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Performance Evaluation of a Subseasonal to Seasonal Model in Predicting Rainfall Onset Over West Africa

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Key Points:

- The RODs obtained by the two definitions used in this study are comparable, as the DEF2 gives a later RODs than DEF1
- The model realistically simulates the observed features of RODs irrespective of the definition used, although with some biases
- The model credibly captures the seasonal movement of the West African Monsoon as in observation, although with few biases

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Abstract The present study evaluates the performance of a Subseasonal to Seasonal (S2S) model (called The China Meteorological Administration) in simulating rainfall onset dates (RODs) over West Africa. Using two ROD definitions, we compared the model's ROD at six lead-time forecasts (10, 20, 30, 40, 50, and 60 days) with the observed ROD from satellite data sets, statistically quantified the model's capability to reproduce the interannual variability of RODs over the climatological zones in the subcontinent, and investigated how well the model links RODs with the dynamics of monsoon system over the subregion. The results show that the mean RODs follow a latitudinal progression and the dates increases northward from the coast. The performance of the S2S model in reproducing RODs largely depends on the definition used. For instance, the ability of the model to replicate the observed spatial pattern of RODs and all the essential features over the three zones in West Africa is stronger with DEF1 than DEF2. Regardless of the ROD definition used, the 20- to 60-day forecasts produced more realistic simulation than the 10-day forecast. We also found that the performance of the model in reproducing the interannual variability of RODs depends on the zones (Guinea, Savanna, and Sahel). Moreover, the model could reproduce the three main phases of the West African Monsoon (the onset, the peak, and the southward retreat of rainfall) and other dynamics. The results of the study have application in improving S2S forecasting over West Africa.

1. Introduction

Reliable seasonal prediction of rainfall onset date (ROD) is crucial for decision-making in various socioeconomic sectors in West Africa. In this region, many vital management decisions in public health cares, agricultural practices, hydroelectric power generation, and water-resource management depend on rainfall, and rainfed agriculture serves as the main source of income for many West African countries. For example, while ROD signals the end of bacterial meningitis (which normally breaks out in dry season), it marks the beginning of national campaign on awareness of malaria spread and its prevention (Fitzpatrick et al., 2015; Mera et al., 2014). In addition, healthy crops require sufficient soil moisture to sustain them from seed germination to the matured stage. So a false ROD prediction can lead to unsuitable agricultural practices (from crop sowing to harvesting), poor crop yields, food scarcity, and famine (Abiodun et al., 2008; Nicholson et al., 2000; Omotosho et al., 2000). Nevertheless, reliable prediction of ROD is a major challenge in West Africa, not only to the weather forecasters but also to farmers and other practitioners whose operations depend on it. Hence, to improve the quality of life and reduce food insecurity in West Africa, there is a need to improve the reliability of ROD prediction in West Africa, and such improvement requires in-depth assessment of existing seasonal forecasting methods and a better understanding of factors controlling the interannual variability of ROD over the region. That is the focus of the present study.

Most past studies on ROD prediction over West Africa have used empirical models (e.g., Ati et al., 2002; Dodd & Jolliffe, 2001; Janicot et al., 1998; Leduc-Leballeur et al., 2013; Omotosho, 1990, 1992; Omotosho et al., 2000). They predicted ROD based on interannual variability of some factors known to influence ROD (e.g., sea surface temperature [SST], African Easterly Jet [AEJ], Tropical Easterly Jet, and Saharan heat low). However, the low predictive skills of the empirical models and their inability to account for other important factors influencing the start of the monsoon season have led some recent studies to use dynamic climate models in studying the characteristics of ROD over the subcontinent with the aim of improving the ROD predictions (e.g., Diaconescu et al., 2015; Le Barbé et al., 2002; Mounkaila et al., 2014; Omotosho &

Abiodun, 2007; Vellinga et al., 2013). For example, Omotosho and Abiodun (2007) applied a regional climate model (RCM) simulation to link ROD with moisture transport and buildup over West Africa. They found that, during wet years, the onset of rainfall occurs in about one and a half months after the maximum moisture buildup, but in dry years, it occurs in two and a half months after the maximum moisture buildup. Mounkaila et al. (2014) also used RCMs to show that there is a relationship between RODs and some atmospheric features (e.g., temperature maximum, moist southwesterly monsoon flow, intertropical discontinuity [ITD], and the associated rainfall) that are linked to the West African Monsoon (WAM) System. The authors found that the RCMs realistically simulated the start and the inland penetration of the monsoon rainfall, as well as the monsoon jump. The study also found that the RCMs exhibit different performance in simulating ROD over West Africa and their bias in the simulation depends on the ROD definition and the observation data used. However, all these studies have applied the models in climate simulation mode (in which the simulation is forced with observed SST) and not in seasonal forecasting mode (in which the simulation is forced with forecast SST). Hence, the bias due to observed SST was not accounted for in their simulation. There is therefore a need to evaluate seasonal forecasting simulations or data set over West Africa.

As the demand for reliable forecasts increases around the globe (Olaniyan et al., 2018), various seasonal climate prediction data sets are now made available publicly for evaluation. An example of such a data set is the European Centre for Medium Range Weather Forecasting (ECMWF) Subseasonal to Seasonal (S2S) model output data. The S2S model data set is a new frontier for atmospheric research. Some researchers in different areas globally have examined the predictive skills of the S2S models for different purposes. For example, Lynch et al. (2014) used the ECMWF-S2S model and found that there is statistically significant skill in predicting weekly mean wind speeds over areas of Europe at lead times of at least 14–20 days. Over Australia, White et al. (2015) used forecasts from the Australian Bureau of Meteorology S2S time scales to examine how forecasting of flood events across a range of prediction time scales could be beneficial in Australia for disaster risk reduction activities, emergency management and response, and strengthening community resilience. Across Africa, Tompkins and Di Giuseppe (2015) have used ECMWF S2S rainfall and temperature data to investigate the forecast of advanced warning on malaria in an idealized experiment. The authors found from a preliminary examination of the forecasts that the ECMWF S2S data are able to predict the years during the last two decades in which documented Uganda and Kenya highlands outbreaks occurred. Some studies have also been done over West Africa using the ECMWF S2S data (e.g., Olaniyan et al., 2018; Tompkins & Feudale, 2010). Tompkins and Feudale (2010) evaluated the ECMWF operational Seasonal Forecast System at a lead time of 2–4 months in a 49-yr hindcast data set, to simulate the WAM precipitation. The authors found that Seasonal Forecast System reproduces the progression of the West Africa monsoon but with some differences from the climatology. Olaniyan et al. (2018) also evaluated the predictive skill of the ECMWF-S2S precipitation forecasts during the peak of West Africa Monsoon in Nigeria, using station data and 10-member ensemble of ECMWF-S2S forecasts, from the Ensemble Prediction System version of the ECMWF. The authors indicated that the model has weak capability in predicting wind strength at 700-mb level to depict the AEJ but capable of adequately and reliably predicting the latitudinal positions of the ITD, mean sea level pressure component of the thermal lows, and SST anomalies over the Pacific and Atlantic Oceans. So far, no study has investigated the skill of the ECMWF S2S model output data in predicting the onset of rainfall over West Africa.

The aim of the present study is to examine how well the S2S reforecasts data sets reproduce past onset dates over West Africa. This paper is structured as follows: Section 2 describes the data and methods used in the study, section 3 presents the results and discussions, and section 4 gives the conclusions of the study.

2. Data and Method

Three types of data sets (i.e., observation, reanalysis, and model simulation) were analyzed. The observation data sets are the African Rainfall Climatology Version 2 (ARC2; Novella & Thiaw, 2013) and the Climate Hazard Group Infrared Precipitation with Stations (CHIRPS; Funk et al., 2014). Both data sets were obtained from the data archive of the Climate System Analysis Group (University of Cape Town, South Africa). ARC2 consists of daily precipitation estimation data over Africa at $0.1° \times 0.1°$ horizontal grid resolution for a period of 30 years (1983–2012), while CHIRPS consists of daily precipitation data over Africa at $0.05° \times 0.05°$

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Table 1
Definitions of ROD Over West Africa

Parameter	Definition of ROD	Reference
Definition 1	The total of at least 20 mm of rainfall within 5 days. The starting day and at least two other days in this 5-day period must be wet (at least 0.1-mm rainfall recorded), followed by a no dry period of seven or more consecutive days occurring in the following 30 days.	Stern et al. (1981)
Definition 2	The first two rains totaling 20 mm or more within 7 days, followed by 2 to 3 weeks each with at least 50% of the weekly crop-water requirement and without a dry spell within 2 to 3 weeks.	Omotosho et al. (2000)

horizontal grid resolution for a period of 35 years (1981–2015). The observed data sets were used to evaluate the simulated rainfall data sets. The reanalysis data sets are the ECMWF Interim Reanalysis (ERAIN; 1979–2015). For easy comparison, 19-year data were extracted from the observation and reanalysis data sets (ARC2, 1994–2012; CHIRPS, 1994–2012, and ERAIN: 1994–2012) and regridded to a resolution of 0.44° × 0.44° before using them.

The global model output data set is from the ECMWF S2S data portal (http://apps.ecmwf.int/datasets/data/s2s/levtype=sfc/type=cf/) and supported by the World Meteorological Organization through the World Weather Research Program and World Climate Research Program. The S2S portal consists of 11 data sets from different global climate centers (https://apps.ecmwf.int/datasets/data/s2s-reforecasts-instantaneous-accum-babj/levtype=sfc/type=cf/). However, the ensemble data produced by the China Meteorological Administration (CMA) were analyzed for this study (http://s2s.cma.cn/Models/CMA_1; Jie et al., 2014; Liu et al., 2017). The CMA model was chosen because it has daily data and fix reforecasts of up to 60 days (the highest number of reforecast days), needed to fulfill the goal for this study. The CMA ensemble data are from Beijing Climate Center Climate Prediction System Version 1 and are coupled to the ocean. Operationally, the forecast systems composed typically of coupled land, ocean, and atmosphere components (White et al., 2015). These are 6-hourly instantaneous and accumulated hindcasts and fix reforecasts precipitation data that covers 21-year period (1994–2014). The reforecasts cover up to 60 days, and the data have four ensemble members. The data have a horizontal grid resolution of 1.5° × 1.5° and regridded to the resolution of the observed data sets (0.44° × 0.44°) for easy comparison with the observed. More details on the CMA simulations are available online (http://s2sprediction.net/).

We used two ROD definitions listed in Table 1. These popular definitions have been shown to give reliable RODs over West Africa (see Dodd & Jolliffe, 2001; Laux et al., 2008; Mounkaila et al., 2014). Here, we applied them on each data set (observation and model) to obtain RODs for a period of 19 years (1994–2012) over each grid point in our study domain (West Africa; Figure 1). The designation of the study area follows that of previous studies (e.g., Abiodun et al., 2012; Diasso & Abiodun, 2017; Kumi & Abiodun, 2018). The 6-hourly instantaneous and accumulated reforecasts data were deaccumulated into daily precipitation data before they were used in the study. The reforecasts data sets are analyzed separately from 10 to 60 days (up to 2 months). To evaluate the capability of the CMA model output data in predicting RODs, the reforecast data (10- to 60-day forecast) were compared with the observed.

3. Results and Discussion

3.1. The Uncertainties in the Observed RODs

Before evaluating the performance of the CMA model in simulating the ROD, it is essential to quantify the uncertainties in observation of ROD over West Africa. A comparison of model biases with the uncertainties will assist in putting the model's performance in the right perspective. We focused on the uncertainties produced by differences in the observation data sets (ARC2 and CHIRPS) and in the ROD definitions (DEF1 and DEF2). However, for easy comparison, the ROD obtained with ARC2 using DEF1 will be used as the reference.

In general, the two observation data sets (CHIRPS and ARC2) produce similar ROD patterns over West Africa regardless of ROD definition used (Figure 2). The correlation between the two ROD patterns is high ($r = 0.98$ for DEF1). Both ROD patterns feature a zonal distribution of ROD with a northward increase from the coast to inland. This northward increase in ROD has been linked to the transport of moisture from the

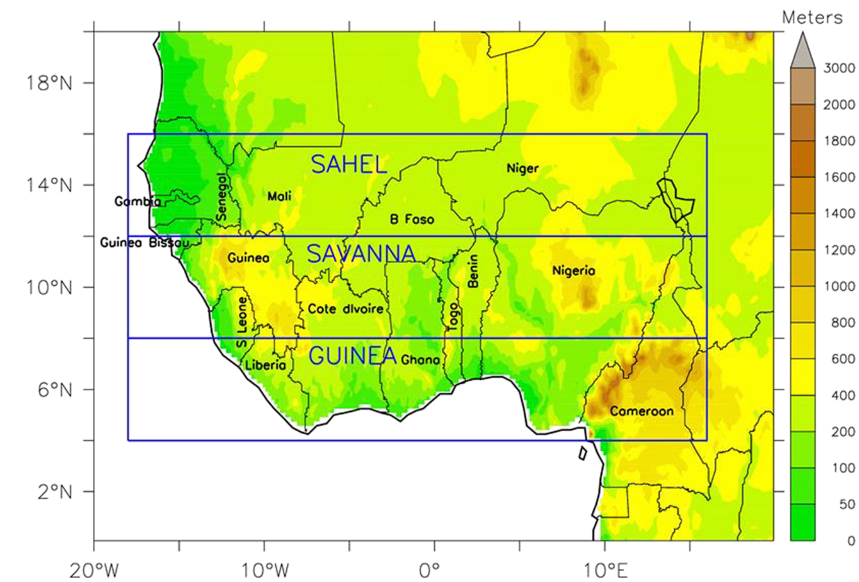

Figure 1. West African domain showing the topography (meters) and the regions designated as Guinea, Savanna, and Sahel zones.

Gulf of Guinea into the subcontinent by the WAM (Omotosho et al., 2000; Sylla et al., 2013; Vellinga et al., 2013). The data sets also show a good agreement in the interannual variability of ROD over each zone, especially over the Guinea and Sahel zones (Figure 3). Nevertheless, there are notable differences between RODs from the data sets. For example, with DEF1, the CHIRPS feature earlier ROD (about 10 days; compared to ARC2) over parts of the coastal area but later ROD (about 10 days) inland (Figure 2b, contours);

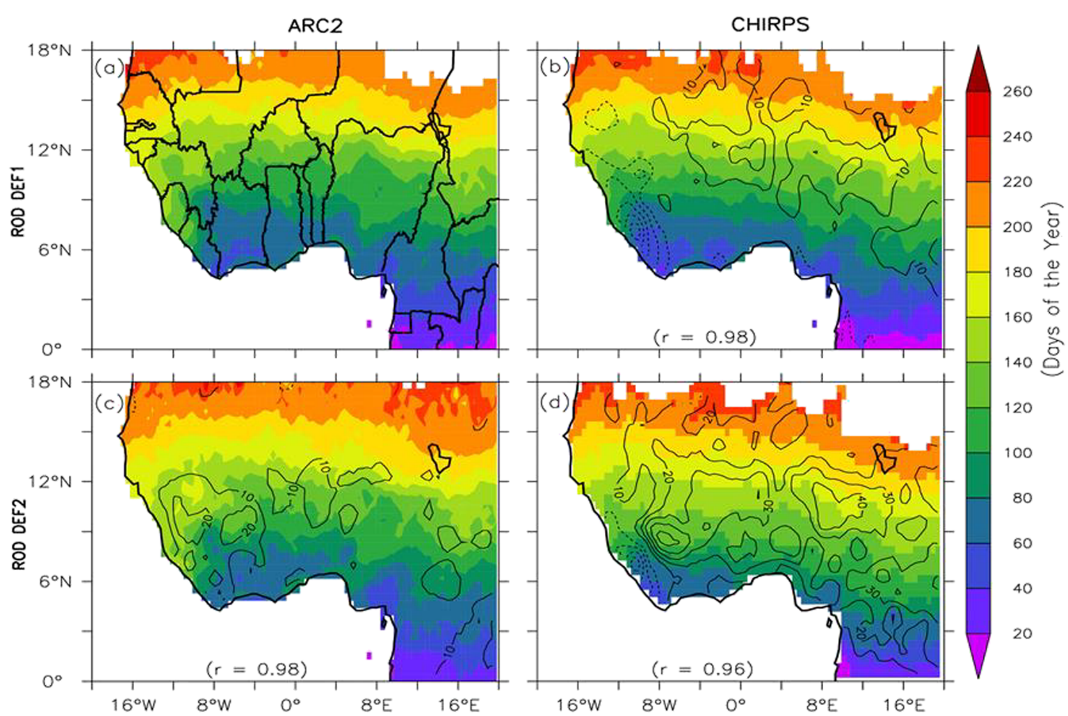

Figure 2. The spatial variation of RODs over West Africa (in 1994–2012) as ARC2 and CHIRPS DEF1 and DEF2. The contours in (b) to (d) show the difference between the ROD in the panels and that of (a); the corresponding spatial correlation (*r*) is indicated.

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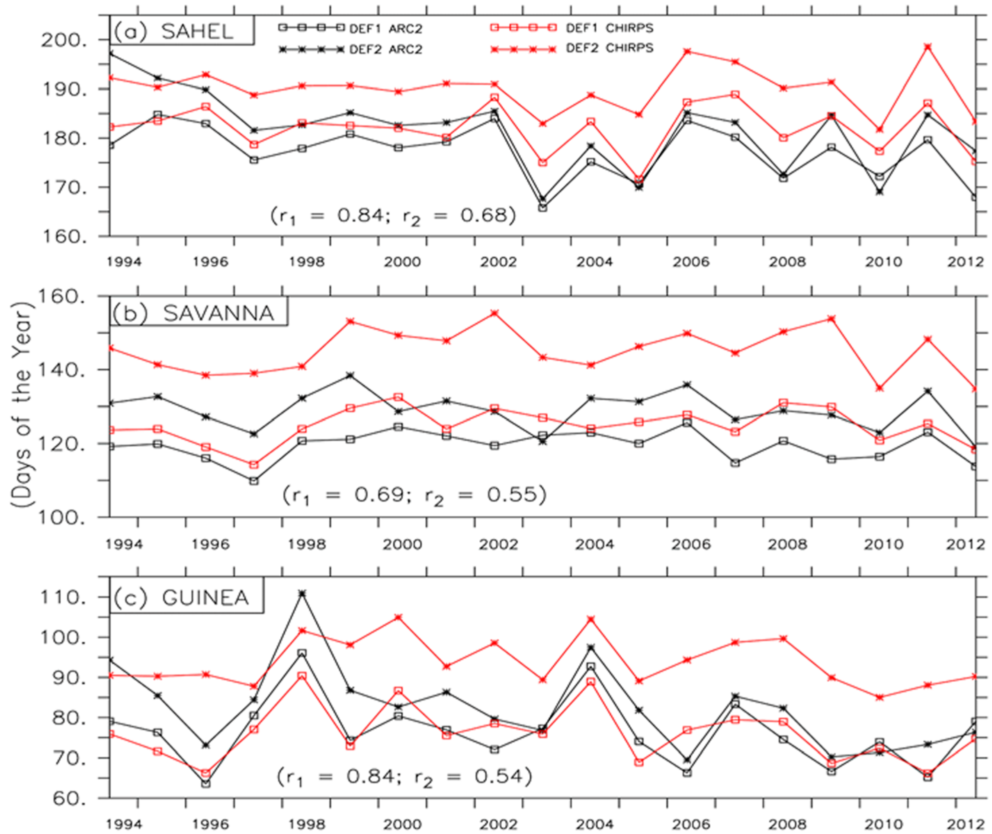

Figure 3. The interannual variability of ROD over (a) Savanna, (b) Sahel, and (c) Guinea coast in the period 1994–2012 as depicted by ARC2 and CHIRPS using DEF1 and DEF2.

the maximum discrepancy between the two data sets (about 20 days) occurs over the southwest mountain range. With DEF2, the pattern of the discrepancy is the same as with DEF1 but the magnitude higher (up to 30 days). This implies that, regardless of the method used, CHIRPS produces earlier ROD than ARC2 over the coastal area but later ROD than ARC2 inland. Similar difference between data sets and ROD definitions have been reported in previous studies who ascribed the differences to the resolution of the data sets (Abiodun et al., 2017; Meque & Abiodun, 2015; Mounkaila et al., 2014; Sylla et al., 2013, 2015). For example, Mounkaila et al. (2014) showed that TRMM gives a later ROD than GPCP over West Africa regardless of ROD definition used. However, the difference between CHIRPS and ARC2 obtained in the present study is larger than the one between TRMM and GPCP in Mounkaila et al. (2014).

The RODs obtained with the two definitions are comparable, but DEF2 generally produces later ROD than the DEF1 (Figure 2, Table 2). The difference is up to 20 days over the Savanna zone in ARC2 (Figure 2c, contours) and up to 30 days over the same area in CHIRPS (not shown). However, the ROD uncertainty due to the differences in rainfall data sets and ROD definitions are within ±40 days in the ROD climatology over the

Table 2
The Mean RODs Over West Africa for the Period 1994–2012, as DEF1 and DEF2 Using ARC2 and CHIRPS Data Sets

	Guinea			Savanna			Sahel		
Methods	ARC2	CHIRPS	Δ	ARC2	CHIRPS	Δ	ARC2	CHIRPS	Δ
DEF1	17 Mar	17 Mar	0	29 Apr	5 May	6	26 Jun	1 Jul	5
DEF2	24 Mar	4 Apr	11	9 May	25 May	16	1 Jul	9 Jul	8

Note. The difference between RODs from the two data sets (Δ in days).

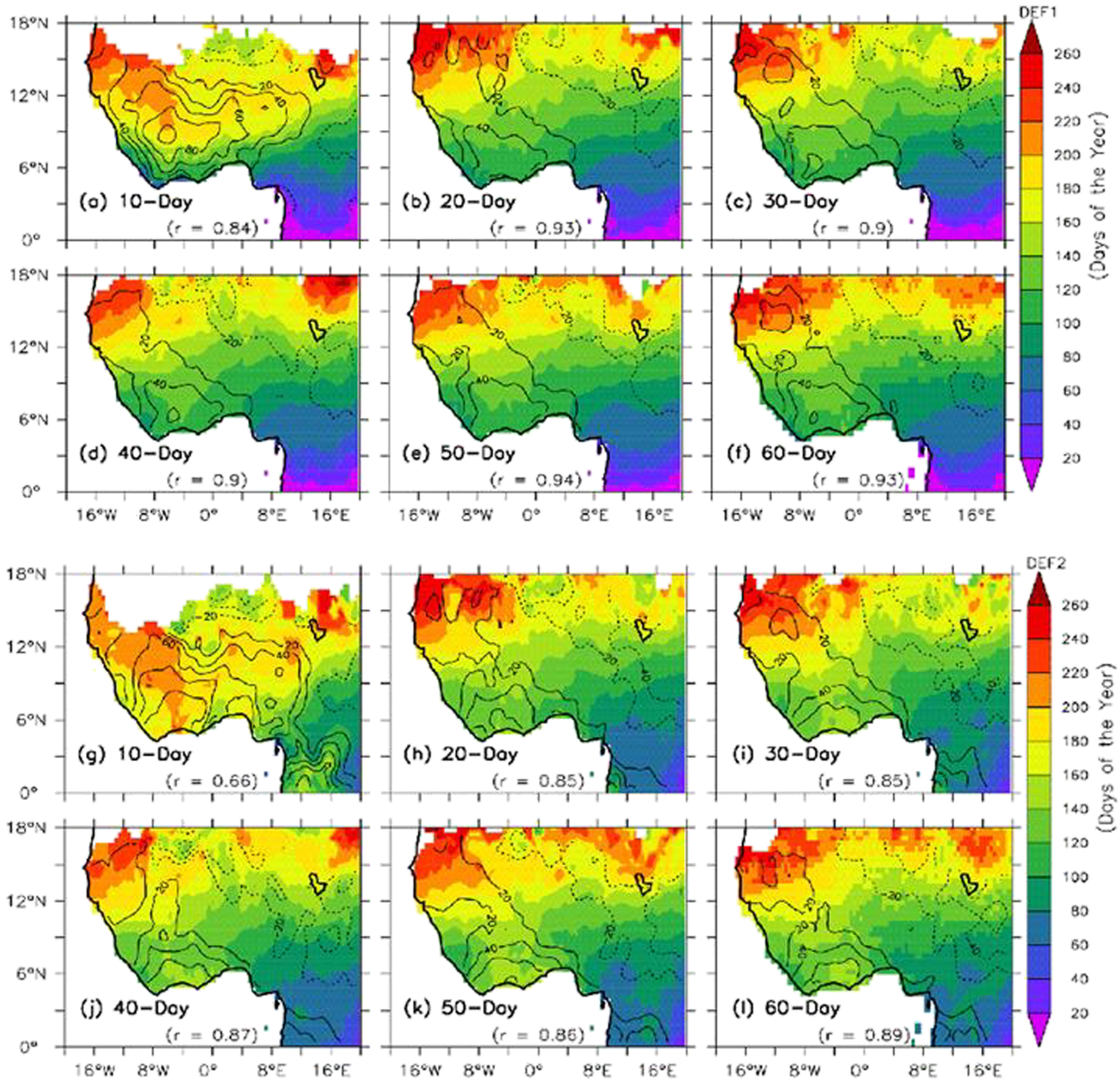

Figure 4. The spatial distribution of rainfall onset date over West Africa (in 1994–2012) as predicted by CMA in different lead forecast days (10–60 days) using (a–f) DEF1 and (g–l) DEF2. The contour shows the spatial distribution of the forecast bias (with reference observation: mean of ARC2 and CHIRPS); the correlation between each forecast and the observation is indicated in the bracket.

region (Figure 2d). While the differences offset each other over parts of eastern (western) Guinea coast, they are additive over most parts of West Africa. The magnitude of the uncertainty varies from year to year over each zone. It ranges from 10 (in 1997) to 25 days (in 1996) over the Guinea zone, from 20 (in 2004) to 30 days (in 2009) over the Savanna, and from 10 (in 2002) to 20 days (in 2003) over the Sahel (Figure 3). However, over each zone, the coefficient of correlation between the two data sets (ARC2 and CHIRPS) is higher with DEF1 than with DEF2. Mounkaila et al. (2014) obtained similar results for GPCP and TRMM data sets.

3.2. Spatial and Temporal Distribution of the CMA Model and Observed RODs

For both ROD definitions, the CMA model gives a realistic simulation of the spatial pattern of ROD over West Africa and reproduces all the essential features in the observed ROD pattern (Figure 4). For example, it reproduces the zonal distribution of observed RODs and simulates the northward progression of RODs over West Africa well. This implies that the model realistically captures the northward movement of the

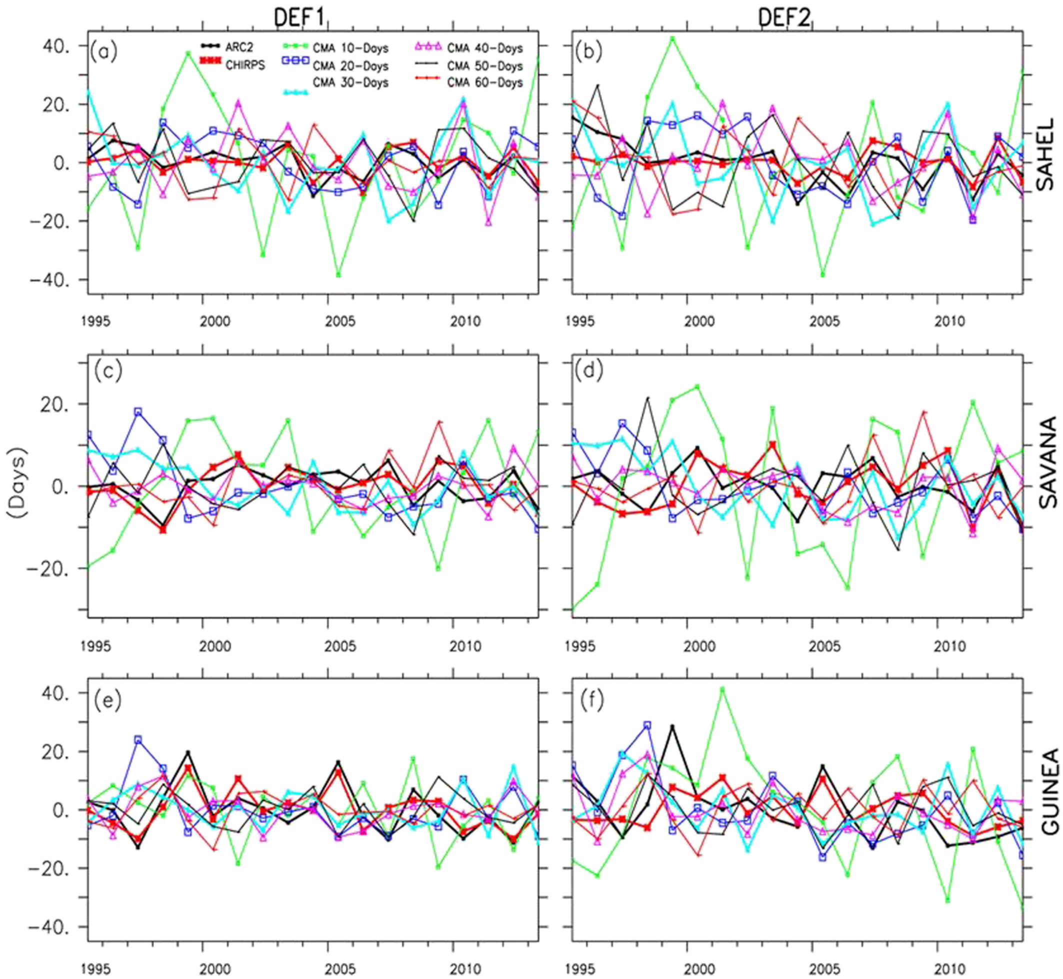

Figure 5. The interannual variation of ROD over (a, b) Sahel, (c, d) Savanna, and (e, f) Guinea for the period 1994–2012, as simulated (CMA 10- to 60-dayforecasts) and observed (CHIRPS and ARC2) using DEF1 and DEF2.

WAM and the associated moisture transport from the Atlantic Ocean into the subcontinent. Nevertheless, the performance of the CMA model in simulating the RODs varies with the definitions. With DEF1, the correlation between the simulated and observed ROD pattern (r) is more than 0.8 for all the forecasts. Among the forecasts (10- to 20-, 30- to 40-, and 50- and 60-day lead time), the 10-day forecast has the lowest correlation ($r = 0.84$) and the largest bias. The 10-day forecast shows a late ROD over most parts of West Africa and an early ROD over the eastern and northern parts of West Africa. While the late bias is up 80 days over much areas in the Savanna and Guinea (Figure 4a for DEF1), the early bias is about 20 days over the central Sahel and the Cameroon mountain range. The 20- to 60-day forecasts produce much better forecast. Although they also feature a late ROD over the southwestern half of the subcontinent and early ROD over the northeastern half, the magnitude of their biases is about 40 days (half of that of 10-day forecast). The weaker performance of the 10-day forecast may be because, at 10 days, the model is still spinning and has not recovered from the imbalance in the initial condition. This suggest that the CMA model requires more than 10 days spin-up to reach an equilibrium state.

Table 3
The Root Mean Square Error of ROD Over West Africa (1994–2012), as Obtained DEF1 and DEF2 Using CMA 10- to 60-Days Predictions

Methods	CMA-10	CMA-20	CMA-30	CMA-40	CMA-50	CMA-60
DEF1	18.6	0.6	0.2	1.9	2.4	1.5
DEF2	32.7	0.6	1.4	1.3	3.3	0.3

The performance of the CMA forecast is weaker with DEF2 than with DEF1 (cf. Figures 4 and 5 and Tables 3 and 4). For instance, the correlation between the forecast and observation is lower with DEF2 ($0.6 \leq r \leq 0.87$) than with DEF1 ($0.84 \leq r \leq 0.94$). Although the pattern of forecast biases with DEF1 and DEF2 are similar, the magnitude of the bias is higher with DEF2. For instance, with DEF2, the

Table 4
The Mean ROD Over West Africa (1994–2012), as Obtained With DEF1 and DEF2 Using CMA 10- to 60-Day Predictions and the Associated Biases (Δ in Days)

ROD DEF DEF1	Guinea	Δ	Savanna	Δ	Sahel	Δ
Obs_Mean	17 Mar		2 May		28 Jun	
CMA-10	4 Apr	18	11 Jun	40	3 Jul	5
CMA-20	30 Mar	13	6 May	4	17 Jun	−11
CMA-30	3 Apr	17	7 May	5	15 Jun	−13
CMA-40	1 Apr	15	5 May	3	15 Jun	−13
CMA-50	1 Apr	15	5 May	3	22 Jun	−6
CMA-60	2 Apr	16	3 May	1	20 Jun	−8
DEF2						
Obs_Mean	29 Mar		17 May		5 Jul	
CMA-10	11 May	43	17 Jun	31	2 Jul	−3
CMA-20	15 Apr	17	13 May	−4	20 Jun	−15
CMA-30	16 Apr	18	15 May	−2	19 Jun	−16
CMA-40	14 Apr	16	13 May	−4	17 Jun	−18
CMA-50	16 Apr	18	13 May	−4	26 Jun	−9
CMA-60	14 Apr	16	11 May	−6	21 Jun	−14

late ROD over the Guinea coast is more than 40 days, and the early ROD over the eastern Sahel is more than 40 days (i.e., in 20- to 60-day forecasts). Nevertheless, the results of both ROD definitions (DEF1 and DEF2) agree that the CMA forecast performs worst at 10-day forecast. Although the CMA model bias for 20- to 60-day forecasts is high (±40 days), the magnitude is close to the uncertainty in observation data sets (±30 days).

The model performs well in capturing the magnitude of the interannual variability of ROD (Figures 5 and 6). Regardless of the definition, the normalized standard deviation of all the forecasts (except 10-day forecast) cluster around 0.8 over the Guinean zone, around 1.0 over Savanna zone, and around 2.0 over the Sahel zone (Figure 6). This implies that the model slightly underestimates the magnitude of interannual variability over the Guinea zone, slightly overestimate it over the Sahel zone, and captures it well over the Savanna zone. Nevertheless, the correlation between the simulated and observed ROD is poor ($r < 0.4$) over all the zones. The CMA model's performance using other forecast verification metrics are shown in Tables 3 and 4. In general, all the metrics show that the CMA forecasts perform better with DEF1 than with DEF2 and perform best over the Savanna zone (Table 4; bias in days). The model's best performance with DEF1 may be because this particular definition is not latitude sensitive, as it does not depend on crop water requirement over each zone in the subcontinent as in DEF2. Also, the model's best performance over the Savanna zone may be because this zone is located between the humid Guinea zone and the dry Sahel. This may mean that the rainfall parameterization schemes in the CMA model might have been set to perform well in not too wet nor too dry environment.

3.3. WAM and RODs

The CMA forecasts give realistic simulations of the seasonal movement of the WAM and its associated rainfall patterns (Figures 7 and 8). The WAM is a large-scale atmospheric circulation characterized by a seasonal reversal of winds, primarily due to the differential heating of the ocean and the land surface during the boreal summer (Afiesimama et al., 2006; Sylla et al., 2013). The WAM system features the ITD and the AEJ; an easterly wind maximum found around the middle troposphere over West Africa. The AEJ has been associated with deep convective activities, such as squall lines and thunderstorms over West Africa. The ITD is a line that separates the warm moist southwesterly monsoon flow (off the tropical Atlantic) from the much hotter and very dry northeasterly wind from the Sahara Desert (Issa Lélé & Lamb, 2010). This boundary has been described by some researchers as a region of “maximum surface gradient”; a humidity discontinuity (Ilesanmi, 1971) and rainfall over West Africa occur a few hundred kilometers south of it, where the monsoon wedge is deeper. The CMA forecasts capture the inland movement of the ITD from 8°N in January to its northernmost position (20°N) in August and retreats to 8°N in December. Following the ITD, the

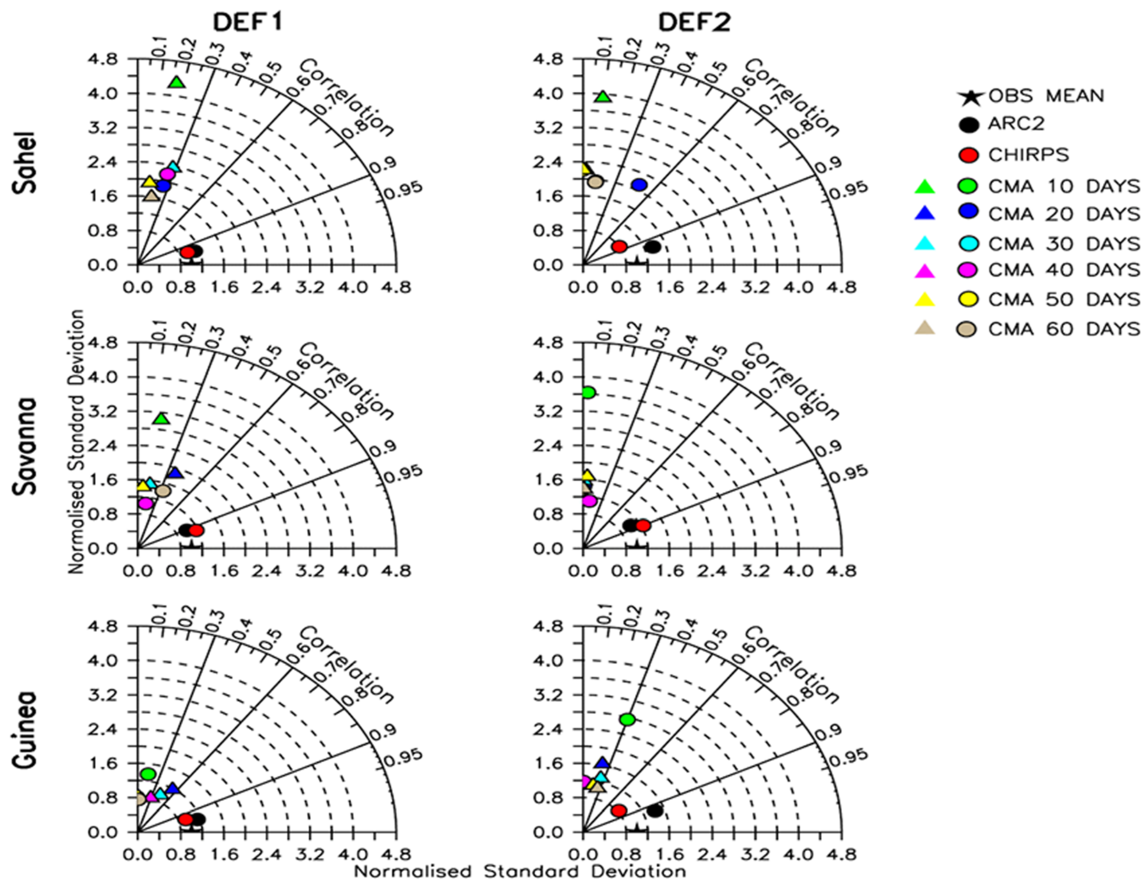

Figure 6. Taylor diagram of ROD, showing the normalized standardize deviation of CMA forecast and the correlation between the forecast and observation (i.e., mean of CHIRPS and ARC2) over there zones (Guinea, Savanna, and Sahel), using the two definitions (DEF1 and DEF2). The standardize deviation is normalized with the observation. The positive correlations are indicated with a circle, while the negative correlations are indicated with a triangle.

monsoon rains start in March over the Guinea zone and move inland to its northernmost position in the Sahel around August (Figures 7a and 7b) and then retreat southward, reaching the Guinea zone in September. This movement of the ITD simulated by the CMA model is in agreement with the findings of Klein et al. (2015). The forecasts (except 10-day forecast) reproduce the three main phases of the WAM rainfall pattern, namely, the onset, the peak, and the southward retreat. Over the Guinea zone, they capture the periods of the major and minor rainy seasons (March to April and September to October, respectively) and feature the break of the monsoon rain period (the so-called "little dry season"; Omotosho & Abiodun, 2007) in August. The forecasts also reproduce the "monsoon jump," which is an important feature in the northward movement of the WAM (e.g., Le Barbé et al., 2002; Mounkaila et al., 2014), between 8°N and 10°N in June and July.

Nevertheless, the CMA model struggles to reproduce the magnitude of the monsoon rainfall and to effectively link the northward progression of the ROD with that of the WAM features. For instance, all the forecasts underestimate the Sahelian rainfall during the peak of the monsoon season (in August). This result agrees with that of Olaniyan et al. (2018), who evaluated the predictive skill of the ECMWF-S2S precipitation forecasts during the peak of the WAM in Nigeria, using station data and a 10-member ensemble of the ECMWF S2S forecasts, from the Ensemble Prediction System version of the ECMWF. The authors concluded that the model was incapable of predicting wind strength at the 700-mb level to depict the AEJ, which appears to modulate the development of the rainy season (Nicholson & Grist, 2003). Furthermore, in both ARC2 and CHIRPS, the ROD (DEF1 and DEF2) over each latitude occurs about 2 months after the passage of the ITD, but it is more than 2 months in some forecasts, especially the 10-day forecast. Nevertheless, the ROD lines are better simulated in the CMA forecasts (10- to 60-day forecasts) than in the ERAINT

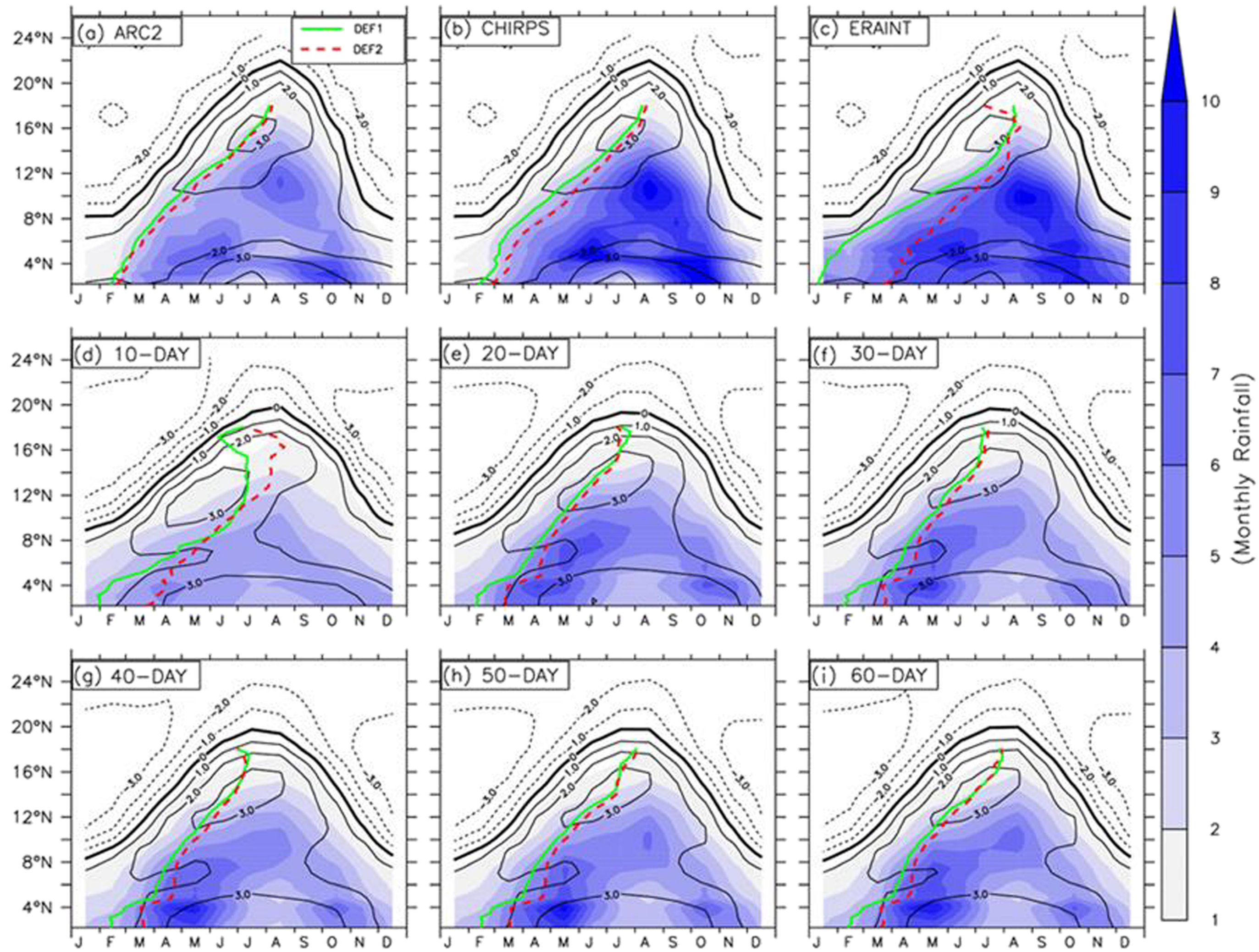

Figure 7. Time-latitude cross section of monthly rainfall (mm day $^{-1}$, shaded) and RODs (DEF1 = green thick lines; DEF2 = red dashed lines) averaged over 15°W to 15°E for observations (a, ARC2; b, CHIRPS), reanalysis (c, ERA_INT), and CMA model prediction (d–i, 10–60 days) over West Africa for the period 1994–2012. The contours represent the corresponding surface meridional winds and ITD (thick continuous lines).

(Figure 7c). Given that the model captures the dynamics and moisture distribution of the WAM well, the biases of the CMA model in simulating the rainfall and ROD may be attributed to the rainfall parameterization schemes in the model. The parameterizations scheme may not sufficiently couple the monsoon dynamics with the boundary layer moisture in producing rainfall over the region.

4. Conclusion

As part of activities toward reliable forecast of the onset of rainfall over West Africa, this study has evaluated the ability of the CMA S2S model to predict RODs at six lead times (10, 20, 30, 40, 50, and 60 days). Two ROD definitions and two satellite data sets (observation; ARC2 and CHIRPS) have been used to quantify the observation uncertainties and the ROD characteristics and evaluate the model's performance. The results of the study are summarized as follows:

1. Two observation data sets (CHIRPS and ARC2) produce similar ROD patterns over West Africa regardless of ROD definition used, although there are notable differences between them.
2. The RODs obtained with the two definitions are comparable, but DEF2 generally produces later ROD than the DEF1.

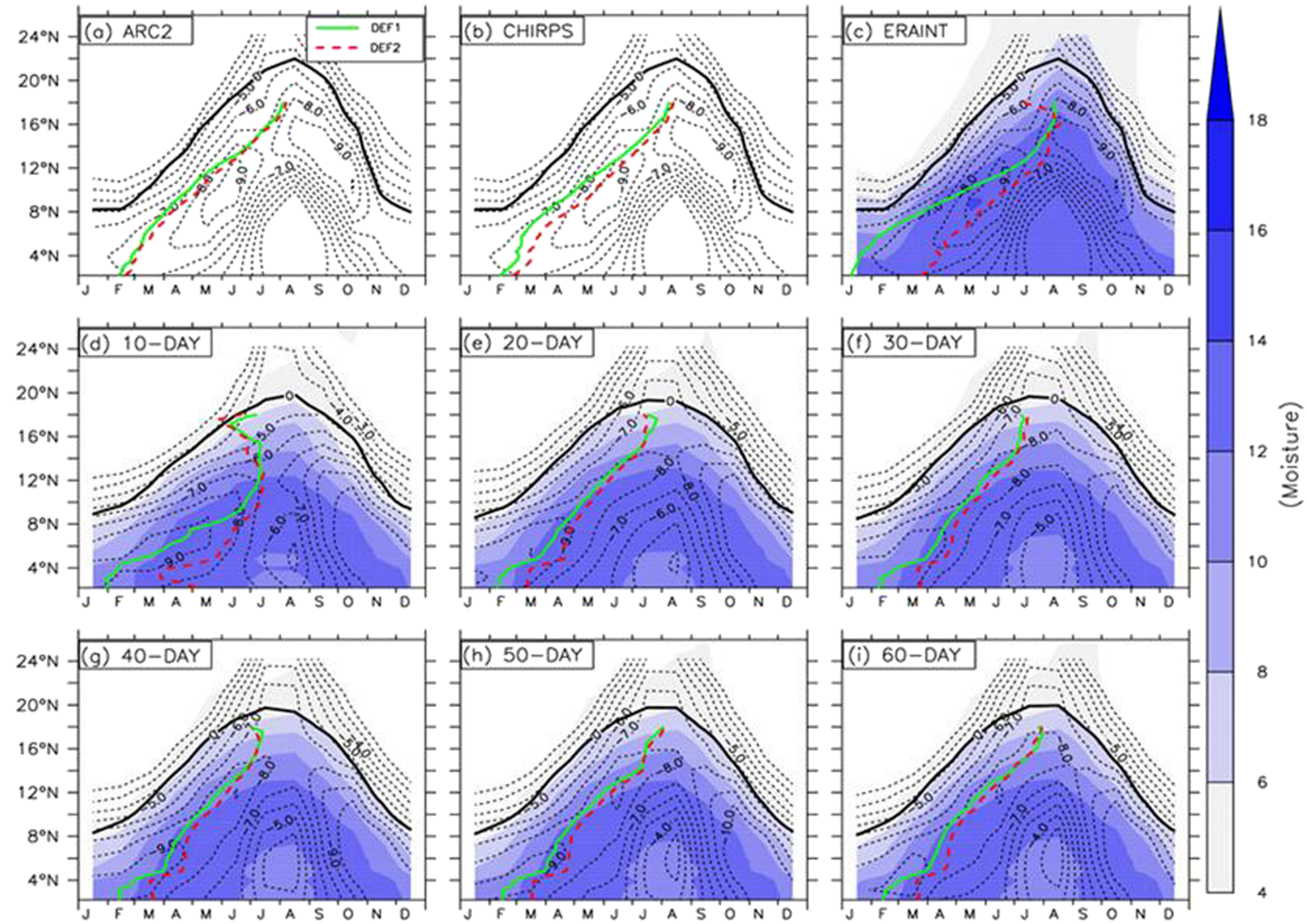

Figure 8. Time-latitude cross section of specific humidity at 850 hPa (kg kg^{-1}; shaded) and RODs (DEF1 = green thick; DEF2 = red dashed lines) averaged over 15°W to 15°E for observations (a, ARC2; b, CHIRPS), reanalysis (c, ERA_INT), and CMA model prediction (d–i, 10–60 days) over West Africa for the period 1994–2012. The contours represent the corresponding 700-hPa zonal winds (the African Easterly Jet) and ITD (thick continuous lines).

3. For both ROD definitions, the CMA model gives a realistic simulation of the spatial pattern of ROD over West Africa and reproduces all the essential features in the observed ROD pattern.
4. The performance of CMA forecast is weaker with DEF2 than with DEF1.
5. The model performs well in capturing the magnitude of the interannual variability of ROD regardless of the definition used.
6. The CMA forecasts give realistic simulations of the seasonal movement of the WAM and its associated rainfall patterns, although it struggles to reproduce the magnitude of the monsoon rainfall and to effectively link the northward progression of the ROD with that of WAM features.

To provide a stronger basis for decision-making and agricultural planning, the results of this study can be improved in many ways. For example, the S2S data sets have some limitations. Their resolution (1.5° × 1.5°) is too low to capture some of the mesoscale convective systems that trigger convection of rainfall, hence the model's inability to well simulate some features of the WAM. Increasing the resolution of the S2S model may account for some of the biases. Again, this study was able to use only 1 out of the 11 S2S data sets because of the dynamics and complexity of the models. For instance, some of the data sets are generated "on the fly," while others are "fixed." The reforecast days are also different from one data set to another. To address these limitations, developers of the models (the global centers) can make the dynamics and even download of the data sets less complex for easy access by many researchers. Nevertheless, the present study has shown that the CMA S2S model has the capability to simulate RODs over West Africa in lead time before the actual start of the monsoon rains. Information from this study may be beneficial to forecasters and researchers within the subregion, in efforts to provide reliable forecast of the onset of the rainy season.

Data Availability Statement

Readers can access the CMA S2S data online (http://s2sprediction.net/).

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