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Integrating user- and data-driven weather forecasts to develop legitimate, credible, and salient information services for smallholders in the Global South

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Climate-related risks and variability pose significant challenges to the livelihoods and food security of smallholder farmers practicing rainfed agriculture. Many smallholders have limited access to weather information from climate services, and this information is often not tailored to their specific context and needs. Therefore, they rely on local ecological knowledge. This study utilizes the second generation of climate services, which provide demand-driven forecast information systems through mobile apps. We present three cases from agricultural communities in Guatemala, Bangladesh, and Ghana where we collaborated with farmers to develop local weather forecasts (LF) and combined them with scientific weather forecasts (SF) to create hybrid weather forecasts (HF). The integration of user-driven forecasts (LF) and data-driven forecasts (SF) enhances the legitimacy of the service, thereby increasing farmers' trust and credibility by providing skilful forecasts. Furthermore, our results demonstrate that the hybrid weather forecast approach facilitates climate-smart, adaptive agricultural decision-making, enhancing the resilience and capacity of smallholder farmers in the Global South to adapt to a changing climate.

Keywords Smallholder farmers, Agricultural community engagement, Local weather forecast, Scientific weather forecast, Adaptation

Rainfed agriculture in the Global South is a key source of food and livelihood security for millions of smallholder farmers and local rural economies[1]. The observed impacts and increasing exposure of these production systems to weather-related risks pose a global challenge to achieving many Sustainable Development Goals (SDGs), as these events lead to crop failures and income losses[2,3].

To prevent, reduce, or cope with the impacts of increased hydro-climatic variability and extreme weather events, farmers need to anticipate and adjust their management practices in advance. For this, they rely on weather forecast information as part of their farming adaptation strategies (e.g. deciding when to apply inputs, which practices to prioritize, etc.). However, unlike most farmers in the Global North who largely rely on skilful modern numerical weather predictions, smallholders in the Global South have limited availability and access to adequate information. Research shows that they primarily rely on two main sources of weather-forecast information: local weather forecast knowledge, and scientific weather forecasts. The former is based on knowledge accumulated over the years, often across generations, using weather-signalling ecological indicators to predict the weather (hereafter: Local weather forecast—LF). In this study, local weather forecasts (LF) are classified as user-driven data, because they are derived from farmers' observations on ecological indicators in their daily life, such as the behaviour of animals, plants, and astronomical phenomena. However, Local weather forecast information is challenged by interactions between changing landscape conditions and climate dynamics.

On the other hand, scientific weather forecasts (SF) are developed by technical and scientific experts using hydro-climate observations and climate models to create scenarios and forecast information. In this study, we categorize scientific weather forecasts (SF) as data-driven since they are derived from numerical weather models, through a top-down approach.

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Information produced by top-down scientific approaches is often communicated through visual scenarios or other available systems (e.g. radio or interpersonal communication) and is frequently unreliable or not tailored to the decision-making context and needs of smallholders[4–6]. In other words, these top-down approaches, commonly implemented in the first generation of climate services, are no longer sufficient for making appropriate decisions under a changing climate and the observed increase in the frequency, intensity, and randomness of weather events, and their impacts on farms' surrounding environments[7–9]. These limitations call for weather forecast systems that address the three major features of knowledge systems for sustainable development[10]: credibility, saliency and legitimacy. Credibility refers to the need for weather forecast systems to be scientifically skillful and capable of providing technical arguments and evidence to smallholders. Saliency emphasizes the importance of forecasts being relevant to smallholders' decision-making problems, ensuring that their assessments of expected weather conditions meet their specific agricultural needs. Legitimacy highlights the importance of valuing local experiential knowledge on the prevailing weather conditions, which not only improves forecast skilfulness but also increases the sense of ownership and cultural alignment. This leads to a more user-oriented approach in the second generation of climate services, where information follows a bottom-up, demand-driven approach to meet the context specific needs of smallholder farmers[11].

The significant increase in the availability and access to Information and Communication Technologies (ICTs) for smallholder farmers provides an opportunity to build credible, salient, and legitimate weather information systems[12]. Mobile phones and web-based platforms can offer farmers timely and accurate information on weather patterns[13], market prices[14], and agricultural best practices[15], among other things. These technologies help farmers make informed and timely farm management decisions and facilitate communication and collaboration between farmers, researchers, agricultural extension officers, and other actors in the agricultural value chain, enabling the co-production of knowledge and innovations[16]. Actively engaging farmers to harness their local knowledge and experience is key to developing climate services, as it ensures the production of tailored and actionable knowledge (i.e. saliency) and fosters ownership and trust (i.e. legitimacy) between weather forecast information providers and end-users, increasing the chances of uptake and good use of information[17]. Moreover, utilizing technological developments accessible to smallholders can enhance forecast reliability and credibility by integrating and optimizing both scientific weather data and farmers' local knowledge on weather forecast.

In the following sections, we showcase our engagement process with farmers to create a hybrid weather forecast that seamlessly integrates scientific and local weather forecast. We do this by presenting case studies from smallholder farmer communities in Guatemala, Bangladesh, and Ghana (see Supplementary Fig. 1). In these cases, we actively involved farmers in developing local weather forecasts (LF). Subsequently, we merged LF with scientific weather forecasts (SF) to produce hybrid weather forecasts (HF). These hybrid forecasts, demonstrated to offer higher accuracy[18,19], not only enhance farmers' trust in weather forecasts[20] but also provide clarity on which forecast system to utilize[19], all while preserving the integrity of local ecological knowledge[21].

Results

Community engagement to develop legitimate weather forecasts

We collaborated closely with smallholder farmers at a local level, through farmers' weather schools (see "Methods") to document and harness their knowledge on local weather patterns. This approach relies on and harnesses farmers' deep understanding of their surrounding environment, shaped by generations of accumulated knowledge and practical farming experience. Furthermore, our aim extended beyond documentation; we sought to empower farmers to effectively incorporate weather forecasts into their farm decision-making. To achieve this, we provided training sessions wherein farmers learned to interpret scientific weather forecasts and engage in community science by measuring rainfall using simple rain buckets. They then input their field observations, such as observed rainfall and local ecological indicators to forecast rainfall 1–2 days ahead into mobile apps (details of which are provided in the "Method"). These apps served as platforms for data collection, generating local weather forecasts, and presenting hybrid forecasts. As an example of this collaborative process, we adapted the local indicator symbols in the app to fit the farmers' cultural production context (i.e. replacing a western barn icon with an image of a typical local barn). Similar adjustments were made for many other symbols, such as local birds and plants. Through this collaborative process involving farmers and agricultural extension officers, we bolstered the legitimacy of the process by aligning with and renown smallholders' cultural values and beliefs, all while enhancing their knowledge and capacity to utilise hybrid weather forecasts for informed farming decisions (refer to Fig. 1, and Supplementary Fig. 2 for details).

During the initial stages, farmers expressed their challenges in embracing scientific forecast due to a lack of ownership of the information, and a general distrust in information providers. Moreover, it became apparent that they faced economic barriers, as many lacked access to the necessary information technology, such as smartphones, to access scientific forecast data. Additionally, farmers disclosed that even when they could access weather forecast information, they encountered communication hurdles due to their low literacy levels, and often found the information unreliable. For instance, in Ghana, farmers noted that the weather forecasts provided by the national meteorological office, originating from a station located 30 kms away from their communities, were typically relayed through intermediaries in the agricultural supply chain (e.g., input retailers). Farmers highlighted that these forecasts did not accurately represent the prevailing weather conditions in their communities. As we further elaborate below, through this collaborative process of co-production, we contributed to the development of credible, salient, and legitimate hybrid weather forecasts. More specifically, Fig. 1 illustrates how the co-production of hybrid weather forecasts is as the result of a dynamic process that requires users and service producers to interact in an iterative process to increase the accuracy of weather forecasts (credibility), while at the same time ensuring context-relevance (salience) and user ownership (legitimacy).

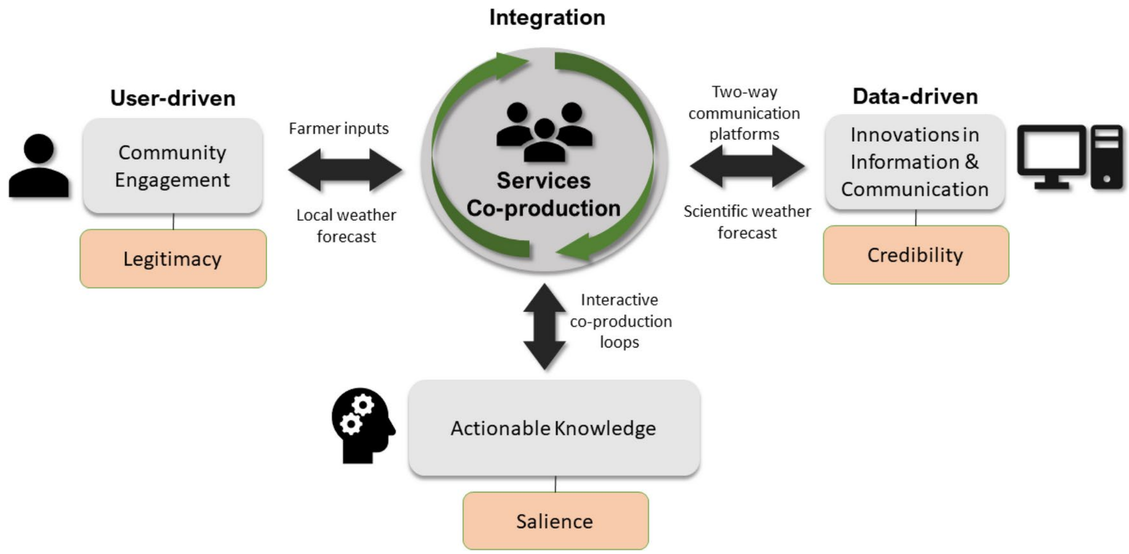

Fig. 1. Conceptual framework of socio-technical integration as design principles to develop hybrid weather forecast.

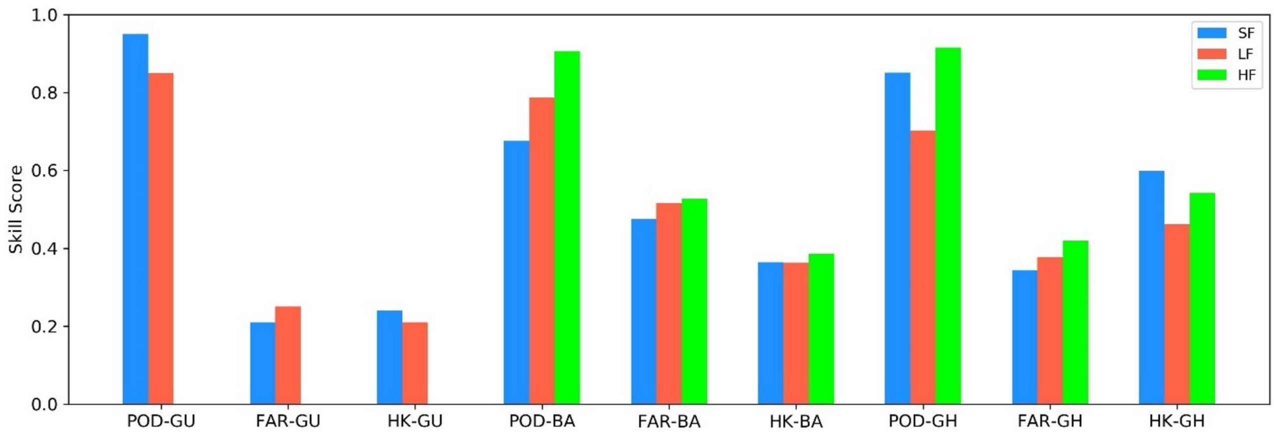

Fig. 2. The performance of scientific, local, and hybrid forecasts through various skills assessment metrics for Guatemala, Ghana, and Bangladesh. POD stands for probability of detection, FAR for false-alarm ratio, and HK for Hanssen-Kuipers skill-score. GU stands for Guatemala, BA for Bangladesh, and GH for Ghana. SF, LF, and HF stands for Scientific, Local and Hybrid Weather forecast, respectively.

Credibility of weather forecast

Ensuring reliable weather forecast information is crucial for farming decisions, including determining optimal planting times, irrigation scheduling, fertilisation, and harvest timing. In the employed methodology, we focused on enhancing the credibility and accuracy of weather forecast information by integrating multiple sources, such as local weather forecast knowledge and scientific data on weather forecasting from numerical models, to generate hybrid forecasts. These hybrid forecasts were validated through field observations, and evaluated using statistical metrics (refer to the "Methods" sections for details). Interestingly, our analysis revealed discrepancies between forecast performance and farmers' perceptions. While farmers tended to place more trust in local weather forecasts than scientific weather forecasts, our evaluation emphasized the importance of assessing both local and scientific forecasts on a location-specific basis to enhance service credibility. Overall, we observed that the performance of scientific forecasts slightly exceeded that of local forecasts, except for the case in Bangladesh where the skill of scientific forecasts matched that of local forecasts (Fig. 2). The SF yielded Hanssen-Kuipers (HK) values of 0.24, 0.36, and 0.59 in Guatemala, Bangladesh, and Ghana, respectively. In contrast, the skill of LF was lower than SF in Guatemala (HK = 0.21) and Ghana (HK = 0.46). It is important to note that the SF provided by the apps are tailored to specific locations within smallholder farming communities and are not generic forecasts obtained from television or radio broadcasts (see Gbangou et al.[22] and Kumar et al.[16]).

The hybrid forecasts derived from integrating user-driven forecasts (LF) and data-driven forecasts (SF) show improved performance in Bangladesh (HK = 0.39) compared to both SF and LF, and outperform LF in

Ghana (HK = 0.54) (Fig. 2). However, the hybrid forecasts do not surpass the performance of SF in Ghana. It is important to note that the HK score could not be calculated in Guatemala due to the absence of misses (predicted rain but no rain observed) and correct negatives (predicted no rain and no rain observed) during data collection. The simple HF approach used in this study generally favours rain detection[23]. Using a straightforward integration method, the hybrid forecast predicts rain events if either SF or LF forecasts see rain (see "Methods"). The main reason the hybrid forecast's performance does not significantly exceed SF and LF is the high false alarm rate (FAR) produced by the hybrid forecasts (Fig. 2).

Promising integration approaches, such as using a statistical method[18], weighted average SF and LF[19], and a machine learning techniques, may help develop more skilled HF. Comparing the study areas reveals that forecasting skills were higher for both SF and LF in Ghana, followed by Bangladesh and Guatemala (Fig. 2). This discrepancy may be attributed to the duration of LF data collection in each study area. In Ghana, LF data were gathered for more than two rainy seasons, whereas in Bangladesh and Guatemala, data were collected for two and one and one rainy seasons, respectively. The long-standing use of local indicators to forecast the weather by smallholder farmers in Africa likely explains the higher skill observed in Ghana. Paparrizos et al.[24] documented a total of 1350 local ecological indicators used by smallholder farmers worldwide, with most indicators collected in Africa, followed by Asia. Their study, however, does not document local indicators in Guatemala. We argue that the longer farmers use local indicators, the more accurate their predictions become. Experienced farmers, typically elders, have long relied on local indicators to forecast weather, which further enhances LF skill.

Salient knowledge for agricultural decision-making

Salient weather forecast knowledge for smallholders can provide them with specific information to make practical farm decisions at various stages of farming. To achieve this, we tailored the development of hybrid weather forecasts to meet farmers' specific information needs operational scales, adopting an user-centred approach (Fig. 1). Analysing surveys and focus group discussions conducted after implementing the FSapp and DROP app during the rainy season, we found significant benefits in using the apps for daily agricultural decisions. Most farmers reported changes in their agricultural planning based on rainfall forecasts. For instance, farmers from the farmer weather schools in Bangladesh adjusted their planning on land preparation (100%), seeding and transplanting (97%), fertilizer application (97%), irrigation scheduling (89%), and harvest dates (86%) according to the forecasts (Fig. 3a). Bangladeshi farmers mentioned altering their irrigation schedules to mitigate the impact of an anticipated dry spell that was forecasted 1–2 weeks in advance. Similarly, farmers in

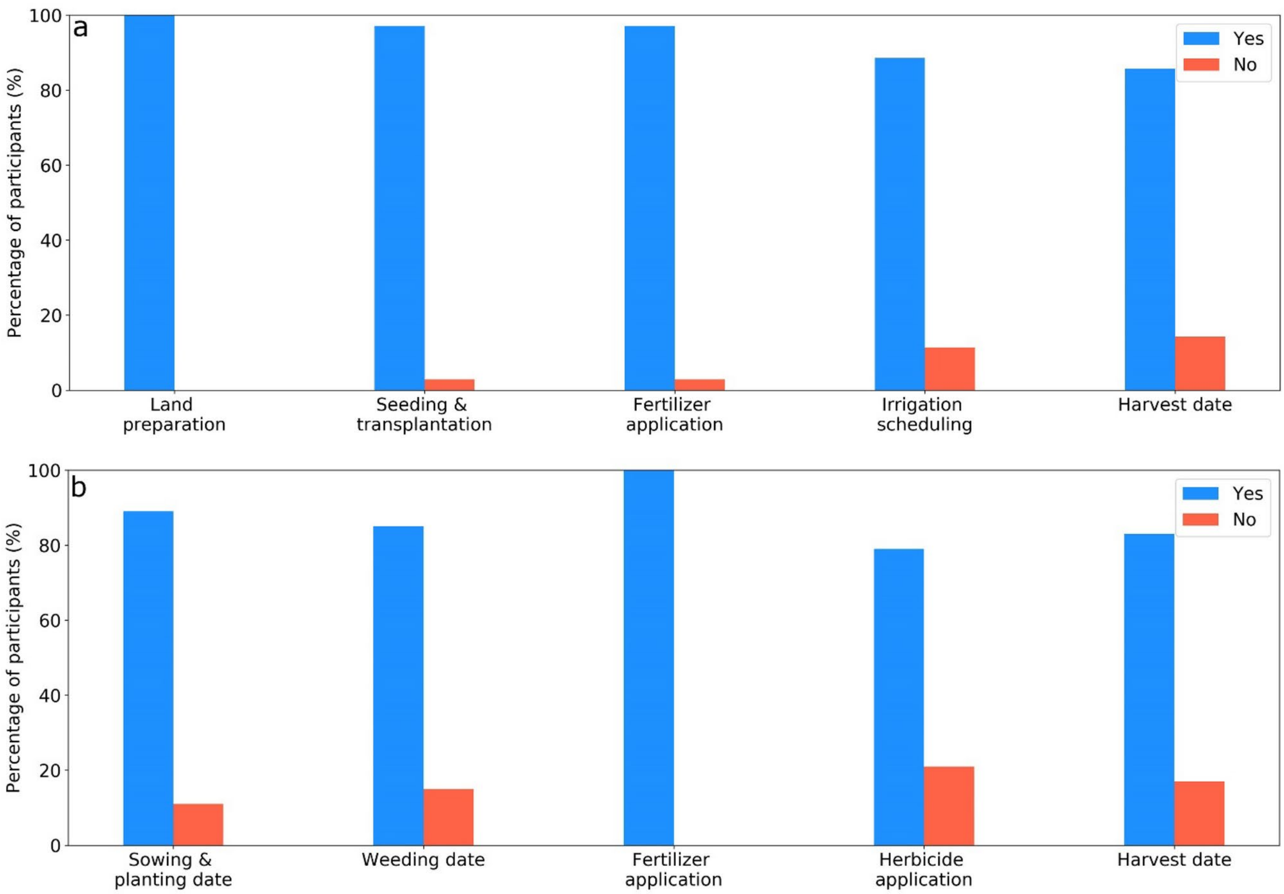

Fig. 3. Changes in agricultural decision-making based on forecast information received by farmers through the app: (**a**) in Bangladesh and (**b**) in Ghana.

Ghana adapted their agricultural activities based on the weather forecasts, including sowing and planting dates (89%), weeding dates (85%), fertilizer application (100%), herbicide application (79%), and harvest dates (83%) (Fig. 3b).

Farmers surveyed confirmed that they used information provided by the apps to decide which agricultural practice to implement or adjust. Many farmers also stated that their investment costs for inputs, such as fertilizer and pesticides, dropped by 50%, since they began using the weather forecasts from the apps, as they could optimize their usage. In the past, they needed to reapply fertilizer due to the rainfall events occurring after application. Farmers also harvested and collected their paddy earlier based on heavy winter rainfall forecasts provided by the farmers' weather schools. Initially, when we asked farmers about their preferred lead-time for receiving weather forecast information, they selected all available options, ranging from real-time (nowcast), to a 3-months seasonal outlook. However, in the endline study, answering the same question, the majority of farmers opted for a 1–2 week lead-time. This shift in preference resulted from our active and regular engagement and capacity building, which helped farmers understand the precise lead-time needed to prepare for various agricultural activities. Receiving information with a 1–2 week lead-time also allowed them to secure their livelihoods during extreme weather events such as cyclones. Farmers mainly preferred weekly forecasts due to their higher accuracy at this lead-time. Seasonal forecasts were also utilised, for example, when selecting the type of crop to cultivate during the season[5]. Farmers noticed that forecast accuracy varied with the lead-time, finding shorter lead-time forecasts more useful for making operational agricultural decisions.

Surveys and interviews in Ghana confirm similar use of app information for agricultural management decisions. For example, farmers adjusted their sowing schedules based on predicted rainfall events to ensure better crop establishment under wetter conditions. Similar to Bangladesh, farmers in Ghana also consulted the apps for decisions regarding fertilizer and herbicide application. Rainfall can wash away these inputs, resulting in additional costs for farmers. The weekly rainfall forecast is crucial for determining harvest timing. For instance, groundnuts need to dry in the sun for three to five days, and rainfall during this period can cause the nuts to germinate, as noted by Ghanaian farmers. By adjusting their agricultural activities based on the weather forecasts, farmers can minimize losses due to unforeseen extreme weather events and maximise productivity. It is important to note that a survey on agricultural changes in Guatemala after using the app could not be conducted due to the short study duration (two months of the rainy season in 2022). A longer period, extending beyond one rainy season, is essential for farmers to fully benefit from the app and feel the need to adapt their agricultural practices.

Discussion and conclusions

In the past, scientific and local weather forecast knowledge were seen as competing sources of information, making integration challenging[25]. However, there is a growing consensus that local weather forecast knowledge adds significant value, particularly for smallholder farmers[13,26,27]. The current work demonstrates an approach to co-produce hybrid weather forecasts, highlighting the benefits of this integration in aiding smallholder farmers' operational decision-making in the Global South.

Many farmers are bound to their local knowledge and believe that their local weather forecasts perform better than scientific forecasts from national weather services[28,29]. Rather than confronting small-scale communities with the 'modern technology' through a top-down approach, we engaged with them to learn about and value their weather forecasting practices developed over generations, before the advent of ICTs. Our bottom-up user-driven approach confirmed that combining locally-identified weather-forecasting ecological indicators with scientific weather forecasts can improve not only forecasting accuracy but also legitimacy, ownership, and uptake among smallholders. However, many of the indicators we identified, such as specific local birds making sounds, or indigenous flower species, are used on a very local scale. Future studies should account for the particularities of each region, such as differences between peri-urban and stand-alone communities, and locally versus globally applicable ecological indicators[24]. Additionally, many indicators based on animals or plants are affected by climate change[30], making it increasingly difficult for farmers to predict the weather. Climate change is causing numerous animal species to alter migration patterns, and plant flowering times are also shifting, with some species blooming earlier or later than usual[31]. Despite these changes, many farmers continue to rely on these indicators for weather predictions, often unaware of the shifts in animal and plant behaviour. It is thus crucial to maintain and regularly update this local weather forecast knowledge based on indicators to preserve, expand, and ensure its relevance in agricultural decision-making.

The provision and use of location-specific, accurate, and timely weather and climate forecasts (data-driven) can help reduce weather risks and uncertainty in smallholder farmers' decision-making[32]. However, many farmers criticize that the forecasts they obtain from television, radio, and other sources (top-down) are not skilful, location-specific, or timely[32,33]. Furthermore, in the tropics, where the largest number of smallholders are located, most weather prediction models lack the necessary skill in forecasting rainfall[34]. The skill analysis of scientific forecasts in our case confirms similar findings on a local scale. Our findings on SF are supported by global precipitation forecast assessment studies using numerical weather prediction models (e.g., Li and Robertson[35] and Roy et al.[36]). Roy et al.[36] demonstrated that the North American Multi-Model Ensemble (NMME) has higher skills in West Africa (representing Ghana) followed by South Asia (representing Bangladesh), with lower skills in Central America (representing Guatemala). Additionally, Li and Robertson[35] concluded that forecasts generally perform better in West Africa compared to South Asia and Central America. The lowest SF performance in Guatemala might also be related to the topography of the farmers' communities, which are located in the mountainous regions. Many models perform poorly in these areas due to issues with orographic precipitation and coarse spatial resolution[37,38]. Nevertheless, our study demonstrates that SF outperforms local weather forecasts in all study regions, thereby increasing the credibility of our forecasts.

Integrating farmers' local perspectives with modern knowledge, as showcased in our study areas, enhances forecast accuracy and transparency. The skill of the forecasts is improved at a much higher spatial scale (Fig. 2), and weather prediction models can be better validated and refined with ground observations from farmers. The hybrid weather forecast information, combined with training and capacity building on its usefulness for farm decision-making (Fig. 3), increases forecast use, while enhancing community inclusivity. This approach fosters a sense of ownership over the information and associated services co-produced with and for the smallholder agricultural communities. Farmers feel entitled to the information they produce, recognizing that their inputs matter and influence both the forecast and the agricultural decisions within their community. Participants have reported that since they began contributing their local weather forecast observations to the apps, and using the scientific and hybrid weather forecasts, their status within and outside the community has improved. They feel their opinions now 'matter more' than before, particularly because they actively contribute to developing the weather forecast themselves. In Ghana, participants mentioned using weather forecast information from all systems (local, scientific, and hybrid) for additional activities such as roadside food vending, trading, and Shea processing[13]. In Bangladesh, farmers also use the forecast information for activities outside agriculture, such as planning visits to extended family, or organizing events. This has significantly helped increase their societal status and bonding within their communities[16].

The approach followed in the study areas, as presented in this work, indicates that an effective way to improve agricultural decision-making is through the provision of skilled hybrid weather forecasts. Understanding how local weather forecast knowledge is produced, and adhering to the particularities of local agricultural communities is essential. Only then can we co-develop information that truly meets the needs of smallholder farmers, empowering them to make more weather- and climate-smart agricultural decisions. This also ensures the long-term sustainability of forecast information use within the communities, as farmers, being owners of the information, remain engaged over time. To achieve this, capacity building through Farmer's weather schools and training is imperative. Such initiatives enable a feedback mechanism through interactive co-production loops, where farmers provide feedback on the usefulness and relevance of the forecast information. The findings of this study are supported by numerous other studies that highlight the importance of active participation of smallholder farmers throughout the entire process to ensure better forecast uptake and decision-making[34,39,40].

To benefit the hundreds of millions of smallholder farmers in the Global South, there is an emerging need to bridge the gap between local initiatives and national efforts. Scaling up through agricultural extension services or in-country meteorological office networks would enable more farmers to benefit from these advances. However, how to achieve this remains a challenge[41]. Addressing these challenges requires a concerted effort from various stakeholders, including governments, development agencies, and private sector actors, to ensure that smallholder farmers can fully benefit from the potential of skilful weather forecasts and the use of ICT services for their livelihoods.

Methods

Data collection and analysis

Qualitative and quantitative data were collected through the FarmerSupport and DROP apps (see sub-section below), weekly monitoring, and participatory interaction during the Focus Group Discussions (FGDs) and interviews with farmers. In this study, we conducted interviews with a total of 28 farmers in Guatemala, 49 farmers in Ghana, and 65 farmers in Bangladesh (Table 1). A Kobotoolbox (www.kobotoolbox.com) was employed for interviewing farmers in the study areas, with a printed version of the questionnaire as a backup. All the collected data, including printed questionnaires, meeting notes, and weekly monitoring data, were translated into Microsoft Word and Excel for further analysis and documentation. The data collected using Kobotoolbox were also organized in Excel.

The FarmerSupport app (FSapp) and DROP app

The FarmerSupport app (FSapp[13]) and DROP app are the first and second generation of hydro-climatic information services developed through a participatory approach, respectively. Their aim is to address the weather and climate information needs of smallholder farmers concerning rainfed agriculture. The mobile apps display local weather forecasts submitted by farmers based on local ecological indicators observed on the field. Additionally, the apps provide scientific weather forecasts derived from numerical weather prediction models, delivering actionable knowledge to smallholders for informed farm decision-making. The apps have been implemented to test their proof-of-concept in smallholder farming communities in northern Ghana,

Region	Number of farmers	Region	Number of farmers	Region	Number of farmers
Guatemala		Ghana		Bangladesh	
Nahuala	6	Nakpanzoo	23	Khulna	16
San Marcos	5	Yapalsi	26	Patuakhali	11
Solola	8			Rajshahi	16
Toliman	4			Mymensingh	10
Yathza	5			Sunamganj	12
Total	**28**		**49**		**65**

Table 1. Communities and participants of the Farmer's weather schools in the three study areas.

Bangladesh, and Guatemala (Supplementary Fig. 1). The FSapp is now discontinued and has been replaced by the second generation of the app, the DROP app. While the FSapp only provided weather forecast information, the DROP app also forecasts soil moisture conditions up to 7 days ahead. Both apps predict rainfall events based on scientific and local weather forecasts.

Farmer's weather schools

Several farmer's weather schools have been established in farming communities around Tamale in northern Ghana and across the Lower Ganges Delta in Bangladesh (Supplementary Fig. 1). These schools were supported by the WATERAPPS, WAGRINNOVA, and WATERAPPscale projects. In Guatemala, however, no schools were established; instead, we conducted Focus Group Discussions (FGDs) with five farmers' communities during the rainy season in 2022. The aim of these schools is to provide a meeting place for the active engagement process between scientists, technology developers, agricultural extension officers, and farmers. The school also offer an excellent opportunity to initiate co-production process, training, FGDs, interviews, and discussions about weather forecasts among peer farmers. Table 1 presents the communities and participants we engaged in each study case. The sample farmers' demographics and characteristics are presented in Supplementary Information Table 1.

More information about the engagement process with smallholder agricultural communities in Ghana through the Farmer's weather schools can be found in Gbangou et al.[18,42], while for Bangladesh in Kumar et al.[43] and Paparrizos et al.[44]. Following projects finalisation, the schools in Ghana and Bangladesh remain operational, providing farmers with a platform to discuss and share upcoming weather events.

FGDs and semi-structured questionnaire

Focus group discussions (FGDs) and semi-structured questionnaires were conducted in all study areas, allowing for questions that are not predefined[45]. At least two FGDs were conducted in each community with men and women participants, both together and separately. Separating the genders in these discussions ensured that women farmers felt comfortable expressing their opinions, as in many communities, women hesitate to speak up when men are present. The goal of the FGDs was to gain a general understanding of the opinions of local farmers regarding weather information and forecasts, and to cross-validate the answers given in the questionnaires[46].

Baseline and endline studies were conducted in Ghana and Bangladesh, while only the baseline study was carried out in Guatemala due to time limitations. Conducting a baseline questionnaire was necessary to gather information on weather and agricultural information needs, forecast availability, and lead-time, which are crucial for developing weather and climate information services. The questionnaires were filled in either individually with a farmers or in group discussions. Baseline studies were essential for developing apps tailored to farmers' needs through co-production processes. Conversely, endline studies allowed for the evaluation of the apps' applicability and whether their use changed farmers' perceptions of scientific and local weather forecasts, as well as their agricultural practices. It is vital to consider farmers' perceptions of the developed apps and forecasts in general. Climate information service providers, might often believe that their product is valuable to users, but if users do not agree, trust, or understand it, the app will not be sustainable in the longer term[47].

Forecast skill assessment

A categorical statistic approach was employed to evaluate the performance of local and scientific weather forecasts, which is common for verifying dichotomous forecasts. A dichotomous forecast predicts whether it will rain or not ('yes rain' versus 'no rain') (Table 2). Several common metrics were used to assess the skill of a forecast in the study, including the probability of detection (POD), false-alarm ratio (FAR), and Hanssen-Kuipers (HK)[48,49]. POD and FAR have scores ranging from 0 to 1, with a score of 1 indicating a perfect forecast for POD and a score of 0 indicating a perfect forecast for FAR. The best skill is achieved when both POD and FAR show high scores close to 1 and low scores close to 0, respectively. The HK score can range from -1 to 1. A score closer to 1 indicates better discrimination between 'yes rain' and 'no rain'. A score below 0 indicates no skill, while a score of 1 represents a perfect score. Table 2 illustrates the contingency table used to calculate the forecast performance. POD, FAR, and HK are calculated as follows:

$$POD = \frac{hits}{hits - misses}$$

$$FAR = \frac{falsealarms}{hits + falsealarm}$$

$$HK = POD - \frac{falsealarms}{falsealarms - correctnegatives}$$

	Event forecasted	
Event observed	Yes	No
Yes	A: Hit	B: Miss
No	C: False alarm	D: correct negative

Table 2. Contingency table that shows possible combinations of forecasted and observed rain events.

Forecasts		
SF	**IF**	**HF**
Rain	No rain	Rain
No rain	Rain	Rain
Rain	Rain	Rain
No rain	No rain	No rain

Table 3. Rain and no rain indicators for building a simple HF.

Simple hybrid weather forecasts

The integration of scientific weather forecasts (SF) with local weather forecasts (LF) is termed hybrid weather forecasts (HF), which may enhance forecast performance, trust among farmers, and preserve local ecological indicators for weather prediction. Some studies have indicated that LF outperforms SF in Ghana and Bangladesh[18,19,23]. The indicators observed by farmers are utilized to predict rainfall occurrences, enabling LF to outperform SF in rainfall predictions. Nevertheless, there are instances where farmers do not observe any indicator that can be used to forecast rain, yet rain still occurs. In such cases, farmers rely on SF. Consequently, we developed a straightforward HF based on forecasted rain events from both SF and LF[23]. If local indicators are submitted by farmers, the HF indicates rain. Conversely, if no indicators are observed, the HF utilizes the SF forecasts. Table 3 provides detailed selection criteria for rain and no rain events for HF.

Data

The scientific forecasts (SF) are obtained from the meteoblue weather provider via an API:URL. The NOAA Environmental Modelling System (NEMS) is used to forecast weather[50], with a horizontal resolution ranging from 4 to 30 km wide and a vertical resolution of 100 m to 2 km high, depending on the region of the world. The apps offer three forecast lead times: 1-day, 7-day, and 14-day forecasts. However, hindcast data is only available with a lead time of 1 day and a spatial resolution of 30 km. In this study, we utilized hourly hindcast data downloaded from the meteoblue data achieve. These data were aggregated to daily rainfall from 9 to 8 AM the following, aligning with the timing of rainfall measurements recorded at 9 AM. Simple bucket rain gauges were installed in Ghana, while rainfall data for Bangladesh were obtained from the Bangladesh Meteorological Department (BMD). The use of BMD precipitation data for skill evaluation analysis might introduce higher uncertainty due to the locations of the BMD rain gauges being further away from the farmers' communities (> 10 km). In Guatemala, several rain gauges were installed close to farmers' communities by a local Non-Governmental Organisation (NGO) and were utilized in the current study.

The local weather forecast (LF) data were recorded in the apps after farmers input their forecasts based on observed indicators, with additional data collected via questionnaires for backup. Each morning before 9 o'clock, farmers submitted their rainfall forecasts for the day (1-day lead time) in the apps under the "Share Forecast" function, indicating whether they predicted rain or not[13]. We did not filter or pre-select the LF provided by the farmers; instead, we displayed all the LF made by farmers as percentages. For example, if out of 10 farmers, 5 forecasted medium rain, 3 forecasted light rain, and 2 forecasted no rain, the DROP app would display: 50% medium rain, 30% light rain, and 20% no rain. Additionally, we trained a couple of farmers in each farming community to measure rainfall using a simple rain bucket. The LF data were collected during rainy season from August to October 2022 in Guatemala, from August 2020 to October 2022 in Ghana, and from October 2021 to August 2022 in Bangladesh.

Data availability

All data and codes generated and/or analysed during this study are available from the corresponding author on request.

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S.P., R.V., and S.J.S. conceived and implemented the research. All authors contributed substantially to the study design, editing, and commenting on the article drafts for several rounds. All authors have read and agreed to the published version of the manuscript.

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The authors declare no competing interests.

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