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ARTICLE

Co-designed Practical Use of Probabilistic Climate Advisories among Smallholder Farmers: A Balance between Confidence and Caution

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ABSTRACT

Especially for smallholder farmers with limited land and financial resources, farming in arid and semi-arid lands (ASALs), where season-to-season rainfall fluctuation dictates production, is a risky business. Through participatory approaches, this study compares deterministic and probabilistic interpretations of climate forecasts and their use by smallholder farmers through a crop-growing season. The study revealed that deterministic advisories are good for smallholder farmers only when formulated from forecasts with higher accuracy than the historical climatological distribution. Otherwise, they cause farm loss in terms of labor and inputs. On the other hand, probabilistic advisories help farmers spread the risk to cater to all the uncertainty and in so doing bring out a balance between confidence and caution. However, farmers must be supported with enough sensitization to comprehend forecast probability, translate it into probabilistic advisories and use that to plan and manage farm activities. The findings support the hypothesis providing packaged climate products in transparent probabilistic terms in place of deterministic form can overcome inherent credibility challenges. The study's conclusion highlights important takeaways and new understandings of the advantage of using probabilistic advisories among resource-poor smallholder farmers.

Keywords: Smallholder farmers; Deterministic advisories; Probabilistic advisories

1. Introduction

proven to help vulnerable communities such as smallholder farmers to better manage climate risks and maximize the opportunities posed by the same.

Climate information access and use have been

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Copyright © 2023 by the author(s). Published by Bilingual Publishing Group. This is an open access article under the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License. (https://creativecommons.org/licenses/by-nc/4.0/). Technological advancement in the collecting, processing and communicating climate information services has led to improved availability of climate information services. However, uptake of these services among the resource-poor smallholder farmers especially in the dryland regions of Sub-Saharan Africa is still low ^[1,2]. The credibility issues associated with climate services are among the many inhibitors of improved uptake ^[1,2].

Forecasters can only provide probabilistic forecasts rather than saving with certainty whether a certain region will receive wet or dry conditions during a particular time scale, for instance, a crop growing season. However, meteorological services providers especially in Sub Saharan Africa do not communicate forecasts in their full probabilistic form but rather translate them into deterministic terms based on the highest tercile probability [3] (Tercile probabilities are the forecast probabilities that the rainfall amount in a particular season will be in the lower 33.3% of the climatology hence dry, the middle 33.3%, hence normal rainfall, or the upper 33.3%, hence wet season). They do this under the impression that providing users with information about forecast probability will confuse them. In this line of thought, deterministic interpretation of the forecasts is then used to formulate deterministic advisories. For instance, if the season forecast says there is a 45%, 30%, and 25% probability of having above-normal, normal and below-normal rainfall respectively, the communicated forecast will be the one with the highest probability of occurrence and in this case, above-normal rainfall. From this forecast, a deterministic advisory is issued advising the farmers to plant seed varieties appropriate for above normal rainfall. This is a deterministic advisory based on a probabilistic forecast. This approach works perfectly well when there is a minimal deviation between the forecast and the observed. Otherwise, if the rainfall event during the season does not unfold exactly as predicted, the providers carry the blame for faulty predictions and farmers' trust in the forecast starts to dwindle. Hence there is a loss of credibility resulting in very poor uptake of climate information services.

In the context of attempts to improve climate information services adoption, this research article provides an overview of the practical use of probabilistic advisories. On the basis of participatory approach methods, this research engaged 327 smallholder farmers through a crop-growing season with the use of a probabilistic derived advisories. As would be expected, revealing forecast uncertainty and considering the same in the formulation of advisories has the potential to uphold the credibility of climate services and hence lead to improved adoption of these services. The results also indicate that trained farmers can understand forecast inherent limitations especially in terms of uncertainty, which disapproves the line of thought that revealing forecast uncertainty confuses the users.

Addressing the issue of credibility is essential to comprehend the value of climate and weather forecasts in support of agricultural decision-making. This constraint can result from past inaccurate forecasts, which can easily occur from forecasts that are communicated in deterministic form and from which a deterministic advisories are formulated. Climate application research has underscored the danger of interpreting climate predictions deterministically ^[1,4-7]. While communicating forecasts in probabilistic form may be difficult, these authors contend that forecasts should be communicated in full probabilistic form. Past research has suggested that climate service users especially smallholder farmers have difficulties understanding forecast probability especially because the producers do not present and explain them well ^[7-9] and hence it may be better to disseminate a deterministic version instead. Recent proponents argue that if farmers' ability to understand and use probabilistic forecasts is enhanced, they are able to understand the forecast's limitations and this increases their trust in the forecasts ^[10-13].

This article's focus is on seasonal climate forecast users (smallholder farmers in an arid and semi-arid region in Kenya), who face a myriad of pressures ranging from land degradation, increasing climate variability, land fragmentation and market forces, and who must make wise decisions to be self-sufficient with respect to household food security ^[14-16]. With technological advancement, climatologists are able to forecast seasonal rainfall and disseminate it to smallholder farmers in Sub Saharan Africa. However, these forecasts are highly uncertain, and forecasters do not report this uncertainty for fear that they will confuse the users ^[17-21]. Using experimental methodology with smallholder farmers in Kitui County, one of the drylands of Kenya, the research examines whether reporting forecast uncertainty can help to improve forecast credibility among resource-poor smallholder farmers. In this regard, the study sought to know whether more forecast credibility would lead to increased levels of adoption of forecasts at the farm level.

2. Methodology

2.1 Sampling procedure

The mixed farming climatic zones within the county include low midland 5 (LM5), low midland 4 (LM4), and upper midland 4 (UM4). A sampling frame that was stratified according to the wards' position in the mixed agricultural climatic zones yielded the identification of three wards. The wards were specifically chosen due to their location in the mixed farming climate zones as follows Kyangwithia westward (which occupies 93% of the LM5 climatic zone and 7% of the LM4 climatic zone), Matinyani ward (which occupies 100% of the UM4 climatic zone), and Kwa-Vonza ward (which occupies 73% of the LM5, and 6% of the LM4). County wards located outside the mixed farming climatic zones were left out. The village names in each of the three wards were arranged in alphabetical order to guarantee a random selection of villages. Every fourth village was chosen to ensure that associated biases would not affect the systematic selection. The results of this sampling were as shown in Table 1. One farmer group was specifically identified in each of the chosen villages on the premise that it owned a group farm and had at least 15 active members. As a result, three farmer groups were created as study units. The farm groups are group owned and farming is done the same as on individual farms.

Table 1. Villages, wards and livelihood zones.

Agro- Climatological Zone	UM4	LM4	LM5
Wards	Kyangwithya west	Matinyani	Kwa-Vonza
	Mbusyani,	Kathuma,	Kawongo / Kathome
Villages	Mulutu,	Kauma,	Makusya,
	Ndumoni	Kavuvuu,	Mikuyuni,
	Tungutu**	Kitumbi**	Kyosini**
		Kyambusya,	Muvitha / Kathemboni
		Kyondoni,	Ndunguni,
		Maseki,	Nyaanyaa,
		Musosya,	
		Nzakame,	

** indicates the study units.

2.2 Stakeholder engagement and capacity building

The study worked with the smallholder farmers to identify the local stakeholders they partner with in relation to climate services. The identified stakeholders included local agricultural extension officers and seed suppliers. Pre-seasonal meetings were used to involve stakeholders and help them better understand the terminology used in climate services, establish their roles in providing climate services to farmers, and assist in the effective use of probabilistic seasonal forecasts. Via an iterative process, the stakeholders were involved in the October November December (OND) 2021 season. The first stage of interaction centered on enhancing stakeholders' climate understanding, using seasonal forecast data at the farm level, and highlighting the probabilistic nature of projections. The second phase concentrated on enhancing the stakeholders' abilities to evaluate probabilistic forecast data in terms of farm management choices. The timelines for the research activities during the season were as shown in Figure 1.

2.3 The provision and use of climate services (probabilistic forecasts combined with advisories)

On the 11th day of September 2021, the initial suites of climate services were introduced to the study sites. The source was the Kenya Meteorological Department. The default tercile probabilities, or probability of the below-normal, normal, and above-normal categories, of expected seasonal rainfall totals supplemented with commencement and cessation dates, were used as the structure of the downscaled seasonal forecast for the study. The demonstration farms consisted of three group farms. The group farms were in distant wards across the county. The main aim behind the involvement of the farm groups was to reinforce the usability of climate information through demonstration effects. It was envisaged that the demonstration would lead the skeptical farmers to adopt the use of climate information after witnessing proof of its effectiveness. In other words, the use of transparent probabilistic forecasts will reinforce trust in the forecasts.



Figure 1. Timelines for OND 2021 activities.

** indicates activities that were carried out iteratively.

In the three demonstration farms, farming activities were directed by a tercile probability forecast. To increase the legitimacy of the process, and to aid social learning (in as far as farm-level use of probabilistic forecast is concerned), discussions and exchange of thoughts were encouraged among the participants in order to brainstorm on the best way to interpret and implement forecast probabilities. As a result of these inclusive deliberations, a scheme to interpret and put into use forecast probabilities at the farm level was co-designed. All the stakeholders agreed that each demonstration farm should be divided into three parts since the forecast probability terciles were three. In this way, the percentages assigned to each probable group were used in the co-designed plan to determine how much acreage to allot to each category. In addition, appropriate seed varieties were also selected for each probability category. For instance, if the forecast gave a 50%, 30% and 20% probability of above normal rains, normal and below normal rains respectively; then 50% of the demonstration land was allocated seed varieties suitable for above normal rain, 30% of the demonstration land was allocated seed varieties suitable for normal rain, and 20% of the demonstration land was allocated seed varieties suitable for below normal rains

This division of land, for each of the demonstration farms, was done by the respective participating farmers in each farm. The extension staff and seed suppliers assisted the farmers in the selection of appropriate seed varieties for each tercile probability to account for the entire projected uncertainty range. Farmers were urged to use their judgment to segment each study site into three pieces, each of which was equal to the various percentage probability groups, rather than engaging in long quantitative calculations. As the season continued, stakeholders were regularly updated with seasonal information in dekadal weather reports via phone calls or brief text messages. After receiving farmers' comments during the research, the delivery of climate services was changed as necessary.

2.4 After-season evaluation

In order to gather farmers' opinions on the overall results of the selected probability forecast interpretation system as well as the efficiency of the delivery of climate services, a post-season evaluation was carried out after the conclusion of the crop growing season. Focus group conversations with participating farmers were used to accomplish this. Of specific interest, group discussions sought to participate farmers' views on whether: 1) the farm subdivision and the subsequent planting of appropriate cultivars on each subdivision as indicated by the tercile probabilities supported farmers' climate risk management, 2) the scheme enabled spreading of climate risk compared to banking on the deterministic forecast, which is based on the highest tercile forecast probability and which, at times can be wrong and 3) this bottom-up approach of forecast probability interpretation brings a balance between caution and confidence in the use climate services at the farm level. In addition to the focus group discussions, the research also attempted to estimate crop yields in each group farm subdivision in the three study sites. This was done using the test weight pre-estimation method.

3. Results and discussions

On the group farms, farming operations were directed by estimated probabilities for OND 2021. This was released with a three-week lead period, allowing for advanced planning. As was indicated in Section 2.3, farmers divided the demonstration farms into three parts to cover all the tercile probabilities. On each sub-division they planted appropriate seeds for the respective probability tercile. **Table 2** presents a summary of the three group farms, the forecast probability that was issued for each of these group farms, the proportioning of the group farms and the appropriate seed varieties that were planted on each farm sub-division.

In **Table 2**, *Pioneer P28*, *Duma 43*, *DH 02*, *DK8031* and sungura are maize seed varieties while Nyayo, *Kat X 56* and *Kayelo* are bean seed varieties suitable for different seasonal rainfall amounts as shown in the table.

After-season evaluation results

Focus group conversations with participating farmers suggested that for the first time, farmers had received seasonal forecasts in probability form and understood how to translate them into farm decisions. The discussions also pointed out that the use of different seed varieties as dictated by probability terciles worked as a mechanism for crop diversification, which enabled the farmers spread the climate risk. The group farms' distribution to account for terciles in all likelihood brought some harmony between caution and certainty, (that is, a balance between reducing risks and increasing returns) unlike before when farmers indicated to have been used to frequent climate-related losses. The individual farms, on the other hand, were planted according to the prediction group with the highest likelihood.

 Table 2. Chosen seed varietals sowed on each farm segment to account for all probable forecast groups.

Group farm	Forecast probability		Partitioning of the group farms to distribute the risk		
Kanzoya	А	50%	Sow 50% of the acreage with <i>Pioneer P28</i>		
	N	30%	Sow 30% of the acreage with Duma 43		
	В	20%	Sow 20% of the acreage with <i>DH02</i>		
Mucerere	А	50%	Sow 50% of the acreage with Nyavo		
	N	30%	Sow 30% of the acreage with Kat X 56		
	В	20%	Sow 20% of the acreage with Kayelo		
Seven-up	А	30%	Sow 30% of the acreage with <i>Nyayo</i> and <i>DK8031</i>		
	Ν	50%	Sow 50% of the acreage with Kayelo and Sungura		
	В	20%	Sow 20% of the acreage with DH02 and Katumbuka		

Pioneer P28, Duma 43, DH02, DK8031 and Sungura are maize see varieties and Nyayo, Kat X 56, Kayelo, and Katumbuka are bean seed varieties. All suitable for Kenyan drylands.

As an illustration, the Kanzoya farm group location, whose climatic services were derived from the above-normal prediction category, experienced average rainfall during this season. As a result of using seed kinds adapted for above-average precipitation, individual farmers in this location did not harvest much from their crops. However the Kanzoya group farm did not suffer a complete loss since farmers had divided the farm into three sections to accommodate the three probability groupings. Because of this, they received a bumper crop of the Duma 43 variety of maize from the group farm's 30% share.

The narrative from the focus group discussions concurred with the quantitative yield estimates, which are presented in **Figure 2**. In line with the communicated forecast, the Mucerere agricultural group experienced above-average rainfall. Participating farmers in this area received a bountiful harvest from their individual farms and from 50% of their collective farms. The Seven-up farm group's participating farmers, however, did not reap much from their individual farms because they had planted seed kinds for normal to above normal conditions in accordance with the stated prognosis, but the actual rainfall received was below average. Yet, their group farm did not completely lose out because 20% of the farm produced an excellent crop of DH02 maize, a seed variety suitable for below-average rains.

The group farm demonstration helped farmers understand the role of probability in forecasts and how they may use it to share the risk, despite the concerns surrounding forecast skills. Because of this, the farmers were able to maintain a healthy mix of caution and assurance throughout the season. According to the majority of farmers, all farmers in the county should have access to climate services because they will all reap similar benefits. Farmers cited the following requirements as necessary in order to make all farmers, train farmers to adopt climate services: Increase accessibility, educate farmers to comprehend and use the services, and transparently communicate forecast probability. These results suggest that improvements could be made to current forecast delivery practices as far as the format is concerned in Kenya.



Figure 2. Yield estimates (kg) for the different cultivars indicated in Table 2 in different study sites.

4. Conclusions

This article set out to advance climate information services adoption by understanding how the interpretation of raw seasonal forecasts into probabilistic advisories can help bring a balance between caution and confidence among resource-poor smallholder farmers. To this end, the practical engagement of smallholder farmers provided insight into the importance of revealing forecast uncertainty and considering the same in the formulation of advisories (probabilistic advisories), which uphold the credibility of climate services and hence improved adoption.

Author Contributions

Mary Mwangi: Conceptualization, Investigation, Writing—First draft; Evans Kituyi: Visualization, Supervision; Gilbert Ouma: Visualization, Supervision.

Conflicts of Interest

The authors declare no conflicts of interest.

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