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Thresholds for operational agro-climatic monitoring and early warning against high impact rainfall events in the Sudan-Sahel region, West Africa.

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DEDICATION

In memory of my late father, Latekoe Amekos LAWSON ZANKLI, for my mother, Delali Ayoavi GALLEY and for my beloved son, Seevah.

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The results of this thesis were used to contribute to this paper:

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ABSTRACT

High impact rainfall events (HIRE) are among the most challenging intra-seasonal climate variability components which threaten human security and natural resources in the West African Sudan-Sahel region (WASS). The exposure and vulnerability of rural communities and farming systems to random onset of rainy seasons, long dry spells, heavy rainfall events, droughts and floods can subsequently increase food insecurity, disasters risks on life and property. The identification and use of thresholds can improve the provision of weather/climate information to people and smallholder farming systems in order to alleviate food crisis and reduce disaster risks in WASS. In-situ observations data (weather, maize cultivars and soil datasets), collected from some reference stations, are combined with crop model simulations data (DSSATV4.6, www.dssat.net), to generate dates of occurrence and amplitudes of first efficient rainfall (FER), extreme dry spells (ExDS), intense rainfall event (IRE) and water requirement satisfaction index (WRSI). The threshold values defining these agro-climatic HIRE as rainfall extremes are identified and analysed, at the station level and upscaled to the WASS level, with respect to observed dry (wet) regime of the cropping seasons. The thresholds' operational rating scales and warning flag colours are suggested for both crop-climate related indices (i.e. FER, ExDS, WRSI) and the disaster reduction related indices (i.e. IRE). Further predictability potentials, at 10-day (dekad) lead time, are investigated for WRSI, using a binary logistic regression (BLR) model developed based on observed candidate predictors and tested using prefect prognostics (PP) forecasting approach. Forecast verification indices show an uneven performance of the PP approach, in predicting WRSI extremes, across reference stations with high probability of detection and bias. From these results, the study demonstrates that thresholds profiling can improve the quality of agro-meteorological information delivery to operational maize monitoring and early warning services against rainfall extremes in the fields of disaster risk reduction and food security in this region.

Key words: High Impact Rainfall Event, Thresholds Analysis, Binary Logistic Regression, Perfect Prognostics, Predictability Potentials, Verification, Sudan-Sahel, West Africa.

RESUME

Les événements pluvieux à haut risque (HIRE) constituent l'une des composantes de la variabilité climatique intra-saisonnière les plus désastreuses dans la région soudano-Sahélienne de Afrique de l'Ouest (WASS). La vulnérabilité des communautés rurales et systèmes agricoles aux débuts hasardeux de la saison pluvieuse, aux longues poches de sécheresse, aux pluies intenses, aux sécheresses et aux inondations peuvent accroître les risques d'insécurité alimentaire, de catastrophes et la pauvreté. L'identification et l'utilisation de seuils peuvent améliorer la qualité de l'information climatique donnée aux petits producteurs afin d'atténuer les crises alimentaires et les catastrophes dans la région. Les données d'observations in situ (données météorologiques, itinéraire technique du maïs et profils des sols), obtenues de certaines stations de référence sont combinées avec des simulations de modèles de cultures (DSSATV4.6, www.dssat.net) pour générer les dates d'occurrence et amplitudes de la première pluie efficace (FER), des poches de sécheresse extrêmes (ExDS), des événements de pluie intense (IRE) et de l'indice de satisfaction des besoins hydriques de la plante (WRSI). Les valeurs seuils définissant la sévérité de ces indices agro-climatiques sont identifiées et analysées à l'échelle des stations puis généralisées sur le Sahel par rapport au caractère sec (humide) des saisons de culture. L'échelle d'évaluation des seuils et les indicateurs d'alerte sont suggérés à la fois pour les indices liés aux cultures et au climat (FER, ExDS, WRSI) et ceux liés aux catastrophes (IRE). De plus, les potentiels de prévisibilité de 10 jours d'intervalle sont étudiés pour WRSI, en utilisant le modèle de régression logistique binaire (BLR) basé sur les prédicteurs observés et testé par l'approche « perfect prognosis » de prévision (PP). Les indices de vérification des prévisions montrent une performance inégale de l'approche PP dans la prévision des WRSI extrêmes, à travers les stations de référence avec une forte probabilité de détection et de biais. À partir de ces résultats, l'étude montre que la connaissance des seuils peut améliorer la qualité de l'information agro-météorologique au service de la surveillance opérationnelle et d'alerte précoce contre les extrêmes pluviométriques dans les domaines de la réduction des risques de catastrophes et de la sécurité alimentaire dans la région Soudano-Sahélienne de l'Afrique de l'Ouest.

Mots clés : Evènements Pluvieux à Haut Risque, Analyse de Seuils, Régression Logistique Binaire, perfect prognosis, Potentiels de Prévisibilité, Vérification, Région Soudano-Sahélienne, Afrique de l'Ouest.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AgMEWS	Agro-climatic Monitoring and Early Warning System
ANACIM	Agence Nationale de l'Aviation Civile et de la Météorologie du Sénégal
ANAM-BF	Agence Nationale de la Météorologie du Burkina Faso
APTE-21	Applying climate forecasts and agricultural practices for translating extreme rainfall of the 21st century in flood-risk area
BLR	Binary Logistic Regression model
BMBF	German Federal Ministry of Education and Research
DNM-TG	Direction Nationale de la Météorologie du Togo
DSSAT	Decision Support System for Agro-technology Transfer
ExDS	Extreme Dry Spells
FER	First Efficient Rainfall
HIRE	High Impact Rainfall Events
IRD	Institut de la Recherche pour le Developpement
IRE	Intense Rainfall Event
ITCZ	Inter-Tropical Convergence Zone
NMHS	National Meteorological and Hydrological Service
PP	Perfect Prognostics
WASCAL	West African Science Service Center for Climate Change and Adapted Land Use
WASS	West African Sudan-Sahel
WRSI	Crop Water Requirement Satisfaction Index

Chapter 1 : INTRODUCTION

1.1.Background

The knowledge of weather and climate impacts on rain-fed agriculture in West Africa has improved over the past decades. For instance, the planting date is, very often, determined based on the soil moisture and the amount of water available for the crop at a given period of time. However, putting this knowledge into action that will spur farming communities to cope with the adverse consequences of extreme events (water stress, heat stress) is not yet completed. The skills required for climate predictions are still imperfect and approaches adopting climate-smart practices in West African farming systems have yet to be tested extensively. Therefore, the idea of developing an operational agro-climatic monitoring and early warning system (AgMEWS) is a breakthrough to technical adaptation measures for the region. For example, smallholder farmers need climate information, but they also need practical advice on how this information can be translated into optimized actions.

To tackle the above challenges in the context of a changing climate, The West African Science Service Center on Climate Change and Adapted Land Use (WASCAL) developed the APTE-21 project ("*Applying climate forecasts and agricultural practices for translating extreme rainfall of the 21st century in flood-risk area*"). The APTE-21 project explores and exploits the potential advantage of rainfall extremes for smallholder farmers. The project will particularly improve the production, access and use of local information on high impact weather/climate events. The output will be accessible for family farms in Bakel (Senegal), Ouahigouya and Dano (Burkina Faso) and Bolgatanga (Ghana). The project uses proactive and participatory dissemination protocols (climate field schools, community co-production, advice and new technology such as mobile phones, applications and internet for agro-climatic information extensions), and builds small on-farm infrastructure to alleviate negative impacts of rainfall extremes.

From the above perspective, the present study on "threshold for operational agro-climatic monitoring and early warning scheme in the Sahel Region, West Africa" explores the thresholds of some agro-climatic indices defining stresses for crops (maize) and builds a perfect prognosis for an early warning system on extremes. The outcomes of this research will be relevant to fine-tune the climate information given to farmers associated with climate-smart agricultural practices. Furthermore, it will help improve decision making from a smallholder farmer perspective in this era of climate change.

1.2.Problem statement

In the context of high risk weather hazards, intra-seasonal variability of rainfall extreme events is the most challenging factor farmers have to face in agriculture and crop water management in Africa. Indeed, in the Sahel region of West Africa, AGRHYMET (2010) demonstrated a new climate variability with a pattern of mixed dry/wet years starting from the year 1994 while, earlier, it showed a succession of wet years (1950-1969) and dry years (1970-1993). This changeability brought about a new rainfall variability which is said to be characterized by false starts, extreme dry spells, floods and droughts, resulting in a reduction in the length of the cropping season (Sarr *et al*., 2015). Moreover, Salack *et al.* (2016) argued that the hybrid rainfall regime (dry/wet) is attributable to global warming and has negative consequences on subsistence farming systems. Consequently, with the challenging climate change, these impacts are likely to become more dramatic for rain-fed agriculture in West Africa.

In addition, recent assessments conducted by Lobell *et al.* (2011) and Waha *et al.* (2013) have shown that the combined impacts of some of these rainfall factors (false starts, extreme dry spells, etc.) on agricultural production have been tremendously negative. The consequences include not only yield/biomass loss and reduced growth, but also farm flooding, water logging of low land crops, arable soil erosion with possible pollen washing and heat stress. As the frequency and intensity of extreme rainfall/drought would certainly increase, farmers are likely to bare dire consequences with significant impacts on their livelihood (Sylla *et al*., 2015).

Under these circumstances, there is a need to find alternative ways to help farmers cope with the challenging situation. Accordingly, the APTE-21 project plans to develop an operational agro-climatic early warning system that will enable National Meteorological and Hydrological Services (NMHSs) to deliver prompt climate services to farmers for appropriate and accurate decisions in crop management under climate change. Key inputs to the system involve near-real-time observations, forecast products, seasonal predictions, crop yield simulations and related smart management practices. The current study essentially focuses on thresholds in an operational agro-climatic monitoring for maize farming, given their importance in, not only most West African countries' economy but also the food security and livelihood of the populations. The aim is to determine threshold values of some agro-climatic indices (first efficient rainfall, extreme dry spells, intense rainfall event and crop water requirement satisfaction index) that will trigger an early warning scheme to provide understandable and efficient climate information to farmers.

1.3.Objectives

The overall objective of the study is to improve climate information provision to farmers through the analysis of thresholds defining agro-climatic extremes for maize production system for monitoring and early warnings.

More specifically, this study aims to:

- Define high impact rainfall events (HIRE) and crop-climate nexus indices
- Identify the threshold values defining HIRE and water satisfaction stress for selected maize cultivars (i.e. Obatampa and EV-8443);
- Develop rating scales, timing intervals, risk areas and flag colours for HIRE in operational services delivery, using thresholds analyses; and
- Test the predictability potentials of crop water satisfaction index for use in monitoring and early warning against drought stress.

1.4. Research Hypotheses

The study hypothesizes that "*identification and use of thresholds can improve the provision of weather/climate information to smallholder farming systems*".

1.5.Research Questions

Important questions to answer include:

- What are the agro-meteorological thresholds defining drought (wetness) stress to maize cultivars (Obatampa and EV-8443)?
- What are the rating scales and risk areas of HIRE in the study area?
- How can threshold analysis be used (extended) in monitoring (warning against) rainfall extremes in smallholder subsistence maize farming system?
- What are the predictability potentials of weather parameters for the crop water requirement satisfaction index?

1.6. Thesis Structure

This thesis is structured into five major chapters. The introduction (chapter one), encompasses the background for the study, problem statement, objectives, research hypotheses and questions. Chapter two summarises the results of a literature review positioning operational agro-climatic monitoring as a climate change adaptation measure globally and specifically in WASS. Chapter three describes the study area, data sources, data types and the methods used to address the research questions. Chapter four provides the results obtained and discussions, and finally chapter five gives conclusion and recommendations. For further information sharing, a list of references and appendices are provided at the end of this document.

Chapter 2 : LITERATURE REVIEW

2.1.Definition of agro-climatic indices

An agro-climatic index is a measure or indicator of an aspect of the climate that has an agricultural significance (http://glossary.ametsoc.org/wiki/Agroclimatic_index). The indices often used in Agrometeorology are the onset, end and length of the growing season, intraseasonal rainfall variations (wet and dry spells), the rainfall amount and duration (Selvaraju, 2012). He stated that rainfall onset is the date of onset of the growing season as the key variable to which all other seasonal rainfall variables are related. A farmer's signal for sowing may be either a fixed calendar period (window), or attainment of some arbitrarily selected build-up of stored soil water or attainment of a fixed rainfall threshold. The definition of the potential sowing date with the most widespread use in agro-meteorological applications was documented by Stern *et al.*, (1982) and is of the general form:

(i) the start of the rainy season is not considered until after a particular date, '*d*';

(ii) the potential start date is defined as the first occurrence of at least '*x*' mm totalled over '*t*' consecutive days; and

(iii) the potential start could be a false start if a dry spell of '*n*' or more days in the next '*m*' days occurs afterwards.

The variables *d, x, t, n* and *m* can be defined locally according to user requirements. Stern et al., (1982) suggested that the earliest possible start date, '*d'*, might be chosen according to previous experience as to whether successful planting had occurred before a particular date, or alternatively, when the probability of a dry spell falls below a certain value. Kniveton *et al.*, (2009) defined the onset date *'d'* as the average daily rainfall minimum prior to the average daily rainfall maximum using different average periods. Three thresholds (10, 20 and 30 mm) for the variable *'x'* were considered over 't'=2 days with dry spells of 'n'=10 days in the next 'm'= 30 days. Sivakumar (1992), defined the onset date as the date after *'d'*=1st May when rainfall accumulated over *'t'*=3 consecutive days is at least *'x'*=20 mm and when no dry spell within the next *'m'*=30 days exceeds *'n'*=7 days. Until recently, this algorithm is used to estimate the potential "planting" date in the West African landscape. Omotosho *et al.*, (2000) defined the onset of the rainy season as 'the beginning of the first two rains totalling 20 mm or more, within 7 days, followed by 2 or 3 weeks each with at least 50% of the weekly crop water requirement. Dry spell refers to the consecutive period with daily precipitation amount that is no more than 1mm/day (She *et al.*, 2016). Sometimes, it is after the onset of the season that farmers observe the occurrence of extreme dry spells (ExDS) events to constitute a false onset of rainy season. In such case, any rainfall amount embedded with the first efficient rainfall may not prevent havoc to seedlings. A situation of false onset of the season causes the topsoil to dry-up and prevents the germination or emergence of seedlings (Ati *et al.,* 2002). Farmers are usually forced to re-plant several times because of false onset of the season. The occurrence of ExDS during the growing season (i.e. post-floral ExDS) also causes a decrease in agricultural yields (Sivakumar, 1992). Salack *et al.*, (2013) developed an extraction algorithm to determine dry spells length and date of occurrence over the West African sudan-Sahel. In addition, they established a regional occurrence index (ROI) to capture the spatial coherence of extreme dry spell types. In building the algorithm, the threshold of 0.1 mm/day is used to define a rainy day in order to capture all daily rainfall events (RR). All daily records are coded into alternating 1 and 0 (for rainy and dry days respectively). After each rainy day, consecutive dry days were counted (i.e. sequence of days in which RR = 0) to define a dry spell (DS). The total numbers of consecutive dry days before the next rainy day was the duration or length (L) of the DS. The Julian day of first count corresponded to the onset date (STDATE). The total number of DS with length L found in a season was the frequency of occurrence (F). Extractions were made on the basis of the first rainfall event recorded by the raingauge after May 1st. They discovered 4 categories of DS. The short categories of DS are 1–4 days (DS1) and 5–7 days (DS2). The medium category of observed DS is the class of 8–14 days (DS3). The long dry spells category is the set of DS greater than 2 weeks (DS4). Froidurot and Diedhiou, (2017) explored the characteristics of wet and dry spells in West Africa. They defined each day as wet or dry using a threshold of 1 mm/day. Wet (respectively dry) spells are sequences of consecutive wet (dry) days, preceded and followed by dry (wet) days. The length of dry spells lower or equal to 21 days were analysed.

Rainfall amount and duration within the rainy season have gained importance for the past decades especially due to the frequency of flood and drought events in West Africa. For instance, many West African countries reported frequent flood and drought events. In 2010, 1.7 million people were affected by floods in Benin, Burkina Faso, Chad, Ghana, Niger, Nigeria, and Togo (Sarr, 2011). In 2009, Benin, Burkina Faso, Niger and Senegal experienced major floods. In 2012 more than 80% of Nigeria was affected by heavy rains which submerged much of Delta and Bayelsa states in the southwest, affecting some 350 communities and making 120,000 people homeless. In 2012, UN agencies estimated that over 16 million people in Mali, Sudan, Niger, Burkina Faso, Senegal, The Gambia, and Chad were affected by drought (UCDP 2017). Unfortunately, these events have a widespread impact on human security. Besides the fact that research on extreme rainfall events in West Africa is scarce, efforts are underway to understand and predict when and where heavy rainfall may damage crops and how this may affect food security (Yabi and Afouda, 2012). New et al. (2006) analysed daily data from six stations in West Africa (two in the Gambia and four in Nigeria) and revealed a rising trend in annual maximum daily rainfall at only one observation site. In Cote d'Ivoire, Goula et al. (2012) analysed annual maximum daily rainfall time series from 34 stations for the period 1947–1995. Using three indices (annual maximum rainfall, number of days where precipitation exceeded a 50 mm threshold, and total days exceeding 50 mm per year), the study highlighted a downward trend in extreme rainfall events. Zahiri *et al.*, (2016) studied the extreme rainfall events in two different climatic zones. Extreme values were determined using the Block Maxima Analysis (BMA) and the Peak Over Threshold (POT) method as documented by Panthou *et al.,* (2012, 2014). The POT method consists of defining a threshold and selecting all variable X occurrences that surpass this threshold and the BMA method defines blocks of n occurrences of the random variable X followed by the selection of the maximum value within each block. For example, when daily rainfall is set as variable X, the daily data for a one year period would be grouped as a single block. The vector of maxima Z, defined as the annual maximum daily rainfall value within each block.

2.2. Operational Agro-climatic Monitoring and Early Warning System

Agro-climatic monitoring and early warning system (AgMEWS) is a term used to define the process of identifying weather/climate conditions appropriate for farming activities and informing farmers for immediate decision-making in crop management practices. It has the advantage of applying climate information (e.g. observations, now-casts, forecasts, predictions) to generate and disseminate timely and meaningful warning information enabling individual farmers to take necessary measures and act appropriately in sufficient time to reduce the possibility of losses(UNISDR, 2009).

In agro-climatic monitoring, various studies have been done to address the impacts of climate change on agriculture and suggest adaptation measures for farmers (Selvaraju, 2012; MacCarthy *et al*., 2013; Kiprotich *et al.,* 2015). The innovative change is the use of climate forecast in agriculture. Anaman and Lellyett (1996) promoted weather information in their study on the Australian cotton industry. Indeed, a survey on farmers' perception of an enhanced weather information service for cotton production revealed that 51% of the 108 sampled farmers have adopted the service due to its timeliness, accuracy, easy understanding and overall usefulness. More so, an assessment of weather information benefits for cotton farmers shown that adopting an enhanced weather information is cost effective and time saving for cotton production, in addition to allowing farmers better plan their household and social activities. Similarly, Nelson *et al*. (2002) developed in the North East of Australia a discussion support software called Whopper

Cropper which provides an effective means to infuse innovations, like seasonal climate forecasting, into farming practice. It consists of a database of simulation output and a graphical user interface to generate analyses of risks associated with crop management options. It provides information on the impact of climate risk on crop yields for crop management alternatives beyond the experience of individual farmers, using historical climate records to obtain a very long-term perspective. Enhancing the importance of weather information in agriculture, Amegnaglo and Mensah-Bonsu (2010) stated that one approach to mitigate climate change is the use of accurate meteorological information in agriculture (60-70%). Another assessment conducted by Berg *et al.*, (2013) on the adverse consequences of climate change on C4 crop productivity over Africa and India, using a newly developed agro- Dynamical Global Vegetation Model (DGVM), revealed the negative impacts of temperature and precipitation variability on crop yield and the need for adaptation measures and smart agriculture practices to ensure food security on the long run in the developing countries. Such practices involve, once again, agro-meteorological solutions especially climate/weather forecast combination with crop management options. For instance, in Senegal (West Africa), seasonal forecast has recently been applied to agricultural practices in order to help smallholder farmers cope with climate change and variability but a holistic approach is needed to allow an efficient use of the information.

A recent innovation is the combination of seasonal forecast with crop simulation models. It was developed in India for groundnut production in order to build a combined seasonal weather and crop productivity forecasting system using empirical orthogonal function analysis with rainfall as predictor, (Challinor *et al.*, 2003). The study concluded that more inputs are important to deliver an accurate prediction for seasonal crop yield (other weather parameters and farming system information). Hansen and Indeje (2004) explored the combination of seasonal climate forecast with crop simulation models for maize yield prediction in semi-arid Kenya. A statistical prediction by a non-linear regression was used to predict field-scale maize yields simulated by CERES-maize with observed daily weather inputs. From their analysis, it appears that the non-linear regression has the potential for translating seasonal climate forecasts into predictions of crop response. Similarly, Hansen (2005) discussed the importance of an integrated climate-crop modelling to improve agricultural use of climate information by smallholder farmers in the developing countries. He reasoned that crop models integrated with seasonal climate forecasts provide a means of translating forecasts of seasonal climate anomalies into forecasts of production impacts. Mishra *et al.*, (2008) applied also statistical method for sorghum yield prediction in Burkina Faso. Their Analyses considered empirical and dynamic rainfall forecasts, two methods (regression and stochastic disaggregation) for linking rainfall forecasts with crop simulation, three levels of production technology and four forecast dates (15 May, June, July and August) based on predictors observed from the preceding month, for the period of available data (1957–1998). The output of their study revealed that there is a good prospect for providing useful food security early warning information, incorporating climate-based yield forecasts, earlier in the growing season than is currently available.

In the field of early warning system, tools have been developed for crop monitoring to alleviate food insecurity. The U.S. Agency for International Development's Famine Early Warning System Network (FEWS NET) provides tools and data for monitoring and forecasting the incidence of drought and flooding to identify shocks to the food supply system that could lead to famine (Funk and Verdin, 2009). It is a reference network in disaster risk reduction over the world. For crop monitoring, the network uses the crop water requirement satisfaction index computed based on satellite rainfall estimates, potential evapotranspiration, water holding capacity of the soil, crop type, start of season, and length of growing season. Therefore, FEWS NET developed the GeoWRSI. It is a Windows application that runs crop-specific water balance models using climatic data, and produces a range of outputs that can either be used to help assess and monitor crop conditions during the crop growing season, or to conduct historical analysis of the impact of seasonal rainfall deficits on crop performance, for a series of years, and for a variety of crops (Magadzire, 2016). Another tool used for crop monitoring and forecasting is the AgroMetShell developed by a team of researchers including the Southern Africa Development Community (SADC) Food Security Program, the Agrometeorology Group, the Environment and Natural Resources Service (SDRN) and the Food and Agriculture organization of the United Nations (FAO). This tool is used to provide targeted analysis based on vulnerability assessment baseline data to determine how the livelihoods of a particular zone will be impacted and to give early information as to what yields and production statistics are expected (Mukhala and Hoefsloot, 2004). The input files to the tool are dekad or daily crop, rain and evapotranspiration data. The various outputs indicate which areas in a region, country or province have received minimal rainfall, water deficits, and excess water at the various stages of crop growth as these affect yield ultimately. As input data is on a dekadal basis, such information can also be obtained at the same intervals and when persistent water deficits or indeed excess water are experienced, this may lead to poor crop yields, resulting in poor production and food insecurity.

The exciting literature shown several ways of using seasonal climate forecast in agricultural practices, for crop yield prediction and for early warnings. The current study proposes the concept of threshold analysis in agro-climatic monitoring for crop yield prediction. An effective Agro-climatic Monitoring and Early Warning System uses both observational data (classical and automatic weather station data) and forecasts (microwave link, satellite-derived or reanalysis data) through indicators or metrics of farming potentials (i.e., Agro-meteorological indices or crop models) to deliver sub-seasonal, seasonal and inter-seasonal information to local farmers. Pre-onset information should provide input information on optimum sowing dates (dry/wet seeding or transplantation), seasonal rainfall flags (representation of probabilities of rainfall amount, onset dates, growth periods) and seasonal predictions of potential crop behaviour. Feedback from farmers about the success and failure of the provided information ensures a continuous cross-validation process to improve the agro-climatic metrics and the science of monitoring and forecasting (Salack *et al.,* 2015).

2.3. Threshold Analysis in Early Warning System

The notion of threshold analysis is relatively new in relation to agro-climatic early warning system in West Africa. Indeed, it has been used in the field of aviation in Burkina Faso by Zabre and Sorgho (2015) to predict precipitate and non-precipitate convective clouds. From Salack *et al*. (2015), the threshold analysis of agro-climatic indices consists of identifying the critical detrimental or optimal values to crops/cropping systems and using them in monitoring and prediction processes. This method can also be used to identify the profile of a typical dry season. Hence, Salack *et al.* (2016) used it to identify the seasonal and intra-seasonal rainfall characteristics, the combination of which, during the life cycle of staple field crops, can strain their growth, development and production, if optimum crop management measures are not applied by the farmer. As this technique applies to rainfall seasons, it also applies to crops themselves by showing the point of inflection in the phenological cycle which can be induced by certain environmental constraints such as water stress, soil nutrient depletion, climate change, etc.

2.4.Maize Production and Climate Change

Maize (*Zea mays* L.) is grown on about 33 million of the total 194 million hectares of cultivated land in sub-Saharan Africa (SSA). It is the region’s most important food crop. Smallholder farmers, in 46 countries with a combined agricultural population of about 553 million, produce maize under diverse and varied agro-ecologies and socioeconomic conditions. Sixteen of those countries sow 25 to 65% of their total cultivated area to maize (http://dtma.cimmyt.org/index.php/about/background). Unfortunately, maize production in SSA is essentially rain-fed and therefore susceptible to drought, water-logging and extreme temperature stresses. A report of the United States Agency for International Development (USAID, 2014), reveals that maize production needs a well-aerated and well-drained soil to avoid water-logging (500-700 mm of well-distributed rainfall and an average temperature range of 21-30^{o}C). Cultivation is not viable when day temperatures are less than 19 °C, with growth stopping at temperatures below 10 °C. During flowering, temperatures at midday that reach 35 °C or above for several days can destroy pollen, and yields are drastically compromised and reduced.

In West Africa, maize is cultivated under different climate and conditions. The rainy season in coastal areas in West Africa is generally observed from the end of April to July with a second and shorter one in September and October. Further inland towards the desert, only one rainy season from July to September is observed (WMO, 2015). Climate change has provoked a modification in the rainfall distribution over the region. The AGRYMET regional centre reported that the crop season 2013 was characterized by a late onset of rains from May to mid-July in the Sahel and Gulf of Guinea region (WMO, 2015). Consequently, farmers are subject to yield loss with economic implications for their countries.

Several projects have been designed and implemented in SSA with funding from diverse donors to improve productivity at the farm level over the last ten years (Macauley, 2015). The Drought Tolerant Maize for Africa (DTMA), the Improved Maize for African Soils (IMAS), the Water Efficient Maize for Africa (WEMA), and the Nutritionally-enriched Maize for Ethiopia (NuME) are among the key projects in SSA, developing and deploying stress resilient and nutritionally enriched maize in SSA. Furthermore, studies are conducted on the impact of climate change on maize yield. For instance, Lobell *et al.* (2011), argued that “roughly 65% of present maize-growing areas in Africa would experience yield losses for 1◦C of warming under optimal rain-fed management, with 100% of areas harmed by warming under drought conditions”. Similarly, Masanganise *et al.*, (2012) predicted the influence of a changing climate on maize yield at the end of the 21st century in Zimbabwe. Their results showed that climate change will shift planting dates towards delayed planting in the period 2046-2065 which will cause yield reduction if farming practices remain traditional. So far, the proposed solutions are mainly the use of drought tolerant varieties or water resistant varieties associated in some cases with seasonal forecast information for a smart crop management (MacCarthy *et al.*, 2013; Belko *et al.*, 2014; Tarhule and Lamb, 2003).

The present thesis is contributing to the existing knowledge by proposing a new approach to tackle yield loss in the agricultural sector and disaster risk reduction. The objective is to deliver an information package to farmers, including climate smart agricultural practices and an early warning system based on agro-climatic indices and seasonal forecasting. Threshold values of maize production, which define stress, will be determined related to the agro-climatic indices.

Chapter 3 : STUDY AREA, DATA AND METHODS

3.1. Physical Characteristics of the Study Area

The West African Sudan-Sahel (WASS) is defined here as the sub-Saharan region stretching from the western coasts of Senegal in West Africa to the Eastern edges of Chad between 10 to 17^{o} N. The rainy season of this region is dominated by the West African monsoon which is confined between May and October with June-September receiving the most important amount of the seasonal totals (figure 3.1). It is a semi-arid expanse of grassland, shrubs, and small, thorny trees lying just to the south of the Sahara Desert. The study area includes much of the southern part of Mauritania, Senegal, Mali, Niger, Burkina Faso, and the northern fringes of Ghana, Benin, Togo, Cote d'Ivoire and Nigeria. Mean annual rainfall in the Sahel is on the order of 200 to 600 mm in the north, and 600 to 1300 mm at its southern limit (figure 3.1).

The mesoscale testbeds also called "*core research watersheds*" of WASCAL include Dano catchment (600 km2) in South-West Burkina Faso, the Vea & Sissili catchments (300 km2 and 12,633 km2 respectively) in Northeast Ghana and Dassari catchment (200 km2) in Northwest Benin (Figure 3.1). The objective of the testbed measurements is adding multiple sensors in parallel to keep long-term monitoring records of hydro-climate and land use processes from local-to-catchment scales using in-situ measurements. The collected panel data is a fundamental asset to improve our understanding of uncertainties in near-surface observations useful for calibrating biophysical models (Salack *et al.,* 2017).

Experimental and surveys information are also collected from the APTE-21 pilot sites and other traditional experimental stations such as Bambey (Senegal), Dapaong and Mango (Togo) for both historical climate data analysis, crop model calibration and sensitivity analyses before the study is extended to the entire WASS. The first pilot site, **Bakel**, is located in Eastern Senegal close to the borders with Mali and Mauritania. The area covered by the Bakel pilot site (15^{o} N, 12.8^{o}W) is close to 22,500 km^{2} across three main towns (Bele, Keniaba and Moudery). The number of inhabitants was estimated at about 220,000 in 2008. The main source of income is small scale farming of millet, sorghum, cowpea and livestock breeding (e.g. cattle, sheep). The second pilot site, **Ouahigouya**, is located in the north central plateau of Burkina Faso, with the total population being approximately 87,500 inhabitants. Millet, sorghum and cowpea are the staple rain-fed crops grown under a rain-fed, subsistence farming system. In **Dano, Bolgatanga** and **Dassari**, the main rain-fed crops include maize, sorghum, millet, cotton and, to a lesser extent, cowpea, groundnut and sesame. Sorghum, cotton and maize are grown in the best soils; millet and sorghum are grown on shallower soils and maize in home gardens. Cowpea is usually grown in combination with a cereal (i.e., millet or maize). Rice is grown in flooded lowlands during the rainy season. **Mango** and **Dapaong** are located in the savannah region of Togo with respectively 41,464 and 58,071 inhabitants. The main activity therein is agriculture with a focus on livestock and crops like maize, millet, cowpea, cotton and tomato. All pilot sites are located in the WASS where the rainfall regime is erratic with mixed dry-wet patterns both at sub-seasonal and seasonal scales.

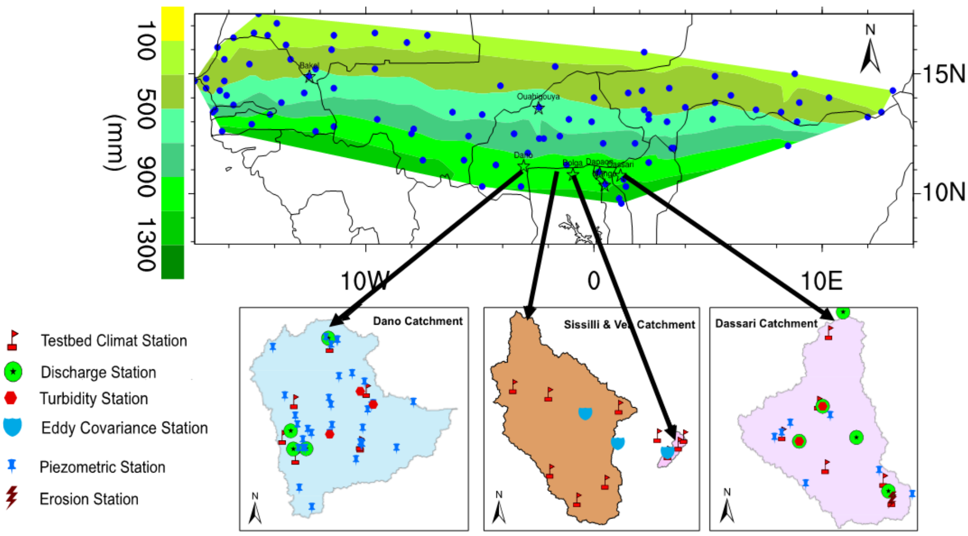


Figure 3.1:Spatial distribution of reference stations and 30-year average rainfall climatology of the Sudan-Sahel region. The stars (*) are the pilot sites where historical climate datasets, surveys, agro-climatic field schools and experimental data are collected.

3.2. Pedoclimatic Characteristics of the Study Area

The natural factors affecting the intra-seasonal variability of the rainfall regime in the Sahel are namely: the local forcing of the Saharan dry air masses, the polluted aerosols and regional scale circulation features including the latitudinal movement of the inter-tropical convergence zone (ITCZ), the Saharan heat low (SHL), the variability of lower-to-upper-tropospheric circulation features such as the African Easterly Jet (AEJ), the Tropical Easterly Jet (TEJ), the African easterly waves and other low-level westerly jets (Salack *et al.*, 2016). The coexistence and interactions of these dynamic processes, with an ever changing local land use land cover types, determine the dominant weather in a season and its associated weather events. The Sudan-Sahel of West Africa is characterized by a long dry season followed by a unique rainy season that gets to its peak in July-August and retreats in September. The spatial distribution of annual rainfall total decreases as one moves northward from ~1300 mm to 100 mm (Figure 3.1), and it is mainly concentrated over a short period of 3-4 months. The organized mesoscale convective systems, also known as squallines, contribute to the majority of the seasonal rainfall totals (Bell and Lamb, 2006; Smith *et al.*, 2012). Beside the inter-annual and inter-decadal variability (Lebel and Ali 2009), rainfall has been dominated by a high intra-seasonal distribution of sub-daily rainfall intensity (Zahiri *et al.*, 2016) and a high variability of daily events observed in the form of mixed dry/wet patterns or hybrid attributed to global and regional warming rates. While the distribution of events is mainly concentrated within the June-September period, the seasonal total rainfall results from some 40-50 rainy events of which only 2.5%-4% can be considered extreme events (Panthou *et al.,* 2014).

A recent literature review shows that from all external forcing factors, the oceans play the major role in modulating the seasonal rainfall of the Sudan-Sahel of West Africa. The Atlantic Ocean controls moisture flux into the ITCZ and the equatorial Indo-Pacific oceans control the vertical stability and upper troposphere temperatures through deep convection (Liepert and Giannini, 2015). The Mediterranean Sea also exerts a positive influence on the Sahel rainfall (Rodríguez-Fonseca *et al.*, 2011). The other external influences include westward wave propagation caused by convection anomalies of the Indian monsoon (Mohino *et al.*, 2012). At seasonal time scales, the most influential oceanic basins to the rainy seasons of the Sudan-Sahel are the sub-tropical north Atlantic (10-40ºN,15-75ºW), the extra-tropical north hemispheric Atlantic (30-75ºN, 15-75ºW), the Mediterranean Sea (0-35ºE, 30-44ºN), the equatorial Atlantic (5ºS-5ºN, 40ºW-15ºE), the South Atlantic (10ºS-0ºN, 20ºW-10ºE) and the Eastern equatorial Indian Ocean (15ºS-15ºN, 50-90ºE) (Salack *et al.,* 2016).

The WASS is located in the Sahel and Savannah zone according to the soil classification in Africa. The Sahel and Savannah area is characterised by a mixed grassland/woodland ecosystem that is adjacent to the forest regions. The soils are generally well drained and possess a thin layer of organic matter, which can be thicker in wetter conditions. They can support limited cultivation but can quickly become impoverished. Most soils are old and deep, with a low nutrient-retention capacity because they are dominated by a kaolinitic clay mineralogy. Exceptions are the large level areas where shrink-swell clays are found; here the dominant mineralogy is montmorillonitic, resulting in a high nutrient-retention capacity. The low leaching also results in the accumulation of carbonates if a source of calcium is present. Carbonates are also deposited as wind-blown dust (e.g. in the Harmattan regions). Many soils are red in colour due of the accumulation of hematite (iron oxide). The dominant soil types are Arenosols, Cambisols, Lixisols, Planosols, Plinthosols, Regosols, Solonetz and Vertisols.

Soil profiles, in the study, are based on exciting literatures related to dominant soil types and their edaphic parameters (e.g. percent clay, silt, stones, organic carbon, total nitrogen, pH in water) in Togo, Burkina Faso, Senegal and Ghana (Worou 1985); Kissou *et al.* (2000); Khouma (2000); Abutiate (2013)). In Bakel, a rhodic regosol mainly sandy loam with 150 cm depth was identified. Its carbon/nitrogen ratio on average is 12 with the water pH of 7. The main constraint of these soils is a low fertility due to the arid climate causing water stress to the crops. Dano, in the south-west of Burkina Faso, was represented with a rhodic lixisol of 120 cm depth. The organic matter ratio is approximately 9 with a water pH of 6.9. For Ouahigouya, the soil profile considered is of type eutric regosol with 193 cm depth, a carbon/nitrogen ratio of 10 and a water pH around 6. Mango and Dapaong soils (ferric ferralsol) are sandy clayed with 120 cm depth. The carbon/nitrogen ratio on average is 9.03 and the water pH around 6. The main development constraints of this kind of soil are a low water retention capacity, a rapid desiccation, a low to medium chemical fertility, a low organic matter content, an average depth, and a susceptibility to erosion. The soil type used for Bolgatanga site is a ferric plinthosol of 75 cm depth with a carbon/nitrogen ratio of roughly 10 and a water pH of about 6.

3.3.Data and Methods

3.3.1. *In situ* Observational Data

Datasets were collected from pilot sites and archives of the national meteorological and hydrological services (NMHSs) of some WASCAL countries including data from synoptic observation. These data cover 1960-2016 period at daily time step of rainfall, maximum temperature (tmax) and minimum temperature (tmin), 2 m wind speed, solar radiation, relative humidity. Table 3.1 gives a summary of the data used, parameters and locations. A quality control was done for all observations data to identify and correct missing data.

Table 3.1: Observed data collected from archives of pilot sites and National meteorological offices of Burkina Faso, Togo, Ghana and Senegal

Stations	**Longitude**	**Latitude**	**Period (source)**	**Variables**
Dapaong	0.201023	10.87331	1981-2016 (DNM-TG)	Rainfall, tmax, tmin, wind speed, sunshine hours, relative humidity (max.min)
Dano	-3.060124	11.14905	1970-2016 (ANAM-BF, WASCAL)	Rainfall, temperature, wind speed, sunshine hours, relative humidity
Bakel	-12.46385	14.90267	1960-2010 (ANACIM)	Rainfall
Ouahigouya	-2.410991	13.56683	1960-2016 (ANAM-BF)	Rainfall
Bolgatanga	-0.8579	10.7875	1976-2016 (Ghana Met office, WASCAL)	Rainfall, temperature, wind speed, sunshine hours, relative humidity
Mango	0.4738293	10.35506	1981-2016 (DNM-TG)	Rainfall, tmax, tmin, wind speed, sunshine hours, relative humidity (max.min)

Missing weather parameters were completed with data provided by the NASA's Prediction of Worldwide Energy Resource (POWER) (http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi?email=agroclim@larc.nasa.gov). The parameters contained in the agro-climatology archive of this portal are based primarily on solar radiation derived from satellite observations and meteorological data from assimilation models. The POWER database gives daily measurements of minimum and maximum temperatures, wind speed at 10m, relative humidity and solar radiation in MJ/m^2/d. The meteorological data collected were essentially rainfall, minimum and maximum temperature, 2m wind speed, insolation hours and relative humidity. In order to use the above information, an excel sheet was established to convert insolation hours to solar radiation and 10m wind speed to 2m. The formula of the relationship between solar radiation and sunshine hours is taken from the FAO corporate document repository website http://www.fao.org/docrep/X0490E/x0490e07.htm, and is expressed as:

$$\boldsymbol{R_s = (a_s + b_s \frac{n}{N})R_a} \quad (3.1)$$

Where: R_s is the solar radiation expressed in Mega Joule per meter square per day (MJ/m^2/d), n, the actual duration of sunshine in hours, N, the maximum possible duration of sunshine or daylight hours in hour, $\frac{n}{N}$, the relative sunshine duration, R_a, the extra-terrestrial radiation in MJ/m^2/d, a_s, the regression constant expressing the fraction of extra-terrestrial radiation reaching the earth on overcast days (n=0), and $a_s + b_s$, the fraction of extra-terrestrial radiation reaching the earth on clear days (n=N). In this study, 0.25 and 0.5 were respectively used for the Amstrong values a_s and b_s since no calibration was conducted. Wind speed conversion, from 10m to 2 m heights is based on equation (3.2):

$$\boldsymbol{Wind_{2m} = Wind_{10m} * 4.87/\ln[67.8 * (10 - 5.42)]} \quad (3.2)$$

Where $\boldsymbol{Wind_{10m}}$ and $\boldsymbol{Wind_{2m}}$ are respectively wind speed measured at 10m and 2m heights.

3.3.2. Crop simulation data

The crop simulation data is useful to estimate crop water requirement satisfaction index (WRSI). To this end, the Decision Support System for Agro-technological Transfer version 4.6 (DSSAT V4.6) is used to determine two of the agro-climatic indices (sowing dates and WRSI). DSSATv4.6 is a process-based model capable of simulating the growth, development and yield of around 20 food-fodder-cash crops. Other modules include water balance, nitrogen, phosphorus and soil carbon models (Jones *et al.*, 2010). All modules are interlinked in an interface called the DSSAT cropping system model (DSSAT-CSM). For the platform to be functional, it is supported by database management programs for soil, weather, and crop management and experimental data, and by utilities and application programs.

DSSATv4.6 simulates growth, development and yield as a function of the soil-plant-atmosphere dynamics. It has been used for many applications ranging from on-farm and precision management to regional assessments of the impact of climate variability and climate change(Alexandrov and Hoogenboom (2000); Basak *et al.*, (2010); Eitzinger *et al.*, (2017)). DSSAT integrates the effects of soil, crop phenotype, weather and management options, and allows users to ask "what if" questions by conducting virtual simulation experiments on a desktop computer in minutes which would consume a significant part of an agronomist's career if conducted as real experiments (Jones *et al.,* (2003); Liu et *al.,* (2011); Corbeels *et al.*, (2016)). DSSAT was provided with information related to the soil profile, maize management practices (crop density, row separation, fertilization scheme and seeding types and calendar) and climate daily data.

The climate daily data were also imported into DSSAT weather data manager and registered as new stations. The CERES-Maize module was calibrated and tested for some maize cultivars [obatampa (90 days) and EV-8443 (100 days)]. For these cultivars, genotype parameters from release version of DSSAT4.6 are used but sensitivity analysis was conducted using survey datasets in order to test the robustness of these parameters.

3.3.3. Definition of Indices and Thresholds

a. Seasonal Drought (wetness)

The generation of the threshold values which define seasonal droughts or seasonal wetness is based on the agro-climatic classification of rainy seasons using cumulated rainfall. In the case of the 6-month (May-October) seasonal rainfall amount, we used the standardized precipitation index (equation 3.3) to identify a season which can be considered abnormally dry (wet) over each stations of the Sahel and pilot sites. We write the individual j station time series of the seasonal standardized precipitation anomaly as $\boldsymbol{\lambda_{ij}^{b}}$ where i denotes the year (i = 1k… n), and b = {1960-2016, 1970-2016, 1976-2016, 1981-2016, 1960-2010, 1961-1990, 1971-2000, 1981-2010, 1991-2010 and 1997-2016} denotes the baseline periods. The baseline periods, considered in this study, include a maximum of 57 years and a minimum of 20 years according to the available time series per station.

$$\boldsymbol{\lambda_{ij}^{b} = \frac{x_{ij} - \overline{x_{jb}}}{\sigma_{jb}}} \quad (3.3)$$

With $\boldsymbol{\lambda_{ij}^{b}}$ as the zero mean and unit variance anomaly, $\boldsymbol{\overline{x_{jb}}}$ and $\boldsymbol{\sigma_{jb}}$ are the mean and inter-annual standard deviation for baseline b at station j, (j=1…m). The sampling of the baseline takes into account the sensitivity of the anomaly to baseline climatology shown by Trenberth *et al.,* (2014). It enables composite groups of dry (wet) seasons to be formed based on the most persistently negative (positive) trend of the index, irrespective of baseline climatology (Salack *et al.,* 2016). This baseline sampling embeds the long term trends and variability found in historical rainfall assessments over this region (Lebel and Ali, 2009; Maidment *et al.,* 2015). In the case of the 6-month (May-October) seasonal rainfall amount, we choose the threshold -0.5 (+0.5) as the number of standard deviations from the mean at which a year is considered abnormally dry (wet) over the region in order to approximately match the intensity of abnormally dry years in the case of other monitoring indices (Mckee *et al.,* 1993; Vicente-Serrano *et al.*, 2010). Base on $\boldsymbol{\lambda_{ij}^{b}}$ threshold values of -0.5 (+0.5), agronomic seasons are classified as dry (wet). Hence, the clusters of dry seasons (DtC) and wet seasons (WtC) are extracted and analysed comparatively (appendix 4). According to Salack *et al.* (2016), any environmental variable belonging to the DtC can constitute a critical limit for most cropping systems to be sustained over larger portions of the Sahel region. Appendix 5 provides the seasonal cycles of atmospheric variables useful for crops growth, development and production. There is a clear and statistically significant difference among rainfall distribution variables such as rainfall amount, number of rainy days as compared to others. This suggest that rainfall distribution pattern is the most crucial asset in determining the quality of a “good” or “bad” season, other variables modulated crop water requirement though.

b. High Impact Rainfall Events (HIRE)

Rainfall related factors of high agricultural impacts are mainly the timing and spatial distribution of rain events (Salack *et al.*, 2011). The agro-climatic indices used as proxy to monitor the potential effects of these rainfall-based factors on crops growth development and yield include onset dates (Laux *et al.*, 2008), dry spells after onset modulating occurrence of rains in relation with principal crop growth stages, rainfall intensity, number of rainfall events. Other factors such as daily temperature range (DTR), wind speeds, relative humidity, and soil moisture depletion and evapotranspiration are also useful. A total of one twenty (120) different households were surveyed in the 12 villages of the pilot sites. These households are continuously monitored throughout the duration of the APTE-21 project to better assess the impact of the agro-climate delivery. The analysis of the results show that farmers need the following climate information:

- The onset and cessation dates of the rainy season will make it possible for them to anticipate on the species / varieties to grow, which plots to use and readjust seed stocks and land capital;
- The amount of rainfall that can cause floods. Farmers can prepare nurseries earlier and transplant sooner so that transplanted crops may be grown larger enough to withstand the arrival of water;
- A long-range forecast of rainfall allowing farmers to prepare the farm before the rain and to transplant the crop;
- After sowing, short range rainfall forecasts (24h and 48h) are important for organizing weeding, fertilization calendars.

By crossing these results from field surveys, experts’ consultation meetings, and other exchange forums with farmers in the APTE-21 pilot sites four agro-climatic indices were identified relevant to smallholder farming systems. These indices are tagged “high impact rainfall events” (HIRE). They include the first efficient rainfall (FER), the extreme dry spells (ExDS), intense rainfall event (IRE) and the crop water requirement satisfaction index (WRSI).

- **First Efficient Rainfall (FER)**

The FER, is the first rainfall event recorded by a raingauge which is higher than the aerodynamic demand of that location. Very often than not, the FER is followed by extreme dry spells which may be detrimental to seedlings leading to re-planting and characterizing false onset of rainy seasons (Salack *et al.,* 2014). The FER is also a proxy meteorological onset definition of rainy season which is different from the agronomic definition of sowing date. Applying partially the definition of Stern et al., (1982), the FER was defined with a date of occurrence (variable *'d'*) and a rainfall intensity (variable *'x'*).

The variable '*x*' is determined based on a range of rainfall amount thresholds (1 to 50 mm) over 1st January-31st December period for the reference stations. An algorithm was built to determine the FER date and intensity per threshold and year at each station. The date of occurrence (considered as day of year) of the FER is computed as the day with a recorded rainfall amount greater than the specified threshold. This scheme is considered for both dry and wet seasons of the stations as defined by the standardized precipitation index in equation 3.3. A cumulative distribution function is used to compare the FER date and intensity of dry and wet seasons. This method allowed the identification of a unique threshold to characterise FER in the WASS region.

- **Intense Rainfall Event (IRE)**

An intense rainfall event (IRE) is defined as the exceeding of a threshold that corresponds to the 99th percentile of daily rainfall amount of a season as stated in Salack *et al.,* (2017). To compute the 99th percentile, a vector of daily values of rainfall RR (RR $\geq$ 1 mm) of each year was created and sorted in ascending order. Then, 99% was multiplied by the total number of those values to generate a rank index (if the index obtained is not a whole number, it is rounded to the nearest whole number). The rank index is used to extract the corresponding value from the ordered vector. This value is considered as the 99th percentile threshold value which is subsequently used to extract all intense rainfall events greater or equal to it in each season. All IRE cases are identified and extracted with respect to the date of occurrence (DTO) and the accumulated daily amount (INT). At each rain gauge location, any daily accumulated rainfall amount is considered as extreme if it belongs to the class of IRE.

To look for possible identical features in all IRE, the same extraction algorithm is applied on an additional data set from primary stations' and stand-alone raingauges owned by National weather offices of WASCAL countries. This daily rainfall dataset is retrieved from archives of manual ordinary rain gauges dating back in 1960s and updated to 2013-2016. The extracted DTO (here the DTO unit is converted from day-of-year to week-of-year, WOY to reduce signal-to-noise ratio) and INT (mm/day) of all IRE are subjected to an unsupervised clustering algorithm that groups data based on the Euclidean distance across sample elements in order to find common patterns. The general procedure is to search for a K-partition with locally optimal within-cluster sum of squares by moving points from one cluster to another (Hartigan and Wong, 1979). As we have to specify the number of clusters to be used to group the data, we computed the percentage of variance explained as a function of a possible number of clusters ranging from 2 to 15. The first two clusters explain the maximum, followed by the 3rd, the 4th and so on until the marginal gain drops, giving an angle in the scree plot. The number of clusters is chosen at this point of the scree plot (also called the “elbow”). Once the optimum number of clusters is chosen, clusters centroids are calculated iteratively by reassigning data points, ordered by their distances to the overall mean of the sample, till the within-cluster variation cannot be reduced any further. The within-cluster variation is calculated as the sum of the Euclidean distance between the data values and their respective cluster centroids which correspond to the mean values assigned to each cluster (Hartigan and Wong, 1979).

- ❖ **Extreme Dry Spells (ExDS)**

. The single and multiple rain gauge scale classification for dry spells developed by Salack *et al.,* (2014) was adapted to the conditions of this study. The total number of consecutive dry days before the next rainy day is the duration or length (L) of the dry spell (DS). The Julian day of first count corresponds to the start date (STDATE). The total number of DS with length L found in a season is the frequency of occurrence (F). The threshold of 1mm/day is considered to record a rainy day followed by 2 consecutive days of rainfall amount less than 1 mm. Dry spells are considered extreme when their length is longer than 9 consecutive days and less than 30 days (ExDS). This corresponds to categories 3 and 4 as suggested by Salack *et al.,* (2014). ExDS observed after FER are called Post-onset dry spells and those observed 65 days after planting date (Abendroth *et al.,* 2011) are considered post-flowering dry spells.. The K-means partitioning technique was also applied for ExDS’s length and week of occurrence categorisation.

c. The Crop Water Requirement Satisfaction Index (WRSI)

Crop water requirement satisfaction index (WRSI) is defined as an indicator of crop performance based on the availability of water to the crop during a growing season (Senay, 2004). WRSI is used worldwide as a monitoring and early warning tool especially for drought-prone regions of sub-Saharan Africa. Studies have been conducted using WRSI to evaluate future crop yield under rainfall variability due to climate change and its performance in predicting crop yield (Senay and Verdin, 2002; Ahmed *et al.*, 2017). It is usually used in the field of agro-meteorology for crop monitoring and early warning for food security (Mukhala and Hoefsloot 2004). In this study, WRSI is computed as the ratio of actual crop evapotranspiration (ETAA) to crop water requirement (equation 3.4) also called the potential crop evapotranspiration (EOAA). The index can be computed on a seasonal or decadal (10 days) basis. A seasonal WRSI reveals the extend of water stress for a crop during the growing season while a WRSI compute on dekads gives the crop's use of water at each development stage:

$$\boldsymbol{WRSI_i = \frac{ETAA_i}{EOAA_i} * 100} \quad \textbf{(3.4)}$$

Where *i* stands for the dekad. A WRSI greater or equal to 50% is interpreted as a "no deficit" condition, meaning, all things being equal, that the crop has enough water for its development. On the contrary, a WRSI lower than 50% is said to be a "deficit" condition where a crop failure can occur due to water stress (Senay, 2004). In this study, WRSI is computed every dekad to estimate the availability of water for the crop during its growth and detect the potential forecast products, in addition to the soil water holding capacity, essential for an early warning system.

The actual and potential evapotranspiration of the reference crops are obtained from the Soil-Plant-Atmosphere output file in DSSATV4.6 experimentation. Maize simulations are useful to estimate potential planting dates and WRSI. The experiments are set-up base on the following technical itinerary (details in appendix 2):

- **Planting period:** For maize, the planting date is defined as the day when minimum soil temperature is not less than 8ºC, the maximum temperature is not above 32ºC (11ºC and 32ºC for cowpea) and soil moisture is between 40% and 100% in the first 20 cm depth.
- **Crop management:** we opted for dry seeds sown in rows at 80 cm interval for maize and 30 cm for cowpea and at 3.5 depth. Planting population at seeding was 6.25 plants/m^2 for maize and 30 for cowpea. At emergence, the number of plants/m^2 was set at 6 for maize and 28 for cowpea. A tillage was done one week before planting with a blade cultivator at 8 cm depth.
- **Fertilizers application:** 150 kg of NPK and 50 kg of urea were applied to maize cultivars respectively 20 and 48 days after sowing. Cowpea crops were simulated without fertilizer application.

3.3.4. Perfect Prognostics and Binary Logistic Regression

Model output statistics (MOS) is an objective forecasting technique in which a statistical relationship is determined between a predictand and variables forecast by a numerical weather prediction model (Shafer and Fuelberg, 2002). A limitation of MOS is that any modification to the numerical weather prediction model (NWP) may amplify systematic errors of the equations derived from MOS (Wilks, 2006). The Perfect Prognostic (PP) method is an alternative to MOS (Shafer and Fuelberg, 2008; Rajeevan *et al.*, 2012). According to Shafer and Fuelberg, (2008), "*the PP approach develops statistical relationships between observed atmospheric parameters and observations of the predictand. Once the statistical relations are determined, forecasts of the predictand are obtained by inserting NWP model forecasts of the predictors into the PP equation*". The PP was used by Klein (1971), to predict precipitation probabilities in the US, Shafer and Fuelberg, (2008) and Rajeevan *et al.,* (2012) for predicting lightning probability. Here, due to the agro-climatic nature of the work, PP approach combined with logistic regression model is used to explain the effects of the explanatory variables on the binary response.

A variety of statistical techniques have been used to develop crop-climate relationship forecast models. The most common method is multiple linear regression (MLR) (Neumann and Nicholson 1972) and Random Forest (RF) methods (Jeong *et al.*, 2016). However, when the predictand is "yes" or "no," binary logistic regression (BLR) often is employed (Shafer and Fuelberg, 2008). The BLR, also known as the binomial logit model, is an estimation technique for equations with dummy dependent variables that avoids the unboundedness problem of the linear probability model by using a variant of the cumulative logistic function (Wooldridge and Jennings, 1995). Logistic regressions are fit to binary predictands according to the nonlinear equation (Shafer and Fuelberg, 2008):

$$\ln\left(\frac{P_i}{1-P_i}\right) = b_0 + b_1 x_1 + \cdots + b_k x_k \quad (3.5)$$

With
$$P_i = \frac{\exp(b_0 + b_1 x_1 + \cdots + b_k\, x_k)}{1 + \exp(b_0 + b_1 x_1 + \cdots + b_k\, x_k)} \quad (3.6)$$

where $\boldsymbol{pi}$ is the predicted probability resulting from the set of candidate predictors $(x_1, x_2, \ldots, x_k)$, rainfall, rainy days, relative humidity, daily temperature range, wind speed and solar radiation. The quantity on the left of equation (3.5) is the logit link function, which relates the log of the odds ratio (p/1-p) to a linear combination of predictors (Shafer and Fuelberg, 2008; Rajeevan *et al.*, 2012). The parameters $(b_0, b_1, \ldots, b_k)$ are estimated by maximizing a log-likelihood function using iterative methods (Wilks, 2006). Equation (3.6) guarantees that the probabilities are bounded within the interval (0, 1) and the relationship between the predictors and the response variable follow Bernoulli distributions.

In this analysis, WRSI is defined as the response variable which values are encrypted into 1 and 0 based on the threshold values extracted from the cluster of dry seasons (DtC):

$$\boldsymbol{WRSI} = \begin{cases} \mathbf{1} \; \boldsymbol{if} \; \boldsymbol{WRSI} \leq \boldsymbol{DtC_{th}} \\ \mathbf{0} \quad \boldsymbol{otherwise} \end{cases} \quad \mathbf{(3.7)}$$

Where $\boldsymbol{DtC_{th}}$ takes one of each three thresholds of dekadal WRSI values drawn from the set of dry seasons also called drought cluster, DtC. Table 3.2 provides an example of $\boldsymbol{DtC_{th}}$ values extracted from DtC observed at each reference station and their associated flag colours when these values are reached at both vegetative and reproductive phases for maize cultivars. These threshold values are considered as reference baseline thresholds useful in monitoring and early warning under climate change.

Table 3.2: Thresholds values of water requirement satisfaction index (WRSI), at vegetative and reproductive phases of maize cultivar, derived from the cluster of drought seasons (DtC) observed at reference stations.

Development stages	**Threshold**	**Flag colour**
VEGETATIVE PHASE	< 0.3	Red
	[0.3, 0.4]	Orange
	]0.4, 0.5]	Yellow
	0.5 <	Green
REPRODUCTIVE PHASE	≤ 0.5	Red
	0.5 <	Green

The optimum conditions of crop water satisfaction are provided by atmospheric and soil variables. Therefore, BLR is used to develop equations giving the probability of WRSI = {1, 0} at each reference station. The objective was to determine whether relationships between observed candidate predictors and WRSI were generally the same for all the reference stations or if they may vary significantly from one to another. Parameters calculated from weather file make the initial set of candidate predictors. Correlation test is conducted using Spearman correlation coefficient to determine possible relationship within the candidate predictors and between WRSI and those predictors.

A comparison of verification performance diagram scores (Roebber, 2009) are used to decide which candidate predictors lead to highest predictability of WRSI thresholds. In this study, PP models are developed based on in-situ observed weather parameters to build the model (training samples include DtC and WtC data sets for training the logistic regression models) and independently verified using data provided by the NASA's Prediction of Worldwide Energy Resource (POWER).

The performance diagram scores are determined based on a 2 x 2 contingency table of dichotomous (yes–no) forecasts using varying thresholds of WRSI (average, 5th & 10th percentile of DtC). The verification scores considered are the Probability of Detection (POD), BIAS, False Alarm Rate (FAR) and the Critical Success Index (CSI; also known as the threat score). The POD is the ratio of the number of events correctly predicted by the model to the total number of observed events in the sample. The FAR is a measure of the forecast events that fail to occur. The bias B indicates the degree of over-forecasting (B>1) or under-forecasting (B<1) an event. Finally, the CSI combines attributes of the POD and FAR and can be viewed as a hit rate (HR) after removing correct no forecasts (Roebber, 2009).

Chapter 4 : RESULTS AND DISCUSSION

4.1. Results

4.1.1. Threshold Analysis for Operational Monitoring and Early Warning

a. First Efficient Rainfall (FER)

Figure 4.1 shows the intensity of rainfall associated with FER as observed over the 6 reference stations (Bakel, Bolgatanga, Dano, Dapaong, Mango and Ouahigouya). Irrespective of the quality of the rainy season (dry/wet), the amount of rainfall associated to FER is not more than the 20th percentile of all seasonal rain events (Figure 4.1a). However, the dates of occurrence of FER exhibit two “break” points common to dry and wet seasons (figure 4.1b). The first date is approximately 15 March and the second one approximately the end of May. Hence, we define FER as the first day between 15 March and 31 May when the accumulated daily rainfall exceeds 9.75 mm.

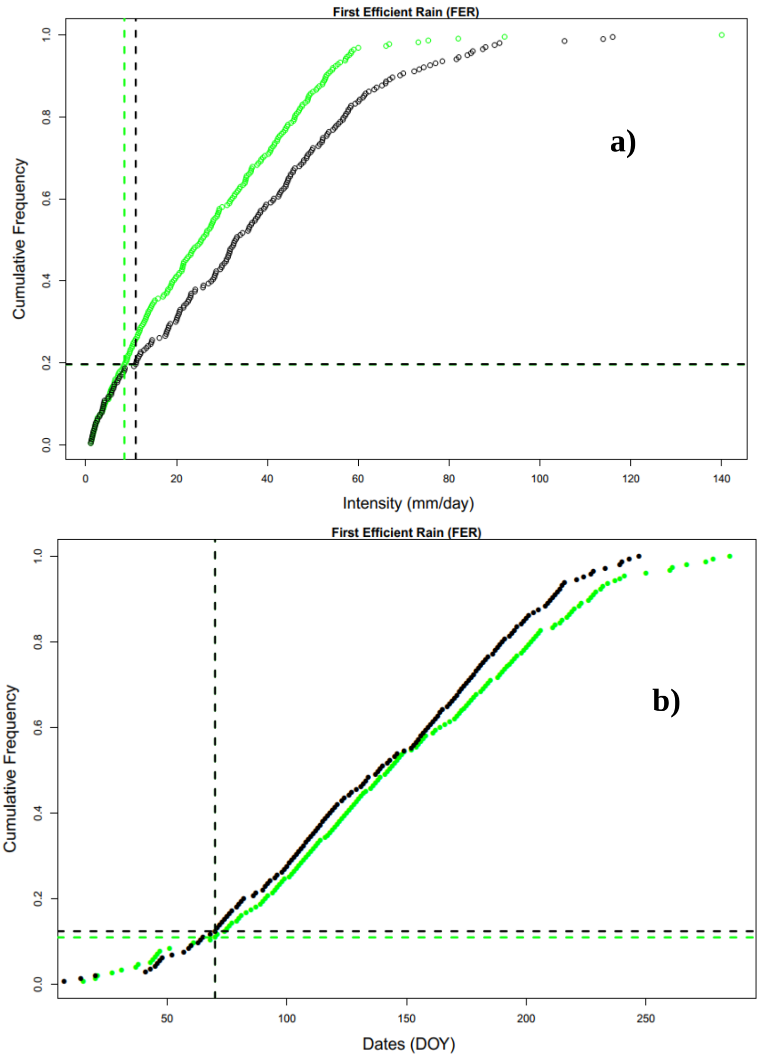


Figure 4.1: Cumulative Frequency of rainfall amount (INT) and dates of occurrence (DOY) of first efficient rainfall (FER) over the 6 reference stations depicted from historical daily data series (1960-2016). The black (white) dots denote dry (wet) season.

Figure 4.2 reveals the distribution of rainfall amounts associated to FER events. The highest mode of variability is 20-30 mm per day. Very often than not, this rainfall amount highly misleads some farmers to sow crop seeds. However, FER are followed by longer dry spells which cause water deficit stress, seeds desiccation and re-planting (Ati *et al.*, 2002; Alhassane *et al.*, 2013).

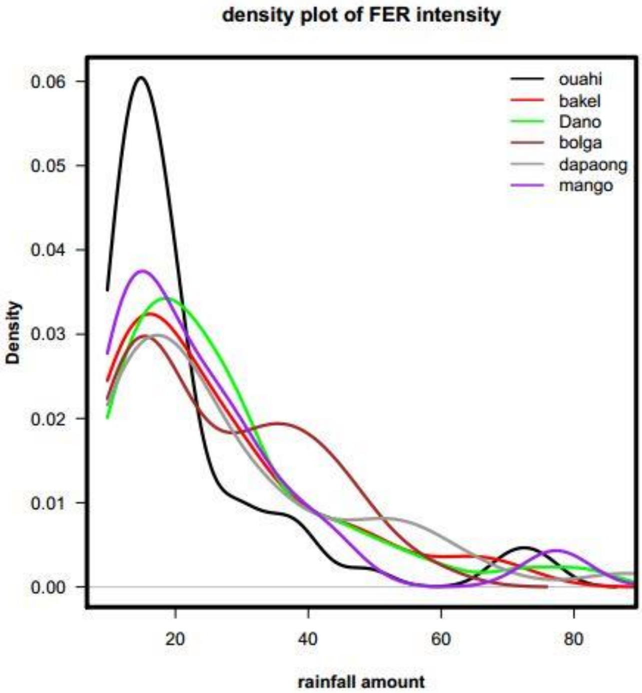


Figure 4.2: the variability mode of the FER quantity at the stations

Trends analysis of the dates of occurrence, at most locations of the northern WASS, shows that FER events are occurring earlier (i.e. decreasing trend) as revealed by figure 4.3. Hence, FER events at the reference stations vary with the location of the station in the study area. Indeed, stations located in the south Sahel (Dapaong, Mango, Dano, Bolgatanga) perceive the FER from the 10th to 20th week of the year on average (March to May), irrespective of the quality of the season (dry/wet). In the center Sahel, Ouahigouya, the FER occurs often from the 10^{th} to 25^{th} week of the year (March to June), be it a dry or wet year. The north Sahel, Bakel, records the FER within the 20^{th} and 30^{th} week of the year (May to July). Figure 4.3 demonstrates the above statements. A linear regression model (the red line) and a local polynomial regression model (the blue curve) represent the overall trend of the FER WOY. The two models have the same interpretation of the inter-annual variability of the FER week of occurrence with respect to the stations.

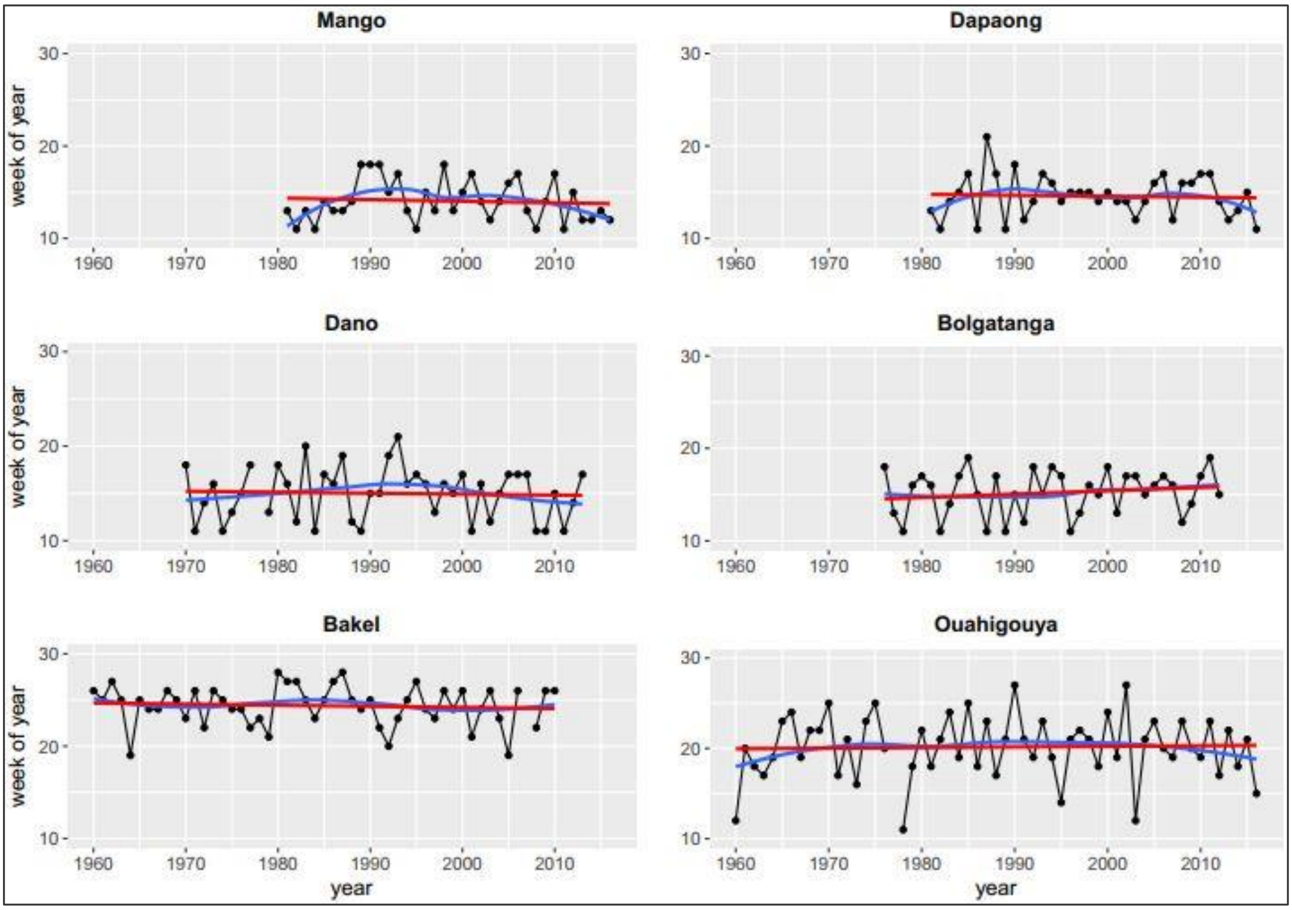


Figure 4.3: the inter-annual variability of the FER date of occurrence at the six stations

The enquiry was conducted over the WASS region to validate not only the results obtained from the 6 stations but also to study the trend over the region. Figure 4.4 summarises the findings where the bubbles represent the location of the stations used and their size and colour are related to a specific interval of values. The FER intensity in the WASS is in the range of [20mm, 27mm] with isolated cases in the western and eastern Sahel where it is from 15 to 20 mm. As for the week of occurrence, the FER is registered earlier in the central Sahel than in the western and eastern Sahel ([13th, 20th] week and [20th, 27th] week respectively).

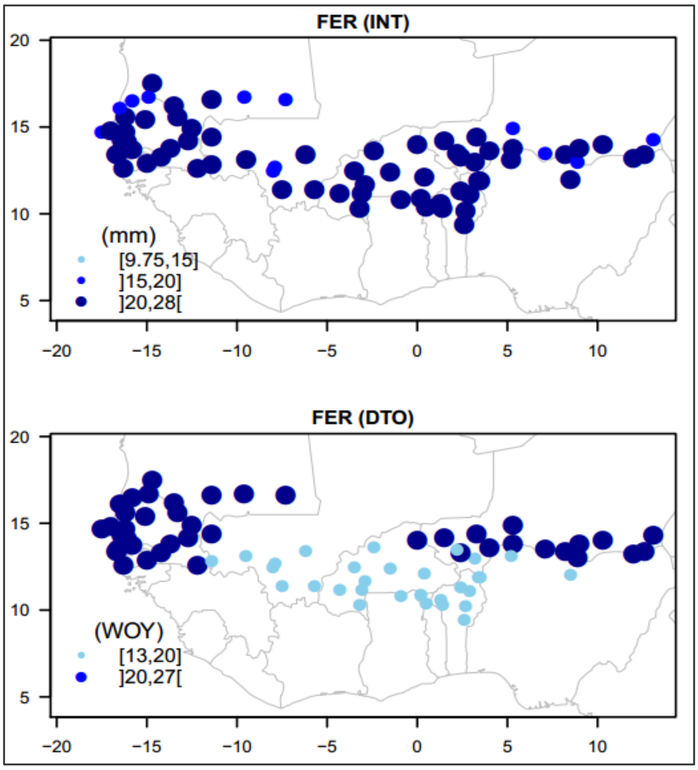


Figure 4.4: Average value of the FER week of occurrence and quantity over the WASS

A comparison of dry and wet seasons on days' difference between the FER date and the planting date obtained from the crop simulation model is established (figure 4.5). The planting date is considered to be the first day of July where soil temperature is within 8-32 ^{o}C and minimum soil water is 40mm at 20 cm depth for both dry and wet seasons. The general remark is an obvious difference between FER and planting dates which is accentuated with the quality of the seasons. Dry seasons register late FER compared to wet seasons. This assertion is demonstrated by the results in figure 4.5, where the days' difference of FER and planting dates is greater in wet seasons. The analysis shows that wet seasons are more susceptible to false onset since rains start early. In addition, opting for an earlier planting period may be either risky or optimal for crops due to the uncertainty of the FER date.

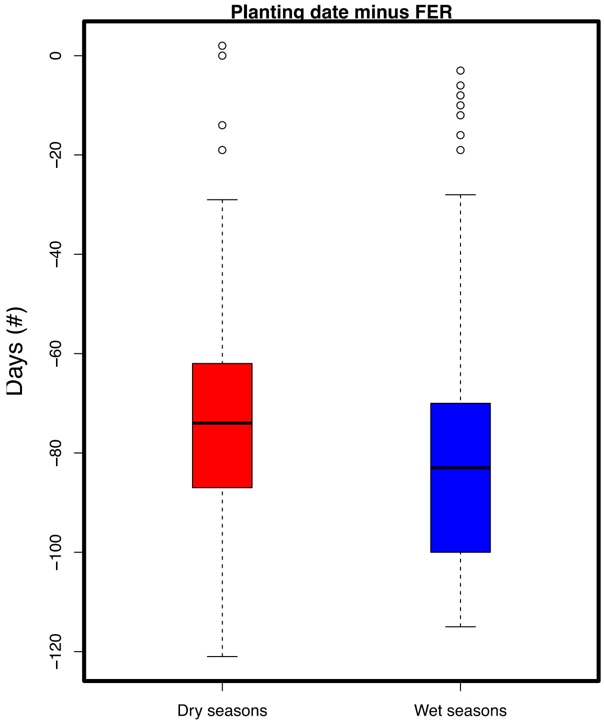


Figure 4.5: Difference between planting dates and first efficient rainfall occurrence dates in the reference stations

b. Extreme Dry Spells (ExDS)

The occurrence of ExDS, in the WASS region, is categorized in terms of week of occurrence (WOY) and length (L). As described in chapter 3, post-onset and post-flowering DS are considered. The kmeans results revealed 3 categories of STDATE of ExDS associated with 2 classes of ExDS length. The post-onset DS can be of different length according to their WOY. The first class of ExDS is likely to be observed from end March to end May (week 13 to week 21) with a length of about 22 days. It is actually the longest DS found right after the FER date (1^{st} post-onset DS). This result confirms the fake character of the FER as onset of the rainy season. The second class of ExDS of about 14 days is localised between June and August. June-July is the seeding period in most of the Sudan-Sahel region (Waongo, 2015) therefore these DSs are considered as the 2^{nd} post-onset ones more likely to affect seeds juvenile phase and cause crop failure if they last long. The third category of ExDS also last for about 14 days but occur from September to October. The period coincides with the flowering stage of crops (65 days after planting), consequently, it is considered as post-flowering ExDS.

Table 4.1: classes of extreme dry spells length and week of occurrence

Category	Parameter	Average	Confidence interval	Proportion (%)
Category 1	Date (WOY)*	17	[13 ; 21]	25
	Length (#)	22	[19 ; 26]	25
Category 2	Date (WOY)	19	[22 ; 35]	53
	Length (#)	14	[10 ; 18]	37.5
Category 3	Date (WOY)	39	[36 ; 43]	22
	Length (#)	14	[10 ; 18]	37.5

At the stations' level, the density of dry spells occurrence varies from a station to the other with some similarities. Figure 4.5a shows similar patterns of DS week of occurrence for Mango, Dapaong, Dano and Bolgatanga on one side, Bakel and Ouahigouya on the other side. According to the FER date, Bakel and Ouahigouya experience, most of the time, late onset of the rainy season, therefore, post-onset DS in those areas follow the same trend. Apart from its WOY, EXDS' length, over the stations, reveals a high probability for length greater or equal to 2 weeks and to a lesser degree DS of length greater or equal to 3 weeks (figure 4.6b). This is explained by the low proportion of the 1st class of DS length (25%) compared to the 2nd class (75%) (Table 4.1). The investigation demonstrates once again, for ExDS, that the geographical position of stations in the Sudan-Sahel has an impact on the vulnerability of crops to water stress. Indeed, Bakel and Ouahigouya having their FER close to the planting period (June-July), expose the crop to potential ExDS at its juvenile stage. The remaining stations experience frequent false onset of the season since the density of DS occurrence is higher from April to May which happen to be the prone period of FER in those areas. In addition, the DS length over that period is also high (22 days) likely to damage the seeds if planting occurred subsequently. Post-flowering DSs are observed at all the stations because they all present similar mode of variability of DS length but at different ratio (figure 4.6b).

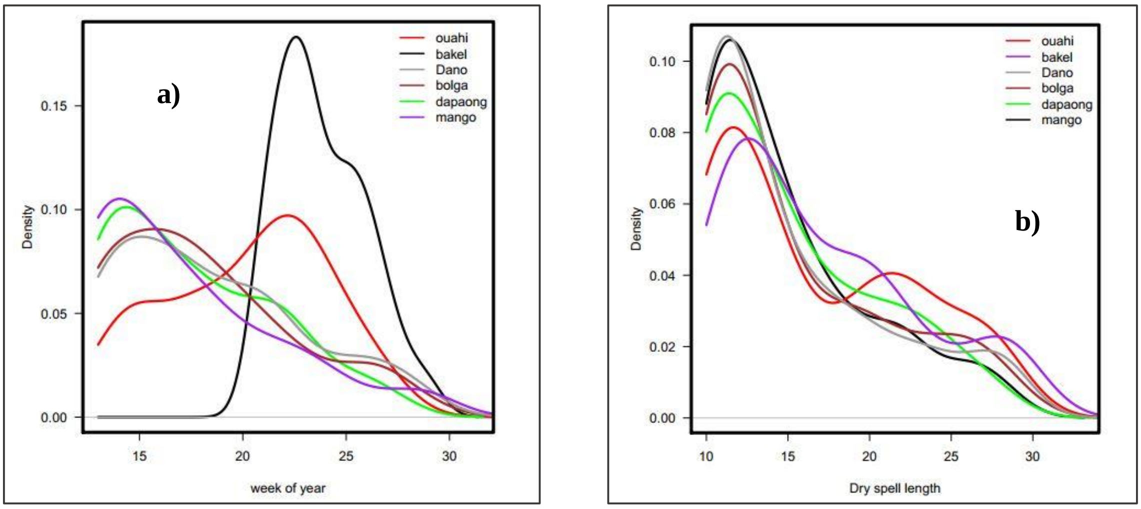


Figure 4.6: Frequency of dry spells week of occurrence (a) and length (b) at the 6 stations

At the WASS level, similar enquiry was conducted and average values of DSs' week of occurrence and length were classified as post-onset or post-flowering. Figure 4.7 presents the observed results symbolised with bubbles' colour and size. DSs' length greater or equal to 10 days as well as their week of occurrence are computed for each available station in the WASS and the average DS is determined to represent a station on the map. On average, the DS lengths obtained were of 3 categories: DS length lower than 10 days, comprises between 10 and 15 days and greater than 15 days. Considering the WOY, the average weeks were classified into 5 intervals: week 15th to 20th, week 21st to 25th, week 26th to 28th, week 29th to 32nd and week 33rd to 35th. The analysis of post-onset DS length and WOY points out a general tendency of DSs' length lower than 10 days with localised ones of 10-15 days in the North-Western Sahel and isolated cases in the Eastern Sahel. The WOY of post-onset DS is within week 15th to 20th (April-May) in the central Sahel while the Eastern and part of the Western Sahel experience such DS within week 21st and week 25th (May-June) with some isolated DS within week 26th to 28th (June-July). Post-flowering DS length in the WASS region has a similar distribution with an additional class (DS greater than 15 days) localised mainly in the North-Western Sahel. The occurrence of these DSs is recorded within week 29th and 32nd (July-August) in the Western and Eastern Sahel while the Central Sahel may experience them within week 33rd and 35th (August-September).

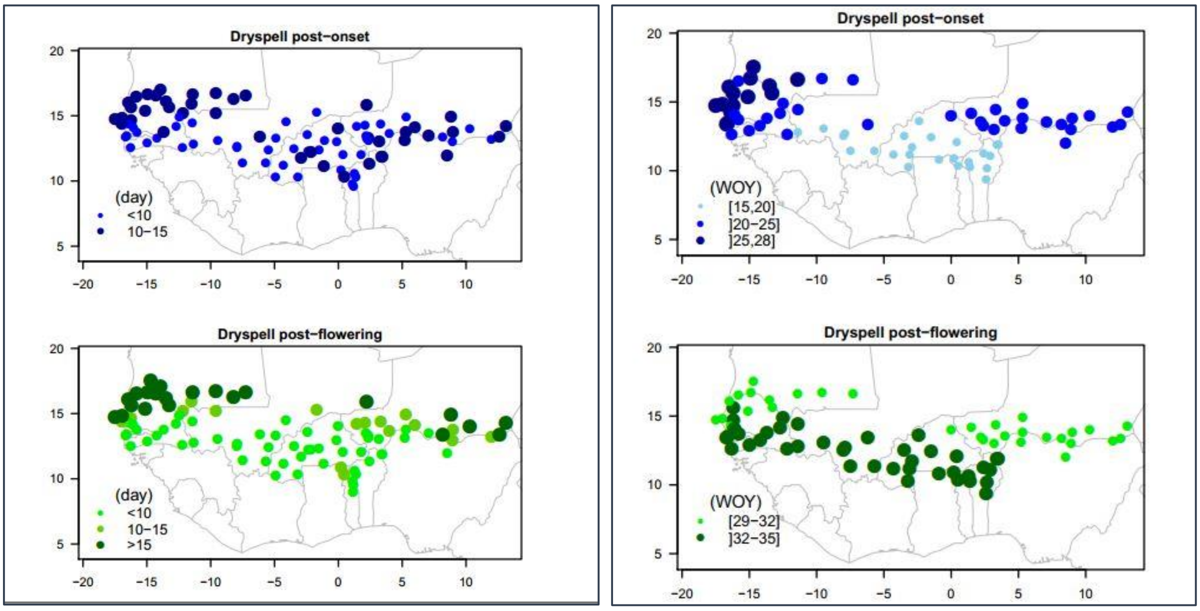


Figure 4.7: Dry spells length and week of occurrence over the WASS region

c. Intense Rainfall Event (IRE)

The analysis of the near-ground records depicted from Dano and Dassari catchments show that the two parallel rain gauges report the same DTOs but fail to agree to the accumulate daily rain rates when INT is above 50-60 mm/day (Figure 4.8). This discrepancy is linked to sensor errors sources. These uncertainties may be related to the basic functionality of tipping buckets. According to Habib et al., (2001), the tipping bucket suffers from accuracy problems at high rain rates: it is usually unable to give an accurate estimate of the peak values within the event. This is mainly due to the high gradient of the rain rates at the peaks and valleys of the rainfall time series.

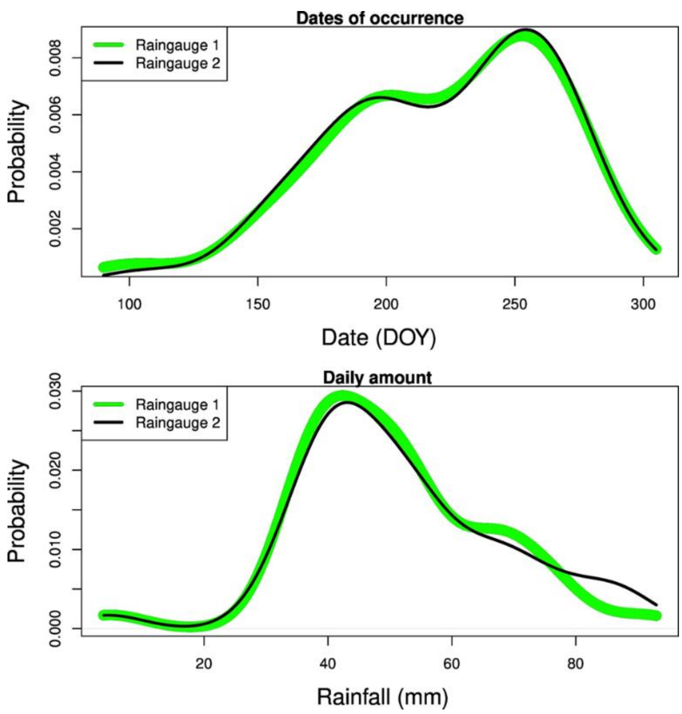


Figure 4.8: Dates and amount of rainfall recorded by two parallel tipping bucket raingauges installed in Dano and Dassari catchments.

The kmeans analysis revealed two classes of DTO and three categories of extreme rainfall INT (Table 4.2).

Table 4.2: Categories of intense rainfall events and operational flagging colours (Salack and Saley, 2017)

Category	Parameter	Average	Confidence interval	Proportion (%)	Flag colour
Category 1	Date (WOY)*	30	[25 ; 35]	92	Yellow
	Intensity (mm/day)	47	[37 ; 65]	52	
Category 2	Date (WOY)	30	[25 ; 35]	92	Orange
	Intensity (mm/day)	75	]65 ; 85]	40	
Category 3	Date (WOY)	33	[28 ; 38]	8	Red
	Intensity (mm/day)	120	> 85	8	

*WOY: Week of a calendar year

The sites of interest for the study fall within all the categories of IRE identified above. The only difference is the probability of occurrence of IRE from a week to the other. Figure 4.9 illustrates the mode of variability of IRE's INT and WOY at each station.

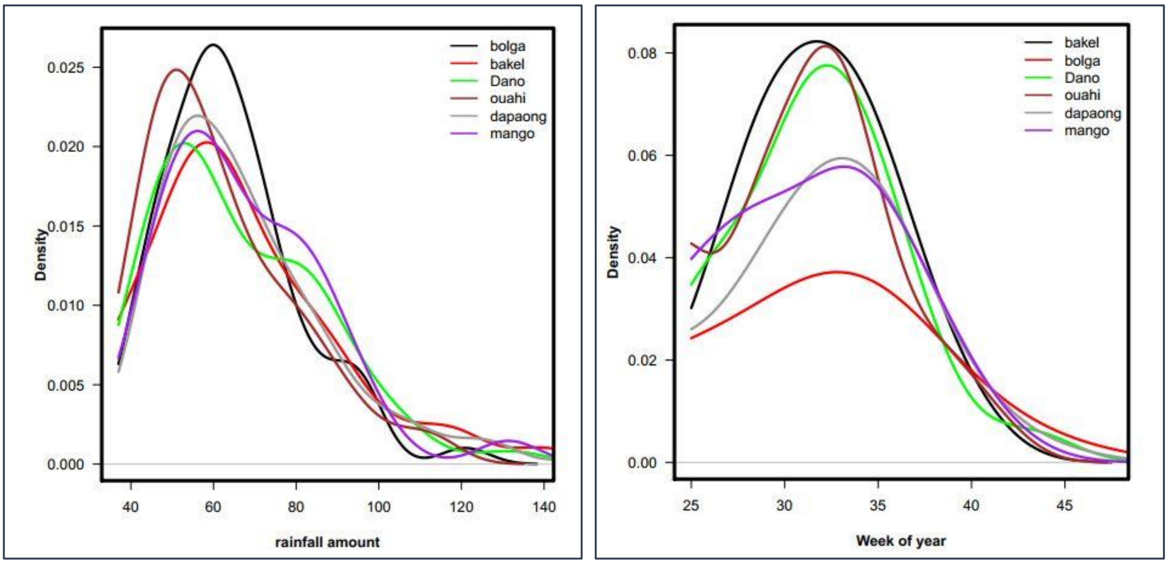


Figure 4.9: densities of intense rainfall event week of occurrence and intensity at the 6 stations

Over the WASS, the inter-annual variability of seasonal 99th percentile threshold values of rainfall intensity depicted over 1960-2016 is illustrated by figure 4.10. There is an increasing trend of extreme rainfall with the recent years being similar to the early 1960s. Meanwhile, the inter-decadal variation of these events, depicted by the blue curve, shows that the recent recovery of rainfall is mainly explained by the rain rates of extreme events. These results are similar to arguments provided by Lodoun *et al.*, (2013), Sanogo *et al.*, (2015), Salack *et al.*, (2015) and Maidment *et al.*, (2015) among others.

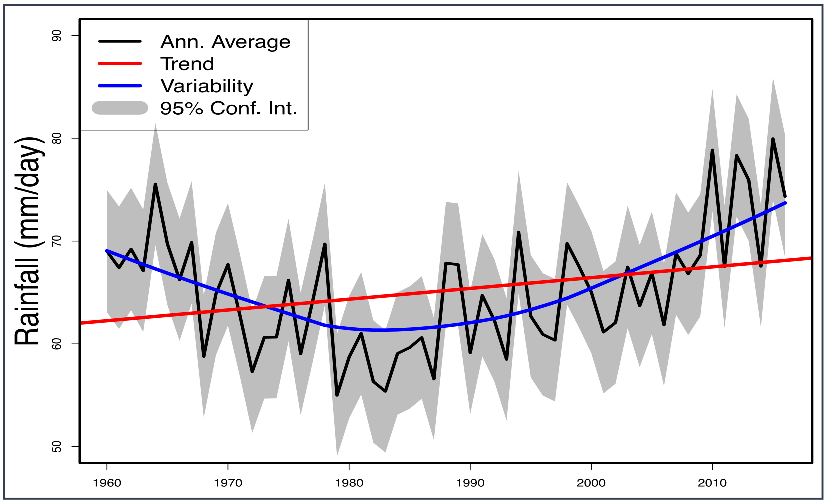


Figure 4.10: Historical inter-annual variability of seasonal intense rainfall events

In the Sudan-Sahel, extreme rainfall events contribute ~50–90% to the seasonal rainfall amount with a South-North gradient (Ta et al. 2016). This inhomogeneous distribution and the nested land-atmosphere phenomena involved in the formation of convective systems makes it difficult to classify rainfall from the event scale of minutes-to-hours (Mathon *et al.*, 2002; Zahiri *et al.*, 2016). Table 4.2 provides the three classes of IRE observed in the Sudan-Sahel region over a time scale of week. The categories 1and 2 occur most likely between week 27 and 35 of the year with an accumulated daily amount waving across 37-65 mm for category 1 and less or equal to 85 mm/day for category 2. The daily accumulated rain rate of category 1 has 52% probability of occurrence against 40% probability for category 2, within the same period. The rain rates of category 3 is identified when more than 85 mm/day, occurring between the 28th and 38th week of the year. It is the most damaging class of heavy rains but very difficult to predict.

The timing of the three categories of IRE (Figure 4.11) falls within three phases of the West African monsoon namely the installation phase (July), the intensification phase (August) and the retreat phase (September). Category 1 is observed in the installation phase over central sub-regions after the abrupt monsoon jump (Sultan *et al.*, 2003) while categories 2 and 3 are recorded in the intensification and retreat phases respectively. In these last two phases, rainfall intensity is characterized by a steady increase until it reaches its maximum at the end of August (also known as the continental phase of West African monsoon) and an abrupt retreat in one month, with residual rainfall in October (Lebel and Ali 2009). The spatial distribution of DTO of Category 2 and 3 suggests an east-west bipolar pattern while category 1 is unevenly observed all over the region. All categories are recorded with a time lag of at least one week and the western Sahel is predominantly influenced by the occurrence of categories 2 and 3 in September. The distribution of DTO also exhibits a coherent sub-regional high risk zones of local extreme rainfall.

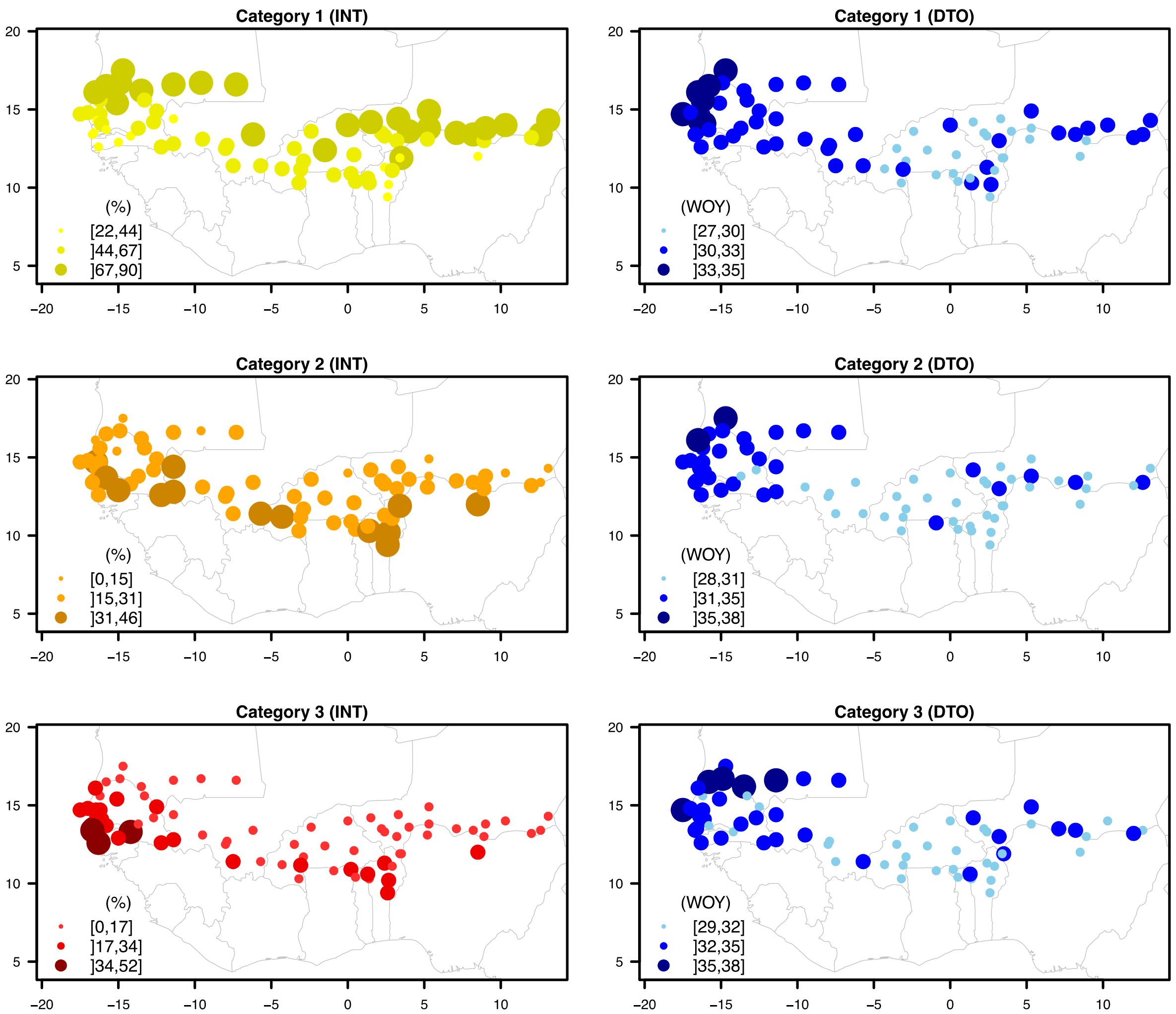


Figure 4.11: Probabilities of IRE occurrence over the WASS region

d. Crop Water Requirement Satisfaction Index (WRSI)

❖ WRSI and the Quality of Seasons

As specified in the methodology, WRSI is the ratio of the actual crop evapotranspiration to the crop water requirement. For comparison purpose, the index is computed for dry and wet years at each station. The analysis was first based on the WRSI obtained for each cultivar across the growing season. It reveals no significant difference between the cultivars, apart from EV-8443 which has a longer growth cycle and therefore a particular expression at the end of the season. Figure 4.12 illustrates the results. Consequently, the WRSI obtained for obatampa cultivar is used for further enquiries on the index bearing in mind that the second cultivar has the same behaviour.

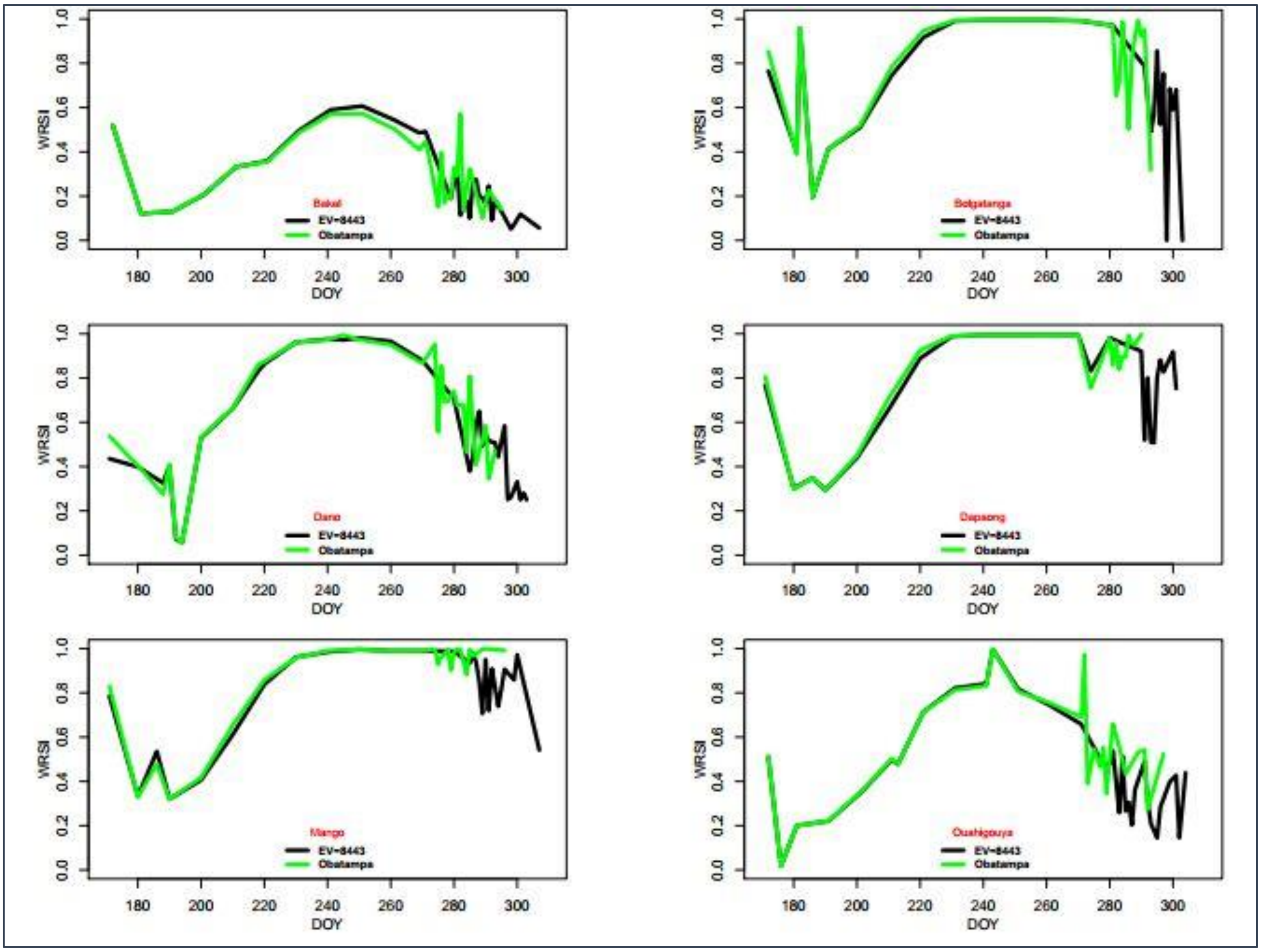
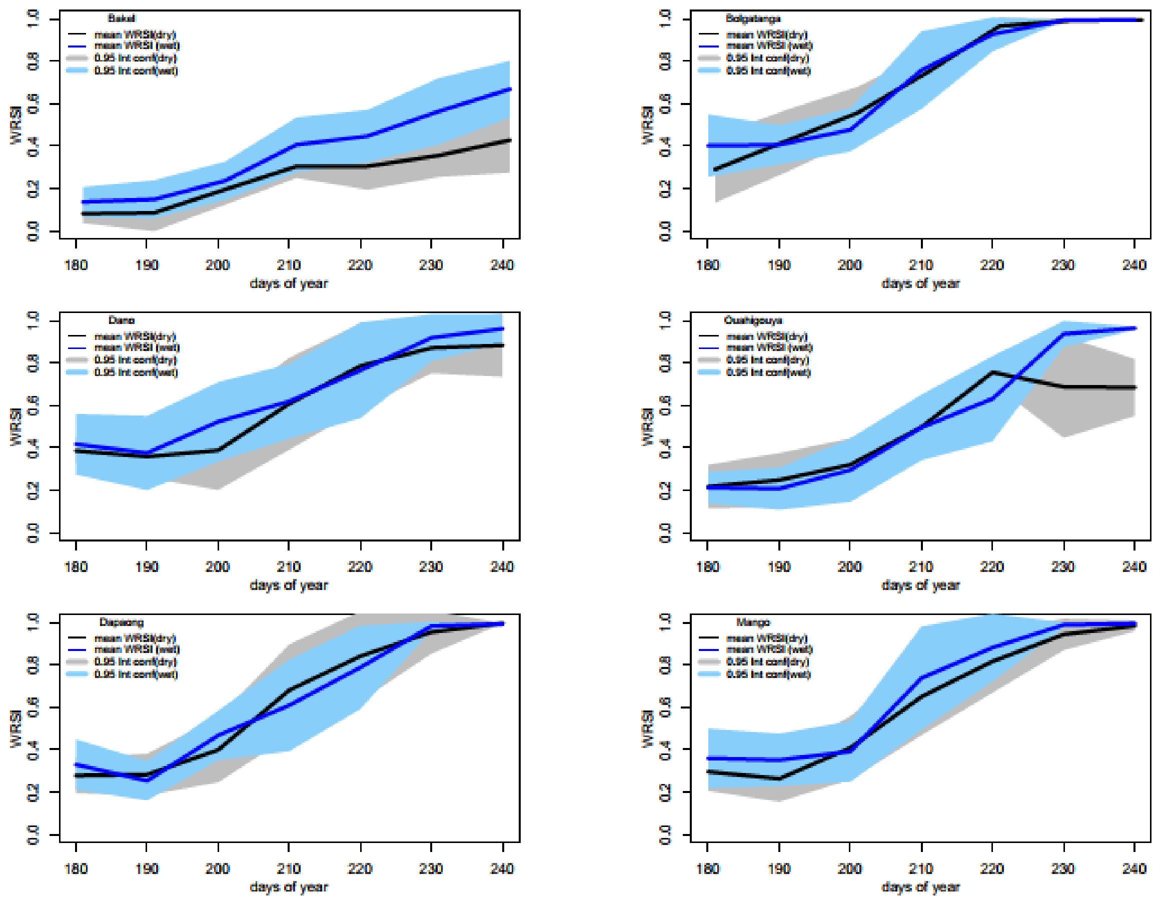


Figure 4.12: compared WRSI of maize cultivars: obatampa (green) and EV-8443 (black)

Maize has specific development stages which are subdivided into two main ones namely the vegetative and the reproductive phases. Each of them has a critical phase highly dependent on water. In the vegetative phase, adequate conditions of water and light are needed for a successful juvenile phase of the seed, whereas, in the reproductive phase, the flowering of the plant is crucial for a good yield. Based on the exciting knowledge, the computed WRSI has been studied according to the 2 phases for dry and wet years over the 6 stations. Figure 4.13 summarizes the outcomes of the analysis. It is noticed that, at the vegetative phase, irrespective of the quality of the seasons, the WRSI has an encrement trend, while at the reproductive phase, it has a decrease trend. The result suggests that a crop is more vulnerable to water stress at the beginning and the end of its growth.

More specifically, dry and wet years follow the same trend but at different rate. Bakel displays a clear difference between the WRSI of dry and wet years, whereas, the other stations present slight variance with wet years recording the highest indices. Globally, apart from Bakel which has an obvious water stress problem compensated during a wet year, and to a lesser degree Mango and Ouahigouya, the other stations seem not to differenciate between wet and dry years.

A way of explaining the results is related to the rainfall amount and its date of occurrence. Indeed, during a wet year, rainfall is more frequent and more or less intense than in a dry year. Unfortunately, a rain is useful for a crop only if it occurs at the right time of its growth. In this study, there is an uncertainty related to the useful rain which is supposed to boost the seasonal WRSI. Subsequently, the relationship between WRSI and the quality of the seasons is real beside the fact that it encompasses some non-neglictible parameters (figure 4.13).



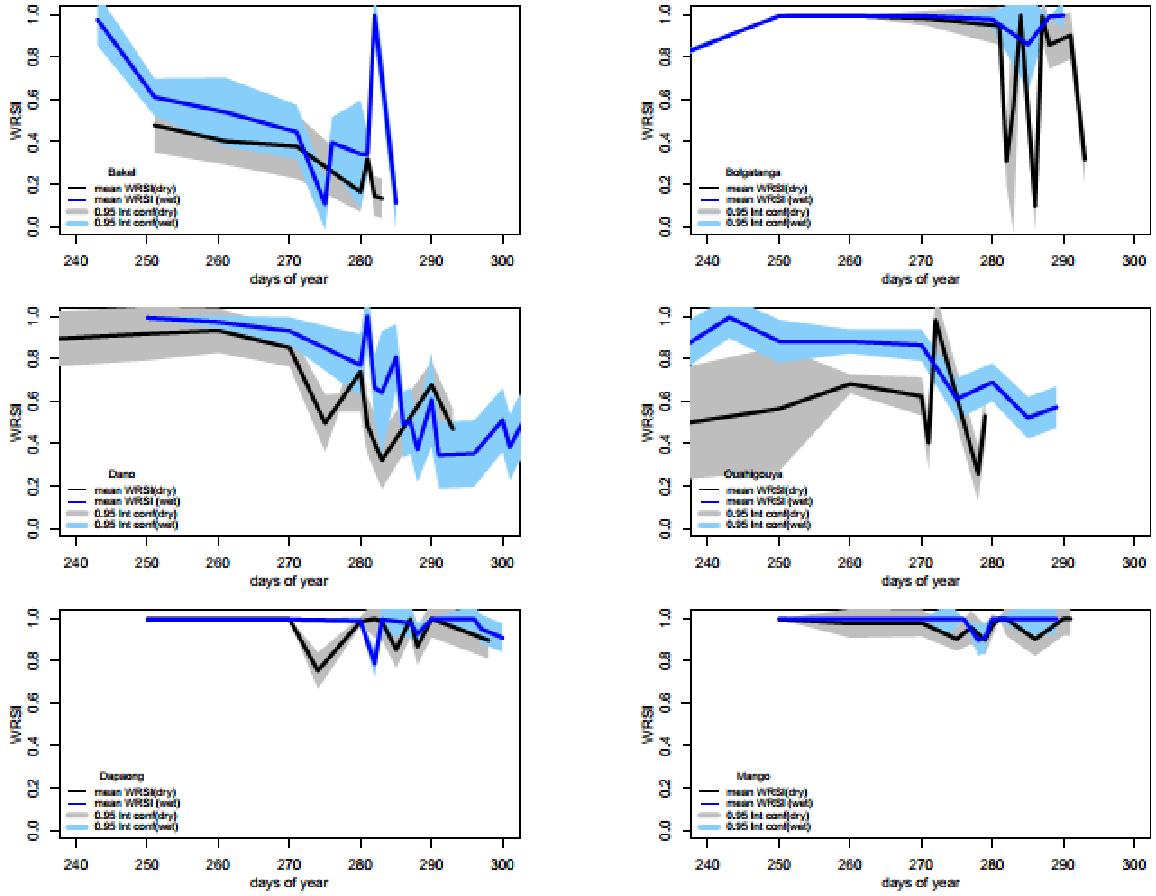


Figure 4.13: Crop water requirements estimated during vegetative (top panel) and reproductive (bottom) phases of dry and wet cluster of seasons at reference stations (1960-2016).

❖ WRSI Versus Crop Yield

The amount of water available for a crop during its growth determines its performance, all things being equal. The WRSI illustrates the impact of water stress on the potential crop yield. Figures 4.14a and 4.14b represent the potential yield obtained with regards to the seasonal WRSI for the considered maize cultivars (Obatampa and EV-8443) at the 6 targeted stations. It is observed that, irrespective of the cultivars, the potential yield evolves according to the availability (WRSI>50%) or the deficit (WRSI<50%) of water in the soil. The analysis, at station level, shows that Bakel and Ouahigouya registered, on average, lower potential yield compared to the other stations for both obatampa and EV-8443. Similar trend is observed at Dano station but to a lesser extent. The general remark is that low yield is obtained when the seasonal WRSI belongs to the range 20-70%.

The available data at Bakel station displays a seasonal WRSI lower than 50% irrespective of years. Besides, the soil profile, used for the site in DSSAT V4.6, has a low fertility due to the local climate causing water stress to the crops. The two maize cultivars have approximately the same performance, even though EV-8443 has a better potential yield, they have not reached 1000 kg/ha.

At Dano and Ouahigouya, the cultivars performed moderately with a maximum potential yield of 2500 kg/ha for obatampa and 3000 kg/ha for EV-8443. Such yields are obtained at these stations due to the seasonal WRSI ranging from 50% to approximately 75%. The three remaining stations, Bolgatanga, Dapaong and Mango, had the highest yields of the season both for obatampa and EV-8443, and the analysis of the seasonal WRSI shows values comprise between 80 to 100% with exceptional years (few of them) recording 50%. The water stress level at these stations is minimized compared to Bakel, Dano and Ouahigouya.

The results observed at the 6 stations allow the detection of thresholds for the WRSI considering the conditions of the simulations. Three categories of WRSI are identified taking into account the yields recorded. The first category is WRSI lower than 50% which results mainly into very low potential yields from the cultivars. The second category is a WRSI within 50 and 75% which permits to moderate potential yields observed also for the 2 cultivars and finally the third category of WRSI greater or equal to 80% resulting in very high potential yields. It is important to recall that these results reflect the applied conditions and methods used to assess water stress at the 6 stations. Further investigations are needed to generalize these thresholds at the WASS level.

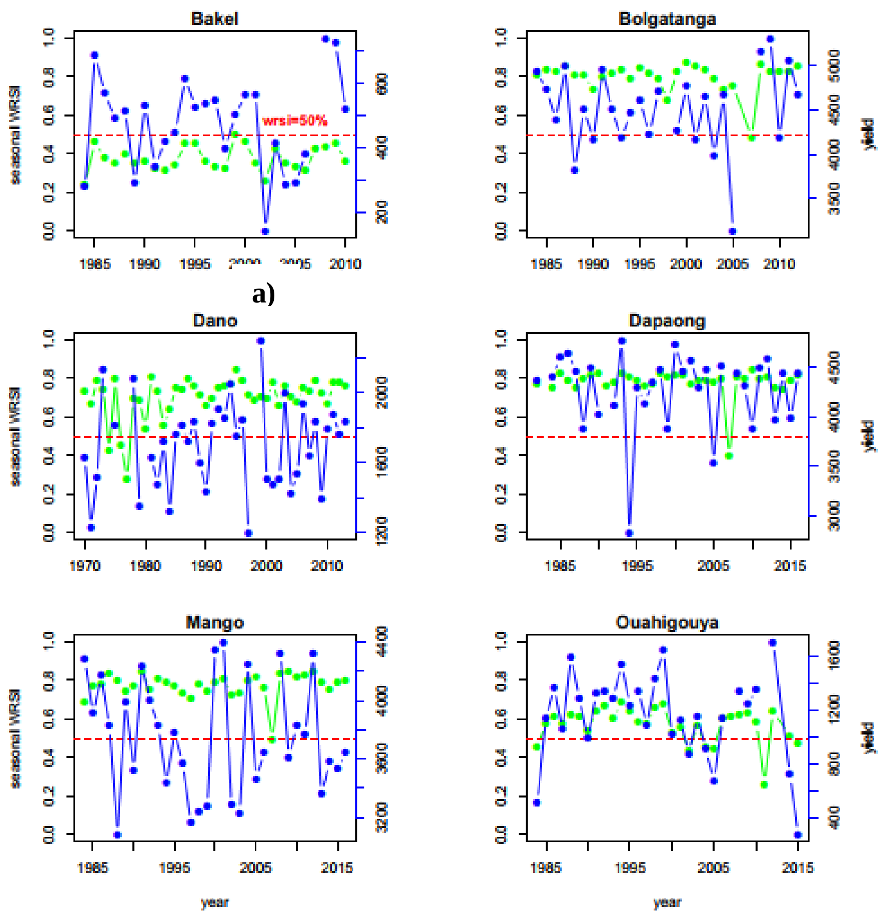


Figure 4.14: relationship between WRSI and crop yield considering (a) Obatampa and (b) EV-8443 cultivars

4.1.2. Predictability Potentials of WRSI

a. Binary Logistic Regression Model Analysis

The BLR model is developed with the candidate predictors for three level of WRSI thresholds. 10-day average, 10th percentile and 5th percentile of the time series are considered. The 10-day average is determined by aggregating the drought cluster series per dekad using the mean function. 10th and 5th percentiles are computed alike the 99th percentile of the IRE. The response variables were then obtained using the equation 3.7. However, it is clear from table 4.3 that some of the candidate predictors contain redundant information leading to high multicollinearity. Mutual correlations were found to be more than 0.6 and statistically significant between daily rainfall and number of rainy days. Including predictors with strong multicollinearity can lead to poor estimates of the regression parameters (Wilks, 2006; Shafer and Fuelberg, 2008).

Table 4.3: Candidate predictors used to develop the regression models and Spearman rank correlations with the binary (yes/no) WRSI thresholds at each reference station. (*) marks the parameters where high multicollinearity is found to be statistically significant

Parameters	Unit	Bakel	Bolgatanga	Dano	Dapaong	Mango	Ouahigouya
Relative humidity	%	0.44	-0.06	0.69	0.4	0.32	0.38
Wind speed	m/s	-0.58	-0.66	-0.57	-0.61	-0.52	-0.71
Solar radiation	$MJ/m^2/d$	-0.51	-0.17	-0.22	-0.25	-0.11	-0.45
Rainfall*	Mm	0.52	0.26	0.44	0.24	0.24	0.46
Rainy days*	Day	0.6	0.37	0.55	0.37	0.38	0.46
Diurnal temperature range	^oC	-0.33	0.11	-0.42	-0.03	-0.05	-0.53

*Multicollinearity variables

Due to the multicollinearity between some predictors, different combinations are tested in developing the BLR model. By removing these variables, a first set of predictors is defined for the forecast of threshold values including rainfall amount (RAIN), relative humidity (RHUM), daily temperature range (DTR), solar radiation (SRAD), wind speed (WIND). The ANOVA statistical test of the BLR model at the reference stations shows significant difference between observed candidate predictors according to the level of thresholds and the stations considered.

In Bakel, an analysis of the thresholds revealed two candidate predictors with statistically significant predictability potential of the WRSI. The predictors are SRAD and RAIN. Besides, RHUM, WIND and DTR are statistically significant and can be used to predict the dekad-average and the 10th percentile of WRSI. The results of Bolgatanga present a heterogeneous pattern of candidate predictors with respect to the thresholds. WIND, RHUM and DTR for the dekad-average, WIND for the 10th percentile and RAIN for the 5th percentile. At Dano station, two thresholds of WRSI can be predicted (dekad-average and 10th percentile) since some predictors (RHUM and RAIN) are statistically significant. In Dapaong, as well as Bolgatanga, the predictors depend on the threshold considered. For the dekad-average, RHUM and SRAD are statistically relevant in forecasting WRSI. For 10th percentile, RHUM, WIND and RAIN are reported potential predictors and for 5th percentile, RHUM and RAIN present a significance in predictability. For Mango station, irrespective of thresholds, RHUM is a strongly significant predictor. Finally, Ouahigouya station presents RAIN as the solely significant predictor for WRSI's thresholds. More details are available in the appendix 7.

The BLR model permits an overview of the potential predictors' performance in forecasting the considered thresholds of WRSI, site specific.

b. Independent Verification Using Perfect Prognostics

In order to test the ability to predict WRSI thresholds, the same candidate predictors are considered, as the observed variables can be taken from another source at historical and near real time. Hence, the same candidate predictors were taken from data provided by the NASA's Prediction of Worldwide Energy Resource (POWER). These variables are based primarily on solar radiation derived from satellite observations and meteorological data from assimilation models. Using data from the POWER website as the input data to the BLR model to forecast WRSI thresholds as defined by equation 3.7. The BLR provides a probability ranging between 0 and 1. To forecast the WRSI at vegetative and/or reproductive phases of maize crops, the probability calculated from the BLR must be close to or equal to 1. If not, the calculated probability will be 0. This is the perfect prognostic (PP) approach. The distribution of the forecasted WRSI are compared to the observed distribution of WRSI thresholds encrypted into {1, 0} with verification scores of a 2 x 2 contingency table included in a performance diagram (Roebber, 2009). The verification scores considered are the Probability of Detection (POD), BIAS, False Alarm Rate (FAR) and the Critical Success Index (CSI).

The independent verification of the PP does not provide "good" probability of detection (POD) in Dapaong and Bolgatanga. However, The POD is higher in Bakel, Dano and Mango with much higher bias compared to climatology. In Ouahigouya, the results of the BLR model based on the PP are not better than the climatology (figure 4.15). The BRL-based PP approach overestimated the 10-day lead time forecasts with higher predictability potentials at some of the reference stations. This uneven performance distribution of the PP model can be related to the limited number of candidate predictors. Therefore, more sensitivity assessment needs to be carried out over a larger spectrum of candidate predictors (e.g. soil temperatures, NDVI etc.) to reach better performance in the WASS.

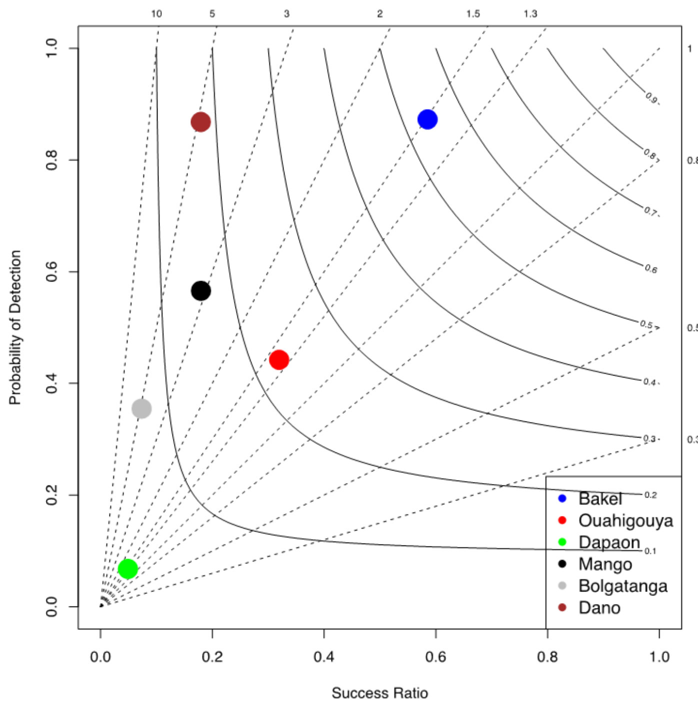


Figure 4.15: Performance diagram of perfect prognostics forecast based on a binary linear regression model for 6 reference stations of the study area.

4.2. Discussion

Seasonal to intra-seasonal rainfall distribution consists of several rainfall extremes of high impact on food security, disaster risk reduction and livelihood. The high impact rainfall events (HIRE) defined in this study are among the most crucial in operational monitoring and early warning services in WASS. Hence, the identified parameters such as first efficient rainfall (FER), extreme dry spells (ExDS), intense rainfall events (IRE) are useful in monitoring farm crops but also directly linked to disaster risk diagnostics in case of drought or floods. While crop water requirement index (WRSI) is seen as a crop-climate related index, its usefulness expends to the area of food security and drought monitoring. These parameters are all related to quality of the rainy season (dry/wet) and complete those defined by Jalloh *et al.*, (2011) for an improved information delivery and adaptation to climate variability and change.

The thresholds found for each element are relevant in making the profile of a possible quality of a rainy season and fine-tuning climate information to smallholder farmers. In West Africa, seasonal forecasting is based on multiple approaches used by National Meteorological and Hydrological Services (Dodd and Jolliffe, 2001; Omotosho *et al.*, 2000; Sivakumar, 1992). The thresholds provided by this study break the ground for an improved seasonal and intra-seasonal forecasts provision with an additional knowledge of rating scales and warning flags for FER, ExDS, IRE and WRSI. In an operational agro-climatic monitoring, this is helpful to identify each parameter as rainfall extreme and improve the quality of weather/climate information to farmers, and others on false onset of the rainy season, dry spells greater or equal to 10 days with precision according to their week of occurrence and the potential occurrence of heavy rainfall in the season. The knowledge of a probable false onset and ExDS enables the farmer to plan farm activities and seeds ahead of optimum planting dates (Sivakumar, 1992, Salack *et al.*, 2014, Sarr *et al.*, 2015). Information about possible ExDS during the growing season can also lead to adoption of drought/flood tolerant cultivars and other climate-smart agricultural practices (Belko *et al.*, 2014). The IRE information is important to disaster management institutions (Salack *et al.*, 2017) but also farmers to plan and adjust on-farm activities against soil erosion, waterlogging, use of fertilizers and chemical.

The crop water requirement satisfaction index (WRSI) indicates the crop performance based on water supply and demand experienced during the growing season. For maize cultivars considered in this study, simulations showed that WRSI below 70 and 50% negatively impact the potential yield. This result is in line with Thole (2009) and Senay and Verdin (2002) investigations in Zambia and Ethiopia respectfully who found that maize yield and WRSI are positively correlated. WRSI is influenced by the quality of the season, it performs better when a year records high rainfall amounts (wet). Studies have shown that precipitation and potential evapotranspiration are the most important inputs for WRSI computation (Senay and Verdin 2002; Funk and Verdin 2009). In the WASS region, rainfall is susceptible to be a limiting factor to high values of WRSI in the region. Therefore, monitoring lower values of WRSI at vegetative and reproduction phases of maize are of crucial importance for food crisis alleviation.

The results of the binary logistic regression (BLR) model based on an independent perfect prognostic (PP) forecasting technic exhibits high predictability potentials. This is breakthrough to early warning services delivery at 10-day lead time against crop water stress. Although, the limited number of candidate predictors selected in this study do not provide the best forecast of WRSI thresholds but show that PP approach has promising performance skills in early warning schemes.

Chapter 5 : Conclusion, Recommendations and Perspectives

5.1. Conclusion

West African Sudan-Sahel is frequently exposed to multiple natural hazards at different scales (Asare-Kyei *et al.*, 2015), notably extreme dry spells, intense rainfall, floods, droughts, air pollution, heat waves, wildfire, etc. and global climate warming may likely increase the frequency and intensity of some of these extreme events or a mixture of some in a unique season/location (Sylla *et al.*, 2015; Salack *et al.*, 2016). A recent Climate Risk and Early Warning Systems (CREWS) analysis shows that West African countries are most vulnerable to weather extremes because they often have the lowest early warning capabilities, weak or non-existent dissemination systems, and lack of effective emergency planning in case of alerts and warning information (http://newsroom.unfccc.int/media/454810/crews-presentation.pdf). Therefore, all adaptation measures that will spur our population to build resilience relay on the ability of climate information producers to monitor and predict HIRE and WRSI thresholds.

All HIRE and WRSI thresholds identified are qualified as rainfall extremes as they relate to the quality of rainy season, crop growth, development and yield in the West African Sudan-Sahel region. In the context of high climate variability, the knowledge of these threshold values, their rating scales, warning flag colours, and risk areas, suggested in this study, can be used in operation climate services provision. Applying these thresholds in climate information production chain (e.g. seasonal, sub-seasonal now casting and/or forecasting, etc.) can improve weather/climate information provision to farmers, disaster risks management organisations, and other application sectors. The usefulness of thresholds analysis and its extension to small holder subsistence farming system is much dependent on the predictability of WRSI thresholds. However, the results of this study prove that the BLR model embedded in a PP forecasting approach provides uneven performance skill over the reference stations of this study.

5.2. Recommendations and Perspectives

Therefore, it is recommended that a sensitivity assessment is carried out on the prediction model to include a larger number of candidate predictors. Another perspective is to extend the predictability potential to other crop types such as cowpea, millet and rice to cover the major staple food and fodder crops of the WASS. In order to improve near-real time monitoring of rainfall extremes and information delivery to users, the identified threshold values can be automatically linked to an observation network of sensors measuring weather/climate variables, in the form of a user-friendly tool kit or application. This perspective would need a permanent collaboration between climate scientists, extension agents and other climate services broker in support of human security in West Africa.

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APPENDIXES

1. Soil profiles information

SOIL TYPE: FERRIC FERRALSOL				
Depth (cm)	0-20	20-50	50-90	90-120
Elements (%)				
Sand	35.15	14.47	10.5	15.67
Silt	6.25	6.5	13.25	16.25
Clay	11	39	44.5	29.25
Organic matter (%)				
Carbon (C)	1.16	0.96	0.83	0.83
Nitrogen (N)	0.1	0.12	0.11	0.1
Ratio C/N	11.6	8	7.5	7.5
Cation exchange capacity (CEC)	8.9	14.2	17.6	12.7
pH				
H_2O	6.8	6.6	6.6	6.7

SOIL TYPE: RHODIC REGOSOL				
Depth (cm)	0-10	10-40	40-56	56-150
Elements (%)				
Sand	87.7	85.9	74.2	77.4
Silt	6.1	3.3	3.3	3.8
Clay	4,8	10,2	12,2	8,4
Organic matter (%)				
Carbon (C)	1,48	1,52	1.52	1.52
Nitrogen (N)	0,12	0,13	0.13	0.13
Ratio C/N	12,3	11,7	11.7	11.7
Cation exchange capacity (CEC)	1,89	3,53	3,57	3,58
pH				
H_2O	7,6	7,5	7,4	8

SOIL TYPE: RHODIC LIXISOL				
Depth (cm)	0-10	10-25	25-70	70-120
Elements (%)				
Sand	36	37	44.4	76.1
Silt	14.4	5.6	15.8	9.4

Clay	49.5	57.5	39.8	14.6
Organic matter (%)				
Carbon (C)	0.73	0.62	0.27	0.1
Nitrogen (N)	0,08	0,06	0.03	0.03
Ratio C/N	9	10	9	3
Cation exchange capacity (CEC)	11.6	11.0	9.6	5.6
pH				
H_2O	6.9	6.7	6.8	7.2

SOIL TYPE: EUTRIC REGOSOL							
Depth (cm)	0-16	16-45	45-74	74-100	100-118	118-155	155-193
Elements (%)							
Sand	81.4	79.8	74.35	64.9	71.4	40.7	40.4
Silt	14.6	13.7	16.6	23.6	14.6	17.8	20.6
Clay	4,00	6,50	9,00	11,50	14.00	41,50	39,00
Organic matter (%)							
Carbon (C)	0,41	0,25	0,22	0,19	0,17	0,17	0,13
Nitrogen (N)	0,031	0,022	0,020	0,017	0,017	0,017	0,014
Ratio C/N	13	11	11	11	11	10	9
Cation exchange capacity (CEC)	3,11	3,62	3,53	3,95	3,44	9,80	10,00
pH							
H_2O	5,87	6,60	6,52	6,90	6,84	7,60	8,42

SOIL TYPE : FERRIC PLINTHOSOL			
Depth (cm)	0 -20	20-40	40-75
Elements (%)			
sand	77.86	77.28	78.84
silt	16.14	16.72	16.16
clay	6	6	5
Organic matter (%)			
Carbon (C)	1.01	0.87	0.89
Nitrogen (N)	0.09	0.08	0.08
Ratio C/N	11.2	10.9	11.1
Cation exchange capacity (ECE)	4.18	3.63	2.87
pH			

H_2O	5.69	5.74	5.93

2. Crop simulation details

CROPS	MAIZE
CROP MANAGEMENT	
Cultivars	Obatampa, EV-8443-TG
Planting date- emergence date	simulated
Planting method	Dry seeds
Planting distribution	rows
Plant population at seeding, plant/m^2	6.25
Plant population at emergence, plant/m^2	6
Row spacing, cm	80
Plant depth, cm	3.5
Fertilizer	20 DAP: 150 kg NPK 48 DAP: 50 kg of Urea
Tillage (Days Before Planting)	Blade cultivator at 8 cm
SIMULATION OPTIONS	
Simulation date	Days before tillage with CEREZ-Maize
Simulation methods	Evapotranspiration: FAO-56 Infiltration: soil conservation service Photosynthesis : radiation efficiency Hydrology : Ritchie water balance Method of soil organic matter: century Parton Soil evaporation method: Ritchie ceres Soil layer distribution: model-specified soil layers
Simulation management	Planting: from 1st to 31st July when soil temperature is within 8-32 ºC, soil water content is in the range 40-100% at 20 cm depth. Harvest at maturity, no irrigation, no organic amendment
Frequency of outputs	10 days

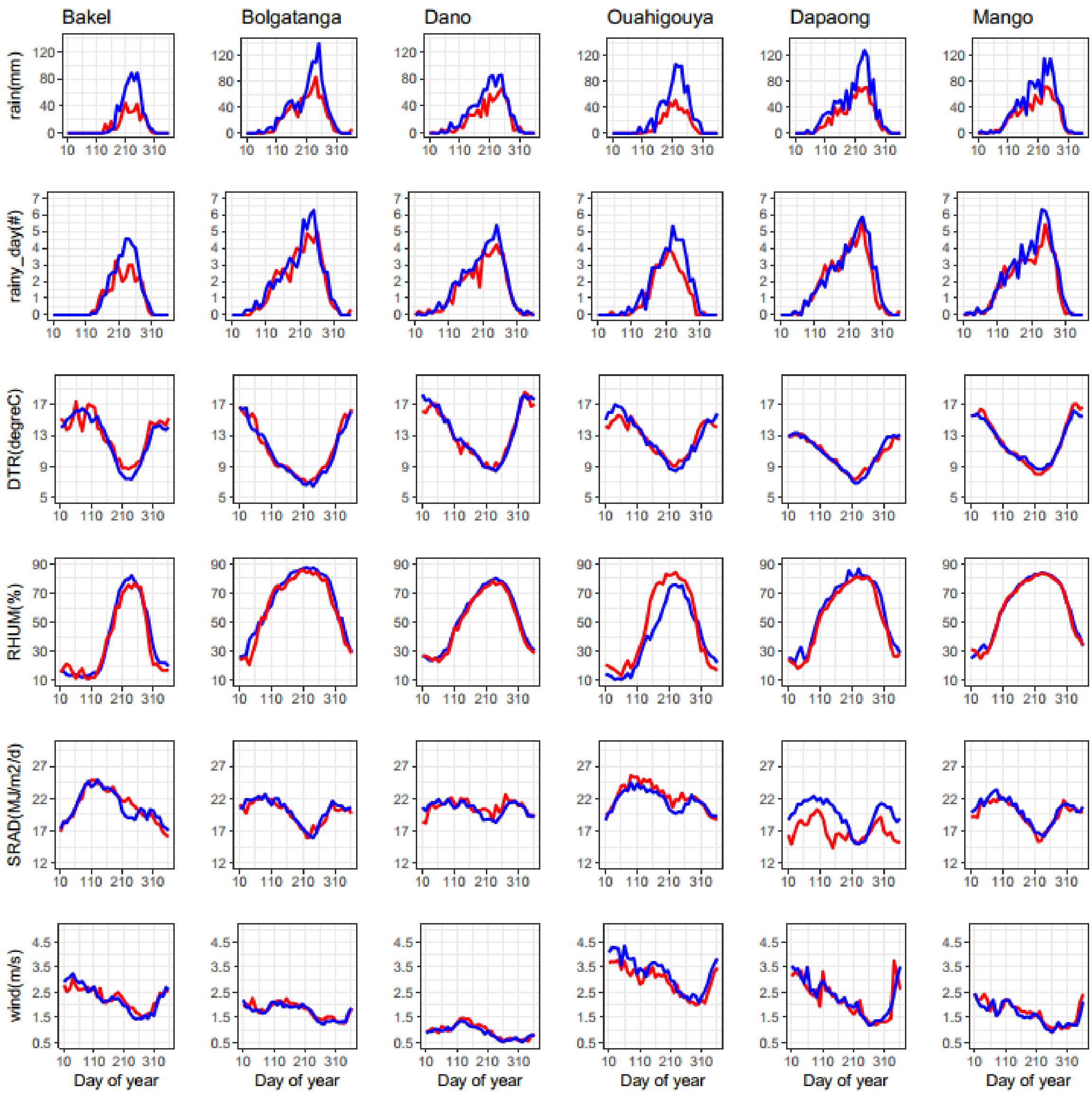
3. Agro-climatic Indices

Definition	Unit	Parameter	Tag name	index
First Efficient Rainfall	WOY	Daily rainfall (mm)	False onset	FER
Start date of dry spells > 9 days	WOY	Dry days	Extreme dry spells	ExDS
Intense Rainfall event	WOY	Daily rainfall (mm)	Intense rainfall	IRE
Crop Water requirement satisfaction index	%	Dekad water requirement and crop evapotranspiration	Drought stress factor	WRSI

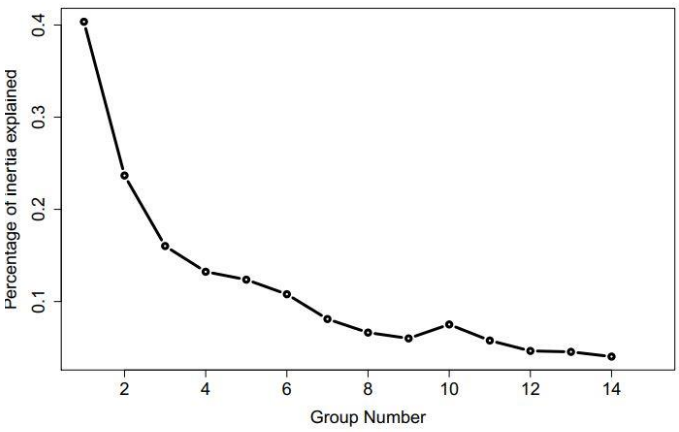
4. Seasonal drought (wetness) distribution at the stations

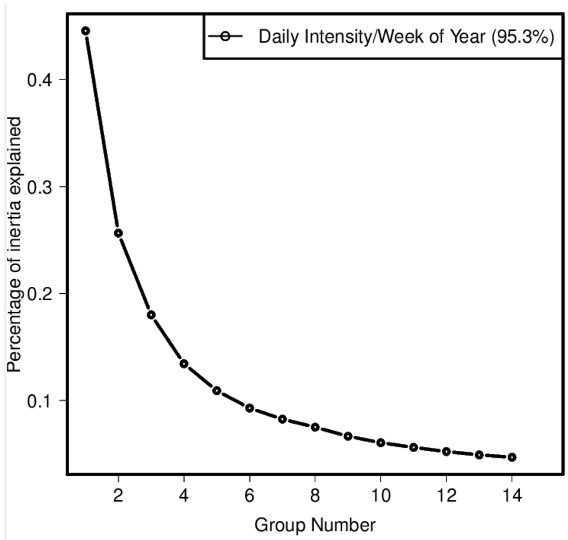
Dapaong		Mango		Dano		Bakel		Ouahigouya		Bolgatanga	
dry	wet	dry	wet	Dry	wet	dry	wet	dry	wet	dry	wet
1983	1994	1981	1982	1973	1970	1960	1964	1971	1962	1977	1989
1984	1998	1990	1987	1977	1971	1972	1965	1972	1963	1980	1991
1985	1999	1992	1996	1980	1972	1973	1966	1973	1981	1981	1996
1986	2001	1995	1998	1983	1981	1976	1967	1977	1994	1984	1999
1990	2003	1997	1999	1984	1986	1977	1974	1982	2007	1985	2007
1991	2007	2000	2004	1990	1988	1979	1975	1983	2010	1990	2009
1995	2009	2001	2007	2002	1989	1980	1988	1984	2012	1995	2012
2000	2013	2002	2009	2005	1995	1984	1994	1985	2015	2002	
	2016	2003	2012	2009	1999	1987	1995	1987	2016	2004	
		2005			2003	1992	1999	1990		2005	
		2006			2010	1996	2000	2011		2006	
		2013			2011		2003			2011	
		2014			2012		2004				
		2015					2007				
							2010				

5. Seasonal cycles of some parameters useful for crops in a dry/wet cluster of years depicted from historical time series (1960-2016) following the standardized precipitation index with variable baseline.



6. Kmeans results for ExDS and IRE





7. ANOVA tables of the BLR model

Threshold 1: dekad-average			threshold 2: 10th percentile		threshold 3: 5th percentile	
Bakel						
Variables	Pr(>Chi)	Significance level	Pr(>Chi)	Significance level	Pr(>Chi)	Significance level
SRAD	0.015414	*	0.001274	**	0.006835	**
RAIN	0.000206	***	0.016981	*	0.002766	**
WIND	0.888368		0.014748	*	1	
RHUM	0.002057	**	0.579629		0.999998	
DTR	0.986737		0.00297	**	1	
Bolgatanga						
SRAD	0.439511		0.12727		0.21552	
RAIN	0.492708		0.1056		0.03493	*
WIND	0.051952	.	0.01124	*	0.27449	
RHUM	0.007523	**	0.10265		0.10384	
DTR	0.000785	***	0.4382		0.23511	
Dano						
RHUM	0.07641	.	0.00681	**	0.1315	
RAIN	3.94E-05	***	0.009734	**	0.2404	
SRAD	0.0171	*	0.313046		0.5393	
WIND	0.2317		0.023218	*	0.2492	
DTR	0.81276		0.78656		0.6798	
Dapaong						
RHUM	0.01896	*	0.001595	**	0.012089	*
WIND	0.17794		0.087546	.	0.198979	
SRAD	0.03508	*	0.726532		0.54589	
RAIN	0.44302		0.000148	***	0.007849	**
DTR	0.13612		0.977086		0.523578	

Mango						
RHUM	0.000247	***	4.88E-07	***	0.000295	***
WIND	0.000246	***	0.2657		0.278475	
SRAD	0.409039		0.7401		0.744738	
RAIN	0.180732		0.2083		0.327737	
DTR	0.451805		0.4746		0.32697	
Ouahigouya						
RAIN	0.000602	***	0.16223		0.2412	
SRAD	0.093537	.	0.05996	.	0.2448	
WIND	0.20722		0.24743		0.7737	
RHUM	0.07496	.	0.32791		0.0883	.
DTR	0.555743		0.32201		0.9072	

8. Research budget

Designation	Unit	Quantity	Unit cost (Euros)	Amount (Euros)
CONTRIBUTION FROM MRP-CCHS				
Research work				
Data acquisition	station	8	15	120
Training on cowpea cultivars (Nigeria)	day	10	50	500
Training on S2S & TIGGE forecasting data management in Paris (France)	day	10	100	1000
Total 1				1620
Mobility				
Bus ticket	ticket	2	35	70
Accommodation	week	17	50	850
Local transport	Per month	4	30	120
Total 2				1040
Printing and binding				
Printing of proposal (black-white)	page	150	0.02	3
Printing of proposal (color pages)	page	36	0.2	7.2
Proposal binding (6 documents)	-	-	-	2
Thesis draft printing	page	70*4	0.02	5.6
Printing of the thesis draft color pages	page	20*4	0.2	16
Final printing of the thesis	page	70*6	0.02	8.4
Final printing of the thesis color pages	page	20*6	0.2	24
Thesis binding (6 documents)	-	-	-	4
Total 3				70.2

MRP total	**T1 + T2 + T3**			**2730.2**
CONTRIBUTION FROM APTE-21 PROJECT				
Field excursion to Paris (France)	day	10	250	2500
Field excursion to International Institute in Tropical Agriculture (IITA) in Nigeria	day	10	70	700
Total 4				**3200**
Grand Total	MRP total + T4			5930.2

9. **Tentative timeline**

ACTIVITIES	Jul-17	Aug-17	Sep-17	Oct-17	Nov-17	Dec-17	Jan-18
Historical data acquisition							
Draft of 1st paper on "perfect prognosis & seasonal forecasting of rainfall extremes"							
Data cleaning and calibration							
Field excursion to IITA for training on cowpea cultivars (Nigeria)							
Training on S2S & TIGGE data management in Paris (France)							
Training on crop modelling in Ouaga							
Development of the early warning toolkit							
Thesis writing							
Draft of 2nd paper on "thresholds analysis in early warning systems"							
Return trip to Togo for thesis defense							