Research Journal of

Environmental Sciences

ISSN 1819-3412

Academic
Journals Inc.

www.academicjournals.com

Research Journal of Environmental Sciences 8 (7): 373-390, 2014
ISSN 1819-3412 / DOI: 10.3923/rjes.2014.373.390

Comparative Analysis of Gridded Datasets and Gauge Measurements of Rainfall in the Niger Delta Region

[1,2]Ugochukwu K. Okoro, [2]Wen Chen, [1]Chidiezie Chineke and [1]Okey Nwofor
[1]Atmospheric Physics Group, Department of Physics, Imo State University, P.M.B. 2000, Owerri, Nigeria
[2]Institute of Atmospheric Physics, Center for Monsoon System Research, Chinese Academy of Sciences, Beijing 100029, China

Corresponding Author: Ugochukwu K. Okoro, Atmospheric Physics Group, Department of Physics, Imo State University, P.M.B. 2000, Owerri, Nigeria

ABSTRACT

Comparative analyses were carried out on observational rainfall datasets over the Niger Delta region (4.15°N-7.17°N, 5.05°E-8.68°E) using six locations within the area for a period of 24 years (1981-2004). Monthly rainfall gridded datasets of the Climatic Research Unit-Time Series (CRU-TS) 3.20 and the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) were compared with the Nigerian Meteorological Agency (NIMET) monthly rain gauge data as the reference. The objectives were to compare the representation of the gridded datasets in small areas, highlighting their similarities and differences on monthly rainfall variability as well as to examine that how these datasets compare with each other in representing the regions annual and wet season interannual rainfall variability. A mapping of rate of change in trend from the signatures of each dataset in representing the normalized monthly anomalous moisture flux accumulation (Ĉ) within the region was done using the potential evapotranspiration data from CRU TS 3.20. The three datasets show significant similarity in the trends of rainfall variability at each of the locations as well as on the areal average over the region. The annual and wet season interannual rainfall variability indexes from the NIMET rain gauges show significant correlation with the gridded datasets. However, the systematic differences in the gridded datasets as well as their relative accuracy and expected uncertainties have been compared to the rain gauge measurements. The three datasets confirm increment in the rate of change in the trend of Ĉ although with CMAP indicating higher reservoir of moisture flux accumulation than CRU when compared to the NIMET over the region. This study should guide researchers to carrying out studies in small areas of this scale on the choice of the rainfall observation gridded datasets for use in various applications.

Key words: Niger Delta, comparison, rainfall variability, gridded data, rain gauge, moisture flux accumulation, trend

INTRODUCTION

Africa is a large continent having input on the global climate yet, little or no ground meteorological observation data exist in most areas of the continent to precisely quantify its impact or influence on the global climate system. Where the ground stations are available, it is noted that there are excessive gaps in space and time over the period of their observation or that they are seriously deteriorating. This is not peculiar to Africa alone but to many developing countries. Noting the importance of observational measurements in representing the state of the atmosphere (Betts *et al*., 2006), efforts have been made to develop observational datasets for data sparse regions although with uncertainties (Xie and Arkin, 1997; Adler *et al*., 2001; McGuffie and Henderson-Sellers, 2005; Mitchell and Jones, 2005). In doing this, conventional data from quality controlled gauges were uniformly gridded and blended using interpolations that are guided by different techniques, which includes satellite patterns and model physics as well as distance weighting functions (Richards and Arkin, 1981; Huffman *et al*., 2001; Robert *et al*., 2003; Joyce *et al*., 2004; Beck *et al*., 2005). These gridded datasets have been subjected to comprehensive quality control over the years (Jones, 1994; Horton, 1995; Easterling *et al*., 1997). Also, the unavailability of detailed local meteorological and station data poses a challenge in validating these gridded datasets (New *et al*., 2000). Previous studies have shown that these datasets typically agree in their key temporal trends and spatial distribution but each of them shows striking differences regionally (Costa and Foley, 1998; Adler *et al*., 2001; Marengo *et al*., 2010). These climate observational gridded data present a reference for comparison, though, with inherent uncertainties in the resultant data products (Bosilovich *et al*., 2008). However, these uncertainties are to a degree revealed when the gridded datasets are compared with alternative data sources.

There have been various methods applied to ascertain the degree of these uncertainties in the available gridded datasets by studying their performances over different locations and at varying time spans. In one of such studies, Gruber *et al*. (2000) in comparing Global Precipitation Climatology Project (GPCP) and Climate Prediction Center Merged Analysis of Precipitation (CMAP) data on a global scale noted that, although, both datasets are a combination of satellite and gauge rainfall estimates, yet CMAP yielded different values owing to the analytical procedures in its interpolation. Also, Tozer *et al*. (2011) opined that gridded datasets are not an exact match to gauged rainfall measurements owing to their uncertainties due to the spatial interpolation methods used. However, Covey *et al*. (2002) comparing the differences in observational data uncertainties used a ‘portrait diagram’ to display root-mean-square differences for 25 variables on the longitude-latitude fields it examined and showed that the data best concurred on zonal wind but with relative large differences for humidity. Also, McCollum and Krajewski (1998), in estimating the error of rain gauge mean in the context of the GPCP, were of the view that using only monthly rain gauge data were not adequate for the reliable estimation of the uncertainties for each monthly estimates hence suggesting for alternative data sources which would account for the uncertainty in the spatial variability of monthly rainfall. Furthermore, Juarez *et al*. (2009) in comparing three gauge-only rainfall data with three gauge and satellite combined rainfall data over the Amazon, Northeast Brazil and the Congo basin showed that the differences among the merged analyses represents a measure of the uncertainties of the analyses thus the need for caution in explaining the variability from individual datasets over the regions.

Laurent *et al*. (1998) validating rainfall estimates using two ground-based and three satellite estimates over the Sahelian region of Africa attributed the performance of the rainfall estimation methods to the rainfall range, which is related to the space and time extent of the validation dataset. Jobard *et al*. (2011) in an intercomparison study over the Sahelian Africa from 2004-2006 for ten satellite precipitation products and rain gauge observations as the ground validation data, found out that three ‘near-real-time’ products showed under-achievements which were attributed to uncertainties in their algorithms. However, Lamptey (2008) from a 22 years period (1979-2000) made comparison of two monthly gridded datasets of GPCP and Global Precipitation Climatology

Centre (GPCC) Variability Analysis of Surface Climate Observations (VASClimO) data over West Africa noted that the analysis in the interpolation of the rain gauge data was responsible for the inability of the GPCC data to succeed in representing the bimodal rainfall pattern along the Guinea coast. Similarly, in comparing the satellite and surface rainfall products over West Africa, Roca *et al.* (2010) analyzed the seasonal cycle, synoptic-scale variability, diurnal cycle rainfall at seasonal scale and diurnal cycle rainfall at diurnal scale using 10 day products, the daily means, a composite and 3 h accumulations, respectively and showed that some of the products achieved better results on day to day comparisons than others while the mean diurnal cycle and its variability in space and during the seasons are relatively well captured by some products which others could not account for. Notwithstanding these comparisons more investigations on the uncertainties of gridded observational data with rain-gauge measurements (although, with its own uncertainties) on regional scales are still imperative as it will avail the dataset users a broad overview of similarities and differences between these datasets as well as their limitations within the context.

It will be of interest to note that the rain gauge data used in most stated comparisons over West Africa were provided by the Agriculture, Hydrology and Meteorology (AGRHYMET) Regional Centre, Niamey in Niger Republic. Hence, the uncertainties for most gridded datasets may not be accounted for areas that are not covered by the network. Also the uncertainties not detected during quality control of these data on regional scales are expected to be obvious at grid points near the gauge stations of comparison (New *et al.*, 2000). In this study, we present a comparison of observational rainfall data over a period of 24 years (1981-2004) between gridded datasets of the Climatic Research Unit (CRU), University of East Anglia UK Time Series (TS) version 3.20 and the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP). The Nigerian Meteorological Agency (NIMET) rain gauge data serves as the reference over the Niger Delta region of Nigeria situated on Lower Guinea Coast region of Africa. Comparison of rainfall data is pertinent as it is primal to West African climate as well as being a vital variable in model predictions performance with outstanding impact on the regions of agriculture and economy. In addition, it has attendant input in engineering applications and water balance calculation, not to mention the need in understanding the complexity of its variability (Fekete *et al.*, 2004; Roca *et al.*, 2010; Jobard *et al.*, 2011; Silva *et al.*, 2011; Tozer *et al.*, 2011). Also, the implication of the three rainfall datasets is investigated in representing the rate of change in trend of the observed monthly moisture flux accumulation over the region using potential evapotranspiration data from CRU-TS 3.20. Moisture flux plays a significant role in the suppression or increase of rainfall over a local area (Trenberth and Guillemot, 1996; Park *et al.*, 2009). Trenberth *et al.* (2003) shows that its increase is vital to moisture convergence into storms hence, increment in the intensity of local rainfall.

The objectives of this study are to perform a comparative analysis on the gridded monthly rainfall data and their nearest monthly rain gauge measurement over the Niger Delta region of Nigeria, highlighting their similarities and differences as well as to examine how these datasets compare with each other in representing the annual and wet season interannual rainfall variability over the region. The differences and the estimated uncertainties in the gridded datasets are compared to the rain gauge measurements. Also, the signature of each dataset investigated in representing the rate of change in moisture flux accumulation within the region. The aim is to guide researchers carrying out studies in small regions of this scale on the choice of the observational rainfall gridded datasets to use for their various applications.

STUDY AREA

Figure 1 shows the map of West Africa indicating the AGRHYMET Regional Center rain gauges (dots) (Ali *et al*., 2005) and the map of Nigeria (insert) showing the Niger Delta region (shaded portion) with the rain gauge locations. The region is located on the tropical rainforest climate zone (latitude 4.15°N-7.17°N and longitude 5.05°E-8.68°E) within the Lower Guinea Coast of Africa. It extends over 70,000 km^2 and constitutes about 7.5% of Nigeria's land mass with an annual rainfall total varying from 2400-4000 mm. The area is influenced by the localized convection of the West African monsoon with less contribution from the mesoscale and synoptic system of the Sahel (Ba *et al*., 1995). The rainy (wet) season over the area starts in May, following the seasonal northward movement of the Intertropical Convergence Zone (ITCZ), with its cessation in October (Druyan *et al*., 2010; Xue *et al*., 2010). The six rain-gauge locations are at Akure, Benin City, Calabar, Eket, Owerri and Portharcourt as shown in Table 1. These locations, apart from being of geographically spread over the region, has the longest history of gauge data with minimal gaps due to missing data.

RAIN GAUGE DATA

The NIMET rain gauge data are monthly rainfall records (mm) from NIMET for the six stations under its operation (Table 1). The agency is responsible for collecting and archiving meteorological

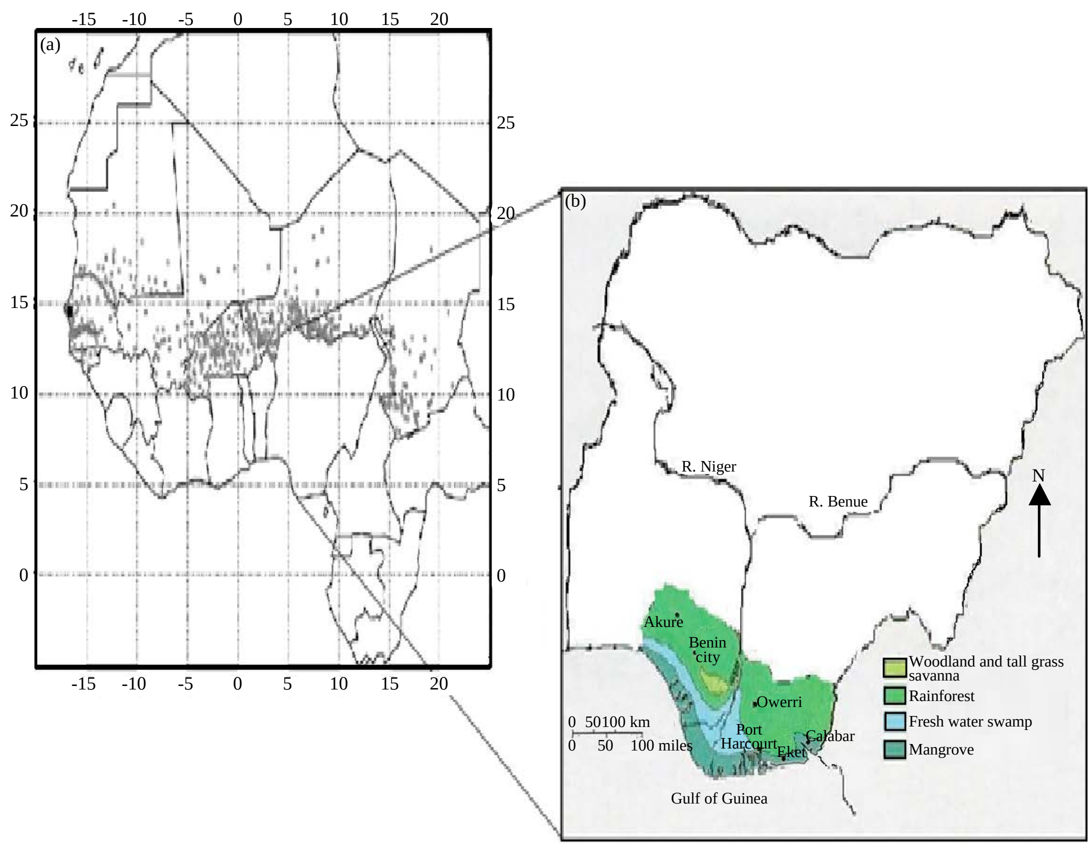

Fig. 1(a-b): Map of (a) West Africa showing the AGRHYMET gauges (dots) and (b) Nigeria showing the Niger Delta region (4.15°N-7.17°N, 5.05°E-8.68°E) (shaded) with the rain gauge locations (dots)

Table 1: Coordinates of the rain gauge locations, their elevations, percentage of missing data and duration of study

Location	Lat (°N)	Lon (°E)	Elevation (m)	Missing data (%)	Duration
Akure	7.247	5.301	335.0	0.694	1981-2004
Benin city	6.317	5.100	78.0	0.000	1981-2004
Calabar	4.976	8.347	63.0	0.000	1981-2004
Eket	4.650	7.933	13.0	1.042	1981-2004
Owerri	5.483	7.033	91.0	1.736	1981-2004
Port Harcourt	4.750	7.016	18.0	0.000	1981-2004

data in Nigeria. The data is the most reliable ground observation data source that exists within the Niger Delta region. The rain gauge data is not fed to the Global Telecommunication System (GTS) and it is not used in the interpolation of both gridded datasets. The data used for the study was from 1981, when satellite data could be used in combination with the 14579 rain gauges in the CRU dataset, to 2004 after which there were observed gaps in the data for the study locations at Owerri, Calabar and Benin City. The percentage of missing data on Table 1 for each location is computed from the months without rainfall records within the duration of the study.

CMAP gridded datasets are monthly and pentad (5 days) global averaged precipitation rate values (mm day^{-1}) prepared on a resolution of 2.5° by 2.5° global grid (approximately 180 km). The data spans from 1979-2009. The interpolation of the gridded fields includes rain gauge and model data as well as values obtained from 5 kinds of satellite estimates (GPI, MSU, OPI, SSM/I emission and SSM/I scattering). The procedure is further discussed in Xie and Arkin (1997). The data is provided by National Oceanic and Atmospheric Administration (NOAA), Boulder, Colorado, USA and it is available online at http://www.esrl.noaa.gov/psd/data/gridded/data.cmap.html.

On the other hand, the CRU TS 3.20 gridded datasets contains interpolation of month-by-month variations in climate variables including rainfall (mm) and potential evapotranspiration (mm day^{-1}). They are constructed on a high-resolution of 0.5° by 0.5° global grids (approximately 50 km) and extend from 1901-2011. The method used for the potential evapotranspiration is discussed in Ekstrom *et al.* (2007) and its interpolation is independent of the rainfall data. Mitchell and Jones (2005) further show the procedures in the data preparation and their presentation. Nevertheless, apart from constructing data for the missing stations in the baseline period, data was also constructed for stations that never existed. The data is provided by the National Centre for Atmospheric Science (NCAS) British Atmospheric Data Centre online at http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_1256223773328276.

METHODOLOGY

Spatially, the rainfall values in the gridded datasets represent the value in a grid box centered on the geographical coordinates given in the dataset. However being conscious of the limitation that the rain gauge represent a single site within a box with its location varying from its center to its edge and that they are not evenly distributed, the comparative analysis was carried out on the value for the grid box in which the rain-gauge lies (Mooney *et al.*, 2011; Tozer *et al.*, 2011). The following statistical criteria for the analysis have been followed:

Anomaly: In order to compare the capability of each of the dataset in representing, in spatial scales, the monthly rainfall anomalies of the datasets were computed from the climatological means using the following Eq. 1:

$$x' = x - \bar{x} \tag{1}$$

where, x is the monthly rainfall data from each of the datasets and $\bar{x}$ is the corresponding climatological mean for that month.

Normalization: The monthly rainfall anomalies were normalized with the aim of putting the datasets on the same scale for comparison as well as to eliminate the influence of location and spread in the various datasets. It is given by follwoing Eq. 2:

$$z = \frac{x' - \bar{x}'}{s_{\bar{x}'}} \tag{2}$$

where, x' is the monthly rainfall anomaly of each dataset, $\bar{x}'$ is the mean of the total monthly rainfall anomaly over the period and s is the corresponding standard deviation from x'.

Bias: The bias represents the average deviation as well as the systematic differences of the monthly normalized rainfall variability of the gridded datasets from the gauge data. It is given by the following Eq. 3:

$$\text{Bias} = \frac{1}{n}\sum_{i=1}^{n}(m_{gi} - q_{pi}) \tag{3}$$

where, m and q are the corresponding time series, n is the length of the time series and the subscripts g and p are the gridded and gauge datasets, respectively.

Linear regression: This shows the linear relationship between the gridded and rain gauge data in representing the rainfall variability over the region. It is computed using the following Eq. 4:

$$q = am+b \tag{4}$$

where, a and b are constants given by Eq. 5:

$$a = \frac{\sum_{i=1}^{n}[(m_i - \bar{m})(q_i - \bar{q})]}{\sum_{i=1}^{n}(m_i - \bar{m})^2} \tag{5}$$

and:

$$b = \bar{q}\text{-}a\bar{m} \tag{6}$$

where, $\bar{m}$ and $\bar{q}$ are the means of the corresponding time series.

Coefficient of correlation: In order to measure the strength in the linear relationship between the gridded and gauge datasets in representing the rainfall variability over the region, the coefficient of correlation is computed from the following Eq. 7:

$$r = \frac{\sum_{i=1}^{n}[(m_{gi} - \bar{m}_g)(q_{pi} - \bar{q}_p)]}{(n-1)\,(s_{m_g}\, s_{q_p})} \tag{7}$$

T-test: The percentages of the dependency and the underlying uncertainty between the associated variables is determined using the T-test and is given by the following Eq. 8:

$$t = \frac{\bar{\Delta} - \beta_{\Delta}}{\left(\frac{s_{\Delta}^{2}}{n}\right)^{\frac{1}{2}}} \tag{8}$$

where, $\bar{\Delta} = \bar{m} - \bar{q}$, whereas the population mean $\beta_{\Delta} = \beta_m - \beta_q = 0$ under H_0 hypothesis.

Root Mean Square Error (RMSE): The absolute measure of the expected uncertainties in the gridded datasets on the areal average of spatial rainfall variability over the region from each grid box were evaluated using the RMSE, with the following Eq. 9:

$$RMSE = \sqrt{\frac{1}{B}\sum_{i=1}^{B}(m_{gi} - q_{pi})^2} \tag{9}$$

where, B is the number of grid boxes.

Skill score: The relative accuracy of the gridded datasets in representing the rainfall variability on the Niger Delta region with respect to the reference NIMET gauge data is evaluated using the Brier Skill Score from the Eq. 10:

$$BSS = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(m_{gi} - q_{pi})^2}{s_{q_p}^2} \tag{10}$$

when, BSS = 1.0 (perfect gridded data), BSS = 0.0 (gridded data has similar skill to reference gauge data); BSS = Negative value (gridded data less skillful than reference gauge data) (Brier, 1950; Murphy, 1988).

Rainfall variability index: In order to show the ability of the datasets to represent the standardized precipitation departure of the annual and wet season rainfall time series at different climate regimes as defined by Oguntunde *et al.* (2011), the interannual rainfall variability index is computed using the following Eq. 11:

$$\delta_k = \frac{(R_k - \bar{R})}{S_R} \tag{11}$$

where, k is the year, R is the total (annual or wet season) rainfall, $\bar{R}$ and s_R are the mean annual rainfall and standard deviation, respectively for the duration of study.

Moisture flux accumulation: Having the difference between the rainfall and evapotranspiration as the first approximation for moisture flux accumulation, a normalized monthly anomalous moisture flux accumulation ($\hat{C}$) over the region was computed using a modification (Calanca and Ohmura, 1994; Banacos and Schultz, 2005; Karam and Bras, 2008) given by following Eq. 12:

$$\hat{C} = \hat{R} - \hat{E}_T \tag{12}$$

where, $\hat{R}$ and $\hat{E}_T$ are the normalized monthly anomalous from Eq. 1 and 2 for rainfall and potential evapotranspiration, respectively.

RESULTS AND DISCUSSION

Similarity and differences on the interannual variability of monthly rainfall: Due to the resolution of the gridded datasets, CRU has a grid box representing each of the NIMET gauges in Table 1. CMAP has three of its grid boxes over the region with each representing Akure, Benin City and Owerri (6.25N, 6.25E), Calabar and Eket (8.75N, 3.75E) and Port Harcourt (6.25N, 3.75E). Figure 2a-f shows the time series of the normalized monthly rainfall anomaly from the three datasets at each of the locations. The gridded datasets showed similarity to the NIMET gauges in representing the monthly rainfall variability at each location. This is evident in the coefficient of correlation values of NIMET data with CRU and CMAP, respectively (Table 2) significant at 99.9% confidence level from t-test. However, the correlation values were higher with CRU than with CMAP. The linear regression equations of the trends from the three datasets indicate that the monthly rainfall variability at each of the locations showed increments over the period but at differing magnitudes. The average deviations in the monthly rainfall variability of the gridded datasets from the gauge data on each location have the bias values shown in Table 3. In Table 3 the BSS of the gridded datasets with the gauge data as the reference at each of the locations is also shown. The skill score values reveal that CMAP is unskillful at all the locations within the region whereas, CRU is unskillful at Calabar, Eket and Owerri.

Figure 3 shows the time series of normalized areal averages of the monthly rainfall anomaly over the Niger Delta region of Nigeria from the NIMET, CRU and CMAP datasets. The trend of the three datasets confirms increment in the monthly rainfall variability over the region though at varying magnitudes. The coefficient of correlation of the normalized areal averages shows that the variability from NIMET has significant relationship with CRU (r = 0.65) and CMAP (r = 0.48) both

Table 2: Correlation values of NIMET gauges with the gridded datasets at each location and on the areal average

					Interannual variability index			
	Monthly anomaly		Normalized areal average		Total annual rainfall		Wet season rainfall	
Location	CRU	CMAP	CRU	CMAP	CRU	CMAP	CRU	CMAP
Akure	0.5826[a]	0.3008[a]	0.4528[a]	0.2347[a]	0.4594[d]	0.2826[f]	0.4336[d]	0.3617[e]
Benin city	0.7407[a]	0.3855[a]	0.4622[a]	0.3908[a]	0.4243[d]	0.6961[a]	0.4358[d]	0.6395[a]
Calabar	0.4843[a]	0.3427[a]	0.3034[a]	0.3009[a]	0.2470[f]	0.5567[b]	0.0999[f]	0.4176[d]
Eket	0.2774[a]	0.2480[a]	0.3172[a]	0.2885[a]	0.4401[d]	0.2914[f]	0.3711[e]	0.2935[f]
Owerri	0.3121[a]	0.3995[a]	0.3588[a]	0.3550[a]	0.1481[f]	0.4815[c]	0.1773[f]	0.4179[d]
Port Harcourt	0.5624[a]	0.2687[a]	0.5383[a]	0.2402[a]	0.4528[d]	0.4378[d]	0.4075[d]	0.3294[f]
Niger Delta (areal average)			0.6510[a]	0.4843[a]	0.6131[b]	0.7753[a]	0.5575[b]	0.7122[a]

Significant at CL [a]99.9, [b]99, [c]97, [d]95 and [e]90%, respectively, [f]Not significant from t-test

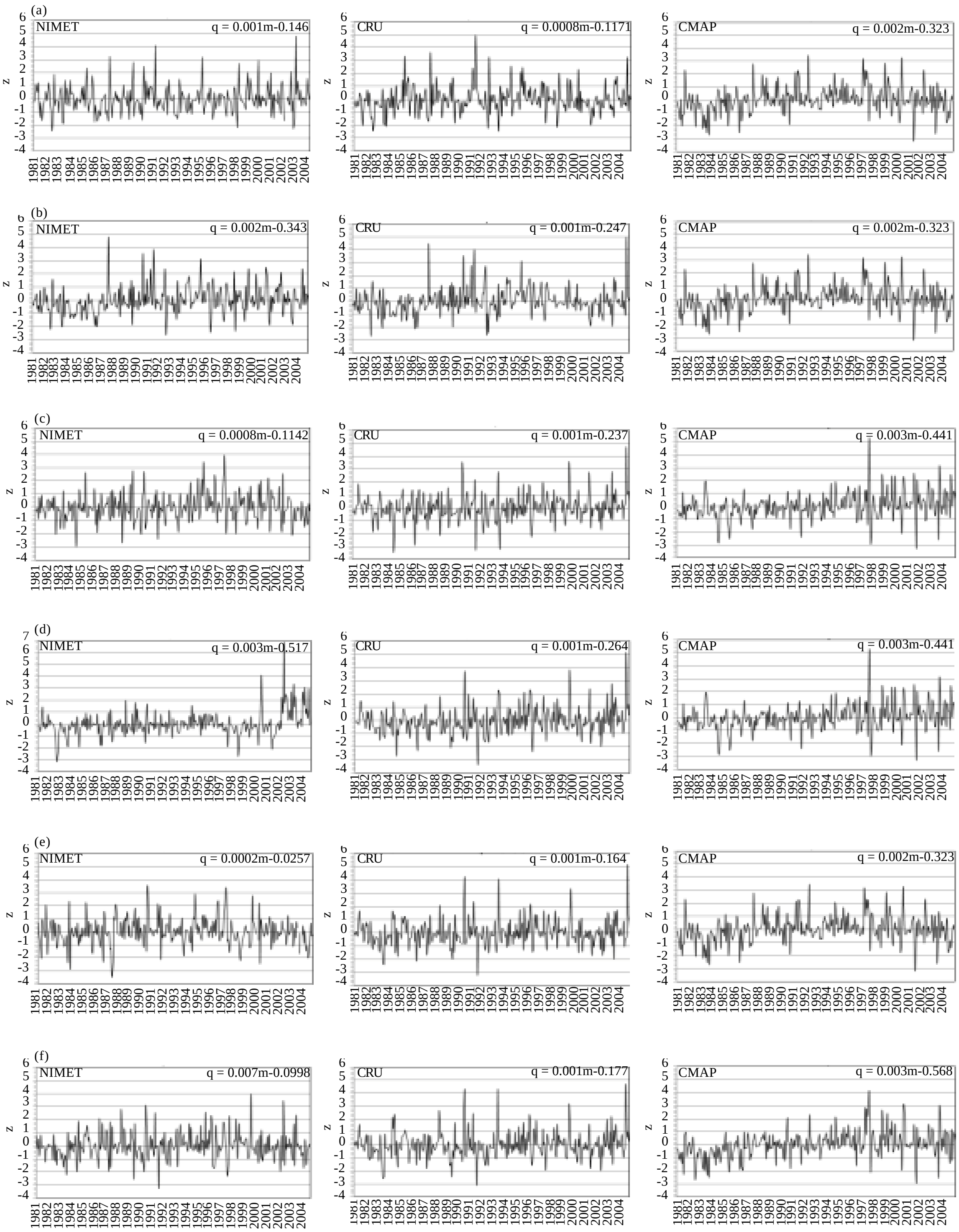

Fig. 2(a-f): Normalized time series of rainfall anomalies from NIMET, CRU and CMAP at (a) Akure, (b) Benin City, (c) Calabar, (d) Eket, (e) Owerri and (f) Port Harcourt. The linear regression equation of the trends are above each panel

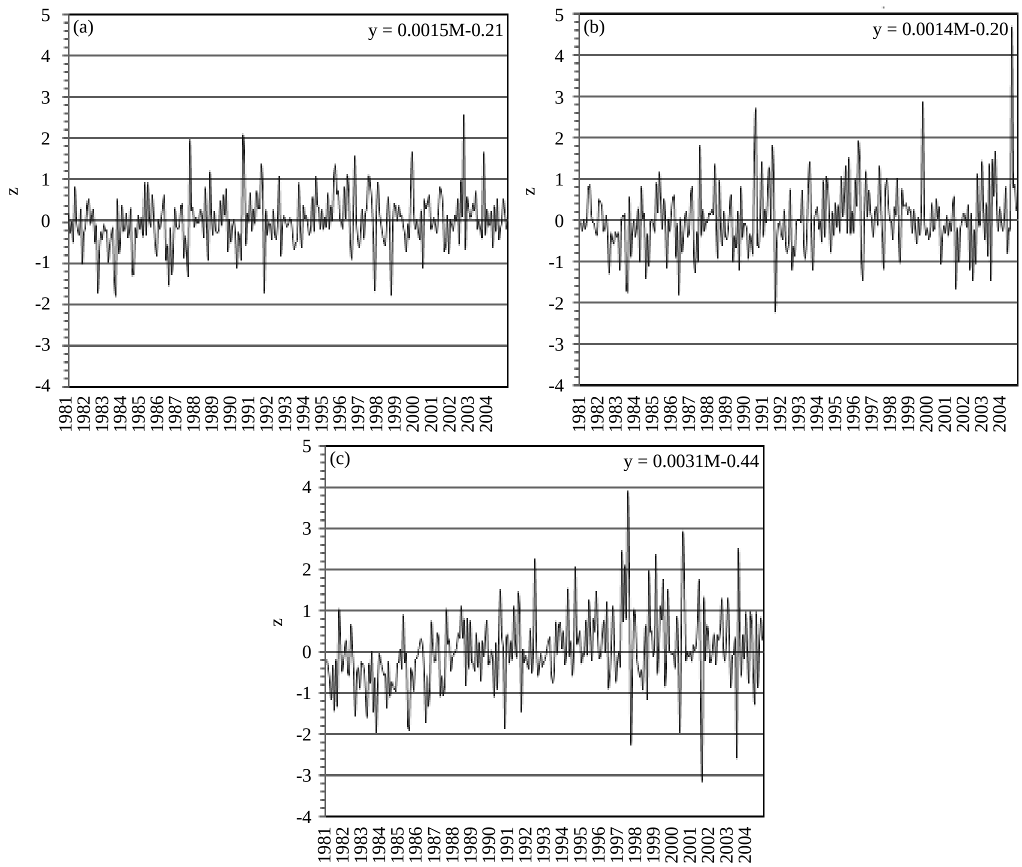

Fig. 3(a-c): Normalized time series of (a) NIMET, (b) CRU and (c) CMAP for the areal averaged monthly rainfall anomaly over the Niger Delta region and the linear regression equation of the trends are above each panal

Table 3: Bias values and the Brier Skill Scores (BSS) of the gridded datasets with the NIMET gauge data at each location and on the areal average

	Bias		BSS	
Location	CRU	CMAP	CRU	CMAP
Akure	8.90×10^{-17}	-4.50×10^{-17}	0.17	-0.39
Benin city	1.07×10^{-16}	3.85×10^{-17}	0.48	-0.22
Calabar	4.63×10^{-18}	6.13×10^{-17}	-0.03	-0.31
Eket	-9.18×10^{-10}	-1.11×10^{-16}	-0.44	-0.50
Owerri	8.53×10^{-09}	8.53×10^{-09}	-0.36	-0.19
Port Harcourt	1.48×10^{-17}	3.66×10^{-16}	0.13	-0.46
Niger Delta (areal average)	-1.87×10^{-03}	-1.87×10^{-03}	0.08	-0.59

at 99.9% confidence level from t-test (Table 2). Significant at 99.9% confidence level from t-test, the rainfall variability of the normalized monthly areal averages from CRU and CMAP show different representation with the NIMET data at each location as shown in their correlation values on Table 2. Both gridded datasets have a bias value of -1.87×10^{-3} with NIMET in representing the

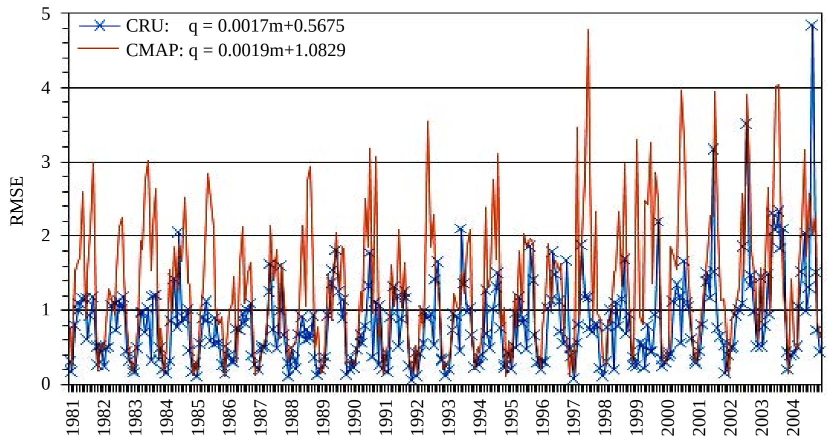

Fig. 4: RMSE from each grid box between the gridded datasets and NIMET gauge data on the areal average of monthly rainfall variability over the region. The linear regression of the trends are above the panel

areal averages of monthly rainfall variability over the region (Table 3). The relative accuracy of the gridded datasets with the gauge data in representing the monthly rainfall variability on the areal average over the Niger Delta shows that NIMET has a skill score of 0.08 and -0.59 with CRU and CMAP, respectively. The absolute measure of the expected uncertainties from each grid box between the gridded datasets and the gauge data representing the areal average of monthly rainfall variability over the region by the RMSE as shown in Fig. 4. The RMSE shows the site to site relationship of both gridded datasets to capture the spatial monthly rainfall variability over the region. The linear equation of the trends indicates that the spatial variability in the monthly rainfall over the region is well represented in CRU than in CMAP.

Representation of datasets on the interannual rainfall variability patterns: Figure 5 shows the interannual variability index of the total annual rainfall from the three datasets at each of the locations. The trends indicate increments in the index at varying magnitudes at each location except at Owerri where NIMET showed a decreasing trend. The correlation of the interannual variability index at each location from the NIMET data with the gridded datasets is shown in Table 2. From t-test, CRU and NIMET showed significant correlation at all the locations except at Calabar and Owerri whereas, CMAP and NIMET did not show significant correlation at Akure and Eket. The percentage of concurrence in the patterns ("+" for wet or "-" for dry) of the interannual variability index between the NIMET and the gridded datasets is shown in Table 4 for the various locations. Figure 6 shows the areal averages of the three datasets in representing the interannual variability index of the total annual rainfall over the region. The linear regression equations of the trends indicate increments, though, at varying magnitudes over the region. The correlation of the areal averaged annual index from NIMET with the CRU and CMAP at each location is shown in Table 2. The skill scores of the gridded datasets in representing the interannual variability index of the total annual rainfall with NIMET are -0.08 and 0.17 with CRU and CMAP, respectively. Figure 7 shows the RMSE of both gridded datasets with NIMET on the annual rainfall variability index. The trends show that CMAP has better improvement in its spatial performance on the representation of the index.

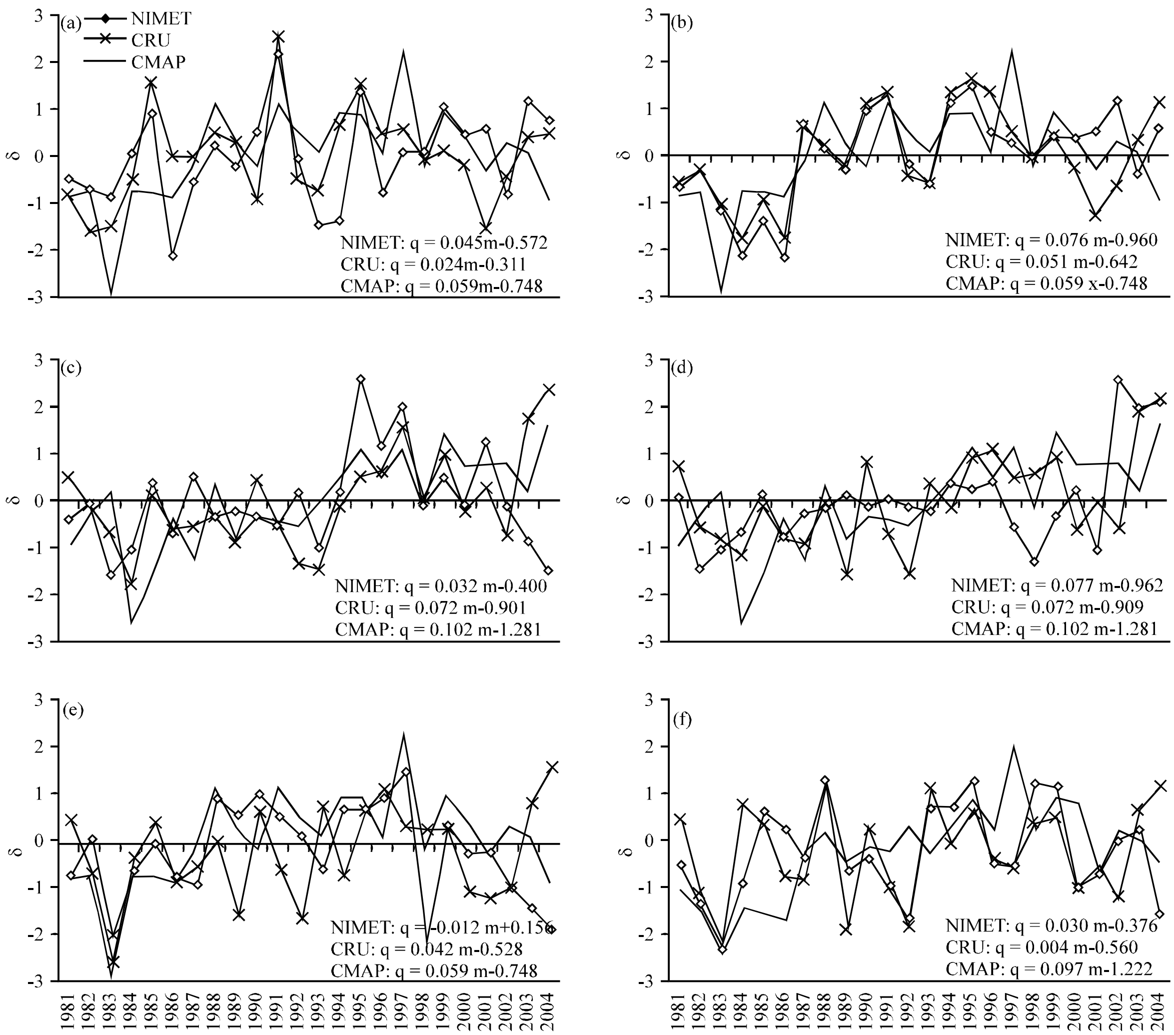

Fig. 5(a-f): Interannual variability index of the total annual rainfall from NIMET, CRU and CMAP at each of the locations of (a) Akure, (b) Benin city, (c) Calabar, (d) Eket, (e) Owerri and (f) Port Harcourt. The linear regression equation of the trends are above each panel

Table 4: Percentage concurrence in the patterns of the interannual variability indexes from the gridded datasets and the gauge data at each location and on the areal average

	Total annual rainfall (%)		Wet season rainfall (%)	
Location	CRU	CMAP	CRU	CMAP
Akure	66.67	50.00	62.50	50.00
Benin city	83.33	66.67	79.17	83.33
Calabar	66.67	62.50	50.00	41.67
Eket	54.17	62.50	50.00	58.33
Owerri	58.33	70.83	58.33	79.17
Port Harcourt	66.67	66.67	75.00	58.33
Niger Delta (areal average)	79.17	75.00	62.50	75.00

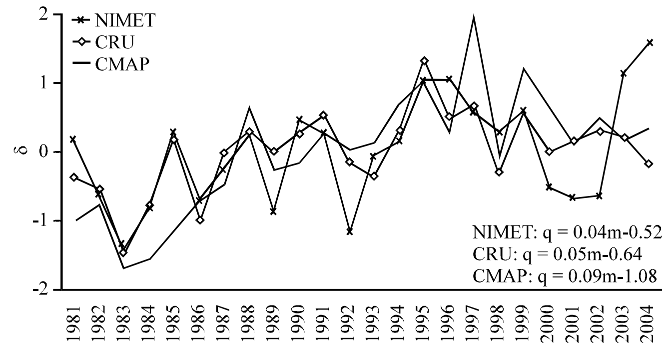

Fig. 6: Areal average of the NIMET, CRU and CMAP in representing the interannual variability index of the total annual rainfall over the Niger Delta region. The linear regression equations of the trends are above the panel

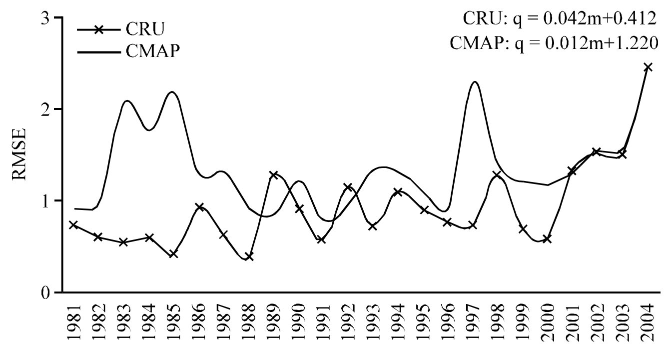

Fig. 7: RMSE of both gridded datasets with NIMET on the annual rainfall variability index. The linear regression equations of the trends are above the panel

Similarly, the interannual variability index of the wet season rainfall from the three datasets indicates increments at each of the locations except at Owerri, where the wet season rainfall variability index showed a decline (Fig. 8). Table 2 shows the correlation between the wet season rainfall variability indexes from the gridded datasets and the NIMET data at each of the locations. The values indicate that CRU shows a poor representation in the wet season rainfall variability index at Calabar and Owerri whereas, CMAP shows poor representations at Eket and Port Harcourt. However, the trends of the three datasets from the areal averages of the wet season rainfall variability index indicate increments at varying magnitudes over the region (Fig. 9). Their correlation shows significant relationship between NIMET with CMAP ($r = 0.71$) and CRU ($r = 0.56$). The percentage of concurrence in the wet season rainfall variability patterns between the gridded and the rain gauge datasets at each of the locations is shown on Table 4. CRU and CMAP agreed on 62.5 and 75%, respectively of the patterns with NIMET on the areal averages. Both gridded datasets have a skill score value of 0.08 (CRU) and (-0.13) with NIMET in representing the wet season rainfall variability index. Figure 10 shows the RMSE of both gridded datasets with NIMET in representing the wet season rainfall variability index and the trends indicates a better spatial performance from CMAP.

Mapping changes in moisture flux accumulation: In view of the significance of the rate of change in moisture flux accumulation in providing important insight into the hydrological cycle of a region (Trenberth *et al.*, 2003; Banacos and Schultz, 2005; Karam and Bras, 2008; Park *et al.*,

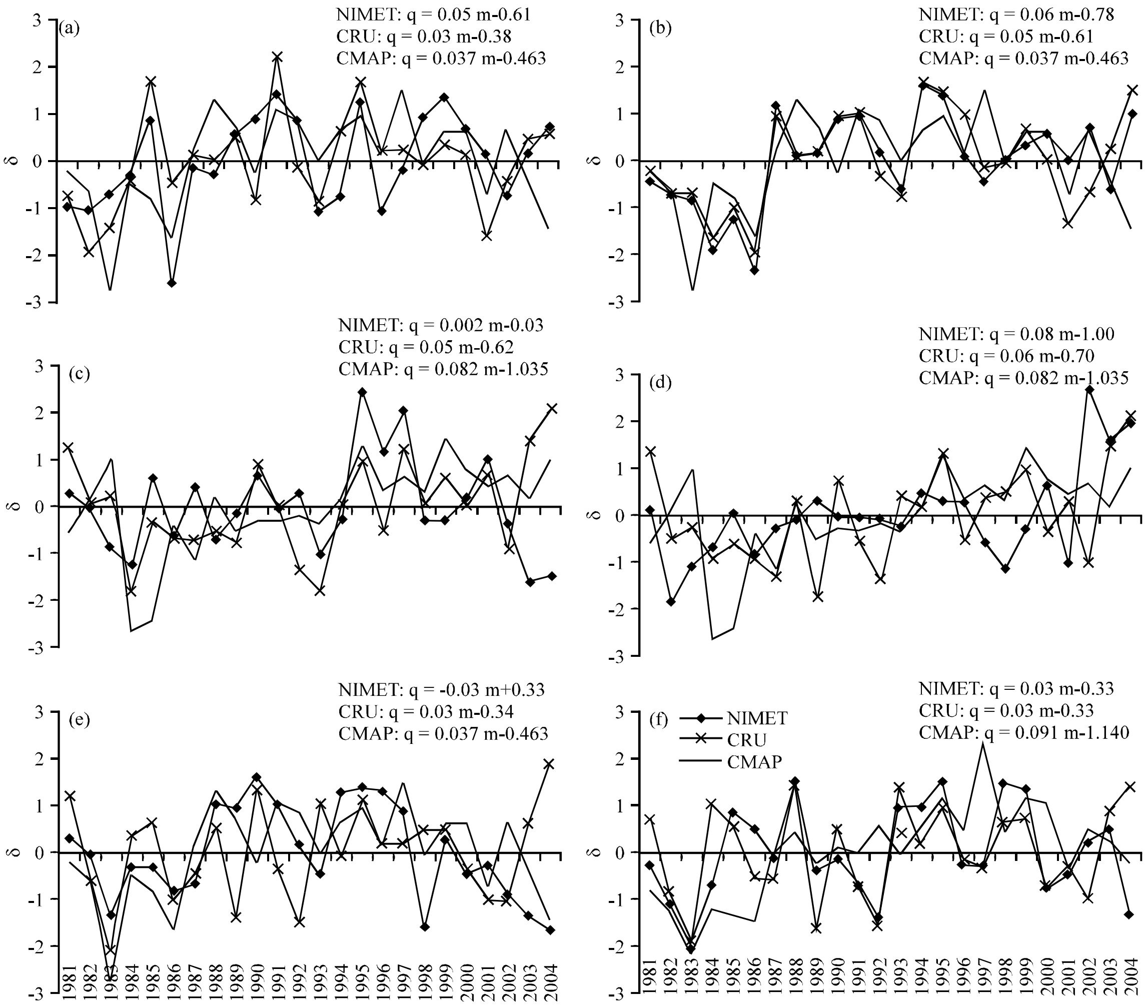

Fig. 8(a-f): Interannual variability index of the wet season (May-October) rainfall from NIMET, CRU and CMAP at each of the locations of (a) Akure, (b) Benin city, (c) Calabar, (d) Eket, (e) Owerri and (f) Port Harcourt. The linear regression equation of the trends are above each panel

Table 5: Rate of change in the normalized monthly anomalous moisture flux accumulation (Ĉ) at each location and on the areal average, calculated from the linear regression equation of the trends

Location	NIMET	CRU	CMAP
Akure	0.00077	0.00057	0.00200
Benin city	0.00287	0.00221	0.00274
Calabar	0.00082	0.00167	0.00308
Eket	0.00427	0.00252	0.00375
Owerri	0.00101	0.00198	0.00307
Port Harcourt	0.00158	0.00212	0.00483
Niger Delta (areal average)	0.00192	0.00185	0.00353

2009), the linear regression of Ĉ over the Niger Delta region was computed. The mapping of the rates of change in the trends of Ĉ from the three datasets for the various locations as well as the areal average as shown in Table 5. It is evident that CMAP showed higher reservoir of Ĉ over the

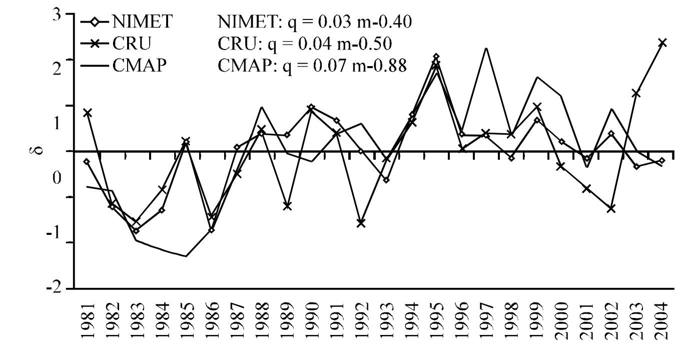

Fig. 9: Areal average of the NIMET, CRU and CMAP in representing the interannual variability index of the wet season (May-October) rainfall over the Niger Delta region. The linear regression equations of the trends are above the panel

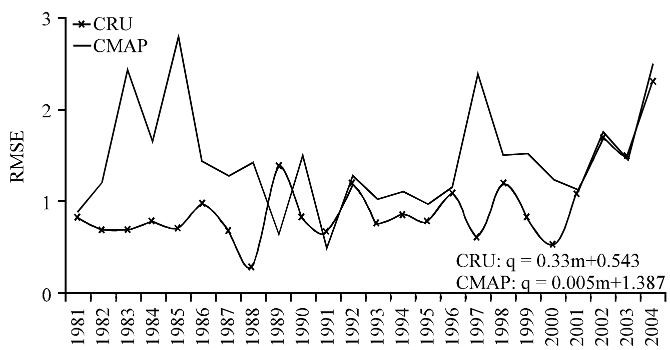

Fig. 10: RMSE of both gridded datasets with NIMET on the wet season rainfall variability index. The linear regression equations of the trends are above the panel

region whereas, CRU showed less value compared to the NIMET. Nonetheless, despite of these differences, all three datasets depict apparent increment in the trend of $\hat{C}$.

CONCLUSION

In the absence of extensive rain gauge networks for describing large scale rainfall fields, this study has compared the similarities and differences between two rainfall observation gridded datasets of CRU and CMAP with the NIMET rain gauge dataset as the reference. This was carried out at six locations over the Niger Delta region of Nigeria for a period of 24 years. Since, the gridded datasets are products of different interpolation techniques whereas, the reference gauge data are presented as were observed, differences are anticipated from their outputs. However, given that the gridded datasets are projected to represent the same observed situations over the region, these differences and uncertainties are expected to be minimal.

The result of the comparative analysis indicate that there is a good measure of agreement between the gridded datasets and NIMET on the monthly rainfall variability at each of the location as well as on the areal average of rainfall variability over the region. It shows the site to site relationship between the gridded datasets and the gauge data on the monthly rainfall variability as well as the ability of the gridded datasets to represent the spatial variability of monthly rainfall when compared to gauge data. The correlation between the areal averaged monthly rainfall variability of both gridded datasets and the gauge rainfall variability at each location shows the signature of the gridded sets at each location. The systematic differences in the monthly rainfall variability from each of the gridded datasets shows varying bias values between the gridded datasets and each gauge location whereas, both gridded data have the same bias with NIMET on the areal average of the monthly rainfall variability over the region. The implication in the use of the gridded datasets to represent the interannual variability index of both the total annual rainfall and the wet season rainfall at each location as well as on the areal averages over the region is evident from the trends of the patterns. The relative accuracy of the gridded datasets in representing the rainfall variability over the region with respect to the gauge data is shown in the skill scores of each gridded dataset.

Although the results, especially the bias and skill of the gridded datasets, are for the study region only, we deduce that CRU performs better in representing NIMET in the monthly rainfall variability over the region on both temporal and spatial scale whereas, CMAP performs better in representing NIMET in the interannual variability index for the total annual and wet season rainfall on both temporal and spatial scale, neglecting uncertainties in the NIMET gauge data. Though the three datasets show increment in the trend of $\hat{C}$, yet the signature from CMAP indicates higher rate of change in the moisture flux accumulation while, CRU show less values when compared to the NIMET. The understanding of the representation of the gridded datasets over the Niger Delta is imperative since agriculture within the region is grossly rain fed. This comparison does not provide all the uncertainties that would be found from each of the gridded datasets but it is a measure of the expected minimum uncertainty in the gridded datasets which should guide researchers carrying out studies on regions of this scale on the choice of observational rainfall gridded datasets to use in their various applications. However, further investigations into the implication of using a variety of other datasets in evaluating hydrological processes within the region are still ongoing within our study group.

ACKNOWLEDGMENT

The corresponding author is grateful to TWAS-CAS for 2012-2013 postgraduate fellowship granted him at the Institute of Atmospheric Physics, Center for Monsoon System Research, Chinese Academy of Sciences and to Imo State University Owerri, Nigeria for the study leave. Appreciation goes to the management of the Nigerian Meteorological Agency for providing the monthly rain gauge data and to Dr. Debashis Nath as well as the anonymous reviewers for their assistance.

REFERENCES

Adler, R.F., C. Kidd, G. Petty, M. Morissey and H.M. Goodman, 2001. Intercomparison of global precipitation products: The third Precipitation Intercomparison Project (PIP-3). Bull. Am. Meteorol. Soc., 82: 1377-1396.

Ali, A., T. Lebel and A. Amani, 2005. Rainfall estimation in the Sahel. Part I: Error function. J. Applied Meteorol., 44: 1691-1706.

Ba, M.B., R. Frouin and S.E. Nicholson, 1995. Satellite-derived interannual variability of West African rainfall during 1983-88. J. Applied Meteorol., 34: 411-431.

Banacos, P.C. and D.M. Schultz, 2005. The use of moisture flux convergence in forecasting convective initiation: Historical and operational perspectives. Weather Forecasting, 20: 351-366.

Beck, C., J. Grieser and B. Rudolf, 2005. A new monthly precipitation climatology for the Global land areas for the period 1951 to 2000. Geophys. Res. Abstr., 7: 181-190.

Betts, A.K., M. Zhao, P.A. Dirmeyer and A.C.M. Beljaars, 2006. Comparison of ERA40 and NCEP/DOE near-surface data sets with other ISLSCP-II data sets. J. Geophys. Res.: Atmos., Vol. 111. 10.1029/2006JD007174

Bosilovich, M.G., J. Chen, F.R. Robertson and R.F. Adler, 2008. Evaluation of global precipitation in reanalyses. J. Applied Meteorol. Climatol., 47: 2279-2299.

Brier, G.W., 1950. Verification of forecasts expressed in terms of probability. Monthly Weather Rev., 78: 1-3.

Calanca, P. and A. Ohmura, 1994. Atmospheric moisture flux convergence and accumulation on the Greenland ice sheet. Proceedings of the Yokohama Symposia on Snow and Ice Covers: Interactions with the Atmosphere and Ecosystems, July 2-5, 1993, Wallingford.

Costa, M.H. and J.A. Foley, 1998. A comparison of precipitation datasets for the Amazon basin. Geophys. Res. Lett., 25: 155-158.

Covey, C., K.M. AchutaRao, M. Fiorino, P.J. Gleckler, K.E. Taylor and M.F. Wehner, 2002. Intercomparison of climate data sets as a measure of observational uncertainty. U.S. Department of Energy, PCMDI Report No. 69, UCRL-ID-147371, pp: 40.

Druyan, L.M., J. Feng, K.H. Cook, Y. Xue and M. Fulakeza *et al*., 2010. The WAMME regional model intercomparison study. Clim. Dyn., 35: 175-192.

Easterling, D.R., B. Horton, P.D. Jones, T.C. Peterson and T.R. Karl *et al*., 1997. Maximum and minimum temperature trends for the globe. Science, 277: 364-367.

Ekstrom, M., P.D. Jones, H.J. Fowler, G. Lenderink, T.A. Buishand and D. Conway, 2007. Regional climate model data used within the SWURVE project-1: Projected changes in seasonal patterns and estimation of PET. Hydrol. Earth Syst. Sci., 11: 1069-1083.

Fekete, B.M., C.J. Vorosmarty, J.O. Roads and C.J. Willmott, 2004. Uncertainties in precipitation and their impacts on runoff estimates. J. Clim., 17: 294-304.

Gruber, A., X. Su, M. Kanamitsu and J. Schemm, 2000. The comparison of two merged rain gauge-satellite precipitation datasets. Bull. Am. Meteorol. Soc., 81: 2631-2644.

Horton, B., 1995. Geographical distribution of changes in maximum and minimum temperatures. Atmos. Res., 37: 101-117.

Huffman, G.J., R.F. Adler, M.M. Morrissey, D.T. Bolvin and S. Curtis *et al*., 2001. Global precipitation at one-degree daily resolution from multisatellite observations. J. Hydrometeorol., 2: 36-50.

Jobard, I., F. Chopin, J.C. Berges and R. Roca, 2011. An intercomparison of 10-day satellite precipitation products during West African monsoon. Int. J. Remote Sensing, 32: 2353-2376.

Jones, P.D., 1994. Hemispheric surface air temperature variations: A reanalysis and an update to 1993. J. Clim., 7: 1794-1802.

Joyce, R.J., J.E. Janowiak, P.A. Arkin and P. Xie, 2004. CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. J. Hydrometeorol., 5: 487-503.

Juarez, R.I.N., W. Li, R. Fu, K. Fernandes and A. de Oliveira Cardoso, 2009. Comparison of precipitation datasets over the tropical South American and African continents. J. Hydrometeorol., 10: 289-299.

Karam, H.N. and R.L. Bras, 2008. Climatological basin-scale Amazonian evapotranspiration estimated through a water budget analysis. J. Hydrometeorol., 9: 1048-1060.

Lamptey, B.L., 2008. Comparison of gridded multisatellite rainfall estimates with gridded gauge rainfall over West Africa. J. Applied Meteorol. Climatol., 47: 185-205.

Laurent, H., I. Jobard and A. Toma, 1998. Validation of satellite and ground-based estimates of precipitation over the Sahel. Atmos. Res., 47: 651-670.

Marengo, J.A., M. Rusticucci, O. Penalba and M. Renom, 2010. An intercomparison of observed and simulated extreme rainfall and temperature events during the last half of the twentieth century: Part 2: Historical trends. Clim. Change, 98: 509-529.

McCollum, J.R. and W.F. Krajewski, 1998. Uncertainty of monthly rainfall estimates from rain gauges in the global precipitation climatology project. Water Resour. Res., 34: 2647-2654.

McGuffie, K. and A. Henderson-Sellers, 2005. A Climate Modelling Primer. 3rd Edn., John Wiley and Sons, New York, USA., ISBN: 9780470026410, Pages: 296.

Mitchell, T.D and P.D. Jones, 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. Int. J. Climatol., 25: 693-712.

Mooney, P.A., F.J. Mulligan and R. Fealy, 2011. Comparison of ERA-40, ERA-interim and NCEP/NCAR reanalysis data with observed surface air temperatures over Ireland. Int. J. Climatol., 31: 545-557.

Murphy, A.H., 1988. Skill scores based on the mean square error and their relationships to the correlation coefficient. Monthly Weather Rev., 116: 2417-2424.

New, M., M. Hulme and P. Jones, 2000. Representing twentieth-century space-time climate variability. Part II: Development of 1901-96 monthly grids of terrestrial surface climate. J. Clim., 13: 2217-2238.

Oguntunde, P.G., B.J. Abiodun and G. Lischeid, 2011. Rainfall trends in Nigeria, 1901-2000. J. Hydrol., 411: 207-218.

Park, J.S., J.G. Jhun and E.J. Lee, 2009. Characteristic large-scale circulation anomalies associated with persistent features of extreme precipitation over northeast Asia from premonsoon season to monsoon season. J. Geophys. Res.: Atmos., Vol. 114. 10.1029/2008JD011031

Richards, F. and P. Arkin, 1981. On the relationship between satellite-observed cloud cover and precipitation. Monthly Weather Rev., 109: 1081-1093.

Robert, F.A., D. George, J. Huffman, A. Chang, R. Ferraro and P.P. Xie *et al*., 2003. The version-2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (1979-present). J. Hydrometeorol., 4: 1147-1167.

Roca, R., P. Chambon, I. Jobard, P.E. Kirstetter, M. Gosset and J.C. Berges, 2010. Comparing satellite and surface rainfall products over West Africa at meteorologically relevant scales during the AMMA campaign using error estimates. J. Applied Meteorol. Climatol., 49: 715-731.

Silva, V., V.E. Kousky and R.W. Higgins, 2011. Daily precipitation statistics for South America: An intercomparison between NCEP reanalyses and observations. J. Hydrometeorol., 12: 101-117.

Tozer, C.R., A.S. Kiem and D.C. Verdon-Kidd, 2011. On the uncertainties associated with using gridded rainfall data as a proxy for observed. Hydrol. Earth Syst. Sci. Discuss., 16: 1481-1499.

Trenberth, K.E. and C.J. Guillemot, 1996. Physical processes involved in the 1988 drought and 1993 floods in North America. J. Clim., 9: 1288-1298.

Trenberth, K.E., A. Dai, R.M. Rasmussen and D.B. Parsons, 2003. The changing character of precipitation. Bull. Am. Meteorol. Soc., 84: 1205-1217.

Xie, P. and P.A. Arkin, 1997. Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates and numerical model outputs. Bull. Am. Meteorol. Soc., 78: 2539-2558.

Xue, Y., F. de Sales, W.M. Lau, A. Boone and J. Feng *et al*., 2010. Intercomparison and analyses of the climatology of the West African monsoon in the West African Monsoon Modeling and Evaluation Project (WAMME) first model intercomparison experiment. Clim. Dyn., 35: 3-27.