BEST OF BOTH WORLDS

Co-Producing Climate Services that Integrate Scientific and Indigenous Weather and Seasonal Climate Forecast for Water Management and Food Production in Ghana

Emmanuel Nyadzi

Propositions

1. Integrating indigenous and scientific forecast improves forecast reliability and acceptability among African farmers. (this thesis)

2. Citizen science enables co-production of climate services. (this thesis)

3. Scientific reductionism remains a valid approach for understanding vast and complicated systems.

4. Developing interdisciplinary research skills is essential for emerging scientists to understand and contribute to solving complex societal problems.

5. Making novel findings part of existing scientific discourse is harder than discovering them.

6. To finish a PhD requires more commitment than competence.

Propositions belonging to the thesis entitled
Best of both worlds: co-producing climate services that integrate scientific and indigenous weather and seasonal climate forecast for water management and food production in Ghana

Emmanuel Nyadzi
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Thesis

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This book is dedicated to:

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&

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Abstract

Climate variability and its impacts on the agriculture system is clearly evident in Ghana. Weather and seasonal climate forecast information service has been in operation for some time in the country. However, farmers generally do not find the information useful for their farm-level decision making. Forecast accuracy, untimeliness, and mismatch of forecast information and needs are often reported constraints for farmers to use weather and climate information. Consequently, the majority of farmers rely on their indigenous ecological knowledge to predict weather and seasonal climate patterns. At the same time, current weather and seasonal climate forecast information systems in Ghana face serious constraints in how they are used (if at all) because of the one-directional assumption behind its development; where only science produces new knowledge and makes it accessible for end-users with no or limited involvement of the end-users. In this context, this study addresses the central question: *How can climate information services be improved through the co-production of farmers and scientist?* It aims at improving the reliability and acceptability of forecast information by integrating indigenous and scientific forecast. In this dissertation, I used a multi-method research approach, consisting of social participatory methods, mental modelling methods, forecast verification methods, and the principle of citizen science for data gathering and analysis. Initial diagnostics revealed certain issues that limit the uptake of climate information services in Northern Ghana: (1) the mismatch between forecast information provided and the farmers' information need (2) poor quality of forecast information, (3) the disconnect between forecast providers (researchers) and farmers, (4) management of unrealistic expectations of farmers. In response, I proposed a framework for second generation climate services that have the potential to facilitate co-production of relevant and accurate weather and seasonal climate forecast information and manages user expectation while strengthening the collaboration between information providers and users. Results of our analysis show that farmers' information needs are linked to the type and timing of farm-level decision making. Also, model-based seasonal forecasts have the potential to provide relevant information at farmers most preferred lead time.

Findings also show that in addition to historical rainfall patterns, farmers also use observational changes in certain indigenous ecological indicators to predict the coming season. In particular, there is a cognitive relationship between the observational changes and the predicted rainfall event. I observed that farmers' indigenous forecasting skills and techniques are not intuitive but rationally developed and improve with age and experience. Results also show that farmers and Ghana Meteorological agency are on average able to accurately forecast one out of every three daily rainfall events. Similar results were obtained at the seasonal timescale. Furthermore, I recognized that forecast reliability and usefulness can be improved if indigenous forecast data are quantitatively collected and integrated with the scientific forecast using the proposed integrated probability forecast method. Finally, this dissertation contributes to the calls for a more integrated, co-learning, and co-production approach to climate services that move away from the current focus on science-driven and user-informed climate services. The approach developed in this dissertation is relevant for managing the impact of climate variability and change, particularly because it includes the knowledge of indigenous peoples which is often overlooked.

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Chapter 1

General introduction

1.1 Background and problem outline

In Africa, extreme weather conditions such as droughts and floods are projected to occur more frequently and more intense, affecting all sectors but especially agriculture (Schlenker & Lobell, 2010). Over the last years, periods of extreme heat and erratic rainfall in Ghana has caused crop failures leading to yield reduction and, food insecurity in the region (Müller-Kuckelberg, 2012). Smallholder farmers are disproportionately affected by climate variability and change (Jalloh et al., 2013; Niang et al., 2014; Sarr et al., 2015). Rainfall variability is a particular problem for Ghanaian farmers; both irrigated and rain-fed farmers in the Northern part of the country are impacted by these changes because of the difficulties to predict the weather and seasonal climate, leaving serious implications for food production (Kranjac-Berisavljevic' et al., 2003; Asante & Amuakwa-Mensah, 2015).

The unpredictability of weather and seasonal climate influences the precision of farm-level decisions that need to be taken from daily to weekly and in months ahead of a season (Asante & Amuakwa-Mensah, 2015; Asante & Amuakwa-Mensah, 2015; Lawson et al., 2019). For example, farmers have to re-sow seeds several times due to delay in rains which affect germination, increasing the cost of production and straining their livelihood (Ndamani & Watanabe, 2013). Irrigation managers and farmers rely on river discharge information to decide the frequency, quantity, and method of water distribution to farms. However, their limited ability to predict the rains and river discharge ahead of the season put them in a dilemma (Ndamani & Watanabe, 2013). Growing concerns about the impacts of climate variability and change on agriculture have attracted the attention of the national and international community to strengthen weather and climate information (Gumucio et al., 2019). Developing weather and climate services is therefore suggested as an important element to manage the risk of climate variability and change (Vaughan & Dessai, 2014; Ouédraogo et al.,2015).

Hereafter, I use the term climate services as a combination of weather services and seasonal climate services although both are distinct in their definition. While weather service provides information on the condition of the atmosphere at a given time and place for up to about 14 days (Fleming, 2008), seasonal climate services deliver information about the average weather conditions from one month to six months period (Bazile et al., 2017). Borrowing from the definition of Climate Services Partnership, climate services are the production, translation, transfer, and use of weather and climate knowledge and information in weather and climate-informed decision making and climate-smart policy and planning (CSP, 2011).

Studies show that current weather and climate information services for agriculture are facing serious constraints in how they are used (if at all). First, most farmers do not find forecast information useful for farm decision making because of forecast inaccuracy, language barriers, use of technical forecast terminologies which are difficult to understand, inconsistency and untimeliness of information provision, as well as forecast not matching their needs (Luseno et al., 2003; Onyango et al., 2014; Feleke, 2015). Secondly, climate services in many parts of the world, including Ghana, are developed in a one-directional manner; where science produces new knowledge and makes it accessible for end-users with no or limited involvement in the production of knowledge. This limits the acceptability and use of forecast information (Cash et al.,2003; Okello et al., 2012; Karpouzoglou et al., 2016). Consequently, local farmers across Africa highly depend on indigenous forecasts for most farm decision making, including in Ghana (Gyampoh et al., 2009; Nyantakyi-Frimpong, 2013), Zimbabwe (Gwenzi et al., 2016), Burkina Faso (Roncoli et al., 2002) and South Africa (Zuma-Netshiukhwi et al., 2013).

In line with the above, the discourse on climate services as tool to support adaptation has stimulated scholars to study it from different angles: improving the skills of scientific forecast models for agriculture decisions (Hammer, 2000; Hansen, 2005; Esquivel et al., 2018), increasing co-production of climate services (Bovaird, 2007; Dilling & Lemos, 2011; Enengel et al., 2012), exploring the value of indigenous knowledge for forecasting and integrating indigenous and scientific forecast (Zuma-Netshiukhwi et al., 2013; Jiri et al., 2015; Radeny et al., 2019). Despite progress, scholarship on the topic is still at its infancy and critical questions remain. First, studies have suggested that climate services can be made more reliable and acceptable when indigenous forecast (IF) and scientific forecast (SF) are integrated (Gagnon & Berteaux, 2009). While this has been acknowledged in the academic literature, very few studies have explored the possibility. Therefore, the question that still remains is whether integration is possible considering the significant differences between IF and SF? Secondly, Buytaert et al., (2014), suggest that citizen science (see also section 1.3) has the potential to complement more traditional ways of scientific data collection and knowledge generation. Citizen science has been applied in different fields of study, yet to the best of my knowledge, no studies have explored citizens science as a way of increasing co-production in climate services. The question, therefore, is how can citizen science contribute to co-production of climate services? In this dissertation, I aim at making weather and seasonal climate information services useful for the decision making of farmers' in Northern Ghana, by integrating scientific and indigenous forecast.

The remainder of this chapter presents the current state of knowledge on climate services for agriculture decision making (section 1.2), the conceptual framework used for this study (section 1.3), Emerging key knowledge gaps, the research objective and questions (section 1.4), an overview of the research methodology used for the study, including study area and research design (section 1.5), and the structure of this dissertation (section 1.6).

1.2 Climate services for agriculture

In general, climate services support a variety of interventions aimed at building resilience by providing basic knowledge about the local climate, inform farmers and institutional decision-making about future changes, as well as creating an enabling setting for adopting new practises such as climate-smart agriculture (Hansen et al., 2019).

The early development of agricultural climate services can be traced back to the dual ambition of matching seasonal climate forecasting to agricultural systems and including agriculture into the development of seasonal climate predictions. In the early to mid-1990s, north-eastern Australian agricultural researchers developed the first decision support tools to translate climate information for agricultural management decisions (Hayman, 2004). In Africa, the 1997/98 El Niño event saw an increase of investment and research on agricultural applications of seasonal climate prediction. At the same time, the Regional Climate Outlook Forums was also launched (RCOF). Climate services in most parts of the continent are currently connected to RCOF (Hansen et al., 2019).

Considered as an integral part of climate change adaptation agenda, climate services have recently received a great deal of attention especially because forecasting capability has been improved in the past two decades (Orlove et al., 2004). A number of frameworks and programs have been proposed for climate services (Lourenço et al., 2016), to provide timely, tailored information and knowledge to a variety of users including smallholder farmers to adapt and increase resilience (Vaughan & Dessai, 2014).

Despite the value of climate information services in making the agriculture sector more resilient to climate variability and change, Ghana has made limited progress. This can be traced back to the dominating role of climate scientist who focuses on producing and evaluating the quality of weather and climate information, rather than understanding the use of the information created (McNie, 2013). As the demand in climate services for agriculture increases in the country, a number of challenges emerge which complicated the generation, dissemination, and use of forecast information for decision making. These challenges are not unique for Ghana but are found for many developing countries in the global south, in particular, sub-Saharan Africa (Vaughan et al., 2019).

In the remainder of this section, I present the use of climate services for agriculture in Ghana, elaborating the reasons for increased demand for climate information services as well as the emerging challenges and proposed solutions that come as a consequence.

1.2.1 Climate services for agriculture in Ghana

In Ghana, climate services have received little attention in agricultural policy (Naab et al., 2019). The Ghana Meteorological Agency (GMet) is the only national provider of climate information working with the Ministry of Food and Agriculture (MoFA), the Ministry of Environment, Science, Technology and Innovation (MESTI), Environmental Protection Agency (EPA), the National Climate Change Committee (NCCC), and the Council for Scientific and Industrial Research (CSIR). As a result of the increasing demand in quality forecast information, a number of private sector providers have emerged providing tailor made forecast information to farmers. Arguably, the private sector involvement in agriculture climate services signals that forecast information provided by GMet has not been sufficiently useful for farmers. For example, GMet provides weather and seasonal climate forecast to the general Ghanaian public yet focus more on the aviation, defence and marine sectors with little to no attention to farmers (Naab et al., 2019). Therefore, climate services for agriculture in Ghana encounter several challenges.

1.2.2 Challenges for successful delivery of agriculture climate services in Ghana

Ghana like many other countries in the sub-region is faced with similar climate related hazards, such as drought and flood. Yet current early warning systems are limited in their operations due to institutional data collection, storage data and sharing problem (NADMO, 2015;). Even though the technology for generating and disseminating reliable climate information has improved over the years, studies show that information provided to end-users does not necessarily reflect their specific needs (Onyango et al., 2014; Feleke, 2015). The challenges of climate information services have kept many smallholder farmers in developing countries including Ghana vulnerable to climate variability. Three key challenges can be identified.

First of all, prediction with a high level of accuracy of forecasts especially rainfall remains a challenge (Johnston et al., 2004; Hansen et al., 2019). In Ghana, for example, sparse weather stations provide limited coverage of areas necessary for rigorous spatial analysis. Moreover, there is incomplete historical climate data available due to poor monitoring and broken weather stations. This makes it difficult to properly evaluate forecast quality and improve the forecast. As a result, GMet provides weather and seasonal climate information at a national and regional scale which is less relevant to farmers. According to Tall et al. (2018), the resulting “wrong” climate forecasts may lead to harmful consequences to farmers’ livelihoods and consequently, on the economy.

Secondly, for climate information to be useful and integrated into farm-level decisions, it must be provided early enough, in formats they can understand, through communication channels they find relevant, or with content they find salient (Carr et al., 2015). Farmers in Ghana do not receive specific climate information to adapt their farming practises; for example, types of crops to grow, and the amount of resources to commit to farming (Naab et al., 2019). Forecast information is provided outside the farmers required time frames and via media that cannot be accessed by farmers. Those provided by the private sector for example via mobile phones are often communicated in English and include technical jargon which cannot be read nor understood by many illiterate farmers (ESOKO, 2016).

Thirdly, limited communication of forecast uncertainties affects usage and uptake of climate services. Communicating climate uncertainty is essential for building trust necessary for successful climate services (Goodwin & Dahlstrom, 2011). Climate is stochastic and variable, and as such predicting it always comes with a degree of uncertainty. When these uncertainties are not properly communicated and forecast provides false alarm, farmers interest and trust in the scientific forecast are impacted (NRC, 2006). Contrary to the assumption that non-experts do not understand the probability of uncertainties, recent research suggests that non-experts can make effective use of probabilistic uncertainty estimates in weather and climate forecasts (LeClerc, 2014). Non-experts made better weather and climate related decisions when forecasts and projections include uncertainty estimates, although some expressions of uncertainty were more effective in some situations than others (LeClerc, 2014). In Ghana, GMet does not communicate forecast information with its probability. Most users, therefore, interpret the information as if it was absolutely certainty, and when it fails they complain, and doubt the quality of information and the relevance of the GMet institution itself.

In addition to the above challenges, the World Meteorological Organisation (WMO) has listed some more challenges that limit the generation and the dissemination of climate information at the required quantity, quality and timeliness. These include existing data policies that inhibit free and open data dissemination; unavailability of digitised climate archives that includes all climate elements; improper data quality checks; existing gaps in climate observations due to malfunctioning of meteorological stations and lack of capacity in using satellite data services (WMO, 2006). These challenges are also found to be affecting climate services for agriculture in Ghana (Ndamani & Watanabe, 2013; Codjoe et al., 2014; Nkrumah et al., 2014; Asante & Amuakwa-Mensah, 2015; Naab et al., 2019).

1.2.3 From first to second generation climate services in Ghana

The above mentioned challenges emerge to a large extent from the first generation of climate services used in Ghana. The first generation of climate services is built on the assumption that if access to climate data is improved, decision making will improve also (Okello et al., 2012; Anoop et al., 2015; Etwire et al., 2017). However, Harvey et al., (2019) argue that for climate services to be successful, there is the need to move towards a demand-driven and science-informed approach. Further, they mention the need for providers to understand and adopt the terminology, regulatory, and cultural conditions of the end-users, rather than the other way around. To do this requires an approach that is more collaborative with effective and regular communication between scientists and end-users.

Karpouzoglou et al. (2016), raised a similar argument for shifting to a more inclusive second generation Environmental Virtual Observatories in general.

EVOs describe the infrastructure, tools and software used for gathering, processing and dissemination information and can enable cross fertilization of different sources of knowledge on shared virtual platforms (Karpouzoglou et al., 2016, Pp 40). The first generations of these information systems failed to deliver a strong knowledge co-creation component and consequently failed to empower local communities to manage their environmental change using actionable knowledge (Dewulf et al., 2005). Therefore a second generation EVOs has been proposed to emphasizes knowledge co-creation between scientists and societal actors, and bidirectional information flows, so as to create actionable knowledge that can support decision-making.

While co-production of climate services is increasingly acknowledged, it is not used in the design and dissemination of climate services in Ghana. Several reasons for the lack of progress exist. First, there is lack of co-ordination among the many organisations and actors who play a role in the generation, dissemination and use of climate forecast in Ghana (Naab et al., 2019). Secondly, farmers who are the main users of agriculture climate services are rarely involved in the process because of the limited appreciation of their local knowledge.

Therefore, the objective of this dissertation is to improve weather and seasonal climate forecast information services in Ghana through co-production by integrating scientific and indigenous forecasts to support farm decision making. In doing so, this dissertation aims to contribute to a second generation of climate services for agriculture in Ghana.

1.3 Conceptual framework

The conceptual framework of this study is depicted in Figure 1.1. The central concept in the dissertation is co-production. Other key concepts include citizen science, second-generation climate services, indigenous and scientific knowledge/forecast, and integration. The framework conceptualises the interaction between scientist and rice farmers (dash double side arrow) through citizen science to collect forecast data combined into an integrated forecast. In this process, farmers contribute their knowledge about forecast information needs and decision making which inform scientists' forecast evaluation. In the remaining of this section, I explain the key concepts and how they link to each other in the dissertation.

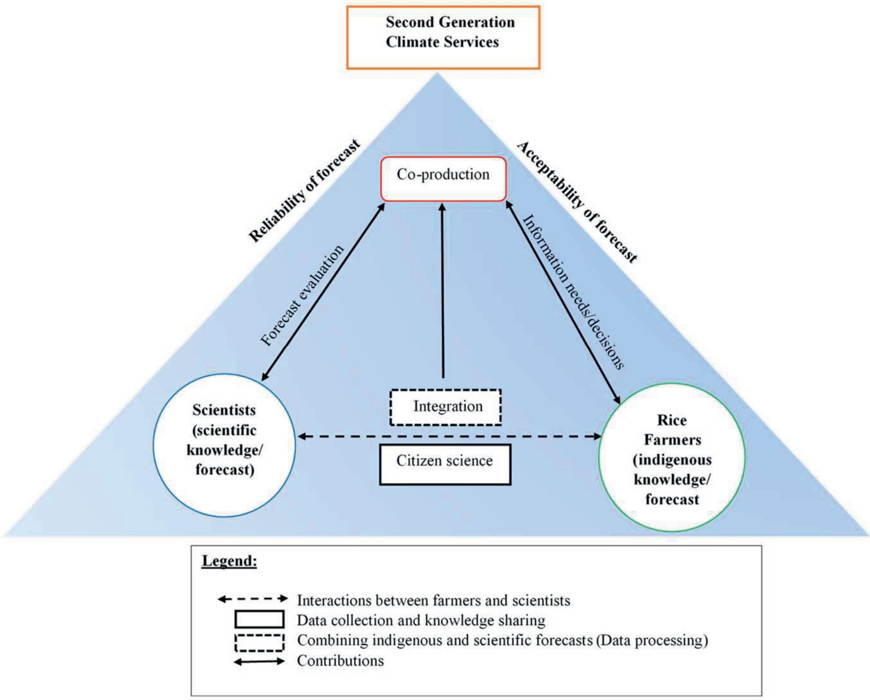

Figure 1.1: Conceptual framework of the study.

Co-production

The concept of co-production is used as the direct involvement of clients' or citizens' in public or private sectors production (Parks et al., 1981). It has been used primarily within the fields of participatory development, science and technology studies, and science policy studies (Miller & Wyborn, 2018). Recently, co-production has increasingly become a relevant research area in which producers and users of knowledge collaboratively engage each other to address complex societal problems (van Kerkhoff & Lebel, 2015; Wyborn, 2015). Co-production highlights the need to encourage the power balance between producers and users of knowledge in order to create an enabling environment for collaborative knowledge production (Vincent et al., 2018). Rice (2002), emphasizes that in co-production, the efforts of end-users are recognized and forms an important part in the production of the output. Therefore, co-production calls for joint efforts between two parties (the producer and end-user) who jointly determine the output of their collaboration.

The logic of co-production may seem simple at first sight but practice shows it is rather challenging. This is particularly true for responding to climate change impacts. As noted in section 1.2, scholars have suggested that to achieve co-production in climate services a shift from supply-driven to demand-driven approach where scientist and end-users engage in a regular and sustained interaction to produce forecast information is needed (Dilling & Lemos, 2011; Kirchhoff et al., 2013; Nel et al., 2016).

Drawing from the definitions and characteristics of co-production, I define and apply the concept of co-production as the active involvement of farmers and scientists in designing, creating and producing climate services to address the complex problem of climate variability and change in a way that recognises and uses different knowledge systems and expertise in forecasting. The concept of co-production as used in this study is expected to enhance the inclusiveness required for successful climate services delivery, thus pushing for a second-generation climate services that centre on co-production.

Second generation climate services

Co-production is an important element of the second generation climate services. Building on the arguments of Karpouzoglou et al. (2016), notwithstanding the significant advancement in the development of innovative information systems, there still exist several instances where the expertise of end-users are isolated from the design and development process. Cash et al. (2003), also indicate that less involvement of users in the development of information systems will result in lack of trust in data and limited ownership of the outputs which are essential values for the success of the system. As a result, the one-directional model (where farmers are informed, not involved) of providing weather and climate services has shown to be flawed, making farmers not to trust scientific information and thus relying on their indigenous forecast (Letson et al., 2001). In most cases, training farmers to adopt this one-directional model of providing weather and climate information services fail to improve climate information uptake (Manyanhaire & Chitura, 2015b). A key reason for this is that scientists often have little understanding of farmers' contexts and needs (Artikov et al., 2006).

Aside from the regular meetings and workshops with farmers, the unique approach adopted in this research is the use of citizen science.

Citizen science

Citizens' involvement in science is not necessarily a new term, although it gained a lot of traction in the last decade. Citizen science can be traced back to the 19th century (Silvertown, 2009). The term is described by Bonney et al. (2009), as "an approach where scientific insight is gained by individuals who do not work professionally in the relevant scientific field, with or without the support of professional researchers". Buytaert et al. (2014) define it as "an approach whereby non-scientists are actively involved, at differing degrees, in the generation of new scientific knowledge, from which they also actively stand to benefit either intrinsically (e.g. increased scientific literacy) or extrinsically (e.g. increased social capital)". The term has also been associated with concepts such as crowd-sourced data (Lowry & Fienen, 2013), community-based management (Keough & Blahna, 2006), community-based monitoring (Palmer Fry, 2011). However, the element of "active" engagement distinct citizen science from other forms of public participation in scientific research (Wiggins & Crowston, 2011).

In the context of this dissertation, I define citizen science as the participation and collaboration of farmers in the collection, sharing and interpretation of data (e.g. rain forecast and observational data) generated at a finer resolution which otherwise could be impossible to achieve by scientist only.

Citizen science, in general, has many challenges; (1) organizational issues; lack of volunteer interest, networking, funding opportunities and information access (Whitelaw et al., 2003; Milner, 2007; Conrad & Daoust, 2008), (2) data collection issues; include data fragmentation, data inaccuracy, and lack of participant objectivity and inadequate training (Whitelaw et al., 2003) and (3) data use issues; including, adequacy of sample size, credibility, non-comparability and completeness of the data (Bradshaw, 2003; Gouveia et al., 2004; Sharpe & Conrad, 2006; Conrad & Daoust, 2008).

Citizen science, however, has several benefits for science, society and participants (See Table A1 of supplementary material for details on the benefit of citizens science) (Pettibone et al., 2016). Generally, citizen science projects have been more successful in advancing scientific knowledge. Such projects involve non-scientist in gathering large amounts of data in different locations for a longer period of time. Recent applications of citizen science includes water quality monitoring (Canfield et al., 2002; NYCWTA, 2014), mapping spatially non-continuous permanent rivers (Turner & Richter, 2011), examining populations distribution and change of birds (Bonter & Harvey, 2008; Bonter et al., 2010), the spread of infectious diseases among wild animal populations (Hochachka et al., 2004; Dhondt et al., 2005), community monitoring of poaching (Stevens et al., 2013), effect of acid rain on bird populations (Hames et al., 2002), modelling ecological systems

(Hochachka et al., 2007; Kelling et al., 2009) and planning and management of local ecosystems (Pollock & Whitelaw, 2005). In meteorology and atmospheric science, however, the adoption has been relatively limited with some applications for precipitation measurement (CoCoRaH, 2010).

The novelty of applying citizen science in this study is not particularly for advancing theories on citizen science, but as part of the approach to actively involve non-scientists in the process of generating integrated forecasts. Integrating both indigenous and scientific forecast has the potential of making forecast information useful for farmers (Gagnon & Berteaux, 2009).

Indigenous knowledge / forecast

The concept of indigenous knowledge has been widely used in different strands of literature and no commonly accepted definition exists. It is therefore valuable to explore the various circumstances under which the term has been used (for example, Mafongoya & Ajayi (2017), Orlove et al., (2010), Gray & Morant, (2003), Berkes et al., (2000) and Ruddle & Johannes (1989). The term indigenous knowledge is often used in reference to knowledge and know-how that is generated by several generations to guide their understanding and interactions with their surrounding environment (Mafongoya & Ajayi, 2017). Indigenous knowledge can also be defined as a cumulative body of knowledge, practice and belief, evolving by adaptation processes and handed down through generations by cultural transmission, about the relationship of living beings (including humans) with their environment (Berkes et al., 2000). Nonetheless, indigenous knowledge is tagged by different names in literature; local knowledge, traditional knowledge, farmers' knowledge, traditional ecological knowledge, ethnoscience, folk knowledge, rural knowledge and indigenous science. Although these terms may have different connotations, they are used interchangeably throughout the literature (Nyota & Mapara, 2008; Mafongoya & Ajayi, 2017).

Generally, indigenous knowledge evolves from long term observations of the local environment and adapted to the specific requirements of local people and conditions; involving a creative, experimental process continuously integrating external influences and internal innovations to meet new conditions (Kassa & Temesgen, 2011). Some scholars have explored the value of indigenous knowledge in natural resource management, water resource management, fisheries and aquatic conservation, risk and disaster management, health among others (Gray & Morant, 2003; Desbiez et al., 2004; Cabrera et al., 2007; David & Ploeger, 2014; Ngodigha et al., 2015).

In this dissertation, I focus on the use of indigenous knowledge for weather and seasonal climate forecasts referred to here as indigenous forecast. Here, I define "indigenous" as native or local and "forecasting" as a prediction of a future occurrence or condition. Indigenous forecasting techniques revolve around the native ways of making predictions based on a body of knowledge built up by a group of people living in close contact with nature (Steiner, 2008; Muita et al., 2016). Before modern scientific weather and climate forecast systems were developed, people made regular forecasts based on past experiences and compared them to current observations (Olsson et al., 2004; Orlove et al., 2010). Indigenous ecological indicators such as the behaviour of insects, birds, and mammals, and positions of the sun and moon and associated shadows, wind speed and direction, cloud position and vegetation physiological changes are used as sources for local people to generate forecasts (Chang'a et al., 2010).

Scientific knowledge/forecast

Scientific knowledge (SK) is generally referred to as "modern knowledge" (Ajibade & Shokemi, 2003). This type of knowledge aims to understand and explain how the natural world works and how it got to its current state (Nickels, 1998). Scientific knowledge is organized in a way that provides testable explanation and predictions. From this perspective, people are separated from their environment and can, therefore, observe from the outside (Settee, 2013). Scientific knowledge has transformed the understanding and control of the world around us, and in the process transformed itself. Scientific knowledge has grown to its present state and reputation through its application to different types of problems in different fields (Ravetz, 1973) including weather and climate for society. The advancement of the scientific method now makes it possible to provide scientific forecast information at different timescales to various sectors including agriculture (Hansen, 2005). Weather and climate forecast generated from SK are hereafter called scientific forecast.

In this dissertation, a scientific forecast refers to the use of modern techniques (models and statistics) to predict the conditions of the atmosphere for a given location and time at different time scales. For the purposes of this study, I focused on daily and seasonal climate forecasts.

Integration of indigenous and scientific knowledge

The shift to a second generation of climate services can benefit from integrating indigenous and scientific knowledge. It is important to acknowledge that different views on knowledge integration, in general, exist. Berggren et al. (2001), define knowledge integration as a combination of specialized knowledge with the aim of reaching considerable results. Okhuysen & Eisenhardt (2002), define the concept of knowledge integration as a process of transforming individual knowledge into collective knowledge. Generally, indigenous and scientific knowledge presents unique features that make one different from the other, although some similarities exist. According to Tsuji & Ho (2002), some of the differences between indigenous and scientific knowledge have been overstated in literature and in most cases the assumptions for the distinctions are incorrect. For example, it is argued that indigenous knowledge is mostly holistic in nature while scientific knowledge is a system-based approach, which is not necessarily true as some community members possess specialized knowledge and skills (Ferguson & Messier, 1997). Another dichotomy is that unlike scientific knowledge which is driven by curiosity and desire to understand for the sake of understanding, indigenous knowledge is obtained for the sake of survival. This difference creates a stereotypical view of indigenous knowledge, since studies have suggested that indigenous people do possess scientific curiosity, and thus study a phenomenon that is not of only immediate practical interest (Berkes, 1993).

Agrawal (1995), argued that there are no real differences between indigenous and scientific knowledge, and rather the accepted differences are political rather than epistemic factors. Table A2 in the supplementary material details some distinct characteristics and similarities of both indigenous and scientific forecast. The similarities make it easier to see how the knowledge from both systems can be combined to create a better understanding of the natural world (Tsuji & Ho, 2002). It is important to note that the debate about integrating indigenous and scientific knowledge is not new. Scientists have always recognised the fact that their work is a conscious and critical revision of indigenous knowledge, often considered superstitious (Rist et al., 2006). It is therefore not surprising that several scholars have called for ways to harmonise both knowledge systems for the benefit of society (Gagnon & Berteaux, 2009; Ziervogel & Opere, 2010; Plotz et al., 2017).

Following the above discussion, I operationalised the concept of knowledge integration as a collective process of synthesising or combining specialized yet differentiated indigenous and scientific knowledge possessed by farmers and scientists into a common knowledge that is efficient, flexible and within scope to improve farm decision making. However, both indigenous and scientific forecasts have benefits and limitations, and integrating them can produce forecasts information that is reliable and acceptable among farmers. Here, reliability refers to a forecast that is timely provided, accurate or skilful in its value and locally relevant for farmers' decision making. Acceptability refers to a forecast that is trusted and used by farmers.

1.4 Research Objective and questions

Given the extent of the many issues raised in the previous sections (1.1, 1.2 and 1.3) of this chapter, it is clear that weather and seasonal climate information plays a significant role in shaping agriculture in Ghana. I identified three main knowledge gaps that are central to this dissertation:

1. There is limited knowledge on socio-ecological issues that has the potential to hinder (or promote) climate information services for farmers.

2. There is a mismatch between forecast information provided and farmers' information needs.

3. There is limited knowledge on how to integrate indigenous knowledge with scientific knowledge to improve forecast reliability and acceptability.

These knowledge gaps have hampered the development of second generation of climate services in Ghana. This PhD research aimed to address the knowledge gaps mentioned above. Therefore, the objective of this dissertation was:

To improve climate services in Ghana through co-production *by integrating scientific and indigenous forecasts to support farm decision making*.

The results of this dissertation will serve as an important building block to formulate strategic ways to improve climate services in Ghana, and in doing so potentially help alleviate food insecurity while increasing farmers' economic status. This dissertation also contributes to the literature on integrating indigenous and scientific forecast and, more specifically, to the research on co-production of climate services. Moreover, the use of citizen science to collect and handle indigenous forecast and observed rainfall provides insights that can be used for future engagement of citizens in the field of meteorology and atmospheric science.

The overarching research question therefore is;

How can climate information services be improved through the co-production of farmers and scientist?

Out of the overarching question I formulated the following five research questions using Northern Ghana as a case:

RQ1. *What is the potential of climate information services to support rice farming systems? (Chapter 2)*

This research question aims to diagnose the core problems in the study area and position these problems within the context of climate variability and change. The question helps explore the empirical evidence for both biophysical and societal-institutional issues necessary for developing a second generation climate service. It further helps to reveal how farmers experience and give meaning to these problems as well as the ways in which the problems are currently been dealt with. Ultimately, this question helps to identify and refine the challenges as well as to reflect and re-examine the feasibility of the initial climate service. Answers to this question suggest ways to improve both the design and implementation of the second generation climate service.

RQ2. *How successful can seasonal climate forecast meet farmers' information needs? (Chapter 3)*

This question aims to first identify specific weather and seasonal climate information needs of farmers and to ascertain whether the state-of-the-art seasonal climate forecast models have enough skills to meet these needs. In this regard, I identify which information is more important to farmers and when they require such information for decision making. Also, the spatial and temporal performance of seasonal climate forecast is determined. Answers to this question help to develop a demand driven climate service that is acceptable and used by the end-users.

RQ3. *What are the skills of indigenous and scientific forecasts to promote effective climate services? (Chapter 4)*

The essence of this question is to determine the performance of indigenous and scientific forecast in the study area. I examine how indigenous forecast is generated and its accuracy for climate service. The accuracy of the scientific forecast is also determined. Answers to this question provided confidence and serve as a foundation for integrating indigenous and scientific forecast.

RQ4. *Can the integration of indigenous and scientific forecast improve reliability and acceptability of climate information services? (Chapter 5)*

This research question guides the process of testing the possibility of quantitatively integrating indigenous and scientific forecast. The process results in a proposed integrated probability forecast method. Further, I investigate the skills in the indigenous and scientific forecast and examine the value of integrating them to improving forecast accuracy and acceptability among farmers. Insights from this question play an important role in further discussions on the integration of indigenous and scientific forecast for weather and climate services.

RQ5. *How do weather and climate information influence farmers' decision making? (Chapter 6)*

This research question aims to unravel the practicality of how end-users (farmers) use the different kinds of forecast information given to them. In particular, the question helped to determine the decision dynamics of farmers given forecast with different forecast probabilities and lead-times. This provides evidence of potential forecast usage and value for decision making. The insights obtained from this question will help the design of climate services in a manner that they become more actionable.

1.5 Methodology

1.5.1 Study Area

This study was conducted in the Kumbungu district of the Northern region of Ghana (see figure 1.2). Agricultural production in the area is already negatively affected by the climatic conditions with six to seven months dry season and five months rainy season (April/May to September/October) (Barry et al., 2005; Amikuzuno & Donkoh, 2012). The northern region of Ghana, including the Kumbungu district, is a tropical Savannah zone with a single rainfall season (Boogaard et al., 2012; Alhassan et al., 2013). According to Owusu & Waylen (2009), by 2050 the region is projected to experience an increase in rainfall intensity with a decrease in rainfall frequency in addition to increasing temperatures. As a result, crop yields are likely to reduce, thereby having a negative impact on food security in the region (Antwi-Agyei et al., 2012).

This dissertation focuses on rice farming for two main reasons. First, demand for rice has steadily increased but with limited growth in supply, resulting in high importation of rice up to an average of USD 450 Million annually (MOFA, 2009; CARD, 2010; Angelucci et al., 2019). This is projected to increase even further as a result of economic growth, and impacts of climate change on future crop yields. Secondly, compared to other crops in Ghana rice will be severely hit by climate variability and change because of the projected water scarcity and over reliance on unpredictable rainfall (Asante & Amuakwa-Mensah, 2015b). Therefore, Ghanaian policy makers are concerned about increasing production, allowing smallholder farmers especially those in Northern Ghana to shift attention to rice production.

Rice production takes place in all the ten regions of Ghana, yet the northern region is ranked as highest in terms of production per region (Angelucci et al., 2019). According to Donkoh et al., (2010) rice production has an enormous potential in reducing poverty levels in Northern Ghana. Rice production just like other crops in Ghana is cultivated by smallholder farmers, with most of them having farms of less than one hectare in size (Angelucci et al., 2019) and have limited access to climate information to manage their farm risk (Ndamani & Watanabe, 2013).

The Bontanga irrigation scheme in the Kumbungu District where most of this research was carried out is a decentralised irrigation scheme managed by communities at local level. The district has a total population of roughly thirty-nine thousand (50% males and 50% females). About 95% of households in the District are engaged in agriculture and 98% thereof are involved in crop farming. A large part of the district is rural with about 26% being literate and 74% non-literate (GSS, 2014).

The area has one of the most prominent and largest gravity-fed public irrigation schemes in the country, the Bontanga. This is built on the tributaries of the White Volta River with an irrigable area of up to 570 ha and a total water requirement of 11 million m^3 per annum. The scheme has 525 farmers from 13 different communities with an average landholding of about 0.6 ha per farmer. There are also a number of small scale irrigation systems in the area (WRCG, 2008). These small-scale reservoirs and large scale irrigation systems were developed to support agriculture production against climate variability (Faulkner et al., 2008; Amisigo et al., 2015). In this area, there are three different groups of farmers (i.e. those into irrigated rice production only, rainfed only, and both irrigated and rainfed rice production) to be considered in the study.

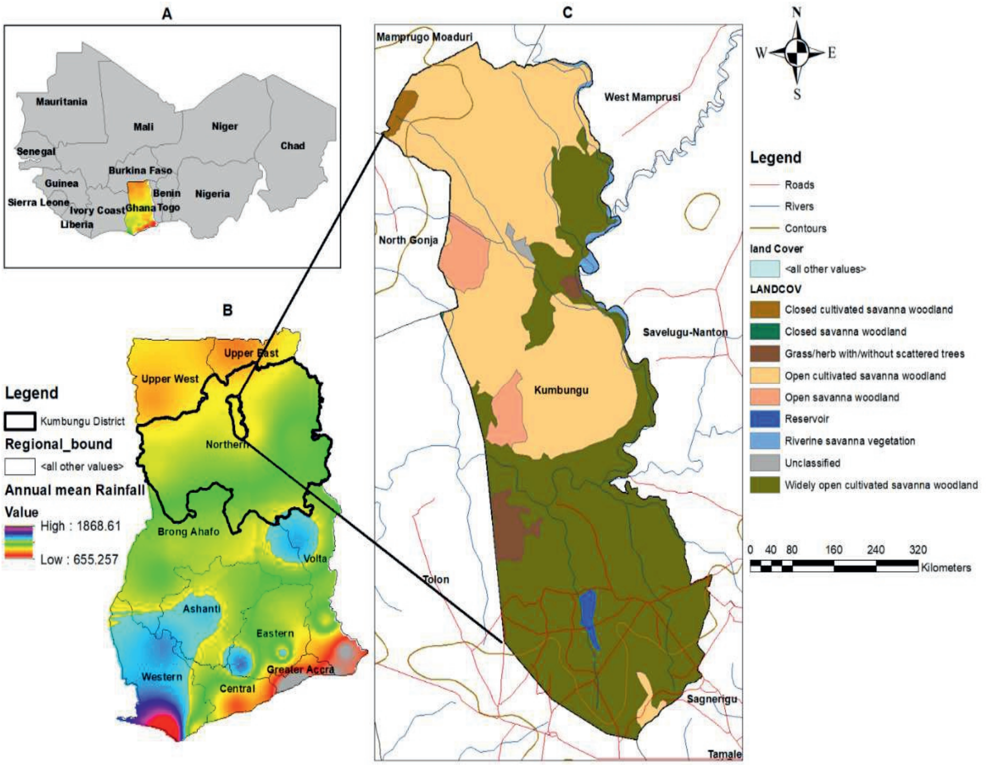

Figure 1.2: Map of Study Area: panel “A” shows the location of Ghana in West Africa. “B” shows the map of Ghana (with annual average rainfall from 1981-2010) indicating the location of Northern region and Kumbungu district. “C” shows the detailed map of Kumbungu district. The seasonal forecast verification in chapter 3 covered the entire Northern region. All other research activity was carried out in Kumbungu district.

NB: *As at January 2019, the regions of Ghana were further divided and the number changed from 10 to 16 regions (See Figure A1 for the map of Ghana showing the new regional divisions). Yet for consistency of the chapters we maintain this map*

1.5.2 Research Design

This dissertation uses a multi-method approach to explore the possibility of making weather and seasonal climate forecast information useful for decision making in rice farming systems. This research design allowed the exploration of both the theoretical and empirical perspectives on the main research objective. The research is designed in an iterative manner with the outcome of each research question informing the next (see figure 1.3). Here, I describe in summary the framework of methods and techniques used to answer the different research questions. Since each dissertation contains published or submitted articles, each chapter has specific sections that explain the method used in more detail.

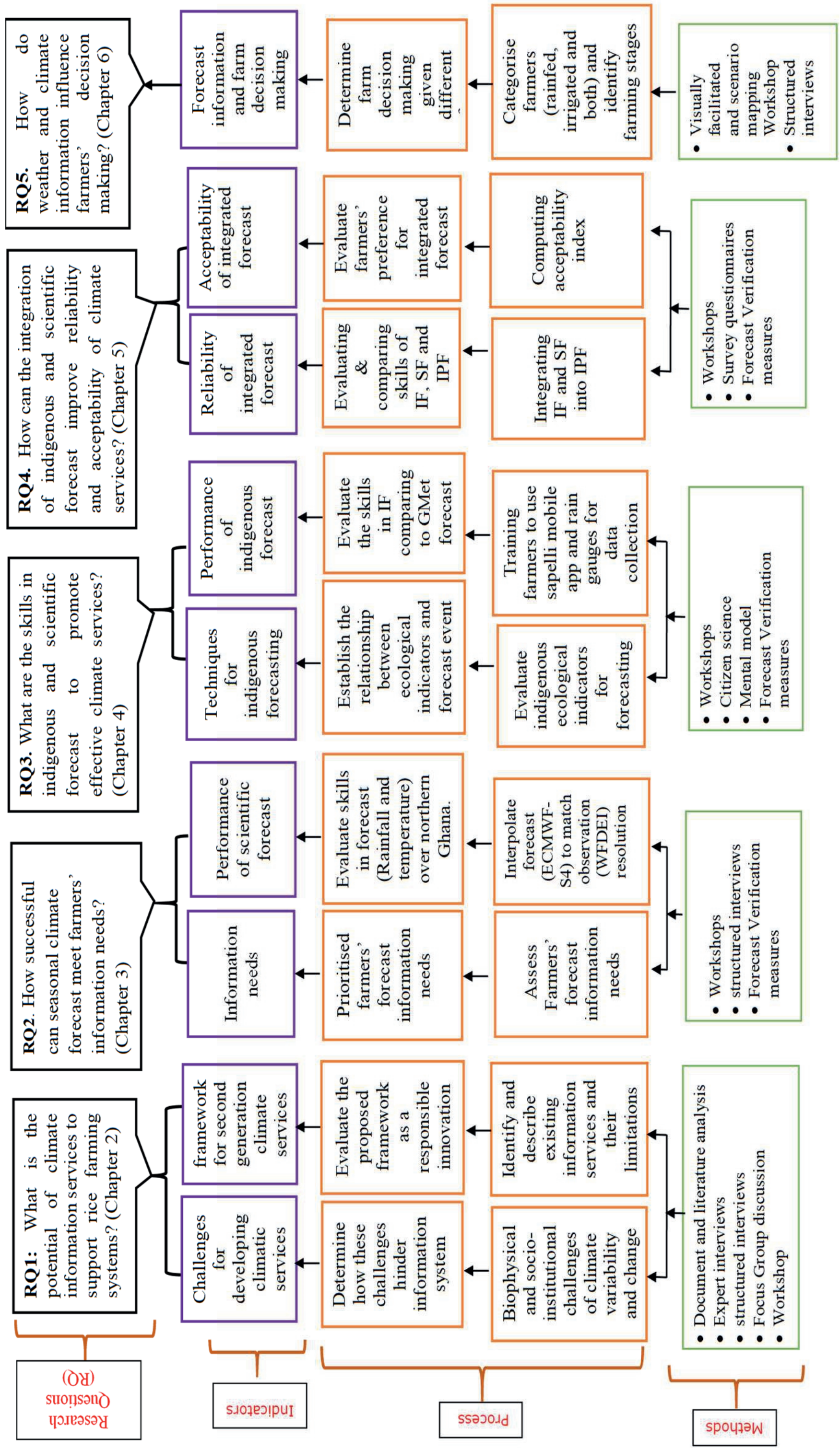

Figure 1.3: Schematic representation of methodological framework

Multi-method research design is a methodology for collecting, analysing and integrating quantitative and qualitative research methods to provide a better understanding of the research problem than either of each alone (Greene et al, 1989). Creswell (2003), indicated that the choice for each method in multi-method research design is based on 'what works' and which research questions are addressed. Therefore, the research design as used in this dissertation incorporates a mix of quantitative and qualitative methods in the stages of the study to answer the overall research question. This is done for several reasons.

First, multi-methods are appropriate for applied research because it has a complementary value that tries to neutralize the weakness of each method (Johnson & Onwuegbuzie, 2007; Brewer & Hunter, 2012). For instance, in RQ1, I used literature review, expert interviews, focus group discussion, and a feedback workshop to assess and establish the core socio-ecological issues farmers perceive as key challenges that require the development of weather and seasonal climate information services. Each method was used to collect data that complement the other and allowed me to check the accuracy and comprehensiveness of the other data collected.

Second, the methods adopted enhance understanding and provide insight into complex problems while confirming and informing the choice of next method in the same study (Brewer & Hunter, 2012; Byrne and Humble, 2007). For example, in RQ2, qualitative methods (interviews) were used to initially assess farmers' information needs which informed which forecast lead times to select for the performance assessment of seasonal forecast using quantitative methods (i.e. forecast verification methods).

Third, the complexity of climate variability and change on social systems requires that different methods are employed to understand these complexities (Byrne & Humble, 2007) and in doing so, increase confidence in the validity of the findings (Onwuegbuzie et al., 2011). Therefore, due to the complex nature of the problem and the interdisciplinary nature of the study, I employed different methods for different aspect and stages of the study depending on their suitability. In RQ3, for example, I used qualitative methods (workshop and interviews) to identify the indigenous ecological indicators farmers use for forecasting and explored the techniques behind indigenous forecast while using the quantitative method (forecast verification methods) to evaluate the performance of both indigenous and scientific weather and seasonal climate forecast data. Similarly, in RQ4, I utilized quantitative methods (weighted arithmetic mean and forecast verification methods) to integrate, validate and estimate the reliability of integrated forecast compared to indigenous and scientific forecasts. I also used a qualitative method (interviews) to evaluate the acceptability of the three forecasts among farmers. To answer RQ5, I employed visually facilitated scenario workshop as a method for testing the impact of forecast probabilities and lead times on farmers' decision making.

Finally, employing the multi-method research design allowed for the exploration of different perspectives that will lead to a more complete understanding and explanation of claims for reliable and acceptable forecast information that is useful for farmers.

1.6 Structure of the dissertation

This dissertation has seven chapters (Figure 1.5). Following a general introduction, the main body of this dissertation consists of five chapters made up of papers, which are either published or submitted to academic journals.

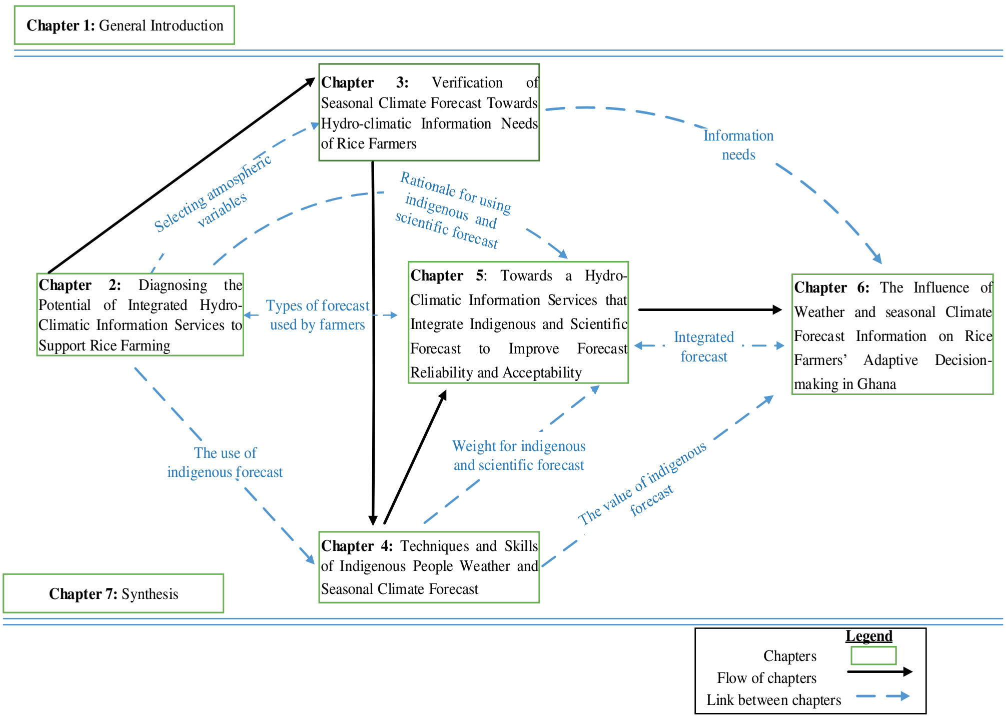

Figure 1.4: Dissertation structure showing the link between the seven chapters

Each chapter addresses one research question. Chapter 2 diagnoses the potential of developing hydroclimatic services to support rice farmers needs in Northern Ghana. It proposes an architecture for such services and we reflect upon its effectiveness using the responsible innovation framework. Chapter 3 centres on information needs of farmers and the performance of seasonal climate forecast in an attempt to meet these needs. Chapter 4 explores the value of indigenous forecast by providing an understanding of how farmers use indigenous ecological indicators to forecast rainfall at daily and seasonal timescale. It further evaluates the skills of indigenous farmers compared to scientific forecast. Chapter 5 builds on the results of chapter 4 and proposes a quantitative approach, the integrated forecast probability method, to integrate indigenous and scientific forecasts with the aim of developing integrated weather and seasonal climate services that are reliable and acceptable for farm-level decision making. Chapter 6 further explores how farmers make decisions based on forecast information provided. Finally, Chapter 7 is the synthesis of the overall chapters. It revisits the research questions, presents a reflection on the main findings and discusses the scientific and societal contributions. This concluding chapter also makes recommendations for the design and operationalization of second generation weather and seasonal climate services in Northern Ghana.

2

Chapter 2

Diagnosing the potential of hydro-climatic information services to support rice farming

Abstract

Hydro-climatic information has the potential to improve agricultural productivity under climate variability. Recent developments in information sharing platforms (Environmental Virtual Observatories, EVOs) could make information provisioning more actionable. Here we present the results of a diagnostic study for the development of a hydro-climatic EVO that enables rice farmers in Northern Ghana to deal with climate variability and water shortage. The hydro-climatic EVO aims to combine data from scientific and indigenous forecast systems, facilitating information exchange using two-way interaction with stakeholders to co-produce knowledge. Data was collected through informal interviews with field practitioners, through focus group discussions with farmers and content analysis of documents. Results show that both the biophysical and socio-institutional circumstances need be taken into account for the development of the EVO. Existing governance and information exchange arrangements and lack of collaboration between actors were found to limit current hydro-climatic information flow, interpretation, and use. My study reveals existing models of information exchange and their limitations in the study area. We discuss the proposed design of a hydro-climatic EVO from a responsible innovation perspective, considering possible future eventualities in a process that aims to be anticipatory, inclusive, reflexive and responsive. We conclude that such a hydro-climatic EVO has the potential to contribute to rice farmers' adaptive decision-making in Northern Ghana, but there are challenges that need to be considered. The diagnostic study has helped to refine these challenges and offers concrete suggestions to improve both the design and implementation of the proposed platform in a responsible way.

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2.1 Introduction

Due to increased anthropogenic greenhouse gas emissions, the global temperatures are rising with a change in the global water cycle resulting in more erratic precipitation patterns. Consequently, both soil and surface water availability is becoming less reliable (IPCC, 2014). This increased climate variability is affecting smallholder farmers in sub-Saharan Africa. Currently, more than 600 million people in rural communities in sub-Saharan Africa depend on agriculture for their livelihoods (Rockström et al., 2014). Many farmers are struggling to cope with challenging conditions, which result in low yields and food insecurity (Falco et al., 2011). One of the main problems for food production in Africa is large-scale climate variability. Both inter-annual and seasonal rainfall variability are a challenge for farming decision-making in Sub-Saharan Africa. Future climate change caused by increased greenhouse gas emissions are likely to result in changing rainfall patterns.

Similar to other countries within Guinea and Sudan Savanna agro-ecological zones, Ghana is vulnerable to climate variability and change (Africa Partnership Forum, 2007). The agricultural sector depends heavily on rainfall that varies annually and seasonally. This significantly affects soil water availability for crops and increases the risks for low crop production and failure (Jung & Kunstmann, 2007; Asante & Amuakwa-Mensah, 2015). Meanwhile, the agriculture sector is very important for the economy of Ghana, employing 44% of the work-force and accounts for nearly one-quarter of GDP(CIA, 2012). The degree of community vulnerability and crop failure is greatest in its three northern regions, namely Upper East, Upper West, and the Northern region. Farmers in these regions are faced with many uncertainties prior to every growing season, most of which are attributed to water and climate variability (Gbetibouo et al., 2017).

Due to increasing climate variability farmers struggle about decisions such as seed variety to plant, when to plant, when to fertilize, when to do supplementary irrigation and sometimes when to harvest. According to Ndamani & Watanabe (2013), a farmer usually starts to make preparations for planting crops with the onset of the rainy season. After months of drought, the soil is dry and hard. In the month of May, the farmer starts to look into the sky every day expecting the first rain clouds to appear, which would indicate the beginning of the major production season. When the rain finally comes, the farmer starts to plough his land and plants his crops. But his mind is filled with worry. How much rain will there be this year? Will there be another dry spell shortly after the first rain, which could destroy the seedlings?

Would it be better to wait and start seeding later? He recalls, however, that two years ago, there was no dry period in May and heavy rain washed away the seeds that he had planted too late.

Finding solution to these dilemmas of a typical farmer is vital and urgent. Several studies have predicted the future climate of Ghana to be more variable and uncertain, making the agriculture sector more vulnerable (WRC, 2010; Obuobie et al., 2012; Kankam-Yeboah et al., 2013). Recent progress in climate modeling has increased the ability to predict rainfall from a few days to seasonal forecasts(Njau, 2010). Being able to predict the weather and climate especially rainfall is indispensable for guiding water users, especially farmers in their planning and decision making (Logah et al., 2013). Empirical studies have shown that climate forecasts can help farmers reduce their vulnerability to drought and climate extremes, while also allowing them to maximize opportunities when favourable conditions are predicted (Rosenzweig et al., 2001; Patt et al., 2005; Roncoli et al., 2009; Crane et al., 2010).

The underlying assumption in the current practices of hydro-climatic information services is that if we provide the farmer with more and better information, they would be able to improve their farming practices (Okello et al., 2012; Anoop et al., 2015; Etwire et al., 2017). This one-directional model of providing climate services has shown to be flawed, as farmers tend not to trust scientific information and experience difficulties in interpreting and using it. They are therefore confident that their indigenous systems work better (McNew, et al., 1991; Hartmann et al., 1999; Letson et al., 2001). Efforts to train farmers to adopt this model of providing climate services generally fail to improve the uptake of climate information (Manyanhaire & Chitura, 2015; Patt & Gwata, 2002), because providers also have little understanding of users, and what drives the influence of indigenous forecasts (Artikov et al., 2006).

We, however, argue that science should not be a one-directional effort, where science produces new knowledge and information and makes it accessible for end-users. Instead, the process should be interactive, where science and practice co-design, co-create and co-produce knowledge by bringing in different forms of expertise. The latter would result in a better appreciation of the scientific expertise as well as indigenous knowledge necessary to improve societal resilience to climate change (Hiwasaki et al., 2014; Mazzocchi, 2006). Increasingly there are calls for involving farmers not only as end-user, but as an active participant who is not only involved in the use of the information, but also in the creation of it.

Environmental Virtual Observatories (EVOs) aim to enable cross fertilization of different sources of environmental knowledge on web based virtual platforms, incorporating information gathering, processing and dissemination technologies (Karpouzoglou et al., 2016). The first generations of these systems aimed to support the scientific process of knowledge creation and mainly targeted scientific audiences. They failed to deliver a strong knowledge creation component especially in information generation and dissemination projects that seek to empower local communities to manage their environmental change using actionable knowledge (Dewulf et al., 2005). Hence, several authors have proposed second generation EVOs that emphasize knowledge co-creation between scientists and societal actors, and bidirectional information flows, so as to create actionable knowledge that can support decision-making (Karpouzoglou et al., 2016). However, these systems are place based and context sensitive, requiring a thorough understanding of the potential to uptake co-develop, co-produce and co-implement such hydro-climatic information systems.

As part of a larger endeavour, we aim to design a "second generation" information system in the form of a hydro-climatic information system called a hydro-climatic Environmental Virtual Observatory. This system will use data from the scientific seasonal climate forecast ECMWF-4 (European Centre for Medium-Range Weather Forecasts-system 4) model, complemented with farmers indigenous forecast collected through citizen science (Pettibone et al., 2016) to generate actionable knowledge for adaptive decision making in rice farming systems. Karpouzoglou et al. (2016) indicate that in the context of emerging open-technologies for information exchange, added value can be achieved by removing institutional and geographical barriers associated with information flow.

In this paper, we aim to diagnose the socio-ecological settings of rice farming systems in northern Ghana in the context of climate variability and change to ensure effective design and operationalisation of hydroclimatic EVO. We first conduct a diagnosis of the socio-ecological settings of the rice production system in Northern Ghana in the context of climate variability and change. In the next step, we elaborate the diagnostics by focused on hydro-climatic information needs and use in rice based farming systems. Based on these diagnostic steps, we identify the specific challenges and opportunities identified in our case region, which could be meaningfully addressed by a potential EVO. We used the four dimensions of Responsible Innovation to reflect on the robustness of the design and processes of hydro-climatic EVO to deal with the challenges and opportunities faced in a responsible way. The outcome of our study is a framework for the hydro-climatic EVO outlining its properties and processes.

2.2 Conceptual framework

Studies show that crop management strategies of farmers (e.g. timing of planting, weeding, fertilizing, application of pesticides) are shaped by predictive weather/climate information. Traditionally farmers make use of indigenous knowledge to produce seasonal and weather forecast (Svotwa et al., 2007). Traditional Ecological Knowledge (TEK) is known by a wide variety of terms, including indigenous knowledge (IK), local knowledge (LK) and traditional knowledge (TK). It has many definitions and there is no consensus on an operational definition applicable across disciplines. Huntington et al., (2004) for example, understands TEK as '…the knowledge and insights acquired through extensive observations of an area or species' (Huntington et al., 2004). In contrast Berkes et al., (1995) in an attempt to more fully incorporate indigenous world views, broadens the scope of TEK and define it as '…a cumulative body of knowledge, practice, and belief, evolving by adaptive processes and handed down through generations by cultural transmission, about the relationship of living beings (including humans) with one another and with their environment (Berkes et al., 1995). In the context of this study, the emphasis is placed on "indigenous", which is defined as native or local knowledge that is passed on from generation to generation. Such knowledge is used for "forecasting", i.e. the prediction of a future occurrence or condition (Nation, 2017). Indigenous forecasts are based on farmers' experience of changes in certain biophysical indicators. Literature shows that African farmers are using various local weather indicators such as plants, animals, insects, the solar system and wind in predicting the weather and climate (Roncoli et al., 2002; Speranza et al., 2010; Tarhule & Lamb, 2003; Ziervogel & Opere, 2010). Studies have therefore suggested that particularly in Africa indigenous knowledge has the potential to enhance farmers' adaptation to climate variability and change (Mikkelsen & Langohr, 2004; Naess, 2013; Derbile et al., 2016). However, it is plausible that indigenous knowledge is not sufficient anymore because of projected climate change.

Increasingly, scientific projections are developed to further inform farmers about short, medium and long-term climate variability and change, particularly for rainfall. It is important, however, to acknowledge that weather and climate forecast systems have limited value unless they can directly influence decisions and have an impact on the systems under consideration (Hammer, 2000). (Manyanhaire & Chitura, 2015) argue for the integration of indigenous knowledge systems with climate change science as a basis for comprehensive community based response to the impacts of climate change. It is argued that farmers are more likely to adopt new ideas when these can be seen in the context of their existing practices. Patt and Gwata (2002) for example observed that farmers' willingness to use seasonal climate forecasts increased when the forecasts presented are combined and compared with local indigenous forecasts.

As indicated in the introduction, creating conditions that allow for knowledge exchange between scientists, decision-makers and citizens is becoming increasingly necessary for building resilience and responding to environmental change (Mol, 2006; Folke et al., 2010; Buytaert et al., 2014; UN, 2014). The concept of Environmental Virtual Observatories (EVOs) offers the opportunity to bring together scientific and indigenous knowledge (Karpouzoglou et al., 2016). Examples of the first generation of these EVOs are (Wilkinson et al., 2015) for communicating flood risk to catchment stakeholders and cloud technology for connecting and integrating fragmented data, models, and tools to deliver new holistic approaches to environmental challenges (Emmett et al., 2014). They have paid less emphasis on how enhanced participation of a variety of users can be achieved via a virtual platform. In many cases, projects that seek to generate and disseminate information that provides actionable knowledge for empowering local communities and enhancing environmental management, for example, have achieved limited success (Dewulf et al., 2005).

Despite considerable progress in recent years, many cases exist where knowledge and perspectives of certain groups of people are either not included or under represented (Karpouzoglou et al., 2016). This is particularly challenging for EVOs that exist on the interface between scientists and non-expert users. Similarly, most of the first generation EVO's are developed and communicated, using mostly top down approaches. For example, local farmers are considered as end users of forecast products developed by scientist from universities and or research institutions. In most cases, farmers do not contribute to the process of developing weather and climate forecast products (Ouédraogo et al., 2015). As a result, the communicated forecasts are often not locally specific or applicable and therefore contribute to limited action. Second generation EVOs seek to resolve this problem by enhancing the participation of all relevant stakeholders.

While first generation EVOs are primed for scientists, second generation EVOs have a benefit to include knowledge co-creation and resilience through their participatory design. Second generation EVOs such as those proposed by Karpouzoglou et al. (2016) have a stronger focus on the processes of knowledge co-creation and interaction between stakeholders. An important aspect of this knowledge co-creation EVO is its potential to achieve greater relevance by engaging with stakeholders. In some cases, citizens become active contributors to science (Buytaert et al., 2014) and EVO's offer the possibility to connect scientist and local farmers via a virtual platform where information is exchanged and knowledge created to support farm decision-making. Active engagement of farmers can range from short-term collection of data to intensive engagement in creating new knowledge with scientists and/or other volunteers (Pettibone et al., 2016).

Introducing new innovations such as EVO's should be undertaken responsibly, especially when directed at socially desirable and socially acceptable ends (Stilgoe et al., 2013). Designing these EVOs responsibly means acknowledging that such frameworks are not only technical but are also socially and politically constituted(Carpenter & Winner, 1978). Innovative technologies that underlie EVO's might have great benefits for society, but unforeseen impacts are not just possible but probable. To guide the design and evaluation of our EVO, we build onto the responsible innovation concept. We make use of the responsible innovation (RI) framework of Stilgoe et al. (2013) which provides a set of basic principles that seek to maintain novelty and at the same time make it responsible: anticipation, reflexivity, inclusion, and responsiveness. *Anticipation* requires that researchers and organizations continuously ask 'what if?' questions, which include but not limited to what are the likely consequences? What are the possible unintended effects? It requires projection and futuristic thinking in a systematic way and consideration of how the EVO is predictable and resilient to change.

For example, it provides early warnings of future unfavourable consequences and estimates risk-based harm of innovations (Hoffmann-Riem & Wynne, 2002; EEA, 2001, 2013). The second dimension, *reflexivity*, refers to the principle that institutions and organizations must reflect on their activities and assumptions and acknowledge that the knowledge they produce and use has limitations. How they frame issues may not be universally applicable and without reflexivity may lead to frame conflicts or unresponsiveness of stakeholders (Wynne, 1993; Stilgoe et al., 2013). The third dimension, *inclusion*, refers to the need to involve minorities and groups without a voice in the innovation process (Felt, 2009; Hajer, 2009; Stilgoe et al., 2013). Whereas the first generation of EVO's placed limited emphasis on stakeholder involvement, responsible innovation requires active involvement of different groups through dialogue and representation throughout the innovation process. The dimension of *responsiveness* as proposed by Stilgoe et al. (2013) requires that systems of innovation have the capacity to change or shape direction in response to stakeholder and public values and changing circumstances. Also in this article, we use the framework to evaluate the proposed hydro-climatic EVO.

2.3 Methodology

In this paper, we address the following research question: How will the existing socio-ecological setting in rice production systems in Northern Ghana promote or hinder a possible hydroclimatic EVO design and operationalisation? To diagnose our case region and analyze the potential for designing a new EVO, the study adopts a systematic approach involving five sequential steps (see Figure 2. 1). We gathered data from both primary and secondary sources using qualitative methods of data collection and analysis.

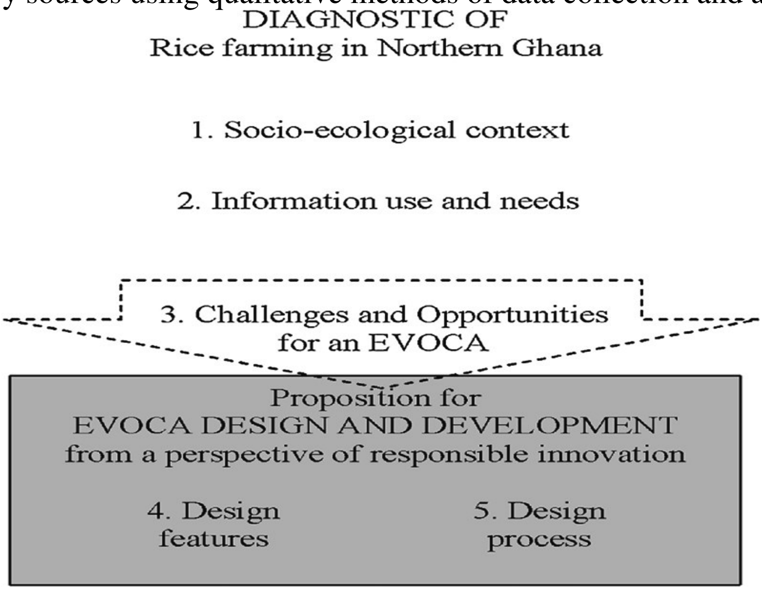

Figure. 2.1: Workflow of the study

2.3.1 Data collection

To collect data, we made use of three qualitative methods: content analysis of existing documents, interviews, and focus group discussions. The selection of methods provided us insight into the socio-ecological context of the case study, information needs and use as well as the challenges of existing systems and opportunities for the development of a hydro-climatic EVO.

a) Research literature and documents analysis

We collected policy documents, donor agency reports, scientific research articles and research reports from related projects and programs by going through government and non-governmental organizations' websites and online repositories. We specifically focused on analysing local governance and institutional documents containing rules, structures and arrangements about farming, irrigation and water use in Northern Ghana to gain a thorough understanding of the decision-making context and practices. The data collected helped us also to guide the interviews.

b) Interviews

We informally engaged in an open conversation with fifteen (15) practitioners from nine different organizations (Table 1). To allow the discussion to move in the direction preferred by the practitioners, we opted not to use a structured interview guide, but rather semi-structured the conversations along topics emerging from the document analysis. The informal setting allowed respondents to speak more freely and openly about their experiences and helped in building relationships for future collaborations.

The practitioners were purposefully selected based on their principal role (civil society representatives, policy and decision makers, researchers and farmer representatives) and expertise in climate, water and farming. The conversation cantered on five thematic areas: (i) perception of the climate-water-food production problem in northern Ghana; (ii) current actions taking by farmers and organizations to manage these problems; (iii) farmers' hydro-climatic informational needs and use; (iv) the value of seasonal climate forecast; and (v) the feasibility of hydro-climatic EVO to ameliorate the challenges. Each conversation lasted for about one hour and the information was recorded digitally and captured in a field notebook

Table 2.1: Stakeholders engaged in informal interviews.

Stakeholders	Number Interviewed	Reason for inclusion
Applied Meteorological Unit - Ghana Meteorological Agency (GMet, 2016)	1	Study and provide weather, climate and meteorological advice to the general public and farmers.
Ghana Irrigation Development Authority (GIDA)	1	Responsible for Irrigation and water management of all irrigation projects and their development
Ministry Of Food & Agriculture (MoFA)- Crop Division (RSSP and GCAP)	3	In charge of the sustainability of food and agriculture. RSSP and GCAP raise awareness and support farmers with inputs and climate related advice that boost domestic rice production and commercialize farming.
Irrigation Water Manager (IWM)	1	Manages the irrigation scheme at Bontanga where research is largely carried out.
Ghana Hydrological Services (GHS)	1	Studies water bodies in the region. Have access to historical data of river flow and other hydrological information.
Faculty of Agriculture and Agricultural Engineering University For Development Studies (UDS)	2	Teach students who major in general agriculture, agriculture engineering, soil and water conservation, and irrigation science. Train farmers and Conduct research into climate, water and agriculture related issues.
Rice Farmers Association (APEX Farmers Group)	2	Members are mainly into rice production in Bontanga.
Savannah Agricultural Research Institute (SARI)	2	Train rice farmers on appropriate agronomic practices. Introduce rice varieties to farmers and conduct climate and agriculture related research.
Agriculture and Development Non-Governmental Organization (IFDC and JICA)	2	Train and support farmers with inputs and advice that will promote local food production including rice production
Total	15	

c. Focus Group Discussions

To collect information about the challenges farmers experienced through the existing governance arrangements, water management practices, information management and decision-making, we organized seven Focus Group Discussions (FGDs) with farmers who were engaged in irrigated and/or rainfed rice farming within the Kumbungu District. FGDs were held at the farm, community and scheme levels. Discussions at the farm level focused on the perception of farmers on problems of the climate-water-food production nexus and steps taken to manage them. In addition, discussions revolved around the hydro-climatic informational needs of farmers.

To broaden the scope, the FGDs organized at the community level included rice farmers, traditional leaders, political representatives and women. This allowed us to discuss the place of hydroclimatic information in their farming cycle, as well as the ways in which governance arrangements and decision-making processes at the community and farm level worked. At the scheme level, similar questions were asked to inquire on the activities of rice farmers within the Bontanga Irrigation Scheme about governance, water management and how that impacted decision-making. Participants were leaders of farmer associations, the manager and representatives of committees (see Table 2.2).

2.3.2 Data analysis

Literature and available Documents were analysed in two stages; we first scanned existing literature and documents for relevant information from empirical and theoretical perspectives. Next was a synthesis of information Secondly, we thoroughly examined them by reading, extracting and synthesising key information from the selected literature and documents; background information of rice farmers as well as insight into the socio-ecological settings of rice production systems in Northern Ghana. It also provided supplementary research data on the importance of rice in the economy of Ghana, historical and current climatic variability and change in Northern Ghana as well as model projections of these changes and their undesirable impact on farmers (see Section 4.1a). In addition, arrangement and rules governing rice farmers' activities in Northern Ghana and the management framework of the irrigation schemes including existing hydroclimatic information systems and their value to rice farming was obtained via literature and document analysis (Section 4.1b).

Using Atlas.ti (Hwang, 2007), we used open-coding methods and clustered the topics of several themes. The analysis was aimed at first verifying our findings from the literature and document analysis to collaborate evidence and secondly to probe further on arising issues such as practical challenges of climate variability and change for farmers and the potential value of hydro-climatic information systems for farmers' adaptive decision making.

Focus Group Discussions were similarly transcribed and processed through thematic analysis. The analysis provided information on the rules of engagement and decision making among rice farmers, their knowledge of existing hydro-climatic information services, information access and utilization, challenges of institutional linkage and information exchange at farm level (see Section 4.1b and 4.2).

2.4 Results

The section outlines the results of the diagnostic analysis (Section 4.1), and the key challenges reported by farmers (Section 4.2).

2.4.1 Diagnostic analysis of the socio-ecological system

To analyse the current setting, we focus on rice farmers in Northern Ghana (Figure 2.2). We specifically explore the socio-ecological aspects of climate change impacts on crop productivity (i.e. yield per unit area) and not 'food production', as this is dependent on many other factors than climate change, such as quality of land, infrastructure investment, available finance, international trade policy, and food market. We analyse this case region by splitting it into two dimensions; the biophysical factors (climate and water) and socio-institutional (actors, rules, practices, decision-making) parameters framing the activities of rice farmers within the study area.

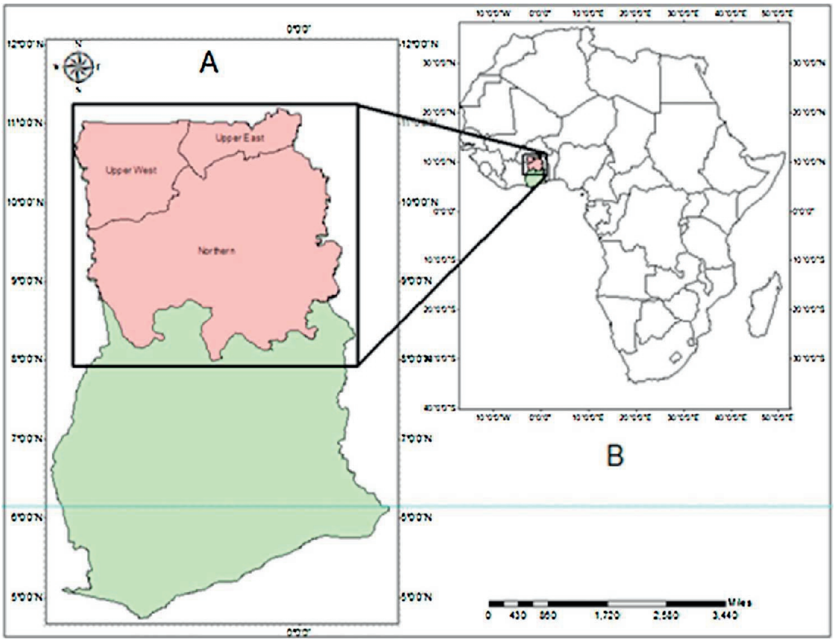

Figure 2.2: Northern sector of Ghana in a black rectangle (A) relative to Africa showing Ghana (B).

2.4.1.2 Biophysical context

From the literature analysis and interviews, the major The biophysical issues in the case area are mapped in Figure 2.3. The main issue in the North of Ghana (~97,702 km² land area) is climate variability which significantly impacts agricultural productivity. Development of the agricultural sector in this region is affected by the climatic conditions, such as the long dry season of about six to seven months followed by five-month rainy season (April/May to September/October) usually characterized by sporadic droughts and/or floods (Barry et al., 2005; Amikuzuno, & Donkoh, 2012). Temperatures in the region are higher compared to those in the southern part of the country. The lowest maximum temperatures are around 26 °C mostly recorded in August and the highest temperatures are between 40–42 °C recorded in March or April (Mdemu et al., 2012). The climate system of Northern Ghana is characterized by distinctive inter-annual and inter-decadal variability in precipitation and temperature (Emmanuel Nyadzi, 2016). The area is associated with an erratic unimodal rainfall of an annual sum between 400 and 1200 mm. Changes in the duration of the rainy season have shortened the length of the growing season, delaying the onset of planting season in most cases, while dry season and rainy season temperatures have increased by about 1 °C and 2 °C respectively (Acquah & Acquah, 2011; Kunstmann & Jung, 2005). The northern part of Ghana experiences the greatest rainfall variations and this is projected to increase along with increasing temperature (2.1–2.4 °C) from 2010 to 2050 (Owusu & Waylen, 2009). According to Kankam-Yeboah et al. (2011), high temperatures that were previously recorded in March (peak of the dry season) are now being recorded also in January. In addition, the onset of the rainy season has become more difficult to predict. They also indicated that in the past, the rainy season started in April and ended around late September or early October. However, in recent times, the rainy season starts in June or July with extremely heavy rainfall in September or October.

These outcomes indicate a potential increase in the intensity and frequency of extreme events, such as droughts and floods and a consequential reduction in the crop growing period with serious implications for crop yields and food security (Abdul-rahaman & Owusu-Sekyere, 2017; Kasei et al., 2014). Current occurrences and long-term climate patterns create future uncertainties with serious implications for climate prediction and agricultural productivity. As re-iterated by(Antwi-Agyei et al., 2012), climate variability, manifested at different time scales and in different ways will significantly impact the agricultural sector of Northern Ghana.

In addition, large temporal and spatial rainfall variability results in high variability in river flow. As results, most rivers flow for only a few months a year with limited or no flow during the rest of the year (Amisigo & van de Giesen, 2005). The combination of climate change, intensive land use, population growth and economic development results in increased water demand and more pressure on the available water resources (Stanturf et al., 2015). To cope with climate variability, hydraulic infrastructure such as small-scale reservoirs and large scale irrigation systems have been constructed mainly for agricultural purposes (Amisigo et al., 2015; Faulkner et al., 2008).

Uncertainties related to climate variability is a major challenge for both rain-fed and irrigated farmers and water managers because to productively manage their activities, critical climate sensitive decisions have to be taken months ahead of a season (Asante and Amuakwa-Mensah, 2015). Sustainability of rain-fed farming systems becomes a challenge with severe impacts on crop yields (Acquah & Acquah, 2011; Fosu-Mensah et al., 2012). Not only does this affect rain-fed farming, but it also has a major toll on irrigation schemes. Water levels in the dry season are low making it difficult to irrigate farmlands limiting production. Farmers have reported re-sowing of seeds due to poor germination following the delay in rains, which increases their cost of production. Irrigation water managers rely on river discharge to decide the frequency, quantity and method of water distribution. The uncertainty associated with predicting seasonal rains and water availability puts farmers in a dilemma when key farming decisions are to be made (Ndamani & Watanabe, 2013).

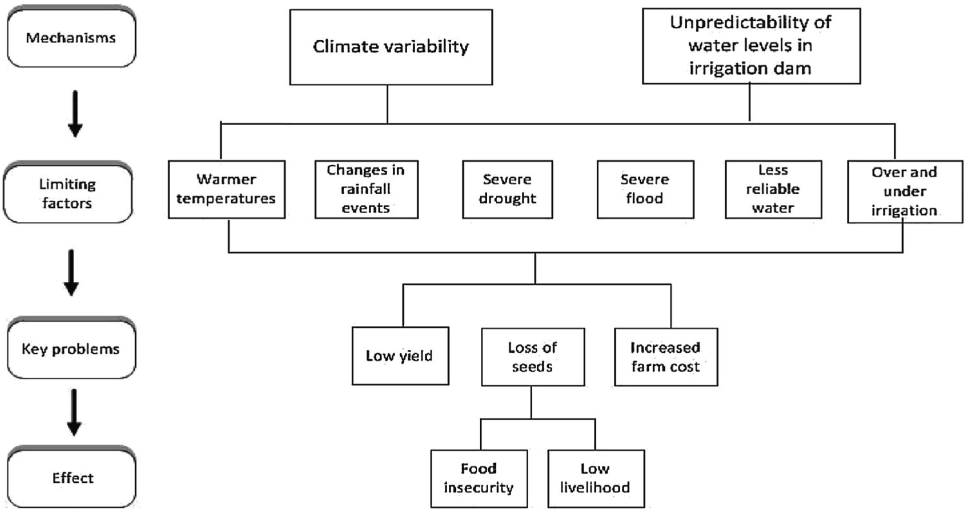

Figure 2. 3: Analysis of the main biophysical issues in Northern Ghana.

In the face of these challenges, rice is a central crop as it accounts for 15% of agricultural output and 45% of the total area used in cereal grain production in Ghana (Stanturf et al., 2011). Rice is produced under irrigation, rain-fed lowland and rain-fed upland systems (SARI, 2016). Studies on climate change project increasing temperatures and declining rainfall, resulting in reduced rice production (e.g. Asante and Amuakwa-Mensah, 2015). In a study carried out by Knox et al., (2012) rice is projected to experience the most variations of all studied crops, since water scarcity, and over reliance on unpredictable rainfall are the major factors affecting rice production in Northern Ghana (Kranjac-Berisavljevic et al., 2003).

2.4.1.2 Socio-institutional context

The North of Ghana is divided into three administrative regions: Upper East, Upper West and Northern Regions (Figure 2.2). The majority of this area is located in the Tropical Guinea Savannah zone, with small parts (extreme north of the upper east and west regions) sharing border with Burkina Faso in the Sudan Savanna. The north of Ghana is the poorest part of the country yet recent reports indicate that about 80% of the economically active population in this part of Ghana engages in agriculture, producing millet, guinea-corn, rice, maize, groundnut, beans, and sorghum with some few others producing dry season tomatoes and onions. Livestock and poultry production are also common in the region (Ghana Statistical Service (GSS), 2014). The north of Ghana is generally endowed with about 20 small and large irrigation schemes. Rice farming periods and practices are similar across the three regions, even though there are individual preferences for different varieties depending on the aim of farming (GIDA, 2011, 2016).

Governance in Ghana is characterised by two main governance arrangements. These are traditional and formal arrangements. Formal governance arrangements have been established by legal and structural definitions captured in the constitution and other working documents dependent on the context. Traditional governance arrangements, although ‘loosely’ framed are embedded in local and community culture expressed in the form of rules, norms and beliefs (see also Myers & Fridy, 2016). In Northern Ghana, the activities of rice farmers are informed by both governance arrangements (Nanedo et al., 2014).

Our engagements revealed that the Ghana Irrigation Development Authority, has the mandate of developing and managing irrigation infrastructure (see also (Namara et al., 2011). The Ghana Meteorological Agency, Water Resource Commission and the Center for Scientific and Industrial Research are also collaborative institutions in meeting information, water security and advice on crop productivity respectively (see also Braimah et al., 2014; Nanedo et al., 2014). The Participatory Irrigation Management Strategy (Namara et al., 2011), adopted in the 1990s has served as the framework for more decentralized management of Irrigation Schemes. At the scheme level, the manager is responsible for the daily operations of the scheme and thus engages farmers and leadership of farmer associations in the drafting of schedules and assigning of roles for effective water management for irrigation purposes. Water is thus discharged through canals onto farmlands within different laterals guided by agreed schedules. The manager also coordinates decisions and information exchange amongst all actors as part of steps to adapt to changing conditions experienced.

Rainfed rice farmers operating within communities are also guided by traditional governance arrangements aimed at ensuring effective engagement and resource use. These are in the form of rules and procedures which community members are expected to adhere to or live by. For example, Chiefs are custodians of lands and thus farmers who do not have family lands would have to consult the leadership for land for farming activities. Water is also perceived as a communal resource and hence farmers are expected to consider the interest of other users in the quest to meet their water needs. Chiefs who are seen to have the highest authority within the community legally enforce communal decisions. Farmers must, therefore, adhere to agreed rules even if it does not satisfy their needs.

In both systems, we found the existing governance arrangements to be faced with multiple challenges limiting stakeholder interaction and information exchange. For instance, information provision through Chief is usually aimed at general community concerns and activities rather than agriculture information required for farm decision-making. Most farmers thus took the initiative of obtaining information from other farmers or platforms such as radio and mobile telecommunication service operators involved in related information provision (See also Alhassan et al., 2013). Community representatives such as Assemblymen are not instrumental in providing relevant farm related information. Within the irrigation scheme, power play and gender imbalance result in bias in engagement. Results of the focus group discussions show that access to water was mostly characterized by power play especially during the dry season as only a few laterals upland could access water for irrigation from the dam. Thus, lands in the upland are allocated to cronies of the irrigation manager, chiefs and heads of committees. Women are also less represented and hence limited in accessing land and obtaining relevant information related to farm activities.

Governance arrangements within the scheme also put the Scheme manager in charge of information directly relevant for scheme operations. In some contexts, farmers receive delayed information relevant for decision making due to inactivity on the side of leadership. Interviews and FGDs pointed to weak institutional collaborations especially on information provision and use (see also (Nugent, 2000). This situation is largely attributable to negligence, poor leadership, weak communication links, inadequate resources and logistical challenges. For example, the Ghana Meteorological Agency provides seasonal climate information only at the start of the season and mostly to radio stations and irrigation scheme managers with little contact with farmers themselves. However, wherever these contacts exist they are inconsistent and generally decrease over the season. Private operators providing hydro-climatic information have limited collaboration with the public sector. Thus, ESOKO, MTN and Vodafone only interact with farmers without consideration of existing programmes and how their interventions could be embedded in them. Braimah et al. (2014) allude to complex local socio-political issues that affect relationships within irrigation schemes. These range from power play to gender inequalities affecting knowledge exchange and resource management.

Interviews also revealed that farmers take a number of key decisions in managing changes in climatic conditions and how they affect water availability and food production. These include when and how to prepare farmlands, when, what and how to plant, perform weed control, apply fertilizer and harvest. Farmers adapt their decisions considering outcomes and what is deemed appropriate in a given context (see also Ndamani and Watanabe, 2013). Under irrigated rice farming, water managers lead the decision process with the design of an irrigation schedule. Farmers, however, are responsible for specific decisions on their farms. Under rain-fed systems, the farmer leads the risk management process by exploring how experience from the previous season and new knowledge or information on weather inter alia, water availability in their decision-making (see also (Abdul-Razak & Kruse, 2017). The survey revealed that adaptive farm decisions of farmers are generally based on information generated from indigenous and scientific forecasts. While farmers were quick to acknowledge the limitations in their personal forecast they, however, considered it better for decision making than the scientific forecast provided by Ghana Meteorological Agency as this was perceived to be generic and not locally specific to their community and needs (See also Gwenzi et al., 2016; Zuma-Netshiukhwi et al., 2013). Information systems within the study area were identified to provide scientific forecast information whereas indigenous forecasts were tied to farmers' observation matched with experience. For example, farmers are able to predict the beginning of the wet season and when to prepare their fields for planting (Ofori-Sarpong, 2001). They base their predictions on a set of indicators, each of which has different levels of reliability. The flowering of the shea nut tree, migratory patterns of birds and position of the constellation Pleiades all help farmers determine when the rainy season is due (Benneh, 1970). They are able to predict the date of seasonal rainfall onset and cessation, and whether the season will receive above, below and normal rainfall. Also, they are able to make daily weather predictions of low, medium and high rainfall (Nyantakyi-Frimpong, 2013). In the next section, the paper presents findings on information systems and how they enable hydroclimatic information access and use.

2.4.2. Hydro-climatic information access and use in rice farming systems in Northern Ghana

The role of hydro-climatic information in knowledge creation, improved adaptation and improved agricultural production has been highlighted in different studies and initiatives (Owolade & Kayode, 2012; Sam & Dzandu, 2015). For example, in 2014 and 2015, the Ghana Meteorological Agency in collaboration with the CGIAR and ESOKO provided weather and seasonal climate information via conventional SMS to farmers in two piloted communities (Doggoh and Bompari) in northern Ghana (ESOKO, 2016). Other media such as radio and television programs are also used to provide relevant information in English and local languages (i.e. Dagbanli, Frafra, Gonja, Kasem etc.).

In spite of these interventions, there are still challenges in information access and interpretation by farmers who are illiterates and can't read text and even literate farmers lack the necessary skills to understand technical information because of the format in which they are presented. Also, the extent to which those who could read adopt the information and new knowledge received is considerably questionable (see also Sam & Dzandu, 2015). Our inventory of existing ICT and media platforms in Ghana as shown in Table 2.1 reveals some potential information transfer models, namely radio, mobile apps, websites and conventional phone-based services (e.g. recorded voice messages and SMS texts for more literate farmers). Other non-ICT means of information transfer include moving vans, extension officers, water managers and head of farmer organizations who disseminate pertinent information to farmers. Table 2.3 provides an assessment of the strengths and limitations of the main communication tools regarding their utilization in hydro-climatic information services delivery in northern Ghana

Table 2.3: Overview of key strengths and limitations of main media platforms in hydro-climatic information services in Ghana.

Communication tool	Strengths	Limitations
Radio services	• Multiple Agro-focused radio stations exist in Northern Ghana (e.g. Radio Tongu, Simli Radio etc.)[1] • Operate at a suitable spatial level/coverage and are powerful communication tools with the potential to benefit agricultural extension(Chapman et al., 2003) • Most radio operators offer services in multiple local languages such as Dagbani, Mampelle, Frafra, Waali and Dagaare which are important for the Northern Ghana context • Farmers generally listen to local radio on a frequent basis and this makes it easier to reach targeted farmers with hydro-climatic information	• Radio services offer few mechanisms for meaningful interactions with farmers. • Information reaching farmers through radio could be adulterated, as there might be difficulties in the translation of some terms into local dialects. • This will hinder information exchange between data users (farmers) and researchers of the hydro-climatic-EVO.
Mobile apps	• Powerful visualization capabilities in mobile apps help to overcome the challenge of limited literacy rate in rural communities (Vitos et al., 2013). • Our experience with developing a prototype offline mobile-app to collect farmers' short-term weather predictions in northern(on-	• Many rural communities in Northern Ghana do not have access to the internet to use online mobile apps. • Many farmers in Northern Ghana do not own smartphones. • Many of the farmers are ICT phobia largely because of language and literacy barrier.

[1] http://gcrn.org.gh/dev/?p=251.

	going project)[2] makes us convinced that mobile apps have great potential in reaching out to rural illiterate farmers.	
Conventional phone services	• High penetration of mobile phones in rural Ghana. Farmers already use phones for calls and the elite farmers use it for text messaging families, friends and businesses (infoDev, 2014). • Existing phone services such as pre-recorded audio phone messages for • illiterate farmers and SMS to literate farmers are currently operated in • Northern Ghana e.g. FARM Radio and ESOKO (FARM Radio • International, 2014; Esoko, 2016). This allows for the integration of hydroclimatic information services into those existing services and business models, which may add to the sustainability of research output.	• Most existing phone-based services are not free and this raises the issue of information asymmetry where only higher-income farmer groups can afford and access hydro-climatic information. • SMS-message fatigue is occurring among literate farmers as the cheapest phone services come with advertisement-messages
Website	• Websites that provide climatic information services exist in Ghana (GMET,2016) • They are rather quick to develop and supports some level of interactions.	• Web-based services often face the challenge of sustaining users to visit on a frequent basis. • They offer limited opportunity for interactions.

[2] https://uclexcites.wordpress.com/2018/05/01/the-role-of-sapelli-in-collecting-indigenous-weather-climate-forecast-data/.

		• Limited internet access is also a major challenge in many rural communities. • Farmers will find it difficult to read and interpret information by themselves because of limited literacy.
Other non-ICT models[3]	• Non-ICT media are effective as farmers are able to have a face-to-face interaction with information providers where demonstrations are carried out for a better understanding of concepts. • Non-ICT models include formal and informal periodic meetings where farmers interact and pass on relevant information to each other within both the irrigation scheme and communities. • Mobile Vans from the Information Services Department readily provide information to farmers in communities.	These models are not responsive enough for daily hydro-climatic information exchange. • Data providers do not have direct interaction with users and information transfer may take several days when moving vans are used. - Moving vans do not create a platform for questions or further clarifications and farmers may miss relevant information. • Female farmers are mostly not invited to attend such meetings and on a few occasions when they are present, they are unable to express their opinion because of the male-dominant conversation. • Farmers held sentiments and affluence may also play a role in making it more difficult for information access.

[3] Non-ICT models include formal and informal periodic meetings where farmers interact and pass on relevant information to each other where information provider is often the irrigation water manager, head of farmer organization and extension officers. Another model is moving vans from the ministries and departments uses megaphones for loud announcements vital for farmers' use

2.5 Discussions

This study set out with the aim of diagnosing how socio-ecological settings of rice farmers in Northern Ghana could affect the design and operationalisation of a hydro-climatic EVO. In this section, we draw on the insights from our diagnostic analysis to outline the characteristics of our hydro-climatic EVO. The design aims to overcome the identified challenges and capitalize on opportunities identified in section 4.2. The framework consists of two main parts: the structural elements of the framework and the processes through which it operates. We discuss the process of designing the EVO through the lens of the four dimensions of RI.

2.5.1 Design features: description of the structural elements

Our diagnostics resulted in different hydro-climatic information needs, challenges and opportunities for an EVO. We propose a hydroclimatic EVO (Figure 2.4) consisting of three major elements; (a) data sources, (b) data handling processes, (c) platform for information and data exchange.

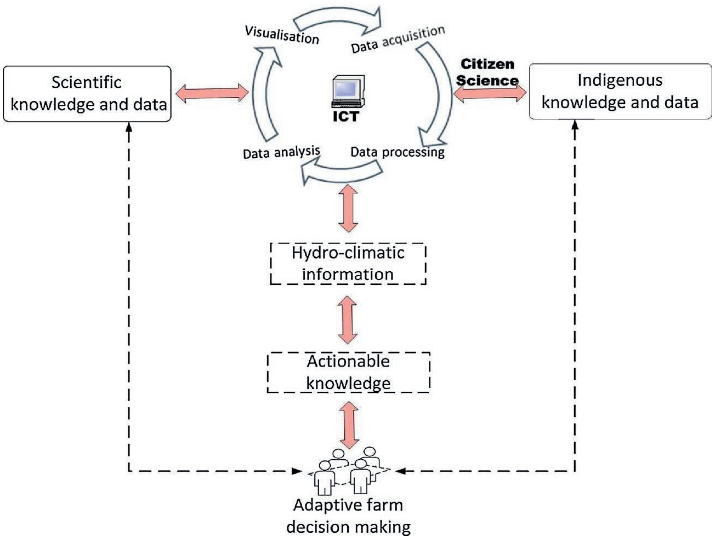

Figure 2.4: Fundamental Architecture of second generation climate services (hydro-climatic EVO).

(a) Data sources

Data will be sourced from two main knowledge systems; indigenous and scientific knowledge systems (see Figure 2.4). First, as explained earlier, Ghanaian farmers use indigenous ecological knowledge to understand weather and climate patterns in order to make decisions about crop and irrigation cycles (Frimpong, 2013). Prior to every season, the EVO will collect farmers' seasonal forecast of rainfall onset and cessation date and, rainfall amount and degree of temperature forecast expressed on a nominal scale of below, normal or above normal. Also within the season, the EVO will collect farmers' twenty- four (24) hours weather forecast of low, medium or high rain.

Second, seasonal temperature and rainfall forecast data from European Centre for Medium Range Weather Forecasts (ECMWF-S4) seasonal forecasts system 4 (Molteni et al., 2011) will be analysed to also provide same seasonal climate information on rainfall onset and cessation date, amount of rainfall and degree of temperature also expressed in a nominal scale of below, normal and above normal. ECMWF-S4 is a state-of-the-art seasonal ensemble climate model that provides seasonal climate forecast on daily timescale into seven months ahead of time. The daily nature of the data will allow us to estimate daily rainfall amount of either low, medium and high.

(b) Data handling processes

The second element of the framework is the data handling process where indigenous and scientific data are *collected*, *processed, analysed, and visualized.* The collection of data will be partly automated. The hydro-climatic-EVO will offer a platform where farmers can regularly upload their seasonal climate and daily weather forecast information. This indigenous forecast information from farmers will be complemented with those from the scientific forecast.

There are clear differences and limitations of both data sources. However, seasonal information such as rainfall onset and cessation date, above, below and normal rainfall generated from the analysis of the ECMWF-S4 temperature and rainfall data will be used to complement those predicted by farmers using their indigenous knowledge. In a similar way, daily weather information such as low, medium and high rainfall predicted by farmers will complement information estimated from the daily data from ECMWF-S4 or any other weather model. There is potentially great value in combining both sources of data. For example, both data sources have an inherent value that will complement the weakness exhibited by each without substituting one for the other and building on their respective strengths. The question that remains is whether information from both sources will be provided independently or combined. Developing a comprehensive approach to either independently present scientific and indigenous forecast information or harmonize them for actionability remained to be further explored in our next study.

(c) Information exchange for adaptive farm decision making

The hydro-climatic EVO has additional features that distinguish it from other EVOs. It offers a participatory opportunity to actively engage end-users to co-create actionable knowledge. Farmers can share their forecast information and receive tangible information for their adaptive farm decision-making. For example, seasonal climate information such as onset and cessation date, rainfall amount (be it above, normal or below normal) and seasonal dam water levels, and the degree of temperature per season will support:

(i) Pre-season decisions: such as when to buy seeds and which variety to buy, irrigation land size allocation and Labour size, which weedicide, pesticide and fertilizer to buy.
(ii) Land preparation decisions: when to clear land, when to harrow and plough,
(iii) Planting decisions: when to nurse, transplant and which planting method to adopt and
(iv) Harvesting decision: when to harvest and by which method.

On the other hand, daily weather information (be it yes/no rain, low, medium or high rainfall) received by farmers will support farm decisions such as

(i) when to fertilize,
(ii) when to apply weedicides and pesticides and(iii) when to carry out supplementary irrigation.

Details of information need and decision-making by rice farmers are discussed by (Nyadzi et al., 2019; Nyamekye et al., 2018).

The EVO offers tailor made information that generates actionable knowledge for decision making at different stages of farming. The interface of the Hydro-climatic EVO will be carefully designed with close collaboration with end-users to ensure effective data and information exchange with a particular focus on non-literate users with little or no prior ICT experience. The hydro-climatic EVO, therefore, envisages opportunities for learning and becoming an integral part of rice production systems in the region.

2.5.2 Hydro-climatic EVO: addressing challenges in existing information systems

The main challenges of existing information systems and what our EVO seek to do differently is summarized in Table 2.4. Challenges with existing systems that limit their usefulness include user unfriendliness of the system, inaccuracies of forecast information, the relevance of information, managing user expectation and weak collaborations.

Table 2.4: Identified challenges in existing information systems and the way forward.

Challenges	Existing systems	What hydro-climatic EVO must do differently
User unfriendlines s	Hydro-climatic information accessed by farmers is difficult to interpret especially by the illiterate farmer population, as farmers are not able to interact with the system. This limits the application of new knowledge.	To maintain its purpose and functionality, a Hydro-climatic-EVO must provide an interactive interface in locally adaptable language. The interface must adopt a participatory process considerate of technical, social and cultural dimensions.
Inaccuracies of forecast informatio n	Existing climate and weather forecast possess poor skills and are very coarse in resolution. Information are often not location-specific and therefore farmers do not find them useful.	We use data from state-of-the-art ensemble forecast model ECMWF-S4 that have better skills (accuracy) for West Africa (Molteni et al., 2011). The hydro-climatic-EVO will provide downscaled information with higher resolution, making it more relevant for local communities. The scientific forecast will be complemented with farmers' indigenous forecast that is locally specific.
Relevance of information	Forecast information is not specific to the exact needs of the farmers. Climate sensitive information such as onset and cessation dates, amount and frequency of rain etc. are untimely provided for decision making.	The hydro-climatic-EVO will provide tailor made water and climate sensitive information and further advice farmers on which decision is suitable based on the provided information. It is possible to provide this information seven (7) months into the future especially before the onset of the season (Molteni et al., 2011).
Managing User expectation	Information provided has failed in some instances thereby dwindling farmer confidence in existing systems. This is also due to a lack of direct engagement of users of information in the data gathering,	The design of the Hydro-climatic-EVO adopts an action research approach and hence engages end users as early as the design stage. Therefore, farmers are exposed to the limitations of the system and give a better understanding of what is possible in the end.

	projection and analysis stages before the information is disseminated. This breaches trust and confidence in the information received.	
Weak collaboration	Existing hydro-climatic information systems adopt a top-down approach where scientists and other technical personnel are the drivers and farmers end users. Little or no attention is given to farmers' involvement and participation in the knowledge creation process. Results of the focus group discussion show that farmers have good knowledge of their own environment and when this is coupled with scientific knowledge, quality of forecast information could be improved.	Hydro-climatic-EVO encourages participation from the point of idea conceptualisation, design and creation. The system will be co-produced by scientists, farmers and other key stakeholders. Both indigenous and scientific knowledge systems are adopted and applied. Aside from regular workshops and meetings to discuss opinions and ideas from both sides, the hydro-climatic-EVO presents a platform where knowledge and information are continuously exchanged. This creates a deep sense of ownership amongst all stakeholders.

2.5.3 Design process: hydro-climatic EVO as responsible innovation

We build on the responsible innovation framework (Stilgoe et al., 2013) to assess the initial steps taken in the process of building a hydroclimatic EVO, and to identify the challenges ahead. For each cardinal principle, we raised some salient questions that seek to guide the development and implementation.

(i) Anticipation

Anticipation involves "systematic thinking aimed at increasing resilience while revealing new opportunities for innovation and the shaping of agendas for socially-robust risk research" (Stilgoe et al., 2013). This relates to forecasting, and imagining possible and desirable futures, but also to the 'ethics of promising'. This dimension of the RI framework makes us ask 'what if…?' questions (Jerome R Ravetz, 1997) to expose the various contingencies associated with the development of the hydro-climatic-EVO. From its conception, the envisaged hydro-climaticEVO anticipates the future by considering the potential impacts of climate variability and change on farmers' daily and seasonal farm decision making. Rather than optimizing for the most likely future scenario, the hydro-climatic-EVO accounts for the associated uncertainty by trying to make variability in water availability manageable for different farming purposes. Climate variability and change is only one of the potentially relevant future developments. Equally important is the unintended consequences which could be the future development of farming in the region, in terms of economic prospects and farmers' aspirations. Will farmers move out of agriculture into other occupations if possible, or do they see a future for themselves and their children that will motivate them to further improve their farmer system and embrace new technologies such as an EVO? The approach is taken to ensure inclusiveness through user-centered design (see below) creates some challenges for the 'ethics' of promising. Developing features that are most relevant to users implies that these may be quite specific and/or novel, making it uncertain to what degree the innovation will be able to deliver on the promised usefulness of the EVO.

(ii) Reflexivity

Reflexivity means "holding a mirror up to one's own activities, commitments and assumptions, being aware of the limits of knowledge and being mindful that a particular framing of an issue may not be universally held" (Stilgoe et al., 2013). It is about questioning the value systems and theories that shape science, innovation and governance. The envisaged hydro-climatic-EVO will be developed through interdisciplinary collaboration, where the absence of shared standard ways of operating leads to mutual questioning and thus some form of reflexivity. This reflexivity prevents natural scientists to retreat into sole modelling and prevents social scientists to retreat into the sole analysis of social processes. Reflexivity also requires carefulness not to violate the social and cultural ethics of the society in which the project is carried out, particularly because different countries and vulnerable populations are involved. This was vital especially during our interaction with farmers, for example regarding their traditional knowledge and regular engagement for information exchange. A continuous challenge is to remain reflexive about assumptions made in building the EVO, and to what extent these are aligned with the users' context. Thus the need for continued scrutiny of project activities and dealing with every farmer and situation distinctively.

(i) Inclusion

The user-centred design framework (Zulkafli et al., 2017) adopted for the development of the hydro-climatic EVO strongly emphasizes inclusion. Various actors and institutions were actively involved in the early development process, with particular attention paid to potential end-users. The engagement of different actors on the project especially during regular workshops and training is expected to play a pivotal role in creating a sense of ownership among the farmers and other actors (public and private sector agencies, local leaders and chiefs). A clear example of inclusiveness is the involvement of both rainfed and irrigated rice farmers on the project. Each of these farmer types has its own need, which must be met. Also, the reliance on both scientific and indigenous data and knowledge systems to generate actionable knowledge enhances the inclusiveness of hydro-climatic EVO. Inclusion is never perfect, however, and pragmatic choices have an impact. The particular study area receives considerable attention from development actors, partly because of its proximity to the city of Tamale and its university. Farmers with higher literacy levels, fluency in English, and familiarity with ICT are easier to involve in e.g. local smartphone-based data gathering.

(ii) Responsiveness

Responsiveness is the capacity to "change shape or direction in response to stakeholders, public values, and changing circumstances" (Stilgoe et al., 2013). Funded by a university programme (INREF[4]) that values "research for development", our hydro-climatic-EVO project has a good starting point for achieving responsiveness. The user-centred design approach to developing the EVO emphasizes the importance of the user context as a starting point – in terms of livelihoods, culture and decision-making. A choice that was made early in the project to include the practice of rainfed farming as well as irrigated farming, was responsive to the importance of rainfed farming for large parts of the rural population, in particular the poorer sectors. The design and structure of the hydro-climatic-EVO aims to meet the needs of users and remain flexible enough to respond to future changes in circumstances, e.g. new knowledge and emerging perspectives, new technical possibilities or demands, as well as changes in livelihoods or cultural values. Being a university-led project with a limited period (5 years) creates some challenges for responsiveness as well. What about responding to changes when paid project members are no longer around? Finally, the responsiveness to stakeholder and public values might be challenged by the responsiveness to academic values and incentives, which prioritize modeling, analysis and publication over stakeholder engagement and practical application. This limitation is therefore recognized and in cases where they emerged efforts must be put in place to amicably deal with them. For example, we seek to understand indigenous forecast techniques and develop methods to quantify them in order to harmonize them with scientific forecast derived from models.

2.6 Conclusion

The diagnostics study presented here offers a number of important insights that help to further refine and implement the hydro-climatic EVO. First, the participatory design will create a sense of ownership among farmers. This is because, being actively involved from the design to production and implementation stages of the project is novel, and it increases the likelihood that the hydro-climatic information services developed will be useful for farmers. Secondly, the diagnostics provide an in-depth appreciation of the socio-ecological conditions in which the EVO will operate. Thirdly, our reflection using the RI framework exposed key challenges, which the hydro-climaticEVO development process needs to deal with. Asking these questions, however, allowed us to discuss plausible solutions at an early stage in the design process.

[4] See http://www.wur.nl/en/Research-Results/Projects-and-programmes/INREF.htm

One of the key challenge anticipated is the reliance on stakeholder participation throughout the project cycle. Farmers need incentives and motivation for continuous participation. In our case, we argue that both rainfed and irrigated farmers are challenged by climate variability and limited water availability and that urgent action is needed. The information services developed can help with improving their farm decision making in order to better cope with climate variability. However, it remains unclear how much time future users and other stakeholders are prepared to devote to the design process. Close monitoring is needed to find out if farmers feel that providing regular data and information is time consuming. Limited commitment of users can potentially reduce data availability and quality. As a response we pay specific attention to openness and transparency in the design process, to allow participants to freely share their opinions and concerns. At the same time, researchers need to be proactive. They should be seen as and perceived to be serious with the process through their active engagement. In the context of decision-making, our reflections and findings present key challenges in terms of language, interpretation and usability. The knowledge co-creation and subsequent provision of actionable knowledge must align with literacy and user confidence in being able to easily relate to outputs.

Our approach and innovation possess the potential to deal with the socio-ecological challenges imposed by climate variability and limited water availability. We argue that one of the most important drivers of success to our project will be the intensive collective interaction of scientist and farmers compelled by the structure and mechanism of the hydro-climatic EVO, in which scientist and other stakeholders think, plan and execute together from common ground. In addition, the responsible line of questioning will reduce the possible surprises and eventualities that may affect EVO development. Important issues to follow-up on are the performance of indigenous and scientific forecast to meet the hydro-climatic information needs of rice farmers in Northern Ghana. Another issue from our diagnostics is how governance systems limit information flow and interpretation. For our follow up studies we aim to investigate governance arrangements and how these are enabling or inhibiting adaptive decision-making amongst farmers and water managers. Also in the next stage of this project is to find out what is the most preferred model of information exchange by rice farmers.

The potential of including farmers in information collection through citizen science potentially bridges part of the gap between scientific and indigenous expertise and constitutes a novel contribution to the field of environmental observations.

We conclude that the socio-ecological conditions in Northern Ghana necessitate the development of an effective second generation hydroclimatic EVO as this potentially responds to the principles of RI expected to drive technological innovation to manage change in natural resource management. Finally, the proposed hydro-climatic EVO has the potential for influencing adaptive farm decision making in Northern Ghana in spite of identifiable challenges. Using the RI framework has helped us to refine these challenges and offer concrete suggestions to improve both the design and implementation of the proposed platform in a responsible way.

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3

Chapter 3

Verification of seasonal climate forecast towards hydroclimatic information needs of rice farmers

Abstract

Farmers in sub-Saharan Africa face many difficulties when making farming decisions due to unexpected changes in weather and climate. Access to hydro-climatic information can potentially assist farmers to adapt. This study explores the extent to which seasonal climate forecasts can meet hydro-climatic information needs of rice farmers in northern Ghana. First, 62 rice farmers across 12 communities were interviewed about their information needs. Results showed that importance of a hydro-climatic information need depends on the frequency of use and farming type (rain fed, irrigated or both). Generally, farmers perceived rainfall distribution, dam water level, and temperature as very important information followed by total rainfall amount and onset ranked as important. These findings informed our skills assessment of rainfall (Prcp), minimum temperature (Tmin) and maximum temperature (Tmax) from European Centre for Medium-Range Weather Forecasts (ECMWF-S4) and at lead times 0 to 2. Forecast bias, correlation and skills for all variables vary with season and location but generally are unsystematic and relatively constant with forecast lead time. Making it possible to meet farmers' needs at their most preferred lead-time of one month before the farming season. ECMWF-S4 exhibited skills in Prcp, Tmin and Tmax in Northern Ghana except some few grid cells in MAM for Prcp and SON for Tmin and Tmax. Tmin and Tmax forecast were more skilful than Prcp. We conclude that the participatory co-production approach used in this study provides better insight for understanding demand driven climate information services and that the ECMWF-S4 seasonal forecast system has the potential to provide actionable hydro-climatic information that may support farmers' decisions.

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3.1 Introduction

The agriculture sector of many West African countries is yet to realize its full production potential in terms of agricultural yield. Compared to levels achieved in the 1960s, the sector is considered to be underperforming (Benin et al., 2011; Nin-Pratt et al., 2011). The low performance of the sector has many reasons, including political and institutional constraints, low adoption rate of socio-technical innovations, and biophysical factors, including highly variable climatic conditions (Baltzer & Hansen, 2011). Climate variability in large parts of Africa is projected to increase due to global warming (Niang et al., 2014; Salack et al., 2019) which is likely to have severe impacts on the agricultural production (Schlenker & Lobell, 2010; Rockström et al., 2014). This is particularly the case for sub-Saharan Africa where smallholder farmers largely depend on rain-fed agriculture and small scale irrigation systems. Changing rainfall patterns could necessitate significant adjustments to farming activities (Sarr et al., 2015). For example, changes in the onset, duration and end of the rainy seasons have already affected planting patterns and the farming calendar (Jotoafrika, 2013).

In Ghana, significant changes in farm activities caused by climate variability and change are already evident and efforts to manage the negative effects of this change on agricultural production have had limited success. Water scarcity and reliance on unpredictable rainfall remain major factors limiting crop production in the country. One of the most important concerns in this regard is the increasing rice yields (Kranjac-Berisavljevic' et al., 2003; Donkoh et al., 2010). Rice is currently a key staple crop in Ghana for which the consumption has increased in recent years (Mabe et al., 2012). As a result, the production of rice needs to increase to meet rising demands under the increasing variable climatic conditions (SARI, 2011). This poses a significant challenge, as farmers have to make several climate-sensitive decisions months in advance to the rice farming season (Asante & Amuakwa-Mensah, 2015). A similar challenge exists in irrigated rice farming. The difficulty to predict rainfall and consequently river discharge affects the decisions of water managers making on water distribution to the irrigated farmlands. The use of weather and climate forecasts could be an instrument that helps farmers in their decision making to improve agricultural productivity and food security (Hansen et al., 2009).

Previous research on hydro-climatic information to support farmers in their decision making can be broadly divided into two directions. Firstly, social science studies that explored in a mostly bottom-up fashion the weather and climate forecast information needs of smallholder farmers and potential challenges they encounter. Results showed that farmers do receive weather and climate information, mainly through radios and local administration (Feleke, 2015). Relatively few farmers find the information useful in their operational decision-making. Language problems, difficulty in understanding forecast terminology and inconsistency in the time of information provision constrain farmers in the use of weather and climate information (Feleke, 2015). Other studies conclude that weather and climate information currently received by farmers are insufficient and service improvements are needed to make better use of the available weather and climate forecasts for informed decision making (Onyango et al., 2014).

The second line of research focusses on technical and top-down approaches assessing the skills of existing forecasts for several regions across the globe (Kumar et al., 2001; Barnston et al., 2010; Ogutu et al., 2017). These studies often conclude that weather and climate forecasts have considerable potential to improve agricultural management and rural livelihoods (Hansen et al., 2009; Roudier et al., 2014; Ouédraogo et al., 2015), but do not connect it to the needs of farmers to make informed decisions. Several forecasting systems have been developed and used (e.g. (Stockdale et al., 1998; Mason, 1999; Kanamitsu et al., 2002; Alves et al., 2003). The European Centre for Medium-Range Weather Forecasts (ECMWF)-System 4 ensemble seasonal climate forecasting system, is the state-of-the-art with an ensemble of 15 members found to be skilful in many regions across the globe. Several have argued that it has potential value for providing climate services for vulnerable sectors including agriculture, energy, and health (Manzanas et al., 2012; GFCS, 2016). Nonetheless, until now only a few studies used ECMWF-S4 for Africa (QWECI, 2013; Trambauer et al., 2015; Ogutu et al., 2017).

In this study, we aim to connect these two different lines of research to gain insights on demand driven climate service for rice farmers' adaptive decision making. More specifically, we explore if and how seasonal climate forecasts of the ECMWF System 4 can meet the hydro-climatic information needs of rice farmers in northern Ghana. To do this, we used social science methods (interviews, workshops) combined with a skills assessment of ECMWF System 4 seasonal climate forecast system. Therefore, to meet the main objective, we implement a 2-step approach: (1) identify the information needs and (2) assess hindcast skills (verification).

The paper proceeds as follows. First, we briefly introduce the case study region. In section 3, we describe the methods used for data collection and analysis, followed by section 4 where we present the findings of the farmers' needs assessment and the performance evaluation of the forecast. We discuss the findings in section 5, followed by a concluding section.

3.2 Study area

The North of Ghana is located within the Inter-Tropical Convergence Zone (ITCZ) where the movement of the two air masses, the Harmattan or North – East (NE) Trade Winds and the South-West Monsoon winds, determines the nature of the climate (Liebe., 2002). The area is associated with erratic unimodal rainfall with total annual precipitation ranging from 400 to 1200 mm. The north of Ghana has challenging climatic conditions such as a long dry season of about six to seven months followed by a five-month rainy season (April/May to September/October). The area is characterized by frequently occurring drought and flood events (Amikuzuno & Donkoh, 2012; Asare-Kyei et al., 2015). Temperatures in this part of Ghana are higher compared to the southern part of the country. Maximum temperatures range from 26°C in August to 40°C in March or April (Mdemu, 2008). This makes its agriculture activities highly vulnerable to climate variability and change.

Northern Ghana comprises of the Upper West Region, the Upper East Region and the Northern Region (Runge-Metzger & Diehl, 1993). The poverty level of Northern Ghana is higher compared to the southern regions even after over 30 years of agricultural-led development projects, the northern regions of Ghana remain impoverished (Morris et al., 1999; IFAD, 2012;). According to a recent report from the Ghana Statistical Service, about 80% of the economically active population in this part of Ghana engages in agriculture (GSS, 2014). The main crops are rice, maize, soybean, millet, cassava guinea-corn, groundnut, beans, and sorghum, with some farmers also producing dry season tomatoes, pepper, cabbage and onions mainly for consumption with surpluses for the market (GSS, 2014). Generally, average farmland size varies with crop type; 0.27 ha for soybean, 0.72 ha for rice and 1.06 ha for maize. Rice production in the area declined from 3.20 MT/ha in 2010 to 2.32 MT/ha in 2015 despite an increasing demand (USAID, 2017). The period of rice farming is similar across the three regions of northern Ghana because of similar agro-ecological conditions, even though there are individual preferences for different rice varieties based on production rational (GIDA, 2016).

To mitigate irregular water availability for farming and domestic activities in the Northern Region, about 20 small and large irrigation schemes have been developed with the Bontanga irrigation scheme being the largest in the Kumbungu District (Figure 3.1). The Bontanga irrigation scheme sources its water from the Bontanga River, a tributary of the White Volta River. The scheme has a potential area of 800 hectares but 450 hectares are currently irrigated. Out of this, 240 hectares is used for lowland rice cultivation. In 2016, the scheme included about 600 farmers (~100 women and ~500 men) from 13 different communities with an average of 0.8 ha per farmer. They engaged in rainfed and irrigated rice farming in the rain and dry season respectively (GIDA, 2011, 2016; The Republic of Ghana, 2012).

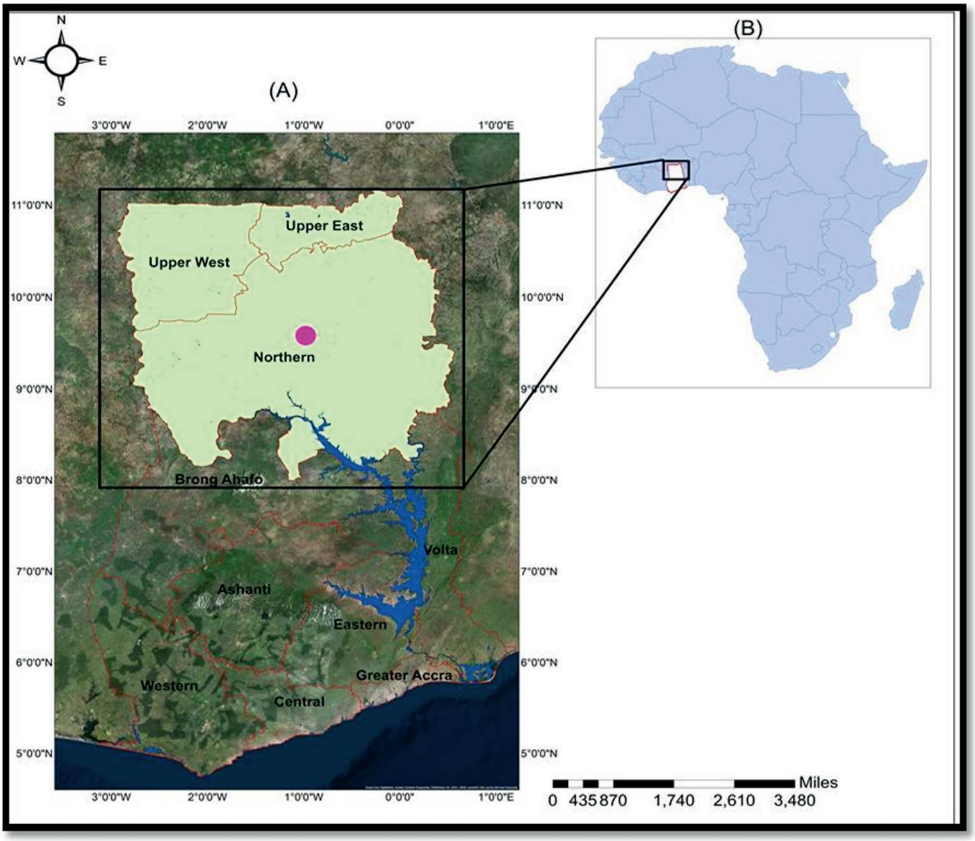

Figure 3.1: Northern Ghana in a black rectangle (A) relative to African showing Ghana (B). The pink circle shows the position of Bontanga river and irrigation dam

3.3. Research Methodology and Data

This research was conducted in three main steps. First, document analyses, interviews (n=62) and a feedback workshop were used to obtain information about the hydro-climatic information needs of rice farmers in the communities around the Bontanga irrigation scheme. In the second step, we evaluated the skills of the European Centre for Medium-Range Weather Forecasts' System 4 ensemble seasonal climate forecasts (ECMWF-S4) using probabilistic verification statistics. Thirdly, we assessed the potential for meeting the hydro-climatic information needs of farmers at their expected lead time.

3.3.1 Data collection and analysis

3.3.1.1 Assessment of hydro-climatic information needs.

To collect data on hydro-climatic information needs for farmers' decision making we designed a structured interview guide based on document analysis (Bowen, 2009) and previous studies (Roncoli et al., 2009; Crane et al., 2010; Roudier et al., 2014). The interview protocol covered both open and closed questions on (i) respondents' general perception of climate variability and change; (ii) hydro-climatic information needs for decision making where farmers could identify their hydro-climatic information requirements in each stage of the farming process; (iii) general information about respondents (see Table A3 of supporting material for the interview guide). The interview guide was pilot-tested twice to ensure that the questions were understandable and unambiguous.

In total 62 rice farmers were interviewed (Table 3.1). Each interview lasted for about 30-40 minutes and was audio recorded. In the sampling process, we aimed to balance between types of farmers; Irrigation only (IO), Rainfed Only (RO) and Both Irrigated and Rainfed (BIR) and their location within the irrigation scheme (up-, mid- and down-stream of the Bontanga River). Individual farmers were selected based on their rice farming experience (more than 5 years) and their willingness to participate in the survey. We included IO farmers (n= 11), RO farmers (n=20) and BIR farmers (n=31). After completing the interviews and processing the data, a one-day feedback workshop was organised to discuss and validate the interview results with representatives from each of the 12 selected communities. The aim was to reduce interpretation bias by the researchers, to collectively rank information needs, to improve understanding of the respondents' needs, to share key insights of the research team, and to identify farmers for follow-up studies. The data and information gathered from the interviews and workshop were analysed using descriptive statistics (frequency and percentage). The analysed demography and farming characteristics of the farmers are presented in Table 3.1 showing frequencies and percentages.

Table 3.1: Socio-demographic structure of respondents (N = 62)

Characteristics	%
Age (N=62)	
21-30	1.6
31- 40	3.2
41-50	12.9
51-60	29
61-70	50
Above 70	0
Gender (N=62)	
Male	79
Female	21
Educational Level (N=62)	
No Formal Education	85.5
Elementary /Primary	8.1
Middle /J*unior* H*igh*	4.8
Senior High	1.6
Tertiary	0
Household Size **(N=62)**	
1-5	1.6
6-10	40.3
11-15	37.1
16-20	19.4
21-25	0
Above 25	1.6
Years In Farming Rice **(N=62)**	
1-5	0
6-10	16.1
11-15	19.4
16-20	29
21-25	14.5
Above 25	21
Farm size in the irrigation scheme in hectares (N=42)	
Less than 1	2.4

1 – 1.9	33.3
2 - 2.9	50
3-3.9	14.3
>4	0
Others	0
Farm size outside irrigation scheme (N=51)	
< 1	0
1 – 1.9	3.9
2 - 2.9	7.8
3-3.9	5.9
4–4.9	25.5
5 -5.9	33.3
Others	23.5
Which Crops do you grow (N=62)	
Okro	50
Yam	61.3
Cassava	41.9
Cabbage	22.6
Rice	100
Maize	98.4
Tomatoes	61.3
Pepper	71
others	0
Which is your main crop (N=62)	
Rice	83.1
Maize	6.8
Rice and Maize	10.2
Other	0

3.3.2 Seasonal Climate Forecast verification

3.3.2.1 Data collection

Thirty (30) years daily hindcast data of total precipitation (Prcp), minimum temperature (Tmin) and maximum temperature (Tmax) were collected from the European Centre for Medium Range Weather Forecast system 4 (ECMWF-S4). The data is an ensemble of 15 members at approximately 0.75 degree horizontal resolution. The data initialization used for this analysis starts on the first day of every month from 1981 to 2010. Each of the 15 ensemble members provides forecast of up to 7 months. Also, 30 years' (1981 to 2010) Water and Global Change (WATCH) forcing data ERA-Interim (WFDEI) daily data of the same variables (Prcp, Tmin and Tmax) were used as reference observation (Weedon et al., 2014) because of the sparse network of weather stations in the area and the quality of data available does not allow for proper spatial validation.

WFDEI has been considered useful for evaluation purposes in East Africa (Ogutu et al., 2017). An inter-comparison analysis of precipitation variability and trends in Ghana has shown that GPCC which is an input data set of WFDEI performed well when compared to Ghana meteorological agency (GMET) station data for monthly totals in Northern Ghana (Manzanas et al., 2014). We performed further analysis of Prcp, Tmin and Tmax to recognize the extent of the existing bias daily timescale (see figure B1 and B2 in supplementary documents). But the results of this validation were not very encouraging as WFDEI could not properly estimate the variables at a daily time scale but capture well temporal trend of variability of the variables. Comparing point data from a wide grid to GMET station data could, therefore, have affected the results.

3.3.2.2 Data analysis

This study uses two well-documented verification measures (Generalised Discrimination Score (GDS) and Relative Operating Curve Skill Score (ROCSS) to assess the performance of the forecast to a standard reference (i.e. the climatological forecasts and observed climatology). Indicator values for these measures range from zero denoting forecast being as good as the reference and positive or negative implying an improvement and no skill respectively).

More in detail, the forecast verification is performed for three different periods of the rainy seasons of Northern Ghana: i.e. MAM (March, April May, coinciding with Onset), JJA (June, July and August for peak monsoon season) and SON (September, October and November for cessation) (Sultan & Janicot, 2003; Amekudzi et al., 2015). Our results from step 1 showed that farmers preferred lead times ranges between 0-2 months (see section 4.1). The skill was verified at 0, 1 and 2 lead times corresponding to the months the forecast started before a growing season. The verification was carried out on the ensemble mean of all members as the accuracy of the verification improves with larger ensemble size. Large ensembles are particularly important if extreme events are to be forecasted (Weigel et al., 2007; Ferro et al., 2008;). Prior to the validation, we matched forecast data spatial resolutions (0.75 degree) to observe data resolution (0.5 degree) using bilinear interpolation which is a widely used method in climate forecast validation exercises (Bedia & Iturbide 2017; Ogutu et al., 2017; Cofiño et al., 2018).3-monthly averages of the forecasts and observations were computed to allow the validation scores on seasonal timescale. The evaluation was carried out at grid points level and the three regions within the north of Ghana where rainfall patterns are similar (Nkrumah et al., 2014). We analysed mean biases for each of the three seasons and for different lead times (Willmott et al., 2012). The strength of the relationship between the ensemble 261 mean and the verifying observations were assessed using Spearman's rank correlation coefficient.

The Generalised Discrimination Score (GDS) was used as a measure to assess how well the forecasts are able to discriminate between varying observations. This was done by quantifying whether a set of observed outcomes can be correctly discriminated by the corresponding forecasts (Weigel & Mason, 2011). The score measures the probability that any two (distinguishable) observations can be correctly discriminated by the corresponding forecasts. Thus, GDS can be interpreted as an indication of how often the forecasts are "correct" regardless of whether forecasts are binary, categorical, continuous, or probabilistic (Mason & Weigel, 2009). Relative Operating Curve Skill Score (ROCSS) was also used to compute the skills in tercile forecasts (i.e. probability forecasts for upper, middle and lower terciles forecasts) considering rainfall forecasts only. The ROCSS measures the hit rate of a forecast against its false-alarm rate as the decision threshold (for example a quantile of a probabilistic forecast) is varied. It is expressed as a percentage and quantifies the improvement over climatological forecast (Jolliffe & Stephenson, 2012). Characteristics of the ROC have been widely discussed (e.g. Kharin & Zwiers, 2003; Mason, 2003). Several other studies have used the technique to diagnose ensemble forecast accuracy (Gallus & Segal, 2004; Legg & Mylne, 2004; Ogutu et al., 2017). Accessing, downloading and analysis of data was carried out using relevant packages within R statistics: SpecsVerification (Siegert, 2017), easyVerification (MeteoSwiss, 2017), downscaleR (Bedia et al., 2017), visualizeR (Frías et al., 2017) and transformeR (Bedia & Iturbide, 2017).

3.4 Results

3.4.1 Farmers Expectations and Hydro-climatic information needs for rice farming decision making

In the face of difficulties posed by climate variability, farmers report having limited access to reliable sources of hydro-climatic information to support their farm decisions. Results showed that almost half of the farmers (43.5%) rely only on experiences and personal predictions based on indigenous ecological knowledge. For example, the croaking of a frog and the movement of ants from their hole is an indication that it will rain the next day. During the workshop, one farmer complained about existing hydro-climatic information available: "*Those people [providers of the hydro-climatic information] are liars, I do my own thing and I don't' rely on them at all. When I say it will rain it will, except for a few occasions when it rains unexpectedly*". More than half of the farmers (56.5%) use indigenous forecast alongside climate forecast information from GMET via radio, TV and in some cases through ESOKO (information service provider for agriculture), and from extension officers of the Ministry of Food and Agriculture. When asked about barriers for the use of hydro-climatic information, farmers mention inaccuracy and untimeliness of information, difficulties interpreting technical information and language barrier. Another reason for farmers not to use forecasts provided by GMET is that these do not fit their purpose, and are provided at a regional scale and do not match the situation in their communities. They showed good understanding of how hydro-climatic information could support their farm decisions and lives; frequently reported benefits include seed usage, rice yield, and appropriate water management, saving money and having enough food for the family.

Throughout a farming cycle, farmers make decisions for which they require information on climate and water (Table 3.2). Pre-season decisions require information mostly on rainfall onset, rainfall distribution, and rainfall amount. Decisions during the season such as land preparation and planting also require information on rainfall onset. The dam water level was highest on the priority list of farmers engaged in irrigation. Temporal distribution of rainfall is the most important information to determine when and how much fertilizer to apply and when to conduct pest- and weed-control. Wind speed and direction was most important for spraying weedicides. However, farmers expressed little need for this information as they already spray early mornings to avoid strong winds. Finally, rainfall cessation and temperature were most needed information to start harvesting, although rainfall distribution and amount are critical to choosing a harvesting method. For instance, it is better to harvest with sickles and knives on wetter than normal fields than use reapers or combine harvesters.

Table 3.2: Percentage of farmers in need of particular information for farm

Farm Management Action	Decision	Rainfall Amount	Rainfall Distribution	Rainfall Onset	Rainfall Cessation	Dam Water Levels	Temperature	Wind Speed	Wind Direction	None Of These
Pre-Season	Buying seeds	53%	77%	**79%**	11%	19%	8%	2%	2%	-
	Seed variety	68%	**86%**	79%	73%	52%	69%	8%	10%	-
	Land size and allocation	**68%**	57%	10%	3%	16%	2%	-	-	7%
	Labour size	**58%**	48%	5%	2%	15%	-	-	-	10%
Land Preparation	When to clear land	5%	48%	**86%**	-	2%	-	-	-	-
	Plowing	3%	48%	**89%**	-	-	-	-	-	-
	Harrowing	3%	44%	**89%**	-	-	2%	-	-	-
Planting	Nurse seeds	3%	44%	**58%**	2%	19%	15%	-	-	11%
	Transplanting seedlings	2%	47%	**57%**	2%	15%	16%	-	-	13%
	Direct seeding	5%	61%	**66%**	2%	8%	15%	-	-	8%
	Sowing method e.g. broadcast by hand or machine.	**39%**	32%	10%	-	8%	5%	-	3%	24%
Irrigation	Additional irrigation	13%	36%	7%	5%	**63%**	2%	-	-	11%
	Amount of water for irrigation	16%	39%	5%	3%	**60%**	3%	-	-	11%
Fertilizer Application	Kind of Fertilizer to buy	**42%**	44%	2%	2%	2%	2%	-	2%	21%

	First fertilizer application	7%	**73%**	29%	10%	-	-	10%	10%	8%
	Second fertilizer application	5%	**74%**	27%	11%	-	-	10%	10%	7%
Weed Control	Type of weedicide to apply	39%	**48%**	5%	2%	-	-	2%	7%	21%
	Timing of first weed control	5%	**68%**	15%	3%	2%	-	29%	40%	3%
	Timing of second weed control	2%	**68%**	15%	5%	2%	-	32%	39%	3%
	Timing of spraying weedicide	2%	32%	8%	2%	-	2%	45%	**66%**	2%
	Type of weed control method (e.g. hand or weedicide)	29%	34%	2%	0%	0%	0%	5%	7%	**37%**
Pest Control	Type of pesticide to buy	26%	37%	0%	0%	0%	0%	3%	5%	**37%**
	Timing of first pest control	0%	**50%**	10%	5%	0%	0%	31%	39%	10%
	Timing of second pest control	0%	**52%**	10%	5%	0%	0%	29%	39%	10%
Harvesting and post-harvest	Start harvesting / drying	10%	57%	7%	**66%**	5%	**66%**	3%	2%	13%
	Method of harvesting to choose (e.g. by hand or machine)	16%	**57%**	2%	23%	2%	23%	0%	0%	7%

Bolded values represent the information needed by the highest percentage of farmers for a specific decision

These results were further confirmed during the evaluation workshop. Farmers ranked rainfall distribution, temperature and dam water level ranking most important followed by total rainfall amount and onset as fairly important before cessation. Wind speed and direction were considered the least important among all the information needs. Temperature and precipitation patterns were found relevant by all farmers irrespective of geographical location or type of farming except dam water level which was top on the list of irrigating farmers (see Table 3.1 of supporting material). Farmers consider the timing of information provision as essential for making decisions and mobilizing resources for farming activities. When asked about which times they would prefer to receive seasonal climate and hydrological (dam water level) information, 74% preferred 1-month lead time, 24% preferred 2 months and only 2% preferred 4 months lead time. Of the 42 rice farmers (IO and B) who required hydrological information, 67% preferred a month lead time and 33% preferred a 2 months' time lead.

3.4.2 Forecast Evaluation

Following the needs assessment, the skill assessment of the ECMWF-S4 climate forecast was performed on three different lead times i.e. 0, 1 and 2 months. Rainfall, minimum and maximum temperature were evaluated by validating forecast with observation to determine their performance in the study area.

3.4.2.1 Rainfall Verification

Analysis of rainfall forecasts showed a general mixture of wet and dry biases (-2 mm/day to 1 mm/day) (see figure B3 of the supplementary document). In most cases, however, rainfall was underestimated (dry bias) except for the upper west region where JJA (June, July, August; peak monsoon season) for all lead times and SON (September, October, November; monsoon cessation) (lead time 0) showed some spread of overestimation (wet bias) of rainfall which decreases with lead time. Dry bias was high in MAM (March, April May; monsoon onset) (irrespective of lead time) compared to SON and then JJA. Wet bias was found largely in the western part of the Northern Region and Upper West region for JJA for all lead times and in Upper West region only for SON lead time 0. Change in bias with respect to forecast lead times could be attributed to the existing influence of local features such as surface topography (see also Ogutu et al., 2016) and for that reason the initial conditions for which the model was run.

For rainfall, there was a positive correlation (0.2≤ r ≤0.6) between forecasted rainfall and observations (significance correlation most grids) for the entire study area for all lead times of SON and JJA. MAM showed a mixture of lower positive and negative (-0.3≤ r ≤0.2) correlation for a large part of Northern region. Negative correlations were mostly found in the northern region at lead time 0 and 1 and Upper East and north of West region at lead time 2. SON showed the strongest correlation followed by JJA before MAM. There is, however, no drastic change in correlation for each season per lead time, except in the Northern region where MAM and SON showed low correlation at an increasing lead time (see figure B4 of supporting document).

Summarizing results showed that rainfall forecasts are able to discriminate between varying observations in large parts of the study area (Figure 3.2). This is the case for all seasons except for the MAM period when the Northern region (lead time 0 and 1) and Upper east region (lead time 2) exhibited poorer skills. SON rainfall forecast is found to be more skilful than JJA. MAM only showed patches of skills in the Upper East and West region (lead time 0 and 1) and for the northern region (lead time 2). Interestingly, while the skills of the forecasted rainfall generally decrease with lead time in JJA and SON, it gets slightly better with lead time in MAM.

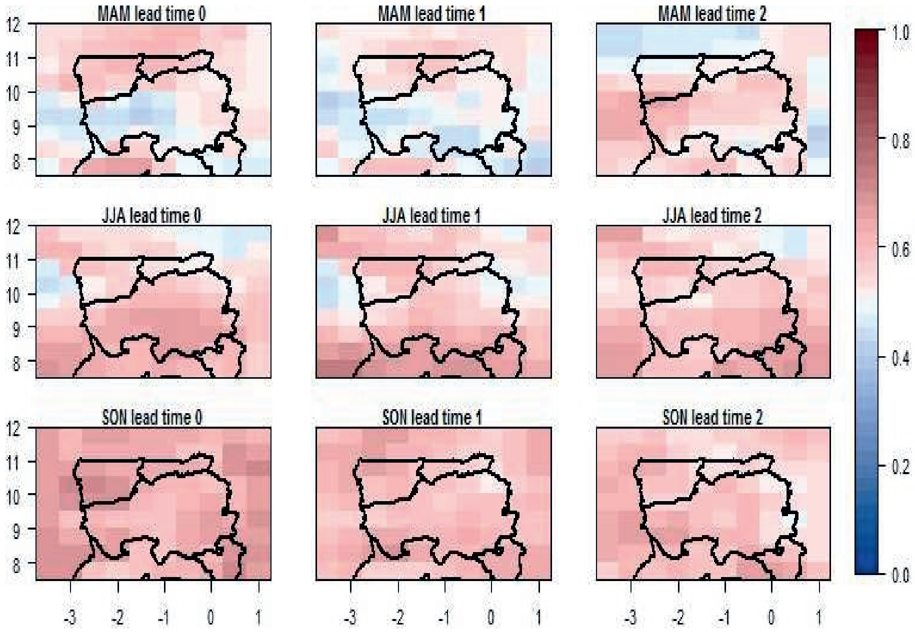

Figure 3. 2: The generalized discrimination score for rainfall (JJA, MAM and SON) ECMWF System4 forecasts against verifying observations from WFDEI for 1981-2010.

The year-to-year tercile performance of rainfall forecast for the entire study area through the exploration of the observation position and the forecast probabilities are shown in Figure 3.3. Tercile probability of 30% – 100% dominated the entire 40 years' period for all lead times. In general, SON showed higher skills than the other seasons especially in the upper and lower tercile of lead time 0 and also at the lower tercile of lead time 1 and 2. The skills within the upper tercile of SON reduce slightly with lead time while the rest differs with lead time. Below and above normal rainfall, forecasts are generally more skilful than the climatological forecasts in all season, except in MAM (lead time 1) and JJA (lead time 0 and 1) where lower and upper tercile showed poor skills. Lower tercile exhibited comparatively higher skills than upper tercile in all season MAM lead time 1.

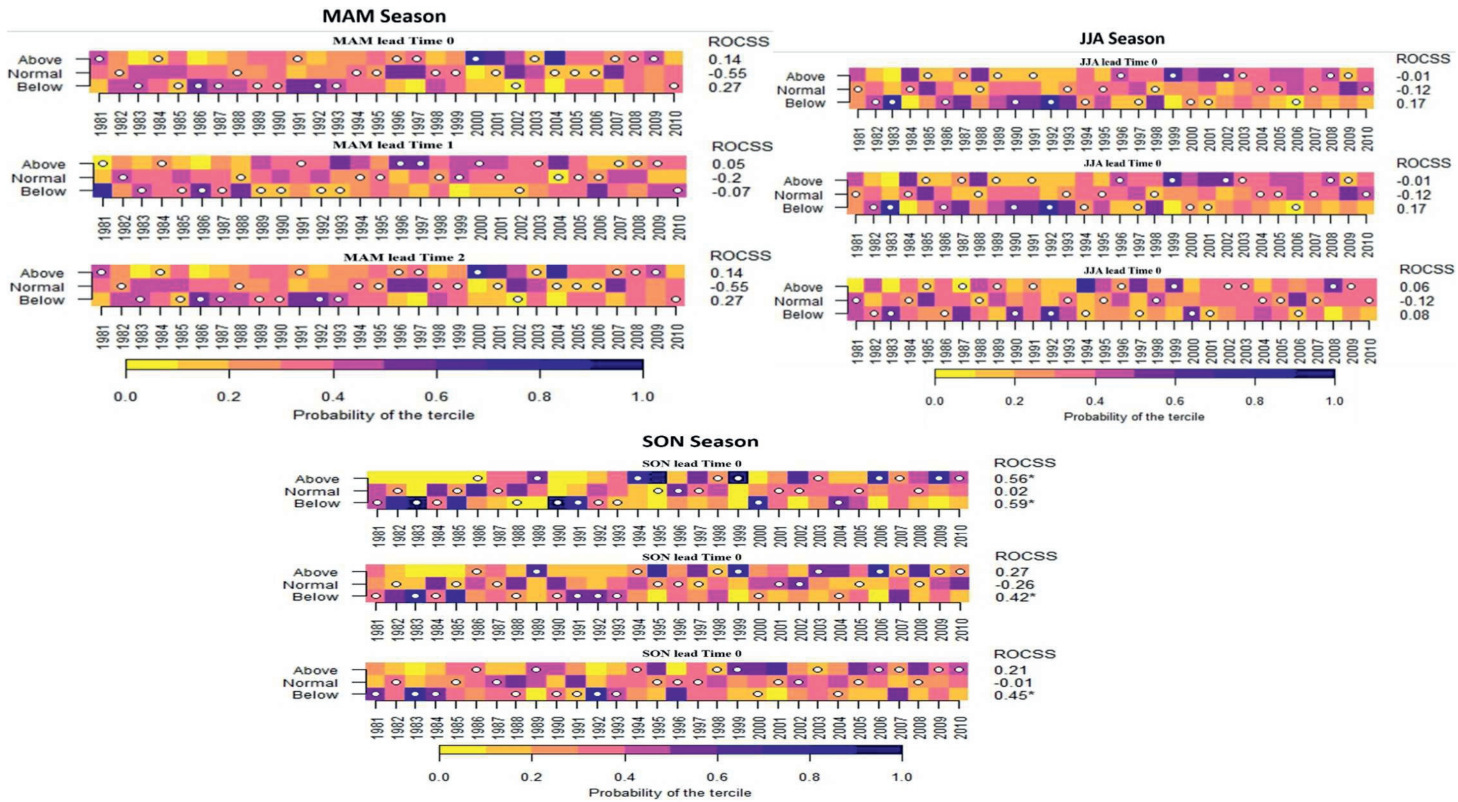

Figure 3.3: Yearly tercile plot of forecast rainfall (1981-2010) over entire Northern Ghana for MAM, JJA and SON seasons. (Shades shows tercile probability, white dots indicate tercile of the observations for each particular year and ROCSS is for the entire study area and for all years). Asteris indicate significant score at 95% level.

3.4.2.2 Minimum Temperature Verification

Tmin forecasts showed a dominating cold bias (up to -2.8 $_{o}$C) for large areas and for all seasons irrespective of lead time (See figure B5 of supporting document). There were, however, spots of warm bias in north eastern part of Northern region for JJA lead time 1 and 2 (stronger in lead time 2 than1). MAM showed higher cold bias compared to SON and JJA. Each season showed similar trends of cold biases irrespective of lead time.

Despite the recorded biases, forecast and observed Tmin showed a positive correlation ($0.4 \leq r \leq 0.6$ dominating grid cells) in MAM, JJA and SON of almost all areas of the study and for all lead times. The correlation in MAM and SON forecasts is weaker in some grid cells but nearly constant in JJA with lead time. SON showed some patches of poor correlation in the north western and north eastern part of Northern region at lead time 2 and extreme eastern part of upper west at lead time 1 and 2 (figure B6 of supporting document). A significant correlation was observed in most grid cells in JJA for all lead times. MAM also exhibited significant correlations in large part of the study area except for the upper west region in lead time 2. A large part of the Northern region exhibited a significant correlation for lead time 1 than 2 before 0. The results of the generalized discrimination score in Figure 3. 4 showed considerable skill in the Tmin forecast in almost all the study areas and lead times. JJA is comparatively skilful than MAM and then SON. Spots of poor skills at the western part of Upper West and south-eastern corner of Northern region for all lead times were found in SON. The poor skill in these areas, however, got poorer with lead time. Generally, the skill of the forecast (Tmin) was nearly constant with increasing lead time.

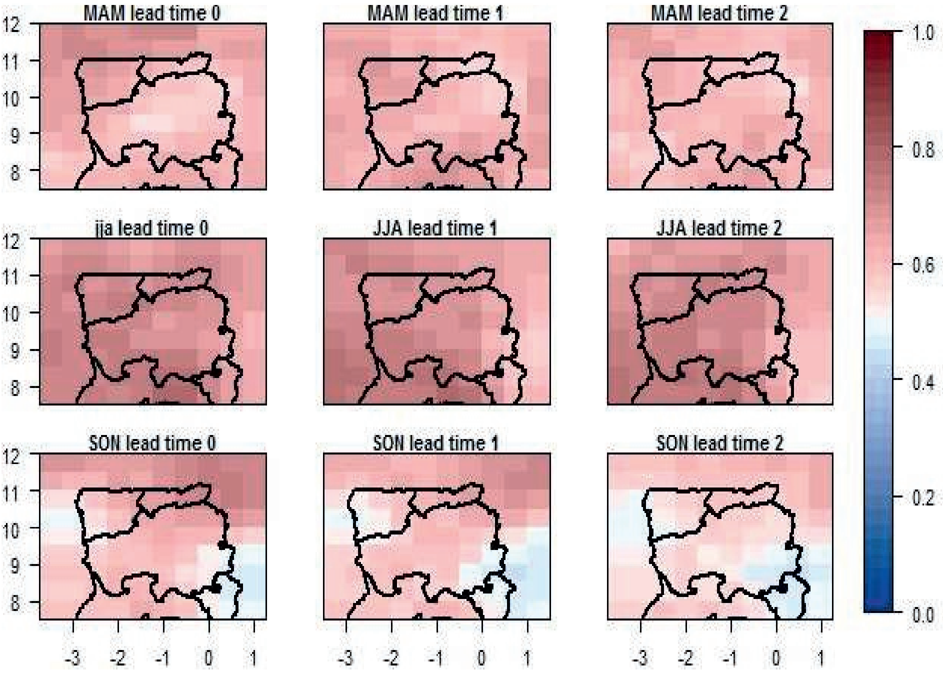

Figure 3.4: The generalized discrimination score for Minimum Temperature (JJA, MAM and SON) ECMWF System4 forecasts against verifying observations from WFDEI for 1981-2010.

3.4.2.3 Maximum Temperature Verification

Tmax showed a cold bias in all parts of the study area for all seasons and lead times (see figure B7 of supporting document). SON showed higher cold bias compared to JJA and MAM. For all the seasons, cold bias showed nearly a constant change in bias with lead time. In spite of the dominating cold biases across the study area (see figure B7 of supporting document), Tmax showed skills across the study area for all seasons and lead times (Figure 3.5). Tmax exhibited a strong relationship between its forecast and the observation in most of Northern Ghana (see figure B8 of supporting document). The relationship between Tmax forecast and observation was generally better in MAM compared to JJA and before SON. It was however comparatively weaker at lead time 1 of JJA and lead time 1 and 2 of SON. The correlation, therefore, reduced with lead time for all seasons but not consistently. MAM and SON at lead time 0 showed a significant correlation in all parts of the study area. However, SON (lead time 1 and 2) showed no statistically significant correlation. Few grid cells in the northern region showed significant correlation for all lead times in JJA and MAM lead time 1 and 2.

Tmax showed extensive skills (MAM higher than JJA and then SON) across the study area for all seasons and lead times (Figure 3.5). Nonetheless, spots of poorer skills were seen at the southern part of Northern region in lead time 1 of SON and at the south and north of Northern region at lead time 2 of SON. Tmax recorded a slight decrease in skills over lead times for MAM and SON while JJA recorded a reduced skill from lead time 0 to 1 but an increase in lead time 3.

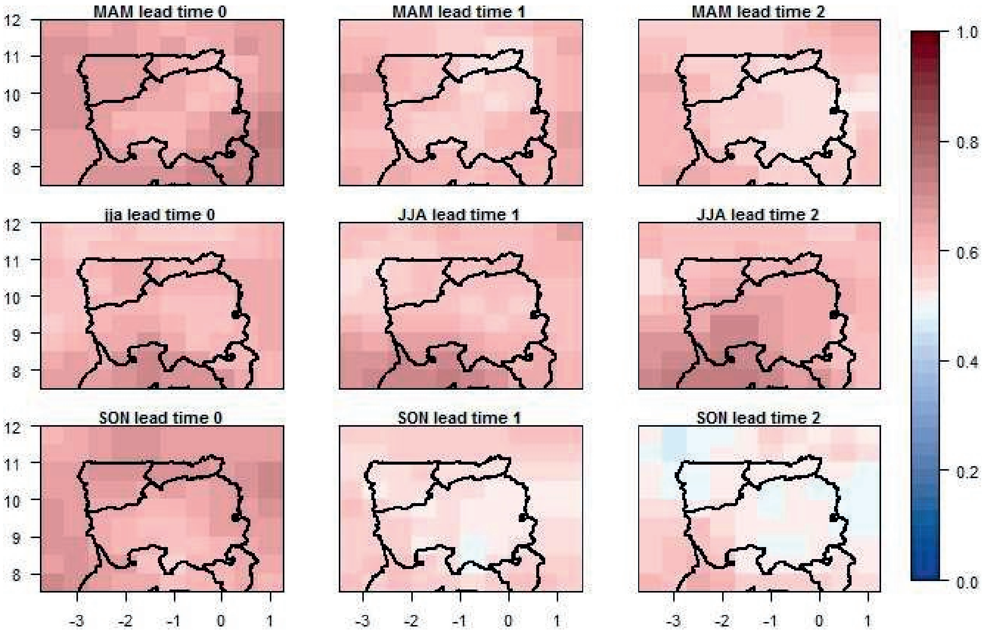

Figure 3.5: The generalized discrimination score for Maximum Temperature (JJA, MAM and SON) ECMWF System4 forecasts against verifying observations from WFDEI for 1981-2010.

3.4.3 Accuracy and association of forecast and the verifying observation

For all the studied variables (rainfall, minimum and maximum temperature), bias is found in ECMWFS4. The model showed dry bias for rainfall (Prcp), and cold bias for minimum temperature (Tmin) and maximum temperature (Tmax) in large areas of the study region. While dry bias and cold bias dominates rainfall and temperatures simulations respectively, the wet bias in JJA rainfall is seen in the western part of the Northern and upper west region. The existence of bias in the forecast may be due to the inability to accurately simulate the mesoscale systems over West Africa (Afiesimama et al, 2006).

Forecast lead time was observed to have little to no effect on the bias and in most times the change was not consistent. Unlike Tmin and Tmax which showed similar bias in all seasons, rainfall exhibited a unique bias in each season. The reason could be differences in mechanisms associated with each season and variation in local features such as vegetation and topography (Indeje et al., 2000).

Despite the biases in the forecast, an overall strong correlation was found between the forecast and observation. The correlation was however poor for MAM Prcp in the Northern region, and north of Upper East and West region. Tmin recorded the strongest correlation in all lead times of MAM and JJA. Tmax, on the other hand, showed correlation in each season but slightly reduce inconsistently with lead time. Prcp, Tmin and Tmax generally showed some significant correlation in parts of the study area.

3.4.4 General performance of the forecast over the study area

Using the generalized discrimination score (Weigel & Mason, 2011), the forecast was able to discriminate between varying observations and thus skilful over large areas of Northern Ghana. Forecasted SON rainfall was more skilful than JJA and MAM. Lower rainfall predictability skills found in MAM could be due to the inability of ECMWF-S4 model to capture well local features and processes. The skills of the forecasted rainfall were not severely influenced by the lead time. The skills exhibited by both Tmin and Tmax were homogeneous. For Tmin however, JJA exhibited slightly higher skill compared to MAM and then SON. Tmax showed higher skill in MAM as compared to JJA and then SON. Good skills in Prcp, Tmin and Tmax for all seasons and lead times make ECMWF-S4 seasonal climate forecast potentially able to meet the identified hydro-climatic information needs of farmers. A summary of the skills according to season and lead time is showed on Table B2 of supporting document.

3.5 Discussions

The main aim of this paper was to study rice farmers' hydro-climatic information needs in Northern Ghana and assessed the performance of ECMWF-S4 seasonal climate forecast in meeting those needs. The study provides better insight for understanding a demand driven climate information services; farmers' have critical seasonal hydro-climatic information needs and unequivocally requires this information within a particular time period for adaptive decision making.

Results show that almost half of the farmers rely on their indigenous forecast for their farm decision making. These forecasts are based on observation matched with long time experiences. Also, Gwenzi et al. (2016), Roncoli et al. (2002), and Zuma-Netshiukhwi et al. (2013) observed that farmers highly depend on indigenous forecast for most farm decision making. Meanwhile, some other farmers use climate information from the national meteorological agency (GMET) and other private communication organizations such as ESOKO. This result is consistent with existing reports on climate information services in Ghana (ESOKO, 2016; Farm Radio International, 2014; Gbetibouo et al., 2017), which state that climate information services are gradually taking root in Ghana and has the potential to help farmers survive adverse effects of climate variability and change. However, almost all farmers find climate information from GMET and ESOKO unreliable and therefore willing to access and use improved climate information from alternative sources if available.

Located in an area with a constantly varying and changing climate, rice farmers could potentially improve their production if they have accessible and usable climate and water information. To do this, however, it is essential to have good inventory of key farming decisions that are responsive to climate and water information so that information generated forecast products can be tailored to support their farming decisions (see also Stone & Meinke, (2006). Also, engaging farmers in formulating these needs will increase their trust for the forecast systems. We found that farmers' information needs are linked with specific farming decisions and stages of the growing season, which makes the timing of providing information relevant. Key information needs relate to rainfall and temperature (c.f. Iizumi & Ramankutty, 2015; Lambert, 2014)

Previous studies have shown how climate variability adversely affects yield and farmers' decision making and the challenges of providing accurate hydro-climatic information for adaptive decision making vis-à-vis seasonal time-scale (Feleke, 2015; Hansen et al., 2009; Ouédraogo, Zougmoré et al., 2015). For seasonal forecast, lead time of a month and beyond has previously been a problem even for the best models limiting its usefulness for farmers (Hansen, 2002). The performance of ECMWF-S4 was mostly independent of season and lead times, which is promising for meeting farmers' needs up to a lead time of 2 months.

This study uses seasonal average as a proxy to assess performance and discuss the possibility of meeting farmers' needs. Further study is needed to make stronger claims on the predictability of each information need with ECMWF-S4. For example, onset and cessation are expressed in calendar dates while dam water level requires a hydrological method to determine its predictability. Nonetheless, the existence of skill in the analysis showed potentials in predicting the identified information needs. For instance, skills in tercile predictability of above and below normal rainfall could provide information on rainfall amount and seasonal flow of water to the irrigation dam. Based on the results of the GDS and ROCSS analysis, Table B2 in supporting document synthesizes these possibilities taking into account the limitations 524 associated with the current analysis.

Generally, ECMWF-S4 is able to simulate well the inter-annual variability, spatial patterns and structure of Prcp, Tmin and Tmax for all seasons at different lead times except MAM in the northern region and north of upper east and west region (figure B4, A6 and A8 of supporting document). This has great implications since increasing rainfall variability results in higher risk for farmers (Graef & Haigis, 2001; Ochieng et al., 2016). Rice farmers in Northern Ghana already complain of loss of seeds at the beginning of the raining season due to delay in rainfall onset and variability between March and May (Ndamani & Watanabe, 2013). While GDS and ROCSS are important attributes for assessing forecast skills, forecast with high discriminative power may still be subject to systematic errors and may require post-processing such as bias correction to become useful (Weigel et al., 2007; Weigel & Mason, 2011). A bias of up to 2 mm/day and 2 to 3 degrees as observed in Tmin and Tmax could adversely affect farm decisions. These forecast biases could be attributed to the consequence of the intrinsic limitations of the physical models related to parameterizations, equation simplification and uncertainties in the initialization procedure (Doblas-Reyes et al., 2013). Such biases could, however, be mitigated through the application of bias correction techniques that are normally based on statistical methods using antecedent series of forecasts and observations (Peng et al., 2014; Piani et al., 2010; Weigel et al., 2007). However, studies have shown that bias correcting ECMWF-S4 probabilistic forecast does not necessarily improve forecast skill (Ogutu et al., 2017) but enhances the usability of the forecast by improving the root-mean-square error (Barnston et al., 2015).

Finally, in this study, we have used an interdisciplinary approach by combining a needs assessment with a forecast skill test, in order to assess the potential for meaningful climate services for local-level decision support. The approach enabled a broader contextualisation of existing research on seasonal climate forecast verification and farmers' information needs which is often done in isolation. In this way, we are able to move away from one directional approach of looking at climate services to two directions where needs and skills are clearly documented and synthesised. Our findings demonstrate the value of linking climate forecasts to farm-level decision making. As such, this study contributes to the need of better matching hydro-climatic information services with needs of end-users and important calls to improve climate services (Stiller-Reeve et al., 2015; Street, 2016; Vogel et al., 2017). Following Stone & Meinke (2006), we showed that developing appropriate interdisciplinary systems to connect forecast products with farm management is needed if uptake of weather and climate information by farmers is to be successful.

3.6 Conclusion

This paper has addressed key aspects of climate information services: matching information needs and forecast performance. Results show homogeneity in rice farmers' hydro-climatic information needs although some of these needs are ranked higher than others depending on the frequency of use and farming type. Majority of farmers prefers to receive hydro-climatic information within a month lead time for proper planning and decision-making. Our analysis concludes that this is possible. ECMWF-S4 possess some skill for forecasting Prcp, Tmin and Tmax in Northern Ghana. The skill varies per season and location but barely on forecast lead time, having significant implications for meeting rice farmers' information needs in Northern Ghana with improved seasonal climate forecast at different lead times. The ECMWF-S4 seasonal climate forecast, therefore, has the potential to provide farmers with information that improves their farm decision making. Yet, information services will require a careful introduction to increase trust in using more tailored results from the forecast systems. Finally, we recommend that due to the limitations of this study discussed in section 3, further research is needed to make stronger claims especially on the predictability of each information need with ECMWF-S4.

Acknowledgements

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4

Chapter 4

Techniques and skills of indigenous weather and seasonal climate forecast

Abstract

There are strong calls to integrate scientific and indigenous forecasts to help farmers' take actionable decision to adapt to climate variability and change. Some studies have investigated indigenous people's techniques for forecasting weather and seasonal climate, yet little is known about the skills or accuracy assessment of their forecasts. Here, we show how farmers use indigenous ecological indicators (IEI) to make weather and seasonal climate forecasts and how accurate these are compared to scientific forecasts using a quantitative approach. Expert farmers in Northern Ghana were selected and trained to send their daily rain forecast and record observed rainfall with mobile apps and rain gauges respectively. Using participatory workshop we identified and characterized the main IEIs for forecasting. Mental model was used to establish the relationship between IEIs and phenomenon forecasted. Results show that farmers have an established cognitive model of the relationship between IEIs and phenomenon predicted and these relationships are subject to modification over time due to environmental changes. Indigenous forecasts are rationally generated; a skill that increases with age and experience. On average, both farmers and Ghana Meteorological Agency (GMet) were able to accurately forecast one out of every three daily rainfall events. Performance at the seasonal scale was not much different, though GMet was unable to predict rainfall cessation in all communities. We conclude that knowledge possessed by local farmers can contribute to climate science and policy development by offering observations and interpretation at a much finer spatial scale with considerable temporal depth, and by highlighting aspects that may be overlooked by climate scientists and policymakers. This is especially so for rural communities where meteorological observations are not available. Finally, the approach adopted in this study empowered farmers and develop their capacity to become more aware of the spatial and temporal variability in rainfall.

Submitted as:

Nyadzi, E., Werners, E. S., Biesbroek, R., & Ludwig, F. (under review). Techniques and Skills of Indigenous Weather and Seasonal Climate Forecast in Northern Ghana.

4.1 Introduction

The weather and climate have a significant influence on crop growth, development and yield as well as pests and diseases infestation, water needs and fertilizer requirements (Doblas-Reyes et al., 2003). The variability of the weather and climate is beyond human control. However, being able to forecast the weather and seasonal climate accurately and timely help farmers to adapt farm decisions from time immemorial (Banerjee et al., 2003)

Around the world, people use indigenous ecological knowledge (IEK) to improve understanding of their living environment. They make regular observations and match them with their experiences and historical knowledge (Olsson et al., 2004; Orlove et al., 2010). The generality and applicability of IEK have been studied across the globe (Desbiez et al., 2004; Cabrera et al., 2006;) and in Africa (Gray & Morant, 2003; Orlove et al., 2010). In this study, we focused on the use of IEK for weather and seasonal climate forecast which has been referred to by (Vervoort et., (2016) as indigenous forecast (IF).

Across the globe farmers still use IF today to adjust their farm practices or diversify their production to respond to local climate variability (Eriksen et al., 2005). Here, we define "indigenous" as native or local and "forecasting" in its elementary form as a prediction of a future occurrence or condition.

Scientific advancements now make it possible to provide short and long-term climate information services to support farmers' decision-making. Several studies showed that farmers use a combination of meteorological information and indigenous knowledge in their weather and seasonal climate forecasting decisions (B. Orlove et al., 2010; Roudier, Muller, D'Aquino, et al., 2014). Although farmers use IEK for forecasting weather and seasonal climate patterns, they are the first to also recognize the limitations in terms of accuracy, timing, and reliability (Roncoli et al., 2002). Studies have also shown that IEK can serve as a basis for developing adaptation and natural resource management strategies and for understanding the potential for certain cost-effective, participatory and sustainable adaptation strategies (IPCC, 2007; Nakashima et al., 2012). Only relatively few studies have explored indigenous ecological knowledge in weather and seasonal climate forecasting and even those that attempted did so qualitatively (Manyanhaire & Chitura, 2015; Roncoli et al., 2002). Furthermore, among those who have studied IF for agriculture production, very few have looked at the underlying mechanism (techniques) for IF and particularly quantitative test skills in these forecasts.

In this study, we address the research question "How accurate are indigenous forecasts of farmers and what are the underlying mechanisms behind farmers' forecasting techniques?". We define forecast technique as the ways in which indigenous forecasting is carried out among local people using local ecological indicators and forecast skills as a measure of accuracy of prediction to an observation. We approach this question in two ways; first, we capture farmers' mental model of how IEIs are used to predict the daily and seasonal rainfall. Secondly, we use binary or dichotomous forecast verification measure to determine the skills in farmers' rainfall forecast compared with the Ghana Meteorological Agency (GMet) forecast. The intention is not to discredit the forecasting skills of farmers or GMet but rather to elaborate on the value of IF and contribute to the argument of integrating both systems for improved weather and climate information services. We focus on rainfall because most communal areas in Northern Ghana practice rain-fed subsistence agriculture (Manyanhaire and Chitura, 2015), and their information need is largely focused on rainfall (Nyadzi et al., 2019). We also selected Northern Ghana because climate variability and change is greatest in this area of Ghana making the communities more vulnerable with consistent crop failures (Gbetibouo et al., 2017; Nyadzi et al., 2018).

4.2 Materials and Methods

A multi-stage approach (see figure 4.1) to identify indigenous ecological indicators (IEI), semi-quantify the relationship between the identified IEIs and the type of phenomenon forecast (rain amount and type, onset cessation etc.) was used. This approach also allowed the quantification of skills (i.e. accuracy) in farmers forecast.

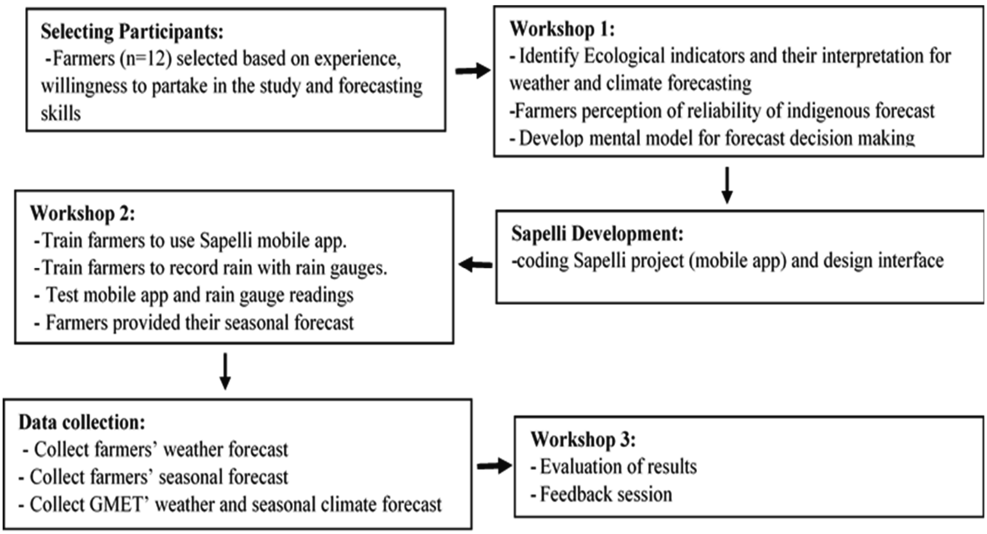

Figure 4.1: Methodological flow of the study

4.2.1 Data collection

Through informal discussions with the head of farmers' association, the manager of the Botanga irrigation scheme and an extension officer for the area, twelve experienced farmers were selected from twelve different communities in Kumbungu district in Northern, Ghana. The selected communities and their locations are shown in Figure 4.2. These farmers practised both irrigated and rainfed rice farming. Each farmer in this study hypothetically represents a forecast system providing forecast and a meteorological station recording observed rainfall for each community. Therefore, although selecting many farmers in each community is not a bad idea, one farmer for each community was representative enough for the exercise. Moreover, we were introducing these farmers to smartphones and mobile apps for the first time and selecting these number allowed us to properly monitor and obtain detail insight into the process for future data collection. The process of selecting these farmers was rigorous and they were representative of farmers with good forecasting techniques and skills. The selection was also based on experience in using indigenous forecast and willingness to partake in the study.

Our initial inquiries show that not all farmers are good at forecasting using indigenous ecological indicators (IEIs). Also, farmers were aware of those good at forecasting in their communities and so, we agreed together who will be involved in the training and forecasting. Moreover, only few farmers were known to have the technique and good skills for forecasting and so we did not collect forecast using surveys from randomly selected farmers. We purposively selected our expert farmers based on their forecast techniques and skills. In general, local forecast experts are known for having this skill (e.g. reading the stars or the direction of the wind) in their community. The selection of these 12 expert farmers was rigorous in order to reduce risk and generate quality data for our analysis. The selection process includes the active involvement of members of the community, manager of the irrigation scheme and extension officers during a workshop. It was clear that community members were aware of who is good at forecasting in their respective communities and so we decided together who will be involved in the training and forecasting. In addition, during the meeting and before the final selection we asked the pre-selected farmers how many rainfall events could each farmer accurately predict out of 10 events. We selected those with the highest numbers. All participants agreed to the selected farmers.

It is not new that Humans are able to forecast the weather and seasons using IEIs since time immemorial. Weather and seasonal climate forecasting models also provides forecast using what we called initial conditions such as wind direction, surface pressure etc. It is also a fact that the IEIs used by humans' changes just as initials conditions used in forecasting models change. Therefore, while differences exist in several aspects of both systems, our focus for comparing both systems are based on the fact that they both provide forecast of the same parameter. In this study, we did not consider humans as weather stations in a literal sense. These expert farmers were given rain gauges to record the rainfall in their community as an observation which we compared to their own forecast for verification. Moreover, we agree that there are several schools of thoughts on scientific reductionism. For those in the field of development, this could be an issue that can affect results. Yet this approach is valid for studies in the field in meteorology and climate forecasting. For instance, one area that uses reductionism extensively is in modelling, forecasting and understanding the weather. If a scientist designs a computer program to model and predict weather patterns, they cannot possibly include every single permutation of such a vast and complicated system. Instead, they simplify many of the elements to allow the program to work without losing accuracy. This was the case also in our study. We could not have considered all other parameters of each farmer. A good reason to select and work with expert farmers who have ample knowledge about indigenous forecasting.

Prior to the rainy season, two workshops (Plate B1-B6) were organized in March 2017, to collect information about IEIs and train farmers. During the first workshop, farmers were asked about their confidence in their own forecasts, key IEIs were identified and collectively discussed among participants, and key terminologies were explained (see Table C1 of the supplementary document). A mental model was used to conceptualize the degree of influence of each IEI on a phenomenon forecast. The developed mental model was analysed using a matrix (Table C10 of the supplementary document) in the mental model software (http://www.mentalmodeler.org/) to define cumulative strength of connections between elements of the system (Gray et al., 2013; Özesmi & Özesmi, 2004). The second workshop aimed at training farmers in two key areas; (i) how to use an android based mobile app to record 24 hours forecasts (see Plate C3) and (ii) How to record observed rainfall using a simple rain gauge. We recognized that timing is very crucial for the data recordings. Therefore, we followed similar timing just as GMet. Rainfall observed are recorded at 9 am against the previous day, and forecast at 6 am for the next 24hours. To ensure farmers stick to this schedule, we set alarms on their mobile phones to remind them on a daily basis. After the training, trial exercises were carried out with the mobile app and rain gauges. The seasonal climate forecasts for the year 2017 were also collected from each farmer during this workshop. We chose to use a mobile phone application for collecting farmers' forecasts for two main reasons; first, to monitor forecast by date, time and location. Secondly, to appreciate how farmers with low literacy levels interact with ICT based tools for future information exchange.

Farmers' weather (24hrs) forecast and observation data for 214 days were collected from April – October (2017) using the Sapelli mobile app (Stevens, Vitos, Altenbuchner, et al., 2013). Weather and seasonal climate forecast data for the same period was acquired from the Ghana Meteorological Agency (GMet). At the end of the data collection period, a third reflection workshop was organized to evaluate the process and discuss preliminary results, challenges and prospects for future hydro-climatic information services.

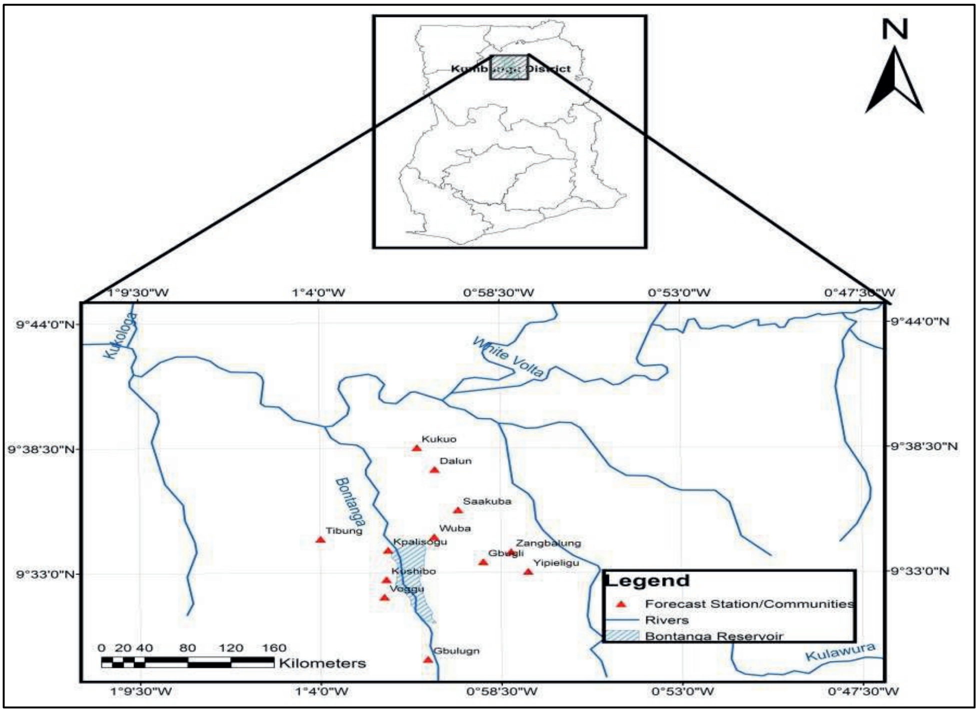

Figure 4.2: Map showing the location of selected communities in Northern Ghana. Socio-institutional and biophysical characteristics of the study area have been described by Nyadzi et al., (2018).

4.2.2 Data analysis

Data were analysed in three main ways. First, the grid function of the mental modeller was used to analyse the relationship (probability of influence) that each IEI had with a predicted phenomenon. Second, 214 days of observational and forecast data from 12 farmers and GMet was used for the statistical analysis. We analysed spatiotemporal variations (monthly, seasonal and annual totals) in GMet and farmers' observed rainfall data using excel 2016 version. Also, we evaluated the skills (accuracy) in predicting rain (Yes/No) and the types of rain (low, medium and high rainfall) using a dichotomous forecast verification method based on the recommendations of the World Meteorological Organization and widely used by meteorologist to evaluate forecast (Mason, 2003; Mariani et al., 2007; Bumke et al., 2012; WMO, 2014; Fekri & Yau, 2016). A 2×2 contingency matrix was generated using a pivot table in excel 2016 version. The pivot table was used to evaluate the sequence of the binary forecasts as a performance measure to determine the number of *(a) hits, (b) false alarms, (c) misses, and (d) correct rejections* (Hogan and Mason, 2012). We estimated onset from farmers' observation by looking at any week in the initial period of a rainy season, within which rainfall amounts total at least 25 mm (Popov & Frere, 1986). We also tested the statistical difference among the 12 farmers, and between farmers and GMet forecast and observation at an alpha level of 95% using R statistical programme. The average performance of farmers was estimated by calculating the average hit rate of the 12 farmers. The performance of GMet forecast in each community was also computed by comparing GMet forecast against each of the community's observation. We also compared GMet and farmers forecast skills. We did this despite existing differences in location of rain gauges and spatial variation of rainfall because comparing the skills and not the method of forecast generation is still meaningful. However, it is worth noting that the performance of farmers forecast is an average of 12 farmers compared to GMet forecast though generated from multiple forecast models but from one source. Third, the reliability and usability of IEIs collected for the season were analysed in addition to forecasting certainty expressed as sure for high, so sure for higher and very sure for highest certainty. Usability denotes the number of times an IEI has been used. Reliability was estimated in two main ways; first from farmers' perception at the workshop presented in Table 4.1. Second, from the empirical data collected from the mobile app with a working definition of the number of times an IEI gave an accurate prediction out of the number of times it was used within the study period, all expressed in percentage. Details of the mental model, binary forecast verification and Sapelli are described in items B1, B2 and B3 of the supplementary document.

4.3 Results

4.3.1 Farmers' techniques and use of indigenous ecological indicators for forecasting

Findings from the workshops show that farmers in Northern Ghana use both indigenous forecasts (IF) and scientific forecast (SF), but give preference to IF because of its reliability for farm decision-making. They find their own indigenous weather forecast more reliable than their seasonal forecast. Farmers unanimously expressed much difficulty in predicting seasonal events than daily weather events, stating that indigenous ecological indicators (IEIs), are often not clear enough for long-term predictions. However, at the workshop, nine farmers claim they could forecast accurately 5 out of 10 times seasonal events such as onset, cessation and wetter/dryer/normal season.

Uncertainties in their own seasonal climate forecasts force farmers to complementarily use SF in addition to their IF. Farmers also recognize the difficulties in making IF in recent years because of continuous environmental changes.

Results show that farmers rely on a number of IEIs for predicting the weather and seasonal climate. Their forecast technique is based on observational changes in IEIs such as sound, phenology, shape and movements in the behaviour of animals, plants, insects and heavenly bodies (such as sun and moon). These observable changes in IEIs have their generally held interpretations depending on which event is to be predicted and whether for short or longer time scale (see Table 3). The presence of observable changes in IEIs generally indicates the occurrence of a particular event while their absence indicates the non-occurrence, except in some situations. For example, IEIs such as rainbow in the sky, lepisiota ant (Lepisiota capensis) carrying its eggs from uphill to downhill in the rainy season and a cloudless sky implies the non-occurrence of rains. According to the farmers, the reliability of IEIs for forecasting varies due to rapid environmental changes (Table 4.1).

Farmers consider forecasting techniques as a skill acquired through long-term learning process and therefore age and experience of the person are crucial for providing a reliable indigenous forecast. Forecasting skills are either learned from the elderly or developed through learning-by-doing, i.e. observation of changes in one's environment. Farmers also acknowledge certain individuals who are locally called "*sabanda*" meaning "bearer of rain knowledge". These persons are known in the community to have extraordinarily accurate prediction skills especially for long-term seasonal climate events. Their predictions are based on instincts, which is purported to be a divine gift, rather than from using IEIs. These individuals consult deity for rains when their communities are experiencing long term dry periods. For these reasons and the fact that their predictions are not rationale, such individuals were not included in our study.

Different IEIs are used to predict different weather and seasonal climate events, as well as their severity. The occurrence or presence of each IEI signals different probability for an event to occur. For example, to forecast daily rainfall; clouds, mosquitoes (Culicidae), butterflies (Amblyscirtes) and frog (Xenopus laevis) have a probability of up to 0.25, 0.5 and 1 for low, medium and high rainfall to occur respectively (see Table C1 for definition of low, medium and high rainfall). The other IEIs have varying probability with the type of rain to expect. The appearance of all the IEIs has different degrees of relationship with onset prediction except for stars and sun. Ants (Lepisiota capensis) and stars are the only indicators that have a relationship with rainfall cessation. For rainfall amount; all the IEIs have a varying relationship with below, normal and above normal rainfall except stars. Details of how each IEI influences the probabilities of an event are presented in the mental model (Figure C4 and Table C10 of the supplementary document). Results show that a large number of the same IEIs are used for both weather and seasonal predictions, depending on the signals they exhibit. However, IEIs such as dogs (Canis lupus familiaris), reptiles (such as snakes - family colubridae), stars and trees (such as baobab tree- adansonia digitate) are used only for seasonal climate forecast while soil texture, for example, is used for weather forecast only.

Table 4.1: Interpretations and reliability (based on farmers' perception) of indigenous ecological indicators for weather/seasonal climate forecast

Ecological indicator (local names)	**Reliability**	**Possible signs and their interpretation**
		WEATHER FORECAST
Earthworm (sambarigu)	***	The appearance of a large number of earthworms (Lumbricina) on the day is a sign of rains the next day or in few hours.
Clouds (sagbona)	***	Dark clouds amidst strong winds signal rain in few hours
		Clouds gathered at north-east imply rain in few hours up to the next day
Duck (gbinyaƒu)	***	Ducks (Anas Platyrhynchos) rapidly flapping, stretching their wings with loud quack sound signify rains in few hours and up to the next day.
Caterpillars (zunzuya)	***	Woolly bear caterpillars (larva) scurrying and burrowing into the soil is an indication of rainfall the next day or up to few days.
Butterfly (kahinpie)	***	A large number of butterflies (Amblyscirtes) continuously flapping their wings in the skies without taking shelter on leaves signals rains in few hours to the next day.
Fog (paƒli)	**	The appearance of fog indicates rain in the next few hours or the next day. Mostly low rains in the form of drizzle.
Wind (pohim)	**	Strong winds from west to east signal rain the next day.
Frog (pololi)	**	High-pitched sound of frogs (Xenopus laevis) in the rainy season strongly signals rains the next day
Birds (alacheyu)	**	Loud singing of coucal bird (Centropus sinensis) is an indication of rains in the next few days.
Cow (naƒnya)	**	Cows (Bos Taurus) repeatedly flapping their ears and tails indicate rainfall the next day or up to 3 days.
Hot weather (walgu be-ni)	**	High temperatures and humidity within rainy season signal rain in the next hours or day. Rainfall is expected the next day if temperatures are high during the night such that one sweats profusely and unable to sleep.

Ants (salinsahi)	**	A lepisiota ant (Lepisiota capensis) carrying its eggs uphill during the rainy season signals rain the next day or in few hours. A rapid increase in anthills in the surroundings indicates rains the next day or up to 3 days.
Moon (Goli)	*	A yellow looking ring around the moon is an indication of rains the next day or latest by 3 days. A downwards appearance of the moon crescent indicates rains the next day or in a few hours.
Sun (wuntana)	*	The appearance of a halo around the sun during the rainy season signals rain in the next day or few hours
Mosquitoes (duunsi)	*	Frequent and painful bites of mosquitoes (Culicidae) in the day during the wet season is an indication of rainfall the next day (latest up to 3 days)
Soil (tankpari)	*	Dry soil with fresh, sweet, powerful smell indicates rains the next day.
SEASONAL FORECAST		
Clouds (sagbona)	***	Cirrostratus clouds indicate the onset of the rain in few days. The thicker they get the closer the rains.
Duck (gbinyaƒu)	***	Ducks (Anas Platyrhynchos) rapidly flapping and stretching their wings while playing in the soil signify the onset of rains.
Hot weather (walgu be-ni)	***	The high temperature that causes profuse sweating in March is an indication of onset in few weeks.
Baobab tree (tuhi)	***	Baobab tree (adansonia digitata) begins to flower and generates new leaves signify rainfall onset. The more the flowers the season is predicted to be wetter than normal.
Butterfly (kahinpie)	***	A large number of migrating butterflies (Amblyscirtes) signal onset and a season with good rains.
Ants (salinsahi)	**	Lepisiota ant (Lepisiota capensis) carrying its eggs uphill during the dry season indicates rainfall onset approaching in up to a week time. When directions of egg-carrying ant change from uphill to downhill then one can predict cessation in few days up to a week. Large army ants (Eciton burchellii) in and around house signal start of the rainfall onset and as such a wetter than normal in the rainy season. Rapid increase in anthills on farm ways indicates the onset of rains in few days for up to 1 or 2 weeks.
Moon	**	Full moon covered by cloudlike appearance signifies a wetter than normal season.

(Goli)		
Wind (pohim)	**	Swirling winds at high frequency in the dry season indicate the onset of rains (good rainy season).
Lightning	**	Lightning accompanied by thunder repetitively occurring especially during the dry season indicate the closeness of onset
Frog (pololi)	**	High-pitched frog (Xenopus laevis) sounds in the dry season signals onset of rains up to a week. The intensity of this sound (the louder it gets) indicates a good season with normal or wetter season.
Sun (wuntana)	*	The appearance of shining spot around the sun during the dry season is an indication of approaching good rainy season.
Mosquitoes (duunsi)	*	Frequent and painful mosquito (Culicidae) bites and high nuisance in the dry season is an indication of rainfall onset in a few days up to about a week.
Stars	*	Stars moving from west to east indicate rainfall onset in a few days. Change in appearance (very bright) of the stars signals rainfall cessation in a week.
Birds (alacheyu)	**	The movement of a large number of Hornbils (Bucerotidae) with loud singing is an indication of a good rainy season. Owl hooting in the evening also signifies the onset of rain. Large flocks of swallow birds (Hirundinidae) migrating with loud sound signals rain onset in few days up to about a week. Crows (Corvus corax) flying in groups signals a normal season. Birds building nests close to rivers or water bodies indicates a below normal rainfall within the season.
Cow (naʄnya)	**	Cows (Bos Taurus) mostly standing and looking restless indicate the start of the rainfall onset in a few days.
Reptiles (tiŋvura)	**	The frequent appearance of reptiles such as snakes (family colubridae) wandering in the afternoon signals onset of rains in a week.
Dogs	**	When dogs (Canis lupus familiaris) loudly bark and run for cover in the day is a strong indication of a rainfall onset in a few days. The louder the noise the dogs make the wetter the seasons is predicted to be.

NB: less (*), somehow (**), highly (***) by unanimous agreement of workshop participants

4.3.2 Skills of Farmers and GMet Rainfall weather forecast

Farmers' observational data show rainfall patterns that begin to build up in April, peaks in July and then start to decline in August until October. At the seasonal time scale, June July August (JJA) recorded the highest rainfall amount, followed by September-October (SO) with the least recorded in April-May (AM) season. The sum of annual rainfall recorded by farmers was on average 15.5% more than what GMet observed. Results also show farmers' locally observed rainfall amounts vary from one community to the other (Figure C1). The total annual rainfall ranged from 492 mm in Saakuba to 1563 mm in Kushibo. Total rainfall amount recorded in Kushibo was 43.9% more than the average annual rainfall of 1000 mm observed by Owusu & Waylen (2009) for the study area. Gbulun and Kukuo showed the same rainfall amount of 1243 mm representing the second highest rainfall total. The study area is characterized by high records of low rainfall days compared to medium and then high rainfall. The total number of rainy days ranged from 22 in Tibung to 49 days in Zangbalun. GMet recorded high number of observed rainy days over the study area compared to what each farmer recorded (see Table C3 of supporting document). The difference in rainy days was largely associated with the high number of low rainfall days recorded by GMet, which could be attributed to the sensitivity of meteorological instruments as compared to the rain gauges used by the farmers in this research. Also, this could be due to the number of farmers' rain gauges (12) compared to one GMet rain gauge and the spatial variation between them, thus reflecting the strong spatial variability in rainfall in even very small areas.

Results of farmers and GMet weather forecast performance within the study area show that, for the seven months period, farmers' performed at an average of 30% while GMet performed at 34% (performance hereafter means hit rate or number of rain events accurately predicted). The average performance of GMet in each community was 32%. Meanwhile, within the seven months, farmers' performance varied from 16% accuracy in Wuba to 61% in Zangbalun. Farmers in Dalun and Gbugli also performed at 43% and 47%, respectively and the rest performed at less than the average of 30%. GMet forecast outperformed farmers forecast in most communities except Dalun, Zangbalun and Gbugli where farmers forecast performed at 3%, 25%, and 14% more (see Table C3 and B4 of supporting documents). However, on the average, both farmers and GMet showed similar performance rate of predicting one out of every three daily rainfall events right. Farmers recorded many correct rejections (No rain/No rain). Results also showed that the monthly performance of GMet and farmers varies but insignificantly (P>0.05), although farmers performed better than GMet in May, June and October. The monthly performance ranged from 21% in September to 46% in October for farmers and 20% in May and October to 56% in August and September for GMet (see Table C3 and B4 of supporting documents).

Out of 214 observational data for the 7 months' period under study, GMet and farmers' forecast show both agreement and disagreement with the actual observations within the communities. On average, both forecast systems disagreed 84 times (39%) and agreed 130 times (61%). Out of the 130 agreed times, 3 hits, 100 correct rejections, 12 miss and 15 false alarms were recorded. Table C5 of the supplementary document provides details of agreement and disagreement of the forecast. In addition, farmers generally have poor ability to forecast rainfall types. They recorded an average hit performance of 17%, 16% and 6% for low, medium and high rainfall types respectively. The hit performance was poor: 0% for high rainfall in 8 communities, 0% for medium rainfall in 4 communities, and 0% for low rainfall in 2 communities. However, each farmer had a better hit rate for low rainfall than medium and high rains (See Table C6 of the supplementary document).

4.3.3 Reliability and usability of IEIs used by farmers for rainfall weather forecast

Figure 4.3 shows how often the indicators were used during the study period and how reliable they were. Here, usability is the number of times an IEI has been used per the seven month period of study and reliability is the number of times an IEI gave an accurate prediction out of the number of times used within the seven months period, all expressed in percentage. Results of reliability presented in Figure 4.3 is empirically determined compared to what is obtained from farmers' perception presented in Table 4.1. Reliability here is the number of times an IEI gave an accurate prediction out of the number of times it was used within the seven month study period, all expressed in percentage. Results show that on the average each IEI was used 42 times. Also, at 95% confident level (19.6), the interval between 22.76 (lower bound) and 61.99 (upper bound) contains the true value of the population parameter (mean). Details of descriptive statistics of this analysis are shown in Table C11 of the supplementary document. Generally, results of empirical analysis in Figure 4.3 show that butterflies (Amblyscirtes), mosquitoes (Culicidae), bird sound, caterpillars (Larva) and moon, were five most reliable IEIs during the study period. Butterflies (Amblyscirtes) and soil appearance were the most reliable (45.5%) and least reliable (7.7%) IEI used respectively. However, according to the farmers, during the evaluation workshop, the appearance of butterflies (Amblyscirtes) is becoming rare in the area, thus it the least used IEI. Meanwhile, hot weather is the most used (138 times, 20.2%) IEI in the study area followed by clouds appearance (118 times, 17.4%).

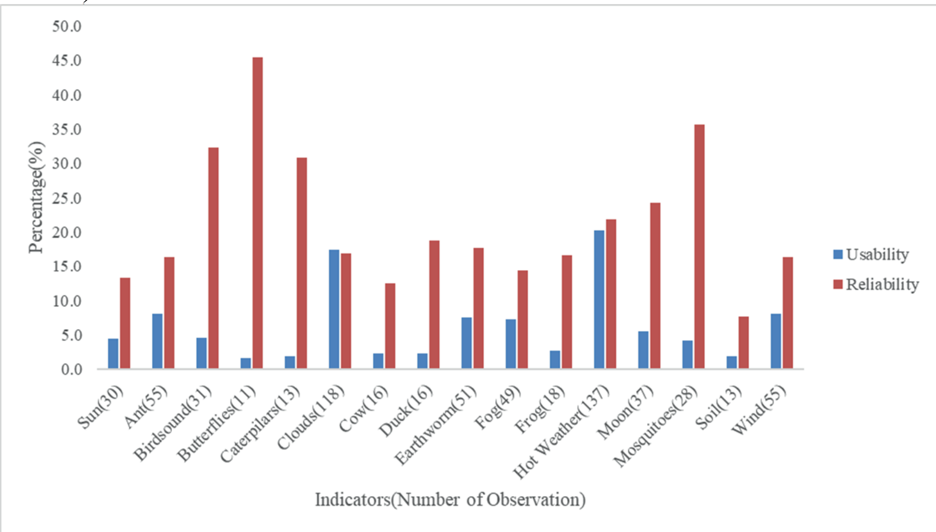

Figure 4.3: Reliability and Usability of indigenous Ecological indicators for predicting Yes/No Rain

Moving a step further, we analyzed the reliability of IEIs for forecasting different types of rain (low, medium and high rains). Results show that ants are the most reliable (83%) IEI for forecasting low rains. Cow (Bos Taurus), duck (Anas Platyrhynchos) and frog showed 100% reliability in forecasting medium rainfall while earthworm (Lumbricina) and wind were the most reliable (100%) IEIs for high rainfall forecast. Hot weather is the most used IEI for forecasting low rains while cloud formation is mostly utilized for medium and high rains (see figure C2 of the supplementary document). Results show that farmers' certainty does not significantly correlate with forecast performance. No consistent trend was observed in their expression of certainty. In most cases, they miss the rains even at higher certainty and hit at a lower certainty (see table C7 and B8 of the supplementary document). When this was raised at the evaluation workshop, one farmer indicated that "*sometimes I see very clear signs of rain and become so sure that it will rain* *in my village only for the rain to rather fall in a neighbouring village*", this justification was unanimously supported by all farmers.

4.3.4 Farmers and GMet forecasting skills at the seasonal timescale

Prior to the rainfall season, GMet provided a seasonal forecast for the period of April to October 2017. The Western and Eastern halves of Northern Ghana were predicted to experience near normal to above normal and normal rainfall amount respectively (GMet, 2017). Based on the location of Kumbungu district, rainfall was expected to be near-normal to normal. The mean onset date of the rainy season was forecast to be from 4th week of April to 1st week of May. The range of the expected rainfall amount over the entire region was 1090-1360 mm and the mean cessation date was forecasted to be the end of October (GMet, 2017). Prior to the season and during the second workshop, farmers forecasted rainfall amount, onset and cessation using various ecological IEIs listed in Table C9 of the supplementary document. They did not use IEIs for rainfall cessation because there were no clear signs. Instead, they relied on their experience. 58% of the farmers predicted normal rainfall season, 33% predicted above normal and only 9% predicted below normal rainfall. For the onset of the season, 25% of the farmers predicted the second week of April, 50% predicted the third week while the remaining 25% predicted it to occur in the fourth week of April.

All farmers agreed rainfall cessation would be in October. Nonetheless, 41% forecast it in the 1st week, 17% forecast 2nd week, 17% in the 3rd week and the remaining 25% forecast it in the 4th week of October. Comparing each farmer's forecast to its own recorded observations, results show that, 33% of the farmers got the onset prediction right while 42% were right with cessation. Using GMet estimated range of annual normal rainfall of 740-1230 mm (GMet, 2017), we observed that 33% of the farmers predicted the near-normal rainfall of their communities right while only 9% predicted the observed above normal rainfall right. The other farmers incorrectly predicted the rainfall cessation. GMet, on the other hand, predicted accurately the rainfall amount (near normal) for 42% of the communities and onset for only 25% of the communities but was unable to forecast correctly cessation for any of the communities (see Supplementary Table C9 for details).

4.4 Discussions

This study aimed to show for the first time, the techniques and skills (accuracy) of indigenous forecast (IF) in semi-quantitative and quantitative terms. It elaborated on how IF are generated by local farmers in northern Ghana and established a communal model of the relationship (semi-quantitatively) between indigenous ecological indicators (IEI) used and the phenomenon forecasted at both daily and seasonal timescale. It also evaluated skills (quantitatively) in IF compared with the Ghana Meteorological Agency (GMet).

Results of the forecast evaluation showed that on the average, both farmers and GMet correctly predict one out of every three daily rainfall events. At the seasonal scale, one out of every three farmers is able to accurately make onset prediction while two out of every five farmers are able to get rainfall amount and cessation right. Similarly, GMet was able to predict rainfall amount accurately in one out of every three communities and one out of every four communities for onset but was unable to accurately predict cessation for the communities. A possible explanation for differences in farmers' forecasts is that, first, each farmer has different predicting skills which stems from the ability to accurately observe and interpret IEIs per one's experience. The second could be attributed to farmers losing interest in the data collection process and thus do not make a critical observation of IEIs before forecasting although monthly skill test did not confirm this trend. While little could be done to improve the former, the latter could be avoided by offering attractive incentives to farmers and maintaining frequent contact. In this study, farmers were promised that they could keep the mobile phones at the end of the study as a way of motivation. The third reason for the differences in the prediction skills of the farmers at the weather time scale could be attributed to the impact of climate change on the ecosystem that might have affected the relationship between the IEIs and the meteorological phenomenon forecasted. Thus, the information fed into the Mental Modeler may not reflect the future relationship between the IEIs and the phenomenon forecasted. For example, onset and cessation dates could be affected if say they occur a number of days after the appearance of butterflies. If the butterflies now appear earlier or later than before, then this could affect the prediction.

Historical patterns of the rains serve as the fundamental template that allows farmers to form expectations for the coming season. Results of this study confirm that observed changes in each IEI strongly influenced farmers' predictions. Farmers' perception of the most reliable indicators was different from the results of empirical analysis. For instance, for weather forecast, farmers mentioned earthworm (Lumbricina), clouds, ducks (Anas Platyrhynchos), caterpillars (Larva) and butterflies (Amblyscirtes) as the five most reliable indicators, meanwhile, empirical results show butterflies

(Amblyscirtes), mosquitoes (Culicidae), bird sound, caterpillars (Larva) and moon, as most reliable. These results indicate the possibility of perceptional measurement being significantly different from the real-time measurement. Therefore, care needs to be taken when testing the reliability of IEIs and farmers forecast skills using perceptional methods only, as in Makwara (2013) and Elia et al., (2014). However, these differences could also be caused by seasonal differences.

Results of the mental model allowed us to establish the underlying mechanism behind farmers' prediction. For instance, when one comes across a high frequency swirling winds in the dry season, this may indicate the onset of rains but also provides a higher probability of above normal rain than below and normal rainfall. The appearance of a halo around the sun has a higher probability for predicting medium rainfall than high and low rainfall. Frequent and painful bite of mosquitoes in the day during the wet season indicate a higher chance of recording high rain the next day compared to medium and low rain. This implies that the process of how IF is made is not only intuitive but also based on a rational skill which can be learned and passed on from one generation to the next. Established communal mental models are modified over time depending on observable environmental changes. The value of IEIs in developing forecasting tools is critical. Careful examination of the relationship between these IEIs and predicted weather and seasonal climate events are useful for developing integrated forecast models that use IEIs in combination with initial conditions of the atmosphere (wind direction and atmospheric pressure etc.) for forecasting local weather and seasonal climate conditions (see Andrade & Gosling, 2011). Also, IEIs could be used as a starting hypothesis for building local predictive models developed with historical observation for local communities (Waiswa et al., 2007). Once the probability of occurrence of an IF is determined, this could be integrated with scientific forecast (SF) using their probabilities.

We acknowledge the limitations of using data from only a single wet season. This did not allow for inter-annual variability assessment. Moreover, the number of farmers in each community should be increased to analyse within and between community variation of results. However, results show that pattern of monthly and seasonal rainfall recorded by farmers are similar to those measured with meteorological instruments in Northern Ghana by GMet and other studies such as Lacombe et al., (2012) and Manzanas et al., (2014). This provides confidence about the quality of farmers' observations. The frequency (rainy days) and amount of rainfall, however, differ significantly among farmers and between farmers and GMet. In addition, we recognise the differences in GMet and farmers forecast as an indication of the distances between rain gauges and strong rainfall variability even over small areas. It is common knowledge how it rains in one place but does not rain at a nearby location. However, a comparison of forecasts could be meaningful as the forecast themselves could be compared irrespective of the variation and method used to arrive at the forecast. Basically, it is a comparison of the skills of the different forecast systems and we did this by taking the average of farmers forecast skills as a representative of the entire area compared it to GMet skills where the performance was almost the same. Moreover, on occasions when GMet forecast was compared to the farmers' observation, this was aimed at establishing how spatial variation could affect forecast skills or accuracy. This was done in order to make a case for every community having rain gauges for recording rainfall and forecast must be issued at community level instead of regional level as done now. For instance, GMet has a single weather station with rain gauge that measures rainfall for a wider area, which in most cases did not represent what is actually happening within the communities making farmers prefer their own forecast to GMet. These variations could have significant implication on impact studies that do not take into account spatial variations in rainfall. There is, therefore, the need to mount in each community additional rain gauges to record locally observed rainfall, in order to generate data that is relevant for studying local rainfall variability and change. In line with this, some studies have argued the need to pay attention to smaller details in each geographic area since this can have a bigger impact on local climate(Frumkin et al., 2008; Maibach et al., 2008).

The result shows that knowledge possessed by local people can contribute to climate science by offering observations and interpretation at a much finer spatial scale with considerable temporal depth, and by highlighting aspects (in this case indigenous ecological indicators) that may not be considered by climate scientists (Mafongoya & Ajayi, 2017). Therefore, farmers in communities where meteorological observation are not available can be engaged to collect community level weather and climate information and data. In the process, local farmers are empowered and become more aware of spatial and temporal variability in rainfall(McCormick, 2009). Finally, some studies have already proposed the integration of indigenous and scientific forecast to increase community resilience (Hiwasaki et al., 2015; Nyadzi et al., 2018). While we found both forecasting systems in general to have similar skills, there were some specific rainfall events that both forecasts disagree, thus making integration both potentially useful especially in increasing forecast accuracy and/or the trust of the forecast. Long term data sets need to be collected to understand the potential of integrating indigenous and scientific forecasts under climate change.

4.5. Conclusion

Local people's contribution to climate science can be vital but is typically overlooked. In this study, we have illustrated the accuracy of indigenous forecasts (IF) generated by farmers and provided insight into the underlying mechanisms behind farmers' forecasting techniques. We observed that in addition to farmers using historical patterns of the rains as a basis for IF, they also use different indigenous ecological indicators (IEIs) for local rain forecast through an established mental model of how these IEI influence the occurrence of different weather and seasonal climate events. They generate IF by observing the presence or absence of IEIs which signals the occurrence or non-occurrence of a particular event at both daily and seasonal time scale. Therefore, IF are not intuitive but a skill rationally developed which improved with age and experience. Also, farmers' perception of reliability of IEIs and skills are different from observational analyses and therefore care should be taken when making a conclusion based on perception studies only. However, farmers and GMet showed similar skills in their forecast; correctly predicting one out of every three daily rainfall occurrences. We conclude that farmers can contribute to climate science by offering their local expertise as well as collect community-level weather and climate information and data that is beneficial to developing climate services and climate change adaptation practices.

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5

Chapter 5

Towards weather and climate services that integrate indigenous and scientific forecast to improve forecast reliability and acceptability

Abstract

Extreme weather events and climate change are affecting the livelihoods of farmers across the world. Accessible and actionable weather and seasonal climate information can be used as an adaptation tool to support farmers to take adaptive farming decisions. There are increasing calls to integrate scientific forecasts with indigenous forecasts to improve weather and seasonal climate information at local scale. In Northern Ghana, farmers complain about the quality of scientific forecast information thereby depending on their own indigenous forecast for taking adaptive decisions. To improve this, we developed an integrated probability forecast (IPF) method to combine scientific and indigenous forecast into a single forecast and tested its reliability using binary forecast verification method as a proof of concept. We also evaluated the acceptability of IPF by farmers by computing an index from multiple-response questions including a good internal consistency check. Results show that, for reliability, IPF performed on average better than indigenous and scientific forecast at a daily timescale. For the seasonal timescale, indigenous forecast overall performed better followed by IPF and then scientific forecast. However, IPF has far greater acceptability potential. About 93% of farmers prefer the IPF method as this provides a reliable forecast, requires less time and at the same time helps to deal with contradicting forecast information. Results also show that farmers already use insights from both forecasts (complementary) to make farming decisions. However, their complementary method does not resolve the issues of contradicting forecast information. We conclude based on our proof of concept that integrating indigenous and scientific forecast has high acceptability and can potentially increase forecast reliability and uptake.

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5.1 Introduction

Farmers across the globe, particularly in Africa use weather and climate information from indigenous and meteorological sources for risk-based decisions (Mapfumo et al., 2015; Orlove et al., 2010; Roudier et al., 2014). In Ghana, farmers often approach a season using indigenous forecast (IF) which is built on past experiences, empirical observations of ecological indicators, and traditional knowledge. Sometimes, they use IF in combination with meteorological scientific forecast (SF) to adjust farm activities against climate variability and change (Furman et al., 2011; Nyantakyi-Frimpong, 2013). However, both IF and SF have distinct weaknesses which pose challenges for their use (Ziervogel & Opere, 2010).

First of all, Klopper and Landman, (2003) observed that end-users are often confused about what decision to take when forecast information comes from different sources, especially in cases where they produce contradicting forecasts. Second, SF is often developed at a coarse spatial scale compared to IF and therefore does not address farmers' local needs (Orlove et al. 2010). Third, policy makers and scientists often view IF with much scepticism as it is qualitative and has a measure of spirituality that is absent in SF (Briggs & Moyo, 2012; Kolawole et al., 2014; Saitabau, 2014). SFs, on the other hand, are not always embraced by farmers due to the absence of a sense of ownership and lack of trust in service providers. This reduces the uptake of weather and climate information (Jiri et al., 2016).

Studies have indicated that forecast information is more acceptable when IF and SF are integrated (Ziervogel & Opere, 2010; Gagnon & Berteaux, 2009). Actionable information is often considered more credible, legitimate and salient to farmers when it is embedded within the context of their existing knowledge (Mafongoya, & Ajayi, 2017; Nyamekye et al., 2018). Moreover, climate change offers challenges that can go beyond the experiences of farmers and scientists (Huntington et al., 2004).

Therefore, finding a meeting point between the two forms of forecasts could set the agenda for integration (Kolawole et al. 2014). Such integration should ideally go beyond the individual outcomes of scientific and indigenous forecasts. Mafongoya and Ajayi (2017) suggest the need for policies and actions that promote knowledge co-production through collective efforts of indigenous people, natural and social scientists (Lemos et al., 2018). However, the question that remains is how IF and SF can be integrated whilst respecting the different norms and values. Therefore, this study investigated two objectives: 1) The potential to integrate IF and SF and 2) The acceptability of a combined forecast, from the receivers' point of view.

This study is a *proof of concept* that aimed at demonstrating how to quantitatively integrate IF and SF to improve the reliability and acceptability of forecast information by farmers in Ghana. To achieve this, the strengths and weaknesses of existing integration methods were first reviewed and analysed in section 2. Section 3 captures the details of the methods adopted for the study. Section 4 presents the results of the reliability and acceptability of the integrated probability forecast (IPF) method proposed. The article ends with a reflection on the findings and the actionability of IPF to support farmers' daily and seasonal decision making in section 5.

5.2 Literature review and conceptual framework

The idea of improving forecast accuracy by integrating forecast from multiple models is certainly not new (Clemen, 1989), but there is substantive room for improvement to make climate information actionable for farmers. For example, Zou & Yang (2004) and Wei (2009) suggested time series analysis combined with multiple regression. Adhikari and Agrawal, (2012) also used a weighted nonlinear mechanism for combining forecasts from multiple time series models. Andersson & Karlsson (2008) and Raftery et al. (2005) proposed Bayesian combinations. Others discussed the possibility of averaging the probabilities of individual forecasts (Ranjan & Gneiting, 2010). Klopper and Landman (2003) created a single probability forecast by combining different model outputs and concluded that the method consistently delivers a more skilful forecast than any individual model on its own.

Recent studies on integrating scientific forecast (SF) with indigenous forecast (IF) can be divided into *consensus methods* and *science integration methods* (Plotz et al., 2017). The consensus methods refer to the subjective ways of establishing agreement on the most convincing forecast information. Methods include meetings of experts from the indigenous and scientific community to discuss their forecasts to develop an agreed forecast for the coming season (Ziervogel and Opere 2010; Guthiga & Newsham, 2011; Mahoo et al., 2015). The science integration method refers to ways that objectively combine forecasts into single source of information using systematically established scientific techniques. For example, combining IF with statistical or dynamical weather or climate model outcomes (Andrade & Gosling, 2011; Chand et al., 2014; Masinde, 2015; Mwagha & Masinde, 2015; Waiswa et al., 2007).

However, consensus and scientific integration methods have some challenges; the consensus method causes delay since neither group would be able to produce a combined forecast in the absence of the other. Also, the combined forecast cannot always be replicated as there are no clear rules or processes involved. In addition, the consensus method is time and cost intensive due to the need for regular and meetings. The science integration method, however, requires large amount of data to develop and verify predictive models, and it is less flexible with regards to cultural sensitivity. The science integration method is also limited in its engagement with farmers. Farmers are only engaged during the time of the initial data gathering required to develop the predictive model. Subsequent activities including data interpretation and analysis are done only by the researchers, limiting the idea and value of co-production. Moreover, rapid environmental changes have the potential to impact the future effectiveness of the science integrated method since farmers are no more involved once predictive models are built (Plotz et al., 2017). The consensus and scientific integration methods do not actually integrate IF and SF into an objective single forecast. Climate information from the science integration methods, for example, is only based on historically observed data from stations with IF serving as a driving hypothesis for trends. Consensus methods are also based on the subjectivity of experts.

Given the limitations of the two groups of methods discussed above, a new method called the integrated probability forecast (IPF) method is proposed. This method is inspired by the approach of Klopper and Landman (2003) who used a simple unweighted average of forecast probability to combine scientific forecast from different forecast models. The difference with the IPF method is that it used a weighted average technique and combines the strength of both consensus and science integration methods. This paper referred to the IPF method as one that seeks to generate the probability of IF and quantitatively combines that with the probability of SF using simple weighted average techniques. The IPF method integrates SF and IF using their forecast probabilities. Unlike IF, weather and seasonal climate forecasts from SF systems are produced with their probabilities. Yet to integrate IF and SF at daily and seasonal time scale, there is a need to estimate the probabilities for IF. The probabilities of IF were calculated based on the number of people forecasting 'Yes rain' for the weather, and near-normal rainfall, above and below for seasonal climate forecast [near-normal rainfall (740-1230 mm) is the average rainfall value for over a 30-year period]. Rainfall for each season or year may very often be either above, below or near the normal. The calculated probability of IF is combined with that of SF to form the IPF (see section 5.3.4.1 for details of the proposed method). The IPF requires expert indigenous forecasters just as in the consensus method, but unlike the consensus method, it does not require regular (in)formal meetings to agree on a forecast. IF from several expert forecasters (farmers) is collected at a particular time, out of which the probability is estimated based on the number of experts that forecast events and those that forecast otherwise.

Reliability and acceptability of integrated probability method

To assess the actionability of the integrated probability forecast (IPF) method, a reliability and acceptability check is necessary (Whitford et al. 2012; Friedman and Wyatt 2005). In this study, the reliability of the IPF method is defined as being able to produce information that performs better than those available, in this case, either the scientific or indigenous forecast. According to Ziegel, (2004), reliability is a concept that is used to determine the performance of a thing, for example a forecast, in order to measure its quality. The acceptability of IPF to end-users and researchers partly depends on its reliability. Acceptance is regarded as a significant factor in determining success or failure of any innovation, particularly information systems (Gould, et al., 1991; Nickerson, 1981). Acceptability can be defined as a demonstrable willingness of an individual or group to *trust and use* forecast information (Dillon & Morris, 1996). Dillon and Morris (1996) report that the likelihood of actual usage could deviate slightly from intended usage, but the essence of acceptance theory is that such deviations are not significant.

5.3 Research Methodology

This section introduces the case region and discusses the methodology used.

5.3.1 Study area

To test the IPF method, the Kumbungu district in the northern region of Ghana located in the guinea savannah ecological zone was selected. Given previous engagement in this region by the research team, the researchers were able to use existing data and resources, as well as the engagement of farmers in the study area.

The region is characterised by lowland and grassland (Abdul-Razak & Kruse, 2017b). The district has a unimodal rainfall pattern which begins from May, peaks in July to September, and ends in October with the rest of the year being

dry (GSS, 2014). The district is generally warm with fluctuating mean monthly minimum and maximum temperatures of 26.6 °C and 35.6 °C the annual temperature is 29.7 °C and an average annual rainfall of about 1043 mm (SARI, 2016). The district like many others in the region is challenged by the impacts of climate variability and change, such as recurring floods and drought (F. A. Asante & Amuakwa-Mensah, 2015). The region is highly vulnerable (both ecologically and socially) to climate change, a situation which is intensified by other biophysical and human-related issues such as overgrazing, deforestation, and human-induced bush fires (Stanturf et al., 2015). The people of the study area belong to the Dagbani ethnic group with agriculture as their main economic activity. Agriculture activities are predominantly rain-fed and therefore seasonal with only a few people engaged in dry season irrigation farming in schemes such as Bontanga (Emmanuel Nyadzi, 2016). About 95% of households in the district are engaged in agriculture with almost 98% involved in crop farming and poultry (chicken) production as the most dominant animal reared (GSS, 2014).
To answer the research questions, the study used multiple methods using primary and secondary data (see Figure 5.1).

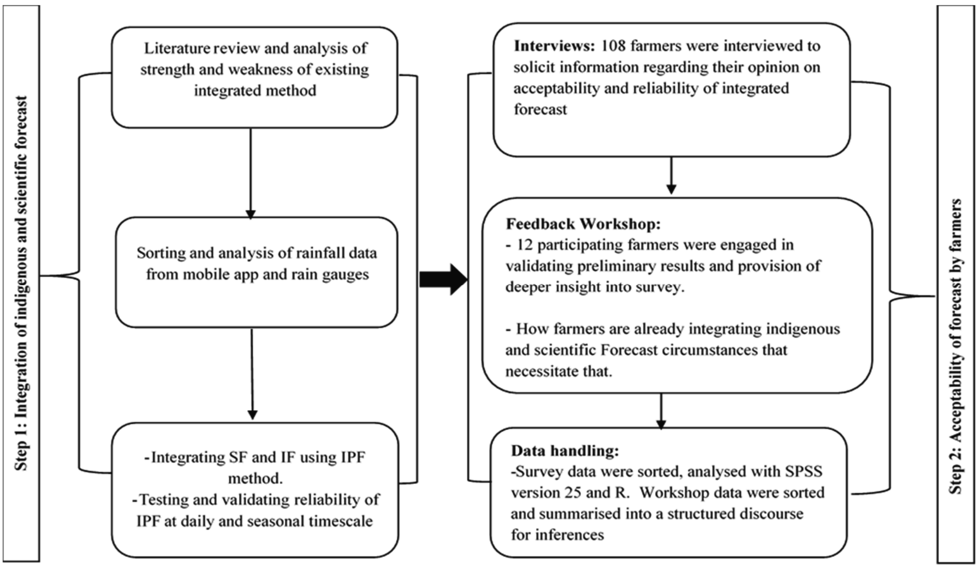

Figure 5.1: Methodological flow of the study

5.3.2 Population and selection of sample

To assess the acceptability of integrated probability forecast (IPF), a stratified random sampling technique was used. A total of 108 rice farmers from 12 different communities (Figure 5.2) were selected for interviews. Using this method allowed us to identify sub-groupings of farmers: 1) irrigated rice farmers, 2) rain-fed rice farmers, and 3) both irrigated and rain-fed rice farmers. It was assumed that different types of farming practices will require different types of climate information and so acceptability of IPF might differ. The study focused on rice farmers because of the high demand for rice in the area and the country at large. Yet rice production is crippled by climate variability and water unavailability challenges (Kranjac-Berisavljevic' et al., 2003). In each of the 12 communities, 9 farmers were randomly selected; 3 irrigation farmers, 3 rain-fed farmers, and 3 both irrigation and rain-fed farmers. The sampled population included male (72%) and female (28%) farmers (see Table D1). In addition to the interviews, a feedback workshop was organised with 12 participating rice farmers (one farmer from each community) engaged in both rain-fed and irrigated rice production.

To assess the reliability of IPF, IF data was collected from 12 expert farmers, all males above 45 years of age from 12 different communities within the study area (Figure 5.2). There was no intention to focus on only males but this emerged due to the local practice. The sampling method adopted concentrated on selecting the best and most trusted forecasters in the community. Farmers above the age of 45 were selected because they have at least 30 years of farming experience to guarantee their knowledge about how the climate has changed and rainfall become variable over the years in their communities. A rigorous process was adopted to select farmers with good forecasting techniques and skills in order to obtain quality data for the analysis. Initial inquiries showed that not all farmers are good at using indigenous ecological indicators (IEIs) for forecasting. Therefore, the selection process actively involved the community members, irrigation manager and an extension officer.

In each community, members have knowledge of who is good at forecasting therefore both researchers and farmers decided on who to involve in the trainings and forecasting. During the meetings and before the final selection the pre-selected farmers were asked to indicate how many rainfall events could each accurately predict out of 10 events. Those with the highest numbers were selected and all participants agreed to the selected expert farmers. The selected farmers were introduced to smartphones and mobile apps for the first time. Only a few farmers were selected in order to monitor and obtain detail insight into the process for forecast data collection. This allowed the collection of quality forecast data for analysis. Farmers were also trained on how to record daily observed rainfall with tailor-made rain gauges. In a previous comparative analysis of observed rainfall, farmers and Ghana meteorological agency (GMet) show similar rainfall pattern of the seasons, increasing our confidence in farmers' data. Also, by involving the community in the selection process and considering their interest as well as confirming who should be involved in the study, one can be certain that forecast information would be trusted by all. Moreover, the expert farmers already mentioned that through this study they have become a source of forecast information for other farmers in their respective communities. The expert farmers have somehow become formally recognised for their expertise thereby increasing the number of people who consult them regularly for forecast information. Roncoli et al., (2009) similarly opined the value of promoting local ownership and generating trust when users of climate information are involved in the production and dissemination.

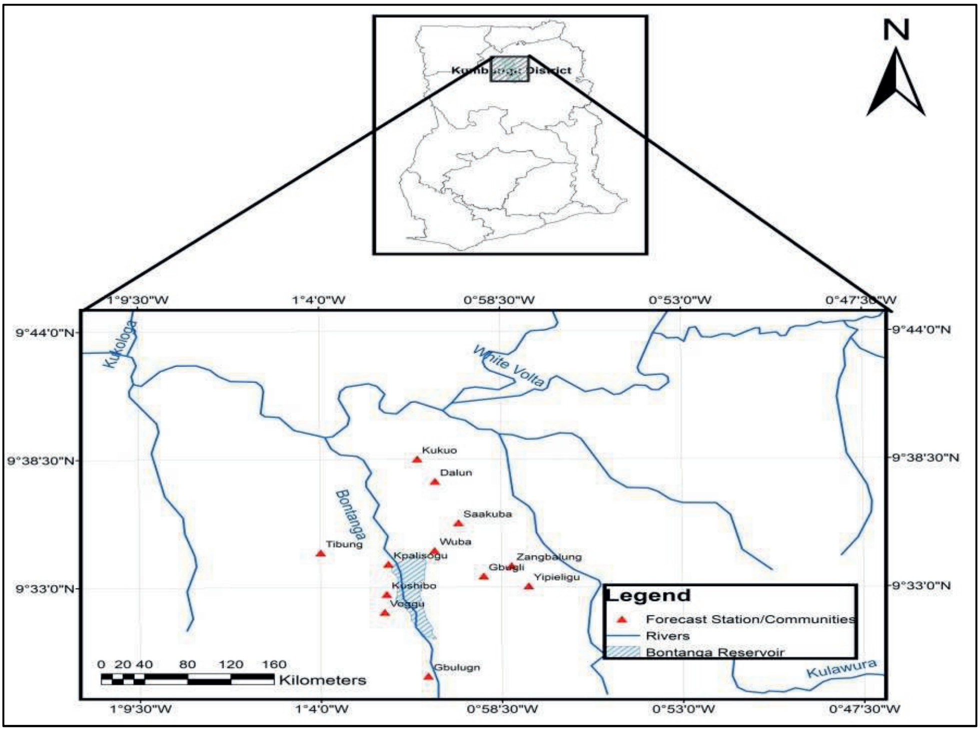

Figure 5.2: Map of the study area positioned in Ghana. The red triangles show the location of farmers and their respective selected communities (Nyadzi et al., 2019).

5.3.3 Research instruments and data collection

The study used three main types of data; (i) indigenous and scientific forecast data (ii) interview data (iii) feedback and discussion workshop data. (i) The indigenous forecast data was collected from 12 expert farmers who sent their daily predictions (in 2017) through smart mobile phones with apps and their seasonal predictions collected at a workshop in 2017 and 2018 (See section 3.3.1 for details on the mobile app). The scientific forecast data at both daily and seasonal timescale were obtained from the Ghana Meteorological Agency. (ii) Interview data from 108 farmers were collected in 2018 and (iii) Feedback and discussion data were gathered during workshops in 2018. Each of these data sets were used for specific analysis. For instance, the indigenous and scientific daily and seasonal forecast data were used for the integration and testing of the IPF method. The interview data were used to evaluate the acceptability of IPF. The workshop data was used to evaluate the preliminary results of the interviews and indigenous forecast collected. In addition, the workshop also provided the opportunity to enhance the discussion of why the IPF method is most preferred by farmers.

In a previous case study in the region, the researchers studied the various ecological indicators farmers use for forecasting and assigned to them scientific names. During one of the workshops, the researchers defined and explained the technical terminologies assigned to what farmers already know using simple illustrations they relate to. For example, researchers and farmers together agreed on *Low rainfall* (0.1 -19mm/day) as rain that starts from drizzling to rains that do not wet the soil to capacity. *Medium rains* (19 - 37mm/day) are rains that wet the soil to capacity and *high or heavy rains* (> 37mm/day) as rains that gathers water in farms and sometimes makes crops fail. The rainfall values were obtained from Lacombe et al., (2012). *Above normal* seasonal *rainfall* was explained as when the season has more rains than often observed and is much wetter than normal (mostly with higher yield). *Below normal* was explained as when the season will have less rain than observed or is much drier than normal (mostly with lower yield), *Near Normal* is when the season will be as it often is (mostly average yield). Onset was also explained as when the rain will start (when to start planting).

5.3.4 Ethical considerations

While there was no formal research ethical clearance required of us before the data collection, we adopted an appropriate community entry procedure seeking permission from chief and leaders of the communities. We gave prior notice to the regional and district offices of the government. It was also vital to respect the opinions and rights of the indigenous people, be aware of local laws, formal and informal governance arrangements in addition to recognizing the diversity of indigenous people (perspective, religious, culture, the language) between and within communities. This is essential for the planning and executing the research and to a larger extent for reporting. For instance, in our case, religion played a role in scheduling our activities. The majority of the farmers were Muslims and do not farm on Fridays. Therefore, we plan most activities on Fridays but outside praying hours. Also, we did not schedule our workshops in the mornings because farmers prefer to be on their farms.

5.3.4.1 Android mobile app ('Sapelli') and Rain Gauges

Indigenous rainfall forecast data was collected using the Sapelli mobile app (see Figure D1). Sapelli is an open-source project that facilitates data collection across language or literacy barriers through highly configurable decision-tree of a pictorial icon-driven user interface. According to Stevens et al., (2013), Sapelli has a powerful visualisation capability that allows usage by people with low literacy. Users can select options by simply touching the screen of the mobile device and do not have to read the text. The Sapelli platform allows offline data collection, postponing data transmission to a later stage and does not rely on internet connection. This function makes it possible to use in areas where network connectivity is rare, unstable, slow or expensive, and when users lack phone experience. Vitos et al., (2013) for example, used Sapelli to support non-literate people to monitor poaching in Congo. In our context, the app was coded to provide an interactive interface, suitable for use by farmers with little or no technical knowledge and education. The app was uploaded on smartphones distributed to the 12 expert forecasters (rice farmers) to send their daily rainfall forecast. On the app, the farmer is asked to first indicate whether in the next 24 hours there will be "Yes rain" or "No rain". If 'Yes rain' is selected, the farmer proceeds to the next step where he indicates which type of rain: "low rain", 'medium rain', and 'high (heavy) rain'. Thereafter a number of indigenous ecological indicators (IEIs) such as ants, the moon, or earthworm are presented from which the farmer selects the ones upon which the forecast is based. These IEIs were mentioned by farmers themselves and collectively discussed in an earlier workshop. After this, the farmer specifies the certainty of the forecast by selecting 'sure', 'very sure' and 'so sure'. The process ends by saving the information unto the mobile phone. However, a farmer could skip a stage on the app if he doesn't want to respond which literally means no idea. We ruled out the possibility of "I do not understand' or 'I am not comfortable answering”. This is because farmers were thoroughly trained to understand each stage of the app and are willing to provide answers unless otherwise they do not know what event to expect because of confusing IEIs.

The farmers also recorded daily rainfall observed in their communities using the tailor-made rain gauges. These rain gauges were built from plastic water bottles by researchers and farmers were trained on how to use it and how to record rainfall.

5.3.4.2 Structured interviews

A structured interview guide was designed based on three core themes; (i) Personal characteristics, (ii) Forecast sources and usage, (iii) Acceptability of integrated forecast. See interview guide in table D2.

The interview guide was pilot-tested twice to ensure questions were understandable and unambiguous. Each interview lasted for about 15 minutes and was mainly administered in the local *Dagbani* language except for some cases with literate farmers where the English language was used. In total 108 interviews were conducted. For each question, background information was provided to ensure that farmers have a good understanding of the questions in order to respond appropriately.

5.3.4.3 Feedback workshop

Following the preliminary analysis of the interview data, and the IF data collected with sapelli mobile app, a feedback workshop was organised to discuss and obtain further insight as well as validate (to reduce interpretation bias) both results. The workshop also discussed how farmers are already using IF and SF and whether they find IPF acceptable. It is worth noting that the workshop was conducted in the Dagbani language and as such, all the quotation used in this paper has been translated into scientific terminologies. For example, a farmer may not say indigenous ecological indicators but rather use expressions (such as *ti bangsim kura*) that imply the same.

5.3.5 Data analysis

Each dataset was handled in a way that it produced the intended purposes. The indigenous and scientific forecast data were analysed on a daily and seasonal timescale. Further, the daily forecast data were aggregated to monthly to provide insights into the monthly variation. The interview data were also sorted and analysed to determine the acceptability of IPF. The workshop data was used to validate the preliminary results of the interviews and the indigenous forecast data collected. Details of the data analysis are presented in section 5.3.5.1 and 5.3.5.2

5.3.5.1 Integrating forecast and testing reliability

Before the integration of IF, indigenous ecological indicators (IEIs) were identified and farmers' rainfall forecasting techniques were explored. Results show that farmers base their forecast on observing and interpreting IEIs and their long term personal experiences. Farmers ensure that there is ample evidence to support their forecast and they do so by observing different IEIs. For example, a farmer would not forecast "no rain" just because of the disappearance of ants but would also refer to other possible indicators.

In addition to IEIs identification and the exploration of indigenous forecast techniques, skills in farmers' forecast were evaluated using a binary forecast verification method to test the reliability of both forecasts. This method analyses rainfall forecasts in the form of yes/no rain and uses the contingency table to score hit rates against miss rates (Barnston, 1992; Ward & Folland, 2007). According to Hammer et al., (1996), using this method of forecast verification is of practical value in the sense that forecast users often have to make a yes/no decision to act on the information provided. Moreover, users do not generally change their practices unless there is a significant shift in probabilities away from random expectation. Integrating SF and IF at daily and seasonal timescale followed the following two stages:

Stage 1: Constructing and Consolidating forecast probabilities for IF and SF

While weather and seasonal climate forecast from SF are issued with the likelihood of rainfall occurrence, IFs are not. The probabilities of daily IF were calculated based on the number of expert farmers forecasting 'Yes rain'. For the seasonal time scale, the probabilities were calculated based on the number of people who indicate above, below, and near-normal rainfall (see table 5.1). The corresponding probabilities of occurrence constructed for IF and SF were merged to form a combined forecast (IPF) using a simple weighted average method. A demonstration of this at the seasonal timescale is depicted in Table 5.1

Table 5.1: Formulae for integrating IF and SF; the example of seasonal climate forecast

Type of forecast	Above normal	Below normal	Near-normal
Indigenous Forecast (IF)	$A_i = An/T$ (%)	$B_i = B_n/T$ (%)	$N_i = N_n/T$(%)
Scientific Forecast (SF)	A_s (%)	B_s(%)	N_s(%)
Integrated Probability Forecast (IPF)	$A_C(\%) = \frac{\alpha A_i(\%)+\beta A_S(\%)}{\alpha+\beta}$	$B_C(\%) = \frac{\alpha B_i(\%)+\beta B_s(\%)}{\alpha+\beta}$	$N_c(\%) = \frac{\alpha N_i(\%)+\beta N_s(\%)}{\alpha+\beta}$
Where **A, B and N** *denotes above-normal, below-normal and near-normal rainfall respectively.* ***T*** *denotes the total number of people who provided an indigenous forecast only (T for SF=1)* ***A_n, B_n and N_n*** *denote the number of people who forecast category A, B and N respectively.* ***A_i (%), B_i (%) and N_i (%)*** *denote the probability of occurrence of the indigenous forecast for category A, B and N respectively.* ***A_s (%), B_s (%) and N_s (%)*** *denotes the probability of occurrence of the scientific forecast for category A, B and N respectively* ***A_c (%), B_c (%) and N_c (%)*** *denote the probability of occurrence of combine forecast for category A, B and N respectively. These are the mean of each category for the indigenous and scientific forecast.* ***α*** *is the weighted value for IF and* ***β*** *is the weighted value of SF*			

Stage 2: Evaluating forecasts (IPF, IF and SF) against observation

To assess the reliability, each forecast (IPF, IF and SF) was compared with observations. The percentage of hit rates for each forecast type were calculated for a probability of ≤0.5 and >0.5. Using equation 1, a weighted value estimated from the results of the skills assessment of IF and SF were assigned to each probability. The values were of 0.3 and 0.34 hit rate for IF and SF respectively. Also, this study hypothetically considered each farmer as a kind of forecast model and their forecast techniques and skills adequately evaluated. The weight assigned to each forecast addresses the tendency to lose the value placed on each forecast during the combination.

$$CF = \frac{\alpha X_1 + \beta X_2}{\alpha + \beta} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eqn. 1}$$

Where $\boldsymbol{X_1}$ *is the probability of indigenous forecast (IF) and* $\boldsymbol{X_2}$ *is the probability of scientific forecast (SF).* $\boldsymbol{\alpha}$ *is the weighted value for IF and* $\boldsymbol{\beta}$ *is the weighted value of SF*

5.3.5.2 Analysis of interview and workshop data for acceptability

Data from the questionnaire were coded and analysed using R statistics, Statistical Package for Social Sciences (SPSS) version 25 and Microsoft Excel 2016. Data from the questionnaire were categorical in nature and so informed our choice of the analytical technique. Analyses of interview data was framed around the hypothesis that farmers will accept an integrated probability forecast. Demography of the respondents in addition to the frequency of the types of forecast used are found in table D1.

First, an index for acceptability was computed from three questions (see question 17-19 of the questionnaire) and collinearity appropriately checked. To do this, the three questions were measured on the same scale and combined into a single measure by taking an average of each respondents' response. Results of the analysis are in table D3. Price (2012) posit that multiple-response measures are generally more reliable than single-response measures. However, it is important to make sure the individual dependent variables correlated with each other. Therefore, before the combination of multiple-response measures the reliability of the variables was checked using Cronbach's Alphas. This test verifies the internal consistency of the variables before proceeding to determine whether farmers will accept an integrated probability forecast or not. Results showed an acceptable Cronbach's Alphas of 0.68 (see Table D3 for detailed result). A Cronbach's alpha value of 0.6 is considered as a high reliability and acceptable index (Nunnally and Bernstein, 1994; Wim et al., 2008). The workshop data were sorted and structured into an inferential discourse. Some salient comments were isolated and presented to improve the narrative. All data collected were anonymously handled.

5.4 Results

5.4.1 Performance of Indigenous, Scientific and Integrated Probability Forecast

Monthly analyses of the daily forecast data showed that on average the IPF performed better than IF and SF (Figure 5.3). In September and October IPF performed better than IF and SF. In July and August, IF performed better than IPF, and IPF also performed better than SF. In June, SF performed better than IF and IPF (see Table D4).

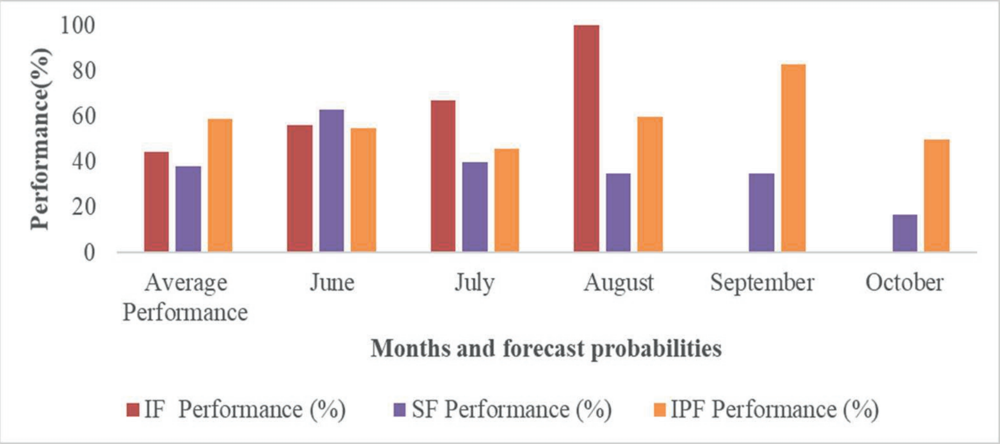

Figure 5.3: Performance of IF, SF and IPF at a resultant probability of >0.5 (details of ≤0.5 in table D5). IF recorded no hit for probability >0.5 in months September and October.

For the seasonal timescale, IF generally performed better than IPF and SF. IPF also performed better than SF. Interestingly, IPF was able to deal with the contradicting forecasts of IF and SF pointing at different directions in both years. For instance, in 2017, whereas IF predicted near-normal rainfall, SF predicted above-normal rainfall. This contradicting forecast which often confuses farmers in their decision making was dealt with by IPF (Table 5.2). Also in 2018, IF predicted above-normal rainfall and SF predicted an equal chance of rain for both above and near-normal rainfall. With this confusing information, IPF was able to forecast accurately the above-normal rainfall observed (Table 5.2).

Table 5.2: IF, SF, and IPF and observation for the 2017 and 2018 seasons. A: above-normal; N: near-normal; B: below-normal. Near normal range of 740-1230 mm (GMet, 2017). Values in bold show the highest forecast probability by each forecast system

	2017				**2018**			
	A	N	B	Observed	A	N	B	Observed
Indigenous Forecast(IF)	33	**58**	9	N	**50**	33	17	A
Scientific Forecast(SF)	**40**	35	25		**35**	**35**	30	
Integrated Probability Forecast (IPF)	36.3	**45.8**	17.5		**42.0**	34.1	23.9	

5.4.2 Acceptability of integrated forecast by farmers

To assess the acceptability of integrated forecasts, a number of questions from the structured interviews were analysed to test our hypotheses “farmers will accept integrated probability forecast”. Results of the acceptability analysis show that cumulatively the majority (96%) of the farmers ***accept*** the integrated forecast but with varying degrees of agreement (Figure 5.4). About 53% of them ‘agree’ and 43% ‘strongly agree’. However, it is expected that a number of factors would influence the acceptability of the integrated forecast. Trust of forecast information significantly correlates (r=0.65) with the acceptability of integrated forecast (Table D5). The majority (96%) of farmers trusted IPF more than their complementary method. However, 99% of farmers would only use IPF if it proves reliable (Table D6).

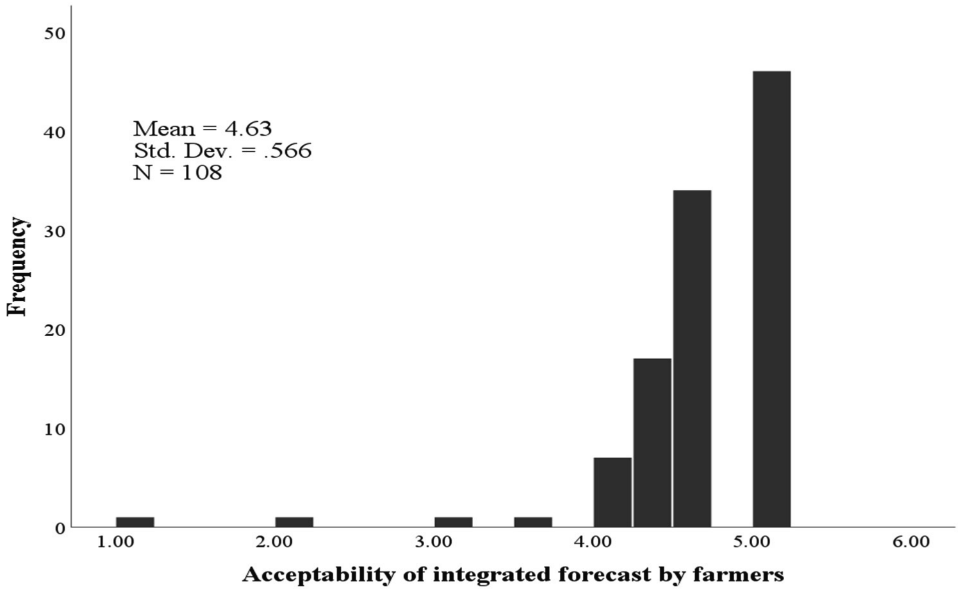

Figure 5.4: Measure of acceptability of integrated forecast obtained from the average of multiple questions in table D3 (Strongly disagree: 1-1.9, Disagree: 2-2.9, Neutral: 3-3.9, Agree: 4-4.9, strongly agree: 5-5.9, I don't know: >6-6.9).

5.4.3 Farmers' forecast preferences and approach to integration

Results from the interviews showed that farmers (93%) already use SF and IF for decision-making, using a complementary technique. The complementary method refers to the act of comparing both forecasts based on farmers' own experience in order to choose the best. This method differs from the IPF method, which combines the two forecast into a single objective forecast. For instance, when farmers receive weather and or seasonal climate forecast information from GMet, they compare it to their own IF and choose the most appropriate information to make predictions for the upcoming farming season. The prediction is use to plan to when and how to carry out almost all their farm activities such as nursing, planting, fertiliser application, weed, and pest and diseases control. However, 3% of the farmers claimed they integrate forecasts by a combination approach in order to produce a single forecast. While they could not explain the process for such a combination, an attempt to do so revealed that they often actually practice the complementary approach. The remaining 4% of the farmers could not tell which kind of integration they do. Overall results of the interview showed that the majority

(93%) of farmers prefered an integrated forecast that is combined than used in a complementary manner (see table D7 for detail results).

Considering how farmers already use SF and IF, farmers do not have any established method for integrating both forecasts. They explained that the selection of the best forecast at a given time and circumstance is based on personal discretion which largely depended on the experience and the degree of confidence they have in each forecast. One farmer said "*even though we(farmers) have much hope in our own forecast, they don't often work, sometimes the Indigenous Ecological Indicators upon which we base our predictions are not so clear for you to depend on for any decision. Under these circumstances, you have no option than to act based on the scientific forecast you received*". The continuous change in climate and land use has caused changes in the landscape and thus affected the migration and extinction of certain animals and trees that were before used for IF.

When asked why they integrate (complementary) the forecasts, farmers mentioned several reasons, which can be summarized into three main points. **First**, farmers recognised that IF has become less reliable over the years and in most cases especially for seasonal predictions, accuracy is not guaranteed. Meanwhile, SF has its own intrinsic weakness that limits its efficacy. Yet both can perform well when used together. Therefore, using both forecasts in a complementary manner help improve their decisions. **Secondly**, confusion arises when SF and IF are confidently pointing in opposite directions. For example, at a daily weather forecast, where IF expects rain and SF indicate no rain or at seasonal time scale when IF forecast near-normal season and SF forecast above-normal season at a higher degree of probability. Under such contradictory circumstances, they compare both forecasts and select one. They do so by first recollecting occasions when such conflicting situations had occurred in the past and the possible outcomes. **Thirdly,** besides comparing both forecast and selecting the best, farmers also compare SF and IF in order to confirm information from each source. Confidence to act is boosted when they compare and realise both forecasts are pointing in the same direction. However, an interesting question to explore is whether they will still look at all three forecasts for comparison once a combined one is issued.

According to the farmers, although the complementary approach of integrating forecasts has been useful in making farm decision, this also comes with some limitations. They, therefore, found the idea of combining two forecasts into a single forecast most appropriate. They foresee such integration to be helpful in ways that their complementary approach could not. For example, the combination approach (IPF) could eliminate the confusion associated with contradicting forecast and perhaps increase accuracy. One farmer said "*If you people (referring to researchers) are able to combine the two into one, then, it is good news for us. Because when SF and IF confidently provide different forecasts, it becomes very difficult to make a decision based on one. Most of the times, we fail even when we compare and choose one.*" Another farmer said "*To be honest our IF has helped us just like the one from GMet, and if we are able to combine them into one, then, it will be good. In fact, our elders say two heads are better than one.*"

Having realised farmers' preference for integrating SF and IF, the most preferred integration method was examined. Describing the three main methods to farmers: the consensus and science integration methods from literature and our proposed integrated probability (IPF) method. Results showed that farmers' most critical concern is not in the type of integrated method but in receiving reliable forecast that can help them take effective decisions. Nonetheless, farmers find it necessary for their IF knowledge is incorporated in forecast generation but were concerned about regular meetings that consume a lot of time. As a result, most (75%) farmers' preferred the new IPF method. In comparing IPF to the other methods, farmers found the opportunity to incorporate their IF knowledge in the forecasting process, with minimal meetings and workshops that saves time very appealing. Considering the fact that IF is adaptive and evolves based on specific events, one may wonder how to guarantee that less frequent meetings to gather IF does not affect updates and the quality of information gathered for IPF. First, it's a fact that the IEIs used by farmers for IF changes just as initials conditions (wind direction, surface pressure) used in scientific forecasting models change. Therefore, farmers also adapt and evolve their forecast accordingly. However, with appropriate feedback mechanisms created, farmers will inform researchers on any new changes that had occurred in the use of IEIs. Moreover, according to the farmers, observed changes in IEIs for IF are not frequent; they happen after several years due to changes in landscape, environment and climate. Therefore, irregular meetings would not affect IF. Moreover, the feedback mechanisms created will keep farmers and researchers connected in order to share new updates about changes in IEIs, thus IF.

One farmer said, "*now that you have understood how we make our forecast, we can send them for you to analyse and give us the final forecast information*". Another farmer said, "*I don't think there will be many* *differences in the outcome of forecast information even when we continuously meet*". However, 25% of the farmers were in favour of the consensus method because of the degree of engagement and frequent meetings and workshops. One farmer in support of this method said, "*I like this method because I want to always be part of the learning process*" another also said, "*I think when we meet continuously, new ideas to improve the forecast information will emerge*". When asked why none of them preferred the science integration method, the farmers' responses pointed to the fact that the idea of temporarily collecting their IF as a hypothesis for building predictive models and not engaging them again in the future is troubling. They believe this will affect the quality of the forecast generated. One farmer said, "*You can't expect the situation to be the same all the time when it comes to the rains. It is good that we keep on monitoring and sending you what is happening in our village so that the information can be accurate*.

5.5 Discussion

This study is a proof of concept that aimed to develop and test a method that combines indigenous forecasts (IF) and meteorological scientific forecast (SF) into a consolidated reliable forecast acceptable by farmers. The analysis started with the hypothesis that an integrated forecast probability (IPF) method can improve the reliability and acceptability of forecast information among farmers. The need for such combined forecast emerged from the idea that SF and IF individually, have inherent weaknesses that affect the accuracy of forecast information and forecast are sometimes contradicting. Therefore, integrating both forecasts could resolve these issues (Nyadzi et al., 2018; Kolawole et al., 2014). Moreover, the potential value of IFs are becoming widely recognised (Nyadzi et al.,2019; Jiri et al., 2016; Manyanhaire & Chitura, 2015), while meteorological scientific forecast (SF) have also advanced (Njau, 2010).

5.5.1 Conceptualising integrated probability method (IPF)

The IPF method used for this proof of concept is a simple weighted average of the conditional probabilities of SF and IF assumed they both do not have an equal likelihood. This was done in recognition of the fact that each forecast has its own skills. However, in our study, this did not produce any significant outcome since the estimated weights used (based on skills assessment of SF and IF) were almost the same. Other comprehensive methods have been suggested to objectively combine SF and IF. For instance, Andrade & Gosling, (2011) suggested using long-term indigenous ecological indicators combined with observed initial conditions of the atmosphere (atmospheric pressure etc.) as input into deterministic predictive models. Chand et al., (2014) proposed documentation of ecological indicators (e.g. flowering of mango trees) that correlate with weather and seasonal climatic conditions combined with data from meteorological stations (e.g. rainfall) to build probabilistic models. These methods may be promising but difficult to operationalise. This is perhaps the reason they have not been carried out.

Results show that SF and IF did not produce the same forecast accuracy at both daily and seasonal timescale, indicating a need to combine both methods into a single objective forecast (i.e. IPF). IPF combined the strengths of SF and IF and subsequently improved their reliability. Our analysis showed that IPF generally performed better than any of the individual forecasts. IPF showed improved reliability at both daily and seasonal timescale although IF performed better at seasonal timescales. The high performance of IF may be attributed to the aggregation of different farmers' forecast. This implies that the number of farmers involved in the process could potentially influence IF quality. However, IPF may be slightly better in terms of reliability but has far greater acceptability potential. This is because farmers preferred method of integration which combines IF and SF into a single forecast than complementary method that does not resolve the issues of contradicting forecast information.

5.2 Acceptability of integrated probability method (IPF)

Results indicated that farmers found IPF as the best way to objectively combine SF and IF. To them, IPF possesses potentials that surpass their own complimentary integration approach and the other methods discussed in the literature (i.e. consensus and science integration methods). Besides, they find the co-production approach of generating reliable and acceptable weather and climate forecast information very vital. However, the relevance of forecast reliability exceeds the choice of integration method. The method of integration also becomes a concern when it consumes much of their time. In the end, a large number of farmers prefer the IPF method to the consensus and science integration methods described by Plotz et al., (2017). Farmers' concern about time consumption of an integration method was related to the consensus and science integration method and not the IPF. Nonetheless, their concern for IPF to generate reliable forecast still stands. To achieve a reliable integrated forecast, adjustment is required from both scientists and farmers. Farmers need to be consistent in IF provision and scientists must do thorough evaluation to include only the best local forecasters in the combination.

From the analysis, we found that trust of forecast information is a significant determinant for uptake. Farmers trust IPF because it combines the best of scientific and indigenous forecasts. Furthermore, the IPF method keeps farmers up to date on activities and emerging issues such as forecast uncertainties and risks. Kasperson et al. (2012) and Renn & Levine (1991) stated that communicating risk is an important part of risk management that revolves around trust. However, farmers trust and preference for IPF over SF and IF does not guarantee uptake, unless IPF information proves reliable for taking farm decisions to reduce risks and increase yield. Furthermore, we expect that building trust among farmers in the study area does not only depend on the confidence they have in forecast information but also the source of the information. In line with this, Steelman et al., (2014) mentioned that the credibility of the source of information could have an effect on how users of information view and respond to messages about environmental risks. Therefore, we propose a transparent and credible co-production process that continuously involves and informs farmers on day-to-day activities.

5.3 Opportunities and limitations of combining indigenous and scientific forecast

Some previous studies have questioned the possibility of combining IF and SF because of the significant differences between the two (see Agrawal, 2002; Plotz et al., 2017). Others, however, have mentioned that both IF and SF converges in some aspects of content and method (Roncoli et al., 2001). Here, we show as a proof of concept that if you collect quantitative data on IF, it is possible to integrate it with SF using the IPF method. To validate the reliability of the IPF method, we used a relatively short dataset. We acknowledge that a longer time series is needed for a more robust validation. Adding more data will provide a more solid basis for validating the reliability of the method. However, it is important to recognise that, long term IF datasets do not exist and the length of our project only made it possible to collect IF data for a single year (in 2017) for the daily forecast analysis and two years (2017 and 2018) for the seasonal analysis. Yet for science-based forecasts it is possible to generate long term datasets using hind-cast methods, this is unfortunately not possible for IF.

Generally, we observe that for both scientists and farmers, the reliability of the forecast is essential and once this is achieved they will probably rally behind the combined forecast irrespective of their inclination to use scientific forecast or indigenous forecast. Therefore, several opportunities exist in combining IF and SF. However, there are some limitations of the combined forecast. First, If the best IF experts are not included in the forecast data collection, then this can introduce errors in the combined forecasts. Secondly, the probability of SF as issued by GMet is also associated with a degree of subjectivity. The best meteorological forecasters are able to produce a more precise probability of rainfall occurrence. Therefore, generating an improved rainfall forecast must be high on the agenda of scientists and meteorological centers including the training of forecasters. Thirdly, to improve the quality of the combined forecast, the spatial resolution at which SF is issued should be as fine as IF. SFs in Ghana are only issued at a regional scale while IF is issued at the village level. This requires an improvement in the use of existing forecasting models and technologies. Fourth, if the combination approach is unclear to both scientist and farmers, they will become sceptical about the combined forecast. Under these circumstances, farmers' attitude to risk becomes an additional factor in using the combined method while scientist open-mindedness becomes important to accept it.

5.4 Implications for knowledge integration and climate services

Finally, findings from this study support the argument that SF and IF have some unique characteristics that make both relevant especially when combined (see also Alexander et al., 2011; Armatas et al., 2016; Nyadzi et al., 2018). Meanwhile, previous studies considered this as either inappropriate or impossible because of possible differences between them (Agrawal, 2002). Therefore, the implications of this study are important for the field of weather and climate services. First, it sets the pace for finding answers to the persistent call by scientists and policy-makers to find ways to objectively integrate SF and IF (Kalanda-Joshua et al., 2011; Hiwasaki et al., 2014; Hoagland, 2016) Secondly, IPF provides an opportunity for both scientists and policy makers to bridge the forecast information gap and thus meet the climate services demands of farmers, particularly in areas where scientific instruments and records are insufficient (Mahoo et al., 2015; Basdew et al., 2017; Nyadzi et al., 2018). Thirdly, IPF could help eliminate the presence of possible human errors associated with a subjective combination of the forecast from meteorological models and indigenous people.

5.5 Recommendations for practice

Previous studies have already proposed frameworks and approaches to be followed when combining indigenous and scientific knowledge, yet they do not have to be static (Plotz et al. 2017). Attempts to combine IF and SF come

with different challenges due to the method, location and context related issues. Therefore, for a successful engagement. We recommend the following;
Local communities should be engaged from the beginning until the end(co-creating), both defining the problem and designing the solution. Also, the short and long term objectives of the project should be clearly communicated. Regular workshops and meetings with local communities offer a greater opportunity to engage farmers. Together, researchers and farmers should agree on who should be involved as an expert forecaster based on forecast skills and how long they are available to provide IF using mobile phones. Since rainfall variability could impact both SF and IF predictions, this can also re-define who is actually a "forecast expert". This could be the case in the future when the variability becomes so difficult for so-called expert farmers to predict, because the ability of a farmer to interpret IEIs under a varying climatic condition to predict rainfall accurately is a determinant of his or her expertise.

Researchers should ensure that the understudied communities already use indigenous forecast and they have a better understanding of how IF is generated from IEIs. This includes consistency and common understanding of the use of scientific terminologies by both researchers and farmers as described in section 5.3.

6.0 Conclusion

This paper describes a proof of concept showing the possibility of combining weather and seasonal climate forecasts using both scientific and indigenous forecast systems. Our study concludes that there is an opportunity to increase forecast reliability and usefulness for farmers if quantitative data on IF is collected and integrated with SF using the IPF method. The IPF method introduces some objectivity into integrated forecast compared to other existing methods.

The most important limitation of the study is the short datasets. With several studies calling for the integration of forecast from IF and SF systems, there is a need to collect long-term datasets for rigorous analysis to substantiate our results. Furthermore, this study directs future research that goes beyond the integration of IF and SF to understanding the consequences of using combine forecast. In particular, the risk of using combined forecast rather than indigenous and scientific forecast in a complementary way by researchers who are more inclined to using scientific methods and farmers who are more comfortable using indigenous methods.

Finally, the insights gained from this study will be relevant for scientists and policy makers in bridging the forecast information gap and thus meet the climate services needs of farmers, particularly those in areas where limited meteorological instruments and records.

Acknowledgements

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6

Chapter 6

The influence of weather and seasonal climate forecast information on rice farmers' decision making

Abstract

Rice farmers in Northern Ghana are susceptible to climate variability and change with its effects in the form of drought, water scarcity, erratic rainfall and high temperatures. In response, farmers resort to weather and seasonal forecast to manage uncertainties in decision-making. However, there is limited empirical research on how forecast lead time and probabilities influence farmer decision-making. In this study, we posed the overall question: how do rice farmers respond to forecast information with different probabilities and lead times? We purposively engaged 36 rice farmers (12 rainfed, 12 irrigated and 12 practising both) in Visually Facilitated Scenario Mapping Workshops (VFSMW) to explore how lead times and probabilities inform their decision-making. Results of the VFSMW showed rainfed rice farmers are most sensitive to forecast probabilities because of their over reliance on rainfall. An increase in forecast probability does not necessarily mean farmers will act. The decision to act based on forecast probability is dependent on which farming stage there is. Also, seasonal forecast information provided at 1 month lead time significantly informed farmer decision-making compared to a lead time 2 or 3 months. Also, weather forecast provided at a lead time of 1 week is more useful for decision-making than at a 3 day or 1 day lead time. We conclude that communicating forecasts information with their probabilities and at an appropriate lead time can help farmers manage risks and improve decision-making. We propose that climate services in Northern Ghana should aim at communicating weather and seasonal climate forecast information at 1 week and 1month lead times respectively. Farmers should also adapt their decisions to the timing and probabilities of the forecast provided.

Submitted as:

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6.1 Introduction

Agriculture development in many parts of Africa is heavily impacted by climate variability and change (Benin et al., 2011; Müller et al., 2011). The increasingly unpredictable and erratic nature of weather and climate conditions on the continent is expected to compromise agricultural production and rural livelihoods, especially in smallholder systems with little adaptive capacity (Kurukulasuriya et al., 2006; Cooper et al., 2008). For instance, changes in rainfall onset, duration and cessation have already caused significant adjustment to farming activities (Jotoafrika, 2013; Salack et al., 2015).

Ghana is one example of such countries facing these challenges. An enormous number of its farmers rely solely on rainfall, with less than 1% of land under irrigation (World Bank, 2010; Armah et al., 2011; De Pinto et al., 2012). The Savanna belt of the country is most impacted throughout the year with irregular rainfall, high temperatures and water scarcity conditions (Akudugu & Dittoh, 2012; Quaye, 2008; Rademacher-Schulz et al., 2014). The advent of climate variability and change has deepened the woes of farmers who mostly rely on rainfall to meet water needs at the farm level. Irrigated farmers are equally threatened when water levels in reservoirs are too low for irrigation (Nyadzi et al., 2018). As a result, rice production in the north of Ghana is severely impacted due to its high crop water requirement (Kranjac-Berisavljevic et al., 2003). Yet, rice is a staple food and the need to meet demand under rapidly changing and varying climatic conditions in the area is a major concern (SARI, 2011).

As part of efforts to manage uncertainties, rice farmers seek forecast information on weather and seasonal climatic conditions (rainfall amount, rainfall distribution, onset, cessation etc.) for informed decision-making (Grothmann & Patt, 2005; Nyamekye et al., 2018). Forecast information is expected to improve farmer decision-making by informing choices on how and when to plant, fertilize and plan supplementary irrigation, amongst others (Defiesta et al., 2014; Risbey et al.,1999).

Currently, farmers in Northern Ghana obtain forecast information from the Ghana Meteorological Services and private information service providers such as ESOKO and Farmerline (Nyamekye et al., 2019). However, the assumption that all seasonal and weather forecast information made available to farmers are useful and used in decision making has been questioned due to a number of challenges (Adiku et al., 2007). First is the timeliness of information. Meteorological information is not made available at the right time could be of limited value to farmers in decision-making. Second is the reliability of meteorological information and how the probability of an event occurring also informs farmer decision-making. Important questions that must be addressed include: How does lead time inform farmer decision-making? At what probability will farmers decide to act or otherwise given meteorological information received? Thus, establishing how farmers make sense of meteorological information considering lead times and probabilities is valuable in ensuring information uptake.

In this study, we build onto the work of Nyadzi et al. (2019) and Nyamekye et al. (2018) who studied forecast information needs and decision making in the Kumbungu district in Northern Ghana respectively. From Nyadzi et al. (2019) we see rice farmers considering hydro-climatic information needs affirming challenges of unreliability and non-applicability of information currently made available especially rainfall. Nyamekye et al. (2018), also explored farmer adaptive decision-making and re-iterate how choice making amongst farmers is highly dependent on the type of meteorological information available. Both studies affirm the need to understand the information-decision-making relationship in rice farming systems in Northern Ghana to improve productivity at the farm level. Building on these studies, we address the overarching question "how do rice farmers respond to forecast information with different probabilities and at different lead times?" To answer this, we pose three specific research questions:

1. How does forecast probability influence farmers' willingness to take decisions?

2. How does seasonal forecast lead time influence farmers' decisions?

3. How does weather forecast lead time influence farmers' decisions?

6.2 Theoretical Framework

In farming systems, farmers as decision makers aim to understand complex conditions such as climate variability and change and its consequences on their choices in their effort to maximize utility (Gigerenzer & Selten, 2002; Olsson et al., 2004; Smit & Wandel, 2006; Buytaert et al., 2010; Termeer et al., 2011). Thus, meteorological information as a resource informs decision dynamics through a process of (re)framing to reduce risks (Barnes et al., 2013; Wallace & Moss, 2002). Where available, the degree to which meteorological information, especially on rainfall, is timely and reliable determines farmers' willingness to act and the kind of decisions they take (Verbeke, 2005; Weaver et al., 2013; Dewulf & Biesbroek, 2018; Gbangou et al., 2019). In climate change literature, uncertainty and forecast lead times have been highlighted in bridging climate information usability gaps in decision-making (Podestá et al., 2002; Lemos et al., 2012; Mase & Prokopy, 2014; Roudier et al., 2014).

This study sought to test three hypotheses in understanding the relationship between meteorological information (focusing on rainfall) and farmer decision-making although there are a lot of factors that determine farmer use of meteorological forecast (Vogel, 2000; Ziervogel, 2004). First, that the higher the probability associated with a forecast, the more farmers are willing to act on their decision at every stage of decision-making within the farming cycle. In this case, although the probability of a forecast cannot be 100 percent, farmers irrespective of practising rainfed or irrigated farming will act out their intended decision when rainfall probability is high. Weisheimer and Palmer (2014) opine that probabilistic reliability should be the foremost measure of the 'goodness' of a forecast. Herewith, the 'goodness' of a forecast is a contextual question requiring the positioning of its interpretation in specific farming systems. Letson et al., (2001) concur with reference to their findings on obstacles to greater use of climate information. (Langford & Hendon, 2013) affirm and buttress how unreliability remains an impediment to the uptake of climate related information.

Our second hypothesis is that seasonal forecast communicated at different lead times has consequences on the choices farmers make in seasonal decision-making. Thirdly, we also posit that weather forecast made available at different lead times significantly drives in-season decision making. Forecast communicated with a 'sufficient' lead time has a positive correlation with productivity (Zinyengere et al., 2011). Seasonal climate forecast has no intrinsic value except for their ability to influence decisions of users (Hammer, 2000). Sub-seasonal-to-seasonal forecasting range seen as 'predictability desert' due to initial difficulties has gained attention in the bid to bridge the gap between weather forecasts and seasonal outlooks (Vitart et al., 2012). Randomizing probability, seasonal and weather information variables in the context of rice farming systems requires holding other conditions (finance, land, labour, etc.) that influence decision-making constant.

6.3 Methodology

6.3.1 Study area

The study was undertaken in the Kumbungu District in the Northern region of Ghana as shown in Figure 6.1. The district, located within the Guinea Savannah agro-ecological zone covers a land area of 1,599km^2 with Kumbungu as its capital. The District shares boundaries to the north with Mamprugu/Moagduri district, Tolon and North Gonja districts to the west, Sagnerigu Municipal to the south and Savelugu Municipal to the east (Abdul-Malik & Mohammed, 2012). Farming is the mainstay of inhabitants cultivating cereals, tubers and vegetables including rice, millet, sorghum, groundnut, tomatoes and pepper. Average annual rainfall is 1000mm with the main cropping season stretching over the period of May to late October (Quaye et al., 2009). The temperature is warm, dry and hazy between February and April. The district is drained by the White Volta and other smaller rivers and their tributaries with most drying up in the dry season. The Bontanga Irrigation Scheme located within the district also supports irrigated farming with crops such as rice and vegetable mostly produced within the scheme.

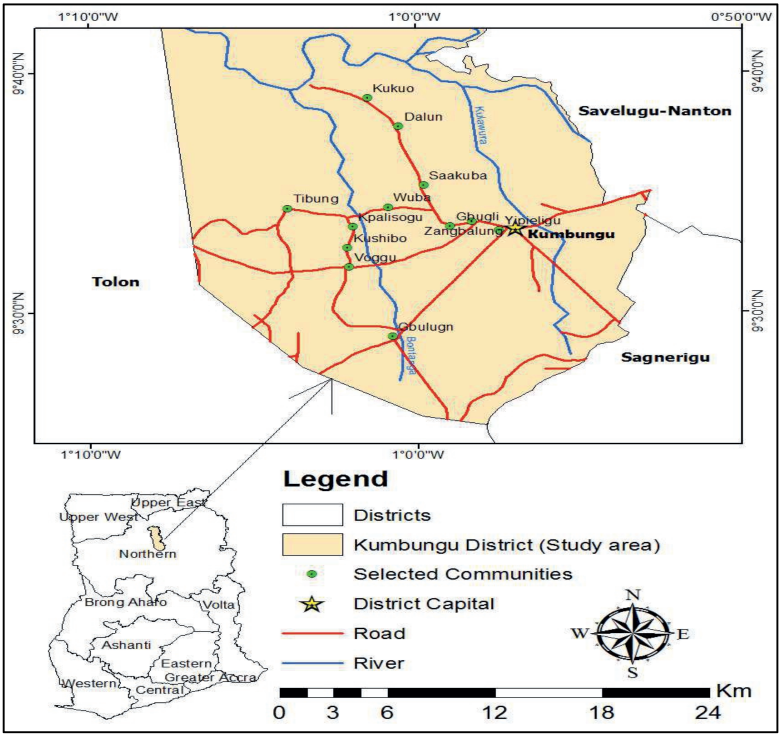

Figure 6.1: Map showing the study location

6.3.2 Research Design

Scenario Workshops (SW) have roots in technological assessments and originally designed to facilitate engagement between scientists and citizens in the appraisal of new technologies (Andersen & Jaeger, 1999). SWs have also dominated planning circles for giving a participatory foresight to resource management and also used in engaging citizens in testing technological solutions (Andersen & Jæger, 1999; Mayer, 1997; Rinaudo et al., 2012). The study adopted a Visual Facilitated and Scenario Mapping Workshops (VFSMW) (Hatzilacou et al., 2007; Mexa, 2002) focused on three main groupings of farmers; irrigated, rain fed and those who practised both.

A total of five workshops were organised. The first workshop was a kick-off workshop with the objective to select and familiarise with the participants and explain to them the rationale of the study. The kick-off workshop also aimed at grouping farmers, setting up the environment with the required tools as well as agreeing on dates for the rest of the activities. In addition, rules of engagement were communicated to the participants and opportunities created for questioning and clarifications. The second, third and fourth workshops were the VFSMW specifically focused on engaging different farmer groups directly to test the different information variables (see section 3.3) and what they mean for farmer decision-making. Here, farmers were given a cardboard and spinning wheels showing the source of information, certainty and forecast lead-times. On the cardboard was a matrix showing the cropping cycle (See figure E1 in supplementary materials) for easy representation and understanding considering literacy levels of the participants. Individually, participant(s) were taken through seven decision points of the cycle.

Participant(s) were randomly exposed to three spinning wheels with each wheel focusing on a key information variable (probability; lead time (seasonal); lead time (weather). Each variable also had three main indicators for which farmers were required to indicate what decision they will make considering these indicators. The purpose of the wheel is to allow for randomization of the information to be tested (See figure E1 in supplementary materials). The fifth workshop was a validation and feedback workshop. At this workshop, preliminary results were communicated and discussed. Participants feedback on key findings were also noted. The process for VFSMW is summarized in Figure 6.2.

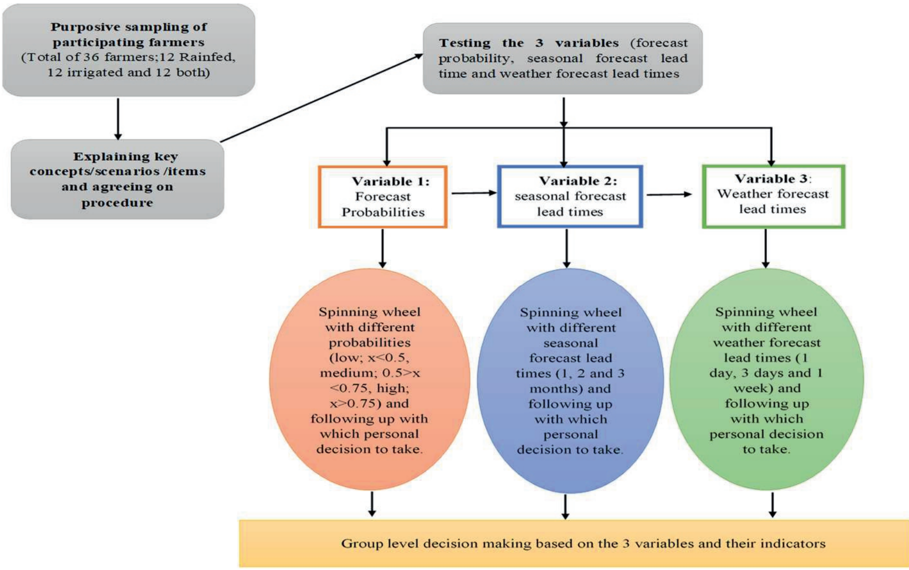

Figure 6.2: Stepwise approach to the VFSMW

6.3.3 Sample and sampling approach

With the support of the leadership of farmer associations and the extension officer in the area, a total of thirty-six (36) rice farmers (3 from each community engaged in either rainfed, irrigated or both) were purposively sampled from 12 different communities for the VFSMW workshops (See Figure 6.1). The VFSMW was used to test three (3) main variables and twelve (12) indicators fashioned out of research questions. The variables include; (i) Probability of rainfall forecast information for decision-making (ii) Lead times of weather forecast for decision-making (iii) lead times of seasonal climate forecast for decision-making. For each of these three variables, a couple of indicators and their influence on decision-making was established focusing on rainfall and what prevails under normal conditions. Farmers were engaged in what decisions they will take under different scenarios. The experiment was carried out in this order: first, the probability of forecast and farmers' decision-making, secondly seasonal forecast lead times and farmer decision-making and thirdly weather forecast lead times and farmer decision-making.

Variable 1: Probability of rainfall forecast and Farmer decision-making

The degree of certainty associated with weather and seasonal climate information is expected to inform farmers' information uptake and adaptive decision-making. Here, participants received information on the probabilities of forecast information categorised as (1) low (x<0.5), (2) medium (0.5>x <0.75) and (3) high (x>0.75). Interactions were based on the assumption that it will rain but at these different probabilities. For each of these probabilities, we recorded whether farmers would act or not given. We treated the probabilities in each case as the independent variable and the decision "will act" and "will not act" as dependent variables.

Variable 2: Seasonal (rainfall) forecast lead times and farmer decision-making

The timing of information provision at seasonal timescale affords decision-makers, in this case, farmers to have either more or less room in deciding what decisions to take. We deduce which decisions farmers take given different lead times (1 month, 2 month and 3 months) under 'normal' conditions and whether there is a substantive difference in actions adopted by farmers in this regard. The dependent variables in this test were also "will act" and "will not act" and the independent variables were the three lead times.

Variable 3: **Weather (rainfall) forecast lead times and farmer decision-making**

Building on from the rationale behind the testing of variable 2, the participants were exposed to varying lead times of weather forecast information. Here, we tested which decision farmers will take given lead times of 1 day, 3 days and 1 week. Unlike variable 2, the dependent variables in this test were the decision options of farmers and the dependent variables were the three lead times.

6.3.4 Data Analysis

We employed both qualitative and quantitative methods in data analysis. The data gathered from the workshop were coded and entered into SPSS version 23 for analysis. The decisions gathered during the workshop were grouped given key expressions and then coded for easy analysis in SPSS. Results of the analysis are presented in frequencies and percentages.

6.4 Results

6.4.1 Forecast Probability as a Determinant of Risk Acceptance Level

Our study findings point to different sensitivities to probability depending on what activities farmers had to undertake. The study showed a positive correlation between forecast probabilities and farmers' decision to act in the pre-season and planting. It emerged that, as probability increased, farmers were willing to take action on forecast information received (see Figure 6.3A). However, an inverse relationship between forecast probability and decision making was observed during the remaining stages of the farming cycle. Farmers would rather withhold intended action at the point of land preparation, weed control and fertilizer application when the probability of rainfall forecast is high (see Figure 6.3B). Clearly, the aforementioned farming stages are very sensitive to the rains and cannot be favourably completed when rains are expected. For example, farmers indicated that fertilizers do take a while to be absorbed in the soil and undertaking such in the moment of expected rainfall could result in the fertilizer being washed away. Thus, although high probability is a good indicator of rainfall occurrence, it also results in non-action taking as a response.

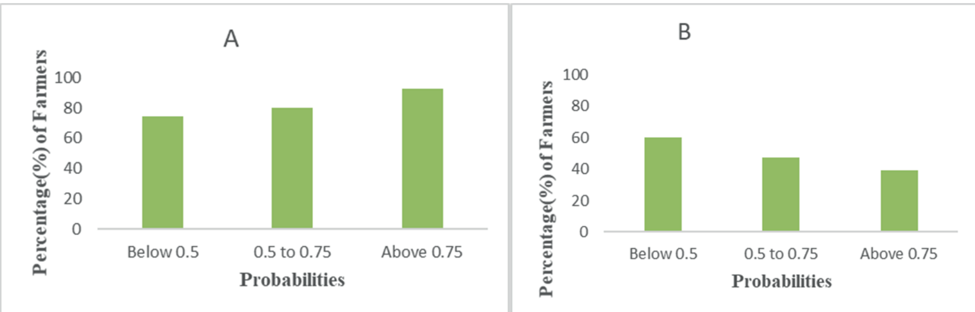

Figure 6.3: The general influence of forecast probabilities on farmers' decision to act (n=36 farmers). [A. Preseason and planting B. Land Preparation, 1^{st} and 2^{nd} weed control, 1^{st} and 2^{nd} fertilizer application and harvesting]

A further disaggregation given different farming type showed that irrigated rice farmers and to an extent those who practised both were least sensitive to different forecast probabilities compared to rainfed farmers (see figure 6.4A and 6.4B). For irrigated farmers, this can be alluded to the option of meeting water needs through supplementary irrigation. Farmers who practised both might also have lesser risk since they may still count on their irrigated farms should the rains failed. Rainfed farmers however, remain sensitive because they have no option except to face their lost and thus are sceptical in their decision making.

At the pre-season and planting stages in Figure 6.4A, irrigated farmers will act irrespective of the probability of the forecast information given. More rainfed farmers and both will act given a forecast information with higher probability. However, during land preparation, weed control and fertilizer application forecast with high probability were faced with negated action by all group of farmers (see Figure 6.4B). For example, irrigated farmers will also not fertilize if rainfall expectations are high because will result in washing away of fertilizer as mentioned earlier.

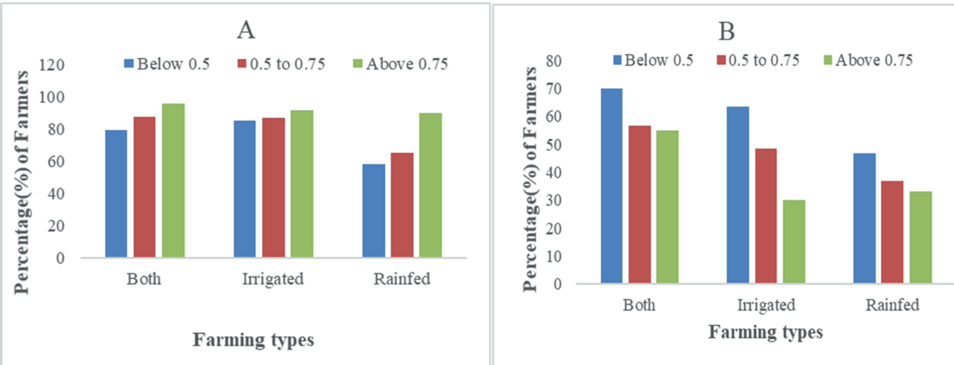

Figure 6.4: The impact of forecast probabilities on different types of farmers' decision to act (n=36 farmers) [A. Preseason and planting B. Land Preparation,1st and 2nd weed control, 1st and 2nd fertilizer application and harvesting]

Furthermore, interaction with farmers at the group level provided further evidence to the results obtained at the individual level decision making. A higher probability (above 0.75) helps farmers in concreting their decision-making through choice making on whether to take action or withhold undertaking an intended activity with the ultimate aim of maximizing yield and productivity. Thus, farmers' respond to communicated forecast probabilities depends on farmers estimated risk aversion. Nevertheless, several external factors including financial capacities and personal attributes (family size, belief, gender) also frame farmer decision-making. Outcomes of group engagement also suggest that uncertainty in forecast information which is currently not communicated to farmers by service providers such as ESOKO and Ghana Meteorological Agency is the reason for non-uptake as compared to lead times.

6.4.2 Seasonal Forecast Lead Time and Farmers Decision-Making

The results of the study showed seasonal forecast provided at a 1 month lead time significantly informed farmer decision-making as part of preparatory arrangements before the season begins. Much also, irrespective of farming type, farmers agree that a lead time of 3 months is of least relevance as the 3 month pre-season period could come with much greater variation in expected seasonal conditions and also the fact that the majority of farmers will do nothing given a 3 month window of opportunity. From the data, there was more agreement between irrigated rice farmers and rainfed rice farmers on how seasonal forecast at different lead times influence their decision-making. This is shown in Figure 6.5.

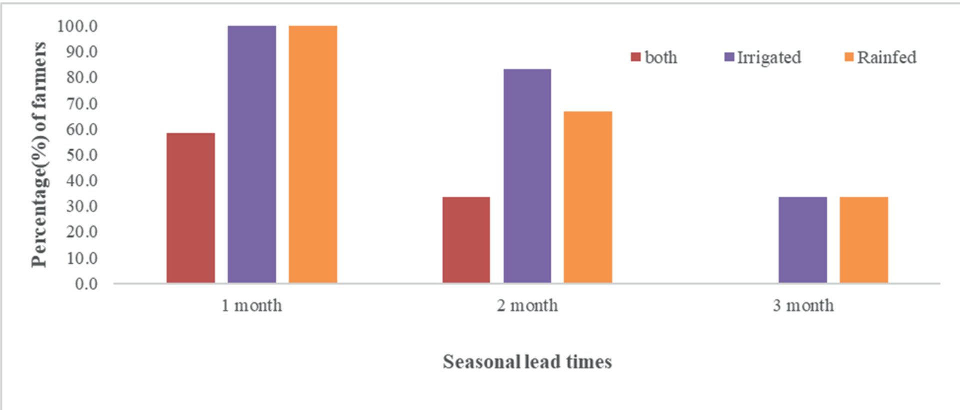

Figure 6.5: Farmers willingness to act given seasonal forecast at different lead times (n=36 farmers) [None of the farmers involved in both indicated they will act on a 3 month seasonal forecast]

Focusing on farming systems dynamics, it emerged that 100% of irrigated and rainfed farmers will act when forecast information is communicated at a lead time of 1 month as compared to those engaged in both (58%). Also, 83%, 68% and 33% of farmers engaged in irrigated, rainfed farming or both respectively confirmed they will act given seasonal forecast at a lead time of 2 months. Forecast information provided at a 3 month lead time is of less relevance to farmers with about 68% of farmers involved in either rainfed or irrigated rice farming confirming they will not take any initiative with such information (See Figure 6.6). All farmers practising both indicated that they will not act on seasonal forecast information at a 3 month lead time as it is too early a period to pursue any farm related activity. (see Table E1 in supplementary materials for more details).

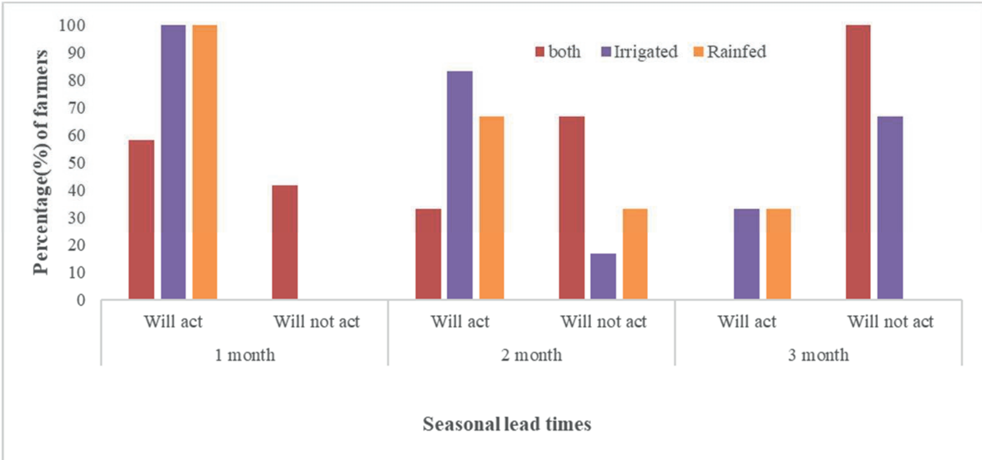

Figure 6.6: Percentage of farmers indicating that they will take a decision to act or not under different seasonal forecast lead times (n=36 farmers).

Further interactions at the group level during workshops showed that although seasonal forecast is important for farmers decision-making, 92% of farmers in all group deliberations confirmed strongly that forecast information at a 3 month lead time is of little relevance for them. Nevertheless, farmers indicated that some important deliberations occur at the household level within this 3 month period. Most of the deliberations focus on financial planning for both farm and non-farm related expenditures such as school fees, medical bills and payment of outstanding loans. Pre-season decisions also entailed arrangements for farm labour and tractor acquisition. However, seasonal forecast presented at 3 months and 2 months lead time were not relevant for such decisions as compared to 1 month with 90% of farmers confirming such.

6.4.3 Weather Forecast Lead Time and Farmer Decision-Making

The results revealed that farmers take different decisions given weather forecast information at different lead times (Table 6.1). At the point of land preparation, 89% of all farmers indicated given rainfall forecast information at a 1 day lead time, they will prepare their lands using a tractor. Similarly, 75% of farmers engaged still indicated they will clear their farmlands using a tractor should they receive rainfall forecast at a 3 day lead time. However, 73% indicated that they will use manual labour to clear their lands when rainfall forecast is provided at a one week lead time.

Regarding decision-making on planting, majority of farmers showed a preference for broadcasting seeds. The findings showed that 89% of farmers will broadcast their seeds when rainfall forecast is provided at a lead time of 1 day. Also, 70% and 64% will broadcast upon receiving rainfall information at a lead time of 3 days and 1 week respectively.

The decision on fertilizer application is one of the most sensitive to water availability conditions. Majority of farmers (97% at 1 day lead time, 83% at 3 days lead time) will apply fertilizer rather after rainfall using placement method and sprinkle in case they intend to apply fertilizer before the rain when such information is communicated. However, given rainfall forecast information at one week lead time, farmers will apply fertilizer by placement. Thus, a 1 week lead time offers much flexibility in decision-making.

The application of weedicide was less sensitive to rainfall with about 92%, 97 % and 100% indicating they will apply weedicide before rainfall when forecast information is communicated at a 1 day, 3 days and 1 week respectively. This is attributable to the fact that farmers only need a few minutes to a couple of hours to complete the task of spraying weedicides although that is also dependent on the size of farmland under cultivation.

The second stage of fertilizer application also pointed to the need for soil moisture or ample time to apply fertilizer before the rains. The results suggest similar practices as the first phase of fertilizer application. Here, 89% of farmers indicated they will apply fertilizer by placement after the rains when forecast information is communicated at a 1 day lead time. Similarly, more farmers (56% and 60%) will prefer to apply fertilizer by placement after rainfall given forecast at a lead time of 3 days and 1 week respectively. Thus, the sensitivity of farmer decision to water availability conditions is more severe at the first stage of fertilizer application than the second. Farmers face a greater risk of crop loss within the period of the first fertilizer application than the second.

Farmers indicated that harvesting is less sensitive to rainfall conditions but more defined by access to harvesting tools and machinery. In effect, given forecast information, 75% of farmers will harvest with a combine harvester at a 1 day, 3 day time and 64% of farmers will use the same method at 1 week lead time.

Indicatively, weather forecast provided at different lead times came with choices farmers found most appropriate that minimise their risk and chances of completing activities at each stage in time. At no point did farmers point to not do anything given forecast at different lead times. Table 6.1 presents the percentage to which a particular choice was made by farmers at a particular farm stage. A more detailed information is presented on Table E2 of the supplementary material.

Table 6.1: Farmer decision making under different weather forecast lead times.

Farming stages	**Decision Choice**	**% of Responses (One Day Lead Time)**	**% of Responses (Three Day Lead Time)**	**% of Responses (One Week Lead Time)**
Land Preparation	Will clear the land using manual labour	11.1	25	72.3
	Will clear land using a tractor	88.9	75	27.8
Planting	Will broadcast seeds	88.9	69.5	63.9
	Will nurse and transplant seedlings	11.1	16.7	19.4
	Will plant using the dibbling method	-	13.9	16.7
1st Fertilizer Application	Will apply fertilizer by broadcasting before the rain	2.8	16.6	47.2
	Will apply fertilizer by placement after the rains	97.2	83.4	52.8
Weed Control	Will apply weedicide after the rains	8.3	2.8	100
	Will apply weedicide before the rains	91.7	97.2	-

2nd Fertilizer Application	Will apply fertilizer by broadcasting before the rain	11.1	44.4	36.1
	Will apply fertilizer by placement after the rains	88.9	55.6	60.4
Weedicide Control	Will apply weedicide by spraying after the rain	80.5	13.9	5.6
	Will apply weedicide by spraying before the rain	19.2	86.1	94.4
Harvesting	Will harvest with a sickle	25	25	36.1
	Will harvest with a combine harvester	75	75	63.9

Generally, forecast provided at 1 week lead time better position farmers to decide on acting or not followed by 3 days and then 1 day. Farmers argued that 1 day lead time is too short a period to undertake most farm activities except weedicide application for weed control and broadcasting in the case of planting. For example, providing forecast information 1 day before land preparation and also fertilizer application leaves limited room to adjust decisions. A 3 day lead time, however, offers more time for farmers to act compared to 1 day.

6.5 Discussion

This paper sets out to understand how different forecast sources, lead times and probabilities influence farmer' decision making. We explored this relationship using different information scenarios and groups of farmers within rice farming systems in a bid to investigate how seasonal and weather information could be tailored to farmer information needs in farming systems. In this section, we discuss inferences from our research findings in relation to other scholarly works on addressing weather and seasonal climate information needs in rice farming systems in Northern Ghana.

Firstly, our findings reveal that communicating forecast information with different probabilities in Northern Ghana significantly informs farmer decision-making thereby addressing the research question 1. We, however, reject the first hypothesis that claims that the higher the probability associated with a forecast, the more farmers are willing to act on their decision at every stage of decision-making within the farming cycle. This hypothesis was rejected because framers respond to different forecast probabilities is dependent on the farming type. For instance, there is a positive correlation between increasing forecast probability and farmers' decision to act during pre-season and planting stages. Meanwhile, a negative correlation exists between increasing forecast probability and the decision to act during Land Preparation, weed control, fertilizer application and harvesting. Furthermore, we discover that farmers understood that 100% certainty in weather and seasonal climate forecast information is non-achievable due to the erratic nature of events and are thus adaptive in their response to forecast probabilities. Breuer et al., (2000) and O'Brien & Vogel, (2003) concur that the probabilistic nature of weather and seasonal climate forecasts present particular challenges. Hence, for effective use of forecast information, decision-making must take into account the probability of forecast. Also, although all farmers expressed the need to minimize uncertainty, farmer response varied and was dependent on the farming system being practised and the estimated risk that had to be managed. For instance, due to water availability for supplementary irrigation within the irrigation scheme, rice farmers operating within the scheme face lower risk levels and will act even when forecast probabilities are less than 0.5. This was contrary in the case of rainfed farmers. Thus, forecast probabilities must be clearly communicated to farmers.

In communicating forecast probabilities one needs to reflect on the ways in which they are presented. From our experience, using simple graphics with appealing colours to represent forecast probabilities is an effective way of making farmers understand what is been communicated. For instance, each farmer type deals with forecast probability differently and so forecast probability could be communicated based on different types of farmers. Less sophisticated farmers will prefer simpler information. Moreover, how one describes forecast probabilities must fit into the domain of farmers' local knowledge, therefore it is essential to understand how farmers generate and describe probabilities. More so, ascertain whether their personal feelings of risk and vulnerability influence their definition. It is important to also communicate change in probabilities in simple terms and in languages that are best understood by farmers. Further follow-ups on how a change in probability impact farmer decision-making or practices will enhance our understanding of the pros and cons of a failed forecast on farmers' livelihood.

Secondly, the study outcome also confirms a part of our first hypothesis given the findings that given different lead times of weather and seasonal climate forecast, farmers made different decisions. However, not all lead times contribute to a change in decision-making. For example, seasonal forecast information provided 3 months ahead of time is irrelevant in taking pre-season decisions. What is strongly recommended is seasonal forecast information at a lead time of 1 month. In our context, this is the period within which most pre-season arrangements (farm machinery, labour, seeds, etc.) and decisions happen. Crane et al., (2010) following their engagement with 38 farmers in Northern Georgia made similar conclusions that farmers are less likely to rely on seasonal forecast with longer lead time. They acknowledge that lead time must conform to users' needs and priorities. Essentially, the lead time for communicating seasonal forecast must be estimated through the lens of farmers. Similarly, not all lead times for communicating weather forecast information can contribute to informed farmer decision-making. As evident in our results, activities such as fertilizer application and planting are highly sensitive and difficult to undertake when forecast information is communicated with a 3 day or 1 day lead time. Also, the period of fertilizer application is the most water sensitive stage of the farming season. Thus, a lead time of 1 week offers more flexibility for farmers to react to weather forecast information. This is however of least significance in the context of decision-making on weed control and harvesting.

The use of Visually Facilitated Scenario Mapping Workshops also renders the opportunity to explore how a future functioning hydroclimatic virtual observatory providing farmers with forecast information under different conditions could inform their decision-making. The approach creates a hypothetical environment for establishing farmer response to information from climate services or hydroclimatic virtual observatory as proposed by Nyadzi et al., (2018). Therefore, the results from this exercise could slightly differ from real time events depending on conditions where social and biophysical conditions of farmers could vary. Scenario workshop methodologies originated in technological assessments and were designed to facilitate engagements between scientists and citizens in the appraisal of new technologies (Mayer, 1997; Andersen et al., 1999). We give more of a visual spin to the methodology which can be applied in other contexts in co-production and citizen science experiments on climate services.

Our methodology also had a number of limitations. First, maintaining other external factors (finance and resource availability, etc.) constant could not depict a vivid environment for which farmers make decisions. Results could be different should we consider the interaction of these factors. Secondly, the experiment focused on rainfall without consideration for other atmospheric variables (temperature, humidity, etc.) which also could have influence farmers' decision outcomes. Hence, a similar study with a broader look at other variables could produce different results in different contexts. Thirdly, our test of focused on farmers' decision making under normal conditions performing this experiment under extreme situations could afford the opportunity to analyse comparatively what decisions farmers take under different situations.

In a nutshell, the results of this study have critical implications for the design and operation of climate services particularly in Northern Ghana and also answers our third research question. First, the results confirm that different farm types (irrigated, rainfed and both) in the study area requires forecast information at specific lead times and probabilities. Hence, operators of weather and seasonal climate information services must understand their audience. Also, for effective decision making, farmers have much preference for weather and seasonal climate information at 1 week and 1 month lead times respectively. This means in the provision of information, emphasis must be placed on the quality of forecast information at these lead times in order to meet farmers' needs. This nevertheless is valid in rice farming systems and hence could though hardly vary in other systems. Thirdly, communicating forecast probabilities to farmers is essential. Different types of farmers relate differently to forecast uncertainty or probabilities. Farmers especially those into rainfed farming have little room for taking huge risk and will only use forecast information with higher probabilities. Hence understanding these dynamics can extensively improve acceptance and uptake of weather and seasonal information making climate services more useful and impact oriented.

6.6 Conclusion

Based on the evidence provided in this study, we conclude that communicating forecast information at the appropriate lead times and probabilities has the potential of making climate services more useful for farmers. More specifically, we discover that, first, an increase in forecast probability does not necessarily mean farmers will act. The decision to act is also dependent on which farming stage there is. Secondly, weather and seasonal climate forecast information at 1 week and 1 month lead time respectively most conveniently informed farmer decision making. Secondly, fertilizer application and planting decisions stages of rice farming are most sensitive to rainfall. Thirdly, irrigated rice farmers have comparatively lower risk level and will act irrespective of forecast probabilities. Farmers should also adapt their decisions to the timing and probabilities of the forecast provided. Finally, user-driven climate services should aim at engaging end-users in the framing of information and content rather than assume the universality of the usefulness of what is presented for uptake.

Acknowledgement

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7

Chapter 7

Synthesis

7.1 Introduction

The observation that climate information services are considered as an essential part of the climate change adaptation agenda (e.g. Orlove et al., 2004; Vaughan & Dessai, 2014; Lourenço et al., 2016) was the starting point of this dissertation. In the past decade, substantial progress has been made in the provision of scientific forecast (SF) information at different timescales to support farmers' decision-making. Yet given the substantial gaps in SF, studies have shown that farmers in rural Africa, complement SF with their own indigenous forecast (IF) and in most cases are more inclined to use IF compared to SF. Several scholarly works have therefore proposed the integration SF and IF to bridge the forecast information gap especially in areas where scientific instruments and records are insufficient (Gagnon & Berteaux, 2009; Chang et al., 2010; Ziervogel & Opere, 2010; Mafongoya, 2017; Nyadzi et al., 2018). In addition, there has been a pressing call in recent times to shift from climate information services that are science-driven and user-informed to a more collaborative approach where both scientist and end-users co-produce. This is what has been referred to in this dissertation as a shift from first to second generation of climate information services, drawing inspiration from the work of Karpouzoglou et al. (2016) on second generation Environmental Virtual Observatories (EVOs).

This study, therefore, sets out to *improve climate services in Ghana through* co-production *by integrating scientific and indigenous forecasts to support farm decision making.* To achieve this, I aim to answer five research questions which are defined in chapter 1 and addressed in chapter 2 - 6. Answers to these five research questions are presented in section 7.2. In section 7.3, I elaborate on the results and discussed how they contribute to the main objective of the dissertation and fit into the broader literature. In addition, the contribution to science and society, key strength and limitations and an outlook for further research on this topic are given.

7.2 Answering the research questions

RQ1. ***What is the potential of climate information services to support rice farming systems?*** *(Chapter 2)*

This research question explored the design and operationalization of second generation climate information services that moderate the existing socio-ecological challenges in rice production systems in Northern Ghana. Using research literature and documents analysis, interviews and focus group discussions, I engaged different stakeholders, and gathered and analysed primary and secondary data.

I conclude that a second generation climate information service is potentially relevant for rice farming systems in Northern Ghana. This is because it has the potential to respond to biophysical (climate variability and water unavailability) challenges that affect farmers daily and seasonal decision making. Also, the analysis of the socio-institutional issues including information delivery platforms informed the design of the services in a manner that enhances stakeholder interaction and information exchange and use. The proposed second generation climate services framework has the potential to address the challenges associated with existing information services such as user unfriendliness, relevance and inaccuracies of forecast information, managing user expectation, weak collaboration between information providers and users. Moreover, an important driver of success to the development of this framework is the intensive and collective interaction of scientist and farmers. Citizen science has been identified as a means of engaging farmers in data collection and information exchange. The structure and mechanism of the second generation climate services framework are supportive in this regard.

Finally, reflecting on the proposed framework using the four principles of responsible innovation (anticipatory, inclusive, reflexive and responsive) revealed some possible future eventualities that allowed the discussion of plausible solutions at an early stage in the design process. One of such key challenge anticipated was the continuous reliance on farmers for data collection. I argue that both rainfed and irrigated farmers in the area are motivated by the awareness of climate variability and limited water availability and therefore, urgently need action to improve farm decision making. However, it remains unclear how much time in the future will farmers devote to this process. I suggested that limited commitment of farmers can potentially reduce data availability and quality and therefore both scientist and farmers must be realistic about the time needed for regular, meetings, data and information exchange. Thus, specific attention to openness and transparency in the design process will allow participants to freely share their opinions and concerns. At the same time, researchers need to be proactive and perceived to be serious with the process through their active engagement. Moreover, motivating farmers will maintain their continuous interest and participation in the process.

RQ2. How successful can seasonal climate forecast meet farmers' information needs? (Chapter 3)

This research question aimed to gain insights on demand-driven climate service for rice farmers' adaptive decision making. To do this, I used interviews and workshops to identify information needs for each stage of rice farming for the different types of farmers in the area (rainfed, irrigated and both rainfed and irrigated). This informed the second step where I carried out skills assessment of the state of the art ECMWF System 4 seasonal climate forecast system, discussing the potential of the forecast in meeting these needs.

Results show that farmers' key information needs are related to rainfall and temperature. The information needs are linked with specific farming decisions and stages of the growing season, which makes the timing of providing information relevant. The information needs of rice farmers in Northern Ghana are homogeneous although some of these needs are ranked higher than others depending on the frequency of use and farming type. Farmers ranked rainfall distribution, temperature and dam water level as their most important information needs, followed by total rainfall amount and onset as fairly important before the cessation of rainfall. Wind speed and direction were considered the least important information need. Temperature and precipitation patterns were found relevant by all farmers irrespective of geographical location or type of farming practised except dam water level which was top on the list of irrigating farmers.

ECMWF-S4 exhibited skills that were mostly independent of the variable, season and lead times. This is promising for meeting farmers' needs at their most preferred lead time of 1 months, ensuring proper planning and decision-making. Generally, ECMWF-S4 is able to simulate well the inter-annual variability, of rainfall, minimum and maximum temperature for all seasons and lead times. This has great implications for farmers' decision making since increasing rainfall variability results in higher risk for farmers. Although at the time of finishing this dissertation the new ECMWF-S5 was launched (see Johnson et al., 2019), my findings already demonstrate the potential use of model based seasonal forecasts and the value of linking forecast information to farm-level decision making, which is an essential step to improving climate services.

RQ3. ***What are the skills in indigenous and scientific forecast to promote effective climate services?*** *(Chapter 4)*

This research question seeks to establish how accurate indigenous forecasts of farmers are and what are the underlying mechanisms behind farmers' forecasting techniques. I resolved this question in two ways; first, I captured farmers' mental model of how indigenous ecological indicators (IEIs) are used to predict the daily and seasonal climate rainfall. Secondly, I used binary or dichotomous forecast verification measure to determine the skills in farmers' rainfall forecast compared with Ghana Meteorological Agency (GMet) forecast with no intention of discrediting neither of the forecasting systems.

I found that observational changes in IEIs in addition to historical rainfall patterns serve as the fundamental template that allows farmers to form expectations for the coming season. Farmers have an established mental model of how IEIs influence the prediction of different weather and seasonal climate events. On average, both farmers and GMet are able to accurately forecast one out of every three daily rainfall events. Monthly analyses indicated that GMet performed better than farmers in the months of April, July, August and September while farmers performed better in May June and October. At the seasonal scale, one out of every three farmers was able to accurately make onset prediction while two out of every five farmers are able to get rainfall amount and cessation right. Similarly, GMet was able to predict rainfall amount accurately in one out of every three communities and one out of every four communities for onset but was unable to accurately predict cessation for the communities. I also found that indigenous forecast is not intuitive but a skill rationally developed which improved with age and experience. This result, therefore, informs the next step which aimed at finding a quantitative method to integrate farmers indigenous forecast and scientific forecast (from GMet).

RQ4. ***How can the integration of indigenous and scientific forecast improve reliability and acceptability of climate services?*** *(Chapter 5)*

This research question aimed at showing whether it is possible to integrate indigenous forecast (IF) and scientific forecast (SF) into a single forecast and whether it will improve the reliability and acceptability of forecast information among farmers in Northern Ghana. I did this by first reviewing and analysing existing literature to determine the strength and weakness of existing integration methods. Secondly, I developed an integrated probability forecast (IPF) method, tested its reliability compared to IF and SF and evaluated the acceptability of the proposed IPF method.

The answer to this research question was positive. The IPF method combines the strengths of IF and SF and subsequently improves their reliability. Therefore, IPF performed generally better than any of the individual forecasts. Specifically, IPF showed improved reliability at both daily and seasonal timescale although IF performed better at seasonal timescales. Furthermore, the IPF method had far greater acceptability potential among farmers (93% of farmers accept) because it combines IF and SF into a single forecast, resolves the issues of contradicting forecast information, requires less meeting time and improves forecast reliability.

Finally, as a proof of concept, I demonstrated that it is possible to combine IF and SF into a single objective forecast despite the potentially significant differences between them. I also showed that using the IPF method to integrate IF and SF improves the reliability and acceptability of the resultant forecast information among farmers.

RQ5. ***How do weather and climate information influence farmers' decision making?*** *(Chapter 6)*

For this research question, I investigated how timeliness (lead times) and certainty (probability) of forecast information will influence farmers' decision making. I explored this using Visually Facilitated Scenario Workshops (VFSW).

I found that different types of farmers (irrigated, rainfed and both) respond to forecast probabilities in different ways depending on their perceived risk levels. For instance, irrigated rice farmers have comparatively lower risk level and will take decisions irrespective of forecast probabilities. Also, given different lead times of weather and seasonal climate forecast, farmers take different decisions. Weather forecast provided at 1 week and seasonal climate forecast provided at 1 month lead times have the most influence on rice farmers' decision making. Also, unlike weed control and harvesting, farming decisions such as fertilizer application and planting are highly sensitive to forecast lead times because they are critical stages of rice farming that are water sensitive.

Finally, forecasts lead times and probabilities are essential for farmers' decision making, yet for existing climate services in Ghana, either information are not provided at the appropriate time or probabilities are not communicated. Therefore, I argue that for climate services to be useful, forecast information needs to be timely provided and probabilities properly communicated to the different groups of farmers, bearing in mind the varying differences in the sensitivity of each group and farm stages. However, for farmers to benefit from this depends on their flexibility and willingness to adapt farm decisions to the timing and probability of the forecast provided.

7.3 Connecting the dots: discussion of the main findings

In this section, I reflect on the link between the research questions and provide a broader perspective on the results.

7.3.1 Contribution to a "second generation" climate services to support rice farmers

The anticipatory, inclusiveness, reflexivity and responsiveness of the proposed framework in Chapter 2 shows the efficiency and robustness for making climate information services useful. This conclusion was drawn from the results of the four dimension of responsible innovation which was used to evaluate the proposed second generation climate services framework in chapter 2. The framework is therefore recommended for the development of a second generation climate services to improve the current practice of climate information provision for rice farmers in Ghana. The information exchange element within the framework offers an additional feature that distinguishes it from current climate information services. Farmers can be actively engaged in the co-production process where they can share their forecast information and receive tangible information and advice for their adaptive farm decision-making. The ICT part of the framework allows for easy and automated data handling activities such as indigenous and scientific data collection, processes, analysis, and visualization once an algorithm is built. Further, the framework, unlike any other affords the opportunity to include indigenous forecast data and information into climate services.

The framework also introduced citizen science as a principle that enables the co-production of climate services. General application and benefit of citizen science have been well documented in literature as an approach to engage non-scientist to gather scientific data and generate knowledge (Gura, 2013). However, its application and value for climate services have not been well explored. A typical example is Community Collaborative Rain, Hail and Snow Network (CoCoRaHS) where volunteers of all ages and backgrounds from United States, Canada, and the Bahamas are engaged to measure and map rain, hail and snow (Phillips et al., 2019). In chapter 4, I demonstrated the value of citizen science as an approach for collecting indigenous forecast and local rainfall observation. I did this by experimenting with rice farmers who recorded and sent in forecast and observed rainfall for a period of time (daily forecast for seven months in 2017 and seasonal forecast for 2017 and 2018). Moreover, in using citizen science, I have shown that knowledge possessed by local people can contribute to climate services by offering observations and interpretation at a much finer spatial scale with considerable temporal depth, and by highlighting aspects (in this case indigenous ecological indicators) that may not be considered by climate scientists in developing climate services and climate change adaptation practices.

The use of sapelli mobile app as a tool for citizen science provided some benefits; first, it ensures spatial and temporal monitoring of indigenous forecast data (i.e. the date, time and location of data). Secondly, it provides insight into how farmers with low literacy levels could interact with ICT based tools for future information exchange. Third, it helps to collate large and detailed data sets over a period for analysis. Furthermore, the results presented in chapter 4 confirms that farmers, when trained, are comfortable and able to use smartphones.

7.3.2 Bridging the gap in forecast integration for improved climate services

Progress has been made in providing climate information services especially in areas where meteorological instruments are inadequate. Yet there are still substantial gaps with regards to providing location-specific forecasts that is reliable and acceptable by smallholder farmers. Consequently, farmers resort to using indigenous forecast (IF) where local ecological indicators and experiences are used to forecast weather and seasonal climatic conditions (Radeny et al., 2019). Sometimes they use IF alongside scientific forecast (SF) (Nyantakyi-Frimpong, 2013; Nyadzi et al., 2018) which in most cases has their own unique challenges thereby leading to the call for integrating IF with SF at the local level (Kolawole et al., 2014; Mahoo et al., 2015).

Chapter 2 of this dissertation provides insight into the fact that farmers in Northern Ghana use both scientific and indigenous forecast information for their daily and seasonal decisions. In chapter 1 (section 1.3), one could appreciate that IF and SF have a distinct weakness which causes challenges for their use. First, as discussed in chapter 4 and 5, farmers are often confused about what decision to take when IF and SF are both provided, especially in cases where they produce contradicting forecasts information. Second, chapter 2 and 3 show that SF issued by GMet are at a coarse spatial scale compared to IF and therefore does not meet the farmers' local information needs. Third, the qualitative nature and the presence of presumed spirituality of IF that is absent in SF have created a bad reputation among policymakers and scientists who view IF with much scepticism. Meanwhile, local farmers have difficulties embracing SFs because of the absence of a sense of ownership and lack of trust in the service provider, affecting uptake. The cynicism of climatologists and meteorologists towards farmers' IF and vice versa limits the opportunity for integration. Moreover, in chapter 5, it was observed that forecast information will be more acceptable by farmers when IF and SF are integrated. Furthermore, information is more acceptable by local people when it is embedded within the context of their existing knowledge.

In spite of the call to integrate IF and SF, one question that remained unanswered is whether combining both IF and SF is even possible? (see Agrawal, 2002; Plotz et al., 2017). In chapter 3, evidence for the use of indigenous forecast by farmers for their farm decision making are shown. Chapter 4 presents an understanding of farmers' techniques and for the first time quantitatively determining the skills of the indigenous forecast. I demonstrated that, in Northern Ghana, the accuracy of farmers' indigenous forecast is generally as good as scientific forecast provided by Ghana Meteorological Agency (GMet). In chapter 5, I tested and accepted the hypothesis that integrated probability forecast (IPF) method improve the reliability and acceptability of forecast information among farmers. Results show that leveraging on the strength of IF and SF, IPF in general, provided reliable forecast information at both daily and seasonal timescale with far greater farmers acceptability potential. Therefore, in this dissertation, I have shown that combining IF and SF into a single forecast is not only possible but has greater potential for acceptability among farmers in Ghana than SF and IF individually.

7.3.3 Improving uptake of climate information services for agriculture decision-making

In most cases where climate information services are introduced, the disconnect between providers and farmers has resulted in low uptake of information. Inadequate knowledge on ways to successfully engage farmers for their information needs, identify appropriate timeframe and medium to deliver information, communicating probability of uncertainties, improving accuracy of information, integrating indigenous knowledge and understanding how information influence decision making have been listed as part of the problem of low uptake of climate services (Lemos et al., 2012; Kniveton et al., 2015; Ouedraogo et al., 2018; Singh et al., 2018; Nyamekye et al., 2019). Given the existing gap leading to reduced uptake of climate information, the five research questions of this dissertation aimed at highlighting the importance of co-producing ‘farmer-useful’ climate information.

Chapter 2 present an overall set up for effectively developing climate services that are useful for rice farming systems in Northern Ghana by identifying and addressing the socio-ecological challenges of the study area in addition to factors that limit the efficiency of existing information systems. Results demonstrated that a two-directional model of climate services where farmers are active in all stages of the process has potential for forecast information uptake. The one-way approach, which is still present in existing information systems has been criticized for its monopoly on the production of knowledge by researchers. In fact, lessons from existing information systems show that the degree of participation of farmers in developing such systems for that matter climate services was often inadequate (Nyadzi et al., 2018; Ouedraogo et al., 2018). In many cases, local people were not involved in data gathering and interpretation. Participation was often limited to a couple of workshops where the aim of the information systems is communicated, giving researchers the choice to determine the problem, gather and interpret the scientific data and plan the approach of information delivery with little consideration for farmers own indigenous knowledge and information need.

Providing seasonal forecast at a lead time of a month and beyond has previously been a problem even for the best models limiting its usefulness for farmers (Hansen, 2002). I demonstrated in chapter 3 that it is possible to help farmers’ seasonal decision making at their most preferred lead time of one month and beyond with the state-of-the-art ECMWF-S4 ensemble forecast product. The key lessons discussed in chapter 3 are that using an interdisciplinary approach to connect forecast products with information needs for farm management can contribute to the successful uptake of forecast information by farmers. This is important because, existing works either concentrate on bottom-up fashion focusing on farmers’ access and use of forecast information and potential challenges they encounter or focusses on technical and top-down approaches, assessing the skills of existing forecasts for several regions across the globe. Combining both approaches in an interdisciplinary manner in this dissertation allowed the identification of pertinent rice farmers' decisions and which information is required to support these decisions.

The utilization of local knowledge and practices in this study provides a range of benefits that the scientific community with their weather and seasonal forecast models could not offer. Engaging farmers throughout the study addresses the challenges of credibility, legitimacy, scale, cognition, familiar institutional practices and complex decision-making currently affecting the uptake of climate information services that focus on scientific information only, as detailed by Patt & Gwata, (2002) and Nyamekye et al. (2019).

Earlier, the scale of forecast is mentioned as a common constraint of forecast uptake. In most cases, this concern arises when the forecast information issued is an average covering a wide geographical area such that local details are left out or remains unclear. A number of scientific techniques (either statistical or dynamical) exist to translate forecast information from a coarser to finer resolutions, collectively known as downscaling. However, these techniques are limited by model inadequacies or the availability and quality of observed data from metrological stations which in most cases are inadequate and unrepresentative in local communities (Caffrey & Farmer, 2014). Farmers, as shown in chapter 3, were well capable of recording local rainfall with tailor-made rain-gauges and in providing indigenous forecast at the community level. They also provided some perspective into the interpretation of local data which might be overlooked by scientists. Moreover, in chapter 4, I observed that indigenous forecast is finer in resolution and more valuable at the community level than GMet forecast which is coarse and issued at a regional level. Kniveton et al. (2015), posit that rather than trying to improve on inherently uncertain scientific forecasts, the techniques of knowledge timelines and participatory downscaling that use local knowledge to understand and downscale scientifically based climate and weather information in time, space and information type to a range of outcomes and risks can be used. In doing so, the authors hoped that this process will extend the ownership of uncertainty to the wider community of users.

The timeliness and probability of forecast information present certain challenges to the uptake of weather and climate information for decision making. I have demonstrated the validity of this observation in chapter 6. In that, forecast lead times and probabilities influence which decision farmers take given forecast information. For instance, the credibility of the forecast can be influenced by the lead time at which the forecast is provided. Forecasts that give enough lead time allow more flexibility and efficient adjustments of farm decision. More so the credibility of forecast becomes a concern when the forecasts are communicated in deterministic rather than probabilistic form. Predicting future atmospheric conditions are inherently uncertain for a number of reasons including, for example, the chaotic nature of the atmosphere and inadequacies of forecasting models (Kniveton et al., 2015). Estimating forecast certainty and communicating them is not only an expected scientific practice but are also potentially useful to everyday decision-making. Yet, in Ghana, as at the time of this research, only seasonal climate forecast is issued with forecast probabilities. Weather forecast for daily decision making are deterministic in nature, provided as a single value for parameters such as rainfall and temperature. In recent times, studies have called for the inclusion of uncertainty in forecast information despite the concerns that forecasts uncertainty will not be well understood by end-users and thus translate into it having no influence on decision making (Joslyn & Savelli, 2010). Farmers decision making is framed around the probability of the forecast given. Therefore, communicating forecast probability supports farmers in taking better decision, proper planning and reducing unrealistic expectations of forecast accuracy and reliability of climate service in general. In chapter 6, I have shown that contrary to popular belief that communicating uncertainty information undermines farmers' confidence in the service, it is rather reassuring and creates a sense of transparency and honesty that boost farmers' confidence that forecast information is objectively provided. However, it is essential to tailor the certainty information in a way that farmers can comprehend regardless of their literacy level.

7.4 Scientific contribution

Relatively few studies have explored the application of indigenous ecological knowledge for weather and seasonal climate forecasting (Roncoli, Ingram, & Kirshen, 2002; Manyanhaire, and Miriam Chitura, & and, 2015). A minority of scholars have identified and discuss indigenous ecological indicators used for IF, but there remains a lack of clarity and empirical evidence for (1) the cognitive underlying mechanism for generating IF and (2) the accuracy (skills) of IF expressed quantitatively. This dissertation, to the best of my knowledge, is the first to use mental modelling approach to establish how farmers use indigenous ecological indicators to predict atmospheric events such as rainfall onset, amount and cessation. It is also the first to quantitatively evaluate the accuracy (skills) of IF. The use of mental model theoretically shows the cognitive process involves in farmers forecast decision making. This is vital for a scholarly debate that focuses on whether generating IF is an intuitive or rational process. In this thesis, I have shown that the process is rational. The skills or accuracy of IF as I have demonstrated contributes to theories and scientific literature that seek to make a case for the validity and possibility of transferring indigenous knowledge for improved climate studies and effective management of ecosystems in general. It is important to mention that citizen science and the mental modelling methods are hardly used in the context of climate change adaptation and thus form an important part of the methodological contribution of this dissertation.

Existing literature suggests that the methodological toolkit is expanding beyond approaches of collecting indigenous knowledge to methods that bring different sources and forms of knowledge together (Bohensky & Maru, 2011). Earlier efforts have proposed a subjective method and more sophisticated untried science integration method (Plotz et al., 2017). Yet in this dissertation, I have developed and tested a simple objective method (integrated probability method) that combine SF and IF into a single forecast for farm decision making. Results from this dissertation have contributed to the theory of knowledge integration that is cognizant of culture and context.

This study is the first to introduce a framework for second-generation climate services that include citizen science as a means of achieving co-production. To improve the degree of engagement between scientist and farmers at data collection and exchange, I employed citizen science approach where local farmers were trained to record rainfall with tailor-made rain gauges while providing their rain forecast using mobile apps. The use of citizen science and mobile apps as an enabling platform for engaging farmers offers a new opportunity for research. For example, downscaling and improving spatial resolution forecast information for climate impact studies. Also, empowering marginalized knowledge systems and facilitating social learning.

This study shows (in chapter 3) that, for climate information services to be useful for farmers, it is essential though not quite simple to understand the various farm actions and decisions that are taken and match them with the required information. Using an interdisciplinary approach to evaluate farmers' information needs and carry out skills assessment of forecast product enabled a broader contextualization of existing research which is often done in isolation. Also been able to show that seasonal climate forecast up to lead month 2 can be provided to meet the needs of farmers in Northern Ghana is essential for recognising the scientific potential for model based seasonal climate forecast. To my knowledge, no previous studies have done this. Also, this study has used what it called visually facilitated scenario mapping to show that, aside providing farmers with the required information need, communicating forecast at appropriate lead times and with its uncertainty or probabilities have substantial influence on which decision farmers will take. The results can be used by researchers who develop climate services for agriculture. The results could also provide a template for making climate services actionable for other sectors.

The notion that second-generation climate information services can improve forecast reliability and acceptability invites a fundamental question that must be continually revisited: are there locally specific social-ecological issues that will hinder or promote operationability of such information services? This dissertation theoretically advocates that climate information systems are place-based and context-sensitive, requiring a thorough understanding of local socio-ecological issues that has the potential to affect co-production and uptake of information. The dissertation is also the first to argue for making climate services responsible by applying the four dimensions of responsible innovation as proposed by Stilgoe et al. (2013), to reflect on the novelty as well as unforeseen implications climate information services on society. Therefore, results obtained have provided insights to conceptualize Responsible Innovation in the context of climate information services. This provides opportunities for case studies to address potential challenges and consequences of developing actionable climate services in a more detailed manner.

Overall, this is the first study that has proposed a framework for a second generation climate services in Ghana. It contributes to addressing the gap that affects the actionability and uptake of climate services provided by the Ghana Meteorological Agency (GMet) and other information providers such as ESOKO. The methodological approach and results of this study could contribute to research that focus on climate services in Ghana.

7.5 Societal contribution

This study unpacks a number of issues that society could benefit from. First I have provided evidence of ways to improve acceptability and usability of weather and seasonal climate information for farmers. For instance, embedding scientific weather and seasonal climate information into farmers cultural and social context is a sure way to get this information accepted. Also, matching information with needs, communicating forecast at the appropriate lead time and with the level of uncertainty will improve forecast uptake.

Secondly, farmers in Northern Ghana have complained about the reliability of available scientific weather and seasonal climate forecast. Uptake of climate information services is dependent on its accuracy. This dissertation has proposed that integrating scientific forecast with indigenous forecast will improve the reliability of the existing forecast. This knowledge will help advance climate services in Ghana in ways that have not been initially thought about. For instance, this study can serve as a template for the Ghana Meteorological Agency (GMet) to improve the spatial resolution of their forecast and thereby improving its reliability for farmers. Moreover, there is currently no guidance on how to engage farmers in collecting and handling their indigenous forecast as well as integrating it with a scientific forecast.

Third, knowledge generated from this dissertation will help to improve the design and/or implementation of agriculture climate services. Documenting the challenges of existing information services in this dissertation is critical for providing insights that improve the design and delivery of climate services. Therefore, it is essential for climate services developers to consider in their design and information delivery practice, (1) the user unfriendliness for easy access and interpretation by farmers especially illiterate farmers, (2) accuracy of forecast information by providing forecast with better skills and at a finer resolution targeting a specific location (3) relevance of forecast information tailored to specific needs and timely provided, (4) managing user expectation by engaging end-users very early in the design process making them familiar with the various limitations as well as communicating uncertainty and (5) strengthening collaboration among scientists, farmers and other key stakeholders by regular consultation and transparent process for all. Importantly, engaging farmers throughout the project life and involving them in data collection has helped build their capacity and empower them as well as deepen their awareness of the difficulties in predicting atmospheric events. Given their new knowledge and capacity, farmers would be more understanding of the challenges that come with climate services.

Finally, this study will be beneficial to climate services projects carried out in Ghana and elsewhere. While this study focused on rice farmers, the approach could also be adapted for other kinds of farmers. Results from this study also show that rice farmers could potentially improve their production if they have accessible and usable weather and seasonal climate information. Moreover, the state-of-the-art ECMWF-S4 forecast system is skilful at predicting rainfall, minimum and maximum temperature in Northern Ghana.

7.6 Reflecting backwards; strength and limitations of the research

The adoption of multimethod research approach in this dissertation ensures the validity of the research designed to better understand empirically, ways to improve the reliability and acceptability of climate services. This section reflects on the methodological choices, the overall research validity, and limitations of the study.

The citizen science method employed in this study deepened the understanding of the role of local people in improving climate services. The method offered a robust approach of gathering and quantitatively interpreting local data in a finer resolution that might be difficult to achieve by the scientific community. However, the citizen science process was laborious and expensive when it comes to using smart mobile phones, training farmers and accessing forecast data.

The validity of indigenous forecast (IF) data was achieved by comparing farmers' observed rainfall data with GMet data. Obtaining a similar pattern in both datasets increased confidence in the quality of IF data provided by farmers. However, using a relatively short dataset to validate the IPF method could not allow stronger claims of results although good enough to prove our concept. Unlike, science-based forecast where long term datasets are available, this is unfortunately not possible for IF. Therefore, longer time series data needs to be collected for a more robust analysis of temporal and spatial variability of forecast and for validating IPF method.

To ensure that quality IF data was collected for the analysis, a rigorous participatory process was used to purposively select 12 expert farmers who were trained to understand and use scientific terminologies and tools to provide data. The sampling method and sample size were relevant considering the fact that not all farmers are good forecasters. Also, it allowed in-depth study of the indigenous people' forecast techniques and skills as well as the use of smart mobile phones. Nevertheless, increasing the number of expert farmers will allow the analysis of the variation of results within and between communities. Therefore, subsequent studies should increase the number of farmers in each community. More so, an expansion in the use of smart phones and better cell phone coverage will make it easier to repeat this with more farmers in future studies.

Using the Fuzzy-logic Cognitive Mapping approach with the aid of a computer-based software (Mental Model), I was able to capture the underlying process behind the indigenous forecasting. The mental model revealed the cognitive mechanism behind farmers use of indigenous ecological indicators for predicting weather and seasonal climate. This method fulfilled an important function of demonstrating that farmers do not generate indigenous forecast intuitively, rather use a rational process where each indicator has a degree of influence on the expected event. The method lay emphasis on the abstraction of farmers thought and perception to anticipate events by providing an imaginary picture of how farmers produce their forecast.

The participatory methods (interviews, focus group discussion, workshops) employed in the study offered the opportunity for the respondent to construct versions of reality in an interactive interplay with the interviewer. However, I acknowledge the possible subjectivity of the data provided by respondents and participants (Gill et al., 2008; Gubrium & Holstein, 2012). This obviously has implications for data validity and reliability. To address this, I embarked on various measures that address both internal and external validity. The protocols for the participatory methods were pre-tested among the target group to ensure unambiguity and clarity. In all circumstances, changes were made to the final protocols based on received feedback. The original protocol for these methods containing the questions in English was translated into the local popular Dagbani language. The validity of the collected data was increased by the response from the feedback workshops that allowed reflection and discussions of results by participants to reduce interpretation bias. Also, the inclusion of open-ended questions allowed further probing for clarity and certainty. The document and literature review method provided a set of secondary data and information that served as a baseline for the research and at the same time gave new insight into data collection and analysis.

Additionally, using interviews to determine farmers' information needs in chapter 3 and acceptability of integrated forecast in chapter 5 had some limitations. A more comprehensive design of the questionnaire might have allowed for a more advanced statistical analysis in search of other possible explanatory variables. I suggest that such an extended analysis is warranted for further studies. For example, understanding how socio-economic factors could affect the acceptability of integrated forecast could provide better context into forecast acceptability and use. Also, in chapter 6, using an ex-ante evaluation approach through the Visually Facilitated Scenario Workshops (VFSW) might not have provided realistic and detail analysis of decision farmers will take, given different forecast lead times and uncertainties. An analysis of real-time information provision and farmer's decision making could provide better insight. Further research is needed to evaluate real-time weather and seasonal climate information services that communicate forecast probabilities and information at different lead times. Doing this will provide a comprehensive understanding of the real-time effect of these two factors on forecast uptake.

The forecast verification methods used in this study provided insights into the quality of ECMWF-S4 over Northern Ghana. Moreover, to first compare WFDEI data to locally observed GMet data ascertain the validity of WFDEI data for the verification exercise. While this analysis was based on system 4, far before system 5 was released, this limits the usefulness of your results. However, it might be easy and useful to repeat the analyses with S5. The Waterapps project (http://www.waterapps.net/en-us/home/) is currently analysing system 5 forecasts, following the same methodology.

Also in this study, I argued that the existence of skill in ECMWF-S4 forecast showed potential for predicting identified information needs. Nonetheless using seasonal average as a proxy to assess performance and discuss the possibility of meeting farmers' needs in chapter 3 does not allow for the evaluation of the predictability of each of the information needs identified. For example, onset and cessation are expressed in calendar dates while the dam water level requires a hydrological method to determine its predictability. As a result, the conclusions on the predictability of information needs are fuzzier rather than objective. Therefore, to make stronger claims on the predictability of each information need with ECMWF-S4, further specific predictability studies are required.

Finally, the proposed framework for second-generation climate services in chapter 2 has only been explored and proposed for Northern Ghana. Yet not practically implemented although several aspects of its elements tested. Therefore, in order to make stronger claims about its potential to improve forecast uptake compared to existing systems, there is a need for further testing.

7.7. Future outlook and directions for further research and policymaking

Interdisciplinary research on societal problems raises many new questions as it seeks to provide answers. This research is in no way different. Based on the findings, I observed the need for further investigation in different areas. In this section, I will translate conclusions drawn from the scientific and societal contributions in addition to the research strength and limitation into a set of recommendations.

First, the suggested second-generation climate services framework in chapter 2 needs to go beyond a conceptual framework. The empirical testing of the framework could refine the underlying assumptions that underpin the current design and operational logic, thereby allowing a better understanding of the framework in providing climate services that are actionable and influence farmers decision making. Applying this framework to different climate services project will reveal which element within the framework needs adjustment and which needs improvement. Already the Wateraps project been implemented in the south of Ghana has adopted this framework to provide weather and seasonal climate information to peri-urban farmers.

Secondly, if one message becomes apparent from this dissertation it is that indigenous forecast has potential value for climate services. However, to enhance the understanding and advancement of this field, long-term data sets are crucial. The amount of data used and the number of farmers engaged in chapter 4 and 5 did not allow making stronger claims. I suggest the need to build a database to collect indigenous forecast for a longer period for analysis. Also, increasing the number of farmers for IF data collection offers the opportunity for analysing variation within and between communities. With Waterapps project, such endeavour is possible as a mobile app is developed with the aim to continue collecting indigenous forecast data. Furthermore, it is expected that climate change will have an impact on land cover and landscape. Therefore, there is a need to investigate how climate variability and change will affect the indigenous indicators used for indigenous forecasting.

Finally, in Ghana, agriculture water management and food production is constrained by climate variability and change. Effective climate services can be crucial to improving farmers' decision making, developing water management strategies and ultimately ensuring food security. Yet climate services/information are scarcely mentioned in agricultural policy documents (Naab et al., 2019). While this study focuses on improving the reliability and acceptability of forecast information by local farmers, mainstreaming climate services should be at the forefront in ensuring resilient agriculture. Ample evidence already suggests the contributory value of climate services in the agriculture sector. However, further research is required to evaluate the actual impact of climate services on farmers' livelihood and to determine how climate services may influence agriculture policy formulation. In addition, this research could play a role in providing scientific evidence and more reliable information about climate services as an adaptation tool against climate variability and change. Policymakers should, therefore, be open to including this in the formulation of policies for the sector. I suggest the following actions as a way of using climate services to enhance climate adaptation and improve the resilience of agriculture systems in Ghana:

- Incorporating climate services into National Agricultural policy for managing climate risk and uncertainty. Results from this research can inform on-going research projects by helping adjust research activities and approaches to address climate risks and explore adaptation options.

- Building a national database for relevant indigenous knowledge and data to improve scientific knowledge and data for effective facilitation of research on weather and climate services towards impacts and adaptation practices.

- Strengthening the capacity of farmers to use advanced tools (such as smartphones and rain gauges) to share their knowledge and data through citizen science to effectively study locally observed phenomenon such as rainfall patterns.

- The Ghana Meteorological Agency should effectively communicate uncertainties (probabilities) to manage expectations as well as provide timely forecast information for flexible farm decision making.

- Improving institutional and governance (formal and informal) structures and arrangements will enhance the operations of GMet in reaching every farmer with useful forecast information that informed decision making.

Finally, this dissertation supports pleas for a more integrated, co-learning and co-production approach to climate services away from the current focus on climate science-driven and user-informed climate services projects. The approach implemented in this dissertation is important in the effort of combating climate change, partly because it allows the inclusion of indigenous people who are often overlooked for several reasons including illiteracy. By involving farmers throughout the process, this exclusion is avoided. One needs to understand that indigenous people know their terrain and have different know-how and opinions that are valuable for climate services. This knowledge needs to be recognized and accorded respect, otherwise, little to no success will be achieved if the so-called scientific knowledge is imposed on people living in rural areas of the world. In the case of this study, it is claimed that even though indigenous and scientific forecast differs from each other, they can be seen as two opposite sides of a coin whose strength complement each other's weakness. It is especially important to highlight this because indigenous knowledge is often viewed as less reliable among certain positivists in the scientific community. Establishing the underlying mechanism, understanding the techniques, quantifying the skills behind IF such that they are included in scientific studies might refute such perceptions.

References

Abdul-Malik, A., & Mohammed, A. (2012). Technical efficiency of beekeeping farmers in Tolon-Kumbungu district of Northern region of Ghana. *Journal of Development and Agricultural Economics*, *4(11)*, 304–310.

Abdul-rahaman, I., & Owusu-Sekyere, E. (2017). Climate variability and sustainable food production : Insights from north-eastern Ghana. *Ghana Journal of Geography*, *9*(2), 67–89.

Abdul-Razak, M., & Kruse, S. (2017a). The adaptive capacity of smallholder farmers to climate change in the Northern Region of Ghana. *Climate Risk Management*, *17*, 104–122.

Abdul-Razak, M., & Kruse, S. (2017b). The adaptive capacity of smallholder farmers to climate change in the Northern Region of Ghana. *Climate Risk Management*, *17*, 104–122. https://doi.org/10.1016/j.crm.2017.06.001

Acquah, H., & Acquah, S. (2011, November). An Assessment of Farmers Perception and Adaptation Strategies to Climate Change in Beposo, Ghana. *Proceedings of The 1st World Sustainability Forum*. https://doi.org/10.3390/wsf-00592

Adiku, S. G. K., Mawunya, F. D., Jones, J. W., & Yangyouru, M. (2007). Can ENSO help in agricultural decision-making in Ghana? In *Climate Prediction and Agriculture: Advances and Challenges* (pp. 205–212). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-44650-7_20

Afiesimama, E. A., Pal, J. S., Abiodun, B. J., Gutowski, W. J., & Adedoyin, A. (2006). Simulation of West African monsoon using the RegCM3. Part I: Model validation and interannual variability. *Theoretical and Applied Climatology*, *86*(1–4), 23–37. https://doi.org/10.1007/s00704-005-0202-8

Africa Partnership Forum. (2007). *Climate change and Africa. In: Summary for Policy-Makers. In: Parry, M.L. (Ed.), 8th Meeting of the Africa Partnership Forum. 2007., Berlin;* Intergovernmental Panel on Climate Change.

Agrawal, A. (1995). Dismantling the Divide Between Indigenous and Scientific Knowledge. *Development and Change*, *26*(3), 413–439. https://doi.org/10.1111/j.1467-7660.1995.tb00560.x

Agrawal, A. (2002). Indigenous knowledge and the politics of classification. *International Social Science Journal*, *54*(173), 287–297. https://doi.org/10.1111/1468-2451.00382

Agrawal, A. (2005). The politics of indigenous knowledge. In *Australian Academic and Research Libraries* (Vol. 36, Issue 2). https://doi.org/10.1080/00048623.2005.10721249

Ajibade, L.T. and Shokemi, O. O. (2003). Indigenous Approach to Weather Forecasting in ASA LGA, Kwara State, Nigeria. *Indilinga African Journal of Indigenous Knowledge Systems, 2*, *37–44*.

Akudugu M. A. Dittoh S., M. E. S. (2012). The Implications of Climate Change on Food Security and Rural Livelihoods: Experiences from Northern Ghana | Akudugu | Journal of Environment and Earth Science. *Journal of Environment and Earth Science*, *2(3)*, 21–29.
https://www.iiste.org/Journals/index.php/JEES/article/view/1626

Alexander, C., Bynum, N., Johnson, E., King, U., Mustonen, T., Neofotis, P., Oettlé, N., Rosenzweig, C., Sakakibara, C., Shadrin, V., Vicarelli, M., Waterhouse, J., & Weeks, B. (2011). Linking Indigenous and Scientific Knowledge of Climate Change. *BioScience*, *61*(6), 477–484. https://doi.org/10.1525/bio.2011.61.6.10

Alhassan, M., Loomis, J., Frasier, M., Davies, S., & Andales, A. (2013). Estimating Farmers' Willingness to Pay for Improved Irrigation: An Economic Study of the Bontanga Irrigation Scheme in Northern Ghana. *Journal of Agricultural Science*, *5*(4). https://doi.org/10.5539/jas.v5n4p31

Alves O., Guomin W., Aihong Z., Neville S., Graham W., A. M. F. T. and A. S. (2003). *POAMA: Bureau of Meteorology operational coupled model seasonal forecast system.* In Proceedings of national drought forum, Brisbane (pp. 49-56).

Amekudzi, L. K., Yamba, E. I., Preko, K., Asare, E. O., Aryee, J., Baidu, M., & Codjoe, S. N. A. (2015). Variabilities in rainfall onset, cessation and length of rainy season for the various agro-ecological zones of Ghana. *Climate*, *3*(2), 416–434. https://doi.org/10.3390/cli3020416

Amikuzuno, J., & Donkoh, S. A. (2012). Climate Variability and Yields of Major Staple Food Crops in Northern Ghana. *African Crop Science*, *20*(2), 349–360.

Amisigo, B., McCluskey, A., & Swanson, R. (2015). Modeling Impact of Climate Change on Water Resources and Agriculture Demand in the Volta Basin and other Basin Systems in Ghana. *Sustainability*, *7*(6), 6957–6975. https://doi.org/10.3390/su7066957

Amisigo, B A, & van de Giesen, N. C. (2005). Using a spatio-temporal dynamic state-space model with the {EM} algorithm to patch gaps in daily riverflow series. *Hydrology and Earth System Sciences*, *9*(3), 209–224. https://doi.org/10.5194/hess-9-209-2005

Amisigo, Barnabas A., McCluskey, A., & Swanson, R. (2015). Modeling impact of climate change on water resources and agriculture demand in the Volta Basin and other basin systems in Ghana. *Sustainability (Switzerland)*, *7*(6), 6957–6975. https://doi.org/10.3390/su7066957

Andersen, I. E., & Jæger, B. (1999). Scenario workshops and consensus conferences: towards more democratic decision-making. *Science and Public Policy*, *26(5)*, 331–340.

Andersson, M. K., & Karlsson, S. (2008). Bayesian forecast combination for VAR models. In *Advances in Econometrics* (Vol. 23, Issue C, pp. 501–524). https://doi.org/10.1016/S0731-9053(08)23015-X

Andrade, J. A. A., & Gosling, J. P. (2011). Predicting rainy seasons: Quantifying the beliefs of prophets. *Journal of Applied Statistics*, *38*(1), 183–193. https://doi.org/10.1080/02664760903301168

Angelucci, F., Asante-Pok, A., Anaadumba, P., Angelucci, F., Asante-Pok, A., & Anaadumba, P. (2019). <p>Analysis of incentives and disincentives for rice in Ghana</p>. *Gates Open Res*, *3*. https://doi.org/10.21955/GATESOPENRES.1116230.1

Anoop, M., Ajjan, N., & Ashok, K. R. (2015). {ICT} based market information services in Kerala - determinants and barriers of adoption. *Economic Affairs*, *60*(1), 117. https://doi.org/10.5958/0976-4666.2015.00016.9

Antwi-Agyei, P., Fraser, E. D. G., Dougill, A. J., Stringer, L. C., & Simelton, E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Applied Geography*, *32*(2), 324–334. https://doi.org/10.1016/j.apgeog.2011.06.010

Armah, F. A., Odoi, J. O., Yengoh, G. T., Obiri, S., Yawson, D. O., & Afrifa, E. K. A. (2011). Food security and climate change in drought-sensitive savanna zones of Ghana. *Mitigation and Adaptation Strategies for Global Change*, *16*(3), 291–306. https://doi.org/10.1007/s11027-010-9263-9

Armatas, C. A., Venn, T. J., McBride, B. B., Watson, A. E., & Carver, S. J. (2016). Opportunities to utilize traditional phenological knowledge to support adaptive management of social-ecological systems vulnerable to changes in climate and fire regimes. *Ecology and Society*, *21*(1). https://doi.org/10.5751/es-07905-210116

Artikov, I., Hoffman, S. J., Lynne, G. D., Zillig, L. M. P., Hu, Q., Tomkins, A. J., Hubbard, K. G., Hayes, M. J., & Waltman, W. (2006). Understanding the Influence of Climate Forecasts on Farmer Decisions as Planned Behavior{\ast}. *Journal of Applied Meteorology and Climatology*, *45*(9), 1202–1214. https://doi.org/10.1175/jam2415.1

Asante, F. A., & Amuakwa-Mensah, F. (2015). Climate change and variability in Ghana: Stocktaking. In *Climate* (Vol. 3, Issue 1, pp. 78–99). MDPI AG. https://doi.org/10.3390/cli3010078

Asante, F., & Amuakwa-Mensah, F. (2014). Climate Change and Variability in Ghana: Stocktaking. *Climate*, *3*(1), 78–99. https://doi.org/10.3390/cli3010078

Asare-Kyei, D. K., Kloos, J., & Renaud, F. G. (2015). Multi-scale participatory indicator development approaches for climate change risk assessment in West Africa. *International Journal of Disaster Risk Reduction, 11*, *13-34.*

Baker, R. M., Davies, J., & Young, E. A. (Eds. . (2001). *Working on country: contemporary indigenous management of Australia's lands and coastal regions.* Oxford University Press.

Baltzer, K. & Hansen, H. (2011). *Agricultural Input Subsidies in Sub-Saharan Africa. Evaluation Study, 2.* International Development Cooperation (DANIDA).

Banerjee, S.K., C. N. and D. H. P. (2003). *Study of weather-based agricultural folklore of West Bengal.* Pre-Published Scientific Report No. 1. New Delhi, India Meteorological Department.

Barnes, A. P., McCalman, H., Buckingham, S., & Thomson, S. (2013). Farmer decision-making and risk perceptions towards outwintering cattle. *Journal of Environmental Management*, *129*, 9–17. https://doi.org/10.1016/j.jenvman.2013.05.026

Barnston, A. G., Li, S., Mason, S. J., DeWitt, D. G., Goddard, L., & Gong, X. (2010). Verification of the first 11 years of IRI's seasonal climate forecasts. *Journal of Applied Meteorology and Climatology, 49(3)*, 493–520.

Barnston, A. G. (1992). Correspondence among the correlation, RMSE, and Meidke Foresast verification measures; Refinement of the Neidke Score. *Weather and Forecasting*, *7*(4), 699–709. https://doi.org/10.1175/1520-0434(1992)007<0699:catcra>2.0.co;2

Barnston, A. G., Tippett, M. K., van den Dool, H. M., & Unger, D. A. (2015). Toward an improved multimodel ENSO prediction. *Journal of Applied Meteorology and Climatology*, *54*(7), 1579–1595. https://doi.org/10.1175/JAMC-D-14-0188.1

Barry, B., Obuobie, E., Andreini, M., Andah, W., Pluquet, M. (2005). *Comprehensive IWMI., Assessment of Water Management in Agriculture (Comparative Study of River Basin Development and Management.* International Water management institute.

Basdew, M., Jiri, O., & Mafongoya, P. L. (2017). Integration of indigenous and scientific knowledge in climate adaptation in {KwaZulu}- Natal, South Africa. *Change and Adaptation in Socio-Ecological Systems*, *3*(1). https://doi.org/10.1515/cass-2017-0006

Bazile, R., Boucher, M. A., Perreault, L., & Leconte, R. (2017). Verification of ECMWF System 4 for seasonal hydrological forecasting in a northern climate. *Hydrology and Earth System Sciences*, *21*(11), 5747–5762. https://doi.org/10.5194/hess-21-5747-2017

Bedia, J., Iturbide, M., Herrera, S., Manzanas, R., Gutiérrez, J. (2017). *DownscaleR: An R package for bias correction and statistical downscaling*. R package version 2.0-0.

Bedia, J., Iturbide, M. (2017). *TransformeR: An R package for climate data manipulation and transformation.* URL: https://github.com/SantanderMetGroup/transformeR/wiki.

Benin, S., Nin Pratt, A., Wood, S. & Guo, Z. (2011). *Trends and Spatial Patterns in Agricultural Productivity in Africa, 1961–2010.* ReSAKSS Annual Trends and Outlook Report 2011. International Food Policy Research Institute (IFPRI).

Benneh, G. (1970). The attitudes of the kusasi farmer of the Upper region of Ghana to his physical environment. *Inst. Afr. Stud. Res. 6.*

Berggren, C., Söderlund, J., & Anderson, C. (2001). Clients, Contractors, and Consultants: The Consequences of Organizational Fragmentation in Contemporary Project Environments. *Project Management Journal*, *32*(3), 39–48. https://doi.org/10.1177/875697280103200306

Berkes, F. (1993). *Traditional ecological knowledge in perspective. In Traditional ecological knowledge: Concepts and cases (Vol. 1).* Canadian Museum of Nature/International Development Research Centre, Ottawa.

Berkes, Fikret, Colding, J., & Folke, C. (2000). Rediscovery of Traditional Ecological Knowledge as adaptive management. In *Ecological Applications* (Vol. 10, Issue 5, pp. 1251–1262). Ecological Society of America. https://doi.org/10.1890/1051-0761(2000)010[1251:ROTEKA]2.0.CO;2

Berkes, Fikret, Folke, C., & Gadgil, M. (1995). Traditional Ecological Knowledge, Biodiversity, Resilience and Sustainability. In *Biodiversity Conservation* (pp. 281–299). Springer Netherlands. https://doi.org/10.1007/978-94-011-0277-3_15

Bohensky, E. L., & Maru, Y. (2011). Indigenous knowledge, science, and resilience: What have we learned from a decade of international literature on "integration"? *Ecology and Society*, *16*(4). https://doi.org/10.5751/ES-04342-160406

Bonney, R., Cooper, C. B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K. V., & Shirk, J. (2009). Citizen Science: A Developing Tool for Expanding Science Knowledge and Scientific Literacy. *BioScience*, *59*(11), 977–984. https://doi.org/10.1525/bio.2009.59.11.9

BONTER, D. N., & HARVEY, M. G. (2008). Winter Survey Data Reveal Rangewide Decline In Evening Grosbeak Populations. *The Condor*, *110*(2), 376–381. https://doi.org/10.1525/cond.2008.8463

Bonter, D. N., Zuckerberg, B., & Dickinson, J. L. (2010). Invasive birds in a novel landscape: Habitat associations and effects on established species. *Ecography*, *33*(3), 494–502. https://doi.org/10.1111/j.1600-0587.2009.06017.x

Boogaard H, Hoek S., Jacobs C., van't Klooster K., Supit I., van der Wijngaart R., andWinsemius H. (2012). *Weather Risk Mapping for Northern Ghana.* Alterra, Wageningen University and Research.

Bovaird, T. (2007). Beyond Engagement and Participation: User and Community Coproduction of Public Services. *Public Administration Review*, *67*(5), 846–860. https://doi.org/10.1111/j.1540-6210.2007.00773.x

Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal*, *9*(2), 27–40. https://doi.org/10.3316/QRJ0902027

Bradshaw, B. (2003). Questioning the credibility and capacity of community-based resource management. *Canadian Geographer*, *47*(2), 137–150. https://doi.org/10.1111/1541-0064.t01-1-00001

Braimah, I., King, R. S., & Sulemana, D. M. (2014). Community-based participatory irrigation management at local government level in Ghana. *Commonwealth Journal of Local Governance*, *15*, 141–159. https://doi.org/10.5130/cjlg.v0i0.4067

Brascoupé, S., Mann, H., & Von Baeyer, E. (2001). *A community guide to protecting Indigenous Knowledge.* Canada: Research and Analysis Directorate, Department of Indian Affairs and Northern Development.

Breuer, N., S. Church, A. Dagang, A. Gough, C. Grier, C. Messina, M. Mudhara M., Mwale, A., Pemme, L., Sol, G. and Vivas, S. (2000). *Potential Use of Long Range Climate Forecasts by Livestock Producers in North-central Florida*. The Florida Consortium Technical Report Series FC-UF-2000-02, Gainesville.

Brewer, J., & Hunter, A. (2012). Foundations of Multimethod Research. In *Foundations of Multimethod Research*. SAGE Publications, Inc. https://doi.org/10.4135/9781412984294

Briggs, J., & Moyo, B. (2012). The Resilience of Indigenous Knowledge in Small-scale African Agriculture: Key Drivers. *Scottish Geographical Journal*, *128*(1), 64–80. https://doi.org/10.1080/14702541.2012.694703

Bumke, K., Fennig, K., Strehz, A., Mecking, R., & Schröder, M. (2012). {HOAPS} precipitation validation with ship-borne rain gauge measurements over the Baltic Sea. *Tellus A: Dynamic Meteorology and Oceanography*, *64*(1), 18486. https://doi.org/10.3402/tellusa.v64i0.18486

Buytaert, W., Vuille, M., Dewulf, A., Urrutia, R., Karmalkar, A., & Célleri, R. (2010). Uncertainties in climate change projections and regional downscaling in the tropical Andes: implications for water resources management. *Hydrology and Earth System Sciences*, *14*(7), 1247–1258. https://doi.org/10.5194/hess-14-1247-2010

Buytaert, Wouter, Zulkafli, Z., Grainger, S., Acosta, L., Alemie, T. C., Bastiaensen, J., BiÃ\textasciidieresisvre, B. De, Bhusal, J., Clark, J., Dewulf, A., Foggin, M., Hannah, D. M., Hergarten, C., Isaeva, A., Karpouzoglou, T., Pandeya, B., Paudel, D., Sharma, K., Steenhuis, T., … Zhumanova, M. (2014). Citizen science in hydrology and water resources: opportunities for knowledge generation, ecosystem service management, and sustainable development. *Frontiers in Earth Science*, *2*. https://doi.org/10.3389/feart.2014.00026

Byrne J. B. A., & H. M. . (2007). *An introduction to mixed method research.* Atlantic Research Centre for family –work issues. Mount Saint Vincent University accessed on 19/8/2019 at http://www.msvu.ca/site/media/msvu/MixedMethodologyHandout.pdf.

Cabrera, V. E., Breuer, N. E., & Hildebrand, P. E. (2006). North Florida Dairy Farmer Perceptions Toward the Use of Seasonal Climate Forecast Technology. *Climatic Change*, *78*(2–4), 479–491. https://doi.org/10.1007/s10584-006-9053-2

Cabrera, V. E., Letson, D., & Podestá, G. (2007). The value of climate information when farm programs matter. *Agricultural Systems*, *93*(1–3), 25–42. https://doi.org/10.1016/j.agsy.2006.04.005

Caffrey, P., & Farmer, A. (2014). (2014). A review of Downscaling methods for climate change projections. *Tetra Tech ARD.* http://www.ciesin.org/documents/Downscaling_CLEARED_000.pdf

Canfield, D. E., Brown, C. D., Bachmann, R. W., & Hoyer, M. V. (2002). Volunteer lake monitoring: Testing the reliability of data collected by the Florida LAKEWATCH Program. *Lake and Reservoir Management*, *18*(1), 1–9. https://doi.org/10.1080/07438140209353924

Carpenter, S. R., & Winner, L. (1978). Autonomous Technology: Technics-out-of-Control as a Theme in Political Thought. *Technology and Culture*, *19*(1), 142. https://doi.org/10.2307/3103332

Carr, E. R., Onzere, S., Kalala, T., Owusu-Daaku, K. N., & Rosko, H. (2015). *Assessing Mali's l'Agence Nationale de la Météorologie's (Mali Meteo) Agrometeorological Advisory Program: Final report in the farmer use of advisories and the implications for climate service design.* Washington, DC.

Cash DW, Clark WC, Alcock F, Dickson NM, Eckley N, Guston DH, Jäger J, M. R. (2003). Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences.*, *100*(14), 8086-91.

Chand, S. S., Chambers, L. E., Waiwai, M., Malsale, P., & Thompson, E. (2014). Indigenous Knowledge for Environmental Prediction in the Pacific Island Countries. *Weather, Climate, and Society*, *6*(4), 445–450. https://doi.org/10.1175/wcas-d-13-00053.1

Chang, L. B., Yanda, P. Z., & Ngana, J. (2010). Indigenous knowledge in seasonal rainfall prediction in Tanzania: A case of the South-western Highland of Tanzania. *Journal of Geography and Regional Planning*, *3*(4), 66–72.

Chapman, R., Blench, R., Kranjac-Berisavljevic, G., Zakariah, A. B. (2003). *Rural Radio in Agricultural Extension: the Example of Vernacular Radio Programmes on Soil and Water Conservation in N. Ghana.* AgREN Network Paper Jan;127:2.

CIA. (2012). *Ghana Economy 2017.* World Factbook [Online]. Sourced on 8/2/2018 at. https://theodora.com/wfbcurrent/ghana/ghana_economy.html.

Clemen, R. T. (1989). Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting*, *5*(4), 559–583. https://doi.org/10.1016/0169-2070(89)90012-5

Climate Services Partnership (CSP). (2011). *What are Climate Services?* http://www.climate-services.org/about-us/what-are-climate-services/.

CoCoRaH, S. (2010). *Community collaborative rain, hail & snow network.* Colorado State University.accesed on 9/8/2019 at https://www.cocorahs.org/.

Codjoe, S. N. A., Owusu, G., & Burkett, V. (2014). Perception, experience, and indigenous knowledge of climate change and variability: The case of Accra, a sub-Saharan African city. *Regional Environmental Change*, *14*(1), 369–383. https://doi.org/10.1007/s10113-013-0500-0

Cofiño, A. S., Bedia, J., Iturbide, M., Vega, M., Herrera, S., Fernández, J., Frías, M. D., Manzanas, R., & Gutiérrez, J. M. (2018). *The ECOMS User Data Gateway: Towards seasonal forecast data provision and research reproducibility in the era of Climate Services*. *9*, 33–43. https://doi.org/10.1016/j.cliser.2017.07.001

Conrad, C. T., & Daoust, T. (2008). Community-based monitoring frameworks: Increasing the effectiveness of environmental stewardship. In *Environmental Management* (Vol. 41, Issue 3, pp. 358–366). https://doi.org/10.1007/s00267-007-9042-x

Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B., Shiferaw, B., & Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? *Agriculture, Ecosystems and Environment*, *126*(1–2), 24–35. https://doi.org/10.1016/j.agee.2008.01.007

Crane, T. A., Roncoli, C., Paz, J., Breuer, N., Broad, K., Ingram, K. T., & Hoogenboom, G. (2010). Forecast skill and farmers' skills: Seasonal climate forecasts and agricultural risk management in the southeastern United States. *Weather, Climate, and Society*, *2*(1), 44–59. https://doi.org/10.1175/2009WCAS1006.1

Creswell, J. W. (2003). *Research design. Qualitative, Quantitative, and Mixed Methods Approaches (second ed.).* London, United Kingdom: Sage Publications, Inc.

David, W., & Ploeger, A. (2014). Indigenous Knowledge (IK) of water resources management in West Sumatra, Indonesia. *Journal on Food, Agriculture and Society*, *Vol. 2*.

De Pinto, A., Demirag, U., & Haruna, A. (2012). *Climate change, agriculture, and foodcrop production in Ghana.* Ghana strategy support programme.International food policy research instituite. Policy Note #3 • September 2012.

Defiesta G. Rapera C.L. (2014). Measuring Adaptive Capacity of Farmers to Climate Change and Variability: Application of a Composite Index to an Agricultural Community in the Philippines. *Journal of Environmental Science and Management*, *17 (2)*, 48–62.

Derbile, E. K., Jarawura, F. X., & Dombo, M. Y. (2016). Climate Change, Local Knowledge and Climate Change Adaptation in Ghana. In *Adaptation to Climate Change and Variability in Rural West Africa* (pp. 83–102). Springer International Publishing. https://doi.org/10.1007/978-3-319-31499-0_6

Desbiez, A., Matthews, R., Tripathi, B., & Ellis-Jones, J. (2004). Perceptions and assessment of soil fertility by farmers in the mid-hills of Nepal. *Agriculture, Ecosystems & Environment*, *103*(1), 191–206. https://doi.org/10.1016/j.agee.2003.10.003

Dewulf, A., & Biesbroek, R. (2018). Nine lives of uncertainty in decision-making: strategies for dealing with uncertainty in environmental governance. *Policy and Society*, *37*(4), 441–458. https://doi.org/10.1080/14494035.2018.1504484

Dewulf, A., Craps, M., Bouwen, R., Abril, F., & Zhingri, M. (2005). How indigenous farmers and university engineers create actionable knowledge for sustainable irrigation. *Action Research*, *3*(2), 175–192. https://doi.org/10.1177/1476750305052141

Dhondt, A. A., Altizer, S., Cooch, E. G., Davis, A. K., Dobson, A., Driscoll, M. J. L., Hartup, B. K., Hawley, D. M., Hochachka, W. M., Hosseini, P. R., Jennelle, C. S., Kollias, G. V, Ley, D. H., Swarthout, E. C. H., & Sydenstricker, K. V. (2005). Dynamics of a novel pathogen in an avian host: Mycoplasmal conjunctivitis in house finches. *Acta Tropica*, *94*(1), 77–93. https://doi.org/10.1016/j.actatropica.2005.01.009

Dilling, L., & Lemos, M. C. (2011). Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. *Global Environmental Change*, *21*(2), 680–689. https://doi.org/10.1016/j.gloenvcha.2010.11.006

Dillon, A., & Morris, M. G. (1996). *User acceptance of new information technology: theories and models.* Medford, NJ: Information Today. http://hdl.handle.net/10150/105584.

Doblas-Reyes, F. J., Garcia, A., Hansen, J., Mariani, L., Nain, A., Ramesh, K., & Venkataraman, R. (2003). *Weather and Climate Forecasts for Agriculture.* Guide to agricultural, meteorological practices, 57.

Doblas-Reyes, F. J., García-Serrano, J., Lienert, F., Biescas, A. P., & Rodrigues, L. R. L. (2013). Seasonal climate predictability and forecasting: Status and prospects. *Wiley Interdisciplinary Reviews: Climate Change*, *4*(4), 245–268. https://doi.org/10.1002/wcc.217

Donkoh, S., Awuni, J., & Namara, R. (2010). Improving the Efficiency of Inland Valley Rice Production in Northern Ghana. *Journal of the Ghana Science Association*, *12*(2). https://doi.org/10.4314/jgsa.v12i2.62818

EEA. (2001). *Late Lessons from Early Warnings: The Precautionary Principle 1896–2000.* Office for Official Publications of the European Communities, Luxemburg.

EEA. (2013). *Late Lessons from EarlyWarnings: Science, Precaution, Innovation. Office for Official Publications of the European Communities, Luxemburg.* Office for Official Publications of the European Communities, Luxemburg.

Elia, E. F., Mutula, S., & Stilwell, C. (2014). Use of Indigenous knowledge in seasonal weather forecasting in semi-arid central Tanzania. *South African Journal of Libraries and Information Science*, *80*(1). https://doi.org/10.7553/80-1-1395

Elith, J., H Graham, C., P Anderson, R., Dudík, M., Ferrier, S., Guisan, A., J Hijmans, R., Huettmann, F., R Leathwick, J., Lehmann, A., Li, J., G Lohmann, L., A Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., McC M Overton, J., Townsend Peterson, A. E., Zimmermann, N. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, *29*(2), 129–151. https://doi.org/10.1111/j.2006.0906-7590.04596.x

Emmett, B.A., Gurney, R.J., McDonald, A.T., Blair, G., Buytaert, W., Freer, J., Haygarth, P., Johnes, P.J., Rees, G.H., Tetzlaff, D., Afgan, E. (2014). *NERC Environmental Virtual Observatory Pilot Final Report.* Natural Environment Research Council, UK. NE.

Enengel, B., Muhar, A., Penker, M., Freyer, B., Drlik, S., & Ritter, F. (2012). Co-production of knowledge in transdisciplinary doctoral theses on landscape development-An analysis of actor roles and knowledge types in different research phases. *Landscape and Urban Planning*, *105*(1–2), 106–117. https://doi.org/10.1016/j.landurbplan.2011.12.004.

ERIKSEN, S. H., BROWN, K., & KELLY, P. M. (2005). The dynamics of vulnerability: locating coping strategies in Kenya and Tanzania. *The Geographical Journal*, *171*(4), 287–305. https://doi.org/10.1111/j.1475-4959.2005.00174.x

ESOKO. (2016). *Access and Use of Seasonal Forecast Information Gives Hope to Farmers in Northern Ghana.* Available at https://www.esoko.com/access-and-use-of-seasonalforecast-information-gives-hope-to-farmers-in-northern-ghana/.

Esquivel, A., Llanos-Herrera, L., Agudelo, D., Prager, S. D., Fernandes, K., Rojas, A., Valencia, J. J., & Ramirez-Villegas, J. (2018). Predictability of seasonal precipitation across major crop growing areas in Colombia. *Climate Services*, *12*(March), 36–47. https://doi.org/10.1016/j.cliser.2018.09.001

Etwire, P. M., Buah, S., Ouédraogo, M., Zougmoré, R., Partey, S. T., Martey, E., Dayamba, S. D., & Bayala, J. (2017). An assessment of mobile phone-based dissemination of weather and market information in the Upper West Region of Ghana. *Agriculture & Food Security*, *6*(1). https://doi.org/10.1186/s40066-016-0088-y

Falco, S. Di, Veronesi, M., & Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

Farm Radio International. (2014). *Implementing Innovative Climate Communication Systems.* Care International.

Faulkner, J. W., Steenhuis, T., van de Giesen, N., Andreini, M., & Liebe, J. R. (2008). Water use and productivity of two small reservoir irrigation schemes in Ghana{\textquotesingle}s upper east region. *Irrigation and Drainage*, *57*(2), 151–163. https://doi.org/10.1002/ird.384

Fekri, M., & Yau, M. K. (2016). An Information-Theoretical Score of Dichotomous Precipitation Forecast. *Monthly Weather Review*, *144*(4), 1633–1647. https://doi.org/10.1175/mwr-d-15-0225.1

Feleke, H. G. (2015). Assessing weather forecasting needs of smallholder farmers for climate change adaptation in the Central Rift Valley of Ethiopia. *Journal of Earth Science and Climate Change, 6(10)*, *1–8*.

Felt, U. (2009). *Taking European knowledge society seriously.* In Science et devenir de l'homme, 2009, n° 59, fascicule thématique" science in society: dialogues and scientific responsibility"-science in society: dialogues and scientific responsibility. In: European Conference, Paris, FRA, 2008-11-24. MURS, Paris (FR.

Ferguson, M. A., & Messier, F. (1997). *Collection and analysis of traditional ecological knowledge about a population of Arctic tundra caribou.* Arctic, 17-28.

Ferro, C. A. T., Richardson, D. S., & Weigel, A. P. (2008). On the effect of ensemble size on the discrete and continuous ranked probability scores. *Meteorological Applications*, *15*(1), 19–24. https://doi.org/10.1002/met.45

Fleming G. (2008). Fleming G. Service delivery and public weather services—an overview. *WMO Bull*, *57*, 208–212.

Folke, C., Carpenter, S. R., Walker, B., Scheffer, M., Chapin, T., & Rockström, J. (2010). Resilience Thinking: Integrating Resilience, Adaptability and Transformability. *Ecology and Society*, *15*(4). https://doi.org/10.5751/es-03610-150420

Fosu-Mensah, B. Y., Vlek, P. L. G., & MacCarthy, D. S. (2012). Farmers' perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. *Environment, Development and Sustainability*, *14*(4), 495–505. https://doi.org/10.1007/s10668-012-9339-7

Frías M. D., Fernandez J., Iturbide M. and Bedia J. (2017). *visualizeR: Visualizing and 0.2.1., Communicating Uncertainty in Seasonal Climate Prediction.* R package version Https://github.com/SantanderMetGroup/visualizeR/wiki.

Frumkin, H., Hess, J., Luber, G., Malilay, J., & McGeehin, M. (2008). Climate Change: The Public Health Response. *American Journal of Public Health*, *98*(3), 435–445. https://doi.org/10.2105/ajph.2007.119362

Furman, C., Roncoli, C., Crane, T., & Hoogenboom, G. (2011). Beyond the {\textquotedblleft}fit{\textquotedblright}: introducing climate forecasts among organic farmers in Georgia (United States). *Climatic Change*, *109*(3–4), 791–799. https://doi.org/10.1007/s10584-011-0238-y

Gagnon, C. A., & Berteaux, D. (2009). Integrating traditional ecological knowledge and ecological science: A question of scale. *Ecology and Society*, *14*(2). https://doi.org/10.5751/ES-02923-140219

Gallus, W. A., & Segal, M. (2004). Does increased predicted warm-season rainfall indicate enhanced likelihood of rain occurrence? *Weather and Forecasting*, *19*(6), 1127–1135. https://doi.org/10.1175/820.1

Gbangou, T., Ludwig, F., van Slobbe, E., Hoang, L., & Gordana Kranjac-Berisavljevic. (2019). Seasonal variability and predictability of agro-meteorological indices: Tailoring onset of rainy season estimation to meet farmers' needs in Ghana. *Climate Services*, *14*, 19–30. https://doi.org/10.1016/j.cliser.2019.04.002

Gbetibouo G., Hill C., Abazaami J., Mills A., Snyman D., and H. O. (2017). *Impact assessment on climate information services for community-based adaptation to climate change*. http://careclimatechange.org/wp-

GFCS. (2016). *Development and Delivery of Climate Services Research Dialogue.* Accessed on 3/11/2016 and available at https://unfccc.int/files/science/workstreams/research/application/pdf/part2.1_wmo_dilley.pdf.

Ghana Statistical Service (GSS). (2014). *2010 Population and Housing Census: District Analytical Report. Kumbungu district.* Ghana Statistical Service. Accra. Accessed on 21/8/2018 and available at http://www2.statsghana.gov.gh/docfiles/2010_District_Report/Northern/Kumbungu.pdf.

GIDA. (2011). *National Irrigation Policy, Strategies and Regulatory Measures.* MOFA/FAO, Accra, Ghana Available at http://www.gida.gov.gh/Downloads/National_Irrigation_Policy_Document.pdf.

GIDA. (2016). *National Irrigation Policy, Strategies and Regulatory Measures.* MOFA/FAO, Accra, Ghana Available at http://www.gida.gov.gh/Downloads/National_Irrigation_Policy_Document.pdf.

Gigerenzer, G., & Selten, R. (Eds.). (2002). *bounded rationality: the adaptive toolbox*. The MIT Press. http://www.amazon.com/Bounded-Rationality-Adaptive-Gerd-Gigerenzer/dp/0262072149

Gill, P., Stewart, K., Treasure, E., & Chadwick, B. (2008). Methods of data collection in qualitative research: Interviews and focus groups. *British Dental Journal*, *204*(6), 291–295. https://doi.org/10.1038/bdj.2008.192

GMet. (2016). *Climate Information of Some Major Cities in Ghana.* Available at Accessed on 4 December 2017 http://www.meteo.gov.gh/website/index.php?option=com_content&view=category&id=38&Itemid=54.

GMet. (2017). *Rainfall Seasonal Forecast for 2017; Highlights Outlook for Northern Region of Ghana.* Accessed on 4/3/10/18 and available at http://www.meteo.gov.gh/website/index.php?option=com_joomdoc&task=document.download&path=seasonal-forecast%2Fseasonal-forecast-for-northern-ghana-2017&Itemid=85.

Goodwin, J., & Dahlstrom, M. F. (2011). *Good reasons for trusting climate science communication.* In American Meteorological Society convention, Seattle, WA.

Gould, J. D., Boies, S. J., & Lewis, C. (1991). Making usable, useful, productivity-enhancing computer applications. *Communications of the {ACM}*, *34*(1), 74–85. https://doi.org/10.1145/99977.99993

Gouveia, C., Fonseca, A., Câmara, A., & Ferreira, F. (2004). Promoting the use of environmental data collected by concerned citizens through information and communication technologies. *Journal of Environmental Management*, *71*(2), 135–154. https://doi.org/10.1016/j.jenvman.2004.01.009

Graef, F., & Haigis, J. (2001). Spatial and temporal rainfall variability in the Sahel and its effects on farmers' management strategies. *Journal of Arid Environments*, *48*(2), 221–231. https://doi.org/10.1006/jare.2000.0747

Gray, L. C., & Morant, P. (2003). Reconciling indigenous knowledge with scientific assessment of soil fertility changes in southwestern Burkina Faso. *Geoderma*, *111*(3–4), 425–437. https://doi.org/10.1016/s0016-7061(02)00275-6

Gray, S. A., Gray, S., Cox, L. J., & Henly-Shepard, S. (2013). Mental Modeler: A fuzzy-logic cognitive mapping modeling tool for adaptive environmental management. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 965–973. https://doi.org/10.1109/HICSS.2013.399

Grothmann, T., & Patt, A. (2005). Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Global Environmental Change*, *15*(3), 199–213. https://doi.org/10.1016/j.gloenvcha.2005.01.002

Gubrium, J., & Holstein, J. (2012). Handbook of Interview Research. In *Handbook of Interview Research*. SAGE Publications, Inc. https://doi.org/10.4135/9781412973588

Gumucio, T., Hansen, J., Huyer, S., & van Huysen, T. (2019). Gender-responsive rural climate services: a review of the literature. In *Climate and Development*. Taylor and Francis Ltd. https://doi.org/10.1080/17565529.2019.1613216

Gura, T. (2013). Citizen science: amateur experts. *Nature*, *496*(7444), 259–261. https://doi.org/10.1038/nj7444-259a

Guthiga, P., & Newsham, A. (2011). Meteorologists Meeting Rainmakers: Indigenous Knowledge and Climate Policy Processes in Kenya. *{IDS} Bulletin*, *42*(3), 104–109. https://doi.org/10.1111/j.1759-5436.2011.00228.x

Gwenzi, J., Mashonjowa, E., Mafongoya, P. L., Rwasoka, D. T., & Stigter, K. (2016). The use of indigenous knowledge systems for short and long range rainfall prediction and farmers' perceptions of science-based seasonal forecasts in Zimbabwe. *International Journal of Climate Change Strategies and Management*, *8*(3), 440–462. https://doi.org/10.1108/ijccsm-03-2015-0032

Gyampoh, B. A., Amisah, S., Idinoba, M., & Nkem, J. (2009). Using traditional knowledge to cope with climate change in rural Ghana. *Unasylva*, *60(281/232*, 70-74.

Habilov M., Sitati A., Vogel E., Zanten van J. A., Zommers Z., Cowell R., Kooiman A., Lacson I ,

Leonard S., (2015). Early Warning as a Human Right: Building Resilience to Climate Related Hazards. https://wedocs.unep.org/bitstream/handle/20.500.11822/7429/-Early_Warning_as_a_Human_Right_Building_Resilience_to_Climate-related_Hazards-2015Early-Warning-As-A-HumanRight-Building-Resilience-For-Climate-Rela.pdf?sequence=4&isAllowed=y

Hajer, M. A. (2009). *Authoritative Governance: Policy Making in the Age of Mediatization.* Oxford University Press.

Hames, R. S., Rosenberg, K. V., Lowe, J. D., Barker, S. E., & Dhondt, A. A. (2002). Adverse effects of acid rain on the distribution of the Wood Thrush Hylocichla mustelina in North America. *Proceedings of the National Academy of Sciences of the United States of America*, *99*(17), 11235–11240. https://doi.org/10.1073/pnas.172700199

Hammer, G. (2000). *Applying Seasonal Climate Forecasts in Agricultural and Natural Ecosystems — A Synthesis* (pp. 453–462). https://doi.org/10.1007/978-94-015-9351-9_27

Hammer, G. L., Holzworth, D. P., & Stone, R. (1996). The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. *Australian Journal of Agricultural Research*, *47*(5), 717. https://doi.org/10.1071/ar9960717

Hansen, J. W. (2002a). Applying seasonal climate prediction to agricultural production. *Agricultural Systems*, *74*(3), 305–307. https://doi.org/10.1016/S0308-521X(02)00042-2

Hansen, J. W. (2002b, December 1). Applying seasonal climate prediction to agricultural production. *Agricultural Systems*, *74*(3), 305–307. https://doi.org/10.1016/S0308-521X(02)00042-2

Hansen, James W. (2005). Integrating seasonal climate prediction and agricultural models for insights into agricultural practice. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1463), 2037–2047. https://doi.org/10.1098/rstb.2005.1747

Hansen, James W., Mishra, A., Rao, K. P. C., Indeje, M., & Ngugi, R. K. (2009). Potential value of GCM-based seasonal rainfall forecasts for maize management in semi-arid Kenya. *Agricultural Systems*, *101*(1–2), 80–90. https://doi.org/10.1016/j.agsy.2009.03.005

Hansen, James W., Vaughan, C., Kagabo, D. M., Dinku, T., Carr, E. R., Körner, J., & Zougmoré, R. B. (2019). Climate Services Can Support African Farmers' Context-Specific Adaptation Needs at Scale. *Frontiers in Sustainable Food Systems*, *3*. https://doi.org/10.3389/fsufs.2019.00021

Hartmann, H. C., Bales, R., & Sorooshian, S. (1999, June). Weather, Climate, and Hydrologic Forecasting for the Southwest U.S. *{WRPMD}{\textquotesingle}99*. https://doi.org/10.1061/40430(1999)228

Harvey, B., Jones, L., Cochrane, L., & Singh, R. (2019). The evolving landscape of climate services in sub-Saharan Africa: What roles have NGOs played. *Climatic Change*. https://doi.org/10.1007/s10584-019-02410-z

Hatzilacou, D., Kallis, G., Mexa, A., Coccosis, H., & Svoronou, E. (2007). Scenario workshops: A useful method for participatory water resources planning? *Water Resources Research*, *43*(6). https://doi.org/10.1029/2006WR004878

Hayman, P. (2004). *Decision support systems in Australian dryland farming: A promising past, a disappointing present and uncertain future*. In Proceedings of 4th International Crop Science Congress'.(Eds T Fischer, et al.).

Hiwasaki, L., Luna, E., Syamsidik, & Marçal, J. A. (2015). Local and indigenous knowledge on climate-related hazards of coastal and small island communities in Southeast Asia. *Climatic Change*, *128*(1–2), 35–56. https://doi.org/10.1007/s10584-014-1288-8

Hiwasaki, L., Luna, E., Syamsidik, & Shaw, R. (2014). Process for integrating local and indigenous knowledge with science for hydro-meteorological disaster risk reduction and climate change adaptation in coastal and small island communities. *International Journal of Disaster Risk Reduction*, *10*, 15–27. https://doi.org/10.1016/j.ijdrr.2014.07.007

Hoagland, S. J. (2016). Integrating Traditional Ecological Knowledge with Western Science for Optimal Natural Resource Management. *IK: Other Ways of Knowing*, *3*(1), 1–15. https://doi.org/10.18113/p8ik359744

Hochachka, W. M., Caruana, R., Fink, D., Munson, A., Riedewald, M., Sorokina, D., & Kelling, S. (2007). Data-Mining Discovery of Pattern and Process in Ecological Systems. *Journal of Wildlife Management*, *71*(7), 2427. https://doi.org/10.2193/2006-503

Hochachka, W. M., Dhondt, A. A., McGowan, K. J., & Kramer, L. D. (2004). Impact of West Nile Virus on American Crows in the Northeastern United States, and Its Relevance to Existing Monitoring Programs. *EcoHealth*, *1*(1), 60–68. https://doi.org/10.1007/s10393-004-0015-8

Hoffmann-Riem, H., & Wynne, B. (2002). In risk assessment, one has to admit ignorance. *Nature*, *416*(6877), 123. https://doi.org/10.1038/416123a

Huntington H. P., Suydam, R. S., & Rosenberg, D. H. (2004). Traditional knowledge and satellite tracking as complementary approaches to ecological understanding. *Environmental Conservation*, *31*(3), 177–180. https://doi.org/10.1017/s0376892904001559

Hwang, S. (2007). Utilizing Qualitative Data Analysis Software. *Social Science Computer Review* (4), *26* 519–527. https://doi.org/10.1177/0894439307312485

IFAD. (2012). *Ghana: country programme evaluation.* IFAD Publ. No. 84, May 2012. http://www.ifad.org/evaluation/public_html/eksyst/doc/profile/pa/ghana2012.htm (retrieved October 4, 2017).

Iizumi, T., & Ramankutty, N. (2015). How do weather and climate influence cropping area and intensity? In *Global Food Security* (Vol. 4, pp. 46–50). Elsevier B.V. https://doi.org/10.1016/j.gfs.2014.11.003

Indeje, M., Semazzi, F. H. M., & Ogallo, L. J. (2000). ENSO signals in East African rainfall seasons. *International Journal of Climatology*, *20*(1), 19–46. https://doi.org/10.1002/(SICI)1097-0088(200001)20:1<19::AID-JOC449>3.0.CO;2-0

IPCC. (2007). *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the IPCC.* (P. J. van der L. and C. E. H. M.L. Parry, O. F. Canziani, J.P. Palutikof (ed.)). Cambridge University Press, Cambridge, UK, pp. 976.

IPCC. (2014). climate change 2014: synthesis report. Contribution of Working Groups I. II and III to the Fifth Assessment Report of the intergovernmental panel on Climate Change. *IPCC, Geneva, Switzerland, 151.*

Jalloh, A., Gerald C. Nelson, Timothy S. Thomas, Robert Zougmoré, & Harold Roy-Macauley (Eds.). (2013). *West African Agriculture and Climate Change*. https://doi.org/10.2499/9780896292048

Jiri, O., Mafongoya, P. L., & Chivenge, P. (2015). Indigenous knowledge systems, seasonal "quality" and climate change adaptation in Zimbabwe. *Climate Research*, *66*(2), 103–111. https://doi.org/10.3354/cr01334

Jiri, Obert, Mafongoya, P. L., Mubaya, C., & Mafongoya, O. (2016). Seasonal Climate Prediction and Adaptation Using Indigenous Knowledge Systems in Agriculture Systems in Southern Africa: A Review. *Journal of Agricultural Science*, *8*(5), 156. https://doi.org/10.5539/jas.v8n5p156

Johnson, R. B., & Onwuegbuzie, A. J. (2007). Toward a Definition of Mixed Methods Research. *Journal of Mixed Methods Research*, *1*(2), 112–133. https://doi.org/10.1177/1558689806298224

Johnston, P. A., Archer, E. R. M., Vogel, C. H., Bezuidenhout, C. N., Tennant, W. J., & Kuschke, R. (2004). Review of seasonal forecasting in South Africa: Producer to end-user. In *Climate Research* (Vol. 28, Issue 1, pp. 67–82). Inter-Research. https://doi.org/10.3354/cr028067

Jolliffe, I. T., & Stephenson, D. B. (2012). *Forecast verification : a practitioner's guide in atmospheric science*. John Wiley & Sons.

Joslyn, S., & Savelli, S. (2010). Communicating forecast uncertainty: Public perception of weather forecast uncertainty. *Meteorological Applications*, *17*(2), 180–195. https://doi.org/10.1002/met.190

Jotoafrika. (2013). *Adapting to climate change in Africa.* http://www.careclimatechange.org/files/JotoAfrika12_FINAL. pdf(retrieved October 4, 2017).

Jung, G., & Kunstmann, H. (2007). High-resolution regional climate modeling for the Volta region of West Africa. *Journal of Geophysical Research*, *112*(D23). https://doi.org/10.1029/2006jd007951

Kalanda-Joshua, M., Ngongondo, C., Chipeta, L., & Mpembeka, F. (2011). Integrating indigenous knowledge with conventional science: Enhancing localised climate and weather forecasts in Nessa, Mulanje, Malawi. *Physics and Chemistry of the Earth, Parts A/B/C*, *36*(14–15), 996–1003. https://doi.org/10.1016/j.pce.2011.08.001

Kanamitsu, M., Kumar, A., Juang, H. M. H., Schemm, J. K., Wang, W., Yang, F., ... & Ji, M. (2002). NCEP dynamical seasonal forecast system 2000. *Bulletin of the American Meteorological Society, 83(7),* 1019-1038.

Kankam-Yeboah, K., Obuobie, E., Amisigo, B., & Opoku-Ankomah, Y. (2013). Impact of climate change on streamflow in selected river basins in Ghana. *Hydrological Sciences Journal*, *58*(4), 773–788. https://doi.org/10.1080/02626667.2013.782101

Karpouzoglou, T., Zulkafli, Z., Grainger, S., Dewulf, A., Buytaert, W., & Hannah, D. M. (2016). Environmental Virtual Observatories ({EVOs}): prospects for knowledge co-creation and resilience in the Information Age. *Current Opinion in Environmental Sustainability*, *18*, 40–48. https://doi.org/10.1016/j.cosust.2015.07.015

Kasei, R. A., Ampadu, B., & Yalevu, S. (2014). Impacts of Climate Variability on Food Security in Northern Ghana. In *Journal of Earth Sciences and Geotechnical Engineering* (Vol. 4, Issue 3). Scienpress Ltd.

Kasperson, Roger E., and Pieter Jan Stallen, E. (2012). Communicating risks to the public: International perspectives. *Springer Science & Business Media*, *Vol. 4*. https://doi.org/10.1007/978-94-009-1952-5

Kassa B. and Temesgen D. (2011). Indigenous Knowledge In Research And Extension. In *Perspective Of Agricultural Extension. Regional Msc Program On: Agricultural Information and Communication Management (Aicm)*. Haramaya University. Pp91-94. Accessed on 11/07/2019/.

Kelling, S., Hochachka, W. M., Fink, D., Riedewald, M., Caruana, R., Ballard, G., & Hooker, G. (2009). Data-intensive Science: A New Paradigm for Biodiversity Studies. *BioScience*, *59*(7), 613–620. https://doi.org/10.1525/bio.2009.59.7.12

Keough, H. L., & Blahna, D. J. (2006). Achieving integrative, collaborative ecosystem management. *Conservation Biology : The Journal of the Society for Conservation Biology*, *20*(5), 1373–1382. https://doi.org/10.1111/j.1523-1739.2006.00445.x

Kharin, V. V., & Zwiers, F. W. (2003). On the ROC score of probability forecasts. *Journal of Climate*, *16*(24), 4145–4150. https://doi.org/10.1175/1520-0442(2003)016<4145:OTRSOP>2.0.CO;2

Kirchhoff, C. J., Carmen Lemos, M., & Dessai, S. (2013). Actionable Knowledge for Environmental Decision Making: Broadening the Usability of Climate Science. *Annual Review of Environment and Resources*, *38*(1), 393–414. https://doi.org/10.1146/annurev-environ-022112-112828

Kniveton, D., Visman, E., Tall, A., Diop, M., Ewbank, R., Njoroge, E., & Pearson, L. (2015a). Dealing with uncertainty: integrating local and scientific knowledge of the climate and weather. *Disasters*, *39 Suppl 1*, S35-53. https://doi.org/10.1111/disa.12108

Kniveton, D., Visman, E., Tall, A., Diop, M., Ewbank, R., Njoroge, E., & Pearson, L. (2015b). Dealing with uncertainty: Integrating local and scientific knowledge of the climate and weather. *Disasters*, *39*(s1), s35–s53. https://doi.org/10.1111/disa.12108

Knox, J., Hess, T., Daccache, A., & Wheeler, T. (2012). Climate change impacts on crop productivity in Africa and South Asia. *Environmental Research Letters*, *7*(3), 34032. https://doi.org/10.1088/1748-9326/7/3/034032

Kolawole, O. D., Wolski, P., Ngwenya, B., & Mmopelwa, G. (2014). Ethno-meteorology and scientific weather forecasting: Small farmers and scientists' perspectives on climate variability in the Okavango Delta, Botswana. *Climate Risk Management*, *4*, 43–58. https://doi.org/10.1016/j.crm.2014.08.002

Kranjac-Berisavljevic' G., Blench R. M., and C. R. (2003). *Rice Production and Livelihoods in Ghana. Multi-Agency Partnerships (Maps) For Technical Change In West African Agriculture.* https://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/3990.pdf

Kumar, A., Barnston, A. G., & Hoerling, M. P. (2001). Seasonal predictions, probabilistic verifications, and ensemble size. *Journal of Climate, 14(7)*, 1671–1676.

Kunstmann, H.A., Jung, G. E. (2005). *Impact of Regional Climate Change on Water Availability in the Volta Basin of West Africa. IAHS publication, pp. 75–85 April (295).* IAHS publication, pp. 75–85 April (295).

Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H. M., Fosu, K. Y., Gbetibouo, G., Jain, S., Mahamadou, A., Mano, R., Kabubo-Mariara, J., El-Marsafawy, S., Molua, E., Ouda, S., Ouedraogo, M., Séne, I., Maddison, D., … Dinar, A. (2006). Will African Agriculture Survive Climate Change? *The World Bank Economic Review*, *20*(3), 367–388. https://doi.org/10.1093/wber/lhl004

Lacombe, G., McCartney, M., & Forkuor, G. (2012a). Drying climate in Ghana over the period 1960–2005: evidence from the resampling-based Mann-Kendall test at local and regional levels. *Hydrological Sciences Journal*, *57*(8), 1594–1609. https://doi.org/10.1080/02626667.2012.728291

Lacombe, G., McCartney, M., & Forkuor, G. (2012b). Drying climate in Ghana over the period 1960{\textendash}2005: evidence from the resampling-based Mann-Kendall test at local and regional levels. *Hydrological Sciences Journal*, *57*(8), 1594–1609. https://doi.org/10.1080/02626667.2012.728291

Lalonde, A. (1993). *African indigenous knowledge and its relevance to sustainable development. Traditional ecological knowledge: Concepts and cases.* 55-62.

Lambert, D. K. (2014). Historical Impacts of Precipitation and Temperature on Farm Production in Kansas. *Journal of Agricultural and Applied Economics*, *46*(4), 439–456. https://doi.org/10.1017/s1074070800029047

Langford, S., & Hendon, H. H. (2013). Improving Reliability of Coupled Model Forecasts of Australian Seasonal Rainfall. *Monthly Weather Review*, *141*(2), 728–741. https://doi.org/10.1175/MWR-D-11-00333.1

Lawson, E. T., Alare, R. S., Salifu, A. R. Z., & Thompson-Hall, M. (2019). Dealing with climate change in semi-arid Ghana: understanding intersectional perceptions and adaptation strategies of women farmers. *GeoJournal*. https://doi.org/10.1007/s10708-019-09974-4

LeClerc, J. (2014). *Communicating Weather and Climate Uncertainty: Exploratory Research in Cognitive Psychology*. (Doctoral dissertation). University of Washington.

Legg, T. P., & Mylne, K. R. (2004). Early warnings of severe weather from ensemble forecast information. *Weather and Forecasting*, *19*(5), 891–906. https://doi.org/10.1175/1520-0434(2004)019<0891:EWOSWF>2.0.CO;2

Lemos, M. C., Arnott, J. C., Ardoin, N. M., Baja, K., Bednarek, A. T., Dewulf, A., Fieseler, C., Goodrich, K. A., Jagannathan, K., Klenk, N., Mach, K. J., Meadow, A. M., Meyer, R., Moss, R., Nichols, L., Sjostrom, K. D., Stults, M., Turnhout, E., Vaughan, C., Wyborn, C. (2018). To co-produce or not to co-produce. *Nature Sustainability*, *1*(12), 722–724. https://doi.org/10.1038/s41893-018-0191-0

Lemos, M. C., Kirchhoff, C. J., & Ramprasad, V. (2012). Narrowing the climate information usability gap. In *Nature Climate Change* (Vol. 2, Issue 11, pp. 789–794). https://doi.org/10.1038/nclimate1614

Letson, D., Llovet, I., Podestá, G., Royce, F., Brescia, V., Lema, D., & Parellada, G. (2001). User perspectives of climate forecasts: crop producers in Pergamino, Argentina. *Climate Research*, *19*, 57–67. https://doi.org/10.3354/cr019057

Liebe, J. (2002). *Estimation of water storage capacity and evaporation losses of small reservoirs in the Upper East Region of Ghana.* Diploma Thesis.Geographische Institute der Rhinischen Friedrich- Wilhelms-Universitat Bonn, 106pp.

Logah, F. Y., Obuobie, E., Ofori, D., & Kankam-Yeboah, K. (2013). Analysis of Rainfall Variability in Ghana. In *International Journal of Latest Research In Engineering and Computing (IJLREC)* (Vol. 1, Issue 8). www.ijlrec.com

Lourenço, T. C., Swart, R., Goosen, H., & Street, R. (2016). The rise of demand-driven climate services. In *Nature Climate Change* (Vol. 6, Issue 1, pp. 13–14). Nature Publishing Group. https://doi.org/10.1038/nclimate2836

Lowry, C. S., & Fienen, M. N. (2013). CrowdHydrology: crowdsourcing hydrologic data and engaging citizen scientists. *Ground Water*, *51*(1), 151–156. https://doi.org/10.1111/j.1745-6584.2012.00956.x

Lugen M. (2016). *The role of climate services for adaptation to climate change in developing countries, with a case study from South Africa, KLIMOS Working Paper n°10,*. KLIMOSACROPOLIS, Brussels, Belgium.

Luseno, W. K., McPeak, J. G., Barrett, C. B., Little, P. D., & Gebru, G. (2003). Assessing the value of climate forecast information for pastoralists: Evidence from Southern Ethiopia and Northern Kenya. *World Development*, *31*(9), 1477–1494. https://doi.org/10.1016/S0305-750X(03)00113-X

Mabe F. N., Sarpong D. B., O.-A. Y. (2012). *Adaptive capacities of farmers to climate change adaptation strategies and their effects on rice production in the northern region of Ghana.* University of Ghana. Http://dx.doi.org/10.18551/rjoas.2012-11.02?nosfx=y.

Mafongoya, P. L., & Ajayi, O. C. (2017). Indigenous knowledge and climate change: Overview and basic propositions. In *Indigenous knowledge systems and climate change management in Africa* (pp. 17–28). CTA, Wageningen - Netherlands.

Mafongoya, P. . (2017). Indigenous Knowledge Systems and Climate Change Management in Africa. In *Publications.Cta.Int* (Issue November). www.cta.int%0ACover

Mahoo, H., Mbungu, W., Yonah, I., Recha, J., Radeny, M., Kimeli, P., & Kinyangi, J. (2015). *Working Paper Integrating Indigenous Knowledge with Scientific Seasonal Forecasts for Climate Risk Management in Lushoto District in Tanzania*. www.ccafs.cgiar.org

Maibach, E. W., Chadwick, A., McBride, D., Chuk, M., Ebi, K. L., & Balbus, J. (2008). Climate Change and Local Public Health in the United States: Preparedness, Programs and Perceptions of Local Public Health Department Directors. *{PLoS} {ONE}*, *3*(7), e2838. https://doi.org/10.1371/journal.pone.0002838

Makwara E. C. (2013). Indigenous Knowledge Systems and Modern Weather Forecasting: Exploring the Linkages. *Journal of Agriculture and Sustainability*, *2*(1), 98–141.

Manyanhaire, I. O., and Miriam Chitura, & and. (2015). Integrating Indigenous Knowledge Systems into Climate Change Interpretation: Perspectives Relevant To Zimbabwe. *Greener Journal of Educational Research*, *5*(2), 27–36. https://doi.org/10.15580/gjer.2015.2.012715022

Manyanhaire, I. O., & Chitura, M. (2015a). Integrating Indigenous Knowledge Systems into Climate Change Interpretation: Perspectives Relevant To Zimbabwe. *Greener Journal of Educational Research*, *5*(2), 027–036. https://doi.org/10.15580/gjer.2015.2.012715022

Manyanhaire, I. O., & Chitura, M. (2015b). Integrating Indigenous Knowledge Systems into Climate Change Interpretation: Perspectives Relevant To Zimbabwe. *Greener Journal of Educational Research*, *5*(2), 027–036. https://doi.org/10.15580/gjer.2015.2.012715022

Manzanas R., Gutiérrez J.M., Fernández J., Frías, M.D., Cofiño, A.S., Sánchez,. E., Voces, J., & Rodríguez E. (2012). *European Provision Of Regional Impact Assessment on a Seasonal-to-decadal timescale.* Report on assessment and combination of S2D predictions.

Manzanas, R., Amekudzi, L. K., Preko, K., Herrera, S., & Gutiérrez, J. M. (2014a). Precipitation variability and trends in Ghana: An intercomparison of observational and reanalysis products. *Climatic Change*, *124*(4), 805–819. https://doi.org/10.1007/s10584-014-1100-9

Manzanas, R., Amekudzi, L. K., Preko, K., Herrera, S., & Gutiérrez, J. M. (2014b). Precipitation variability and trends in Ghana: An intercomparison of observational and reanalysis products. *Climatic Change*, *124*(4), 805–819. https://doi.org/10.1007/s10584-014-1100-9

Mapfumo, P., Mtambanengwe, F., & Chikowo, R. (2015). Building on indigenous knowledge to strengthen the capacity of smallholder farming communities to adapt to climate change and variability in southern Africa. *Climate and Development*, *8*(1), 72–82. https://doi.org/10.1080/17565529.2014.998604

Mariani, S., M. Casaioli, C. Accadia, A. Lanciani, and N. T. (2007). *Verification and intercomparison of precipitation fields modelled by LAMs in the alpine area: Two FORALPS case studies. Pp 14 in Forecast verification: a summary of common approaches, and examples of application.* Univ. degli Studi di Trento, Dipartimento di Ingegneria Civile e Ambientale.

Mase, A. S., & Prokopy, L. S. (2014). Unrealized potential: A review of perceptions and use of weather and climate information in agricultural decision making. *Weather, Climate, and Society*, *6*(1), 47–61. https://doi.org/10.1175/WCAS-D-12-00062.1

Masinde, M. (2015). An innovative drought early warning system for sub-Saharan Africa: integrating modern and indigenous approaches. *African Journal of Science, Technology, Innovation and Development*, *7*(1), 8–25. https://doi.org/10.1080/20421338.2014.971558

Mason, I. B. (1999). *Integrated verification procedures for forecasts and warnings Consultancy Report*. *June*.

Mason, I. B. 2003: (2003). Binary events. In E. I. T. J. and D. B. Stephenson. (Ed.), *Forecast Verification: A Practitioner's Guide in Atmospheric Science.* (pp. 37–76). John Wiley, Hoboken, NJ, USA.

Mason, S. J., & Weigel, A. P. (2009). A generic forecast verification framework for administrative purposes. *Monthly Weather Review*, *137*(1), 331–349. https://doi.org/10.1175/2008MWR2553.1

Mayer, I. S. (Igor S. (1997). *Debating technologies : a methodological contribution to the design and evaluation of participatory policy analysis*. Tilburg University Press.

Mazzocchi, F. (2006). Western science and traditional knowledge: Despite their variations, different forms of knowledge can learn from each other. *{EMBO} Reports*, *7*(5), 463–466. https://doi.org/10.1038/sj.embor.7400693

McCormick, S. 2009. (2009). Mobilizing Science: Movements, Participation, and the Remaking of Knowledge. In *Isis* (Vol. 101, Issue 4). Temple University Press, Philadelphia, PA. 212 pp. https://doi.org/10.1086/659725

McNew, K. P., Mapp, H. P., Duchon, C. E., & Merritt, E. S. (1991). Sources and Uses of Weather Information for Agricultural Decision Makers. *Bulletin of the American Meteorological Society*, *72*(4), 491–498. https://doi.org/10.1175/1520-0477(1991)072<0491:sauowi>2.0.co;2

McNie, E. C. (2013). Delivering climate services: Organizational strategies and approaches for producing useful climate-science information. *Weather, Climate, and Society*, *5*(1), 14–26. https://doi.org/10.1175/WCAS-D-11-00034.1

Mdemu, M., Kashaigili. J.J., Lupala, J., Levira, P,. Liwenga, E,. Nduganda, A. & Mwakapuja, F. (2012). Proceedings of the first Climate Change Impacts, Mitigation and Adaptation Programme Scientific Conference, 2012. *Proceedings of the First Climate Change Impacts, Mitigation and Adaptation Programme Scientific Conference, 2012*, 8–17.

Mdemu, M.V. (2008). *Water Productivity in Medium and Small Reservoirs in the Upper East Region (UER) of Ghana.* ZEF.

MeteoSwiss. (2017). *EasyVerification: Ensemble Forecast Verification for Large Data Sets.* R package version Https://CRAN.R-project.org/package=easyVerification., 0.4.2. URL:

Mexa A. (2002). The scenario method in strategic environmental planning. *Topos*, *18 (19)*, 215–227.

Mikkelsen, J. H., & Langohr, R. (2004). Indigenous knowledge about soils and a sustainable crop production, a case study from the Guinea Woodland Savannah (Northern Region, Ghana). *Geografisk Tidsskrift-Danish Journal of Geography*, *104*(2), 13–26. https://doi.org/10.1080/00167223.2004.10649515

Miller, C. A., & Wyborn, C. (2018). Co-production in global sustainability: Histories and theories. *Environmental Science and Policy*. https://doi.org/10.1016/j.envsci.2018.01.016

Milner, A. (2007). Arctic climate impact assessment Arctic climate impact assessment. Cambridge University Press, New York, 2005. {ISBN} 0521865093. *International Journal of Climatology*, *27*(3), 413–414. https://doi.org/10.1002/joc.1445

Mol, A. P. J. (2006). Environmental Governance in the Information Age: The Emergence of Informational Governance. *Environment and Planning C: Government and Policy*, *24*(4), 497–514. https://doi.org/10.1068/c0508j

Molteni, F., Stockdale, T., Balmaseda, M., Balsamo, G., Buizza, R., Ferranti, L., Magnusson, L., Mogensen, K., & Palmer, T. (2011). forecast system (System 4). *ECMWF Technical Memoranda*, *October*.

Morris, M. L., Tripp R., and D. A. A. (1999). *Adoption and Impacts of Improved Maize Production Technology: A Case Study of the Ghana Grains Development Project.* Economic Program Paper No. 99-01. CIMMYT: International Maize and Wheat Improvement Center. http://fsg.afre.msu.edu/zambia/sweet/CIMMYT_Ghana_maize_adoption_impact.pdf (retrieved October 4, 2017).

Muita, R. R., van Ogtrop, F., Ampt, P., & Vervoort, R. W. (2016). Managing the water cycle in Kenyan small-scale maize farming systems: Part 1. Farmer perceptions of drought and climate variability. *Wiley Interdisciplinary Reviews: Water*, *3*(1), 105–125. https://doi.org/10.1002/wat2.1118

Müller-Kuckelberg, K. (2012). *Climate change and its impact on the livelihood of farmers and agricultural workers in Ghana. Preliminary Research Results*. General Agricultural Workers' Union of GTUC. Friedrich Ebert Stiftung (Fes).%0A

Müller, C., Cramer, W., Hare, W. L., & Lotze-Campen, H. (2011). Climate change risks for African agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(11), 4313–4315. https://doi.org/10.1073/pnas.1015078108

Mwagha, S. M., & Masinde, M. (2015). *Scientific Verification of Weather Lore for Drought Forecasting–The Role of Fuzzy Cognitive Mapping.* In Proceedings of the IST-Africa 2015 Conference, Lilongwe, Malawi (pp. 6-8).

Myers, W. M., & Fridy, K. S. (2016). Formal versus traditional institutions: evidence from Ghana. *Democratization*, *24*(2), 367–382. https://doi.org/10.1080/13510347.2016.1184247

Naab, F. Z., Abubakari, Z., & Ahmed, A. (2019). The role of climate services in agricultural productivity in Ghana: The perspectives of farmers and institutions. *Climate Services*, *13*, 24–32. https://doi.org/10.1016/j.cliser.2019.01.007

NADMO (National Disaster Management Organisation). (2015). *National progress report on the implementation of the Hyogo Framework for Action (2013-2015).* https://www.preventionweb.net/files/41995_GHA_NationalHFAprogress_2013-15.pdf.

Naess, L. O. (2013). The role of local knowledge in adaptation to climate change. *Wiley Interdisciplinary Reviews: Climate Change*, *4*(2), 99–106. https://doi.org/10.1002/wcc.204

Nakashima, D.J., Galloway McLean, K., Thulstrup, H.D., Ramos Castillo, A. and Rubis, J. T. (2012). *Weathering Uncertainty: Traditional Knowledge for Climate Change Assessment and Adaptation.* Paris, UNESCO, and Darwin, UNU, 1Ó0 pp.

Namara, R. E., Horowitz, L., Nyamadi, B., & Barry, B. (2011). Irrigation Development in Ghana: Past experiences, emerging opportunities, and future directions. *Ghana Strategy Support Program (GSSP) GSSP Working Paper No. 0027*, 41. https://doi.org/10.5194/hess-15-1577-2011

Nanedo, N. A., Prior, J. C., de Bruyn, L. L., & Marshall, G. R. (2014, June). Capacities for irrigation water resource governance at the local level: a case study from the Upper East Region of Ghana. *Sustainable Irrigation and Drainage V*. https://doi.org/10.2495/si140021

Nation, D. (2017). *Indigenous Forecasting Techniques.* Accessed on 20/2/2017 at. https://www.dailynation.news/indigenous-forecasting-techniques.

Ndamani, F., & Watanabe, T. (2013). Rainfall variability and crop production in northern Ghana : The case of Lawra district. *ResearchGate*, *December*. https://doi.org/10.13140/2.1.2343.7125

Nel, J. L., Roux, D. J., Driver, A., Hill, L., Maherry, A. C., Snaddon, K., Petersen, C. R., Smith-Adao, L. B., Van Deventer, H., & Reyers, B. (2016). Knowledge co-production and boundary work to promote implementation of conservation plans. *Conservation Biology,* 30(1),176-188. https://doi.org/10.1111/cobi.12560

Ngodigha, S. A., Abowei, J. F. N., & Ogamba, E. N. (2015). The Role of Indigenous Knowledge in Fisheries Research in Ogbia Creek, Niger Delta. *International Journal of Novel Research in Life Sciences*, *2(5).*

Niang, I., Ruppel, O. C., Abdrabo, M. A., Essel, A., Lennard, C., Padgham, J., & Urquhart, P. (2014). *Africa* (Part B: Re). Cambridge University Press, Cambridge (pp. 1199–1265).

Nickels M. (1998). *The Nature of Modern Science & Scientific Knowledge.* Anthropology Program, Illinois State University. Accessed on 10/8/2019. Retrieved from http://www.indiana.edu/~ensiweb/mart.nos.pdf on 12/4/2019.

Nickerson, R. S. (1981). Why interactive computer systems are sometimes not used by people who might benefit from them. *International Journal of Man-Machine Studies*, *15*(4), 469–483. https://doi.org/10.1016/s0020-7373(81)80054-5

Nin-Pratt, A., Johnson, M., Magalhaes, E., You, L., Diao, X. & Chamberlin, J. (2011). *Yield Gaps and Potential Agricultural Growth in West and Central Africa.* International Food Policy Research Institute, Washington, D.C.

Njau, L. N. (2010). Seasonal-to-Interannual Climate Variability in the Context of Development and Delivery of Science-based Climate Prediction and Information Services Worldwide for the Benefit of Society. *Procedia Environmental Sciences,1,*411-420. https://doi.org/10.1016/j.proenv.2010.09.029

Nkrumah, F., Klutse, N. A. B., Adukpo, D. C., Owusu, K., Quagraine, K. A., Owusu, A., & Gutowski, W. (2014). Rainfall Variability over Ghana: Model versus Rain Gauge Observation. *International Journal of Geosciences*, *05*(07), 673–683. https://doi.org/10.4236/ijg.2014.57060

NRC. (2006). *Completing the Forecast: Characterizing and Communicating Uncertainty for Better Decisions Using Weather and Climate Forecasts.* National Academies Press, 124 pp.

Nugent, R. (2000). *The impact of urban agriculture on the household and local economies.* In: Bakker, N., Dubbeling, M., Gündel, S., Sabel-Koshella, U., de Zeeuw, H. (Eds.), Growing Cities, Growing Food. Urban Agriculture on the Policy Agenda Feldafing. Zentralstelle für Ernährung und Landwirtschaft (ZEL), Germany, pp. 67–95 Apr.

Nunnally, J.C. and Bernstein, I. R. (1994). *Psychometric theory*. Ed. ke-3, McGraw-Hill, New York.

Nyadzi, E., Nyamekye, A. B., Werners, S. E., Biesbroek, R. G., Dewulf, A., Slobbe, E. V., Long, H. P., Termeer, C. J. A. M., & Ludwig, F. (2018). Diagnosing the potential of hydro-climatic information services to support rice farming in northern Ghana. *NJAS - Wageningen Journal of Life Sciences*, *86–87*. https://doi.org/10.1016/j.njas.2018.07.002

Nyadzi, E., Saskia Werners, E., Biesbroek, R., Long, P. H., Franssen, W., & Ludwig, F. (2019). Verification of seasonal climate forecast toward hydroclimatic information needs of rice farmers in northern Ghana. *Weather, Climate, and Society*, *11*(1). https://doi.org/10.1175/WCAS-D-17-0137.1

Nyadzi, Emmanuel. (2016). Climate Variability Since 1970 and Farmers' Observations in Northern Ghana. *Sustainable Agriculture Research*, *5*(2), 41. https://doi.org/10.5539/sar.v5n2p41

Nyadzi, Emmanuel, Nyamekye, A. B., Werners, S. E., Biesbroek, R. G., Dewulf, A., Slobbe, E. Van, Long, H. P., Termeer, C. J. A. M., & Ludwig, F. (2018). Diagnosing the potential of hydro-climatic information services to support rice farming in northern Ghana. *NJAS - Wageningen Journal of Life Sciences*, *86–87*, 51–63. https://doi.org/10.1016/j.njas.2018.07.002

Nyamekye, A. B., Dewulf, A., Slobbe, E. Van, Termeer, K., & Pinto, C. (2018a). Governance arrangements and adaptive decision-making in rice farming systems in Northern Ghana. *{NJAS} - Wageningen Journal of Life Sciences*, 100272. https://doi.org/10.1016/j.njas.2018.07.001

Nyamekye, A. B., Dewulf, A., Slobbe, E. Van, Termeer, K., & Pinto, C. (2018b). Governance arrangements and adaptive decision-making in rice farming systems in Northern Ghana. *{NJAS} - Wageningen Journal of Life Sciences*, *86–87*, 39–50. https://doi.org/10.1016/j.njas.2018.07.004

Nyamekye, A. B., Dewulf, A., Van Slobbe, E., & Termeer, K. (2019). Information systems and actionable knowledge creation in rice-farming systems in Northern Ghana. *African Geographical Review*,1-18. https://doi.org/10.1080/19376812.2019.1659153

Nyantakyi-Frimpong, H. (2013). *Indigenous Knowledge and Climate Adaptation Policy in Northern Ghana*. Centre for International Governance Innovation (CIGI).

Nyota, S., & Mapara, J. (2008). Shona Traditional Children's Games and Play: Songs as Indigenous Ways of Knowing. *Journal of Pan African Studies, 2(4)*.

O'Brien, K. L., & Vogel, C. (2003). *Coping with climate variability : the use of seasonal climate forecasts in Southern Africa*. Ashgate.

Obuobie, E., Kankam-Yeboah, K., Amisigo, B., Opoku-Ankomah, Y., & Ofori, D. (2012). Assessment of vulnerability of river basins in Ghana to water stress conditions under climate change. *Journal of Water and Climate Change*, *3*(4), 276–286. https://doi.org/10.2166/wcc.2012.030

Ochieng, J., Kirimi, L., & Mathenge, M. (2016). Effects of climate variability and change on agricultural production: The case of small scale farmers in Kenya. *NJAS - Wageningen Journal of Life Sciences*, *77*, 71–78. https://doi.org/10.1016/j.njas.2016.03.005

Ofori-Sarpong, E. (2001). Impact of climate change on agriculture and farmers coping strategies in the upper east region of Ghana. *West. Afr. J. Appl. Ecol.*, *2*, *21–35*.

Ogutu, G. E. O., Franssen, W. H. P., Supit, I., Omondi, P., & Hutjes, R. W. A. (2017). Skill of ECMWF system-4 ensemble seasonal climate forecasts for East Africa. *International Journal of Climatology*, *37*(5), 2734–2756. https://doi.org/10.1002/joc.4876

Okello, J. J., Kirui, O., Njiraini, G. W., & Gitonga, Z. (2012). Drivers of Use of Information and Communication Technologies by Farm Households: The Case of Smallholder Farmers in Kenya. *Journal of Agricultural Science*, *4*(2). https://doi.org/10.5539/jas.v4n2p111

Okhuysen, G. A., & Eisenhardt, K. M. (2002). Integrating knowledge in groups: How formal interventions enable flexibility. In *Organization Science* (Vol. 13, Issue 4, pp. 370-386+457). https://doi.org/10.1287/orsc.13.4.370.2947

Olsson, P., Folke, C., & Berkes, F. (2004). Adaptive Comanagement for Building Resilience in Social?Ecological Systems. *Environmental Management*, *34*(1). https://doi.org/10.1007/s00267-003-0101-7

Onwuegbuzie, A. J., Johnson, R. B., & Collins, K. M. T. (2011). Assessing legitimation in mixed research: A new framework. *Quality and Quantity*, *45*(6), 1253–1271. https://doi.org/10.1007/s11135-009-9289-9

Onyango, E., Ochieng, S., Awiti, A. (2014). Weather and climate information needs of small-scale farming and fishing communities in western Kenya for enhanced adaptive potential to climate change. *Proceedings of Sustainable Research and Innovation Conference, 4*, 187–193.

Orlove, B., Roncoli, C., Kabugo, M., & Majugu, A. (2010). Indigenous climate knowledge in southern Uganda: The multiple components of a dynamic regional System.*Climatic Change,100*(2),243-265. https://doi.org/10.1007/s10584-009-9586-2

Orlove, B. S., Broad, K., & Petty, A. M. (2004). Factors that influence the use of climate forecasts: Evidence from the 1997/98 El Niño event in Peru. *Bulletin of the American Meteorological Society*, *85*(11), 1735–17433. https://doi.org/10.1175/BAMS-85-11-1735

Ouedraogo, I., Diouf, N. S., Ouédraogo, M., Ndiaye, O., & Zougmoré, R. B. (2018). Closing the gap between climate information producers and users: Assessment of needs and uptake in Senegal.*Climate*,6(1). https://doi.org/10.3390/cli6010013

Ouédraogo, M., Zougmoré, R., Barry, S., Somé, L., & Grégoire, B. (2015). The value and benefits of using seasonal climate forecasts in agriculture : evidence from cowpea and sesame sectors in climate-smart villages of Burkina Faso. *CCAFS Info Note*, *September*, 1–4.

Ouédraogo, M., Zougmoré, R., Barry, S., Somé, L., Grégoire, B., & 2015, S. (2015). The value and benefits of using seasonal climate forecasts in agriculture: evidence from cowpea and sesame sectors in climate-smart villages of Burkina Faso. *CCAFS Info Note*,01-04.

Owolade, E. O., & Kayode, A. (2012). Information-Seeking Behavior and Utilization among Snail Farmers in Oyo State, Nigeria: Implications for Sustainable Animal Production. *Journal of International Agricultural and Extension Education*, *19*(3). https://doi.org/10.5191/jiaee.2012.19304

Owusu-Sekyere, E., Owusu, V., & Jordaan, H. (2014). Consumer preferences and willingness to pay for beef food safety assurance labels in the Kumasi Metropolis and Sunyani Municipality of Ghana. *Food Control*, *46*, 152–159. https://doi.org/10.1016/j.foodcont.2014.05.019

Owusu, K., & Waylen, P. (2009). Trends in spatio-temporal variability in annual rainfall in Ghana (1951-2000). *Weather*, *64*(5), 115–120. https://doi.org/10.1002/wea.255

Özesmi, U., & Özesmi, S. L. (2004). Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach. *Ecological Modelling*, *176*(1–2), 43–64. https://doi.org/10.1016/j.ecolmodel.2003.10.027

Palmer Fry, B. (2011). Community forest monitoring in REDD+: The "M" in MRV? *Environmental Science and Policy*, *14*(2), 181–187. https://doi.org/10.1016/j.envsci.2010.12.004

Parks, R. B., Baker, P. C., Kiser, L., Oakerson, R., Ostrom, E., Ostrom, V., Percy, S. L., Vandivort, M. B., Whitaker, G. P., & Wilson, R. (1981). Consumers As Coproducers Of Public Services: Some Economic And Institutional Considerations. *Policy Studies Journal*, *9*(7), 1001–1011. https://doi.org/10.1111/j.1541-0072.1981.tb01208.x

Patt, A, Suarez, P., & Gwata, C. (2005). Effects of seasonal climate forecasts and participatory workshops among subsistence farmers in Zimbabwe. *Proceedings of the National Academy of Sciences*, *102*(35), 12623–12628. https://doi.org/10.1073/pnas.0506125102

Patt, Anthony, & Gwata, C. (2002). Effective seasonal climate forecast applications: examining constraints for subsistence farmers in Zimbabwe. *Global Environmental Change*, *12*(3), 185–195. https://doi.org/10.1016/s0959-3780(02)00013-4

Peng, Z., Wang, Q. J., Bennett, J. C., Schepen, A., Pappenberger, F., Pokhrel, P., & Wang, Z. (2014). Statistical calibration and bridging of ECMWF system4 outputs for forecasting seasonal precipitation over China. *Journal of Geophysical Research*, *119*(12), 7116–7135. https://doi.org/10.1002/2013JD021162

Pettibone, L., Vohland, K., Bonn, A., Richter, A., Bauhus, W., Behrisch, B., ... & Elbertse, I. (2016). *Citizen science for all–a guide for citizen science practitioners.* Berlin & Leipzig.

Phillips, T. B., Ballard, H. L., Lewenstein, B. V., & Bonney, R. (2019). Engagement in science through citizen science: Moving beyond data collection. *Science Education*, *103*(3), 665–690. https://doi.org/10.1002/sce.21501

Piani, C., Haerter, J. O., & Coppola, E. (2010). Statistical bias correction for daily precipitation in regional climate models over Europe. *Theoretical and Applied Climatology*, *99*(1–2), 187–192. https://doi.org/10.1007/s00704-009-0134-9

Plotz, R. D., Chambers, L. E., & Finn, C. K. (2017a). The best of both worlds: A decision-making framework for combining traditional and contemporary forecast systems. *Journal of Applied Meteorology and Climatology*, *56*(8), 2377–2392. https://doi.org/10.1175/JAMC-D-17-0012.1

Plotz, R. D., Chambers, L. E., & Finn, C. K. (2017b). The Best of Both Worlds: A Decision-Making Framework for Combining Traditional and Contemporary Forecast Systems. *Journal of Applied Meteorology and Climatology*, *56*(8), 2377–2392. https://doi.org/10.1175/jamc-d-17-0012.1

Podestá, G., Letson, D., Messina, C., Royce, F., Ferreyra, R. A., Jones, J., Hansen, J., Llovet, I., Grondona, M., & O'Brien, J. J. (2002). Use of ENSO-related climate information in agricultural decision making in Argentina: a pilot experience. *Agricultural Systems*, *74*(3), 371–392. https://doi.org/10.1016/S0308-521X(02)00046-X

Pollock, R. M., & Whitelaw, G. S. (2005). Community-based monitoring in support of local sustainability. *Local Environment*, *10*(3), 211–228. https://doi.org/10.1080/13549839.2005.9684248

Popov, G., & Frere, M. (1986). *Early agrometeorological crop yield assessment.* FAO Plant Production and Protection Paper, 73, 155.

Price, P. (2012). *Psychology research methods: Core skills and concepts.* Flat World Knowledge Publisher: Irvington, NY.

Quaye W. (2008). Food security situation in northern Ghana, coping strategies and related constraints. *African Journal of Agricultural Research*, *3(5),* 334–342.

Quaye, W., Adofo, K., Madode, Y. E., & Abizari, A.-R. (2009). Exploratory and multidisciplinary survey of the cowpea network in Tolon-Kumbungu district of Ghana: A food sovereignty perspective. In *African Journal of Agricultural Research* (Vol. 4, Issue 4). http://www.academicjournals.org/AJAR

QWECI. (2013). *Quantifying Weather and Climate Impacts on Health in Developing Countries.* Final project report on Ghana. Accessed on 8/11/2016 and at https://www.liverpool.ac.uk/media/livacuk/qweci/SYS4_Report_Ghana.pdf.

Rademacher-Schulz, C., Schraven, B., & Mahama, E. S. (2014). Time matters: shifting seasonal migration in Northern Ghana in response to rainfall variability and food insecurity. *Climate and Development*, *6*(1), 46–52. https://doi.org/10.1080/17565529.2013.830955

Radeny, M., Desalegn, A., Mubiru, D., Kyazze, F., Mahoo, H., Recha, J., Kimeli, P., & Solomon, D. (2019a). Indigenous knowledge for seasonal weather and climate forecasting across East Africa. *Climatic Change*. https://doi.org/10.1007/s10584-019-02476-9

Radeny, M., Desalegn, A., Mubiru, D., Kyazze, F., Mahoo, H., Recha, J., Kimeli, P., & Solomon, D. (2019b). Indigenous knowledge for seasonal weather and climate forecasting across East Africa. *Climatic Change*. https://doi.org/10.1007/s10584-019-02476-9

Raftery, A. E., Gneiting, T., Balabdaoui, F., & Polakowski, M. (2005). Using Bayesian Model Averaging to Calibrate Forecast Ensembles. *Monthly Weather Review*, *133*(5), 1155–1174. https://doi.org/10.1175/mwr2906.1

Ranjan, R., & Gneiting, T. (2010). Combining probability forecasts. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *72*(1), 71–91. https://doi.org/10.1111/j.1467-9868.2009.00726.x

Rankoana, S. A., Nel, K., Mothibi, K., Mothiba, T. M., Mamogobo, P., & Setwaba, M. (2015). The use of indigenous knowledge in primary health care: a case study of Makanye community in Limpopo Province, South Africa: indigenous knowledge system in health care. *African Journal for Physical Health Education, Recreation and Dance, 2*, *1(Suppleme*.

Ravetz, J. R. (1973). *Scientific knowledge and its social problems.* Transaction Publishers.

Ravetz, Jerome R. (1997). The science of `what-if?'. *Futures*, *29*(6), 533–539. https://doi.org/10.1016/s0016-3287(97)00026-8

Renn, O., & Levine, D. (1991). Credibility and trust in risk communication. In *Communicating Risks to the Public* (pp. 175–217). Springer Netherlands. https://doi.org/10.1007/978-94-009-1952-5_10

Rice, M. P. (2002). Co-production of business assistance in business incubators: An exploratory study. *Journal of Business Venturing*, *17*(2), 163–187. https://doi.org/10.1016/S0883-9026(00)00055-0

Rinaudo, J.-D., Montginoul, M., Varanda, M., & Bento, S. (2012). *Irrigation and Drainage*. 61. https://doi.org/10.1002/ird.1661ï

Risbey, J., Kandlikar, M., Dowlatabadi, H., & Graetz, D. (1999). Scale, context, and decision making in agricultural adaptation to climate variability and change. *Mitigation and Adaptation Strategies for Global Change*, *4*(2), 137–165. https://doi.org/10.1023/A:1009636607038

Rist, S., Dahdouh-Guebas, F., & Rist Farid Dahdouh-Guebas, S. A. (2006). Ethnosciences-A step towards the integration of scientific and indigenous forms of knowledge in the management of natural resources for the future. *Environ Dev Sustain*, *8*, 467–493. https://doi.org/10.1007/s10668-006-9050-7

Rockström, J., Falkenmark, M., Folke, C., Lannerstad, M., Barron, J., Enfors, E., Gordon, L., Heinke, J., Hoff, H., Pahl-Wostl, C. (2014). *Water Resilience for Human Prosperity.* Cambridge University Press.

Roncoli, C., Kirshen, P., Ingram, K., & Jost, C. (2001). *Burkina Faso-Integrating Indigenous and Scientific Rainfall Forecasting.* (Https://openknowledge.worldbank.org/bitstream/handle/10986/10799/multi0 page.pdf?sequence=1&isAllowed=y (Ed.)).

Roncoli, C., Ingram, K., & Kirshen, P. (2002a). Reading the rains: Local knowledge and rainfall forecasting in Burkina Faso. *Society and Natural Resources*, *15*(5), 409–427. https://doi.org/10.1080/08941920252866774

Roncoli, C., Ingram, K., & Kirshen, P. (2002b). Reading the rains: Local knowledge and rainfall forecasting in Burkina Faso. *Society and Natural Resources*, *15*(5), 409–427. https://doi.org/10.1080/08941920252866774

Roncoli, C., Ingram, K., & Kirshen, P. (2002c). Reading the Rains: Local Knowledge and Rainfall Forecasting in Burkina Faso. *Society & Natural Resources*, *15*(5), 409–427. https://doi.org/10.1080/08941920252866774

Roncoli, C., Jost, C., Kirshen, P., Sanon, M., Ingram, K. T., Woodin, M., Somé, L., Ouattara, F., Sanfo, B. J., Sia, C., Yaka, P., & Hoogenboom, G. (2009a). From accessing to assessing forecasts: An end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). *Climatic Change*, *92*(3–4), 433–460. https://doi.org/10.1007/s10584-008-9445-6

Roncoli, C., Jost, C., Kirshen, P., Sanon, M., Ingram, K. T., Woodin, M., Somé, L., Ouattara, F., Sanfo, B. J., Sia, C., Yaka, P., & Hoogenboom, G. (2009b). From accessing to assessing forecasts: an end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). *Climatic Change*, *92*(3–4), 433–460. https://doi.org/10.1007/s10584-008-9445-6

Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumaré, M. A., Batté, L., & Sultan, B. (2014). The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal. *Climate Risk Management*, *2*, 42–55. https://doi.org/10.1016/j.crm.2014.02.001

Roudier, P., Muller, B., D'Aquino, P., Roncoli, C., Soumaré, M. A., Batté, L., & Sultan, B. (2014). The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal. *Climate Risk Management*, *2*(December), 42–55. https://doi.org/10.1016/j.crm.2014.02.001

Ruddle, K., & Johannes, R. E. (1989). *Traditional marine resource management in the Pacific basin: an anthology (No. 2).* Unesco/ROSTSEA.

Runge-Metzger, A. and Diehl, L. (1993). *Farm household systems in Northern Ghana. A case study in farming systems oriented research for the development of improved crop production systems.* NAES-Research Report, GTZ.

Saitabau, O. H. (2014). *Impacts of climate change on the livelihoods of Loita Maasai pastoral community and related indigenous knowledge on adaptation and mitigation.* Directorate of Research and Collections, National Museums of Kenya, Nairobi, Kenya. Retrieved, 28(11), 2015. www.emeraldinsight.com/doi/abs/10.1016/S0731-9053(08)23015-X.

Salack, S., Klein, C., Giannini, A., Sarr, B., Worou, O. N., Belko, N., Bliefernicht, J., & Kunstman, H. (2016). Global warming induced hybrid rainy seasons in the Sahel. *Environmental Research Letters*, *11*(10). https://doi.org/10.1088/1748-9326/11/10/104008

Salack, S., Sarr, B., Sangare, S. K., Ly, M., Sanda, I. S., & Kunstmann, H. (2015). Crop-climate ensemble scenarios to improve risk assessment and resilience in the semi-arid regions of West Africa. *Climate Research*, *65*, 107–121. https://doi.org/10.3354/cr01282

Sam, J., & Dzandu, L. (2015). *Information and Knowledge Resources in GAINS — Databases*. *7*.

SARI. (2011). *Contract for research- Enhanced adaptive research responsive to productive and environmental needs of the ecological zone, Rice Sector Support Project.* PCU. http://www.csir.org.gh/images/CSIR-SARI_Reports/CSIR- SARI%20Annual%20Report%202011.pdf.

SARI. (2016). *Savanna Agricultural Research Institute.* Agro-meteorological Unit, Nyankpala, Tamale Ghana (p. 27). In: Abukari, A., Abunyewa, A. A., & Issifu, H. (2018). Effect Of Rice Husk Biochar On Nitrogen Uptake And Grain Yield Of Maize In The Guinea Savanna Zone Of Ghana. UDS International Journal of Dev.

Sarr, B., Atta, S., Ly, M., Salack, S., Ourback, T., Subsol, S., & George, D. A. (2015). *Adapting to climate variability and change in smallholder farming communities: A case study from Burkina Faso, Chad and Niger Journal of Agricultural Extension and Rural Develop. 7 (1),* 418- 429. https://doi.org/10.5897/JAERD14.0595

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, *5*(1). https://doi.org/10.1088/1748-9326/5/1/014010

Settee, P. (2013). *Pimatisiwin: The good life, global Indigenous knowledge systems.* JCharlton Publishing Limited.

Sharpe, A., & Conrad, C. (2006). Community based ecological monitoring in Nova Scotia: Challenges and opportunities. *Environmental Monitoring and Assessment*, *113*(1–3), 395–409. https://doi.org/10.1007/s10661-005-9091-7

Siegert, S. (2017). *SpecsVerification: Forecast Verification Routines for Ensemble Forecasts of Weather and Climate. R package version 0.5-2.* URL: Https://cran.r-project.org/web/packages/SpecsVerification/index.html.

Silvertown, J. (2009). A new dawn for citizen science. In *Trends in Ecology and Evolution* (Vol. 24, Issue 9, pp. 467–471). Elsevier Ltd. https://doi.org/10.1016/j.tree.2009.03.017

Singh, C., Daron, J., Bazaz, A., Ziervogel, G., Spear, D., Krishnaswamy, J., Zaroug, M., & Kituyi, E. (2018). The utility of weather and climate information for adaptation decision-making: current uses and future prospects in Africa and India. In *Climate and Development* (Vol. 10, Issue 5, pp. 389–405). Taylor and Francis Ltd. https://doi.org/10.1080/17565529.2017.1318744

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, *16*(3), 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Speranza, C. I., Kiteme, B., Ambenje, P., Wiesmann, U., & Makali, S. (2010). Indigenous knowledge related to climate variability and change: Insights from droughts in semi-arid areas of former Makueni District, Kenya. *Climatic Change*, *100*(2), 295–315. https://doi.org/10.1007/s10584-009-9713-0

Stanturf, J.A., Warren, M.L., Charnley, S., Polasky, S.C., Goodrick, S.L., Armah, F., Nyako, Y. A. (2011). *Ghana Climate Change Vulnerability and Adaptation Assessment.* United States Agency for International Development, Washington.

Stanturf, J. A., Goodrick, S. L., Warren, M. L., Charnley, S., & Stegall, C. M. (2015). Social Vulnerability and Ebola Virus Disease in Rural Liberia. *{PLOS} {ONE}*, *10*(9), e0137208. https://doi.org/10.1371/journal.pone.0137208

Steelman, T. A., McCaffrey, S. M., Velez, A.-L. K., & Briefel, J. A. (2014). What information do people use, trust, and find useful during a disaster? Evidence from five large wildfires. *Natural Hazards*, *76*(1), 615–634. https://doi.org/10.1007/s11069-014-1512-x

Steiner, A. (2008). *Indigenous knowledge in disaster management in Africa.* United Nations Environment Programme (UNEP). Available at https://www.humanitarianlibrary.org/sites/default/files/2013/07/Appendix9IndigenousBookletUNEP.pdf. Retrieved on 14/7/2019.

Stevens, M., Vitos, M., Altenbuchner, J., Conquest, G., Lewis, J., & Haklay, M. (2013). Introducing Sapelli. *Proceedings of the 4th Annual Symposium on Computing for Development - {ACM} {DEV}-4 {\textquotesingle}13*. https://doi.org/10.1145/2537052.2537069

Stevens, M., Vitos, M., Lewis, J., & Haklay, M. (2013). *Participatory monitoring of poaching in the Congo basin*. http://tes-ne.com.

Stevenson, M. G. (1996). Indigenous Knowledge in Environmental Assessment. In *ARCTIC* (Vol. 49, Issue 3).

Stilgoe, J., Owen, R., & Macnaghten, P. (2013). Developing a framework for responsible innovation. *Research Policy*, *42*(9), 1568–1580. https://doi.org/10.1016/j.respol.2013.05.008

Stiller-Reeve, M. A., Syed, M. A., Spengler, T., Spinney, J. A., & Hossain, R. (2015). Complementing scientific monsoon definitions with social perception in Bangladesh. *Bulletin of the American Meteorological Society*, *96*(1), 49–57. https://doi.org/10.1175/BAMS-D-13-00144.1

Stockdale, T. N., Anderson, D. L., Alves, J. O. S., & Balmaseda, M. A. (1998). Global seasonal rainfall forecasts using a coupled ocean–atmosphere model. *Nature, 392(6674),*.

Stone, R. C., & Meinke, H. (2006). Weather, climate, and farmers: an overview. *Meteorol. Appl*, 7–20. https://doi.org/10.1017/S1350482706002519

Street, R. B. (2016). Towards a leading role on climate services in Europe: A research and innovation roadmap. *Climate Services*, *1*, 2–5. https://doi.org/10.1016/j.cliser.2015.12.001

Sultan, B., & Janicot, S. (2003). The West African monsoon dynamics. Part II: The "preonset" and "onset" of the summer monsoon. *Journal of Climate*, *16*(21), 3407–3427. https://doi.org/10.1175/1520-0442(2003)016<3407:TWAMDP>2.0.CO;2

Svotwa, E., Manyanhaire, J., & Makanyire, J. (2007). Integrating Traditional Knowledge Systems with Agriculture and Disaster Management: A Case for Chitora Communal Lands. *Journal of Sustainable Development in Africa*, *9*(3), 50–63.

Tall, A., Coulibaly, J. Y., & Diop, M. (2018). Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. In *Climate Services* (Vol. 11, pp. 1–12). Elsevier B.V. https://doi.org/10.1016/j.cliser.2018.06.001

Tarhule, A., & Lamb, P. J. (2003). Climate Research and Seasonal Forecasting for West Africans: Perceptions, Dissemination, and Use? *Bulletin of the American Meteorological Society*, *84*(12), 1741–1760. https://doi.org/10.1175/bams-84-12-1741

Termeer, C., Dewulf, A., Van Rijswick, H., Van Buuren, A., Huitema, D., Meijerink, S., Rayner T. & Wiering, M. (2011). The regional governance of climate adaptation: a framework for developing legitimate, effective, and resilient governance arrangements. *Climate Law*, *2(2)*, 159–179.

The Republic of Ghana. (2012). *Draft National Irrigation policy, Strategies and Regulatory Measures.* Published by the Ministry of Food and Agriculture, Accra.

Trambauer, P., Werner, M., Winsemius, H. C., Maskey, S., Dutra, E., & Uhlenbrook, S. (2015). Hydrological drought forecasting and skill assessment for the Limpopo River basin, southern Africa. *Hydrology and Earth System Sciences*, *19*(4), 1695–1711. https://doi.org/10.5194/hess-19-1695-2015

Tsuji, L., & Ho, E. (2002). Traditional environmental knowledge and western science: in search of common ground. *Canadian Journal of Native Studies*, *22*(2), 327–360.

Turner, D. S., & Richter, H. E. (2011). Wet/dry mapping: Using citizen scientists to monitor the extent of perennial surface flow in dryland regions. *Environmental Management*, *47*(3), 497–505. https://doi.org/10.1007/s00267-010-9607-y

UN. (2014). *A World that Counts: Mobilising the Data Revolution for Sustainable*. Development. http://www.undatarevolution.org/wp-content/uploads/2014/11/A-World-That-Counts.pdf.p. 2.

USAID. (2017). *Feed the Future Ghana District Profile Series –Kumbungu District February 2017.* Issue1 accessed on 17/03/108 at https://ghanalinks.org/elibrary.

van Kerkhoff, L. E., & Lebel, L. (2015). Coproductive capacities: Rethinking science-governance relations in a diverse world. *Ecology and Society*, *20*(1). https://doi.org/10.5751/ES-07188-200114

Vaughan, C., & Dessai, S. (2014). Climate services for society: Origins, institutional arrangements, and design elements for an evaluation framework. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(5), 587–603. https://doi.org/10.1002/wcc.290

Vaughan, C., Hansen, J., Roudier, P., Watkiss, P., & Carr, E. (2019). Evaluating agricultural weather and climate services in Africa: Evidence, methods, and a learning agenda. *Wiley Interdisciplinary Reviews: Climate Change*, e586. https://doi.org/10.1002/wcc.586

Verbeke, W. (2005). Agriculture and the food industry in the information age. *European Review of Agricultural Economics*, *32*(3), 347–368. https://doi.org/10.1093/eurrag/jbi017

Vervoort, R. W., Muita, R., Ampt, P., & van Ogtrop, F. (2016). Managing the water cycle in Kenyan small-scale maize farming systems: Part 2. Farmers' use of formal and informal climate forecasts. *Wiley Interdisciplinary Reviews: Water*, *3*(1), 127–140. https://doi.org/10.1002/wat2.1121

Vincent, K., Daly, M., Scannell, C., & Leathes, B. (2018). What can climate services learn from theory and practice of co-production? *Climate Services*, *12*, 48–58. https://doi.org/10.1016/j.cliser.2018.11.001

Vitart, F., Robertson, A. W., & Anderson, D. L. (2012). Subseasonal to Seasonal Prediction Project: Bridging the gap between weather and climate. *Bulletin of the World Meteorological Organization, 61(2), 23*.

Vitos, M., Stevens, M., Lewis, J., & Haklay, M. (2013). Making local knowledge matter: Supporting non-literate people to monitor poaching in Congo. *Proceedings of the 3rd ACM Symposium on Computing for Development, DEV 2013*, *February 2014*. https://doi.org/10.1145/2442882.2442884

Vogel, C. (2000). Usable science: An assessment of long-term seasonal forecasts amongst farmers in rural areas of sourth africa. *South African Geographical Journal*, *82*(2), 107–116. https://doi.org/10.1080/03736245.2000.9713700

Vogel, J., Letson, D., & Herrick, C. (2017). A framework for climate services evaluation and its application to the Caribbean Agrometeorological Initiative. *Climate Services*, *6*, 65–76. https://doi.org/10.1016/j.cliser.2017.07.003

Waiswa, M., Mulamba, P., & Isabirye, P. (2007). Climate Information for Food Security: Responding to User's Climate Information Needs. In *Climate Prediction and Agriculture* (pp. 225–248). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-44650-7_22

Wallace, M. T., & Moss, J. E. (2002). Farmer Decision-Making with Conflicting Goals: A Recursive Strategic Programming Analysis. *Journal of Agricultural Economics*, *53*(1), 82–100. https://doi.org/10.1111/j.1477-9552.2002.tb00007.x

Ward, M. N., & Folland, C. K. (2007). Prediction of seasonal rainfall in the north nordeste of Brazil using eigenvectors of sea-surface temperature. *International Journal of Climatology*, *11*(7), 711–743. https://doi.org/10.1002/joc.3370110703

Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., & Sarewitz, D. (2013). Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks. *Wiley Interdisciplinary Reviews: Climate Change*, *4*(1), 39–60. https://doi.org/10.1002/wcc.202

Weedon, G. P., Balsamo, G., Bellouin, N., Gomes, S., Best, M. J., & Viterbo, P. (2014). The WFDEI meteorological forcing data set: WATCH Forcing data methodology applied to ERA-Interim reanalysis data. *Water Resources Research*, *50*(9), 7505–7514. https://doi.org/10.1002/2014WR015638

Wei, X. (2009). Regression-based forecast combination methods. *Romanian Journal of Economic Forecasting*, *12*(4), 5–18.

Weigel, A. P., Liniger, M. A., & Appenzeller, C. (2007). \href{http://dx.doi.org/10.1175/MWR3280.1}{The Discrete Brier and Ranked Probability Skill Scores}. *Mon. Weather Rev.*, *135*(1), 118–124. https://doi.org/10.1175/MWR3280.1

Weigel, A. P., & Mason, S. J. (2011). The generalized discrimination score for ensemble forecasts. *Monthly Weather Review*, *139*(9), 3069–3074. https://doi.org/10.1175/MWR-D-10-05069.1

Weisheimer, A., & Palmer, T. N. (2014). On the reliability of seasonal climate forecasts. *Journal of the Royal Society Interface*, *11*(96). https://doi.org/10.1098/rsif.2013.1162

Whitelaw, G., Vaughan, H., Craig, B., & Atkinson, D. (2003). Establishing the Canadian community monitoring network. *Environmental Monitoring and Assessment*, *88*(1–3), 409–418. https://doi.org/10.1023/A:1025545813057

Wiggins, A., & Crowston, K. (2011). From conservation to crowdsourcing: A typology of citizen science. *Proceedings of the Annual Hawaii International Conference on System Sciences*. https://doi.org/10.1109/HICSS.2011.207

Wilkinson, M. E., Mackay, E., Quinn, P. F., Stutter, M., Beven, K. J., MacLeod, C. J. A., Macklin, M. G., Elkhatib, Y., Percy, B., Vitolo, C., & Haygarth, P. M. (2015). A cloud based tool for knowledge exchange on local scale flood risk. *Journal of Environmental Management*, *161*, 38–50. https://doi.org/10.1016/j.jenvman.2015.06.009

Willmott, C. J., Robeson, S. M., & Matsuura, K. (2012). Short Communication A refined index of model performance. *International Journal of Climatology*, *32*(13), 2088–2094. https://doi.org/10.1002/joc.2419

Wim J., Katrien W., Patrick D. P., and P. V. K. (2008). *Marketing Research with SPSS*. 274-275., Prentice Hall; Pearson Education. ISBN: 978-0-273-70383-9.

WMO. (2006). *Climate Information for Development Needs: An Action Plan for Africa, Report and Implementation Strategy.* GCOS 108, WMO/TD No. 1358, Geneva.

WMO. (2014). *Forecast Verification for the African Severe Weather Forecasting Demonstration Projects. WMO*. No. 1132. Accessed on 11/6/2019 at https://www.wmo.int/pages/prog/www/Documents/1132_en.pdf.

World Bank. (2010). *Economics of Adaptation to Climate Change: Ghana.* Washington, DC.

WRC. (2010). *ìClimate Change, Water and Diseases. Perspectivee from Ghanaís Three Northern Regions of Ghana.* î Water Resources Commission, WRC-CCA Report Series No. 1, 2010.

WRCG [Water Resources Commission, G. (2008). *White Volta River Basin - Integrated Water Resources Management Plan, Ghana.* Accessed on 18th march2016 at http://www.wrc-gh.org/dmsdocument/19.

Wyborn, C. A. (2015). Connecting knowledge with action through coproductive capacities: Adaptive governance and connectivity conservation. *Ecology and Society*, *20*(1). https://doi.org/10.5751/ES-06510-200111

Wynne, B. (1993). Public uptake of science: a case for institutional reflexivity. *Public Understanding of Science*, *2*(4), 321–337. https://doi.org/10.1088/0963-6625/2/4/003

Ziegel, E. R. (2004). System Reliability Theory: Models, Statistical Methods, and Applications. *Technometrics*, *46*(4), 495–496. https://doi.org/10.1198/tech.2004.s242

Ziervogel, G.; Opere, A. (2010). No Title. *Integrating Meteorological and Indigenous Knowledge-Based Seasonal Climate Forecasts for the Agricultural Sector.*

Ziervogel, G. (2004). Targeting seasonal climate forecasts for integration into household level decisions: The case of smallholder farmers in Lesotho. *Geographical Journal*, *170*(1), 6–21. https://doi.org/10.1111/j.0016-7398.2004.05002.x

Zinyengere, N., Mhizha, T., Mashonjowa, E., Chipindu, B., Geerts, S., & Raes, D. (2011). Using seasonal climate forecasts to improve maize production decision support in Zimbabwe. *Agricultural and Forest Meteorology*, *151*(12), 1792–1799. https://doi.org/10.1016/j.agrformet.2011.07.015

Zou, H., & Yang, Y. (2004). Combining time series models for forecasting. *International Journal of Forecasting*, *20*(1), 69–84. https://doi.org/10.1016/s0169-2070(03)00004-9

Zulkafli, Z., Perez, K., Vitolo, C., Buytaert, W., Karpouzoglou, T., Dewulf, A., Bièvre, B. De, Clark, J., Hannah, D. M., & Shaheed, S. (2017). User-driven design of decision support systems for polycentric environmental resources management. *Environmental Modelling & Software*, *88*, 58–73. https://doi.org/10.1016/j.envsoft.2016.10.012

Zuma-Netshiukhwi, G., Stigter, K., & Walker, S. (2013a). Use of traditional weather/climate knowledge by farmers in the South-Western free State of South Africa: Agrometeorological learning by scientists. *Atmosphere*, *4*(4), 383–410. https://doi.org/10.3390/atmos4040383

Zuma-Netshiukhwi, G., Stigter, K., & Walker, S. (2013b). Use of traditional weather/climate knowledge by farmers in the South-Western free State of South Africa: Agrometeorological learning by scientists. *Atmosphere*, *4*(4), 383–410. https://doi.org/10.3390/atmos4040383

Zuma-Netshiukhwi, G., Stigter, K., & Walker, S. (2013c). Use of Traditional Weather/Climate Knowledge by Farmers in the South-Western Free State of South Africa: Agrometeorological Learning by Scientists. *Atmosphere*, *4*(4), 383–410. https://doi.org/10.3390/atmos4040383

Supplementary information

A. General Introduction (Chapter 1)

Table A1: The benefits of citizen science

Benefits for Science	Benefits for Society	Benefits for Participants
• Inspires new research topics by inviting new ideas, questions, methods, and societal knowledge	• Generates and communicates socially relevant research topics	• Allows contributions to scientific discoveries
• Creates large datasets (spatially and temporally) that can be adapted to various uses	• Allows co-creation of transparent research	• Improves understanding of science and sometimes advances scientific qualifications
• Allows diverse evaluation capacities including photos, scans and video sequences	• Allows society to take on responsibility for research	• Increases understanding of complex problems
• Increases public acceptance of research results	• Introduces all participants to new perspectives	• Introduces innovative ideas into science
• Promotes public evaluation of research	• Develops opportunities for societal transformation, e.g. towards sustainability	• Facilitates participation in political decision-making through scientific contributions
• Verifies the practical relevance and applicability of scientific results	• Promotes better transfer of research results into practice through early involvement of societal actors	• Contributes ideas and suggestions for alternatives
	• Democratizes the discursive meaning of science	• Allows critical examination of scientific results
	• Strengthens civil society and government agencies	• Promotes a better environment and a better society
		• Is fun and promotes sharing

Table A2: Differences between indigenous and scientific forecast

	Major differences		Major Similarities
Factors	**Scientific forecast**	**Indigenous forecast**	
Mode of transmission	Forecast information is written and formally documented	The forecast is Orally transmitted and visually confirmed	Both describes the state of the weather and climate
Source	The scientific forecast is from the simulation of dynamic numerical models that are representative of the earth system or statistically generated	The forecast is based on peoples long term experience and observation of indigenous indicators	Both are based on long term observation
Approach of production	Systematic, objectively produced	non-systematic and subjectively produced	Both change over time
context	It is system-based and universally validated	Holistic (not compartmentalized) and based on a specific locality	Both are verified through repetition
Generation	Theories and mathematical	social values, observance of ecological indicators and sometimes Spiritual	Both forecasts are done in probabilistic terms
Skill acquisition	Rapid acquisition and through formal education	Long term experiences through learning by doing	There is a logic system behind both forecast and they are very much analytical
Resolution	Course and a bit wider in area	Very fine and locality specific.	Both fall in the domain of statistics
approach	linear modelling as a first approximation	Mental modelling	

Factors	**Scientific forecast**	**Indigenous forecast**
Underlying Explanations	Explanations are based on hypothesis, theories, laws	explanations based on changes in ecological indicators, stories, parables and sometimes supernatural and intuitive
Reliability	assumed to be the best approximation	assumed to be the truth
Derivation	analytical, based on subsets of the whole	integrated, based on a whole system
Nature of forecast	Issued in quantitative terms	The forecast is often qualitative
Data storage	Written	Oral and visual

Source: (Lalonde, 1993; Stevenson, 1996; Baker et al., 2001; Brascoupé et al., 2001; Tsuji & Ho, 2002)

Figure A1: The map of Ghana showing the new regional divisions as at January 2019

B. Verification of seasonal climate forecast towards hydroclimatic information needs of rice farmers (Chapter 3)

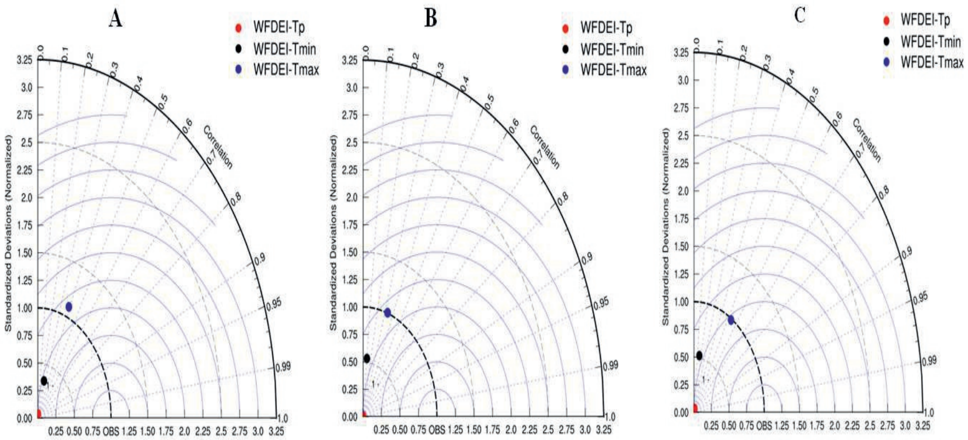


Figure B1: Taylor diagram showing the Comparative statistics of WFDEI and GMET (Tp, Tmin and Tmax data) for MAM(A), JJA(B) and SON(C).

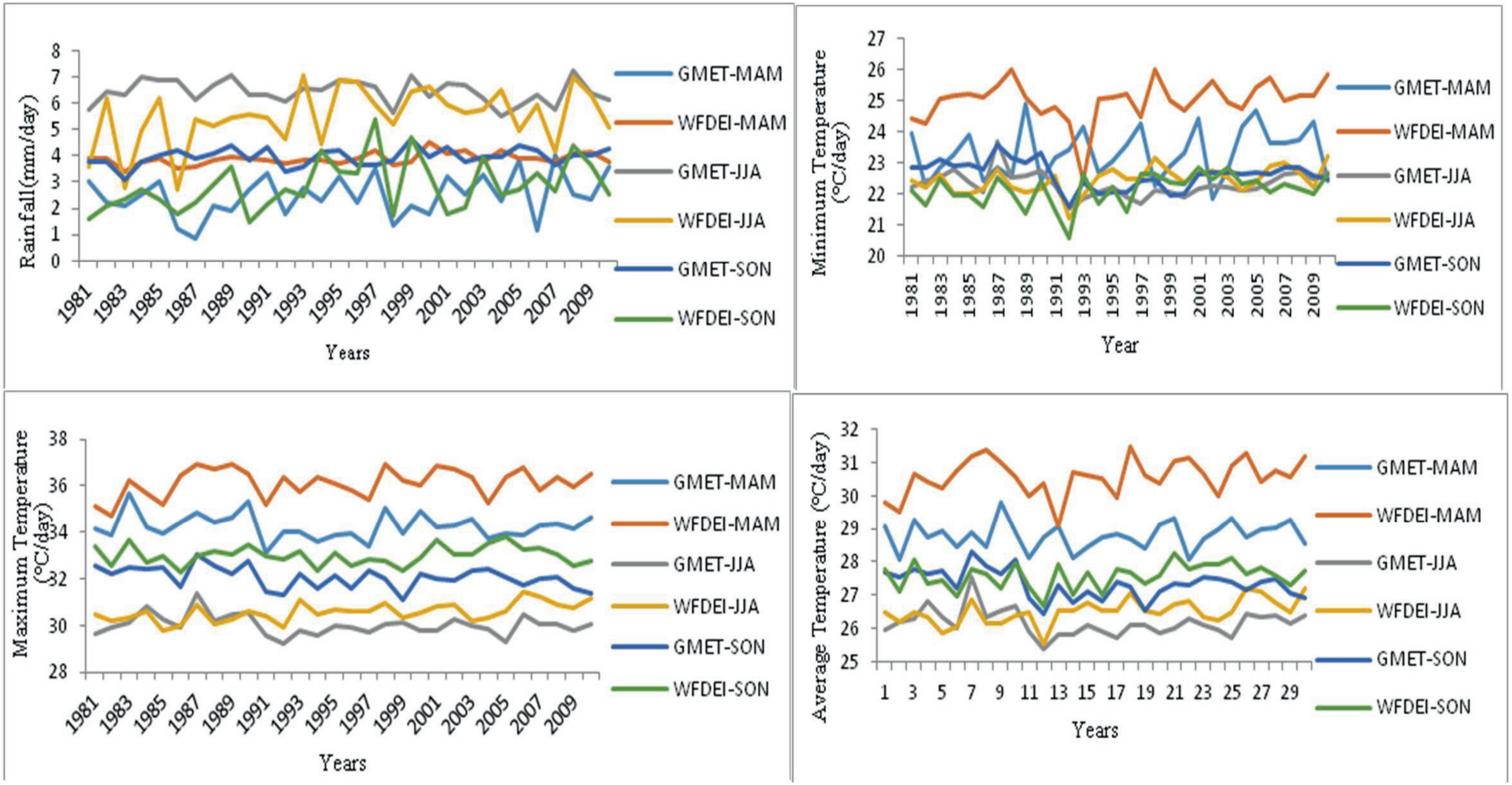


Figure B2: Year to year average Tp (mm/day), Tmin (°C/day), Tmax (°C/day) and Tave. (Average temperature of both Tmin and Tmax) of WFDEI and GMET from 1981-2010 for MAM, JJA and SON at Tamale station.

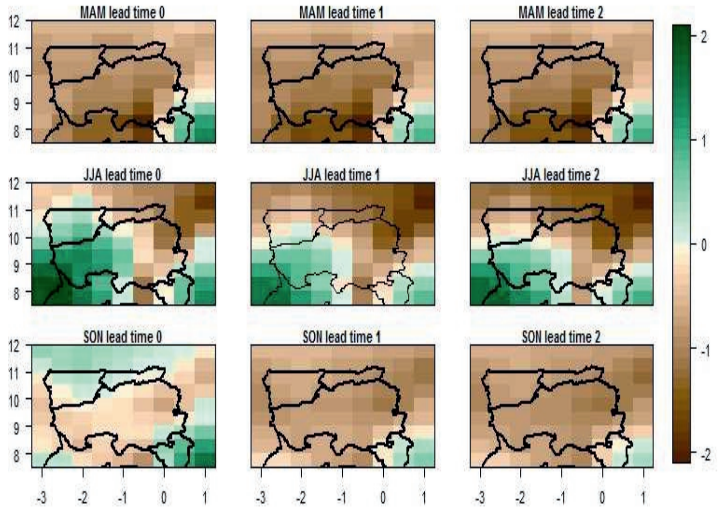


Figure B3: Mean bias in Rainfall (mm/day) forecasts from ECMWF-S4 against the verifying observations of JJA, MAM and SON from WFDEI for 1981-2010. Positive and Negative denotes forecast over estimation (wet bias-green) and underestimation (dry bias-brown) respectively for 0, 1 and 2 months prior to start of each season

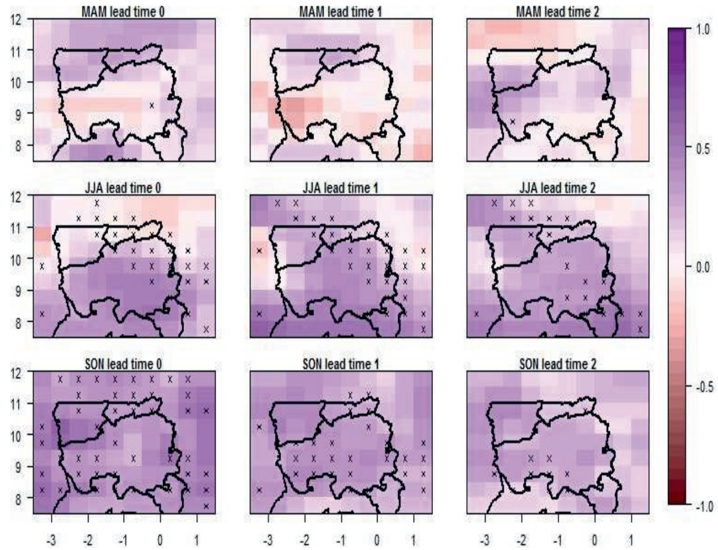


Figure B4: Correlation of ensemble mean rainfall forecast (ECMWF System 4) and observations (WFDEI) from 1981 to 2010 for JJA, MAM and SON for 0, 1 and 2 month lead times. Cross show areas of significant correlation at 95% level.

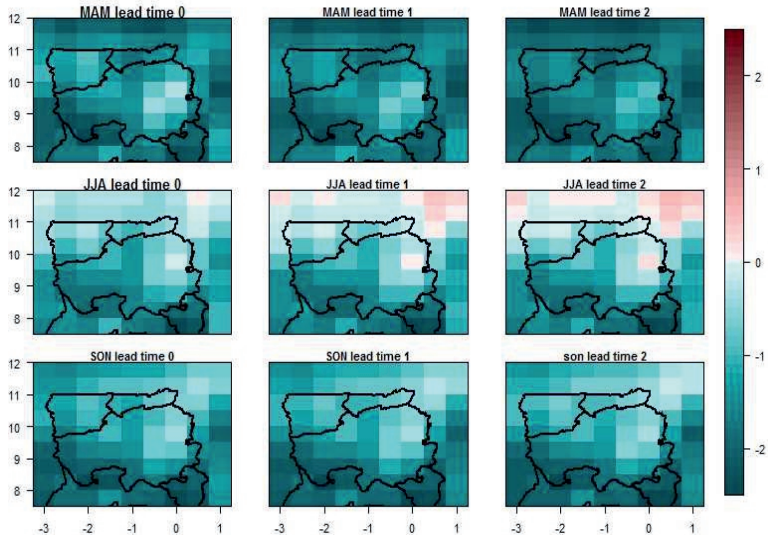


Figure B5: Mean bias in minimum Temperature forecasts from ECMWF-S4 against the verifying observations of JJA, MAM and SON from WFDEI for 19981-2010. Negative (positive) showed cold (warm) biases for 0, 1 and 2 months prior to start of each season.

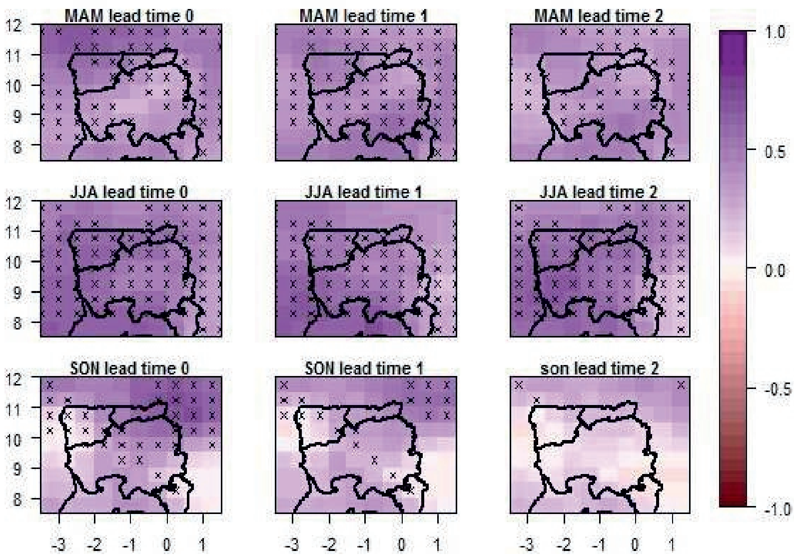


Figure B6: Correlation of ensemble mean minimum temperature forecast (ECMWF System4) and observations (WFDEI) from 1981 to 2010 for JJA, MAM and SON

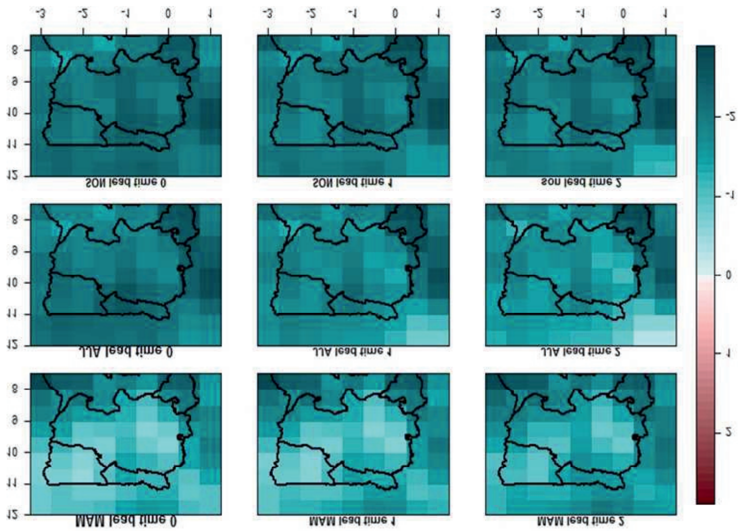


Figure B7: Mean bias in maximum temperature forecasts from ECMWF-S4 against the verifying observations of JJA, MAM and SON from WFDEI for 19981-2010. Negative (positive) showed cold (warm) biases for 0, 1 and 2 months prior to start of each season.

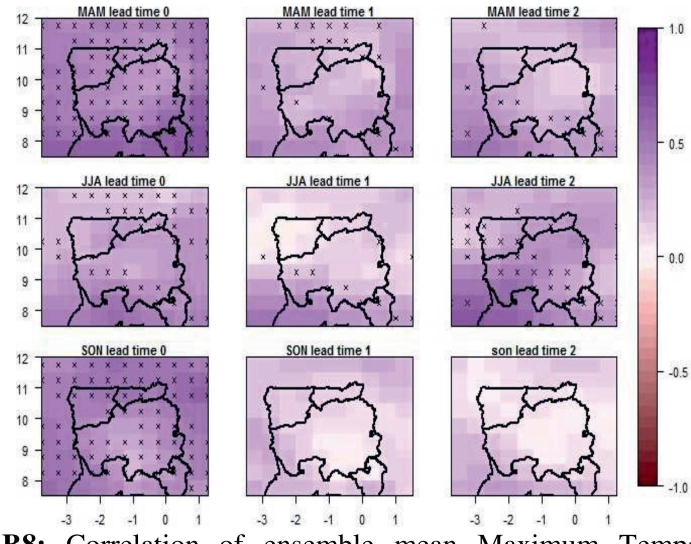


Figure B8: Correlation of ensemble mean Maximum Temperature forecast (ECMWF System4) and observations (WFDEI) from 1981 to 2010 for JJA, MAM and SON

Table B1: Farmers' ranking of hydro-climatic information based on importance (n=12).

Information about	**Rank**				
	Very Important	**Important**	**Moderately important**	**Slightly Important**	**Not Important**
Total rainfall amount	17%	33%	25%	8%	17%
Rainfall distribution	67%	25%	8%	0%	0%
Rainfall onset	25%	50%	8%	8%	8%
Rainfall cessation	17%	17%	50%	8%	8%
Dam water level	75%	17%	8%	0%	0%
Temperature	58%	42%	0%	0%	0%
Winds speed	0%	0%	8%	8%	83%
Wind direction	8%	8%	8%	8%	67%

Bolded values represent the highest percentage per information need.

Table B2: Summary of skills (xxx indicates most skilful followed by xx and then x) per season and lead times

Variables	**Seasons**			**Generalized discrimination skills(GDS) (Lead times)**								
	MAM	**JJA**	**SON**	**MAM-0**	**MAM-1**	**MAM-2**	**JJA-0**	**JJA-1**	**JJA-2**	**SON-0**	**SON-1**	**SON-2**
Prcp	X	XX	XXX	X	XX	XXX	XX	X	XXX	XXX	XX	X
Tmin	XX	XXX	X	X	XX	XXX	XXX	XX	X	XXX	XX	X
Tmax	XXX	X	XX	XXX	XX	X	XX	X	XXX	XXX	XX	X
Tercile	**Seasons**			**Tercile skills of Prcp (Lead times)**								
	MAM	JJA	SON	MAM-0	MAM-1	MAM-2	JJA-0	JJA-1	JJA-2	SON-0	SON-1	SON-2
Above	XXX	XX	XX	XXX	XX	X	XXX	XX	X	XXX	XX	XX
Normal	X	X	X	X	XXX	XX	XXX	X	XX	XX	X	XXX
Below	XX	XXX	XXX	XXX	XX	X	XXX	XX	X	XXX	X	XX

Table B3: Questionnaire for interviews

Kindly read out the following introduction and consent note to the respondent, and ensure that he/she understands and thus give his or her consent before beginning interview.

Hello Sir/Madam,
My name is ………………………. from Wageningen University and Research in Netherlands. We have permission from the irrigation managers and office of the district assembly. We are currently working on a research project about seasonal hydrological and climate information services to rice farmers. Most of this research is being carried out in Northern Ghana, and you have been selected by our sampling method to ensure we received a representative picture views.
We would like to ask you some one-on-one questions that should take not more than thirty minutes. Your answers to these questions will be invaluable for the study. We will use this information to help farmers in their decisions during planting and growing rice and other crops. If you agree to participate, all the information you provide will be completely anonymous and confidential. Your answers will not affect any benefits or subsidies you may receive now or in the future. Do you consent to be part of this study? You may withdraw from the study at any time and if there are questions that you would prefer not to answer, we will respect your right not to answer them.

Questionnaire No: ……………… Community name: ……………………………………………

SECTION 1:
PERCEPTION OF CLIMATE VARIABILITY

1. What kind of rice farming do you do? □ irrigated □ rain-fed □ both irrigated and rain-fed
2. a. Do you grow other crops aside rice? □ Yes □ No
   b. If yes, which crops? …………………………………
   c. which of them is your maize crop? ....
3. In your experience, has the TEMPERATURE for the last 30 years in this area stayed □ the same □ has increased □ has decreased □ is different every year □ do not know
4. In your experience, has the average RAINFALL for the last 30 years in this area stayed □ Same □ has increased □ has decreased □ different every year □ do not know

Do not answer question 5 and 6 if you indicated "same" for question 3 and 4

5. In the next 10 years, do you think there will be more variability in the climate?
   □ YES □ No □ Do not know
6. In your own opinion, what do you think might have caused this variability in the climate? ....

SECTION 2:
HYDRO-CLIMATIC INFORMATION NEEDS AND DECISION MAKING

7. When would you prefer to receive climate forecast information before a farming season?
☐ 1 month ☐ 2 months ☐ 3 months ☐ 4 months ☐5 months ☐other…………...

8. When would you prefer to receive hydrological (dam water level) information forecast before a farming season? ☐ 1 month ☐ 2 months ☐ 3 months ☐ 4 months ☐5 months ☐other

9. a. Do you use weather/climate forecasts information now? ☐ YES ☐ NO
b. If no, please why not? ……..

10. How would good hydro-climatic forecast information affect you?
☐ Good seed usage ☐ high yield ☐ appropriate water management ☐ save money ☐enough food for my family ☐ others …………………

11. What are the key reasons for you to use a climate forecasts?
☐ Too much climate variability already ☐ my existing forecast methods are unreliable
☐ Hope it improves crop yield ☐ for better water management
☐ Others

12. What are possible reasons / barriers for you not to use climate forecasts?
☐ Too complex for me to understand ☐ Not realistic in projections
☐ I don't believe it is useful/don't care ☐ I have bad experiences with forecast information
☐ I did not know forecasts existed ☐ the way I do it now works fine
☐ I don't have access to this information ☐others ………………

13. There are a number of actions and key decisions needed for rice farming, for each decision; you might need particular type of information to make it better. Please indicate for each decision which information you need most. Rank the most important type of information with 3, followed by 2 and 1. If the information is not relevant, please leave the column blank.

Action	**Decision**	**Information**									
		seasonal rainfall amount	**Seasonal rainfall distribution**	**Rainfall**	**Rainfall cessation**	**Dam water levels**	**Temperatur**	**Wind speed**	**Wind direction**	**do not know / none of**	**Other(more specifically)**
Pre-season	Buying seeds										
	Seed variety										
	Land size and allocation										
	Labour size										

Land preparation	When to clear Land When to plowing When to harrowing
Planting	When to nurse seeds When to transplanting When to do direct seeding Sowing method e.g. broadcast by hand or machine.
Irrigation	when to do supplementary irrigation Amount of water to use for irrigation
Fertilizer application	The kind of fertilizer to buy When to carry out first fertilizer application When to carry out second fertilizer application
Weed control	The kind of weedicide to apply

	When to carry out first weed control
	When to carry out second weed control
	Which time to spray weedicide
	Which weed control method to choose(e.g. hand or weedicide)
Pest control	The kind of pesticide to buy
	When to carry out first pest control
	When to carry out second pest control
Harvesting	When to start harvesting
	Which method of harvesting to choose(e.g. by hand or machine)

14. Which medium do you prefer to receive information stated in question 13?
☐ Radio ☐ mobile phone (text messaging) ☐ Extension officer ☐ Irrigation manager ☐ TV☐ Internet ☐ Head of Farmers Association ☐ specially trained personnel ☐ other ……………………

SECTION 3:
BRIEF BIOGRAPHICAL INFORMATION

15. Name…………………………………………………………………………
16. How old are you (age in years)? 21-30 31- 40 41-50 51-60 61-70 above 70
17. Gender? Male Female
18. What is your highest educational level attained?
 Elementary /primary Middle school certificate/JHS SSS/O-level/WASSCE
 Tertiary No formal Education
19. a. What is your farm size on the irrigation scheme (in acres)? less than 1 1 – 1.9 2 - 2.9
 3-3.9 4–4.9 5 -5.9 others…………………………………………………………
b. What is your farm size outside the irrigation scheme (in acres)? less than 1 1 – 1.9 2 -2.9
 3 -3.9 4–4.9 5 -5.9 others………………………….
20. What is your household size? 1-5 6- 10 11-15 16-20 21-25 above 25
21. How long have you been doing rice farming (years)? 1-5 6- 10 11-15 16-20 21-25
 Above 25
22. Would you like to stay involved in our work? YES NO
23. Would you be interested in participating in a feedback workshop on this survey? YES NO
24. Is there anything else you would like to share with us? Something we should look into in more detail? ……………………………

THANK YOU FOR PARTICIPATING

(To be filled by the interviewer)

Specific circumstances observed during interview (e.g. whether interviewee was struggling with questions or could answer easily. Whether interviewee seemed particularly interested and a good candidate to follow up with)

……………………………………………………………………..............................

C. Techniques and skills of indigenous weather and seasonal climate forecast (Chapter 4)

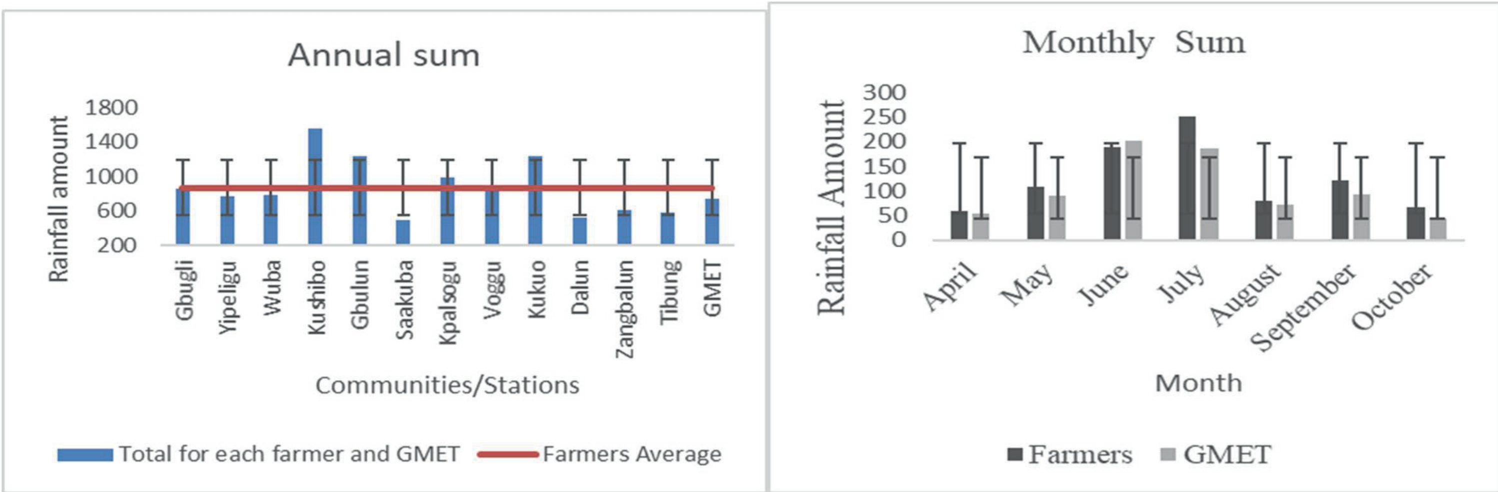
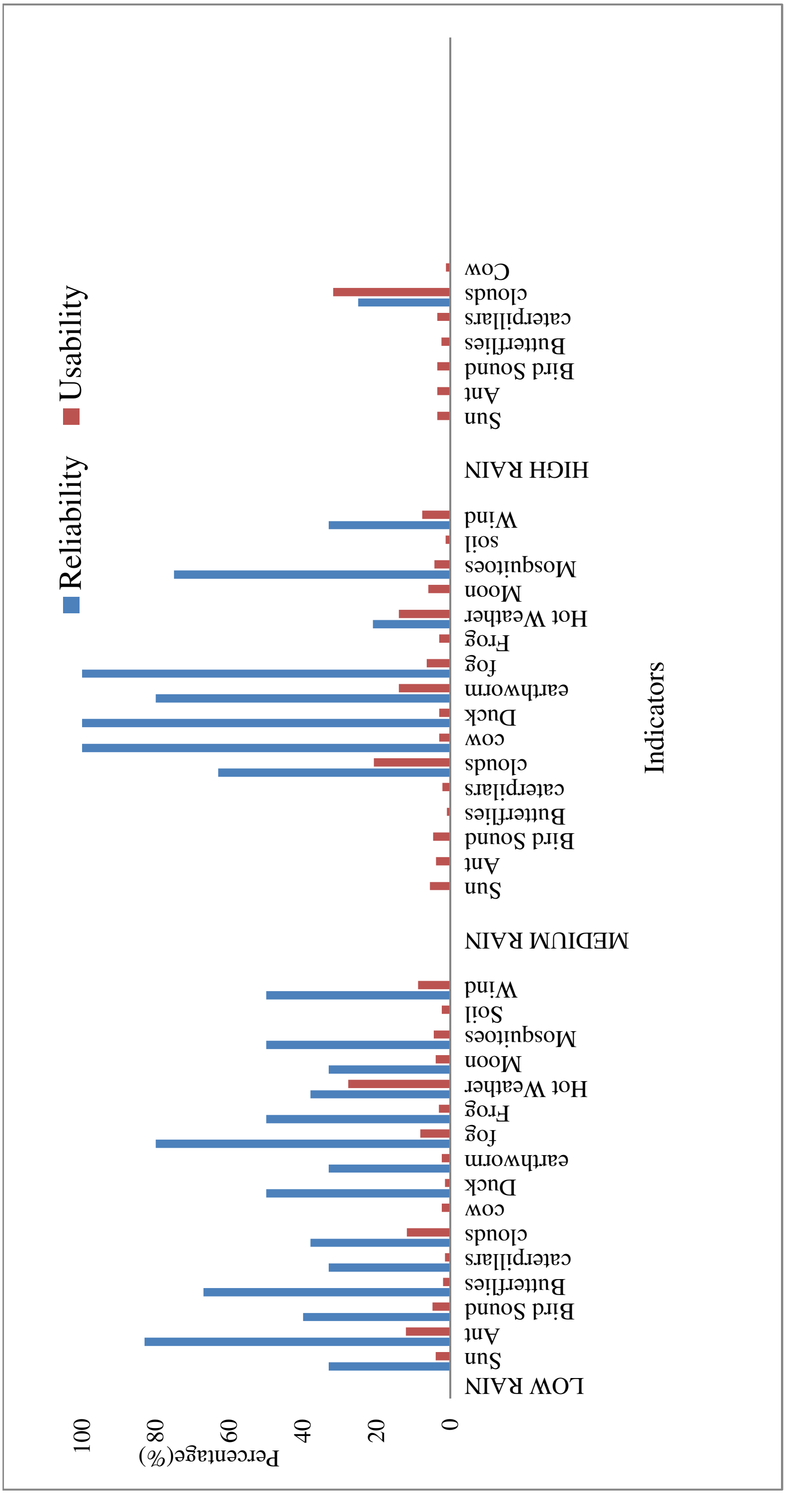


Figure C1: The sum of accumulated observed rainfall per annum and month in the communities against GMET for the period of study (April – October 2017).


Reliability
Usability
Percentage(%)
0
20
40
60
80
100
Indicators
LOW RAIN
Sun
Ant
Bird Sound
Butterflies
caterpillars
clouds
cow
Duck
earthworm
fog
Frog
Hot Weather
Moon
Mosquitoes
Soil
Wind
MEDIUM RAIN
Sun
Ant
Bird Sound
Butterflies
caterpillars
clouds
cow
Duck
earthworm
fog
Frog
Hot Weather
Moon
Mosquitoes
soil
Wind
HIGH RAIN
Sun
Ant
Bird Sound
Butterflies
caterpillars
clouds
Cow

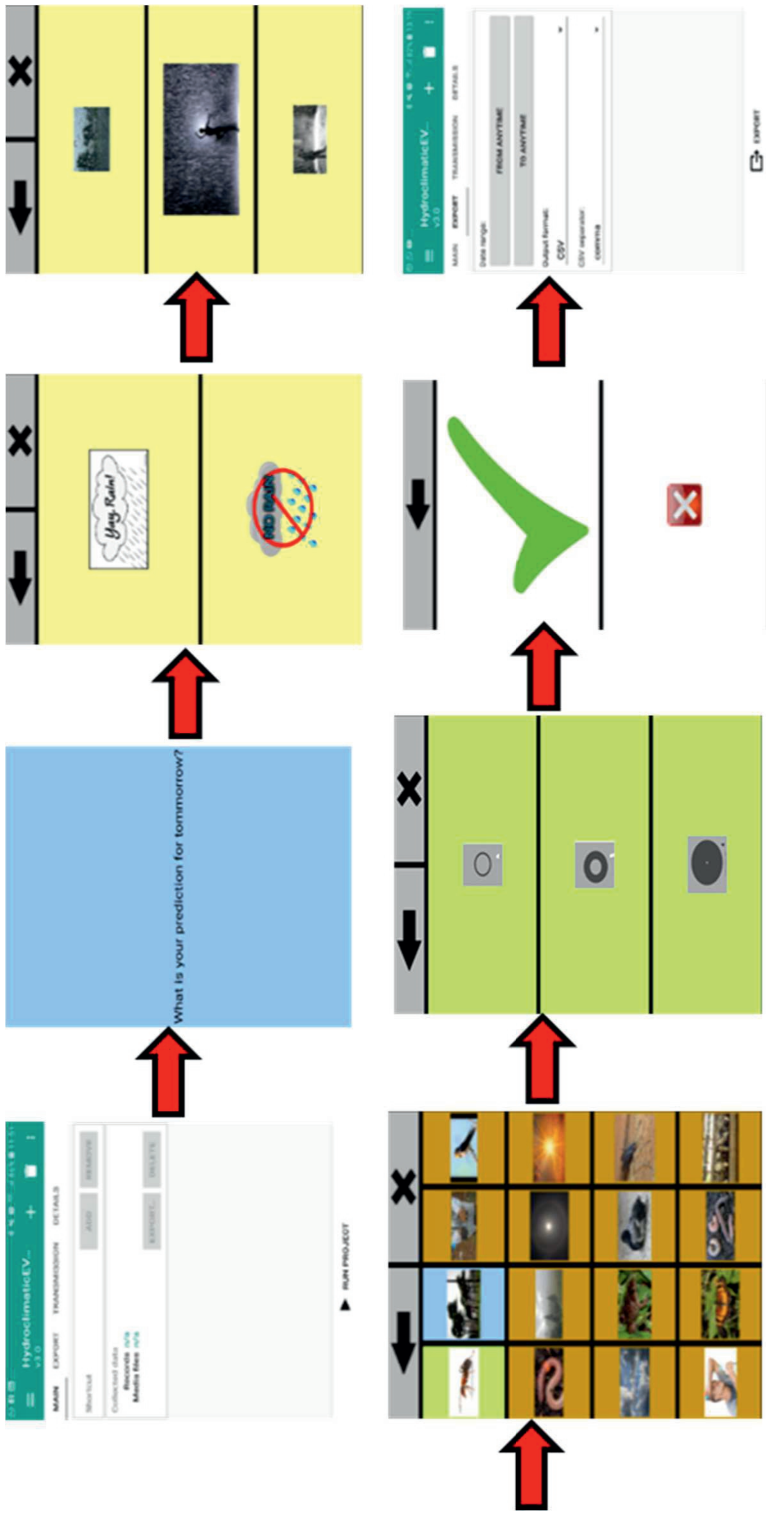


Figure C3: The stepwise interface of Sapelli android mobile app for recording and sending forecast.

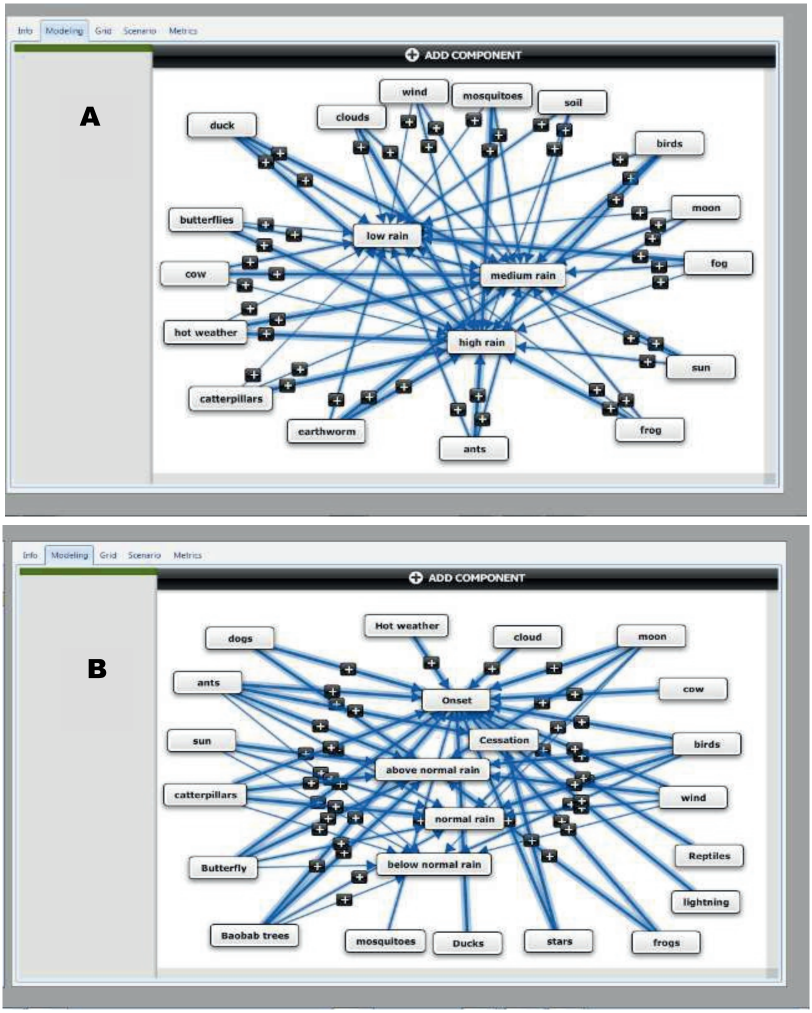


Figure C4: Communal mental model of degree of influence of IEIs used for weather (A) and seasonal climate (B) forecast. The matrix of these relationships are in Table S12 of supplementary material, Participants assign probability of 0.25 (low), 0.5(medium) and 1 (high) for each IEI. The probability is depicted by the thickness of the arrow (the bigger the arrow the higher the probability).

Table C1: Explaining and agreeing to key meteorological terms.

Type of rainfall	Agreed explanations
No Rain (0 mm/day)	When rain does not fall at all
Low: (0.1 -18.8 mm/day)	From drizzling to rains that does not wet the soil to capacity
Medium: (18.9 -36.7 mm/day)	Rains that wet the soil to capacity
High: (> 36.8 mm/day)	Rains that gathers water in farms and sometimes makes crops fail
Above normal	When the season will have more rains than often observed and get very wet than normal (mostly with more yield)
Below normal	When the season have less rains than observed get very dry than normal(mostly with low yield)
Near Normal	When the season will be just as it often is with normal experienced (mostly normal yield)
Onset	When the rain start (When you will start planting)
Cessation	When the rain will end (Often harvesting start)

Table C2: Frequency of low, medium and high rain days recorded by farmers and GMET

Community / Station	Low rainy Days	Medium rainy Days	High rainy Days	Total rainy Days
Gbugli	16	17	3	36
Yipeligu	19	13	4	36
Wuba	5	14	6	25
Kushibo	14	9	17	40
Gbulun	0	2	19	21
Saakuba	25	3	2	30
Kpalsogu	10	19	8	37
Voggu	12	14	5	31
Kukuo	11	22	8	41

Dalun	15	13	2	30
Zangbalun	39	9	1	49
Tibung	6	7	9	22
Average of farmers	14	12	7	33
Tamale (GMET)[>0.1 mm/day]	53	11	3	67
Tamale (GMET)[>1 mm /day]	42	11	3	57

Table C3: Performance of Farmers and GMET in Rainfall Weather Forecast

Community / Stations	forecast/observation				Total observe (n=214)			Monthly Hit performance						
	Hit	Miss	False Alarm	Correct Rejection										
	Yes rain/ Yes Rain	No rain/ Yes Rain	Yes, rain/ No Rain	No rain/ No Rain	Yes Rain	No Rain	Seven months Hit Performance (%)	April (%)	May (%)	June (%)	July (%)	August (%)	September (%)	October (%)
Kushibo	8	32	38	136	40	174	20	0	25	42	14	25	0	0
Gbulun	5	16	38	155	21	193	24	0	0	20	20	100	20	100
Saakuba	8	22	57	127	30	184	27	0	0	33	17	0	33	100
Kpalsogu	8	29	43	134	37	177	22	25	0	14	25	60	20	0
Voggu	8	23	43	140	31	183	26	0	0	29	33	33	0	67
Kukuo	10	31	41	132	41	173	24	33	60	67	67	0	29	33

Dalun	13	17	59	125	30	184	43	33	25	83	50	0	29	50
Zangbalun	30	19	54	111	49	165	61	60	67	55	44	75	75	67
Tibung	6	16	50	142	22	192	27	0	25	40	43	0	0	0
Gbugli	17	19	44	134	36	178	47	75	40	38	63	33	40	33
Yipelgu	9	27	48	130	36	178	25	0	33	40	11	33	0	67
Wuba	4	21	34	155	25	189	16	33	0	20	20	0	0	33
Average Community (%)							30	22	23	40	34	30	21	46
GMET(Tamale) at (>0.1 mm/day)	23	44	35	112	67	147	34	33	20	13	46	56	56	20

Table C4: Performance of GMET Rainfall Weather Forecast Within the communities (GMET forecast against community observation)

Community	GMET forecast/ farmer observation				Total observe (n=214)		
	Hit	**Miss**	**False Alarm**	**Correct Rejection**			
	Yes rain / Yes Rain	No rain / Yes Rain	Yes rain / No Rain	No rain / No Rain	Yes Rain	No Rain	Hit Performance (%)
Kushibo	9	31	49	125	40	174	23
Gbulun	11	10	47	146	21	193	52
Saakuba	12	18	46	138	30	184	40
Kpalsogu	15	22	43	134	37	177	41
Voggu	11	20	47	136	31	183	35
Kukuo	11	30	47	126	41	173	27
Dalun	7	23	51	133	30	184	23
Zangbalun	15	34	43	122	49	165	31
Tibun	6	16	52	140	22	192	27
Gbugli	11	25	47	131	36	178	31
Yipelgu	11	25	47	131	36	178	31
Wuba	7	18	51	138	25	189	28
Average Performance (%)							32

Table C5: Agreement and disagreement of Farmers and GMET rainfall weather forecast

Communities	Agree				disagree				
	Both hit	both miss	both false alarm	both correct rejection	GMET hit, farmer miss	GMET miss, Farmer hit	GMET false alarm, farmer correct rejection	GMET correct rejection, Farmer false alarm	Total
Kushibo	1	12	24	99	8	7	37	26	214
Gbulun	3	10	8	118	8	2	37	28	214
Saakuba	4	15	14	96	8	4	31	42	214
Kpalsogu	4	9	18	100	11	4	34	34	214
Voggu	3	11	15	104	8	5	36	32	214
Kukuo	6	7	17	93	5	13	40	33	214

Dalun	3	16	13	90	4	10	35	43	214
Zangbalun	9	17	13	85	6	21	26	37	214
Tibun	0	14	10	104	6	6	38	36	214
Gbugli	5	10	13	97	6	12	37	34	214
Yipelgu	2	14	18	97	9	7	33	34	214
Wuba	2	10	16	114	5	2	41	24	214
Average	3	12	15	100	7	8	35	34	214

Hit: Both Forecast Yes Rain and observed Yes Rain. Miss: Both Forecast Yes Rain and observed No Rain. False Alarm: Both Forecast Yes Rain and observed No Rain. Correct Rejection: Both Forecast No Rain and observed No Rain.

Table C6: Farmers ability to detect low, medium and high Rain Forecast signal

community	Forecast/Observation																						
	Hit			Miss			False Alarm									CR	Total observed				Performance (%)		
	L/L	M/M	H/H	N/L	N/M	N/H	L/M	L/H	L/N	M/L	M/H	M/N	H/L	H/M	H/N	N/N	L	M	H	N	L	M	H
Kushibo	2	0	1	11	8	13	1	3	24	0	0	5	1	0	9	136	14	9	17	174	14	0	6
Gbulun	-	1	2	-	1	15	0	2	16	-	0	12	-	0	10	155	0	2	19	193	-	50	11
Saakuba	3	0	1	19	2	1	0	0	31	3	0	13	0	1	13	127	25	3	2	184	12	0	50
Kpalsogu	4	0	0	6	16	7	2	0	19	0	1	13	0	1	11	134	10	19	8	177	40	0	0
Voggu	3	2	0	9	10	4	2	1	25	0	2	0	16	0	0	140	12	14	5	183	25	14	0
Kukuo	3	6	-	7	11	4	11	4	23	3	0	17	-	-	-	133	11	22	8	173	27	27	-
Dalun	6	0	0	6	10	1	2	1	34	1	0	14	2	1	11	125	15	13	2	184	40	0	0
Zangbalun	8	3	0	16	3	0	3	0	20	14	1	32	1	0	2	111	39	9	1	165	21	33	0
Tibun	0	1	0	6	4	6	2	1	35	0	2	14	0	0	1	142	6	7	9	192	0	14	0

Gbugli	1	4	0	9	7	3	6	0	24	5	0	17	0	0	3	134	16	17	3	178	6	24	0
Yipelgu	1	1	0	16	8	3	4	1	31	2	0	15	0	0	2	130	19	13	4	178	5	8	0
Wuba	0	3	0	4	11	6	0	0	8	1	0	16	0	0	10	155	5	14	6	189	0	21	0
Average performance (%)																					17	16	6

L=Low Rain, M =medium Rain, H=High Rain, N = No Rain, CR=Correct Rejection, - = such forecast was not made, 0 = no count

Table C7: Certainty of using indicators for Yes/No Rain Forecast (Sure =high certainty, so sure= higher certainty, Very sure = Highest Certainty)

Indicators	Hit			Miss			
	Yes/Yes Rain			Yes/No Rain			Total number of times used
	sure	So sure	Very sure	sure	So sure	Very sure	
Sun	0(0%)	4(13%)	0(0%)	14(47%)	11(37%)	1(3%)	30
Ant	6(11%)	1(2%)	2(4%)	23(42%)	17(31%)	6(11%)	55
Bird Sound	5(17%)	2(7%)	2(7%)	9(31%)	5(17%)	6(21%)	29
Butterflies	1(9%)	4(36%)	0(0%)	4(36)	1(9%)	1(9%)	11
Caterpillars	1(8%)	3(23%)	0(0%)	1(8%)	5(38%)	3(23%)	13
Clouds	3(3%)	13(11%)	4(3%)	44(37%)	38(32%)	16(14%)	118
Cow	1(6%)	1(6%)	0(0%)	7(44%)	6(38%)	1(6%)	16
Duck	1(6%)	2(13%)	0(0%)	1(6%)	10(63%)	2(13%)	16
Earthworm	1(2%)	6(12%)	2(4%)	7(14%)	24(47)	11(22%)	51
Fog	3(6%)	4(8%)	0(0%)	13(27%)	23(48%)	5(10%)	48
Frog	2(11%)	1(6%)	0(0%)	6(33%)	7(39%)	2(11%)	18
Hot Weather	10(8%)	18(14%)	1(1%)	51(38%)	39(29%)	14(11%)	133
Moon	3(8%)	5(14%)	1(3%)	14(39%	12(33%)	1(3%)	36
Mosquitoes	4(14%)	5(18)	1(4%)	10(36%)	4(14%)	4(14%)	28
Soil	1(8%)	0(0%)	0(0%)	3(23%)	7(54%)	2(15%)	13
Wind	2(4%)	5(9%)	2(4%)	20(36%)	22(40)	4(7%)	55

Table C8: Certainty of using indicators for low, medium and high Rain forecast (Sure =high certainty, so sure= higher certainty, Very sure = Highest Certainty)

		Forecast								
		High Rain			**Low Rain**			**Medium Rain**		
		So sure	Very sure	sure	So sure	Very sure	sure	So sure	Very sure	sure
Observed	High Rain									
	Sun	0	0	0	1	0	0	0	0	0
	Ant	0	0	0	0	0	1	0	0	0
	Bird Sound	0	0	0	1	0	1	0	0	0
	Butterflies	0	0	0	1	0	0	0	0	0
	caterpillars	0	0	0	0	0	1	0	0	0
	clouds	0	1	0	1	0	0	1	1	0
	earthworm	0	0	1	0	0	0	0	0	0
	Hot Weather	0	0	0	0	0	2	0	0	0
	Moon	0	1	0	1	0	1	1	0	0
	Mosquitoes	0	0	0	1	0	1	0	0	0
	Wind	1	0	0	0	0	0	0	0	0
	Low Rain									
	Sun	0	0	0	1	0		2	0	0
	Ant	0	0	0	1	1	3		1	0
	Bird Sound	0	1	0		0	2	1	1	0
	Butterflies	0	0	0	2	0	0	1	0	0
	caterpillars	1	0	0	1	0	0	1	0	0
	clouds	0	1	0	2	0	1	4	0	0
	cow	0	0	0	0	0	0	1	0	0

Duck	0	0	0	0	0	1	1	0	0
earthworm	0	0	0	1	0	0	2	0	0
fog	0	0	0	2	0	2	0	0	1
Frog	0	0	0	0	0	1	1	0	0
Hot Weather	0	0	0	4	1	0	8	0	0
Moon	1	0	0	1	0	0	0	0	1
Mosquitoes	0	0	0	0	0	2	1	0	1
Wind	0	0	0	0	1	0	1	0	0
Medium Rain									
Ant	0	0	0	0	0	2	0	2	0
Bird Sound	0	0	0	0	0	2	1	3	0
Butterflies	0	0	0	0	0	1	0	1	0
clouds	2	0	0	0	0	1	0	1	3
cow	0	0	0	0	0	0	0	0	0
Duck	0	0	0	0	0	0	0	0	1
earthworm	0	1	0	0	0	0	0	0	3
fog	0	0	0	0	0	0	0	0	2
Frog	0	0	0	0	0	1	0	1	0
Hot Weather	0	0	0	5	0	6	0	11	1
Moon	0	0	0	1	0	1	0	2	0
Mosquitoes	0	0	0	1	0		0	1	2
soil	0	0	0	0	0	1	0	1	0
Wind	0	0	0	1	1	2	0	4	2
No Rain									
Sun	1	0	2	2	1	9	0	12	8
Ant	0	1	2	12	4	19	0	35	5

Bird Sound	1	1		3	2	5		10	1
Butterflies	1	1	0	0	0	3	0	3	
caterpillars	2	0	0	1	2	0	0	3	2
clouds	10	6	7	6	5	26	0	37	22
cow	1	0	0	3	1	4	0	8	2
Duck	2	2	0	3	0	1	0	4	5
earthworm	3	3	2	2	3	2	0	7	19
fog	2	2	1	10	2	12	1	25	11
Frog	0	0	0	3	1	5	0	9	4
Hot Weather	2	2	1	26	9	44	2	81	11
Moon	3	1	3	3	0	5	1	9	6
Mosquitoes	0	1	1	3	3	5	0	11	1
soil	1	1	0	3	1	3	0	7	3
Wind	5	0	0	10	1	15	0	26	7

Table C9: Farmers and GMET 2017 seasonal forecast against observation in each community

communities	Total Rainfall amount forecast	Indicators Used	Total Rainfall Observed	Onset Forecast	Indicators Used	Onset Observed	Cessation Forecast	Indicators Used	Cessation Observed
Kushibo	above normal	a large number of migrating butterflies	1563	2nd Week April	large flocks of swallow birds migrating with a loud sound	4th week April	1st Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
Gbulun	Near Normal	The hotness of the weather over the dry season has been moderate	1243	3rd Week April	The flowering of the Baobab tree and the emergence of new leaves	3rd week April	2nd Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
Saakuba	Near Normal	Normal appearance of the sun	492	4th Week April	The hotness of the weather/ temperature	2nd week may	4th Week October	No clear sign. Used previous experience and total rain forecast	1st Week October

Kpalsogu	above normal	1. A large number of Hornbills with a loud singing noise 2. Frequently occurring wind swirling at a high frequency	982	4th Week April	A rapid increase in anthills	4th week April	2nd Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
Voggu	Near Normal	Saw crows flying in groups	879	3rd Week April	the appearance of a large number of migrating butterflies	3rd week April	1st Week October	No clear sign. Used previous experience	1st Week October
Kukuo	Near Normal	Only a few Woolly bears Caterpillars have emerged	1243	2nd Week April	swirling wind at a high frequency	2nd week April	3rd Week October	No clear sign. Used previous experience and total rain forecast	2nd Week October
Dalun	Below normal	birds built nest close to dam	519.5	3rd Week April	Rapid increase in anthills	1st week April	1st Week October	No clear sign. Used previous experience and total rain forecast	1st Week October

Zangbalun	above normal	flowering of Baobab tree and leaves emergence moon are covered by cloudlike appearance	606	3rd Week April	Hearing an owl hooting in the evening is an indication of the rain onset	1st week April	4th Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
Tibun	Near Normal	Normal appearance of the sun	587	4th Week April	High temperature that leads to profuse sweating	1st week of June	1st Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
Gbugli	Near Normal	Saw crows flying in groups	862	2nd Week April	Burning heat from the high temperatures	1st week April	4th Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
Yipelgu	above normal	moon are covered by cloudlike appearance	774	3rd Week April	large number of migrating butterflies	4th week April	3rd Week October	No clear sign. Used previous experience and total	3rd Week October

								rain forecast	
Wuba	Near Normal	The number of migrating butterflies is normal	784	3rd Week April	Burning heat from the high temperatures	2nd week may	1st Week October	No clear sign. Used previous experience and total rain forecast	1st Week October
GMET(Tamale)	Near Normal	forecast model simulations and statistical estimation results	741.8	4th week April-1st week of May	forecast model simulations and statistical estimation results	4th week April	End of October	forecast model simulations and statistical estimation	1st Week October

Table C10: Summarised matrix of the communal mental model of degree of influence of IEIs used for weather and seasonal climate forecast. Participants assign probability of 0.25 (L=low), 0.5(M=medium) and 1 (H=high) for each IEI. " –" means no relationship.

	Weather					**Seasonal Climate**			
Indicators	Low Rain	**Medium Rain**	**High Rain**	**Indicators**	**Onset**	**Above normal rain**	**Below normal rain**	**Normal rain**	**Cessation**
Clouds	L	M	H	Birds	H	H	M	H	-
Mosquitoes	L	M	H	Frog	H	H	-	-	-
Hot Weather	L	H	H	Dogs	H	H	-	-	-
Cow	M	H	L	Hot Weather	H	-	-	-	-
Butterflies	L	M	H	Ants	H	H	L	M	H
Moon	L	M	M	Moon	H	H	L	M	-
Frog	L	M	H	Stars	-	-	-		H
Caterpillars	L	L	H	Baobab Tree	H	H	L	M	-
Duck	M	H	H	Cows	H	-		-	-
Fog	H	M	L	Duck	H	-	-	-	-
Soil	M	M	L	Reptiles	H	-	-	-	-
Birds	M	H	H	Wind	H	H	L	M	-
Ant	M	M	H	Sun	-	H	L	M	-
Earthworm	M	H	H	Clouds	H	-	-	-	-
Sun	L	H	M	Lightening	H	-	-	-	-
Wind	L	M	M	Mosquitoes	H	-	-	-	-
				Butterflies	H	H	L	M	-
				Caterpillars	H	H	L	H	-

Table C11: Descriptive statistics of IEIs used

Statistics	Value
Mean	42.375
Standard Error	9.202298173
Median	30.5
Mode	55
Standard Deviation	36.80919269
Sample Variance	1354.916667
Kurtosis	2.630349998
Skewness	1.749922916
Range	126
Minimum	11
Maximum	137
Sum	678
Count	16
Confidence Level (95.0%)	19.61423426
lower bound	22.76076574
upper bound	61.98923426

C1. Mental modeller and Fuzzy-logic cognitive mapping (FCM)

Fuzzy-logic cognitive mapping (FCM) is a semi-quantitative modelling approach used to understand behaviours of many complex systems (Glykas, 2010). They collect and standardize individual and collective community knowledge using simple modelling tasks (Ozesmi and Ozesmi, 2004; Gray et al., 2012) in a real-time and participatory modelling environment (Gray et al., 2013). FCMs are capable of collecting qualitative information from stakeholders and quantitatively assigned weighted edges usually between -1 and 1, to define mathematical pairwise associations. The pairwise relationships between concepts are used to calculate the cumulative strength of connections between elements with weighted edges, highlighting any domain as a system. Further, developed semi-quantitative scenarios allow scenario analysis of plausible outcomes (Özesmi and Özesmi, 2004). This approach is becoming an increasingly popular way to incorporate local or expert knowledge into ecological decision-making (Nyaki et al., 2014; Halbrendt et al., 2014). Mental Modeller uses a participatory modelling approach to capture both individual and group mental models using a fuzzy-logic cognitive mapping (FCM). It describes how a person views the world and how those views affect their interactions (Giordano et al., 2005). The mental modeller is widely used in facilitating group decisions and consensus in risk analysis, natural resource management, and climate change adaptation (Biggs et al., 2011). It depends on social and cultural influences, to understand the factors that influence the decision-making of cultural groups (Biggs et al., 2011) such as farmers (Halbrendt et al., 2014). However, the location of interviews used in the development of mental models can have an effect on outcomes. Despite these shortcomings, perhaps one of the most important characteristics of this approach is that it affords transparency to information gathering and knowledge transfer between science and policy (Kolkman et al., 2005). This research uses representations of knowledge and belief systems held by rural farmers in Northern Ghana to forecast seasonal and weather rainfall. Through a multi-step process based on Fuzzy-logic Cognitive Mapping (FCM), we captured the underlying mechanism for farmers to forecast the weather (low, medium and high rainfall) and the seasonal climate (above, below and normal rainfall, onset and cessation), using a novel computer-based FCM software called Mental Modeler (Gray et al., 2013).

C2. Deterministic Binary forecast Verification

Many meteorological phenomena such as rain, floods, severe storms, frosts, and fogs can be regarded as simple binary (dichotomous) events, and forecasts or warnings for these events are often issued as unqualified statements that they will or will not take place. These kinds of predictions are sometimes referred to as yes/no forecasts, and represent the simplest type of forecasting and decision-making situation (Hogan and Mason 2012). For this study, we used a 2 × 2 possible outcomes (contingencies) presented in table 1 to evaluate the forecast. For a sequence of binary forecasts, we used this as a performance measure to determine the number of *hits* (*a*), *false alarms* (*b*), *misses* (*c*) and *correct rejections* (*d*).

Table 1: Schematic contingency table for deterministic forecasts of a sequence of n binary events. The numbers of observations/forecasts in each category are represented by a, b, c and d.

Event forecast	**Event observed**		
	Yes	**No**	**Total**
Yes	*a* (Hits)	*b* (False alarms)	*a* + *b*
No	*c* (Misses)	*d* (Correct rejections)	c + d
Total	*a* + *c*	*b* + *d*	*a*+ *b* + *c* + *d* = *n*

C3. Sapelli android mobile app for collecting forecast

Collecting farmers' indigenous forecast could be done via different methods; primarily paper-based or mobile-based recording. We resorted to using a mobile phone approach for two main reasons: first, it helped us monitor when farmers send their forecast based on date and time and location. Secondly, to appreciate how farmers with low literacy levels interact with ICT based tools for future information exchange. Several options exist for using a mobile-based platform because a growing number of mobile data collection platforms have emerged in the last decades. CyberTracker (Liebenberg et al., 1999), EpiCollect (Aanensen et al., 2009) and Open Data Kit (Anokwa et al., 2009) are some few examples. These platforms generate large and detailed data sets and make it possible for scientists to have instant access to all the information gathered over a period. However, in our research, we selected an android mobile app called Sapelli (Stevens et al., 2013). Sapelli is an open-source project that facilitates data collection across language or literacy barriers through highly configurable decision-tree of a pictorial icon-driven user interface. According to Stevens et al. (2014) Sapelli has a powerful visualisation capability that allows usage among users with low literacy. Users can select options by simply touching the screen of the mobile device and not have to necessarily read the text. While all other platform allows offline data collection, postponing data transmission to a later stage, only Sapelli does not rely on an Internet connection. This function makes it possible to use in areas where network connectivity is rare, unstable, slow or expensive, and when users lack phone experience. Vitos et al., (2013) for example, used Sapelli to Support non-literate people to monitor poaching in Congo. The project was coded in XML and uploaded to Sapelli android platform. The app presented a simple iterative process with an interactive interface showing images agreed upon with farmers (see Figure 3 in the manuscript). The farmer first has the chance to predict yes or no rain. Should he predict a yes rain, he has the option of selecting if the predicted rain will be low, medium or high rain. He further indicates the particular indicator upon which he based his prediction. Next, he indicates the degree of certainty (sure, so sure and very sure) of his predictions. He finalizes the prediction process by saving the data for export else, he cancels and re-start the process. While farmers are sometimes able to combine different ecological indicators for a particular forecast, the process was focused on the use of one indicator and a short stepwise process to avoid possible complications likely to be associated with a laborious process. Moreover, farmers have low literacy in smartphone usage and therefore called for simple, easy and effortless processes that require less engagement and technical competencies.


Plate C1: Identifying ecological indicators, interpretations of their signs and their reliability **(left)** and developing a communal mental model for weather and climate forecast techniques using the mental modeler software **(right)**


Plate C2: Training farmers on how to use the rain gauges **(left)** and record rains in the logbook **(right)**

Plate C3: Farmers asking questions for clarity during a workshop **(Left),** Rain gauge mounted in a Farmer's house **(middle)** and training farmers on how to use the Sapelli mobile app to send their forecast **(Right).**

D. Towards weather and climate services that integrate indigenous and scientific forecast to improve forecast reliability and acceptability (Chapter 5)

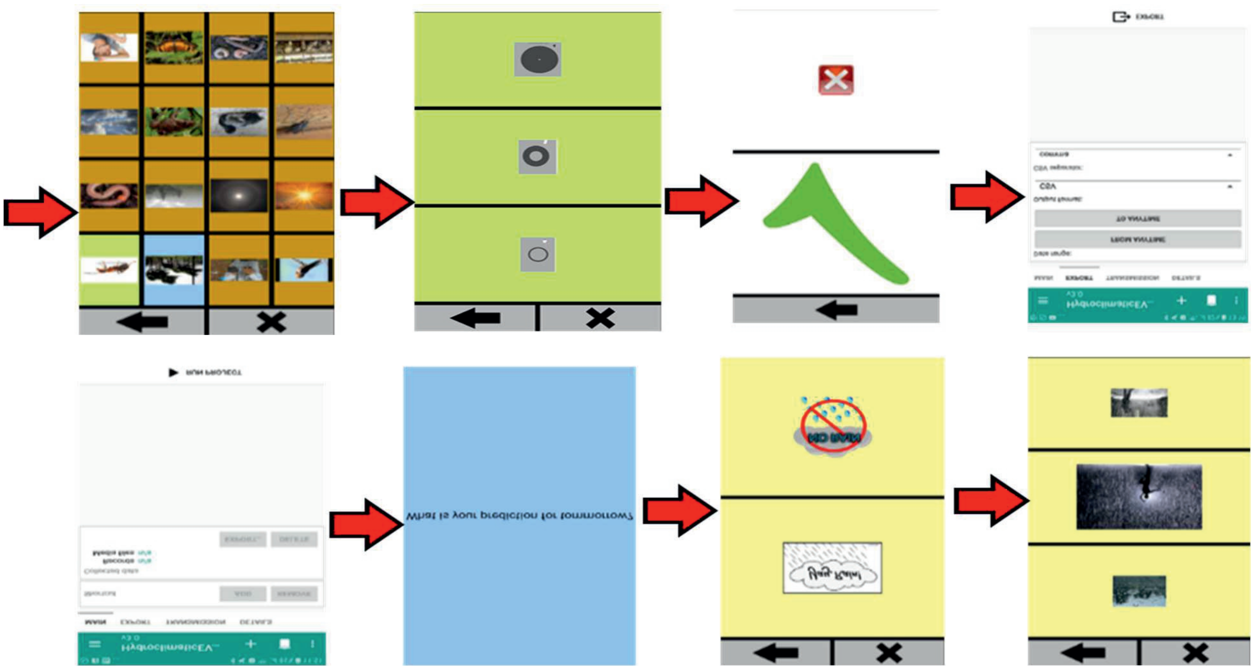


Figure D1: The stepwise interface of Sapelli android mobile app for recording and sending forecast.

Table D1: Background characteristics of respondents (N = 108)

Characteristics	**%**	**Characteristics**	**%**	**Characteristics**	**%**
Gender		**Literacy**		***Type of forecast use(Indigenous)***	
Male	72	Yes(literate)	16	Always	60
Female	28	No (illiterate)	65	Very often	35
Age		Somehow (partially literate)	17	Sometimes	5
<30	4	I don't know	2	Rarely	0
30-40	17	***Farm size in acres (Rainfed farmers only. N=36)***		Never	0
40-50	34	<1	6	***Type of forecast use (scientific)***	
50-60	32	1-1.9	33	Always	7
>60	14	2-2.9	8	Very often	74
Household Size		3-3.9	11	Sometimes	17
1-5 persons	18	4-4.9	17	Rarely	3
6-10 persons	32	5-6	17	Never	0
11-15 person	23	>6	8	***Type of forecast use (Integrated)***	
16-20 persons	19	***Farm size in acres (Both irrigated and rain fed farmers only. N=36)***		Always	6
21-25 persons	8	<1	6	Very often	52
>25 persons	0	1-1.9	28	Sometimes	37
Educational Level		2-2.9	8	Rarely	5
No education	69	3-3.9	6	Never	1
Primary education	12	4-4.49	22		
Secondary education	12	5-6	17		
Tertiary education	5	>6	14		

Non-formal Education (adult education)	3	***Farm size in acres (irrigated farmers only (N=36)***	
		<1	11
		1-1.9	44
		2-2.9	39
		3-3.9	6
		4-4.49	0
		5-6	0
		>6	0

Table D2: Questionnaire for Acceptability of Integrated Forecast among Farmers

Hello Sir/Madam. My name is…. from Wageningen University and Research in the Netherlands. We are currently working on a research project that focuses on weather and climatic information services that integrate indigenous and scientific forecast for rice farmers' decision making. ***You have been selected by our sampling method for the interviews. All the information you provide will be treated with confidentiality. You may withdraw from the study at any time and if there are questions that you would prefer not to answer, we will respect your right not to answer them.***	
Do you consent to be part of the study?..................	Questionnaire No: ………….
Part A: Personal characteristics	
Question	***Response***
1. Name of the village	
2. Sex of the respondent?	(a) Male (b) Female
3. Household size (Number of people living in one house and under your care)?	(a) 1-5 (b) 6- 10 (c) 11-15 (d) 16-20 (e) 21-25 (f) > 25
4. How old are you (In years)?	(a) <30 (b) 30-40 (c) 41-50 (d)51-60 (e) >60
5. What is your highest level of education?	(a)No education (b)Primary education (c) Secondary education (d)Tertiary education (e)Non-formal (Adult education)

6. Can you read the local newspaper and weather forecasts on your phone?	(a)Yes [Literate] (b) No [Illiterate] (c) Somehow [Partially literate] (d) I don’t know
7. What is your farm size (In acres)?	(a) < 1 (b)1 – 1.9 (c) 2 -2.9 (d)3 -3.9 (e)4–4.9 (f)5 -6 (g) >6
8. Was there any natural hazard(s) (e.g. flood, drought) that affected your yield level in recent years?	(a) Yes (b) No (c) I don’t know
Part B: Forecast sources and usage	
From our earlier interactions, we realised three sources of forecasts information for farm decision making. 1. Scientific forecasts, provided by GMet. 2. Indigenous forecasts which are based on observation of traditional environmental indicators, such as ant movement and cloud formation etc. 3. Integrated forecast based on using both scientific and indigenous forecast together. We will be asking you a number of questions about the use of these forecasts.	
9. I use Indigenous forecast	(a)Always (b) Very Often (c)Sometimes (d)Rarely (e) Never
10. I use Scientific forecast	(a)Always (b) Very Often (c)Sometimes (d)Rarely (e) Never
11. I use Integrated forecast	(a)Always (b) Very Often (c)Sometimes (d)Rarely (e) Never
12. Imagine you are at the beginning of the cropping season and you need to know when the rains will start in order to start land preparation. Which of the following sources would you seek information from?	(a) GMet scientific forecast (b) indigenous forecast (c) integration of GMet scientific and indigenous forecast (d) I don’t care (e) I don’t know
13. Imagine you have rainfall forecast information from *only an integrated forecast* to help you decide when to transplant/plant your rice. Which of the following would you do?	(a) I will use it only when it is proven to be reliable (b) I will use it even if it is proven to be unreliable (c) I won’t use whether I consider it to be reliable or not (d) I don’t know
14. How do you integrate scientific and indigenous forecast?	(a) Put them together as one forecast [combine] (b) compare both and chose one based on my experience [complementarily] (c) I can’t tell

Part C: Acceptability of integrated forecast	
On a scale of 1-6, with 5 being "strongly agree" and 1 being "strongly disagree," and 6 being "I don't know". Please describe your feelings:	
15. I prefer an integrated forecast that is combined than used complementarily	(1) Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
16. If I am not certain about the scientific and indigenous forecast information, I will try to integrate or combine both	(1) Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
17. Scientific and indigenous forecasts are not always aligned, for example, GMet scientific forecast says it will rain and my own forecast saying it won't rain. In those cases, I become confuse and find it problematic.	(1) Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
18. I will accept information from an integrated forecast more because it combines the best of scientific and indigenous forecasts.	(1) Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
19. In making farming decisions, I prefer to have integrate scientific and indigenous forecasts rather than separate	1)Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
20. I prefer to use indigenous forecasts over scientific forecasts when possible	(1) Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
21. I will only accept an integrated forecast after using it for a while	(1) Strongly disagree (2) Disagree (3) Neutral (4) Agree (5) Strongly agree (6) I don't know
22. If you agree to question 20 above, how long will it take for you to accept an integrated forecast?	(a) After 1 farming season (b) after 2 farming seasons (c) after 3 farming seasons (d) after 4 farming seasons (e) Others……………… (f) I don't know

Table D3: Multiple questions that measured acceptability integrated forecast

Questions	Scientific and indigenous forecasts are not always aligned, for example, GMet scientific forecast says it will rain and my own forecast saying it won't rain. In those cases, I become confuse and find it problematic.		I will accept information from an integrated forecast more because it combines the best of scientific and indigenous forecasts.		In making farming decisions, I prefer to have integrated scientific and indigenous forecasts rather than separate	
Responses	Frequency	Percent	Frequency	Percent	Frequency	Percent
Strongly Disagree	2	1.9	2	1.9	1	0.9
Disagree	3	2.8	1	.9	-	-
Neutral	1	0.9	31	28.7	2	1.9
Agree	23	21.3	73	67.6	29	26.9
Strongly Agree	79	73.1	1	.9	76	70.4
I don't know	-	-	-	-	-	-
Total	108	100.0	108	100.0	108	100.0

Table D4: Reliability of the three questions for measuring Acceptability

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.686	0.682	3

Item Statistics

	Mean	Std. Deviation	N
Scientific and indigenous forecasts are not always aligned, for example, GMet scientific forecast says it will rain and my own	4.61	0.807	108

forecast saying it won't rain. In those cases, I become confuse and find it problematic			
I will accept information from an integrated forecast more because it combines the best of scientific and indigenous forecasts.	4.62	0.733	108
In making farming decisions, I prefer to have integrated scientific and indigenous forecasts rather than separate	4.66	0.614	108

Table D5: Monthly Performance of IF, SF, and IPF probability forecasts (Bolden values are the highest performed values under each probability).

Probability of rainfall occurrence	**Indigenous Performance (%)**		**GMet Performance (%)**		**Integrated Performance (%)**	
	Yes Rain	No Rain	Yes Rain	No Rain	Yes Rain	No Rain
June						
≤0.5	52	48	36	64	50	50
>0.5	56	44	63	37	55	45
July						
≤0.5	38	63	45	55	33	67
>0.5	67	33	40	60	46	54
August						
≤0.5	40	60	13	88	24	76
>0.5	100	0	35	65	60	40
September						
≤0.5	32	68	25	75	33	67
>0.5	0	100	35	65	83	17
October						
≤0.5	17	83	16	84	14	86

>0.5	0	100	17	83	50	50
Monthly Average Performance						
≤0.5	35.8	64.4	27	73.2	30.8	69.2
>0.5	44.6	55.4	38	62	58.8	41.2

Table D6: Relationship between Acceptability of integrated probability forecast (IPF) and trust

Trust = I will accept information from an integrated forecast more because it combines the best of scientific and indigenous forecasts				
			Acceptability	Trust
Spearman's correlation	Acceptability	Correlation Coefficient	1.000	0.652**
		Sig. (1-tailed)		0.000
		N	108	108
	Trust	Correlation Coefficient	0.652**	1.000
		Sig. (1-tailed)	0.000	
		N	108	108
**. Correlation is significant at the 0.01 level (1-tailed).				

Table D7: Farmers' acceptability of integrated forecast based on Trust and reliability

I will accept information from an integrated forecast more because it combines the best of scientific and indigenous forecasts		
Strongly disagree	2	1.9
Disagree	1	0.9
Agree	31	28.7
Strongly agree	73	67.6
I don't know	1	0.9
Total	108	100
Imagine you have rainfall forecast information from *only an integrated forecast* to help you decide when to transplant/plant your rice. Which of the following would you do?		
	Frequency	Percentage
(a) I will use it only when it is proven to be reliable	106	99
(b) I will use it even if it is proven to be unreliable	2	1
(c) I won't use whether I consider it to be reliable or not	-	-
(d) I don't know	-	-

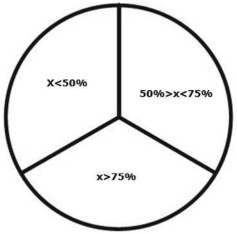
Table D8: Farmers' choice of forecast type and integration approach

Questions	I prefer to use indigenous forecasts over scientific forecasts when possible		I prefer an integrated forecast that is combined than used complementarily		If I am not certain about the scientific and indigenous forecast information, I will try to integrate or combine both	
Responses	Frequency	Percent	Frequency	Percent	Frequency	Percent
Strongly Disagree	1	0.9	-	-	-	-
Disagree	-	-	-	-	-	-
Neutral	3	3	2	2	-	-
Agree	34	32	32	30	27	25
Strongly Agree	70	65	69	64	81	75
I don't know			5	5	-	-
Total	108	100	108	100	108	100

How do you integrate scientific and indigenous forecast?

	Frequency	Percent
Put them together as one forecast [combine]	3	2.8
compare both and chose one based on my experience [complementarily]	101	93.5
I can't tell	4	3.7
Total	108	100.0

E. The influence of weather and seasonal climate forecast information on rice farmers' decision-making (Chapter 6)



Wheel 1: Forecast probability Wheel 2: Forecast Lead Time (Seasonal) Wheel 3: Forecast Lead Time (Weather)

Decision Card Board

Pre-season	Land Preparation	Planting	1st Fertilizer Application	Weed Control	2nd Fertilizer Application	Harvesting

Table E1: Seasonal forecast lead time and farmer decision-making.

	One Month Lead Time		Two Months Lead Time		Three Months Lead Time	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Will Act	31	86.1	22	61.1	8	22.2
Will not Act	5	13.9	14	38.9	28	77.8

Table F2: Weather lead time and farmer decision-making

Farming stages	Decision Choice	*One Day Lead Time*		*Three Day Lead Time*		*One Week Lead Time*	
		Freq.	*%*	*Freq.*	*%*	*Freq.*	*%*
Land Preparation	Will clear the land using manual labour	4	11.1	9	*25*	26	72.3
	Will clear land using a tractor	32	88.9	27	75	10	*27.8*
Planting	Will broadcast seeds	32	88.9	25	69.5	23	63.9
	Will nurse and transplant seedlings	4	11.1	6	16.7	7	19.4
	Will plant using dibbling method	-	-	5	13.9	6	16.7
1st Fertilizer Application	Will apply fertilizer by broadcasting before the rain	1	2.8	6	16.6	17	47.2
	Will apply fertilizer by placement after the rains	35	97.2	30	83.4	19	52.8
Weed Control	Will apply weedicide after the rains	3	8.3	1	2.8	36	100
	Will apply weedicide before the rains	33	91.7	35	97.2	-	-
2nd Fertilizer Application	Will apply fertilizer by broadcasting before the rain	4	11.1	16	44.4	13	36.1
	Will apply fertilizer by placement after the rains	32	88.9	20	55.6	2	60.4

Weedicide Control	Will apply weedicide by spraying after the rain	29	80.5	5	13.9	2	5.6
	Will apply weedicide by spraying before the rain	7	19.2	31	86.1	34	94.4
Harvesting	Will harvest with a sickle	27	25	27	25	13	36.1
	Will harvest with a combine harvester	9	75	9	75	23	63.9

Summary

Local communities are adaptive and have in the past managed different risk (such as droughts and floods, disease and pest outbreaks, and famines). Yet, in recent times, many of these communities are overwhelmed by the impact of climate variability and change on their farming activities. Ghanaian farmers particularly those in the North are faced with many decision making dilemmas due to water and climate variability. They struggle about decisions such as which seed variety to plant, when to plant, when to fertilize, when to do supplementary irrigation and sometimes when to harvest. In discussing possible spheres of enhancing farmers' adaptive capacity to deal with these challenges, mainstreaming climate services into agriculture is tipped to have great potential. However, climate information service in Ghana has had no intrinsic value for farmers as it is unable to influence their farming decisions. Thereby making farmers rely on their own indigenous forecast for daily and seasonal farm decision making.

This thesis, therefore, explored ways to make climate services useful for farmers in the Northern region of Ghana. It aimed at improving the reliability and acceptability of forecast information by integrating indigenous and scientific forecast. I formulated five iterative research questions with each question informing the other and in whole address the objective. They are:

1. What is the potential of climate information services to support rice farming systems? (Chapter 2)
2. How successful can seasonal climate forecast meet farmers' information needs? (Chapter 3)
3. What are the skills in indigenous and scientific forecast to promote effective climate services? (Chapter 4)
4. How can the integration of indigenous and scientific forecast improve reliability and acceptability of climate services? (Chapter 5)
5. How do weather and climate information influence farmers'decisionmaking? (Chapter 6)

I adopted a multi-method approach where a number of concepts are combined and different qualitative and quantitative methods were used for data collection and analysis to gain understanding into the research objective. This PhD dissertation consists of seven chapters. Chapters 1 and 7 are respectively meant to provide a general background to the study and a synthesis of the major findings. The remaining chapters (Chapter 2 to 6) addresses the five research questions, each chapter is independently written to address one research question.

In Chapter 2, I carried out a diagnostic of the existing socio-ecological issues including the limitations and strengths of agriculture information systems in rice production systems in Northern Ghana. I did this by first conducting literature and documents review, followed by interviews and focus group discussions with different relevant stakeholders. The central part of this chapter is the proposed framework for second generation climate services that when adopted and implemented could improve the uptake of forecast information services. The framework was evaluated with the four dimensions of responsible innovation (anticipatory, inclusive, reflexive and responsive) and found to be robust for effective climate services in the area. The framework is developed to ensure the provision of relevant and accurate forecast information via a user friendly platform in a way that manages user expectation and strengthens collaboration between information providers and users. The diagnostics also revealed some essential issues that affect the uptake of climate information services in the region. These issues form the basis for the subsequent chapters. They include (1) the mismatch between forecast information and farmers need (2) poor quality of forecast information (3) the disconnect between forecast information providers and farmers (4) management of unrealistic expectations of farmers.

Building on the challenge of mismatch between forecast information and farmers need, Chapter 3 was aimed at ensuring that forecast information meets the desired needs of farmers. Using interviews and workshops, farmers' hydroclimatic information needs were identified and evaluated according to farming types; rainfed, irrigated and both rainfed and irrigated. Findings show that farmers need rainfall distribution, temperature variations, dam water level, total rainfall amount, onset and cessation, wind speed and direction. However, some information needs are ranked higher than others depending on the frequency of use and farming type. Also, information needs are linked to the type and timing of farm decision making and that farmers would work with up to lead time 2 seasonal forecast information although prefer lead time 1 the most. Thus, I evaluated the performance of the state of the art ECMWF System 4 seasonal climate forecast system up to lead time 2 and discussed the potential of meeting these the identified needs. The skill analysis shows the possibility of meeting farmers' need at their most preferred lead time of 1 month allowing time for proper planning and decision-making. Therefore, model based seasonal forecasts have the potential to provide relevant information required for farmers' farm-level decision making if information providers ensure that information meets the expected needs. However, inaccurate forecast information will negatively affect the reliability even if relevant information is provided.

Chapter 4 and 5 focused on the second and third issue identified during the diagnostics; improving the quality of forecast information and connecting forecast providers and farmers to co-produce. The two chapters focussed on the reliability and acceptability of scientific forecast information using farmers' indigenous forecast and in the process improve co-production of climate services. The call to integrate indigenous and scientific forecast is not new, yet attempt to achieve this is at its infancy stage. A glance through the literature on the subject reveals that very few studies have explored the underlying mechanism (techniques) for generating indigenous forecast and none has particularly tested quantitatively the skills in indigenous forecast as well as develop an objective method to integrate it with scientific forecast. Therefore, in chapter 4 I first explored the techniques for generating indigenous forecast (both weather and seasonal forecast) using a mental modeling approach and assessed the skills in these forecast comparing it to GMet forecast. This form the basis for the integration of indigenous and scientific forecast in addition to testing the reliability and acceptability of integrated forecast among farmers in chapter 5.

In chapter 4, I first used a fuzzy expert system called mental model to investigate the underlying process behind farmers indigenous forecasting techniques. Results show that farmers use observational changes in indigenous ecological indicators (IEIs) in addition to historical rainfall patterns to predict the coming season. In particular, there is a relationship between these observational changes and event predicted (rainfall onset, cessation and amount [below, normal and above] for seasonal forecast or low, medium and high rainfall for weather forecast). The technique to make these predictions are not intuitive but rational and improves with age and experience. Secondly, I employed the concept of citizen science that allowed the collection and exchange of data and knowledge between scientists and farmers, enhancing the co-production process that is currently absent in climate services in the area. Further, I quantitatively evaluated farmers forecast using the World Meteorological organization's acceptable binary forecast verification measure vis-à-vis GMet's forecast. Results show that on average, both farmers and GMet are able to accurately forecast one out of every three daily rainfall events. At the seasonal scale, one out of every three farmers was able to accurately make onset prediction while two out of every five farmers are able to get rainfall amount and cessation right. Similarly, GMet was able to predict rainfall amount accurately in one out of every three communities and one out of every four communities for onset but was unable to accurately predict cessation for the communities. This result, therefore, informs the integration of farmers' indigenous forecast and scientific forecast (from GMet) in chapter 4.

Chapter 5 showed that it is possible to integrate indigenous and scientific forecast into a more reliable forecast that is acceptable by farmers in Northern Ghana. First, following a review of existing literature to determine the strength and weakness of existing integration methods, I developed an integrated probability forecast (IPF) method that is able to integrate both indigenous and scientific forecasts into an objective and reliable forecast information compared to each in isolation. Specifically, The IPF method combines the strengths of IF and SF and subsequently improves their reliability at both daily and seasonal timescale. Secondly, result of an interview with farmers shows that the IPF method had far greater acceptability potential among farmers (93% of farmers accept) because it combines IF and SF into a single forecast, resolves the issues of contradicting forecast information, requires less meeting time and improves forecast reliability.

In chapter 6, I used a Visually Facilitated Scenario Workshops (VFSW) to investigate the impact of forecast probability and lead times on farmers' decision making. Results show that based on their varying degree of risk different types of farmers (irrigated, rainfed and both) respond to forecast probabilities in different ways. Rainfed rice farmers have high risk level and a forecast probability of less than 0.5 will make them hesitate in taking decisions. Weather forecast provided at 1 week and seasonal climate forecast provided at 1 month lead times have the most influence on rice farmers' decision making. Also, fertilizer application and planting are highly sensitive to forecast lead times because of their reliance on water. Finally, for climate services to be useful, forecast information needs to be timely provided and probabilities properly communicated to the different groups of farmers, bearing in mind the varying differences in the sensitivity of each group.

Chapter 7 conclude the dissertation by synthesising the salient findings and providing some recommendations. This dissertation has pushed the agenda to move to a second-generation climate service to support farmers. The anticipatory, inclusiveness, reflexivity and responsiveness nature of the proposed framework in Chapter 2 shows the efficiency and robustness for making climate information services useful for farmers. The framework champions co-production of climate service where farmers are actively engaged in the design, creation and production process. The framework did so by introducing citizen science as a principle that enables the co-production of climate services. This dissertation also provides a novel insight into how to collect, handle, quantitatively evaluate and integrate indigenous and scientific forecast in an objective manner such that the reliability and acceptability of forecast information are achieved for farmers' benefit. The development of the Integrated Forecast Probability (IPF) method provides an answer to the long awaiting question of whether it is possible to integrate indigenous and scientific forecast? My dissertation has not only shown that it is possible but then it also improves the reliability and acceptability of forecast information among farmers. Lastly, findings from this study contribute to improving the uptake of climate information services for agriculture decision-making. Results demonstrated that a two-directional model of climate services where farmers are actively involved in all stages of the process has the potential for forecast information uptake. Showing the potential of providing seasonal forecast at farmers prefered lead time of 1 month and beyond which was previously problematic for even the best models is useful to support farmers' decision in a more flexible manner. Also, I have demonstrated that forecast information with the best possible accuracy will still remain invaluable to farmers if does not meet their farming needs. Therefore, using an interdisciplinary approach to connect forecast products with information needs will contribute to the successful uptake of forecast information by farmers. Furthermore, the utilization of farmers in this study provides fresh insights into the interpretation of local data and methods which otherwise may not be possible to generate in the scientific community even with their best models. For instance, I observed that indigenous forecast is finer in resolution and more valuable at the community level than GMet forecast which is coarse and issued at a regional level. Rather than using scientific downscaling techniques (often limited by model inadequacies and unavailability of observed data) to transform forecast information from a coarser to finer resolutions, local knowledge could be helpful. In addition, communicating forecast information at the appropriate lead time and with the probability of occurrence have a positive influence on farmers to take better decision, proper planning and reducing unrealistic expectations of forecast accuracy and reliability of climate service in general.

The most important recommendation of this thesis, therefore, is to test and incorporate the proposed second generation climate services into National Agricultural policy. Doing this will not only offer the opportunity to manage climate risk and uncertainty in practice but also create a new perspective that will advance our scientific understanding of climate information services.

About the author

Emmanuel Nyadzi was born on 26th August 1987 in Koforidua, Ghana. He completed his Bachelor of Science degree in Agricultural Technology at University for Development Studies, Ghana (2007-2011). After graduating he continued to work as a teaching and research assistant in the same university from 2011-2012. From 2012-2014, he was awarded a scholarship by the German Federal Ministry of Education and Research through the West Africa Science Service Centre on Climate Change and Adapted land use (WASCAL) to pursue a Master of Technology in Climate Change and Adapted Land Use at Federal University of Technology, Minna.

Emmanuel has been involved in several interdisciplinary research projects that focus on climate change. In particular, he sought to understand and model the complexities of climate and environmental change on natural and human systems and develop appropriate measures for adaptation. His ultimate goal is to address relevant scientific gaps while serving practical needs of society.

In January 2016, he started his PhD study at Wageningen University working between the Water Systems and Global Change group, Knowledge technology and innovation and the Public Administration and Policy group, all at the same university. The research focused on developing climate services for water management and food production in Ghana. Within this period, Emmanuel also worked as a research officer / Consultant at MDF west Africa. In January 2020 he started as a postdoctoral researcher at the Water system and Global change group at Wageningen University where he continues to focus on climate services with particular focus on climate change risk assessment and management for the financial and transportation (rail) sector in the Netherlands.

List of publications

1. **Nyadzi, E.,** Werners, E. S., Biesbroek, R., Long, P. H., Franssen, W., & Ludwig, F. (2018). Verification of Seasonal Climate Forecast Towards Hydro-Climatic Information Needs of Rice Farmers in Northern Ghana. Weather, Climate, and Society, 11(1), 127-142.

2. **Nyadzi E.,** Nyamekye B. A., Werners E. S., Dewulf A, Biesbroek G. R., Van Slobbe E., Hoang P. L., Termeer J.A.M. C., Ludwig F. (2018). Diagnosing the Potential of Hydro-Climatic Information Services to Support Rice Farming in Northern Ghana. NJAS-Wageningen Journal of Life Sciences, 86, 51-63.

3. **Nyadzi E.** (2016). Climate Variability since 1970 and Farmers´ Observations in Northern Ghana. Sustainable Agriculture Research; Vol. 5, No. 2; 2016

4. **Nyadzi E.,** Nyarko. K. B, Ezenwa I.S. M. (2019). Distribution of Soil organic carbon stocks on burnt and unburnt fallow lands of different vegetation types in Northern Ghana. Earth Science Research; Vol. 8, No. 1; 2019

5. **Nyadzi E.,** Ezenwa I.S. M., Nyarko. K. B., Okhimamhe A. A. Bagamsah T. T., Okelola, O. F. (2015). Assessment of trace gas emissions from wildfires under different vegetation types in northern Ghana: implications for global warming. Environment and Natural Resources Research; Vol. 5, No. 2; 2015.

6. Abagale F. K., Coffie J. and **Nyadzi E.** (2012). Quantification and Nutrient Levels of Eroded Soil of Farmlands in Northern Ghana. International Journal of Forest, Soil and Erosion (IJFSE), 2012 2 (4): pp. 192-194.

7. Osei, R. A., Abagale, F. K. and **Nyadzi, E.** (2011). Chemical Contaminants Reduction of Wastewater Used for Peri-Urban Agriculture in Northern Ghana. International Journal of Current Research Vol. 3, 4 Issue, 11, pp.030-036.

8. **Nyadzi E.,** Werners E. S., Biesbroek G. R., Ludwig F. (2018). The role of Sapelli in collecting indigenous Weather/climate forecast data. Extreme Citizen Science blog: University of Central London's Interdisciplinary Research Group on Extreme Citizen Science.

https://uclexcites.wordpress.com/2018/05/01/the-role-of-sapelli-in-collecting-indigenous-weather-climate-forecast-data/

9. **Nyadzi E**., Werners, E. S., Biesbroek, R., & Ludwig, F. (Under review). Towards Weather and Climate Services that Integrate Indigenous and Scientific Forecast to Improve Forecast Reliability and Acceptability in Ghana.

10. **Nyadzi E.,** Werners, E. S., Biesbroek, R., & Ludwig, F. (under review). Techniques and Skills of Indigenous Weather and Seasonal Climate Forecasting in Northern Ghana.

11. Nyamekye, A. B., **Nyadzi, E**., Werners, S. E., Biesbroek, R. G., Dewulf, A., Van Slobbe, E., Termeer C. J.A.M. & Ludwig, F. (under review) Forecast probability, lead time and farmer decision-making in rice farming systems in Northern Ghana.

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SENSE PhD Courses

- Environmental research in context (2016)
- Research in context activity: 'Winner of Famelab regional contest(Netherlands): explaining a scientific concept to a general audience (2018)'

Selection of Other PhD and Advanced MSc Courses

- Environmental Virtual Observatories for Connective Action: modules on 'Environmental virtual observatories for connective action; Input, output and Context', 'Responsible life-sciences innovations for development in the digital age; from theory to practice, 'Dynamic duos – presentation and critical comparison of cases from an interdisciplinary perspective', 'Cooperative, collaborative, connective – visions and modes of participatory action and 'The Art of Integrated Research', Wageningen University (2016)
- Climate change adaptation in the water sector, Wageningen University (2016)
- School on climate and environmental modelling, ICTP, Italy (2019)

External training at a foreign research institute

- Training 'Extreme citizen science', University College London (2016)
- Masterclass: 'Climate services for water, health and food security in a changing climate', EUPORIAS (2016)
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Oral Presentations

- *Water monitoring in irrigated rice production systems in Ghana*, 1stInternational EVOCA workshop, 11-13th May 201, Wageningen, The Netherlands
- *Collecting and handling indigenous forecast; the citizen science approach*, 4th International EVOCA workshop, 27-29th August 2019, Wageningen, The Netherlands
- *Two heads are better than one: A climate services that integrate indigenous and scientific forecast in Ghana*, African Climate Risk Conference, 7-9th October 2019, Addis Ababa, Ethiopia

SENSE coordinator PhD education

Dr. ir. Peter Vermeulen

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