

Food security benefits of more accurate weather forecasts in the context of a changing climate

**Elizabeth JZ Robinson, Shouro Dasgupta,
Kestrel Lambert, Paolo Avner, Bramka Jafino
and Moussa Sidibe**

October 2026

**Grantham Research Institute on
Climate Change and the Environment
Working Paper No. 459**

ISSN 2515-5717 (Online)

The Grantham Research Institute on Climate Change and the Environment was established in 2008 at the London School of Economics and Political Science. The Institute brings together international expertise on economics, as well as finance, geography, the environment, international development and political economy to establish a world-leading centre for policy-relevant research, teaching and training in climate change and the environment. It is hosted by the Global School of Sustainability at LSE and is funded by the Grantham Foundation for the Protection of the Environment.

www.lse.ac.uk/granthaminstitute

This working paper is intended to stimulate discussion within the research community and among users of research, and its content may have been submitted for publication in academic journals. It has been reviewed by at least one referee before publication. The views in this paper are those of the authors and do not necessarily represent the position of the Grantham Research Institute's senior management or funders. Any errors and omissions remain those of the authors.

Authors' declaration of AI use: The authors declare that no generative AI or AI-assisted tools were used in the research, analysis or preparation of this publication.

This paper was first published in October 2026 by the Grantham Research Institute on Climate Change and the Environment at the London School of Economics and Political Science.

© The authors, 2026

Licensed under [CC BY-NC 4.0](https://creativecommons.org/licenses/by-nc/4.0/)

Suggested citation:

Robinson EJZ, Dasgupta S, Lambert K, Avner P, Jafino B and Sidibe M (2026) *Food security benefits of more accurate weather forecasts in the context of a changing climate*. Grantham Research Institute on Climate Change and the Environment Working Paper 459. London: London School of Economics and Political Science.

DOI: [10.21953/researchonline.lse.ac.uk.00140965](https://doi.org/10.21953/researchonline.lse.ac.uk.00140965)

Food security benefits of more accurate weather forecasts in the context of a changing climate

13 October 2026

Final Draft

Elizabeth J Z Robinson^{a,b*}, Shouro Dasgupta^{a,c,d}, Kestrel Lambert^a,
Paolo Avner^e, Bramka Jafino^f, Moussa Sidibe^e

^a Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science (LSE), London, UK

^b Department of Geography and Environment, London School of Economics and Political Science (LSE), London, UK

^c Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Venice, Italy

^d Università Ca' Foscari Venezia, Venice, Italy

^e World Bank Group

^f Asian Development Bank

* Corresponding author, e.j.z.robinson@lse.ac.uk

The authors acknowledge support from the Work Bank Group and the Grantham Foundation for the Protection of the Environment in publishing this work.

Abstract

Climate change is making it increasingly difficult for farmers, particularly those in lower-income countries reliant on rainfed agriculture, to avoid crop losses, with implications for food security and livelihoods more broadly. In this paper we provide robust evidence from Ethiopia, Tanzania, Uganda, and Bangladesh, that farmers with access to more accurate weather forecasts are less likely to report crop losses. Our analysis further highlights one plausible mechanism by which farmers are able to act on weather forecasts, by changing their labour hiring decisions during the harvest season in response to forecasts of extreme weather. Our findings suggest that investment in improved weather forecasting can improve agricultural productivity, which has the potential to reduce food insecurity.

1 Introduction

Farming in low- and middle-income countries (LMICs), particularly without access to irrigation, is highly risky. Compounding this, climate change, as manifested through increasing heat, increasing length and intensity of heatwaves, and increasing extremes of precipitation, is already harming crop yields across the globe (Schlenker and Roberts, 2008; Agnolucci, et al., 2020; Lesk et al., 2022; Schmitt et al., 2022). Crop losses due to hot droughts, for example, have resulted in up to 30% yield losses in many parts of the world, including India, the USA, and Russia (Lesk et al., 2022). This threatens agricultural production and food security at both local and global scales (Lesk et al., 2016).

To avoid the worst effects of extreme weather events, such as droughts, extreme heat, or floods that can destroy harvests, farmers attempt to predict the best times to plant and harvest, which are generally linked to seasonal rainfall levels, daily average air temperatures, and groundwater levels (Sacks et al., 2010; Apriyana et al., 2021). Many farmers in LMICs traditionally rely on indigenous knowledge systems built around past experiences when planning weather-sensitive activities. Yet in an era of climate change, manifested in shifting rainfall patterns, and more frequent and intense periods of heat, future extremes of weather and climate can no longer be predicted by past experiences, and so farmers' past experiences of rainfall patterns are less reliable as predictors of future weather patterns. This makes access to reliable hydromet services, such as weather, water, early warning, and climate information, ever more important, whether, for example, for determining optimal planting times, shifting harvesting times to reduce losses from extreme events, or enabling improved water management for irrigated crops. Hydromet services may also contribute to increased risk management through improved provision of crop insurance and agricultural financial planning. Without informed hydromet information, including climate data, temperature and precipitation forecasts, forecasts of extreme events, seasonal forecasts, and early warning, it is increasingly challenging for farmers to adapt to the changing climate, which is causing considerable social and economic loss (Diaz & Moore, 2017).

The overarching goal of this paper is to contribute to improving farmer livelihoods and food security by improving farmers' ability to adapt to the changing climate. A key element of this, that is addressed by this research, is likely to be providing farmers with better weather and climate forecasts, a core component of hydromet services. Yet there is still insufficient understanding of whether indeed farmers can and do take advantage of improved hydromet services such as improved weather forecasts, to reduce crop losses and therefore protect their livelihoods and food security more broadly. To contribute to this goal, in this paper we provide some of the first robust quantified evidence of the benefits of better weather forecasts observations and services to the agriculture sector. We ask the following two research questions. First, to what extent are farmers who have access to improved weather forecasts more likely to avoid crop losses. Second, to what extent do farmers with access to more accurate weather forecasts adjust their harvesting dates and labour hiring decisions. To address these two questions, we combine reanalysis meteorological data, weather forecasting data, and household surveys, and analyse the data using micro-econometrics.

Provision of national and international forecasting systems to provide reliable weather forecasts is expensive. As such, the influence of weather forecasts on people's decision-making processes and the societal benefits generated by improvements in forecast skill are important. Determining the value of seasonal forecasts to farmers in LMICs is complex. First, data sources are often scattered and varied. Weather stations are not evenly distributed within countries, and the rationale for where they are located is often far from being linked to agricultural demand or need. Second, farmers may have access to a broad range of hydromet services, including weather forecasts, but may not be able to use the data, or may choose not to use the data. Third, analysts must stitch together data sets that vary in their temporal and spatial reach and resolution. That said, there is still tremendous value in working with the available secondary data, despite all the compromises that must be made, because it is possible to make robust estimates that provide clues as to the value of weather forecasts, an important hydromet service. This is what we set out to do in this paper, which should be seen as a starting point for demonstrating robustly the significant values that hydromet services can offer; highlighting what data are needed, and in what format, for analysts and policy makers to put more accurate values on the provision of additional hydromet services in LMICs; and showing the need for greater efforts to ensure that farmers can access and make use of existing, additional, and more accurate weather and climate data.

While estimates of the accuracy of probabilistic forecasts are available in the climatic science literature (for example, Palmer, 2000; Weisheimer and Palmer, 2014), this is the first analysis, as far as we know, to study the impact of forecast skill on whether or not a farmer experienced crop losses, and on decision making of farmers regarding labour hiring, undertaken across multiple countries. We therefore contribute to the broader literatures on accessing information and estimating the social benefit of land-based weather forecasting.

The rest of the paper is as follows. In Section 2 we review the literature most relevant to our task, focusing on what is known to date on the value of weather forecasts to farmers. In Section 3 we detail our methodological approach; Section 4 presents the results; and we finish with a discussion and concluding comments in Section 5.

2 The state and benefits of hydromet services for the agriculture sector in LMICs

This section takes a broad look at the literature on hydromet services, with a focus on establishing the extent to which there is evidence that hydromet services benefit farmers. We start with some background information on the role of National Meteorological Departments (NMDs), and then summarise some of the key findings of the value of hydromet services to farmers. The final section provides a more nuanced discussion of how hydromet services could be more useful to farmers, particularly those in LMICs.

2.1 The role and state of National Meteorological Departments

Under guidance from the World Meteorological Organization, WMO, NMDs serve as trusted government sources for weather forecasts and provide alerts during natural disasters (Rogers

and Tsirkunov, 2013). Delivery vehicles for hydromet information vary widely, ranging from radio reports to mobile phone notifications (Lo and Dieng, 2015; Samonte et al., 2017; Agyekum et al., 2022). Access to hydromet services can assist responsiveness to time-sensitive climate events for nearly all sectors of the economy, but especially agriculture. However, the quality of hydromet information tends to be highly dependent on sector, governance strategy, and context of a specific region (Goddard, et al., 2010).

The services that NMDs offer to the agricultural sector, agrometeorological services, are designed to aid time-sensitive decisions such as managing plant pests and emergency responses (Cegnar et al., 2022). However, an assessment by the WMO reveals a substantial gap between generating effective climate information and delivering to its intended users, which is in part due to an insufficient level of understanding of the needs of farmers (WMO, 2020; FAO, 2021). This contributes to LMIC agriculture remaining characterized by low levels of productivity and investment (Sonwa, et al., 2017). The problem is arguably less so with the data itself, but with the type and vehicle of information shared with agricultural workers as a service. That said, the extent of hydromet data in LMICs tends to be lower than in higher-income countries.

Although NMDs traditionally received most of their funding from government and aviation, the costs of continuing to install up-to-date weather stations have increased considerably, in part due to the continuous advancements of technologies such as sensor suites coupled with the privatization of hardware companies, which is becoming a significant barrier to countries with less public income (WMO, 2015). Perhaps not surprisingly, the state and capacity of many NMDs are in decline. A World Bank (2018) report suggests that two-thirds of observation networks in lower-income countries are in a poor or declining condition. Those areas where NMDs require greater support include parts of Sub-Saharan Africa, Southeast Asia and South Asia. Although the report identified many reasons for weakness, such as fragmented policy environments, insufficient budgets, and lack of maintenance, other literature suggests governing bodies responsible for managing NMDs still appear not to be sufficiently able to identify the population's needs (Rogers and Tsirkunov, 2013; Kull et al., 2021).

There are considerable differences in hydromet modelling capabilities across countries and regions. Many southern African countries have struggled to update numerical weather prediction and climate modelling abilities, resulting in poorly analysed data (Meque, et al., 2021). This is compounded by the uneven geographical spread of weather stations across Africa, where stations tend to either be built in clusters or are non-uniformly spread out (Botai et al., 2015). This results in end-users of hydromet services being more likely to receive irrelevant or incorrect information related to their specific location. In contrast, higher-income countries often have higher operational hydromet capacity to assist with forecasting and warning, as well as reliable public warning systems.

A further compounding problem is that lower-income African and Asian countries struggle to attract talents sufficiently skilled and specialized in hydromet forecasting, with a strong knowledge gap in interpreting pre- and post-natural disaster data being observed (Paparrizos et al., 2020). That said, some countries have made considerable progress in their hydromet service

capability, including India and Bangladesh, which have improved their modelling capabilities and partnered with academic institutions (Mason et al., 2022).

There are further obstacles due to the combined lack of collected historical data and year-on-year changes in local climates. Although global weather data from thousands of weather stations are substantially documented, repositories often lack sufficiently well-organized data from LMICs (Colston, et al., 2018). This points to a shortage in data to build high quality climate models, because historical data are needed to provide reliable estimates (McSweeney et al., 2010). Furthermore, because weather and climate measurements are stochastic in nature, recent climate variations further complicate climate model calibrations (Vaughan et al., 2019), resulting in systematically poor hydromet services.

2.2 The value of hydromet services

The links between agricultural users of hydromet services and perceived value is complex. The WMO (2019) estimates that quality forecasting could unlock US\$ 30 billion annually in global agricultural productivity, yet there is debate on whether farmers desire advanced hydromet services, and whether they would actually make use of greater access. This is in some respects curious. For example, in sub-Saharan African, the evidence suggests that for regions that typically rely on rain-fed agriculture, periodic water scarcity is becoming more frequent, yet many farmers are not taking these changes into account by, for example, adopting irrigation or water storage methods (Lottering et al., 2021). This may be because of lack of knowledge about the changes in weather and climate, due to climate change, or a lack of ability or finances to adapt, suggesting a clear need for hydromet services, but such services could be necessary but not sufficient. There is also some evidence that farmers struggle to perceive gains and losses accurately (Gardezi et al., 2018; Ding et al., 2021).

A large body of literature studies the subjective value and qualitative impact for farmers of hydromet or climate services (Vaughan et al., 2019). Age, gender, labour availability, income, farm size, and financing facilities have been shown to affect the adoption of hydromet services (Abegunde et al. 2019; Waaswa et al. 2022). But despite the perceived importance of hydromet services for farmers in LMICs, there is still a lack of sufficiently rigorous evidence on the economic benefits of improved hydromet services, particularly for smaller LMICs (Suckall and Soares, 2022). Two useful reviews of the relevant literature are Meza et al. (2008) and the more recent Farkas et al. (2025). Meza et al. (2008) conclude that there are still considerable knowledge gaps, which they attribute in part to insufficient valuation studies. They emphasise the need to expand the range of farming systems and geographies, incorporate qualitative social science methods, and to broaden the scope of studies to focus on development indicators including food security and poverty reduction. Farkas et al. (2025), focusing on the economic value of weather forecasts, find a paucity of studies that focus on lower-income countries, and that whilst studies determine the benefits of forecast improvements, they rarely consider the costs.

Farmer willingness-to-pay (WTP) studies offer one approach to estimating and quantifying the value of hydromet services. A study in Burkina Faso suggests that farmers there would be willing

to pay anywhere from US \$1.19 to \$15.36 for better weather and climate information (Ouédraogo et al., 2015; Zongo et al., 2016). A possible reason for the considerable range of values could be the income levels of participating farmers within each sample. For example, Ouédraogo et al. (2015) studied farmers who had higher gross margins and thereby could afford extra expenditure on hydromet services, whereas Zongo et al. (2016) featured a much larger sample that included farmers with lower incomes.

Higher WTP values for hydromet services are correlated with higher awareness and experience of these services. For example, in one study, groups that had positive past experiences with hydromet services prior to the study reported higher values (Amegnaglo et al., 2017). In an experiment conducted by Paparrizos et al. (2021) in Bangladesh, 90.4% of farmer respondents who were engaged in the participatory development of climate information services were willing to pay for climate information that would help them manage their farming activities, compare with 76.3% in a control group that did not participate. Farmers in this region are reported by the authors to be highly vulnerable to climate change, rendering traditional decision-making systems less reliable and therefore hydromet services may be more valued.

The delivery and format of hydromet information influences its value to farmers and their agricultural decisions. For example, in Pakistan, over 55% of farm households in a study by Nepal et al. (2024) reported using hydromet services from the NMD for time-sensitive agricultural decisions. Timely and accurate weather forecasts aided in adjustments in planting schedules, irrigation practices, and harvesting times. However, Pakistan frequently faces infrastructural issues, such as power cuts and mobile network charges, negatively affecting the timeliness of information and thereby effectiveness of hydromet services. A preference for timely information is also found by Nkiaka et al. (2019). Their work suggests that farmers in SSA prefer shorter timescale forecasts, specifically hourly rather than daily or season-specific forecasts, allowing for immediate actions to reduce the impacts of severe weather events.

Smallholder farmers in African and Asian countries with less than two hectares of land tend to be particularly vulnerable to climate and weather shocks (Fanzo, 2017). As such, it might be assumed that they would benefit more from access to accurate weather forecasts. Yet smallholder farmers have been found to be less reliant on hydromet services than farmers with larger holdings (Waldman, et al., 2019). Smallholder farmers tend instead to rely on personal experiences to predict weather events (Waldman, et al., 2019). Although mobile phones and radio can be used to access hydromet information, smallholder farmers tend to lack formal education, which could make it harder for them to use and understand hydromet services from these media (Anuga and Gordon, 2016), suggesting they might benefit from additional training (Mitter et al., 2024).

Those farmers who least frequently use hydromet services are pastoralists (Egeru, 2016). The nature of pastoral farming requires these farmers to frequently move, and hydromet services, are not tailored to pastoralists' needs which are more likely to be around livestock prices and availability of grazing resources (Rasmussen, et al., 2014). Instead, pastoralists tend to rely more on indigenous knowledge or word of mouth (Ng'asike, 2019).

Relying on past experiences is becoming less useful for farmers, given that climate and weather patterns are changing due to climate change. Yet there is very little research focused on the tangible benefits to be had from improved hydromet services, despite the albeit limited evidence that there are clear benefits to farmers. A review by Vaughan et al. (2019) mapped and evaluated 66 studies, which revealed a number of key gaps. One key challenge these authors find is that farmers are not comfortable discussing their productivity or economic performance, making it tricky to determine the economic value of better hydromet services. Further, farmers may incorrectly report yields or costs with biased over- or underestimates. This highlights the uneven nature of evidence, especially as there is no inclusion of private sector and government/NGO usage of hydromet services.

2.3 Potential improvements to hydromet services

Considerable research has explored how hydromet data can be improved and made more useful for farmers. For example, it has been suggested that instead of relying on easily tracked yet less-meaningful metrics, there are specific kinds of information that farmers can benefit from (Meadow, et al., 2015). These metrics include the likelihood of drought, which is particularly damaging for crops, and which can be more effectively measured using large-scale hydrological modelling informed by satellite data, as opposed to commonly used statistical regressions, to communicate probabilities of occurrence (Orke and Li, 2022). Other studies echo the need to move away from simple analysis methods, suggesting a systematic integration of advanced information offers more opportunities for action (Hansen et al., 2011; Stern and Cooper, 2011).

Another challenge of hydromet service mechanisms is the path of communication to relevant agricultural users. In LMICs, where communication infrastructure tends to be less developed in rural areas, knowledge of weather and climate is often passed across family members and social networks (Takenouchi, 2020). Regardless of the quality of the source, the transfer of information often becomes distorted and incomplete.

Significantly, smallholder farmers have been found to prefer their own indigenous knowledge to inform weather and climate expectations (Naab et al., 2019), with ancestral climate interpretations serving as important historical records, and enabling farmers to at least partially protect their harvests (Mapfumo et al., 2016). For example, farmers in southern parts of Africa use moon phases coupled with temperature and wind changes to indicate the onset of rain (Jiri et al., 2016).

Finally, the proportion of the population of LMICs that can currently access weather forecasts is very low in some regions. In eastern regions of Africa, for example, the estimated range for populations able to access weather services varies considerably between 15–82% (Vaughan et al., 2019). Compounding this, there is also largely a low uptake of hydromet services amongst certain agricultural regions and communities (Ngugi et al., 2011).

3 Methodology

The literatures on the impact of climate change on agricultural outcomes (production, yield, avoided loss), and the economic valuation of weather and climatic forecasting in the context of improved agricultural outcomes, have tended to use decision theory (Ivkovic and Jegadeesh, 2004), avoided cost calculations (Goodarzi, Perera and Bunn, 2019), partial equilibrium models, game theory, contingent valuation (Katz and Murphy, 2005), benefits transfer, and econometric modelling (Rosenzweig and Udry, 2019; Lazo et al., 2009; Yuan et al., 2016). In general, in these approaches, a decision maker, the farmer, is assumed to maximise their expected utility subject to the information available. The farmer's weather and climate information set is likely to be from a combination of sources including their previous experiences, their peer group, and, where available, hydromet services. A particular focus of our paper is to consider how the provision of more skilful weather forecasts can help farmers to avoid crop losses, which could contribute to reduced food insecurity and food poverty.

3.1 Conceptual model

We recognise explicitly that agricultural production is a multistage, sequential decision process. Farmers operate with a fixed land area, uncertainty is induced by weather shocks and long-term climate change, and labour can be flexibly hired on short notice. In this paper, we assume that farmers' activities, including harvesting and labour hiring decisions, are influenced by a combination of farmers' local knowledge of past weather and climate patterns, and, where available, weather forecasts of varying skill. We consider two outcome measures. The first outcome measure is whether or not a farmer experienced crop loss. Conceptually, we hypothesise that the less extreme the weather or climate, and the closer forecasts are to realised weather patterns, the lower the likelihood that farmers experience crop losses. The second outcome measure is linked to labour decisions. Our underlying assumption is that farmers change their labour hiring decisions when they get a forecast of a weather shock that they believe to be accurate (Jessee et al., 2018). Farmers have been observed changing their labour-hiring decisions in response to weather forecasts, in line with what economic theory would predict. Examples from the literature include farmers cancelling planned pesticide spraying after a weather forecast of rain the next day (Guo-Huai et al., 2011; Shen et al., 2024); and positive rainfall forecasts having an ambiguous effect on labour demand (Rosenzweig and Udry, 2014). One hydromet service provider writes explicitly that "typical farming activities such as planting, irrigating, or hiring labour workers are scheduled based on our services" ([Agro-Meteorological Forecasts | Weather Impact](#)). We assume that farmers have some prior expectations over whether weather forecasts in their area have historically been useful, and we assume more accurate forecasts are considered more useful.

Our empirical analysis includes "forecast skill", as an interaction term with forecasted temperature and forecasted precipitation, to explore whether there is evidence to suggest that farmers are more likely to use forecast data to plan their activities if that forecast data has historically been more accurate.

3.2 Determining and measuring weather forecast skill

We define weather forecast skill as the difference between forecast and realised weather. Whilst conceptually simple, in practice determining this variable requires several steps, combining multiple data sources and making a number of assumptions with respect to how we aggregate these differences between forecast and realised weather. We begin by collecting weather forecast data from the national meteorological agencies for each of the four countries. Our dataset consists of forecasted temperature and precipitation at the second administrative level. The weather forecasts that these national agencies provide predict the conditions of the atmosphere for a given location and time period and are informed by land-based weather stations (see Section 3.4 for details). Forecasting weather, as undertaken by these agencies, generally involves several processes. First, the agencies use standard numerical weather prediction frameworks to combine real-time and historical observations from land-based weather stations with satellite-derived information on atmospheric conditions. Several local geographic factors such as elevation are considered to provide weather forecasts such as temperatures and precipitations for the immediate and medium-term future. Next, the agencies assimilate observational data into numerical models that simulate atmospheric dynamics and generate forecasts of temperature and precipitation over short- to medium-term horizons. National meteorological agencies in each of the four countries then post-process these model outputs by incorporating local geographic information such as elevation and regional climate characteristics. The agencies disseminate multiple weather and agrometeorological products in various formats and at various temporal resolutions for multiple purposes. For example, they aggregate forecast data to the subnational level, and provide a synthesis of the information in the form of weather forecast bulletins that include tables and graphs and that are made available to end users, including farmers.

Within an administrative division, we assume that all farmers get the same weather forecast. We also assume all farmers within a grid cell get the same realised weather, but we aggregate the grid cell variables to the sub-national levels to match the spatial aggregation of the forecasts to the second administrative division level for each of the four countries. Therefore, the forecast skill is assumed constant within administrative divisions. Finally, we spatially merge the realised weather and forecasted data with survey data from households from each of the countries using coordinates provided in the surveys.

We compute weather forecast skill in three different ways: Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and the Root-Mean-Squared-Error (RMSE). When using RMSE (details and results can be found in the appendix), we have to do two separate empirical analyses, one for precipitation forecast skill, and a separate one for temperature forecast skill. It is reasonable to assume that farmers are more likely to respond to weather forecasts if they believe that they are accurate, which would plausibly be based on their prior experiences of the accuracy of historical forecasts. Therefore, when considering how to define the “forecast skill” metrics, we use an average based on historical forecasts. Specifically, we use a six-month historical average for the skill metrics, which aligns with the survey period.

MAD measures the accuracy of the prediction, and therefore forecasting skill, by averaging the absolute error in each period, where the error is defined as the difference between forecast weather and realised weather in a given location. This metric is useful when measuring prediction errors in the same unit as the original series (Moon and Tao, 2011; Leys et al., 2023).

$$MAD = \frac{1}{n} \sum_{t=1}^n |y_1 - y'_t|$$

MAPE is computed using the absolute error in each period divided by the observed values that are evident for that period, then those fixed percentages are averaged. This approach is useful when the size or size of a prediction variable is significant in evaluating the accuracy of a prediction (McKenzie, 2011; Myttenaere, 2016). MAPE indicates the error in prediction weather forecasts compared to the real value.

$$MAPE = \frac{\frac{\sum |y_1 - y'_t|}{y_1}}{n} \times 100\%$$

RMSE is the square root of average sum of square errors over the rolling window. The RMSE metric weights both bias and precision of forecasts by averaging instantaneous errors for the previous periods. As such, lower RMSE indicates more accurate forecasts. If we consider the mean temperature forecasted over the next three months for sub-national region i , the accuracy of forecasts can be represented with the root-mean-squared-error between forecast ($C_{its}^{forecast}$) and realised temperatures and precipitation (C_{its}^{real}). As such, lower RMSE indicates more accurate forecasts. RMSE across the four countries ranges from $\sim 1^\circ\text{C}$ to $\sim 4.5^\circ\text{C}$. Temporal variations in RMSE are smaller due to smoothing over six-month window.

$$RMSE_{it}^C = \sqrt{\frac{1}{R} \sum_{s=1}^R (C_{its}^{real} - C_{its}^{forecast})^2}$$

For sub-national region i , the accuracy of forecasts can be represented by the error metric between the forecasted weather and the realised temperatures or precipitation.

3.3 Econometric framework

The first step in setting up the econometric framework is to link weather forecasting associated variables to the two outcomes of interest, whether a farmer reported a crop loss, and whether a farmer changed their labour hiring decision. Our identification strategy assumes that farmers with access to more accurate weather forecast information are less likely to experience crop

losses, which implies that farmers are using these forecasts to influence their agricultural practices ahead of weather realisations.

We control for the accuracy of land-based weather forecasts. We also include interaction-terms between temperature/precipitation response and forecast skill. This allows us to investigate whether farmers' decisions are influenced by weather forecasts, in as much as we assume that if farmers take into account forecasts when making their decision, that they see value in these forecasts. We assume that forecast errors are as-good-as-randomly assigned within locations over time, conditional on other covariates.

$$y_{ift} = f(\mathbf{C}_{it}^{forecast}; \beta_1) + f(\mathbf{C}_{it}^{forecast}; \beta_2) \times Forecast\ accuracy_{it} + \gamma' \mathbf{X}_{ift} + \varepsilon_{it}$$

$\mathbf{C}_{it}$ is a vector of temperature and precipitation measures. $\mathbf{X}_{ift}$ is vector including other control variables that affect whether a farmer reported a crop loss, and whether a farmer changed their labour hiring decision including farm size; access to finance; farm location; and time fixed-effects. We run this specification individually for the two distinct dependent variables y_{ift} , reported crop losses, and labour hiring decisions. For whether or not a farmer experienced crop loss in farm f in location i in time period t , we use a quadratic functional form for precipitation, recognising that crop losses are non-linear, and can be driven both by too much and too little precipitation. When we consider number of additional workers hired as the dependent variable, we use a linear-term for precipitation variability, measured by standard deviation of precipitation.

To explore the impact of forecast skill, for the reported crop loss outcome, we use a standard fixed-effects specification; and for labour hiring decisions, we use a Poisson model. Standard errors are clustered at the second administrative level for each country to control for local level policies related to agriculture and access to finance. We conduct a number of robustness tests to determine whether there is a causal link between realised weather and our outcome variables (Appendix x). This involves the estimation of experienced crop losses or labour hiring decisions linked to access to improved weather forecasts.

3.4 Data

Our choice of countries, Tanzania, Ethiopia, Uganda, and Bangladesh, is influenced in part by the fact that all these countries have networks of functioning meteorological weather stations that have been in operation for an extended period and provide reliable temporal and spatial coverage across the respective countries. Here we first contextualise the data we use for our analysis by providing some historical background to the four countries' development of their land-based weather stations. We then provide detail on how we assembled the realised weather data set, and we finally describe the household datasets we use for each country.

Land-based observations

Land or ground-based meteorological measurements refer to those made close to the Earth's surface, typically from a mast or tower at a height of a few meters to over a hundred meters above ground. They provide direct physical parameters such as temperature, pressure, wind, and

precipitation. For example, in Bangladesh most ground-based observations at the weather stations provide air temperature data at two meters height above surface.

Ethiopia's first meteorological stations were established in the 19th century by missionaries and explorers. In 1951 the country established under the Civil Aviation Department a unit to provide meteorological information, focusing on aviation. The [Ethiopia National Meteorological Agency](#), officially established in 1980, evolved out of this unit, in recognition of the importance of weather forecasting services for other parts of the economy, including agriculture. The agency, which evolved into the Ethiopian Meteorology Institute in 2021, operates a national network of meteorological stations designed to represent various climatic regions of Ethiopia and to contribute to the needs of various national development plans. Ethiopia's meteorological stations currently provide weather forecast and early warnings on the adverse effects of weather and climate of Ethiopia using more than 1,600 stations (Figure 1). The country had 16 synoptic weather stations at the time of writing, those that make weather observations at specific and pre-determined times, which are then transmitted to a central weather service, and which are used for global reporting. The agency provides separate weather forecast information including anticipated temperature and precipitation for the following week, ten-days, three-months, and six-months. This data and information including early warnings on the adverse effects of weather and climate is disseminated through climatological bulletins. These bulletins can be found on, and downloaded from, the Ethiopian Meteorological institute's [website](#). The agency's data platform on this website provides spatially resolved time-stamped weather forecasts which we use to merge with the households. We go to the monthly forecast, which gives rainfall and temperature patterns. For each wave of household data, we identify in what month in the survey period the reported crop losses occurred, and from the Forecast website, we find the weather forecasts for the month preceding that period. Farmers have access to the same forecast data through these bulletins. In the case of precipitation, the forecast might show the total expected rainfall in the month for which the forecast is produced. We do a simple average all forecasts for each subnational region.

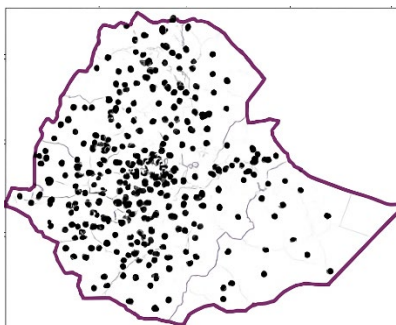


Figure 1: Location of land-based meteorological stations in Ethiopia
Source: Ethiopian Meteorological Institute Annual Report 2024

The [Tanzania Meteorological Authority \(TMA\)](#) was established by the Government Executive Agency Act no.30 of 1997 and was then officially launched in 1999. The agency operates a

network of surface and upper air stations to establish records of weather and climatic conditions and provides weather and climate services for various users of meteorological information. TMA issues agrometeorological information and advisories, irrigation scheduling on ten day and monthly basis. A special issue bulletin that contains seasonal weather forecast is issued in September and February each year. An example of one such bulletin, that focuses on rainfall, can be found [here](#). The bulletin highlights, for example, whether rains are likely to be normal or above or below normal, and when they are likely to start; and climate systems information such as sea surface temperatures. Overall Tanzania has 28 synoptic weather stations, and over 2000 rainfall stations across Tanzania.

The [Uganda National Meteorological Authority](#) (UNMA) is responsible for establishing and maintaining weather and climate observing stations network, collection, analysis and production of weather and climate information (including warnings/advisories) to support social and economic development. The agency provides short-term, monthly, seasonal, and annual forecasts together with dedicated farmer advisories, covering rainfall and temperature. An example of a decadal agro-met bulletin can be found [here](#). It provides ten-day forecasts for rainfall, temperature, and heat stress, by subnational region. Uganda has a network of 205 weather stations, plus 12 synoptic stations, and 150 rain gauge stations. UNMA also maintains structured, spatially resolved climate data through its data platform (the UNMA Maproom), from which we obtained the monthly temperature and precipitation forecasts and aggregated them to the second administrative level.

Bangladesh Meteorological Department maintains a network of surface and upper air observatories, radar and satellite stations, agrometeorological observatories, geomagnetic, and seismological observatories and meteorological telecommunication system of Bangladesh. There are 46 synoptic weather stations in the country that are designed for broad weather monitoring, and around 34 weather monitoring stations. BMD is responsible for providing weather forecasts for public, farmers, mariners, and aviators and to issue warnings for severe weather phenomena such as tropical cyclones, tornadoes, nor 'westers (a stormy weather pattern in India and Bangladesh occurring in the spring), and heavy precipitation events. Relevant outputs include five days, ten days, and three-month temperature and precipitation forecasts for farmers.

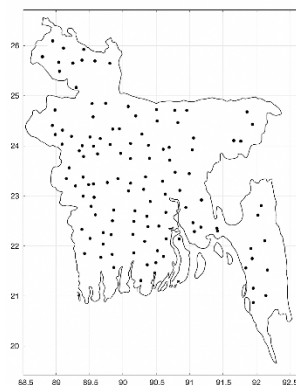


Figure 2: Location of land-based meteorological stations in Bangladesh
Source. Bangladesh Meteorological Department

We summarise the weather station data in Table 1 below. Whilst there is fairly robust recording of the number of synoptic stations and other official weather monitoring stations in each country, the number of additional stations, typically rain gauges or rainfall stations, is less well defined.

	Ethiopia	Tanzania	Uganda	Bangladesh
Number of synoptic stations	16	39	12	46
Number of other weather monitoring stations	1,600	161	205	34
Number of rain gauge/rainfall stations	Not publicly available	>2,000 (rainfall station)	150 (rain gauge)	243 (mixed rainfall/gauge)
Density of stations, per '000km ² (synoptic)	0.014	0.030	0.050	0.311
Density of stations per '000km ² (synoptic plus other monitoring)	1.449	0.211	1.473	0.230
Land area ('000km ²)	1,104	947	241	1,104

Table 1: Summary of weather and monitoring stations across the four countries

Source. The [Ethiopia National Meteorological Agency](#), [Tanzania Meteorological Authority](#), [Uganda National Meteorological Authority](#), [Bangladesh Meteorological Department](#)

Realised weather data

For the purposes of this analysis, we use ERA5-Land reanalysis climate data (temperature and precipitation) from European Centre for Medium-Range Weather Forecast (ECMWF) as the source of our realised weather (Muñoz, 2019). Reanalysed climate data combines global climate model data (numerical representation of the recent climate) with observational and satellite observations. ERA5-Land is a reanalysis dataset providing an hourly high-resolution information of surface variables over several decades at ~9km grid spacing and covering the period from 1950 to 2-3 months before the present. We use six months Standardized Precipitation Evapotranspiration Index (SPEI) as an indicator of drought. SPEI that takes into account both precipitation and potential evapotranspiration in determining the probability of drought conditions. We consider a month to be a drought month if SPEI for that particular month is below -1.5.

First, we spatially merge the forecast data to the sub-national regions from the household surveys using coordinates from the from the land-based stations. For each survey wave we take the monthly forecast of temperature and precipitation for the period preceding reported crop losses, and pair it with realised weather for the same period from ERA5-Land, aggregated to the same administrative units. Second, we aggregate the gridded realised weather variables from ERA5-Land using population weights to and match them to the forecast weather data and household survey data.

Household survey datasets

These datasets provide comparable information that are needed for our analysis including on agricultural productivity (production and yields), crop roster, harvesting and planting decisions, hired labour, and other inputs along with relevant sociodemographic factors. These datasets are nationally representative population-based surveys (except the case of Bangladesh), conducted using two-stage probability sampling methods to ensure sub-national representation and allow for improved estimates across the rural-urban divide. The datasets also provide dates of planting and harvesting allowing the study of seasonality.

Ethiopia's Socioeconomic Survey (ESS) collects information on agricultural activities along with data on education and health, labour force status and labour supply, economic activities, and access to services and resources. The ESS is conducted with a two-stage probability sample and implemented in collaboration with the World Bank Living Standards Measurement Study (LSMS) and collects information on agricultural data, socioeconomic characteristics at the household-level, welfare indicators, occupational and income characteristics, and food security. ESS is a nationally representative longitudinal survey of over 5,000 households followed over time living in rural and urban areas. Wave 1 is from 2011-2012; wave 2, 2012-2014; wave 3, 2015-2016; wave 4, 2018-2019; and wave 5, 2021-2022. Some of the topics covered are: post-harvest, including household roster, crop roster, crop harvest by field, unit and size codes, harvest labour, crop roster, and crop disposition; post planting, including parcel roster, field roster, crop roster, seeds roster, miscellaneous questions for the holder, agriculture capital, irrigation, land use and agriculture income tax, and crop cut by field; and livestock, including ownership, change in stock, breeding, house, water and feed, animal health, milk production, egg production, animal power and dung, and household roster.

The main objective of the Tanzania National Panel Survey (NPS) is to provide high-quality household-level data to the Tanzanian government and other stakeholders for monitoring poverty dynamics, tracking the progress of poverty reduction strategies, and evaluating the impact of other major, national-level government policy initiatives. The NPS is a panel household survey of more than 4,000 households in which the same households are revisited over time. The NPS allows for the study of poverty and welfare transitions and the determinants of living standard changes. There are five waves: Wave 1, 2008-2009; wave 2, 2010-2011; wave 3, 2012-2013; wave 4, 2014-2016; and wave 5, 2020-2022. Some of the topics covered are: household, including household roster, education, health, labour, food outside the household, subject welfare, food security, housing, water and sanitation, food and non-food expenditure, household assets, family/household non-farm enterprises, assistance and groups, credit, finance, recent shocks to household welfare, deaths in the household, household re-contact information, filter question, and anthropometry; and agriculture, including plot details, crops by plot, crops - household totals production and sales, permanent crops by plot, permanent crops - household totals (production and sales), input vouchers, out grower schemes and contract farming, processed agricultural products and agricultural by-products, farm implements and machinery extension.

The Uganda National Panel Survey (NPS) is collected by the Uganda Bureau of Statistics, with support from the World Bank LSMS. The sample of around 3,200 households is nationally representative and covers demographics, socioeconomic characteristics, occupation, income, food security, and agricultural practices. There are six waves: wave 1, 2005-2006; wave 2, 2010-2011; wave 3, 2011-2012; wave 4, 2013-2014, wave 5, 2018-2019; and wave 6, 2019-2020. Some of the topics covered are: household, including household identification particulars, household roster, general information on household members, education, health, child nutrition and health, labour force status, housing conditions, water and sanitation, energy use, other household income, non-agricultural household enterprise/activities, household assets, household consumption expenditure, shocks and coping strategies, welfare and food security and link with the agriculture questionnaire; and agriculture; including household identification particulars, staff details and survey time, current land holdings and land that the household accessed through use rights, agricultural and labour inputs, crops grown, and types of seeds used, quantification of agricultural production, livestock ownership, cattle and pack animals, livestock inputs, livestock production, extension services, farm implements and machinery and animal groups.

The Bangladesh Integrated Household Survey (BIHS) was designed by IFPRI-PRSSP, and is the most comprehensive, nationally representative rural household panel survey in the country. BIHS covers 5,604 households and is statistically representative at the following levels: (a) nationally representative of rural Bangladesh; and (b) representative of rural areas of each of the seven administrative divisions of the country. To date, BIHS is the most comprehensive, nationally representative household survey ever conducted in Bangladesh. BIHS has uncovered some of the underlying dynamics of poverty, food security, and agricultural development in Bangladesh. There are six waves: wave 1, 2011-2012; wave 2, 2015; wave 3, 2018-2019; wave 4, 2013-2014, wave 5, 2018-2019; and wave 6, 2019-2020. Some of the relevant topics are: household characteristics including marital status, literacy and education, dietary intake of individual household members, anthropometric measurements (height and weight) of all household members, and data on women's empowerment in agriculture. and other sociodemographic characteristics; and agriculture, including plot-level agricultural production and yields, irrigation practices, fertilizer use, labour and other inputs, access to credit. There is also a community survey that supplements the BIHS data to provide information on area-specific contextual factors.

4 Results

We present our findings for the impact of forecast skill on whether farmers report crop losses and on labour hiring decisions for the four countries, Ethiopia, Bangladesh, Tanzania, and Uganda. We provide some of the key descriptive statistics, including the distribution of weather forecast skill metrics, then discuss the empirical results.

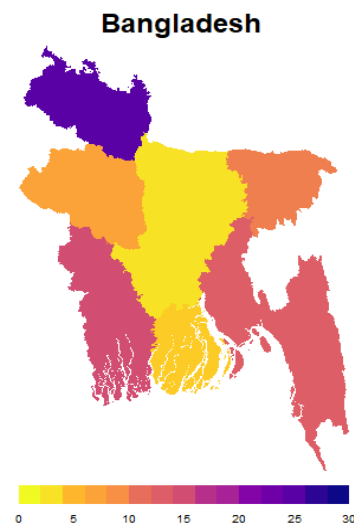
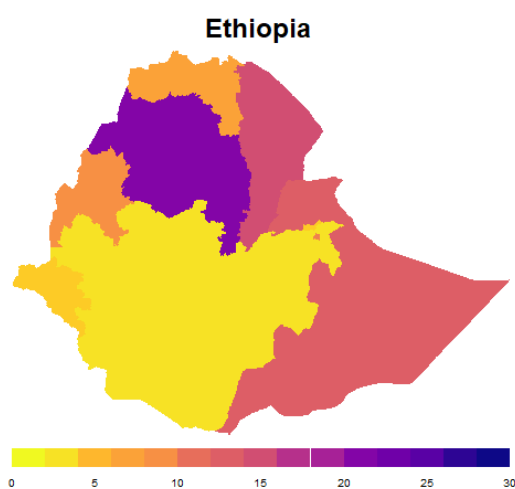
4.1 Descriptive statistics

We focus particularly on forecasting skill. Both MAD and MAPE have substantial spatial variation across and within the four countries we analyse. For example, in Ethiopia the estimated accuracy metrics are relatively lower in the Afar, Amhara, and Somali regions of the country. Across Ethiopia, MAD ranges from 2.1 to 23.3 for temperature and 2.7 to 28.1 for precipitation. Weather

forecasts across Ethiopia tend to be least accurate in October and November, reflecting temporal variation linked to the flood season. The accuracy of weather forecasts also varies spatially and temporally across Bangladesh. Accuracy is relatively lower in Chuadanga (Khulna Division), Hatiya (Chittagong Division), and Rangpur, as indicated by both MAD and MAPE. These districts have fewer land-based weather stations. In Bangladesh, MAD ranges from 2.6 to 25.2 for temperature and 3.3 to 30.4 for precipitation. Forecast skill tends to be lowest in July and August, the warmest months of the year and generally some of the most flood-prone times of the year ([Letsch et al., 2023](#)). In Tanzania, MAD ranges from 2.9 to 26.9 for temperature and 3.0 to 28.2 for precipitation. For Uganda, MAD ranges from 3.1 to 27.1 for temperature and 3.8 to 32.1 for precipitation (Table 2).

	Forecast skill - MAD (temperature)	Forecast skill - MAD (precipitation)	Farmers reporting crop losses (%)	Labour hiring (number)
Ethiopia	8.73 (6.63)	9.65 (7.02)	8.71 (2.21)	13.47 (1.24)
Bangladesh	11.36 (7.50)	12.28 (8.33)	6.58 (2.58)	14.12 (1.89)
Tanzania	10.19 (6.12)	11.05 (5.66)	7.80 (3.06)	15.36 (2.33)
Uganda	12.09 (6.91)	14.23 (6.22)	4.38 (1.85)	13.84 (1.41)

Table 2: Descriptive statistics during the survey years
Ethiopia: 2011-2022; Tanzania: 2008-2022; Uganda: 2005-2020; Bangladesh: 2011-2020
Standard deviation is in parentheses



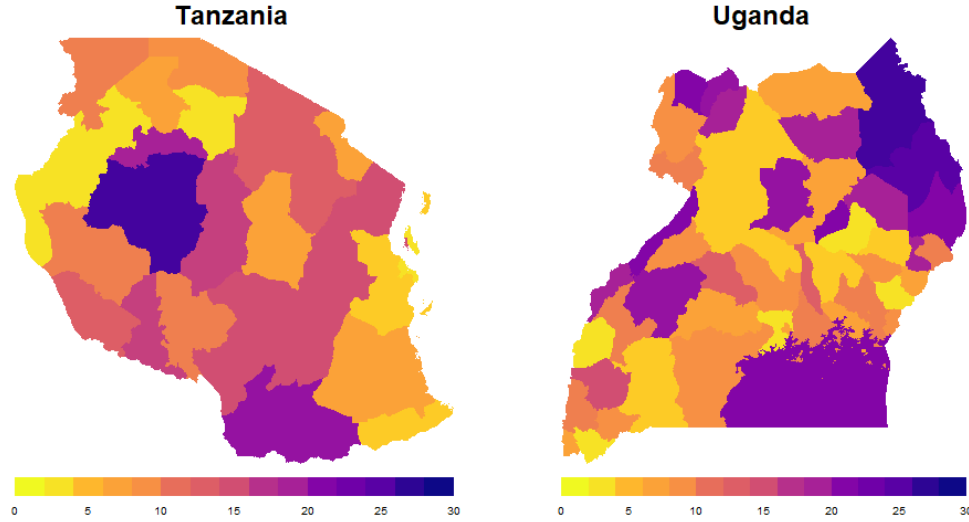


Figure 3: Spatial heterogeneity in temperature forecasting skills

4.2 Empirical findings

We first compare the results for the different measures of forecast skill. We find that for each of the four country regressions, the coefficients are consistent for each of the parameters whether we use MAD, MAPE, or RMSE (Table 3, results for RMSE are in the appendices). This suggests that our findings are not sensitive to the choice of measure of forecast skill.

Next, we consider the coefficients for the “weather” variables, specifically “precipitation realised”, “precipitation realised squared”, and “temperature realised.” The signs of the coefficients are consistent across measures of forecast skill and across countries. Focusing on “precipitation realised”, the coefficients provide strong evidence that, for lower levels of precipitation, a precipitation increment in the previous six-months is associated with fewer farmers reporting losses, but at higher levels of precipitation above a threshold that is country specific (Ethiopia: 115.8-117.2mm per month averaged over a year; Bangladesh: 247.0-239.3; Tanzania: 72.2-68.2; Uganda: 118.5-119.8), a precipitation increment is associated with more farmers reporting losses. When we consider “temperature realised”, for each of the four countries, a higher temperature is associated with more farmers reporting losses. Climate also matters. The coefficient on the “drought” variable is statistically significant for all four countries, and positive. That is, the higher number of drought months the farmer experiences, the more likely they are to report crop losses.

Five of our independent variables are associated with forecast skill, which we address both as a separate and distinct variable, and as a term interacted with weather variables. This is because the benefits of forecast skill are more likely to be realised when there is a deviation of weather from what farmers might perceive as “normal”. The five variables are “forecast skill-precipitation”; “forecast skill” x “precipitation realised”; “forecast skill” x “precipitation realised-squared”; “forecast skill-temperature”; and “forecast skill-temperature realised”. Our findings provide evidence that farmers in locations where weather forecasts are more accurate are less likely to experience crop losses, and that accurate weather forecasts are particularly important

for weather extremes. For precipitation forecast skill, the main effects are negative and statistically significant across all four countries, ranging from -0.091 in Ethiopia to -0.130 in Bangladesh, indicating that improved precipitation forecasting reduces reported crop losses under average conditions. However, the interaction terms between forecast skill and precipitation realised are also negative and significant in all countries (-0.018 to -0.029), while the interactions with precipitation realised-squared are similarly negative (-0.001 to -0.002). This pattern indicates that the marginal benefit of precipitation forecast improvements increases as precipitation levels rise, suggesting a non-linear relationship where forecast skill becomes increasingly valuable during periods of higher levels of precipitation.

The interaction-terms between temperature and forecast skill metrics, and precipitation and forecast skill metrics, show that more accurate forecasts of both temperature and precipitation (indicated by lower MAD and MAPE, shown by marginal effect or the change in the proportion of farmers reporting crop losses and the number of workers hired during the harvest season due to forecast skill), are associated with a smaller number of farmers reporting crop losses, and this relationship is more pronounced for larger temperature anomalies (Table 3; columns 1 and 2). Temperature forecast skill show similar patterns, with negative main effects ranging from -0.105 in Tanzania to -0.141 in Bangladesh, and negative interaction terms with temperature realised across all countries (-0.030 to -0.041). The marginal effect of temperature forecast improvements depends on the level of temperature realised, with greater benefits occurring during periods of temperature stress.

More accurate forecasts are associated with a smaller number of farmers reporting crop losses, and this relationship is more pronounced for larger temperature anomalies. This can be seen in Table 3. "Temperature realised" has a positive and significant coefficient, suggesting that at higher temperatures, experienced crop losses are higher. "Temperature realised" has a positive and significant coefficient, indicating that higher realised temperatures are associated with more reported crop losses. The forecast skill variable, defined so that it increases with forecast accuracy, has a negative coefficient, indicating that more accurate temperature forecasts are associated with a lower probability of reported crop losses. The negative interaction between forecast skill and realised temperature indicates that this benefit is larger at higher temperatures. Coefficients for access to finance are consistently negative with our findings suggesting that a 1% increase in access to finance leads to a between 0.124 percentage-point to 0.169 percentage-point reduction in the share of farmers reporting crop losses, providing evidence that improved access to finance can act as a complementary risk management tool.

	Ethiopia		Bangladesh		Tanzania		Uganda	
	MAD	MAPE	MAD	MAPE	MAD	MAPE	MAD	MAPE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation realised	-0.695*** (0.005)	-0.703*** (0.007)	-0.988** (0.029)	-0.957** (0.007)	-0.433** (0.021)	-0.409** (0.015)	-0.711*** (0.000)	-0.719*** (0.006)
Precipitation realised-squared	0.003** (0.036)	0.003** (0.025)	0.002** (0.020)	0.002** (0.041)	0.003*** (0.001)	0.003*** (0.022)	0.003** (0.027)	0.003*** (0.000)
Forecast skill - precipitation	-0.091** (0.029)	-0.091** (0.020)	-0.130** (0.038)	-0.102** (0.017)	-0.093** (0.042)	-0.083** (0.037)	-0.124** (0.029)	-0.114** (0.016)
Forecast skill × Precipitation realised	-0.018** (0.021)	0.017** (0.033)	-0.025** (0.028)	0.029** (0.025)	-0.029*** (0.000)	0.032** (0.011)	-0.027** (0.015)	-0.031** (0.012)

Forecast skill × Precipitation realised-squared		-0.001*** (0.007)	-0.001*** (0.002)	-0.002** (0.015)	-0.002** (0.019)	-0.001*** (0.009)	-0.001*** (0.009)	-0.002*** (0.002)	-0.002*** (0.009)
Forecast skill - temperature		-0.112** (0.022)	-0.116** (0.029)	-0.141** (0.031)	-0.120** (0.036)	-0.105** (0.015)	-0.109** (0.026)	-0.139** (0.030)	-0.130** (0.022)
Temperature realised		0.255*** (0.008)	0.301** (0.028)	0.303** (0.022)	0.320** (0.021)	0.313*** (0.000)	0.380** (0.006)	0.284** (0.030)	0.290** (0.024)
Forecast skill × Temperature realised		-0.035** (0.030)	-0.039* (0.023)	-0.030** (0.027)	-0.034* (0.018)	-0.036*** (0.002)	-0.045** (0.000)	-0.041** (0.017)	-0.046*** (0.000)
Drought		0.901*** (0.000)	0.906*** (0.002)	0.988*** (0.006)	0.967*** (0.000)	0.941*** (0.003)	0.976*** (0.007)	0.753*** (0.000)	0.740*** (0.008)
Access to finance		-0.124*** (0.004)	-0.126*** (0.002)	-0.169*** (0.000)	-0.155*** (0.000)	-0.153** (0.032)	-0.188*** (0.006)	-0.147** (0.026)	-0.161** (0.033)
Farm size									
	Small	0.157** (0.033)	0.179** (0.030)	0.402** (0.040)	0.516** (0.020)	0.304 (0.114)	0.267 (0.505)	0.131** (0.016)	0.135** (0.019)
	Large	-0.214*** (0.009)	-0.247*** (0.002)	-0.391*** (0.006)	-0.500** (0.039)	-0.439*** (0.000)	-0.501*** (0.006)	-0.355*** (0.000)	-0.371*** (0.002)
Robust p-values in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 3: Impact of realised weather on number of farmers reporting crop losses by forecast metrics

Across all four countries, more accurate precipitation and temperature forecasts are significantly associated with fewer farmers reporting crop losses. The forecast skill regressor increases with accuracy, and because realised weather enters as a standardized anomaly with mean zero, the main forecast skill coefficient is the average marginal effect evaluated at the sample mean. The full marginal effect combines this coefficient with its interaction with realised weather, so the effect grows with the size of the anomaly. For Ethiopia, a given improvement in temperature forecast accuracy is associated with a 1.9 percentage-point reduction in the share of farmers reporting crop losses at the mean, rising to 2.5 and 3.0 percentage points at anomalies of one and two standard deviations, where accurate forecasts are most valuable. The corresponding precipitation effect, which additionally includes the interactions with realised precipitation and its square, is 1.7 percentage points at the mean, rising to 2.1 and 2.5 percentage points at one and two standard deviations. The full set of values across countries is presented in Figure 4.

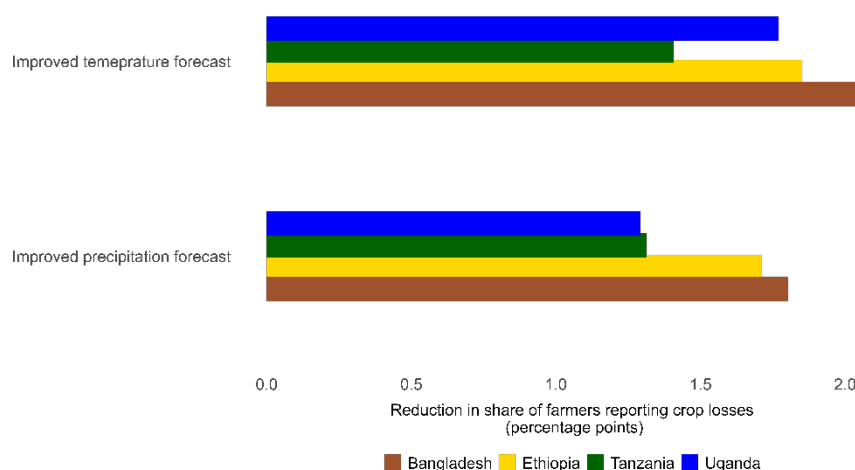


Figure 4: Improved forecast accuracy and avoided crop losses

Across all four countries, better forecasting skill of temperature and precipitation is linked to farmers being more likely to report hiring a higher number of workers during the harvest period for more extremes of weather (Table 4). This is likely to be in anticipation of greater extremes of precipitation and temperatures that could destroy a harvest, so it is better to harvest earlier than anticipated, which requires hiring to be increased to bring forward the harvest. These findings are consistent across farm sizes, with larger farms appearing to benefit more (indicated by positive coefficients of large farms). This could be due to these farms being more likely to have individuals who can make decisions based on weather forecasts.

The interaction terms between precipitation forecast skill and realised precipitation realised are positive and significant in all countries (0.455 to 0.563), suggesting for higher levels of realised precipitation, the marginal effect of forecast skill on labour hiring changes. The interaction terms with realised temperature are consistently positive and significant (0.377 to 0.624), suggesting that better temperature forecasts help farmers anticipate increased labour needs during warmer periods, possibly for irrigation, pest management, or harvest timing adjustments. The positive interaction effects reflect farmers' abilities to proactively hire workers when accurate temperature forecasts indicate conditions that will require more intensive agricultural activities.

Drought conditions are consistently associated with higher levels of labour hiring (1.224 to 1.699), potentially reflecting farmers needing to harvest their crops in a short period of time. Access to finance positively affects labour hiring (1.654 to 2.516), enabling farmers to hire more workers when needed. As one might expect, farm size coefficients suggest smaller farms tend to hire fewer workers (-0.220 to -0.556) and large farms hire more (0.245 to 0.456) compared to medium-sized operations.

The findings show that with improved accuracy of forecasts of extreme weather, farmers hire more workers during the harvest season. A 1% improvement in temperature and precipitation forecast accuracy (measured by MAD) would on average increase labour hiring during the harvest period in Bangladesh by approximately 4.9% and by 6.1%, respectively. In the case of Tanzania, these effects would be approximately 5.5% and 7.3%, respectively (Figure 5).

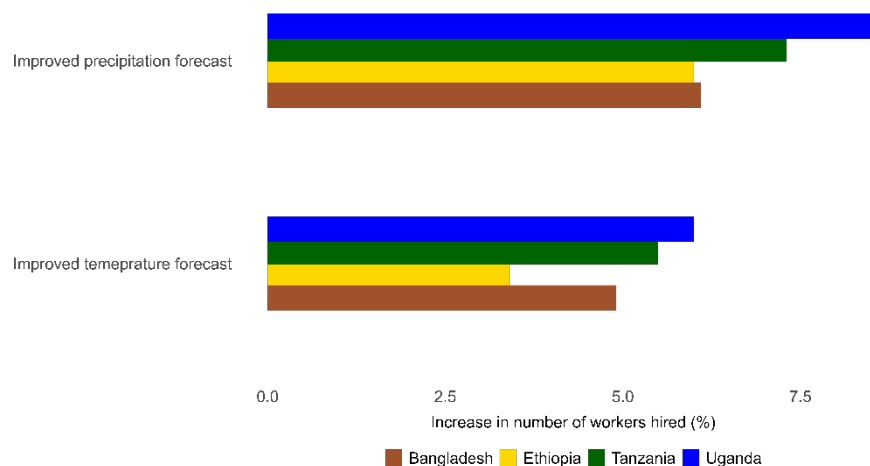


Figure 5: Improved forecast accuracy and labour hiring decisions

Our findings suggest that forecast skill enables dynamic labour allocation that responds to weather forecasts, especially prior to adverse weather conditions.

	Ethiopia		Bangladesh		Tanzania		Uganda	
	MAD	MAPE	MAD	MAPE	MAD	MAPE	MAD	MAPE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation realised	2.178** (0.018)	2.244** (0.023)	3.051** (0.021)	3.010** (0.014)	2.201*** (0.002)	2.308*** (0.002)	2.502*** (0.007)	2.444*** (0.002)
Forecast skill - precipitation	-0.103** (0.019)	-0.096** (0.025)	-0.104** (0.019)	-0.120** (0.028)	-0.082** (0.023)	-0.079** (0.025)	-0.103** (0.013)	-0.106*** (0.009)
Forecast skill × Precipitation realised	0.477** (0.030)	0.409** (0.023)	0.455** (0.025)	0.470** (0.028)	0.530** (0.025)	0.563** (0.030)	0.561** (0.029)	0.466** (0.015)
Forecast skill - temperature	-0.118** (0.014)	-0.110** (0.020)	-0.139** (0.014)	-0.132** (0.019)	-0.091** (0.039)	-0.096** (0.042)	-0.120** (0.025)	-0.128*** (0.001)
Temperature realised	1.244** (0.021)	1.331** (0.033)	1.410** (0.016)	1.344** (0.019)	1.312** (0.035)	1.315** (0.027)	1.461** (0.024)	1.333** (0.028)
Forecast skill × Temperature realised	0.377** (0.021)	0.418** (0.032)	0.501*** (0.001)	0.534*** (0.009)	0.456** (0.003)	0.503** (0.019)	0.506** (0.000)	0.624** (0.001)
Drought	1.224*** (0.000)	1.338*** (0.002)	1.407*** (0.000)	1.490*** (0.006)	1.699** (0.032)	1.716*** (0.009)	1.369** (0.019)	1.487** (0.031)
Access to finance	1.654** (0.029)	1.707** (0.012)	2.234*** (0.008)	2.251*** (0.004)	1.791** (0.016)	1.907** (0.020)	2.152*** (0.002)	2.402*** (0.009)
Farm size								
Small	-0.220** (0.029)	-0.222** (0.022)	-0.421** (0.016)	-0.556** (0.039)	-0.220 (0.500)	-0.335 (0.402)	-0.300 (0.325)	-0.251 (0.420)
Large	0.245*** (0.000)	0.303*** (0.009)	0.398*** (0.001)	0.456*** (0.009)	0.304** (0.023)	0.352*** (0.001)	0.296*** (0.006)	0.311*** (0.002)
Robust p-values in parentheses								
*** p<0.01, ** p<0.05, * p<0.1								

Table 4: Impact of realised weather on labour hiring decisions by forecast metrics

5 Discussion

In this paper we demonstrate clearly that farmers who live in areas where more skilful weather and climate forecasts, an important hydromet service, are available are less likely to report experiencing crop losses. To do so was no simple task. We use unique household and farm-level datasets from multiple countries, and combine these individual household level survey data sets with short to medium-term weather forecasts from the relevant national meteorological agencies, with high resolution reanalysis climate and weather data, each available at different scales and resolutions. Leveraging non-linear regression with key forecast-weather interaction terms, we estimate how temperature and forecasts, and the perceived historical medium-run forecast skill affect the proportion of farmers reporting that they have experienced crop losses, and farmers' decision making with respect to labour hiring decisions. Importantly, our approach identifies farmers' responses to weather forecasts based on their sensitivity to forecast skill. Though such an analysis does not allow us to compute accurate economic values of an improved hydromet service, in this case, improved access to and accuracy of weather forecasts, a critique of the literature by Farkas et al. (2025), we do provide the first robust analysis demonstrating that weather forecasting services are valuable in reducing crop losses and therefore almost certainly contributing to reducing food insecurity by increasing the availability of food, if not access to food.

Across four different countries, our results provide strong evidence not just that access to weather forecasts matters for farmers, but that farmers are more likely to change their farming behaviour when local weather forecasts have historically been more accurate, and when more extreme weather is forecast than might have been anticipated. Specifically, improved forecast skill leads to a statistically significant smaller proportion of farmers experiencing crop losses, and so implicitly a smaller reduction in crop yields overall, particularly for relatively high temperature and extreme precipitation forecasts.

Our analysis of how farmers change their labour hiring decisions as a function of access to more skilful weather forecasts provides some clues as to the extent to which and how farmers adapt their farming practices when they receive a forecast suggesting extreme precipitation in the near future (three to six months). Specifically, we find that improved forecast skill is associated with farmers hiring additional labour in anticipation of extreme weather. This behaviour change, in response to a hydromet service, suggests a plausible pathway through which access to more skilled weather forecasts results in farmers being less likely to report experiencing crop losses. That is, farmers hire more labour to bring forward harvesting in response to more accurate forecasts of extreme weather. Our findings suggest further that this is particularly so where weather forecasts are more accurate, and where the deviation of the weather from the norm is more extreme; and that farmers are more responsive to more accurate extreme precipitation forecasts than more accurate extreme temperature forecasts, which could in turn be because precipitation extremes are more likely to rapidly harm harvests. This is an important contribution, by showing not just that more accurate hydromet services, in this case weather forecasts reduce the number of farmers reporting crop losses, but also by identifying one likely mechanism by which farmers are able to act on the information to avoid crop losses.

Unlike past studies, we use rigorous econometric approaches, with detailed data on weather forecasts and realised weather, so that we can also address the accuracy of actual weather forecasts that farmers have access to, controlling for a swathe of additional variables. In part, studies such as ours are so rare because consistent data of sufficient quality and spatial and temporal granularity are simply not available in many lower-income countries. Whilst our study cannot provide an economic value of weather forecasts for farmers, because household surveys rarely collect crop production and/or loss, it provides the first step in doing so, a step that to date has been missing.

6 Conclusions and next steps

To date there are no studies that provide robust measures of the value of weather forecasting services for farmers in lower-income countries, incorporating both forecasting skill and realised weather. More broadly, only a small number of peer-reviewed analyses of the value of weather forecasts in the agriculture sector have been identified by arguably the most up to date systematic review of the economic value of weather forecasts (Farkas et al., 2025). Those studies that have been identified tend to focus methodologically on “ex-ante theoretical evaluations ... stated preference studies (in particular contingent valuation) of hypothetical weather and climate services, experimental interventions; and ex-post observational studies using survey data and revealed preferences methods (in particular travel cost incurred to obtain the forecasts)”.

Ideally any attempt to provide more than a local case study requires not only accurate data on the location and accuracy of weather stations, but also an understanding of which farmers can access weather forecast data and which of those farmers actually use the data, combined with the farmers’ realised yields, and taking into account a wide range of confounding factors. Local case studies that, for example, might undertake some kind of randomised control trial where farmers have differential access to weather forecasts, could be a way to enable researchers to determine, on a small scale, the extent to which more accurate weather and climate forecasts enable farmers to reduce crop losses, and by how much, and therefore impute the economic value of improved such services.

An important next step would be to quantify those crop losses and therefore the marginal benefit of providing farmers with improved forecasting, and compare this with the cost of providing access to more accurate weather forecasts. This might also include considering in more detail how early warning systems could be explicitly incorporated to be most effective; what forecasts – monthly, three monthly, six monthly, for example – would be most useful for farmers; and how extension services could work better with these forecasts.

It is not obvious that farmers would benefit equally from access to improved weather forecasts. As such, it is likely to be important for policy makers to understand how, for example, this improved access affects development indicators more broadly, that could include food insecurity and distributional implications. A particularly important focal area could be smallholder farmers. In the literature there is considerable evidence that smallholder farmers are not as responsive to weather forecasts as farmers with larger landholdings. As such, it is particularly important to

understand not just whether farmers have access to weather forecasts but whether these forecasts are used and by whom. Increasingly it is recognised that farmers benefit from access to improved weather forecasts paired with specific recommendations on what needs to be done to optimize food production, such as how to minimize evaporation (Jones et al., 2000; Mabhaudhi et al, 2025). And further, it is ever more important to understand how indigenous knowledge can be incorporated into messaging to farmers in the context of a changing climate where historic understanding of weather and climate patterns has less relevance to the future.

We recognise that there are limitations to our analysis, given the current available data. Weather stations are unevenly distributed within each country, and may not have been sited with agricultural production in mind. Datasets have to be combined that have different spatial and temporal resolutions. And ideally we would have data on the extent of farmer crop losses, though these would be subject to considerable error, not just whether farmers reported that they experienced crop losses. Further, because the labour and crop-loss channels represent only part of the farmer's adjustment set, our estimates are likely a lower bound on the total value of improved forecast accuracy, since gains operating through the omitted margins are not captured, due to data limitations. That said, our findings are sufficiently robust that we can say with confidence that we have identified in the data clear evidence of farmers benefiting from more accurate weather and climate forecasts. Improved hydromet services, including improved access to accurate weather forecasts that we focus on in this paper, are going to be ever more important in the future, because the past experiences that farmers often rely on will, in a climate change world, become less useful as proxies for likely future weather.

References

- Abegunde, V.O., Sibanda, M. and Obi, A., 2019. Determinants of the adoption of climate-smart agricultural practices by small-scale farming households in King Cetshwayo District Municipality, South Africa. *Sustainability*, 12(1), p.195.
- Agnolucci, P., Rapti, C., Alexander, P., De Lipsis, V., Holland, R.A., Eigenbrod, F. and Ekins, P., 2020. Impacts of rising temperatures and farm management practices on global yields of 18 crops. *Nature Food*, 1(9), pp.562-571.
- Agyekum, T.P., Antwi-Agyei, P. and Dougill, A.J., 2022. The contribution of weather forecast information to agriculture, water, and energy sectors in East and West Africa: A systematic review. *Frontiers in Environmental Science*, 10, p.935696.
- Amegnaglo, C.J., Anaman, K.A., Mensah-Bonsu, A., Onumah, E.E. and Gero, F.A., 2017. Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa. *Climate Services*, 6, pp.1-11.
- Anuga, S.W. and Gordon, C., 2016. Adoption of climate-smart weather practices among smallholder food crop farmers in the Techiman municipal: Implication for crop yield. *Research Journal of Agriculture and Environmental Management*, 5(9), pp.279-286.
- Apriyana, Y., Surmaini, E., Estiningtyas, W., Pramudia, A., Ramadhani, F., Suciantini, S., Susanti, E., Purnamayani, R. and Syahbuddin, H., 2021. The Integrated Cropping Calendar Information System: A coping mechanism to climate variability for sustainable agriculture in Indonesia. *Sustainability*, 13(11), p.6495.
- Botai, C.M., Botai, J.O., Muchuru, S. and Ngwana, I., 2015. Hydrometeorological research in South Africa: A review. *Water*, 7(4), pp.1580-1594.
- Cegnar, T., Boogaard, H., Finkele, K., Lalic, B., Raymond, J., Lifka, S., Schultz, D.M. and Tarchiani, V., 2023. Toward effective communication of agrometeorological services. *Advances in Science and Research*, 20, pp.9-16.
- Colston, J.M., Ahmed, T., Mahopo, C., Kang, G., Kosek, M., de Sousa Junior, F., Shrestha, P.S., Svensen, E., Turab, A., Zaitchik, B. and The, M.E., 2018. Evaluating meteorological data from weather stations, and from satellites and global models for a multi-site epidemiological study. *Environmental research*, 165, pp.91-109.
- Diaz, D. and Moore, F., 2017. Quantifying the economic risks of climate change. *Nature Climate Change*, 7(11), pp.774-782.
- Ding, Y., Balcombe, K. and Robinson, E., 2021. Time discounting and implications for Chinese farmer responses to an upward trend in precipitation. *Journal of Agricultural Economics*, 72(3), pp.916-930.
- Egeru, A., 2016. Climate risk management information, sources and responses in a pastoral region in East Africa. *Climate Risk Management*, 11, pp.1-14.
- Fanzo, J., 2017. From big to small: the significance of smallholder farms in the global food system. *The Lancet Planetary Health*, 1(1), pp.e15-e16.
- FAO, 2021, *The State of Food and Agriculture 2021*
- Farkas, Hannah, Manuel Linsenmeier, Marta Talevi, Paolo Avner, Bramka Arga Jafino, and Moussa Sidibe. 2025. "The Economic Value of Weather Forecasts: A Quantitative Systematic Literature Review." *World Bank Policy Research Working Papers*, no. 11213 (September). <https://hdl.handle.net/10986/43709>.

- Gardezi, M. and Bronson, K., 2020. Examining the social and biophysical determinants of US Midwestern corn farmers' adoption of precision agriculture. *Precision Agriculture*, 21(3), pp.549-568.
- Goddard, L., Aitchellouche, Y., Baethgen, W., Dettinger, M., Graham, R., Hayman, P., Kadi, M., Martínez, R. and Meinke, H., 2010. Providing seasonal-to-interannual climate information for risk management and decision-making. *Procedia Environmental Sciences*, 1, pp.81-101.
- Guttman, A., Cooke, N., & Starr, C. M. (1994). Capillary electrophoresis separation of oligosaccharides: I. Effect of operational variables. *Electrophoresis*, 15(1), 1518-1522.
- Hansen, J.W., Mason, S.J., Sun, L. and Tall, A., 2011. Review of seasonal climate forecasting for agriculture in sub-Saharan Africa. *Experimental agriculture*, 47(2), pp.205-240.
- Jessoe, K., Manning, D.T. and Taylor, J.E., 2018. Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather. *The Economic Journal*, 128(608), pp.230-261.
- Jiri, O., Mafongoya, P.L., Mubaya, C. and Mafongoya, O., 2016. Seasonal climate prediction and adaptation using indigenous knowledge systems in agriculture systems in Southern Africa: a review. *Journal of Agricultural Science*, 8(5), pp.156-172.
- Jones, J.W., Hansen, J.W., Royce, F.S. and Messina, C.D., 2000. Potential benefits of climate forecasting to agriculture. *Agriculture, ecosystems & environment*, 82(1-3), pp.169-184.
- Kull, D., Riishojgaard, L.P., Eyre, J. and Varley, R.A., 2021. The value of surface-based meteorological observation data (p. 41). World Bank.
- Lesk, C., Anderson, W., Rigden, A., Coast, O., Jägermeyr, J., McDermid, S., Davis, K.F. and Konar, M., 2022. Compound heat and moisture extreme impacts on global crop yields under climate change. *Nature Reviews Earth & Environment*, 3(12), pp.872-889.
- Lesk, C., Rowhani, P. and Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), pp.84-87.
- Lo, H.M. and Dieng, M., 2015. Impact assessment of communicating seasonal climate forecasts in Kaffrine, Diourbel, Louga, Thies and Fatick (Niakhar) regions in Senegal: Final Report for CCAFS West Africa Regional Program.
- Lottering, S., Mafongoya, P. and Lottering, R., 2021. Drought and its impacts on small-scale farmers in sub-Saharan Africa: a review. *South African Geographical Journal*, 103(3), pp.319-341.
- Mabhaudhi, T., Dirwai, T.L., Taguta, C., Senzanje, A., Abera, W., Govid, A., Dossou-Yovo, E., Aynekulu, E. and Chimonyo, V.G.P., 2025. Linking weather and climate information services (WCIS) to Climate-Smart Agriculture (CSA) practices.
- Mapfumo, P., Mtambanengwe, F. and Chikowo, R., 2016. Building on indigenous knowledge to strengthen the capacity of smallholder farming communities to adapt to climate change and variability in southern Africa. *Climate and Development*, 8(1), pp.72-82.
- Mason, S.J., Krupnik, T.J., Hansen, J.W., Braun, M., Hussain, S.G., Khan, M.S.K., Mannan, A., Curtis, A., Han, E. and Kruczkiewicz, A., 2022. Re-prioritizing climate services for agriculture: Insights from Bangladesh. *Climate Services*, 27, p.100306.
- Meadow, A.M., Ferguson, D.B., Guido, Z., Horangic, A., Owen, G. and Wall, T., 2015. Moving toward the deliberate coproduction of climate science knowledge. *Weather, Climate, and Society*, 7(2), pp.179-191.

- Meque, A., Gamedze, S., Moitlhobogi, T., Booneedy, P., Samuel, S. and Mpalang, L., 2021. Numerical weather prediction and climate modelling: Challenges and opportunities for improving climate services delivery in Southern Africa. *Climate Services*, 23, p.100243.
- Meza, F.J., Hansen, J.W. and Osgood, D., 2008. Economic value of seasonal climate forecasts for agriculture: review of ex-ante assessments and recommendations for future research. *Journal of applied meteorology and climatology*, 47(5), pp.1269-1286.
- Mitter, H., Obermeier, K. and Schmid, E., 2024. Exploring smallholder farmers' climate change adaptation intentions in Tiruchirappalli District, South India. *Agriculture and Human Values*, pp.1-17.
- Naab, F.Z., Abubakari, Z. and Ahmed, A., 2019. The role of climate services in agricultural productivity in Ghana: The perspectives of farmers and institutions. *Climate Services*, 13, pp.24-32.
- Nepal, M., Ashfaq, M., Sharma, B.R., Shrestha, M.S., Khadgi, V.R. and Bruno Soares, M., 2024. Impact of weather and climate advisories on agricultural outcomes in Pakistan. *Scientific Reports*, 14(1), p.1036.
- Ng'asike, J.T., 2019. Indigenous knowledge practices for sustainable lifelong education in pastoralist communities of Kenya. *International Review of education*, 65(1), pp.19-46.
- Ngugi, R., Mureithi, S. and Kamande, P., 2011. Climate forecast information: the status, needs and expectations among smallholder agro-pastoralists in Machakos District, Kenya.
- Nkiaka, E., Taylor, A., Dougill, A.J., Antwi-Agyei, P., Fournier, N., Bosire, E.N., Konte, O., Lawal, K.A., Mutai, B., Mwangi, E. and Ticehurst, H., 2019. Identifying user needs for weather and climate services to enhance resilience to climate shocks in sub-Saharan Africa. *Environmental Research Letters*, 14(12), p.123003.
- Orke, Y.A. and Li, M.H., 2022. Impact of climate change on hydrometeorology and droughts in the Bilate Watershed, Ethiopia. *Water*, 14(5), p.729.
- Ouédraogo, M., Barry, S., Zougmore, R.B., Partey, S.T., Somé, L. and Baki, G., 2018. Farmers' willingness to pay for climate information services: Evidence from cowpea and sesame producers in Northern Burkina Faso. *Sustainability*, 10(3), p.611.
- Palmer, T.N., 2000. Predicting uncertainty in forecasts of weather and climate. *Reports on progress in Physics*, 63(2), pp.71-116.
- Paparrizos, S., Kumar, U., Amjath-Babu, T.S. and Ludwig, F., 2021. Are farmers willing to pay for participatory climate information services? Insights from a case study in peri-urban Khulna, Bangladesh. *Climate Services*, 23, p.100241.
- Paparrizos, S., Smolenaars, W., Gbangou, T., Slobbe, E.V. and 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(10), p.1041.
- Rasmussen, L.V., Mertz, O., Rasmussen, K., Nieto, H., Ali, A. and Maiga, I., 2014. Weather, climate, and resource information should meet the needs of Sahelian pastoralists. *Weather, Climate, and Society*, 6(4), pp.482-494.
- Rogers, D.P. and Tsirkunov, V.V., 2013. Weather and climate resilience: Effective preparedness through national meteorological and hydrological services. World Bank Publications.
- Sacks, W.J., Deryng, D., Foley, J.A. and Ramankutty, N., 2010. Crop planting dates: an analysis of global patterns. *Global ecology and biogeography*, 19(5), pp.607-620.

- Samonte, G.P., 2017. Economics of *Kappaphycus* spp. seaweed farming with special reference to the Central Philippines. *Tropical Seaweed Farming Trends, Problems and Opportunities: Focus on Kappaphycus and Eucheuma of Commerce*, pp.147-154.
- Schlenker, W. and Roberts, M.J., 2008. Estimating the impact of climate change on crop yields: The importance of nonlinear temperature effects (No. w13799). National Bureau of Economic Research.
- Schmitt, J., Offermann, F., Söder, M., Frühauf, C. and Finger, R., 2022. Extreme weather events cause significant crop yield losses at the farm level in German agriculture. *Food Policy*, 112, p.102359.
- Sonwa, D.J., Dieye, A., El Mzouri, E.H., Majule, A., Mugabe, F.T., Omolo, N., Wouapi, H., Obando, J. and Brooks, N., 2017. Drivers of climate risk in African agriculture. *Climate and Development*, 9(5), pp.383-398.
- Stern, R.D. and Cooper, P.J.M., 2011. Assessing climate risk and climate change using rainfall data—a case study from Zambia. *Experimental Agriculture*, 47(2), pp.241-266.
- Suckall, N. and Soares, M.B., 2022. Evaluating the benefits of weather and climate services in South Asia: a systematic review. *Regional Environmental Change*, 22(3), p.104.
- Takenouchi, K., 2020. Collaborative community weather information. *Disaster risk communication: A challenge from a social psychological perspective*, pp.65-81.
- Vaughan, C., Hansen, J., Roudier, P., Watkiss, P. and Carr, E., 2019. Evaluating agricultural weather and climate services in Africa: Evidence, methods, and a learning agenda. *Wiley Interdisciplinary Reviews: Climate Change*, 10(4), p.e586.
- Waaswa, A., Oywaya Nkurumwa, A., Mwangi Kibe, A. and Ngeno Kipkemai, J., 2022. Climate-Smart agriculture and potato production in Kenya: review of the determinants of practice. *Climate and Development*, 14(1), pp.75-90.
- Waldman, K.B., Vergopolan, N., Attari, S.Z., Sheffield, J., Estes, L.D., Caylor, K.K. and Evans, T.P., 2019. Cognitive biases about climate variability in smallholder farming systems in Zambia. *Weather, Climate, and Society*, 11(2), pp.369-383.
- Weisheimer, A. and Palmer, T.N., 2014. On the reliability of seasonal climate forecasts. *Journal of the Royal Society Interface*, 11(96), p.20131162.
- WMO, 2020. State of the Global Climate 2020
- WMO, 2023. WMO State of the Global Climate report
- WMO, 2015. Status of the global observing system for climate.
- World Bank, 2018. World Bank's Annual Report 2018.
- Zongo, B., Diarra, A., Barbier, B., Zorom, M., Yacouba, H. and Dogot, T., 2016. Farmers' perception and willingness to pay for climate information in Burkina Faso.

Appendix 1. Forecast skill as proxied by RMSE

We provide in this appendix a third measure of forecast skill, RMSE for all four countries. RMSE is the square root of average sum of square errors over the rolling window. The RMSE metric weights both bias and precision of forecasts by averaging instantaneous errors for the previous periods. As such, lower RMSE indicates more accurate forecasts. If we consider the mean temperature forecasted over the next three months for sub-national region i , the accuracy of forecasts can be represented with the root-mean-squared-error between forecast and realised temperatures and precipitation. As such, lower RMSE indicates more accurate forecasts. RMSE incorporates squared deviations, penalising large errors more heavily. As such, higher RMSE values represent worse forecast accuracy and the positive coefficient on RMSE indicates that larger forecast errors are associated with higher crop loss reporting by farmers. Across all three metrics, the relationship between forecast accuracy and crop loss outcomes is consistent: improved forecast skill is associated with reduced crop loss reporting.

RMSE across the four countries ranges from $\sim 1^\circ\text{C}$ to $\sim 4.5^\circ\text{C}$, these are represented in the columns of the regression tables below. Temporal variations in RMSE are smaller due to smoothing over six-month window. Our findings suggest that with more accurate forecasts indicated by lower RMSE – shown by marginal effect or the change in the proportion of farmers reporting crop losses due to increase in RMSE in the columns).

		(1)	(2)	(3)
Variable/RMSE		1-2	2-3	3-4
Temperature forecast		0.923*** (0.003)	2.452** (0.028)	4.914** (0.021)
Access to finance		-0.124*** (0.004)	-0.126*** (0.002)	-0.091*** (0.008)
Farm size	Small	0.157** (0.033)	0.179** (0.030)	0.196** (0.039)
	Large	-0.214*** (0.009)	-0.247*** (0.002)	-0.271*** (0.008)
Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table A1: Impact on number of farmers reporting crop losses by forecast skill in Ethiopia

		(1)	(2)	(3)	(4)
Variable/RMSE		1-2	2-3	3-4	4-4.5
Temperature forecast		0.817** (0.016)	1.963** (0.024)	2.687** (0.029)	4.113** (0.041)
Access to finance		-0.169*** (0.000)	-0.155*** (0.007)	-0.119*** (0.003)	-0.072* (0.059)
Farm size	Small	0.313** (0.022)	0.408** (0.043)	0.511** (0.023)	0.633** (0.045)
	Large	-0.303** (0.019)	-0.397*** (0.008)	-0.509** (0.031)	-0.587*** (0.004)
Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table A2: Impact on number of farmers reporting crop losses by forecast skill in Bangladesh

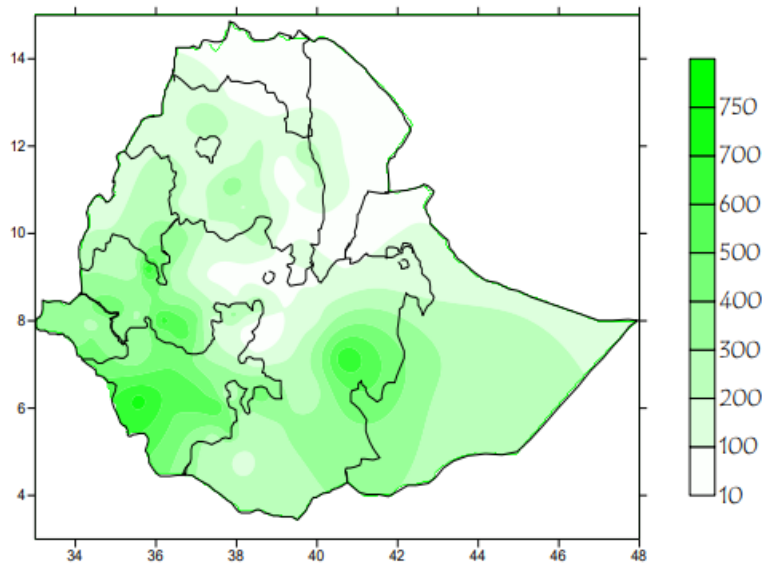
		(1)	(2)	(3)	(4)
Variable/RMSE		1-2	2-3	3-4	4-4.5
Temperature forecast		0.755** (0.024)	1.622** (0.029)	2.224** (0.021)	3.907** (0.026)
Access to finance		-0.110*** (0.006)	-0.180** (0.018)	-0.208*** (0.006)	-0.395 (0.127)
Farm size	Small	0.241** (0.038)	0.371** (0.031)	0.453** (0.030)	0.580** (0.037)
	Large	-0.214** (0.016)	-0.317*** (0.004)	-0.469*** (0.000)	0.600*** (0.001)
Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Table A3: Impact on number of farmers reporting crop losses by forecast skill in Tanzania

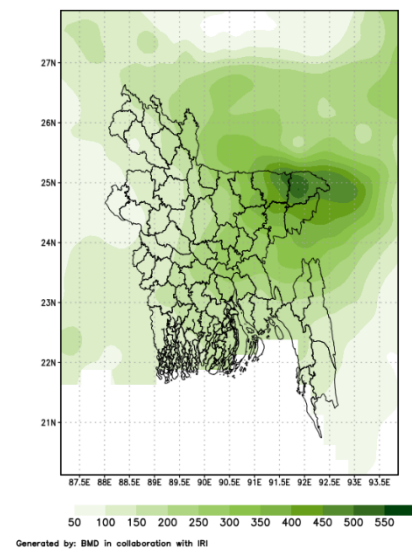
		(1)	(2)	(3)
Variable/RMSE		1-2	2-3	3-4
Temperature forecast		0.853** (0.022)	2.009** (0.015)	3.566** (0.030)
Access to finance		-0.107*** (0.000)	-0.137*** (0.006)	-0.203*** (0.000)
Farm size	Small	0.183** (0.028)	0.244** (0.026)	0.288** (0.023)
	Large	-0.189** (0.017)	-0.260*** (0.006)	-0.368*** (0.000)
Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Table A4: Impact on number of farmers reporting crop losses by forecast skill in Uganda

Appendix 2. Examples of forecast bulletins issued



**Ethiopia: Forecasted total precipitation
(October – December 2019)**



**Bangladesh: Forecasted total
precipitation (January – March 2019)**