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Full length Research

Application of Sub-Seasonal to Seasonal (S2S) Weather Forecasts in Predicting Recent Malaria Occurrence in Nigeria Using a Regional Scale Dynamical Malaria Model

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The need to develop a robust Malaria Early Warning System (MEWS) in a right time-scale just for effective action, is growing in Nigeria due to the yearly recorded number of deaths from malaria disease. This paper uses two hierarchical evaluations technique to investigate the skill of VECTRI model in predicting malaria incidences in Nigeria. It evaluates the skill of three S2S models – China Meteorological Administration (CMA), European Centre for Medium-Range Weather Forecasts (ECMWF), and United Kingdom Meteorological Office (UKMO) in driving the VECTRI model. The simulated Entomological Inoculation Rate (EIR) from observation driven VECTRI is also evaluated with the simulated EIR from the three S2S models. The results show that VECTRI model driven by the observed station rainfall and temperature can simulate the hyper-endemic characteristics of malaria occurrence in Nigeria. This suggests that simulated EIR could be used as a measure of interpolation for reporting cases of malaria in Nigeria. The three S2S models used in driving the VECTRI-Model also reproduced the EIR that signifies the hyper-endemic nature of malaria cases in Nigeria, but with different characteristics over the climatological zones. Besides, the models also reproduced the inter-annual variability of the malaria cases over each zone with different inherent biases. The simulated EIR from the S2S-driven-VECTRI increases from the Gulf of Guinea (GoG) to the Sahel following the population profiles. Notwithstanding the inherent biases, the prospect of using VECTRI-Malaria model as a MEWS driven by S2S prediction system is potentially strong and economically viable.

Keywords: S2S models**,** Malaria Early Warning System (MEWS), Entomological Inoculation Rate (EIR), VECTRI-model, Nigeria.

INTRODUCTION

Malaria is hyper-endemic with stable transmission in Nigeria (Ofovwe and Eregie, 2001). It is considered as one of the main causes of death especially among children and pregnant women in sub-Sahara Africa (Snow et al., 2005). An estimated 300,000 deaths per year, including 11% of maternal mortality is caused by malaria (Angyo et al., 1996; NMCP, 2007). Besides the gross amount of death, studies have shown that malaria could impair the ability of people to work. Alaba and Olumuyiwa (2006) revealed that malaria attacks can incapacitate individuals for an average of 10 to 14 days. Salihu and Sanni (2013) also documented that malaria illness often generate huge financial demands from cost of medical treatments leading to shortage of home food supply. The cost implications in terms of treatment, prevention and loss of man-hours from malaria illness in Nigeria have been estimated to be 132 billion Naira (NGN) (Federal Ministry of Health (FMOH), 2007).

Despite the huge sum spent in combating malaria and its obviously enormous socio-economy impacts in Nigeria, there has been no available tool in place to support pre-emptive disaster risk management actions. No system has been in place to give an early warning on the potential distribution and transmission of malaria in Nigeria. This is an important gap in epidemiological research that this work is set to fill.

THEORETICAL UNDERPINNINGS

In susceptible humans, malaria sickness is mainly caused by a parasite called *plasmodium gambiae*. Several of this parasite exists all over the tropical world, however, the most commonly found in Africa especially Nigeria, is the *Plasmodium falciparum* (World Malaria Report, 2018; Kar et al., 2014). Different studies (Githeko and Ndegwa, 2001; Jones and Morse, 2010) have shown that human beings are connected to the malaria parasite through a third party; "the mosquito". Mosquito acts as a vector through which the parasite is transmitted into humans. The female anopheles' mosquito is the main vector of the malaria parasite (Jone and Morse, 2010; Tompkin and Ermert, 2013). This is because the female anopheles during pregnancy needs human blood to nourish her eggs with proteins and it is usually during the process that the malaria parasite is transmitted into humans (Detinova, 1962; Lindsay and Martens, 1998; Githeko et al., 2000; Bayoh and Lindsay, 2004).

Several studies have shown that the survival of mosquito is largely influenced by environmental and climatic factors (Abiodun et al., 2016; Asare et al., 2016, Asare and Amekudzi, 2017). In general, most atmospheric variables attributed to mosquito survival are Relative Humidity, Winds, Temperature, and Rainfall. However, of the four aforementioned variables, only temperature and Rainfall are mostly regarded. For instance, temperature aids the rate of mosquito larval development, the frequency of blood-feeding by adult females on humans, and the time it takes the malaria parasites to mature into female mosquitoes. On the other hand, rainfall creates breeding sites for mosquitoes where eggs are laid. It is therefore apparent that accurate real-time monitoring of temperature and rainfall conditions could provide useful information concerning malaria transmission in malaria early-warning systems (Tompkin and Ermert, 2013).

Models for Malaria Early-Warning Systems (MEWS)

Many malaria models that could account for malaria dynamics from climatic variables as early warning systems in epidemic regions have been formulated (Thomson et al., 2006; Ceccato et al., 2007). Despite the growing number of available models, only a few are actually dynamic and operationally in use. The two most commonly used dynamical malaria models in West Africa are the Liverpool Malaria Model (LMM) (Jones and Morse, 2010) and the VECtor borne disease community model of ICTP, Trieste (VECTRI) (Tompkin and Ermert, 2013). In this paper, the VECTRI malaria model was adopted. This is because the VECTRI model is the only freely available dynamical open-sourced malaria model. It also considers the impact of climate, surface hydrology, and population density on malaria distribution and can be used operationally.

Studies have shown the predictive skill of the VECTRI model over different regions in Africa using both simulated and observed climate drivers: for instance, Tompkins and Ermert, (2013) drive the new VECTRI model using observed rainfall and temperature. Malaria cases from a wide range of location in Africa are compared with the Entomological Inoculation rate (EIR) as simulated by

Table 1. Summary of data used in this study. NA=Not Applicable.

	Parameters	Source	No Ensemble	Period
Station Observation	Rainfall Temperature Malaria Cases	NiMet Roll Back Malaria	NA	1998 - 2017
S2S-Reforecast (ECMWF)	Rainfall Temperature(2m)	ECMWF	10	1998 - 2017
S2S-Reforecast (CMA)	Rainfall Temperature(2m)	ECMWF	3	1998 - 2017
S2S-Reforecast (UKMO)	Rainfall Temperature(2m)	ECMWF	2	1998 - 2017

the VECTRI model. Focusing on Bobo-Dioulasso in Eastern Africa, they found out that the model can adequately reproduce differences in transmission rates between rural and semi-urban areas in addition to the seasonality of malaria. Again, Tompkins and Di Giuseppe, (2015) in an Idealized model experiment investigated advanced malaria warning system by driving the VECTRI model with temperature and rainfall forecasts from monthly and seasonal simulated prediction system. Although with inherent lags between rainy season and malaria transmission, a preliminary examination over the highland of Uganda and Kenya shows that the system has considerable skill in predicting the years during the last two decades in which documented highland outbreaks occurred. While Tompkins and Di Giuseppe, (2015) focused mainly on Eastern Africa, Asare and Amekudzi, (2017) evaluated the VECTRI model focusing particularly on Ghana in Western Africa. They used a modified VECTRI model to investigate spatio-temporal variability in malaria transmission. They found out that EIR simulated by the VECTRI model agreed and demonstrated appreciable skill in reproducing monthly variations in reported malaria cases.

Despite the use of the VECTRI model in different parts of Africa by different studies, yet, none of these above-mentioned studies focused on the abilities of the VECTRI model in predicting malaria distribution particularly in Nigeria, the country with the highest number of malaria cases in Africa (World Malaria Report, 2018), Again, the aspect of using the VECTRI model as an early warning tool for malaria distribution within a forecast-range that is right for tangible decision making in Nigeria is unfortunately lacking. Several studies (Robertson and Wang 2012; Vitart et al, 2014; Lynch et al., 2014; White et al, 2015) have recently identified the Sub-Seasonal to Seasonal (S2S) time range to be the forecast-range that is just right for making effective decisions. As a new frontier in weather forecasting, the predictive skill of S2S models has also been carried out by different studies on different areas for different purposes (Lynch et al., 2014; White et al, 2015, Olaniyan et al., 2018). Besides the aforementioned piece of facts on the skill of the VECTRI model in different regions using different methods in Africa, some fundamental questions are yet to be answered based on the use of VECTRI model in Nigeria. Firstly, how skilful is the VECTRI Malaria model in predicting malaria occurrences in Nigeria from the simulated Entomological Inoculation Rate (EIR); Secondly how skilful can the rainfall and temperature forecast from S2S models be in driving VECTRI model; and lastly what is the significant of improvements in using multi-model ensembles prediction system in driving VECTRI model. In this respect, this study aims at addressing these concerns to be able to have a robust system for Malaria Early Warning at S2S time-scale using the VECTRI model.

DATASETS, METHODS AND DESCRIPTION OF MODELS

Dataset and methods

This study utilized three sets of data from with time scale spanning from 1998 to 2017 (Table 1). The first two datasets are used to drive the VECTRI-model. They are:

1; observed daily temperature and rainfall datasets retrieved from the archive of the Nigerian Meteorological Agency (NiMet:

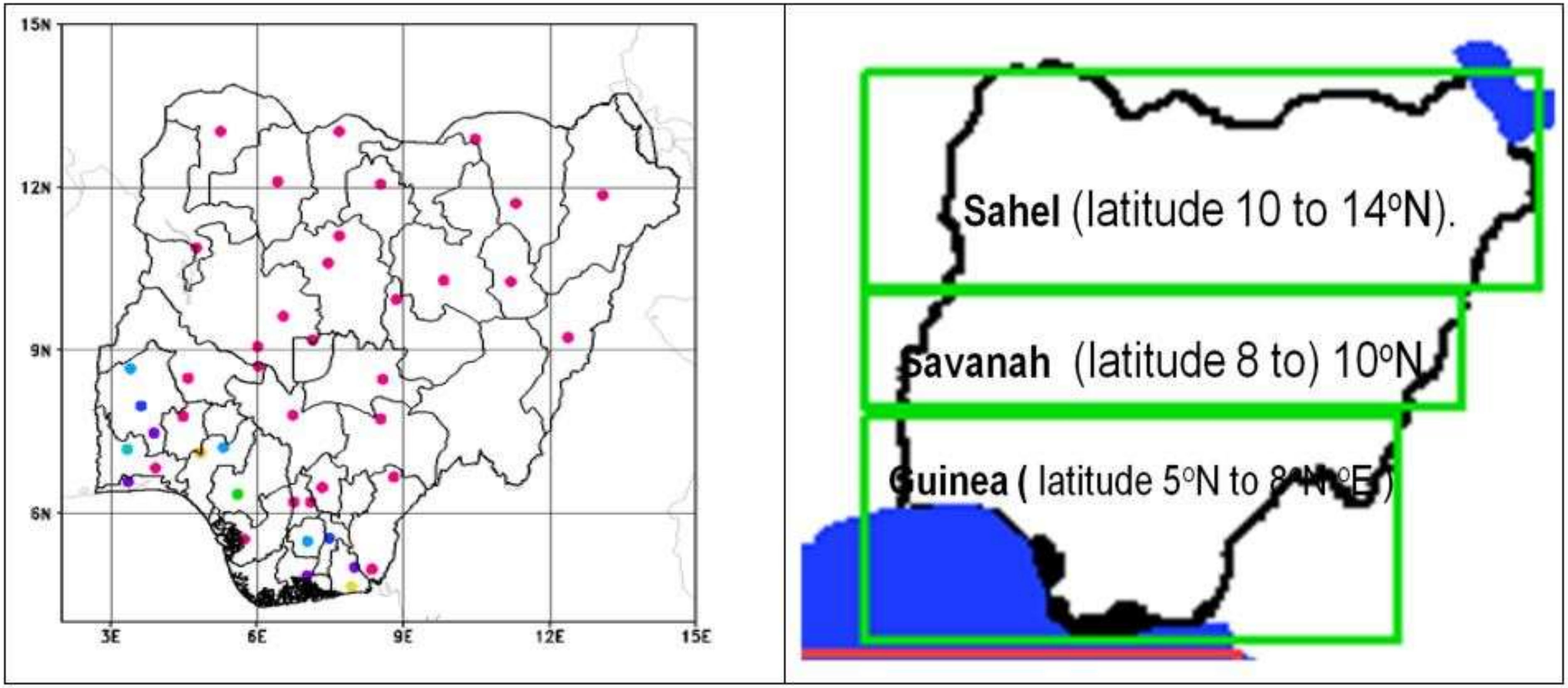

Figure 1. Maps showing **(a)** locations of synoptic stations used in this study (source: Olaniyan et al. 2018); **(b)** three climatological zones in Nigeria in (green boxess.

http://www.nimet.gov.ng) as shown in Figure 1a.

2; temperature and rainfall from three global S2S reforecast datasets. These are from the CMA-S2S ensemble hind-casts produced by the BCC-CPSv1, the ECMWF-S2S ensemble hind-casts produced by the VarEPS and the UKMO-S2S ensemble hind-casts produced by the GloSea4. They were all retrieved from the ECMWF-S2S database, as supported by the World Meteorological Organization (WMO) through the World Weather Research Program (WWRP) and World Climate Research Program (WCRP).

3; the confirmed clinically reported malaria cases data are obtained from the annual and monthly records of the "ROLL BACK MALARIA" program in Nigeria.

Twenty (20)-years datasets were obtained from the annual record (from 1998 to 2017) and 5 years (2013 to 2017) from the monthly records. However, based on data availability and the subject to sub-seasonal time scale being used in this paper, emphasis was laid on

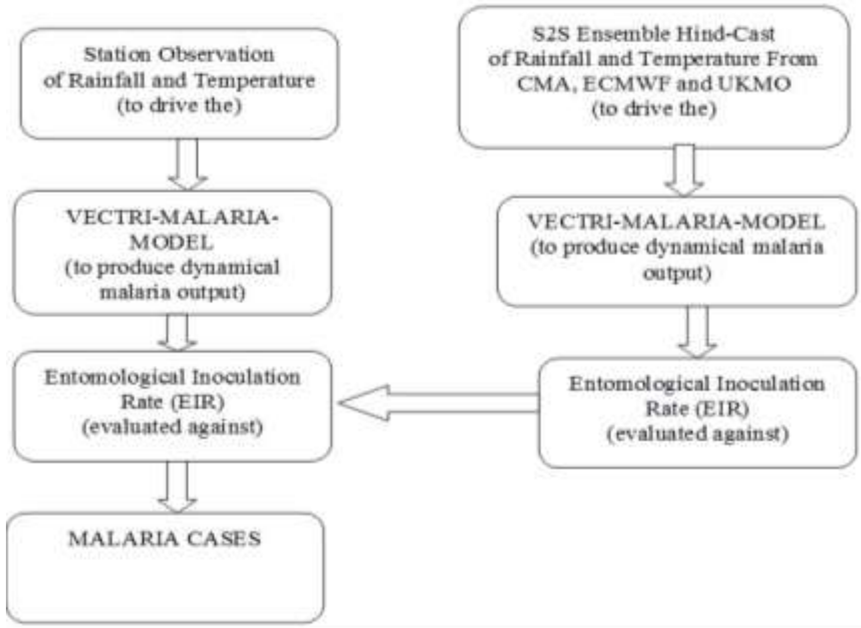

Figure 2. Schematic of the forecast-system setup, Adapted from Tompkins and Giuseppe, (2015).

discussion of the results from the recent 5-years monthly analysis. Two hierarchical evaluations as explained in Figure 2 were carried out in the study. Firstly, the reported malaria cases were used to evaluate the skill of VECTRI model using the simulated EIR. Although, VECTRI model simulates array of malaria dynamics (Tompkins and Ermert, 2013; Asare and Amekudzi, 2017) however the EIR given as mosquito bite per person per day (b/p/d) has been widely used as malaria variable that could be compared with actual cases of malaria occurrence (Jones and Morse, 2010; Tompkins and Ermert, 2013; Aju-Ameh et al., 2016; Asare and Amekudzi, 2017). Secondly, we evaluate the skill of the S2S models in driving the VECTRI model. Here, the simulated EIR from observed driven VECTRI was evaluated with the simulated EIR from the three S2S models used. To further justifies the performance of the S2S models, the forecast rainfall and temperature from the S2S models are evaluated using the observed rainfall and temperature datasets from NiMet.

Statistical measures, in the form of Taylor diagrams (Taylor, 2001), were used to determine the monthly and annual variability of all parameters. Quantitatively, correlation coefficients (r) and the normalized standard deviation (NSD) between all the S2S-models (their ensemble members and the ensemble mean) with reference to the observations (EIR) were also determined. Furthermore, some measures of statistical significance, such as p-value (Mason, 2008), were performed for the correlation skills that were determined in this study. The level of significance was estimated, where p-value = 0.05, for a two-tailed experiment to decide whatever the linear association that may exist between the correlated parameters are plausible. Nigeria is divided into 3 climatological zones based on common climatology (Figure 1b).

DESCRIPTIONS OF MODELS USED IN THIS STUDY

Brief descriptions of VECTRI model

VECTRI is a grid-cell distributed open source dynamical model which simulates malaria transmission dynamics (Tompkins et al., 2013). VECTRI model was developed at the International Center for Theoretical Physics. The model runs with a daily integration time-step. The spatial resolution of the model is flexible as it depends on the resolution of the driving climate data; it ranges from a single location to a regional scale of 10 to 100 km. The model explicitly resolves the growth stages of the egg-larvae-pupa cycle in addition to the gonotrophic and the sporogonic cycles using an array of bins for each process (Tompkins and Ermert, 2013; Asare and Amekudzi, 2017). This process continues to advance within the boxes once temperatures are within the range for growth.

One unique feature of the VECTRI model is its ability to incorporate human population that influences vector–host interaction dynamics in estimating biting rates. Therefore, the Entomological Inoculation Rate (EIR) simulated by the model reduces with increasing population density (Tompkins and Ermert, 2013). The model also includes a simple hydrological scheme. Modified by Asare et al. (2016), the scheme indirectly controls habitat productivity and adult density as larvae are killed once the habitat dries out. In addition, the scheme is also able to account for the negative effect of high intensity rainfall on habitat productivity through flushing away of larvae (Paaijmans et al., 2007). Detailed description of the VECTRI model is available in Tompkins and Ermert (2013) and Asare et al. (2016).

Brief descriptions of the S2S models used in this study

The three S2S models used in this study, is based on different model configurations, from three different global prediction centres. These global prediction centres are the China Meteorological Administration (CMA), European Centre for Medium-Range Weather Forecasts (ECMWF), and United Kingdom Meteorological Office (UKMO). The earliest mentioned centre utilizes the Beijing Climate Center Climate Prediction System (BCC-CPS-S2Sv1) version 1. The configuration is based on lagged average forecasting (LAF) method using a fully-coupled BCC Climate System Model BCC-CSM1.2. The S2S Forecasts are running every day since 1 January 1994 and end with a 60-day integration. Each forecast consists of 4 LAF ensemble members, which are initialized at 00 UTC of the first forecast day (Wu et al., 2014; Li et al., 2017). ECMWF utilizes the integrated forecasting System (IFS) version 41r1. The ECMWF-S2S ensemble hind-casts Variable Resolution Ensemble Prediction System (VarEPS) is based on IFS version 41r1. It runs on an octahedral grid with 51 members ensemble (Buizza et al., 2006; Vitart et al., 2012). Operationally, the system is composed typically of coupled land, ocean and atmosphere components. The system provides daily ensemble forecasts of a wide variety of atmospheric variables (e.g. precipitation, 2m temperature, sea surface temperature (SST), horizontal components of wind flow at 700 hPa level, mean sea level pressure (MSLP), dew point temperatures, etc.) with daily and sub-daily temporal resolution of the order of 6 hours. More details on the ECMWF-S2S are available at: http://s2sprediction.net/. S2S forecasting system from the UKMO prediction centre made use of the GloSea4 modeling technique. The technique is an ensemble prediction system that uses the HadGEM3 coupled GCM to model interactions across all physical components of the climate system: ocean, atmosphere, land surface and sea ice (Arribas et al., 2011). Summaries of the above descriptions are presented in Table 2.

RESULTS AND DISCUSSION

Malaria cases

Malaria occurrence is an all year-round phenomenon (Figures 3 - 5). The characteristics of occurrences may differ from region to region; however, the number of malaria cases increases from the Gulf of Guinea (GoG) to the Sahel. Occurrence of malaria is in concomitance with rainfall characteristics over the three regions. Studies have shown that rainfall characteristics over Nigeria follows the annual oscillation of the sun and it is controlled by the advection of moisture from GoG in the low levels of the atmosphere (e.g. Sultan and Janicot, 2003; Couvreux et al., 2010; Lawal et al., 2016; Olaniyan et al., 2018). The increase in malaria occurrence northwards implies that the number of malaria cases increases with increasing population. This is in line with different studies such as Martens et al. (1999); Marten and Hall (2000), and Tompkins and Di Giuseppe (2015). As shown in Figures 3a, 4a and 5a, the occurrence of malaria over both the GoG and the Savannah is mostly bi-modal with a uni-modal characteristic over the Sahel. The peak of malaria occurrence generally coincides with the peak of the rainfall. However, Figure 5a showed a month lag between the peak of the rainfall and the peak of malaria occurrence over the Sahel. The assumption here, as suggested by suggested by Berg et al. (2017), is that the lag may be as a result of the retention capacity of soil moisture, which studies have shown to have a feedback effect on rainfall variability. On all the regions as shown in Figures 3b,

Table 2. Summary of VECTRI Model Constant.

Symbol	Value	Units	Description
E + I	250	mm day−1	Total evaporation and infiltration losses
KL,Jepson	90.9	K day	Larvae growth degree days
KL,Bayoh	200	K day	Larvae growth degree days
Kgono	37.1	K day	Gonotrophic cycle degree days
Ksporo	111	K day	Sporogonic cycle degree days
Kflush,∞	0.4		Larvae flushing factor for infinite rain rate
Kw	1	m^{-1}	Pond growth rate factor
Kmar1,0	0.45		Constant of Martens I vector survival scheme
Kmar1,1	0.054	$°C^{-1}$	Constant of Martens I vector survival scheme
Kmar1,2	-0.0016	$°C^{-2}$	Constant of Martens I vector survival scheme
ML,max	300	mg m^{-2}	Carrying capacity of water bodies
Negg	120		Number of eggs per batch that result in female vectors
PL,surv0	0.825		Larvae base daily survival rate
Phv	0.2		Probability of transmission from infective host to vector during single bloodmeal
Pvh	0.3		Probability of transmission from infective vector to host during single bloodmeal
Twat	2	K	Pond water offset from air temperature
TL,min	16	°C	Minimum *Twat* for larvae development
TL,max	38	°C	Maximum *Twat* for larvae development
Tgono,min	7.7	°C	Minimum *T2m* for egg development
Tsporo,min	16	°C	Minimum *T2m* for sporogonic cycle
τflush	50	mm day^{-1}	Larvae-flushing rainfall e-folding factor
wmax	0.04		Maximum temporary pond fraction in cell

Source: Tomkins and Ernest 2013.

4b and 5b the peak of malaria occurrence happens two months after the temperature maximum.

VARIABILITY DISTRIBUTION OF NIGERIAN RAINFALL AND TEMPERATURE

Running VECTRI-Model with observed datasets

The VECTRI model driven by the observed station rainfall and temperature is able to simulate the hyper endemic characteristics of malaria occurrence in Nigeria. This is in conformity with other studies that show that malaria occurs when the EIR is more than 0.01 (e.g., Jones and Morse, 2010; Aju-Ameh et al., 2016; Asare and Amekudzi, 2017). The simulated EIR follows the monthly evolution of the monsoon rainfall. This implies that VECTRI simulated EIR could be interpolated with reported cases of malaria in GoG and Savannah where the peak of malaria

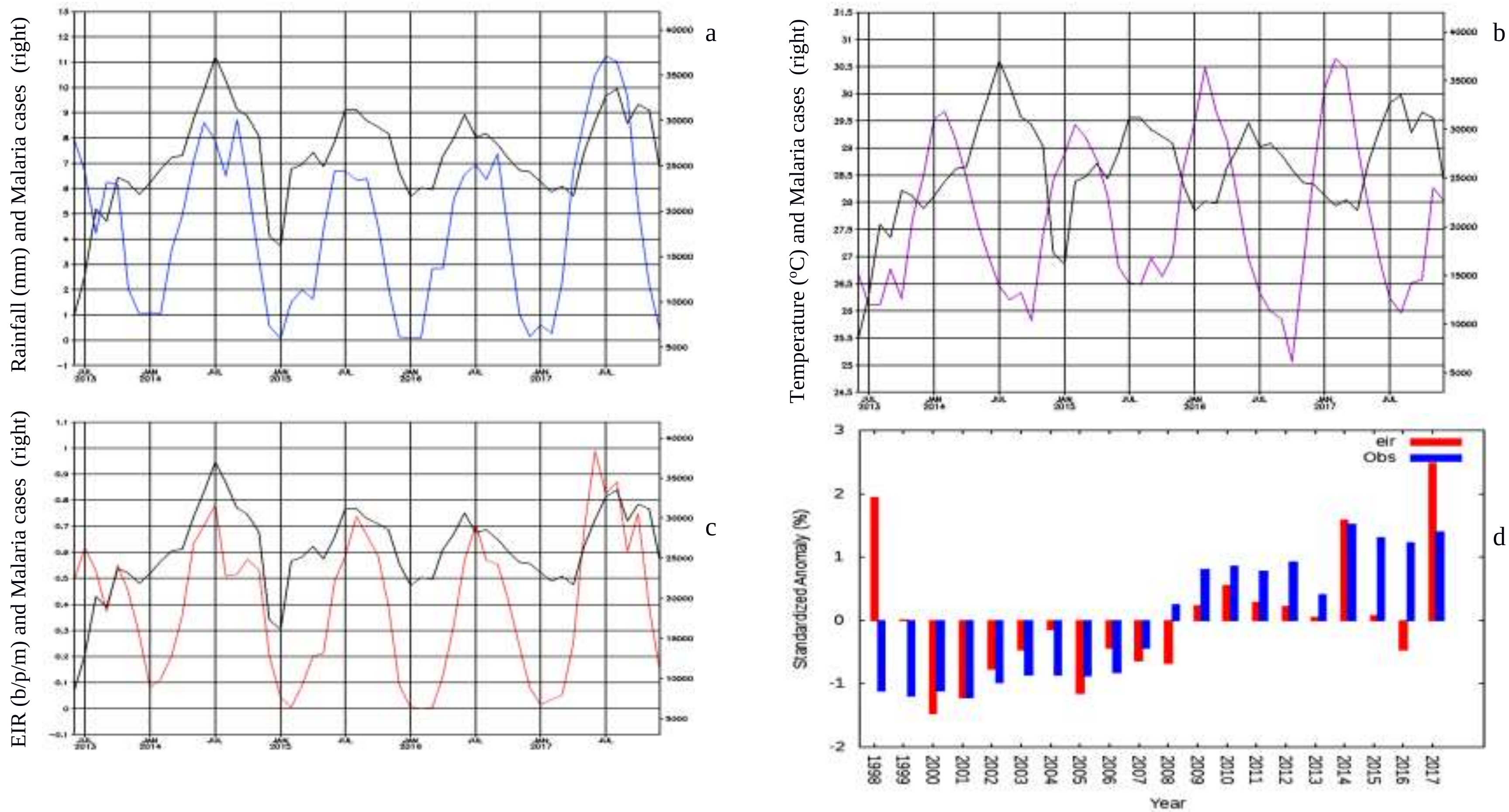

Figure 3. Monthly variability of malaria cases (in black) over the Gulf of Guinea with (a), rainfall, (b), mean temperature (ºC) and (c) simulated EIR(red) from VECTRI model; d is the standardized anomaly of annual variability of malaria cases (blue bar) and simulated EIR(red bar).

occurrence coincides with the peak of the simulated EIR (Figures 3c, 4c and 5c). However, the peak of the simulated EIR over the Sahel occurs a month before the peak of malaria occurrence. The model also generally captured the inter-annual variability of the malaria cases over each region with different inherent biases. VECTRI is able to capture the yearly anomalies over GoG except for 1998, 2008 and 2016 (Figure 3d). It deviates over the Savannah in 1998 1999 2003 2004 2009 2010 and 2011 and over the Sahel in 1998,

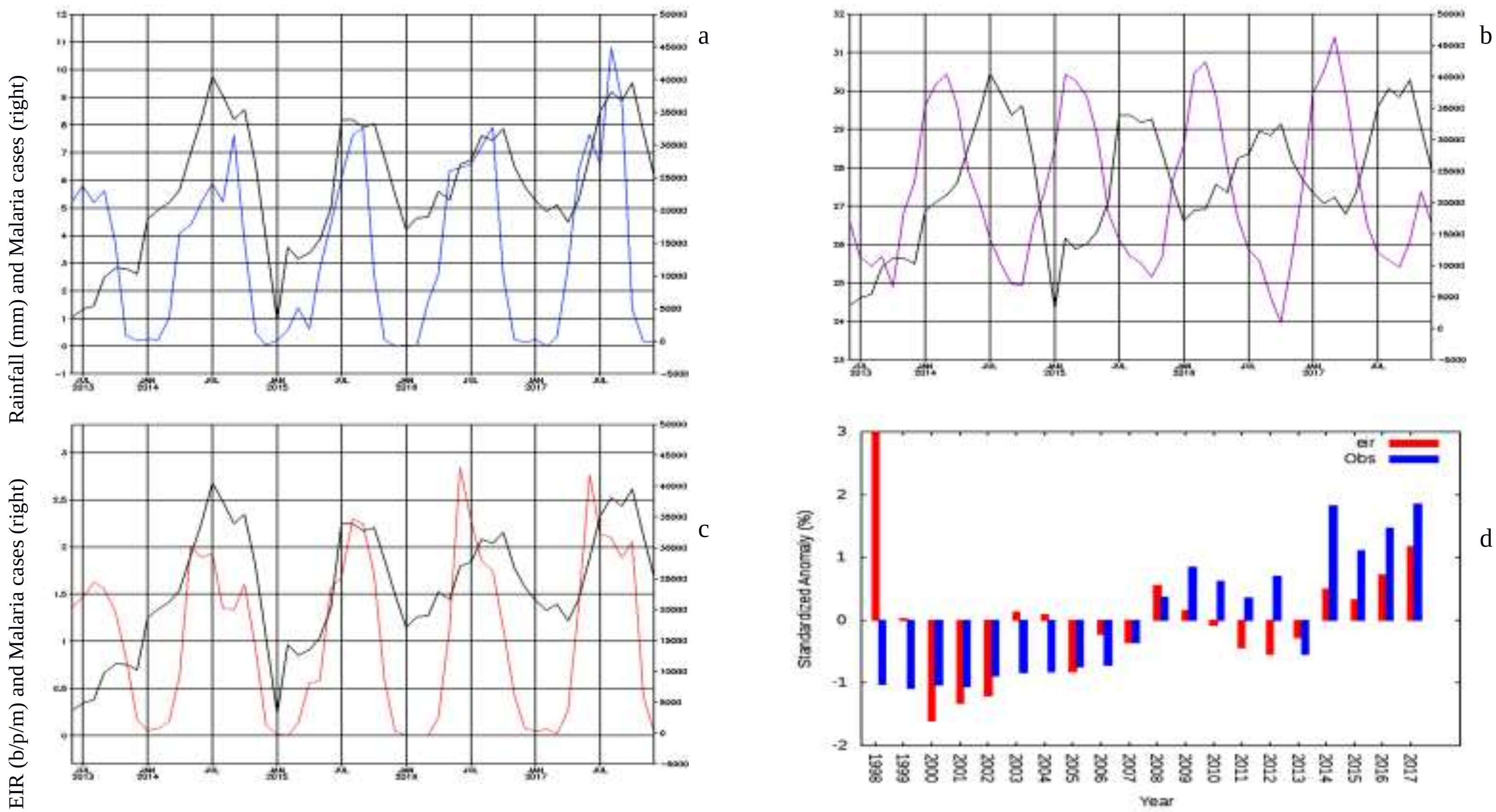

Figure 4. Monthly variability of malaria cases (in black) over Savannah with (a), rainfall, (b), mean temperature (ºC) and (c) simulated EIR (red) from VECTRI model; d is the standardized anomaly of annual variability of malaria cases (blue bar) and simulated EIR (red bar).

2007, 2008, 2009 and 2014 (Figures 4d and 5d).

Running VECTRI-Model with datasets from S2S-Models

The S2S models used in driving the VECTRI-Model reproduced the EIR with different characteristics over different regions. For instance, the EIR simulated from the S2S-driven-VECTRI increases from the GoG to the Sahel following the population profiles (Figures 6 - 8). The EIR is also greater than 0.01/b/p/m signifying the hyper-endemic characteristics of malaria occurrence in Nigeria. Evidence of uniqueness of the variability of the EIR from the S2S-driven-VECTRI is depicted in Figures 6(b, d, and f), 7 (b, d, and f) and 8(b, d, and f). For instance, the simulated EIR from the UKMO displayed good variability with the observed over the

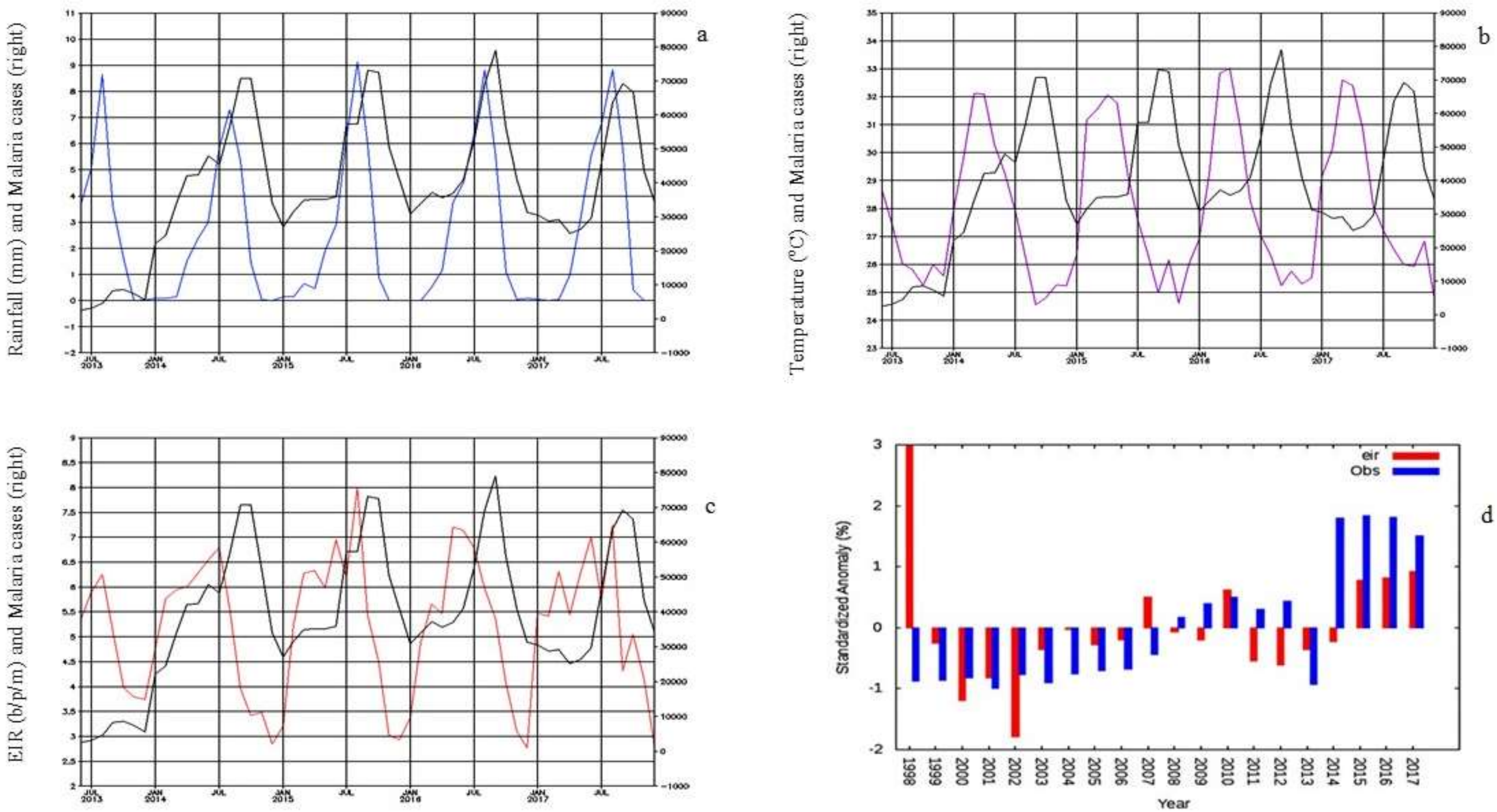

Figure 5. Monthly variability of malaria cases (in black) over Sahel with (a), rainfall, (b), mean temperature (oC) and (c) simulated EIR(red) from VECTRI model; d is the standardized anomaly of annual variability of malaria cases (blue bar) and simulated EIR(red bar).

three regions with NSD between 0.8-1.0. On the other hand, the variability from the ECMWF-EIR improved over the Savannah and the Sahel with NSD of about 0.8. Here, overall, the region the variability of simulated CMA-EIR is poor. Additionally, the direct relationship between the all S2S simulated EIR and the observation is strong but unique in different regions.

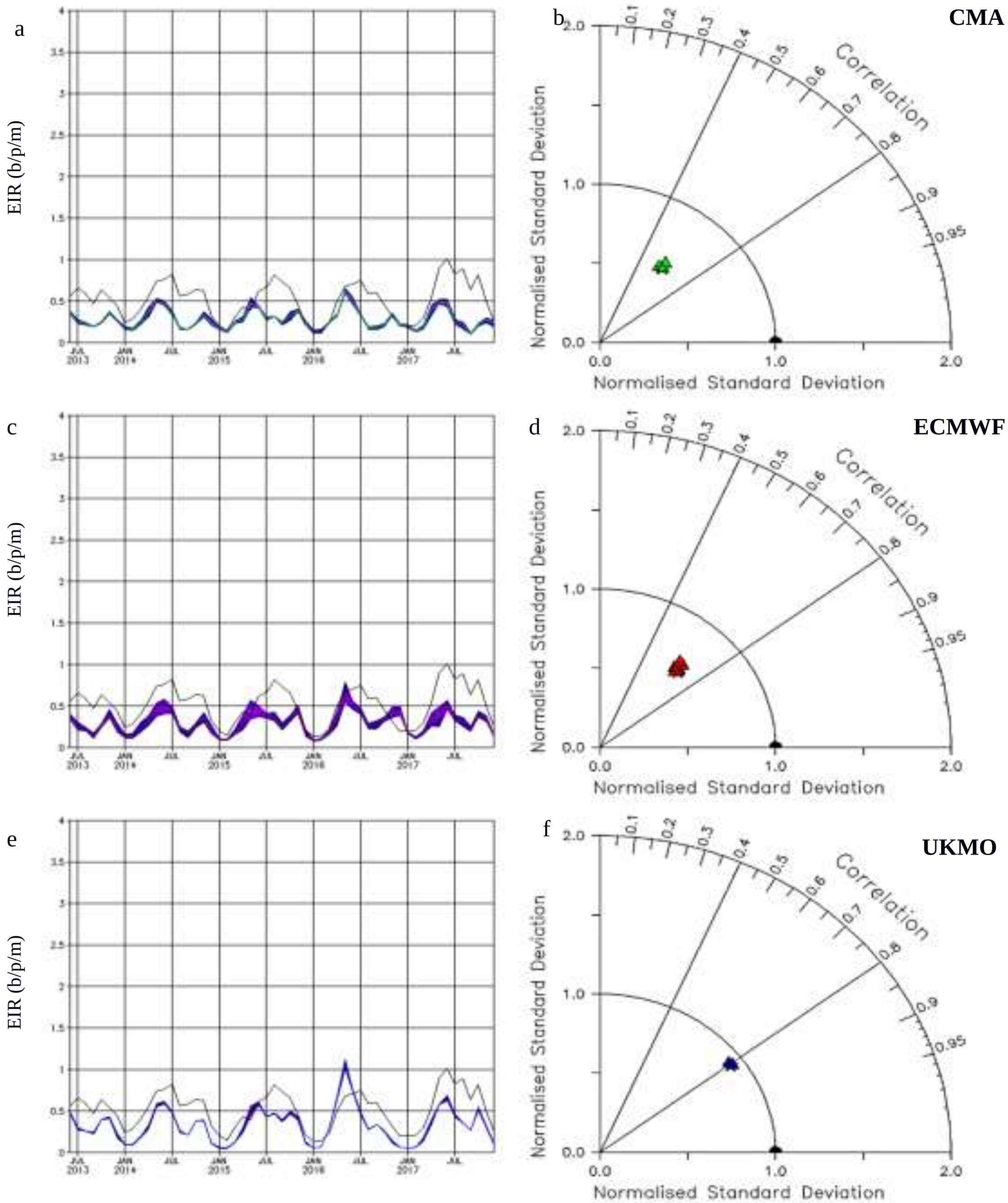

Figure 6. Monthly variability of VECTRI simulated EIR over the GOG by S2S -model Forecasts from CMA ensemble mean (green-lines), the ECMWF ensemble mean (red-line), the UK-METOFFICE ensemble mean (blue-line) ,all ensemble members(shaded) and by observation; (B, D, F) Taylor diagrams showing the normalized standard deviations and the correlation coefficients of CMA(green) , ECMWF(red) and UK-METOFFICE(blue) S2S ensemble simulations with observation respectfully (triangle--ensemble members), ensemble mean—star and (observation)—black semi-circle

For instance, all the ensemble members and ensemble means of both the CMA-EIR and ECMWF-EIR improve correlation skill from the GOG to the Sahel with values ranging from 0.7 - 0.85. Meanwhile,

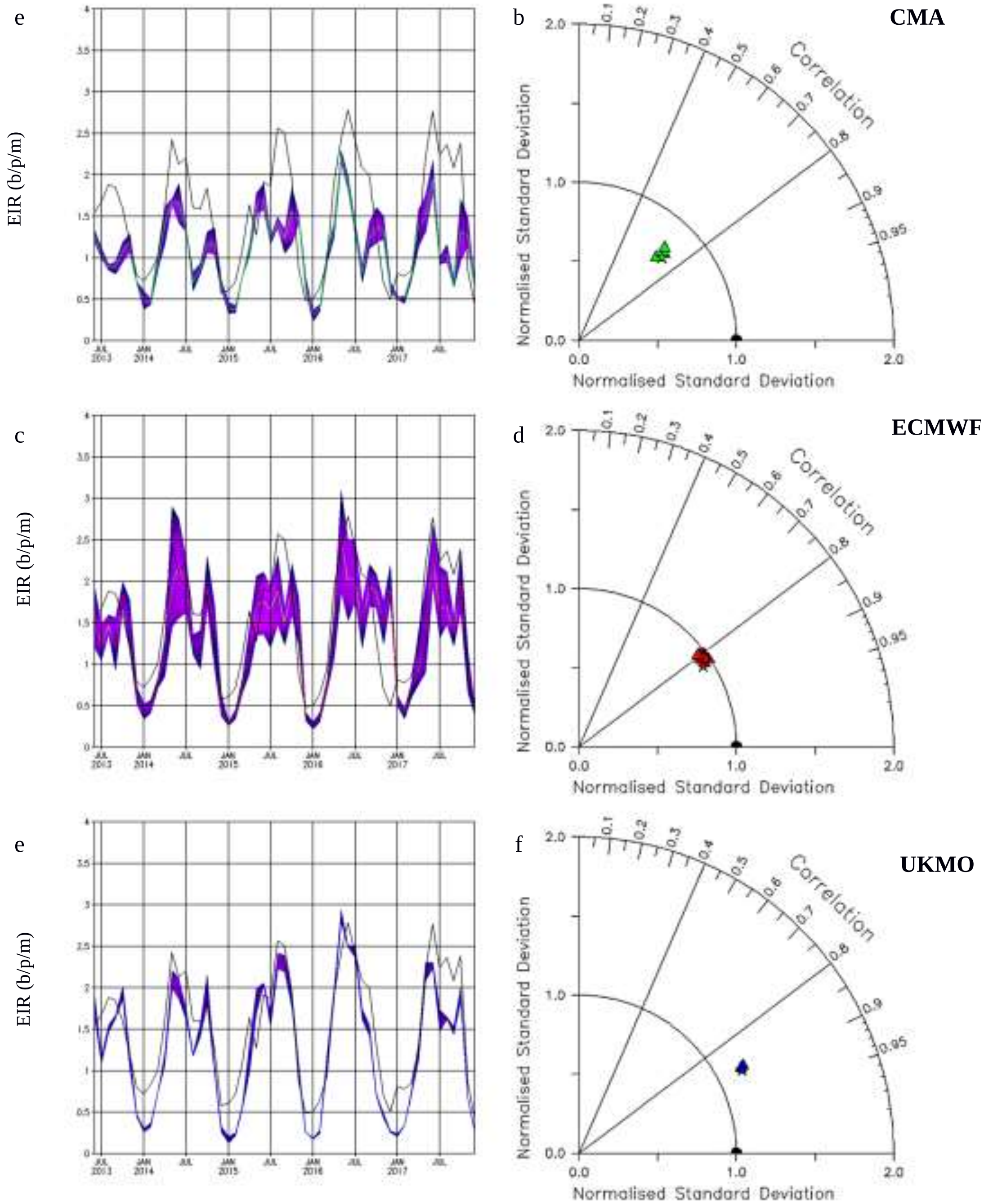

Figure 7. Monthly variability of VECTRI simulated EIR over the Savannah by S2S -model Forecasts from CMA ensemble mean (green-lines), the ECMWF ensemble mean (red-line), the UK-METOFFICE ensemble mean (blue-line) ,all ensemble members(shaded) and by observation; (B, D, F) Taylor diagrams showing the normalized standard deviations and the correlation coefficients of CMA(green) , ECMWF(red) and UK-METOFFICE(blue) S2S ensemble simulations with observation respectfully (triangle--ensemble members), ensemble mean—star and (observation)—black semi-circle.

the UMKO-EIR maintained very strong correlation skill of approximately 0.9 overall the regions from all the ensemble members the mean. The different performance of each of the S2S- driven-VECTRI on

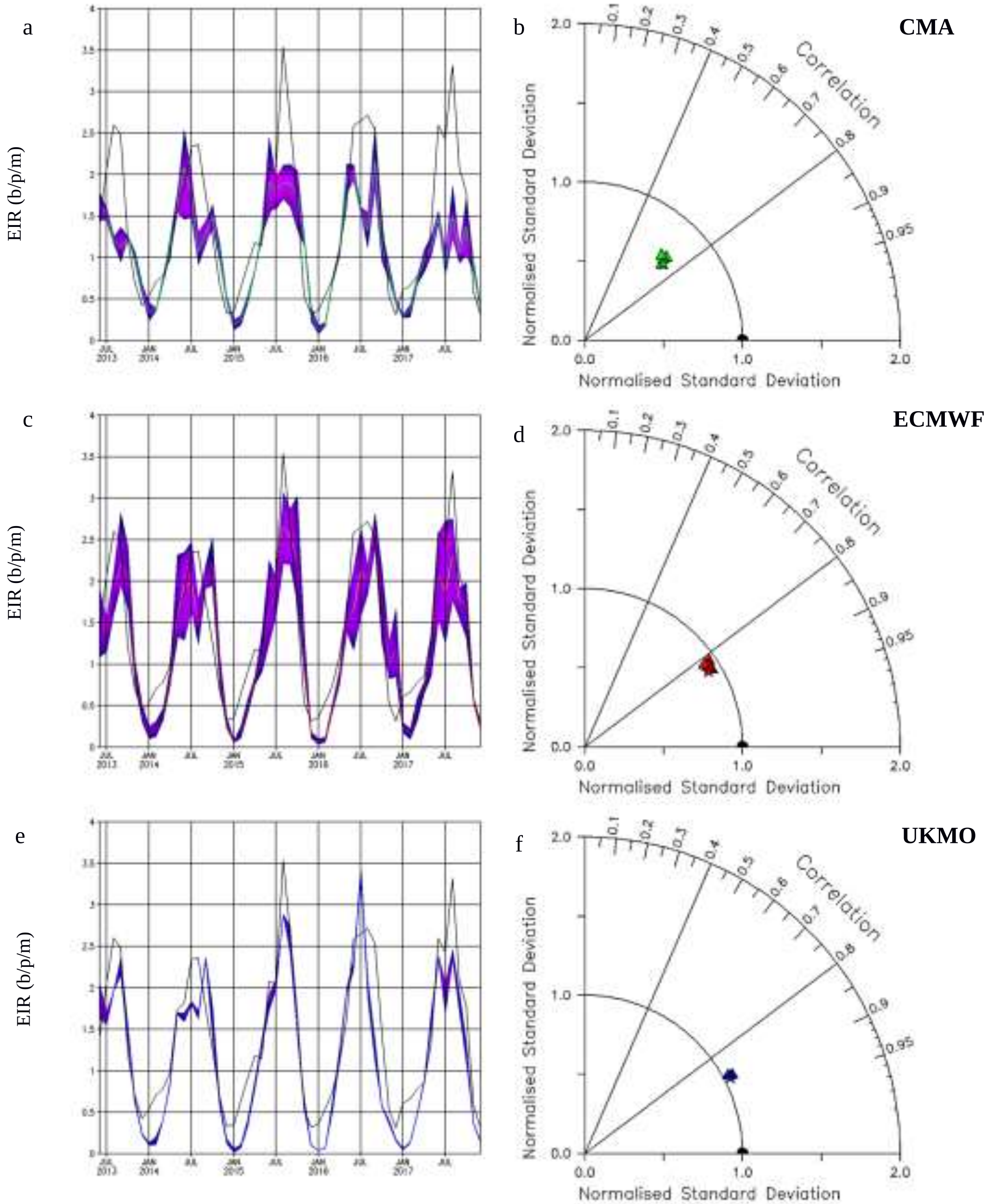

Figure 8. Monthly variability of VECTRI simulated EIR over the Sahel by S2S -model Forecasts from CMA ensemble mean (green-lines), the ECMWF ensemble mean (red-line), the UK-METOFFICE ensemble mean (blue-line) ,all ensemble members(shaded) and by observation; (B, D, F) Taylor diagrams showing the normalized standard deviations and the correlation coefficients of CMA(green) , ECMWF(red) and UK-METOFFICE(blue) S2S ensemble simulations with observation respectfully (triangle--ensemble members), ensemble mean—star and (observation)—black semi-circle.

different regions may not be unconnected with the predictive skill of the S2S models in simulating rainfall and temperature over these regions. For instance, in terms of rainfall all the three models can reproduce the climatology of monsoon evolution and characteristics over the GoG, the Savannah and the

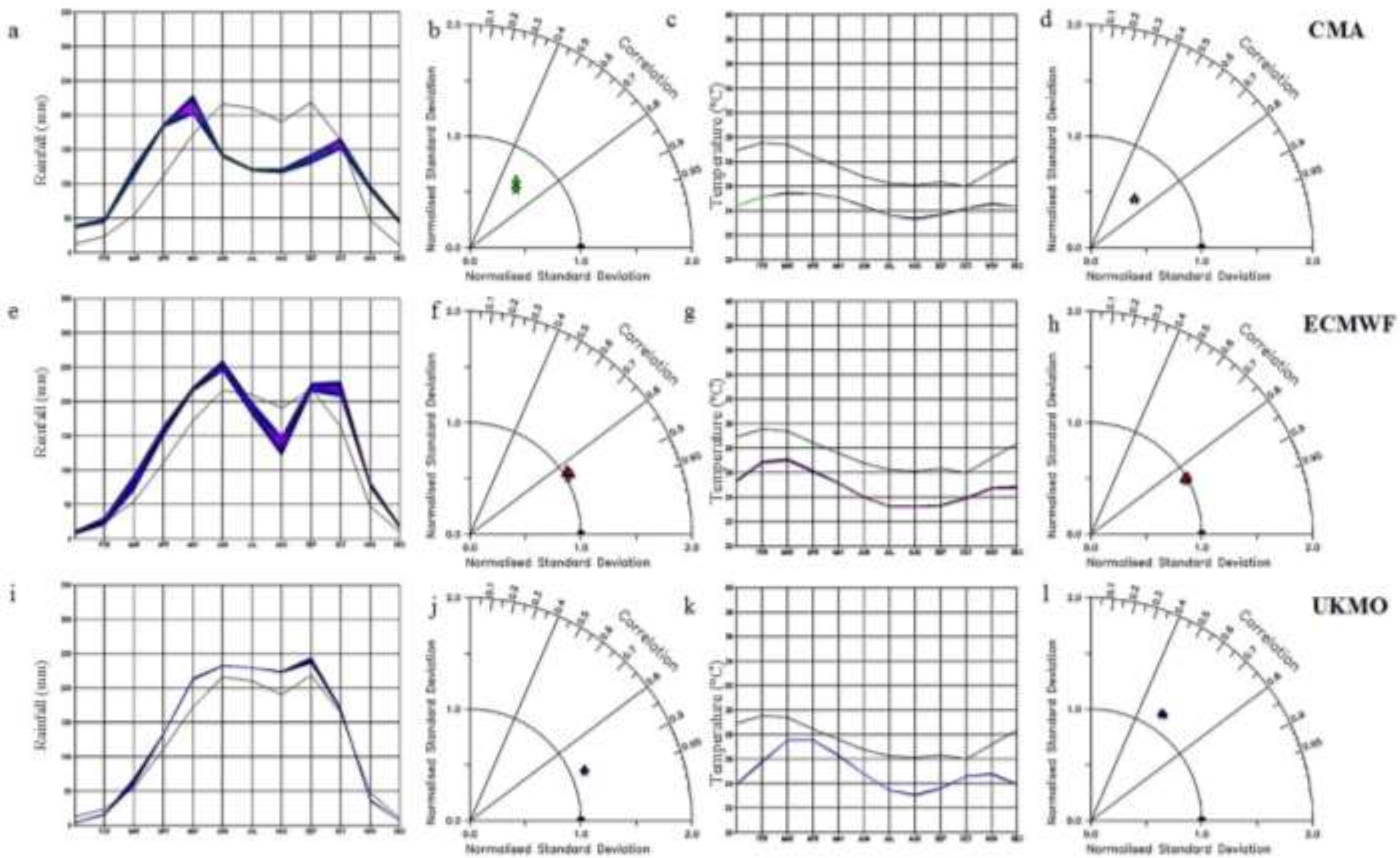

Figure 9. Monthly Climatology of Rainfall and temperature over the Gulf of Guinea by S2S -model Forecasts (A,C,E,G,I,K) from CMA ensemble mean (green-lines), the ECMWF ensemble mean (red-line), the UKMO ensemble mean (blue-line) , all models ensemble members(shaded) and by observation (Black line); (B, D, F,H,J,L) Taylor diagrams showing the normalized standard deviations and the correlation coefficients of CMA(green) , ECMWF(red) and UK-METOFFICE(blue) S2S ensemble simulations with observation respectfully (triangle--ensemble members), ensemble mean—star and (observation)—black semi-circle.

Sahel. As shown in Figures 9 (a, e and j), 10(a, e and j) and 11 (a, e and j), this is because all the models reproduced the bi-modal rainfall pattern over the GoG and the uni-modal rainfall peculiar to the Savannah and Sahel areas. With inherent differences, each of the models also exhibits unique characteristics over each of the regions considered.

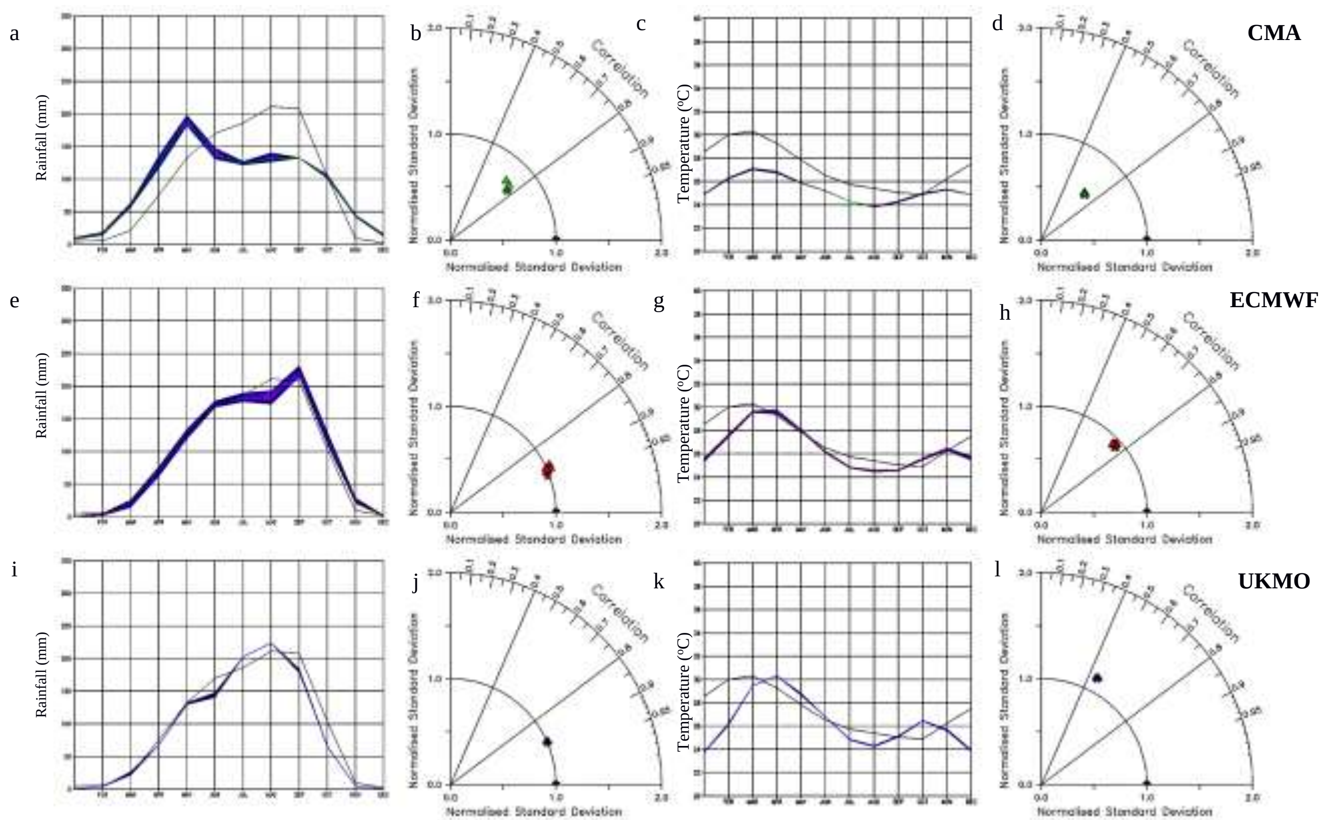

Figure 10. Monthly Climatology of Rainfall and temperature over the Savannah by S2S -model Forecasts (A,C,E,G,I,K) from CMA ensemble mean (green-lines), the ECMWF ensemble mean (red-line), the UKMO ensemble mean (blue-line) , all models ensemble members(shaded) and by observation (Black line); (B, D, F,H,J,L) Taylor diagrams showing the normalized standard deviations and the correlation coefficients of CMA(green) , ECMWF(red) and UK-METOFFICE(blue) S2S ensemble simulations with observation respectfully (triangle--ensemble members), ensemble mean—star and (observation)—black semi-circle.

For instance, the ECMWF model showed a degree of consistency in variability and correlation skill over all the regions as depicted in Figures 9(e and f) 10(e and f) and 11(e and f). The NSD over the entire region is almost 1.0 implying no significant changes from the observation.

The skill of producing monthly quantitative rainfall amount and the correlation skill improves from the GoG to the Sahel with a mean correlation of 0.95. The ECMWF model overestimates the monthly rainfall amount

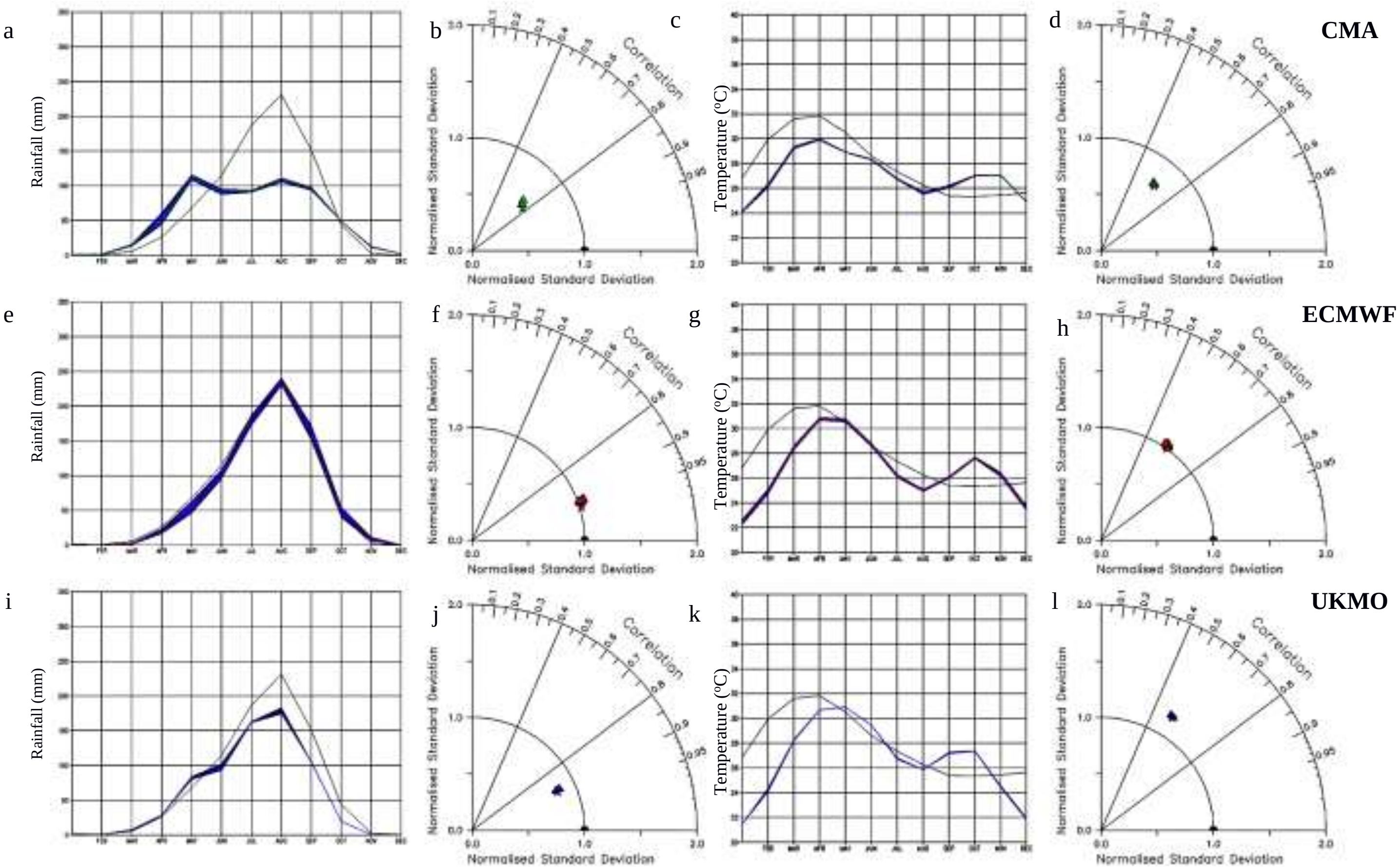

Figure 11. Monthly Climatology of Rainfall and temperature over the Sahel by S2S -model Forecasts (A,C,E,G,I,K) from CMA ensemble mean (green-lines), the ECMWF ensemble mean (red-line), the UKMO ensemble mean (blue-line) , all models ensemble members(shaded) and by observation (Black line); (B, D, F,H,J,L) Taylor diagrams showing the normalized standard deviations and the correlation coefficients of CMA(green) , ECMWF(red) and UK-METOFFICE(blue) S2S ensemble simulations with observation respectfully (triangle--ensemble members), ensemble mean—star and (observation)—black semi-circle.

before and after the peak of the monsoon but underestimate the rainfall during August the peak of the monsoon over the GoG (Figure 9c). Similarly, over the Sahel, the agreement between the model's ensemble members and the ensemble mean in terms of correlation surpasses that of GoG (Figures 10(e) and 11(e)).

The UKMO also show very strong

correlation skill in producing the climatology of monthly variability in Nigeria. Its correlation value in each region is approximately 0.9. However, it has lower variability and consistent biases in the entire region (Figures 9(i and j), 10(i and j) and 11 (i and j)). CMA model also have relatively strong correlation skill of about 0.7 in all the regions in term of simulating monthly rainfall, it is however weak in term of the variability, NSD = 0.5 (Figures 9 (a and b), 10(a and b) and 11(a and b)). Again, the ability of the CMA model to reliably forecast quantitative precipitation especially during the peak of the summer monsoon is weak. The significant test of all the correlation values from all the ensemble members and their means on all the regions are statistically significant as the p values are << 0.005. In addition to the ability of the models to reproduce rainfall climatology of each climatological zone (Figures 9 - 11(a, b, e, f, i and j)), ECMWF model does not deviate significantly from observation in terms of variability (panels h of Figures 9 – 11). However, the correlation skill for temperature reverses. This implies the correlation of all the ensemble members and the mean is strongest over the GoG and weakest over the Sahel. The UKMO also show very strong correlation skill in producing the climatology of monthly variability of temperature in Nigeria but with lower variability and consistent biases in all the region (panels k and l of Figures 9 – 11). In comparison to ECMWF, the UKMO correlation skill in terms of temperature is on the average with the weakest skill over the Savannah. While the CMA may have relatively strong correlation about 0.7 on all the regions in term of simulating monthly rainfall (panels a and b of Figures 9 – 11), temperature variability reproduced by CMA is however lower in comparisons to observation; NSD in the regions is about 0.5 (panels c and d of Figures 9 – 11). Again, the significant test of all the correlation values from all the ensemble members and their means on all the regions are statistically significant as the p values are << 0.005.

CONCLUSION

Malaria continues to be one of the biggest contributors to the global disease burden in terms of death, financial burden and suffering. This study uses a two hierarchical evaluations technique to investigate the skill of VECTRI model using the simulated EIR and to evaluate the skill of the S2S models in driving the VECTRI model. The results show that VECTRI model driven from observed station rainfall and temperature is able to simulate the hyper endemic characteristics of malaria occurrence in Nigeria. It suggests that simulated EIR could be used as a measure of interpolation for reporting cases of malaria in Nigeria. In addition, the model generally captured the inter-annual variability of the malaria cases over each region with different biases. Furthermore, all the three S2S models used in driving the VECTRI-Model reproduced the EIR that signifies the hyper-endemic nature of malaria in Nigeria; though with different characteristics over different regions. The simulated EIR from the S2S-driven-VECTRI increases from GoG to the Sahel following the population profiles. In addition, all the ensemble members and ensemble means of both the CMA-EIR and ECMWF-EIR improve correlation skill from the GOG to Sahel with values ranging from 0.7 - 0.85; with the strongest correlation skill of approximately 0.9 from UMKO-EIR over all the regions from all the ensemble members and the mean. The inherent differences in the performance of each of the S2S-driven-VECTRI on different regions may not be strongly connected with the predictive skill of the S2S models in simulating rainfall and temperature over these regions as earlier discussed.

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