Harnessing Local Forecasting Knowledge on Weather and Climate in Ghana: Documentation, Skills, and Integration with Scientific Forecasting Knowledge

TALARDIA GBANGOU,[a,c] ERIK VAN SLOBBE,[a] FULCO LUDWIG,[a] GORDANA KRANJAC-BERISAVLJEVIC,[b] AND SPYRIDON PAPARRIZOS[a]

[a] *Water System and Global Change Group, Wageningen University and Research, Wageningen, Netherlands;* [b] *University for Development Studies, Tamale, Ghana*

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ABSTRACT: Improved weather and climate forecast information services are important to sustain small-scale crop production in many developing countries. Previous studies recognized the value of integrating local forecasting knowledge (LFK) with scientific forecasting knowledge (SFK) to support farmers' decision-making. Yet, little work has focused on proper documentation, quality verification, and integration techniques. The skills of local and scientific forecasts were compared, and new integration approaches were derived over the coastal zone of Ghana. LFK indicators were documented, and farmers were trained to collect indicators' observations and record rainfall in real time using digital tools and rain gauges, respectively, in 2019. Dichotomous forecasts verification metrics were then used to verify the skills of both local and scientific forecasts against rainfall records. Farmers use a diverse set of LKF indicators for both weather and seasonal climate time-scale predictions. LFK indicators are mainly used to predict rainfall occurrence, amount of seasonal rainfall, dry spell occurrence, and onset and cessation of the rainy season. The average skill of a set of LFK indicators in predicting one-day rainfall is higher than individual LFK indicators. Also, the skills of a set of LFK indicators can potentially be higher than the forecasts given by the Ghana Meteorological Agency for the Ada District. The results of the documentation and skills indicate that approaches and methods developed for integrating LFK and SFK can contribute to increasing forecast resolution and skills and reducing recurring tensions between the two knowledge systems. Future research and application of these methods can help improve weather and climate information services in Ghana.

SIGNIFICANCE STATEMENT: Most African farmers still rely on local or traditional knowledge on weather and climate forecasts to manage climate variability and change, although there is much effort to reach farmers with the increasing availability of scientific forecasts and data. Exploring the potential of local forecasts and the possible integration with modern forecasts has been suggested as a path to reach out to farmers with more accessible and credible climate information services (CIS). We aimed to understand the contribution of this local knowledge by documenting and investigating its quality. We found that local forecast indicators used by farmers are diverse, and their level of quality can potentially improve the development of CIS, especially when they are combined or integrated with scientific forecasts.

KEYWORDS: Africa; Climate prediction; Forecast verification/skill; Agriculture; Climate services; Decision support

1. Introduction

There is a strong need for better and more accessible weather and climate information services to support, especially, small-scale farmers in their decision-making. In large parts of Africa, the climate is highly variable, and improved climate information services can potentially help farmers to manage climate variability and change. In Ghana, food production contributes substantially to the national economy, with 80% of total agricultural production of the country being attributed to smallholder farmers (Barnett et al. 2017). These farmers predominantly rely on rainwater for agricultural production. This dependence on rains makes the region vulnerable to climate change and variability such as shifts in onset of rains and amounts of seasonal rainfall and dry spell occurrences (Owusu and Waylen 2009; Yaro 2013; Gbangou et al. 2019). As a result, local farmers struggle to meet food and income security. Improved and tailored forecast information on weather and climate can help them adapt and make better decisions to increase their crop yields (Derbile et al. 2016; Gbangou et al. 2018, 2019).

Although previous studies showed that African farmers use both local and scientific forecasting knowledge on weather and climate across Africa (Orlove et al. 2010; Roudier et al. 2014; Codjoe et al. 2014), several limitations remain. First, scientific

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[c] ORCID: 0000-0002-8929-7108.

Corresponding author: Gbangou Talardia, talardia.gbangou@wur.nl; talardia.gbangou@gmail.com

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forecast information often has limited skills and accuracy at high spatial resolutions (i.e., local scale) (Derbile et al. 2016; Fitzpatrick et al. 2015; Vellinga et al. 2013). In addition, the understanding and acceptability of modern forecasts by farmers sometimes limit forecast usefulness and usability (Ingram et al. 2002). Moreover, this knowledge is usually not tailored to end users' needs. Second, there are claims that local forecasting knowledge is subjected to a decrease in trust due to the loss of indicators probably caused by changing weather and climate conditions (Kalanda-Joshua et al. 2011; Ziervogel and Downing 2004; Ziervogel 2001). Local knowledge is also subject to skepticism due to replicability issues that limit knowledge spread in practical applications and science (Huntington 2000; Pierotti and Wildcat 2000; Gilchrist et al. 2005). According to Lebel (2013), the systematic assessment of the consistency and validity of local knowledge is still lacking.

In view of these constraints, there is a need to integrate local and scientific knowledge to provide improved information services (Riedlinger and Berkes 2001; Luseno et al. 2003; Speranza et al. 2010). Speranza et al. (2010) showed that the density and diversity of local knowledge indicators used for weather and climate monitoring and prediction have the potential to improve meteorological forecasts. This study focuses on local forecasting knowledge (LFK) and scientific forecasting knowledge (SFK) on weather and climate. Scientific knowledge refers to the expert or modern knowledge based on rigorous methods through observation and experimentation (e.g., forecasts from large-scale models, station, or satellite observational data). LFK is a knowledge that is rooted in local culture and generally associated with long-settled communities that have strong ties to their natural environment (Ingram et al. 2002; Orlove et al. 2010; Codjoe et al. 2014; Derbile et al. 2016). This local knowledge, inherently, also follows a rigorous process based on observations of biophysical indicators, experimentation in its production and analysis to build trusted cause–effect relationships between indicators and their predictive outcomes in terms of current and future weather and climate conditions (Aronson 2007; Gearheard et al. 2010; Balehegn et al. 2019).

Despite the increasing interest in the use and integration of LFK with SFK, there are only a few studies on the performance assessment of the LFK and its integration with SFK (Speranza et al. 2010). Few studies that focus on integration exist, especially in Ghana. The majority of the studies focused on understanding and interpreting local knowledge related to environmental and social impact assessments for climate change adaption and mitigation (Berkes 1999; Huntington 2000; Nakashima and Roué 2002; Olsson and Folke 2001). Also, the few studies that assessed the performance of LFK have done so qualitatively (Crane et al. 2010; Radeny et al. 2019), and therefore can hardly be used for a quantitative comparison with scientific knowledge (see Fig. 1). Until now, no attempt has been made to assess the skills of LFK and integrate it with the modern forecasting system in the periurban delta areas of Ghana. To explore these skills, proper documentation of the local forecast indicators, specific to this area, is also needed.

This paper attempts to bridge this gap by both documenting and assessing the skills of LFK, and comparing these skills with conventional forecasts and observations. The paper further discusses the possible integration of LFK and SFK. We stress that the paper intends to propose new approaches and methods for collecting and assessing the quality of local knowledge, and integrating both local and scientific forecasting knowledge systems. These approaches and methods are both qualitative and quantitative (Fig. 1). Farmers in Ada East District, Ghana (see the study area; Fig. 2), have also recognized the decline in LFK confidence through evidence from the surveys conducted by the WaterApps research project (http://www.waterapps.net/). Assessing the quality in LFK against SFK with local observations as a reference can help increase the confidence in LFK for both farmers and scientists toward improved climate services.

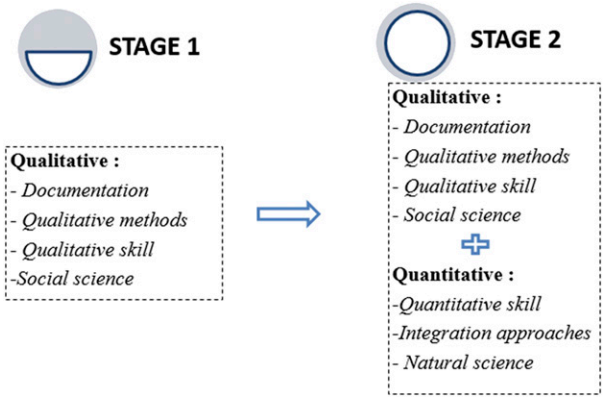

FIG. 1. Framework showing current literature on LFK (stage 1) and the desired goal of the study presented (stage 2).

The work was designed to answer the following questions in the case study:

(i) What are the most frequently used indicators for predicting daily and seasonal rainfall by local farmers?
(ii) What is the perceived reliability of local forecasting knowledge?
(iii) How are the skills of local forecasting knowledge indicators compared to those of scientific forecasting?
(iv) How can we integrate local with scientific forecasting knowledge for improvement?

2. Study area

The study was carried out in the Ada East District (AED), which is located in Ghana's coastal savannah along the delta area of the Volta River (Fig. 1). A dry equatorial climate and coastal savanna vegetation are found in the area. AED is one of the hottest districts in Ghana with average temperatures ranging between 23° and 28°C (Ghana Statistical Service 2014). Average annual rainfall is about 750 mm (Lazar et al. 2015). AED is a periurban area located within the greater Accra region of Ghana. The district produces mainly vegetables for big cities like Tema and Accra. According to the Ghana Statistical Service (2014), the engagement of young adults in crop farming is a major boost to the district and the economy of Ghana. Also, the potential for digital technology to be adopted is high due to proximity to urban areas. The most economically

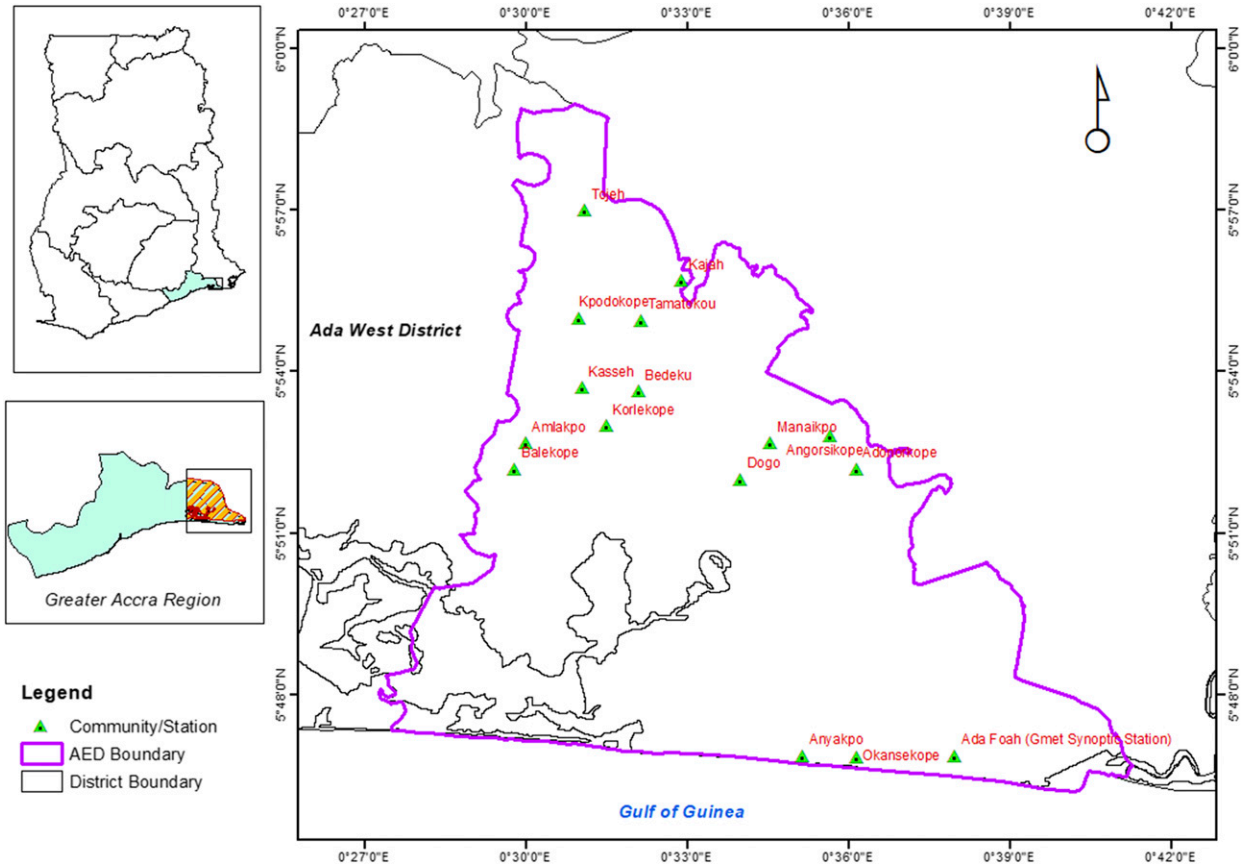

FIG. 2. Map of the study area in the greater Accra region showing various communities of AED.

important crops include cassava, pepper, rice, maize, and tomato (Amisigo et al. 2015). The majority of the agricultural households are either into monocropping or intercropping type of farming (Ghana Statistical Service 2012).

Crop production along the periurban delta area is vital to safeguard sustainable food production (Gbangou et al. 2019). This is because of agricultural intensification, water availability issues, and the increasing possibilities of farmers to use information and communication technology (ICT; e.g., cellular telephones, television, radio, and internet services), for climate information service. Also, risks of crop failure due to unpredictable rainfall events are growing and hence the need for improved rainfall forecasts.

3. Methods

This section presents the methodological approach for data collection and analysis.

a. Data

1) DOCUMENTATION OF LOCAL FORESTING KNOWLEDGE DATA

Respondents for documenting of LFK were selected through purposeful nonrandom sampling, which is the most adapted sampling method for collecting data from experienced targeted people, as in this context (Santha et al. 2010). The subcategory snowball sampling (Quinn Patton 2002) was adopted and focused on farmers that had local knowledge and experience in weather and climate forecasts across five communities of Ada East District (Fig. 2), namely, Balekope, Amlakpo, Bedeku, Kasseh, and Korlekope (see demographic information in Fig. 3a). With the help of agricultural extension agents, 32 respondents across communities were identified and in-depth key informant interviews and five focus group discussions (FGDs) were carried out to collect the qualitative data. FGDs were done with a group of 5–9 farmers per community. Questions focused on identifying (i) indicators used for weather and climate predictions, (ii) their signals, (iii) the period, and (iv) the corresponding outcomes (predictions) as described by Codjoe et al. (2014). The survey was carried out during the 2017 growing season before the real-time data collection at Ada East District during the 2019 season.

2) PERCEIVED RELIABILITY OF LOCAL AND SCIENTIFIC FORECAST DATA

Farmers' perceptions of the performance of local and scientific forecasts were investigated with 68 respondents also in 2017 (see demographic information in Fig. 3b). Farmers who used both forecasting systems in their daily farming activities were purposely identified by a presurvey, and a random

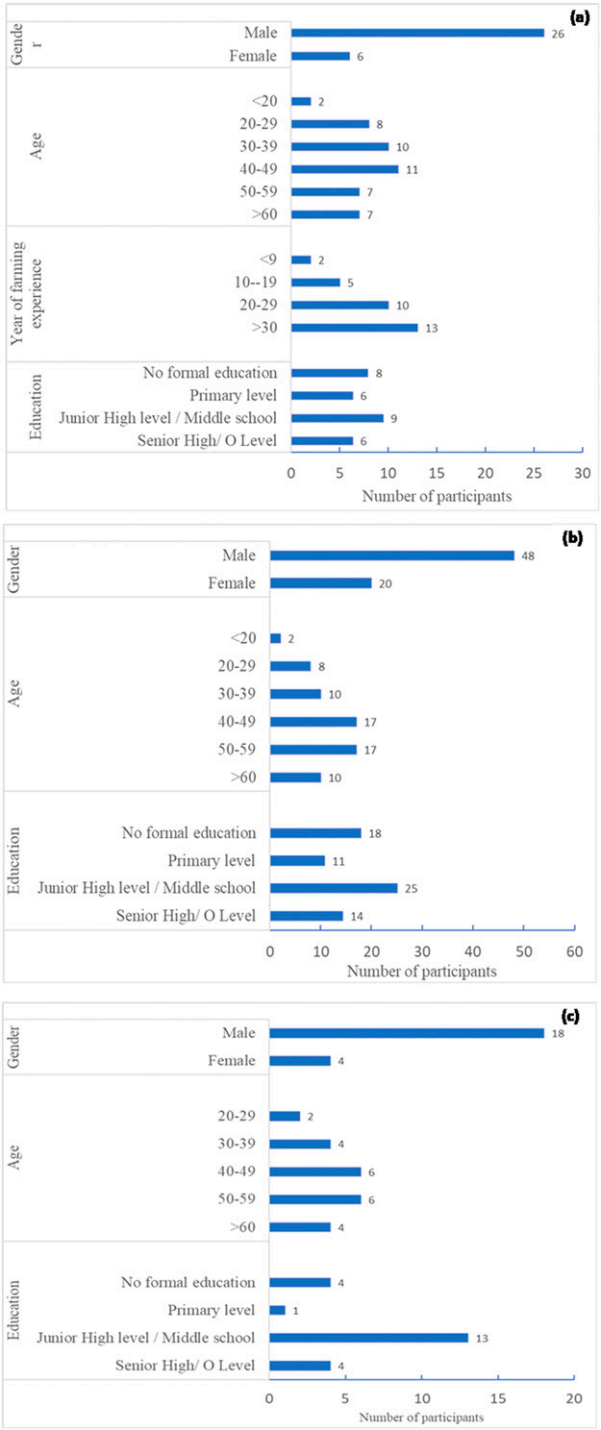

FIG. 3. Sociodemographic characteristics of (a) the 32 participants (farmers) involved in the focus group discussions and interviews for the documentation of local forecasting knowledge in the 2017 season [including their level (years) of experience], (b) the 68 farmers involved in the assessment of the perceived reliability of local forecasting knowledge as compared with the 24-h forecast from GMet (survey carried out in the 2017 season), and (c) the 22 farmers who participated in the real-time collection of LFK indicators observations in AED from 5 Apr to 17 Jul 2019.

selection was performed to choose the final respondents across the communities of the district. Hence, this final sample could give a credible comparative appreciation of the reliability of local and scientific forecasting systems. This method allows to identify the population of interest and ensure the credibility of the findings even with small samples (Palinkas et al. 2015). The sampling focused on rainfed farmers who have used both local and scientific forecasts across Ada East District communities. Farmers were asked to rank the performance of each forecasting system in terms of reliability level: not reliable, somewhat reliable, and reliable. Local forecasting knowledge comes from their own knowledge and experience while scientific knowledge comes from the Ghana Meteorological Agency (GMet) mainly through radio and television.

3) LFK INDICATORS OBSERVATION DATA

We also used a purposeful sample to select 22 farmers for collecting real-time LFK indicators' observations (see demography in Fig. 3c). For this stage, we selected individuals who had prior experience in local forecasting. We focused on the knowledge, availability, and willingness to participate, gender, and involvement of younger farmers in view to ensure the generational knowledge sharing and sustainability of the coproduction process (see Fig. 3c). To also ensure that those with less experience (e.g., younger farmers) in LFK can provide good observations, we trained all participants on the indicators' signals used and their outcomes. This was done during the 2018 and 2019 seasons. LFK indicators' observations are based on the frequently used indicators documented during the 2017 season. We used a web-based application (WeatherApp; see Fig. 4) tailored for the collection of LFK indicators observations. LFK indicators' observations were subsequently converted into forecasts based on the database on indicators' signals and outcomes collected during the 2017 season [see section 3a(1)].

4) RAINFALL RECORDS DATA

Farmers were provided with manual rain gauges (Fig. S1 in the online supplemental material) and were trained by a meteorological extension agent from GMet on how to set up the gauges and measure and record rainfall data from 5 April to 17 July 2019. A total number of 20 manual rain gauges were provided across communities (Fig. 2). Rainfall data were recorded on a daily basis for 105 days starting from 5 April 2019 until 17 July 2019. These data were used as a reference to assess the skills (verify) both local and scientific forecasts from GMet and meteoblue (https://www.meteoblue.com/).

5) GMET AND METEOBLUE DATASETS

Two scientific weather forecasts were used and compared with gauges data collected during the 105 days coproduction experiment. These include GMet and meteoblue 24 h forecast (i.e., daily) data. For consistency with the terms LFK and SFK, daily forecast from GMet and meteoblue are named SFK-GMet and SFK-meteoblue, respectively, throughout the paper. GMet provides the daily forecasts for different agroecological zones in Ghana (see Gbangou et al. 2019) that are much larger than the Ada East District area. Forecast data for the coastal zone that

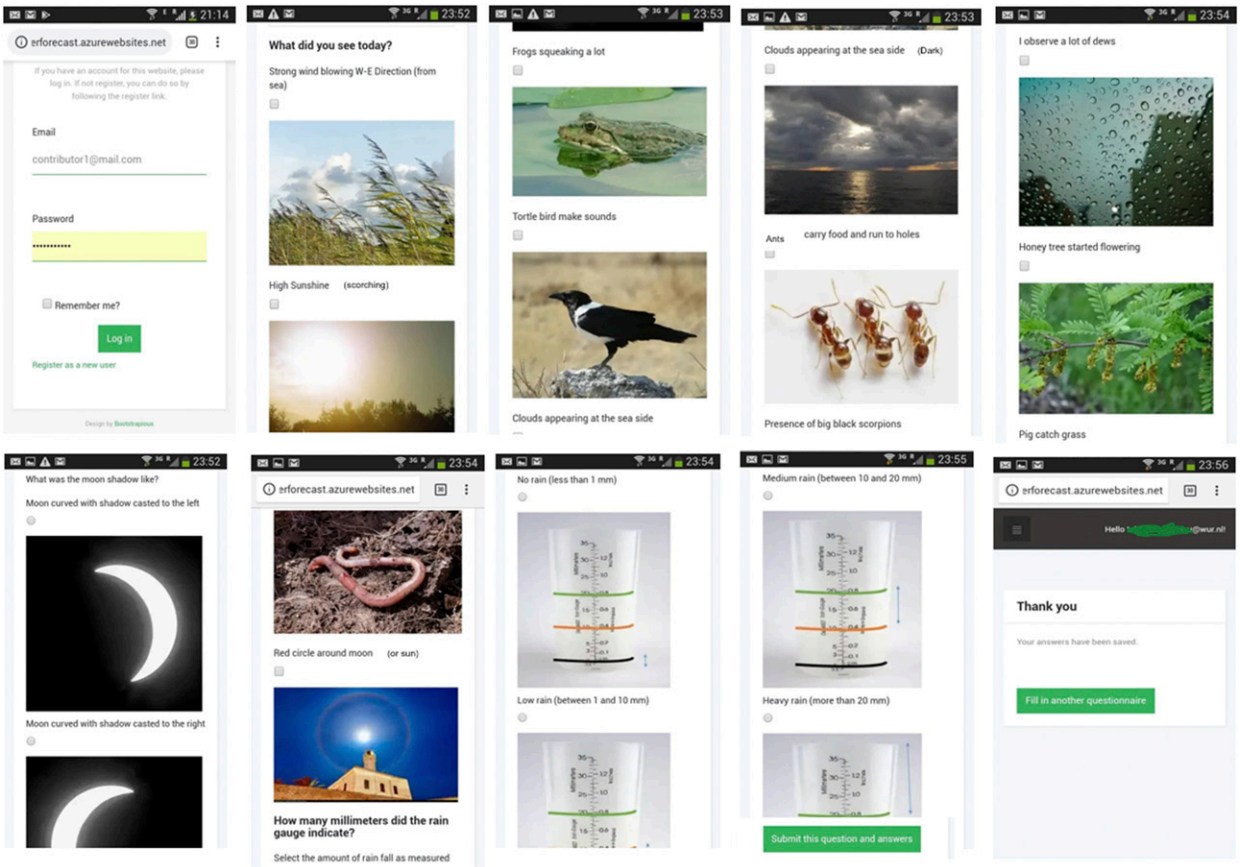

FIG. 4. The interface of the WeatherApp web application (http://waterapps-weatherforecast.azurewebsites.net/Account/Login) showing some of the symbolic images of local weather indicators and data collection procedure. The WeatherApp was designed, tested, and improved to collect farmers' knowledge remotely from 2018 to 2019. More details on the application are described in a follow-up research output focusing on the evaluation of the coproduction experiment carried out in AED under the WaterApps project.

contains the district were therefore considered. These forecasts are shared with the public through the official GMet website, social networks, TV, and radio. Forecasts from meteoblue are raw simulations from the most appropriate (usually the one with the highest resolution) model, depending on location and period. They cover a spatial resolution of 30 km around Ada East District. These meteoblue forecasts are given for illustrative purposes only since the best guess forecast used cannot be known in advance. The skill of the meteoblue real forecast that farmers can see in real time might be much lower.

b. *Analysis of documentation and perceived reliability of local forecasting knowledge*

LFK indicators were compiled, described, and grouped into existing local knowledge spheres identified in previous studies (Codjoe et al. 2014; Speranza et al. 2010). The main spheres are atmospheric conditions, celestial elements, fauna, and flora. Indicators were also classified into weather and seasonal time scales. The perceived reliability was grouped into three categories using data on farmers' perceptions of the performance of local and scientific forecasts as applied in Radeny et al. (2019). These categories include not reliable [0%–33%), somewhat reliable [33%–66%], and reliable (66%–100%]. These categories for the two forecasting systems were subsequently compared.

c. *Analysis of skills of local and scientific forecasting knowledge*

The actual (quantitative) skills of local and scientific forecasts for predicting rainfall occurrence were assessed using a contingency table (Table 1). In this table, the "forecast" indicates LFK indicators, SFK-GMet, and SFK-meteoblue forecasts and the "observation" refers to gauge observations measured by farmers (see details in the appendix and in Fig. S1 of the online supplemental material). The table was used to compute the most relevant skill metrics such as the hit rate [probability of detection (POD)], the false-alarm rate [probability of false detection (POFD)], the false-alarm ratio (FAR):

$$\mathrm{FAR} = \frac{b}{(a+b)}, \tag{1}$$

which ranges from 0 to 1 (FAR = 0 is the perfect score), and the Hanssen-Kuipers (H-K) discriminant (or Pierce)

TABLE 1. Contingency table for categories of events (Gbangou et al. 2019).

	Event was observed	Event was not observed	Total
Event was forecast	Hits (a)	False alarms (b)	Yes forecast ($a + b$)
Event was not forecast	Misses (c)	Correct rejection (d)	No forecast ($c + d$)
Total	Yes observed ($a + c$)	No observed ($b + d$)	Total forecasts (n)

skill score (Hanssen and Kuipers 1965) as described in Gbangou et al. (2019):

$$\text{H-K} = \text{POD} - \text{POFD}, \quad \text{with} \quad \text{POD} = \frac{a}{(a+c)} \quad \text{and} \quad \text{POFD} = \frac{b}{(b+d)}. \tag{2}$$

POD and POFD represent respectively the probability of detection or hit rate and the probability of false detection or false-alarm rate; H-K ranges from -1 to 1; H-K ≤ 0 indicates no skill, and H-K $= 1$ is the perfect score; a, b, c, and d are described in Table 1. This set of metrics allows for a complete analysis of the performance of forecast data (Gbangou et al. 2019). H-K skill measures the ability of the LFK indicator or SFK forecast to discriminate rainfall occurrence events. Skill scores were computed for both individuals LFK indicators and the realization of combined LFK indicators. All possible combinations of scenarios were derived using the formula presented in Eq. (3).

$$C_n^k = \frac{n!}{k!(n-k)!}, \tag{3}$$

where C_n^k is the possible combinations of k elements from the set of the element with size n. The combinations are carried out without repetition (i.e., number of arrangements of k from n). Here, n is the total number of LFK indicators tested.

d. *Analysis of skills of integrated forecasts (local and scientific)*

The word "integration" has several synonyms including combination, completion, and connection. Here, analyses focused on combining LFK and SFK. Therefore, we considered alternating LFK and SFK systems (i.e., GMet and meteoblue) whenever suitable based on the statistical results from the analyses described above (section 3c). We choose to call this integration approach a "statistical integration" implying that the integration is based on statistical combination of local forecast indicators. This integration focused mainly on the prediction of daily rainfall occurrence.

Other approaches of integration (e.g., completion, connection) where identified from the results on the documentation and are only discussed for future research and application. These approaches aimed to help enrich both local and scientific forecasting knowledge. They include the approach (i) that uses specific weather and climate indicators from LFK to enrich SFK and vice versa called "intuitive integration," (ii) that explores the scientific/meteorological patterns of LFK based on scientific historical observations called "patterns evidence from meteorological data," and (iii) that seeks to update some invariable LFK indicators using scientific evidence called "updating invariable LFK indicators." Each approach was provided with an example.

In theory, the intuitive integration is a judgmental approach because it uses expert or experience-based judgment to derive the forecasts (Lawrence et al. 2006), while all other approaches are statistically related approaches for integrating local and scientific knowledge. The judgment or "intuition" can be derived by the scientist, the farmers, or both (if they are working together to make a joint prediction).

4. Results

a. *Documentation of local forecasting knowledge*

Several LFK indicators used by farmers to monitor or forecast local weather and climate conditions are identified and documented in Tables 2 and 3 based on interviews and discussions with experienced local knowledge holders. Farmers from the five communities identified 22 indicators related to weather time-scale prediction (Table 2) and 12 indicators used for seasonal time-scale predictions (Table 3). The indicators documented pertain to different features of atmospheric conditions (wind, clouds, and dew), celestial elements (sun, moon, and sky), fauna (ants, frogs, goats, scorpions, worms, birds, and pigs), and flora (trees). Results showed that the same indicator can have different signals and therefore indicates a different predictive outcome (see Tables 2 and 3). Also, similar indicators can be found for the two time scales (i.e., weather and seasonal) but with different signals and predictions. Moreover, outcomes or predictions depend on the period the indicator is observed. This period expands from December until July, which coincided with the major rainfall season's first and highest peak of the bimodal pattern of the rainy season.

Weather time-scale indicators, listed in Table 2, give predictions of rainfall occurrence ranging from 1 to 14 days. The majority of the indicators are used to predict if it will rain within the coming three days. For instance, rainfall occurring within the next 1 to 3 days is predicted when farmers have observed: strong wind blowing from west to east; the halo (red circle around the sun or moon); croaking of frogs; half of the moon visible at night; thick and dark clouds form in the eastern side; presence of dew; movement of ants, behavior of pig, and scorching sun. Some indicators give predictions about rainfall distribution: when the moon shape is curved such that the shadow is on the left side, rain is expected to occur inland, away from the coast; if the shadow is on the right side, rain will occur inland close to the coast; and if the shadow is on the top, rain is expected in both locations (see Table 2). Other indicators give information about dry spell occurrence, for example, scorpions appearing frequently on the farm indicate that rains occur

TABLE 2. Documentation of local forecasting knowledge indicators for the weather time scale in AED.

Indicator name	Indicator's signal	Month/period	Outcome (prediction)
Wind	When strong winds blow from the sea (usually from west to east direction)	Rainy season (March–July)	Rain is expected within 1–3 days
Wind	When the wind is blowing from the sea carrying dust (west–east direction) with high intensity of the sun	Rainy season	Rain expected within 3 days; intensity depends on the strength of wind observed
Halo (around the sun)	If at sunset there is a red circle around the sun	Rainy season (March–July)	Rain expected within 1–3 days
Sun	If high intensity of sunshine is observed	Rainy season (March–July)	Rain expected within 1–7 days
Sun	If high intensity of sunshine and dust-wind blowing (from west to east) is observed	Rainy season	Rain expected within 1–2 days
Bird (Torle, *Clamator jacobinus*)	Make a lot of sounds	At the onset of the rainy season (from February on)	Onset of the rainy season is expected in next 1 or 2 weeks
Bird (Torle, *Clamator jacobinus*)	When making sounds	Rainy season	Rain is expected within 1–2 weeks
Bird (Gbonyu, *Ploceus cucullatus*)	Sings a lot	Rainy season	Rain expected within 1–2 days
Frog	When frogs start croaking a lot	Rainy season	Rain is expected within 1–3 days
Pig	When pigs catch the grass and turning around it	Rainy season	Rain is expecting within 1 day
Goat	When goat are gathered in the evening and run together	Rainy season	Rain is expected within a day
Moon (distribution)	When the moon shape is curved such that the shadow is on the left side	Rainy season	Rain is expected within 2 weeks inland
Moon (distribution)	When the moon shape is curved such that the shadow is on the right side	Rainy season	Rain is expected within 2 weeks inland in the coastal part
Moon (distribution)	When the moon shape is curved such that the shadow is on the top side	Rainy season	Rain is expected within 2 weeks both inland and coastal part
Moon	When the moon disappears and before it reappears (from the west)	Rainy season	Rain expected generally after 3 days
Moon	At night, if you see that half of the moon is visible	Rainy season	Rain is expected within the next 2 days
Moon	At night, if you see a red circle (like a rainbow) around the moon	Rainy season	It may rain within the next 3 days
Worm (Abotele)	Spread all over the grass after a previous rain	After February	It will rain again that same day or within 1 week time
Scorpion	When big black scorpions appear frequently on the farm	Rainy season	More frequent rains event are expected (that is less dry spell)
Clouds	A thick cloud appears at the eastern side of the sea	Rainy season	It will rain on the same day or within 3 days, but the distribution can be different
Ants	Carry their food or eggs to their holes	Rainy season	Rain expected within next the two days
Dew	If from midnight to the following morning there is a lot of dew falling		No rain is expected the next day (sunny day)

more frequently, in other words, frequency of dry spell and length is reduced during that season.

Subseasonal and seasonal time-scale indicators are used to predict rainfall amounts and the start and end of the rainy season (Table 3). These indicators are used for predictions beyond the 2-week time scale. Rainfall amount prediction refers to the below- and above-normal rainfall occurrence. For example, above-normal rainfall is expected when: a persisting strong wind is blowing at the start of the season (February/March) or one month before Easter; a feeling of cold weather is experienced during February–March, or big black scorpions are abundant on farms. Other indicators for below-normal rainfall include if heavy rainfall is occurring at the onset of the rainy season (March–April) when the season falls on a leap year. Onset of the rainy season is also predicted to be early when harmattan winds appear early.

In summary, a rich source of data on LFK exists in Ada, Ghana. A total number of 34 LFK indicators on weather and climate forecast were identified and documented. Results revealed that LFK indicators are associated with weather forecast time scale in the majority (22 indicators) followed by subseasonal or seasonal climate forecast time scale (12 indicators). Most indicators are used during the major rainfall season in Ada East District.

TABLE 3. Documentation of local forecasting knowledge indicators for the subseasonal and seasonal time scale in AED.

Indicator's name	Indicator's signal	Month/period	Outcome (prediction)
Wind	When early persisting, strong winds appear (harmattan winds).	During February–March	Onset of the rainy season is expected to be early as well
Sun	If a scorching sun is observed (i.e., above-normal temperature)	During the Christmas period (December)	The upcoming season is likely to be good (i.e., above-normal rainfall with regular rains is expected)
Temperature patterns	When feeling or experiencing cold weather condition (i.e., below-normal temperature)	During the two months to Easter (February–March)	The upcoming season is likely to be good (above-normal rainfall with regular rains is expected)
Temperature patterns	If chilling weather (cold) is experienced	Middle of June	Cessation of the rainy season is likely to be early
Rainfall patterns	When it rains heavily at the onset (March–April)	At the beginning of the growing season	Cessation of the rainy season is expected to be early
Leap year	If the season falls on a leap year	Rainy season (March–July)	The upcoming season will not be good (i.e., below-normal rainfall expected with important dry spells)
Insect (Manubi-Tetey)	When they are abundant on farms	Rainy season	The season is likely to be good (above-normal rainfall expected with regular rains)
Dew	If there is a lot of dews	At the beginning of rainy season (March–April)	Onset of the rainy season is expected to be late
Sky	If there are a lot of stars in the sky	From March ongoing	Onset of the rainy season is expected to be late
Moon (traditional lunar calendar)	Counting 7 months from September	September until March/April	Onset of the rainy season is expected on 6 Mar. When rains starting before or after this date then onset is respectively early or late
Scorpion	When big black scorpions are abundant on farms	Rainy season	It will rain heavily in that particular year (e.g., above-normal rainfall expected)
Tree (Odokpo, honey tree)	When start flowering early	Rainy season	Early onset of the rainy season is expected

b. Distribution of LFK indicators observations collected

The distribution of LFK indicators observations collected using the WeatherApp is presented in Fig. 5. The monthly distribution of indicators shows that the number of observations varies by month and with the indicator. It shows the monthly variation in local weather conditions. The difference in the distribution is also related to the number of days where observations on local indicators were collected differ per month. For example, during April data collection started on 5 April, whereas in July data were collected until 17 July 2019. Over the 105 days of data collection, some indicators were seen more often than others (Fig. 5). For instance, sun, clouds, birds, wind, dew, ants, frog, and halo were among the 8 most often observed indicators with more than 25 observations recorded; while the moon, worms, stars, pig, and scorpions were the least frequently observed indicators. Only the skills of the 8 most frequently observed indicators were analyzed.

c. Farmers' perception of the performance of local and scientific weather forecasts

The perceived reliability of 24 h local forecasts are compared with the national scientific forecasts (GMet) in Ada East District (Table 4). The largest share of farmers (40% responses) believed that local forecasting knowledge is reliable as compared with 22% for the national scientific forecasts. More than half of the farmers (67%) thought scientific forecasts were somehow reliable, as compared with 45% for local forecasts. Very few farmers believed that neither local (14%) nor scientific (11%) forecasts were reliable. These results suggest that a large share of local farmers who are using both local and scientific forecasts believe that local forecasting knowledge is more reliable. This finding also implies that the majority of farmers believe the reliability of both systems is low or moderate.

d. Comparative skills between individual local and scientific forecasting systems

Analyses of the POD, POFD, FAR, and H-K skill score of LFK indicators are presented together on Figs. 6 and 7 for the 8 indicators. The skills of various indicators vary per month and per indicators (Fig. 6). However, when the skill is aggregated over the 105 days period, the pattern of the best performing indicators becomes clear (see Fig. 7). Results in Fig. 7 show high probabilities of detection (ranging from 0.75 to 0.90) but also show an important level of false detection probabilities (i.e., 0.24–0.80) that contribute to reduce the skill score of the LFK indicators. Halo, dew, frog, wind, ant, sun, and bird are, respectively, the most performing indicators with H-K skill score > 0. The highest score is the halo with H-K $= 0.56$.

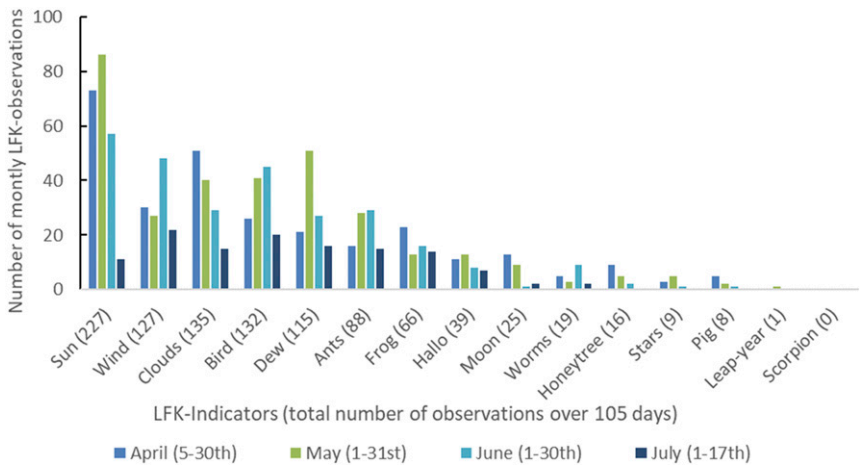

FIG. 5. Distribution of LFK indicators observations collected for the period 5 Apr to 17 Jul 2019. Number of observations is presented (y axis), and the total number over the whole period is shown in parentheses (x axis).

Similar analyses for scientific forecasts from Ghana meteorological agency (SFK-GMet) and from meteoblue (SFK-meteoblue) are presented in Fig. 7 over from 5 April to 17 July 2019 period. Skills in both scientific forecasting systems vary by month as in the case of LFK. SFK-GMet shows an aggregated H-K skill score of 0.50 whereas the SFK-meteoblue has an overall skill of 0.59. This implies that the skill of meteoblue is higher than GMet in Ada with a difference of HK = 0.09. Also, the best performing LKF indicator (i.e., the halo with H-K = 0.56) performs slightly better than SFK-GMet (i.e., H-K = 0.50) but show a little less skill than SFK-meteoblue (i.e., H-K = 0.59).

e. *Performance of combined LFK indicators*

The skills of combined LFK indicators are presented in Fig. 8 for all possible combination scenarios together with the two scientific forecasting systems. H-K skill scores for each forecast are only presented here from the period from 5 April to 17 July 2019. The figure shows that the more indicators are combined, the higher the aggregated (average) skill is. For example, the skill of individual LFK indicators presented above (see Fig. 7) corresponds to $k = 1$ and that of all eight indicators corresponds to $k = 8$. By combining indicators, the average skill improves from 0.22 to 0.80 for the eight indicators tested. Also, the average skill of LFK indicator starts to surpass national and meteoblue forecasts when combining $k = 3$ and $k = 4$ elements, respectively. The figure also shows that the average number of days (i.e., frequency), where a set of indicators is used simultaneously, decrease as the combination of k elements increases. In other words, scenarios of combined indicators with higher skills were less frequently observed by local farmers.

Together these results provide important insights on the monthly distribution and overall performance of LFK indicators in comparison to SFK from GMet and meteoblue. Results suggest that combined LFK indicators can compete or often surpass scientific forecasts from GMet and meteoblue, which are given for a much broader area.

5. Discussion

a. *Documentation and skills of LFK*

Documentation of LFK showed a rich source of data in terms of amount, diversity, and forecast time scales that include both weather and seasonal time frame. The performance of weather time-scale indicators in discriminating daily rainfall occurrence varies depending on whether an individual or a set of indicators is used. If a set of several LFK indicators is used, LFK can potentially predict daily rainfall occurrence better than national forecast and meteoblue that are given for a much broader area. Although scenarios in which local farmers observe several LFK indicators tend to have higher skills, such scenarios occur less frequently. These results are in agreement with the perceived reliability of local weather forecasts when compared with the national daily forecast.

The diversity of indicators is comparable to those found in other regions of Africa (Roncoli et al. 2009; Speranza et al. 2010; Radeny et al. 2019) and more particularly in Ghana (Codjoe et al. 2014). However, results achieved surpass the earlier work in Ghana (Codjoe et al. 2014) in terms of amount and diversity of indicators documented as they pertain not only to the weather but also to subseasonal and seasonal climate time-scale predictions. Moreover, LFK outcomes (see Tables 2 and 3) provide insights on tailored forecast information needs in the district: rainfall occurrence, categorical season rainfall amount, dry spell occurrence, and onset and cessation of the rainy season (Gbangou et al. 2019; Nyadzi et al. 2019).

TABLE 4. Farmers' perception on the reliability of daily local and scientific forecasts.

Forecasting systems/performance	Not reliable	Somewhat reliable	Reliable
Local forecast (daily)	14%	45%	40%
Scientific forecast (daily)	11%	67%	22%

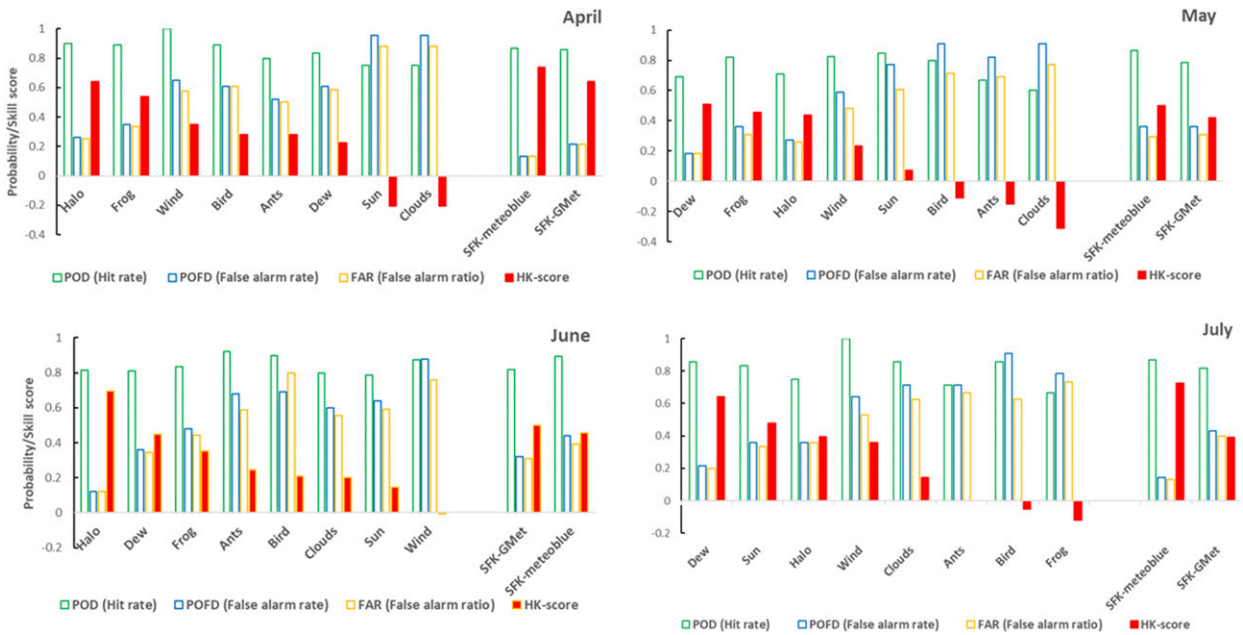

FIG. 6. Skill of local forecast (LFK indicators) and scientific forecast (SFK-GMet; SFK-meteoblue) for April, May, June, and July 2019. Hit rate (POD), false-alarm rate (POFD), and false-alarm ratio (FAR) are presented in different colors. LFK indicator skills are assessed against gauge observations. Skills are classified from the highest to the lowest.

Findings on the skills imply that some LFK indicators still stand and can even compete with advance modern forecasting systems despite the decrease in the reliability of local knowledge due to climate change and variability and due to the fast urbanization that has resulted in the loss of some local forecast indicators (Ziervogel 2001; Ziervogel and Downing 2004; Kalanda-Joshua et al. 2011; Balehegn et al. 2019). Hence, this study supports evidence from previous observations that local weather forecasting is still valuable for local farmers (Balehegn et al. 2019; Chisadza et al. 2015; Green et al. 2010).

b. *Integration opportunities between local and scientific forecasting knowledge*

1) METHOD USED TO INTEGRATE LOCAL AND SCIENTIFIC DAILY RAINFALL OCCURRENCE FORECAST

Based on the statistics found for individual and combined skills of LFK indicators (see section 4e), an approach that we called statistical integration can be used to optimize local and modern forecasts' performance by alternating both systems

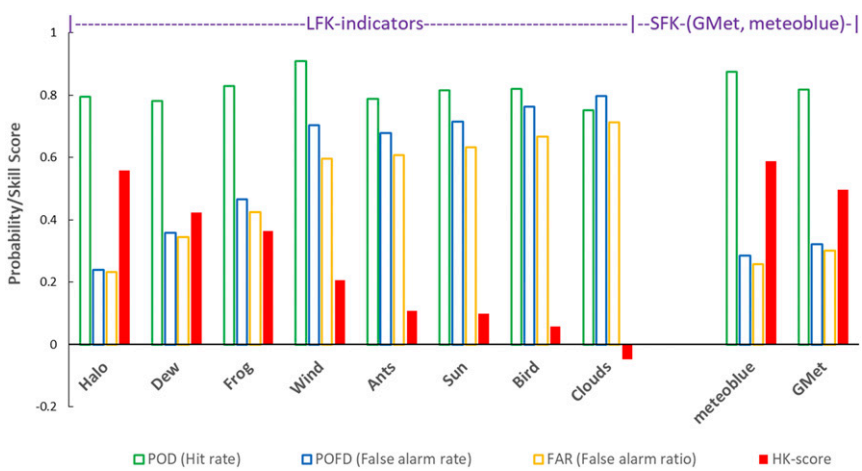

FIG. 7. Overall skills of local forecast (LFK indicators) and scientific forecasts (GMet; meteoblue) over the period from 5 Apr to 17 Jul 2019. POD, POFD, and FAR are presented in different colors. Local and scientific forecasts skills are assessed against gauge observations. Skills are classified from the highest to the lowest.

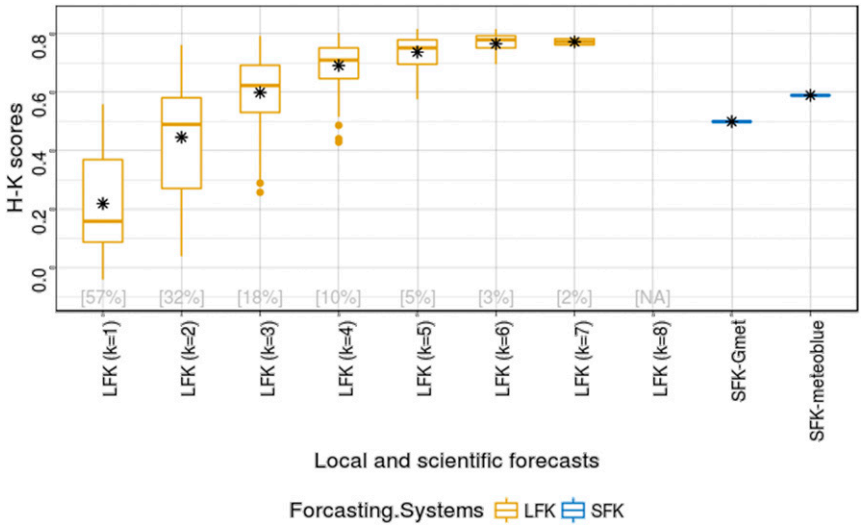

FIG. 8. Skills of combined LFK indicators compared with the skills of scientific forecasts from GMet and meteoblue from 5 Apr to 17 Jul 2019; $K = 1, 2, 3, 4, 5, 6, 7$, and 8 indicate the possible combination of eight LFK indicators observed; the combination is carried out without repetition and generates 8, 28, 56, 70, 56, 28, 8, and 1 scenarios, respectively. Boxplots also represent the skill of these scenarios. Asterisks indicate the average skill of each scenario. The square brackets [X%] indicate the frequency (i.e., average number of days over the whole period) at which each scenario of combined indicators was observed simultaneously by local farmers, with NA indicating that the scenario was not observed.

whenever suitable (Table 5). The table shows that farmers can alternate the choice of local and modern forecasting systems based on the set of local indicators that are observed. For instance, with a set of more than three specific indicators observed, farmers would choose the local forecast instead of the scientific one, and, when fewer than three specific indicators are observed, they would go for the scientific forecast (Table 5). This approach can contribute to increasing the skill for predicting daily rainfall occurrence despite the difference in scale and configuration of the two knowledge systems. It is not necessary for the two systems to have a similar spatial resolution to make sense, as in modern forecasting systems. In that sense, this integration approach offers an added value in accordance with Speranza et al. (2010), as it helps farmers select the most appropriate forecasts depending on the set of data observed/collected at the local scale. This is particularly useful when scientific forecast information available to farmers covers much larger areas and/or has fewer skills than local knowledge.

In summary, statistical integration, which refers to an integration based on the statistics that combine a set of several indicators, was developed and applied in this study. This integration approach suggests that local and modern forecasts can be alternated on the basis of the set of local indicators observed by local farmers. This approach can improve the quality in daily weather forecast information for local farmers in Ada East District.

2) OTHER INTEGRATION POSSIBILITIES BETWEEN LOCAL AND SCIENTIFIC FORECASTING SYSTEMS

The rich diversity and performance of LFK indicators create opportunities for more different integration approaches with the scientific forecasts (albeit not applied in this study). Based on the abovementioned results, three additional approaches for integration were identified and discussed. These include (i) an intuitive integration, (ii) a patterns evidence analyses, and (iii) an updating of invariable LFK indicators. Table 6 summaries the three other recommended approaches with an example.

The intuitive integration consists of complementing each knowledge system using the strength and weaknesses of the other to derive improved forecast information (Table 6). In this integration, scientific information on large-scale weather and climate dynamics, which is often not visible to farmers is used to enrich local knowledge. Inversely, observations on local-scale dynamics that are not visible to meteorologists can enrich scientific knowledge. The intuitive integration approach can

TABLE 5. Proposed approach for integrating weather of local and scientific for daily rainfall occurrence in AED (approach tested in this study and called the statistical integration). The approach alternates local and modern daily forecasts based on the combination of a set of local forecast indicators (k) observed by local farmers.

No. of elements combined (k)	Choice of the weather forecasting system
≤2 LFK indicators are observed ($k \leq 2$)	Farmers are advised to adopt the scientific forecasts for decision-making
3 LFK indicators are observed ($k = 3$)	Farmers can adopt either local or scientific forecasts for decision-making
>3 LFK indicators are observed ($k > 3$)	Farmers are advised to adopt the local forecasting system for decision-making

TABLE 6. Proposed approaches/opportunities (albeit not tested in this study) for integrating local and scientific forecasting knowledge.

Recommended integration approaches	Description	Examples
1) Intuitive integration	An intuitive approach consists of supporting local forecasting knowledge with insights from scientific forecasting knowledge and vice versa. This is because the coastal area in Ghana is more subjected to strong atmospheric–sea–land interactions (Gbangou et al. 2019). Ada being at a coastal area, the district is affected by local land–sea-breeze interactions due to the heating or pressure gradient. Also, remote large-scale disturbances such as storms or thunderstorms can move toward the coastal zone and affect AED.	For example, local farmers are often unable to perceive storm clouds forming far away (e.g., from Nigeria or Benin) as well as its momentum (see Fig. S2 in the online supplemental material for details). When such a strong storm is located in those regions and moving toward Ada, farmers might not observe the cloud indicator from their location. Satellite imagery data can help informed local knowledge by estimating a storm cloud speed and direction moving toward the AED environment. Similarly, observations on LFK indicators such as the halo, wind, and dew can be used as a piece of real-time additional information to informs modern weather forecasts for Ada location. For instance, dew observation is connected with atmospheric stability (i.e., clear skies, light winds) and therefore implies an absence of turbulence, vertical motion, clouds, and thunderstorm precipitation.
2) Patterns evidence from meteorological data	This approach consists of exploring hidden patterns on weather and climate conditions, identified by local forecasting knowledge, using historical scientific observations.	For example, in the LFK system, cold weather experienced during February–March indicates an above-normal rainfall season, or if the cold weather is experienced in June, an early cessation is expected. Hence, historical meteorological data can be used to explore whether below-normal temperature during February–March is associated with above-normal seasonal rainfall, or if early cessation is associated with below-normal temperature in June. LFK indicator on rain patterns indicated that heavy rains observe in March–April is a sign of early cessation.
3) Updating invariable LFK indicators	This method is close to the pattern evidence approach. It seeks to make changes or adjustments into LFK indicators that are invariable by looking into variability and shifts from meteorological data. This can allow for taking into account the recurring high variability in weather and climate conditions especially in the coastal zone of Ghana (Gbangou et al. 2019).	An interesting example, in this case, is the traditional calendar indicator used by farmers to predict a fixed date of onset by counting 7 months from September. The work done by Gbangou et al. (2019) can help inform farmers that, because of climate variability and change, there has been important shifts in the mean onset date as well as an increased variability in the year-to-year onset dates. This can be applied to the leap-year indicator as well.

provide a much richer forecast outcome since it uses specific information available from each forecasting system to enrich the other. This can result in a higher predictive skill especially for weather time-scale predictions of one or the other knowledge systems. Each knowledge system can benefit from a piece of punctual information or indicator from the other system to enhance its skills. However, it is important to recognize that intuitive forecasting is subjective and comes with limitations (Daan and Murphy 1982). Therefore, good judgmental forecast requires close collaboration between well experienced local and scientific forecasters in the area to inform and update each other in time (Lawrence et al. 2006). This can be facilitated through the coproduction of climate services with and for farmers.

The "patterns evidence method" uses historical meteorological data to assess patterns in weather and climate conditions identified by local farmers through experience (Table 6). This can bring new discoveries of relationships and time lag teleconnections (correlations) between local weather variables and agrometeorological indices at a local scale. Insights from this integration approach can be useful to improve seasonal predictions by identifying, scientifically, existing lag correlation claims by local forecasters.

The "updating invariable LFK indicators" approach seeks to adjust LFK static indicators to the changing weather and climatic conditions (Table 6). It has similarities with the pattern evidence approach as it uses meteorological data to give insights on variability and changes related to some LFK static indicators in order to update and improve this knowledge. The method can allow taking into account indicators that have changed as a result of the climate change and variability mentioned in the previous works (Kalanda-Joshua et al. 2011; Ziervogel and Downing 2004; Ziervogel 2001).

All said, exploring these integration methods can help to reduce the recurring tensions that exist between local and scientific knowledge (Briggs 2005; Wohling 2009) and increasing the replicability and spread of local knowledge in practice and in science.

c. *Limitation and cautious interpretation of the results*

A number of limitations are applicable to this new approach for documentation, quantitative skill assessment, and integration of local and scientific forecasting knowledge. The most important one relates to LFK indicators' observations and rainfall records that were collected during one single rainy season, and therefore do not allow for a multiyear analysis that will give more insights on the performance of LFK in Ada. However, these results reflect well farmers' long-term perceptions of the reliability of their indicators. To further validate our results and test the long-term skills of LFK indicators, including significance tests, longer-term historical data are needed.

In this study, the performance of local and scientific forecasts is compared, although they are not on the same scale or resolution. For instance, LFK is provided for the Ada East District level, while SFK-GMet forecast is provided for the coastal agroecological zone level (see Fig. 2). Similarly, SFK-meteoblue is valid for a spatial resolution of 30 km. This is because the scientific forecasts used in the area are not yet available at a finer spatial resolution. However, this does not affect the outcome of the study as findings intend to show the value of documenting and integrating LFK with modern forecasts toward downscaling and improvement of forecast information.

Results of the indicators and skills cannot easily be transferred to other regions. This is because a different region/community can have different weather patterns and indicators with different performances in predicting rainfall occurrence. In other words, an LFK indicator performing in Ada may not be present or have similar performance elsewhere. Further documentation of indicators for different regions is needed. However, the approaches for the quantitative assessment of the skills and integration can be adapted and applied anywhere.

Also, in this study, we have mainly used a scientific approach (e.g., skills assessment metrics, validation with rainfall measurements, etc.) to analyze the performance of both the local and scientific forecasting systems. And we recognize that we could have also used in the other way round a local approach to evaluate both the local and scientific forecasts performance (Balehegn et al. 2019). Further research should be undertaken to investigate the approaches for local forecast quality assessment, specific to the location of interest, and use this local method to get further insights on the performance. This can contribute to further stimulate the reconciliation between the two knowledge systems.

d. *Practical implication for local farming and the development of climate services*

Our study shows similar results as Codjoe et al. (2014) indicating that LFKs have several practical applications for local farmers and can also contribute to improve scientific knowledge. Adopting the integration approaches of local and scientific forecasts support the idea of Deloria (1996) that scientific research can benefit from more or sometimes better weather and climate information. This can be done through a better collaboration of local and scientific communities through a coproduction process of weather and climate information. Such collaboration requires appropriate infrastructure, capacity building, and user-friendly environmental monitoring tools such as interactive mobile apps (Buytaert et al. 2014; Nyadzi et al. 2018) to facilitate the exchange, understandability, and acceptability of the information (Ingram et al. 2002).

Our work shows potential for exploring new approaches and methods to deal with challenges related to weather and climate information especially for farmers in the developing countries where meteorological observations are not often available or accessible. Moreover, collecting LFK observations can be used for continuous improvement of farmers' forecasts through the process of verification alike hindcasts used for scientific forecasting systems. If these data are collected for several years, they can help build LFK hindcast datasets for future studies and provide better insight for both weather and seasonal time-scale predictions. This approach is built on citizen science approaches, thus the performance of local forecasts may be dependent on the education levels, experiences, engagement, and motivation of the farmers involved. Therefore, local forecasts performance/quality can be improved through better engagement and training of local farmers. Improving the tools used for data collection and exchange is also important to facilitate and get qualitative data.

Documenting local forecasting has helped to reveal local forecast information needs that can help farmers enhance their decision-making. Although this study tested only daily rainfall occurrence, many other agrometeorological indices can be predicted by LFK (e.g., onset, cessation, and dry spell) and can be used in future studies as well.

6. Conclusions

This study provides new insights into the diversity and performance of farmers' contributions to weather and climate forecasting in the Ada case study. New approaches for integrating local and scientific forecasting knowledge are identified for future research and applications in climate service development. Local forecasting knowledge is proven to go beyond the weather time scale as it also includes subseasonal or seasonal time-scale prediction indicators. Besides, this knowledge focuses on forecasting tailor-made agrometeorological indices such as rainfall occurrence and amount and dry spell occurrence, onset, and cessation. In that sense, it also contributes to the understanding of local information needs for weather and climate service development.

The level of skills found also reveals that the local forecasting system can potentially compete with modern forecasting systems with regard to the prediction of rainfall occurrence. This is especially applicable when local knowledge indicators are combined. More importantly, local and scientific forecasting can enrich each other through several integration approaches. Although further research and development are

necessary to bring more evidence and insights. Such integrated forecast information can help in developing improved climate services for and with farmers toward a better adaptation to climate change and variability in Ghana and other regions of the world. Integration can reduce the recurrent tensions between the two knowledge systems and foster acceptance by both farmers and scientists.

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APPENDIX

Notes on the Analysis of the Skills of Local Forecasting Knowledge Indicators in Predicting One-Day Rainfall Occurrence

The skills of LFK indicators are based on indicators, observations, and rainfall records. We looked at indicators observed by farmers and the rainfall occurrence ($P > 1$ mm) recorded by farmers within the next 24 h (i.e., daily). For instance, when an indicator or a set of indicators is/is not observed and rainfall has/has not occurred, respectively, within the next 24 h, it is a hit. Both LFK indicators and rain observations are aggregated on a daily basis.

REFERENCES

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

Aronson, S. M., 2007: *Local Science vs. Global Science: Approaches to Indigenous Knowledge in International Development*. Berghahn Books, 288 pp.

Balehegn, M., S. Balehey, C. Fu, and W. Liang, 2019: Indigenous weather and climate forecasting knowledge among Afar pastoralists of north eastern Ethiopia: Role in adaptation to weather and climate variability. *Pastoralism*, **9**, 8, https://doi.org/10.1186/s13570-019-0143-y.

Barnett, I., and Coauthors, 2017: External evaluation of mobile phone technology-based nutrition and agriculture advisory services in Africa and South Asia. Institute of Development Studies Doc., 104 pp., https://opendocs.ids.ac.uk/opendocs/bitstream/handle/20.500.12413/13465/mNutrition%20Inception%20Report_for%20publication%20Nov17.pdf?sequence=1&isAllowed=y.

Berkes, F., 1999: *Sacred Ecology: Traditional Ecological Knowledge and Management Systems*. Taylor and Francis, 209 pp.

Briggs, J., 2005: The use of indigenous knowledge in development: Problems and challenges. *Prog. Dev. Stud.*, **5**, 99–114, https://doi.org/10.1191/1464993405ps105oa.

Buytaert, W., and Coauthors, 2014: Citizen science in hydrology and water resources: Opportunities for knowledge generation, ecosystem service management, and sustainable development. *Front. Earth Sci.*, **2**, 26, https://doi.org/10.3389/feart.2014.00026.

Chisadza, B., M. J. Tumbare, W. R. Nyabeze, and I. Nhapi, 2015: Linkages between local knowledge drought forecasting indicators and scientific drought forecasting parameters in the Limpopo River Basin in southern Africa. *Int. J. Disaster Risk Reduct.*, **12**, 226–233, https://doi.org/10.1016/j.ijdrr.2015.01.007.

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

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

Daan, H., and A. H. Murphy, 1982: Subjective probability, forecasting in the Netherlands: Some operational and experimental results. *Meteor. Rundsch.*, **35**, 99–112.

Deloria, V., 1996: If you think about it, you will see that it is true. *ReVision*, **18**, 37–44.

Derbile, E. K., A. Abdul-Moomin, and I. Yakubu, 2016: Local knowledge and community-based assessment of environmental change in Ghana. *Ghana J. Geogr.*, **8**, 59–83.

Fitzpatrick, R. G., C. L. Bain, P. Knippertz, J. H. Marsham, and D. J. Parker, 2015: The West African monsoon onset: A concise comparison of definitions. *J. Climate*, **28**, 8673–8694, https://doi.org/10.1175/JCLI-D-15-0265.1.

Gbangou, T., M. B. Sylla, O. D. Jimoh, and A. A. Okhimamhe, 2018: Assessment of projected agro-climatic indices over Awun River basin, Nigeria for the late twenty-first century. *Climatic Change*, **151**, 445–462, https://doi.org/10.1007/s10584-018-2295-y.

——, F. Ludwig, E. Van Slobbe, L. Hoang, and G. Kranjac-Berisavljevic, 2019: Seasonal variability and predictability of agro-meteorological indices: Tailoring onset of rainy season estimation to meet farmers' needs in Ghana. *Climate Serv.*, **14**, 19–30, https://doi.org/10.1016/j.cliser.2019.04.002.

Gearheard, S., M. Pocernich, R. Stewart, J. Sanguya, and H. P. Huntington, 2010: Linking Inuit knowledge and meteorological station observations to understand changing wind patterns at Clyde River, Nunavut. *Climatic Change*, **100**, 267–294, https://doi.org/10.1007/s10584-009-9587-1.

Ghana Statistical Service, 2012: 2010 population and housing census: Summary report of final results. GSS Accra Rep., 117 pp., https://www.statsghana.gov.gh/gssmain/storage/img/marqueeupdater/Census2010_Summary_report_of_final_results.pdf.

——, 2014: 2010 population and housing census. GSS Accra Rep., 81 pp., https://www2.statsghana.gov.gh/docfiles/2010_District_Report/Northern/Kumbungu.pdf.

Gilchrist, G., M. Mallory, and F. Merkel, 2005: Can local ecological knowledge contribute to wildlife management? Case studies of migratory birds. *Ecol. Soc.*, **10**, 12, https://www.jstor.org/stable/26267752.

Green, D., J. Billy, and A. Tapim, 2010: Indigenous Australians' knowledge of weather and climate. *Climatic Change*, **100**, 337–354, https://doi.org/10.1007/s10584-010-9803-z.

Hanssen, A. J., and W. J. Kuipers, 1965: On the relationship between the frequency of rain and various meteorological parameters. *K. Ned. Meteor. Inst.*, **81**, 2–25.

Huntington, H. P., 2000: Using traditional ecological knowledge in science: Methods and applications. *Ecol. Appl.*, **10**, 1270–1274, https://doi.org/10.1890/1051-0761(2000)010[1270:UTEKIS]2.0.CO;2.

Ingram, K., M. Roncoli, and P. Kirshen, 2002: Opportunities and constraints for farmers of West Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. *Agric. Syst.*, **74**, 331–349, https://doi.org/10.1016/S0308-521X(02)00044-6.

Kalanda-Joshua, M., C. Ngongondo, L. Chipeta, and F. Mpembeka, 2011: Integrating indigenous knowledge with conventional science: Enhancing localised climate and weather forecasts in Nessa, Mulanje, Malawi. *Phys. Chem. Earth*, **36**, 996–1003, https://doi.org/10.1016/j.pce.2011.08.001.

Lawrence, M., P. Goodwin, M. O'Connor, and D. Önkal, 2006: Judgmental forecasting: A review of progress over the last 25 years. *Int. J. Forecasting*, **22**, 493–518, https://doi.org/10.1016/j.ijforecast.2006.03.007.

Lazar, A. N., and Coauthors, 2015: A method to assess migration and adaptation in deltas: A preliminary fast-track assessment. DECCMA Working Paper, 29 pp., http://www.kulima.com/wp-content/uploads/2011/03/Lazar-et-al-15-WP5_Fast_Track_Report_2015.pdf.

Lebel, L., 2013: Local knowledge and adaptation to climate change in natural resource-based societies of the Asia-Pacific. *Mitigation Adapt. Strategies Global Change*, **18**, 1057–1076, https://doi.org/10.1007/s11027-012-9407-1.

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

Nakashima, D., and M. Roué, 2002: Indigenous knowledge, peoples and sustainable practice. *Social and Economic Dimensions of Global Environmental Change*, P. Timmerman and T. Munn, Eds., Vol. 5, *Encyclopedia of Global Environmental Change*, John Wiley and Sons, 314–324.

Nyadzi, E., and Coauthors, 2018: Diagnosing the potential of hydro-climatic information services to support rice farming in northern Ghana. *NJAS Wageningen J. Life Sci.*, **86–87**, 51–63, https://doi.org/10.1016/j.njas.2018.07.002.

——, E. S. Werners, R. Biesbroek, P. H. Long, W. Franssen, and F. Ludwig, 2019: Verification of seasonal climate forecast toward hydroclimatic information needs of rice farmers in northern Ghana. *Wea. Climate Soc.*, **11**, 127–142, https://doi.org/10.1175/WCAS-D-17-0137.1.

Olsson, P., and C. Folke, 2001: Local ecological knowledge and institutional dynamics for ecosystem management: A study of Lake Racken watershed, Sweden. *Ecosystems*, **4**, 85–104, https://doi.org/10.1007/s100210000061.

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

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

Palinkas, L. A., S. M. Horwitz, C. A. Green, J. P. Wisdom, N. Duan, and K. Hoagwood, 2015: Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Adm. Policy Ment. Health*, **42**, 533–544, https://doi.org/10.1007/s10488-013-0528-y.

Pierotti, R., and D. Wildcat, 2000: Traditional ecological knowledge: The third alternative. *Ecol. Appl.*, **10**, 1333–1340, https://doi.org/10.1890/1051-0761(2000)010[1333:TEKTTA]2.0.CO;2.

Quinn Patton, M., 2002: *Qualitative Research and Evaluation Methods*. SAGE, 598 pp.

Radeny, M., A. Desalegn, D. Mubiru, F. Kyazze, H. Mahoo, J. Recha, P. Kimeli, and D. Solomon, 2019: Indigenous knowledge for seasonal weather and climate forecasting across East Africa. *Climatic Change*, **156**, 509–526, https://doi.org/10.1007/s10584-019-02476-9.

Riedlinger, D., and F. Berkes, 2001: Contributions of traditional knowledge to understanding climate change in the Canadian Arctic. *Polar Rec.*, **37**, 315–328, https://doi.org/10.1017/S0032247400017058.

Roncoli, C., and Coauthors, 2009: From accessing to assessing forecasts: An end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). *Climatic Change*, **92**, 433–460, https://doi.org/10.1007/s10584-008-9445-6.

Roudier, P., B. Muller, P. D'Aquino, C. Roncoli, M. A. Soumaré, L. Batté, and B. Sultan, 2014: The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal. *Climate Risk Manage.*, **2**, 42–55, https://doi.org/10.1016/j.crm.2014.02.001.

Santha, S. D., B. Fraunholz, and C. Unnithan, 2010: A societal knowledge management system: Harnessing indigenous wisdom to build sustainable predictors for adaptation to climate change. *Int. J. Climate Change*, **2**, 49–64, https://doi.org/10.18848/1835-7156/CGP/v02i01/37293.

Speranza, C. I., B. Kiteme, P. Ambenje, U. Wiesmann, and S. Makali, 2010: Indigenous knowledge related to climate variability and change: Insights from droughts in semi-arid areas of former Makueni District, Kenya. *Climatic Change*, **100**, 295–315, https://doi.org/10.1007/s10584-009-9713-0.

Vellinga, M., A. Arribas, and R. Graham, 2013: Seasonal forecasts for regional onset of the West African monsoon. *Climate Dyn.*, **40**, 3047–3070, https://doi.org/10.1007/s00382-012-1520-z.

Wohling, M., 2009: The problem of scale in indigenous knowledge: A perspective from northern Australia. *Ecol. Soc.*, **14**, 1, https://doi.org/10.5751/ES-02574-140101.

Yaro, J. A., 2013: The perception of and adaptation to climate variability/change in Ghana by small-scale and commercial farmers. *Reg. Environ. Change*, **13**, 1259–1272, https://doi.org/10.1007/s10113-013-0443-5.

Ziervogel, G., 2001: Global science, local problems: Seasonal forecast use in a Basotho village. *Open Meeting of the Global Environmental Change Research Community*, Rio de Janeiro, Brazil, Brazilian Academy of Sciences.

——, and T. E. Downing, 2004: Stakeholder networks: Improving seasonal climate forecasts. *Climatic Change*, **65**, 73–101, https://doi.org/10.1023/B:CLIM.0000037492.18679.9e.