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Forecast probability, lead time and farmer decision-making in rice farming systems in Northern Ghana

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A R T I C L E I N F O

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A B S T R A C T

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 probabilities and lead times 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. Also, an increase in forecast probability does not necessarily mean farmers will act. The decision to act based on forecast probability is dependent on the stage of the farming cycle. Also, seasonal forecast information provided at a 1 month lead time significantly informed farmer decision-making compared to a lead time of 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 forecast information with their probabilities and at an appropriate lead time has the potential to 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 1 month lead times respectively. Farmers should also adapt their decisions to the timing and probabilities of the forecast provided.

1. Introduction

Agriculture development in many parts of Africa is heavily impacted by climate variability and change (Harris and Consulting, 2014; Pereira, 2017). The increasingly unpredictable and erratic nature of weather and seasonal conditions on the continent is

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expected to compromise agricultural production and rural livelihoods, especially in smallholder systems with little adaptive capacity (Cooper et al., 2008; Kurukulasuriya et al., 2006). 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 about 1.6% of land under irrigation (Fao, 2014; World Bank, 2010). The Savanna belt of the country is most impacted throughout the year with irregular rainfall, high temperatures and water scarcity conditions (Nyadzi, 2016; Akudugu et al., 2012; 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).

Access to useful and usable climate information is considered as an important step in making the agriculture sector climate-resilient (Vaughan and Dessai, 2014). This realisation is fast-growing and different stakeholders are putting in efforts to develop and promote climate services that assist farmers to take adaptive farm decisions (Hansen et al., 2019; Lourenço et al., 2016). However, there has been little progress in providing actionable climate information that makes a difference to farmers (Tall et al., 2018). Climate services for the agriculture sector have been criticised for several reasons. First, they provide information at a more coarse resolution rather than farmers locality (Vogel and OBrien, 2006). Second, they are too technical in format to be interpreted by illiterate farmers (Pennesi, 2007). Third, the accuracy of forecast information remains a challenge (Johnston et al., 2004). Fourth, limitations in communicating forecast probabilities (Goodwin and Dahlstrom, 2011). These challenges are exacerbated by the disconnect between service providers and end-users (Ouedraogo et al., 2018), and unavailability of quality data in most parts of Africa attributable to existing gaps in climate observations due to malfunctioning of meteorological stations and lack of capacity in using satellite data services (WMO, 2006).

In Ghana, farmers seek forecast information such as rainfall amount, rainfall distribution, onset, cessation etc. for informed decision-making(Grothmann and 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 and Rapera, 2014; Nyadzi et al., 2019). Currently, farmers in Northern Ghana obtain forecast information from public and private service providers such as the Ghana Meteorological Services, ESOKO and Farmerline (Nyamekye et al., 2019). Despite the expansion in climate information services, smallholder farmers are yet to see the significant effect on their production and productivity in farming systems with the underlying reason that not all meteorological information made available to farmers is accessible, and if accessed could sometimes not be useful nor usable (Adiku et al., 2007). For example, whilst focusing on gender-responsiveness to climate services, Partey et al. (2020) in a study in the Upper West Region of Ghana opine that women are more constrained in accessing climate information due to illiteracy and the limited access to mobile phone technology which is essential for meteorological information uptake. Similarly Antwi-Agyei et al. (2015) whilst highlighting the barriers to climate adaptation among farming households in north-east Ghana point to technological barriers, the lack of, as well as the need for effective communication of climate information as challenges worth addressing through research and programme intervention. Although the aforementioned scholarly works make significant contributions to information uptake challenges, further research is needed to address the gap in information provision and use in farming systems by establishing what component of meteorological information is relevant for farmers.

This paper contributes to understanding farmers forecast information needs by focusing on several variables. First, to ascertain how the timeliness of information could enhance or otherwise inhibit adaptation through informed 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 on the works of Nyadzi et al. (2019) and Nyamekye et al. (2018) who studied forecast information needs and decision making amongst rice farmers 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 regarding rainfall. Nyamekye et al. (2018) also explored farmer adaptive decision-making and reiterate 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 as Ghana aims to make climate services more functional and impactful in farming systems especially in the Savannah zone, which happens to be a major food basket. 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 make decisions?
2. How does seasonal forecast lead time influence farmers' decisions?
3. How does weather forecast lead time influence farmers' decisions?

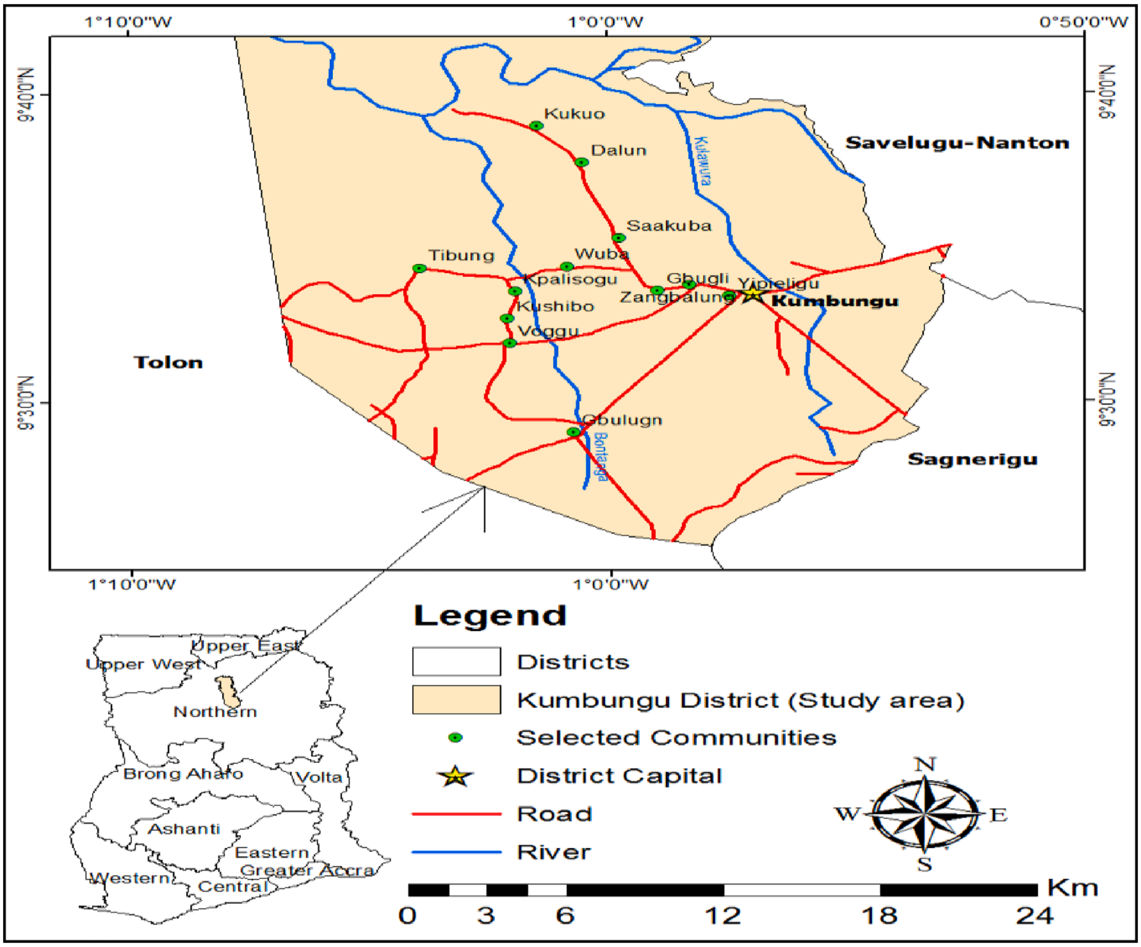

Fig. 1. Map showing the study location.

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 productivity (Buytaert et al., 2010; Termeer et al., 2011). Thus, a knowledge of what alternatives farmers consider in optimizing utility is central in understanding decision-making. Implicitly, the introduction of new information all things being equal could change decision dynamics due to new frames which could increase or reduce risks farmers are faced with (Barnes et al., 2013; Wallace and Moss, 2002). Where available, the degree to which such information is accurate matters for decision-making (Weaver et al., 2013).

Meteorological information as a resource informs decision dynamics through a process of (re)framing to reduce risks (Barnes et al., 2013; Wallace and 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 (Dewulf and Biesbroek, 2018; Weaver et al., 2013). In climate change literature, communicating forecast probability and at the appropriate lead times have been highlighted in bridging climate information usability gaps in decision-making (Lemos et al., 2012; Mase and Prokopy, 2014; Podestá et al., 2002; Roudier et al., 2014). The literature explains forecast lead time as the length of time between the issuance of a forecast and the occurrence of the phenomena that was predicted (Ogutu et al., 2017; Glossary, 2012). Probability remains an important and best way to consistently and verifiably show uncertainty in forecasts in a manner that assists users to determine the risk related to particular weather or seasonal climate events. Forecast probability denotes the likelihood that an event will occur usually expressed in percentage (Gmoser, 2008; Doswell and Brooks, 2001). Uncertainty about future events requires that decision-makers continuously adjust farm practices by adopting proactive and reactive strategies in managing events (Dewulf and Biesbroek, 2018). Forecast probability equally has a significant implication on choice making as farmers attempt to minimize the adverse effect of seasonal and weather conditions. In this study, weather forecast is interpreted as the probability that at least the minimum amount of rainfall will occur on a particular day

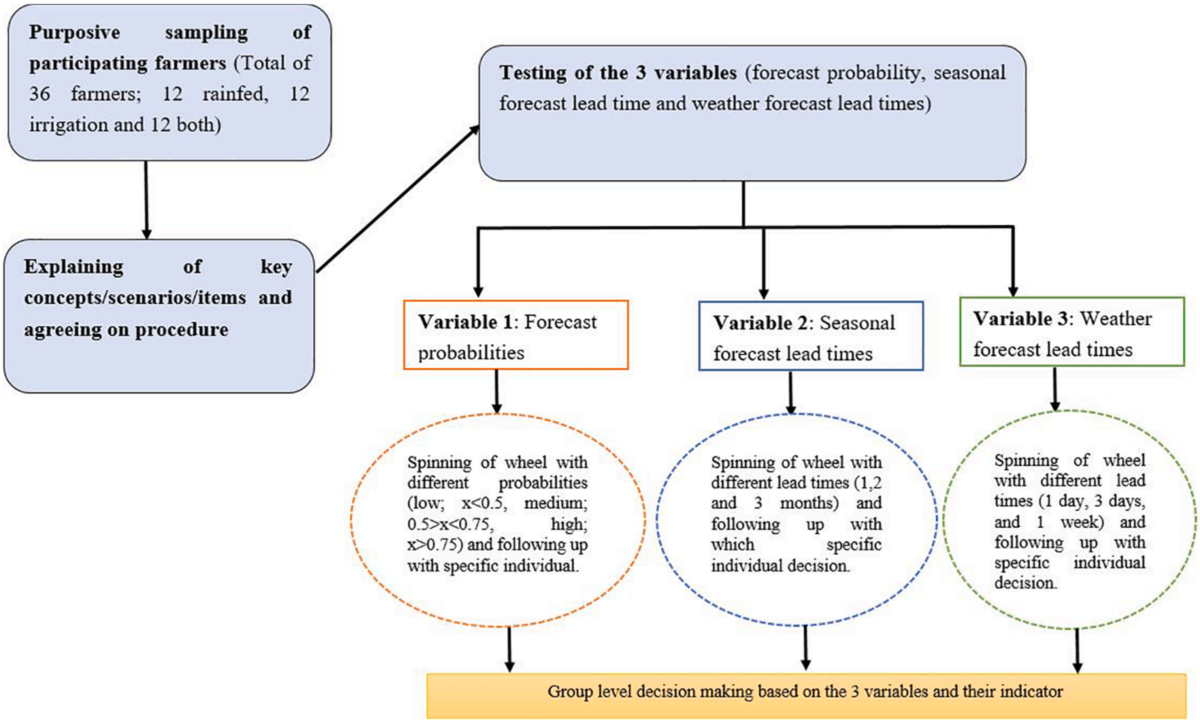

Fig. 2. Stepwise approach to the VFSMW.

whereas seasonal forecast is explained as on the onset of the rains for the season. 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 and Hendon (2013) affirm and buttress how unreliability remains an impediment to the uptake of climate-related information. On the subject of lead time, seminal works such as that by Apipattanavis et al. (2010) conclude that providing forecast information with a sufficient lead time to adjust critical agricultural decisions, have significant potential to improve the efficiency of agricultural management and to ensure food and livelihood security.

Drawing on the aforementioned, discussions on climate services have sought to shift the emphasis on forecast provision to understanding the conditions under which such becomes valuable for decision making (Kirchhoff et al., 2013). Hammer, (2000) whilst referring to seasonal climate forecast is quick to indicate that meteorological forecast is of no value except when it can influence decisions of users. In further positioning this study, we postulate that the meteorological forecast that informs farmer decisions and can be described as useful is that which is sensitive to lead time and indicative of probability. In this respect, the relationship between probability or lead time and farmer decision-making when explored will result in choice-making amongst farmers geared towards optimizing utility. Singh et al. (2016) thus re-iterate that whilst decisions are shaped by asset availability, risk perception, time and experience, there is the need to affirm that a farmer in question has the intention to act. Thus, we theorise that for farmers engaged in this study, decision-making will entail both intentions and actions given meteorological forecasts with explicit communication of lead time and probability.

3. Methodology

3.1. *Study area*

The study was undertaken in the Kumbungu District in the Northern region of Ghana as shown in Fig. 1. The district, located within the Guinea Savannah agro-ecological zone covers a land area of 1,599 km^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 and 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 1000 mm with the main cropping season stretching throughout 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 vegetables mostly produced within the scheme.

3.2. Research design

This study adopted an exploratory research methodology which generates generally qualitative results to provide insight into whys and what of problems in this case with the use of Scenario Workshops (SW). SWs have roots in technological assessments and originally designed to facilitate engagement between scientists and citizens in the appraisal of new technologies (Andersen and Jaeger, 1999). SWs have also dominated planning circles for giving a participatory foresight to resource management and also in engaging citizens in testing technological solutions (Andersen, and Jaeger, 1999; Rinaudo et al., 2012). The study adopted a so-called Visually Facilitated Scenario Mapping Workshop (VFSMW) approach (Hatzilacou et al., 2007; Mexa, 2002; van Vliet and Kok, 2015) whilst focusing on three main groups of farmers; irrigated, rain-fed and those who practised both. The design involved a series of workshops where farmers were exposed to different scenarios involving information variables of interest with the aid of visual diagrams to establish insight into decision-making by farmers when faced with different scenarios.

A total of five workshops were organised at a meeting hall within the confines of the Bontanga Irrigation Scheme between November 2018 and January 2019. The first workshop, held in the first week of November, was aimed at selecting and familiarising with the participants and explaining to them the rationale of the study. This 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. Besides, rules of engagement were communicated to the participants and opportunities created for questions and clarifications. The second, third and fourth workshops, held within agreed 2-week intervals, were the VFSMW specifically focused on engaging different farmer groups directly to explore how they will relate with the different information variables (see Section 3.3) and what that means for farmer decision-making. The second, third and fourth workshops were held with irrigated, rainfed and those engaged in both respectively. In the second, third and fourth workshops, farmers were presented with cardboard and spinning wheels showing the different levels of certainty and forecast lead times. On the cardboard was a matrix showing the cropping cycle (See Fig. A.1) for easy representation and understanding considering literacy levels of participants. Individually, the 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), and lead time (weather). Each variable also had three main indicators for which farmers were required to show what decision they will take given these indicators. The purpose of the wheel is to allow for randomization of the information to be tested (See Fig. A.1). Beginning with the first wheel (probability wheel-variable 1), each participant spins the wheel and depending on the probability observed, tells whether or she will take action. The participant continues the exercise and provides feedback on the different probabilities recorded. The participant then moves to wheel 2 (seasonal lead time wheel-variable 2), spins the wheel and indicates what decision he or she will take if seasonal forecast is communicated at the different recorded lead times. The participant then completes the same process for the third wheel (weather lead time). The fifth workshop was finally organised to validate findings and provide an opportunity for feedback from participants. The process for VFSMW is summarized in Fig. 2.

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 were purposely sampled for the VFSMW workshops (See Fig. 1). Although about 90 percent inhabitants in the district are engaged in agriculture-related activities, the study focused on rice farmers with a convenient sample chosen for the exercise. The farmers were purposively selected on the basis that they are experienced and have ample knowledge of rice farming stages and decisions. The selection was spread across 12 different communities in the area and an equal number of farmers were selected from each community and based on farming type; 3 per community engaged in either rainfed, irrigated or both. The socio-demographic characteristics of the selected farmers were typical of those in the area. The characteristics of the farmers and the homogeneity of their information needs are described elsewhere (Nyadzi et al., 2019). According to Patton (2002) even though this sampling technique may use a small sample, they are particularly useful in exploratory qualitative research where a small number of cases can be decisive in explaining the phenomenon of interest.

3.4. Testing the variables

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. The exercise was carried out in this order: first, how the probability of forecast informs farmers' decision-making, secondly how seasonal forecast lead times influence farmer decision-making and thirdly how weather forecast lead times shape farmer decision-making.

Variable 1: Probability of rainfall forecast

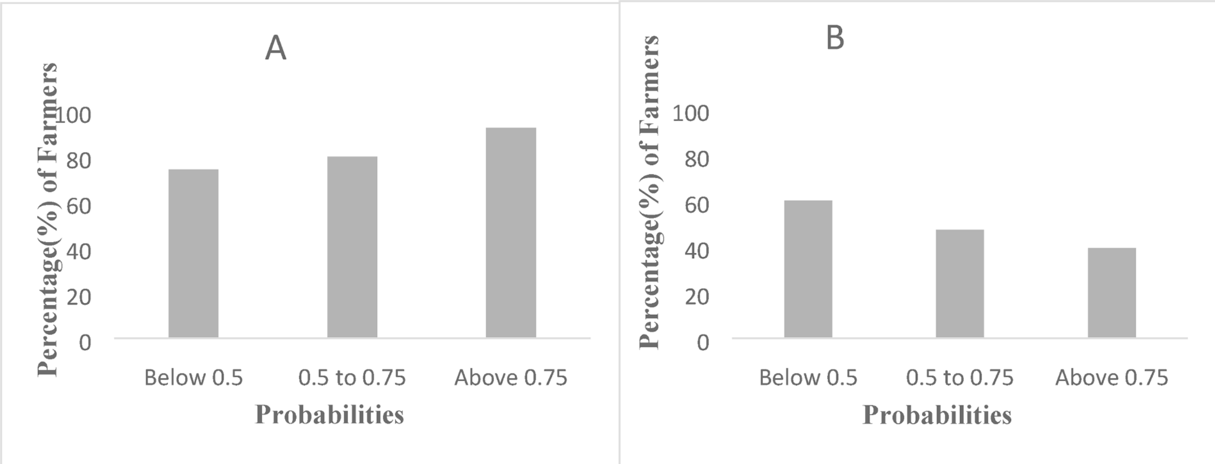

Fig. 3. The general influence of forecast probabilities on farmers' decision to act (n = 36 farmers). [A. Preseason and planting B. Land Preparation,1st and 2nd weed control, 1st and 2nd fertilizer application and harvesting].

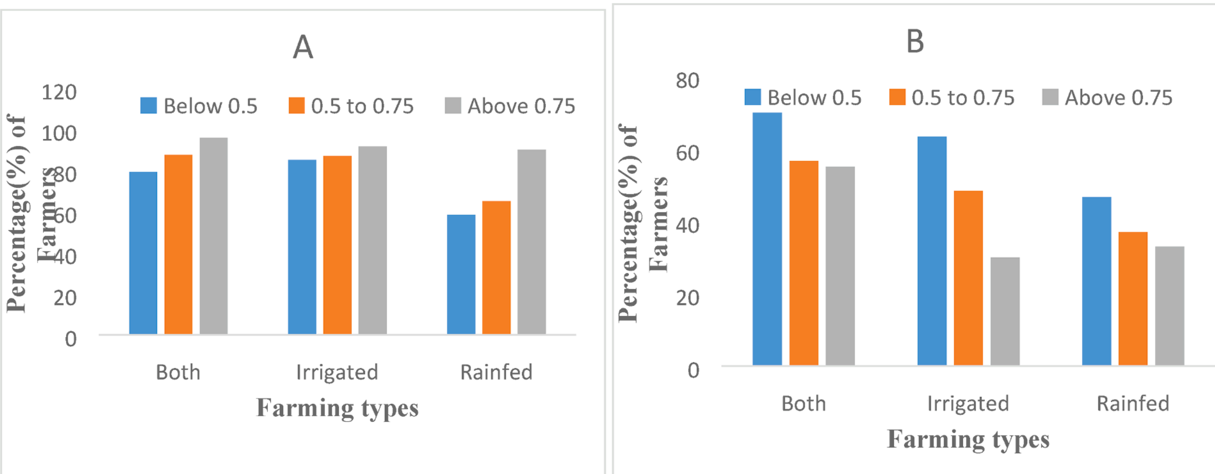

Fig. 4. The impact of forecast probabilities on different types of farmers' decision to act (n = 36 farmers) [A. Preseason and planting B. Land Preparation,1st and 2nd weed control, 1st and 2nd fertilizer application and harvesting].

The degree of certainty associated with weather and seasonal climate information is expected to inform farmers' information uptake and adaptive decision-making. Here, participants were presented with information showing different probabilities of forecast (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 inquired whether farmers would act or not given the different probabilities associated with forecasts on rainfall.

Variable 2: Seasonal (rainfall) forecast lead times

The timing of information provision at seasonal timescale all things being equal affords decision-makers, in this case, farmers to have more room in deciding what to do. 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 assumption is that given different lead times, farmers will take different decisions.

Variable 3: Weather (rainfall) forecast lead times

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 identified which decisions farmers will take given lead times of 1 day, 3 days and 1 week. The assumption is that farmers take different decisions when forecast on rainfall is provided at a lead time of 1 day, 3 days and 1 week.

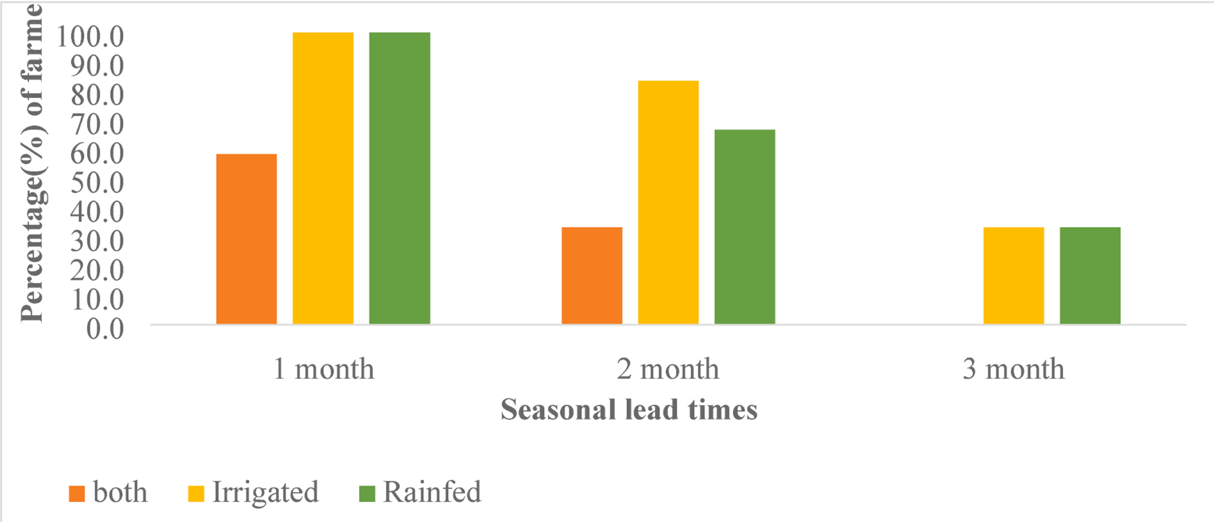

Fig. 5. Farmers willingness to act given seasonal forecast at different lead times (n = 36 farmers) [*None of the farmers practising both indicated they will act on a 3 month seasonal forecast]

3.5. Data analysis

We employed a qualitative approach to our data analysis. Farmers responses were documented based on farming type, variables and indicators. Responses during farmer engagement in the 2nd, 3rd and 4th workshops were recorded in excel sheets. Outcomes of the 5th workshop (validation workshop) were also recorded and transcribed. Key themes developed from the data include pre-season and in-season decision making; lead time, uncertainty and forecast information uptake. Using SPSS version 23 data collected from the workshop were collated, cleaned and sorted. Data was then analysed given qualitative responses and supported by quantitative representations such as frequencies and percentages where feasible.

4. Results

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 that decisions taken during pre-season and planting are most sensitive to forecast probabilities. It emerged that, as probability increases, farmers are willing to take action on forecast information received (see Fig. 3A). However, an inverse relationship between forecast probability and decision making was observed during the remaining stages of the farming cycle. The study showed that 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 Fig. 3B). 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 into the soil and undertaking such in the moment of expected rainfall could result in the fertilizer being washed away. Thus, although a high probability is a good indicator of rainfall occurrence, it also results in non-action taking as a response. A detailed breakdown of the farmer’s specific response under each farming type for each stage is presented in Table B1.

A further disaggregation given different farming types, and the proportion of participants who indicated that they would use the forecast information to inform any of the multiple land management decisions are shown on Fig. 4A and B. Irrigated rice farmers and to an extent, those who practised both are least sensitive to different forecast probabilities compared to rainfed farmers. For irrigated farmers, this is due to the option of meeting water needs through supplementary irrigation. Farmers who practised both also faced lesser risk since they can still count on their irrigated farms should the rains fail. Rainfed farmers remain most sensitive because they have no option except to face their loss and thus are more sceptical in their decision making.

At the pre-season and planting stages as shown in Fig. 4A, irrigated farmers will act irrespective of the probability of rainfall occurring as communicated in the forecast. Also, more rainfed farmers and those practising both will act given forecast information with higher probability. However, during land preparation, weed control and fertilizer application, forecasts with high probability were faced with negated action by all groups of farmers (see Fig. 4B). For example, irrigated farmers will also not fertilize if the probability of rainfall is high as this will result in the washing away of fertilizer. Detailed results are presented in Table B1.

Furthermore, interaction with farmers at the group level in the 5th workshop provided further evidence to confirm or otherwise the

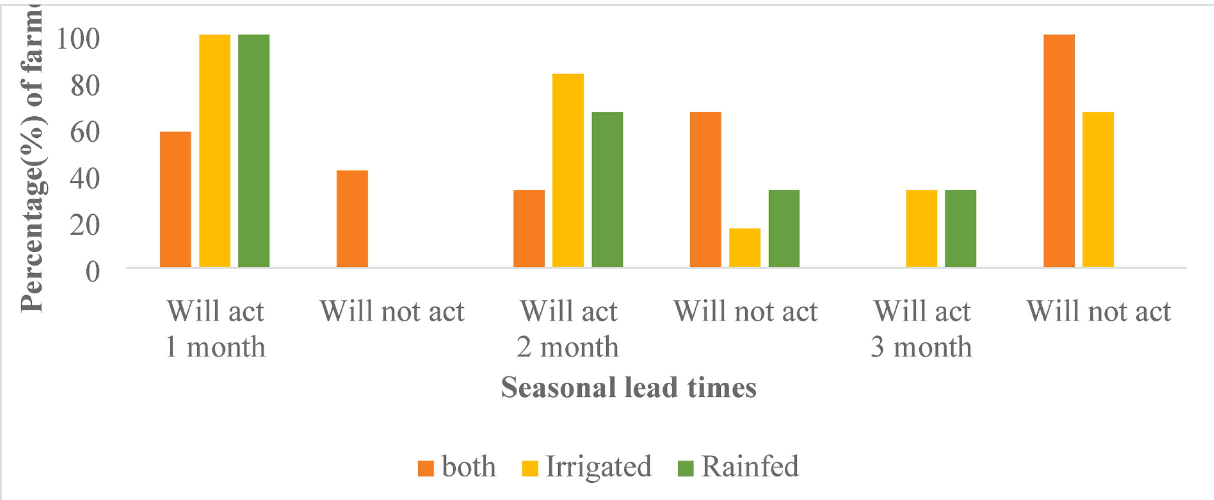

Fig. 6. Percentage of farmers indicating that they will take a decision to act or not under different seasonal forecast lead times (n = 36 farmers).

Table 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	25	72
	Will clear land using a tractor	88	75	28
Planting	Will broadcast seeds	88	70	64
	Will nurse and transplant seedlings	11	17	19
	Will plant using the dibbling method	–	14	17
1st Fertilizer Application	Will apply fertilizer by broadcasting before the rain	3	17	47
	Will apply fertilizer by placement after the rains	97	83	53
Weed Control	Will apply weedicide before the rains	92	97	–
	Will apply weedicide after the rains	8	3	100
2nd Fertilizer Application	Will apply fertilizer by broadcasting before the rain	11	44	36
	Will apply fertilizer by placement after the rains	89	56	60
Weedicide Control	Will apply weedicide by spraying before the rain	19	86	94
	Will apply weedicide by spraying after the rain	18	14	6
Harvesting	Will harvest with a sickle	25	25	36
	Will harvest with a combine harvester	75	75	64

results obtained from individual farmer engagement. Farmers confirmed that a higher probability (above 0.75) helps in concreting choice making on whether to take action or withhold undertaking an intended activity with the ultimate aim of maximizing yield and productivity.

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 informs 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 is a convergence in opinions between irrigated rice farmers and rainfed rice farmers on how seasonal forecasts at different lead times influence their decision-making. This is shown in Fig. 5.

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 Fig. 6). All farmers practising both indicated that they will not act on seasonal forecast information communicated at a 3 month lead time as it is too early a period to pursue any farm-related activity (see Table C1).

Further interactions at the group level during the workshops showed that although seasonal forecast is important for decision-making, 92% of farmers in 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 the 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 entail arrangements for farm labour and tractor acquisition. However, seasonal forecasts presented at 3 months and 2 months lead time are not relevant for such decisions as compared to 1 month with 90% of farmers confirming such.

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 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 during planting, the majority of farmers indicated they prefer to broadcast 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 the 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 is less sensitive to rainfall with about 92%, 97% and 100% indicating they will apply weedicide before rainfall when forecast information is communicated at 1 day, 3 days and 1 week respectively. Here, farmers indicated they 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.

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 1 day, 3 day time and 64% of farmers will use the same method at 1 week lead time.

It emerged that weather forecasts provided at different lead times come with choices farmers find most appropriate that minimise their risk and increase their chances of completing activities. At no point did farmers point to not doing anything given weather forecast at different lead times. Table 1 presents the percentage to which a particular choice is made by farmers at different stages. A more detailed information is presented in Table D1.

Generally, forecasts provided at 1 week lead time better positions farmers to decide on acting or otherwise, 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.

5. Discussion

This paper sets out to understand how forecast sources, lead times and probability inform farmer decision making in rice farming systems. We explored this relationship using different information scenarios and groups of farmers in a bid to investigate how seasonal and weather forecasts could be tailored to farmer information needs in farming systems. In this section, we discuss how key findings from the study contribute to insight on meteorological information needs and broadly the operations of climate services in Ghana.

Firstly, our findings reveal that communicating forecast information with different probabilities in Northern Ghana significantly inform farmer decision-making. However, a high probability does not necessarily result in action on the side of farmers. Our findings indicate that farmers respond to different forecast probabilities depending on the stage of the farming cycle and activities involved. For instance, farmers will undertake planned actions during pre-season and planting when forecast information hints of a higher probability of rainfall occurring. On the contrary, a higher probability does not translate into action during land preparation, weed control, fertilizer application and harvesting. Thus, farmers' response 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 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.

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 and Vogel, (2003) concur that the probabilistic nature of weather and seasonal climate forecasts present particular challenges. Hence, for effective use of forecast information, farmers 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 probability is<0.5. This was contrary in the case of rainfed farmers.

Also, in communicating forecast probabilities information services need to reflect on the ways in which they are presented. From the study, using simple graphics with appealing colours to represent forecast probabilities is an effective way of making farmers understand what is being communicated. Non-literate 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 probability. 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. Furthermore, follow-ups on how a change in probability impacts farmer decision-making or practices will enhance our understanding of the pros and cons of a failed forecast on farmers' livelihood.

The study outcomes also confirm that farmers made different decisions when presented with forecasts detailing different seasonal and weather lead times. However, not all lead times essentially inform decision-making. For example, seasonal forecast information provided 3 months ahead of time is irrelevant in taking pre-season decisions. Majority of farmers prefer seasonal forecast information to be communicated at a 1 month lead time. In our context, this is the period within which most pre-season arrangements (farm machinery, labour, seeds, etc.) are initiated. 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 forecasts when provided too early. They acknowledge that lead time must conform to users' needs and priorities. Essentially, the lead time for communicating seasonal forecasts 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 (Mase and Prokopy, 2014; Stone et al., 2006). 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. Also, the sensitivity of farmer decision to water availability conditions is more severe at the first stage of fertilizer application than the second. Farmers thus face a greater risk of crop loss within the period of the first fertilizer application than the second.

The use of Visually Facilitated Scenario Mapping Workshops also renders the opportunity to explore hypothetically how a future functioning climate service providing farmers with forecast information under different conditions could inform their decision-making. Our methodology builds on existing presentations on Scenario Workshops by introducing visuals and hence more convenient in co-production and citizen science experiments on climate services. However, the results of this exercise could slightly differ from real time events where other social and biophysical conditions are not held constant (Andersen and Jaeger, 1999; Mayer, 1997).

Our methodology also had a number of limitations. First, maintaining other external factors (finance and resource availability, etc.) constantly could not depict a vivid environment for which farmers make decisions. Secondly, the experiment focused on rainfall without consideration for other atmospheric variables (temperature, humidity, etc.) which also could have influenced farmers' decision outcomes. Hence, a similar study with a broader look at other variables could produce different results in different contexts. Thirdly, our test focused on farmer decision-making under normal conditions. However, performing this experiment under extreme situations could afford the opportunity to analyse comparatively what decisions farmers take under different situations. Also, the selection of a convenient sample for the exercise limits the generalisability of the study findings. Hence even though the outcomes offer insight into farmer decision-making, a more rigorous quantitative process with a larger sample will be needed to substantiate findings and possible generalisation.

6. Conclusion

In a nutshell, the results of this study have critical implications for the design and operation of climate services, particularly in Northern Ghana. First, the results confirm that different farm types (irrigated, rainfed and both) in the study area require forecast information at specific lead times and probabilities. Hence, operators of climate 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. Also, 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. Thus, understanding these dynamics can extensively improve acceptance and uptake of weather and seasonal information making climate services more useful and impact oriented.

The study makes a novel contribution to understanding how forecast information communicated at the appropriate lead times and probabilities could make climate services more useful for farmers. Specifically, we discover that 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 communicated at 1 week and 1 month lead times respectively most conveniently informed farmer decision making. Also, fertilizer application and planting decisions are most sensitive to rainfall. Irrigated rice farmers also have comparatively lower risk levels and will act irrespective of forecast probabilities. 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.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices

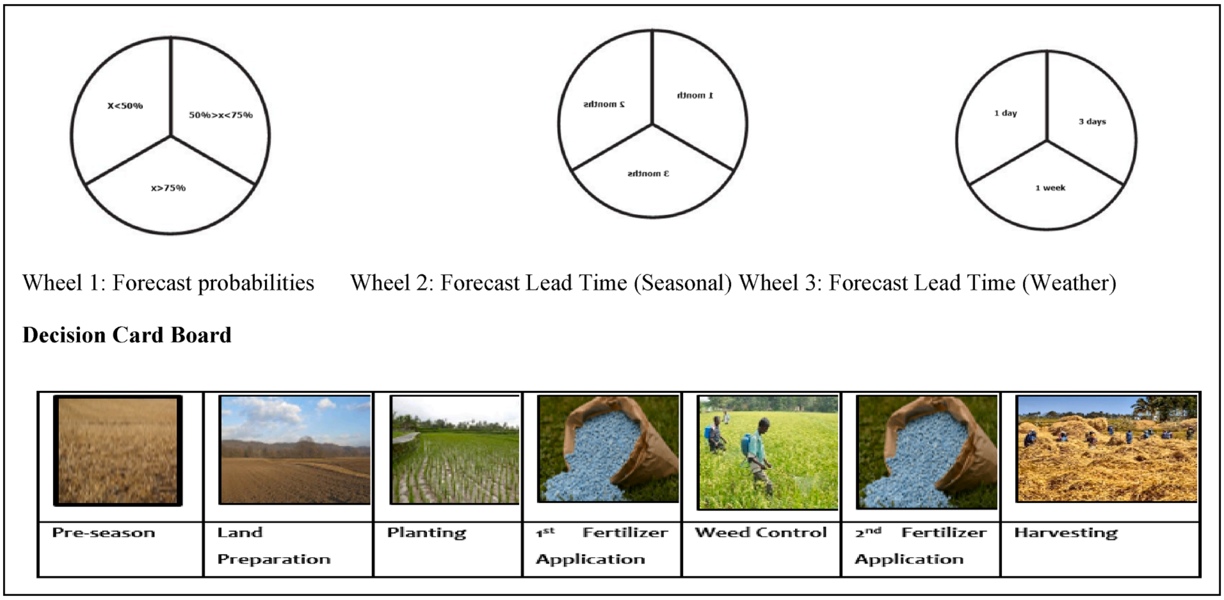

Fig. A1. Farming stages as shown on the cardboard.

Table B1
Farmers decision choices given forecast probabilities (n = 36).

Farming stage (Probability)	Decision	Both	Irrigated	Rainfed
Pre-season (Below 50)	Will act	11	10	7
	Will not act	1	2	5
Pre-season (50–75)	Will act	10	12	7
	Will not act	2	0	5
Pre-season (Above 75)	Will act	12	12	11
	Will not act	0	0	1
Land Preparation (Below 50)	Will act	12	5	9
	Will not act	0	7	3
Land Preparation (50–75)	Will act	12	9	4
	Will not act	0	3	8
Land Preparation (Above 75)	Will act	9	5	6
	Will not act	3	7	6
Planting (Below 50)	Will act	8	12	7
	Will not act	4	0	5
Planting (50–75)	Will act	11	10	7
	Will not act	1	2	5
Planting (Above 75)	Will act	11	10	7
	Will not act	1	2	5
First Fertilizer Application (Below 50)	Will act	5	6	0
	Will not act	7	6	12
First Fertilizer Application (50–75)	Will act	1	3	0
	Will not act	11	9	12
First Fertilizer Application (Above 75)	Will act	0	0	0
	Will not act	12	12	12
Weed Control (Below 50)	Will act	12	12	8
	Will not act	0	0	4
Weed Control (50–75)	Will act	9	7	6
	Will not act	3	5	6
Weed Control (Above 75)	Will act	8	4	6
	Will not act	4	8	6
Second Fertilizer Application (Below 50)	Will act	2	4	0
	Will not act	10	8	12
Second Fertilizer Application (50–75)	Will act	1	1	1
	Will not act	11	11	11
Second Fertilizer Application (Above 75)	Will act	0	1	1
	Will not act	12	11	11
Harvesting (Below 50)	Will act	11	11	11
	Will not act	1	1	1
Harvesting (50–75)	Will act	11	9	9
	Will not act	1	3	3
Harvesting (Above 75)	Will act	10	7	9
	Will not act	2	5	3

Table C1
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	22	61	8	22
Will not Act	5	14	14	39	28	78

Table D1
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	9	*25*	26	72
	Will clear land using a tractor	32	89	27	75	10	*28*
Planting	Will broadcast seeds	32	89	25	70	23	64
	Will nurse and transplant seedlings	4	11	6	17	7	19
	Will plant using dibbling method	–	–	5	14	6	17
1st Fertilizer Application	Will apply fertilizer by broadcasting before the rain	1	3	6	17	17	47
	Will apply fertilizer by placement after the rains	35	97	30	83	19	53
Weed Control	Will apply weedicide after the rains	3	8	1	3	36	100
	Will apply weedicide before the rains	33	92	35	97	–	–
2nd Fertilizer Application	Will apply fertilizer by broadcasting before the rain	4	11	16	44	13	36
	Will apply fertilizer by placement after the rains	32	89	20	56	2	60
Weedicide Control	Will apply weedicide by spraying after the rain	29	81	5	13.9	2	56
	Will apply weedicide by spraying before the rain	7	19	31	86	34	94
Harvesting	Will harvest with a sickle	27	25	27	25	13	36
	Will harvest with a combine harvester	9	75	9	75	23	64

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