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

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ABSTRACT

The livelihood of many farmers across the globe is affected by climate variability and change. Providing weather and seasonal climate information is expected to support farmers to make adaptive farming decisions. Yet, for many farmers, scientific forecast information provided remains unreliable for decision-making. Scholars have called for the need to integrate indigenous and scientific forecasts to improve forecast information at the local level. In Northern Ghana, scientific forecast information from meteorological agency is unacceptable to farmers, making them rely on indigenous forecasts for adaptive decisions. This study proposed an integrated probability forecasting (IPF) method that integrates indigenous and scientific forecasts into a single forecast. As a proof of concept, we tested the reliability of IPF using binary forecast verification method and evaluated its acceptability to farmers through internally consistent multiple-response questions. Results of the reliability test show that IPF performed on average better than indigenous and scientific forecasts at a daily timescale. At the seasonal timescale, IPF and indigenous forecast performed better than Scientific forecast, although in terms of probability IF showed better results overall. Majority of the farmers (93%) prefer the IPF method as this provides a reliable forecast, requires less time, and at the same time resolves the contradictions arising from forecast information from different sources. The results also show that farmers already integrate (complementary) scientific and indigenous forecasts to make farming decisions. However, their complementary approach does not resolve the issue of contradictory forecast information. From our proof of concept, we conclude that integrating indigenous and scientific forecasts can potentially increase forecast reliability and uptake.

1. Introduction

Farmers across the globe, and particularly in Africa, use weather and climate information from indigenous and meteorological sources when making risk-based decisions (Mapfumo et al., 2015; Roudier et al., 2014; Orlove et al., 2010). The potential value of indigenous knowledge in forecasting is increasingly recognised (Nyadzi et al., 2018; Jiri et al., 2016; Manyanhaire and Chitura, 2015;

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Kolawole et al., 2014), and scientific forecasts have improved (Njau, 2010).

In Ghana, farmers often approach a season using indigenous forecasting (IF), which is built on past experiences, empirical observations of ecological indicators, and traditional knowledge. Sometimes, they use IF in combination with meteorological scientific forecasting (SF) to adjust farm activities in light of climate variability and change (Nyadzi et al., 2018; Nyantakyi-Frimpong, 2013). However, both IF and SF have distinct weaknesses that pose challenges for their use (Ziervogel and Opere, 2010).

First, end-users are often confused about what decision to make when forecasts come from different sources, especially when they produce contradictory information (Klopper and Landman, 2003). Second, SF is often developed at a coarse spatial scale compared to IF and therefore does not address local farmers' needs (Orlove et al., 2010). Third, policymakers and scientists often view IF with scepticism as, unlike SF, it is qualitative and grounded in local experience and spiritual beliefs (Kolawole et al., 2014; Saitabau, 2014; Briggs and Moyo, 2012). SF, on the other hand, is not always embraced by farmers because they lack ownership of the process and trust in service providers. This reduces the uptake of weather and climate information (Jiri et al., 2016).

Studies have indicated that forecast information may be more acceptable if IF and SF are integrated (Ziervogel and Opere, 2010; Gagnon and 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 (Nyamekye et al., 2018; Mafongoya and Ajayi, 2017). Moreover, climate change presents challenges that can go beyond the experiences of farmers and scientists (HUNTINGTON et al., 2004).

Finding a meeting point between the two forms of forecasting could set the agenda for integration (Kolawole et al., 2014). Such integration should 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 and natural and social scientists (Lemos et al., 2018). However, the question that remains is how IF and SF can be integrated whilst retaining and respecting their different norms and values. Therefore, this study addressed two objectives: to assess 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* aimed at demonstrating how to quantitatively integrate IF and SF to improve the reliability and acceptability of forecast information for farmers in Ghana. To achieve this, the strengths and weaknesses of existing integration approaches are first reviewed and analysed in section 2. Section 3 details the methods adopted for the study. Section 4 presents the results regarding the reliability and acceptability of the integrated probability forecasting (IPF) method proposed. The article ends in section 5, reflecting on the findings and the actionability of IPF to support farmers' daily and seasonal decision-making processes.

2. Literature review and conceptual framework

The idea of improving forecast accuracy by integrating forecasts 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 and Yang (2004) and Wei (2009) suggested time series analysis combined with multiple regression. Adhikari & Agrawal (2012) used a weighted nonlinear mechanism for combining forecasts from multiple time series models. Andersson and Karlsson (2008) and Raftery et al. (2005) proposed Bayesian combinations. Others discussed the possibility of averaging the probabilities of individual forecasts (Ranjan and Gneiting, 2010). Klopper and Landman (2003) created a single probability forecast by combining different model outputs and concluded that the method consistently delivered a more skilful forecast than any individual model on its own.

Recent studies on integrating SF with IF advocate either the *consensus method* or the *science integration method* (Plotz et al., 2017). In the consensus method, agreement is subjectively established on what appears to be the most convincing forecast information. This can occur via meetings of experts from the indigenous and the scientific community to discuss their forecasts and develop a consensus forecast for the coming season (Mahoo et al., 2015; Ziervogel and Opere, 2010; Guthiga and Newsham, 2011). The science integration method consists of objectively combining forecasts into a single source of information using systematically established scientific techniques. For example, IF may be combined with statistical or dynamical weather or climate model outcomes (Masinde, 2015; Mwagha and Masinde, 2015; Chand et al., 2014; Andrade and Gosling, 2011; Waiswa et al., 2007).

However, both the consensus and the scientific integration method have some challenges. The consensus method is time- and cost-intensive because of the need for regular workshops and meetings. It may result in delays in dissemination, as neither indigenous nor scientific experts could produce a combined forecast in the absence of the other. Additionally, the combined forecast cannot always be replicated, as there are no clear rules or processes involved. On the other hand, the science integration method requires a large amount of data to develop and verify predictive models. Furthermore, it is less amenable to engaging farmers and less sensitive and less responsive to cultural concerns. Science integration approaches have utilised IF only during the initial data-gathering phase of development. Subsequent activities, including data interpretation and analysis, involve only the researchers who produce the model. This approach does not represent a co-production of knowledge. Moreover, rapid environmental changes have the potential to impact the future effectiveness of integrated scientific approaches because real-time IF and SF forecasts are not incorporated. For example, seasonal climate information from science integration approaches is based only on historically observed data from weather stations, and IF serves only as a driving hypothesis for trends. Both the consensus and the scientific integration method fail to integrate IF and SF into a single forecast, but rather produce a third forecast that is equally difficult to accept, as IF and SF are sometimes contradictory.

Given the limitations of these two methods, we propose a new approach, which we call integrated probability forecasting (IPF). This method is inspired by Klopper and Landman's (2003) approach, which used a simple unweighted average of forecast probability to combine scientific forecasts from different forecast models. The difference with the IPF method is that it uses a weighted average technique and combines the strengths of both the consensus and the science integration method. The present study characterises the IPF method as one that seeks to generate the probability of IF and quantitatively combine it with the probability of SF using simple weighted average techniques. Thus, 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. However, to integrate IF and SF at a daily and seasonal timescale, it is necessary to estimate the probability of IF forecasts. These are calculated based on the number of people forecasting 'Yes rain' for the weather and near-normal, above-normal, and below-normal rainfall, for the seasonal climate forecast (near-normal rainfall [740–1230 mm] is the average rainfall range over 30-years). Rainfall for each season or year is either above, below, or near normal. The calculated probability of IF is combined with that of SF to form the IPF (see section 3.4.1 for details of the proposed method). The IPF requires expert indigenous forecasters just as in the consensus method, but, unlike the latter method, it does not require regular formal or informal meetings to develop a consensus forecast. IF forecasts from several expert local forecasters (farmers) are collected at a particular time, from which the probability is estimated based on the number of experts that issue a particular forecast, compared with those that forecast otherwise.

2.1. *The concept of reliability and acceptability*

To assess the actionability of the IPF method, a reliability and acceptability check is necessary (Whitford et al. 2012). In this study, the reliability of the IPF method is defined as the ability to produce information that performs better than other available forecasts, in this case, either the SF or the IF method. The acceptability of IPF to end-users depends partly on its reliability. Acceptability is regarded as a significant factor in determining the success or failure of any innovation or technology, particularly with regard to information systems (Kim, 2015; Gould et al., 1991; Nickerson, 1981). A forecast's acceptability can be defined as a demonstrable willingness of an individual or a group to *trust and use* the forecast information (Dillon and Morris, 1996). The likelihood of actual usage could deviate slightly from intended usage, but acceptance theory stresses that such deviations should not be significant.

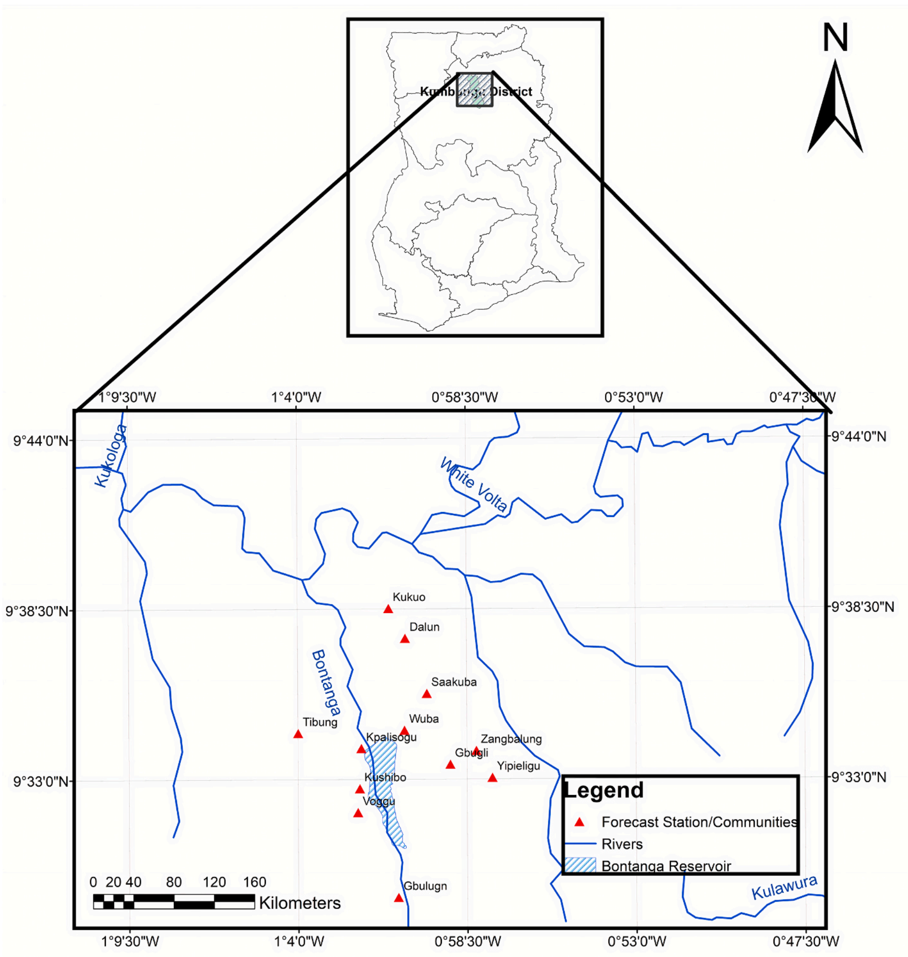

Fig. 1. Map of the study area positioned in Ghana. The red triangles show the location of farmers who participated in the study and their respective selected communities (Nyadzi et al., 2021).

3. Research methodology

This section introduces the case-study context and discusses the methodology used.

3.1. Study area

Kumbungu District (Fig. 1) in the northern region of Ghana, which is located in the guinea savannah ecological zone, was selected for the research. Given previous research engagement in this region where indigenous forecast data was collected and evaluated (Nyadzi et al. 202), the research team relied upon existing data and resources as well as relationships with farmers in the study area. Twelve communities were chosen to participate in the study (Fig. 1).

The region is characterised by lowland and grassland (Abdul-Razak and Kruse, 2017). The district has a unimodal rainfall pattern that begins in May, peaks in July to September, and ends in October, with the rest of the year being dry (GSS, 2014). The climate is generally warm, with fluctuating mean monthly minimum and maximum temperatures of 26.6 °C and 35.6 °C, respectively. The annual mean temperature is 29.7 °C and the average annual rainfall is about 1043 mm (SARI, 2016, cited in Abukari et al., 2018). The region is highly vulnerable (both ecologically and socially) to the impact of climate variability and change, including recurring floods and drought (Asante and Amuakwa-Mensah, 2015; Stanturf et al., 2015). The local population belongs to the Dagbani ethnic group, and they rely on agriculture as their main economic activity. Crop production is predominantly rain-fed and, therefore, seasonal. Only a few households are engaged in dry season irrigated schemes; for example, those in Bontanga (Nyadzi, 2016). About 95% of the households in the district are engaged in agriculture, with almost all (98%) of these households being involved in crop and poultry production (GSS, 2014).

3.2. Sample selection and profile

To address the research questions, the study used multiple methods using primary and secondary data (see Fig. 2).

The study focused on rice farmers because of the high demand for rice in the area and the country at large, but rice production is crippled by climate variability and water unavailability challenges (Mabe et al., 2014; Kranjac-Berisavljevic' et al., 2003). To assess the acceptability of IPF, a quota sampling technique was used. This technique was based on the assumption that the different farming practices (irrigated, rainfed and both irrigated and rainfed) require different types of climate information and so IPF acceptability might differ. Also, farmers within each farming category have similar characteristics in terms of needs for forecast information and therefore farmers selected from each group was based on the judgement of the researchers. In each of the 12 chosen communities (Fig. 1), nine farmers were selected for the interview: three irrigation farmers, three rain-fed farmers, and three both irrigation and rain-fed farmers. The sampled population (N = 108) included male (72%) and female (28%) farmers (see Appendix 1). In addition to these interviews, a feedback workshop was organised with 12 participating rice farmers engaged in both rain-fed and irrigated rice production.

To assess the reliability of IPF, IF data were collected from 12 expert farmers, all males above 45 years of age from the 12 chosen

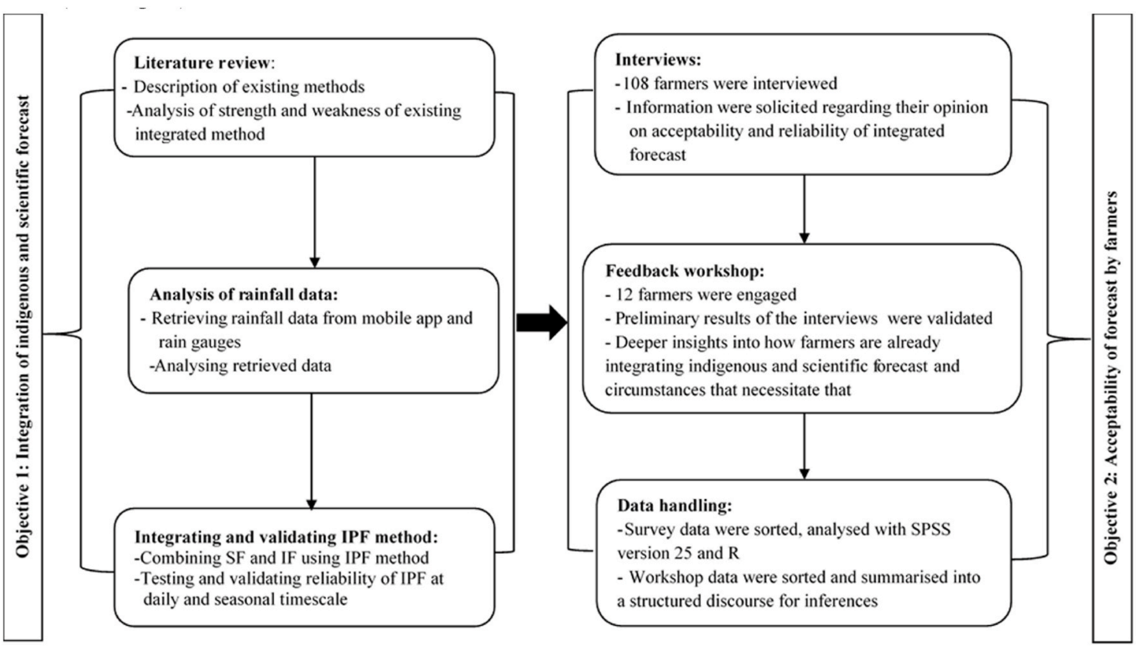

Fig. 2. The methodological flow of the study.

communities. The sampling method adopted concentrated on selecting the best and most trusted forecasters in each community. These farmers happened to be all males. Farmers above the age of 45 were selected because they have at least 30 years of farming experience and cumulative knowledge about changes in climate and rainfall in their communities.

A rigorous process was adopted to select farmers with good forecasting skills to obtain quality data for the analysis. First, initial inquiries showed that not all farmers were good at using indigenous ecological indicators (IEIs) for forecasting. Therefore, the selection process actively involved the community members. In each community, members know who is good at forecasting, therefore both researchers and farmers decided on who to involve in the training and forecasting. Roncoli et al. (2009) highlight the importance of promoting local ownership and generating trust when the users of climate information are involved in its production and dissemination. If the community is involved in the selection process, we can expect forecast information to be trusted by all. Moreover, the expert farmers reported serving as a source of forecast information for increasing numbers of farmers in their respective communities.

The selected farmers were introduced to smartphones and mobile apps, most of them for the first time. Farmers were also trained on how to record daily observed rainfall with custom-made rain gauges. A comparative analysis of daily and seasonal forecast (where rainfall data observed by farmers and by the Ghana meteorological agency [GMet] were compared) by Nyadzi et al. (2021) showed that both farmers and GMet recorded similar rainfall patterns throughout the seasons, increasing our confidence in the farmers' ability to record data.

3.3. Research instruments and data collection

The study used three main types of data: (i) indigenous forecast (IF) and scientific forecast (SF) data, (ii) interview data, and (iii) feedback and discussion workshop data. (i) IF and SF data was used for integrating and testing forecast reliability The IF data were collected from 12 expert farmers who sent in daily predictions (in 2017) through a smartphone app (see section 3.3.1 for details on the mobile app). Their seasonal predictions were collected at workshops in 2017 and 2018. The SF data at both daily and seasonal timescales were obtained from the GMet. (ii) Interview data from the 108 farmers were collected in 2018 for acceptability analysis, and (iii) feedback and discussion data were gathered during workshops in 2018. The IF and the SF 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 were used to evaluate the preliminary results of the interviews and IF forecasts collected. In addition, the workshop enabled a discussion of why the IPF method was most preferred by farmers.

In preliminary research in the region, the researchers identified IEIs used by farmers for forecasting. During one of the workshops, the researchers defined and explained the technical classifications that corresponded to farmers' indicators, using simple illustrations to which farmers could relate. For example, researchers and farmers together agreed on *low rainfall* (0.1–19 mm/day) as drizzling or light rains that do not penetrate beneath the soil surface; *medium rains* (19–37 mm/day) as rains that wet the soil to capacity; and *high* or *heavy rains* (>37 mm/day) as rains that flood farms and may cause crop failure. The rainfall values were obtained from Lacombe et al. (2012). *Above/below seasonal rainfall* is explained as a scenario in which the total seasonal quantity of rainfall is either above or below the long-term average. *Near normal* indicates a typical amount of rain, which often corresponds to average yield. *Onset* refers to the time in the rainy season when precipitation is sufficient for planting.

3.3.1. Android mobile app ('Sapelli') and rain gauges

IF rainfall forecast data were collected using the Sapelli mobile app (see Appendix 2). Sapelli is an open-source project that facilitates data collection across language or literacy barriers through the highly configurable decision-tree of a pictorial-icon-driven user interface. Sapelli has a powerful visualisation capability that enables people with a low literacy level to use it, as users can select options without reading any text, by simply touching the screen of the mobile device. The Sapelli platform allows offline data collection and re-scheduling data transmission and does not require an internet connection, making it useable in areas where network connectivity is rare, unstable, slow, or expensive. Vitos et al. (2013), for example, used Sapelli to involve local people in efforts 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, which were distributed to the 12 local forecasting experts to collect their daily rainfall forecasts.

On the app, the farmer is asked to first indicate whether in the next 24 h 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,' or 'high (heavy) rain'. Thereafter, a number of IEIs such as ants and earthworms, or moon phases, are presented, and farmers can select the indicators on which they have based their forecasts. These IEIs were elicited from farmers themselves in the course of the preliminary workshop. After this, the farmer specifies the certainty of the forecast by selecting 'sure', 'very sure', or 'so sure'. The process ends by saving the information onto the mobile phone. However, if a farmer skipped a stage on the app, we understood the response to mean 'no idea.' We did not include options such as 'I do not understand' or 'I am not comfortable answering' because the farmers were thoroughly trained to understand each stage of the app. They were willing to provide answers unless they did not know what weather event to expect because of confusing IEIs. The farmers were also trained and asked to record daily rainfall observed in their communities using custom-made rain gauges, constructed from plastic water bottles by researchers.

3.3.2. Structured interviews

The structured interview guide was based on three core themes: (i) personal characteristics, (ii) forecast sources and usage, (iii) acceptability of integrated forecast. The interview protocol was piloted to ensure robustness. Each interview lasted about 15 min and was administered in the local *Dagbani* language, except for some cases with literate farmers where the English language was used.

3.3.3. Feedback workshop

Following the preliminary analysis of the interview data and the IF data collected with the Sapelli mobile app, a feedback workshop was organised to discuss and obtain further insights as well as validate results. The workshop elicited information about whether and how farmers were using IF and SF and whether they found IPF acceptable. The workshop was conducted in *Dagbani* (quotations used in this paper have been translated into English).

3.4. Data analysis

The IF and the SF forecast data were analysed at a daily and seasonal timescale. Further, daily forecast data were aggregated monthly to assess trends. The interview data were analysed to determine the acceptability of IPF. Details of the analysis are presented in sections 3.4.1 and 3.4.2.

3.4.1. Integrating forecast and testing reliability

Before the integration of IF, IEIs were identified, and farmers' rainfall forecasting techniques were explored. The results show that farmers base their forecasts on observing and interpreting a range of different IEIs and compare those observations with their long-term personal experiences.

In addition to IEI identification and exploration of IF techniques, the binary forecast verification method was used to test the reliability of forecasts. This method analyses rainfall forecasts in the form of yes/no rain and uses a contingency table to score hit rates against miss rates (Ward and Folland, 2007). Using this method of forecast verification is of practical value because users often have to make a yes/no decision to act on the information provided. Integrating SF and IF at a daily and a seasonal timescale followed the following two stages:

3.5. Stage 1: constructing and consolidating forecast probabilities for IF and SF

Whereas SF weather and seasonal climate forecasts are issued with the likelihood of rainfall occurrence, IFs are not. The probabilities of daily IFs were calculated based on the number of expert farmers forecasting 'Yes rain'. For the seasonal timescale, the probabilities were calculated based on the number of people who indicated above-, below-, and near-normal rainfall (see Table 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 1.

3.6. Stage 2: evaluating forecasts (IPF, IF, and SF) against observation

To assess their reliability, each forecast (IPF, IF, and SF) was compared with observations. The percentage of hit rates for each forecast type was 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 was assigned to each probability. The values were a 0.3 and a 0.34 hit rate for IF and SF, respectively. Hypothetically, each farmer represents a forecast model with his 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.

$$CF = \frac{\alpha X_1 + \beta X_2}{\alpha + \beta} \tag{1}$$

Where $\mathbf{X_1}$ is the probability of IF and $\mathbf{X_2}$ is the probability of SF. $\boldsymbol{\alpha}$ is the weighted value of IF and $\boldsymbol{\beta}$ is the weighted value of SF.

3.6.1. Analysis of interview and workshop data for acceptability

The questionnaire data were coded and analysed with R statistics, SPSS version 25, and Microsoft Excel 2016. Analyses of interview data were framed around the hypothesis that farmers will accept an IPF. Data on demographic and socioeconomic characteristics of the

Table 1
Formulae for integrating indigenous forecasts and scientific forecasts: example for integrating seasonal climate forecast.

Type of forecast	Above normal	Below normal	Near normal
Indigenous forecast	$A_i = An/T$ (%)	$B_i = B_n/T$ (%)	$N_i = N_n/T$ (%)
Scientific forecast	A_s (%)	B_s (%)	N_s (%)
Integrated probability forecast	$A_C\,(\%) = \frac{\alpha A_i(\%) + \beta A_s(\%)}{\alpha + \beta}$	$B_C\,(\%) = \frac{\alpha B_i(\%) + \beta B_s(\%)}{\alpha + \beta}$	$N_c\,(\%) = \frac{\alpha N_i(\%) + \beta N_s(\%)}{\alpha + \beta}$

Where:

A, B, and N *denote 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 categories A, B, and N, respectively.*
A_i (%), B_i (%), and N_i (%) *denote the probability of occurrence of the indigenous forecast for categories A, B, and N, respectively.*
A_s (%), B_s (%), and N_s (%) *denote the probability of occurrence of the scientific forecast for categories A, B, and N, respectively*
A_c (%), B_c (%), and N_c (%) *denote the probability of occurrence of combined forecast for categories A, B, and N, respectively. These are the mean of each category for the IF and the SF.*
α *is the weighted value of IF and* ***β*** *is the weighted value of SF.*

sample and their forecast-use patterns are found in Appendix 1.

First, an index for acceptability was computed from three questions and collinearity was 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 respondent's response. Details of the results of the analysis are provided in Appendix 3. Price (2012) posits that multiple-response measures are generally more reliable than single-response measures. However, it is important to ensure that the individual dependent variables correlate with one another. Therefore, before the multiple-response measures were combined, the reliability of the variables was checked using Cronbach's alphas to verify the internal consistency of the variables before proceeding to determine whether farmers would accept an IPF or not. The results showed an acceptable Cronbach's alpha of 0.68 (see Appendix 3 for detailed results). A Cronbach's alpha value of 0.6 is considered as a high reliability and acceptability index (Ommen et al., 2008). The workshop data were sorted and structured into an inferential discourse. All data collected were anonymously handled.

4. Results

4.1. Performance of indigenous, scientific, and integrated probability forecasts

Monthly analyses of the daily forecast data showed that, on average, IPF performed better than IF and SF (Fig. 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 Appendix 4).

At the seasonal timescale, IPF and IF performed better than SF although in terms of probability IF showed better results and IPF also performed better than SF. Interestingly, IPF was able to deal with the contradictory forecasts of IF and SF, pointing in different directions in both years. For instance, in 2017, whereas IF predicted near-normal rainfall, SF predicted above-normal rainfall. Contradictory forecasts, which confuse farmers, were eliminated by IPF (Table 2). In 2018, another confusing forecast was observed: IF predicted above-normal rainfall whereas SF predicted an equal chance of both above- and near-normal rainfall. With this confusing information, IPF was able to forecast accurately the above-normal rainfall observed (Table 2).

4.2. Acceptability of integrated forecast to farmers

The results of the acceptability analysis show that, cumulatively, the majority (96%) of the farmers ***accept*** the integrated forecasts with varying degrees of agreement (Fig. 4). About 53% of them 'agree' and 43% 'strongly agree'. However, a number of factors may influence the acceptability of the integrated forecast. Trust in forecast information correlates significantly ($r = 0.65$) with the acceptability of the integrated forecast (Appendix 5). The majority (96%) of farmers trusted IPF more than their complementary method. However, 99% of farmers would use IPF only if it proved reliable (Appendix 6).

4.3. Farmers' forecast preferences and approaches to integration

Regarding the combined and the complementary integrated method, the interview results show that the majority (93%) of the farmers already integrate SF and IF for decision making using a complementary technique, whereby they compare both SF and IF forecasts with their own experiences to choose the more relevant or credible. This approach differs from the IPF method, in that it combines the two forecasts into a single forecast. About 3% of the farmers claimed to integrate forecasts by a combination technique. However, attempts to explain the combination process revealed that they actually practice the complementary technique. The remaining 4% of the farmers could not tell which kind of integration they applied. Overall, the interview results showed that the majority (93%) preferred an integrated forecast that is combined rather than complementary (Appendix 7). Also, integrating both forecasts is driven only by farmers' personal experiences – this can be challenging, as environmental change has brought about

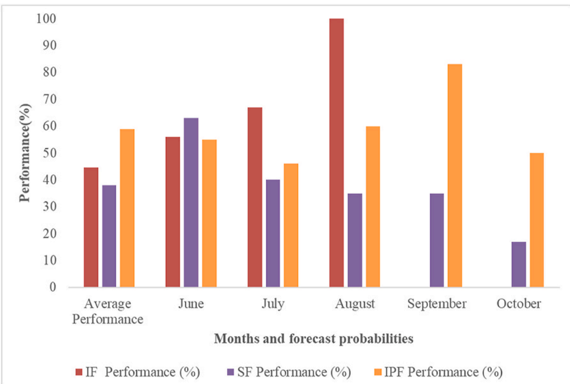

Fig. 3. Performance of indigenous forecasting, scientific forecasting, and integrated probability forecasting at a resultant probability of >0.5 (details of ≤0.5 in Appendix 5). IF recorded no hit for probability >0.5 in months September and October.

Table 2
Indigenous forecasting, scientific forecasting, and integrated probability forecasting and observation for the 2017 and 2018 seasons. A: above-normal rainfall; N: near-normal rainfall; B: below-normal rainfall. 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	33	**58**	9	N	**50**	33	17	A
Scientific forecast	**40**	35	25		**35**	**35**	30	
Integrated probability forecast	36.3	**45.8**	17.5		**42.0**	34.1	23.9	

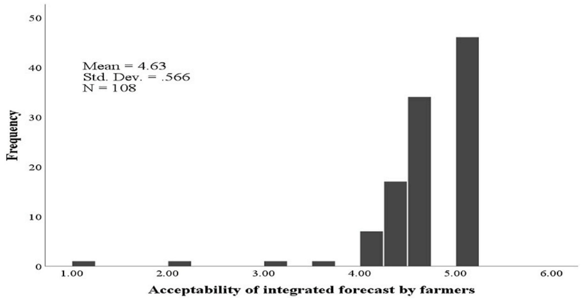

Fig. 4. Measure of acceptability of integrated forecast obtained from the average of multiple questions in Appendix 5 (Strongly disagree: 1–1.9, Disagree: 2–2.9, Neutral: 3–3.9, Agree: 4–4.9, Strongly agree: 5–5.9, I don't know: >6–6.9).

behavioural change in IEIs, like animals or trees.

Farmers integrate forecasts (using the complementary method) for several reasons. *Firstly,* they recognised that IF has become less reliable over the years, and especially for seasonal predictions. Likewise, SF has its intrinsic weaknesses that limit its efficacy, yet IF and SF can perform well and improve farmers' decisions when used together. *Secondly*, confusion arises when SF and IF provide different forecasts at a higher probability; for example, in a daily weather forecast where IF expects rain and SF indicates no rain, or at a seasonal timescale when IF forecasts a near-normal season and SF forecasts an above-normal season. Under such contradictory circumstances, farmers compare both forecasts and select one, based on past experiences. *Thirdly,* farmers' confidence to act is boosted when forecasts are all pointing in the same direction.

The farmers found the combination approach (IPF) of combining two forecasts appealing, as it removes forecast contradictions and possibly increases accuracy. One farmer explained, "*Most of the time, we fail at comparing to choose one. If you people [researchers] can combine the two into one, then, it is good news for us. When SF and IF confidently provide different forecasts, it becomes very difficult to make a decision based on one.*" Another farmer remarked, "*Our elders say two heads are better than one. IF and SF have both helped but combining them into one will be very good.*"

Comparing the IPF method with the consensus and science integration methods, the majority (75%) of the farmers expressed a preference for the IPF method because their IF knowledge is incorporated in forecast generation and the need for frequent meetings is minimised. However, 25% of the farmers favoured the consensus method, because it engages them continuously in the learning process, though they also noted that doing so may be time consuming. One farmer explained that "*when we meet continuously, new ideas to improve the forecast information will emerge*". None of the farmers preferred the science integration method. They found it problematic that their knowledge would be elicited only to build predictive models, without engaging them further in the process. They believed that this would affect the quality of the forecast generated, as explained by one farmer, "*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*".

Nonetheless, the results show that farmers are more concerned with forecast reliability than with how it is integrated. Moreover, given that IF evolves in specific contexts, how to ensure that changes are taken into account remains an open question. Appropriate feedback loop mechanisms will need to be created so that farmers can update researchers on any changes in observed IEIs.

5. Discussion

This study is a proof of concept that aimed to develop and test a method that combines IF and SF into a single, reliable forecast acceptable to farmers. The analysis started with the hypothesis that an IPF method could improve the reliability and acceptability of forecast information among farmers. The need for such a combined forecast emerged from the observation that SF and IF individually have inherent weaknesses, including issues related to accuracy and consistency, that could be addressed by integrating both forecasts.

Given that SF and IF often produce a forecast with different levels of accuracy at both daily and seasonal timescales, the need to combine both into a single forecast becomes necessary. The monthly differences in the performance of each system could be attributed to the (in)ability of SF and IF to capture the strong rainfall variability even over small areas and also the spatial coverage of both systems.

The proposed IPF method combines the strengths of SF and IF and can therefore potentially improve their reliability, as demonstrated by this study. The IPF method is a simple weighted average of the conditional probabilities of SF and IF, assuming that they have different skills. However, in this study, the differences in the estimated weights (based on assessed skills of SF and IF) were insignificant and so did not affect the resultant forecast. Some methods have been suggested in the literature (e.g., Chand et al., 2014; Andrade and Gosling, 2011) to combine SF and IF. These methods are promising but difficult to operationalise as discussed in section 2. The IPF method is potentially more practical in implementation and reliable at both daily and seasonal timescales. The IPF also has far greater acceptability (93%) potential, because it resolves the issue of contradictions usually associated with forecast information generated by the complementary method.

IPF ensures co-production of forecast information. Given the level of engagement of both researchers and farmers in generating IPF, uptake of forecast information can be guaranteed. Our analysis shows that trust in forecast information is enhanced by co-production, which in turn is a significant determinant of uptake. Farmers trust IPF because it combines the best of SF and IF and keeps farmers up to date on forecast uncertainties and risks. Furthermore, the credibility of the information source can affect how users perceive and respond to environmental risk messages (Steelman et al., 2014). Therefore, we contend that the co-production process for generating IPF should be transparent and continuously inform farmers in iterative engagement activities. Thus, both researchers and farmers need to be committed to the process: farmers should be consistent in IF provision, and researchers must ensure (together with farmers) that local forecasters with the best skills are included in the process.

We acknowledge that this study is a proof of concept and entails the particular challenge of using a relatively short dataset to validate the reliability of the IPF method. We recognise that a longer time series is needed for a more robust validation. Adding more data would provide a solid basis for validating the reliability of the proposed method. However, long-term IF datasets do not exist, and the limited length of our project made it possible to collect IF data for only a single year (in 2017) for the daily forecast analysis and two years (2017 and 2018) for the seasonal forecast analysis. Whereas for science-based forecasts it is possible to generate long-term datasets using hind-cast methods, this is not possible for IF.

This study has important implications for meeting farmers' weather and climate information needs. First, it responds to calls by scientists and policymakers to objectively integrate SF and IF (Hoagland, 2016; Hiwasaki et al., 2014; Kalanda-Joshua et al., 2011). Second, IPF provides an opportunity for both scientists and policymakers to bridge the forecast information gap and thus meet farmers' weather and climate information demands, particularly in areas where scientific meteorological infrastructure and records are insufficient (Basdew et al., 2017; Mahoo et al., 2015). Third, IPF could help eliminate human errors associated with a subjective combination of forecasts from climate models and indigenous knowledge.

Previous studies as discussed earlier in section two of this paper have proposed frameworks and approaches for combining indigenous and scientific knowledge, but these do not have to be static in their applications in terms of location and context-related issues (Plotz et al., 2017). Therefore, for a successful engagement and use of the IPF method, we recommend that, *first*, researchers should understand how IF is generated from IEIs and confirm that target communities use IF. Even more, it is vital to engage local communities from the beginning to the end (co-creating), both defining the discrepancy between scientific and indigenous knowledge and designing the solution to the discrepancy. Workshops and meetings offer opportunities to engage with local communities.

Secondly, if the best IF experts are not included in the forecast data collection, then this can introduce errors in the combined forecasts. Together, researchers and farmers should agree on who should be involved as an expert forecaster based on forecast skills and availability to provide IF using mobile phones. Increased rainfall variability could lead to a re-definition of who actually is a 'forecast expert'. It may be the case in the future that, with increasing climate variability, former IF experts, techniques, and IEIs will no longer effectively forecast weather and seasonal climate events. In time, a new group of experts, techniques, and different indicators may be used to forecast more accurately.

Thirdly, aside from data quality and the predictability of the climate system, which both influence forecast accuracy, 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, improving rainfall forecasts must be high on the agenda of researchers and meteorological agencies, and this must include the consistent training of forecasters.

Fourthly, to improve the quality of the combined forecast, the spatial resolution at which SF is issued should be as fine as that of IF. SFs in Ghana are issued only at a regional (sub-national) scale, whereas IFs are issued at the village level. This requires the downscaling of existing forecasting models. *Fifthly*, if the combination approach is unclear to both scientists and farmers, both groups become sceptical about the combined forecast. Under these circumstances, farmers' risk tolerance is important for their using the combined method, and researchers' open-mindedness becomes important for their accepting the method.

Finally, moving beyond the integration of IF and SF, this study points to the need for future research directed at understanding the consequences of using combined forecasts. In particular, special attention must be paid to evaluating risk in the usage of combined forecasts, as compared to the usage of IF and SF individually or in each farmer's chosen method of combination.

6. Conclusion

This paper is a proof of concept that shows the possibility of combining scientific and indigenous forecast systems at both weather and seasonal climate timescales. Our study concludes that there is an opportunity to increase forecast reliability and usefulness for farmers if quantitative data on Indigenous Forecasts (IF) is collected and integrated with Scientific Forecasts (SF) using the Integrated Probability Forecast (IPF) method. The IPF method introduces a quantitative rigour into integrated forecasts, compared with other existing methods.

A key limitation of the study is the short timeframe for the datasets. Given the several studies calling for the integration of forecasts from IF and SF systems, there is a need for long-term datasets to enable a rigorous analysis to substantiate our results.

Despite these limitations, the insights gained from this study are relevant for researchers and policymakers, allowing them to meet farmers' weather and seasonal climate needs, particularly in areas with limited meteorological infrastructure and records.

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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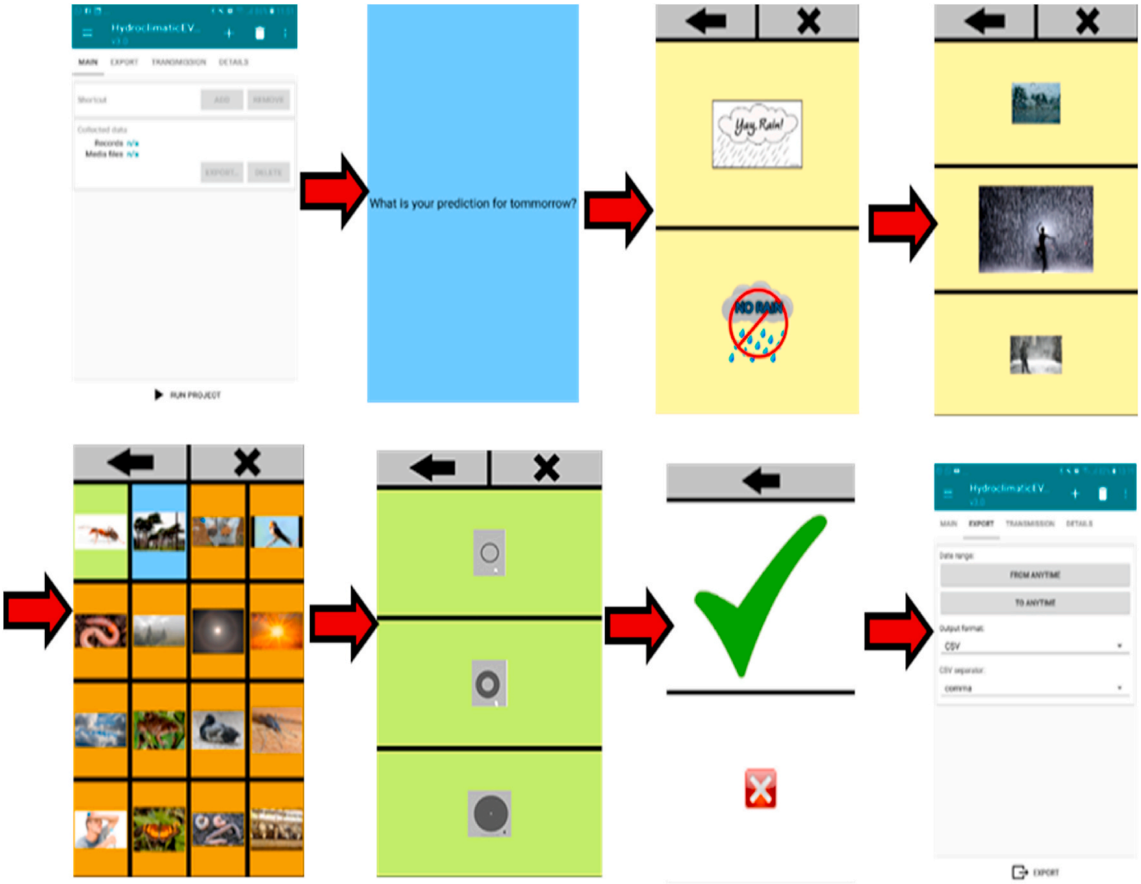
Appendices.

Appendix 1. Background characteristics of respondents (N = 108)

Sex	%	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		

Appendix 2. The stepwise interface of Sapelli android mobile app for recording and sending forecasts.



Appendix 3. Reliability of the three questions for measuring acceptability

Reliability Statistics			
Cronbach's Alpha	Cronbach's Alpha Based on standardised 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 forecast says it won't rain. In those cases, I become confuse and find it problematic.	4.61	0.807	108
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

Appendix 4. Monthly performance of IF, SF, and IPF probability forecasts

Probability of rainfall occurrence	Indigenous	GMet	Integrated
	performance (%)	performance (%)	performance (%)

(continued on next page)

(*continued*)

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

Appendix 5. Relationship between acceptability of integrated probability forecast 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).**

Appendix 6. 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

	Frequency	Percentage
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	100.0

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	–	–

Appendix 7. 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 the 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 forecasts?

	Frequency	Percent
Put them together as one forecast [combined]	3	2.8

(*continued on next page*)

(*continued*)

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 the indigenous forecast information, I will try to integrate or combine both	
Responses	Frequency	Percent	Frequency	Percent	Frequency	Percent
Compare both and choose one based on my experience [complementarily]					101	93.5
I can't tell					4	3.7
Total					108	100.0

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