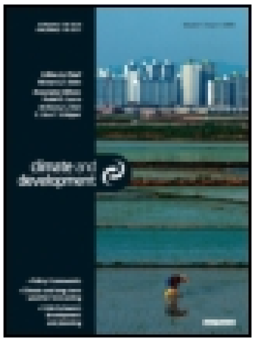

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Techniques and skills of indigenous weather and seasonal climate forecast in Northern Ghana

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ABSTRACT
There are strong calls to integrate scientific and indigenous forecasts to help farmers adapt to climate variability and change. Some studies used qualitative approaches to investigate indigenous people's techniques for forecasting weather and seasonal climate. In this study, we demonstrate how to quantitatively collect indigenous forecast and connect this to scientific forecasts. We identified and characterized the main indigenous ecological indicators (IEIs) local farmers in Northern Ghana use for forecasting. Mental model was constructed to establish the relationship between IEIs and their forecasts. Local farmers were trained to send their rainfall forecast with mobile apps and record observed rainfall with rain gauges. Results show that farmers forecast techniques are based on established cognitive relationship between IEIs and forecast events. Skill assessment shows that on the average both farmers and Ghana Meteorological Agency (GMet) were able to accurately forecast one out of every three daily rainfall events. Performance at the seasonal scale showed that unlike farmers, GMet was unable to predict rainfall cessation in all communities. We conclude that it is possible to determine the techniques and skills of indigenous forecasts in quantitative terms and that indigenous forecasts are not just intuitive but a skill developed over time and with practice.

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Climate services; Indigenous forecast; forecast skills; forecast techniques; climate change; farmers; Ghana

1. Introduction

Extreme weather conditions such as droughts and floods are projected to occur more frequently and become more intense, affecting all sectors especially agriculture in Africa (Alemaw, 2020; Gebrechorkos et al., 2020; Ibe & Amikuzuno, 2019; Schlenker & Lobell, 2010). Over the last years, periods of extreme heat and erratic rainfall in Ghana have caused crop failures leading to yield reduction and food insecurity in the region (Müller-Kuckelberg, 2012). Smallholder farmers are disproportionately affected by climate variability and change (Jalloh et al., 2013; Niang et al., 2014; Sarr et al., 2015). Rainfall variability is a problem for Ghanaian farmers, particularly rain-fed farmers in the Northern part of the country who are impacted by these changes because of the difficulties to predict the weather and seasonal climate, leaving serious implications for food production and their livelihoods (Asante & Amuakwa-Mensah, 2015; Kranjac-Berisavljevic' et al., 2003; Nyadzi, 2016).

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

Scientific advancements now make it possible to provide short and long-term climate information services to support farmers' decision-making (Gubler et al., 2020; Johnson et al., 2019; Mullen, 2007; Nyadzi et al., 2019; Scaife et al., 2019). Yet many farmers still use indigenous knowledge (IK) to adjust their farm practices or diversify their production to respond to local climate variability (Ebhuoma & Simatele, 2019; Eriksen et al., 2005; Radeny et al., 2019; Shoko & Shoko, 2012). Other farmers use a combination of meteorological information and IK for their weather and seasonal climate forecasting decisions (Nyadzi et al., 2018; Orlove et al., 2010; Roudier et al., 2014). Studies have also shown that IK can serve as a basis for developing adaptation and natural resource management strategies and for understanding the potential for certain cost-effective, participatory and sustainable adaptation strategies (Nakashima et al., 2012; Parry et al., 2007). Yet only few studies have explored IK in weather and seasonal climate forecasting and those who attempted, did so using qualitative and descriptive approach (Manyanhaire & Chitura, 2015;

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Roncoli et al., 2002). Furthermore, among those who have studied IK for weather and climate predictions, very few have looked at the underlying mechanisms behind farmers' techniques and in particular, none has attempted to quantitatively test skills or accuracy of these forecasts.

In this study, we aim to show that it is possible to collect indigenous forecasts and quantitatively analyse its accuracy. We address the specific research question: "what are the underlying mechanisms behind farmers' forecasting techniques and how accurate are farmers indigenous forecasts?". We first analysed farmers' mental model of how indigenous ecological indicators (IEIs) are interpreted to predict daily and seasonal rainfall. Second, we determined the accuracy of farmers' rainfall forecasts compared with the Ghana Meteorological Agency (GMet) forecasts. We focus on rainfall because most communal areas in Northern Ghana practice rain-fed subsistence agriculture (Manyanhaire & Chitura, 2015), and their hydroclimatic information needs are largely focused on rainfall (Nyadzi et al., 2019). We also selected Northern Ghana because climate variability and change is greatest in this area of Ghana making the communities more vulnerable with consistent crop failures (Gbetibouo et al., 2017; Nyadzi et al., 2018). The intention for this study is not to discredit the forecasting skills of farmers or GMet but rather to elaborate on the value of IF and contribute to the argument that it is possible to quantitatively collect and analyse the accuracy of IF in order to integrate it with scientific forecast for improved weather and climate information services.

2. Methodology

2.1. Analytical framework

The concept of indigenous knowledge (IK) has been widely used in different strands of literature. Mafongoya and Ajayi (2017) referred to it as a know-how that is generated by several generations to guide their understanding and interactions with their surrounding environment. Berkes et al., (2000) also defined IK as a cumulative body of knowledge, practice and belief, evolving by changing practices and handed down through generations by cultural transmission. According to Luseno et al. (2003), IK is knowledge generated within communities through a variety of means, some of which are traditional, others appear to evolve and emerge in response to changing circumstances. Kassa and Temesgen (2011) explains IK as the knowledge that evolves from long term observations of the local environment and adapted to the specific requirements of local people and conditions; involving a creative, experimental process continuously integrating external influences and internal innovations to meet new conditions. Roncoli et al. (2002) also defined it as knowledge developed from long cultural experiences.

IK is tagged by different names in literature; local knowledge, traditional knowledge, farmers' knowledge, traditional ecological knowledge, ethnoscience, folk knowledge, rural knowledge and indigenous science. Although these terms may have different connotations, they are used interchangeably throughout the literature (Mafongoya & Ajayi, 2017; Nyota & Mapara, 2008).

The generality and applicability of IK have been studied across the globe (Cabrera et al., 2006; Desbiez et al., 2004) and in Africa (Balehegn et al., 2019; Elia et al., 2014; Gray & Morant, 2003; Orlove et al., 2010). Some scholars have explored the value of indigenous knowledge in natural resource management, water resource management, fisheries and aquatic conservation, risk and disaster management, health, among others (Cabrera et al., 2006; David & Ploeger, 2014; Desbiez et al., 2004; Gray & Morant, 2003). In this study, we focused on IK for weather and seasonal climate forecasting which has been referred to by Vervoort et al. (2016) as indigenous forecast (IF). Here, we define "indigenous" as native or local and "forecasting" in its elementary form as a prediction of a future occurrence or condition. Therefore we operationalize IF as the use of recognizable IK among local farmers which is used to predict daily and seasonal rainfall in Northern Ghana. We consider the "forecast technique" as the method of interpreting ecological indicators used for IF. "Forecast skills" on the other hand, is defined as a measure of the accuracy of prediction; by comparing rainfall forecast with actual observation.

Studies have shown that before modern scientific weather and climate forecast systems were developed, people made regular forecasts based on past experiences and compared them to current observations (Olsson et al., 2004; Orlove et al., 2010). Indigenous ecological indicators (IEIs) such as the behaviour of insects, birds, and mammals, and positions of the sun and moon and associated shadows, wind speed and direction, cloud position and vegetation physiological changes are used as sources for local people to generate forecasts (Chang'a et al., 2010). The methodology for collecting and analysing IK has always been qualitative and descriptive even for those that are explored for weather and seasonal climate forecast. Most of these studies only make an inventory of the IEIs using surveys and focus group discussions (Ebhuoma & Simatele, 2019; Nkuba et al., 2020; Radeny et al., 2019). Therefore a critical knowledge gap in the literature is whether it is possible to collect indigenous forecasts and quantitatively analyse them. As proof of concept, this study employed a stepwise methodological approach (see Figure 1) drawing from different methodologies.

First, the study aimed to understand the complexity of using IEIs for forecasting the weather and seasonal climate by capturing local farmers mental models of how this is done. For this, we used a computer-based software called mental model (http://www.mentalmodeler.org/). The mental model is a participatory modelling approach based on a fuzzy-logic cognitive mapping (Glykas, 2010; Gray et al., 2013; Henly-Shepard et al., 2015). It collects qualitative information from stakeholders and quantitatively assigns weighted edges usually between -1 and 1, to define mathematical pairwise associations (Gray et al., 2013). Further, a semi-quantitative scenarios feature of the software allows scenario analysis of plausible outcomes (Özesmi & Özesmi, 2004). This approach is becoming an increasingly popular way to incorporate local or expert knowledge into ecological decision-making (Halbrendt et al., 2014; Nyaki et al., 2014). This research uses representations of knowledge and belief systems held by rural farmers in Northern Ghana to analyse the underlying

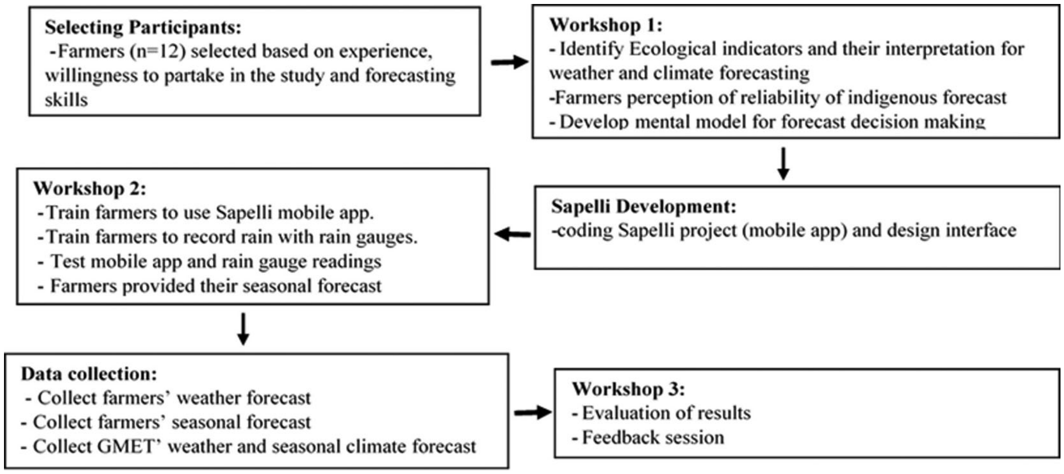

Figure 1. Methodological flow of the study.

mechanism for which farmers forecast the weather (low, medium and high rainfall) and the seasonal climate (above, below and normal rainfall, onset and cessation).

Secondly, we utilized an android mobile app called Sapelli, an open-source project that facilitates data collection by using highly configurable decision-tree with a pictorial icon-driven user interface (Stevens et al., 2013). Sapelli has a powerful visualization capability that allows usage among users with low literacy. Users can select options by simply touching the screen of the mobile device and not have to necessarily read the text. Sapelli does not rely on an internet connection and allows offline data collection and postponing data transmission to a later stage. This function makes it possible to use in areas where network connectivity is rare, unstable, slow or expensive, and when users lack phone experience (2014).

Thirdly, we used a well-established and widely used deterministic (binary or dichotomy) forecast verification method to evaluate the skills or accuracy of the forecast (Bumke et al., 2012; Fekri & Yau, 2016; Mariani et al., 2008; Mason, 2003; WMO, 2014). Many meteorological phenomena such as rain, floods, severe storms, frosts, and fogs can be regarded as simple binary (dichotomous) events, and forecasts or warnings for these events are often issued as unqualified statements that they will or will not take place. These kinds of predictions are sometimes referred to as yes/no forecasts, and represent the simplest type of forecasting and decision-making situation (Hogan & Mason, 2012). For this study, we used a 2 × 2 possible outcomes to evaluate the forecast. For a sequence of binary forecasts, we used this as a performance measure to determine the number of *hits* (a), *false alarms* (b), *misses* (c) and *correct rejections* (d). (see Table S12 of the supplementary materials).

2.2. Data collection

2.2.1. Selecting participating farmers

This study adopted a purposive sampling approach in selecting participating farmers. Through informal discussions with the head of farmers' association, the manager of the Botanga irrigation scheme and an extension officer for the area, twelve experienced farmers were purposively selected from twelve different communities in Kumbungu district of Northern Ghana (Figure 2). The selection was based on farmers experience in using indigenous forecast and willingness to partake in the study. These farmers practiced both irrigated and rainfed rice farming and were known by their respective communities to have good forecasting techniques and skills. Our initial inquiries show that not all farmers are good at forecasting using IEIs so we decided together with the community who will be involved in the training and forecasting. In the end, the most experienced and trusted forecasters, all above the age of 45 with at least 30 years of farming experience and cumulative knowledge about changes in climate and rainfall in their communities, were included. Although increasing the number of farmers in each community could result in a more robust conclusion, the number of experienced farmers offers a good indication to proof our conceptual argument.

In general, data collection was primarily performed using workshops (2.2.2), the Sapelli mobile app (2.2.3) and rain gauges.

2.2.2. Workshops

During the first workshop in march 2017, key IEIs were identified and collectively discussed among participants. The researchers defined and explained the technical classifications that corresponded to farmers' indicators, using simple illustrations which farmers could relate to. For example, researchers and farmers agreed on *low rainfall* (0.1–19 mm/day) as drizzling or light rains that do not penetrate the soil surface; *medium rains* (19–37mm/day) as rains that wet the soil to capacity; and *high* or *heavy rains* (> 37mm/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* was considered 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 corresponds to the average yield. *Onset* refers to the time in the rainy season when precipitation is sufficient for planting (see Table S1of supplementary materials). In addition, the mental model was used to conceptualize the degree of influence of each IEI on a phenomenon forecasted (rainfall onset, cessation

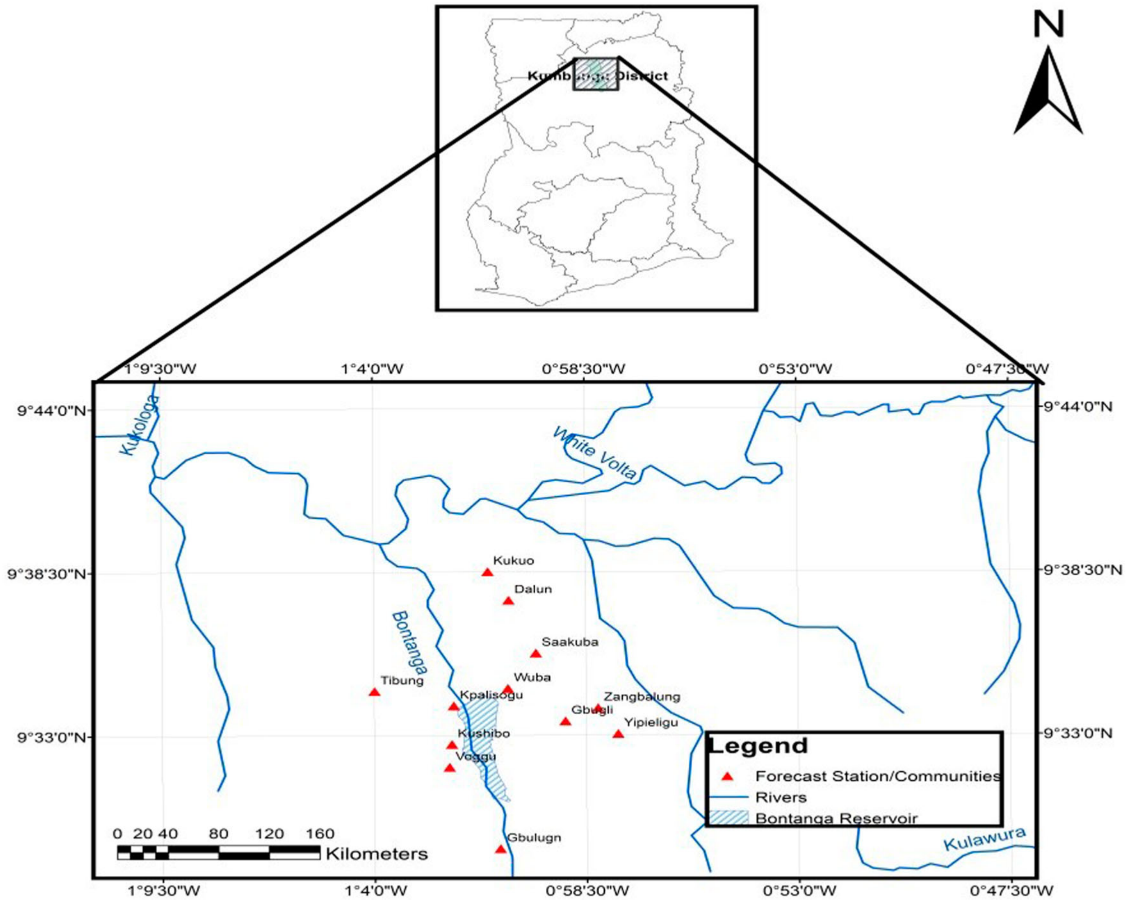

Figure 2. Map showing the location of selected communities in Northern Ghana. Socio-institutional and biophysical characteristics of the study area have been described by Nyadzi et al. (2018).

etc.). The developed mental model was analyzed using a matrix (Table S10 of the supplementary document). The mental model software was used to define the cumulative strength of connections between elements of the mental model (Gray et al., 2013; Özesmi & Özesmi, 2004).

The second workshop shortly thereafter aimed at training farmers in two key areas; (i) how to use an android based mobile app to record 24 hours forecasts, and (ii) how to record observed rainfall using a simple rain gauge. After the training, trial exercises were carried out with the mobile app and rain gauges. The seasonal climate IF for the year 2017 were also collected from each farmer during the workshop (Seasonal forecast is often generated once to cover the entire season).

At the end of the data collection period in 2017, a third reflection workshop was organized to evaluate the process and discuss preliminary results, challenges and prospects for future hydro-climatic information services.

2.2.3. 'sapelli' mobile app and rain gauges

IF rainfall forecast data were collected using the Sapelli mobile app. The app was formatted 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.

The app presented a simple iterative process with an interactive interface showing images agreed upon with farmers (see Appendix C). First the farmer has the option to select yes or no rain. Should he predict a yes rain, he then has the option of selecting which type of rain (low, medium or high). He further selects the IEI for his prediction. Next, he indicates the degree of certainty (sure, very sure, or extremely sure) for his predictions. He finalizes the prediction process by saving data onto the phone. If a farmer skipped a stage on the app, we interpreted the response as '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. It is worth noting that the selected participants produced their forecasts exclusively with IEIs without the interference of scientific forecasts. Farmers sent the daily IF data from April to October 2017 using the app.

The farmers were also trained and asked to record daily rainfall observed in their communities using custom-made rain gauges, built with plastic water bottles by researchers.

2.3. Data analysis

Data were analyzed in three main ways. First, the grid function of the mental modeller was used to analyze the relationship (probability of influence) that each IEI had with a predicted weather or seasonal climate phenomenon. Second, we analyzed spatiotemporal variations (monthly, seasonal and annual totals) in GMet and farmers' observed rainfall data using excel. For this, we used GMet (scientific) rainfall forecast data that covers the same seven months period as the IF data collected with the app. We evaluated the skills (accuracy) in predicting rain (Yes/No) and the types of rain (low, medium and high rainfall) using a deterministic forecast verification method. We estimated onset from farmers' observation by looking at any week in the initial period of a rainy season, within which rainfall amounts total at least 25 mm (Popov & Frere, 1986). We also tested the statistical difference among the 12 farmers, and between farmers and GMet forecast and observation at an alpha level of 95% using R statistical programme. The average performance of farmers was estimated by calculating the average hit rate of the 12 farmers. The performance of GMet forecast in each community was also computed by comparing the forecast against the observed rainfall in each community. We also compared GMet and farmers forecast skills despite existing differences and spatial variation. Third, the reliability and usability of IEIs were analyzed. Usability denotes the number of times an IEI has been used. Reliability was estimated in two main ways; first from farmers' perception at the workshop (see Table 1) and secondly from the empirical analysis of IF data.

2.4. Limitations

This study is a proof of concept and therefore utilized few farmers for a more in-depth analysis. Moreover, resources constrained us from engaging more farmers and/or field sites for this study. However, the farmers selected have vast knowledge and experience about indigenous forecasting, which arguably will offer more insight. Second, the research covered only a limited period of seven months for the same reasons. As a result, the empirical findings of this study may not be generally applied. However results of the analysis show that it is possible to quantitatively collect and analyzed the techniques and accuracy of indigenous forecast.

3. Results

3.1. Farmers' techniques for forecasting weather and seasonal forecast

3.1.1. Farmers use of indigenous ecological indicators for forecasting

Results show that farmers rely on several IEIs for predicting the weather and seasonal climate. Their forecast technique is based on observational changes in IEIs such as sound, phenology, shape and movements in the behaviour of animals, plants, insects and heavenly bodies (sun and moon). The observable changes in IEIs have their generally held interpretations depending on which event is to be predicted and whether for short or longer time scale (see Table 1). The presence of observable changes in IEIs generally indicates the occurrence of a particular event while their absence indicates the non-occurrence, except in a few cases. For example appearance of a rainbow, lepisiota ant (Lepisiota capensis) carrying its eggs from uphill to downhill in the rainy season and a cloudless sky implies the non-occurrence of rains. According to the farmers, the reliability of IEIs for forecasting is affected by rapid environmental changes.

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

3.1.2. Farmers mental model for forecasting

Different IEIs are used to predict different weather and seasonal climate events, as well as their severity. Also, different IEIs have different probability for an event to occur. For example, to forecast daily rainfall; clouds, mosquitoes (Culicidae), butterflies (Amblyscirtes) and frog (Xenopus laevis) have a probability of up to 0.25, 0.5 and 1 for low, medium and high rainfall to occur respectively. All IEIs has different degrees of relationship with rainfall onset prediction except for stars and sun. Ants (Lepisiota capensis) and stars are the only indicators that have a relationship with rainfall cessation. For rainfall amount; all IEIs have a varying relationship with below, normal and above normal rainfall except stars. Details of how each IEI influences the probabilities of an event are presented in the mental model (Figure S3 and Table S10 of the supplementary document). Results show that the same IEIs are used for both weather and seasonal predictions, depending on the signals they exhibit. However, dogs (Canis lupus familiaris), reptiles (such as snakes - family colubridae), stars and trees (such as baobab tree- adansonia digitate) are used only for seasonal climate forecast while soil texture, for example, is used for weather forecast only.

3.2. Analysis of farmers' rainfall observational data

Farmers' observational data show rainfall patterns that begin to build up in April, peak in July and then start to decline in August until October. At the seasonal time scale, June July August (JJA) recorded the highest rainfall amount, followed by September-October (SO) with the least recorded in April-May (AM) season. The sum of annual rainfall recorded by farmers was on average 15.5% more than what GMet observed. Results also show farmers' locally observed rainfall amounts varies among communities (Figure S1). The total annual rainfall ranged from 492 mm in Saakuba to 1563 mm in Kushibo. Total rainfall amount recorded by farmers in Kushibo was 43.9% more than the average annual rainfall of 1000 mm

Table 1. Interpretations and reliability (based on farmers' perception) of indigenous ecological indicators for weather/seasonal climate forecast.

Ecological indicator (local names)	Reliability	Possible signs and their interpretation
WEATHER FORECAST		
Earthworm (sambarigu)	***	The appearance of a large number of earthworms (Lumbricina) on the day is a sign of rains the next day or in few hours.
Clouds (sagbona)	***	Dark clouds amidst strong winds signal rain in few hours Clouds gathered at north-east imply rain in few hours up to the next day
Duck (gbinyaʄu)	***	Ducks (Anas Platyrhynchos) rapidly flapping, stretching their wings with loud quack sound signify rains in few hours and up to the next day.
Caterpillars (zunzuya)	***	Woolly bear caterpillars (larva) scurrying and burrowing into the soil is an indication of rainfall the next day or up to few days.
Butterfly (kahinpie)	***	A large number of butterflies (Amblyscirtes) continuously flapping their wings in the skies without taking shelter on leaves signals rains in few hours to the next day.
Fog (paʄli)	**	The appearance of fog indicates rain in the next few hours or the next day. Mostly low rains in the form of drizzle.
Wind (pohim)	**	Strong winds from west to east signal rain the next day.
Frog (pololi)	**	High-pitched sound of frogs (Xenopus laevis) in the rainy season strongly signals rains the next day
Birds (alacheyu)	**	Loud singing of coucal bird (Centropus sinensis) is an indication of rains in the next few days.
Cow (naʄnya)	**	Cows (Bos Taurus) repeatedly flapping their ears and tails indicate rainfall the next day or up to 3 days.
Hot weather (walgu be-ni)	**	High temperatures and humidity within rainy season signal rain in the next hours or day. Rainfall is expected the next day if temperatures are high during the night such that one sweats profusely and unable to sleep.
Ants (salinsahi)	**	A lepisiota ant (Lepisiota capensis) carrying its eggs uphill during the rainy season signals rain the next day or in few hours. A rapid increase in anthills in the surroundings indicates rains the next day or up to 3 days.
Moon (Goli)	*	A yellow looking ring around the moon is an indication of rains the next day or latest by 3 days. A downwards appearance of the moon crescent indicates rains the next day or in a few hours.
Sun (wuntana)	*	The appearance of a halo around the sun during the rainy season signals rain in the next day or few hours
Mosquitoes (duunsi)	*	Frequent and painful bites of mosquitoes (Culicidae) in the day during the wet season is an indication of rainfall the next day (latest up to 3 days)
Soil (tankpari)	*	Dry soil with fresh, sweet, powerful smell indicates rains the next day.
SEASONAL FORECAST		
Clouds (sagbona)	***	Cirrostratus clouds indicate the onset of the rain in few days. The thicker they get the closer the rains.
Duck (gbinyaʄu)	***	Ducks (Anas Platyrhynchos) rapidly flapping and stretching their wings while playing in the soil signify the onset of rains.
Hot weather (walgu be-ni)	***	The high temperature that causes profuse sweating in March is an indication of onset in few weeks.
Baobab tree (tuhi)	***	Baobab tree (adansonia digitate) begins to flower and generates new leaves signify rainfall onset. The more the flowers the season is predicted to be wetter than normal.
Butterfly (kahinpie)	***	A large number of migrating butterflies (Amblyscirtes) signal onset and a season with good rains.
Ants (salinsahi)	**	Lepisiota ant (Lepisiota capensis) carrying its eggs uphill during the dry season indicates rainfall onset approaching in up to a week time. When directions of egg-carrying ant change from uphill to downhill then one can predict cessation in few days up to a week. Large army ants (Eciton burchellii) in and around house signal start of the rainfall onset and as such a wetter than normal in the rainy season. Rapid increase in anthills on farm ways indicates the onset of rains in few days for up to 1 or 2 weeks.
Moon (Goli)	**	Full moon covered by cloudlike appearance signifies a wetter than normal season.
Wind (pohim)	**	Swirling winds at high frequency in the dry season indicate the onset of rains (good rainy season).
Lightning	**	Lightning accompanied by thunder repetitively occurring especially during the dry season indicate the closeness of onset
Frog (pololi)	**	High-pitched frog (Xenopus laevis) sounds in the dry season signals onset of rains up to a week. The intensity of this sound (the louder it gets) indicates a good season with normal or wetter season.
Sun (wuntana)	*	The appearance of shining spot around the sun during the dry season is an indication of approaching good rainy season.
Mosquitoes (duunsi)	*	Frequent and painful mosquito (Culicidae) bites and high nuisance in the dry season is an indication of rainfall onset in a few days up to about a week.
Stars	*	Stars moving from west to east indicate rainfall onset in a few days. Change in appearance (very bright) of the stars signals rainfall cessation in a week.
Birds (alacheyu)	**	The movement of a large number of Hornbils (Bucerotidae) with loud singing is an indication of a good rainy season. Owl hooting in the evening also signifies the onset of rain. Large flocks of swallow birds (Hirundinidae) migrating with loud sound signals rain onset in few days up to about a week. Crows (Corvus corax) flying in groups signals a normal season. Birds building nests close to rivers or water bodies indicates a below normal rainfall within the season.
Cow (naʄnya)	**	Cows (Bos Taurus) mostly standing and looking restless indicate the start of the rainfall onset in a few days.
Reptiles (tiŋvura)	**	The frequent appearance of reptiles such as snakes (family colubridae) wandering in the afternoon signals onset of rains in a week.
Dogs	**	When dogs (Canis lupus familiaris) loudly bark and run for cover in the day is a strong indication of a rainfall onset in a few days. The louder the noise the dogs make the wetter the seasons is predicted to be.

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

observed by Owusu and Waylen (2009) for the study area. Gbulun and Kukuo showed the same rainfall amount of 1243 mm representing the second highest rainfall total. The total number of rainy days ranged from 22 in Tibung to 49 days in Zangbalun. GMet recorded a higher number of observed rainy days over the study area compared to farmers recording (see Table S3 of supporting document). The differences in rainy days can be alluded to the high number of low rainfall days recorded by GMet, which could be attributed to the sensitivity of meteorological instruments as compared to the rain gauges used by the farmers.

3.3. Skills of farmers and GMet rainfall weather forecast

Results show that farmers and GMet performed at an average of 30% and 34% respectively (performance hereafter means accuracy or skills or hit rate; meaning the number of rain events accurately predicted). For the seven months, farmers' performance varied from 16% accuracy in Wuba to 61% in Zangbalun. Farmers in Dalun and Gbugli also performed at 43% and 47%, respectively and the rest performed at less than the 30% average. GMet forecast outperformed farmers forecast in most communities except Dalun, Zangbalun and Gbugli where farmers forecast performed at 3%, 25%, and 14% more (see Table S3 and S4 of supporting documents). However, on the average, both farmers and GMet showed similar performance rate of predicting one out of every three daily rainfall events right. Results also showed that the monthly performance of GMet and farmers varies but insignificantly (P>0.05), although farmers performed better than GMet in May, June and October. The monthly (aggregation) performance ranged from 21% in September to 46% in October for farmers and 20% in May and October to 56% in August and September for GMet (see Table S3 and S4 of supporting documents).

GMet and farmers' forecasts show both agreement and disagreement with the actual observations within the communities. On average, both forecast systems disagreed 84 times (39%) and agreed 130 times (61%). Out of the 130 agreed times, 3 hits, 100 correct rejections, 12 miss and 15 false alarms were recorded. Table S5 of the supplementary document provides details of agreement and disagreement of the forecast. In addition, farmers generally have poor ability to forecast rainfall types. They recorded an average hit performance of 17%, 16% and 6% for low, medium and high rainfall types respectively. The hit performance was poor: 0% for high rainfall in 8 communities, 0% for medium rainfall in 4 communities, and 0% for low rainfall in 2 communities. However, each farmer had a better hit rate for low rainfall than medium and high rains (See Table S6 of the supplementary document).

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

Figure 3 shows how often the indicators were used during the study period and how reliable they were. Here, the researchers operationalized *usability* as the number of times an IEI has been used per the seven months of study, and *reliability* is the number of times an IEI gave an accurate prediction out of the number of times used within the seven months, all expressed in percentages. Results of reliability presented in Figure 3 are empirically determined, while those in Table 1 are based on farmers' perception. Results show that on average each IEI was used 42 times. Also, at 95% confident level (19.6), the interval between 22.76 (lower bound) and 61.99 (upper bound) contains the true value of the population parameter (mean). See Table S11 of the supplementary document for detail results of the descriptive statistics. Figure 3 shows that butterflies (Amblyscirtes), mosquitoes (Culicidae), bird sound, caterpillars (Larva) and moon, were the five most reliable IEIs when it comes to forecasting rains. Butterflies (Amblyscirtes) and soil appearances were the most reliable (45.5%) and least reliable (7.7%) IEIs respectively. However, according to the farmers at the evaluation workshop, the appearance of butterflies (Amblyscirtes) is becoming rare in the area, thus remained the least used IEI. Meanwhile, hot weather is the most used (138 times, 20.2%) IEI followed by clouds appearance (118 times, 17.4%).

Moving a step further, we analyzed the reliability of IEIs for forecasting different types of rain (low, medium and high rains). Results show that ants are the most reliable (83%) IEI for forecasting low rains. Cow (Bos Taurus), duck (Anas Platyrhynchos) and frog showed 100% reliability in forecasting medium rainfall while earthworm (Lumbricina) and wind were the most reliable (100%) IEIs for high rainfall forecast. Hot weather was the most used IEI for forecasting low rains while cloud formation is mostly utilized for medium and high rains (see figure S2 of the supplementary document). No consistent trend was observed in their expression of certainty and forecast performance. In most cases, they miss the rains even at higher certainty and hit at a lower certainty (see Table S7 and S8 of the supplementary document). When this was raised at the evaluation workshop, one farmer indicated that "*sometimes I see very clear signs of rain and become so sure that it will rain in my village only for the rain to fall in a neighbouring village*", this justification was unanimously supported by all farmers.

3.4. Farmers and GMet forecasting skills at the seasonal timescale

Before every rainy season, GMet provides seasonal forecasts intended for farmers use. In 2017, the Western and Eastern halves of Northern Ghana were predicted to experience near normal to above normal and normal rainfall amount respectively (GMet, 2017). Based on the location of Kumbungu district, rainfall was expected to be near-normal to normal. The mean onset date of the rainy season was forecast to be from 4th week of April to 1st week of May. The range of the expected rainfall amount over the entire region was 1090 mm–1360 mm and the mean cessation date was forecasted to be the end of October (GMet, 2017). Before the

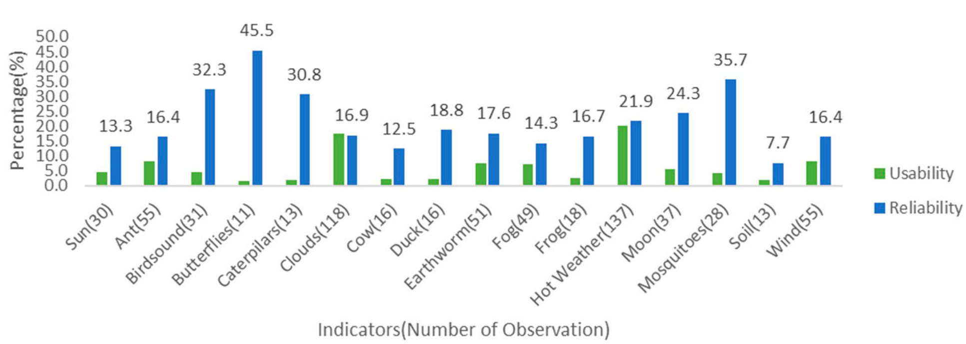

Figure 3. Reliability and Usability of indigenous Ecological indicators for predicting Yes/No Rain.

2017 season (a time farmers often produce their seasonal forecast) and during the second workshop, farmers forecasted rainfall amount, onset and cessation using various ecological IEIs listed in Table S9 of the supplementary document. They did not use IEIs for rainfall cessation because there were no clear signs of them. Instead, they relied on their experience when the rains often end. 58% of the farmers predicted normal rainfall season, 33% predicted above normal and only 9% predicted below normal rainfall. For the onset of the season, 25% of the farmers predicted the second week of April, 50% predicted the third week while the remaining 25% predicted it to occur in the fourth week of April.

All farmers agreed rainfall cessation would be in October. Nonetheless, 41% forecast it in the 1st week, 17% forecast 2nd week, 17% in the 3rd week and the remaining 25% forecast it in the 4th week of October. Comparing each farmer's forecast to recorded observations, results show that, 33% of the farmers got the onset prediction right while 42% were right with cessation. Using GMet estimated range of annual normal rainfall of 740-1230 mm (GMet, 2017), we observed that 33% of the farmers accurately predicted near-normal rainfall of their communities while only 9% predicted the observed above normal rainfall right. The remaining farmers incorrectly predicted the rainfall cessation. GMet, on the other hand, predicted accurately the rainfall amount (near normal) for 42% of the communities and onset for only 25% of the communities but was unable to forecast correctly cessation for any of the communities (see supplementary Table S9 for details).

4. Discussions

This study aimed at showing for the first time that it is possible to collect indigenous forecasts (IF) data and analyse the techniques and skills (accuracy) in semi-quantitative and quantitative terms. We elaborated how IF are generated by local farmers in northern Ghana and established a mental model of the relationship between indigenous ecological indicators (IEIs) used and the phenomenon forecasted at both daily and seasonal timescale. We also tested quantitatively the performance of the farmers IF and compared it with the forecast of the Ghana Meteorological Agency (GMet).

Historical patterns of the rains serve as the fundamental template that allows farmers to form expectations for the coming season. Results of this study confirm that observed changes in each IEIs strongly influenced farmers' predictions. Farmers' perception of the most reliable indicators was different from the results of empirical analysis. For instance, for the weather forecast, farmers mentioned earthworm (Lumbricina), clouds, ducks (Anas Platyrhynchos), caterpillars (Larva) and butterflies (Amblyscirtes) as the five most reliable indicators, meanwhile, empirical results show butterflies (Amblyscirtes), mosquitoes (Culicidae), bird sound, caterpillars (Larva) and moon, as most reliable. These results indicate the possibility of perceptional measurement being significantly different from the real-time measurement. Therefore, care needs to be taken when testing the reliability of IEIs and farmers forecast skills using perceptional methods only, as in Makwara (2013) and Elia et al. (2014) who assess the perceptions of the local communities on the application and reliability of indigenous knowledge for forecasting. However, it is expected that local farmers and researchers may have different understandings of how "reliability" is measured. For researchers reliability can be related to forecasts hits rate, this may not be the case for farmers. It is also important to recognize that no concept of "reliability" is necessarily more legitimate than the other; none of them more efficient either, if they are assessed on their terms.

Results of the mental model allowed us to establish the underlying mechanism behind farmers' prediction. For instance, when one comes across a high frequency swirling winds in the dry season, this may indicate the onset of rains but also provides a higher probability of above normal rain than below and normal rainfall. The appearance of a halo around the sun has a higher probability for predicting medium rainfall than high and low rainfall. Frequent and painful bite of mosquitoes in the day during the wet season indicate a higher chance of recording high rain the next day compared to medium and low rain. This implies that the process generating IF is not intuitive rather a rational skill which can be learned and passed on from one generation to the next.

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

We acknowledge that this study is a proof of concept to collect and analyzed IF quantitatively, yet the process entails the particular challenge of using a relatively short dataset and only 12 farmers. We recognize that longer time series are needed for a more robust conclusion. Adding more data would provide a more solid basis for our analyses and conclusions. 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. Whereas for science-based forecasts it is possible to generate long-term datasets using hind-cast methods, this is not possible for IF. Moreover, the aim of this paper is not to present a full forecast evaluation but to show that it is possible to collect indigenous forecasts and quantitatively analyse them. Additionally, these farmers were experts and provided enough data that allowed meaningful analysis for this proof of concept. Moreover, the process of selecting these farmers was rigorous and includes the entire community to select only farmers with good forecasting techniques and skills. Also, results show that the trend in the monthly aggregation and seasonal rainfall recorded by farmers are similar to those measured with meteorological instruments in Northern Ghana by GMet and other studies such as Manzanas et al. (2014) and Lacombe et al. (2012). This provides confidence about the quality of farmers' observations.

Finally, It is common knowledge how it rains in one place but does not rain at a close by location. Results show that the frequency (rainy days) and amount of rainfall differ significantly among farmers and between farmers and GMet. The differences in GMet and farmers forecast is due to the spatial variability between rain gauges and strong rainfall variability even over small areas. There is, therefore, the need to mount in each community additional rain gauges to record locally observed rainfall, to generate data that is relevant for studying local rainfall variability and change. In line with this, some studies have argued the need to pay attention to smaller details in each geographic area since this can have a bigger impact on local climate (Frumkin et al., 2008; Maibach et al., 2008). Therefore, farmers in communities where meteorological observation are not available can be engaged to collect community level weather and climate information and data. In the process, local farmers are empowered and become more aware of spatial and temporal variability in rainfall (McCormick, 2009).

5. Conclusion

In this study, we show that unlike studies that investigate indigenous forecast using qualitative and descriptive approaches, it is possible to collect indigenous forecasts and analyse the techniques and skills or accuracy in quantitative terms. Results of the techniques analysis indicate that in addition to farmers using historical patterns of the rains as a basis for generating IF, they have established a mental model of how IEIs such as butterflies, earthworms, moon caterpillars, winds directions influence the prediction of a particular event at both daily and seasonal time scales. Different IEIs have different probabilities for an event to occur. For example, the appearance of woolly bear caterpillars (larva) scurrying and burrowing into the soil indicate a high probability of a heavy rainfall event compared to a low rainfall event. Hot and sweaty weather indicates a high probability for the onset of seasonal rainfall. Results of the skills assessment also show that Farmers and GMet showed similar skills in their forecast; both correctly predicting about one out of every three daily rainfall events. Despite the limitations, this study is able to conduct a meaningful analysis of available data to contribute to the yawning gap in the literature; how to quantitatively collect and analyse the techniques and skills or accuracy of IF. Finally, our results indicate that indigenous forecasts are not just intuitive but are a skill which is developed. Also, local farmers can contribute to the development of local climate services through the use of their local expertise and the collection of weather and climate information and data.

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