WISER

Weather and Climate Information Services for Africa

Pan-Africa Component

Regional Pilot Research Project on Subseasonal to Seasonal Forecasts in the Perspective of Building Climate Information Services for Agriculture in Central Africa

United Nations
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Project

CR4D Regional Pilot Project – Central Africa

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Institutions

University of Yaoundé 1 (UoY1)
National Meteorological Service – Cameroon (NMS-Cam)
National Meteorological Service – Democratic Republic of Congo (NMS-DRC)
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Final Report

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Acronyms and Explanatory Notes

ACMAD - African Centre of Meteorological Applications for Development
AGRHYMET - *Le Centre Régional de Formation et d'Application en Agrométéorologie et Hydrologie Opérationnelle* (Regional Centre for Training and Application in Agrometeorology and Operational Hydrology)
ASECNA - *Agence pour la sécurité de la navigation aérienne en Afrique et à Madagascar* - (The Agency for Aerial Navigation Safety in Africa and Madagascar
BoM - Bureau of Meteorology (Australia)

CARBAP - *Centre Africain de Recherches sur Bananiers et Plantains*
CGIAR - Consultative Group on International Agricultural Research
CIFOR - Centre for International Forestry Research
CMA - Chinese Meteorological Administration
CR4D - Climate Research for Development
DRC - Democratic Republic of the Congo
ECCC - Environment and Climate Change Canada
ECMWF - European Centre for Medium-Range Weather Forecast
ENSO - El Niño–Southern Oscillation
ETS - Equitable threat score
FEWS NET - Famine Early Warning Systems Network (of USAID)
GCM - Global climate model
HMCR - Hydrometeorological Centre of Russia
INERA - *Institut de l'Environnement et des Recherches Agricoles – (*Environmental Institute for Agricultural Research)
IRAD - Institute of Agricultural Research for Development
IRI - International Research Institute for Climate and Society (of Columbia University)
IQR - Interquartile range
ISAC-CNR - Institute of Atmospheric Sciences and Climate
JMA - Japan Meteorological Agency
KMA - Korea Meteorological Administration
Meteo-France/CNRM - the French National Centre of Meteorology
METTELSAT - National Meteorological Service of the DRC
MINADER - Ministry of Agriculture and Rural Development
NCEP - National Centers for Environmental Prediction
NMS - National Meteorological Service
NMHS - National Meteorological and Hydrological Service
SAI - Standardized Anomaly Index
S2S - Subseasonal to seasonal
PANA-ASA - *Plan d'Action National d'Adaptation au changement climatique-Adaptation du Secteur Agricole* - (National Action Plan for Climate Change Adaptation/Adapatation of the Agricultural Sector)
UKMO - United Kingdom Met Office
WMO - World Meteorological Organization

Executive Summary

The CR4D Regional Pilot Project-Central Africa focuses on subseasonal to seasonal (S2S) forecasts in building climate information services for agriculture in Central Africa. This project was scheduled to begin on 25 May 2016 and expire four months later on the satisfactory completion of the services described in the terms of reference. The project was a partnership owned by the United Nations Economic Commission for Africa and operated by the African Climate Policy Centre (ACPC) of the Special Initiatives Divisions, along with a multi-stakeholder team in Central Africa.

The project was designed to define a wide array of prototype climate information and services at the subseasonal to seasonal timescale that would be developed in partnership with University of Yaoundé 1, national meteorological and hydrological services (NMHS) and research institutions, by improving or enhancing existing prediction tools.

The project targeted research and data sets needed to develop and use the products at the S2S timescale. The project sought major S2S forecasts and hindcasts from the global data archives at multiweek lead times (15-90 days) in order to be used more efficiently in agriculture. Those fore- and hindcasts from the global data archives were assessed using specific metrics in ways that are tailored to the needs of farmers.

There is a growing demand in Central Africa for refining the agricultural calendar through reliable onset dates of growing seasons and the length of dry spells. The identification of these farmers' needs to co-design, co-produce and co-evaluate climate information is among the best options to evaluate climate models' performance at S2S timescale in Central Africa.

This initiative appeared as a good opportunity to practice sustainable agriculture in Central Africa. The target countries were Cameroon and the Democratic Republic of the Congo (DRC). Other countries should follow. In Cameroon, the agricultural sector employs at least 70 per cent of the labour force. The sector accounts for about 30 per cent of the country's gross domestic product. Agriculture also accounts for at least 40 per cent of total foreign exchange earnings constituted of perennial export crops (bananas, cocoa, coffee, cotton, timber, tobacco, and palm oil). The DRC has a good potential for agricultural development but 70 per cent of the country's population lack access to good and sufficient food. The country's maincrops are cassava, maize and rice.

Since the purpose of this project was delivery of climate information relevant to agriculture in Central Africa, it focused on the agricultural calendar with the starting dates of the growing season. For Cameroon, a south-north positive gradient can be determined from the start dates of the agricultural season. Thus, the growing season starts in March for most of the southern localities, continues through April in the central part of the country (including the Adamawa region), and then June for the northern regions. Concerning the DRC, the growing period, called season A, begins in September for areas near the central part of the country. Growing starts in October for the north-east, and November for the south.

Researchers from UY1 and CIFOR-IITA have co-designed metrics to improve prototype climate predictions for agriculture at the S2S timescale in Central Africa. Now, “onset dates of the growing season” and “prolonged dry spells during the growing season” have been identified as critical climate pressure periods on crops during the sowing and growth phases that reduce crop yields. Criteria (including precipitation thresholds) used to compute these metrics were co-designed by researchers form UY1 and forecasters from national meteorological and hydrological services. Because of the strong spatial variability of the annual rainfall cycle, criteria used to define these metrics for Cameroon are different for those of Congo.

Five global climate model forecasts (BOM, CMA, ECMWF, HCMR, NCEP) were assessed among the 11 models of the S2S forecast database. These five model were selected based on specific criteria such as forecasts must be done at least two weeks before the target period of onset of rainy season, with forecast spans of 2, 3 and 4 weeks ahead the target date, knowing that S2S time ranges are defined between 2 weeks and 3-month scales.

Researchers and forecasters co-evaluated performance of models considering precipitation thresholds used to compute metrics with observation. However, in order to explore potential application bias correction to model forecasts other precipitation thresholds were applied to model outputs to compute metrics.

Analysis of observation data shows that in Cameroon mean onset dates commonly occur during the first half of the year, the earliest in the southern part and the latest in the far north. In DRC, a relative moving trend (earlier to later) of onset dates has been depicted, from north-east to south-west. It gradually becomes late with decreasing latitude. There is a relative pattern of increasing variability of onset date of growing season from the north to the south. Weak variability occurs in the north, where standard deviation is about 8 days, whereas highest variability appears in the southern region, reaching 25 days.

Hindcast analysis shows that for the growing season in Cameroon all models seem to depict a well-observed average (near normal) onset date category. The Chinese Meteorological Administration (CMA) is more skillful compared with the European Centre for Medium-Range Weather Forecast (ECMWF) but even both models show strong deficiencies for the earlier and later onset date categories. Australia’s Bureau of Meteorology (BoM) displays better skill for all onset categories. Over DRC, all models present deficiencies to predict an observed early onset date category. For others onset date category models show improvement, with highest performance for BoM whereas skills of CMA and ECMWF are close together.

A verification of forecasts was conducted using the Standardized Anomaly Index, mean bias, frequency bias, and equitable threat score. Broadly, considering onset dates, models show good skill to forecast “average” or “normal” category of onset dates over Cameroon and DRC with higher frequency bias across large number of stations for CMA, followed by BOM and then ECMWF. In the case of dry spells, exploration of potential application of bias correction to model forecasts, and dry spell detection at a threshold of 1millimetre (mm) reveals that CMA, followed by BoM forecasts, are clearly improved.

Another important output of this pilot project is the established partnership between the regional project team and the International Research Institute (IRI) for Climate and Society of Columbia University. This was launched during a workshop on S2S forecasts organized in the region, and managed by a researcher from the Institute.

As outlooks, much could be furthered after this study in terms of additional agrometeorological metrics such as water availability during the growing season. This is because decisions on cropping patterns can benefit from S2S forecasts during dry spells and on rainfall water available under dry to driest conditions, covering the full growing season. This enables the application of supplemental irrigation, which may require forecasts with lead times of 14 to 30 days. Also, the remaining countries of Central Africa should be involved.

1 Introduction

The economies of Central African countries and their rural households depend largely on agriculture. For this reason, agriculture may be expected to be a key component of growth and development. However, agriculture in Central African is extremely sensitive to climate fluctuations, which may hamper livelihoods, food security and national development in the region. This situation, then, underlines the need to bring suitable climate information into the mainstream of agricultural planning.

The Climate Research for Development (CR4D) initiative promotes and nurtures collaborative user-driven, climate research activities to improve climate information needed for decision-making and development planning in various climate sensitive to socioeconomic sectors over Africa. This initiative appears as a good opportunity to practice sustainable agriculture throughout Central Africa.

Within the framework of CR4D, a four-month pilot research project was implemented in Central Africa. This pilot project set out to assess the effectiveness of global climate model prediction based on selected metrics, in order to improve prototype climate predictions at subseasonal to seasonal (S2S) timescale, with relevance to agriculture in Central Africa. Metrics assessed in this report are onset dates of the growing season and the length of dry spells during the critical phase of the growing season.

The report aims to present outputs from activities of the pilot project. In this report, a unique assessment of modern global climate model prediction database to capture weather indices useful for agricultural planning in Central Africa is presented. This database is an opportunity to explore forecasting events from a subseasonal to seasonal timescale.

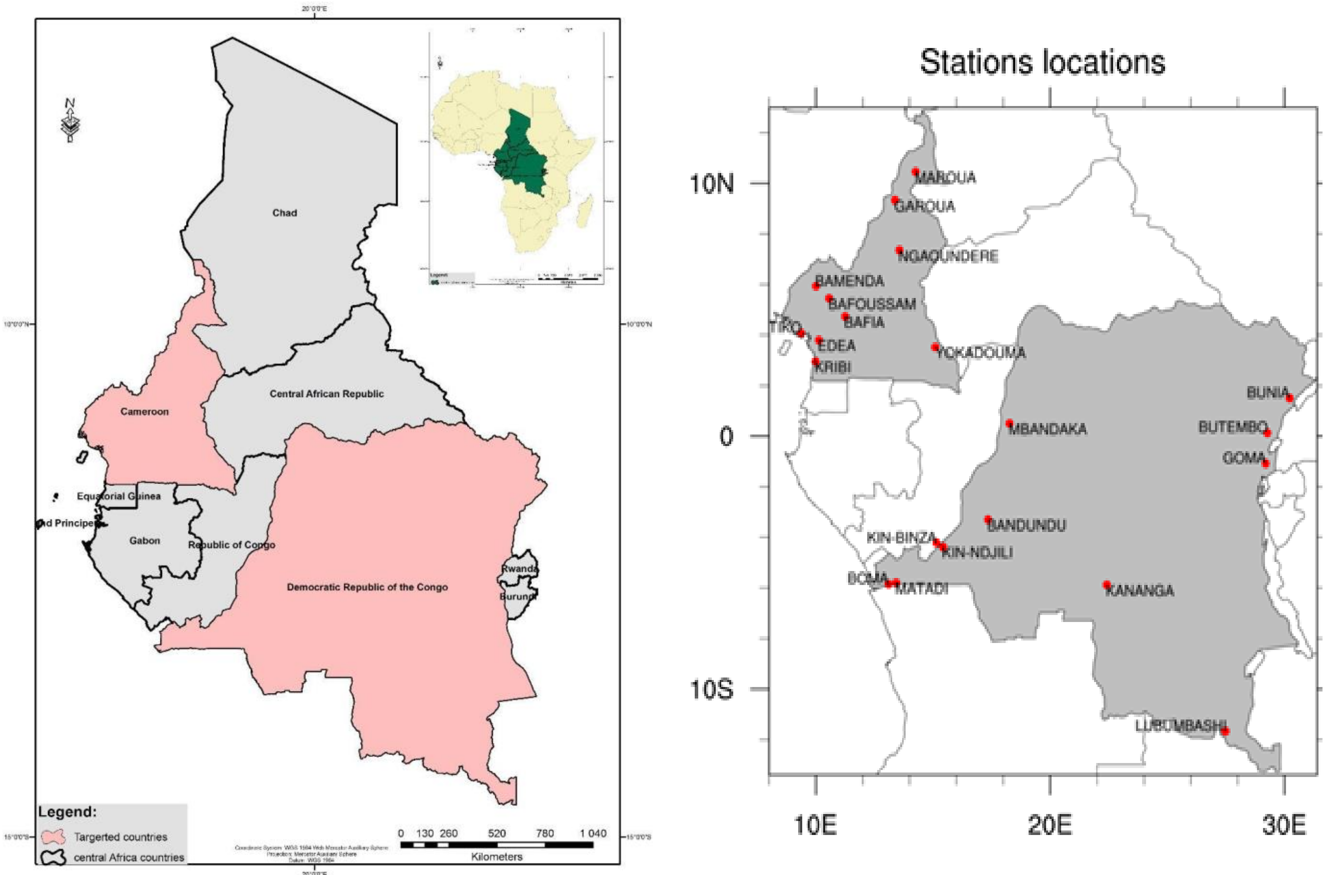
1.1 Target countries and institutions

The pilot project focuses on Cameroon and the Democratic Republic of the Congo (DRC) (see figure 1). These two countries form part of the Congo Basin forest and are members of the *Commission des Forets d'Afrique Centrale* (Central Africa Forests Commission). The stakeholders are from climate information producing units, universities and international non-governmental organizations involved in agricultural research in the region.

In Cameroon, the institution in charge of meteorology is distinct from that of hydrology for Cameroon, while in the DRC both functions are carried out by the same institution. Therefore, for issues related to weather prediction and related climate services, it is apt to use the names National Meteorological Service (NMS) or the Cameroon Meteorological Department for that country, and for DRC the National Meteorological and Hydrological Services.

In Cameroon, four institutions are involved in the project. The first is the NMS, one of whose main mandates is the provision of climate information to all users. Climate information that this service provides consists mainly of weather forecasts and a dekadal agrometeorological bulletin.

Figure 1
Targeted countries in Central Africa (Cameroon an DRC) (left); selected meteorological observation station (right).



Research on weather prediction at the University of Yaoundé 1 (UoY1) is conducted in the Laboratory of Environmental Modelling and Atmospheric Physics, and at the Center for International Forestry Research (CIFOR), a facility of the Consultative Group on International Agricultural Research (CGIAR). A team member working at CIFOR is also involved in activities at the International Institute for Tropical Agriculture. In Central Africa, activities of these research institutions integrate management of information to farmers for the application of sustainable agriculture.

The meteorological and hydrological services of DRC also partake in this project. These services have great experience in co-design and provision of weather information to farmers across the country.

1.2 Target user sector

In Cameroon, at least 70 per cent of the labour force is employed in the agricultural sector, which makes for about 30 per cent of the country's gross domestic product. Agriculture also accounts for at least 40 per cent of total foreign exchange earning constituted of perennial export crops: banana, cacoa, coffee, cotton, palm oil, timber and tobacco (Gbetnkom and Khan, 2002; Binam et al., 2004). This position has been maintained since the 1970s by neighbouring Central African Republic, Chad, Equatorial Guinea, Gabon, and the Republic of Congo. The crops are mainly maize, plantain, potatoes, bell peppers, carrots, onion and tomato. In this way, Nkendah (2010) concluded that Cameroon was the leading trading partner in the Economic and Monetary Community of Central African countries even if 96 per cent of this trade was informal and constituted agricultural and horticultural commodities.

In the Democratic Republic of Congo, 70 per cent of the population does not have access to good and sufficient food yet the country has a huge potential for agricultural development. The principal crops in the country are cassava, maize, rice (MAPE, 2009). Rubber, cacao and palm oil production has been growing since the governmental institution in charge of agriculture has granted large areas of land to agro-industries.

The report is organized as follows. An overview of agroecological context in Central Africa is the aim of section 2. Section 3 presents the type of climate information need for Central Africa, and the related metrics. Global climate model (GCM) prediction database and methods used to assess their accuracy to represent metrics are presented in section 4. In section 5, the subset of GCM forecasts used to assess the accuracy of forecasts to capture onset date and dry spell length over Central Africa is analyzed. Section 6 ends the report with conclusion and outlooks.

2 Overview of Agroecological Context in Central Africa

Daily precipitation data used in this study was provided by the Cameroon and DRC national meteorological services, which are 30 years of daily rainfall available from 1971 to 2000. For Cameroon, 10 meteorological stations in the country's five agroecological zones were used (see figure 1, right). For DRC, daily precipitation data came from 11 of the country's 24 stations. It was very important that all agricultural meteorological data be carefully scrutinized. Quality control was done according to Wijngaard et al. (2003) WMO-TD No. 1236 (WMO, 2004*a*) and following the *Guide to Climatological Practices* (WMO, 1983). When a value was unreasonable, it was corrected immediately. After being scrutinized, metadata were needed. Though, these details and history of local conditions, and instrumentation, operational, data processing and other factors relevant to the observation process (WMO 2003*a*, 2003*b, 2004a*) are missing or often incomplete.

2.1 Climatology of selected stations' observations

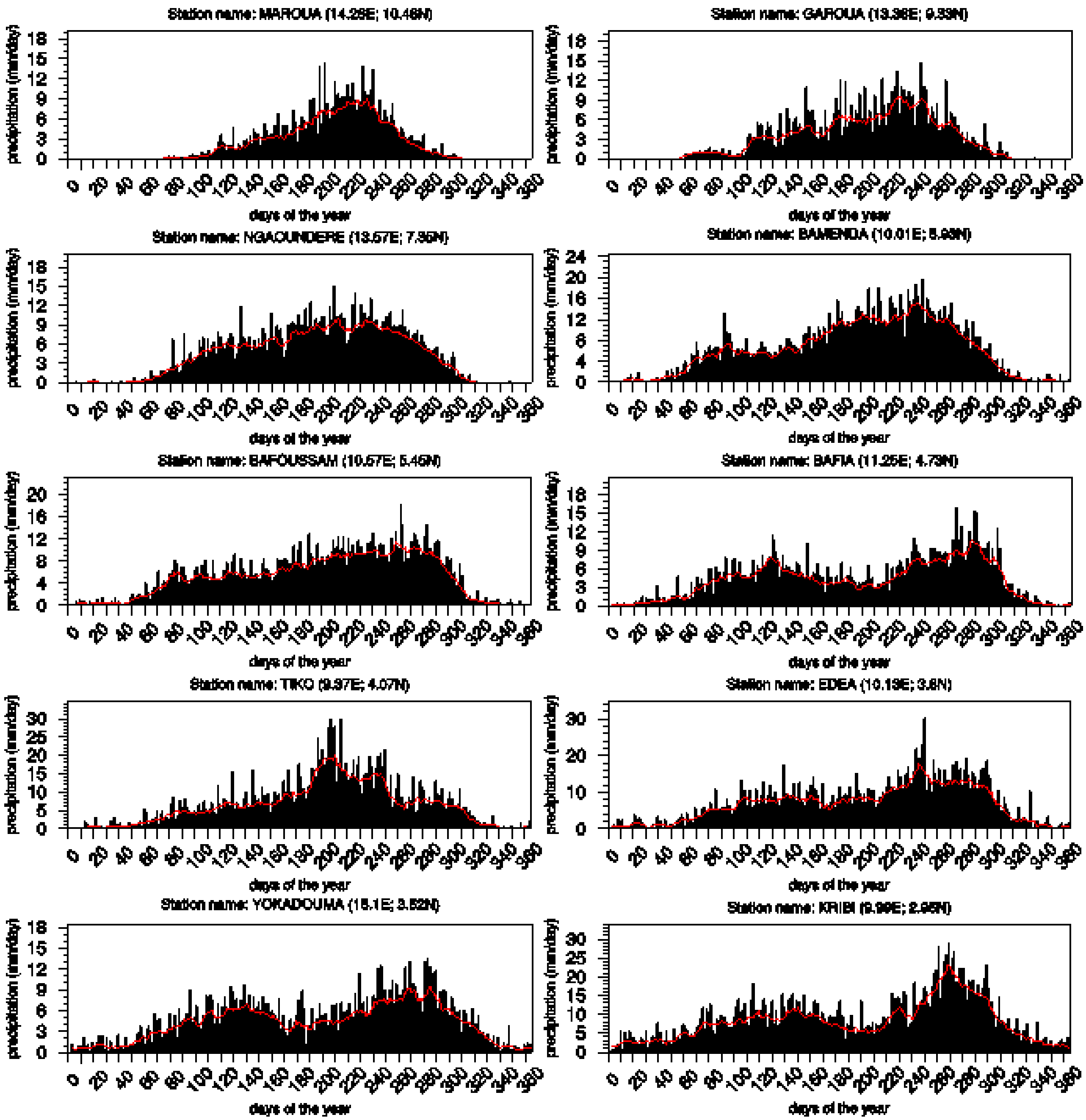
Cameroon

In Cameroon, observation data originate from stations in the following agroecological zones across the country:

- The northern Sudano-Sahelian zone encompasses the country's northernmost regions. The region is characterized by yearly total rainfall ranging from 500 to 1,000 mm with only one modal rainy season. The region includes Maroua and Garoua meteorological stations. Less than 10 per cent of missing data was found and filled with those of neighbouring stations such as Yagoua and Tchollire. The region is characterized by unimodal annual cycle of rainfall (figure 2). The peak of rainy season is commonly recorded in August. Climatic constraints over here contribute largely to the fluctuation of sowing dates.

Figure2

Climatology (1971-2000) of annual cycle of rainfall at meteorological observation stations in Cameroon



The Central Adamawa Plateau includes the Adamawa Highlands, parts of eastern and central regions, with mean annual rainfall approximating 1,500 mm/year. It hosts the Ngaoundéré meteorological station (figure 1). The rainy season spreads over the year with a higher amount of rainfall compared with the northern Sudano-Sahelian zone. The Adamawa Plateau's transitional soil is fertile and cultivated with maize and cotton, while tightly limited by protected pastoral areas. Here also, less than 08% of missing data were found and filled with those of Tibati. The humid southern tropical forest zone has the highest yearly average rainfall, approaching 2,000 mm. A bi-modal rainfall regime and two dry seasons characterize the zone, which incorporates the Bafia and Yokadouma meteorological stations. Less than 5 per cent was filled with data from Yaoundé and Abong-Mbang. The association of food crops with modest agro-industrial activity in palm oil, coffee and cocoa contribute noticeably to deforestation.

- The Atlantic Ocean coastline is the wettest of the zones, receiving about 4,000 to 11,000 mm of annual rainfall. This is due to the year-round high content of relative humidity. The zone hosts the Douala, Tiko and Kribi meteorological stations (see figure 1). Just few data were missing here. The most best agro-industrial farms are in this coastal belt, supporting rubber trees, palm oil, banana, and many other cash or food crops.

- The Western Highlands, which is the coolest area in the country, is still fairly moist to the north of the forest due to the mountain chain that brings increased rainfall to the towns of Koundja, Bafoussam and Bamenda, while dominated by bimodal annual cycle of rainfall (see figure 2). These towns are served by meteorological stations (see figure 1). Very little missing data was found at these stations. Soil fertility varies with the terrain and that is why different types of cultivation are applied in double annual cycles, combining perennial culture like coffee and fruits trees, rice, tea and tobacco.

Democratic Republic of Congo

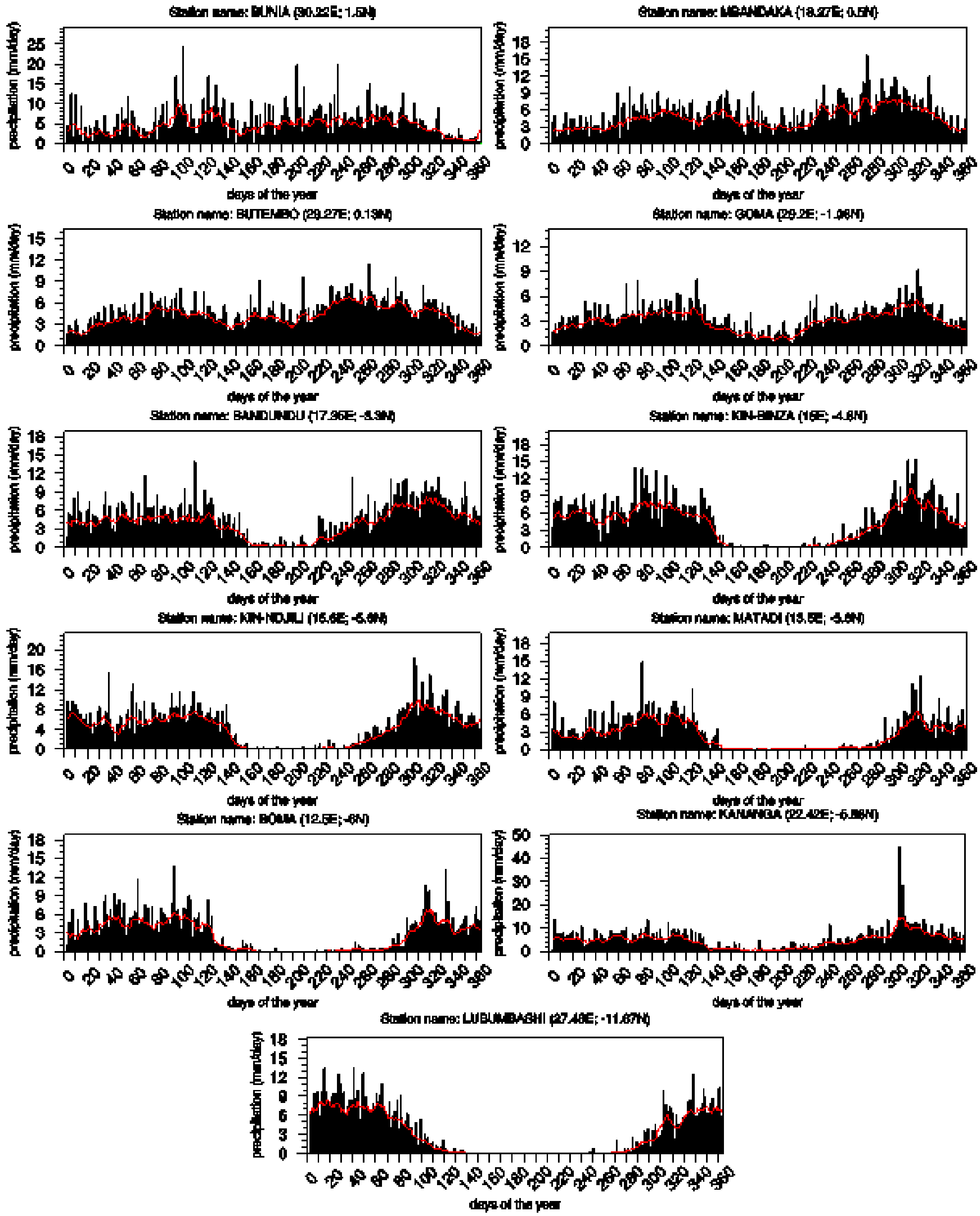
DRC data used are daily precipitation records from 11 of the 24 stations spread across the vast country. The mountainous climatic zone in the north hosts the Bunia meteorological station (see figure 1). Annual precipitation exceeds 1,800 mm in the north-east in which Bunia lies, with nine months of rainfall from mid-December to mid- or end of February (see figure 3). Butembo (figure 1), also in the north-east where climatic conditions are typically equatorial, experiences two rainy seasons (March to May, and September to November) (see figure 3) and two relatively dry seasons from June to July and from mid-December to mid-February. So, the dry season covers about two months, while the remaining 10 months are dominated by 9 months of rain. The eastern city of Goma (figure 1) receives 1,250 mm of rain per year, even though these are not plentiful from mid-June to mid-August. The station in the north-western records annual rainfall of 1,600 to 2,000 mm.

For stations in the south-western part of the country such as Bandundu (figure 1), rainfall still resembles the equatorial type with 1,500 to 2,000 mm per year. There are profusions August to May (figure 3), and much more in early season from September to December. June and July form the dry season. Rainfall in

Kinshasa, the nation's capital, is heavy from mid-September to mid-May,

Figure 3

Annual rainfall cycles across DRC (1971-2000)



With an average annual volume of 1,529 mm, Matadi and Boma are in the rainiest region of the country. The climate characteristic in this region is that it rains progressive less as one moves from the coastal belt inland toward the east. The dry season here is longer, from May to November, with another short and sharp dry season in February. This is a region with an inter-annual variation between 900 and 1,500 mm. Farming is concentrated between November and May.

Over the south-east around Kananga, the annual average rainfall is about 1,500 mm, and it generally presents well-marked rainy seasons running from August to December and from January to April, with a dry period in February, and from May to July. Lubumbashi's dry season starts between May and mid-October and a rainy period stretching more than six months. The rainfall total is about 1,200 mm per year, which peaks December to February.

2.2 Agricultural calendar

The project aims to deliver needed climate information to farmers in Central Africa that would help them plan their activities, efficiently. The date to start growing crops is vital information farmers need for them to gain maximum harvest yields.

For Cameroonian stations, a south-to-north positive gradient can be determined from the start dates of the agricultural season. This has been identified as March for most of the southern localities (except the stations of Bafia, see figure 4); April for the central part of the country (including the Adamawa region represented by the Ngaoundéré meteorological station); and June for the northern stations that include Garoua and Maroua.

The Democratic Republic of the Congo's (DRC) growing seasons are in three segments: A, B and C. Some areas have two or three growing seasons (see table 1). Refer to figure 1 for the country's meteorological observation stations.

Table 1.
Growing season for different regions of DRC

Province	Season A	Season B	Season C
Kinshasa	October/November	February/March	June/July
Bandundu, Kananga	October/December	March/May	
Goma, Butembo	March/April	September/	
Mbandaka/Bunia	March/April	October	
Lubumbashi	November/December	March/April	May/August

The DRC has huge agricultural potential. Its climate is warm equatorial, humid in the central axis of the country, and increasingly tropical the farther away from the equator. The rainy season lasts 2 to 9 months a year depending on the region, and supports two types of growing seasons.

- Method in two cropping seasons: The long rainy season A allows for two annual crops without the need for irrigation. Season B represents the short rains. Both seasons occur in the humid equatorial areas where the longer rainy season is interrupted by a short dry spell; and in an area with two short but heavy rainy seasons, and two long dry seasons.

- Method in three growing seasons: The other situation is on of growing seasons A, B and C. Seasons A and B are during the period when crops are rainfed. Growing season C requires irrigation. All three cropping seasons are practiced in wet and dry tropical areas; there two long and short rainy seasons with a longer dry season.

2.3 Main crops

Cameroon is considered as a granary of Central Africa. The country is divided into five agroecological zones. The national adaptation plan to climate change has provided a list of crops that could be grown per agroecological zone see table 2.

Table 2
Agroecological zones of Cameroon and corresponding crops

Agroecological Zones	Rainfall and Temperature (Annual Value)	Crops
Sudano-Sahel	☐ Rainfall: 400-1,200 mm ☐ Temperature: from 28°C to 35°C	Sorghum, cowpeas, millet, maize, rice, vegetable crops, melon, vegetable, cotton.
High Guinea Savannah	☐ Rainfall: 1,500 mm with 150 rainy days and 5 dry days per year ☐ Temperature: 25°C to 28°C	Peanuts, rice, maize, cassava sweet potato, yam, cocoyam
Western Highland	☐ Rainfall: 1,500-2,000 mm with 180 rainy days and 4-5 dry months ☐ Temperature: 22°C to 25°C	maize, rice, taro tubers, cocoyam cassava, palm oil, tree, citrus, arabica and robusta coffee, tea, cocoa
Humid forest with bimodal rainfall	☐ Rainfall: 1,500-2,000 mm in two distinct wet seasons and 3 dry months ☐ Temperature: 24°C to 26°C	Sugar cane, plantain, cassava, palm oil, peanut, cocoyam, yam, leaf vegetable, condiments, robusta coffee, tobacco, rubber, cocoa
Humid forest with	☐ Rainfall: 2,500 to 9,000 mm with	Cocoa, coffee, palm oil, vegetable

unimodal rainfall	unimodal Plan and 3 dry months Temperature: 25°C to 27°C (15°C to 24°C at Mt Cameroon)	crops, rubber, tea, pepper, pineapple, plantain

Source: MINEPDED (2015)

From table 2, it can be deduced that Cameroon's climatic diversity enables the country to produce a variety of perennial and annual crops.

The Democratic Republic of Congo has three agroecological zones: humid, sub-humid and highland. The Food and Agricultural Organization of the United Nations has supported agroecological zone studies that have identified the best regions for the production of key perennial crops such as rubber, coffee, palm oil, cotton, tobacco; and annual crops such as rice, soya beans, sugar cane, cassava, peanuts, plantain, maize, beans, potatoes and wheat. In terms of value, the main agricultural products are cassava, plantains, "game meat", maize mangoes, and mangosteens. The main agricultural exports in terms of value are raw tobacco, green coffee, raw centrifugal sugar, wheat bran and natural dry rubber. The main agricultural imports in terms of value are wheat, maize, wheat flour, palm oil and chicken meat (UNDP, 2013).

Table 3

Agroecological zones in DRC and corresponding crops

Crop Region	Rainfall and Temperature (Annual Value)	Crops
Bandundu	• Annual Temperature: 20°C to 25°C • Annual Rainfall: 1,500 to 2,000 mm/an	Cassava, maize, rice, carrot, peanut, palm tree, gombo, zucchini, cucumber, cabbage, tomato, aubergine (also called eggplant), chili, basal, amaranth and roselle
Bas Congo	• Annual Temperature: 19°C to 30° C • Annual Rainfall: 1,000 to 1,500 mm	Cassava, maize, rice, carrot, cucumber, cabbage, tomato, aubergine (eggplant), chili, basal, amaranth, roselle
Equateur	• Annual Temperature: 21°C to 30° C • Annual Rainfall: 1,200 to 1,800 mm	Pantain, cassava, corn, rice, palm, yams, amaranth, basal, zucchini, pumpkin, peanuts, soybeans and cowpea

Kasai Occidental and Oriental (West and East Kasai)	• Annual Temperature: 24.2°C to 31.4° C • Annual Rainfall: 1,400 to 1,900 mm	Maize, cassava, rice, gombo (okra), zucchini, pumpkin, aubergine (eggplant), chili, tomato, cucumber, amaranth, cowpea, and voandzou
Katanga	• Annual Temperature: 11.3°C to 24.6° C • Annual Rainfall: 1,150 to 1,568 mm	Maize, cassava, gombo (okra), zucchini, pumpkin, aubergine (eggplant), chili, tomato, cucumber, amaranth and roselle
Kivu Nord & Sud (North and South Kivu)	• Annual Temperature: 1°C to 19°C • Annual Rainfall: 1,000 to 2,000 mm	Sweet potato, potato, taro, cassava, beans, plantain, headed, cabbage, onion, tomato, cucumber, chili and wheat
Maniema	• Annual Temperature: 18°C to 26°C • Annual Rainfall: 1,300 to 2,300 mm	Cassava, rice and palm
Province Orientale (Oriental Province)	• Annual Temperature: 23.9°C to 30.1°C • Annual Rainfall: 1,400 to 2,000 mm	Cassava, plantain, rice, palm, taro, sweet potato, potato, bean, peanut, soy, tomato, chili, aubergine (eggplant), okra, cabbage and cowpea

3 Climate Information Agriculture Needs in Central Africa

In Central Africa, adaptation to climate change is required urgently because agriculture remains the main, if not the only, source of income and food security for the rural population. This means that adaptation measures need to focus on climate-related vulnerabilities. Improving the resilience of farmers by providing agrometeorological information and capacity-building of key stakeholders in agricultural development can enable those engaged in the sector to understand and respond to climate risks, profitably.

3.1 Impact assessment of climate variability on crops

Agricultural activities across Central Africa are limited to the rainy season. Therefore, any seasonal climatic change places severe constraints on farming. Reliable climate information is needed for efficient agricultural planning. Providing such information requires assessment of how weather affects fields and other agricultural activities. This section aims to present the impact of climate variability on crops in Central Africa.

- The onset and quantity of rainfall has become highly variable. Some parts of Central Africa experience a decrease in annual rainfall and farmers are unable to know when to plant and where to find pasture for their animals. Climate variability can lead to massive flooding and land erosion in drylands. These situations can worsen when crops are affected by diseases that appear during heavy rains, flooding and drought. These conditions have stagnated crop. Information of climate constraints faced by farmers in central Africa is assessed, with focus on
Cameroon and DRC

Cameroon

Cameroon has been identified (Burke et al., 2009) as one of the countries susceptible to the negative effects of climatic variability. This climate phenomenon may lengthen or shorten the dry and rainy seasons, the duration of rains, make rains unpredictable, cause floods, or lead to prolong droughts. For example, climate variability has led to the withering of rainfed rice, peanuts and corn, and cocoa trees have failed to flower (Bele et al., 2011). At times, some plants may bloom too early. Similarly, with variability farmers must delay planting of cotton from 5 to 10 days (Gérardeaux, Sultan et al. 2013). Variability can also extend the growing season, expanded range of some insect pests, and cause wind damage. The Institute for Agricultural Research for Development of Cameroon has discovered water stress on cocoa trees. The stress is that the amount of water the plant transpires is greater than the amount it absorbs. An abnormal loss of flowers, severe attacks by pests and diseases result in a considerable drop in yields (Ndoumbe-Nkeng, 2009).

Democratic Republic of the Congo

In DRC, 90 per cent of farmers have already experienced at least one natural climate-related disaster (MINECT, 2006). A study in Kisantu shows that drought had caused seeds to shrivel. Moreover, pollen and seeds lost their germination capacity. Therefore, the withering of grains and formation of shriveled, seedless pods worsened. Increased heat also leads to poor harvests of cassava, which is the main crop. During cassava's tuber formation when it needs water to mobilize the nutrients, being in suspension, the crop is highly sensitive to soil moisture content. The frequency of heavy rainfall has favoured the emergence of telluric microorganic gnawing tubers. DRC might face serious problems of nutrition due to global change (Liu, Fritz et al. 2008). For this reason, the National Service of Seed (SENASEM) is providing new seeds of maize, rice and cassava that can adapt to this climate variability. The banana weevil has developed these recent years in Bas-Congo Province's Luki region, where recent climate conditions has favoured the pest's development as rainfall has increased by 392 mm, temperature by 1.6°C, and relative humidity by 3 per cent (Ngombo-Vangu, 2007).

3.2 Climate information needs for agriculture

This section aims to identify current climate services information delivery and related tailored products, and suggests a design for such products for Central Africa.

Climate information for agriculture

To improve the availability, quality and use of climate information in the region this information should cover different timescales: medium term (from one week to one month) and long term (more than a month, including the seasonal timescale). Outputs from surveys show that main climate hazards that negatively impact agriculture are heavy and erratic rains, floods, drought, and unpredictable dry spells in the rainy season, and rain during the dry season. Other climate stresses are increasing temperatures with prolonged dry periods, lengthening and shortening of dry and rainy seasons, strong winds and drought (Bele et al, 2013 and 2014; Mukakamari and Cheteu, 2014; Denis J Sonwa et al., 2016). Table 1 presents recorded climate hazard and related climate information that can help farmers plan to be more resilient to variability.

Table 4

Climate hazards recorded over Central Africa and related climate information

Events that Can Affect Agriculture	Climate Information Related to Event	Climate Information Farmers Need
Prolonged episode of heavy rain	Number of days of heavy rain	• Onset of rainy season • Period of heavy precipitation during the rainy season • Duration of heavy rain episode
Prolonged episode of drought	Length of dry spell during the rainy season	• Onset of rainy season • Dry spells distribution during the rainy season • Dry spells duration
Floods	Heavy rain	Occurrence of heavy rain
Pockets of drought in the rainy season	Number of dry spells in the rainy season	• Number of days of drought in rainy season • Period of drought in rainy season
intense of drought	Length of dry season	Onset and cessation of dry season
Pockets of rain in the dry season	Occurrence of wet spell in dry season	• Onset of dry season • Number of raining days in dry season
Violent winds	Wind speed	Occurrence of day with strong wind speed
Torrential rains in the season	Heavy rainfall	• Onset of rainy season • Occurrence of heavy rainfall
More intense and longer	Number of hot days	• Onset of dry season

heat spells in the dry season	during the dry season	• Occurrence of hot day • Length of consecutive hot days
Shifts in seasons	• Onset of dry season • Cessation of dry season • Onset of rainy season • Cessation of rainy season	• Beginning of dry season • End of dry season • Beginning of rainy season • End of rainy season
Severe frequent drought	Occurrence of hot days	• Onset of dry season • Occurrence of very hot days during the dry season

This information can form newsletter comments on the state of the atmosphere at the weekly, monthly, seasonal, and dekadal timelines. The type of products specific to the agricultural component of climate information are the following:

- Seasonal forecasting, and early and late seasons for varieties of agricultural seeds
- Weather forecasting, dekadal and the beginning of the season for field preparation
- Climate Monitoring Bulletin (forecasting and observation humidity, temperature, rainfall, extreme events treatment) for pest monitoring
- Climate Monitoring Bulletin (weekly or dekadal rainfall, observation, for irrigation flowering activity
- Climate Monitoring Bulletin for harvesting, seed storage
- Maximum water deficit or surplus experienced in any one dekad
- Total water deficit or requirement at different stages of crop growth
- Dekadal to seasonal total rainfall forecast
- Rainy season onset
- Standardized precipitation index
- Soil water content
- Dry spells

Definitely, Cameroon must establish a climate service able to provide information that will enable farmers to make better decisions for sustainable agricultural production. Some interactions needed between farmers and national meteorological services are presented here:

- Awareness of farmers on progress to be made to disseminate weather and climate information to help them make decisions about their activities. Taking farmers into account, national meteorological services can design products better suited to farmers' needs and improve the flow of information

- Establish demonstration phases of experience gained elsewhere, to help farmers understand current methods used to manage climate and weather risks on the scale of farming in different regions. In addition, they contribute to the development of better risk management tools for farmers.

Current climate services in Central Africa

In Central Africa, climate information and services are obtained from different sources, mainly national meteorological and hydrological services that serve their governments and other users in their respective countries. These services maintain observation networks and provide raw data on demand. They often provide weather and climate forecasting for one, five, or seven days, and on seasonal timescales. In addition, some national meteorological services occasionally provide agrometeorological bulletins.

National meteorological services collaborate with several institutions outside the region for climate service deliveries. The World Meteorological Organization, African Centre of Meteorological Applications for Development (ACMAD) and AGRHYMET often provide services and training for meteorologists of some Central African countries. These organizations help these countries to use meteorological forecasts to study the application of the science to various aspects of farming. ACMAD encourages the use of meteorological data for development. Together with AGRHYMET they are main providers of climate information through early warnings, severe weather watch and seasonal forecasts applicable in agriculture.

ACMAD transfers weather and climatic knowledge to national meteorological services throughout Central Africa. For example, in addition to the African Climate Watch Bulletin, ACMAD has developed Numerical Weather Product analysis, translated the remote sensing meteorological products shared with global and regional climatic centres, research establishments and universities. Alongside climate services providing spatial and temporal extreme weather and climate warnings, ACMAD makes available a climate risks cartography and climate raw data from remote sensing, as well as developing a regional database or archives. ACMAD and AGRHYMET are facilitating a data exchange network between WMO, national meteorological services, and international research centres, and are developing tools for research and application in agriculture. ACMAD and SMNH have organized regional climate outlook fora to improve climate information products and dissemination. The information is usually broadcast by radio, television, newsletters and, in some cases, by email.

National meteorological services use FEWS NET's material to produce information in support of agriculture. These include:

- Dekadal (10 days) rainfall estimates
- Monthly (30 days) rain and dry days, and anomalies
- Seasonal evapotranspiration anomaly d surface temperature
- Total precipitable water
- Drought status monitor tool based on weather and crop conditions (experimental)
- Standardized precipitation index maps (SPI-Z score)
- Soil water index

At the national level, communication and counselling skills need to be developed in order to translate the atmospheric knowledge of forecasts throughout specific applications and formats that meet the needs of particular development sectors, in this case agriculture. This kind of climate service is currently very restricted. A few countries, including Cameroon and the Democratic Republic of Congo, strive to issue agrometeorological bulletins on a dekadal basis, but the limitation in forecast communication and dissemination means end users are unable to get the information. Additionally, information that regional climate outlook provide are not in a form that farmers can understand.

Current satellite imagery provided by the African Monitoring of the Environment for Sustainable Development project (or updated PUMA2015-MESA) is scrutinized for indications of dust storms so that early warnings can be given to farmers to take appropriate precautions. Wind patterns such as the north-easterly dry and dusty *Harmattan* is monitored because it carries germs that can (mechanically or physiologically) attack certain crops like cocoa and cassava. However, some additional information like rainfall estimates, vegetation index and ancillary data on temperature and wind need to be refined to target requirements at each local level.

3.3 Capabilities of national meteorological and hydrological services to deliver downscaled climate information at S2S timescale

This section presents the following characteristics of meteorological services in Cameroon and DRC.

- Evaluation of the current agrometeorological observation network
- Evaluation of current agrometeorological forecasts at S2S timescale
- Evaluation of material resources and capacity-building useful to the agricultural sector

3.3.1 Cameroon Meteorological Service

The Cameroon meteorological service is known as *Direction de la Météorologie Nationale*, and was founded before 1962. Since then, it has been under supervision of the Ministry of Transport. The Met service is staffed by about 64 individuals for the whole country; at least 100 more engineers, technicians and observers will be recruited in the next decade. The meteorological service engages in eight activities. Of these, agrometeorology furnishes climatological information and forecasts for the agriculture community, which includes Government agencies, planning authorities, and academia. The service is supposed to issue climate reports on a regular basis and, on special occasions, develop different specialized agricultural forecasts like evapotranspiration, floods and drought warnings, in association with the Forecasting Unit.

The national meteorological network comprises about 5 synoptic stations, 20 automatic weather stations, 34 climatic stations and about 200 rain gauges. For field observations being collected and transmitted efficiently, the Observation Network should be operated and maintained continuously in all subdivisions. Presently, agricultural observations are made only by 10 automated weather stations in addition to the rainfall measurements from the 200 rain gauge stations. Some of these stations are not operating at world meteorological standard because they lack appropriate instruments and qualified observers. Many synoptic agrometeorological stations have been closed, while only 10 per cent of information is able to reach the national meteorological centre monthly for processing because of difficulties in transmission. Therefore, only data that the ASECNA airport facilities provides can attain the international transmission network standard.

Even though the Cameroon Meteorological Service has the legal mandate to provide nationwide services to the agricultural sector, other institutions can develop their own climate information amenities at local level. For example, the Ministry of Agriculture and Rural Development (MINADER), the Cameroon Development Cooperation the Institute of Research in Agriculture and Development (IRAD) maintain their own meteorological stations, which enable them to monitor specific parameters (rainfall, temperature and humidity). Yet they rely on the national meteorological service for timely tailored and downscaled forecast at subseasonal to seasonal timescales.

At times, national Met services issue seasonal, monthly and dekadal forecast bulletins to the Ministry of Agriculture and Rural Development's Department of Agriculture Statistics and Surveys for information and early warnings. But it is really difficult to know if these types of climate information are useful, since there is no feedback from end users in order to meet their needs. During the first meeting launching the National Framework for Climate Services, it was recognized that few frameworks exist that can institutionalize interactions between the National Framework, agricultural technicians and local users for the co-production of tailored climate services. On the ground, exceptional climate information that is not yet produced at S2S timescales could be undertaken. These are, for example, the onset and cessation of rains, dekadal and monthly forecast of dry spells, and early warning of severe weather.

Consequently, national meteorological services are rarely, if ever, prepared for these specific events. No precise information is issued except routine 10-day agrometeorological bulletins. This deprives policymakers of the ability to decide on suitable measures to mitigate or adapt to adverse climate phenomenon. To fulfill its responsibility, national meteorological services must be given the sufficient qualified staff, technology and telecommunication facilities for climate monitoring, forecasting and research, alongside with capacity-building. They must also be responsible for providing climate information to agrometeorological users. This would be the stepping stone to modernizing these services, which would enable them to contribute to sustainable development once fully equipped with modern instruments and automatic weather stations. Accordingly, the services should be responsible for gathering, assessing, archiving and sharing lessons about all weather or climate impacts. Moreover, because impacts are cross-sectorial, the services must be empowered to deal with disaster risk reduction management in agriculture and other related development sectors.

Routine climatological and agrometeorological services including queries required as evidence in a court law and consultation advisories. Among climatological and agrometeorological routine publications there are the following:

- Regular dekadal (10 days) – climate bulletins, Agromet. Bulletin
- Monthly – rainfall bulletin, Agromet. Summaries to agricultural journals
- Seasonal forecast – ACMAD rainfall report. A climatological report**.**

Cameroon Meteorological Department strives as far as possible to provide tailored products for that requested by the following sectors:

- Governmental authorities and public institutions (Ministry of Agriculture)
- General public
- Media
- Commercial and industrial sectors
- Universities and academic institutions
- Agricultural Growers’ Organization
- Agricultural settlements (not yet operational)
- Small farmers
- Faculties of Agriculture and Agricultural engineering, research institutes (IRAD) & regional research and developments (CARBAP) units
- Insurance Fund for Natural Damage in Agriculture
- Agricultural insurance companies
- Agricultural assessors

Planning and public policies as well as the incorporation of information at S2S science-based forecasts are necessary to achieve better management of risks related to climate variability and change, in order to promote adaptation at all levels. Research, modelling and prediction at the S2S timeline of the thermal comfort of main crops, in addition to the development of new index (ENSO), as well as information on the dry and wet periods are valuable. Accordingly, there is a need for communication expertise, training in downscaling “regional-specific” S2S forecasts, roving seminars, and computing resources in order to communicate timely and reliable forecast. Henceforth, when people adopt a “wait and see” attitude, accurate information of these meteorological services can influence the decision governments take on the agricultural sector.

3.3.2 METTELSAT (National Meteorological Service of the DRC)

DRC’s national weather service has been known since 1991 as the National Agency of Meteorology and Remote Sensing by Satellite (METTELSAT). The service was created in the 1930s under the Department of Agriculture and became the National Meteorological Institute to provide meteorological and climatological services through forecasts for the safety of air navigation. Additionally, with agricultural services and research centres, the service published climatological journal directories.

METTELSAT’s 750 workforce is aging; 73 per cent of employees are nearing retirement, which forewarns of a looming critical skills shortage. Current staffs include 37 engineers (meteorologists, hydrologists and agrometeorologists), 143 meteorological technicians, and an environmentalist.

The service established a network of 60 weather observation stations in 1933. After Independence in1960 the weather service had 126 major synoptic observation stations, and 900 rainfalls stations which no longer exist today. Recently, 22 automatic weather stations were installed but four are non-functional due to lack of maintenance. No altitude network station is effective and only 10 stations store data from 1960 to 2014. The remaining stations have a timeline of data from 40 to 90 years, with gaps. All the data available are in hard copy, and sometimes dating from 1945 to 2017.

The data processing system organized within METTELSAT is based on raw data. Quality control is exercised by corrections of transcription errors when entering or while watching data needed for a study, or to produce weather and climate forecasts. The service provides daily weather bulletins for 24 hours, the dekadal bulletin containing information on weather and climate conditions observed over past 10 days, a rainfall prediction for the 10 coming days, and the seasonal climate forecasting newsletter produced monthly for a three-month season.

The dekadal bulletin was established in 2012, through the National Climate Change Adaptation Programme to implement a project of adapting the agriculture and food security sector (PANA/ASA project) to climate change. The PANA-ASA project comes as a response to vulnerability, increasingly apparent in the agricultural sector due to climate change challenges in the country. This vulnerability mainly affects rural areas, where agriculture remains the mainstay for incomes and food security. The project contributed to improve resilience through the provision of technological packages, agrometeorological information, and capacity-building of key stakeholders in agricultural development, enabling them to understand, analyze and respond to climate risks adequately. For weather information, the project has set up a hydro-agroclimatic advisory network with the following activities:

- Alignment and analysis of existing agroclimatic data
- Acquisition or rehabilitation of infrastructure monitoring
- Agrometeorological observations
- Development of agricultural calendars
- Early warning

The project involved METTELSAT, which upgraded the skills of personnel at agrometeorological stations of the Environmental Institute for Agricultural Research (INERA), and helped local communities to receive and use agrometeorological information in planning their farming. METTELSAT supported the INERA research centre at Ngandajika (Kasai Oriental) and at Kipopo (Katanga), Kiyaka (Bandundu) and Gimbi (Bas Congo) to carry out the following:

- Establish a standardized database (data encryption, file format, software for the analysis and exploitation of existing data and harvest)
- Treat and use weather data recorded for several decades with INERA agrometeorological stations
- Develop weather and climate forecasting (choice and reliability of the model)
- Carry out meteorological observations
- Maintain recording equipment meteorological data
- Establish and manage an early warning system
- Contribute to the development of a dynamic agricultural calendar in each region with the project

Disseminated data are often weather forecasts, sent by email to media establishments and other interested parties.

Despite the national meteorological service's infrastructure, operations and staff difficulties to meet WMO standards and apply the Global Framework Recommendations, the Climatology Unit is able to provide agrometeorological information needed by farmers. However, it is important that the service strengthens its ability to implement the following:

- A dense network of observation stations
- Another network of stations where agricultural activities
- Establish partnership with public and private institutions with weather stations and post rainfall
- Establish a weather and climate database with information from the partners
- Increase personal recruitment
- Set up an effective communications network to transmit data and information
- Set up an agrometeorological assistance programme on agricultural production to provide the following information:
    - Meteorological conditions, climate and dekadal forecasting

- Seasonal prediction
- Early warning of climatic hazards
- Insolation
- Evapotranspiration
- Bird and insect migration monitoring
- Agricultural production forecasting
- Monitoring of cultivated areas and managed valleys
- Mapping of surface water resources and depths

4 Data and Methodology

4.1 Data

4.1.1 Observation data

The Cameroonian and DRC national Met services provided daily precipitation data used in this study. It consisted of daily rainfall data from 1971 to 2000. Ten meteorological stations in the five agroecological zones across the country were used for Cameroon. For the DRC, daily precipitation data from 10 stations across the country were used. Quality control was applied on these data (Wijngaard et al. 2003; WMO, 2004a; WMO, 1983).

4.1.2 Model data

Description

The S2S data were provided by the Australian Bureau of Meteorology (BoM), the Chinese Meteorological Administration (CMA), Environment and Climate Change Canada (ECCC), the European Centre for Medium-Range Weather Forecast (ECMWF), the Hydro Meteorological Centre of Russia (HMCR), the Institute of Atmospheric Sciences and Climate (ISAC-CNR), the Japan Meteorological Agency (JMA), the Korea Meteorological Administration (KMA)[1], the French National Centre of Meteorology (Meteo-France/CNRM), the United States National Centers for Environmental Prediction (NCEP), and the United Kingdom Met Office (UKMO).

S2S database archives include near real-time ensemble forecasts and hindcast (reforecasts) up to 60 days from 11 centres (Vitart et al., 2016). Reforecasts (or hindcasts) were run using the current version of the forecast model but for past several years on the same (or nearby) calendar day as the forecast. As the known (or closely estimated) climate state of these past periods were used to initialized models, hindcasts could be used to see how well model output matched observation, and also to calibrate actual forecast.

The frequency of initializing forecast varies from one model to another, and the main characteristics are

[1] That of South Korea

described in table 6. Some models are run sub-weekly with a large ensemble size (BoM, ECCC, ECMWF, HCMR, Institute of Atmospheric Sciences and Climate/ISAC-CNR, JMA). Others like the Chinese/CMA, Korean/KMA, the National Centers for Environmental Prediction/NCEP, British/UKMO, are run in continuous mode on a daily basis with a small ensemble size. The Météo-France is the only one with a monthly initiated run.

Table 5

Main characteristics of the 11 contributions to the S2S database

Model	Time range (days)	Hindcast (Reforecast)			Forecast			Ocean Coupling
		Period	Init Freq.	Ens size	Start date	Init Freq.	Ens Size	
BoM	0-62	1981-2013	6/month	33	January 2015	2/week	33	YES
CMA	0-60	1994-2014	Daily	4	January 2015	daily	4	YES
ECCC	0-32	1995-2012	weekly	4	January 2016	weekly	21	NO
ECMWF	0-46	past 20years	2/week	11	January 2015	2/week	51	YES
HMCR	0-61	1985-2010	weekly	10	January 2015	weekly	20	NO
ISAC-CNR	0-31	1981-2010	Every 5 days	1	November 2015	weekly	40	NO
JMA	0-33	1981-2010	3/month	5	January 2015	2/week	25	NO
KMA	0-60	1996-2009	4/month	3	Not available	daily	4	YES
Météo-France	0-61	1993-2014	2/monthly	15	May 2015	monthly	51	YES
NCEP	0-44	1999-2010	Day	4	January 2015	daily	16	YES
UKMO	0-60	1996-2009	4/month	3	December 2015	daily	4	YES

The models BoM, CMA, ECMWF, KMA, CNRM, NCEP and UKMO have an atmosphere component coupled to an ocean, while others use the combination of persistence of initial conditions and climatology to define the oceanic and ice boundary conditions. The forecast time range varies from 31 to 62 days and is available with a 3-week delay. The ensemble prediction systems have a combined total of 269 members. Until now, KMA data has not been available, so only 10 models can be found in the S2S data portal. Table 6 shows main models characteristics.

Model selection

Two types of evaluation have been done: hindcast and forecast analysis. Criteria for model selection differ for each of these analyses. For hindcast evaluation, the following criteria were applied:

- First, given the official sowing calendar of selected countries in this project (figure 1). It is necessary to choose the models whose forecasts start in January. This criterion eliminates the GCM's predictions of ISAC-CNR, KMA, Météo-France and UKMO
- Second, the criterion for determining the start of the growing season requires at least 30 days of forecasts. To fit with the S2S timescale, forecast must be done at least 14 days before the target period of onset of rainy season. Then, the lead time of the selected model must be at least 44 days. This criterion eliminates the models ECCC and JMA

Based on these criteria, five models were selected: BoM, CMA, ECMWF, HMCR and NCEP.
The NCEP model has shortest common period (only two years; see table 7) with observation, and HMCR is initialized only once a week. Because of these shortcomings, the two models were discarded from the hindcast analysis.

For forecast evaluation, only models with start dates in January 2015 (table 5) were selected. Therefore, forecasts of the following models were evaluated: BoM, CMA, ECMWF, HMCR and NCEP.

Table 6
Length in day of each model run and overlap periods between observations and GCM forecasts

Model Name	**Common Period**	**Number of Years**
BoM	1981-2000	20
CMA	1994-2000	7
ECMWF	1995-2000	6
NCEP	1999-2000	2

HCMR	1985-2000	15

Models data collection

The climatological data were used to determine the most likely growing start season (hereafter target period) in each station. Model data were extracted at each grid point nearest each station and from forecasts for 2, 3 and 4 weeks before the target period. We choose at least 2 weeks because subseasonal to seasonal time ranges are defined between 2-week and 3-month scales.

4.2 Methodology

4.2.1 Overview

Central African farmers are deeply concerned about knowing the beginning of the rainy season and when there will be no rain during that period. Then two parameters appear crucial to evaluate the usefulness of GCMs forecasts for regional agriculture: onset of rainy season and the duration of dry spells (see table 4**).** The length of dry spells can be defined as the number of consecutive days with precipitation below a given threshold, preceded and followed by at least one day with rainfall exceeding this threshold. Generally, the rainfall threshold used to distinguish between wet or dry days is the resolution of the pluviometer (0.1 mm/day; Lana et al, 2012).

It is important to differentiate between rainfall onset date and onset date of growing season. Rainfall onset date is when the rains start over an area with the possibility of short or long breaks; the onset date of the growing season marks the beginning of meaningful rains with fewer breaks that can hinder the growth of specific crops or seed. Hereafter, focus will be on the onset date of growing season.

4.2.2 Detection of agrometeorological metrics

4.2.2.1 Onset date determination

In Central Africa, the strong spatial heterogeneity of rainfall regime marks the official start of the growing season to be dependent on local criteria. Thus, in Cameroon the onset date of growing season is set when 20 mm of precipitation is recorded with no more than 5 consecutive dry days within the next 30 days. In DRC, growing season starts when 20 mm is registered and followed by an accumulation of at least 10 mm the next 20 days. Only growing season “A” was investigated for DRC (see table 1).

These criteria were applied for both observation and model databases. For models, skills to detect onset date of the growing season were evaluated for various outputs obtained by initializing them at lead times of 2, 3 and 4 weeks before the observed onset date. For some models, the dates corresponding to these lead times fell nearest to their initialization dates and, logically, were considered as such. Thresholds of 5 mm, 10 mm and 15 mm were applied on forecasts to detect the onset date in order to explore potential application of bias correction to model forecasts.

4.2.2.2 Maximum dry spell duration

Dry break (consecutive days with no rain) monitoring is important for several reasons. It contributes to assessment of water availability during the critical stage of crop development, and to efficient planning of agricultural activities. Daybreak monitoring was vital in dealing with Dry breaks within the three months after the start of the growing season. This period includes the duration of the earlier stage of the meaningful rainy season for each station. Where Dry break is not harmful to sowing, plants are expected to reach maturity. The parameter calculated for the control of this index is the maximum dry spell; that is the maximum number of consecutive dry days.

Based on data from observation stations in Cameroon and DRC, estimation of maximum dry spell duration was made from the 25th to 90th day (period of 65 days) after the start of the growing season. It was not pertinent to examine this parameter 25 days before the start of the season because the criteria applied for determining the growing season onset date already imposed favorable conditions to sustain plant growth.

For models, this parameter was computed at 2-, 3- and 4-week lead times before the first day of the observed dry spell period for each station. An analysis of modelled and observed daily precipitation data shows that low rain intensities were overestimated. Consequently, the precipitation threshold below which a day is considered dry was set to three different values (0.1 mm, 0.5 mm and 1 mm) and for each model against 0.1 mm for observation.

4.2.3 Comparison of forecasts and observations: skill scores

To assess the skill of GCM forecast to represent the onset of the growing season and maximum dry spells length over Cameroon and the Democratic Republic of Congo, a verification of forecasts was conducted using the following metrics and skills scores:

4.2.3.1 Computing Standardized Anomaly Index (SAI)

The index is computed by subtracting the long-term mean to daily rainfall amount and dividing by the standard deviation for each station. It is helpful for a quick look of model biases to compare this index computed from observation to that from model databases (here hindcasts). The computation of the SAI for models was done using rainfall means and standard deviation using observations data. However, using arithmetic means to compute this index may lead to artificial bias value. This is because of dispersion of the growing season onset date due to some occurrence of too early and late onset dates. Lo et al. (2007) have pointed out this issue. They proposed to use “trimmed” mean, which is based on the removal of extremely earliest and latest onset dates. Here, taking advantage of this trimmed mean we proceeded as follow: (1) sorting the onset dates’ historical database from earliest to latest; (2) compute the interquartile range (IQR), defined as the difference between the third (Q_3) and the first (Q_1) quartile; and (3) compute the arithmetic mean and the standard deviation (rounded to the next integers) with the onset date whose values encompassed the interval $[Q_1 - 0.25 \times IQR;\ Q_3 + 0.25 \times IQR]$.

4.2.3.2 Mean biases

The mean bias helps to answer the question: what is the average forecast error? The mean bias gives a measure of systematic error but does not provide information neither on the magnitude of the errors nor the matching between forecasts and observations. With values ranging from minus infinity to plus infinity, the perfect score is zero. It is possible to get a perfect score with a bad forecast if there are compensating errors.

4.2.3.3 Skills scores

These are based on a dichotomous method: "yes, an event will occur", or "no, the event will not occur" based on a contingency table. This table contains frequency of "yes" and "no" in forecasts and observations. The four combinations of forecasts (yes or no) and observations (yes or no), called the joint distribution, are presented in table 7.

Table 7

Contingency table for forecast of a sequence of binary event (Yes/No)

		Event Observed		
		Yes	No	Marginal Total
Event Forecast	Yes	h (Hits)	f (False Alarms)	h+f
	No	m (Misses)	c (Correct rejections)	m+c
	Marginal Total	h+m	f+c	h+f+m+c

Hits: event forecast to occur, and did occur
Misses: event forecast not to occur, but did occur
False alarms: event forecast to occur, but did not occur
Correct rejection: event forecast not to occur, and did not occur

Also called the Two-by-Two Contingency Table, table 2 represents a binary system where the following outcomes are possible: “a hit”, if an event occurred and a warning was provided (*h* is the number of hits); “a false alarm”, if an event did not occur but a warning was provided (*f* is the number of false alarms); “a miss”, if an event occurred but a warning was not provided (*m* is the number of misses); and a “correct rejection”, if an event did not occur and a warning was not provided (*c* is the number of correct rejections).

Several scores can be computed from this contingency table (see, Wilks 2011; Jolliffe and Stephenson 2003). In this study, the following scores are used:

Frequency bias defined as:

$$Frequency\ Bias = \frac{Hits + FalseAlarms}{Hits + Misses}$$

The frequency bias (or bias score) answers the following question: How did the forecast frequency of "yes" events compare with the observed frequency of "yes" events? Bias values ranges from 0 to infinity, with the perfect score equal to 1. The frequency measures the ratio of the frequency of forecast events to the frequency of observed events, indicating whether the forecast system has a tendency to underforecast (*BIAS* < 1) or overforecast (*BIAS* > 1) an event. It does not measure how well the forecast corresponds to the observations, but only measures relative frequencies.

The equitable threat score (ETS) is defined by the following relation:

$$ETS = \frac{Hits - Hits_{random}}{(Hits + Misses + FalseAlarms - Hits_{random})},$$

where$Hits_{random}$ is defined as:

$$Hits_{random} = \frac{(Hits + FalseAlarms)(Hits + Misses)}{(Hits + Misses + FalseAlarms + CorrectNegatives)}$$

The threat score answers the following question: how well did the forecast "yes" events correspond to the observed "yes" events (accounting for hits due to chance)? It ranges between -1/3 and 1, which indicates the fringe from no skill to perfect score. As it is easier, for example, to forecast rain correctly in a wet rather than a dry climate, the threat score allows for fairer comparison across different regimes. However, it is not truly equitable. Rather, it measures the fraction of observed events that are correctly predicted, adjusted for the frequency of hits that would be expected to occur simply by random chance. Sensitive to hits, it penalizes misses and false alarms in the same way; it does not distinguish the source of forecast error, and should be used in combination with at least one other contingency table statistic (for example, bias).

5 Skills of GCMs Forecast Database to Predict Selected Metrics at S2S Timescales

5.1 Hindcast evaluation

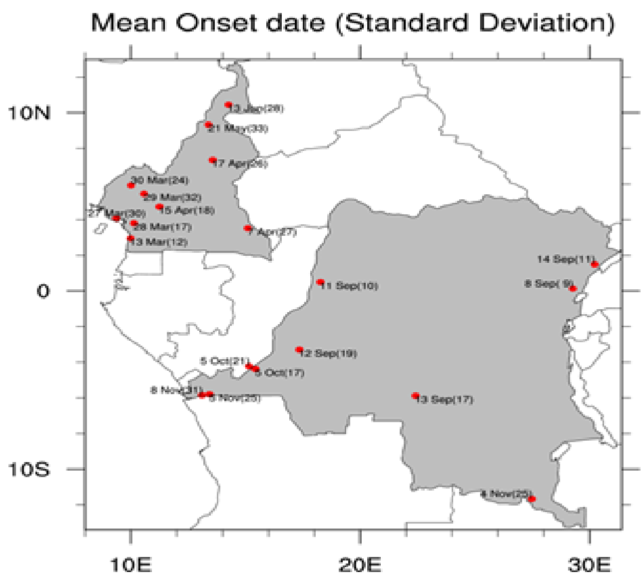
5.1.1 Growing season onset dates

5.1.1.1 Observed onset dates

This section focuses on the major agricultural seasons in Cameroon and DRC (called season "A").

Figure 4

Mean observed onset dates of growing season and corresponding standard for selected meteorological stations in Cameroon and DRC



In Cameroon mean onset dates of the growing season occur during the first half of the year, with the earliest in the southern part (that is 13 March in Kribi) and the latest in the far north (mid-June in Maroua) - see figure 4. Spatial propagation of these dates moves northward following displacement of the Intertropical Convergence Zone. The magnitude of the inter-annual variability of these dates is correlated to their standard deviations (figure 4), of which a careful examination shows no consistent south-north pattern as for growing season onset date. It clearly appears that variabilities are predominantly low over southern Cameroon (with the least value equals to 12 days) and high in the northern region reaching up to 33 days. Determinant factors causing this inhomogeneous variability are probably due to the proximity of the southern part of the country to the Atlantic Ocean and diversity of the vegetation cover.

In DRC (figure 4, country shaded below), it is noticeable that the onset date of the growing season shows a dominance of a north-south positive gradient (with occurrence of onset earlier in the north than in the south). Late onset (8 November in Boma, or 5 November in Matadi) mainly occur over the coastal region. Except Lubumbashi (with a mean onset date around 4 November), inland stations record earlier onset dates (8 September and 14 September in Butembo and Bunia, respectively) as compared with coastal stations. The magnitude of the inter-annual variability of onset dates can be appreciated by examining their standard deviation (figure 4). Relatively, there is a pattern of increasing variability from the north to the south. The lowest variability (standard deviation equals to 8 days) is observed for the northern stations whereas the southern stations exhibit highest values (standard deviation equals to 25 days).

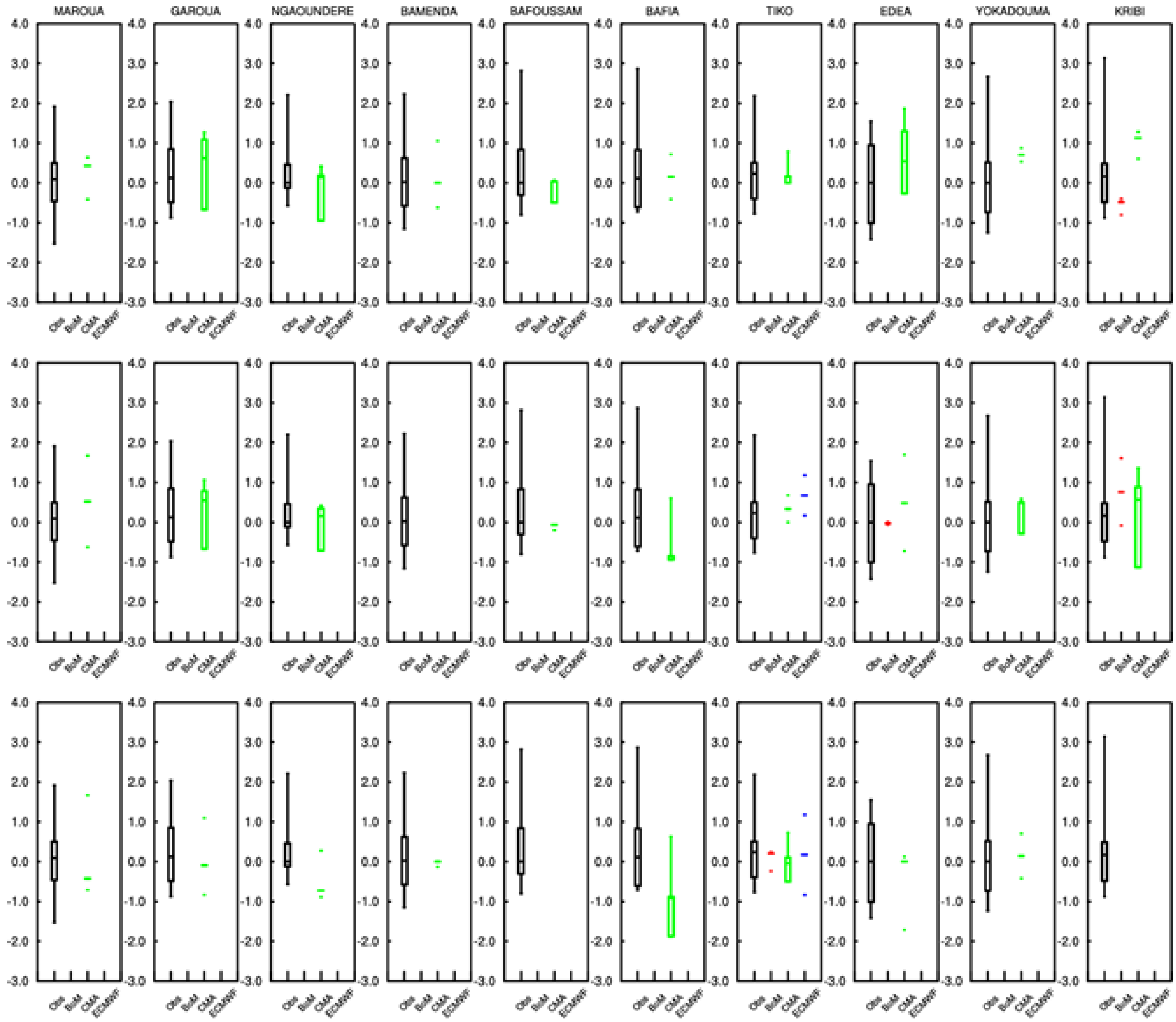
5.1.1.2 Standardized Anomaly Index (SAI) of growing season onsets

Figures 5 and 6 show the standard anomaly index distribution of growing season onset dates (using 20 mm as a threshold for onset dates determination criteria) for Cameroon and the DRC, respectively. The sub-figures in a column represent those for a station and those in a row refer to a lead time (1st, 2nd and 3rd rows corresponding to 2, 3 and 4 weeks before a target observed onset date at station). For each station, the statistics are shown for observations (black boxes) and for the different GCMs, namely BoM (red boxes), CMA (green boxes) and ECMWF (blue boxes). Here, the questions asked are how well the model outputs capture onset dates derived from station observation data: Is it earlier, later or in normal range? Do the biases have a coherent spatial distribution? What is the degree of variation with the lead time? In order to assess the biases in hindcast, the index has been computed following Robertson et al. (2009), by using the observed precipitation station's mean and standard deviation.

We have noticed that using 20 mm as a threshold to detect the onset date in hindcasts (figures 5 and 6). Only the CMA model succeeds in giving some values of onset dates. This indicates that the 20-mm threshold is hardly reached in model databases, and suggests that models tend to underestimate heavy rainfall. A qualitative analysis of figure 5 shows that in Cameroon and for all stations, the distribution of forecasted onset dates of the growing season by CMA fall approximately into the observed distribution. This suggests that forecast onset dates of growing seasons tend to be in normal range compared with observations. This occurs at all lead times, except at the Bafia station at a 4-week lead time where CMA shows an earlier forecast onset date.

Figure 5
Standardized anomaly index for observations and models
at Cameroon's stations

Box plots of standardized anomaly index for observations are in black and models
BoM, red; CMA, green; and ECMWF, blue. The name of each station is indicated at the top of each column.

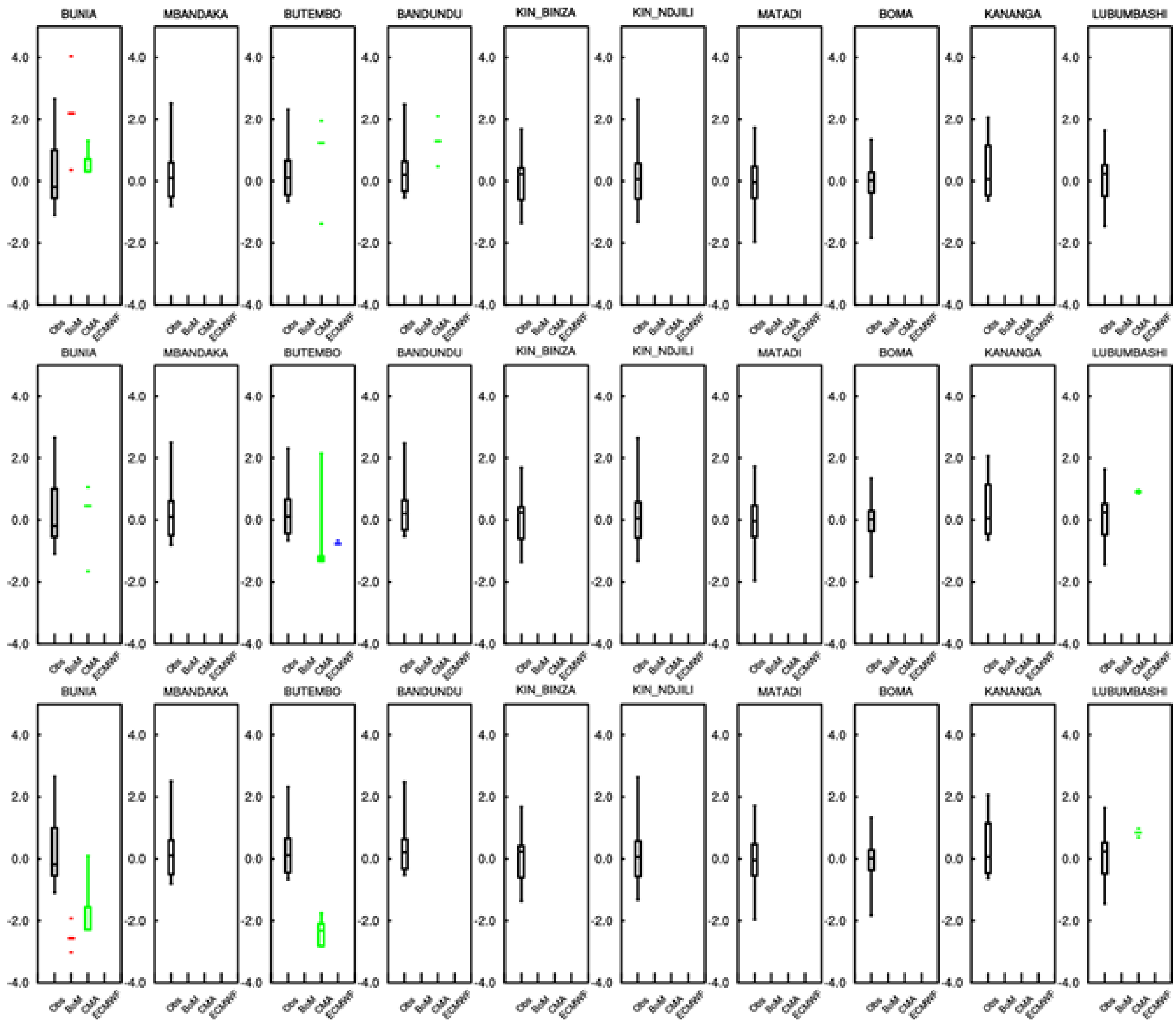


Standardized anomaly indexes are produced using 30 years (1971-2000) precipitation data for observations. For models, the time period used is presented in table 6. Upper, middle and bottom panels are for 2-, 3- and 4-week lead times respectively. The rainfall statistic presented here is rainfall onset date using the 20-mm threshold. Boxes denote the median and interquartile range (IQR). Whiskers extend 1.5 IQR from box ends.

In the DRC (see figure 6) and for the same threshold, only CMA shows some skills to detect onset date of growing season at Bunia and Butembo. CMA forecasts onset date earlier compared with observation at all lead times, except in Bunia at a two-week lead time where the model predicts onset date later. Others models fail to capture onset dates at all lead times. These weak skills indicate that models were only able to capture onset dates successfully for very few years.

Figure 6

Standardized anomaly index for observations and models at DRC's stations

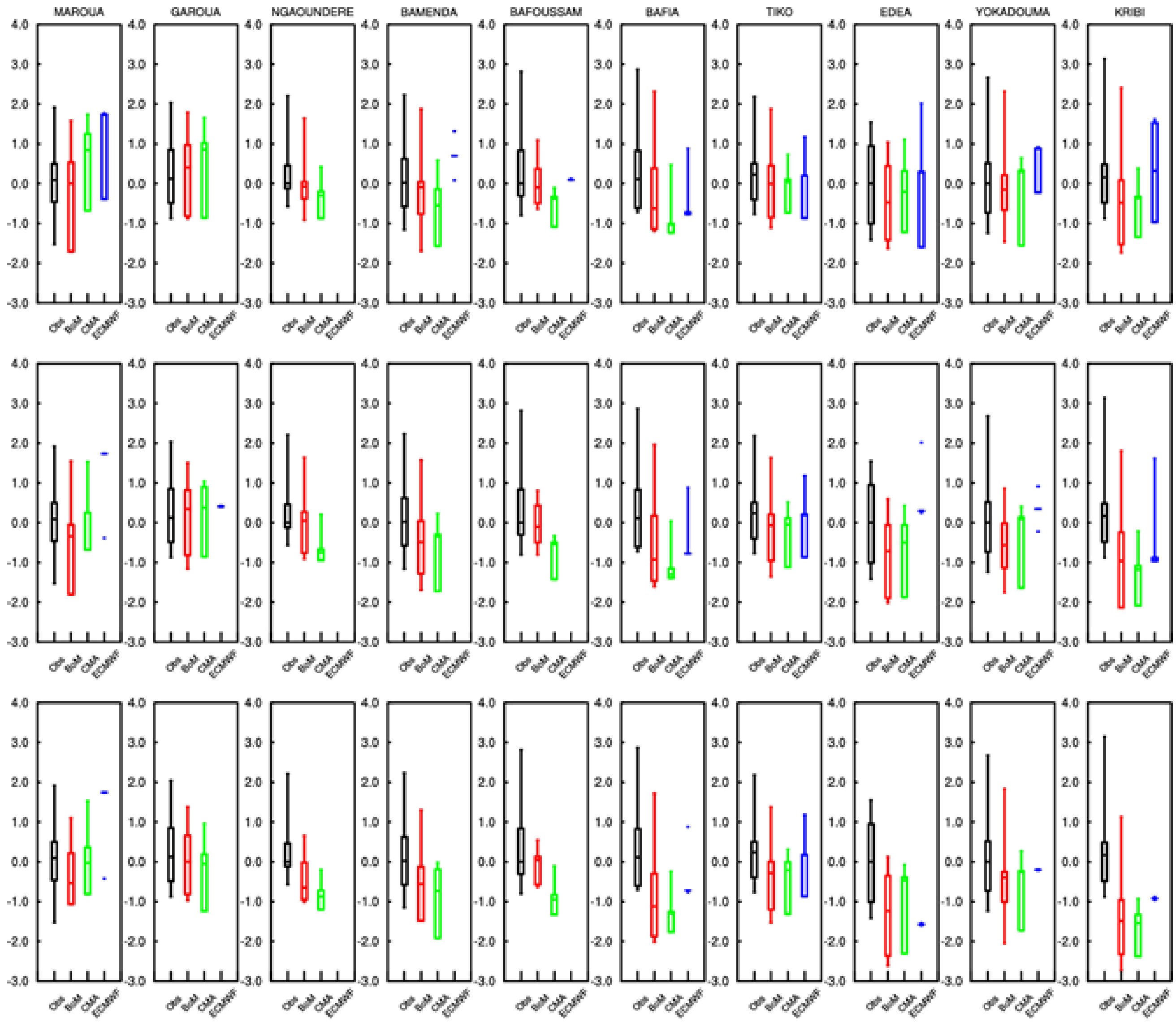


The capability of models to predict growing season onset dates using the 20-mm threshold lead to investigate models' abilities at lower thresholds was weak. Therefore, supplementary analyses were undertaken for each model at the 15-mm, 10-mm, and 5-mm thresholds. Hereafter, in addition of results for 20 mm, only those at 5 mm were presented in this section because of more meaningful results obtained compared with other thresholds (10 mm and 15 mm).

Figures 7 and 8 show forecast onset date distribution for the 5-mm threshold in Cameroon and DRC, respectively. Note that the observed onset date distribution in figures 7 and 8 (black boxes) are similar to those in figures 5 and 6 (that is estimated with 20 mm threshold). As expected, in Cameroon and DRC the number of onset dates detected by the BoM, CMA and ECMWF models is higher than those obtained for the 20-mm threshold (figures 5 and 6). Overall, there is a predominance of negative values of SAI in models. This suggests that models tend to forecast onset date early compared with observations. However, median values from model outputs and observations data are close, suggesting good skills of models to capture onset dates of growing season using 5 mm threshold. This result is valid for all lead times.

Figure 7

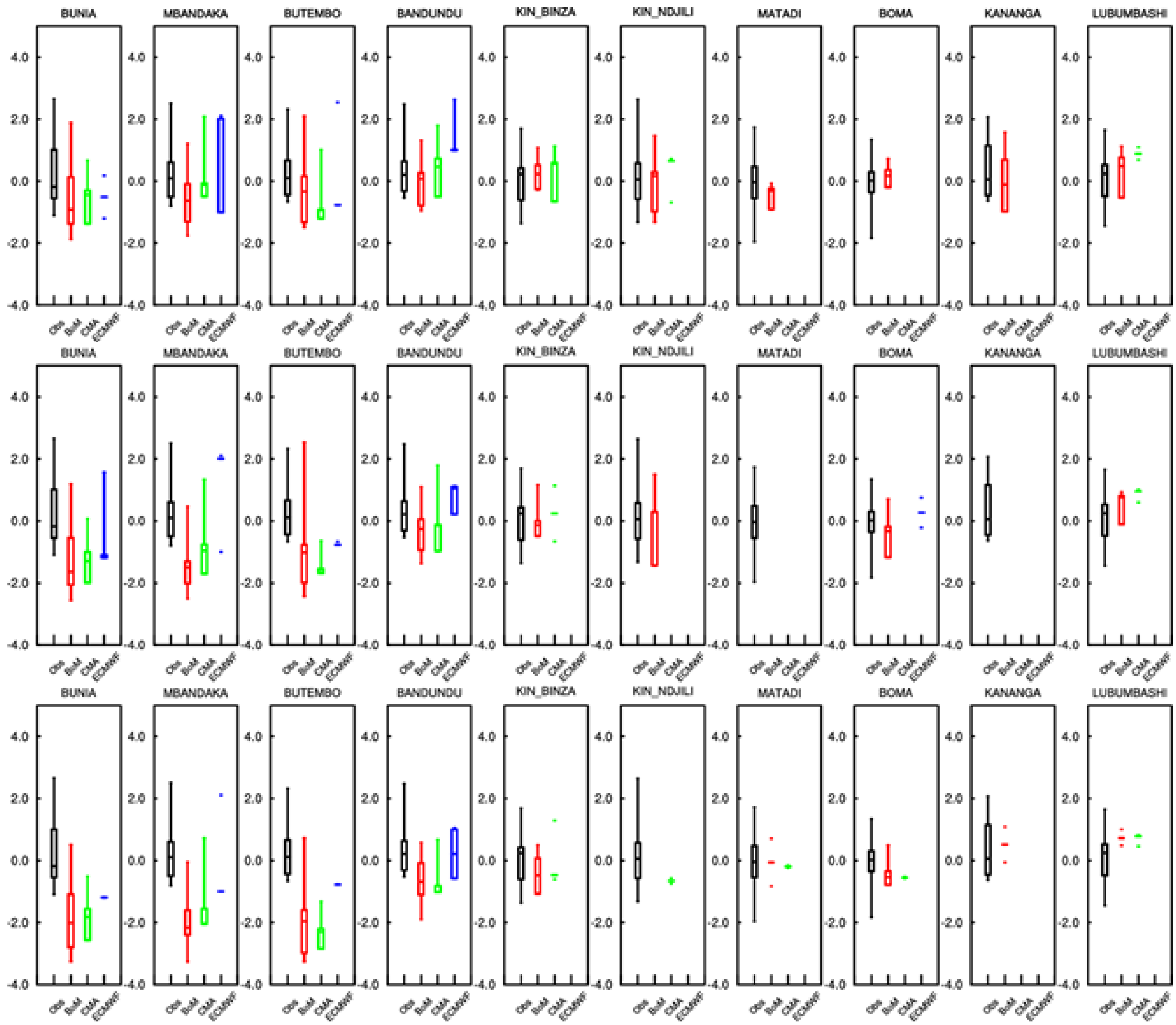
Standardized anomaly index for observations and models at Cameroon's stations at the 5-mm threshold



In Cameroon (figure 7) and for a 2-week lead time, observations are less skewed than models, with their medians mostly centrally located in the IQR. At 3-week lead time, the models tend to be more negatively skewed given that their medians are more positioned in the upper side of IQR than those from observations. As for the 4-week lead time, almost all models show negative skew.

Figure 8

Standardized anomaly index for observations and models at DRC's stations at the 5-mm threshold



In the DRC (figure 8), for all lead times, observations are less skewed than models. At 2-week lead time, compared with observations, all models display negative skew. At 3- and 4-week lead time, there is no constancy in skew trends because for the same model they are either negative, positive or null in different stations. In general, observations are less skewed than models and the tails of their boxplots are longer.

A striking feature of Cameroon is the trend to negative values of forecast SAI with 2- to 4-week lead time (figure 7). This is also recorded in DRC (figure 8). This may suggest that models tend to forecast an earlier onset date of growing season with increasing lead time. Another striking feature is the low skill of ECMWF and CMA to capture the onset date of the growing season at several station and lead times compared with BoM. But skills are lowest for ECMWF. This may be related to the short period of model data used for assessment of SAI. Only six years (1995 through 2000) forecast data from ECMWF and seven years (1994 through 2000) for CMA was used (see table 6) against 20 years for the BoM model. However, lowest skill of ECMWF may suggest that on model sample size there are strong biases in model physics.

A high skew in models compared with observation indicates that there are more extreme forecast onset dates of growing season compared with observations. This suggest that onset dates of the growing season occur too early (positively skewed) or later (negatively skewed) in forecasts compared with observations.

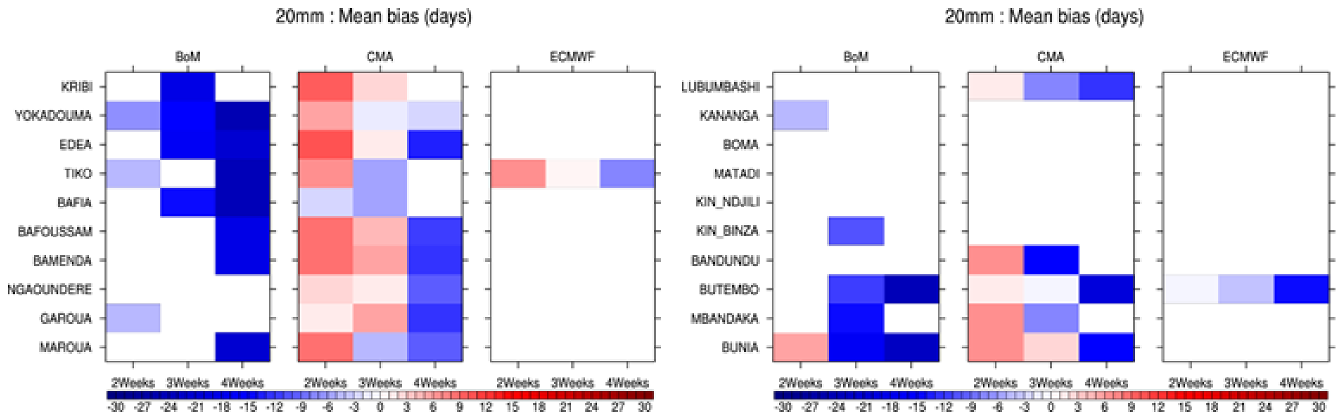
5.1.1.3 Models' mean biases

Figure 9 shows the mean bias (for the models BoM, CMA and ECMWF) sequences as a function of lead time across Cameroon (figure 9a, b; left panel) and the DRC (figure 9a, b; right panel), respectively.

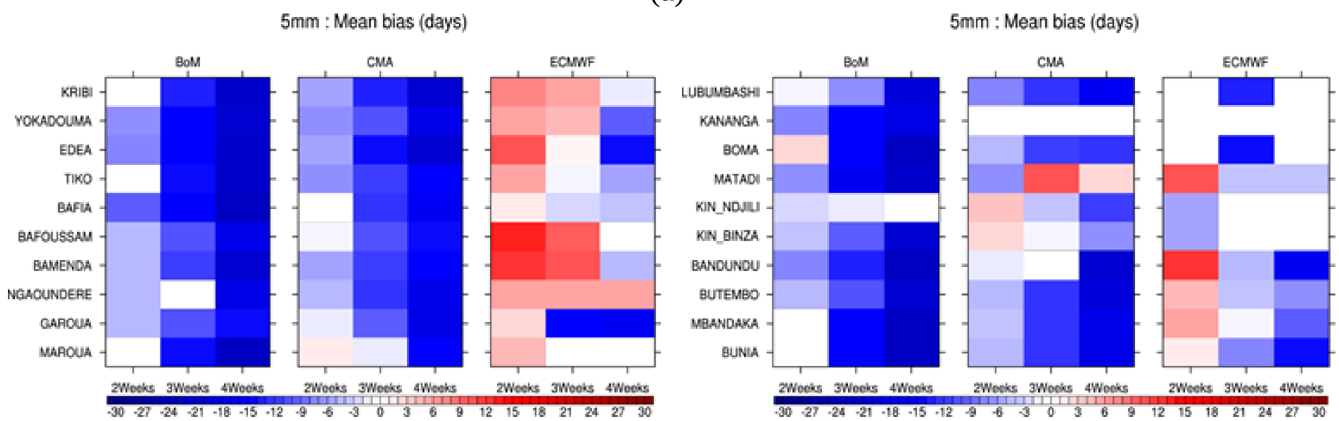
Figure 9
S2S database onset date forecast mean biases as function of lead time and models for Cameroon and DRC at selected stations

For each column, upper panel (figure 9a) and lower panel (figure 9b) present results using 20 mm and 5 mm thresholds, respectively.

Cameroon DRC



(a)



(b)

Stations are represented on a vertical axis and lead times on the horizontal. Blank areas indicate that the model was unable to detect occurrence of onset date for the defined threshold. Negative values (blue shaded) indicate early onset detection in models, while positive values (red shades) designate later onset detection as compared with observed dates.

Considering the mean biases for 20 mm threshold (figure 9a) over Cameroon (figure 9a, left panel), BoM predicts earlier onset going from moderate to too early onset dates as the lead time increases. BoM presents the same feature across DRC stations (figure 9a, right panel), except at Bunia where forecast values move from late to too early with increasing lead time. For a 2-week lead time, the BoM model predicts onset dates with approximately one week in advance on Cameroon and the DRC, except for the Bunia station where the model predicts onset with a delay of approximately one week.

For the CMA forecast values over Cameroon and DRC, bias values range from later to early as lead time increases. For a 2-week lead time, the CMA model foresees onset dates with a delay ranging between 3 and 12 days. For 3- and 4-week lead times, the onsets provided by the models are generally in advance. It was found that the biases are greater as contrasted to that of 2 weeks. ECMWF clearly shows bad skill at capturing growing season onset dates, except at the Tiko (Cameroon) and Butembo (DRC) stations.

At Tiko, the bias values show a change from “moderately late” to earlier onset dates as the lead time increases. In Butembo, the bias shows earlier onset dates which are more pronounced with increasing lead time.

For the 5-mm threshold (figure 9b), there is less blank area compared with the 20-mm threshold. This suggests that, in this case, all models succeeded in capturing the onset dates. The predominance of negative bias values indicates a general tendency for models to forecast earlier onset dates. This is well captured by the BoM and CMA models (figure 9b). These negative biases strengthen with increasing lead time, with earlier onsets ranging from about 3 days at a 2-week lead, to 18 days at a 4-week lead. This indicates that the longer the lead time, the less the quality of the forecast because errors are amplified as lead time is farther away from the target date. For ECMWF, the mean bias scores depict a tendency to forecast late to early onset dates with an increase of lead time. This model forecasts onset dates with a delay of 12 days (at a 2-week lead time) to an earlier onset of 3 days (at a 4-week lead time).

5.1.1.4 Models’ skill scores

The distribution of observed onset dates of the growing season (figures 5 and 6) suggests a classification in term of their occurrence according to the mean onset date. Then, observed onset dates of growing season were classified into three categories: early, normal and late onset dates. Hereafter, models’ skills to detect each of these categories of onset dates are assessed.

Onset skill scores using a 20-mm threshold

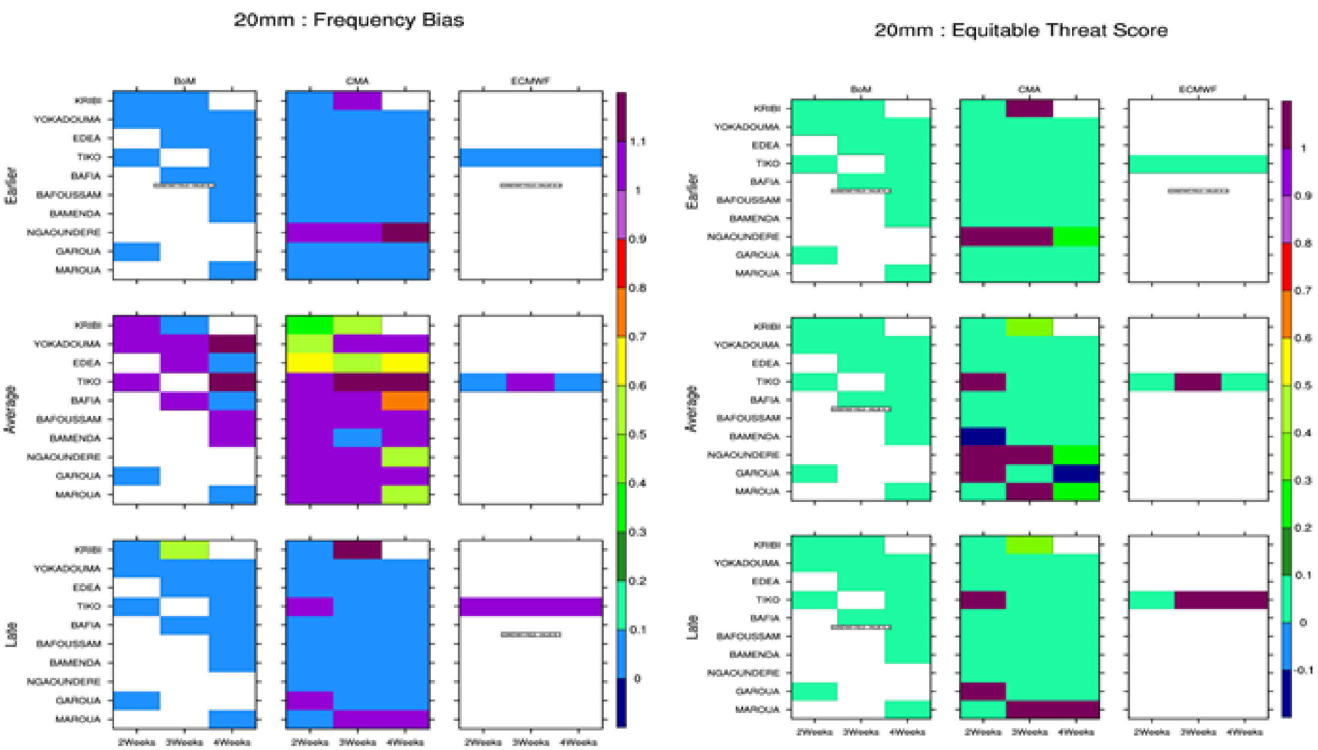
Figures 10 and 11 show for each model the results of equitable threat score across stations in Cameroon and DRC, respectively. Each score was computed using the 20-mm threshold for each of the three defined onset date categories. For Cameroon, analysis (figure 10.b) reveals that for all onset dates categories BoM model shows a weak threat score ranging between 0 and 0.1. This occurs at all lead times. For the CMA model, except in Kribi (3-week) and in Ngaoundéré (2- and 3-week), the threat score for the early category is generally weak. For the normal category, good skill is recorded at Garoua, Ngaoundéré and Tiko. CMA also presents good skill at Maroua, Garoua and Tiko for the late category where ETS is great. The ECMWF model gives a result only for the Tiko station. This score is very low for “early” category at all lead times. But, it is quite high for the normal and late categories at 3-week and 4-week lead times.

Results of frequency bias (figure 10.a) for the BoM model reveals that for the early and late categories and at all lead times, this score ranges between 0 and 0.1 indicating an underestimation of the occurrence of events of these onset date categories. The frequency bias score is close to 1 for the average category, inferring that the “forecast yes” proportion is sensibly equal to that of “observed yes”. CMA’s frequency bias results lie between 0 and 0.1 for the early and late categories, while it is near to 1 for the average category. The ECMWF model shows results only at Tiko with frequency bias values between 0 and 0.1 for the early category, and close to 1 for the average as well as late categories. Broadly, models show good skills to forecast average category of onset dates over Cameroon, with a higher frequency bias at a large number of stations for the CMA model.

Figure 10

S2S database (BoM, CMA and ECMWF models) skills score for the categorical onset date forecast

For each panel, frequency bias and equitable threat score are displayed as a function of lead time. Scores are for the 20-mm threshold at Cameroon's selected stations whose names are on the left side of the figures).



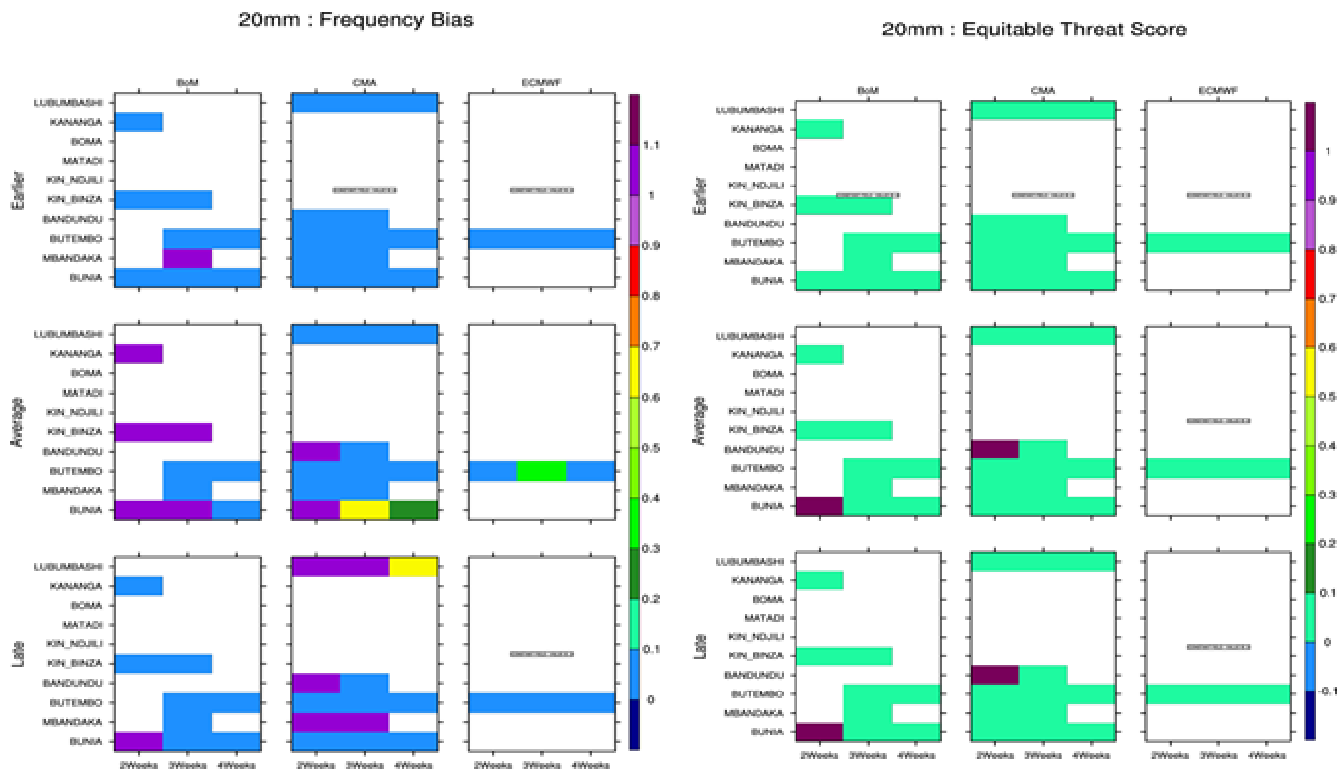
(a) (b)

Figure 11 presents results of equitable threat scores and frequency bias scores for DRC. Broadly, the threat score shows weak skill regardless of models, lead time and onset date categories. Only the Bunia station presents a different threat score, approximately equal to 1 for a 2-week lead time. For the CMA and BoM models, the threat scores are very close and low across stations except in Bandudu, where the score is high and close to 1 for a 2-week lead time. The ECMWF model shows bad skills because only the Butembo station was depicted and its score was very low, ranging between 0 and 0.1 for all onset date categories.

Frequency bias results for the BoM model shows that for all onset date categories and at all lead times the score lies between 0 and 0.1, portraying an underforecast of the onset date category (figure 11, left panel). At the Bunia, Kinshasa-Bindza and Kananga stations, frequency bias is close to 1 for the average category and for 2- and 3-week lead times. This infers that the “forecast yes” proportion is quite equal to that of the “observed yes”. The CMA model exhibits low frequency bias values ranging between 0 and 0.1 for the early category, and close to 1 for both “average” and the late categories. The ECMWF model shows results only at Butembo with a score between 0 and 0.1 for almost all categories.

Figure 11

S2S database (BoM, CMA and ECMWF models) skills score for the categorical onset date Forecast at DRC stations



(a) (b)

l.

The S2S databases are from the BoM, CMA and ECMWF models, and the skills score for the categorical onset date forecast for DRC stations. It appears that equitable threat score generally depicts low values for all onset date categories: these are earlier, average and late. However, the CMA model shows higher scores than those of BoM, while ECMWF presents the lowest scores. It was found that for the early and late categories, the frequency bias score was less than 1. This means that models have a tendency to underforecast onset dates for this threshold.

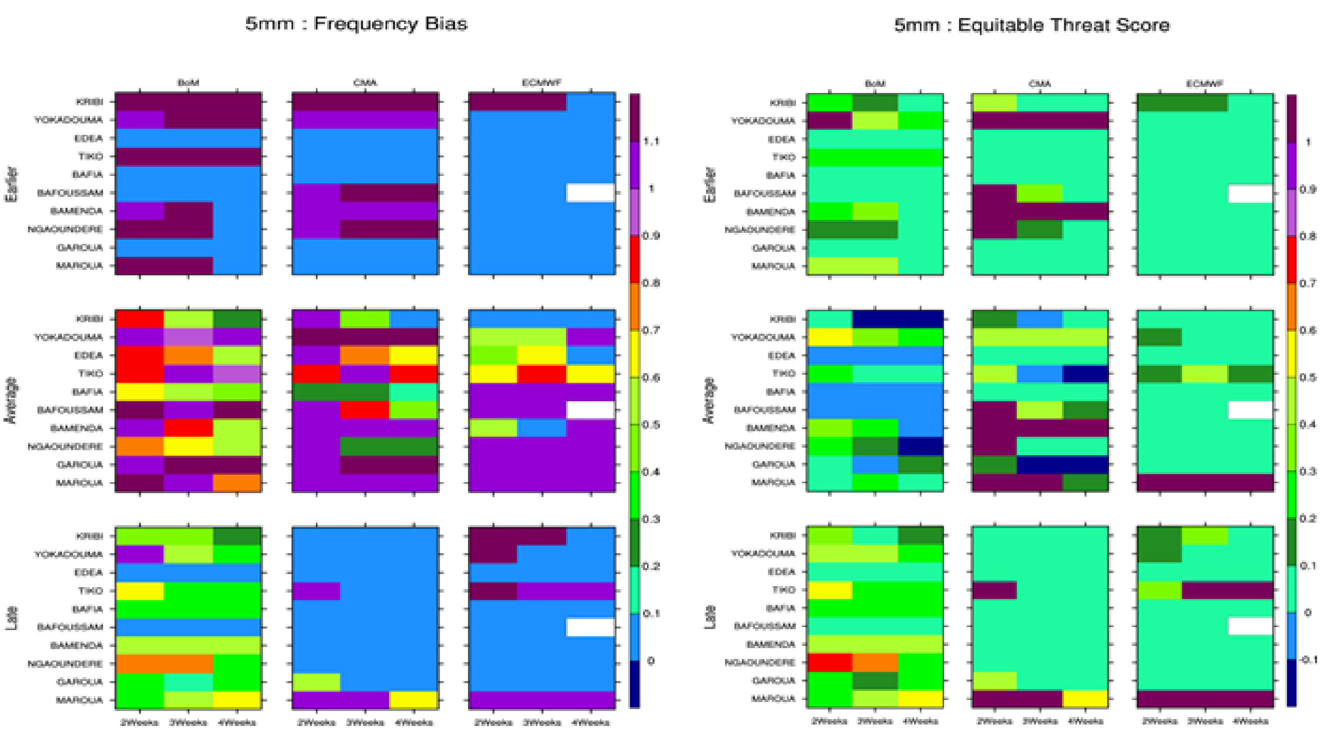
Onset skill scores using a 5-mm threshold

As mentioned previously, the underestimation of heavy rainfall by Global climate model forecasts causes the failure of models to detect onset dates at the 20-mm threshold. In order to explore potential bias correction in models, analyses were made with a 5-mm threshold. The results are presented in figures 12 and 13 for Cameroon and DRC, respectively. These figures display frequency bias and equitable threat scores in figures 10 and 11.

For Cameroon at the 5-mm threshold (figure 12), the equitable threat score (figure 12.b) values of the BoM and CMA models are more skillful compared with ECMWF forecasts. BoM display skill for all onset categories while CMA shows good skill for earlier and average categories. Over Garoua, Ngaoundéré and Tiko, CMA produces high threat scores for the normal category, indicating good skills of the model to detect observed onset date of this category. For the late category, CMA exhibits high threat score at Maroua, Garoua and Tiko. ECMWF shows skills only at the Tiko station, with weak threat scores for the early category at all lead times. However, a high score is obtained for normal and late categories at 3- or 4-week lead times.

Figure 12

S2S database (BoM, CMA and ECMWF models) skills score for the categorical onset date forecast at the 5-mm threshold over Cameroon's selected stations



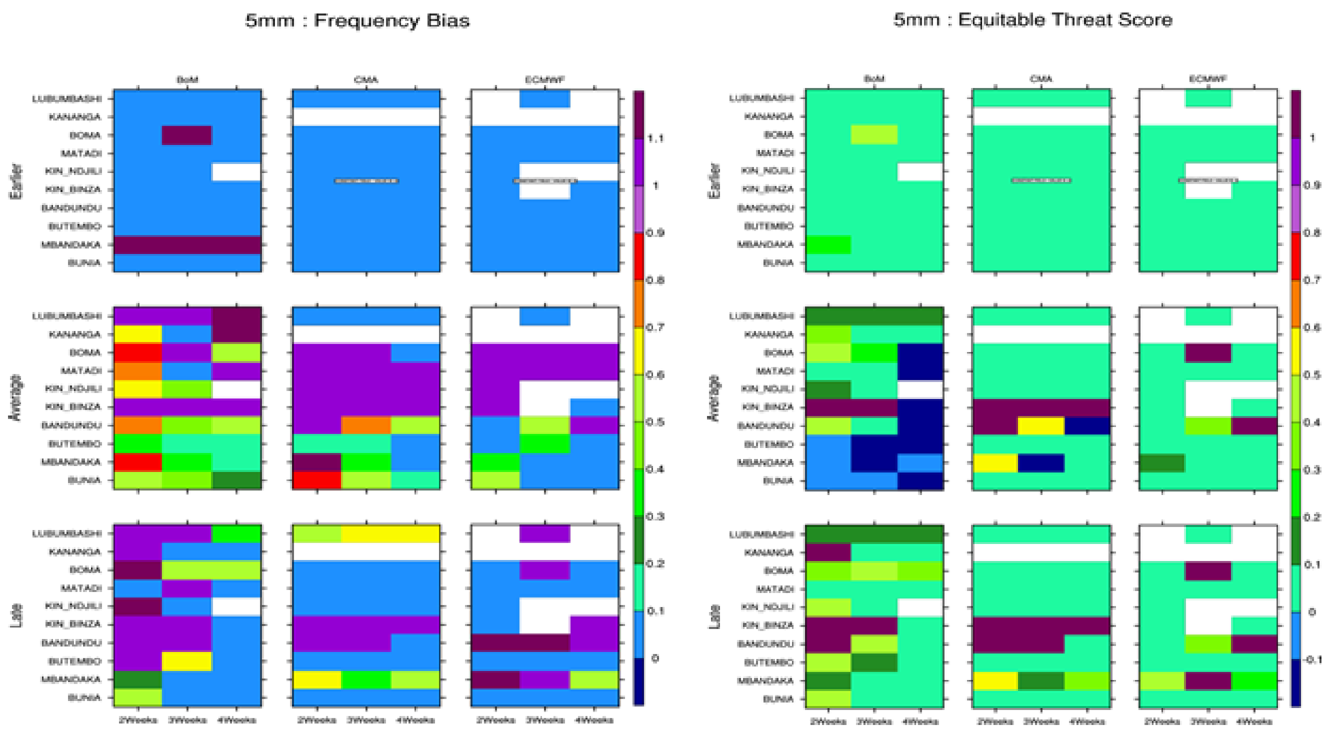
(a) (b)

Regarding the frequency bias scores (figure 12.a), values decrease as lead time increases and all models seem to depict good skill in the forecast of the near normal (average) onset date category over the whole country. Broadly, the BoM model shows better skill at forecasting the observed onset date category compared with ECMWF and CMA. Strong deficiencies in CMA and ECMWF forecasts are recorded for the early and later onset date categories. However, all models present good skill for detection of the observed average onset date category.

Figure 13 presents results for equitable threat scores and frequency bias at the DRC stations. Analysis of the threat score values (figure 13.b) show strong model deficiencies for the early onset date category. Models exhibits predominance of weak threat scores (between 0 and 0.1) for all onset date categories and lead times.

Figure 13.a presents results for DRC's frequency bias. Overall, models show good skills for average and later onset date categories. All models present deficiencies to predict observed early onset date categories with frequency bias values ranging from -0.1 to 0. The BoM model captures the occurrence of observed average onset date category quite well, with higher scores for Kinshasa-Binza and Lubumbashi. BoM also performed well for the late onset date category, except at 4-week lead time for some stations. Broadly, performances of CMA and ECMWF for average and late onset date categories are close together. Both models capture the occurrence of observed average onset date category quite well, except at some stations like Mbandaka and Bunia) for ECMWF at 4-week lead time, whereas for the late onset date category CMA and ECMWF present weak skills at many stations for all lead times.

Figure13(a) and (b)
Frequency bias and threat score at 5 mm threshold over DRC's selected stations



(a) (b)

For Cameroon, all models seem to depict well the observed near normal (average) onset date category over the whole country. CMA is more skillful compared with ECMWF forecast, even though both models show strong deficiencies for the early and later onset date categories. The BoM model displays better skill for all onset categories while CMA shows good skill for earlier and average categories. In the DRC, all models are deficient in predicting the observed early onset dates category. For others onset date category models show improvement, with highest performance for BoM. Whereas, skills of CMA and ECMWF are close together.

5.1.2 Dry spells lengths: model assessment

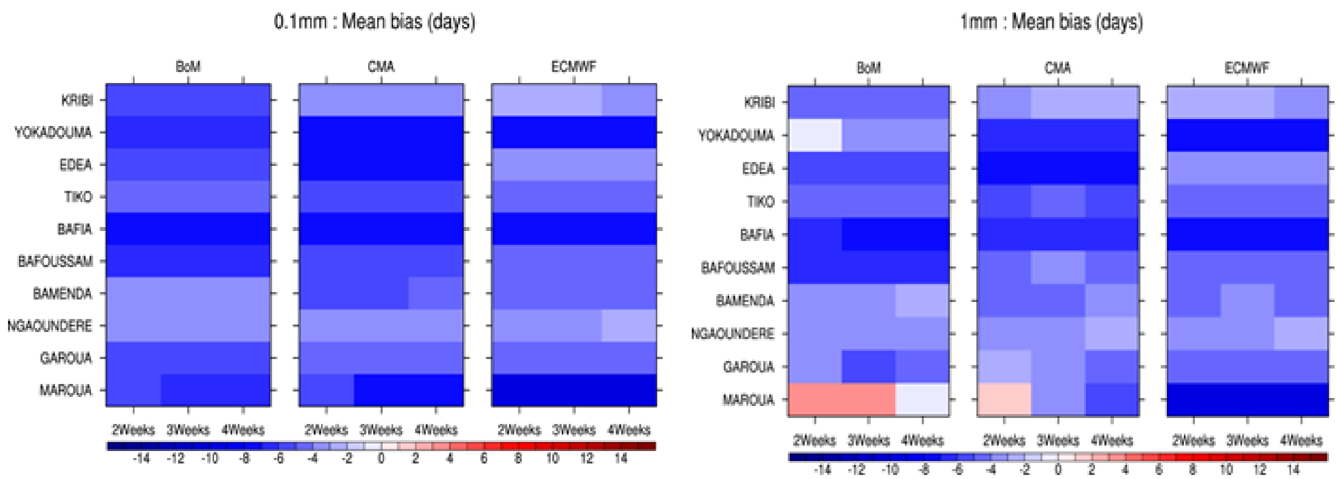
5.1.2.1 Mean biases of models

1) Quantitative analysis

Figures 14 (a and b) and 15 (a and b) show the distribution of mean bias of the forecast of dry spells lengths (using 0.1 mm and 1 mm) over Cameroon and the DRC, respectively. Each column carries results of the forecasts from different centres such as BoM, CMA and ECMWF. Here mean bias is presented as a function of station and forecast lead time (2-, 3-, and 4-week on the x-axis). Statistics for each station are assessed according to hindcast mean biases (Robertson et al., 2009) and expressed by the means of colour bars specified by a bottom legend. The aim of this analysis is to find out how well the models forecast dry spell occurrence by classifying performances into various categories: underestimation, normal and overestimation. Therefore, it is possible to sketch the bias spatial distribution alongside the variation with lead time.

Figure.14

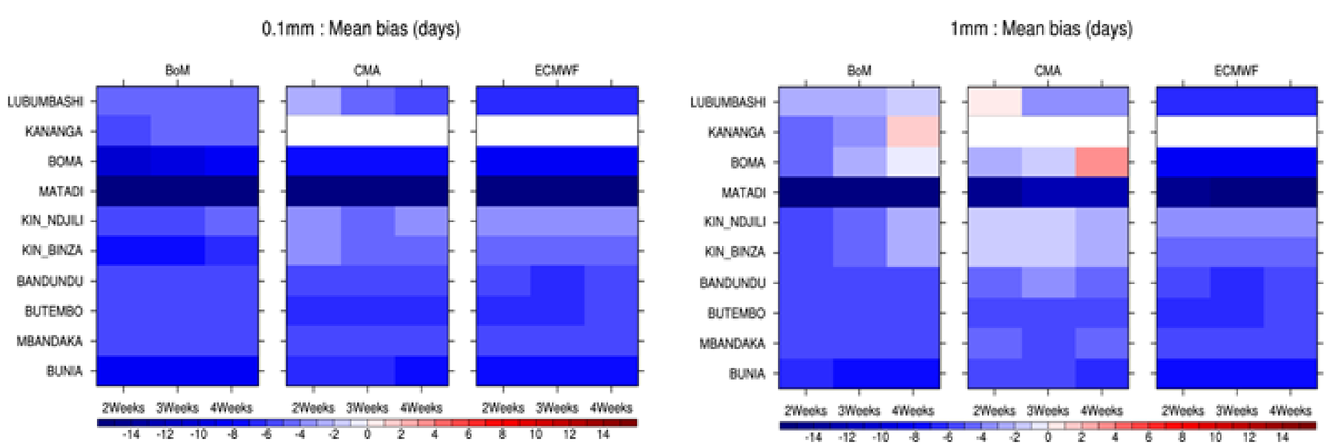
Mean biases of S2S models dry spell lengths (BoM, CMA, ECMWF) as a function of forecast lead times for 0.1 and 1 mm thresholds for Cameroon



(a) (b)

Figure 15

Mean biases of S2S models dry spell lengths (BoM, CMA, ECMWF) as a function of forecast lead times for 0.1 and 1 mm thresholds over DRC stations



(a) (b)

At Cameroonian stations (figure 14.a), results are all negative showing models' underestimations of dry spell lengths at all lead times. The BoM model shows near normal dry spell forecasts (up to 6 days of underperformance) at Kribi, Edéa, Tiko, Bamenda, Ngaoundéré, and Garoua at all lead times, while

Maroua appears in this category only at a 2-week lead time. At 3- and 4-week lead times, the model forecasts are underestimated in Yokadouma, Bafia and Bafoussam. The CMA model depicts near normal forecasts in Kribi, Tiko, Bafoussam, Bamenda, Ngaoundéré, and Garoua for all lead times, while Maroua emerges in this batch for just the 2-week lead time. Other forecasts at 3- and 4-week lead times in Maroua as well as those in Yokadouma, Edéa and Bafia for all lead times are underestimated. The ECMWF model shows near normal forecasts in most stations (Kribi, Edéa, Tiko, Bafoussam, Bamenda, Ngaoundéré, and Garoua) at all lead times, while underestimations are registered in Maroua, Bafia and Yokadouma.

For the DRC (figure 15.a), results expand from near normal to underestimated forecasts at all lead times, but only the Kananga station failed to be detected by CMA and ECMWF. The BoM model forecast shows near normal dry spells in most stations (Lubumbashi, Kananga, Kinshasa-djili, Bandundu, Butembo and Bandaka) whereas Boma, Matadi, Kinshasa-binza and Bunia come into sight at all lead times as stations where dry spell lengths are underestimated. The CMA model portrays a near normal forecast category at all lead times in Lubumbashi, Kinshasa-djili, Kinshasa-binza, Bandundu, Butembo, Mbandaka, and Bunia at 2- and 3-week lead times. Boma and Matadi stations emerge in early batch at all lead times, though Bunia comes early only at the 4-week lead time. The ECMWF model shows near normal forecasts for Kinshasa-djili, Kinshasa-Binza, Bandundu, Butembo and MBandaka at all lead times, while Lubumbashi, Boma, Matadi and Bunia appear for all lead times as underestimated forecasts.

In order to explore potential application bias correction to model forecasts, an additional threshold of 1 mm was applied to detect eventual upgrading. For both countries, forecasts over many stations (except Edea and Bafia for Cameroon, and Matadi, Bunia, Mbandaka and Butembo for DRC) are clearly improved tending to be more normal.

2) Qualitative analysis

The mean biases of models derived from comparison between forecast and observed dry spell lengths over Cameroon and the DRC are shown in figures 14 and 15, respectively. A qualitative analysis of these figures (Figures 14a and 15a) at 0.1 mm threshold (below which a day is considered dry) are recapitulated in tables 8 and 9 for Cameroon and the DRC stations, respectively. It appears that models have a propensity to forecast near-normal events except in the southern humid forest agroecological zone in Cameroon and in the far-western part of the DRC, whereby dry spells are underforecasted. These results and more explanation are recapitulated in table 8.

Table 8
Propensity of models to forecast dry spells over Cameroon

HINDCA	SUDANO-	ADAMAW	WESTERN	ATLANTIC	SOUTHERN

ST	SAHELIAN		A PLATEAU	HIGHLANDS		COAST			HUMID FOREST	
	Maroua	Garoua	Ngaoundéré	Bamenda	Bafoussam	Kribi	Tiko	Edea	Bafia	Yokadouma
BoM	**N**	**N**	**N**	**N**	**U**	**N**	**N**	**N**	**U**	**U**
CMA	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**U**	**U**	**U**
ECMWF	**U**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**U**	**U**

Key - N: near-normal to normal, **U**: underestimation, **NA**: not available

At 1 mm threshold in Cameroon and the DRC (figures 14b and 15b), results are approximately similar to those at 0.1 mm in most cases but with some weak overestimation of dry spells lengths in very few cases for the models BoM and CMA (two cases or less).

Table 9

Models propensity to forecast dry spells over the DRC

HINDCAST	WESTERN						CENTRAL	SOUTHERN	EASTERN	
	Mbandaka	*Bandundu*	*K-djili*	*K-binza*	*Boma*	*Matadi*	*Kananga*	*Lumbumbashi*	*Butembo*	*Bunia*
BoM	**N**	**N**	**N**	**U**	**U**	**U**	**N**	**N**	**N**	**U**
CMA	**N**	**N**	**N**	**N**	**U**	**U**	**NA**	**N**	**N**	**N**
ECMWF	**N**	**N**	**N**	**N**	**U**	**U**	**NA**	**U**	**N**	**U**

***Key* - N**: near-normal to normal, **U**: underestimation, **NA**: not available

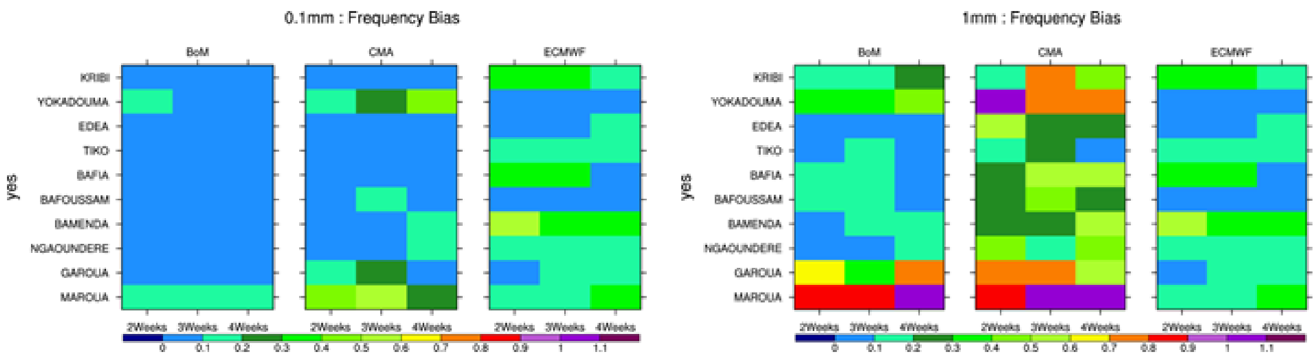
5.1.2.2 Models' skill scores

Figure 16 shows frequency bias of subseasonal to seasonal model dry spell lengths (BoM, CMA and ECMWF) as a function of forecast lead times for 0.1 and 1 mm thresholds over Cameroon. The BoM model displays strong underestimated forecasts (with frequency bias ranging between 0 and 0.1) of dry spells at almost all stations, except Maroua at all lead times, and Yokadouma at 2-week lead times with a frequency bias range of 0.1 to 0.2. The CMA model gives a picture of near normal forecasts (with a frequency bias of 0.5 to 1.0) only in Maroua at 2- and 3-week lead times, while for other stations forecasts are underestimated with a frequency bias variation more or less of 0 to 0.5 at all lead times.

The ECMWF model depicts near normal forecasts (frequency bias of 0.6 to 0.7) in Bamenda only at a 2-week lead time, while the others are underestimated (frequency bias of 0 to 0.4) at all lead times.

Figure 16

Frequency bias of S2S models dry spell lengths as function of forecast lead times for 0.1 and 1 mm thresholds over Cameroon

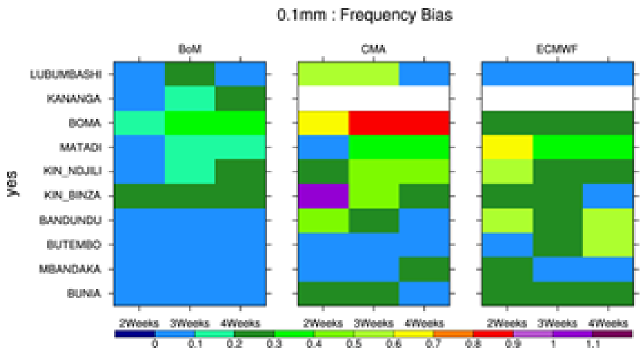


(a) (b)

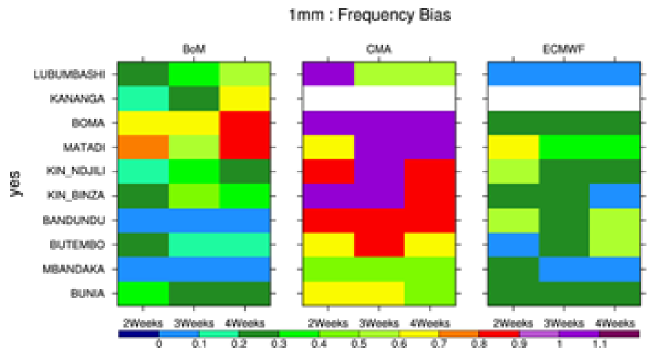
As for the DRC, figure 17 shows a frequency bias of S2S model dry spells lengths (BoM, CMA and ECMWF) as a function of forecast lead times for 0.1 and 1 mm thresholds. For a 0.1-mm threshold in the DRC, all the results also portray a constant field illustrating relative weak frequency bias ranging between 0 and 0.1 at all lead times (figure 17a). |The BoM model comes into sight as underestimating dry spells for all stations and at all lead times (frequency bias 0 to 0.3). The CMA model shows no skill in Kananga and forecasts dry spell frequency at Kinshasa-Binza at 2-weeks lead time quite well. The CMA model also slightly underestimates dry spell frequency at Lubumbashi, Kinshasa-ndjili, Bandundu and Boma for different lead times. Low skills are recorded at the Butembo, Matadi, Mbandaka and Bunia stations with strong underestimation of dry spell events. The ECMWF model also could not detect Kananga, but shows near normal forecasts for Kinshasa-djili, Bandundu, and Butembo at 2- and 4-week lead times, whilst the remainder come out at various lead times as underestimated (frequency bias 0 to 0.4) forecasts.

Figure 17

Frequency bias of S2S models dry spell lengths as a function of forecast lead times for 0.1 and 1 mm thresholds for the DRC



(a)



(b)

In order to explore potential application bias correction to model forecasts as usual, an extra threshold of 1 mm was applied on forecasts to detect an eventual subsequent improvement. Analyses of the results (figures not shown) shows that for this threshold, the forecasts of the CMA model followed by BoM were clearly improved over the DRC and Cameroon.

5.2 Forecast evaluation: onset date of the 2015 growing season

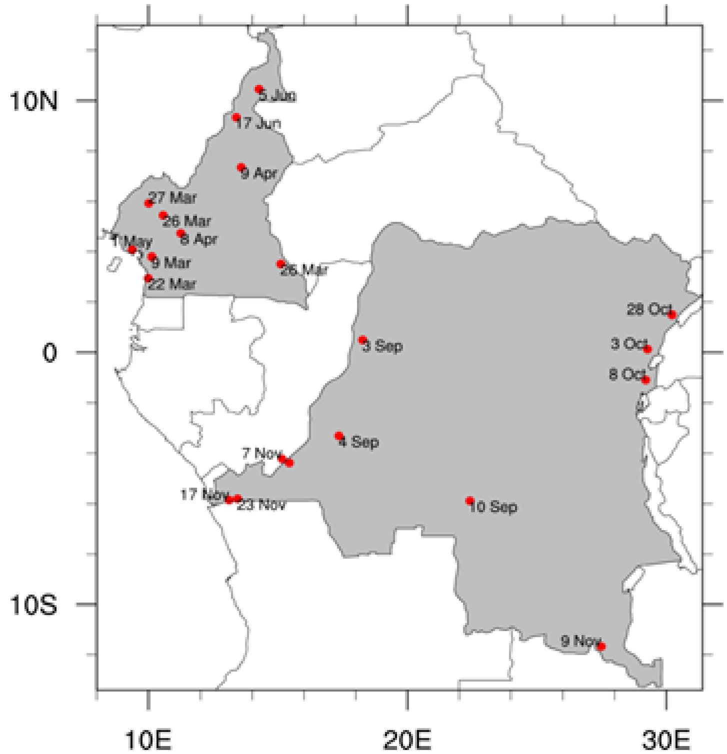
In this section, the skill of model forecasts to capture onset dates of the growing season in 2015 is examined. Analyses start with computation of observed onset dates of the growing season using an operational threshold of 20 mm (see section 4.2.2.1), followed by assessment of GCMs forecasts (at 2-, 3- and 4-week lead time) to detect these onsets. Other thresholds (5 mm, 10 mm and 15 mm) were applied to forecasts to detect the onset date in order to explore potential application of bias correction to model predictions.

5.2.1 Observed onset dates

Figure 18 shows the start dates of the growing season for the selected stations over the area of study, based principally on observed meteorological station data.

Figure 18

Observed onset dates of growing season for 2015 at selected Met stations in Cameroon and DRC



For most stations over southern Cameroon, the onset date of growing season occurs during March, except for the Bafia and Tiko stations for which the dates fall in and out of their 1971-2000 climate (see figures 4 and 18). Over central Cameroon, and in the Adamawa Highland area, the onset is registered in April, and in June for northern stations at Garoua and Maroua.

Concerning DRC, the growing season, called season A, begins in September for the three stations approximately in the middle of the country (Mbandaka, Bandundu, Kananga). For the north-eastern and the southern parts of the country, onset occurs in October and November respectively.

5.2.2 Models verification for 2015 onset dates

a) Operational threshold of 20 mm

The deviation, in terms of number of days, from the observation and forecast onset dates of the 2015 growing season is shown in figure 19. Detection of the onset was made for five subseasonal to seasonal forecasting models (BoM, CMA, ECMWF, NCEP and HCMR), at lead times of 2, 3 and 4 weeks. Onset dates were computed using observations and model forecasts with a 20-mm precipitation threshold. Positive (negative) value indicates late (earlier) start of forecasted onset of growing season compared with observations. A station with no record indicates a forecast daily rainfall amount below a 20-mm threshold, leading to no detection of onset date of the growing season.

One striking feature is all the stations with no record, at all lead times, in BoM and HCMR (figure 19). This suggests that BoM and HCMR are not proficient at capturing the onset date of growing season in DRC and Cameroon based on a 20-mm precipitation threshold. This result may be related to an underestimation of heavy rains in BoM and HCRM compared with observations.

In general, CMA shows good skill to detect onset dates of the growing season at many stations compared with other models. At a 2-week lead time for northern Cameroon (north of 7°N) and DRC, CMA predicts the growing season onset from 3 days to 5 weeks in advance (earlier start) compared with observations. This is illustrated by negative values of between -3 and -35 (see figure 19) over these areas, respectively.

Over southern Cameroon (south of 7°N), along the coastal region, onset of the growing season is forecast later in CMA compared with observations. At the Garoua station (see figures 4 and 19), at 3- and 4-week lead times, CMA forecasts the start of the growing season earlier and up to 10 days ahead the date obtained at a 2-week lead time. In Maroua (figures 4 and 19) the forecast onset date is still earlier and around 13 days after the onset at a 2-week lead time (figure 19), and close to observations. At Ngaoundéré, the forecast onset date is not consistent with a lead time of 2 to 4 weeks. Hence, over northern Cameroon, there is no clear signal of improvement or decay of the CMA's skill to forecast growing season onset dates with 2- to 4-week lead times. This characteristic of CMA's forecast across lead times in northern Cameroon is also observed in the south and in the DRC. The CMA model shows better forecast growing season start date at the 2-week lead time in Bafoussam, Kribi, Tiko and Butembo, whereas for Edéa in Cameroon and Goma in DRC it is 3 weeks, or 4-weeks for Bamenda in Cameroon and Lubumbashi in the DRC (see figures 4 and 19).

The ECMWF model shows some skills over coastal region in Cameroon and north-eastern DRC.

Figure 19

Model forecast skills of growing season start dates in 2015 for selected meteorological stations in the DRC and Cameroon

In these areas, the model forecast onset date is in advance compared with observation at all lead times, whereas NCEP presents some results for Cameroon and north-western DRC. Results clearly show that for a 20-mm precipitation threshold, models BoM and HCMR cannot be used whatever the considered lead time. However, other models do better and CMA shows greater skill for all lead times, followed by ECMWF and NCEP.

a) Analysis for other precipitation thresholds

The weakness of models in the detection of the growing season onset with a 20-mm threshold (figure 19) suggests that GCMs forecast might underestimate heavy rain events. This is a well-known issue of the coarse resolution model (Kendon et al., 2012). Thus, the analysis went further by assessing forecast onset dates by reducing the threshold to 15 mm, 10 mm and 5 mm (see figures 20 to 22). The reason behind assessing skills of GCMs prediction using other thresholds was to investigate potential application of bias correction on the outputs of the models. The actual objective was to investigate precipitation threshold for which the forecast onset dates fit better results with observations using a threshold of 20 mm.

Figure 20 shows the biases between simulated and observed start dates of the growing season for a precipitation threshold of 15 mm. For this threshold, BoM and HCMR are not able to capture the onset growing season date, except at the Bunia and Bafia stations. At these stations, forecast dates at 3-week lead time are18 and 36 days in advance, respectively, compared with observations. But, CMA and NCEP simulated dates are almost similar to those obtained with a 20-mm threshold (figures 19 and 20). These models show better skill over southern Cameroon for all lead times (figure 20). As expected, the number of stations where models predict start dates of the growing season has increased compared with results at the 20-mm threshold. Accordingly, the results for a 10-mm threshold (figure 21) show an increase number of stations with a value of forecast growing season onset dates for all models. CMA shows some improvement (figure 21) compared with a 20-mm (figure 19) threshold with less than 2 weeks between forecast and observed onset dates. Moreover, CMA seems to better forecast the dates over the region compared with other models. BoM shows better skill to capture the onset dates over north-eastern DRC at 2- and 3-week lead times. Some models still lack records at many stations in northern Cameroon and the DRC.

All models are able to simulate onset dates of the growing season for 5 mm precipitation thresholds, at almost all stations (figure 22). Broadly, at 2-week lead time over the region, models forecast earlier onset dates of the growing season. Few stations exhibit delays in forecast onset dates over southern Cameroon and western DRC (figure 22 and figure 19). Over central Cameroon, BoM, CMA and ECMWF show better skill to detect onset dates compared with observations. The skill of BoM over this area remains consistent across lead times. In other part of the regions, all models predict onset of the growing season at least three weeks in advance at all lead times.

Assessment of forecast onset dates by reducing the threshold show an improvement in the number of stations were onset dates are forecast. However, there is no clear evidence of bias reduction compared with observed onset dates using a threshold of 20 mm.

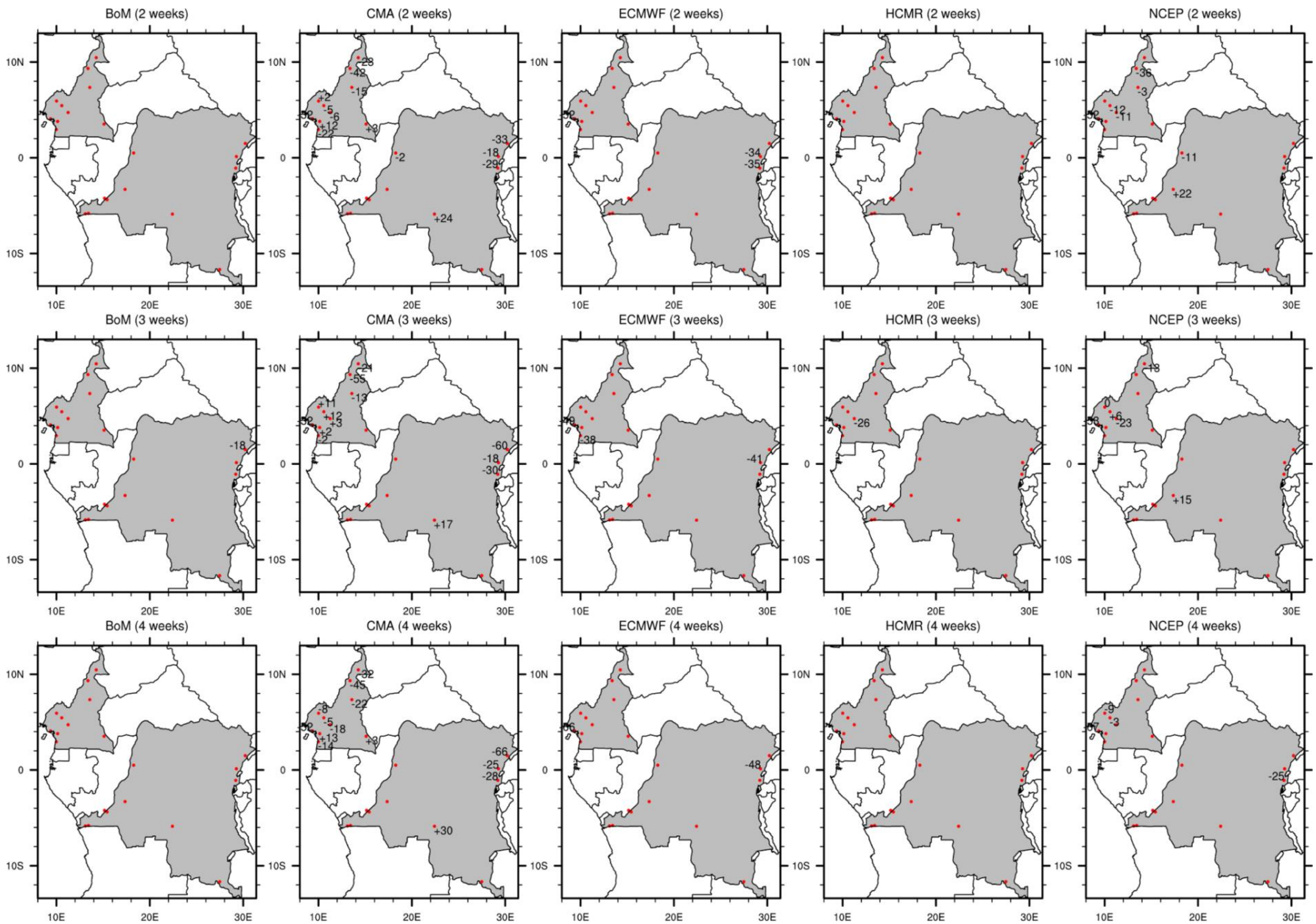


Figure 20 - **Biases between simulated and observed start dates of the growing season for precipitation threshold of 15 mm over DRC and Cameroon**

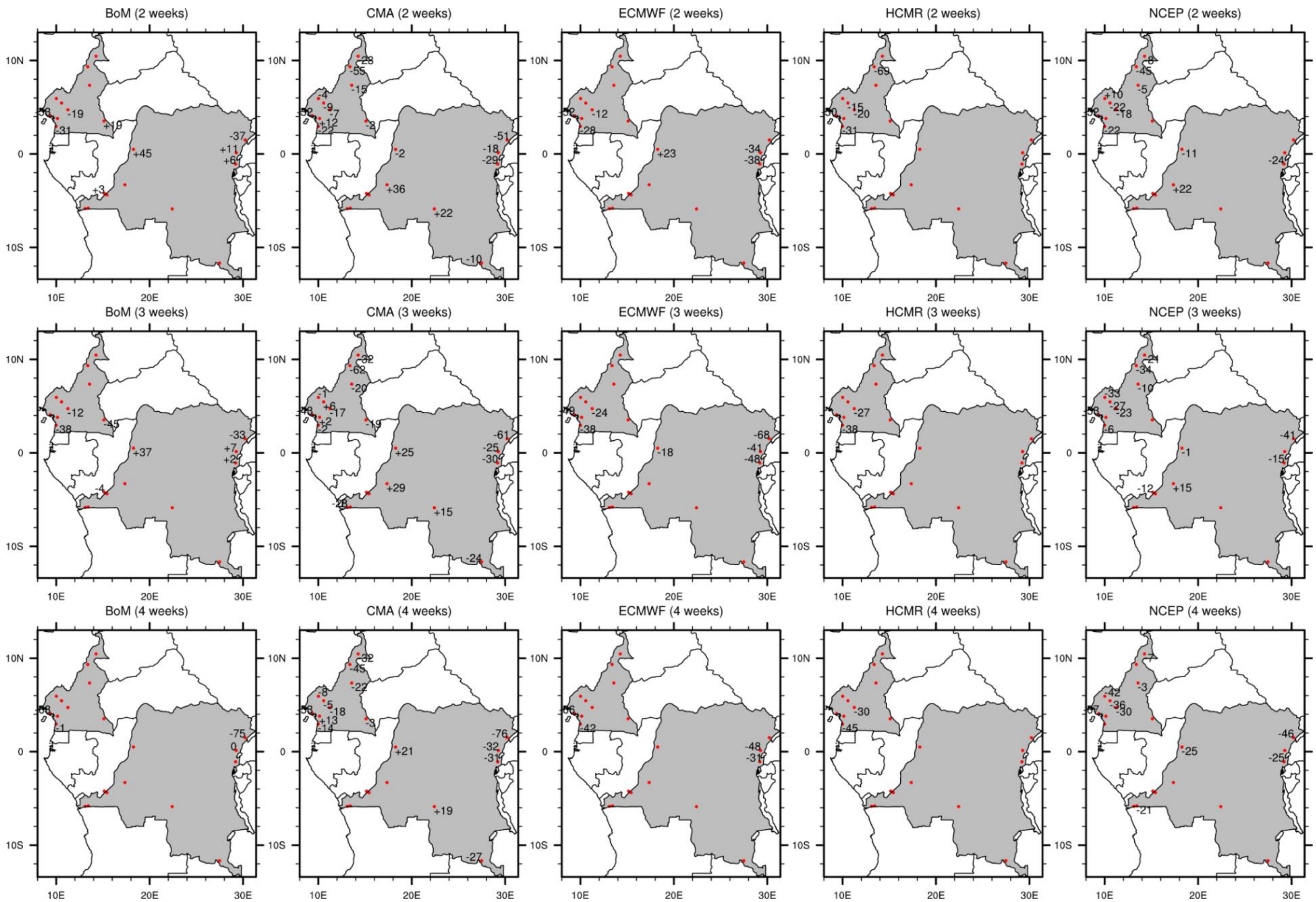


Figure 21- **Biases between simulated and observed start dates of growing season for precipitation threshold of 15 mm over DRC and Cameroon**

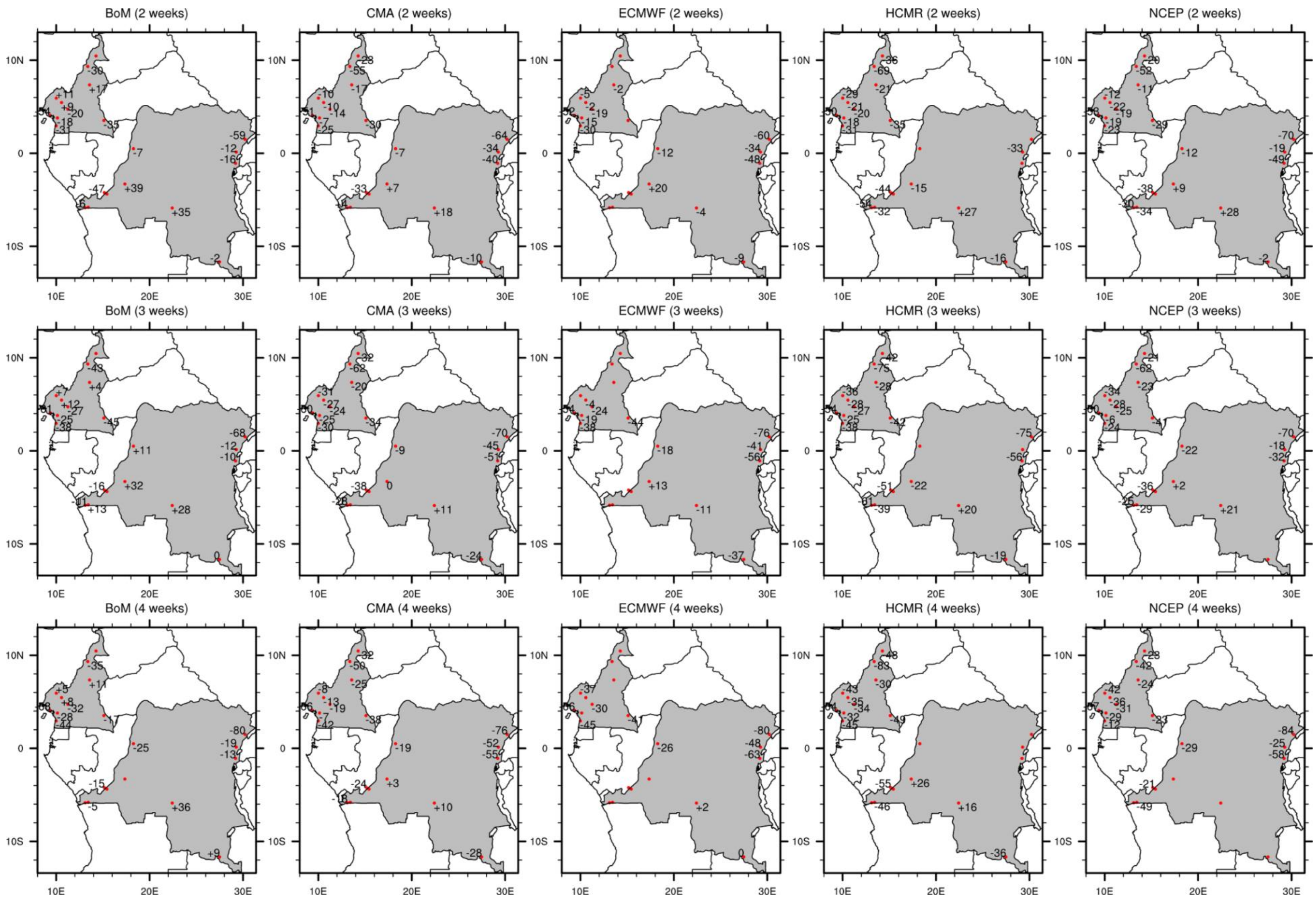


Figure 22 - **Biases between simulated and observed growing season start dates for precipitation threshold of 5 mm over DRC and Cameroon**

6 Partnership and Capacity-building

An important goal of this pilot project was to mobilize multi-institutional participation and partnerships. During the project's second month a meeting was organized in Yaoundé, which aimed to strengthen team members on subseasonal to seasonal prediction, build and strengthen links with the International Research Institute (IRI) for Climate and Society of Columbia. The institute has extensive experience in forecasting and leads many activities in this area. The head of Climate Group at the institute, Andrew Robertson, is also co-chair of the steering group of the S2S prediction project. He trained the team on methods and data used for prediction.

Materials of the meeting were posted to the following link:
http://wiki.iri.columbia.edu/index.php?n=Climate.S2S-CentralAfrica

7 Conclusion and Outlooks

The study made here aimed to evaluate the ability of global IRID (GCMs) to provide useful forecast products relevant to agriculture in Central Africa. Based on the subseasonal to seasonal (S2S) database, analyses aimed to assess the skill of different models to predict metrics useful for agricultural planning over the region. This database is an opportunity to explore forecasting events at S2S timescale, in order to improve prototype climate predictions over Central Africa.

To achieve the above goal, identification of farmers' needs for climate information was a necessary step. This was crucial in developing meteorological metrics useful for farming. Based on climate hazards and what farmers identified as elements which have negative impacts on crop production, researchers from universities and from institutes of agriculture jointly designed metrics focusing on these problems. Among these metrics, onsets of growing season and maximum dry spell length duration were selected to assess global climate model forecasts. Researchers and forecasters co-designed the criteria used to compute these precipitation-based metrics. According to these criteria, five global model (BoM, CMA, ECMWF, HCMR, and NCEP) forecasts were selected from the S2S database. Forecast data from the five models were evaluated, and for hindcast analysis only BoM, CMA, and ECMWF were assessed. Both analyses were performed at 2-, 3- and 4-week lead times for each model.

Hindcast analysis shows that for the growing season onset date in Cameroon all models seem to depict a well-observed average (near normal) category. CMA was more skillful compared with ECMWF, even though both models showed strong deficiencies for earlier and later onset date categories. BoM displayed better skill for all onset categories. In DRC, all models present deficiencies to predict an observed early onset date category. For others, models of this category showed improvement, with highest performance for BoM; whereas, skills of CMA and ECMWF were close together.

The dry spell length analysis showed that in the southern humid forest area of Cameroon the models made underestimations, while for the other areas the near-normal-to-normal category dominated and models showed good skill. In DRC, across the different climatic areas, according to dominance of the near-normal category, there is a general tendency of good skill to forecast dry spell length. But some local specificities are noticeable. For the western region, over the inland area, all the models show good skill, while at coastal stations skill is weak.

Additional agrometeorological metrics such as water availability during the growing season can be investigated after this study. This is because subsesasonal to seasonal forecasts can help farmers and others make decisions on cropping patterns for onset dates, dry spell occurrence, rainfall water availability in dry to driest conditions covering the full growing season. This is so that supplemental irrigation may be applied, which may require forecasts with lead times of 14 to 30 days. Additionally, the remaining countries of Central Africa should be involved.

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