration (NOAA) rainfall estimate (RFE2) and NOAA's Climatology of Rainfall in Africa or the University of Reading's Climatology of Rainfall in Africa and Time Series (TARCAT) (Funk et al., 2015). Its algorithm is shown in figure 6.

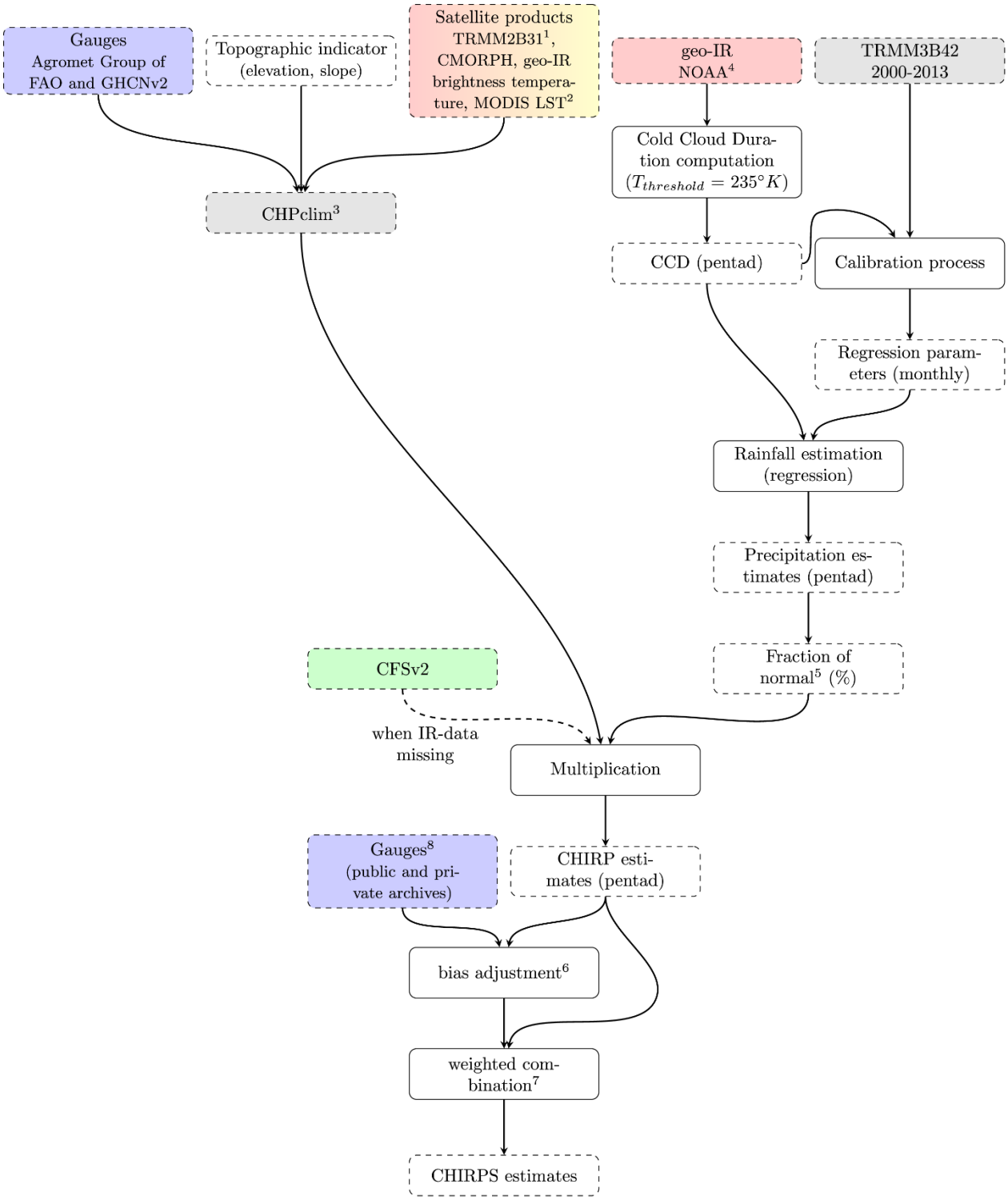
This high-resolution CHIRPS rainfall product has low latency, low bias, long recording duration and provides mixed gauge and satellite rainfall assessments covering a large part of the land surface. CHIRPS was designed for mid-season drought forecasts and assessments of rainfall and rainfall change in regions with scattered data based on convective rainfall (Funk et al., 2015).

Within the framework of a project entitled Scientific Support Project for National Adaptation Plan Processes, a study on the assessment of climate variability and future climate trends in the Fatick region, Senegal was carried out. In the 1950s, 2010, 2016 and 2017 a temperature increase was recorded in the African continental regions. In West Africa, an increase of 1°C has been recorded since 1950 and 2°C in the Sahel zone. This warming of the temperature can have harmful consequences on agriculture. It is in this context that Senegal decided, in 2015, to launch a National Adaptation Plan (NAP) project financed by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety and implemented by the Deutsche Gesellschaft fur International Zusammenarbeit (GIZ) with the collaboration of

Climate Analytics. The study focused on three sectors: agriculture, water resources and coastal zones for the strengthening of adaptive capacity to global warming. The study led to analyses on three climate parameters: precipitation, maximum and minimum temperatures. This led to the use of the CHIRPS rainfall product (Camara et al., 2019).

The CHIRPS has been also used for model performance evaluation as was the case in a study on Regional Multimodel Climate Analysis of Rainfall and Temperature Regimes conducted in Niger by Mahamadou et al. (2018). The performance of Cordex-Africa regional climate models in simulating rainfall and temperature regimes were evaluated for the period June to September 1997-2008. The validation of the performance of these models was done with CHIRPS and GPCP observation data. This validation was based on the comparison of their spatial distribution, seasonal diversity, bias and correlation coefficient with the CHIRPS and GPCP observations.

CHIRPS satellite data can be used for the analysis of rainfall characterization as it is the case of a study that was conducted in Morocco by Lo et al. (2019) on the Spatio-temporal monitoring of rains likely to cause erosion and the degree of their impact with the use of free satellite data. The objective of this study was to obtain reliable rainfall data to help decision-makers in the proper management of natural resources.



Notes

[1]MicroWave precipitation estimates
[2]Land Surface Temprature
[3]CHPclim is described in Funk et al. (2015)
[4]GriSat-B1 archive (1981-2008) and CPC TIR dataset (2000-present)
[5]each grid cell's value is divided by the grid cell's 1981-2013 mean precipitation estimate
[6]the bias is computed from the five closest stations with a modified inverse distance weighting algorithm
[7]the weights are based on the expected correlation with the nearest station and the expected correlation between the 'truth' and the CHIRP estimates
[8]GHCN monthly, GHCN daily, Global Summary of the Day(GSOD), GTS, Southern African Science Service Center for Climate Change and Adaptive Land Management(SASSCAL) and different national meteorological agencies

Figure 6: Presentation of CHIRPS-0.05 algorithm (Le Coz & van de Giesen, 2020).

3.5.3 Africa rainfall estimate climatology version 2 (ARC 2)

Arc Version 2 is the new revised version of Arc 1 developed in 2004 for climatology. It is a new set of daily estimated rainfall data that was developed in 2012 (Le Coz & van de Giesen, 2020; Novella & Thiaw, 2013). Arc 2 has been designed to forecast rainfall over Africa on a 0.1° × 0.1°grid of latitude/longitude from 20° W to 55° E and 40° S to 40° N and uses data from two sources: European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) geostationary infrared (IR) data with a temporal resolution of 3 hours centred on Africa and Global Telecommunications System (GTS) quality-controlled gauge records providing rainfall observation sets over Africa with daily temporal resolution (Novella & Thiaw, 2013).

In general, this rainfall product is capable of describing the spatial distribution of mean rainfall climatology (Akinsanola et al., 2017). But it is also a rainfall product adapted to hydrological applications thanks to these characteristics: availability in long time series, in near real-time, good spatial and temporal resolution and is publicly licensed (Novella & Thiaw 2013). It shows an improvement of ARC 1 and is consistent with RFE2, GPCP and CMAP according to Le Coz & van de Giesen, (2020) and Novella & Thiaw, (2013) research. Its algorithm is shown in figure 7.

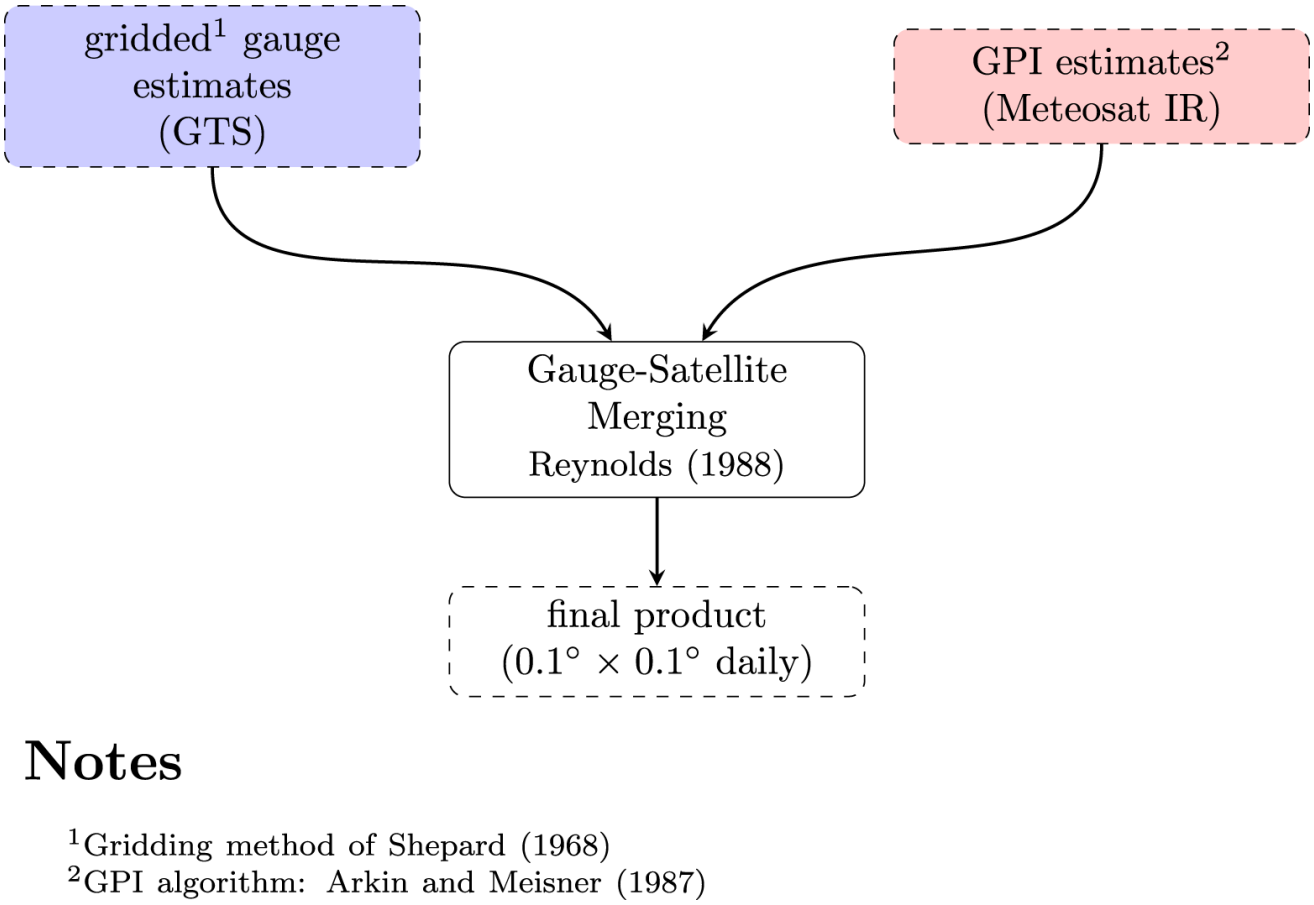


Figure 7**:** Presentation of ARC Version 2 algorithm (Le Coz & van de Giesen, 2020).

The creation of ARC 2 was intended to solve some problems encountered with ARC 1 to improve the rainfall product. Among these problems is the dry bias from 1998 to 2000 (Le Coz & van de Giesen, 2020). However, the problem has not been completely resolved because at the level of the northern hemisphere this type of error (dry bias) persists, as mentioned in Novella & Thiaw, (2013) and Maidment et al. (2014). In general, the ARC 2 shows good performance over Africa, especially in the Sahel at the daily scale (Novella & Thiaw, 2013) and the dekad scale (Burkina Faso) as mentioned by Dembélé & Zwart (2016). Nevertheless, the satellite product had overestimated rainfall at six stations in western Uganda (Diem et al., 2014) and recorded poor performance in Ethiopia, the Gulf of Guinea and Burkina Faso at the daily scale (Novella & Thiaw, 2013; Dembélé & Zwart, 2016).

Dinku et al (2011a), Novella & Thiaw (2013), Maidment et al. (2014), Dinku et al. (2007) explained that these poor results were caused by the limited availability of GTS data in the Ethiopian highlands and the Gulf of Guinea and the failure of infrared-based estimates to capture precipitation from warm clouds over the coastal and orographic regions.

3.5.4 African rainfall estimation version 2 (RFE 2)

Implemented in January 2001 based on the method of Xie and Arkin (1996), RFE 2 is the second version of RFE developed by the Climate Prediction Center (CPC) of NOAA (Herman et al., 1997) and functional from 1995 to 2000 (Le Coz & van de Giesen, 2020). RFE 2 is designed exclusively for the famine early warning system network to support disaster monitoring activities in Africa (Dembélé and Zwart, 2016). It operates on a 0.1 ° × 0.1 ° grid latitude/longitude for Africa (20 ° W - 55 ° E and 40 ° S - 40 ° N) (Le Coz & van de Giesen, 2020) with four data sources: daily rainfall data from the Global Telecommunications System (GTS), rainfall estimates based on the Advanced Microwave Sounding Unit (AMSU), estimates based on the Special Sensor Microwave Imager (SSM/I) and the Geostationary Operational Environmental Satellite (GOES) precipitation index (GPI) calculated from infrared (IR) data of cloud top temperatures over 30 minutes (Dembélé & Zwart, 2016; Le Coz & van de Giesen, 2020). The two new entries in RFE 2 are SSM / I estimates and AMSU estimates. The GPI estimates and passive microwave estimates (SSM / I and AMSU inputs) are compared with daily GTS rainfall data, then linearly associated by the maximum likelihood method and finally assembled with the GTS rainfall data. This process is illustrated in the figure 8, which represents the algorithm of RFE 2 (Le Coz & van de Giesen, 2020).

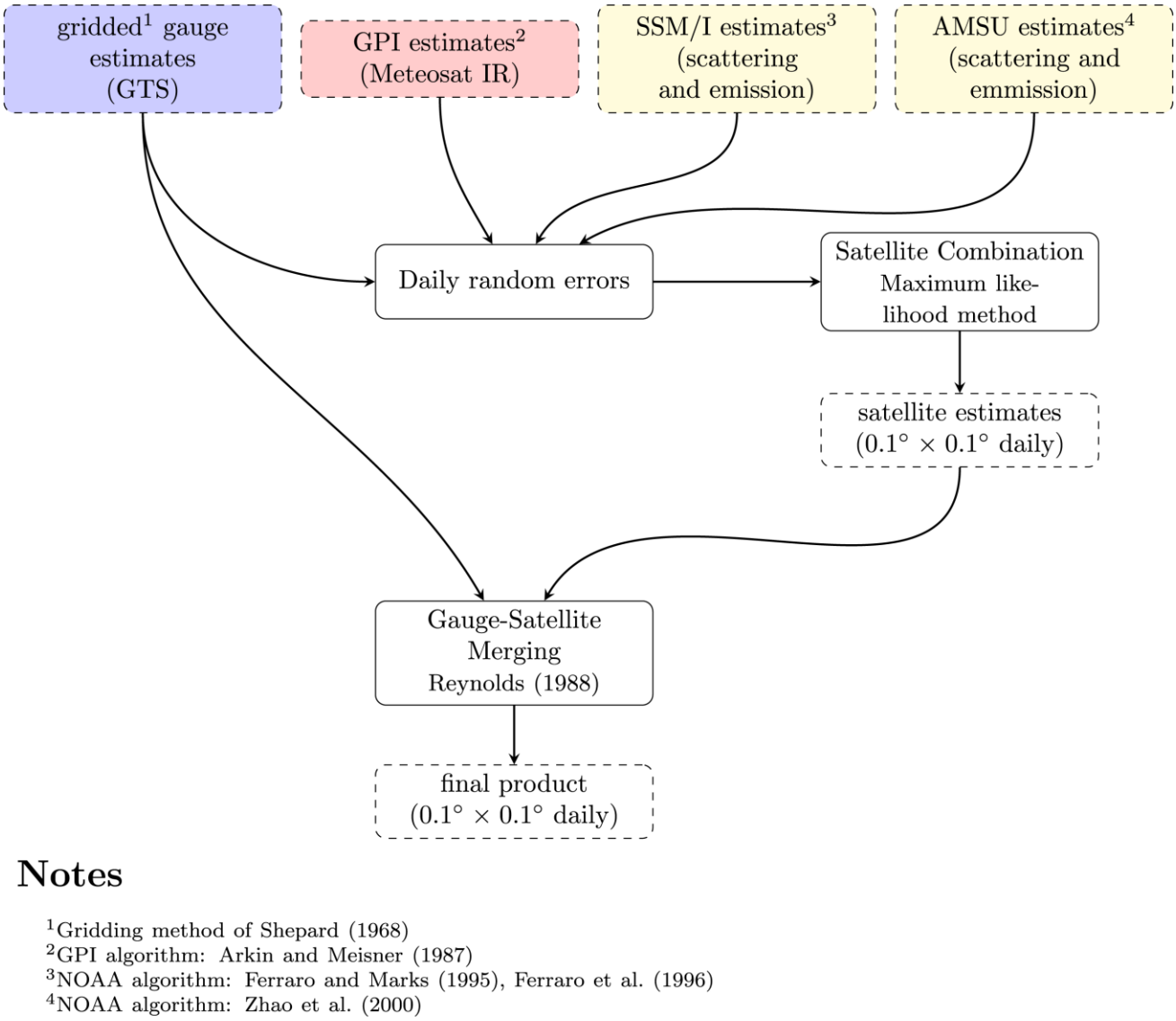


Figure 8: Presentation of RFE Version 2 algorithm (Le Coz & van de Giesen, 2020).

The RFE 2 algorithm does not incorporate orographic effects and applies a constant temperature threshold, which makes it difficult to capture precipitation originating from warm clouds, because of an orographic effect (Le Coz & van de Giesen, 2020). This problem of RFE 2 was at the origin of the underestimation of orographic precipitation and its poor observed performance (over the Ethiopian highlands for example) by Le Coz & van de Giesen, (2020), Dinku et al (2011a), Dinku et al (2011b), Cattani et al (2016), Diem et al (2014) and Thiemig et al (2012).

The performance of RFE 2 depended on the region, however, it often tended to underestimate the rainfall (i.e. dry bias) (Le Coz & van de Giesen, 2020). In the Sahel region, RFE 2 had a high capacity to identify rainy and non-rainy days and showed good performance in estimating the decadal rainfall rate even with its tendency to underestimate (Novella and

Thiaw 2010; Dembélé and Zwart 2016; Le Coz and van de Giesen, 2020). A study in Benin by Gosset et al. (2013) also showed that RFE 2 had underestimated rainfall and overestimated the occurrence of low rainfall and underestimated the highest rainfall according to a study in Niger. RFE 2 appears to be performing well in West Africa despite its tendency to underestimate observed rainfall (Le Coz & van de Giesen, 2020). This was confirmed in a study by Thiemig et al. (2012) who observed good performance of RFE 2 over the Volta Basin in Ghana despite a small underestimate.

ARC 2 and RFE 2 are using comparable algorithms; the major difference being that ARC 2 uses fewer input data. Therefore, there are certain similitudes between their performances, for example, the regions where they perform well or poorly, or their challenges in mountain areas (Le Coz & van de Giesen, 2020).

Dembele & Zwart, (2016) did some studies in West Africa specifically in Burkina Faso. They compared the performance of seven satellite-based rainfall products (ARC 2.0, CHIRPS, TRMM, RFE 2.0, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), Tropical Applications of Meteorology using Satellite (TAMSAT) and African Rainfall Climatology and Time-series (TARCAT)). The finding of this research shows that all the satellite-based rainfall products have different levels of accuracy and RFE 2.0 got the best results of this study. However, the choice of the best product for the studied area depends on the specific application. Thus, ARC, RFE and TARCAT found to be the best rainfall products for drought monitoring in Burkina Faso and PERSIANN, CHIRPS and TRMM daily are considered better for flood monitoring. Similarly, a similar research conducted in China to compare and evaluate the remote sensing with precipitation products. Several Statistical Evaluation methods including the linear correlation coefficient (CC), Relative Bias (BIAS), Root Mean Square Error (RMSE), the Frequency Bias Index (FBI), probability of detection (POD), False Alarm Ratio (FAR) and Critical Success Index (CSI) was used for the comparison of different rainfall products (Zeng et al., 2018). Five precipitation products were compared (TRMM 3BV42, PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) CDR, GSMaP (Global Satellite Mapping of Precipitation) RENALYSIS, CMORPH (Climate Prediction Center's morphing technique) BLD and CMORPH_RAW) with the precipitations observed by rain gauges over China and GSMaP_RENALYSIS got the best results and thus, demonstrated that it had the best performance (Zeng et al., 2018).

In an area like Senegal, the evaluation of the performance of four datasets for previous studies depended on satellite data (TRMM-3B42 V7, TAMSAT V3, CMORPHV1.0, CHIRPS V2.0). Two were based on re-analyses (NCEP-CFSR, ERAS), one attributed to gauge observations (CPC Unified V1.0/RT) and two were on the detection and evolution of 65 rainfall data of ANACIM using the spatial interpolation (Ordinary kriging (OK) and block kriging (BK)) (Fall et al., 2019). The studies focused on the evaluation of dry and wet periods. The dry period indicators show that the TRMM, CPC, ERA5, NCEP and OK data series recorded more dry days than TAMSAT, CHIRPS, CMORPH and BK, while wet periods were much higher with TRMM and OK than with the remaining data sets. Nevertheless, they show similarities in their temporal frequencies (Fall et al., 2019).

Based on the literature review it is concluded that different remote sensing derived rainfall products based perform with different levels of accuracy in a given specific area and hence it is important to evaluate and compare the different rainfall products for their accuracy based on ground observed data before its use.

4. MATERIALS AND METHODS

Four commonly used remote sensing derived rainfall products were considered for the evaluation and comparison for their rainfall estimation accuracy against the ground measure rainfall in the study area. The considered rainfall products are: CHIRPS (0.05), TRMM (3B42RT); ARC (version 2), RFE (version 2).

The statistical evaluation methods that have been applied are: CC: Correlation Coefficient, BIAS: relative bias, RMSE: Root Mean Square Error, MAE: Mean Absolute Error, accuracy, POD: Probability of Detection, FAR: False Alarm Ratio, CSI: Critical Success Index and FBI: Frequency Bias Index. The observed rainfall data were obtained from five rainfall stations installed at five different regions of the basin (Bignona, Boukinling, Kolda, Ziguinchor and Oussouye), represented in Figure 1. The rainfall data were collected at daily time steps from 2000 to 2010 (11 years). The data providing agency is National Agency of Civil Aviation and Meteorology (ANACIM), Senegal. The observed rainfall data measured at five rainfall stations were considered as the reference data for evaluation and inter comparison of different remote sensing derived rainfall products at their respective rainfall station locations.

The rainfall data estimated by remote sensing considered in this study were downloaded from NASA GES DISC website (source link: https://disc.gsfc.nasa.gov/) and the rainfall data corresponding to the five observed rainfall locations were extracted on a point to pixel basis. The details of the four remote sensing derived rainfall products used in this study (CHIRPS (0.05), TRMM (3B42RT); ARC (version 2), RFE (version 2)) are mentioned in Table 1 and described in detail in section 3.5.

The study started with a comparative analysis between the rainfall observed in the study area for each station and the estimates of remote sensing derived rainfall products. The comparative study is carried out on four different time scales: daily, monthly, annual and seasonal. The analyses focus on the spatial and temporal distribution of precipitation, the relationship that might exist between observed and estimated precipitation, and the impacts of the characteristics (climate, topography) of the study area on the accuracy of precipitation products.

The Spatio-temporal analysis of the precipitation and the impact of the characteristics of the topography on the performance (accuracy) of the satellite products is carried out using the ArcGIS software through interpolation by using Inverse Distance Weighting (IDW) and an overlay of layers (elevation and differences between the estimated precipitation of the satellite products and the observed precipitation of the rainfall stations). The analysis of the accuracy of the precipitation products is based on the statistical comparison (calculation of the correlation coefficient, mean error, t-test and P-value between observed and estimated precipitation). The analysis of the estimation capacity of precipitation products to detect rainy days and non-rainy days is based on the comparison of categorical statistics.

4.1 Criteria for Selection of Remote Sensing Derived Rainfall Products

Rainfall products were selected according to the following criteria:

(1) Products that have good spatial resolution and varied according to the rainfall products to be analysed, good coverage covering all of West Africa and daily temporal resolution.

(2) Easily and freely accessible data.

(3) Products that can produce the data necessary for the prevention of natural disasters (drought and floods) often encountered in Africa, especially in West Africa.

According to the above criteria and the characteristics of the remote sensing rainfall products detailed in section 3.5; ARC 2, RFE 2, TRMM-3B42RT and CHIRPS-0.05 are considered in this study.

4.2 Description of Statistical Methods

Statistical evaluation methods were used to evaluate the characteristics of the rainfall and the performance of remote sensing derived rainfall estimates based on observed rainfall measurements. Both continuous and categorical statistical indices are considered and presented in Table 2.

The continuous statistical indices are CC: Correlation Coefficient, BIAS: relative bias, RMSE: Root Mean Square Error, MAE: Mean Absolute Error and the categorical statistical indices considered are POD: Probability of Detection, FAR: False Alarm Ratio, CSI: Critical Success Index and FBI: Frequency Bias Index.

Table 2: Indices used to evaluate the characteristics of the precipitation and the performance of satellite precipitation estimates (Zhang et al., 2018).

Statistical Metric	Unit	Equations	Range	Perfect Value
Correlation Coefficient r	-	$1-\frac{6\sum_{i=1}^{n}[X(i)-Y(i)]^2}{n(n^2-1)}$	-1 to 1	1
RMSE	mm	$\sqrt{\frac{\sum_{i=1}^{n}(S_i-G_i)^2}{n}}$	0 to ∞	0
MAE	mm	$\frac{\sum_{i=1}^{n}\lvert S_i-G_i\rvert}{n}$	0 to ∞	0
Bias	%	$\frac{\sum_{i=1}^{n}(S_i-G_i)}{\sum_{i=1}^{n}G_i}\times 100\%$	$-\infty$ to ∞	0
POD	-	$\frac{N_{11}}{N_{11}+N_{01}}$	0 to 1	1
FAR	-	$\frac{N_{10}}{N_{11}+N_{10}}$	0 to 1	0
CSI	-	$\frac{N_{11}}{N_{11}+N_{01}+N_{10}}$	0 to 1	1
FBI	-	$\mathrm{FBI}=\frac{\mathrm{N}_{11}+\mathrm{N}_{10}}{\mathrm{N}_{11}+\mathrm{N}_{01}}$	0 to ∞	1

Notation: **n**, number of samples; $\mathbf{S_i}$, satellite precipitation; $\mathbf{G_i}$, gauged observation; $\mathbf{N_{11}}$: Satellite is > 0 and gauge is > 0; $\mathbf{N_{10}}$: Satellite is > 0 and gauge equals 0; $\mathbf{N_{01}}$: Satellite equals 0 and gauge is > 0; $\mathbf{N_{00}}$: Satellite equals 0 and gauge equals 0.

4.2.1 Evaluation of estimated daily rainfall by remote sensing

Estimated daily rainfall is evaluated by applying statistical calculations (correlation coefficient, Bias, RMSE and MAE).

4.2.1.1 Correlation Coefficient (r)

The correlation coefficient method was used to allow spatial and temporal comparison between precipitation products and rainfall stations.

$$r=1-\frac{6\sum_{i=1}^{n}[X(i)-Y(i)]^2}{n(n^2-1)}$$

With **n**, number of samples; $\mathbf{S_i}$, satellite precipitation; $\mathbf{G_i}$, gauged observation; **X(i)**=rank[S(i)]; **Y(i)**=rank[G(i)].

The analysis of the results obtained was done by plotting the graphs to evaluate the difference between the data over time. The graphs represent a scatter of estimated precipitation relative to observed precipitation. Existing differences between the data are calculated by using the correlation coefficient and error bars showing the disparities over time. The positive values obtained indicate an overestimate, the negative values: an underestimate and the zero values: a perfect estimate.

4.2.1.2 The Root Mean Square Error (RMSE)

RMSE is a statistical calculation tool for evaluating the errors of a model in estimating quantitative data. The calculation of the RMSE gives us information on the amplitude of the differences estimated by the BIAS. The magnitude is the average of the squares of the deviations which; at the initiative, could be positive values as well as negative values that offset each other at the mean. However, these values are made positive by the mean of the squares. Also, the square root of the calculation used to return to the same unit as that of the variable being compared.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - G_i)^2}{n}}$$

The result of the calculation must be between 0 and infinity. The perfect value is 0.

4.2.1.3 Relative bias

Relative bias is a means to measure the average errors obtained when comparing two values. The values are evaluated according to a given interval (-∞ to +∞) and the perfect score is zero. Errors with a negative sign show an underestimation of the data and errors with a positive sign; indicates an overestimation of the data. The equation used was:

$$BIAS = \frac{\sum_{i=1}^{n}(S_i - G_i)}{\sum_{i=1}^{n} G_i} \times 100\%$$

4.2.1.4 Mean Absolute Error (MAE)

The difference between the MAE and the bias is the absolute value of the differences between observed values (gauge) and estimated values (rainfall products). The purpose of using the MAE indicator is to obtain a better idea of the quality of prediction. However, it is

not possible to know whether the model tends to under or overestimate predictions because of the absolute value. The values are evaluated according to a given interval (0 to infinity) and the perfect score is zero.

$$MAE = \frac{\sum_{i=1}^{n} |S_i - G_i|}{n}$$

4.2.2 Evaluation of rainy and no rainy days

The evaluation of the ability of rainfall products to detect wet and dry days was carried out using statistical equations. These statistics, which are accuracy, FAR, POD, CSI and FBI are based on the possibility that an event does or does not occur, thus verifying the effectiveness of the rainfall products or the model. For this study rainy or non-rainy days were described as follows:

A rainy day corresponds to an estimate or observation greater than 0 mm/day.

The classification of the days was as follows:

N_{11}: Estimated>0 and observed>0

N_{10}: Estimated>0 and observed=0

N_{01}: Estimated=0 and observed>0

N_{00}: Estimated=0 and observed=0

4.2.2.1 Accuracy

The evaluation of rainy and non-rainy days allows the analysis of the accuracy, which varies between 0 and 1. The best value of the accuracy is 1. Accuracy is the ratio between correctly estimated events and the total number of days to be evaluated.

$$\text{Accuracy} = \frac{N_{11} + N_{10}}{n}$$

4.2.2.2 Frequency Bias Index (FBI)

The FBI aims to indicate whether remote sensing products tend to be overestimated or underestimated. The equation is written as follows:

$$\text{FBI} = \frac{\text{N}_{11} + \text{N}_{10}}{\text{N}_{11} + \text{N}_{01}}$$

4.2.2.3 Probability of Detection (POD)

POD allows evaluating the correct estimation of the products (percentage of correct estimates). Its score range is 0 to 1 and its perfect score 1. The equation used for the operation is

$$POD = \frac{N_{11}}{N_{11} + N_{01}}$$

4.2.2.4 False Alarm Ratio (FAR)

FAR gives the ratio of estimated rainfall not observed by rainfall stations. The FAR score range is 0 to 1 and the perfect value 0. It is always better to use the FAR and POD together for better analyses; because when a product always and everywhere records data: the POD will give a perfect result (1) while the FAR will give the worst result (1).

$$FAR = \frac{N_{10}}{N_{11} + N_{10}}$$

4.2.2.5 Critical Success Index (CSI)

CSI represents relative accuracy by taking into account estimated and unobserved events; and observed and no estimated events. It does not consider ordinary non-rainy days. Its score interval is 0 to 1 and its perfect value 1.

$$CSI = \frac{N_{11}}{N_{11} + N_{01} + N_{10}}$$

4.2.3 Evaluation of estimated monthly rainfall by remote sensing

The monthly evaluation of the estimated rainfall carried out by selecting a representative period of the data. The time distribution and the average monthly difference between observed and estimated rainfall are represented by two diagrams. The relationship between observed and estimated precipitation is evaluated by calculating the correlation coefficient.

Student t-test and P-value are used to evaluate the significance of the correlation coefficient and the averages of the differences between the observed and estimated rainfall data with a significance level of 5%.

The Student's test is a parametric test that applies to populations of unknown variances and means from which samples of the same size are randomly drawn (Paturel et al., 2010).

The P-value is a randomly derived variable from the distribution of the test statistic used to analyse a dataset and to test whether a null hypothesis is accepted or rejected (Hung et al., 1997). In this study, the t-test and the P-value are used to analyse the degree of significance of differences between observed and estimated means and the correlation between observed and estimated precipitation values.

4.2.4 Assessment of spatial rainfall

The assessment of the spatial distribution of observed and estimated rainfall led to the production of interpolation maps of rain gauge data and estimated rainfall product data. The type of interpolation used here is the Inverse Distance Weighting (IDW). The data were interpolated from the points of the rainfall stations listed. The maps are based on a Digital Elevation Model (DEM) downloaded from http://srtm.csi.cgiar.org and have been processed on the ArcGIS software.

Spatial interpolation is a process that allows points with known values to be used at unknown values for estimated values at other points. During the IDW interpolation procedure used in this study, the sampled points are weighted so that the influence of one point relative to another declines with the distance from the unknown point to be created. The weighting influence on the newly created points decreases with increasing distance through the weighting applied to a set of points by using a weighting coefficient. Indeed, the greater the weighting coefficient is, the less effect the points will have if they are far from the unknown point. Maximum and minimum values at the interpolated area can be observed only at the data points (Gaye & Sow, 2019).

5. RESULTS AND DISCUSSION

The data analysed here are data obtained from five rainfall stations located in Bignona, Bounkiling, Kolda, Oussouye and Ziguinchor. The data are daily rainfall recorded from 2000 to 2010 and used as reference data for the evaluation of the accuracy and performance of different rainfall products derived from remote sensing (ARC Version 2, CHIRPS-0.05, RFE Version 2 and TRMM-3B42RT) using various statistical methods mentioned in section 4.1. The evaluation and comparison of the rainfall products with the observed data were carried out at three levels: daily, monthly and annual.

5.1 Statistical Analysis of Observed Rainfall from The Five Rainfall Stations and The Average Rainfall of Casamance Basin for The Time Period Between 2000 And 2010

Figure 9 shows that rainfall is highly variable in the Casamance zone from one year to the next and even between rainfall stations. The lowest annual rainfall was recorded by the Oussouye station with a value of 530.3mm during 2008, and the highest was recorded by the Kolda station with a value of 1868.2mm during 2003. However, in general, the year 2002 shows the lowest rainfall. Casamance is characterised by high interannual variability in rainfall.

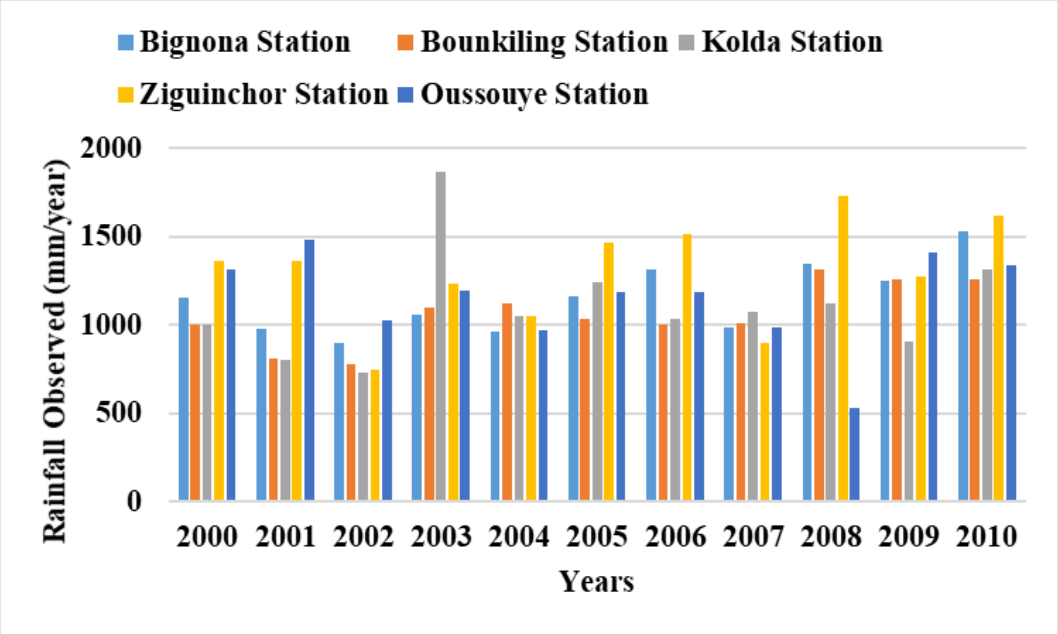


Figure 9: Annual rainfall observed in the Casamance basin between the different rainfall stations.

From 2000 to 2010, the variability of annual precipitation is very pronounced. This rainfall instability that has been noted since 1990 and has been explained by Sané et al. (2010); Sagna et al. (2015) and Descroix et al. (2015) as being caused by climate variability, often resulting in rainfall disruption.

In Senegal, there are 2 types of seasons (summer and rainy season). Usually the summer season is between November and May and the rainy season occurs between June and October. However, in the years 2000 to 2010, the beginning of the rainy season is early; in other words, rainfall begins to be observed in May instead of late June or early July as in previous years (2000) (Camberlin et al., 2003; Bacci, 2015; Sagna et al., 2015; Descroix et al., 2015). Figure 10 shows that the rainy season begins most often in June on average and ends in October in the Casamance zone. The graph (figure 11) shows that the highest mean daily rainfall recorded in 2010 with an average of 3.87 mm/day and the lowest mean daily rainfall recorded in 2002 with 2.29 mm/day.

Figure 10 shows a time series from 2000 to 2010 of the rainfall in the Casamance basin. The daily time series shows that most of the precipitations are between 0 and 20 mm/day. However, rainfall up to more than 80 mm/day has been recorded over the basin. Monthly analysis of observed precipitations in the Casamance basin shows the onset of the rainy season in May and the end of the rainy season in October. Rainfall reaches its maximum in August with a value around 410 and 420 mm/month. That means that August is the wettest month in the last ten years; nevertheless, monthly rainfall of up to 500 mm/month has been recorded. The monthly average at the beginning of the rainy season is less than 50 mm/month and the mean at the end of the rainy season is between 100 and 200 mm/month. The precipitation average of the rainiest month (August) is between 300 and 400 mm/month, that is, around 360 mm/month.

The average daily rainfall at the different stations is very low generally. Figures 10 (b, c, d, e and f) show a homogeneous distribution of daily rainfall. However, each station has various maximum daily precipitation. The station of Bignona recorded a maximum daily rainfall of 218.8 mm/day, the station of Bounkiling recorded a maximum rainfall of more than 152 mm/day, the station of Kolda recorded a maximum rainfall of 401 mm/day, the station of Ziguinchor recorded a maximum rainfall of 186.2 mm/day and the station of Oussouye recorded a maximum rainfall of 136 mm/day. The maximum amount of precipitation recorded at the Kolda station could be due to an error in recording the data.

The station of Bignona recorded its maximum and minimum rainfall in September with a value of more than 600 mm/month and less than 50 mm/month respectively. However, the average obtained during the month of September is lower than the maximum monthly average; which has a value of 400 mm/month in August.

The stations of Bounkiling, Kolda, Ziguinchor and Oussouye recorded their maximum monthly rainfall during the month of August and obtained more than 500 mm/month for Bounkiling, Kolda and Ossouye, and more than 600 mm/month for Ziguinchor. Bounkiling, Oussouye, Bignona and Kolda recorded their first rains in May. The monthly rainfall recorded showed that they are more intense in July, August and September at all stations.

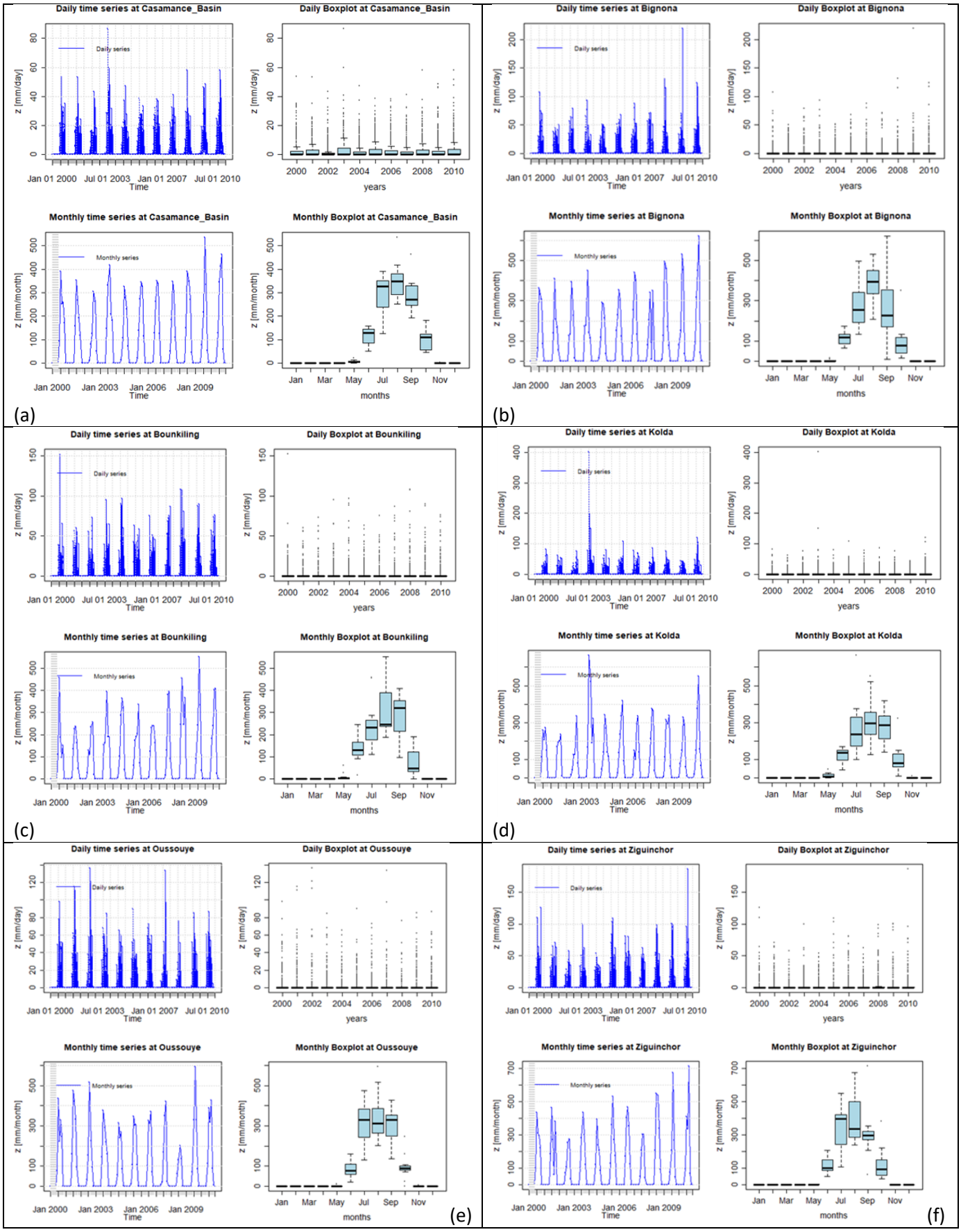


Figure 10 : Rainfall characteristics of rainfall pattern at Casamance basin and the five rainfall stations

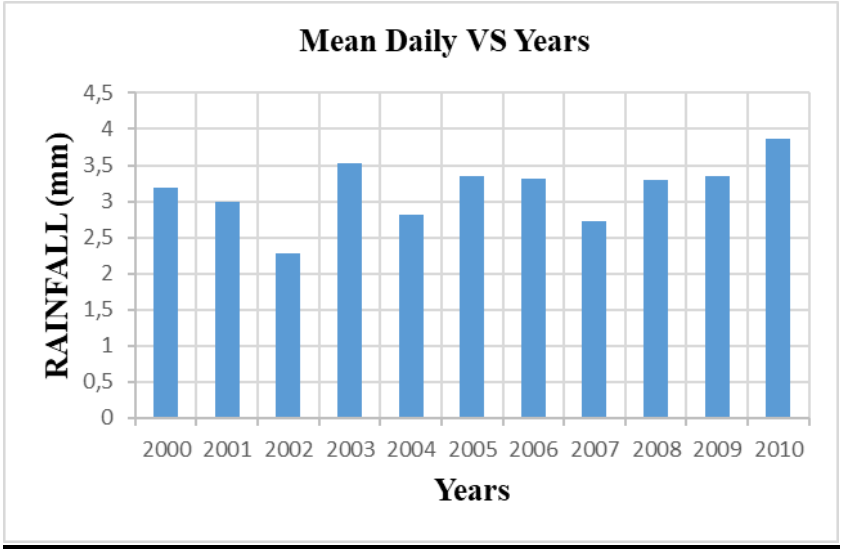


Figure 11: Variability of the mean daily rainfall observed by the rain gauges according to the years.

Monthly Rainfall Statistics

Analysis of Figure 12 shows that in 2009, the Casamance basin received the highest monthly rainfall in August. As explained in section 5.1; the rainy season ends in October; however, low rainfall was recorded in November in 2009 and 2010 by Kolda and Oussouye stations respectively. The month of the beginning of the rainy season changes according to the year; for example in the Bignona station area, the years in which the month of the onset of the rainy season is May are: 2004, 2005, 2006, 2008 and 2010; for the Bounkiling station area, the years are 2001, 2002, 2004, 2005, 2006 and 2008; for the Kolda station zone, the years are from 2002 to 2010; for the Oussouye station zone, the years are 2005 and 2007; and at the end for the Ziguinchor station zone, the years are 2002, 2005, 2008 and 2009. In the remaining years, the rainy season starts in June. In May 2005, the Bounkiling station recorded slightly higher rainfall (about 50 mm/month). The maximum intensity of precipitations, which is above 600 mm/month, was recorded in September 2010 and in August 2009 respectively at the stations of Bignona and Oussouye. The rainfall stations of Bounkiling and Kolda respectively recorded their maximum rainfall in August 2009 (above 500 mm/month) and in July 2003 (700 mm/month). The station of Ziguinchor recorded the highest rainfall with an intensity exceeding 700 mm/month in September 2010.

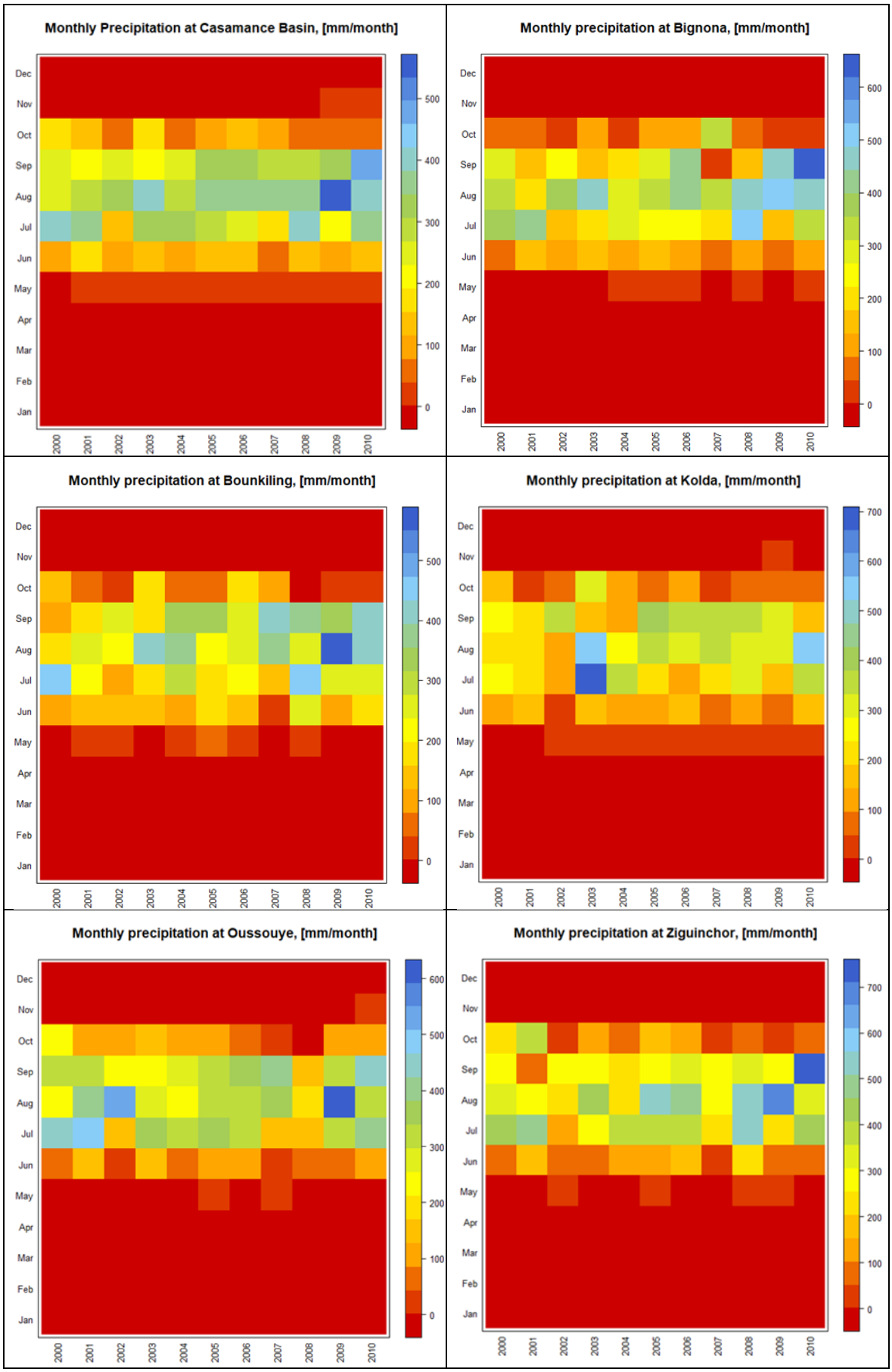


Figure 12: Statistics on time series of monthly rainfall amounts.

5.1.1 Correlation matrix for the rainfall stations in Casamance basin

Analysis of the correlation between rain gauges (figure 13) showed a correlation between Bignona and Bounkiling (r=0.46), Oussouye and Ziguinchor (r=0.47). However, between the rainfall stations Ziguinchor and Bignona (r=0.19), Oussouye and Bignona (r=0.19); there is no correlation. This lack of relationship between these stations may be due to a change in altitude between the rain gauge sites. In general, the correlation coefficients obtained between the rainfall stations are low.

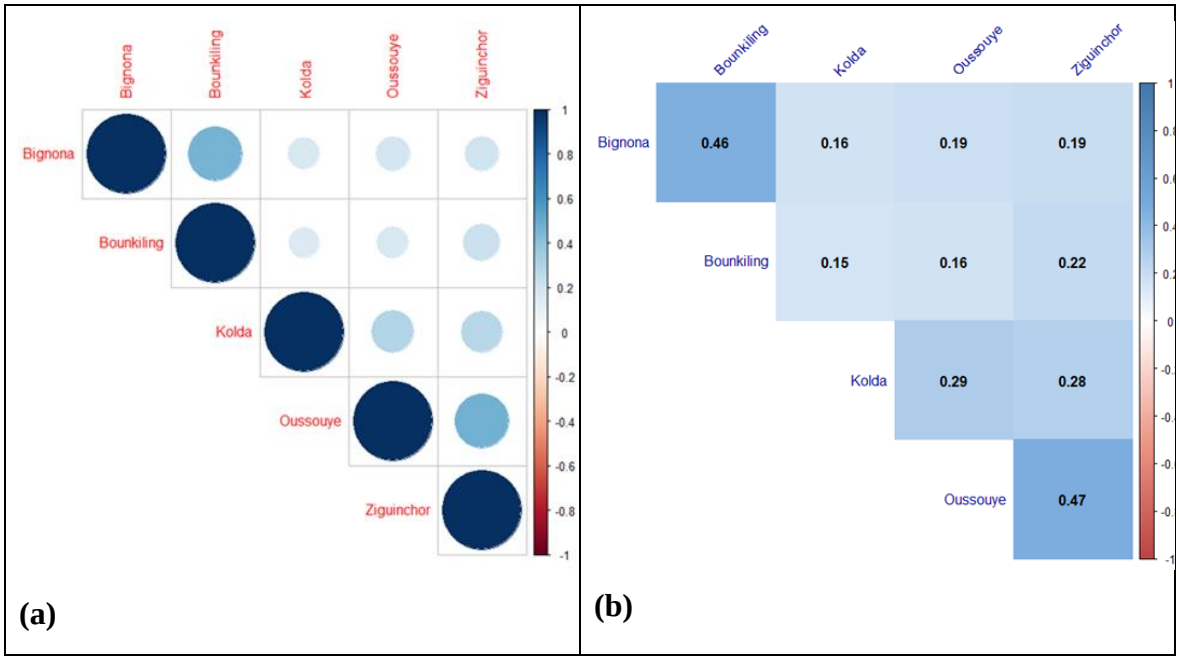


Figure 13: Correlation between the rain gauges in Casamance basin.

Note: Y axis represents the correlation coefficient & the tests are highly significant at $p < 0.0001$ level of statistical significance.

5.2 Daily Rainfall Assessment of Remote Sensing Derived Rainfall Products

Figure 14 shows the over and underestimates of daily precipitation made by precipitation products. ARC 2 underestimated 22% and overestimated 20% of the rainfall estimate days; which means that ARC 2 underestimated more days than it overestimated. The amplitude of the highest underestimates was -76 mm/day and the amplitude of the highest overestimates was 51.3 mm/day. Similarly, for RFE 2, the number of underestimated days (23%) is higher than the number of overestimated days (22%). The maximum underestimation of RFE 2

reached is -76.64 mm/day and its maximum overestimation is 86.2 mm/day. However, the number of days CHIRPS overestimated (24%) is higher than the number of days it underestimated (19%). CHIRPS' highest underestimation is -7.9 mm/day and its maximum overestimation was 4 mm/day. On the other hand, the magnitude of the maximum overestimation of TRMM is 51.94 mm/day and the amplitude of its underestimation reached -86.52 mm/day. TRMM also overestimated more days (50%) than it underestimated (32%); which means that TRMM tends to overestimate rainfall in general.

It can be noted that unlike CHIRPS; Arc Version 2, RFE Version 2 and TRMM present estimates for days that are often not considered as rainy days in normal time in a sub-Saharan zone such as the Casamance basin area. These days are part of the dry season period (absence of observed rainfall). During this period the estimates are very low or absent (CHIRPS) except for the TRMM.

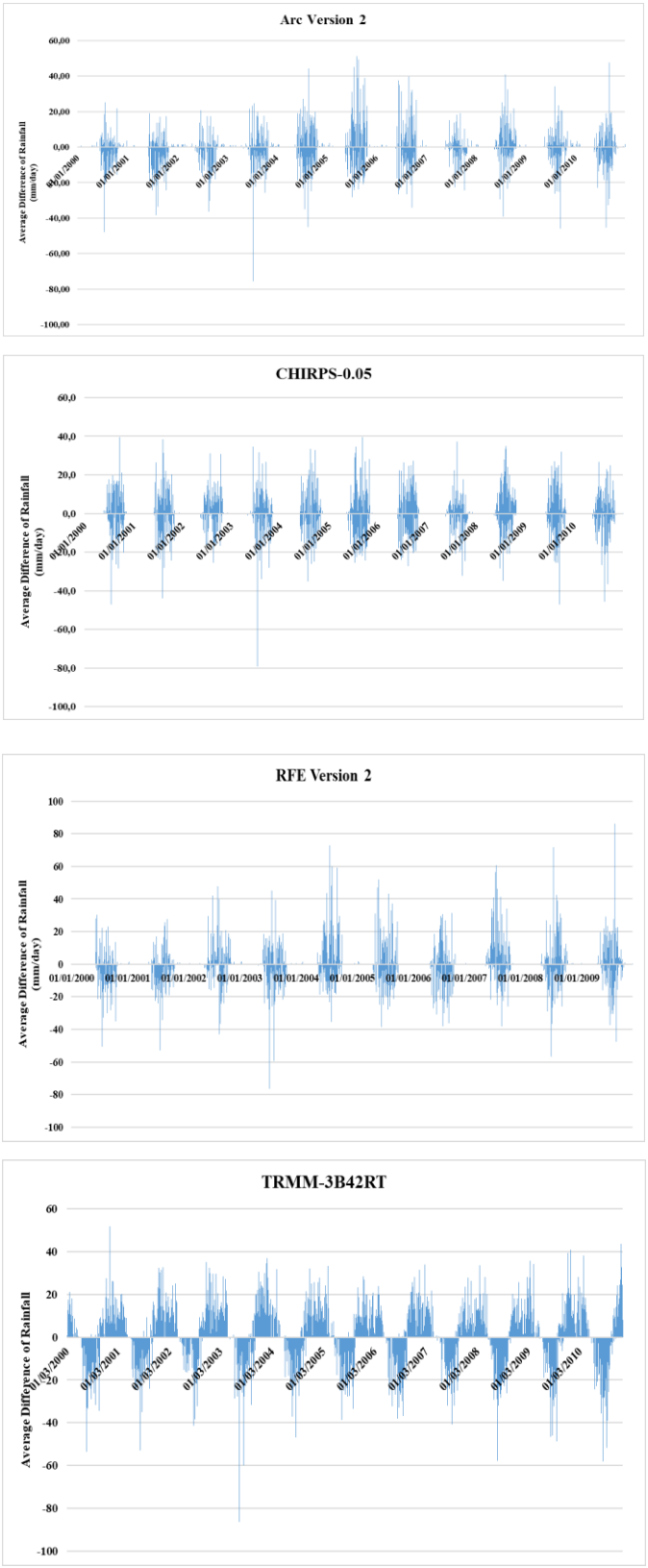


Figure 14: Average daily Difference between observed and Estimated data by Arc Version2, CHIRPS, RFE Version 2 and TRMM (Overestimation and underestimation).

5.2.1 Relationship between rainfall products and gauge stations

Determining a relationship between the estimated data and the observed data requires the analysis of the statistical calculations as listed above.

5.2.1.1 The correlation coefficient

The correlation coefficient demonstrates the existence of a relationship between in situ measurement rainfall data and remote sensing derived rainfall estimates.

The results obtained show a weak relationship between the rainfall products and the rainfall data from the different stations at daily time steps. ARC 2 and CHIRPS had the best performance with, respectively, r=0.32 and r=0.31, and RFE 2 and TRMM recorded the poorest results with respectively r=0.15 and r=-0.12. The best correlations were obtained with the Ziguinchor and Oussouye stations for ARC 2 (r=0.57 and r=0.41 respectively) and CHIRPS (r=0.43 and r=0.38 respectively). On the other hand, for RFE 2 and TRMM, their best correlations were obtained respectively with the stations of Bounkiling (r=0.17) and Ziguinchor (r=0.18), and the stations of Bounkiling (r=-12), Kolda (r=-0.11) and Oussouye (r=-12) (See Table 3). These results could indicate that a daily time-step analysis shows poor performance for the precipitation products selected in this study.

5.2.1.2 BIAS

BIAS is a means of determining the direction of estimation of the data to be measured; whether they are overestimated or underestimated. In this study, the calculated BIAS is mostly negative (Bignona, Ziguinchor and Oussouye) for Arc Version 2 and RFE Version 2. It is mostly positive for CHIRPS (Bounkiling, Kolda and Ziguinchor) and TRMM (Bignona, Bounkiling, Kolda and Oussouye). This means that Arc Version 2 and RFE Version 2 tend to underestimate the observed rainfall, while CHIRPS and TRMM tend to overestimate it (Table 3).

5.2.1.3 RMSE and MAE

The RMSE results obtained are in the range of 9.83 to 13.01 mm/day for ARC 2, 10.30 to 12.17 mm/day for CHIRPS-0.05, 11.90 to 14.61 mm/day for RFE 2 and 13.15 to 15.03 mm/day for TRMM-3B42RT. The highest RMSE was obtained with TRMM (15.03 mm/day) at the Bignona station and the lowest was obtained with ARC 2 (9.83 mm/day) at the Ziguinchor station. These results show that the deviations of the errors are more

accentuated with TRMM (14.16 mm/day) and less accentuated with CHIRPS (11.28 mm/day) which has the lowest RMSE overall. On the other hand, with the MAE results obtained, ARC 2 recorded the lowest value overall. The MAE results are in the range of 3.26 to 4.55 mm/day for ARC 2, 3.71 to 4.54 mm/day for CHIRPS-0.05, 4.17 to 4.71 mm/day for RFE 2 and 6.24 to 7.39 mm/day for TRMM-3B42RT. In general, ARC 2 (3.86 mm/day) has the lowest error amplitude while TRMM (6.69 mm/day) has the highest amplitude of MAE (table 3).

Table 3: Statistical results of rainfall products (ARC 2, RFE 2, CHIRPS, TRMM) at daily time, which are the correlation coefficient (r), RMSE, MAE and BIAS.

ARC Version 2	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0,16	0,16	0,32	0,57	0,41	0,32
RMSE (mm)	12,67	12,32	13,01	9,83	10,07	11,58
MAE (mm)	4,27	4,55	3,89	3,26	3,33	3,86
BIAS	-36,04	2,72	3,41	-23,83	-40,26	-18,80
CHIRPS-0,05	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0,25	0,21	0,29	0,43	0,38	0,31
RMSE (mm)	11,27	11,6	12,17	11,08	10,3	11,28
MAE (mm)	4,20	4,54	4,17	4,23	3,71	4,17
BIAS	-7,81	15,31	11,21	0,34	-14,08	0,99
RFE Version 2	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0,13	0,17	0,13	0,18	0,13	0,15
RMSE (mm)	12,73	12,2	14,61	12,78	11,9	12,84
MAE (mm)	4,33	4,31	4,71	4,69	4,17	4,44
BIAS	-18,57	1,4	6,05	-17,81	-25,86	-10,96

TRMM-3B42RT	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	-0,13	-0,12	-0,11	-0,13	-0,12	-0,12
RMSE (mm)	15,03	13,15	14,37	14,21	14,06	14,16
MAE (mm)	7,39	6,24	6,37	6,79	6,66	6,69
BIAS	36,1	14,7	10,41	-6,76	12,72	13,43

5.2.2 Summary of daily rainfall assessment

Analysis of the estimated daily data led to the conclusion that CHIRPS and TRMM overestimated rainfall, while ARC 2 and RFE 2 underestimated rainfall. This was confirmed by the BIAS calculation (table 3); which produced the same result. In this analysis, CHIRPS shows the lowest value of overestimation and RFE 2 shows the lowest value of underestimation. The analysis of the obtained correlation coefficients shows an average to a weak relationship between the estimated and observed rainfall. The better results of correlation were obtained by ARC 2 (r=0.32) and CHIRPS (r=0.31). ARC 2 and CHIRPS had the best values for RMSE (11.58 mm/day and 11.28 mm/day respectively) and MAE (3.86 mm/day and 4.17 mm/day respectively). Overall, ARC 2 and CHIRPS recorded the best results at all levels (Table 3), although ARC 2 had the highest error rate with BIAS. TRMM recorded the worst performance.

5.3 Assessment of Statistics for The Detection of Rainy and Non-Rainy Days

5.3.1 Accuracy, POD, FAR, CSI and FBI

Accuracy, POD, FAR, CSI and FBI are computed to study the quality of errors between data from satellite products and data from measuring stations.

5.3.1.1 ARC 2

The accuracy of ARC 2 varies between 0.79 and 0.86 depending on the different stations (table 4). The perfect accuracy score is 1, while the average accuracy obtained here (table 4) is 0.83. This means that the ARC 2 satellite product detected correctly 83% of rainy and non-rainy days.

The POD indicates 0.65 on average; this means that ARC 2 can detect 65% of rainy days observed by rainfall stations. The FAR rate recorded by the rainfall product is 0.44 on average; i.e. 44% of the rainy days estimated by ARC 2 did not occur. The CSI gives a value of 0.43; i.e. 43% of the estimated rainy days occurred taking into account the rainy days estimated and not occurring and the rainy days not estimated by ARC 2 but occurring. The FBI reports a slight overestimation of the frequency of rainy days with a value of 1.19 since the FBI's perfect score is 1.

Table 4 : Statistic results for Arc Version 2 at the Casamance catchment.

	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	average
Accuracy	0,82	0,79	0,86	0,85	0,83	0,83
POD	0,51	0,64	0,75	0,70	0,65	0,65
FAR	0,46	0,58	0,38	0,33	0,47	0,44
CSI	0,36	0,34	0,51	0,52	0,41	0,43
FBI	0,94	1,53	1,20	1,05	1,22	1,19

5.3.1.2 CHIRPS-0.05

The accuracy of CHIRPS-0.05 varies between 0.78 and 0.83 depending on the different stations. The perfect accuracy score is 1, while the average accuracy obtained here is 0.81 (table 5). This means that the CHIRPS-0.05 satellite product correctly detected 81% of rainy and non-rainy days.

The statistical results in Table 5 show that the POD indicates 0.61 on average; this means that CHIRPS-0.05 can detect 61% of rainy days observed by the precipitation stations. The FAR obtained with the rainfall product is 0.50 on average, i.e. 50% of the rainy days estimated by CHIRPS-0.05 did not occur. The CSI gives a value of 0.38; i.e. 38% of the estimated rainy days occurred taking into account the rainy days estimated and not occurring and the rainy days not estimated by CHIRPS-0.05 but occurring. The FBI reports an overestimation of the frequency of rainy days with a value of 1.24 since the FBI's perfect score is 1.

Table 5: Statistic results for CHIRPS-0.05 at the Casamance catchment.

	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	average
Accuracy	0,78	0,79	0,81	0,83	0,83	0,81
POD	0,55	0,58	0,65	0,65	0,63	0,61
FAR	0,56	0,59	0,49	0,37	0,48	0,50
CSI	0,32	0,31	0,40	0,47	0,40	0,38
FBI	1,25	1,42	1,27	1,04	1,22	1,24

5.3.1.3 RFE VERSION 2

The results obtained and illustrated in Table 6 show that the accuracy of RFE VERSION 2 varies between 0.77 and 0.81 depending on the different stations. The perfect accuracy score is 1, while the average accuracy obtained here is 0.79. This means that the satellite product RFE VERSION 2 has correctly detected 79% of rainy and non-rainy days.

The POD indicates 0.62 on average; this means that RFE VERSION 2 has estimated 62% of rainy days observed by the rain stations. The FAR obtained with this satellite product is on average 0.54; in other words, 54% of the rainy days estimated by RFE VERSION 2 did not occur.

The CSI gives a value of 0.36; i.e. 36% of the estimated rainy days occurred taking into account the rainy days estimated and that did not occur and the rainy days not estimated by RFE VERSION 2 but that did occur.

The FBI reports an overestimation of the frequency of rainy days with a value of 1.37 since the FBI's perfect score is 1.

Table 6: Statistic results for RFE VERSION 2 at the Casamance catchment.

	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	average
Accuracy	0,80	0,77	0,81	0,80	0,77	0,79
POD	0,51	0,69	0,63	0,62	0,65	0,62
FAR	0,53	0,61	0,50	0,44	0,60	0,54
CSI	0,33	0,33	0,39	0,42	0,33	0,36
FBI	1,09	1,78	1,25	1,12	1,63	1,37

5.3.1.4 TRMM-3B42RT

The accuracy of TRMM-3B42RT varies between 0.43 and 0.46 depending on the different stations. The perfect accuracy score is 1, whereas the average accuracy obtained here is 0.44. This means that the TRMM-3B42RT satellite product correctly detected 44% of rainy and non-rainy days.

The POD indicates 0.28 on average; this means that TRMM-3B42RT estimated 28% of rainy days observed by the rainfall stations. These results are very low compared to the other results of the previous rainfall products. The average FAR obtained with this satellite product is 0.89; i.e. 89% of the rainy days estimated by TRMM-3B42RT did not occur. This result shows that the false alarm rate is very high. The CSI gives a value of 0.09; i.e. 9% of the estimated rainy days occurred considering the estimated rainy days that did not occur and the rainy days that were not estimated by TRMM-3B42RT but did occur. The FBI reports a large overestimation of the frequency of rainy days with a value of 2.43, knowing that the FBI's perfect score is 1.

Table 7: Statistic results for TRMM-3B42RT at the Casamance catchment.

	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	average
Accuracy	0,44	0,45	0,43	0,43	0,46	0,44
POD	0,22	0,29	0,28	0,35	0,24	0,28
FAR	0,90	0,90	0,89	0,84	0,90	0,89
CSI	0,07	0,08	0,09	0,13	0,07	0,09
FBI	2,28	2,82	2,46	2,13	2,44	2,43

5.3.2 Summary on the evaluation of statistics for the detection of rainy days and days without rain.

The accuracy of remote sensing products ranges from 0.83 to 0.44. This means that these products have a large enough capacity to accurately detect both rainy and non-rainy days (except TRMM-3B42RT). This high result, especially obtained with ARC 2 and CHIRPS-0.05, since non-rainy days are more frequent in the Casamance zone because of its climatic characteristic (sub-Saharan zone); which considerably affects the percentage of accuracy since these days were more easily detected by rainfall products.

The rainy days were also fairly well detected by most of these remote sensing products (except TRMM-3B42RT) for the Casamance basin as showed in table 8: POD between 0.65 and 0.28.

Furthermore, false alarms are generally low with results ranging from 0.44 to 0.89 (table 8) except for TRMM-3B42RT.

All the rainfall products evaluated in this study tend to overestimate the number of rainy days (FBI between 1.19 and 2.43). This brings us to their detection performance of rainy days which is low (CSI from 0.43 to 0.09) (table 8).

The best results were obtained by Arc Version 2. However, CHIRPS -0.05 and RFE 2 got good performance also, whereas TRMM had the worst performance.

Table 8: Statistic results at the Casamance catchment.

	Arc Version 2	CHIRPS-0.05	RFE Version 2	TRMM-3B42RT
Accuracy	0,83	0,81	0,79	0,44
POD	0,65	0,61	0,62	0,28
FAR	0,44	0,50	0,54	0,89
CSI	0,43	0,38	0,36	0,09
FBI	1,19	1,24	1,37	2,43

5.4 Monthly Rainfall Assessment of Remote Sensing Derived Rainfall Products

Figure 15 shows that monthly observed rainfall was generally recorded between May and October. The highest amount of rainfall was observed in September 2010 with a value of 711.40 mm/month at the Ziguinchor station. During the same period, ARC 2 recorded monthly precipitation of 694.51 mm/month (Kolda station), which represents its highest estimated precipitation value, while CHIRPS-0.05 estimated precipitation of 553.03 mm/month (Ziguinchor station). In the same year of 2010, TRMM-3B42RT estimated maximum value of 504.24 mm/month in December (Oussouye station). These values represent only the maximum values estimated in 2010 (except for ARC 2). This means that ARC 2, CHIRPS-0.05 and TRMM-3B42RT underestimated the maximum rainfall value observed in 2010. However, overall, the maximum rainfall amounts estimated by CHIRPS-0.05, RFE 2 and TRMM-3B42RT were recorded respectively in August 2009, September

2009 and December 2009 with values that reached 611.09 mm/month (Bounkiling station), 683.91 mm/month (Kolda station) and 537.06 mm/month (Oussouye station). This analysis showed that TRMM-3B42RT estimated high rainfall outside the rainy season. The least rainy year was 2004 for observed rainfall, while the least rainy years estimated by ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT were 2001, 2002 and 2000 respectively.

Figure 15: Comparison between the monthly rainfall observed by the rain gauge stations and the monthly rainfall estimated by the rainfall products.

The graphs (Figure 16) represent over- and underestimates of precipitation products. ARC 2 and RFE 2 underestimated the observed rainfall with maximum error magnitude of -215.01 mm/month (July 2001) and -287.68 mm/month (July 2001) respectively. However, CHIRPS-0.05 and TRMM-3B42RT overestimated the observed rainfall with maximum values reaching 111.83 mm/month (July 2002) and 424.47 mm/month (December 2009) respectively. TRMM-3B42RT tends to estimate rainfall during the dry season period. It is that explains its overestimation performance. The small overestimates noted in Figures 16 (a) and 16 (b) represent rainfall estimates recorded by ARC 2 and RFE 2, respectively, during the dry season period. These estimates during the dry season are estimates with very small intensities that represent a few months of overestimation that could not influence their tendency to underestimate rainfall in general.

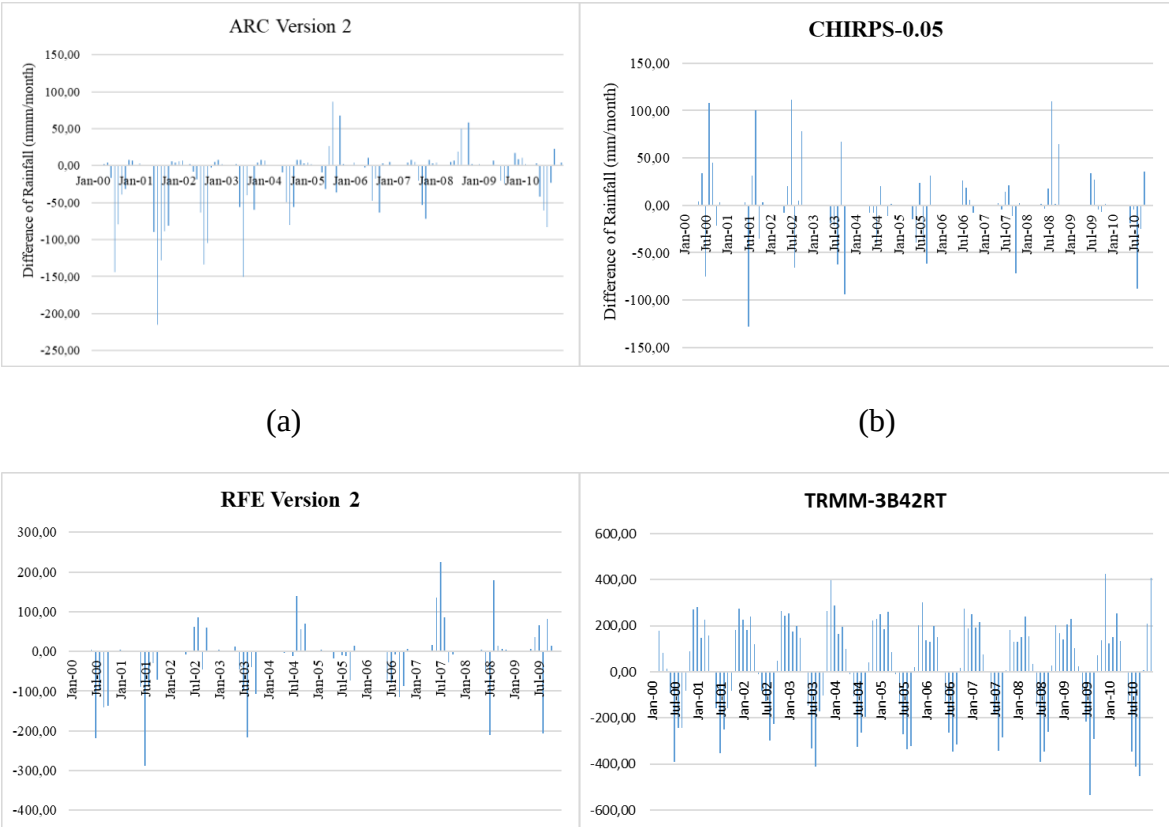


Figure 16: Average monthly Difference between observed and estimated data by Arc Version2, CHIRPS, RFE Version 2 and TRMM (Overestimation and underestimation).

5.4.1 Assessment of the relationship between observed monthly rainfall and estimated monthly rainfall

The monthly analysis showed a strong correlation between CHIRPS-0.05 (r=0.90), ARC 2 (r=0.85) and the observed monthly data. RFE 2 is moderately correlated (r=0.70) with the observed monthly data, while TRMM-3B42RT is negatively correlated with the observed monthly data (r= -0.55); this means that the data recorded by TRMM-3B42RT and the data observed by the rainfall stations evolve inversely.

The realization of a t-test shows that the correlation obtained by ARC 2 is statistically very significant at a significance level of 5% and a confidence interval of 95%, with a P-value=0, Df= 131, observed t= -3.81, critical t= 1.98, N= 132 (figure 17 and table 9).

The difference between the averages of the monthly data observed by the rainfall stations (96.08 mm/month) and the averages of the monthly data estimated by ARC 2 (82.50 mm/month) is -13.58 mm/month in the Casamance basin. This difference is statically significant, with a P-value of less than 5% (level significance) (table 9).

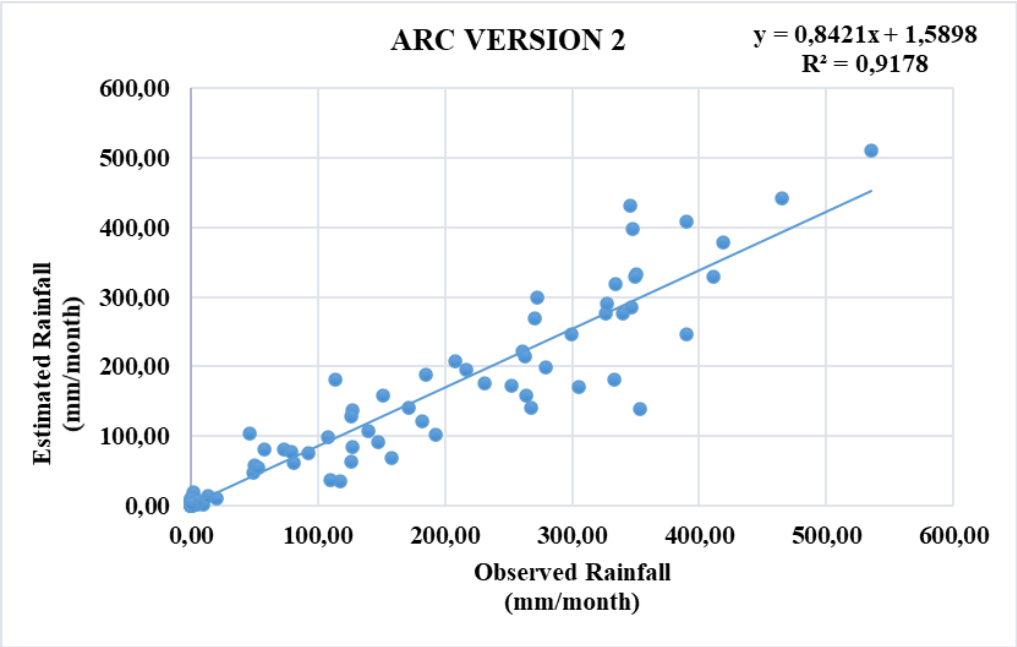


Figure 17: Degree of correlation between observed and estimated monthly rainfall by Arc Version 2.

Table 9: P-value of the correlation coefficient for Arc Version 2

Variables	Arc Version 2	Rain Gauge
Arc Version 2	**0**	**<0,0001**
Rain Gauge	**<0,0001**	**0**

The correlation between the monthly CHIRPS data (r=0.90) and the monthly data from the rainfall stations is very strong and very significant according to the t-test performed (Figure 18 and Table 10). The results obtained from the test with a significance level of 5% and a confidence interval of 95% are: P-value= 0.81, Df= 131, observed t= 0.24, critical t= 1.98 and N=132.

The difference between the averages is 0.67 mm/month. This confirms that the difference between the means of the monthly CHIRPS-0.05 data (96.75 mm/month) and the means of the monthly data observed by the rainfall stations (96.08 mm/month) is not statistically significant and the hypothesis that their difference may be equal to 0 is not rejected. This confirms that there is a very strong relationship between the estimated CHIRPS data and the observed data (P- value of the correlation coefficient < 5%) (table 10).

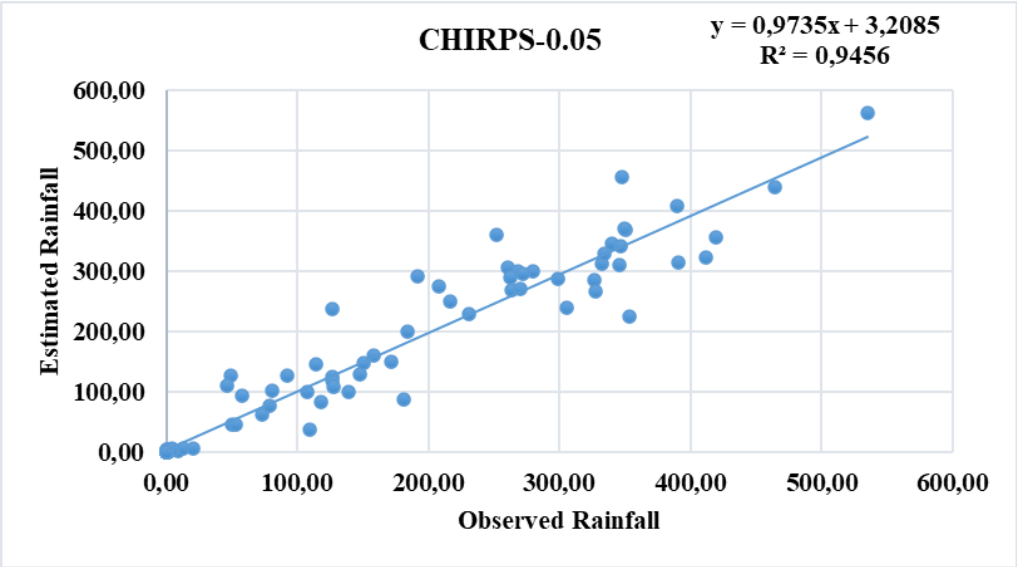


Figure 18: Degree of correlation between observed and estimated monthly rainfall by Chirps-0.05

Table 10: P-value of the correlation coefficient for CHIRPS-0.05.

Variables	CHIRPS-0.05	Rain Gauge
CHIRPS-0.05	**0**	**<0,0001**
Rain Gauge	**<0,0001**	**0**

The correlation that exists between the monthly data from the RFE 2 and the monthly data from the rainfall stations is r = 0.70. This shows that the two data have a linear relationship at 70%, which is not very representative compared to the two previous results obtained but is still strong. The results obtained from the t-test carried out with a significance level of 5% and a confidence interval of 95% are: P-value= 0.01, Df= 131, observed t= -2.64, critical t= 1.98, N=132 (Figure 19 and Table 11).

The difference between the averages is -20.45 mm/month. The difference between the averages of the monthly data of RFE 2 (75.63 mm/month) and the averages of the monthly data observed by the rainfall stations (96.08 mm/month) is found statistically significant at p less than 5% (level of statistical significance).

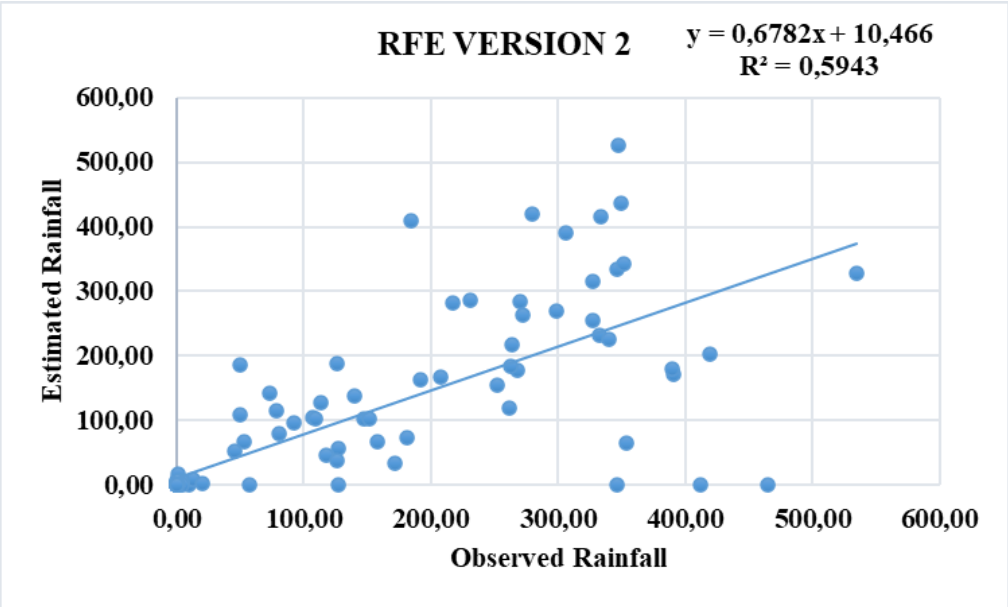


Figure 19: Degree of correlation between observed and estimated monthly rainfall by RFE 2.

Table 11: P-value of the correlation coefficient for RFE 2.

Variables	RFE Version 2	Rain Gauge
RFE Version 2	**0**	**<0,0001**
Rain Gauge	**<0,0001**	**0**

The correlation between the TRMM-3B42RT monthly data (r= -0.55) and the monthly rainfall station data shows that the two data have a negatively linear relationship at 55%. This means that when TRMM-3B42RT estimates rainfall there is a 55% chance that it will not occur. The results obtained from the t-test performed with a significance level of 5% and a confidence interval of 95% are: P-value= 0.52, Df= 131, observed t= 0.65, critical t= 1.98, N=132.

The difference between the averages is 12.43 mm/month. The difference between the mean monthly data from TRMM-3B42RT (108.51 mm/month) and the mean monthly data observed by the rainfall stations (96.08 mm/month) is not statistically significant. This is confirmed by the P-value (P< 5%) of the correlation (table 12) which shows that there is a negative linear relationship between observed and estimated rainfall for TRMM-3B42RT as showed in the figure 20.

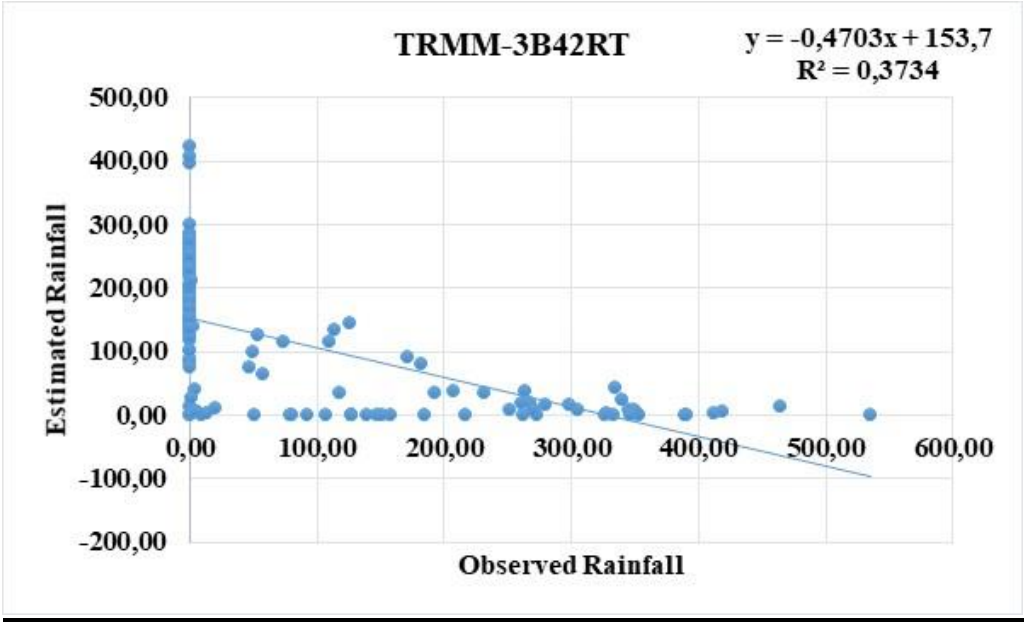


Figure 20: Degree of correlation between observed and estimated monthly rainfall by TRMM-3B42RT.

Table 12: P-value of the correlation coefficient for TRMM-3B42RT.

Variables	TRMM-3B42RT	Rain Gauge
TRMM-3B42RT	**0**	**<0,0001**
Rain Gauge	**<0,0001**	**0**

5.4.1.1 BIAS

In this monthly analysis, the calculated BIAS is mostly negative (Bignona, Ziguinchor and Oussouye) for ARC 2, which means that this satellite product has underestimated the rainfall with a monthly average value of 13.62%. It should be noted that the highest BIAS for ARC 2 was -28.70 with the Oussouye station. RFE 2 underestimated the rainfall at all stations with an average relative error amplitude of 20.85%. Nevertheless, the highest monthly BIAS of RFE 2 was obtained over Oussouye station (BIAS=-33.75) and the lowest was obtained over Kolda station (BIAS=-5.43). The BIAS calculation confirmed the trend of CHIRPS-0.05 and TRMM-3B42RT overestimated the rainfall with mean values of 0.99% and 13.44%, respectively. The highest BIAS of CHIRPS-0.05 and the highest BIAS of TRMM-3B42RT are 15.31 and 36.10 respectively for Boukiling and Bignona stations.

5.4.1.2 RMSE and MAE

The monthly RMSE results obtained range from 92.62 to 62.19 mm/month for ARC 2; 77.67 to 62.23 mm/month for CHIRPS-0.05; 122.65 to 96.13 mm/month for RFE 2 and 249.36 to 208.23 mm/month for TRMM-3B42RT. The highest RMSE was obtained with TRMM-3B42RT at the Bignona station and the lowest was obtained with ARC 2 at the Bounkiling station. However, overall, these results showed that the error deviations are more pronounced with TRMM-3B42RT with a mean value of 226.92 mm/month and less pronounced with CHIRPS-0.05 with a mean value of 66.80 mm/month. On the other hand, with the results obtained for MAE, CHIRPS-0.05 recorded the lowest value, overall, and TRMM-3B42RT had the highest MAE with mean values of 32.01 mm/month and 188.12 mm/month, respectively. The MAE results ranged from 31.54 to 45.45 mm/month for ARC 2; 26.91 to 37.46 mm/month for CHIRPS-0.05; 47.26 mm/month to 57.70 mm/month for RFE 2 and 176.03 to 209.32 mm/month for TRMM-3B42RT (Table 13).

Overall, the monthly statistical calculations showed that CHIRPS had the best performance and TRMM the worst performance.

Table 13: Statistical results of rainfall products (ARC 2, RFE 2, CHIRPS, TRMM) at monthly time step, which are the correlation coefficient (r), RMSE, MAE and BIAS.

ARC Version 2	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0,81	0,89	0,79	0,94	0,84	0,85
RMSE (mm)	91.94	62.19	92.62	64.25	87.96	79.79
MAE (mm)	43,63	34,48	40,01	31,54	45,45	39,02
BIAS	-26,49	2,80	3,53	-19,24	-28,70	-13,62
CHIRPS-0,05	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0,89	0,91	0,86	0,93	0,91	0,90
RMSE (mm)	67,90	63,50	77,67	62,23	62,71	66,80
MAE (mm)	31,17	33,36	37,46	26,91	31,16	32,01
BIAS	-7,81	15,31	11,21	0,34	-14,08	0,99
RFE Version 2	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0,68	0,73	0,71	0,70	0,69	0,70
RMSE (mm)	112,61	96,13	110,09	122,65	109,82	110,26
MAE (mm)	51,94	47,26	52,15	57,70	54,14	52,64
BIAS	-28,42	-9,50	-5,43	-27,14	-33,75	-20,85
TRMM-3B42RT	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	-0,54	-0,58	-0,56	-0,55	-0,52	-0,55
RMSE (mm)	249,36	208,23	212,62	237,72	226,68	226,92
MAE (mm)	209,32	176,03	177,29	192,01	185,93	188,12
BIAS	36,10	14,70	10,41	-6,76	12,72	13,44

5.4.2 Summary of monthly rainfall assessment of remote sensing derived rainfall products

Based on the results mentioned in Table 13: the monthly assessment of rainfall, estimated by the four rainfall products (Arc Version 2, CHIRPS-0.05, RFE Version 2 and TRMM-3B42RT), showed that rainfall was generally overestimated by CHIRPS-0.05 and TRMM-3B42RT; and underestimated by ARC 2 and RFE 2.

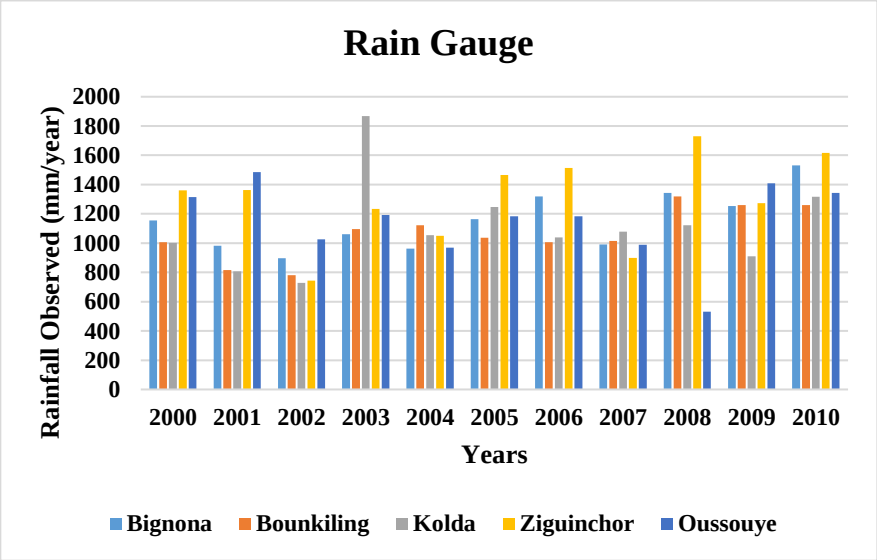
The relationship between estimated and observed precipitation was evaluated by the correlation coefficient, the p-value of the different correlation coefficients and the differences in the averages. The p-value of the coefficients of the four products showed that each of their correlation coefficients was significant. CHIRPS-0.05 performed best with the smallest difference in the means (not statistically significant) and the correlation coefficient closest to 1. ARC 2 and RFE 2 also performed well with the correlation coefficient. However, the difference between their average estimated rainfall and their average observed rainfall is statistically significant. TRMM-3B42RT had the worst performance with a significant negative correlation between estimated and observed rainfall data.

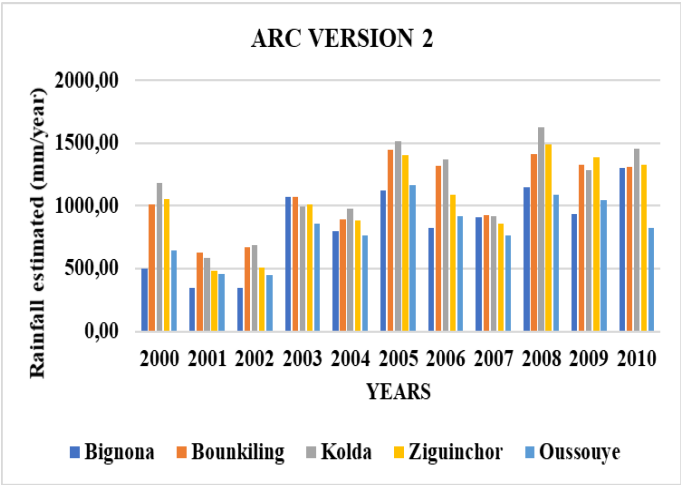
In general, the monthly assessment of estimated rainfall by satellite products revealed that, through statistical calculation methods, CHIRPS-0.05 had the best performance with the best statistical results (r= 0.90, RMSE=66.80, MAE= 32.01 and BIAS= 0.99) followed by ARC 2 with a very good correlation (r= 0.85). RFE 2 also had a good correlation (r=0.70) but with high RMSE, MAE and BIAS. On the other hand, TRMM-3B42RT had the worst performance with a negative correlation (r=-0.55).

5.5 Annual Rainfall Assessment of Remote Sensing Derived Rainfall Products

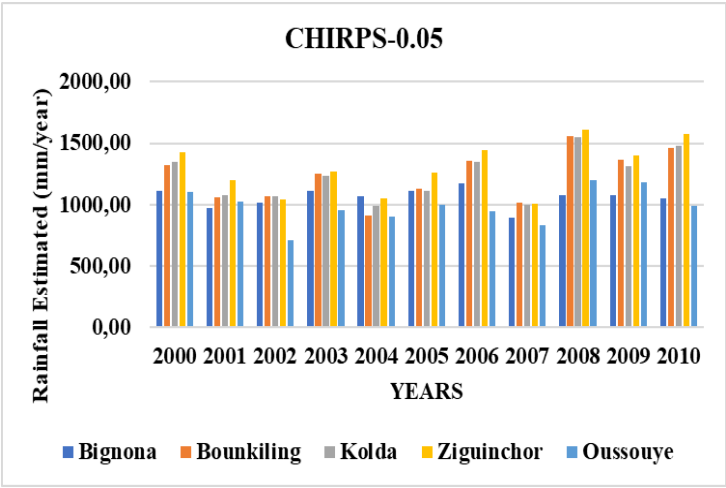
The mean rainfall obtained from the five rainfall stations represents the Casamance area. Figure 21 shows the annual rainfall obtained from in situ measurements and from precipitation products between the year 2000 and 2010. The rainfall data reached a maximum of 1868.20 mm/year recorded with the Kolda station and an average of 1152.97 mm/year. Maximum rainfall was underestimated by all three precipitation products (ARC 2, CHIRPS-0.05 and RFE 2) except TRMM-3B42RT which significantly overestimated them. On the other hand, for the average and minimum rainfall ARC 2 and RFE 2 underestimated

the rainfall amounts which are at the same time overestimated by CHIRPS-0.05 and TRMM-3B42RT. The maximum rainfall values of ARC 2, RFE 2 and CHIRPS-0.05 are close to each other. Also, these maximum precipitations were estimated in 2008 for ARC 2 (Kolda station) and CHIRPS-0.05 (Ziguinchor station), in 2007 for RFE 2 (Kolda station) and 2002 for TRMM -3B42RT (Bignona station). The mean rainfall data recorded by CHIRPS-0.05 are much closer to the in situ measured data.

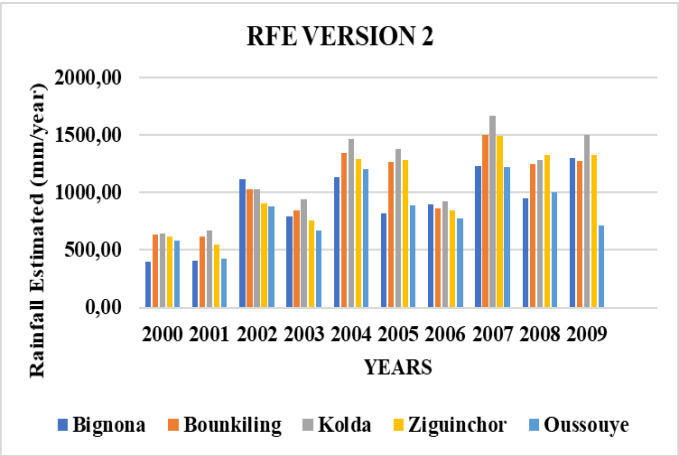




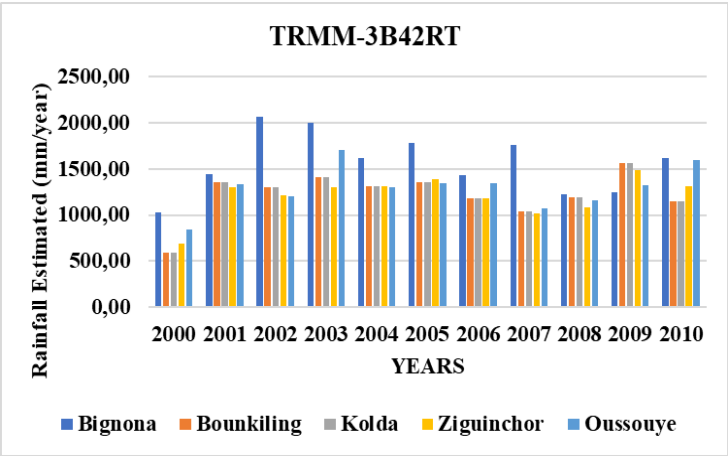
(a)



(b)



(c)



(d)

Figure 21: Annual rainfall observed by rain gauges and estimated by the precipitation products in the Casamance basin with the different rainfall stations.

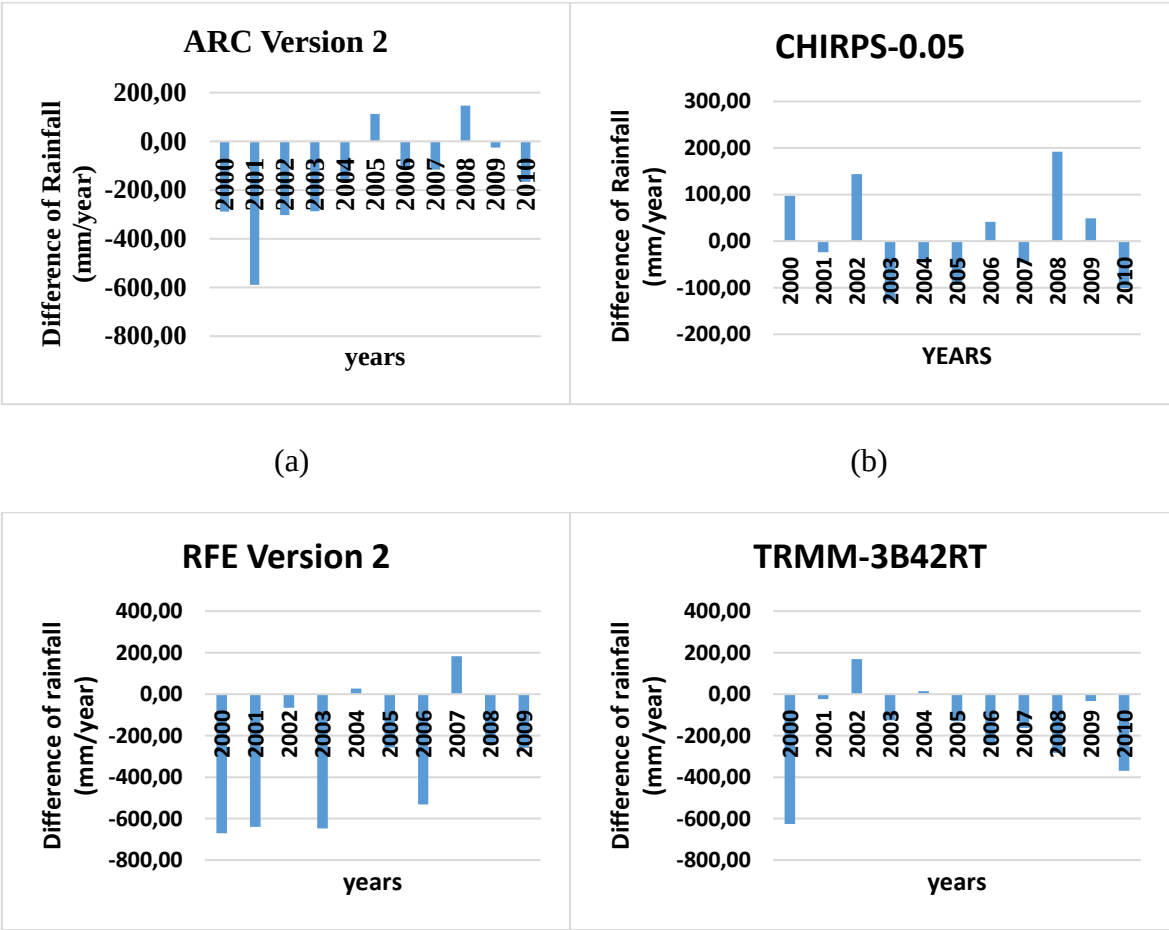
	Rain Gauge	**ARC 2**	**CHIRPS-0,05**	**RFE 2**	**TRMM_3B42RT**
Maximum (mm/year)	1868.20	1623.86	1610.83	1670.82	2070.39
Minimum (mm/year)	530.30	345.41	706.86	402.66	592.92
Average (mm/year)	1152.97	990.04	1160.96	998.33	1302.11

Table 14: comparison between the maximum, minimum and average rainfall observed by the rain gauges and the rainfall estimated by the precipitation products.

The underestimation of ARC 2 and RFE 2 was confirmed by Figures 22 (a) and 22 (c). Indeed, ARC 2 and RFE 2 overestimated only two years out of eleven years (2005 and 2008 for ARC 2; 2004 and 2007 for RFE 2) with a maximum value of 146.04 mm/year in 2008 and 183.51 mm/year in 2007. The underestimates for ARC 2 and RFE 2 range respectively from -589.36 mm/year in 2001 to -25.19 mm/year in 2009 and from -670.13 mm/year in 2000 to -66.16 mm/year in 2002.

TRMM-3B42RT also underestimated rainfall (Figure 22 (d)) with values ranging from -23.17 mm/year in 2001 to -625.14 mm/year in 2000. However, for CHIRPS-0.05, Figure 22 (b) showed that the number of underestimated years is higher than the number of overestimated years with values ranging from -126.12 mm/year in 2003 to -23.64 mm/year

in 2001, while its overestimates vary from 191.95 mm/year in 2008 to 41.50 mm/year in 2006. These results show that the magnitude of the overestimates is greater than the magnitude of the underestimates, which means that although the number of years of underestimates is greater than the number of years of overestimates; it can be considered that CHIRPS has generally overestimated the annual rainfall.



(a) (b)

(b) (d)

Figure 22: Average annual Difference between observed and Estimated data by ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT (Overestimation and underestimation).

5.5.1 Assessment of the relationship at annual level

The annual rainfall analysis gave a slender correlation between estimated and observed rainfall. ARC 2 and CHIRPS have respectively r= 0.43 and r= 0.46, which represent the best results of this analysis. RFE 2 and TRMM had a poor performance with extra-low correlations which are equal respectively to r=-0.31 and r=0.004, which means that RFE 2

and TRMM show no relationship with observed rainfall on an annual scale. All this supports the explanation for the increase in the error amplitudes RMSE, MAE, and BIAS (Table 15). However, ARC 2 performed well with the correlations obtained locally at the stations of Bignona (r=0.68), Bounkiling (r=0.76) and Ziguinchor (r=0.70). CHIRPS-0.05 also obtained very good correlation results at the stations of Ziguinchor (r=0.90) and Bounkiling (r=0.64). The low average correlation results obtained can be explained by the fact that the minimal correlation results obtained with the stations of Kolda and Oussouye for ARC 2 and the stations of Bignona, Kolda and Oussouye for CHIRPS-0.05 influenced the calculation of the average correlation of the Casamance basin. That means that ARC 2 and CHIRPS-0.05 did not perform well in general over the whole basin, but rather well in only some localities. ARC 2 obtained an average RMSE of 357.93mm/year, an MAE of 287.71mm/year and a BIAS of -13.62% and CHIRPS-0.05 obtained an RMSE of 241.79mm/year, an MAE of 205.40mm/year and a BIAS of 0.99% which is very low. The BIAS of TRMM-3B42RT and RFE 2 (BIAS= -14.02% and BIAS= -34.80% respectively) show that they underestimated the annual rainfall.

In general, in this analysis at the annual scale, CHIRPS-0.05 had the best results and therefore the best performance followed by ARC 2.

Table 15: Statistical results of rainfall products (ARC 2, RFE 2, CHIRPS, TRMM) at annual time step, which are the correlation coefficient (r), RMSE, MAE and BIAS.

ARC Version 2	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0.68	0.76	0.31	0.70	-0.28	0.43
RMSE (mm)	382.20	188.90	364.69	347.75	506.11	357.93
MAE (mm)	306.53	143.59	287.15	269.51	431.77	287.71
BIAS	-26.49	2.80	3.53	-19.24	-28.70	-13.62
CHIRPS-0,05	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	0.46	0.64	0.22	0.90	0.07	0.46
RMSE (mm)	188.74	225.05	332.83	138.47	323.87	241.79
MAE (mm)	140.11	202.14	288.85	112.78	283.12	205.40
BIAS	-7.81	15.31	11.21	0.34	-14.08	0.99
RFE Version 2	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	-0.45	0.03	-0.14	-0.32	-0.66	-0.31
RMSE (mm)	559.72	481.68	579.71	755.29	1175.28	710.33
MAE (mm)	393.15	350.94	431.44	645.84	1147.67	593.81
BIAS	-16.25	-1.75	-14.70	-41.29	-100.00	-34.80
TRMM-3B42RT	Bignona	Bounkiling	Kolda	Ziguinchor	Oussouye	Average
r	-0.45	0.11	0.10	0.02	0.24	0.004
RMSE (mm)	326.57	317.96	349.24	326.71	1175.28	499.15
MAE (mm)	294.17	274.40	279.42	258.40	1147.67	450.81
BIAS	6.15	14.70	9.15	-0.11	-100.00	-14.02

5.5.2 Summary of annual Rainfall Assessment

Based on the results mentioned in Table 15: the comparison between estimated rainfall from satellite products and observed rainfall from annual time step rain gauges showed that over the whole Casamance basin rainfall products showed weak correlations ranging from r=0.46 (CHIRPS-0.05) to r=-0.31 (RFE 2) through r=0.43 (ARC 2) and r=0.04 (TRMM-3B42RT). Nevertheless, locally, excellent correlation results were obtained by CHIRPS-0.05 at Ziguinchor and Bounkiling, and by ARC 2 at Bignona, Bounkiling and Ziguinchor.

ARC 2, CHIRPS-0.05 and RFE 2 underestimated the maximum rainfall value recorded by the rain gauges; only TRMM-3B42RT largely overestimated this value. However, in general, CHIRPS-0.05 (confirmed by the annual BIAS calculated) and TRMM-3B42RT overestimated the rainfall with average values of 1160.96 mm/year and 1302.11 mm/year, respectively, which are higher than the average amount of rainfall observed which is equal to 1152.97 mm/year. The same mean rainfall amount was underestimated by ARC 2 and RFE 2 (Table 14). However, the results of TRMM-3B42RT are ambiguous; because according to its BIAS obtained; it underestimates the precipitation, whereas, according to the average amount of rainfall that has been estimated, TRMM-3B42RT overestimates rainfall.

The annual comparison again demonstrated the good performance of CHIRPS-0.05 followed by ARC 2 and the poor performance of TRMM-3B42RT.

5.6 Evaluation of Spatial Rainfall

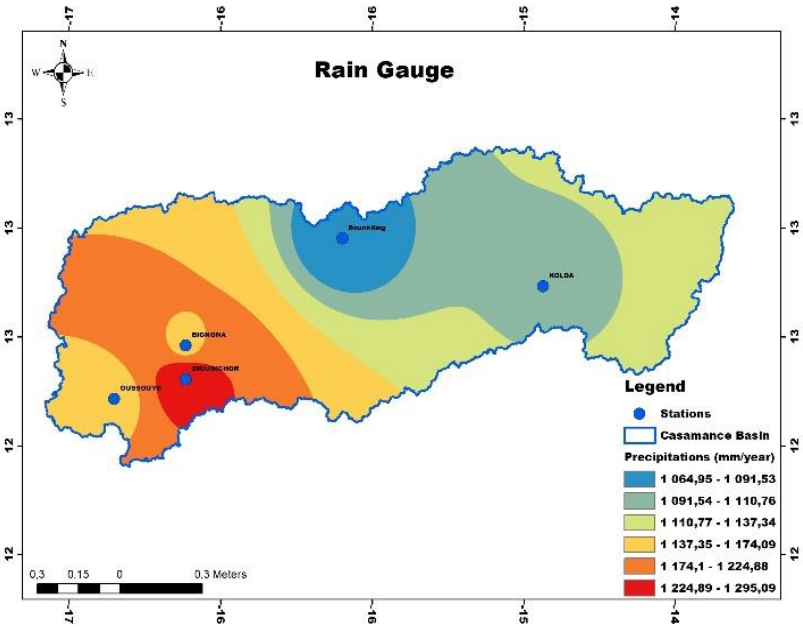
In this chapter, the spatial assessment of rainfall is elaborated according to the measurement tool (rainfall stations or remote sensing derived rainfall products). The assessment consists of comparing data from interpolated rainfall stations and estimates from different satellite products. In the same perspective, the impacts of topography and altitudes on the accuracy of the estimates are elaborated, and finally, the performance of the rainfall products according to the two different seasons (dry season and rainy season) have been studied.

5.6.1 Comparison of rainfall products on an annual scale based on the interpolated maps

In this study, interpolated rainfall data presents the rainfall obtained over the entire Casamance basin. Figure 23 highlights the spatial representation of the interpolated data from the rainfall stations and the estimates from the satellite products, which do not show

any apparent similarity (except for CHIRPS-0.05) between the one mapped by the observed data and the one mapped by the estimated data. On the other hand, a slight similarity is noted between the three other satellite products (ARC 2, CHIRPS-0.05 and RFE 2). The observations of the rainfall stations show a maximum of 1295.09 mm/year, a minimum of 1064.95 mm/year and an annual average of 1137.27 mm/year. In general, CHIRPS-0.05 and TRMM-3B42RT overestimated the rainfall with a maximum of 1299.41 mm/year and 1566.10 mm/year respectively, a minimum of 986.12 mm/year and 1207.68 mm/year and an average of 1179.05 mm/year and 1289.33 mm/year. However, the remaining satellite products (ARC 2 and RFE 2) underestimated rainfall with a maximum of 1145.42 mm/year and 1046.33 mm/year, minimum of 818.28 mm/year and 760.40 mm/year and an average of 1024.72 mm/year and 936.48 mm/year respectively.

CHIRPS-0.05 obtained the closest average to the average of interpolated rainfall from the rainfall stations. Similarly, they recorded their maximum in the same sector as the Ziguinchor station.



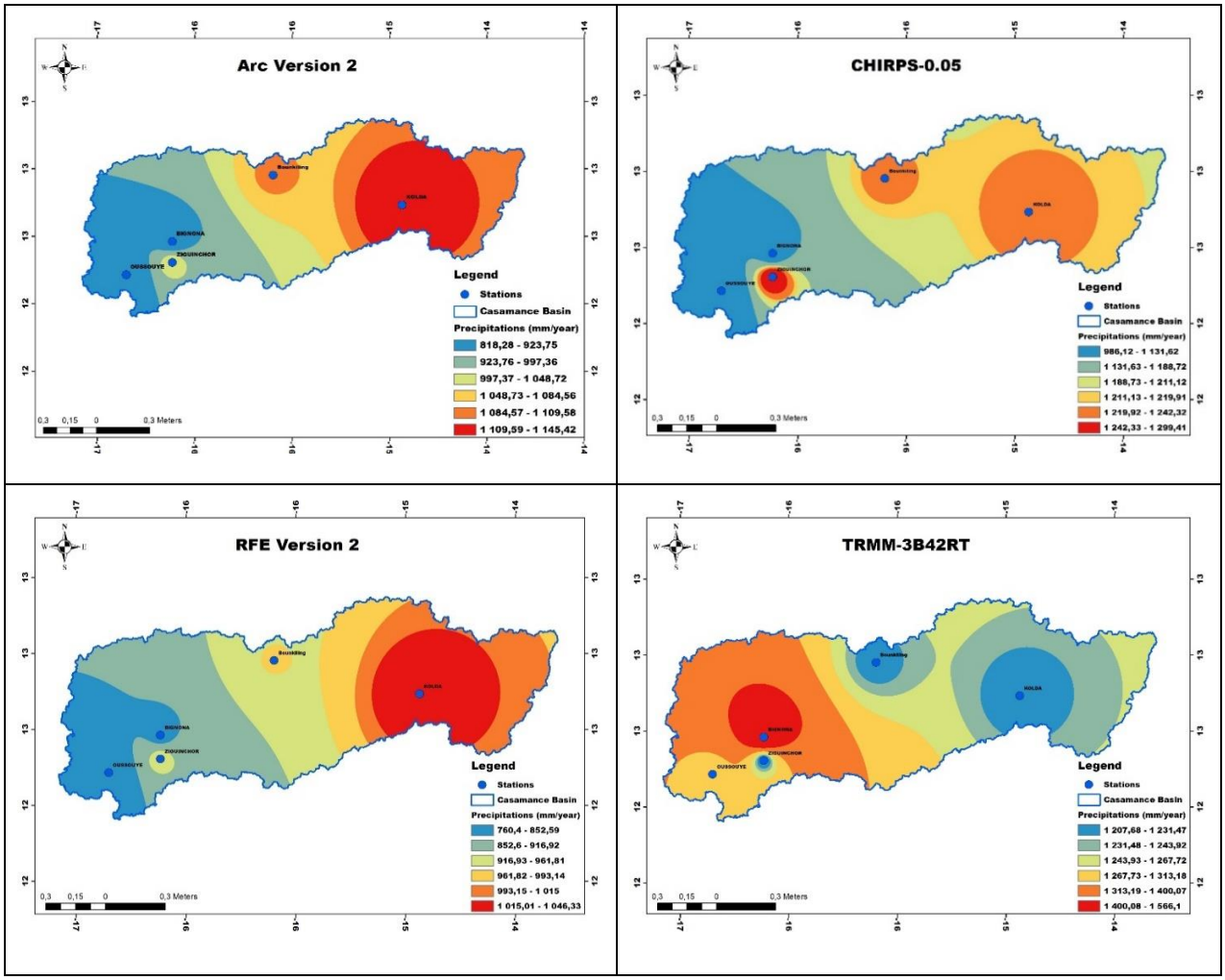


Figure 23: Comparison spatial between Rain gauge and the rainfall products.

Table 16: List of statistics obtained from the spatial distribution of observed and estimated rainfall.

	Maximum Precipitation (mm/year)	Minimum Precipitation (mm/year)	Average Precipitation (mm/year)	Std. deviation
Rain Gauge	1295.09	1064.95	1137.27	39.86
ARC 2	1145.42	818.28	1024.72	90.22
CHIRPS-0.05	1299.41	986.12	1179.05	54.73
RFE 2	1046.33	760.40	936.48	73.02
TRMM-3B42RT	1566.10	1207.68	1289.33	63.75

ARC 2, CHIRPS-0.05 and RFE 2 all three underestimated the rainfall in the western part of the basin with maximum underestimation of -329.4 mm/year, -161.55 mm/year and -387.28 mm/year respectively. However, TRMM-3B42RT recorded an underestimation of -87.41 mm/year in the eastern (Kolda) and southwestern (Ziguinchor) parts of the basin (Figure 27). Only ARC 2 and RFE 2 have practically underestimated the rainfall observed over all parts of the basin (Figure 24 and Figure 26 respectively). CHIRPS-0.05 and TRMM-3B42RT generally overestimated the rainfall with a maximum of 163.04 mm/year in the northern part of the basin (Boukiling) and a maximum of 415.34 mm/year in the Bignona area respectively (Figure 25 and Figure 27 respectively). From a spatial point of view, the behaviour of the satellite products (ARC 2 and RFE 2) in underestimating the measured data is almost similar.

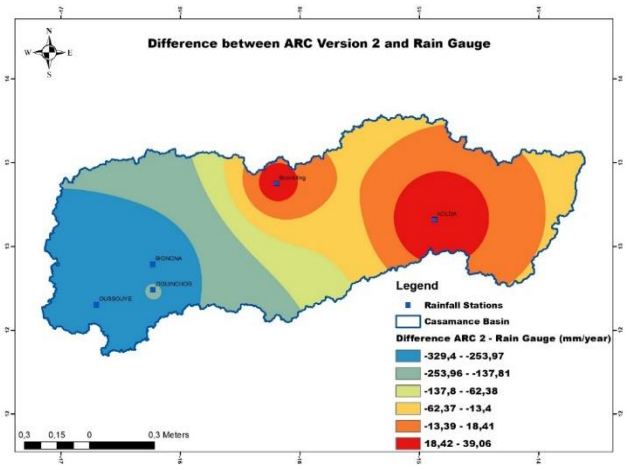


Figure 24: Difference between observed rainfall station data and ARC Version 2 rainfall product estimates spatially represented.

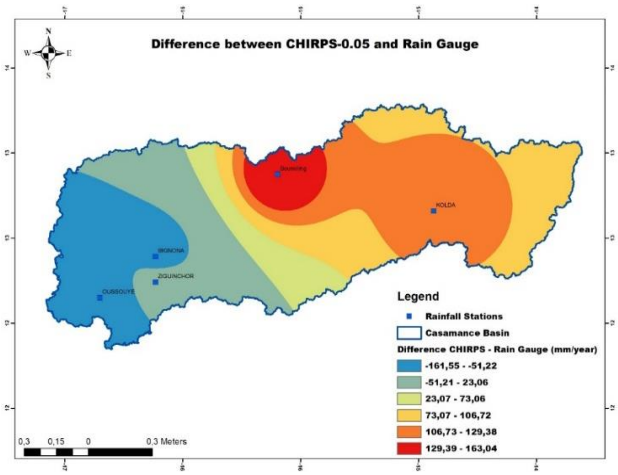


Figure 25: Difference between observed rainfall station data and CHIRPS-0.05 rainfall product estimates spatially represented.

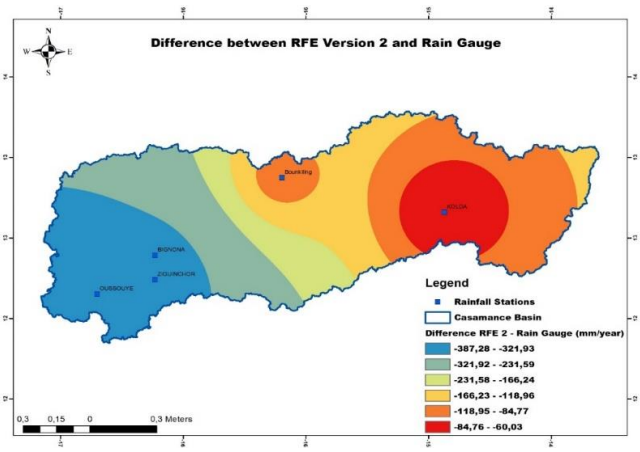


Figure 26: Difference between observed rainfall station data and RFE 2 rainfall product estimates spatially represented.

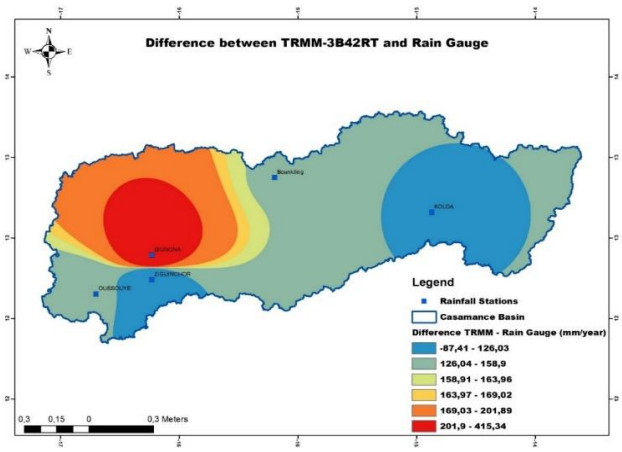


Figure 27: Difference between observed rainfall station data and TRMM-3B42RT rainfall product estimates spatially represented.

Table 17: List of statistics obtained from the spatial distribution of the difference between observed and estimated rainfall data.

	Minimum (mm/year)	Maximum (mm/year)	Mean (mm/year)	Std. deviation
ARC 2	-329.40	39.06	-112.55	123.44
CHIRPS-0.05	-161.55	163.04	41.77	83.98
RFE 2	-387.28	-60.03	-200.80	105.35
TRMM-3B42RT	-87.41	415.34	152.06	45.23

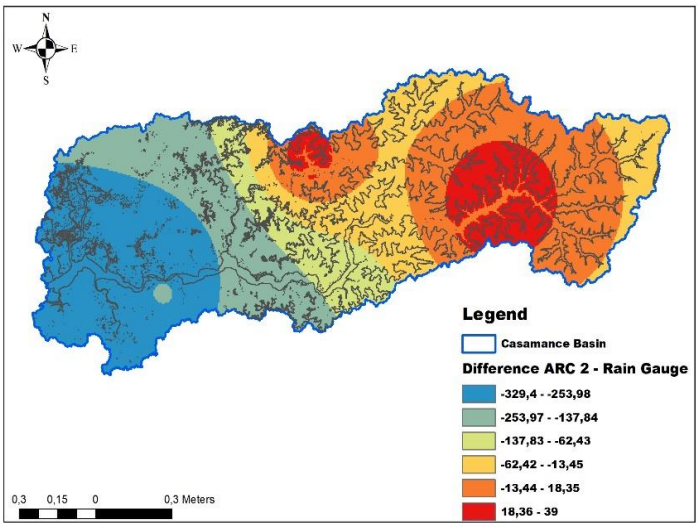
All products had a very low correlation with the observed data. ARC 2 and RFE 2 obtained negative correlations (r=-0.14 and r= -0.13 respectively). However, CHIRPS-0.05 and TRMM-3B42RT recorded positive correlations with r=0.26 and r=0.06 respectively.

A t-test carried out with a significance level of 5% showed that the mean annual rainfall estimated by Arc 2 (t=-1.996; P-value=0.117), CHIRPS-0.05 (t=0.13; P-value=0.903) and TRMM-3B42RT (t=1.86; P-value=0.14) could be equal to the mean annual rainfall observed in some regions and different in other parts of the basin. On the other hand, for RFE 2 (t=-3.59; P-value=0.023), the test revealed that its estimated annual average is totally different from the observed rainfall.

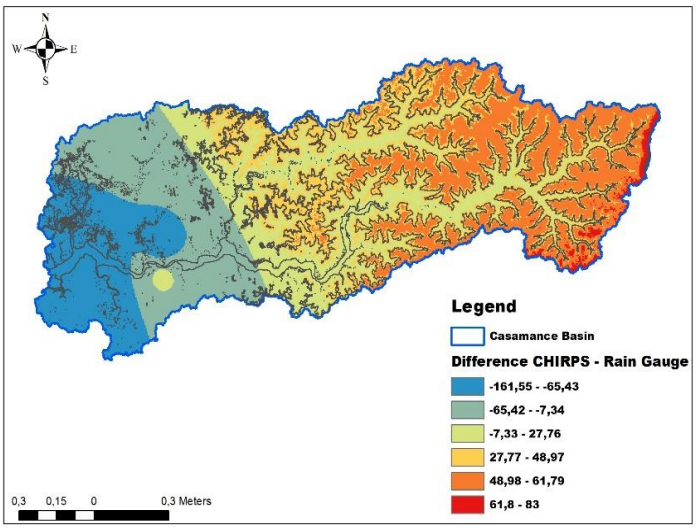
5.6.2 Analysis of the effects of elevation on the performance of precipitation products.

Figure 30 shows that variation in elevation affects the accuracy of ARC 2, CHIRPS-0.05 and TRMM-3B42RT, while it does not affect the accuracy of RFE 2.

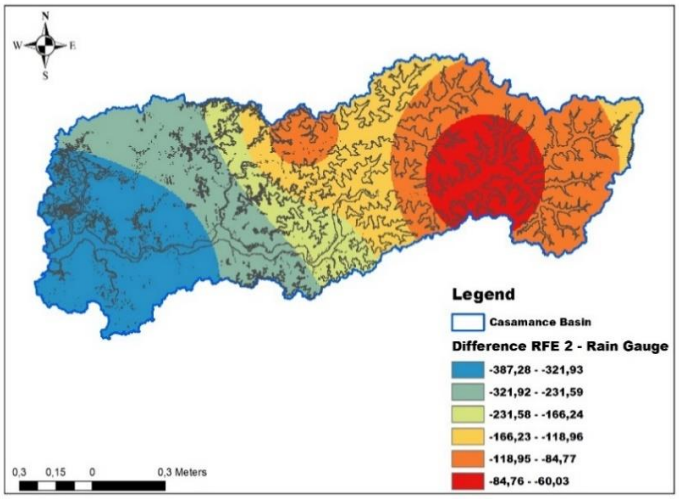
The superposition of the altitudes obtained from the Casamance basin and the differences between observed and estimated rainfall showed changes in the spatial distribution of rainfall. Under the influence of elevation, the differences between the estimated precipitation of the precipitation products (ARC 2, CHIRPS-0.05 and TRMM-3B42RT) and the observed precipitation of the rain gauges have been modified. The overestimates values recorded by these products have decreased and the underestimates recorded have increased. Figures 28(a), 28(b) and 28(d) clearly show the influences on the differences, especially in the areas with the highest difference values. Overall, the variation in altitude tended to reduce the difference between estimated and observed rainfall.



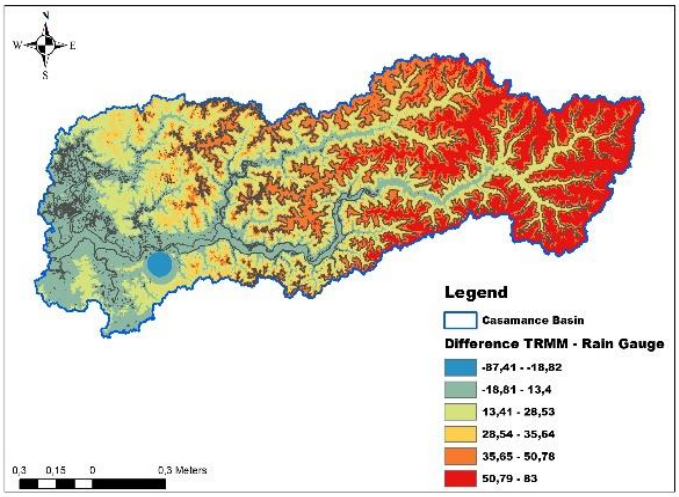
(a)



(b)



(c)



(d)

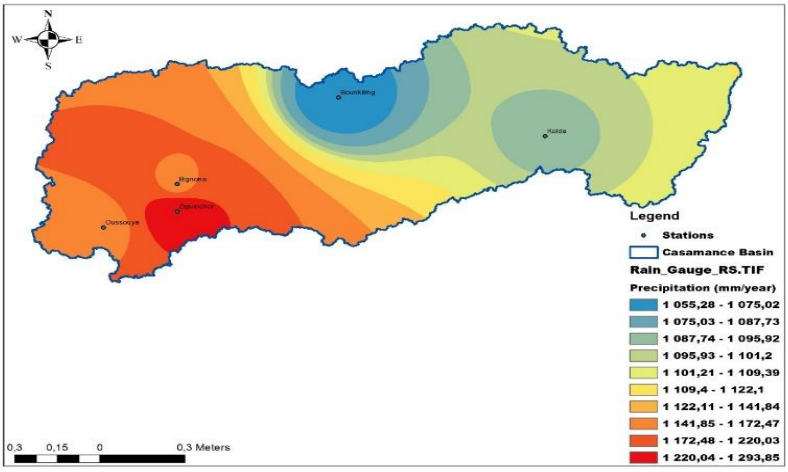
Figure 28: Impacts of the elevation of the Casamance basin on the performance of precipitation products (from right to left: ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT).

5.6.3 Comparison of rainfall products according to the seasons

5.6.3.1 Rainy season

The accuracy of satellite products is affected by several factors including the seasonal distribution of precipitation (Le Coz & van de Giesen, 2020). Seasonally, the highest rainfall recorded by rainfall stations is located in the southwestern part of Casamance and the lowest is observed in the northern part of the basin as showed in the figure 29.

CHIRPS-0.05 detected the Ziguinchor zone as the wettest and the almost totality of the western part (except Ziguinchor) as the region with the least rainfall. ARC 2 and RFE 2 have a similar spatial distribution. They estimated the lowest rainfall in the western region of the basin (Bignona and Oussouye) and the highest rainfall in the eastern part of the basin (Kolda sector). TRMM-3B42RT estimated the lowest rainfall values in the rainy season. It predicted its highest estimated values in the north-western part (Bignona) and its lowest values in the northern part (Boukiling) and the eastern part (Kolda).



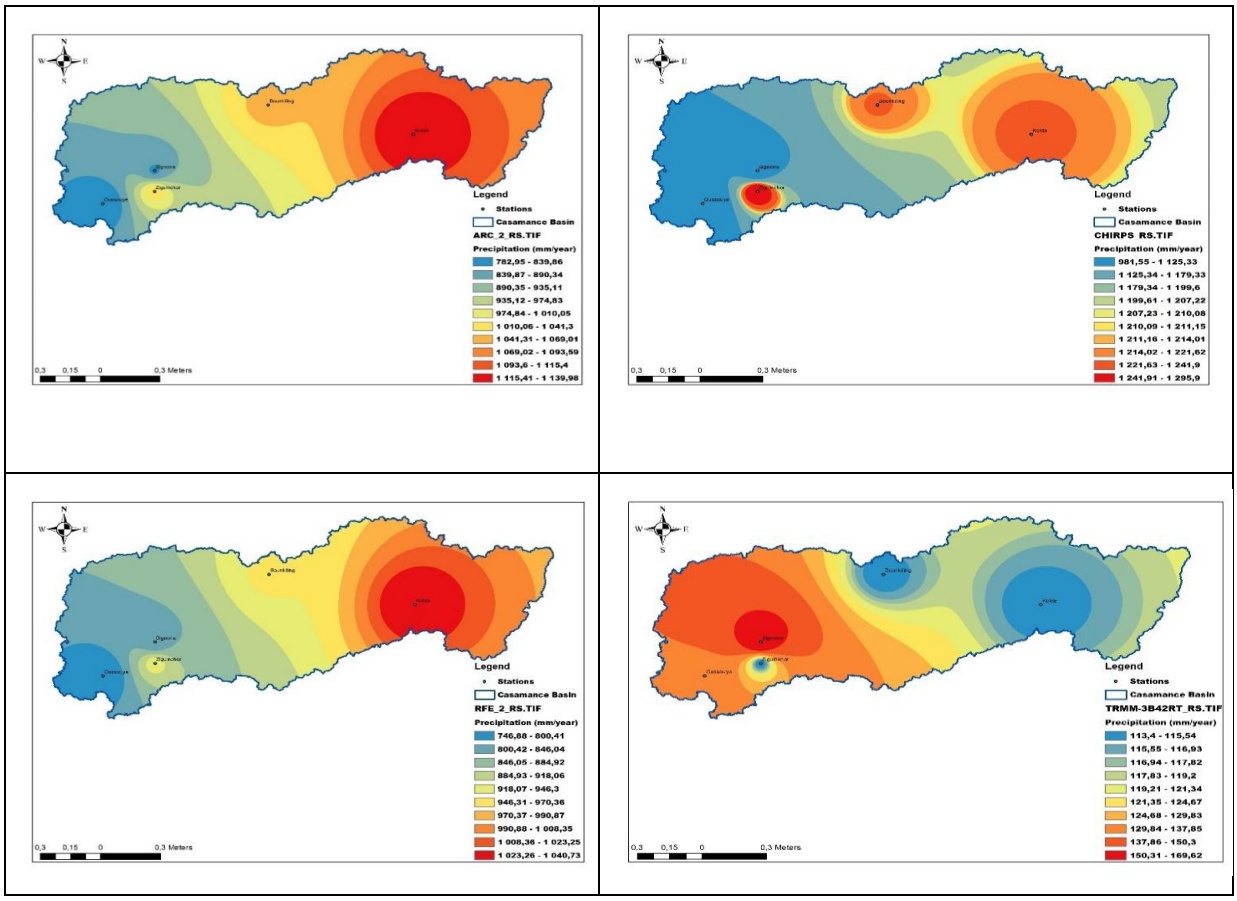


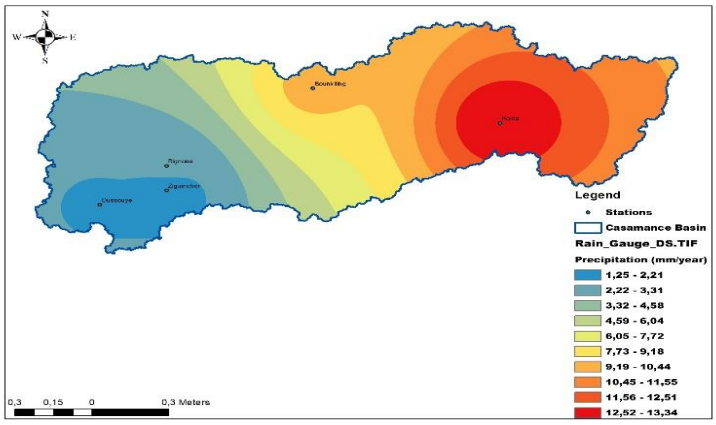
Figure 29: Comparison of the rainfall recorded during the rainy season (June to October) in the Casamance basin by the rainfall stations, ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT respectively.

Table 18: List of statistics obtained from the spatial distribution of observed and estimated rainfall during the rainy season.

	Minimum (mm/year)	Maximum (mm/year)	Mean (mm/year)	Std. Deviation
Rain Gauge	1055.28	1293.85	1129.35	43.18
ARC 2	782.95	1139.98	1003.04	93.92
CHIRPS-0.05	981.55	1295.9	1172.94	55.81
RFE 2	746.88	1040.73	925.63	75.56
TRMM-3B42RT	113.4	169.62	126.44	11.19

5.6.3.2 Dry season

The figure 30 shows that; during the dry season, the rainfall stations recorded very low annual rainfall ranging from 1.25 mm/year (southern zone of the basin) to 13.34 mm/year (eastern zone of the basin) as illustrated in table 20. This annual rainfall was underestimated in general by the CHIRPS-0.05 satellite product with values ranging from 3.46 mm/year (eastern part: Kolda) to 13.06 mm/year (Bignona region). The three remaining rainfall products (ARC 2, RFE 2 and TRMM-3B42RT) overestimated the number of millimetres of rain observed by the rainfall stations. The highest value estimated by ARC 2 was 43.78 mm/year (northern part of the basin) and the lowest 5.44 mm/year (eastern part of the basin). RFE 2 detected a small area around the Bignona area as the region that received more rainfall than the other regions of the basin with a value of 18.6 mm/year and detected the eastern part and a small part of the south as the regions that received less rainfall with a value of 5.6 mm/year (figure 30). The rainfall estimate by TRMM-3B42RT is highest in the dry season period (figure 31). Its estimates range from 1094.28 mm/year (a small part of the southwestern part of the basin) to 1396.49 mm/year (the western part around Bignona) (figure 30). The rainfall noticed during the dry season period showed by the figure 31 is due to an early start of the rainy season in May which is part of the dry season (except for TRMM-3B42RT).



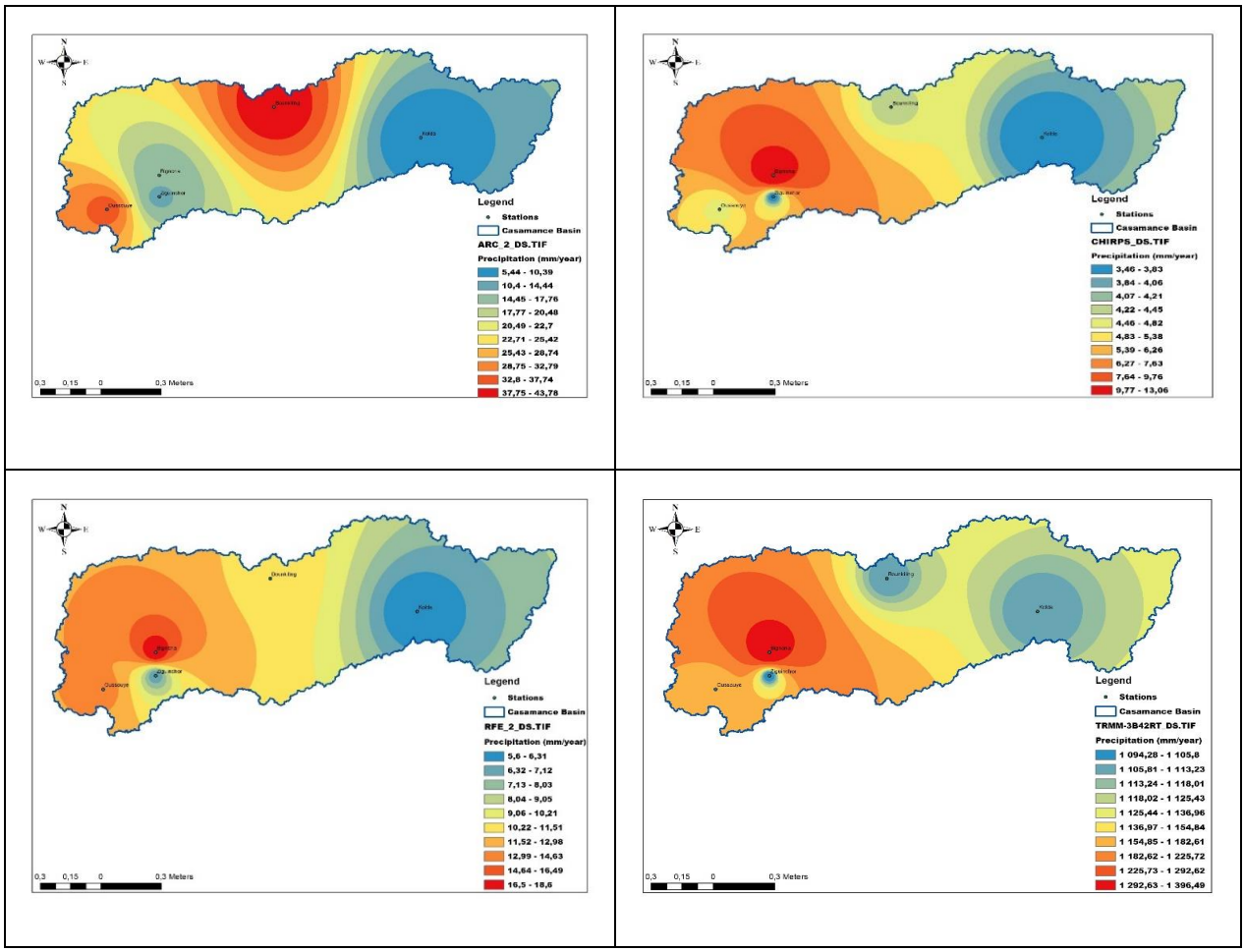


Figure 30: Comparison of the rainfall recorded during the dry season (November to May) in the Casamance basin by the rainfall stations, ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT respectively.

Table 19: List of statistics obtained from the spatial distribution of observed and estimated rainfall during the dry season.

	Minimum (mm/year)	Maximum (mm/year)	Mean (mm/year)	Std. Deviation
Rain Gauge	1.25	13.34	7.43	3.86
ARC Version 2	5.44	43.78	20.91	9.09
CHIRPS-0.05	3.46	13.06	5.47	1.71
RFE Version 2	5.6	18.6	10.24	2.76
TRMM-3B42RT	1094.28	1396.49	1162.19	52.76

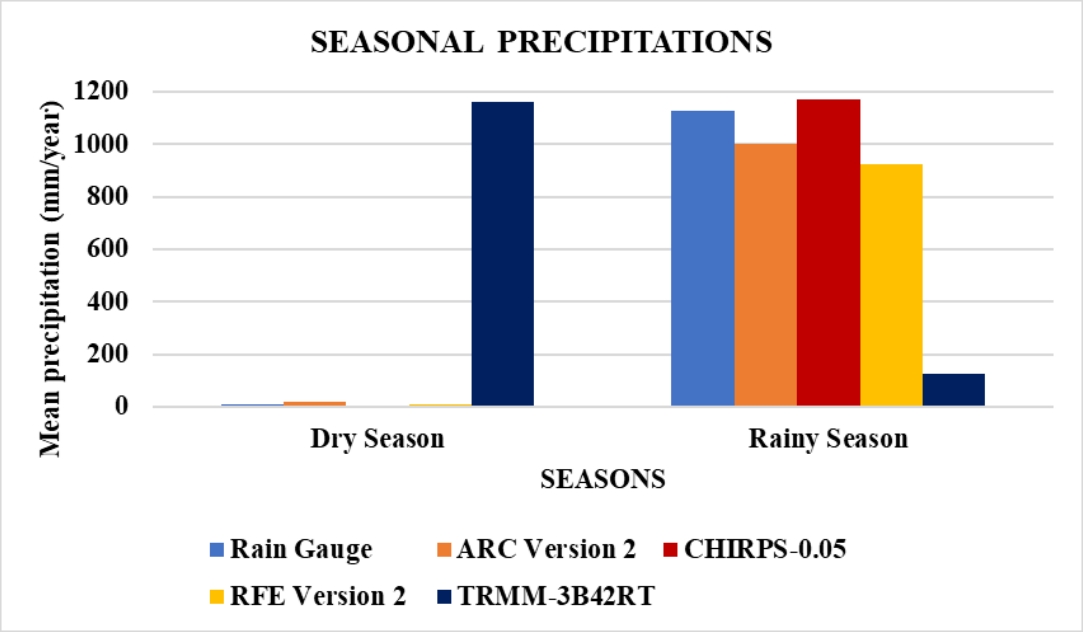


Figure 31: Comparison of annual rainfall observed by rainfall stations and estimated by ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT during the two different seasons.

5.6.4 Summary of evaluation of spatial rainfall

In this part, the analyses showed that the correlation between the spatial distributions of rainfall stations and rainfall products is very weak or even non-existent. CHIRPS-0.05 and TRMM-3B42RT tended to overestimate the observed rainfall. However, ARC 2 and REF 2 underestimated rainfall. The heaviest rains that fell on the basin were recorded on the south-western side by the rainfall stations. These same rains were underestimated by ARC 2 and RFE 2, and overestimated by CHIRPS-0.05 and TRMM-3B42RT. ARC 2 and RFE 2 estimated their heavy rains in the East of the basin, while CHIRPS-0.05 and TRMM-3B42RT estimated their heaviest rains over a small part of the South and West parts of the basin respectively.

Analysis of the influence of elevation on the accuracy of precipitation products showed that the variation in elevation had consequences on the spatial distribution of ARC 2, CHIRPS-0.05 and TRMM-3B42RT estimated precipitation. The values of the differences between observed precipitation from rain gauges and estimated precipitation from satellite products are underestimated under the influence of elevation, which means that under the effects of elevation, over- or under-estimates of precipitation from satellite products could be reduced. However, the variation in elevation showed no effect on the estimates of RFE 2.

Rainfall was observed during the dry season and this was due to the early onset of the rainy season except for TRMM-3B42RT. These rainfall amounts were overestimated by ARC 2, RFE 2 and TRMM-3B42RT which greatly overestimated the rainfall observed during this period, while CHIRPS-0.05 underestimated it. Nevertheless, during the rainy season, only CHIRPS-0.05 overestimated the rainfall and has the closest average to that of the rainfall stations in all the comparative analyses carried out in this part. Overall, CHIRPS-0.05 had the best performance.

6. GENERAL DISCUSSION

The rainfall observed in the Casamance basin which is recorded from 2000 to 2010 is varied between the years. The variation of rainfall in the Casamance area has been demonstrated through numerous research studies such as those of Sane et al. (2008), Salack et al. (2012), Ndiaye et al. (2017), and Mballo et al. (2019). Early-onset and cessation of rainfall are one of the characteristics of this variation.

Daily analysis of observed rainfall from 2000 to 2010 showed an annual maximum of 3.87 mm/day and a minimum of 2.29 mm/day.

The analysis of the four rainfall products (ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT) at four-time scales: daily, monthly, annual and seasonal allowed the evaluation of the performance of these satellite products over the Casamance basin. The daily assessment of estimated rainfall showed that ARC 2 and CHIRPS-0.05 had poor performance with correlation (r=0.32 and r=0.31 respectively), while RFE 2 and TRMM-3B42RT recorded a very poor performance (r=0.15 and r=-0.12 respectively); meaning that on a daily scale, they do not correlate with observed daily rainfall. Analysis of the differences between estimated and observed daily data leads to the conclusion that ARC 2 and RFE 2 underestimate the rainfall data, while CHIRPS-0.05 and TRMM-3B42RT overestimate it. These results were confirmed with the BIAS calculation. ARC 2 and CHIRPS-0.05 recorded the best results with RMSE and MAE, but also with the categorical statistics. ARC 2, CHIRPS-0.05 and RFE 2 performed well with high accuracy and POD and low to medium for FAR. These three precipitation products tend to overestimate the rainy days with an FBI greater than 1 especially with TRMM-3B42RT (FBI=2.43). The detection of rainy days that have been estimated and that have taken place has been evaluated through CSI and gave low results ranging from 0.43 (ARC 2) to 0.09 (TRMM-3B42RT). Overall, during this analysis of daily rainfall, TRMM-3B42RT had the worst performance (r=-0.12, Accuracy=0.44, POD=0.28, FAR=0.89, CSI=0.09 and FBI=2.43) and ARC 2 had the best performance followed by CHIRPS-0.05 and RFE 2.

The monthly time step analysis showed that CHIRPS-0.05, ARC 2, RFE 2 performed well with high correlation coefficients. However, ARC 2 and RFE 2 had statistically significant differences in mean with the observed rainfall after their p-value calculation. The best performing rainfall product was CHIRPS-0.05 with a correlation coefficient very close to 1 (r=0.90) and a difference in averages that is not statistically significant. Similarly, ARC 2

had a correlation coefficient close to 1 (r=0.85). TRMM-3B42RT had the worst performance (r=-0.61).

The annual time step evaluation showed a low correlation of satellite products, with CHIRPS-0.05 having the best performance, followed by ARC 2. The worst performances were recorded by RFE 2 and TRMM-3B42RT which demonstrated with their correlation coefficients that there was no relationship between their annual estimates and annual rainfall observations. However, these results are contrasted by the good correlations obtained at stations such as Ziguinchor, Bounkiling and Bignona by CHIRPS-0.05 and ARC 2. The tendency of ARC 2 and RFE 2 to underestimate the precipitations was confirmed with the results of this annual analysis (BIAS negative, maximum, minimum and mean estimates inferior to maximum, minimum and mean observations). The results obtained with TRMM-3B42RT are contrasted as it overestimates rainfall according to its maximum, minimum and mean estimates and underestimates rainfall according to the negative BIAS found and the calculated rainfall differences. These poor results of TRMM-3B42RT may be due to the incompatibility of its algorithm with the climatic conditions of the Casamance basin.

CHIRPS-0.05 presents the best results with the highest correlation, a low positive BIAS which confirms its tendency to overestimate rainfall and also the lowest RMSE and MAE values obtained in the analysis.

Spatial comparison between observed and estimated rainfall data showed that CHIRPS-0.05 and TRMM-3B42RT always tend to overestimate rainfall, while ARC 2 and RFE 2 tend to underestimate rainfall. The spatial representation of observed rainfall over the Casamance basin shows no similarity with the spatial representation of estimated rainfall products. The similarity is encountered between the spatial distributions of estimated rainfall of ARC 2 and RFE 2. This may be because they have similar algorithms. The spatial representation shows that the maximum values of estimated precipitation were recorded at the Kolda station for ARC 2 and RFE 2, at the Ziguinchor station for CHIRPS-0.05 and the Bignona station for TRMM-3B42RT. Only CHIRPS-0.05 recorded its maximum rainfall values at the same station as the rain gauges. The influence of altitude variation had effects on the spatial representation of over- and underestimates of the different precipitation products except for RFE 2. The impact of altitude change has led to a decrease in the values of the difference between observed and estimated precipitation. The largest change was noticed with TRMM-3B42RT and the small change was recorded with ARC 2, which means that it had the best performance in this analysis. However, on a seasonal scale, CHIRPS-0.05 had the best

performance with an average of estimated precipitation close to that of observed precipitation. Nevertheless, it overestimated rainfall during the rainy season and underestimated it during the dry season, unlike ARC 2, RFE 2 and TRMM-3B42RT which overestimated rainfall during the dry season and underestimated it during the rainy season.

7. CONCLUSION AND RECOMMENDATIONS

7.1 General Conclusion

In this study, four satellite products were evaluated and compared ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT. The evaluation was carried out on four-time scales: daily, monthly, annual and seasonal.

At the daily scale, the remotely sensed precipitation products did not perform well with low correlation coefficients. This may be due to the loss of convective rains according to Dembélé and Zwart, (2016); who carried out a similar study in Burkina Faso (West Africa). ARC 2 and CHIRPS-0.05 performed much better than the RFE 2 and TRMM-3B42RT. CHIRPS-0.05 and TRMM-3B42RT overestimated precipitation while RFE 2 and ARC 2 underestimated it. ARC 2, RFE 2 and CHIRPS-0.05 detected rainy days well from non-rainy days with good results obtained from categorical statistical equations (high POD and accuracy; low FAR). The satellite products that performed best in this daily analysis were ARC 2 followed by CHIRPS-0.05 and RFE 2. TRMM-3B42RT performed very poorly.

The monthly assessment showed much better results with high correlations of ARC 2 (r=0.85), RFE 2(r=0.70) and CHIRPS-0.05(r=0.90). However, the satellite products ARC 2 and RFE 2 showed very significant differences in average precipitation. The best performance was obtained with CHIRPS-0.05 which had a very good correlation and a difference between the average of estimated rainfall data and the average of observed rainfall data that is not statically significant (p-value<5%). According to the statistics results, ARC 2 also had a good performance on a monthly scale.

The evaluation on the annual scale showed, as on the daily scale, weak correlations between estimated and observed rainfall over the entire Casamance basin. This could be caused by the limited number of rainfall stations considered during this study and therefore the number of rainfall data also. The best results from this analysis were obtained with CHIRPS-0.05 and ARC 2, while RFE 2 and TRMM-3B42RT recorded very poor performances. However, excellent correlations of CHIRPS-0.05 and ARC 2 were recorded at some of the rainfall station locations of the basin. As in previous analyses CHIRPS-0.05 always tends to overestimate rainfall, while ARC 2 and RFE 2 always tend to underestimate rainfall. These results were confirmed with the analysis and spatial comparison between rainfall estimates and rainfall observations.

The spatial representation of rainfall does not show any similarity between the spatial distribution of remote sensing estimated rainfall data and the spatial distribution of observed rainfall data. Existing similarities were observed between ARC 2 and RFE 2.

It has been noted that the change in elevation had an influence on the accuracy of remote sensing products except for RFE 2. This was also observed with the correlation coefficients calculated between rainfall stations, which are low to slightly high depending on the differences in altitude between rainfall station locations. CHIRPS-0.05 demonstrated good performance in detecting rainfall in the seasonal scale analysis. However, it is noted that it overestimated rainfall during the rainy season and underestimated it during the dry season in contrast to ARC 2, RFE 2 and TRMM-3B42RT.

In conclusion, this study demonstrated that CHIRPS-0.05 is the best performing rainfall product at all levels and time scales followed by ARC 2. RFE 2 only performed poorly in the annual analysis, while TRMM-3B42RT performed very poorly throughout this study. It was also noted that ARC 2 and RFE 2 often had similar results, sometimes close to those of CHIRPS-0.05. This is justified by the fact that ARC 2 and RFE 2 have similar algorithms.

7.2 Recommendations

The different results obtained showed us the performance of each precipitation product at different temporal scales. Therefore, the suggestions that can be considered are the use of each precipitation product according to a specific application. For CHIRPS-0.05, given its tendency to always overestimate rainfall and according to its statistical results, it is better to use it for flood risk monitoring and crop modelling, which is an essential element for Casamance and the whole country.

For ARC 2 and RFE 2, according to their tendency to always underestimate rainfall; it is suggested to use them for drought monitoring.

Thus, given the performance of these satellite products in estimating rainfall amounts, it is suggested that further and more in-depth studies on the detection and assessment of moisture and drought indices for better management of water resources and agriculture in the basin and throughout Senegal and Africa, as well as for improving the effectiveness in preventing the risks of floods and droughts to put in place adequate adaptation policies.

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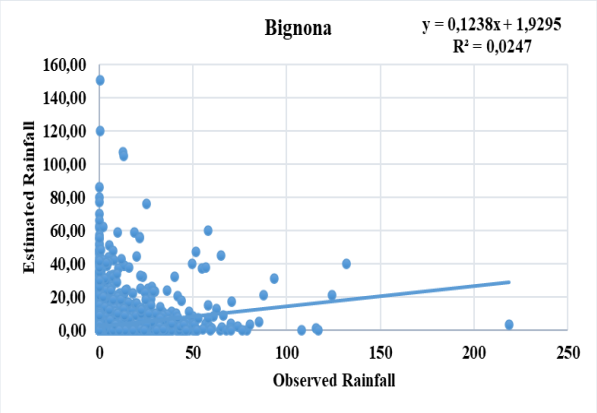
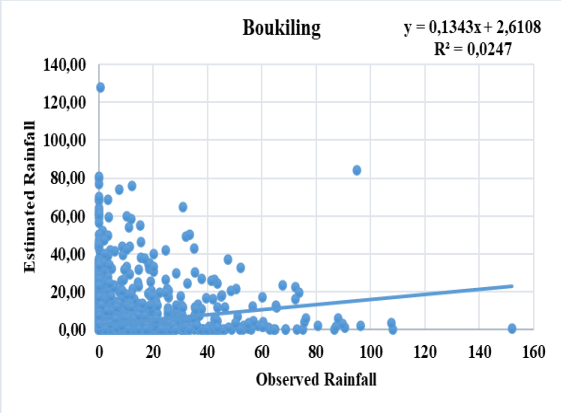
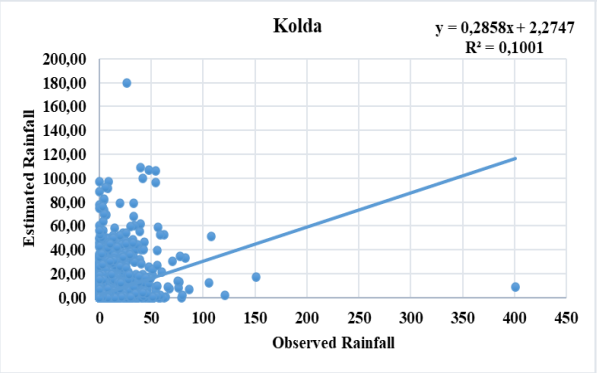
Appendix

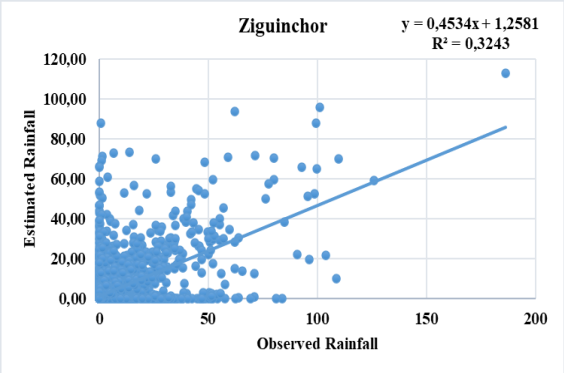
Appendix 1: **C**orrelation between observed and estimated daily rainfall by ARC 2, CHIRPS-0.05, RFE 2 and TRMM-3B42RT.

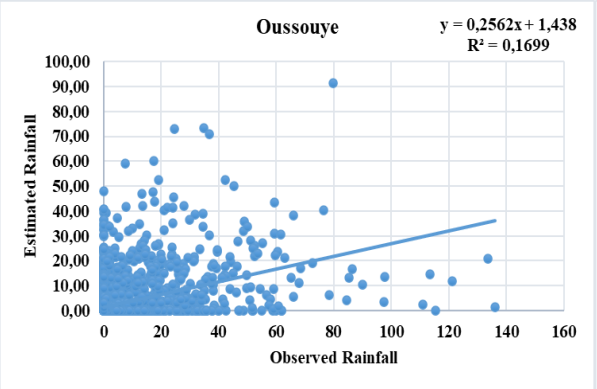
→ **ARC VERSION 2**

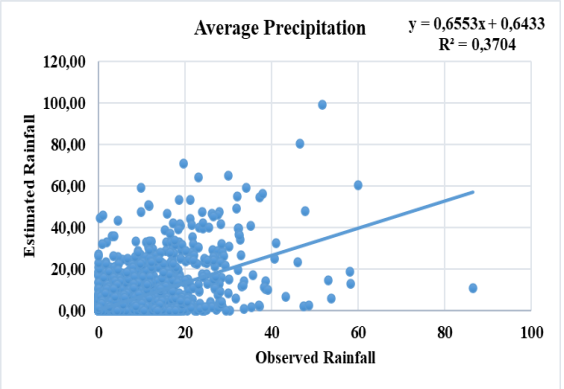




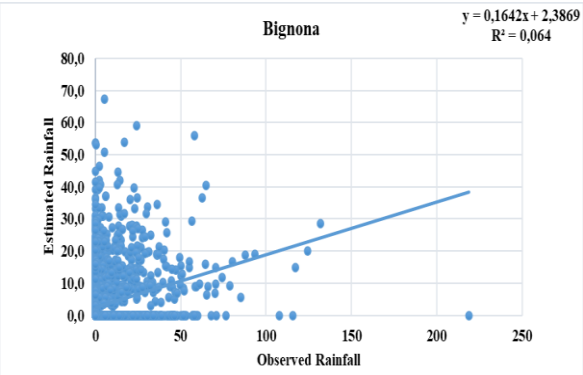


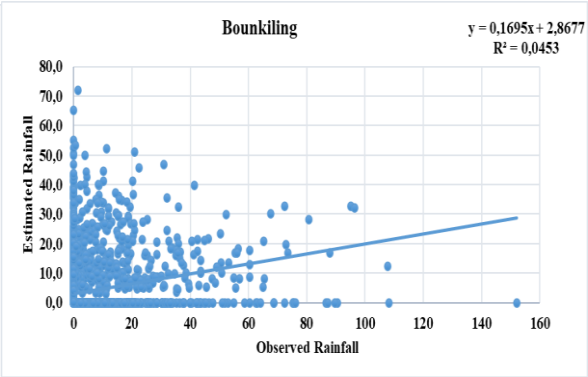


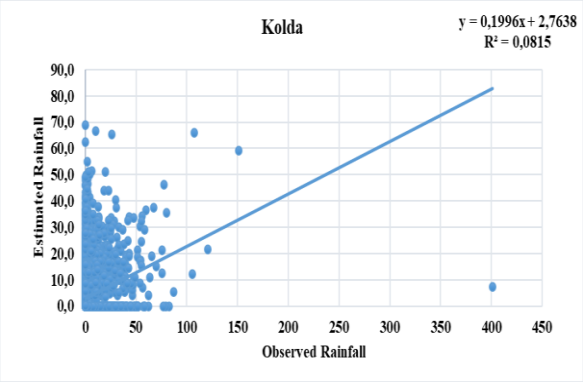


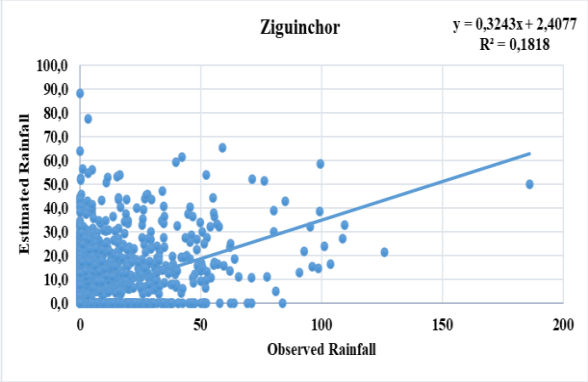


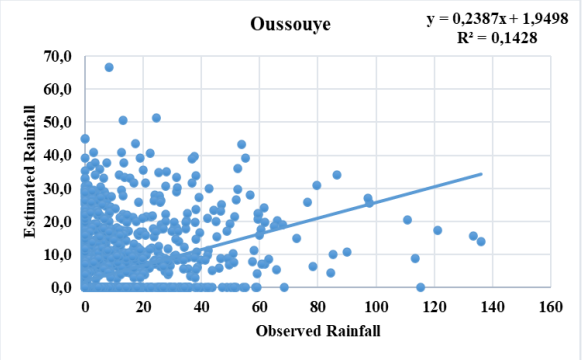
CHIRPS

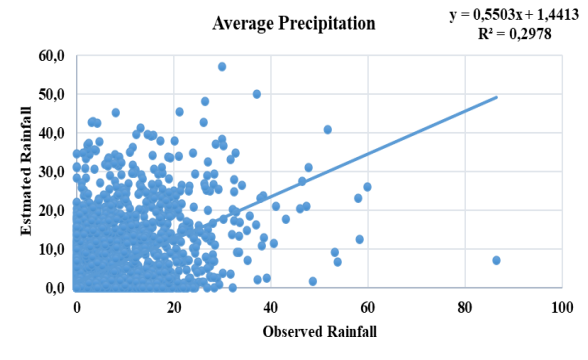

Bignona
y = 0,1642x + 2,3869
R² = 0,064
Estimated Rainfall
Observed Rainfall


Bounkiling
y = 0,1695x + 2,8677
R² = 0,0453
Estimated Rainfall
Observed Rainfall

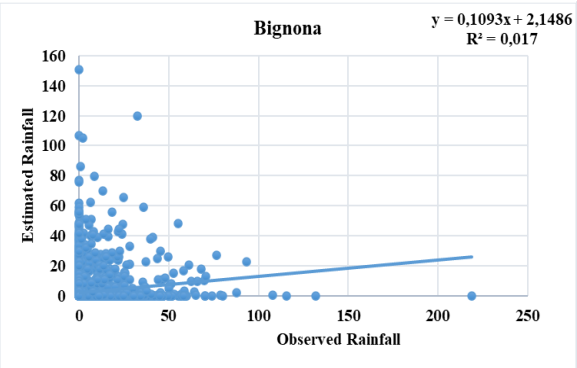

Kolda
y = 0,1996x + 2,7638
R² = 0,0815
Estimated Rainfall
Observed Rainfall

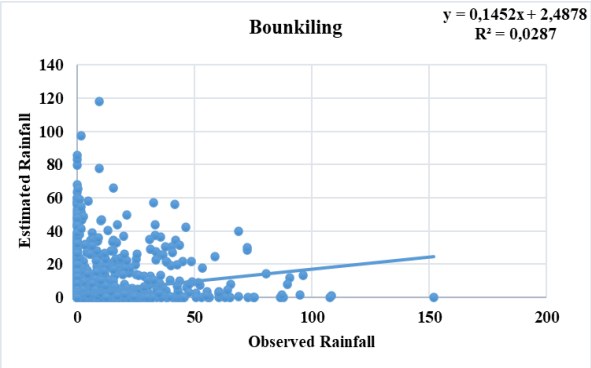

Ziguinchor
y = 0,3243x + 2,4077
R² = 0,1818
Estimated Rainfall
Observed Rainfall

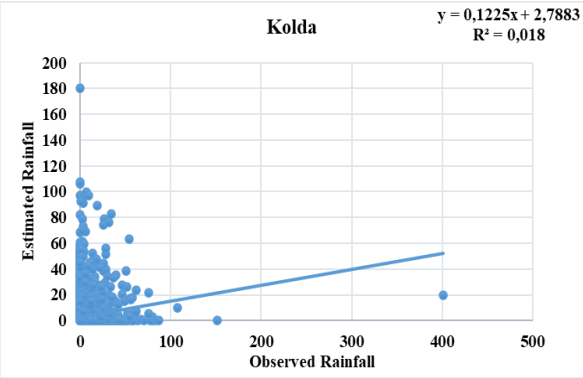

Oussouye
y = 0,2387x + 1,9498
R² = 0,1428
Estimated Rainfall
Observed Rainfall

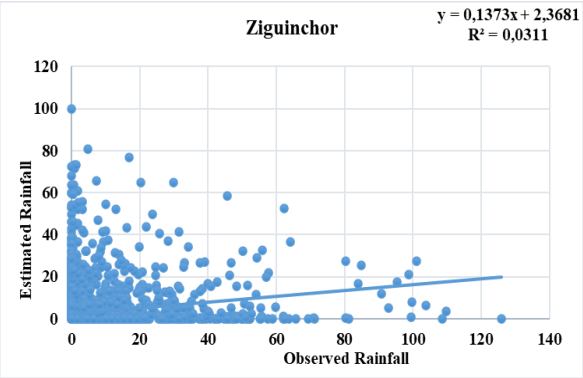

Average Precipitation
y = 0,5503x + 1,4413
R² = 0,2978
Estimated Rainfall
Observed Rainfall

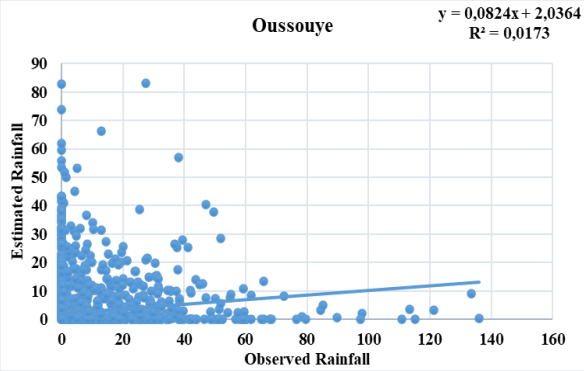
RFE VERSION 2

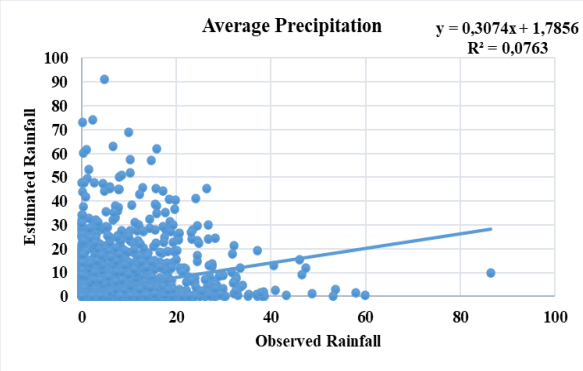




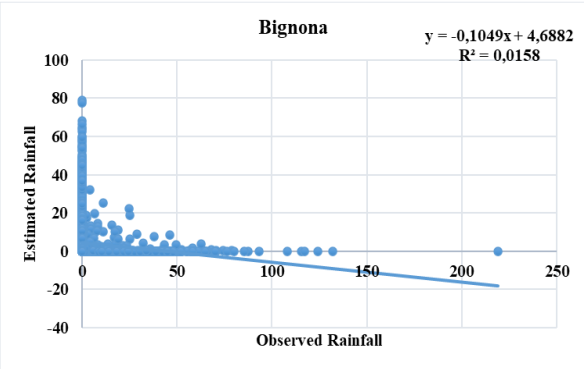


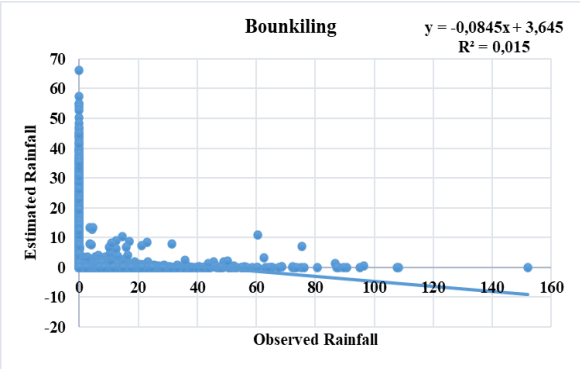


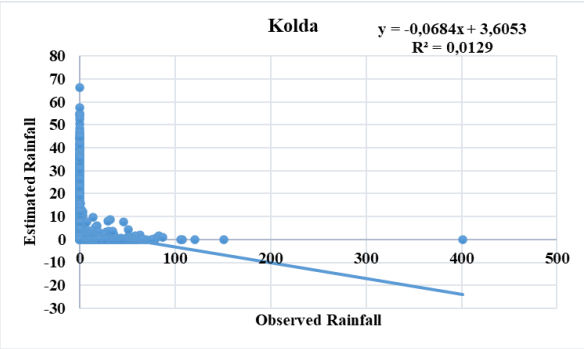


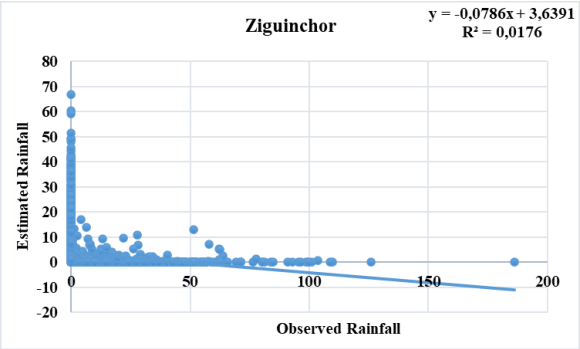


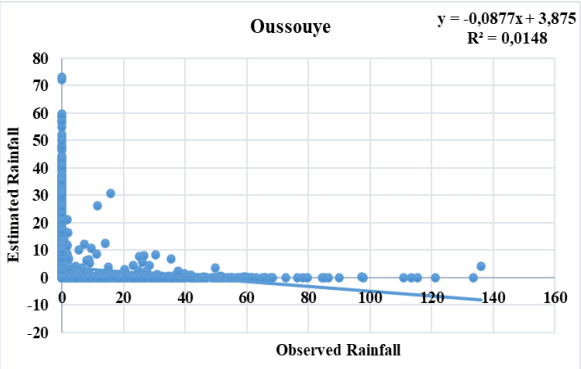
→ **TRMM-3B42RT**

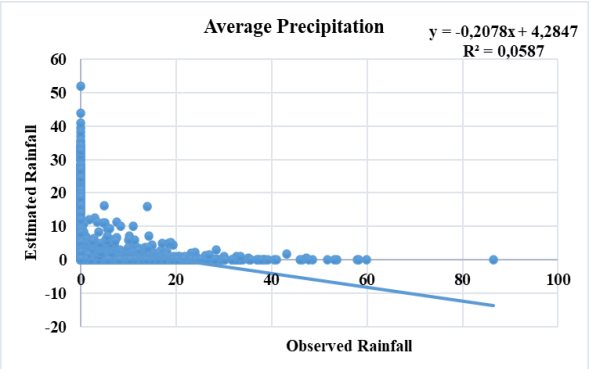

Bignona
y = -0,1049x + 4,6882
R² = 0,0158
Estimated Rainfall
Observed Rainfall


Bounkiling
y = -0,0845x + 3,645
R² = 0,015
Estimated Rainfall
Observed Rainfall


Kolda
y = -0,0684x + 3,6053
R² = 0,0129
Estimated Rainfall
Observed Rainfall


Ziguinchor
y = -0,0786x + 3,6391
R² = 0,0176
Estimated Rainfall
Observed Rainfall


Oussouye
y = -0,0877x + 3,875
R² = 0,0148
Estimated Rainfall
Observed Rainfall


Average Precipitation
y = -0,2078x + 4,2847
R² = 0,0587
Estimated Rainfall
Observed Rainfall