American Journal of Climate Change, 2022, 11, 265-283
https://www.scirp.org/journal/ajcc
ISSN Online: 2167-9509
ISSN Print: 2167-9495

The Potential of Hydro-Climate Forecast Strategies in Sustaining Agricultural Productivity amongst Rainfed Farmers in West Africa: A Review

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How to cite this paper: Dogbey, R. K., Kranjac-Berisavljevic, G., & Gandaa, B. Z. (2022). The Potential of Hydro-Climate Forecast Strategies in Sustaining Agricultural Productivity amongst Rainfed Farmers in West Africa: A Review. *American Journal of Climate Change, 11,* 265-283.
https://doi.org/10.4236/ajcc.2022.114013

Received: June 3, 2022
Accepted: November 3, 2022
Published: November 7, 2022

Abstract

Several studies have reported a significant yearly decrease in forest cover globally, using satellite images. This is especially true in West Africa, where rapid urbanisation acerbates the problem, and both of these changes lead to alterations in rainfall regime and other changes in climatic parameters. Several studies reveal that adaptation which reduces vulnerability to adverse climatic variation effects is the key to developing resilience against climate change. In this region, over 90% of farmers are engaged in small-scale rainfed crop cultivation and rely on their own weather perception, instincts and what they observe from the surrounding biota (flora and fauna) to forecast the weather and plan their agricultural activities. The pressing nature of the problem of climate variability in Africa had provoked a lot of research into developing and testing several adaptation strategies to control the situation. Various strategies to improve and localize global, regional and national climate services (Local Forecast, Scientific Forecast and Integrated Forecast) needed by the farmers are being developed to build resilience against climate change. This review illustrates the situation in Ghana and identifies various forecast strategies developed to mitigate the adverse effects of climate variability on agricultural productivity. These mitigation methods include the development of climate services to provide users with forecast information in order to make climate-smart decisions to minimize the risk.

Keywords

Climate Variability, Adaptation Strategies, Forecast Strategies, Resilience, Rainfed Agriculture

1. Introduction

According to the Oxford dictionary, a strategy is a plan of action designed to achieve a long-term goal or an overall aim. Strategies are mostly employed to facilitate decision-making on delicate subjects such as that regarding decision-making concerning water availability for rainfed agriculture.

Adaptation refers to the decision-making process and the set of actions performed to maintain the capacity to deal with current or future predicted change (Nelson et al., 2007). Adaptation is a multi-faceted decision-making process. It is a function of an individual or situational circumstances of the subject to the decision and the characteristics of the innovation under consideration which occurs within a situation of changing economic, political, social and biophysical conditions (Smit & Skinner, 2002). Adaptation strategies in the context of climate change refer to the medium to long-term adjustments of human beings to a varying climate at present, or to an expected future climate (IPCC, 2014).

Forecast strategies on the other hand are a subset of adaptation strategies and in the context of climate change, refer to the various approaches orchestrated to predict the status of the weather to mitigate the adverse effects of climate variability on small-scale rainfed farmers whose vulnerability to climate variability is alarming.

Adaptation to climate variability through weather forecasting is a topic discussed by several researchers (Abeysinghe, 2013; Boansi et al., 2017; Codjoe et al., 2014; Dinku et al., 2017; Gbangou et al., 2019; Lemos & Morehouse, 2005; Naab et al., 2019; Nyadzi et al., 2021; Tume et al., 2019) and institutions (GCA, 2019; IPCC, 2017; UNESCO, 2002; WMO, 2021). It is widely seen to be the most appropriate short to medium-term means of mitigating the impacts of climate change in other to support farmers and ensure food security.

The majority of small-scale farmers in sub-Saharan Africa are engaged in rainfed agriculture (Ramasamy, 2012) making them vulnerable to climate variability (Dunning et al., 2016). Due to the advancements of climate variability in recent years, the demand for weather and climate forecast information in support of agricultural decision-making has grown rapidly and is expected to grow even faster (Tall et al., 2018; Vaughan et al., 2019). There has been great success in the utilization of weather forecast information in many areas of human activities, especially agriculture. Nevertheless, improvement in spatio-temporal precision, accuracy, and awareness creation of uncertainty are all needed to realize the full potential of weather/climate forecasts (WMO, 2021).

The success of rain-fed agriculture depends on how farmers can match their agricultural practices to the prevailing weather. Due to this, accessibility to hydro-climatic information services is essential for sustainable agricultural practices and therefore, increased the adaptation potential that will lead to better yields and minimal risk of crop failure (Gbangou et al., 2020; Nyadzi et al., 2019). Gbangou et al. (2021) also mentioned that the collection and integration of indigenous or local knowledge with scientific data can help increase the credibility and accuracy of forecasts (Nyadzi et al., 2021).

Climate change in West Africa and Ghana is advancing fast and it's projected to affect vital water resources and food security. Ghana is already experiencing increased extreme weather events, with higher incidences and more prolonged periods of flooding and droughts, most evident in the five northern regions of Ghana. It is also anticipated that most, if not all, indigenous ecological indicators that farmers base both seasonal and daily weather forecast on may be lost in the near future (Nyadzi et al., 2021; van der Burdt et al., 2018), thus making traditional identification of rainfall patterns less certain.

The most pressing concern of farmers in Ghana and elsewhere in Africa with regard to agricultural productivity is the unpredictable nature of rainfall and the incidence of long dry spells (IPCC, 2014). These two are the most critical issues farmers have to face when adequate water control is not available. The problem of the unpredictability of rainfall is further compounded by the low water holding capacity of many soils of the various African countries. High temperatures prevalent in the region also tend to deplete soil moisture quickly through evapotranspiration. Under this set of physical conditions, water stress is the most critical factor facing agricultural production (FAO, 2017; IPCC, 2014).

The success of small-scale farmers in Africa is largely influenced by rainfall (distribution, duration and intensity) (FAO, 2019). To these farmers, the slightest change in the rainfall pattern could lead to either a complete loss of produce or a great reduction in yield, directly affecting their livelihoods (Rockström et al., 2014). The majority of small-scale farmers rely on local knowledge (LK) for weather forecasting (Gbangou et al., 2021; Naab et al., 2019), which comprises the use of indigenous indicators in the farmers surrounding, observation of celestial bodies and consultations with custodians of LK, such as rainmakers and soothsayers (Gbangou et al., 2020, 2021; Radeny et al., 2019).

Lack of the ability for small-scale farmers in Africa to properly manage and control water for optimum and increased production puts their livelihoods at risk, alongside their families who also remain hostage to climate variability (FAO, 2019). To address these threats, there are options such as the introduction of scientific forecast and the integration of scientific forecast with local forecast (FAO, 2019; Gbangou et al., 2021; ICID, 2017). The latter has proven to produce better results in terms of mitigating risk and improving yields as compared to the former. In as much as a combination of scientific and local forecast results in a better outcome, it is still not enough to support the needs of farmers. This has called for the research development and implementation of more complex simulation models to further improve the forecast.

By 2050, the world's population is estimated to reach 10 billion people and the global food demand will increase by 70%. In Africa, the challenge of food insecurity is intensified by agriculture's extreme vulnerability to climate change (FAO, 2017, 2019). The population is growing fast, and agricultural production lags since less than 10% of arable lands are irrigated, which signifies little insurance against erratic rains and climate shocks (FAO, 2019; GCA, 2019; ICID, 2017;

IPCC, 2017). Therefore, globally there is a felt need to improve upon our ability to predict the climate/weather. This has been the core ambition of scientists and practitioners, leading to the development of several forecast strategies (WMO, 2021).

2. Global Measures to Counteract the Impact of Climate Variability on Agricultural Productivity

The advancements in science and technology such as the advances in satellite-based observations and telecommunications implemented in the numerical earth-systems and weather to climate prediction (NEWP) are the recent innovative technologies meant to improve on the accuracy and reliability of forecast (Charney et al., 1950; WMO, 2021). Modern earth-system models are incorporating additional processes and more essential multiple observations and communication of diverse elements of the environment (biosphere, atmosphere and lithosphere) (WMO, 2021).

Weather and climate variability in recent years is a leading environmental, agricultural and socioeconomic challenge. Agricultural productivity in Africa, which is largely dependent on the ability to forecast weather, suffers the most (Woetzel et al., 2020). Collaboration between many institutions including academia, research, and public and private sectors both nationally and internationally has contributed remarkably to the progress of the NEWP over the past six decades, thus advancing weather forecasting. As the new decade begins (2021-2030), vigorous developments of NEWP, high-performance computing (HPC) programmes and the application of artificial intelligence to climate models are making innovative contributions to this ongoing challenge of climate variability (WMO, 2021).

3. The Need for Weather Forecasting: Update on Annual Tree Cover Losses in Ghana

Inferences from recent analysis show that the rate of annual deforestation in Africa was estimated to be four (4) million hectares, which was twice the global average deforestation rate (Hyunshik & Tamirat, 2018). The rapid disappearance of the forest is motivated by the activities of loggers, miners, charcoal producers and farmers in exploiting the forests in unsustainable ways as means of subsistence. These groups, individuals and their activities are the primary actors in forest decline and their immediate motivations are the direct causes of deforestation and land degradation (Contreras-Hermosilla, 2000; Curtis et al., 2018). Other factors that influence the forest cover include; large-scale investments and infrastructure development in the areas of road construction and modernization (Contreras-Hermosilla, 2000; Hyunshik & Tamirat, 2018; Laurance et al., 2017). According to Contreras-Hermosilla (2000) the principal causes of these problems originate in some of the most fundamental components of society, such as population growth, the distribution of economic and political power, attitudes towards corruption, flaws in the market system and also in seemingly unrelated government policies. The relative aggravating rate of deforestation in Africa increases the likelihood of climate change. Shifting agriculture amounts to 94% of the five (5) main drivers of tree cover loss, namely: Forestry (large-scale forestry operations), Commodity-Driven Deforestation, Wildfire, Shifting Agriculture and Urbanization (Curtis et al., 2018; Hansen et al., 2013).

As of the year 2000, 30.6% of the total land area (238,535 km^2) of Ghana was covered with trees, but tree cover decreased to 18.9% in 2020. Figure 1 presents the trend of tree cover loss from 2000 to 2020. The red bars in Figure 1 represent the annual tree cover loss in Ghana whilst the trend line represents cumulative losses. It is obvious from Figure 1 that tree cover loss has increased sharply over the years. In recent times the loss is greater than it had ever been (Figure 1 and Figure 2).

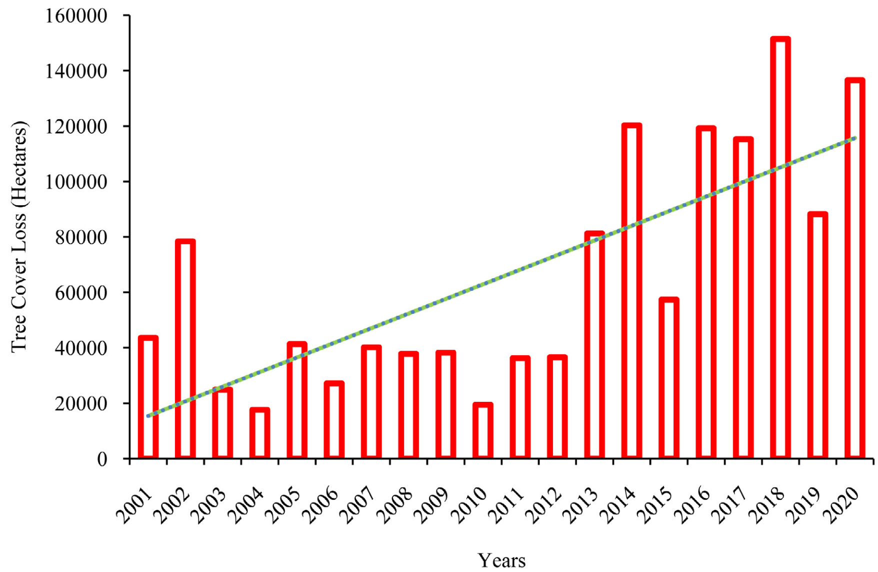

Figure 1. Trend of tree cover loss in Ghana. Source: (GFW, 2020; Hansen et al., 2013).

4. Local Forecast Knowledge

More than 90% of Agriculture in Africa is rainfed amidst climate variability and this implies that the Livelihoods of most small-scale farmers depend on their ability to understand their environment to mitigate the numerous risks and uncertainties associated with rainfed agriculture.

"Local" is synonymous with native or indigenous whereas "forecasting" is to predict a future condition or outcome. People living in rural settings around the world can understand their natural environment, through observations and interactions with their surroundings. These, combined with experience and historical knowledge enable rural people to develop skills and historical trends that can be depended on for decision making referred to as indigenous knowledge (IK) or Local Forecast Knowledge (LFK) (Gray & Morant, 2003; Olsson et al., 2004; Orlove et al., 2010).

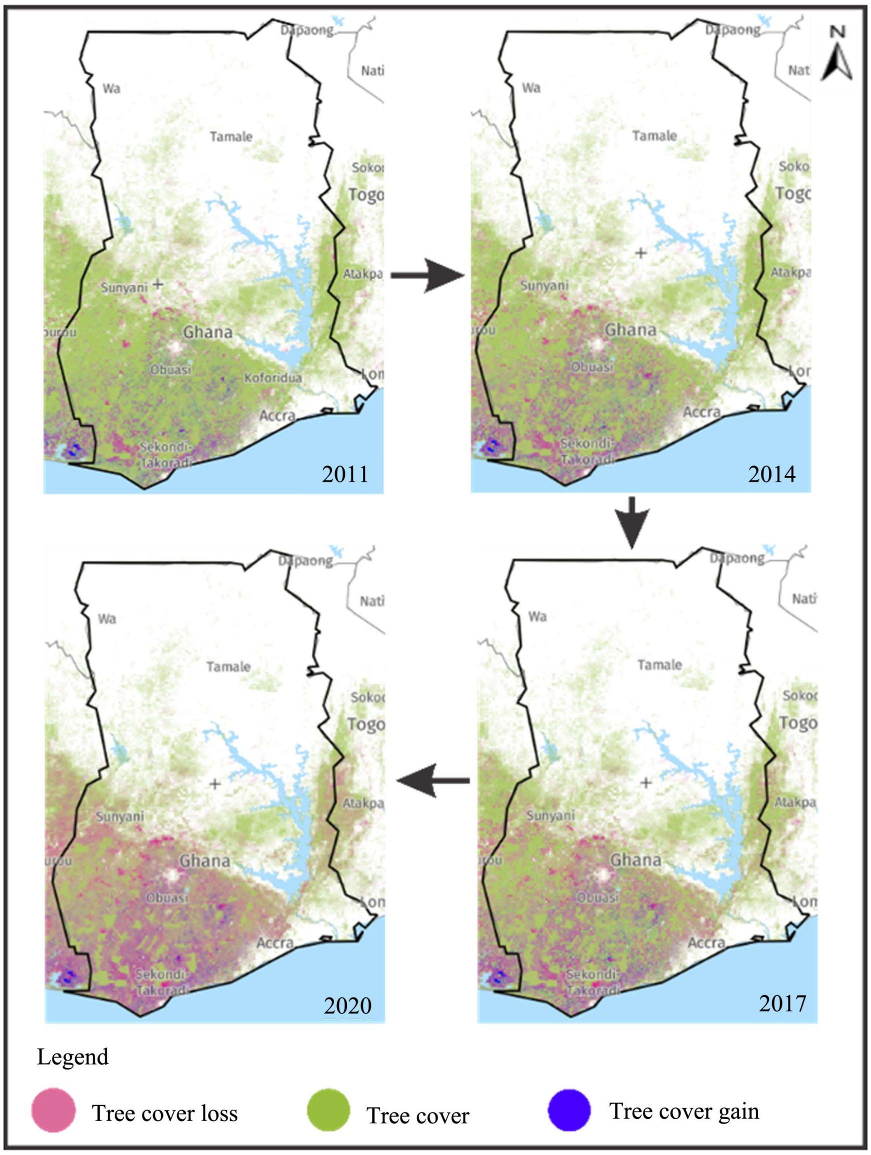

Figure 2. Graphical representation of the extent of deforestation in Ghana (measured at 30 × 30 meter resolution, displayed as a 12-year cumulative layer). Source: (GFW, 2020; Hansen et al., 2013).

Indigenous knowledge is relatively cheap, readily available to rural people and an environmentally smart tool for sustainable development and adapting to climate variability (Abeysinghe, 2013; Boansi et al., 2017; Nchu et al., 2019). IK is spatio-temporarily localised, therefore capable of solving location-specific weather related problems. The United Nations Educational, Scientific and Cultural Organisation (UNESCO) has a well-established program on preserving indigenous/traditional knowledge, called Local and Indigenous Knowledge Systems, LINKS. This program was one of the key pillars that contributed to the framing of the Millennium Development Goals (MDGs) of poverty eradication and of environmental sustainability (Tume et al., 2019; UNESCO, 2002). The current trend of loss of biodiversity which stems from the loss of tree cover possess a threat to the preservation and advancement of the "LINKS", as proposed by UNESCO.

The applicability of IK has been studied and verified across the globe (Cabrera et al., 2006; Desbiez et al., 2004). Worldwide, farmers still use indigenous forecast (IF) today to adapt their farm practices to respond to local climate variability (Eriksen et al., 2005). The diverse forms of knowledge of these farmers, anchored in their relationships with the environment as well as in cultural cohesion, have allowed many rural communities to maintain a sustainable use and management of natural resources, to protect their environment and to enhance their resilience. Ability to critically observe their environment, adapt and mitigate, has aided many indigenous communities to withstand new and complex circumstances that have often severely impacted their way of living and their territories (Magni, 2017).

Weather Forecasting Using Indigenous Forecast Knowledge and Associated Challenges

Small-scale farmers living in the rural communities of Ghana and other countries in Sub-Saharan Africa depend on indigenous knowledge, indigenous ecological indicators and traditional procedures and strategies as a means of forecasting the weather and climate (Antwi-Agyei et al., 2012; Tume et al., 2019). Some of the indigenous rainfall parameters and indicators used in the rural areas for weather and climate predictions are presented in **Table 1**.

Researchers such as (Codjoe et al., 2014; Gbangou et al., 2021; Nyadzi et al., 2021), have investigated the forecasting techniques of indigenous people and their accuracy in predicting the ground truth. Gbangou et al. (2021) mentioned that individual assessments of indigenous ecological indicators revealed that local forecast techniques performed better at predicting rainfall at an accuracy level of 0.56 as compared to Ghana Meteorological Agency (GMet) with a score of 0.50, using the Hanssen-Kuipers (H-K) discriminant (or Pierce) skill score analysis (Hanssen & Kuipers, 1965) which measures the ability of predictions to discriminate the occurrence of rainfall events and non-events. Gbangou et al. (2021) also reported that a combination of the indigenous ecological indicators provided an even better H-K score of 0.8, which was found to be higher than the scores of both the GMet and Meteoblue in predicting rainfall among small-scale farmers in Ada, Ghana.

However, climate services provided to farmers are mostly of scientific origin and often too generalized, relative to being localised in order to provide specific information patterning to farmers' specific locality. It is mentioned by (Gbangou et al., 2020; Lemos & Morehouse, 2005; Naab et al., 2019) that for climate information to be usable, all stakeholders must be involved in its production, interpretation and dissemination. Naab et al. (2019) further mentioned that, with the increasing rate of tree cover loss which results in loss of biodiversity and ecological equilibrium, the sole dependence on local forecast by small-scale farmers will no longer suffice.

Table 1. Documentation of local forecasting knowledge indicators for the weather time scale.

Indicator	Description	Period	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;
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	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*)	Makes 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*)	Makes a lot of 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
Frogs	When frogs start croaking a lot	Rainy season	Rain is expected within 1 - 3 days
Pigs	When pigs turn the grass around	Rainy season	Rain is expected within 1 day
Goats	Goats are gathered in the evening and run together	Rainy season	Rain is expected within a day
Moon	When the moon shadow is on the left side	Rainy season	Rain is expected within 2 weeks inland
Moon	When the moon shadow is on the right side	Rainy season	Rain is expected within 2 weeks inland in the coastal part
Moon	When the moon shadow is on the top	Rainy season	Rain is expected within 2 weeks both inland and coastal part
Moon	When the moon reappears from the west	Rainy season	Rain is expected generally after 3 days
Moon	If half of the moon is visible	Rainy season	Rain is expected within the next 2 days
Moon	A red circle (like a rainbow) around the moon	Rainy season	It may rain within the next 3 days
Worms (Abotele)	Spread all over the grass after a previous rain	After February	It will rain again that same day or within 1 week's time

Continued

Scorpions	When big black scorpions appear frequently on the farm	Rainy season	More frequent rains event are expected (less dry spells)
Clouds	A thick cloud appears at the eastern side from the sea	Rainy season	It will rain on the same day orwithin 3 days, but the distribution can be different
Ants	Carry their food or eggs to the holes	Rainy season	Rain is 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)

Source: (Gbangou et al., 2021).

The uncertainty associated with the weather often increases the risk that small-scale farmers are exposed to since they depend solely on the rains to supply the required amount of water to their crops (Naab et al., 2019). This puts farmers in a very tight position in terms of decision-making in areas such as; Land preparation, Sowing/transplanting, Pest control, Fertilizer application and Harvesting.

5. Scientific Forecast Knowledge

Scientific Weather forecasting is the application of science and technology to predict the conditions of the atmosphere. Scientific weather forecasting only started in the 19th century amidst all the efforts and attempts made by people to forecast the weather for millennia. Scientific weather forecasts are made by collecting quantitative, spatio-temporal historical data about the state of the atmosphere to project the pattern of change in the atmosphere. Weather forecasting in the present day relies on computer-based models that take many atmospheric factors into account (Dirmeyer et al., 2009). Aside from all the computer models and state-of-the-art technologies used in the meteorological sector, human inputs are required to screen and pick the best possible forecast model to base the forecast upon. These include teleconnections, pattern recognition skills, knowledge of model performance, and knowledge of model biases (Meteoblue, 2018). Despite the massive development in the meteorological sector, forecast inaccuracy persists due to the; chaotic nature of the atmosphere, the error involved in measuring the initial conditions, the massive computational power required to solve the equations that describe the atmosphere and an incomplete understanding of atmospheric processes.

Several scientific weather forecast generators and service providers exist both locally and globally. GMet is the major meteorological service provider in Ghana. GMet provides daily forecasts for different agroecological zones in Ghana (Gbangou et al., 2021). Prominent among the international forecast service providers is Meteoblue, which is one of the leading scientific weather forecast service providers globally. Meteoblue was created at the University of Basel, Switzerland, in collaboration with the United States National Oceanic and Atmospheric Administration and the National Centers for Environmental Prediction. Meteoblue was then established as a subsidiary company in 2006 to run as an independent company to serve customers, particularly in the areas of agriculture, as well as solar and wind power (Meteoblue, 2018).

5.1. Scientific Forecast Knowledge Predictions

Numerical weather forecasting before the 19th century was mostly considered a failure (WMO, 2021). The success of the first numerical prediction by Charney et al. (1950) initiated a spectacular routine of innovations in the numerical Earth system and weather to climate prediction (NEWP) over the following decades. Real-time forecasting with NEWP began in the mid-1950s and was introduced in operations in the 1960s.

Improved observational coverage, the advent of satellite-based meteorological observations, the steady growth and advancement of computer power and breakthroughs in the theory of Earth-system coupled processes all signify progress of scientific weather forecasting in the NEWP era.

The potential of Scientific Forecast Knowledge (SFK) in improving the adaptation capabilities of small-scale farmers had been highlighted in several studies (Dunning et al., 2016; Gbangou et al., 2019; Naab et al., 2019; Nyadzi et al., 2018; Paparrizos et al., 2020). Ghana Meteorological Agency in the year 2015 and 2014 (GMet, 2016) in collaboration with ESOKO and CGIAR provided information on the seasonal onset of rains and daily weather forecast via conventional SMS to farmers in several communities (ESOKO, 2016; Nyadzi et al., 2018). Various media, such as the radio and television are other means through which relevant forecast information was channelled to farmers. These interventions enabled farmers to control farm uncertainties to a certain level, but were not continuous, and thus, not sustainable. Also, inadequate understanding and interpretation of forecasts on the side of farmers, when left alone, was the major constraint relative to the accuracy of predictions.

The results from a study carried out by (Gbangou et al., 2021) to verify the accuracy of scientific weather forecast showed that GMet recorded an H-K score of 0.50 and Meteoblue recorded an H-K score of 0.59. These scores suggest a significant skill with the potential of forecasting the weather at an appreciable accuracy.

5.2. Challenges of Scientific Forecast Knowledge

Lack of co-production of forecasts with farmers, which is known to build a sense of responsibility among beneficiaries, enhance adoption, build trust and encourage information sharing among stakeholders, and the spatio-temporal localization of scientific forecast information had been mentioned by researchers like (Gbangou et al., 2020; Lemos & Morehouse, 2005; Naab et al., 2019; Tall et al., 2018) as one of the major limitations of scientific forecast in solving the hydro-meteorological information needs of small scale farmers.

The capital investment for computers, including the high cost of NEWP and their running and maintenance costs, as well as resource requirements, is a deterrent to most developing nations. Despite that, cooperation, data and knowledge-sharing with scientists and researchers from lots of countries and organisations have brought about a meaningful advancement of NEWP.

Considerable progress has been made in weather and climate forecasting (Doblas-Reyes et al., 2013), but because of its probable nature, seasonal forecasting presents systematic errors which is a significant challenge globally (Bauer et al., 2015). Much of the information generated for weather and climate predictions is limited where practical decision-making is concerned, leading to less accurate forecasts, as predictions are being made more into the future (Paparrizos et al., 2020).

Due to this, Paparrizos et al. (2020) suggested that verification of forecasts is a necessary component of a prediction system and an essential part of hydro-meteorological and operational forecast activities. Results of verification can provide essential information and can effectively address the needs of diverse groups, such as end-users of predictive information (Casati et al., 2008).

Inferences from (Gbangou et al., 2020; Nyadzi et al., 2018) revealed that information access and interpretation remain a challenge for farmers who are illiterate due to the format in which forecast information is being generated and presented.

6. Integrated Forecast

The recent advancements in science and technology (satellite use, etc.) had made it possible to provide short and long-term climate information services to support the farmers' decision-making. Several researchers have observed that small-scale farmers use a combination of meteorological information (scientific forecast) and indigenous knowledge (IK) for weather and seasonal climate forecasting (Orlove et al., 2010; Roudier et al., 2014; Tume et al., 2019; Dogbey, 2021). Farmers are the first to recognize the limitations in terms of accuracy, timing, and reliability of local forecast, which is based on indigenous knowledge, although they rely on IK for daily weather forecasting and the seasonal onset of rains (Naess, 2013; Roncoli et al., 2002). Studies have also shown that IK is capable of serving 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 (Naess, 2013; Nakashima & Krupnik, 2018). Relatively, not many studies have been done to systematically investigate the potential of indigenous knowledge used by farmers for weather and seasonal climate predictions. The outcome was largely qualitative and limited in looking into the underlying mechanisms (techniques) of IF without quantitative test skills in these forecasts. It therefore became necessary to investigate and verify the accuracy of indigenous forecasts and the mechanisms underlying farmers' forecasting techniques for a possible integration (Manyanhaire & Chitura, 2015). Results of research conducted by Gbangou et al. (2020) to investigate farmer's preferences for the various forecast systems (Local forecast and Scientific forecast) are presented in **Table 2**.

Table 2. Suitability of decisions made from the local forecast as compared to scientific forecast (farmer's preferences).

	Prepare land	Amount of water to allocate	Seeding/ Transplant	Fertilizing	Pesticide application	Labour/ weeding	Others
Rainfall monitoring data	64%	29%	68%	64%	50%	61%	50%
Daily forecasts from farmers	50%	25%	57%	50%	46%	46%	50%
Daily forecasts from scientific models (Meteoblue)	57%	29%	61%	57%	46%	46%	50%

Source: (Gbangou et al., 2020).

Agriculture production involves several activities (**Table 2**). Most of these activities are climate sensitive and need to be carefully timed to avoid uncertainties. Gbangou et al. (2020) carried out an experiment to investigate the form of forecast farmers deem suitable for their farming decisions. **Table 2** gives the percentage of decisions that were of more interest to the 28 participants which comprised 22 Farmers and 6 extension agents. The results in **Table 2** present the percentages of the suitability of daily forecast from farmers (LFK) and daily forecast from scientific models (SFK). Farmer's level of acceptance and performance-scoring of both forecast is on a significantly similar level (no significant differences between the responses) signifying a possible integration between these two (2) forecast sections.

7. The Way Forward in Weather Forecasting

The various challenges of both local and scientific forecast reduce their accuracy and reliability for making delicate climate-dependant decisions on the farm. An integration between Scientific Forecast and Local Forecast would bring a balance between the challenges of both forecast systems and enhance their performance. This has led to the development of the "FarmerSupport" mobile application (FSApp) (Gbangou et al., 2020) which was built with a pictorial interface to enhance easy accessibility by both literate and illiterate farmers under the "WATERAPPS" project (http://www.waterapps.net/) which was launched in 2016 with the clear objective to improve food security and for sustainable agriculture productivity in rural areas through co-creation of tailor-made weather information services for small scale farmers (Gbangou et al., 2020; Paparrizos et al., 2020; Dogbey, 2021).

The "FarmerSupport" Application which is a tool developed through a participatory approach to address the climate information needs of farmers with regards to rain-fed agriculture works by receiving scientific forecast from Meteoblue and farmer's forecast, displaying both scientific and local forecast information to farmers.

Analysis of the predictive accuracy of LFK, SFK and its integrations was done to assess the skills of the FSApp in predicting the weather in relation to the ground truth using the Hanssen-Kuipers discriminant or Pierce Skill Score (H-K Score). This analysis was done using data collected over 92 days in two communities. The datasets include; Local Forecast data obtained from farmers through the FSApp server, scientific forecast data (from 1 mm and above) obtained from Meteoblue and the rainfall data collected from rain gauges installed in the 2 project communities Nakpanzoo and Yapalsi in Northern Ghana. **Table 3** presents the result of the various forecast sections.

Table 3. H-K scores of the various forecast sections of the FSApp.

	Probability of Detection (POD)	Probability of False Detection (POFD)	Hanssen-Kuipers discriminant (HK-score)
Local Forecast Knowledge (LFK)	0.61	0.11	0.50
Scientific Forecast Knowledge (SFK)	0.78	0.17	0.61
Integrated Forecast	0.86	0.24	0.62

Source: (Dogbey, 2021).

Results presented in **Table 3** show that integrated forecast recorded the highest predictive accuracy as measured by the H-K score methodology followed by SFK and LFK recording the least. Nevertheless, all forecast systems predicted at an appreciable accuracy where approximately 2 out of every 3 rainfall occurrences were accurately predicted by SFK and integrated forecast systems (Gbangou et al., 2021; Dogbey, 2021). An H-K score of 0.62 as seen for the Integrated forecast was not significantly different from that of the SFK forecast.

Dogbey (2021) stated that; it will be a valid inference to associate the relatively low LFK in forecasting the weather with diminishing biota in the farmer's surroundings. This diminishing fauna and flora could be associated to population increase inducing tree cover removal putting the sustainability of LFK at risk.

8. Modes of Integration

Efforts made by many of the earlier researchers on the concept of integration of LFK and SFK suggested the model presented in **Figure 3**. An example of forecast aid tools that followed the former archetype was the "FarmerSupport" Application which was earlier mentioned by (Gbangou et al., 2020). These applications followed the former archetype of integration where decisions from Satellite Observations (Scientific weather monitoring) were compared with Ground Observations (Ecological Signals) to forecast the weather and make better-informed decisions, particularly in relation to the timing of agricultural activities. The idea here was that merging science with society will draw forecast closer to accuracy by cushioning the limitations of both scientific and local forecast and therefore increasing the accuracy and reliability of forecast (Gbangou et al., 2020; Nyadzi et al., 2019). Several statistical methods for forecast integration had been mentioned in literature (Gbangou et al., 2021; Karpatne et al., 2017) most of which are focused on the daily predictive outputs of both LFK and SFK for daily rainfall occurrence. These methods rely on the comparisons of individual means and outputs which do not incorporate auto-correction and adjustments due to a lack of feedback incorporation at the data generation stage. Even though the accuracy of the integration scenario (former archetype) has not been fully tested, the concept theoretically possesses great potential in accurately forecasting the weather. As a means of improving the accuracy of integration models, the new archetype in **Figure 4** was suggested as a model to foster continuous communication between ground observations and satellite observations in the form of feedback

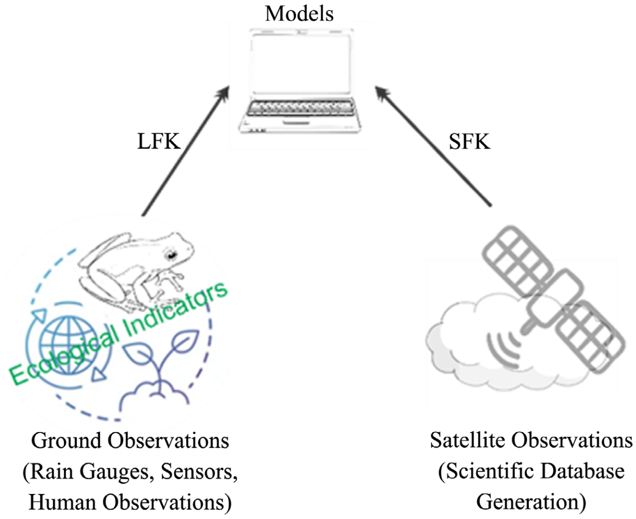

Figure 3. Former archetype of the integration between SFK and LFK.

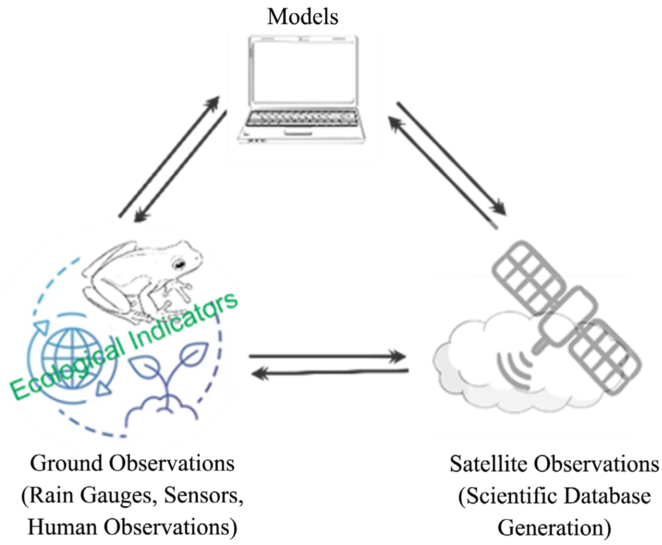

Figure 4. A suggested archetype of the integration between SFK and LFK.

which will better shape the end product (forecast). The suggested archetype is deemed to possess great prospects in improving upon the former archetype to make improved and more accurate predictions.

9. Conclusion

Information provision is very important for farmers in making climate-sensitive decisions. The joint production and dissemination of climate information offers an important mechanism for farmers' adaptation to climate change and ensures resistance among small-scale farmers.

Scientific forecast is valuable but becomes weaker when generalized. Therefore, it is important to generate meteorological data locally to generate a reliable forecast for decision-making.

Forecast integration offers great potential for better prediction and making reliable decisions and advancing agricultural production to foster food security among small-scale farmers in Africa. Predictive accuracy of the integrated forecast will increase with increasing accuracy of LFK and SFK in addition to selecting the right archetype.

I recommend that further work is done to investigate the predictive accuracy of the various systems of forecasting (LFK, SFK and Integrated forecast) to serve as the basis for a more conclusive analysis of the subject.

Acknowledgements

This publication was made possible through support provided by the WAGRINNOVA Project and the West African Centre for Water, Irrigation and Sustainable Agriculture (WACWISA), University for Development Studies, Ghana with funding support from the Government of Ghana and the World Bank through the African Centres of Excellence for Development Impact (ACE Impact) initiative.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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