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Combined Use Of Satellite Estimates And Rain Gauge Observations Over Ivory Coast

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Abstract :
Background *: Climate data are used in a number of applications including climate risk management and adaptation to climate change. However, the availability of data, particularly throughout rural Africa, is very limited. Available rain gauge are unevenly distributed and mainly located along main roads in cities and towns. This impose severe limitations to the availability of climate information and services for the rural community where, arguably, these services are needed most. gauging data also suffer from gaps in the time series. Satellite proxies, particularly satellite rainfall estimate, have been used as alternatives because of their availability even over remote parts of the world. However, satellite rainfall estimates also suffer from a number of critical shortcomings that include heterogeneous time series, short time period of observation, and poor accuracy particularly at higher temporal and spatial resolutions.*
Materials and Methods *: In this study, an attempt is made here to alleviate these problems by combining rain gauge measurements from national station network with the complete spatial coverage of satellite rainfall estimates. A framework for merging satellite and gauge precipitation data is developed based on a simple bias adjustment approach. Four satellite-based precipitation products such as TAMSAT v.3, TRMM 3B42 v.7, RFE 2.0 and ARC 2.0 were used.*
Results*: Merging satellite estimates and ground-based gauge measurements help to improve precipitation estimation in both better resolution and accuracy. Spatial and temporal analysis on an annual and seasonal scale has been carried out using merged satellite data. There is no substantial difference between the gridded-gauge and combined satellite products. The results show the remarkable improvement in the quality of the final product.*
Conclusion : *The merged product was shown to be significantly better than satellite estimate. There is no significant difference between gridded gauge and the merged product.*
Keywords : *climate data ; satellite ; rainfall ; merging ; Ivory Coast*

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I. Introduction

Atmospheric precipitation is the driving component of the hydrologic cycle. Its spatiotemporal distribution is very important for providing crucial information for weather forecasting [1,2], climate change impact studies [3], water resource management studies [4], drought and flood prediction [5,6], agricultural studies [7], hydrological simulation [8], and other areas of studies. Accurate and reliable precipitation information is therefore necessary to ensure better water resource management and decision-makings [9-13]. Traditionally, precipitation data obtained using ground-based observations can be very accurate; however, there are some limitations associated with their cost and the insufficient density of ground stations [14]. There are around 163 rain gauge stations in Ivory Coast. They are mainly located in the southern part of the country, which is not very useful for hydrological forecasting. The few stations located in the central and the northern part do not provide sufficiently accurate information to feed a hydrological model. In addition, there is the thorny problem of data transmission, which is necessary for real-time operational use. Mapping rainfall is always challenging. Interpolation of point rainfall measured by rain gauges is the conventional method (for example, with Thiessen polygons, inverse distance weighting, or kriging techniques), but this may be subject to great uncertainty when the rain gauge network is sparse, as the gauges can only represent rainfall information within a limited distance [15]. In contrast, remote sensing techniques provide an evolutionary method of spatial continuous rainfall observation with a high temporal sampling frequency. With the advent of meteorological satellites in the 1970s, remotely sensed estimates of precipitation from satellite become a research hotspot. Satellite estimates provide important information about precipitation especially over the remote regions and mountainous regions. Scientists developed techniques to estimate precipitation with advanced infrared (IR) and microwave (MW) instruments from satellites in recent dacades. With the launch of Tropical Rainfall Measuring Mission satellite (TRMM) in the late 1990s, various algorithms have been developed and applied to derive precipitation estimates exploit the high sampling rate of the geostationary satellites, the greater accuracy and more direct precipitation measurement provided by satellite observation. Satellite precipitation products are widely accepted as an alternative source to overcome the limitations of ground techniques [16]. However, remote sensing products may also generate major quantitative errors, due to cloud effects and limitations in remote sensor performance and retrieval algorithms [17, 18]. In terms of studying climate, currently available data sets suffer from a number of shortcomings that include short time series, coarse spatial and temporal resolutions, temporal inhomogeneity and sometimes of poor quality. Merging weather satellite rainfall estimates and rain gauge data has proved to be a successful solution compared to the use of a single source of information [19-27]. This paper describes a methodology for merging satellite estimates and gauge data. In this case, TAMSAT v.3, TRMM 3B42 v.7, RFE 2.0 and ARC 2.0 are used as a high-quality rainfall algorithm. Rain gauge database is used to correct the bias on monthly and seasonal basis over the country. Validation tests (including pairwise comparison statistics and intercomparisons between rain gauge observations and satellite retrievals) have been carried out.

Section 2 describes the dataset used in this paper, section 3 presents the techniques used for the evaluation of satellite rainfall estimates and the merging methodology. The results and the discussion are presented in section 4. The conclusions are drawn in section 5.

II. Meterials and Methods

Study area

Ivory Coast is located in the western part of Africa covering 322 462 km2. It borders are Liberia, Guinea, Mali, Burkin Faso, Ghana. Its southern boundary is along the Gulf of Guinea and a total coastline of 515 km. Ivory Coast is located in the transition zone between the humid equatorial climate that characterizes the southern part of the country, and the dry tropical climate in the northern part. The country generally experiences a rainy season from June to October and average annual temperatures range from 24-28°C. In the northern, the rainy season occurs from June to October, while the dry season is between the months of November to May. The southern region of Ivory Coast generally experiences four seasons. May to June brings heavy rains due to the African monsoon while shorter rains occur during August and September. A shorter dry season occurs during October to November and the main dry season occurring from December to April. Along the coast, the rains are significant also in March and November, and even in December on the westernmost part. Rainfall is more abundant on the coast, where it's between 1,500 and 2,500 millimeters per year, while in inland areas, it's generally less intense and ranges from 1,200 to 1,500 mm per year, even though it reaches 2,000 mm in the small western mountainous area [28].

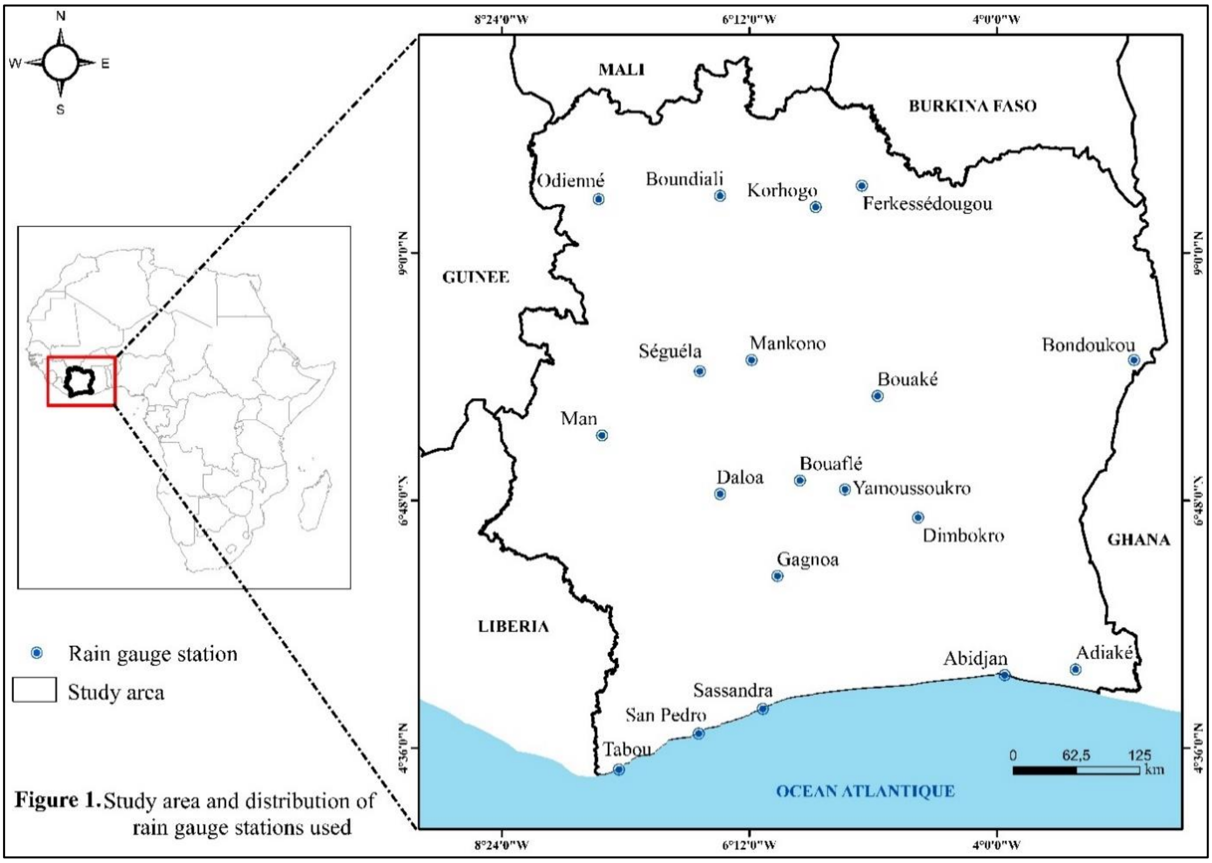

Figure 1. Study area and distribution of rain gauge stations used

Data set-up

Rain gauge data

In addition to the satellite data, we used station precipitation data measured by the national meteorological agency (SODEXAM). 19 stations (Figure 1) are used to generate gridded rain gauge time series, and combine them with the satellite-based rainfall estimates. The use of such large number of rain gauges was possible because the work has been a collaborative effort of African Centre of Excellence on Climate Change, Biodiversity and Sustainable Agriculture (CEA CCBAD/WASCAL) with SODEXAM.

Satellite-Based Precipitation Products

This section provides a brief description of the four gridded satellite rainfall products (Table no 1). These products were selected because of their long time series availability; their spatial and temporal resolutions, which make them particularly suitable for hydrological applications; their near-real-time availability; and their public domain availability. We analysed data from different sources, namely Africa Rainfall Estimate Climatology version 2 (ARC 2.0), African Rainfall Estimation version 2 (RFE 2.0), Tropical Applications of Meteorology using SATellite data (TAMSAT) and Tropical Rainfall Measuring Mission (TRMM) research version product.

RFE 2.0 is developed by the NOAA Climate Prediction Center (CPC) [29]. It is mainly produced for Famine Early Warning Systems Network to assist in disaster-monitoring activities over Africa. The input data for RFE 2.0 comprise four operational sources : (1) daily Global Telecommunications System (GTS) rain-gauge data, (2) Advanced Microwave Sounding Unit (AMSU)-based rainfall estimates, (3) Special Sensor Microwave Imager (SSM/I) based estimates [30,31], and (4) the Geostationary Operational Environmental Satellite (GOES) precipitation index (GPI) calculated from cloud-top infrared (IR) temperatures on a half-hourly basis.

The ARC 2.0 is based on the same algorithm used in RFE 2.0 [32]. The latest version ARC 2.0 is very similar to that of RFE 2.0, but uses inputs from two sources : (1) 3 hourly geostationary IR data centred over Africa from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT), and (2) quality controlled GTS gauge observations reporting 24 hours rainfall accumulations over Africa. However, there are differences between ARC and RFE in the use of polar-orbiting PM and geostationary IR data [33-35]. ARC uses only 3 hourly IR data, and does not include PM estimates, which RFE does.

The TRMM is a joint space mission between NASA and the Japan Aerospace Exploration Agency (JAXA) designed to monitor and study tropical and subtropical precipitation and the associated release of energy. The most widely used outputs are the TMPA 3 hourly (TRMM 3B42) accumulated to daily, and monthly (TRMM 3B43) products [36]. The TMPA depends on input from a variety of sensors and sources: the TRMM Precipitation

Radar (PR), the TRMM Microwave Imager (TMI), the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) on Aqua, the SSM/I and the Special Sensor Microwave Imager/Sounder (SSMIS) both on Defense Meteorological Satellite Program (DMSP), the AMSU-B and the Microwave Humidity Sounder (MHS) both on the NOAA satellite series, the IR data collected by the international constellation of geosynchronous earth orbit (GEO) satellites, and the GPCP precipitation gauge analysis from the Global Precipitation Climatology Centre (GPCC). Some of these sensors are no longer functional [37,38]. The TRMM 3B42 V7 products have been used in this study.

In January 2017, the TAMSAT Group released TAMSAT v.3 based on high resolution Meteosat thermal-infrared (TIR) observations for all of Africa, available from 1983 to the present and updated in near-real time. TAMSAT v.3 is based on the disaggregation [39] TAMSAT version 3.0 pentadal rainfall estimates, to a daily time-step using daily calibrated cold cloud duration (CCD) observations. The characteristics of the data are presented in Table 2. The algorithm described in [40], [41] and [39], is based on the principle of the use of METEOSAT Thermal Infrared images allowing to monitor the tops of cold clouds of rainy convective systems of cumulonimbus types which constitute a useful indicator for rainfall in the tropics. The data are obtained every 15 minutes from July 2006 and every 30 minutes before that date [42] and is then calibrated with ground observations. With a spatial resolution of 0.0375° (4 km), available for all of Africa from 1983 up to now, free of charge, on the TAMSAT group site of the University of Reading at the United Kingdoms.

Table no 1: *Summary of the four satellite products used*.

Satellite data	Temporal Coverage	Spatial Coverage	Spatial Resolution	Developer	Data format	Temporal resolution
TAMSAT v.3	1983-present	Africa 38° N-36°S, 19°W-52°E	0.0375° (~4 km)	Univ. of Reading (UK)	NetCDF	Daily
RFE v.2	2001-present	Africa 43.7°N–42.2°S, 23.5° W–63.4° E	0.1° (~10 km)	NOAA (CPC)	NetCDF	Daily
ARC 2.0	1983-present	Africa 40°N – 40°S, 20°W – 55°E	0.1°(~10km)	NOAA (CPC)	NetCDF	Daily
TRMM 3B42 v.7	1998-present	50° S-50° N	0.25° (27.8 km)	NASA/JAXA	NetCDF	Daily

Methodology

The overall process involves two major tasks such as (1) assessment of each satellite-based precipitation product and (2) merging satellite rainfall estimates and rain gauge data. This section provides a brief description of these tasks.

Evaluation of satellite rainfall estimates

Three statistical indictors, summarized in Table no 2 were computed for the pairwise comparison statistics [43,44]: (1) the Pearson correlation coefficient (R) is used to evaluate how well the estimates corresponded to the observed values; (2) the root mean square error (RMSE) is a frequently used measure of differences between two variables – it measures the average magnitude of the estimate errors: lower RMSE values indicate greater central tendencies and generally smaller extreme errors; (3) the Nash–Sutcliffe Efficiency coefficient (NSE) shows how well the estimate predicted the observed time series, and it varies from minus infinity to one: negative values mean that the gauge mean is better than the satellite-based estimate, zero means that the gauge mean is as good as the estimate, and 1 corresponds to a perfect match between gauge measurements and satellite-based estimates.

Table no 2: Continuous statistics with G = gauge rainfall measurement, $\bar{G}$ = average gauge rainfall measurement,
S = satellite rainfall estimate, $\bar{S}$ = average satellite rainfall estimate, and n = number of data pairs

Indicateurs quantitatifs	Formula	Values range
Pearson correlation coefficient (R)	$R = \frac{\sum(G-\bar{G})(S-\bar{S})}{\sqrt{\sum(G-\bar{G})^2}.\sqrt{\sum(S-\bar{S})^2}}$ (8)	[0 ; 1]
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S-G)^2}{n}}$ (9)	[0; +∞[
Nash–Sutcliffe efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^{n}(S-G)^2}{\sum_{i=1}^{n}(G-\bar{G})^2}$ (10)	] -∞ ; 1]

Precipitation Merging Approache

Different approaches have been tested to merge satellite based rainfall estimates and rain gauge observations [45-52]. The simple bias adjustment was tested in this work. This merging method involves the following steps :

i. Extract satellite rainfall estimates at rain gauge locations ;
ii. Compute the difference between the satellite estimate and rain gauge values at each station location ;

iii. Interpolate these differences to each grid point (same as satellite pixel centres) using inverse distance weighting; and
iv. Add the interpolated differences back to the satellite estimate.

III. Results and discussion

Evaluation of the products

The statistical indicators are shown in Table no 3. Good agreement with the rain-gauge data was observed for all the satellite products ($R \geq 0.80$). Whereas ARC 2.0 data presented the best correlation (R = 0.93) and the greatest NSE (0.87), TRMM 3B42 v.7 data showed the smallest but good R (0.80) and the weakest NSE (0.45). Both ARC 2.0 and RFE 2.0 had the highest RMSE (0.25 and 0.33). All satellite products underestimated rainfall, except for PERSIANN, which overestimated it. RFE 2.0 also presented both good R and NSE. TRMM 3B42 v.7 value of RMSE is close to those of TAMSAT v.3. TRMM 3B42 v.7 showed the weakest performance for continuous statistics (R, NSE, RMSE), followed by TAMSAT v.3. Although ARC 2.0 was the best of the satellite products, which is in full agreement with the other findings for West Africa [53-58], it was followed closely by RFE 2.0 and TAMSAT v.3, whereas TRMM 3B42 v.7 had the lowest performance. Most of the microwave techniques rely indeed on high frequencies (≥85 GHz), which are more adapted to ice particle detection than to liquid water over a land area, thus explaining why microwave satellites miss most of the warm and light precipitation events. Satellite products performed differently, depending on a number of factors. Satellite products using a combination of thermal infrared (TIR), passive microwave and GPCC observation data as input showed better performance than those using fewer sources. In addition, the good performance of some satellite products may be due to their smaller grid size, as this reduces the effect of pixel-to-point comparison [18,59-62]. These differences may be also explained by the origin of precipitation with convective weather systems being more accurately detected by satellite sensors. Satellite rainfall estimates, on the other hand, contain random errors and bias because of the indirect relation between observations and precipitation, inadequate sampling and algorithm imperfections. The underestimation of heavy rainfall may be caused by the low sampling frequency and consequently missed short-duration precipitation events between satellite measurements [18,60].

Table no 3 : *Statistical indicators*

SATELLITE DATA	INDICATORS			
	R [0 ; 1] 1= perfect	R^2 [0 ; 1] 1= perfect	NSE] -∞, 1] 1= perfect	RMSE [0 ; +∞ [0= perfect
TAMSAT v.3	0.86	0.74	0.57	48
RFE 2.0	0.90	0.81	0.80	33
ARC 2.0	0.93	0.86	0.87	25
TRMM 3B42 v.7	0.80	0.64	0.45	54

Precipitation Products

Figure 2 and Figure 3 show the spatial distribution of mean annual precipitation of the reference ground data, raw satellite precipitation products (Figure 2) and the merged satellite estimates (Figure 3). The spatial distribution of average seasonal rainfall is shown in figure 4 and figure 5. The satellite rainfall estimates used for the merging are four widely used satellite products. Two of these products are generated by the CPC at the National Oceanic and Atmospheric Administration (NOAA) : the CPC rainfall estimate (RFE 2.0) [29,63] and ARC 2.0 [64]. The product from the National Aeronautics and Space Administration (NASA), TRMM (Tropical Rainfall Measuring Mission) Multi-satellite Precipitation Analysis [37], version 7 (TRMM 3B42.V7) was used here. TAMSAT v.3 generated by the University of Reading was used. The TRMM 3B42 v.7 and RFE 2.0 algorithms also employ some gauge adjustments. The reference data used for the comparison is the gridded rain gauge product generated using 19 rain gauge.

The merged annual and seasonal precipitation series exhibit high data quality after blending. When compared with the original and downscaled satellite products, the simple bias adjustment merged results reduced the estimation error. The annual precipitation in the southeastern and southwestern part of Ivory Coast was observed to be significantly overestimated. which could not be identified by the few existing weather stations. As there has not been any rainfall data merging research in Ivory Coast before, we can only just compare the rainfall product estimated by our merging framework with the estimates obtained by other merging techniques. Annual precipitation shows a similar spatial pattern. Real-time merging of rain gauge and remote sensing data has become a new perspective in hydrological forecasting [49,65-74]. By far, however, the merging framework proposed in this study can be used only to back-analyze past rainfall events, which may strongly restrict its scope of application. The rain gauge data shows the overall rainfall pattern. The main weakness of the rain gauge map is the lack of stations. The merged satellite product depicts the overall spatial structure of the rainfall field reasonably well. The combined product overcomes, to some degree, both the lack of stations over the lowlands and the underestimation by the satellite product. The merged product combines the spatial information from the satellite estimates with the point measurements at gauge locations. The combined and gridded products are similar over station-rich parts of the country. Thus, the main advantage of the merged product is over data-sparse parts of the country. The combined product has spatial structure that looks more like the gauge data. The merging method also highlights the North-south gradient [75,76].

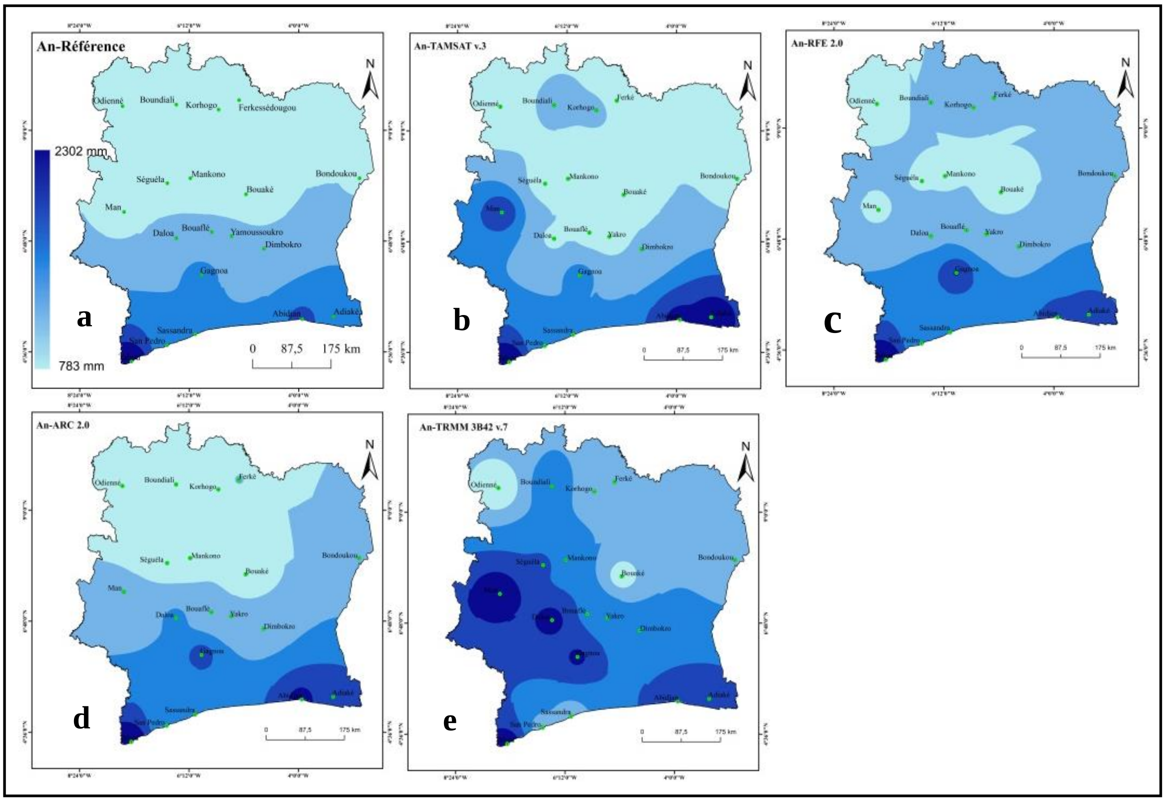

Figure 2. Mean total annual rainfall for the different rainfall products : reference gridded rain gauge data (a), TAMSAT v.3 (c), RFE 2.0 (d), ARC 2.0 (e) et TRMM 3B42 v.7 (f)

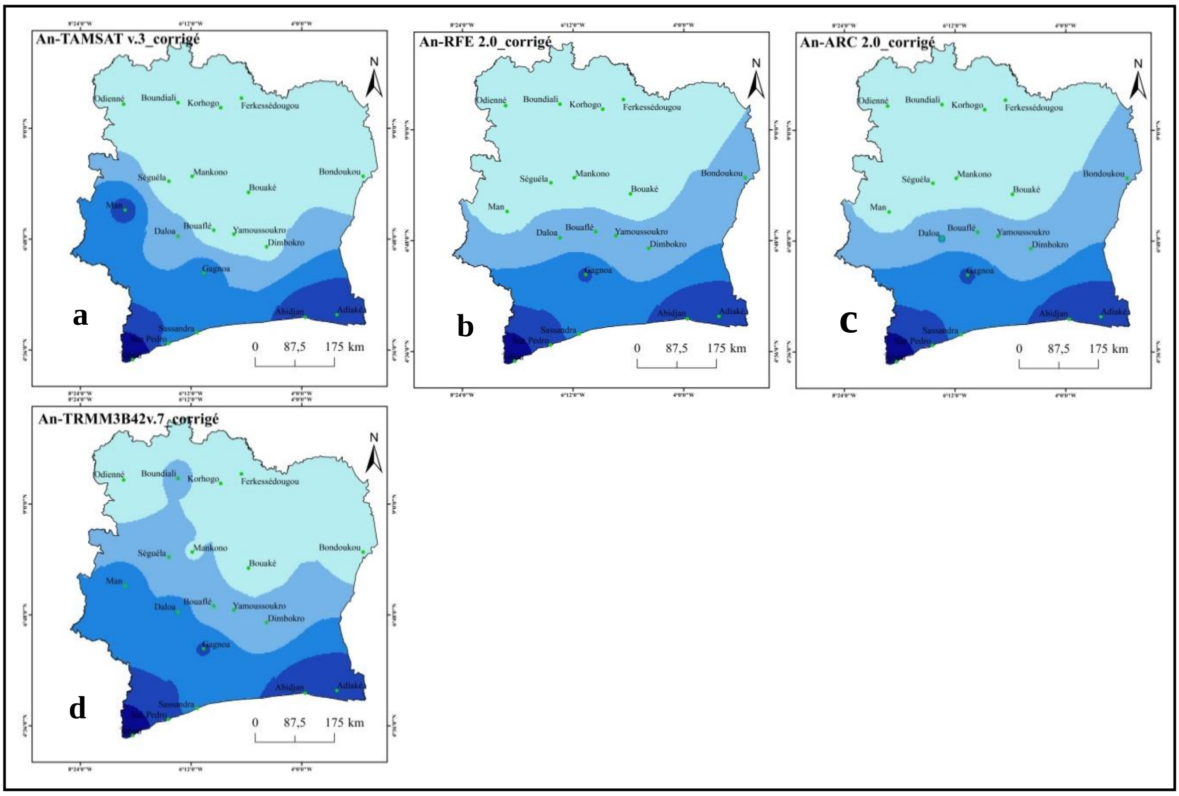

Figure 3. Mean total annual rainfall for the different merged satellite-based rainfall products : TAMSAT v.3 (a), RFE 2.0 (b), ARC 2.0 (c) et TRMM 3B42 v.7 (d)

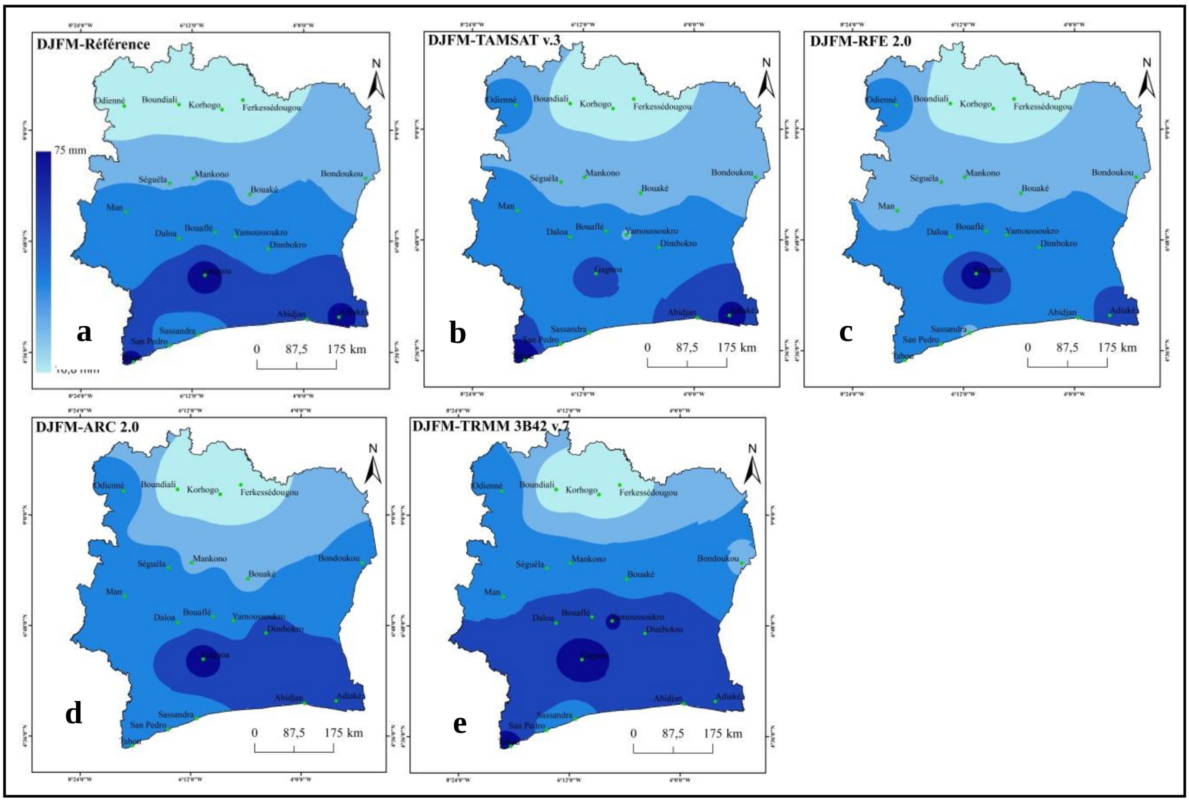

Figure 4. Mean seasonal rainfall for the different rainfall products : reference gridded rain gauge data (a), TAMSAT v.3 (b), RFE 2.0 (c), ARC 2.0 (d) et TRMM 3B42 v.7 (e)

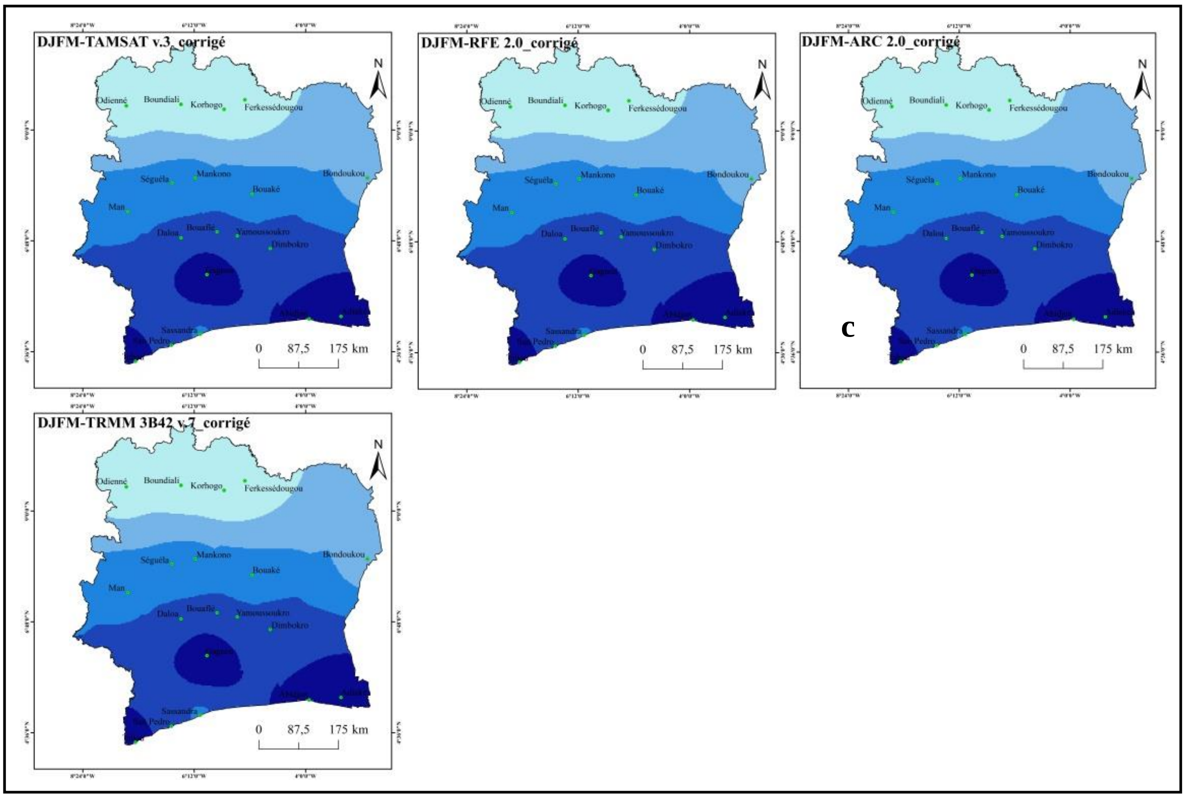

Figure 5. Mean seasonal rainfall for the different merged rainfall products : TAMSAT v.3 (a), RFE 2.0 (b), ARC 2.0 (c) et TRMM 3B42 v.7 (d)

IV. Conclusion

The evolution and availability of continental and global satellite-based rainfall products with high spatial and temporal resolution are increasingly facilitating and stimulating the implementation of climatic early warning activities in data-scarce region. However, the accuracy, strengths, and weaknesses of these satellite products must be assessed before they are used for any specific application. The performance of the satellite products in estimating and reproducing rainfall was investigated for Ivory Coast. Four satellite-based rainfall data sets such as ARC 2.0, RFE 2.0, TAMSAT v.3, TRMM 3B42 v.7 were compared and evaluated using rain-gauge data. ARC 2.0 and RFE 2.0 show better performance than TAMSAT v.3 and TRMM3B42.V7 in the statistics. However, part of this discrepancy could also be due to the mismatch between point gauge data and pixel-average satellite estimates. The performance of RFE 2.0 is almost similar to that of ARC 2.0. The good performance of TAMSAT v.3 is very significant considering that it is a TIR-only product. Underestimation of high rainfall values is a known weakness of TIR-based retrieval algorithms It is interesting to note that it is as good as or better than TRMM 3B42 v.7, which use what is considered to be state of the art operational algorithms with PMW inputs. This study explored a satellite and rain gauge data merging framework. An experimental study for merging the satellite rain data and gauge measured was conducted over Ivory Coast. The satellite rainfall estimates were then combined with station measurements. As a result, simple bias adjustment was used. The merged product was shown to be significantly better than satellite estimate. There is no significant difference between gridded gauge and the merged product This is a desired result as the main objective of this work has been to improve data availability over regions with few or no meteorological observations. The advantage of the gridded data is that it is not limited by availability of satellite data ; thus, it could be used to generate a time series over a much longer period. Main conclusions are : (1) the performance of the simple bias adjustment based rainfall merging method generally improves with increasing raingauge density ; (2) satellite based precipitation products actually provides useful information for generating rainfall fields. However, the gain achieved by the merging scheme relative to traditional interpolation is only substantial when the raingauges are rather sparse in space. The current work needs to be extended to monthly and daily rainfall data. Extending this to a daily time scale would be more challenging. Work on improving satellite estimates must continue.

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Conflicts of Interest :

The authors declare no conflict of interest.

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