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Original research article

The performance of Climate Information Service in delivering scientific, local, and hybrid weather forecasts: A study case in Bangladesh

Samuel J. Sutanto [a,*], Spyridon Paparrizos [a], Uthpal Kumar [a,b], Dilip K. Datta [c], Fulco Ludwig [a]

[a] Water Systems and Global Change Group, Wageningen University and Research, P.O. Box 47, Wageningen, 6700 AA, the Netherlands
[b] International Fertilizer Development Center (IFDC), Dhaka, Bangladesh
[c] Environmental Science Discipline, Life Science School, Khulna University, RG2M+X59, Khulna 9208, Bangladesh

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ABSTRACT

Access to reliable and skillful Climate Information Service (CIS) is crucial for smallholder farmers in Bangladesh to mitigate the impacts of rainfall variability and extremes. This study aims to systematically evaluate the performance of CIS in providing Scientific Forecast (SF) and Local Forecast (LF) to smallholders in Bangladesh. The results were then compared with farmers' perceptions of the forecast accuracy. Additionally, the skill of a simple hybrid forecast (HF), which is an integrated system of SF and LF, was assessed using the ERA5 and ground observation datasets as benchmarks. The SF and LF data were obtained from the meteoblue hindcast and from the interview, respectively. The results indicate that, overall, LF exhibits slightly higher skill compared to SF when evaluated against the ERA5 dataset. The forecast performance, however, declines by almost half when the ground-based observations are used, associated with high false alarms. Farmers, on the other hand, perceived SF to possess superior performance compared to LF. This study demonstrates that combining the SF and LF into a simple HF yields higher forecast skill than either individual forecast, highlighting the importance of HF to deliver a reliable and trustworthy weather forecast.

Practical implicationss

Many farmers worldwide rely heavily on rain for farming and rainfed agriculture serves as an important source of food and income for smallholder farmers. Changes in rainfall patterns and extreme events due to climate change are significantly impacted farmers on their socio-economic conditions. To help farmers facing these problems, various Weather and Climate Information Services (WCIS) have been developed, but they mostly provide scientific forecasts (SF), which may not always be accurate for specific locations, tailored to the farmers' needs, and not understandable. Because of these reasons, many farmers in the global south use local ecological indicators, like observing animals or plants, to predict the weather, known as local forecasting (LF) knowledge.

Research has shown that LF can sometimes be more accurate than SF, especially in regions like Africa. Moreover, some studies recommend combining SF with LF, known as hybrid forecasts (HF) for better results. The WATERAPPscale project that was conducted in five regions of Bangladesh provided farmers with WCIS derived from both the SF and LF. This project also recognizes the value of HF in delivering accurate rainfall predictions since a skillful rainfall prediction is crucial for farmers in Bangladesh to cope with frequent rainfall variability. Moreover, reliable WCIS can help farmers in their daily farming activities, such as seeding, planting, sowing, and applying fertiliser. This study, therefore, aims to document the local indicators used by Bangladeshi farmers, evaluate the accuracy of different forecasting methods provided by WCIS, and understand farmers' perceptions of these forecasts.

Based on farmers' perceptions, WCIS generates a more accurate SF than LF in predicting rainfall. Conversely, systematic evaluations show that LF actually performs slightly better performance than SF, but when ground observations are used instead of ERA5 data, LF's skill decreases due to high false alarm rates. A simple HF developed by integrating SF and LF performs better than either SF or LF individually when using both ERA5 and rain gauges. This highlights the importance of combining scientific and indigenous forecasting approaches for effective farm decision-making. We suggest continuing documenting forecasts issued by farmers based

* Corresponding author.
E-mail address: samuel.sutanto@wur.nl (S.J. Sutanto).

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on their local knowledge (LF), as this can contribute to the development of more accurate HF systems.

Currently, there's a lack of studies evaluating LF performance over longer time periods, which limits the development of skillful HF using data-driven approaches like machine learning. Implementing such HF systems could greatly benefit farmers in Bangladesh by providing accurate WCIS, improving decision-making processes, and unlocking the agricultural potential of the region. By combining scientific advancements with local knowledge, farmers can better manage the risks associated with climate variability and change.

Data availability

Data will be made available on request.

1. Introduction

The livelihoods and food security of farmers worldwide are under threat due to climate variability (FAO, 2019; IPCC, 2014; IPCC, 2022). With over 60% of farmers globally practicing rainfed agriculture, this sector is vulnerable to climate change (Cooper et al., 2008). This is also the case for Bangladesh, where the agricultural sector heavily relies on monsoon rainfall during the rainy season (Abedin and Shaw, 2013; Kumar et al., 2020b). In Bangladesh, the agricultural sector plays a pivotal role in the national economy and contributes to more than 15% of the Gross Domestic Product (GDP) and supporting around 43% of the population in terms of income and employment (Paparrizos et al., 2020; Kumar et al., 2020b). Rainfed agriculture serves as a vital source of food and livelihood security for millions of smallholder farmers and rural Bangladeshi communities. These farmers rely on weather forecast information to inform their adaptative farming strategies, including decisions regarding the timing of seeding and prioritization of farming practices. However, changes in rainfall variability and extreme high or low rainfall leading to flood and drought, respectively, have significant socio-economic impact on farmers' livelihoods and agricultural decision-making. Given these challenges, access to reliable and context-specific climate information becomes crucial for farmers to adjust their short-term operational and long-term strategic farming practices accordingly (Prokopy et al., 2013; Rautela and Karki, 2015; Mousumi et al., 2023).

Weather and Climate Information Services (WCIS) have been implemented in many countries or regions, demonstrating their potential to assist farmers in mitigating the impacts of hydroclimatic extremes, such as flood and drought, and allow them to improve agricultural productivity (Phillips et al., 2001; Patt et al., 2005; Roncoli et al., 2009). WCIS generally relies on modern numerical weather prediction (NWP) models to generate weather and climate information. However, it should be noted that the scientific forecast (SF) information derived from NWP models still has limitations in providing daily location-specific weather information for smallholder farmers in the global south (Kumar et al., 2021).

Previous studies have extensively documented the various barriers that hinder the utilization of SF by smallholder farmers. These barriers include issues such as low reliability, limited skills, coarse spatial resolution, and limited accessibility in rural communities (Orlove et al., 2010; Vaughan and Dessai, 2014; Fitzpatrick et al., 2015; Sultan et al., 2020). Furthermore, SF's probabilistic or deterministic nature, coupled with inherent uncertainties, poses challenges for comprehension, particularly among farmers with limited training and educational backgrounds (Ingram et al., 2002; Kumar et al., 2020a). Consequently, many smallholders either do not use or have limited access to weather information provided by climate services, as its fails to cater to their specific context and needs. Instead, they rely on local ecological knowledge as a primary source of information for their agricultural practices.

The use of local ecological indicators to forecast weather (referred to local forecast, LF) is a more favorable and affordable way of accessing weather information for many farmers in low latitude developing countries (Haiden et al., 2012; Derbile et al., 2016; Gbangou et al., 2021). LF involves observing and interpreting local ecological indicators derived from meteorology, animals, astronomy, plants, and other sources, drawing upon intergenerational knowledge and experience (Rautela and Karki, 2015; Gwenzi et al., 2016; Balehegn et al., 2019). These indicators, which are specific to local conditions can be categorized into three categories, such as atmospheric conditions, celestial elements, and flora and fauna (Gbangou et al., 2021). However, LF encounters several challenges, such as LF knowledge being lost since it is communicated orally, not documented, being replaced by SF steered by western knowledge and technologies, or not deemed useful (Codjoe et al., 2014; Balehegn et al., 2019; Chowdhooree, 2019; Chowdhooree and Das, 2021). Furthermore, increasing climate variability may cause a challenge as LF indicators such as certain insect species, may change or disappear due to climate change (Radeny et al., 2019). A recent study conducted by Paparrizos et al. (2023) found that more than 1350 local indicators have been used by farmers worldwide for weather forecasting, especially in Africa where 948 indicators have been identified.

Recent available WCISs mainly offer SF (e.g., Chiputwa et al., 2020; Gudoshava et al., 2022) and to the authors' knowledge, only the FarmerSupport app integrates both SF and LF (Paparrizos et al., 2023). The use of both SF and LF systems is expected to deliver a seamless forecasting system, addressing the limitations inherent in single forecasting systems, as mentioned in the previous paragraphs. For example, LF may yield more accurate forecasts compared to SF in within specific regions (Gbangou et al., 2021; Nyadzi et al., 2022). However, LF strongly relies on local indicators, which may not always be observable, whereas SF provides continuous forecasts. In addition, many WCISs forecast weather conditions for nearby cities, which are often far away from farming communities. LF, on the other hand, is more applicable to specific farming area where indicators are observed. Despite approximately 314 local indicators were found in Asia (Paparrizos et al., 2023), there is a gap in research regarding the utilization of local indicators in Bangladesh to forecast weather events, particularly for the agricultural sector.

In Bangladesh, the Bangladesh Meteorological Department (BMD) as the national meteorological agency provides SF with a lead time of 7 days (Kumar et al., 2020a). While the BMD forecasts have a significant impact in disseminating warnings related to cyclones and storm surges in the Bengal Delta (Habib et al., 2012), they are not specifically targeted at smallholder farmers. Recognizing this gap, the WATERAPPs project was initiated in 2016 with the goal of developing tailor-made weather and water forecast information designed specifically for farmers. One of the study areas is located in Khulna Bangladesh (Paparrizos et al., 2020). Since then, the WATERAPPs project has brought significant benefits to farmers in the Khulna district of Bangladesh, providing them with relevant SF information to support their daily farming activities (Kumar et al., 2020b). For instance, based on information received through the WATERAPPs WCIS, farmers in Khulna were able to take timely measures to protect their crops before the Cyclone Jawab hit Bangladesh. This proactive action helped them avoid significant losses in harvested rice, as experienced by many farmers in the Lower Ganges Delta. Building on the success in Khulna, the services have been expanded to five different locations across Bangladesh through the WATERAPPscale project, ensuring that farmers can access tailored weather information specific to their locations. Moreover, the project recognizes the value of local ecological indicators (LF) in providing seamless weather forecasts for smallholders in Bangladesh, echoing similar findings in Africa (Kalanda-Joshua et al., 2011; Balehegn et al., 2019; Gbangou et al., 2021; Nyadzi et al., 2021; Nyadzi et al., 2022).

Research conducted by Mani and Mukherjee (2016) and Paparrizos et al. (2020) has assessed the performance of rainfall forecast for the Bengal Delta, revealing that SF exhibits low skill during the pre-monsoon and monsoon periods. However, these studies focused solely on evaluating SF performance. In contrast, LF may offer added value in improving forecast performance in Bangladesh. Studies conducted in Africa evaluating LF skill have demonstrated that the skill of LF is comparable to or even outperforms the SF, depending on the indicators used and the number of indicators included in the skill assessment (Gbangou et al., 2021; Nyadzi et al., 2022). These studies also highlight that the integration of SF and LF, known as hybrid forecast (HF), yields higher forecast performance than either SF or LF alone. A skillful weather prediction, whether derived from SF, LF, or HF, is crucial for farmers in Bangladesh to effectively manage the uncertainties and

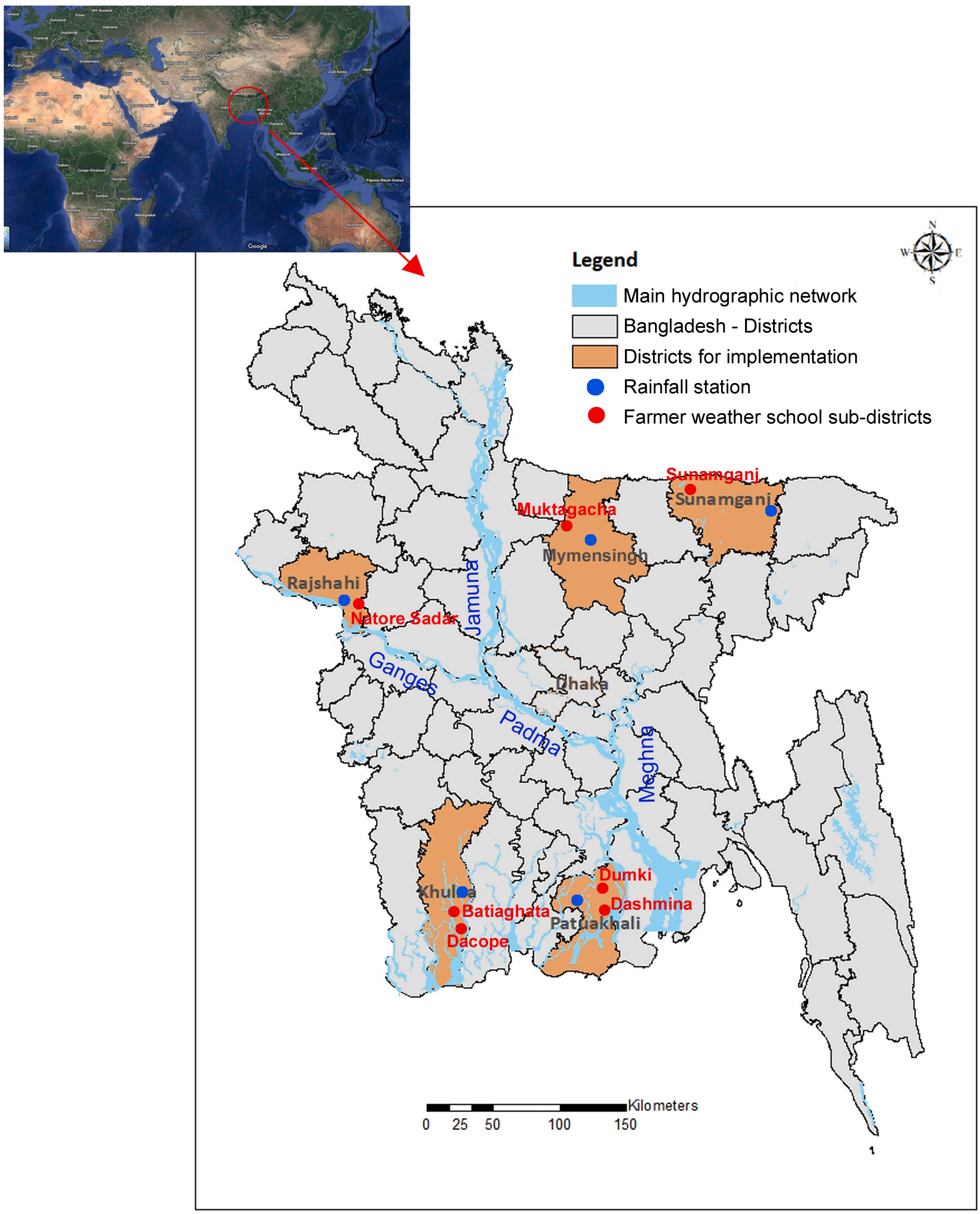

Fig. 1. The map showing five study districts (Khulna, Patuakhali, Rajshahi, Mymensingh, and Sylhet) and locations of the farmers weather schools in Bangladesh where the forecast skills were evaluated. 5 schools are located in the Batiaghata Khulna, 1 school in the Dacope Khulna, 2 schools in the Natore Rajshahi, 2 schools in Muktagacha Mymensingh, 2 schools in Sunamganj Sylhet, 2 schools in Dumi Patuakhali, and 2 schools in Dashmina Patuakhali.

frequent hydroclimatic variability they face. It enables farmers to make informed farm decision-making and to prepare for potential extreme weather events.

This study is driven by four primary objectives, which are 1) to systematically document the local ecological indicators employed by farmers in Bangladesh for short-term rainfall forecasting, 2) to evaluate the skills of the rainfall predictions generated by SF and LF in five different locations across Bangladesh, 3) to develop a simple HF and compare its skill with SF and LF, and 4) to assess farmers' perception of SF and LF performance. This study represents the first comprehensive evaluation of SF, LF, and HF forecast skills in Bangladesh. To the authors' knowledge, only two prior studies have evaluated the performance of LF (Gbangou et al., 2021; Nyadzi et al., 2022) and none have assessed the performance of LF in Bangladesh. Furthermore, this research introduces a simple HF approach that holds the potential to be implemented in the WCIS that offers higher skill than any single forecast alone. The methodology and findings of this study are applicable elsewhere and not only for Bangladesh. As such, this research contributes to the broader understanding of integrating traditional and scientific weather forecasting approaches to improve decision-making processes in agriculture and disaster risk reduction globally.

2. Material and methods

2.1. Study area and farmers' weather schools

The skill of the forecasts was evaluated in five study locations across Bangladesh, which are Khulna, Patuakhali, Rajshahi, Mymensingh, and Sunamganj-Sylhet (Fig. 1). Khulna and Patuakhali are situated in the Bengal Delta, which is the lower delta plain of the Ganges-Brahmaputra–Meghna (GBM) Delta (Kuehl et al., 2005). This lowland region is one of the most densely populated deltas in the world (Kida and Yamazaki, 2020). The agricultural sectors in these regions are agriculturally dominated salt-affected districts in Bangladesh and are often affected by tidal surge-related inundation, tropical cyclones, and hydroclimatic variabilities (Akter et al., 2020; Al Masud et al., 2020). Rajshahi district, located in the Northwest of Bangladesh, is renowned as a significant agricultural production center in the country. However, it is characterized by low rainfall and high temperature region, making it susceptible to drought conditions (Ali et al., 2021; Al Faisal et al., 2021). Sunamganj-Sylhet is located in the Haor basin (Surma basin) of Northeast Bangladesh. This region is characterized by large to medium floodplain depressions and wetland ecosystems, which provide local indicators related to animals that are mostly used by farmers in Bangladesh. Like other regions in Bangladesh, the Sylhet district also encounters high climate variability, leading to natural hazards, such as (flash) floods and drought (Bagchi et al., 2020). All study sites lie within the flat terrain across four agro-ecological zones. Khulna and Patuakhali are located in the Ganges Tidal Floodplain zone, Rajshahi is located in the High Ganges River Floodplain zone, Mymensingh is located in the Old Brahmaputra Floodplain zone, and Sunamganj-Sylhet is located in the Eastern Surma-Kushiyara Floodplain zone (Rahaman et al., 2019). The monthly average precipitation and temperature for these five study locations are presented in the Appendix Fig. A.1.

In general, the study areas are situated in a hot and humid subtropical climate zone, characterized by four distinct hydroclimatic seasons: Winter (December-February), pre-monsoon summer (March-June), monsoon (July-September), and post-monsoon (October-November) (Shahid, 2010). In these regions, farmers engage in diverse crop cultivation throughout three crop seasons: Kharif-I, which takes place from mid-March to mid-July; Kharif-II, which occurs from mid-July to mid-November; and Rabi, which spans from mid-November to mid-March (Kumar et al., 2021). The primary agricultural commodities in these areas include rice, fish, and year-round fruit and vegetable crops (Kumar et al., 2021).

A total of 16 farmers' weather schools were established in the study areas to facilitate the training and engagement of farmers. Specifically, in the Batiaghata sub-district Khulna, five schools were established, along with one school in Dacope sub-district Khulna, two schools in sub-district Natore Rajshahi, two schools in sub-district Muktagacha Mymensingh, two schools in sub-district Sunamganj Sylhet, two schools in sub-district Dumki Patuakhali, and two schools in sub-district Dashmina Patuakhali (red circles in Fig. 1). The farmers' weather schools served as places to conduct focus group discussion (FGD) (Kumar et al., 2021). The participation in these schools was determined based on the farmers' experience in hydroclimatic information services. The schools, however, were open to all farmers because they provide an excellent opportunity where farmers can discuss their needs, upcoming weather events, and foster the engagement process with their peers and local agricultural extension officers.

2.2. Weather data

2.2.1. Scientific weather forecast

In the previous projects (WATERAPPs and WATERAPPscale), hydroclimate information services were provided to smallholder farmers in Bangladesh through the co-development of a mobile app (Paparrizos et al., 2023). The app utilizes scientific forecasts (SF) issued by meteoblue weather provider. meteoblue delivers high-resolution local weather information based on the NOAA Environmental Modelling System (NEMS) (Black et al., 2009), providing accurate and of high-quality data for any point on land worldwide. The model has a horizontal resolution ranging from 4 km to 30 km, and a vertical resolution between 100 m and 2 km, depending on the specific region. For Asia and Japan, meteoblue uses the NEMS8, which has a spatial resolution of 8 km. The SF forecasts are updated twice a day at 0:00 and 12:00 UTC. Although meteoblue provides hourly forecasts, the app only displays daily forecasts with three different lead times i.e. 1-day, 7-day, and 14-day. This limitation is in place to reduce the computational resources required, considering that farmers often have limited economic resources for mobile internet credits. meteoblue stores hourly hindcast rainfall data with a lead time of 1 day in their archive. Thus, hourly hindcast rainfall data with a lead time of 1 day is used for analysis in our study. These hindcasts have a spatial resolution of 30 km, which is coarser compared to the 8 km resolution of the SF forecasts in Asia. In the analysis, the hourly hindcast data was aggregated to daily rainfall from 9 AM until 8 AM the following day at local time. This aligns with the timing of recorded rainfall observations, which were also recorded at 9 AM. The hindcast data is available from 1st January 1985 to the present. It's important to note that the meteoblue scientific forecasts are available for farmers in the study locations while the forecasts from the BMD are disseminated via radio and television and not through the app. Currently, there are more than 250 registered individuals, including farmers and agricultural extension officers in the app database.

2.2.2. Local weather forecast

Weather forecasts based on indigenous knowledge are referred as local forecasts (LF). The LF is derived from indigenous knowledge and observations of biophysical indicators by local people, particularly farmers. These indicators can encompass a wide range of components, including plant phenology, animal behavior, atmospheric conditions, and even astronomy (Roncoli et al., 2002). In many parts of the global south, mainly in Africa and Asia, farmers rely on their local knowledge and observations to predict the weather (Paparrizos et al., 2023). For example, the appearance of ants is an indication of expected or imminent rainfall and a good season (Sarkar et al., 2015; Vervoort et al., 2016). In the Northern Region of Ghana, farmers predict rain within a few hours when the wind moves towards the sun (Gyampoh et al., 2011). In various African regions, the observation of a halo around the moon is associated with rainfall or a good season (Gyampoh et al., 2011; Mahoo et al., 2015; Jiri et al., 2015; Gbangou et al., 2020). These local forecasting practices demonstrate the deep understanding that local communities have developed over time by closely observing their environment and natural phenomena.

It is interesting to note that in the study locations in Bangladesh, the use of LF is not well documented, compared to many countries in Africa. The use of SF, on the other hand, has become an essential resource for small-scale-farm households in Bangladesh (Kumar et al., 2020b). One of the reasons might be due to limited studies conducted in Bangladesh concerning the use of LF for agriculture in Bangladesh. During the FGDs, it was found that farmers in Bangladesh rely on a limited number of indigenous indicators for predicting rainfall, unlike their counterparts in Africa who use a broader range of Indicators (Roncoli et al., 2002; Offat and Miriam, 2015; Gbangou et al., 2021; Nyadzi et al., 2021). Gbangou et al. (2021) found that LF in Ghana had higher skill than SF when farmers observed more than three out of total 30 indicators. However, in the case of Bangladesh, farmers reported observing a maximum of two different indicators per day and often only one indicator was observed. This suggests that the skill and effectiveness of LF may vary depending on the number and diversity of indicators utilized in a particular region. The indicators identified in Bangladesh included ant, dragonfly, frog, butterfly, bird, grasshopper, cloud, moon, wind, and hot weather. Animals were the primary indicators observed by farmers in Bangladesh, who documented these indicators solely to predict the onset of rainfall, rather than the cessation of rainfall.

The LF data was collected from October 2021 to August 2022 through questionaries distributed in the farmers' weather schools. It is important to acknowledge that there were certain limitations in the collection of LF data, such as farmers not filling in their observations on a daily basis, particularly during the dry season. On average, 85 days of LF forecasts were collected. To ensure a diverse representation of LF indicators, a purposive sampling approach was employed, selecting farmers from different communities who actively relied on local indicators for rainfall forecasting. We also trained the farmers who do not have prior knowledge of LF, usually young farmers, together with more experienced farmers (usually elderly), with the aim of preserving and transmitting local knowledge to future generations. The majority of the farmers submitted their daily predictions before 9 AM in the morning by observing local indicators from their surroundings.

2.2.3. In situ observation and ERA5

For this study, rainfall data were obtained from the Bangladesh Meteorological Department (BMD) for five stations: Mymensing (90.4°E, 24.7°N), Khulna (89.5°E, 22.7°N), Patuakhali (90.3°E, 22.3°N), Rajshahi (88.7°E, 24.3°N), and Sylhet (91.8°E, 24.9°N) (see Fig. 1, blue circles). The availability of daily rainfall data varied among the stations, and any periods with missing data were removed from the evaluation. We obtained in situ observation data up to 2018 for all stations. Hence, the assessment of scientific forecast skill was conducted using data spanning from 1985 to 2018 for all datasets, including meteoblue hindcasts, in situ observation, and European Centre for Medium-range Weather Forecasts (ECMWF) Reanalysis version 5 (ERA5). To ensure fair evaluation among the datasets, all days with missing values (−999) in the forecast and ERA5 datasets were removed, aligning the evaluation of SF versus ERA5 and SF versus in situ observations with the same data length. Additionally, ground station data and ERA5 for the period from October 2021 to August 2022 were collected to match the LF period, enabling a comparative assessment of SF and LF within this timeframe.

ERA5 is a public dataset generated and hosted by the ECMWF (Hersbach et al., 2019). It is a global dataset that can be accessed and downloaded from the Copernicus data store (CDS). One should note that ERA5 is not a product of direct observations but rather a reanalysis product that combines historical observational datasets with advanced models to generate weather data on a global scale. Due to the assimilation of a vast amount of observation data, approximately 94.6 billion observations, ERA5 is sometimes used as a proxy for observed data in situations where actual observational data is not available (Hersbach et al., 2019). Many studies utilized ERA5 as a substitute for observational data to evaluate the forecast performance (e.g. Rasp et al., 2020; Bento et al., 2022; Lavers et al., 2022; Paparrizos et al., 2020). ERA5 provides hourly temporal resolution and a spatial resolution of 31 km. In this study, hourly rainfall data from 1985 to August 2022 were obtained for the entire country of Bangladesh and subsequently aggregated into daily data by summing the rainfall recorded from 9 AM to 8 AM on the next day. This temporal aggregation was performed to maintain consistency with the in situ data dan both SF and IF forecasts. Rainfall values equal to or less than 0.1 mm in a 24-h period were considered as no rain event (Xin et al., 2021; Harjupa et al., 2022). Later, grid points in the ERA5 dataset that were closest to the locations of the study sites were extracted. The inclusion of the ERA5 dataset has an objective to facilitate the comparison of forecast skill between the meteoblue forecasts and a blended product derived from the assimilation of model simulations and observations, serving as an alternative source of observational data.

2.3. Methods

2.3.1. Focus Group Discussion (FGD)

Initially, two FGDs were held in the farmers' weather schools, with an average of 25 participating farmers in each school. However, the number of participants decreased significantly due to COVID-19 restrictions that were implemented. The FGDs have dual objectives, which are to gather the farmers' perspectives on weather information and LF forecasts via semi-structured interview, and to provide advisory services related to agricultural decision-making based on the forecasts, with the assistance of local agricultural extension officers (Kumar et al., 2020a). During the FGDs, various topics were discussed, including SF weather forecasts, cropping practices, local knowledge and farming practices, and measures to address weather challenges. The onset of rainfall, cessation of rainfall, and duration of rainfall season were only briefly discussed during the FGDs since they were not the focus of the study. Following the lifting of COVID-19 restrictions, five research assistants were employed in the five locations to support bi-weekly meetings in the FGDs, as well as to collect local forecast data throughout the study period. The meetings were arranged twice a month for collecting the farmers' perceptions of the forecasts and administer a bi-weekly interview on the LF indicators (Section 2.3.2). The number of participants in these meetings ranged from 10 to 15 farmers in each school because not all farmers were able to attend the FGD every two weeks. Farmers, however, often shared the outcome of the FGDs with their peers, particularly when significant rain events were anticipated. In total, 20 FGDs were conducted from October 2021 to September 2022, covering three crop seasons in Bangladesh.

We collected in total 65 farmers' profiles participated in FGD, with 60% of the participants being male farmers and 40% being female farmers. During the FGDs, male and female farmers were not separated. Interestingly, a few of female farmers actively engaged in the FGDs, and we identified them as key farmers to assist others in disseminating forecasts. Among the participants, the majority (49%) had a secondary education level, while only 11% had a graduate level of education. It is worth nothing that many young farmers with age under 29 years old participated in the FGDs. As a result, 51% of the participating farmers had less than 10 years' experience in farming. For further detailed farmers' characteristics, please refer to Appendix Table A.1.

2.3.2. Semi-structured interviews

This study employed an exploratory research approach (Maxwell, 2012) to investigate the perceptions of farmers in Bangladesh regarding the skill of SF and LF. To gather this information, an online survey tool called Kobotoolbox was utilized, along with semi-structured personal interviews conducted during group discussions with farmers in five study locations. The purposive sampling method or judgment sampling was applied in selecting the farmers for interviews (Guarte and Barrios, 2006; Etikan et al., 2016). Bi-weekly questionnaires were distributed to the farmers' weather schools and forecast performance data were collected from 10 October 2021 to August 2022. The interview and questionnaire covered various aspects, including a) the performance of scientific forecasts in the previous week, b) the local forecast indicators observed by farmers and their performance, and c) the farmers' forecasts of short-term (1–3 days) rainfall events based on local indicators. However, it is important to note that the local indicators to forecast rainfall with a lead time of more than 1 day were limited and not well documented. Therefore, only LF with a 1-day lead time was used, which aligns with the available hindcast data from meteoblue. In terms of forecast performance, farmers' perceptions were categorized into five classes, which are very accurate (VA), accurate (Acu), acceptable (Ace), poor (P), and very poor (VP). All data and information used in this study were obtained as part of an endline study conducted after capacity building, training on weather forecasts, and frequent discussion had been implemented in the five study locations. Kumar et al. (2020a) conducted a precursor study to introduce the app and SF but they did not collect local indicators.

2.3.3. Skill evaluation metrics

The performance of the forecasts was assessed using the categorical statistic approach (Woodcock, 1976), which is a commonly used method for verifying dichotomous forecasts. This approach involves calculating various metrics based on a contingency table (Table 1). A hit is counted when a rain event is forecasted and observed. A miss is counted when the forecast shows no rainfall event, but it did occur. A false alarm is counted when the forecast indicates a rainfall event, but it did not occur. Lastly, the correct negative is counted when the forecast predicts no rainfall event, and it did not occur. In this study, we utilized the probability of detection (POD), the false alarm ratio (FAR), and the Hanssen-Kuipers discriminant (HK) metrics. POD and FAR are widely recognized statistical metrics for evaluating the accuracy of the forecasts (WMO, 2014). POD measures the proportion of forecasted rain events that actually occurred (see Eq. 1), while FAR indicates the proportion of forecasted rain events that did not occur (see Eq. 2). In addition, POD does not consider false alarms and can be influenced by an increased in the number of 'yes' predictions, and FAR is highly sensitive to false alarms. These two metrics, thus, should be used together to interpret forecast skill effectively. POD has scores ranging from 0 to 1, with a score of 1 indicating a perfect forecast. FAR, on the other hand, shows a perfect forecast if the FAR value is zero. The best skill is achieved when both POD and FAR exhibit high scores close to 1 and low scores close to 0, respectively.

The HK determines to what extent the forecast can discriminate between rain and no rain events (see Eq. 3). The HK ranges from −1 to 1 and the closer the HK value to 1, the better the forecast discriminates between rain and no rain events. Vice versa, the HK value of 0 indicates no skill and negative HK means that the misses exceed the number of hits. Furthermore, HK has been shown to be an unbiased categorical measure as opposed to many other skill scores and universally acceptable for evaluating yes/no forecasts (Woodcock, 1976). There is no clear definition of which HK value is classified as 'bad' or 'good' forecast found in the literature. However, WMO (2014) and Gbangou et al. (2021) classify $HK \leqslant 0.15$ as 'does not discriminate between yes/no events', $0.15 < HK \leqslant 0.35$ as 'somewhat discriminate', and $HK > 0.35$ as 'discriminate between yes/no event'. In this study, we will use these classifications for skill assessment based on the HK metric. All the skill metrics used in this study have been widely applied to verify the skill of climate predictions (Paparrizos et al., 2020; Gbangou et al., 2021; Jiang et al., 2021; Harjupa et al., 2022). The POD, FAR, and HK are calculated as follows (see also Table 1):

Table 1
Contingency table that shows possible combinations of forecasted and observed rain events.

		Event observed		Total
		Yes	No	
Event forecasted	Yes	Hits	False alarms	Forecast yes
	No	Misses	Correct negatives	Forecast no
Total		Observed yes	Observed no	Total

$$POD = \frac{hits}{hits + misses} \tag{1}$$

$$FAR = \frac{falsealarms}{hits + falsealarms} \tag{2}$$

$$HK = \frac{hits}{hits - misses} - \frac{falsealarms}{falsealarms - correctnegatives} \tag{3}$$

The evaluation of forecast skill was carried out in two distinct periods, taking into account the availability of LF data. The first period used a long-term rainfall time series from January 1985 to December 2018. This period was exclusively used to assess the skill of SF in comparison to in situ observation and ERA5. The long time series employed in the skill assessment warrant the reliability and robustness of the forecast verification. The second period considered for evaluation spanned from October 2021 to August 2022 to match with the LF data collection period. Both SF and LF forecasts were evaluated using the same period to facilitate a fair comparison and to determine which forecast demonstrated greater skill in Bangladesh. It is important to note that the evaluation was conducted only for 1 day forecast lead time due to hindcast data availability.

In the Appendix, a Fisher's statistical significance test (Fisher, 1922) was conducted to determine if there are nonrandom associations between forecast and observed (see Table 1). This test is widely employed in the analysis of contingency tables and is particularly suitable when the sample is small, which is from October 2021 to August 2022 in our case (Fisher, 1922; Fisher, 1954; Agresti, 1992). We applied a significance level of 0.05 to determine whether a statistically significant relationship exists between forecasted and observed data. The results of the test indicate that the SF evaluated using observation data is not statistically significant ($p > 0.005$) for Khulna and Rajshahi (Appendix Table A.2). Similarly for LF, the forecasts are not significant in Mymensingh and Patuakhali. This suggests that there is no relationship between SF and observed data in Khulna and Rajshahi and between LF and observed data in Mymensingh and Patuakhali. The highest p-value of 0.103 was obtained in Patuakhali for LF-OBS, which still falls within the 10% significance level range.

2.3.4. A simple hybrid weather forecast

Several studies acknowledge the value of LF and suggest the integration of SF and LF systems, rather than discarding one in favor of the other (Janif et al., 2016; Plotz et al., 2017; Balehegn et al., 2019). This integration, known as a hybrid forecast (HF), has shown promising results in terms of forecast skill, as it was shown in Ghana (Gbangou et al., 2021; Nyadzi et al., 2022). In addition, combining forecasts from multiple sources tends to be more accurate because of the integration of information gleaned from different sources (Wang et al., 2022). Building upon this insight, our study developed a simple HF system that combines both SF and LF approaches. We then evaluated the skill of the HF to prove whether the integration of SF and LF could yield higher forecast skill than a single forecasting system, either SF or LF alone.

The simple HF system was constructed based on the forecasted rain events provided by SF or LF. In principle, HF will forecast rain if either SF or LF indicates a rain event. Consequently, the HF will only display either SF forecasts or LF forecasts if rain is predicted by one of them. However, if both SF and LF forecasts predict rain, the HF will prioritize displaying the SF forecasts, considering the familiarity of farmers in Bangladesh with SF (Kumar et al., 2020a; Kumar et al., 2021). The underlying assumption of this simple HF system is that farmers may not observe the local indicators to forecast the rainfall on a daily basis. In such cases, the SF forecasts can serve as a reliable alternative. On the other hand, the LF may exhibit better performance in predicting rainfall events than SF, as found in some studies (Gbangou et al., 2021; Nyadzi et al., 2021). Thus, the HF will predict rain when LF predicts rain no matter if SF predicts rain or not. Based on this assumption, the HF system predicts rain when either SF or LF predicts rain. Vice versa, if both SF and LF predict no rain event, then the HF will predict no rain event. The detailed selection of rain and no rain events for HF is described in Table 2.

3. Results

3.1. *The skill of scientific forecast to predict rainfall events*

Fig. 2 shows the values of the POD, FAR, and HK skill metrics for SF forecasts across all study locations, utilizing data from 1985 to 2018. In the context of POD and HK, higher values closer to 1 indicate high forecast skills. Conversely, in the case of FAR, high forecast skill is obtained if the FAR value is close to 0 (Section 2.3.3). The result demonstrates that the meteoblue forecast has a high detection rate or hit rate in all locations, as indicated by POD values above 0.64. The POD and FAR values across all locations, in general, vary within the range of 0.64 to 0.79 for POD and 0.02 to 0.52 for FAR. Forecast evaluation using the ERA5 dataset generates lower POD values (0.69 on average) than the observations (0.77 on average). However, in situ observations result in significantly higher FAR values (0.41 on average) than ERA5 (0.04 on average). The coarse model resolution and ERA5 may minimize the false alarm (Gong et al., 2003; Gubler et al., 2020). Overall, the evaluation using ERA5 demonstrates higher forecast skills compared to using observations due to the high number of false alarms in the observations. From the user's perspective, a high number of false alarms can undermine the user's trust, here is farmer, in the reliability and consistency of the forecasting system (Walker et al., 2019; Harjupa et al., 2022; Imhoff et al., 2022).

The HK metric provides insight into the forecast performance, with ERA-MY achieving the highest score of 0.70 and the lowest is found for OBS-KH with a HK score of 0.46 (Fig. 2). A relatively low POD and a high FAR lead to a lower HK score and thus to lower forecast performance. The HK approach takes into account both the hit rate and the false alarm (see Eq. 3). In general, the forecast performance is higher when evaluated using ERA5 data (HK = 0.66) than the evaluation using in situ observation data (HK = 0.49). These results indicate that the forecasts in all stations are capable of distinguishing rain and no rain events, as evidenced by HK values >0.35.

3.2. *Comparison of scientific and local forecast skill*

The previous section evaluates the skill of SF compared to ERA5 and ground observations from 1985 to 2018. In this section, we compare the performance of SF and LF with data obtained from ERA5 (Section 3.2.1) and in situ observations (Section 3.2.2). The skill evaluations were conducted from October 2021 to August 2022 to match with LF data.

3.2.1. *Comparison with ERA5*

The skills of SF and LF are evaluated against the ERA5 re-analysis data for the five study locations (Fig. 3). The LF yields higher POD values on average (0.74) compared to SF (0.62), indicating that LF has a higher detection rate for rainfall events. The lowest POD value is obtained in Khulna for SF (0.54). This means that at least more than 54% of the SF and LF forecasts correctly predicted the occurrence of rainfall events. In terms of false alarm ratio (FAR), both SF and LF show higher values in Patuakhali than in other locations, with FAR values of 0.21 and 0.23, respectively. Interestingly, all rain events forecasted by SF in Mymensingh and Sylhet were observed by ERA5 during the study period, associated with FAR = 0.

Fig. 3 also shows the skill of the forecasts assessed using the HK metric. The skill of the forecasts varies in each location, with the highest skill found in SF-MY (HK = 0.75) and the lowest skill in SF-RA (HK = 0.39). The highest POD value generated by LF in Khulna does not necessarily correspond to the highest HK value due to high FAR value. Thus, the FAR value for LF in Khulna negatively impacts the performance of the forecasts based on HK. On the other hand, zero FAR value for SF in Mymensingh yields the highest forecast performance compared to others (HK = 0.75). This highlights the importance of considering both POD and FAR when evaluating forecast performance, for instance using the HK metric instead of only using POD or FAR. Overall, LF has similar skills compared to SF, with HK values of 0.55 and 0.54, respectively. This suggests that both forecasting systems perform comparably in terms of their ability to differentiate between rain and no rain events, taking into account both hits and false alarms.

3.2.2. *Comparison with ground observations*

When ground observation is used as a benchmark for forecast evaluation, the performance of both SF and LF decreases by a factor of two in some locations, associated with high false alarms (Fig. 4). In general, replacing ERA5 with ground observation data leads to higher POD values for both SF (0.68) and LF (0.79). The FAR values, however, also increase. with SF having an average FAR of 0.47 and LF having an average FAR of 0.52. The best forecast performance is obtained with SF in Patuakhali, yielding a HK value of 0.52. Conversely, the lowest forecast performance is obtained for SF-KH (HK = 0.22). Although the performance of the forecasts assessed using observation data is lower, the forecasts have some level of skill, as indicated by HK>0.22.

3.3. *Skill of simple hybrid forecast*

In Fig. 5, the skill assessment of the HF is presented using ERA5 and ground observation data as benchmarks. The highest POD value of 0.94 is achieved by the HF in Mymensingh when evaluated against ERA5 data. The use of in situ observations alleviates the skill of correct prediction of rain events (POD). The HF correctly predicts the occurrences of rainfall in Mymensingh (POD = 1), while the lowest POD value is obtained in Sylhet (POD = 0.81). Conversely, the use of ground observations leads to higher FAR values, associated with low skill. Because of the high FAR, the HK values of the HF using in situ observation are lower compared to using ERA5. These results highlight the impact of using different observation sources on the performance evaluation of the HF, with ERA5 data generally yielding higher skill scores compared to ground observations.

We summarize the forecast skills of SF, LF, and HF using both ERA5 and ground stations as observations in Table 3. The results clearly show that the integrated forecast (HF) generates higher forecast skills compared to SF and LF alone. In terms of correct predicting rain events, the HF yields average POD values of 0.88 and 0.91 when compared with ERA5 (HF-ERA5) and ground observation (HF-OBS), respectively. For the single forecasts, the LF has higher average POD value compared to SF. The HF, however, also exhibits high FAR, especially for HF-OBS. Similar to SF and LF, the use of ground observation data increases the FAR values of HF from 0.13 (HF-ERA5) to 0.53 (HF-OBS). As expected, higher FAR values lead to lower forecast skill. Nevertheless, the forecast skill obtained from HF is still higher than SF and LF. Here we demonstrate that integrated or combined forecasts (HF) provides higher skill

Table 2
Determination of HF based on rain and no rain occurrences of SF and LF.

Forecasts		
SF	LF	HF
Rain	No rain	Rain
No rain	Rain	Rain
Rain	Rain	Rain
No rain	No rain	No rain

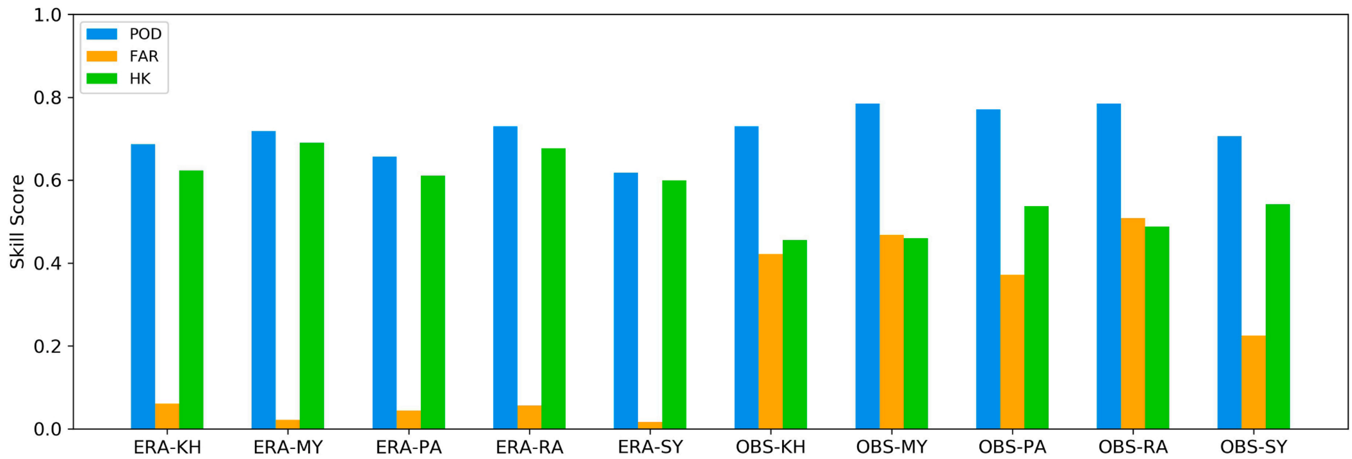

Fig. 2. Scientific forecast (SF) skills identified using HK, POD, and FAR metrics for the five study locations: Khulna (KH), Mymensingh (MY), Patuakhali (PA), Rajshahi (RA), and Sylhet (SY). We analyzed the skills by comparing the meteoblue forecasts with ERA5 (ERA) and in situ observation (OBS).

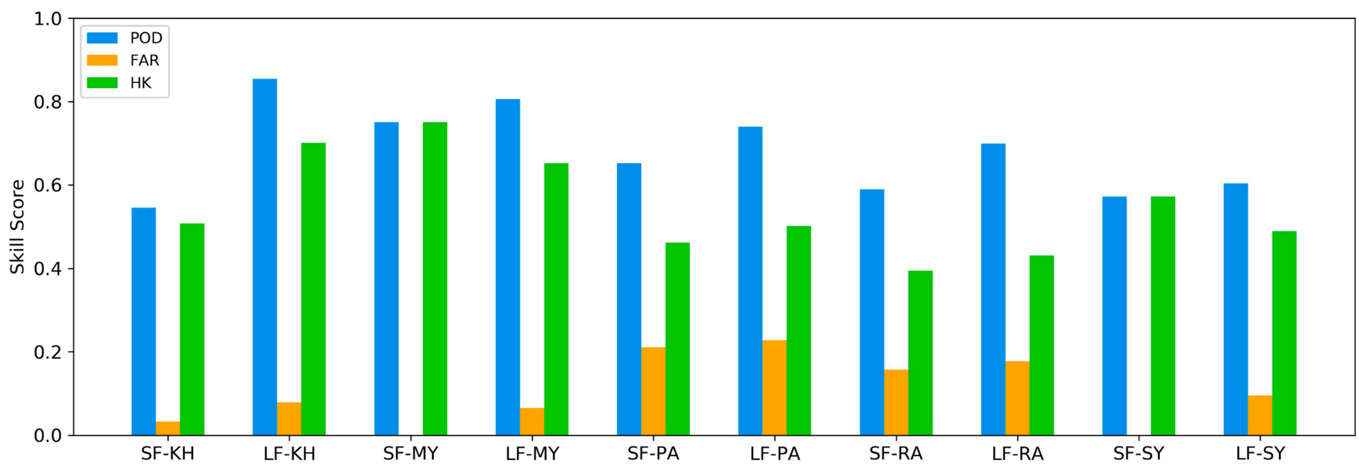

Fig. 3. Scientific (SF) and local forecast (LF) skills compared to the ERA5 dataset for the five study locations: Khulna (KH), Mymensingh (MY), Patuakhali (PA), Rajshahi (RA), and Sylhet (SY).

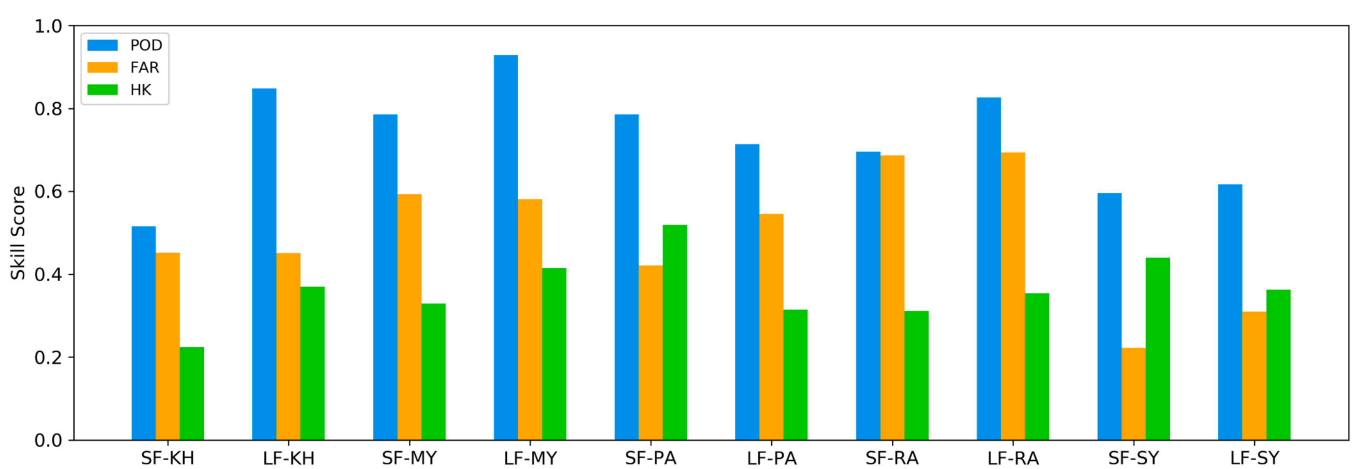

Fig. 4. Scientific (SF) and local forecast (LF) skills compared to in situ observation dataset for the five study locations: Khulna (KH), Mymensingh (MY), Patuakhali (PA), Rajshahi (RA), and Sylhet (SY).

than any single forecast systems.

3.4. Farmers' perception of forecast performance

During the study period, farmers in the five locations were surveyed about their perception of the quality of SF and LF forecasts. The results

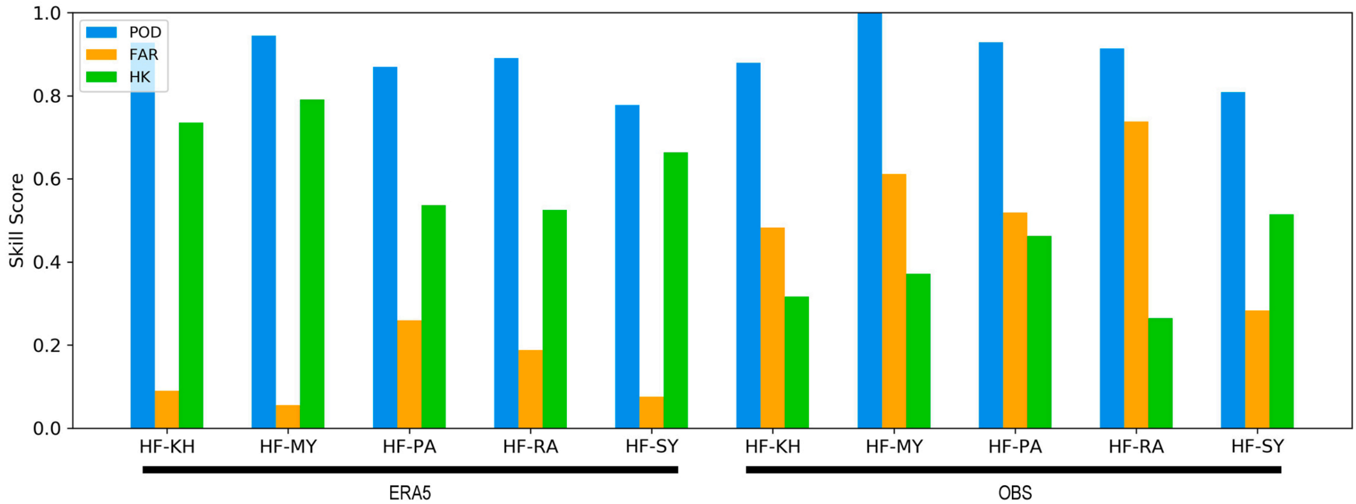

Fig. 5. Hybrid forecast (HF) skill assessment for the five study locations: Khulna (KH), Mymensingh (MY), Patuakhali (PA), Rajshahi (RA), and Sylhet (SY).

Table 3
Summary of the forecast skills averaged from five locations.

Indicator	Forecast system					
	SF-ERA5	LF-ERA5	SF-OBS	LF-OBS	HF-ERA5	HF-OBS
POD	0.62	0.74	0.68	0.79	0.88	0.91
FAR	0.08	0.13	0.47	0.52	0.13	0.53
HK	0.54	0.55	0.36	0.36	0.65	0.39

indicate that the SF forecasts for rainfall and temperature are considered very accurate by 28% and 33% of respondents, respectively (Fig. 6). However, many farmers consider that the forecasts of rainfall (50% of respondents) and temperature (46% of respondents) are accurate. When considering both very accurate and accurate forecasts as indicators of good forecast quality, the temperature is selected by 79% of respondents as the most accurate forecast. Our result shows that rainfall, which is considered the most important variable for farm decision-making (Kumar et al., 2020a; Sutanto et al., 2022), is selected by 78% of respondents as having good forecast quality, ranking second after temperature. Only 9% of farmers indicate that rainfall forecast has poor performance. According to the perceptions of many farmers in Bangladesh, LF forecasts are commonly viewed as less accurate when compared to SF forecast for weather prediction (Fig. 6). Temperature, a weather variable with higher predictability using SF, is not easily predicted using LF. Around 54% of the farmers indicated that LF predicts precipitation events to be very accurate and accurate. However, a low number of respondents (18% and 3%) expressed that rainfall prediction using LF has poor and very poor quality, respectively.

4. Discussion

4.1. Difference in farmers' perception and systematic evaluation

According to the perception of farmers in our study areas, the SF is perceived to have better performance in predicting weather than the LF. Farmers claimed that the SF forecast of precipitation has better skill than the LF forecast (Fig. 6). This finding contradicts to algorithm aversion introduced by Dietvorst et al. (2015). In algorithm aversion, it is suggested that people tend to lose confidence in algorithmic predictions (here is SF) compared to forecasts provided by human experts (here is LF). When systematically evaluating the forecast skills for rainfall using the dichotomous method, the results show that LF indeed yields slightly higher performance than SF (Fig. 3 and 4). These findings align with previous studies by Kalanda-Joshua et al. (2011), Mahoo et al. (2015), and Nyadzi et al. (2022). In Malawi, farmers believe that their local forecast (LF) is more reliable than the SF because it is built on local

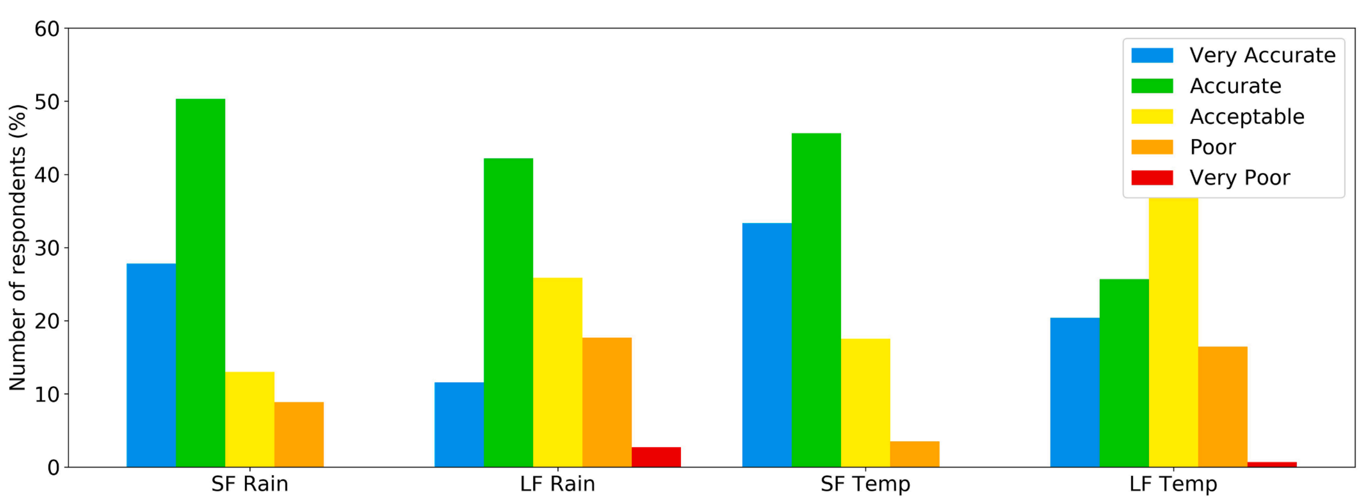

Fig. 6. Farmers' perception of the performance of both scientific forecast (SF) and local forecast (LF). Y axis shows the ratio of the number of days that most farmers filled in the forecast performance divided by the total observed days in percent. Abbreviation Temp stands for temperature.

experience and knowledge (Kalanda-Joshua et al., 2011). They further highlighted the necessity to tailor weather and climate information specifically to their local areas. These are the foremost reasons why the LF is more trustworthy than the SF, according to farmers' perceptions in Malawi. In Tanzania, a majority of farmers (>90%) are aware of local weather and climate forecasts and rely on LF in planning their agricultural activities (Mahoo et al., 2015). In that study, more than half of respondents believed that LF is more reliable compared to SF, while only a few claimed that SF is more skillful. Similarly, in a study in northern Ghana by Nyadzi et al. (2022), the performance of SF and LF varied each month during the rainy season, with LF generating higher overall skill compared to SF.

Indigenous knowledge and local indicators also play a significant role in weather forecasting In Asia, as documented in several studies (Hiwasaki et al., 2015; Rautela and Karki, 2015; Cuaton and Su, 2020). Hiwasaki et al. (2015) found that small island communities in Indonesia, Philippines, and Timor-Leste rely on local indicators based on animals and trees to forecast extreme weather events, such as strong wind, heavy rain, and drought. Similarly, Rautela and Karki (2015) demonstrated the dependence of people in the Himalayan region on LF due to limited access to scientific weather forecasts. According to Cuaton and Su (2020), the Mamanwa people in the Philippines observe some animals and celestial bodies to forecast weather and natural hazards. In Bangladesh, the use of local indicators to forecast weather is not well reported. Paul and Routray (2013) explored the use of local indicators, such as animal behavior, water and weather conditions to predict cyclones on the coast of Bangladesh. The aforementioned studies in Asia, however, primarily focus on the utilization of local indicators and traditional knowledge, rather than comparing the forecast performance between SF and LF. Therefore, drawing definitive conclusions regarding the forecast performance of SF and LF in Asia based solely on these studies is challenging.

There is a possible explanations for the disparity between the perceived performance of SF and LF by farmers and evaluation using a systematic approach. Farmers in our study locations have easy access to SF information through mobile phones (see Kumar et al. (2020b)), allowing them to make tactical agricultural decision-making, such as when to plant, seed, and apply fertilizer. The training and forum group discussion on SF interpretation, uncertainty, and probability of the forecasts have also contributed to increased confidence and trust in SF among farmers (Kumar et al., 2021). In contrast, indicators used in indigenous knowledge-based forecasts may not be observable on a daily basis (Nyadzi et al., 2021), leading to uncertainty among farmers about the weather conditions that they may encounter if the indicators are not observed on a particular day. Due to these factors, farmers perceive SF as being more reliable and skillful than their indigenous knowledge of weather forecasting.

4.2. Difference in ERA5 and ground observations

The use of ERA5 and ground station as a forecast benchmark shows higher skill when the ERA5 is used compared to observation measured by rain gauges (Fig. 3 and 4). The disparity in skill between using ERA5 and in situ observations can be attributed to several factors. One possible explanation is the spatial variability of rainfall and micro-scale processes over the study regions (Tripathi and Dominguez, 2013; Paparrizos et al., 2020; Nyadzi et al., 2021). These localized weather patterns and processes may not be adequately captured by ERA5, leading to differences in forecast skill compared to in situ observations. Additionally, the presence of high false alarms (FAR) in the observations measured by rain gauges could contribute to the discrepancy. Undetected drizzle precipitation by the rain gauge may result in inflated FAR values. It is important to consider the geographical locations of the rain gauged and the farmer communities. The rain gauges are typically installed in or near cities or airports, while the farmer communities are situated in peri-urban areas or villages, located further away (>10 km, Fig. 1). Given the localized nature of weather patterns in the region, the distance between the rain gauges and farmer communities may lead to missed recordings of local rainfall events, thereby affecting the forecast skill and resulting in higher FAR values (see A Fig. A.2). However, it is noteworthy that the POD scores of SF-ERA and LF-ERA are similar to SF-OBS and LF-OBS (Table 3). Previous studies by Nystuen (1999) and Liu et al. (2019) have highlighted the tendency of rain gauges to underestimate very light rainfall events (i.e., rainfall < 1 mm). Thus, low-intensity rainfall might not be recorded but it is forecasted by the model as a drizzle. To address the mismatch between forecasts, ERA5, and observations caused by local rainfall occurrences, it is advisable to install simple rain gauges in the farmer communities and measure rainfall on a daily basis, particularly during the rainy season, to capture the local rainfall patterns accurately (Landman et al., 2020; Nkuba et al., 2023).

The coarse spatial resolutions of the models, here are ERA5 (30 km) and meteoblue (30 km for hindcast), could attribute to the higher forecast skill found when using ERA5 as observational data. The coarse datasets tend to increase the prediction accuracy of yes/no precipitation events rather than providing detailed information about precipitation amount (Gong et al., 2003; Gubler et al., 2020). The use of ERA5, which has low model resolution, may lead to missed forecasts and lower POD score, particularly for local convective precipitation events occurring in neighboring locations just a few kilometers away. In contrast, these events might be captured by the meteoblue forecast but not by the ground stations, resulting in a higher false alarm ratio as observed in our study. While the use of high spatial aggregation improves the forecast performance (e.g., meteoblue forecasts used by farmers in Asia has 8 km spatial resolution), it limits the practical utility of the forecast for smallholder farmers (Bauer et al., 2015; Paparrizos et al., 2020). The goal should be to provide location- and time-specific information that is accurate and relevant for smallholder farmers. Therefore, the trade-off of obtaining higher forecast skill by using coarse resolutions is not justified (Robert, 2008). Instead, efforts should be directed toward developing forecasting systems that can deliver precise and timely information tailored to the needs of smallholder farmers.

Some studies define "a rain day" as one having rainfall > 1 mm (Herold et al., 2016; Benestad, 2018; Contractor et al., 2018). Hence, we conducted an experiment where rainfall amounts less than 1 mm/d were considered as no rain event to explore the impact of low-intensity rainfall on forecast skill scores. The experiment was performed with the assumption that the model tends to produce drizzle so that the skill scores are very dependent on the occurrences of drizzle. By filtering low-intensity rainfall in all datasets, we aimed to remove the drizzle precipitation from the forecasts and ERA5 that might not have been observed by ground stations. The result shows that increasing the rainfall threshold from 0.1 mm/d to 1 mm/d did not lead to a significant reduction in the FAR values for all stations (A Fig. A.3). Instead, we observed a decrease in the POD values and a slight increase in the FAR values, indicating lower forecast performance (low HK). These findings suggest that the high FAR values obtained when using ground observations are not solely due to the presence of drizzle precipitation events. There are two possible explanations for the high FAR values. Firstly, human error could contribute to the discrepancy, where e.g., the observers might have failed to measure rainfall on days with low-intensity rainfall (<1 mm/d) because they assumed that no rain occurred. Installing automatic rainfall recorder and providing training for rainfall observers to account for light rainfall events could help to reduce the uncertainty. Secondly, it is also plausible that there is a bias in the forecast model and ERA5, leading to an overestimation of light rain events (Davis et al., 2006; Hu and Yuan, 2020; Bandhauer et al., 2021).

4.3. Towards developing an integrated forecasting system

The integration of local knowledge with scientific knowledge, known as hybrid forecast (HF), has been suggested by several previous studies as a valuable approach for weather and climate prediction (Kalanda-

Joshua et al., 2011; Mahoo et al., 2015; Radeny et al., 2019; Guodaar et al., 2021). The HF will generate a seamless forecasting system that is more skillful than any single forecast, consistently available on daily basis, location-specific, and capable of enhancing the acceptability of forecast information among farmers, leading to a trusted system. Our findings demonstrate that, overall, the prediction skill of yes/no rain events using HF outperforms both SF and LF (Fig. 5, Table 3). However, one should note that HF has outstanding performance in terms of predicting the POD but also exhibits a high FAR, which is influenced by either SF or LF (comparison Fig. 3–5). This indicates that HF combines not only the strengths of SF and LF but also their weakness, mainly when relying on ground observations (Gbangou et al., 2021). The high POD alleviates the performance of HF compared to others. The simple HF method employed in our study is designed to primarily forecast rain events by combining the prediction of rain from SF and LF (Section 2.4.3). In addition, integrating scientific knowledge with local knowledge will increase farmers' trust as their indigenous knowledge is not disregarded (Ebhuoma, 2020). The participatory process and the level of engagement with farmers, which were followed in the current study to develop the HF, ensure the uptake of forecast information. Moreover, HF also reduces the farmer's confusion in choosing which forecast should be chosen for agricultural decision-making, especially when the prediction is contradictory between the two forecasting systems (SF and LF) (Nyadzi et al., 2022).

In this study, we developed a skillful HF by adopting a simple approach, wherein rainfall events were predicted if either SF or LF forecasted rain (see Section 2.4.3). To the best of our knowledge, only two studies have developed and evaluated the skill of HF (Gbangou et al., 2021; Nyadzi et al., 2022). Many only suggest the importance of integrating SF and LF without providing specific guidance on how this should be carried out. Gbangou et al. (2021) applied a statistical integration technique that optimized both SF and LF based on the number of observed indicators. Their study recommends farmers to rely on SF if >2 local indicators were observed, use either SF or LF if 3 local indicators were observed, and solely rely on LF if >3 local indicators were observed. This method, however, does not guarantee the success of the HF, as in many cases, only 1 or 2 indicators are observed on the same day, particularly in our studied regions. Another approach proposed by Nyadzi et al. (2022), involved using a weighted average of SF and LF forecast probabilities. This method enabled the estimation of the probability of the HF, providing a unified forecast to eliminate contradictions and confusion among farmers. This method, however, cannot be applied in our study areas due to the limited availability of farmers' data to derive LF probabilities. As we mentioned earlier, the LF is not widely used by farmers in Bangladesh, unlike in Africa. Both the studies by Gbangou et al. (2021) and Nyadzi et al. (2022) applied sophisticated approaches to build skillful HF that outperformed individual forecast. In contrast, our study focused on a simple yet practical approach to develop a skillful HF, which proved to be effective. Another approach such as machine learning that gains popularity nowadays can be considered for developing a skillful HF. Such method has been applied in the development of hybrid hydroclimatic forecasting systems that integrate a wide variety of predictions from numerical weather prediction, and earth system models including climate, land, and hydrology, into a hybrid product (Slater et al., 2022). These methods hold potential for enhancing the skill and accuracy of HF in the future.

Given many approaches can be utilized to develop hybrid forecasts for smallholder farmers, one of the key challenges is the sustainability of local ecological indicators and the availability of long-term weather data series based on these indicators. Various factors, such as land use change, policies, globalization, and climate change have resulted in a decline and the loss of indicators (Fratkin and Roth, 2006; Gilberthorpe and Hilson, 2014; Balehegn et al., 2019; Radeny et al., 2019). Many of these indicators present shifting patterns due to climate change (e.g. migratory animals and extinction of specific flora), rendering them unreliable for farmers' predictions compared to how their ancestors used them. Furthermore, local knowledge is subject to skepticism due to the peculiar indicators used by the indigenous people, such as the color of animal intestines (Ayal et al., 2015; Kagunyu et al., 2016), the gender of the newborn (Soropa et al., 2015), or the paint in the joints (Ubisi et al., 2020). Nevertheless, there are more than 1350 indicators that have been documented in numerous locations across the world, mainly in the global south, which require systematic documentation (Snoeren, 2020; Paparrizos et al., 2023). These local indicators, however, are location-specific and not globally applicable, as the occurrence of the same indicators in multiple regions may signify different prediction signals. We collected local indicators specifically used by farmers in Bangladesh to predict weather since there was no documentation of local indicators in Bangladesh. Moreover, a diverse range of indicators observed will increase the temporal resolution of LF, as rainfall event can be predicted using different indicators, such as butterfly flying, the sound of frogs, and ants carrying eggs. Therefore, continued efforts are needed to document indigenous forecast data through questionnaires or other methods, as the availability of LF data is often limited.

4.4. Study limitations

The evaluation of SF and LF in our study, as well as in other literature (Gbangou et al., 2021; Nyadzi et al., 2022) comes with important caveats that should be taken into consideration for future studies. The evaluation was conducted on dates when farmers observed local indicators. This favorable condition for LF might have influenced the evaluation of forecast performance using statistical metrics such as POD, FAR, and HK. It should be noted that farmers did not provide forecasts based on their local knowledge if no indicator was observed in the field (personal communication with field assistants). This might also increase the perception of farmers in SF since it always provides weather information on a daily basis. Moreover, we collected the LF data for a single rainy season, which is insufficient to draw definitive conclusions about the overall performance of local weather forecasts in Bangladesh. Further data collection over multiple seasons will contribute to a better understanding of how these local indicators perform and their potential to enhance weather forecasting for smallholder farmers in the Bangladesh Delta. These limitations should be acknowledged to ensure a fair forecast evaluation.

5. Conclusions and recommendations

This research represents the first comprehensive evaluation of both scientific (SF) and local forecast (LF) performance in Bangladesh. The results of this study demonstrate that, overall, LF exhibits slightly higher forecast performance compared to SF. However, when ground observations are used instead of ERA5, the skill of LF decreases, associated with high FAR. The simple HF developed by integrating the SF and LF outperforms the individual performance of the SF and LF when using both ERA5 and rain gauges. These findings emphasize the importance of developing a hybrid forecast that combines scientific and indigenous weather forecasting approaches for effective farm decision-making. Furthermore, the simple HF approach as demonstrated in our study can be easily implemented in the Weather and Climate Information Services (WCIS) to provide a seamless rainfall forecast for smallholder farmers not only in Bangladesh but also elsewhere in the global south. The HF system not only provides a reliable and trustworthy forecast but also preserves and incorporates indigenous knowledge that has been passed down through generations, fostering trust and confidence among farmers.

We suggest installing rain gauges in close proximity to farmers' weather schools to address the issue of distance between farmer communities and existing rain gauges. This would facilitate more accurate and localized rainfall measurements for specific agricultural areas. The data, however, need to be collected by the farmers themselves since the gauges are not registered in the Bangladesh Meteorological Department

(BMD), thus training on the measurement of rainfall is of utmost importance. Additionally, the BMD could consider to document the rainfall data measured by farmers in their system to increase their rainfall network and provide extension services to the communities. Furthermore, it is essential to emphasize the continuation and documentation of forecasts issued by farmers based on their local knowledge. This indigenous forecasting knowledge is valuable and can contribute to the development of hybrid forecasts (HF) with improved skill and accuracy. Currently, there is a lack of studies evaluating the performance of LF using a longer time series spanning more than two years. This hampers the potential development of skillful HF using data-driven approaches like machine learning. Such HF system can help farmers in Bangladesh by providing skillful weather and climate information. This system has the potential to improve their decision-making processes, enabling better farm planning and unlocking the agricultural potential of the region. By combining scientific advancements with local knowledge, farmers can make more informed choices and mitigate the risks associated with climate variability and change.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors would like to thank field research assistants and all farmer weather school participants for their contribution as without them the current study would not have been possible.

Appendix A

The average monthly temperature and precipitation for the five study locations are similar, with higher temperature and precipitation observed in the northeast of Bangladesh (Fig. A.1). Khulna and Patuakhali, which are located in the south have a maximum temperature of around 38 °C and 36 °C, respectively. Maximum precipitation of 150 mm was observed in Khulna in June and 180 mm was observed in Patuakhali for the same month. Rajshahi has the highest temperature of 39 °C and precipitation amount of 175 mm. Mymensingh has a maximum temperature of 36 °C and precipitation amount of 220 mm. The lowest maximum temperature and highest precipitation amount were observed in Sylhet, with a maximum temperature of 33 °C and precipitation amount above 400 mm.

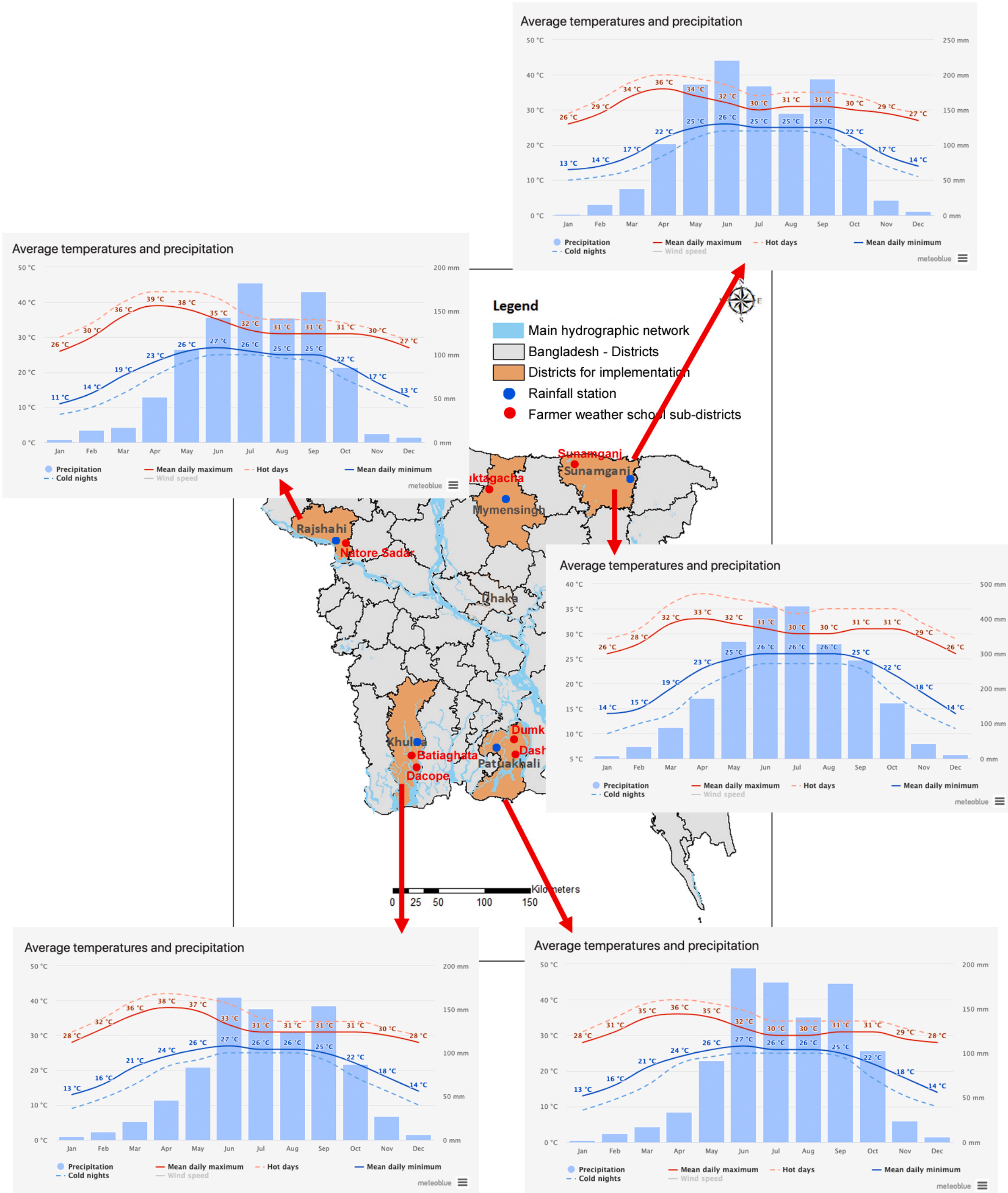

Fig. A.1. Monthly temperature and precipitation for five study locations averaged from monthly data for the last 30 years. Source: meteoblue.

The characteristics of farmers in the five locations is presented in Table A.1. Among them, 60% were men and 40% were women farmers. Most farmers prefer to cultivate rice and vegetables in the three different crop seasons, the Aus (29%), the Aman (91%), and the Boro (71%). Please keep in mind that one farmer can cultivate more than one crop. Education status shows that about half (49%) of farmers had secondary-level education and about one-fourth (22%) had primary-level education. The interviewed farmers had substantial farming experience ranging from 1–10 years (51%), 11–20 years (25%), and above 20 years (2%). Among the respondents, 43% were young farmers between the age group 16–29 years old, 45% were mid-age farmers between the age group 30–49 years, and only 12% were old-age farmers between ages 50 and above.

Table A.1
Profile of the smallholder farmers in Bangladesh. For farming practices, one farmer can cultivate for more than one crop.

Variables	Frequency (N = 65)	Percentage (%)	Variables	Frequency (N = 65)	Percentage (%)
Locations			Education		
Khulna	16	25	No education	9	14
Mymensingh	10	15	Primary	14	22
Rajshahi	16	25	Secondary	32	49
Patuakhali	11	17	Diploma	3	5
Sylhet	12	19	Graduate	7	11
Gender			Experience (year)		
Male	39	60	1–10	33	51
Female	26	40	11–20	16	25
			>20	16	25
Age group (year)			Farming practices		
16–29	28	43	Aus	19	29
30–39	18	28	Aman	59	91
40–49	11	17	Boro	46	71
>50	8	12	Vegetables	50	77

Fisher's exact test was employed to test the significance level of the forecasts. This method was applied because it can be used in the analysis of contingency tables and for small samples. In our study, we only have 85 days of LF. Forecast evaluations using ERA5 as a benchmark show that all forecasts (SF and LF) are statistically significant with $p > 0.005$ (Table A.2). However, the use of ground observation to evaluate the SF skill in Khulna and Rajshahi yields high p-values. Similar results are also found in LF if in situ observations are used as a benchmark.

Table A.2
Significance test based on Fisher's exact test for SF and LF in the study locations. Values in red indicates that the forecast is not statistically significant ($p > 0.005$).

Location	p value			
	SF-ERA5	SF-OBS	LF-ERA5	LF-OBS
Khulna	0.00000	0.06233	0.00000	0.00092
Mymensingh	0.00000	0.00451	0.00006	0.00815
Patuakhali	0.00270	0.00255	0.00216	0.10399
Rajshahi	0.00007	0.00969	0.00001	0.00235
Sylhet	0.00000	0.00001	0.00000	0.00046

To test the accuracy of ERA5 compared to ground stations, we plotted the number of rain and no rain events in Fig. A.2. Fig. A.2 clearly shows the mismatch between ERA5 and observation in predicting rain and no rain events. The highest miss prediction is seen in Rajshahi where ERA5 predicts rain and no rain more than double compared to observation. In general, ERA5 simulates higher rain events than observation and consequently affects the low no rain prediction of ERA5.

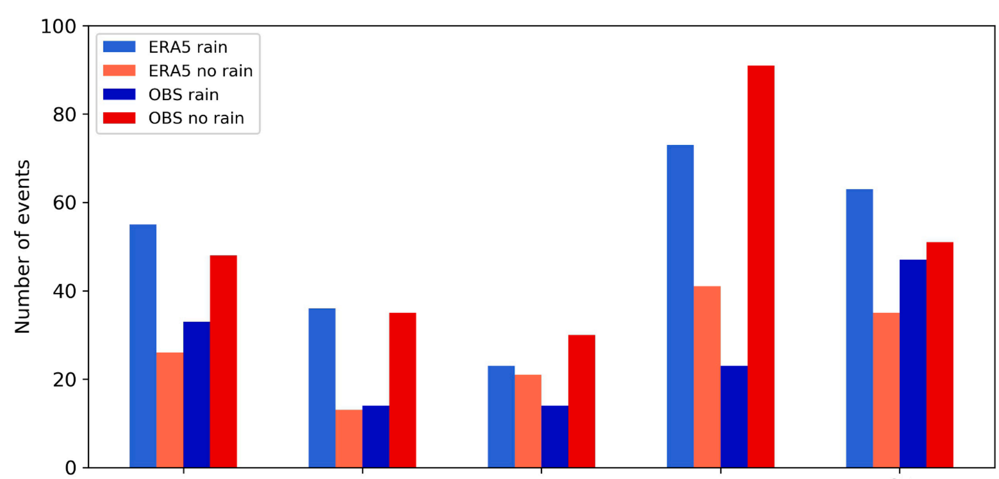

Fig. A.2. Number of rain and no rain events derived from ERA5 and observed by rain gauge in five locations: Khulna (KH), Mymensingh (MY), Patuakhali (PA), Rajshahi (RA), and Sylhet (SY) during study period.

Fig. A.3 shows the SF performance if we raised the threshold of rain event from 0.1 mm/d to 1 mm/d. Increasing the threshold to 1 mm/d does not support the previous hypothesis that high FAR found in the observation and not in the ERA5 is caused by the low-intensity rainfall or drizzle. Here, we confirmed that ERA5 tends to simulate more rain events, or the rain was not observed due to e.g., human error.

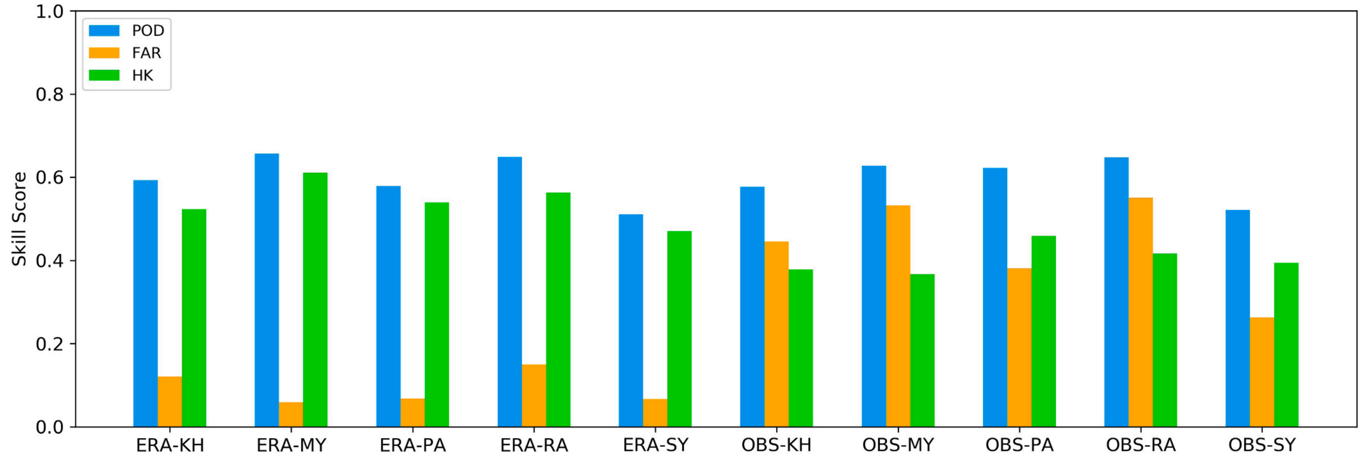

Fig. A.3. Same as Fig. 2 but for rainfall higher than 1 mm/d.

References

Abedin, A., Shaw, R., 2013. Agriculture Adaptation in Coastal Zone of Bangladesh.

Agresti, A., 1992. A survey of exact inference for contingency tables. Stat. Sci. 7, 131–153.

Akter, S., Ahmed, K.R., Marandi, A., Schth, C., 2020. Possible factors for increasing water salinity in an embanked coastal island in the southwest Bengal Delta of Bangladesh. Sci. Total Environ. 713, 136668.

Al Faisal, A., Al Kafy, A., Rahman, A.N.M.F., Al Rakib, A., Akter, K.S., Raikwar, V., Jahir, D.M.A., Ferdousi, J., Kona, M.A., 2021. Assessment and prediction of seasonal land surface temperature change using multi-temporal landsat images and their impacts on agricultural yields in Rajshahi, Bangladesh. Environ. Challenges 4, 100147.

Al Masud, M.M., Gain, A.K., Azad, A.K., 2020. Tidal river management for sustainable agriculture in the Ganges-Brahmaputra delta: Implication for land use policy. Land Use Policy 92, 104443.

Ali, S., Ghosh, B.C., Osmani, A.G., Hossain, E., Fogarassy, C., 2021. Farmers' climate change adaptation strategies for reducing the risk of rice production: evidence from Rajshahi district in Bangladesh. Agronomy 11, 600.

Ayal, D.Y., Desta, S., Gebru, G., Kinyangi, J., Recha, J., Radeny, M., 2015. Opportunities and challenges of indigenous biotic weather forecasting among the borena herders of southern Ethiopia. SpringerPlus 4 (1), 617.

Bagchi, R., Miah, M.A., Hazra, P., Hasan, R., Mondal, H.S., Paul, S.K., 2020. Exploring the effect of rainfall variability and water extent in Tanguar Haor, Sunamganj. Australian J. Eng. Innov. Technol. 2 (4), 66–76.

Balehegn, M., Balehey, S., Fu, C., Liang, W., 2019. Indigenous weather and climate forecasting knowledge among afar pastoralists of north eastern Ethiopia: Role in adaptation to weather and climate variability. Pastoralism: Res. Policy Practice, p. 9.

Bandhauer, M., Isotta, F., Lakatos, M., Lussana, C., Båserud, L., Izsák, B., Szentes, O., Tveito, O.E., Frei, C., 2021. Evaluation of daily precipitation analyses in E-OBS (v19.0e) and ERA5 by comparison to regional high-resolution datasets in European regions. Int. J. Climatol. 42, 727–747.

Bauer, P., Thorpe, A., Brunet, G., 2015. The quiet revolution of numerical weather prediction. Nature 525, 47–55.

Benestad, R., 2018. Implications of a decrease in the precipitation area for the past and the future. Environ. Res. Lett. 13, 044022.

Bento, V.A., Russo, A., Dutra, E., Ribeiro, A.F.S., Gouveia, C.M., Trigo, R.M., 2022. Persistence versus dynamical seasonal forecasts of cereal crop yields. Scientific Rep. 12, 7422.

Black, T., Juang, H.M.H., Iredell, M., 2009. The NOAA environmental modeling system at NCEP. In: 23rd Conference on Weather Analysis and Forecasting/19th Conference on Numerical Weather Prediction, Omaga, NE, USA, 1–5 June 2009, Ameri. Met. Soc.

Chiputwa, B., Wainaina, P., Nakelse, T., Makui, P., Zougmore, R.B., Ndiaye, O., Minang, P.A., 2020. Transforming climate science into usable services: the effectiveness of co-production in promoting uptake of climate information by smallholder farmers in Senegal. Clim. Services 20, 100203.

Chowdhooree, I., 2019. Indigenous knowledge for enhancing community resilience: an experience from the south-western coastal region of Bangladesh. Int. J. Disaster Risk Reduction 40, 101259.

Chowdhooree, I., Das, K.K., 2021. Indigenous knowledge of mud architecture: experiences of surviving against multiple natural hazards. Int. J. Disaster Resilience Built Environ. 13 (4), 451–469.

Codjoe, S.N.A., Owusu, G., Burkett, V., 2014. Perception, experience, and indigenous knowledge of climate change and variability: The case of Accra, a sub-saharan African city. Reg. Environ. Change 14 (1), 369–383.

Contractor, S., Donat, M.G., Alexander, L.V., 2018. Intensification of the daily wet day rainfall distribution across Australia. Geophys. Res. Lett. 45 (16), 8568–8576.

Cooper, P.J.M., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B., Twomlow, S., 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? Agric. Ecosyst. Environ. 126 (1–2), 24–35.

Cuaton, G.P., Su, Y., 2020. Local-indigenous knowledge on disaster risk reduction: Insight from the Mamanwa indigenous peoples in Basey, Samar after typhoon Haiyan in the Philippines. Int. J. Disaster Risk Reduction 48, 101596.

Davis, C., Brown, B., Bullock, R., 2006. Object-based verification of precipitation forecasts. Part II: application to convective rain systems. Mon. Weather Rev. 134, 1785–1795.

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

Dietvorst, B.J., Simmons, J.P., Massey, C., 2015. Algorithm aversion: people erroneously avoid algorithms after seeing them err. J. Exp. Psychol. Gen. 144 (1), 114–126.

Ebhuoma, E.E., 2020. A framework for integrating scientific forecasts with indigenous systems of weather forecasting in southern Nigeria. Develop. Practice 30 (4), 472–484.

Etikan, I., Musa, S.A., Alkassim, R.S., 2016. Comparison of convenience sampling and purposive sampling. Am. J. Theor. Appl. Stat. 5 (1), 1–4.

FAO, 2019. Handbook on climate information for farming communities – what farmers need and what is available. Rome, 184 pp, isbn 978-92-5-131370-1. https://www.fao.org/publications/card/fr/c/CA4059EN/.

Fisher, R.A., 1922. On the interpretation of x_2 from contingency tables, and the calculation of p. J. Roy. Stat. Soc. 85 (1), 87–94.

Fisher, R.A., 1954. Statistical Methods for Research Workers.

Fitzpatrick, R.G., Bain, C.L., Knippertz, P., Marsham, J.H., Parker, D.J., 2015. The West African monsoon onset: A concise comparison of definitions. J. Clim. 28, 8673–8694.

Fratkin, E., Roth, E.A., 2006. As pastoralists settle: Social, health, and economic consequences of the pastoral sedentarization in Marsabit District. Kenya.

Gbangou, T., Sarku, R., Van Slobbe, E., Ludwig, F., Kranjac-Berisavljevic, G., Paparrizos, S., 2020. Coproducing weather forecast information with and for smallholder farmers in Ghana: Evaluation and design principles. Atmosphere 11, 902.

Gbangou, T., Van Slobbe, E., Ludwig, F., Kranjac-Berisavljevic, G., Paparrizos, S., 2021. Harnessing local forecasting knowledge on weather and climate in Ghana: documentation, skills, and integration with scientific forecasting knowledge. Weather Clim. Soc. 13 (1), 23–37.

Gilberthorpe, E., Hilson, G., 2014. Natural resource extraction and indigenous livelihoods: Development challenges in an era of globalization.

Gong, X., Barnston, A.G., Ward, M.N., 2003. The effect of spatial aggregation on the skill of seasonal precipitation forecasts. J. Clim. 16, 3059–3071.

Guarte, J.M., Barrios, E.B., 2006. Estimation under purposive sampling. Commun. Stat. Simul. Comput. 35 (2), 277–284.

Gubler, S., Sedlmeier, K., Bhend, J., Avalos, G., Coelho, C.A.S., Escajadillo, Y., Jacques-Coper, M., Martinez, R., Schwierz, C., de Skansi, M., Spirig, C., 2020. Assessment of ECMWF SEAS5 seasonal forecast performance over South America. Weather Forecast 35, 561–584.

Gudoshava, M., Wanzala, M., Thompson, E., Mwesigwa, J., Endris, H.S., Segele, Z., Hirons, L., Kipkogei, O., Mumbua, C., Njoka, W., Baraibar, M., de Andrade, F., Woolnough, S., Atheru, Z., Artan, G., 2022. Application of real time S2S forecasts over Eastern Africa in the co-production of climate services. Clim. Services 27, 100319.

Guodaar, L., Bardsley, D.K., Suh, J., 2021. Integrating local perception with scientific evidence to understand climate change variability in northern Ghana: A mixed-methods approach. Appl. Geogr. 130, 102440.

Gwenzi, J., Mashonjowa, E., Mafongoya, P.L., Rwasoka, D.T., Stigter, K., 2016. The use of indigenous knowledge systems for short and long range rainfall prediction and farmers' perceptions of science-based seasonal forecasts in Zimbabwe. Int. J. Clim. Change Strategies Manage. 8 (3), 440–462.
Gyampoh, B.A., Asante, W.A., La Rose, D.J., Adu-Acheampong, G., Assimeng, T., Opoku, A.G., 2011. Mapping and documenting indigenous knowledge in climate change adaptation in Ghana, Africa adaptation programme. United Nations Development Programme.
Habib, A., Shahidullah, M., Ahmed, D., 2012. The Bangladesh cyclone preparedness program. A vital component of the nation's multi-hazard early warning system.
Haiden, T., Rodwell, M.J., Richardson, D.S., Okagaki, A., Robinson, T., Hewson, T., 2012. Intercomparison of global model precipitation forecast skill in 2010/11 using the seeps score. Mon. Weather Rev. 140 (8), 2720–2733.
Harjupa, W., Abdillah, M.R., Azura, A., Putranto, M.F., Marzuki, M., Nauval, F., Risyanto, Saufina, E., Jumianti, N., Fathrio, I., 2022. On the utilization of rdca method for detecting and predicting the occurrence of heavy rainfall in Indonesia. Remote Sens. Appl.: Soc. Environ. 25, 100681.
Herold, N., Alexander, L.V., Donat, M.G., Contractor, S., Becker, A., 2016. How much does it rain over land? Geophys. Res. Lett. 43, 341–348.
Hersbach, H., Bell, B., Berrisford, P., Horányi, A., Muñoz Sabater, J., Nicolas, J., Radu, R., Schepers, D., Simmons, A., Soci, C., Dee, D., 2019. Global reanalysis: goodbye ERA-Interim, hello ERA5. In: ECMWF Newsletter no, 159. European Centre for Medium-Range Weather Forecasts, Reading, UK. https://doi.org/10.21957/vf291hehd7.
Hiwasaki, L., Luna, E., Syamsidik, Marçal, J.A., 2015. Local and indigenous knowledge on climate-related hazards of coastal and small island communities in Southeast Asia. Clim. Change 128, 35–56.
Hu, X., Yuan, W., 2020. Evaluation of ERA5 precipitation over the eastern periphery of the Tibetan plateau from the perspective of regional rainfall events. Int. J. Climatol. 41, 2625–2637.
Imhoff, R.O., Brauer, C.C., van Heeringen, K.J., Uilenhoet, R., Weert, A.H., 2022. Large-sample evaluation of radar rainfall nowcasting for flood early warning. Water Resour. Res. 58 e2021WR031591.
Ingram, K., Roncoli, M., Kirshen, P., 2002. Opportunities and constraints for farmers of West Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. Agric. Syst. 74, 331–349.
IPCC, 2014. In: Pachauri, R.K. (Ed.). https://doi.org/10.1017/CBO9781139177245.003.
IPCC, 2022. In: Pörtner, H.-O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., Rama, B. (Eds.), Climate change 2022: Impacts, adaptation and vulnerability. Contribution of working group II to the sixth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 37–118. https://doi.org/10.1017/9781009325844.002.
Janif, S.Z., Nunn, P.D., Geraghty, P., Aalbersberg, W., Thomas, F.R., Camailakeba, M., 2016. Value of traditional oral narratives in building climate-change resilience: insights from rural communities in Fiji. Ecol. Soc. 21 (2).
Jiang, Q., Li, W., Fan, Z., He, X., Sun, W., Chen, S., Wen, J., Gao, J., W., J., 2021. Evaluation of the ERA5 reanalysis precipitation dataset over Chinese mainland. J. Hydrol. 595, 125660.
Jiri, O., Mafongoya, P.L., Chivenge, P., 2015. Indigenous knowledge systems, seasonal 'quality' and climate change adaptation in Zimbabwe. Clim. Res. 66 (2), 103–111.
Kagunyu, A., Wandibba, S., Wanjohi, J.G., 2016. The use of indigenous climate forecasting methods by the pastoralists of northern Kenya. Pastoralism 6 (1).
Kalanda-Joshua, M., Ngongondo, C., Chipeta, L., Mpembeka, F., 2011. Integrating indigenous knowledge with conventional science: Enhancing localized climate and weather forecasts in Nessa, Mulanje, Malawi. Phys. Chem. Earth 36, 996–1003.
Kida, S., Yamazaki, D., 2020. The mechanism of the freshwater outflow through the Ganges–Brahmaputra–Meghna delta. Water Resour. Res. 56 e2019WR026412.
Kuehl, S.A., Allison, M.A., Goodbred, S.L., Kudrass, H., 2005. The Ganges-Brahmaputra Delta. In SEPM River Deltas – Concepts, Models and Examples. SEPM Spec. Publ. 83, 413–434.
Kumar, U., Werners, S., Paparrizos, S., Datta, D.K., Ludwig, F., 2020a. Hydroclimatic information needs of smallholder farmers in the lower Bengal Delta, Bangladesh. Atmosphere 11, 1009.
Kumar, U., Werners, S., Roy, S., Ashraf, S., Hoang, L.P., Datta, D.K., Ludwig, F., 2020b. Role of information in farmers' response to weather and water related stresses in the lower Bengal Delta, Bangladesh. Sustainability 12 (16), 6598.
Kumar, U., Werners, S.E., Paparrizos, S., Datta, D.K., Ludwig, F., 2021. Co-producing climate information services with smallholder farmers in the lower Bengal Delta: How forecast visualization and communication support farmers' decision-making. Clim. Risk Manage. 33, 100346.
Landman, W.A., Archer, E.R.M., Tadross, M.A., 2020. Citizen science for the prediction of climate extremes in South Africa and Namibia. Front. Clim. 2, 5.
Lavers, D.A., Simmons, A., Vamborg, F., Rodwell, M.J., 2022. An evaluation of ERA5 precipitation for climate monitoring. Q. J. R. Meteorol. Soc. 148, 3152–3165.
Liu, X., He, B., Zhao, S., Hu, S., Liu, L., 2019. Comparative measurement of rainfall with a precipitation micro-physical characteristics sensor, a 2D video disdrometer, an OTT PARSIVEL disdrometer, and a rain gauge. Atmos. Res. 229, 100–114.
Mahoo, H., Mbungu, W., Yonah, I., Recha, J., Radeny, M., Kimeli, P., Kinyangi, J. Integrating indigenous knowledge with scientific seasonal forecasts for climate risk management in Lushoto district in Tanzania, CCAFS working paper no. 103, CGIAR research program on climate change, agriculture and food security (CCAFS). Copenhagen, Denmark.
Mani, J.K., Mukherjee, D., 2016. Accuracy of weather forecast for hill zone of West Bengal for better agricultural management practices. Indian J. Res. 5, 325–328.
Maxwell, J.A., 2012. Qualitative research design: An interactive approach, vol. 41, e-book: Sage. https://us.sagepub.com/en-us/nam/qualitative-research-design/book234502.
Mousumi, M.A., Paparrizos, S., Ahmed, M.Z., Kumar, U., Uddin, M.E., Ludwig, F., 2023. Common sources and needs of weather information for rice disease forecasting and management in coastal Bangladesh. NJAS: Impact Agric. Life Sci. 95 (1), 2191794.
Nkuba, M.R., Chanda, R., Mmopelwa, G., Kato, E., Mangheni, M.N., Lesolle, D., G., M., 2023. Effect of indigenous and scientific forecasts on pastoralists' climate change perceptions in the Rwenzori region, Western Uganda. Clim. Dev. 15 (6), 522–534.
Nyadzi, E., Werners, S.E., Biesbroek, R., Ludwig, F., 2021. Techniques and skills of indigenous weather and seasonal climate forecast in northern Ghana. Clim. Develop. 13 (6), 551–562.
Nyadzi, E., Werners, S.E., Biesbroek, R., Ludwig, F., 2022. Towards weather and climate services that integrate indigenous and scientific forecasts to improve forecast reliability and acceptability in Ghana. Environ. Develop. 42, 100698.
Nystuen, J.A., 1999. Relative performance of automatic rain gauges under different rainfall conditions. J. Atmos. Ocean. Technol. 16 (8), 1025–1043.
Offat, M.I., Miriam, C., 2015. Integrating indigenous knowledge systems into climate change interpretation: Perspectives relevant to Zimbabwe. Greener J. Educ. Res. 5 (2), 27–36.
Orlove, B., Roncoli, C., Kabugo, M., Majugu, A., 2010. Indigenous climate knowledge in southern Uganda: The multiple components of a dynamic regional system. Clim. Change 100, 243–265.
Paparrizos, S., Attoh, E.M.N.A.N., Sutanto, S.J., Snoeren, N., Ludwig, F., 2023. Local weather forecast knowledge across the globe for agricultural decision-making. STOTEN 899, 165539.
Paparrizos, S., Dogbey, R.K., Sutanto, S.J., Gbangou, T., Kranjac-Berisavljevic, G., Gandaa, B.Z., Ludwig, F., van Slobbe, E., 2023. Hydro-climate information services for smallholder farmers: farmer support app principles, implementation, and evaluation. Clim. Services 30, 100387.
Paparrizos, S., Gbangou, T., Kumar, U., Sarku, R., Merks, J., Werners, S., Dewulf, A., Ludwig, F., van Slobbe, E., 2020. Co-producing tailor-made water and weather information services with and for farmers for sustainable agriculture in peri-urban delta areas in Ghana and Bangladesh. EGU General Assembly. EGU2020-5712.
Paparrizos, S., Smolenaars, W., Gbangou, T., van Slobbe, E., Ludwig, F., 2020. Verification of weather and seasonal forecast information concerning the peri-urban farmers' needs in the lower Ganges Delta in Bangladesh. Atmosphere 11, 1041.
Patt, A., Suarez, P., Gwata, C., 2005. Effects of seasonal climate forecasts and participatory workshops among subsistence farmers in Zimbabwe. Proc. Nat. Acad. Sci. 102, 12623–12628.
Paul, S.K., Routray, J.K., 2013. An Analysis of the Causes of Non-Responses to Cyclone Warnings and the Use of Indigenous Knowledge for Cyclone Forecasting in Bangladesh.
Phillips, J., Makaudze, E., Unganai, L., 2001. Current and potential use of climate forecasts for resource-poor farmers in Zimbabwe.
Plotz, R.D., Chambers, L.E., Finn, C.K., 2017. The best of both worlds: a decision-making framework for combining traditional and contemporary forecast systems. J. Appl. Meteorol. Climatol. 56 (8), 2377–2392.
Prokopy, L.S., Haigh, T., Mase, A.S., Angel, J., Hart, C., Knutson, C., Lemos, M.C., Lo, Y. J., McGuire, J., Morton, L.W., Perron, J., Todey, D., Widhalm, M., 2013. Agricultural advisors: a receptive audience for weather and climate information? Weather Clim. Soc. 5 (2), 162–167.
Radeny, M., Desalegn, A., Mubiru, D., Kyazze, F., Mahoo, H., Recha, J., Kimeli, P., Solomon, D., 2019. Indigenous knowledge for seasonal weather and climate forecasting across East Africa. Climatic Change 156 (4), 509–526.
Rahaman, M.A., Rahman, M.M., Hossain, M.S., 2019. Climate-Resilient Agricultural Practices in Different Agro-ecological Zones of Bangladesh.
Rasp, S., Dueben, P.D., Scher, S., Weyn, J.A., Mouatadid, S., Thuerey, N., 2020. Weatherbench: a benchmark data set for data-driven weather forecasting. J. Adv. Model. Earth Syst. 12 e2020MS002203.
Rautela, P., Karki, B., 2015. Weather forecasting: Traditional knowledge of the people of Uttarakhand Himalaya. J. Geogr. Environ. Earth Sci. Int. 3 (3), 1–14.
Robert, N., 2008. Assessing the spatial and temporal variation in the skill of precipitation forecasts from an NWP model. Meteorol. Appl. 15, 163–169.
Roncoli, C., Ingram, K., Kirshen, P., 2002. Reading the rains: Local knowledge and rainfall forecasting in Burkina Faso. Soc. Nat. Resour. 15 (5), 409–427.
Roncoli, C., Jost, C., Kirshen, P., Sanon, M., Ingram, K.T., Woodin, M., Somé, L., Ouattara, F., Sanfo, B.J., Sia, C., Yaka, P., Hoogenboom, G., 2009. From accessing to assessing forecasts: an end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). Clim. Change 92, 433–460.
Sarkar, S., Padaria, R.N., Vijayragavan, K., Pathak, H., Kumar, P., Jha, G.K., 2015. Assessing the potential of Indigenous Technological Knowledge (ITK) for adaptation to climate change in the Himalayan and arid ecosystems. Indian J. Traditional Knowl. 14 (2), 251–257.
Shahid, S., 2010. Rainfall variability and the trends of wet and dry periods in Bangladesh. Int. J. Climatol. 30, 2299–2313.
Slater, L., Arnal, L., Boucher, M.-A., Chang, A.Y.-Y., Moulds, S., Murphy, C., Nearing, G., Shalev, G., Shen, C., Speight, L., Villarini, G., Wilby, R.L., Wood, A., Zappa, M., 2022. Hybrid forecasting: using statistics and machine learning to integrate predictions from dynamical models. Hydrol. Earth Syst. Sci. Discuss. [preprint].
Snoeren, N., 2020. Global sources of local forecast knowledge for agricultural decision-making: An identification of agro-meteorological indicators, Master Thesis, Wageningen University and Research.
Soropa, G., Gwatibaya, S., Musiyiwa, K., Rusere, F., Mavima, G.A., Bag, P., Prospect, N., 2015. Indigenous knowledge system weather forecasts as a climate change

adaptation strategy in smallholder farming systems of Zimbabwe: Case study of Murehwa, Tsholotsho and Chiredzi districts. African J. Agric. Res. 10, 1067–1075.
Sultan, B., Lejeune, Q., Menke, I., Maskell, G., Lee, K., Noblet, M., Sy, I., Roudier, P., 2020. Current needs for climate services in West Africa: Results from two stakeholder surveys. Clim. Services 18, 100166.
Sutanto, S.J., Paparrizos, S., Kranjac-Berisavljevic, G., Jamaldeen, B.M., Issahaku, A.K., Gandaa, B.Z., Supit, I., van Slobe, E., 2022. The role of soil moisture information in developing robust climate services for smallholder farmers: Evidence from Ghana. Agronomy 12, 541.
Tripathi, O.P., Dominguez, F., 2013. Effects of spatial resolution in the simulation of daily and subdaily precipitation in the southwestern US. J. Geophys. Res.: Atmospheres 118, 7591–7605.
Ubisi, N.R., Kolanisi, U., Jiri, O., 2020. The role of indigenous knowledge systems in rural smallholder farmers' response to climate change: Case study of Nkomazi local municipality, Mpumalanga, south Africa. J. Asian Afr. Stud. 55 (2), 273–284.
Vaughan, C., Dessai, S., 2014. Climate services for society: Origins, institutional arrangements, and design elements for an evaluation framework. WIREs Clim. Change 5, 587–603.
Vervoort, R.W., Muita, R., Ampt, P., van Ogtrop, F., 2016. Managing the water cycle in Kenyan small-scale maize farming systems: Part 2. farmers' use of formal and informal climate forecasts. Wiley Interdiscip. Rev.: Water 3 (1), 127–140.
Walker, D.P., Birch, C.E., Marsham, J.H., Scaife, A.A., Graham, R.J., Segele, Z.T., 2019. Skill of dynamical and ghacof consensus seasonal forecasts of East African rainfall. Clim. Dyn. 53, 4911–4935.
Wang, X., Hyndman, R.J., Li, F., Kang, Y., 2022. Forecast combinations: an over 50-year review. Int. J. Forecast.
WMO, 2014. Forecast verification for the african severe weather forecasting demonstration projects. WMO-No 1132. https://library.wmo.int/doc_num.php?explnum_id=7868.
Woodcock, F., 1976. The evaluation of yes/no forecasts for scientific and administrative purposes. Mon. Weather Rev. 104 (10), 1209–1214.
Xin, Y., Lu, N., Jiang, H., Liu, Y., Yao, L., 2021. Performance of ERA5 reanalysis precipitation products in the Guangdong-Hong Kong-Macao greater Bay area, china. J. Hydrol. 602, 126791.