Tailored forecasts can predict extreme climate informing proactive interventions in East Africa

Chris Funk[1], Laura Harrison[1], Zewdu Segele[2], Todd Stuart Rosenstock[3], peter steward[4], leigh anderson[5], Erin Coughlan-Perez[6], daniel maxwell[7], Hussen Seid Endris[8], Eunice Koech[8], guleid artan[8], Fetene Teshome[9], Stella Aura[10], Gideon Galu[11], Diriba Korecha[12], weston anderson[13], Andrew Hoell[14], kerstin damerau[15], Emily L Williams[16], Aniruddha gosh[4], Julian Ramirez Villegas[10], and david Peter hughes[17]

[1]University of California, Santa Barbara
[2]IGAD Climate Prediction and Applications Centre [ICPAC]
[3]World Agroforestry Centre
[4]Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity - CIAT)
[5]Marc Lindenberg Professor for Humanitarian Action, International Development and Global Citizenship, University of Washing
[6]Tufts University
[7]Friedman School of Nutrition, Tufts University
[8]IGAD Climate Prediction and Applications Center
[9]Ethiopian National Meteorology Department
[10]Unknown
[11]United States Geological Survey
[12]Famine Early Warning Systems Network
[13]Goddard Space Flight Center
[14]NOAA/ESRL/PSD
[15]Department of Global Development, Cornell University
[16]University of California Santa Barbara
[17]USAID Innovation Lab on Current and Emerging Threats to Crops, Pennsylvania State University

February 9, 2023

Abstract

This commentary discusses new advances in the predictability of east African rains and highlights the potential for improved early warning systems (EWS), humanitarian relief efforts, and agricultural decision-making. Following an unprecedented sequence of five droughts, in 2022 23 million east Africans faced starvation, requiring >$2 billion in aid. Here, we update climate attribution studies showing that these droughts resulted from an interaction of climate change and La Niña. Then we describe, for the first time, how attribution-based insights can be combined with the latest dynamic models to predict droughts at eight-month lead-times. We then discuss behavioral and social barriers to forecast use, and review literature examining how EWS might (or might not) enhance agro-pastoral advisories and humanitarian interventions. Finally, in reference to the new World Meteorological Organization (WMO) "Early Warning for All" plan, we conclude with a set of recommendations supporting actionable and

authoritative climate services. Trust, urgency, and accuracy can help overcome barriers created by limited funding, uncertain tradeoffs, and inertia. Understanding how climate change is producing predictable climate extremes now, investing in African-led EWS, and building better links between EWS and agricultural development efforts can support long-term adaptation, reducing chronic needs for billions of dollars in reactive assistance. The main messages of this commentary will be widely. Climate change is interacting with La Niña to produce extreme, but extremely predictable, Pacific sea surface temperature gradients. These gradients will affect the climate in many countries creating opportunities for prediction. Effective use of such predictions, however, will demand cross-silo collaboration.

Tailored forecasts can predict extreme climate informing proactive interventions in East Africa

Author	Position
Chris Funk	Director, Climate Hazards Center, University of California, Santa Barbara
Laura Harrison	Researcher, Climate Hazards Center
Zewdu Segele	Senior Climate Scientist, IGAD Climate Prediction and Applications Center
Todd Rosenstock	Principal Scientist, Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT)
Peter Steward	Scientist, Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT)
C. Leigh Anderson	Marc Lindenberg Professor for Humanitarian Action, International Development and Global Citizenship, University of Washington
Erin Coughlan-Perez	Research Director, Dignitas Professor, Friedman School of Nutrition, Tufts University
Daniel Maxwell	Henry J. Leir Professor in Food Security, Tufts University
Hussen Seid Endris	Researcher, IGAD Climate Prediction and Applications Center
Eunice Koch	Climate Modeling Assistant, IGAD Climate Prediction and Applications Center
Guleid Artan	Director, IGAD Climate Prediction and Applications Center
Fetene Teshome	Director, Ethiopian National Meteorological Agency
Stella Maris Aura	Director, Kenya Meteorological Department
Gideon Galu	FEWS NET Regional Scientist, East Africa
Diriba Korecha	FEWS NET Regional Scientist, Ethiopia
Andrew Hoell	NOAA Physical Sciences Laboratory
Weston Anderson	NASA GSFC, FEWS NET Science Team
Kerstin Damerau	Research Associate, Department of Global Development, Cornell University
Emily Williams	Researcher, Climate Hazards Center
Aniruddha Ghosh	Scientist – Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT)
Julian Ramirez-Villegas	Principal Scientist, Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT); Professor, Plant Production Systems group, Wageningen University & Research
David Hughes	Director of USAID Innovation Lab on Current and Emerging Threats to Crops, Pennsylvania State University

Abstract:

This commentary discusses new advances in the predictability of east African rains and highlights the potential for improved early warning systems (EWS), humanitarian relief efforts, and agricultural decision-making. Following an unprecedented sequence of five droughts, in 2022 23 million east Africans faced starvation, requiring >$2 billion in aid. Here, we update climate attribution studies showing that these droughts resulted from an interaction of climate change and La Niña. Then we describe, for the first time, how attribution-based insights can be combined with the latest dynamic models to predict droughts at eight-month lead-times. We then discuss behavioral and social barriers to forecast use, and review literature examining how EWS might (or might not) enhance agro-pastoral advisories and humanitarian interventions. Finally, in reference to the new World Meteorological Organization (WMO) "Early Warning for All" plan, we conclude with a set of recommendations supporting actionable and authoritative climate services. *Trust*, *urgency*, and *accuracy* can help overcome barriers created by *limited funding*, *uncertain tradeoffs,* and *inertia*. Understanding how climate change is producing predictable climate extremes now, investing in African-led EWS, and building better links between EWS and agricultural development efforts can support long-term adaptation, reducing chronic needs for billions of dollars in reactive assistance.

The main messages of this commentary will be widely. Climate change is interacting with La Niña to produce extreme, but extremely predictable, Pacific sea surface temperature gradients. These gradients will affect the climate in many countries creating opportunities for prediction. Effective use of such predictions, however, will demand cross-silo collaboration.

Plain language summary

Eastern East Africa is extremely food insecure. Millions of farmers and pastoralists rely on two meagre rainy seasons that arrive twice a year. In the thirteen seasons since late 2016, the region experienced eight droughts and three exceptionally wet seasons. Seven droughts were linked to exceptionally strong Pacific sea surface temperature gradients, which arose through an interaction between climate change and La Niña. For the first time, we show that these gradients can be very well predicted by the current generation of climate models. We then discuss how such information might be used to inform risk management, harvests, and livestock management practices. The IGAD Climate Predictions and Applications Center, Ethiopian and Kenyan meteorological agencies, and other groups are providing increasingly accurate climate information. This provides opportunities for more proactive and effective agricultural and pastoral advisory services. Trust, urgency and accuracy can lower uncertainty, reduce risk aversion, and empower poor households and cash-strapped institutions to act and innovate. As Climate change will bring more extreme (but predictable) Pacific and Indian Ocean sea surface temperature gradients. Investing now in collaborative African climate services, participatory advisory services and proactive risk management will help counter these threatening climate extremes.

Main Points

1. Climate change and La Niña are producing extreme Pacific temperature gradients, which can be predicted very far in advance.

2. These Pacific temperature forecasts provide opportunities for predicting wet and dry outcomes very well in East Africa.

3. Increased *trust, urgency and accuracy* can help overcome barriers associated with *limited funding*, *uncertain tradeoffs,* and *inertia.*

Main

In this commentary, an interdisciplinary, international set of authors describes how climate attribution studies have led to new advances in the predictability of Eastern Horn of Africa (EHoA) rains, and then explores how these forecasts might better guide humanitarian relief and proactive agricultural decisions in the future, leading to increased resilience (Fig. 1A). The team includes scientists from the IGAD Climate Prediction and Applications Center (ICPAC), the Famine Early Warning Systems Network (FEWS NET), Ethiopian and Kenyan Meteorological Departments, and scientists engaged in agricultural development, advisory services, and humanitarian relief efforts. Updating previously published climate attribution studies[1-7], we show that sequential EHoA droughts are tied to strong east-west sea surface temperature (SST) gradients, which arise through an interaction of human-caused climate change (hereafter referred to simply as climate change) and La Niña (Fig. 1). We then describe, for the first time in print, how the latest generation of climate models can predict these gradients and very warm west Pacific SSTs, and consequently EHoA droughts, at surprisingly long (eight-month) lead-times (Fig. 2). Given that climate change is likely to increase the frequency of these events (Fig. 3), we conclude with a discussion of the long-term implications of a potential increase in drought frequency. While many countries in East Africa have, in theory, policies supporting increased agricultural productivity and disaster risk management[8], in practice, millions of poor households remain vulnerable to climate shocks[9]. Could improved forecasts and EWS be useful to agricultural and food security decision-makers?

The schema in Fig. 1A lays out the logic of this Commentary. We first describe how climate change attribution leads to a tailored forecast process that produce more accurate long lead time forecasts. We then discuss how these forecasts might improve humanitarian relief planning, agricultural outcomes and food security *if* decision-makers are able to translate predictions into effective practice. Appropriately interpreting and communicating forecasts can decrease the uncertainty associated with trade-offs. This improves decision-making and makes information more actionable via technically feasible cost-effective response that addresses limited resources. Social and individual inertia potentially is reduced through localized, relevant information. We conclude by discussing how *trust*, *urgency*, and *accuracy* may help overcome barriers created by *limited funding*, *uncertain tradeoffs,* and *inertia*, and provide a set of recommendations related to effective EWS development and implementation in the context of climate change.

While focused on the EHoA, the techniques, opportunities, and barriers discussed here may be widely applicable to many areas exposed to risks associated with La Niñas. Human-induced warming in the west Pacific is interacting with natural El Niño-Southern Oscillation (ENSO) variability, but tailored forecasting approaches can translate the influence of climate change into expanded opportunities for prediction.

Background – volatile climate, humanitarian crises, but opportunities for predictions

Since late 2016, the EHoA (Ethiopia, Kenya, and Somalia to the east and south of 38°E and 8°N) has experienced a high degree of climate volatility, with recurrent shocks due to frequent droughts and floods. During this period, nine seasons were dry, three were wet, and only two had normal rains (Fig. 1B). Below-normal rains are inadequate to support productive crops and rangeland[10].

Seven of the dry eight dry seasons in Fig. 1B were anticipated with operational "tailored" forecasts[11], based on climate-change-enhanced west Pacific SST, La Niña, and strong Pacific SST gradients (with one false alarm in March-April-May, or MAM, 2018[11]). Hits, i.e., droughts that were accurately forecasted, included the back-to-back drought sequence in 2016/17[12] and the five sequential below-normal seasons stretching from October-November-December (OND) 2020 through OND 2022. These tailored forecasts benefitted from a two-step approach that 1) attributes droughts to extreme SST states, which arise through the interaction of natural variability and climate change (Fig. 1), then 2) predicts these states using the latest state-of-the-science climate forecast ensembles (Fig. 2).

EHoA's position makes it uniquely exposed to climatic hazards driven by Indo-Pacific SSTs. When SST gradients increase rains above the eastern Indian Ocean and western Pacific, rains decrease over EHoA. This links EHoA precipitation to La Niña and Indian Ocean Dipole (IOD) events. During OND, these connections are well-established. There is less consensus for MAM. Some research suggests MAM rains are weakly linked to SSTs[13-15], and hence, largely unpredictable. However, many FEWS NET studies[1-7] have attributed sequential OND/MAM dry seasons to Pacific SST gradients which arise through an interaction between La Niña and climate change.

These insights, combined with increasingly sophisticated climate forecast systems, has supported five successful long-lead forecasts in a row[11]. Eight months before the end of OND and MAM, strong Pacific SST gradients can be accurately predicted. In May[16] and November[17] of 2022, these inputs helped motivate exceptional multi-agency drought alerts. Never before had such a broad coalition of EHoA early warning experts acted so successfully so far in advance of the next rainy season. Yet, by late 2022, the interaction of five sequential droughts, COVID-19, conflict, inflation, and pre-existing vulnerabilities placed 23 million people in food security crises[17]. In Somalia, despite massive humanitarian responses reaching more than 7 million people, experts anticipated the outbreak of famine in 2023. Despite repeated, accurate predictions of drought (Fig. 1B), the magnitude of this crisis continued to grow. An EWS may begin with climate information, but requires effective transformation into actions which can increase resilience (Fig. 1A). This requires a shared understanding of how climate change and ENSO, together, offer opportunities for long lead predictions. Hence, we describe here the potential of these forecasts, and then discuss the opportunities and barriers associated with using such information within participatory agricultural advisory systems and humanitarian EWS for incentivizing adaption and reducing food insecurity. With more research and dialogue, the incorporation of such forecasts into operational forecast systems and policy-relevant decision-making processes may help our communities cope with increasing climate volatility, both in EHoA and in other areas linked to Indo-Pacific SSTs.

Data and Methods

This study relies on widely used Climate Hazard Center rainfall data sets[18,19] and NOAA Extended Reconstruction SST data[20]. The terms dry, normal, and wet correspond to bottom, middle, and top-tercile rainy season outcomes. To reduce repetition, we also use "drought" to refer to below-normal rainy seasons. Seasonal SST forecasts are based on the North American Multi-Model Ensemble (NMME)[21]. A 152-member, 25 model ensemble from the Coupled Model Intercomparison Project Phase 6 (CMIP6) is used to examine projected human-induced SST increases, based on a moderate emissions scenario (Shared Socioeconomic Pathway 2-4.5, SSP2-4.5)[22]. The attribution analyses, detailed in our first results section and presented in Fig. 1, are updates of climate attribution studies focused on the 2016/17 droughts[6,7]. These results[6,7] informed accurate tailored forecasts[11] (Fig. 2), which we describe in our second results section. We then describe increasing risks associated with CMIP6 projections of stronger future Pacific SST gradients, new spatially-explicit forecast results, and biochar-based farming practices in a third results section (Fig. 3). We then discuss how improved "climate-smart" decision-making might help regions cope with more frequent climate extremes. This discussion is guided by existing literature, ongoing policy-relevant activities in East Africa, the authors' experience, and the recently announced WMO "Early Warning for All" project[23].

Inclusion and Ethics: By design, this Commentary includes numerous authors from East Africa, as well as numerous collaborators in the US or Europe. The authors also represent several different communities of practice: climate, agricultural development, and food security. Effective dialog across these communities will be needed to guide effective adaptation. The collaboration supporting this article furthers that objective.

Results 1 – linking recent droughts to extremely warm Pacific SSTs and climate change

Scientists have long emphasized the societal dangers[24,25] associated with predictable[21,26-28] El Niños and La Niñas and climate change is expected to increase the frequency of strong ENSO and IOD events[29-32]. What is less appreciated is that the interaction of climate change and ENSO is creating opportunities for prediction—now. As climate change rapidly warms[33] dynamically important regions in the Indian[34-36] and Pacific Oceans[37,38], exceptionally warm ocean conditions can produce potentially predictable droughts and wet seasons[6,7,39]. For EHoA, this may be especially important for MAM, due to a strengthening connection to La Niña[40]. Figure 1C-F updates attribution studies that identified how extremely warm west Pacific SST contributed to droughts in 2016/17[6,7]. Composites of standardized contemporaneous SSTs during recent OND and MAM dry seasons (Fig. 1C,D) can help identify predictor zones. OND rains are influenced by IOD[41-43], ENSO/NINO3.4 SSTs[44], and the SSTs in the equatorial west Pacific[3,4,6]. The MAM rains are linked to SSTs in the southern Indian Ocean[45], and the Pacific

"Western V" and equatorial eastern Pacific regions[6,7]. When the equatorial west Pacific and "Western V" regions are exceptionally warm, the area around Indonesia sees increases in rainfall, while the EHoA often experiences sequential dry conditions in OND and MAM[3-7]. While the OND teleconnections (Fig. 1C) are well-appreciated, the strong MAM "teleconnections" implicit in Fig. 1D are not as well-appreciated.

Gradient indices provide a convenient short-hand to describe Indian and Pacific Basin SST patterns. While gradients are commonly used in the Indian Ocean[41], there remains a tendency to only describe the Pacific with equatorial eastern Pacific SSTs[46]. Such a focus can miss important interactions with climate change and lead to missed opportunities for skillful predictions[5,6].

We define two gradients useful for such predictions. For OND, we describe the Pacific via the "West Pacific Gradient" (WPG)[3]: the difference between standardized equatorial western and eastern Pacific SSTs (Pacific boxes in Fig. 1C). For MAM, we use a similar "Western V Gradient" (WVG), based on the difference between NINO3.4 and Western V temperatures (boxes in Fig. 1D). During MAM, there are important extratropical interactions with the northern and southern hemisphere subtropical westerly jets over the Pacific Ocean, which link warm extra-tropical northern and southern Pacific SST to La Niña-like climate impacts[6,7].

Following the 1997/98 El Niño, the western Pacific warmed substantially, and WPG and WVG values decreased dramatically (Fig. 1E). This set the stage for numerous, often sequential, EHoA dry seasons (noted with short vertical lines). This trend towards more frequent strong gradient events has been attributed to a combination of natural ENSO variability and human-induced warming in the western Pacific[6,7,47,48]. Strong upward SST trends in the equatorial west

Pacific[3], the western North Pacific[6], and the "Western V" region[7] have been formally linked to human-induced warming[6,7]. Warming in the already very warm west Pacific has enhanced observed La Niñas[3,6] in ways similar to climate change projections[49,50]. These exceptional Pacific gradient events have arisen alongside an exceptional number of 1998-2022 La Niña events—thirteen events in twenty-five years since 1998. Historically, La Niña events occur every three-to-five years[24,25]. Hence, very frequent La Niñas, a lack of a warming trend in the eastern Pacific[47,48], and rapid warming in the west Pacific have created a large increase in Pacific SST gradients (Fig. 1E), setting the stage for sequential droughts, especially during multi-year La Niñas[51]. However, wet EHoA rainy seasons, associated with exceptionally warm western Indian Ocean and eastern Pacific conditions, are also expected[29-36].

We briefly assess the role of climate change in recent extremely warm SST hot spots (Fig. 1F). The extremity of SST hot spots during recent extreme EHoA rainfall seasons is clear when compared to the past ~70 years, while climate model SST simulations highlight the very likely role of climate change. During the droughts in OND 2016/2020/2021 and MAM 2017/2021/2022, and the flooding in OND 2019[39], either the western Pacific or the western Indian Ocean was exceptionally warm. In Fig.1F, the observed SST anomalies for these seasons, represented as vertical black lines, are compared with CMIP6 ensemble PDFs for 1950-1979 and 2016-2022. The observed hot spots were +0.5 to 1°C above the 1950-2021 baseline. In a cooler world with less climate change (1950-1979), climate models indicate that the observed anomalies during these seasons were virtually impossible in such a world without climate change (Fig. 1F). The large offset between modeled SST in the recent period and historically much cooler conditions reflects a strong climate change signature in these areas. Diagnostic studies link EHoA rainfall extremes to these very warm SSTs[3,4,6,7,39]. Climate change helped produce these extreme WPG, WVG, and IOD values, and associated EHoA rainfall extremes. Can these warm ocean conditions be predicted well, offering opportunities for improved decision-making?

Results 2. The latest generation of climate models can predict these extreme ocean states well at eight month leads

Figure 2 presents exciting new examples of how climate change is interacting with natural variability to produce opportunities for long lead prediction. Each scatterplot shows NMME ***eight-month*** lead forecasts and actual outcomes: OND forecasts (left panels) were made in May, while MAM forecasts (right panels) were made in September. The first row presents the WPG and WVG indices, the western region component of the WPG and WVG indices. The second row displays equatorial west Pacific and Western V SSTs. Since mid-2020, such scatter plots have been used operationally[11] to inform FEWS NET's Food Security Outlook process[52]. These plots convey information about the predictability (high R^2) of the SSTs, as well as the potential association between extreme SST states and observed EHoA dry and wet rainy season outcomes (circle color).

At long leads, the WPG and WVG are predicted well (Fig. 2A), with R^2 values of greater than 70%. The uncertainty surrounding these forecasts are shown with 80% confidence intervals. These 80% confidence intervals can be used to assess the probability of being within a strong gradient season. In May, the models robustly anticipated strong negative WPG values associated with eight OND La Niña events. When such forecasts were made, there were below-normal EHoA seasons ***seven times out of eight***. These dry seasons are shown with orange circles in the left of 2A. When forecast MAM WVG values have been less than -0.4Z, as was anticipated in September 2023, dry seasons occurred ***nine times out of thirteen*** (orange circles, right side Fig.

2A). In late 2016, 2020, and 2021, WVG forecasts helped anticipate dry outcomes the following MAM[11,12]. Used in concert, WPG/WVG forecasts can anticipate sequential droughts (Fig. 1B).

Extreme West Pacific SST predictions, alone, are also useful drought indicators. Forecasts of exceptionally warm west Pacific SST clearly indicate strong tendencies for dry EHoA outcomes (Fig. 2B), and diagnostic studies have explained how these warm conditions modify winds in ways that reduce EHoA rains[6,7]. This information builds on the information contained in more traditional predictors, such as equatorial eastern Pacific (NINO3.4) SST forecasts. Knowing, with a high degree of certainty at long leads, that the western Pacific will be extremely warm allows us to bracket future drought events with higher confidence. These extreme SSTs are associated with climate change (Fig. 1F).

Results 3. Climate change simulations anticipate more 2020-2050 strong gradient La Niñas

Should we anticipate more WPG and WVG events in the future? To address this question, we examine the 1920-2050 OND and MAM Pacific SST gradients, derived from 152 CMIP6 SSP2-4.5 SST simulations[22]. For each year, for all of the simulations, we count the number of strong gradient events (WPG or WVG values less than -1Z) and translate those counts into a summary time-series (Fig. 3A). Due to warming in the west Pacific, all of the models indicate substantial (>30%) event frequency increases between 2020-2030 and 1920-1979. There is very consistent agreement on these changes across all the models (inset in Fig. 3A). The simulations (Fig. 3A), like the observations (Fig. 1E), suggest a strong tendency towards more frequent strong gradient events, such that in the 2020s, we expect strong gradient La Niña-like conditions about 50% of the time. This tendency is related to a strong anthropogenic ENSO-residual trend mode[53] that is closely related to the west Pacific warming, and will almost certainly increase over the next several decades (Fig. 3A) as the west Pacific continues to warm. This creates both an opportunity and a need for improved forecast information.

Results 4. Exploring spatially-explicit WVG-based MAM forecasts

If WPG/WVG events do become even more frequent, then enhanced forecast systems will be a critical tool for managing risk. One challenge associated with improving forecasts is the difficulty in linking research-based attribution studies[6,7,51] with the operational "consolidated" forecast system used by groups such as ICPAC (https://www.icpac.net/seasonal-forecast/). These forecasts use spatially explicit maps and are presented at seasonal Climate Outlook Fora in East Africa. The OND and MAM seasons differ in that MAM rains are not predicted well by climate models[54], because these rains are less spatially homogeneous[55] and can have non-linear relationships to SSTs, with more coherent links during droughts (e.g., Fig. 1D). ICPAC scientists, however, are now exploring the use of logistic regression, in conjunction with WVG forecasts, to produce experimental MAM forecast maps at long-leads (Fig. 3B), and such predictions are being used to support long-lead alerts[17]. Preliminary results from such approaches appear promising. Unlike Fig. 3B, the scatter plot-based forecasts shown in Fig. 2 lack the spatial dimension required to fit into ICPAC's map-based forecast streams. If gradient events become more frequent (Fig. 3A), these novel forecasting techniques may help capture the predictability inherent in extremely warm SST (Fig. 2A).

Discussion 1. Implications of these advances in the predictability: challenges

While Ethiopia, Kenya, and Somalia face many barriers to increased food security[56-59] and agricultural development[9] better climate predictions can support relief planning, policy, agricultural advising, and adaptation decisions. Yet, translating prediction to action is not straightforward[9]. Most east Africans are small-scale farmers with little mechanization and often nutrient-depleted soils[60]. These farmers are typically poor and risk-averse[9], which limits their ability and willingness to change farming practices. There is very limited uptake of innovative farming practices, crop insurance, and advisory services[9]. Since 2015, extreme climate has contributed to large increases in food insecurity[61,62].

While research has demonstrated that combinations of investment in resilience and early action can both protect lives and livelihoods and save money on humanitarian response in EHoA[63], research has also explored why humanitarian relief responses have often been inadequate[56-59]. The latter work has identified barriers associated with **limited funding**, **uncertain tradeoffs**, and **inertia**[56-59]. Adequate relief funding is always a challenge. Organizations face a financial trade-off: "*do I use these limited resources for real, known needs now, or do I devote them to mitigating future problems?*" This barrier also incorporates uncertainty and the fear that resources might be squandered, especially if the information is contradictory or confusing. Social inertia within national or international agencies provides another barrier. Relief agencies design their programs, identify their partners and beneficiaries, and make security arrangements. Changing these plans is difficult and slow because the plans are complex, and involve many partners.

Governments operate within limited budgets. Uncertain tradeoffs involve multiple stakeholders, the media, and competing goals. Will national insurance schemes reduce incentives for households to adapt? While traditional models assume that individuals make fully reasoned choices, decision-making itself is cognitively costly, individuals often employ "fast and frugal" heuristics[64,65]. These rules support decisions in the absence of full information. Despite some encouraging signs, there remain inconsistent findings in research on associations between farmers' perceptions of climate variability and the likelihood of them using weather and climate information services[66-68]. Decisions involve tradeoffs. Forecasts provide information on the probability of an adverse event, but they are silent on the risk of moving from the status quo. Yet, moving from the status quo also involves risk: adopting a new practice, crop, technology, or livelihood mix that may increase short-term resilience but prove to be maladaptive, resulting in negative impacts on crop yields, ecological health, or socioeconomic systems in the long run. For example, switching from a water-demanding crop like maize to drought-tolerant cassava often involves a tradeoff between lower risk and lower returns. A heuristic that mimics neighbor behaviors under conditions of covariant risk exposure and thin markets can lead to suboptimal outcomes, such as deflated prices for the livestock everyone is simultaneously selling to cope with a shock. Better predictions do not always translate into better decisions, as individuals tend to favor the known over the unknown, including known risks over unknown risks[69]. The risk-perception literature finds that individuals systematically overestimate the size of risks that are small, unfamiliar, involuntary, and uncertain, and contrastingly underestimate the size of risks that are larger, more certain, more familiar, or, over which they have some control[70-72]. The risk of extreme climate events in the EHoA is growing, unfortunately familiar, and now more predictable, but certainly not voluntary.

Discussion 2. Implications of these advances in the predictability of East African rains: opportunities

In theory, improving EWS may be one of the most cost-effective mechanisms for reducing food insecurity[73]. In practice, individual behavior change may never be sufficient to offset the negative consequences of catastrophic, covariant risks without public investment in large-scale insurance schemes and rural infrastructure. However, within that context, improving EWS and the distribution of related advisories is a crucial component in improving resilience.

The availability and influence of agricultural advisories remains very low in Africa[9]. Furthermore, such advisories may not respond to the unique needs of farmers: a recent survey[74] found that "*most climate services have been developed using a 'loading dock model', whereby products are designed by information suppliers with little input from … users.*" In contrast, co-developed services involve engagement and discussion between data providers, advisory service developers, and farmers. Table 1 provides some good examples of co-developed participatory agricultural advisory systems in Ghana, Rwanda[75], and Senegal[76,77]. In some non-African La Niña-impacted countries like Colombia, agro-advisories have helped maize farmers[78] and rice farmers[79,80] increase profits. Modest expenditures on improved advisories can improve yields by 30% or more.

In Ethiopia, multi-agency collaborators have developed the Ethiopian Digital AgroClimate Advisory Platform[81] (EDACaP, advisory.ethioagroclimate.net). EDACaP uses climate and weather forecasts in conjunction with soil and crop data to develop local language advisories that are distributed to development agents and farmers via text messages and radio.

In Kenya, collaboration between the Kenya Meteorological Department, PlantVillage, Shamba Shape Up, and the Climate Hazards Center is providing text and television-based advisories to more than 9 million Kenyans. These advisories incorporate high-resolution rainfall observations[19], weather forecasts[82], and WPG/WVG-based climate outlooks (Fig. 2). In addition to outreach, PlantVillage is piloting innovative strategies that promote drought resilience via labor-intensive cultivation practices that involve the digging of moisture retaining "Zai" pits and the introduction of biochar. Zai pits can hold up to nine seeds of maize and can be filled with organic manure, biochar, or dry plant biomass. Derived from local organic waste, biochar attracts and maintains nutrients and water in the soil. Despite the dry MAM 2022 rains, a pilot project based in Kilifi county in eastern Kenya (Fig. 3C) demonstrated the potential benefits. While control plots exhibited very low maize yields (< one ton per hectare), harvests in the test plots ranged from three-to-four tons per hectare. While more research and evaluation are required, WVG-based forecasts (Fig. 3B) hold the promise of supporting increased resilience, even in the face of severe droughts, as suggested by the pilot from Kilifi.

These advisory services are not costless, but are relatively inexpensive when compared to post-impact, response-based alternatives such as humanitarian assistance and/or funding safety-net programs. In Kenya, the cost of getting a single SMS-advisory into the hands of a farmer is \$0.006, and a farmer might typically receive 15 advisories per season. To reach 6-8 million farmers per week on TV is approximately \$3,000. Reaching 50 million farmers each year via SMS might cost \$4.5 million dollars. Localizing climate information, however, to agro-ecological and social contexts will require a considerable increase in resources.

From a policy perspective, the potential costs of EWS-empowered advisory systems might be compared to the >\$2 billion USD in humanitarian relief being provided in 2022 to Ethiopia, Kenya, and Somalia. Investments in advisory systems might save millions of dollars a year in east Africa alone, if they reduced the need for very expensive emergency relief while supporting resilience and autonomy.

Pilot studies (Table 1) suggest that ~30% increases in yields are plausible. In terms of historical variations, a 30% increase is a substantial increase. For example, in Kenya, poor MAM rains typically appear in association with a ~15% reduction in national maize yields. A 30% increase in national maize production (~1MT), represents a large sum of money, when valued at 2022 wholesale Kenyan maize prices (~US \$320 million). In addition to increased economic outcomes, increased crop production can reduce price volatility.

Discussion 3. Can long-lead forecasts be used to improve decision-making and increase resilience?

As sequential droughts become more common during La Niña events, responding to the first drought, which consistently arises in OND, may be a low-regret intervention, especially since MAM dry seasons often follow. Social protection via safety nets and insurance programs can support more effective resilience building at scale by integrating early action and preparedness[83]. Guaranteed funding before a shock can enhance the scalability, timeliness, predictability, and adequacy of social protection benefits. In 1998, 2010, 2016, 2020, 2021 and 2022, June forecasts of extremely warm west Pacific SSTs clearly indicated OND droughts (Fig. 2B) that led to widespread livestock loss and plummeting livestock prices. Index-Based Livestock Insurance (IBLI) is another promising intervention strategy that targets pastoralists and agropastoralists who face some of the most-extreme risks from drought[84]. Climate forecasts (Fig. 3B) might be combined with Predictive Livestock Early Warning Systems (PLEWS)[85] to improve predictions of forage conditions. More extreme precipitation may be recharging deep aquifers[86]. Accessing this water via boreholes might help buffer rainfall deficits.

There are opportunities to better link EWS with adaptation research. For example, the Evidence for Resilient Agriculture (ERA, https://era.ccafs.cgiar.org/) project provides data and tools that pinpoint what agricultural technologies work where. Resources like the Adaptation Atlas (http://adaptationatlas.cgiar.org/riskmap) allow decision-makers to examine climate change-related risks alongside potential solutions. Agroforestry, micro-credit, insurance, digital advisories, improved breeds, crops, forages and diets, fertilizer, intercropping, irrigation, mulch, trees, planting decisions, stress-adapted varietals, and water harvesting—the list of potential adaptations is long. African-led efforts that link EWS to appropriate local solutions can help us anticipate and adapt to more extreme climate.

Conclusion: recommendations vis-à-vis calls for improved early warning systems

In November 2022, at COP27, the UN Secretary-General unveiled the "Early Warnings for All Plan"[23] which provides $3.1 billion USD to support EWS in developing countries. The plan supports four disaster-risk reduction[84] pillars: 1) Disaster-risk knowledge, 2) Observations and Forecasting, 3) Preparedness and response, and 4) Dissemination and communication. EWS "*are a proven, effective, and feasible climate adaptation measure, that save lives, and provide a tenfold return on investment,"*[73] which have been recognized by the IPCC as a key adaptation strategy[87]. Within Africa, ICPAC, FEWS NET and the Kenyan and Ethiopian Meteorological Departments provide some of the most sophisticated EWS. This sophistication, the long-standing climate volatility, and food insecurity in the Horn, in addition to the many years of collective research and practical experience represented by the authors, provide us a vantage point from which to provide ten recommendations related to effective EWS development and implementation in the context of climate change. These recommendations are relevant for many regions linked to Indo-Pacific SSTs:

1. Realize that climate change is happening now and offers opportunities for prediction.
2. Realize that climate change contributed to recent extreme SSTs and associated EHoA droughts and floods, and that many of these extremes were predictable.
3. Realize that extreme SST gradients provide opportunities for forecasts.
4. Pay attention to extremely warm SSTs, these can drive predictable droughts and floods.
5. Be concerned about increasing aridity and declining per capita resources.
6. Work towards integrated observation/forecast systems.

7. Invest in building capacity. Utilize local expertise.
8. Look for places or seasons where conditions will likely be clement. Teleconnections will produce droughts, but also areas with bountiful rains.
9. Leverage agricultural adaptation resources to build resilience. Link EWS to the latest agricultural adaptation science.
10. Pay attention to barriers to climate information use, and learn from them.

Trust, **urgency**, and **accuracy** can enable action, helping overcome barriers associated with **funding**, **uncertain tradeoffs,** and **inertia**. Trust and urgency involve a shared understanding of how climate change is interacting with natural variability to produce frequent climate extremes, now. Trust also involves developing (and investing in) co-developed participatory advisory services: localized, culturally appropriate flows of information. Accuracy arises when we carefully combine domain-specific insights with the best-available information. For example, satellite observations and numerical model predictions are tremendous sources of information, but transforming this information into accurate rainfall estimates[19] or forecasts (Fig. 2, 3B) demands expertise. Predictions of exceptionally warm west Pacific SSTs (Fig. 2B) help anticipate the influence of climate change. While still evolving, inter-disciplinary collaboration is leading to first-in-kind long-lead alerts[16,17]. But the development of effective EWS in developing countries will require large investments in human capacity. "Loading dock" approaches to climate services can fail to provide locally appropriate advisory services[74] just as "raw" climate model forecasts may miss important teleconnections and opportunities for prediction, such as those shown in Fig. 2. Especially for MAM, long-lead drought outlooks would be substantially less skillful if they were just based on climate model rainfall forecasts[54] or equatorial east Pacific

SST predictions. Skill matters. For OND La Niña-related droughts, which the models capture well, effective actions based early alerts can build resilience in the face of sequential droughts.

Urgency arises from the long-term implications of extreme SST gradients (Fig. 3A), warming air temperatures, population growth, income gaps, and other socioeconomic and political stressors. Strong negative WPG/WVG gradients have become common (Fig. 1E). Climate change contributed to extreme gradients in 2016/17 and 2020/22 (Fig. 1F). These gradients helped produce an unprecedented five-season drought in the Horn. Given that the serial correlation of EHoA MAM and OND rains is very close to zero, the chance of a five-season drought sequence happening randomly is extremely low ($0.333^5 \approx 0.4\%$).

The frequency of strong gradient events is expected to increase dramatically (by >50%) by mid-century (Fig. 3A), which will likely increase in the frequency of poor EHoA rainy seasons. More frequent dry seasons may also be accompanied by more frequent El Niños and positive IOD events and extreme precipitation[30,31,50]. Increasing air temperatures contribute to both droughts and floods. Under dry conditions, warmer air draws more moisture from plants. Under wet conditions, warmer air holds more water vapor, leading to more extreme precipitation. Such influences contribute to "wet-getting-wetter" and "dry-getting-drier" tendencies in the Horn[88]. Observed EHoA crop water requirements are also trending upward during dry seasons, and these influences appear preferentially in hot-arid lowland areas[10,89]. Importantly, the spatial signature of these impacts largely aligns with the footprint of WPG/WVG-related drought tendencies.

Finally, increases in population and water scarcity are also likely to expand insecurity. UN projections suggest that between 2022 and 2050, the population of Ethiopia, Kenya, and Somalia, will increase by 70%. Holding other factors constant, population-driven per capita water availability projections for 2050 indicate the potential for severe water stress and scarcity[61]. Population-driven projections of Kenyan per capita maize production also indicate 40% reductions by 2050[89]. Planning for more frequent and severe extremes by enhancing EWS and advisory services can help mitigate these climate shocks.

The long-term implications of these compound stresses are very concerning, especially for the hot, dry EHoA lowlands. Yet, there is also hope that crop productivity can be increased in humid areas. Many areas of Ethiopia, and substantial portions of Kenya, are climatically secure. Some of these areas (most of Ethiopia) tend to experience rainfall increases during La Niña-like seasons. Closing yield gaps in humid regions would create wealth and lower food prices, and there is growing evidence that climate-enhanced advisories can contribute (Table 1). But achieving this promise will require much greater investments in African experts, experts who can improve and interpret forecasts, link to agricultural ministries, extension programs, and agricultural research centers, and, ultimately, farmers and pastoralists.

Data Availability:

The time series data supporting the primary results of this study are available via Dryad. Funk, Chris (2022), Data - Tailored forecasts can predict extreme climate informing proactive interventions in East Africa, Dryad, Dataset, https://doi.org/10.25349/D9MC8Z.

For now, the data is available at:

https://datadryad.org/stash/share/PxI2GIJv-4Q_C51wiHw-gySoI72xjRpl9_2euUONcM4

Code Availability: The bulk of the analysis presented in this paper are based on simple time-series manipulations, and are presented in the excel file in the Dryad link above. The most salient results can be recreated without coding, using the time series provided in the Dryad repository. Time-series extraction and the simple SST composite plots shown in Fig. 2C,D were done using Interactive Data Language version 8.7, and the related code is contained with the Dryad Repository. Zip files in that directory also contain NOAA extended reconstruction version 5 gridded SST data, NMME SST forecasts from May and September, and regionally averaged CMIP6 SSP245 SST time-series. For the convenience of the reviewers, the contents of the data repository are also available at: https://data.chc.ucsb.edu/people/chris/DataRepository.zip.

Table 1 | Exemplar case studies demonstrating the benefits of co-production and social networks in scaling climate-informed advisories.

Location	Agriculture decision affected	Benefit	Scaling potential	Behavior science for scaling	Distribution channel
Senegal	Crop varieties, field location, intercrop, crop type, crop mix, timing of sales, harvest & weeding, fertilizer use, water harvesting	Crop income increased between 10 and 25%	PICSA and WMG approaches can be easily scaled.	Multidisciplinary Working Groups (WMG) increase farmer's awareness of forecasts by 18%, access by 12% and uptake by 10%.	SMS, phone, Interactive radio, farmers share information word of mouth.
Rwanda	Crop type, Crop varieties, Timing of planting and land preparation, When and how to prepare land	With PICSA +24% production +36% income With PICSA+RLC +47% production +56% income	-PICSA and RLC approaches can be easily scaled.	Participatory Integrated Climate Services for Agriculture (PICSA) approach. Radio Learning Clubs (RLC) address disparities.	Radio, Phone, TV (43:11:7%) With RLC (81:37:9 %)
Ghana	Land preparation planting & harvest dates, crop varieties, fertilizer scheduling	+35% sorghum yields +6% technical Efficiency	Easily replicated. Requires mobile access. $35 subscription plus training costs	The most significant factor in forecast use was training.	Mobile (Voice Message, SMS, Call Centre)
Colombia, Guatemala, Honduras	Sowing & harvesting dates, rainwater harvesting, pest prevention, crop rotations, variety changes	Avoided income loss of 20%. +20-to-50% yield gain for rice, maize, bean	Government and local stakeholder uptake of LTAC approach enables scaling	Local Technical Agro-Climatic Committees (LTACs) where stakeholders discuss forecasts and develop recommendations.	Agroclimatic bulletin, radio, TV, newspaper, extension service, social networks

Figures

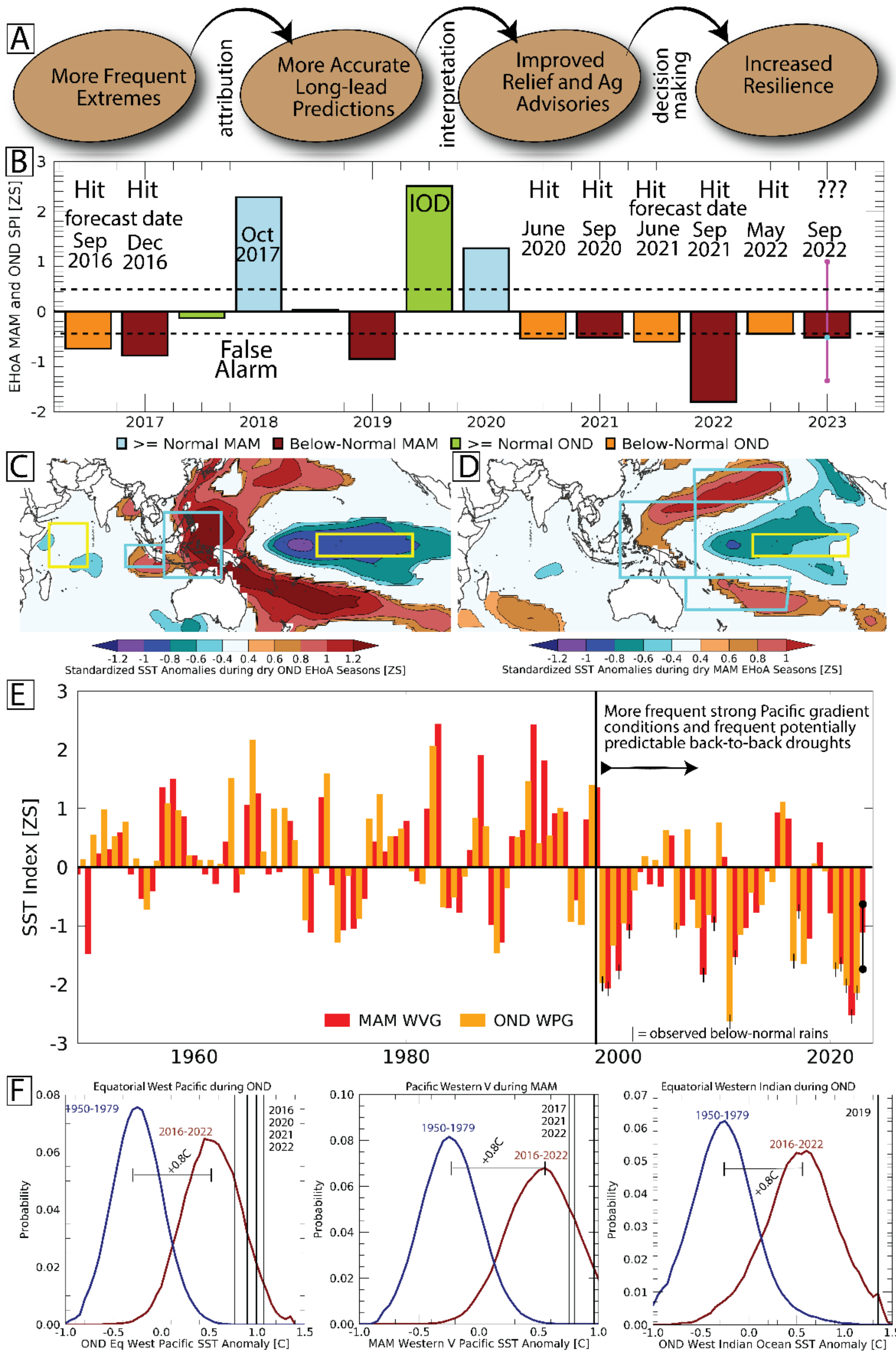

Figure 1. A. Schematic diagram describing the links between climate attribution, prediction and improved interventions. **B**. Barplot showing 2016-2023 regionally averaged EHoA MAM and

OND Standardized Precipitation Index values. Western Pacific Gradient (WPG) and Western 'V'-Gradient (WVG)-based drought forecast dates are noted for La Niña-related dry seasons, along with hit or false alarm outcomes. MAM 2023 result is a forecast, shown with 80% confidence intervals. **C**. Standardized OND SST composites for post-1996 dry EHoA OND seasons. Screened for significance at p=0.1. Boxes denote the western and eastern IOD regions, the equatorial west Pacific (110°E-140°E, 15°S-15°N), and the NINO3.4 region. **D**. Same for MAM EHoA dry seasons. Boxes denote the Western V (blue) (110°E-140°E, 15°S-15°N, 160°E-160°W, 20°N-35°N, 155°E-160°W, 15°S-30°S) and NINO3.4 (yellow) regions. **E**. SST index values for the observed MAM WVG and OND WPG. Anomalies calculated using a 1950-2020 baseline. The Pacific gradients associated with droughts (**1C,D**) are becoming more frequent (**1E**). Recent below-normal EHoA rainy seasons are marked with short vertical lines. The 2023 MAM WVG values are based on forecasts in Fig. 2. The black circles denote the associated 80% confidence intervals. The associated question mark conveys our concerns for a 6th dry season, based on the 2023 WVG forecast in Fig. 2. **F**. Equatorial OND western Pacific, MAM Western V, and OND western Indian Ocean CMIP6 SSP245 SST anomalies for 1950-1979 and 2016-2022, along with observed SST anomalies for selected drought seasons. Anomalies based on a 1950-2020 baseline.

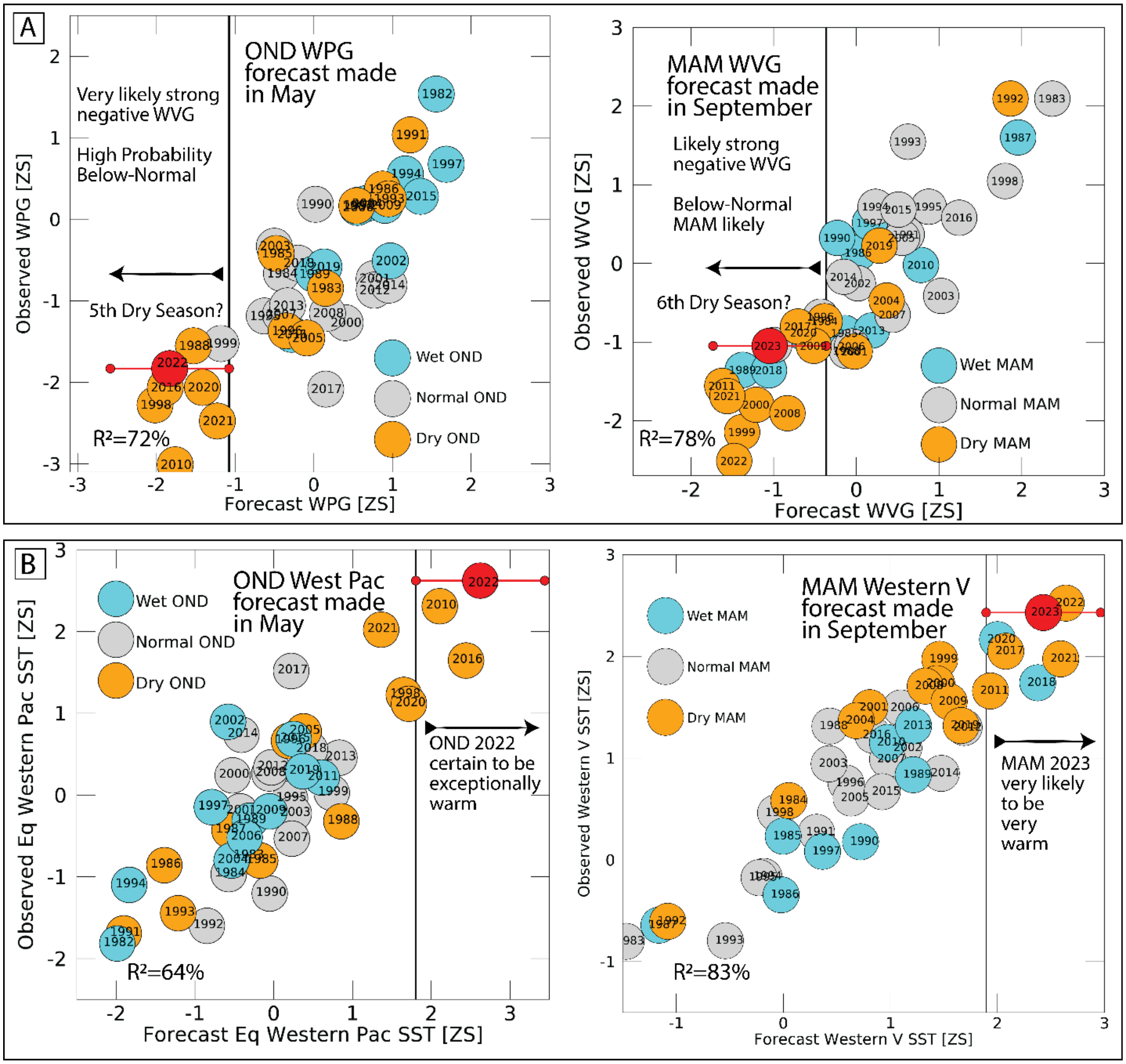

Figure 2. **A.** Scatterplots of forecast and observed WPG and WVG values. Left panels show 1982-2022 OND forecasts made in May. Right panels show 1983-2023 MAM forecasts made in September. OND 2022 and MAM 2023 'observations' are assumed to equal the forecasts. Vertical bars indicate 80% confidence intervals. Blue, gray and red circles denote the EHoA rainfall outcomes for each OND or MAM season. **B.** Same but for regionally averaged SST in equatorial western Pacific and Western V regions. Regions described in Fig. 1C,D.

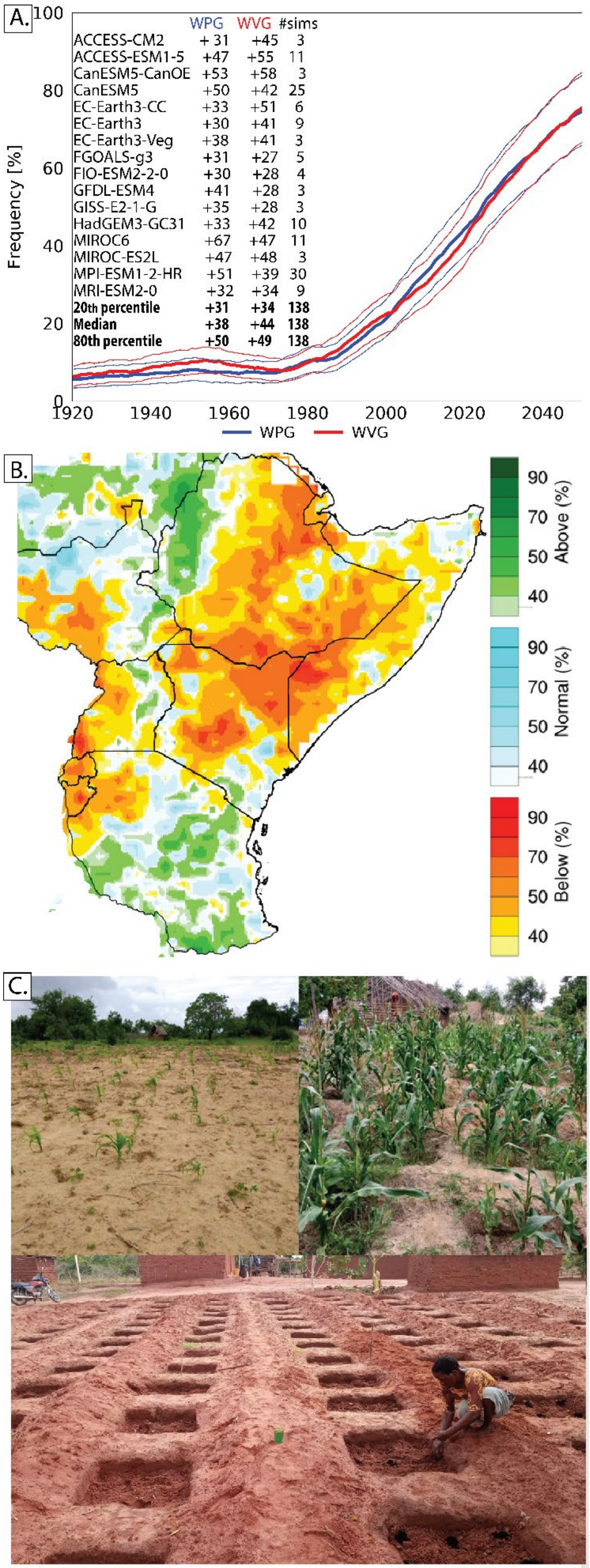
A.
WPG WVG #sims
ACCESS-CM2 +31 +45 3
ACCESS-ESM1-5 +47 +55 11
CanESM5-CanOE +53 +58 3
CanESM5 +50 +42 25
EC-Earth3-CC +33 +51 6
EC-Earth3 +30 +41 9
EC-Earth3-Veg +38 +41 3
FGOALS-g3 +31 +27 5
FIO-ESM2-2-0 +30 +28 4
GFDL-ESM4 +41 +28 3
GISS-E2-1-G +35 +28 3
HadGEM3-GC31 +33 +42 10
MIROC6 +67 +47 11
MIROC-ES2L +47 +48 3
MPI-ESM1-2-HR +51 +39 30
MRI-ESM2-0 +32 +34 9
20th percentile +31 +34 138
Median +38 +44 138
80th percentile +50 +49 138
Frequency [%]
WPG
WVG
B.
Above (%)
Normal (%)
Below (%)
C.

Figure 3. **A**. Time-series showing the median frequency of extreme OND WPG and MAM WVG events, based on standardized time-series from the CMIP6 SSP245 climate change ensemble, along with 95% confidence intervals. The WPG and WVG are calculated using SSTs from the Pacific boxes in Fig. 1A and 1B, respectively. Extreme negative OND WPG and MAM WVG events are associated with values less than -1Z. Change in extreme event frequencies (# of events per 100 years) were calculated by taking the frequency differences between 2020-2030 and 1920-1979, and are reported in the inset table for each model with at least three simulations. The 20^{th}, 50^{th} and 80^{th} percentile values of the per-model changes are shown in the last three columns. Time series were standardized using a 1950-2020 baseline. Human-induced warming in the western Pacific results in strong inter-model agreement on more frequent WPG and WVG events, in line with the observed gradient values shown in Fig. 1C. **B**. Experimental ICPAC forecasts for MAM 2023, based on localized logistic regressions and WVG forecasts. **C**. Test plot results in eastern Kenya from MAM 2022. Upper-left and right panels show adjacent control and test plots. Bottom panel shows field preparation using Zai pits and biochar.

References

1 Funk, C. *et al.* Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. *Proc Nat Acad Sci USA* **105**, 11081-11086 (2008).

2 Williams, P. & Funk, C. A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. *Climate Dynamics* **37**, 2417-2435 (2011).

3 Hoell, A. & Funk, C. The ENSO-Related West Pacific Sea Surface Temperature Gradient. *Journal of Climate* **26**, 9545-9562 (2013).

4 Hoell, A. & Funk, C. Indo-Pacific sea surface temperature influences on failed consecutive rainy seasons over eastern Africa. *Climate Dynamics* **43**, 1645-1660 (2013).

5 Funk , C. *et al.* Predicting East African spring droughts using Pacific and Indian Ocean sea surface temperature indices. *Hydrology and Earth System Sciences Discussions* **11**, 3111-3136 (2014).

6 Funk, C. *et al.* Examining the role of unusually warm Indo-Pacific sea surface temperatures in recent African droughts *Quart J Roy Meteor Soc* **144**, 360-383, doi:10.1002/qj.3266 (2018).

7 Funk, C. *et al.* Examining the potential contributions of extreme 'Western V' sea surface temperatures to the 2017 March-June East African Drought. *Bull. Amer. Meteor. Soc.* **100**, S55-S60 (2019).

8 Tadesse, T. Strategic framework for drought risk management and enhancing resilience in Africa, in *African Drought Conference.* 15-19 (2016).

9 Hansen, J. *et al.* Climate risk management and rural poverty reduction. *Agricultural Systems* **172**, 28-46 (2019).

10 Funk, C. *et al.* An Agro-Pastoral Phenological Water Balance Framework for Monitoring and Predicting Growing Season Water Deficits and Drought Stress. *Frontiers in Climate* **3**, doi:10.3389/fclim.2021.716568 (2021).

11 CHC/FEWSNET. in *blog.chc.ucsb.edu* (Climate Hazards Center, University of California, Santa Barbara, 2022). blog.chc.ucsb.edu/?p=10, blog.chc.ucsb.edu/?p=94, blog.chc.ucsb.edu/?p=283, blog.chc.ucsb.edu/?p=757, blog.chc.ucsb.edu/?p=868, blog.chc.ucsb.edu/?p=991, blog.chc.ucsb.edu/?p=1030, blog.chc.ucsb.edu/?p=1192, https://blog.chc.ucsb.edu/?p=1240.

12 Voosen, P. The hunger forecast. *Science* **368**, 226-229, doi:DOI: 10.1126/science.368.6488.226 (2020).

13 Yang, W., Seager, R., Cane, M. A. & Lyon, B. The East African Long Rains in Observations and Models. *Journal of Climate* **27**, 7185-7202, doi:10.1175/JCLI-D-13-00447.1 (2014).

14 Lyon, B. & DeWitt, D. G. A recent and abrupt decline in the East African long rains. *GEOPHYSICAL RESEARCH LETTERS* **39** (2012).

15 Lyon, B. Seasonal Drought in the Greater Horn of Africa and its Recent Increase During the March-May Long Rains. *Journal of Climate* **27**, 7953-7975 (2014).

16 ICPAC, C., FEWS NET, CHC, FAO, WMO, OCHA, IRI, WFP, Mercy Corps, UK Met Office, UKAID, UNHCR, Islamic Relief. The Threat of Starvation Looms in East Africa After Four Failed Rainy Seasons. *Multi-Agency Drought Alert* (2022). <https://www.fao.org/3/cc0312en/cc0312en.pdf>.

17 ICPAC *et al.* Immediate global action required to prevent Famine in the Horn of Africa. *Multi-agency Drought Alert* (2022). <https://fews.net/sites/default/files/Joint%20Alert%20on%202023%20MAM%20Rains%20Final_0.pdf>.

18 Funk, C. *et al.* The Centennial Trends Greater Horn of Africa precipitation dataset. *Scientific Data* **2**, doi:10.1038/sdata.2015.50 (2015).

19 Funk, C. *et al.* The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data* **2** (2015).

20 Huang, B. *et al.* Extended Reconstructed Sea Surface Temperature, Version 5 (ERSSTv5): Upgrades, Validations, and Intercomparisons. *Journal of Climate* **30**, 8179-8205, doi:10.1175/JCLI-D-16-0836.1 (2017).

21 Becker, E. J., Kirtman, B. P., L'Heureux, M., Muñoz, Á. G. & Pegion, K. A Decade of the North American Multimodel Ensemble (NMME): Research, Application, and Future Directions. *B Am Meteorol Soc* **103**, E973-E995 (2022).

22 Eyring, V. *et al.* Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development* **9**, 1937-1958 (2016).

23 WMO. *Early Warnings for All Action Plan unveiled at COP27*, <https://public.wmo.int/en/media/press-release/early-warnings-all-action-plan-unveiled-cop27> (2022).

24 Diaz, H. F. *El Niño and the Southern Oscillation: multiscale variability and global and regional impacts*. (Cambridge University Press, 2000).

25 Glantz, M. H. *Currents of change: impacts of El Niño and La Niña on climate and society*. (Cambridge University Press, 2001).

26 Barnston, A. G., Tippett, M. K., Ranganathan, M. & L'Heureux, M. L. Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. *Climate Dynamics* **53**, 7215-7234 (2019).

27 L'Heureux, M. L. *et al.* Observing and predicting the 2015/16 El Niño. *B Am Meteorol Soc* **98**, 1363-1382 (2017).

28 Tippett, M. K., Ranganathan, M., L'Heureux, M., Barnston, A. G. & DelSole, T. Assessing probabilistic predictions of ENSO phase and intensity from the North American Multimodel Ensemble. *Climate Dynamics*, doi:10.1007/s00382-017-3721-y (2017).

29 Cai, W. *et al.* Increasing frequency of extreme El Nino events due to greenhouse warming. *Nature Clim. Change* **4**, 111-116, doi:10.1038/nclimate2100 (2014).

30 Cai, W. *et al.* Increased ENSO sea surface temperature variability under four IPCC emission scenarios. *Nature Climate Change* **12**, 228-231, doi:10.1038/s41558-022-01282-z (2022).

31 Cai, W. *et al.* Increased frequency of extreme Indian Ocean Dipole events due to greenhouse warming. *Nature* **510**, 254-258 (2014).

32 Cai, W. *et al.* ENSO and greenhouse warming. *Nature Climate Change* (2015).

33 Cheng, L., Abraham, J., Hausfather, Z. & Trenberth, K. E. How fast are the oceans warming? *Science* **363**, 128-129 (2019).

34 Cai, W. *et al.* Opposite response of strong and moderate positive Indian Ocean Dipole to global warming. *Nature Climate Change* **11**, 27-32 (2021).

35 Ihara, C., Kushnir, Y. & Cane, M. A. Warming trend of the Indian Ocean SST and Indian Ocean dipole from 1880 to 2004. *Journal of Climate* **21**, 2035-2046 (2008).

36 Abram, N. J., Gagan, M. K., Cole, J. E., Hantoro, W. S. & Mudelsee, M. Recent intensification of tropical climate variability in the Indian Ocean. *Nat Geosci* **1**, 849-853 (2008).

37 Cravatte, S., Delcroix, T., Zhang, D., McPhaden, M. & Leloup, J. Observed freshening and warming of the western Pacific warm pool. *Climate Dynamics* **33**, 565-589 (2009).

38 Roxy, M. *et al.* Twofold expansion of the Indo-Pacific warm pool warps the MJO life cycle. *Nature* **575**, 647-651 (2019).

39 Nicholson, S. E., Fink, A. H., Funk, C., Klotter, D. A. & Satheesh, A. R. Meteorological causes of the catastrophic rains of October/November 2019 in equatorial Africa. *Global and Planetary Change* **208**, 103687 (2022).

40 Park, S., Kang, D., Yoo, C., Im, J. & Lee, M.-I. Recent ENSO influence on East African drought during rainy seasons through the synergistic use of satellite and reanalysis data. *ISPRS Journal of Photogrammetry and Remote Sensing* **162**, 17-26 (2020).

41 Saji, N. H., Goswami, B. N., Vinayachandran, P. N. & Yamagata, T. A dipole mode in the tropical Indian Ocean. *Nature* **401**, 360-363 (1999).

42 Saji, N. & Yamagata, T. Possible impacts of Indian Ocean dipole mode events on global climate. *Clim Res* **25**, 151-169 (2003).

43 Behera, S. K. *et al.* Paramount impact of the Indian Ocean dipole on the East African short rains: A CGCM study. *Journal of Climate* **18**, 4514-4530 (2005).

44 Indeje, M., Semazzi, F. H. & Ogallo, L. J. ENSO signals in East African rainfall seasons. *International Journal of Climatology* **20**, 19-46 (2000).

45 Wainwright, C. M. *et al.* 'Eastern African Paradox'rainfall decline due to shorter not less intense Long Rains. *npj Climate and Atmospheric Science* **2**, 1-9 (2019).

46 Trenberth, K. E. The definition of el nino. *B Am Meteorol Soc* **78**, 2771-2778 (1997).

47 Seager, R., Henderson, N. & Cane, M. Persistent discrepancies between observed and modeled trends in the tropical Pacific Ocean. *Journal of Climate*, 1-41, doi:10.1175/jcli-d-21-0648.1 (2022).

48 Seager, R. *et al.* Strengthening tropical Pacific zonal sea surface temperature gradient consistent with rising greenhouse gases. *Nature Climate Change* **9**, 517-522, doi:10.1038/s41558-019-0505-x (2019).

49 Cai, W. *et al.* Increased frequency of extreme La Niña events under greenhouse warming. *Nature Climate Change* **5**, 132-137 (2015).

50 Cai, W. *et al.* Increased variability of eastern Pacific El Niño under greenhouse warming. *Nature* **564**, 201-206 (2018).

51 Anderson, W. *et al.* Multi-year La Niña events and multi-season drought in the Horn of Africa. *Journal of Hydrometeorology* (2022).

52 Magadzire, T., Galu, G. & Verdin, J. How climate forecasts strengthen food security. *World Meteorological Organisation Bulletin - Special Issue on Water* **67** (2017). <https://public.wmo.int/en/resources/bulletin/how-climate-forecasts-strengthen-food-security>.

53 Funk, C. & Hoell, A. The leading mode of observed and CMIP5 ENSO-residual sea surface temperatures and associated changes in Indo-Pacific climate. *Journal of Climate* **28**, 4309-4329 (2015).

54 Shukla, S. *et al.* Assessing North American multimodel ensemble (NMME) seasonal forecast skill to assist in the early warning of anomalous hydrometeorological events over East Africa. *Climate Dynamics*, 1-17, doi:10.1007/s00382-016-3296-z (2016).

55 Nicholson, S. E. Climate and Climatic Variability of Rainfall over Eastern Africa. *Reviews of Geophysics*, doi:10.1002/2016RG000544 (2017).

56 Lentz, E. & Maxwell, D. G. Anticipating, Mitigating, and Responding to Crises: How Do Information Problems Constrain Action? *International Journal of Disaster Risk Reduction*, 81, 103242, https://doi.org/10.1016/j.ijdrr.2022.103242 (2022).

57 Maxwell, D. & Hailey, P. Towards anticipatory information systems and action: Notes on early warning and early action in East Africa. (Tufts University, Feinstein International Center, Friedman School of Nutrition Science and Policy, Boston, MA, 2020).

58 Maxwell, D. G. *Famine in Somalia*. (Oxford University Press, 2016).

59 Sarkar, A., Spatz, B. J., de Waal, A., Newton, C. & Maxwell, D. The Political Marketplace Framework and Mass Starvation: How Can Humanitarian Analysis, Early Warning and Response Be Improved? *Journal of Humanitarian Affairs* **3**, 43-55 (2021).

60 Giller, K. E. *et al.* Small farms and development in sub-Saharan Africa: Farming for food, for income or for lack of better options? *Food Sec* **13**, 1431-1454 (2021).

61 Funk, C. & Shukla, S. *Drought early warning and forecasting: theory and practice*. (Elsevier, 2020).

62 ICPAC *et al.* Unprecedented drought brings threat of starvation to millions in Ethiopia, Kenya, and Somalia. *Multi-Agency Drought Alert* (2022). <https://fews.net/sites/default/files/Joint%20Statement%20Horn%20of%20Africa%209%20June%202022.pdf>.

63 Venton, C. C., Fitzgibbon, C., Shitarek, T., Coulter, L. & Dooley, O. The economics of early response and disaster resilience: Lessons from Kenya and Ethiopia. *Final report* (2012).

64 Dosi, G., Napoletano, M., Roventini, A., Stiglitz, J. E. & Treibich, T. Rational heuristics? Expectations and behaviors in evolving economies with heterogeneous interacting agents. *Economic Inquiry* **58**, 1487-1516 (2020).

65 Luan, S., Reb, J. & Gigerenzer, G. Ecological rationality: Fast-and-frugal heuristics for managerial decision making under uncertainty. *Academy of Management Journal* **62**, 1735-1759 (2019).

66 Djido, A. *et al.* To what extent do weather and climate information services drive the adoption of climate-smart agriculture practices in Ghana? *Climate Risk Management* **32**, 100309 (2021).

67 Diouf, N. S. *et al.* Factors influencing gendered access to climate information services for farming in Senegal. *Gender, Technology and Development* **23**, 93-110 (2019).

68 Owusu Danquah, E. *et al.* Monitoring and modelling analysis of maize (Zea mays L.) yield gap in smallholder farming in Ghana. *Agriculture* **10**, 420 (2020).

69 Ellsberg, D. Risk, ambiguity, and the Savage axioms. *The quarterly journal of economics*, 643-669 (1961).

70 Cullen, A. C., Anderson, C. L., Biscaye, P. & Reynolds, T. W. Variability in cross-domain risk perception among smallholder farmers in Mali by gender and other demographic and attitudinal characteristics. *Risk analysis* **38**, 1361-1377 (2018).

71 Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S. & Combs, B. How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy sciences* **9**, 127-152 (1978).

72 Slovic, P. Perception of risk. *Science* **236**, 280-285 (1987).

73 Global Commission on Adaptation. Adapt now: A global call for leadership on climate resilience. (World Resources Institute, 2019).

74 Born, L., Prager, S., Ramirez-Villegas, J. & Imbach, P. A global meta-analysis of climate services and decision-making in agriculture. *Climate Services* **22**, 100231 (2021).
75 Ingabire, C. Closing Gender Gaps in Farmers' Access to Climate Information: The Case of Radio Listeners Clubs (RLCs) in Rwanda: Preliminary results of a mixed-method analysis. (2021).
76 Chiputwa, B., Blundo-Canto, G., Steward, P., Andrieu, N. & Ndiaye, O. Co-production, uptake of weather and climate services, and welfare impacts on farmers in Senegal: A panel data approach. *Agricultural Systems* **195**, 103309 (2022).
77 Chiputwa, B. *et al.* Transforming climate science into usable services: The effectiveness of co-production in promoting uptake of climate information by smallholder farmers in Senegal. *Climate Services* **20**, 100203 (2020).
78 Jimenez, D. *et al.* A scalable scheme to implement data-driven agriculture for small-scale farmers. *Global Food Security* **23**, 256-266 (2019).
79 Case, C. O., America, L. & Läderach, P. Cracking patterns in big data saves Colombian rice farmers' huge losses. *Tropical Agriculture (CIAT)* (2014).
80 Delerce, S. *et al.* Assessing weather-yield relationships in rice at local scale using data mining approaches. *PloS one* **11**, e0161620 (2016).
81 Seid, J., Demissie, T., Tesfaye, K., Tamene, L. & Solomon, D. Ethiopian Digital AgroClimate Advisory Platform (EDACaP) Technical Working Document| Brief version. (2020).
82 Harrison, L. *et al.* Advancing early warning capabilities with CHIRPS-compatible NCEP GEFS precipitation forecasts. *Scientific Data* **9**, 1-13 (2022).
83 Costella, C. *et al.* Scalable and sustainable: How to build anticipatory capacity into social protection systems. (2017).
84 Syll, M. M. A. Willingness to Pay for Index-Based Livestock Insurance by Pastoralists and Agropastoralists: Evidence from Senegal. *Int. J. of Innovative Science and Research* (2021).
85 Matere, J. *et al.* Predictive Livestock Early Warning System (PLEWS): Monitoring forage condition and implications for animal production in Kenya. *Weather and Climate Extremes* **27**, 100209 (2020).
86 Adloff, M. *et al.* Sustained water storage in Horn of Africa drylands dominated by seasonal rainfall extremes. *Geophysical Research Letters*, e2022GL099299 (2022).
87 Pörtner, H.-O. *et al.* Climate change 2022: Impacts, adaptation and vulnerability. *IPCC Sixth Assessment Report* (2022).
88 Haile, G. G. *et al.* Projected Impacts of Climate Change on Drought Patterns Over East Africa. *Earth's Future* **8**, e2020EF001502, doi:https://doi.org/10.1029/2020EF001502 (2020).
89 Funk, C., Way-Henthorne, J. & Turner, W. Phenological Water Balance Applications for Trend Analyses and Risk Management. *Frontiers in Climate* **3**, doi:10.3389/fclim.2021.716588 (2021).

Tailored forecasts can predict extreme climate informing proactive interventions in East Africa

Author	Position
Chris Funk	Director, Climate Hazards Center, University of California, Santa Barbara
Laura Harrison	Researcher, Climate Hazards Center
Zewdu Segele	Senior Climate Scientist, IGAD Climate Prediction and Applications Center
Todd Rosenstock	Principal Scientist, Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT)
Peter Steward	Scientist, Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT)
C. Leigh Anderson	Marc Lindenberg Professor for Humanitarian Action, International Development and Global Citizenship, University of Washington
Erin Coughlan-Perez	Research Director, Dignitas Professor, Friedman School of Nutrition, Tufts University
Daniel Maxwell	Henry J. Leir Professor in Food Security, Tufts University
Hussen Seid Endris	Researcher, IGAD Climate Prediction and Applications Center
Eunice Koch	Climate Modeling Assistant, IGAD Climate Prediction and Applications Center
Guleid Artan	Director, IGAD Climate Prediction and Applications Center
Fetene Teshome	Director, Ethiopian National Meteorological Agency
Stella Maris Aura	Director, Kenya Meteorological Department
Gideon Galu	FEWS NET Regional Scientist, East Africa
Diriba Korecha	FEWS NET Regional Scientist, Ethiopia
Andrew Hoell	NOAA Physical Sciences Laboratory
Weston Anderson	NASA GSFC, FEWS NET Science Team
Kerstin Damerau	Research Associate, Department of Global Development, Cornell University
Emily Williams	Researcher, Climate Hazards Center
Aniruddha Ghosh	Scientist – Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT)
Julian Ramirez-Villegas	Principal Scientist, Alliance of Biodiversity International and the International Center for Tropical Agriculture (Biodiversity – CIAT); Professor, Plant Production Systems group, Wageningen University & Research
David Hughes	Director of USAID Innovation Lab on Current and Emerging Threats to Crops, Pennsylvania State University

Abstract:

This commentary discusses new advances in the predictability of east African rains and highlights the potential for improved early warning systems (EWS), humanitarian relief efforts, and agricultural decision-making. Following an unprecedented sequence of five droughts, in 2022 23 million east Africans faced starvation, requiring >$2 billion in aid. Here, we update climate attribution studies showing that these droughts resulted from an interaction of climate change and La Niña. Then we describe, for the first time, how attribution-based insights can be combined with the latest dynamic models to predict droughts at eight-month lead-times. We then discuss behavioral and social barriers to forecast use, and review literature examining how EWS might (or might not) enhance agro-pastoral advisories and humanitarian interventions. Finally, in reference to the new World Meteorological Organization (WMO) "Early Warning for All" plan, we conclude with a set of recommendations supporting actionable and authoritative climate services. *Trust*, *urgency*, and *accuracy* can help overcome barriers created by *limited funding*, *uncertain tradeoffs,* and *inertia*. Understanding how climate change is producing predictable climate extremes now, investing in African-led EWS, and building better links between EWS and agricultural development efforts can support long-term adaptation, reducing chronic needs for billions of dollars in reactive assistance.

The main messages of this commentary will be widely. Climate change is interacting with La Niña to produce extreme, but extremely predictable, Pacific sea surface temperature gradients. These gradients will affect the climate in many countries creating opportunities for prediction. Effective use of such predictions, however, will demand cross-silo collaboration.

Plain language summary

Eastern East Africa is extremely food insecure. Millions of farmers and pastoralists rely on two meagre rainy seasons that arrive twice a year. In the thirteen seasons since late 2016, the region experienced eight droughts and three exceptionally wet seasons. Seven droughts were linked to exceptionally strong Pacific sea surface temperature gradients, which arose through an interaction between climate change and La Niña. For the first time, we show that these gradients can be very well predicted by the current generation of climate models. We then discuss how such information might be used to inform risk management, harvests, and livestock management practices. The IGAD Climate Predictions and Applications Center, Ethiopian and Kenyan meteorological agencies, and other groups are providing increasingly accurate climate information. This provides opportunities for more proactive and effective agricultural and pastoral advisory services. Trust, urgency and accuracy can lower uncertainty, reduce risk aversion, and empower poor households and cash-strapped institutions to act and innovate. As Climate change will bring more extreme (but predictable) Pacific and Indian Ocean sea surface temperature gradients. Investing now in collaborative African climate services, participatory advisory services and proactive risk management will help counter these threatening climate extremes.

Main Points

1. Climate change and La Niña are producing extreme Pacific temperature gradients, which can be predicted very far in advance.

2. These Pacific temperature forecasts provide opportunities for predicting wet and dry outcomes very well in East Africa.

3. Increased *trust, urgency and accuracy* can help overcome barriers associated with *limited funding*, *uncertain tradeoffs,* and *inertia.*

Main

In this commentary, an interdisciplinary, international set of authors describes how climate attribution studies have led to new advances in the predictability of Eastern Horn of Africa (EHoA) rains, and then explores how these forecasts might better guide humanitarian relief and proactive agricultural decisions in the future, leading to increased resilience (Fig. 1A). The team includes scientists from the IGAD Climate Prediction and Applications Center (ICPAC), the Famine Early Warning Systems Network (FEWS NET), Ethiopian and Kenyan Meteorological Departments, and scientists engaged in agricultural development, advisory services, and humanitarian relief efforts. Updating previously published climate attribution studies[1-7], we show that sequential EHoA droughts are tied to strong east-west sea surface temperature (SST) gradients, which arise through an interaction of human-caused climate change (hereafter referred to simply as climate change) and La Niña (Fig. 1). We then describe, for the first time in print, how the latest generation of climate models can predict these gradients and very warm west Pacific SSTs, and consequently EHoA droughts, at surprisingly long (eight-month) lead-times (Fig. 2). Given that climate change is likely to increase the frequency of these events (Fig. 3), we conclude with a discussion of the long-term implications of a potential increase in drought frequency. While many countries in East Africa have, in theory, policies supporting increased agricultural productivity and disaster risk management[8], in practice, millions of poor households remain vulnerable to climate shocks[9]. Could improved forecasts and EWS be useful to agricultural and food security decision-makers?

The schema in Fig. 1A lays out the logic of this Commentary. We first describe how climate change attribution leads to a tailored forecast process that produce more accurate long lead time forecasts. We then discuss how these forecasts might improve humanitarian relief planning, agricultural outcomes and food security *if* decision-makers are able to translate predictions into effective practice. Appropriately interpreting and communicating forecasts can decrease the uncertainty associated with trade-offs. This improves decision-making and makes information more actionable via technically feasible cost-effective response that addresses limited resources. Social and individual inertia potentially is reduced through localized, relevant information. We conclude by discussing how *trust*, *urgency*, and *accuracy* may help overcome barriers created by *limited funding*, *uncertain tradeoffs,* and *inertia*, and provide a set of recommendations related to effective EWS development and implementation in the context of climate change.

While focused on the EHoA, the techniques, opportunities, and barriers discussed here may be widely applicable to many areas exposed to risks associated with La Niñas. Human-induced warming in the west Pacific is interacting with natural El Niño-Southern Oscillation (ENSO) variability, but tailored forecasting approaches can translate the influence of climate change into expanded opportunities for prediction.

Background – volatile climate, humanitarian crises, but opportunities for predictions

Since late 2016, the EHoA (Ethiopia, Kenya, and Somalia to the east and south of 38°E and 8°N) has experienced a high degree of climate volatility, with recurrent shocks due to frequent droughts and floods. During this period, nine seasons were dry, three were wet, and only two had normal rains (Fig. 1B). Below-normal rains are inadequate to support productive crops and rangeland[10].

Seven of the dry eight dry seasons in Fig. 1B were anticipated with operational "tailored" forecasts[11], based on climate-change-enhanced west Pacific SST, La Niña, and strong Pacific SST gradients (with one false alarm in March-April-May, or MAM, 2018[11]). Hits, i.e., droughts that were accurately forecasted, included the back-to-back drought sequence in 2016/17[12] and the five sequential below-normal seasons stretching from October-November-December (OND) 2020 through OND 2022. These tailored forecasts benefitted from a two-step approach that 1) attributes droughts to extreme SST states, which arise through the interaction of natural variability and climate change (Fig. 1), then 2) predicts these states using the latest state-of-the-science climate forecast ensembles (Fig. 2).

EHoA's position makes it uniquely exposed to climatic hazards driven by Indo-Pacific SSTs. When SST gradients increase rains above the eastern Indian Ocean and western Pacific, rains decrease over EHoA. This links EHoA precipitation to La Niña and Indian Ocean Dipole (IOD) events. During OND, these connections are well-established. There is less consensus for MAM. Some research suggests MAM rains are weakly linked to SSTs[13-15], and hence, largely unpredictable. However, many FEWS NET studies[1-7] have attributed sequential OND/MAM dry seasons to Pacific SST gradients which arise through an interaction between La Niña and climate change.

These insights, combined with increasingly sophisticated climate forecast systems, has supported five successful long-lead forecasts in a row[11]. Eight months before the end of OND and MAM, strong Pacific SST gradients can be accurately predicted. In May[16] and November[17] of 2022, these inputs helped motivate exceptional multi-agency drought alerts. Never before had such a broad coalition of EHoA early warning experts acted so successfully so far in advance of the next rainy season. Yet, by late 2022, the interaction of five sequential droughts, COVID-19, conflict, inflation, and pre-existing vulnerabilities placed 23 million people in food security crises[17]. In Somalia, despite massive humanitarian responses reaching more than 7 million people, experts anticipated the outbreak of famine in 2023. Despite repeated, accurate predictions of drought (Fig. 1B), the magnitude of this crisis continued to grow. An EWS may begin with climate information, but requires effective transformation into actions which can increase resilience (Fig. 1A). This requires a shared understanding of how climate change and ENSO, together, offer opportunities for long lead predictions. Hence, we describe here the potential of these forecasts, and then discuss the opportunities and barriers associated with using such information within participatory agricultural advisory systems and humanitarian EWS for incentivizing adaption and reducing food insecurity. With more research and dialogue, the incorporation of such forecasts into operational forecast systems and policy-relevant decision-making processes may help our communities cope with increasing climate volatility, both in EHoA and in other areas linked to Indo-Pacific SSTs.

Data and Methods

This study relies on widely used Climate Hazard Center rainfall data sets[18,19] and NOAA Extended Reconstruction SST data[20]. The terms dry, normal, and wet correspond to bottom, middle, and top-tercile rainy season outcomes. To reduce repetition, we also use "drought" to refer to below-normal rainy seasons. Seasonal SST forecasts are based on the North American Multi-Model Ensemble (NMME)[21]. A 152-member, 25 model ensemble from the Coupled Model Intercomparison Project Phase 6 (CMIP6) is used to examine projected human-induced SST increases, based on a moderate emissions scenario (Shared Socioeconomic Pathway 2-4.5, SSP2-4.5)[22]. The attribution analyses, detailed in our first results section and presented in Fig. 1, are updates of climate attribution studies focused on the 2016/17 droughts[6,7]. These results[6,7] informed accurate tailored forecasts[11] (Fig. 2), which we describe in our second results section. We then describe increasing risks associated with CMIP6 projections of stronger future Pacific SST gradients, new spatially-explicit forecast results, and biochar-based farming practices in a third results section (Fig. 3). We then discuss how improved "climate-smart" decision-making might help regions cope with more frequent climate extremes. This discussion is guided by existing literature, ongoing policy-relevant activities in East Africa, the authors' experience, and the recently announced WMO "Early Warning for All" project[23].

Inclusion and Ethics: By design, this Commentary includes numerous authors from East Africa, as well as numerous collaborators in the US or Europe. The authors also represent several different communities of practice: climate, agricultural development, and food security. Effective dialog across these communities will be needed to guide effective adaptation. The collaboration supporting this article furthers that objective.

Results 1 – linking recent droughts to extremely warm Pacific SSTs and climate change

Scientists have long emphasized the societal dangers[24,25] associated with predictable[21,26-28] El Niños and La Niñas and climate change is expected to increase the frequency of strong ENSO and IOD events[29-32]. What is less appreciated is that the interaction of climate change and ENSO is creating opportunities for prediction—now. As climate change rapidly warms[33] dynamically important regions in the Indian[34-36] and Pacific Oceans[37,38], exceptionally warm ocean conditions can produce potentially predictable droughts and wet seasons[6,7,39]. For EHoA, this may be especially important for MAM, due to a strengthening connection to La Niña[40]. Figure 1C-F updates attribution studies that identified how extremely warm west Pacific SST contributed to droughts in 2016/17[6,7]. Composites of standardized contemporaneous SSTs during recent OND and MAM dry seasons (Fig. 1C,D) can help identify predictor zones. OND rains are influenced by IOD[41-43], ENSO/NINO3.4 SSTs[44], and the SSTs in the equatorial west Pacific[3,4,6]. The MAM rains are linked to SSTs in the southern Indian Ocean[45], and the Pacific

"Western V" and equatorial eastern Pacific regions[6,7]. When the equatorial west Pacific and "Western V" regions are exceptionally warm, the area around Indonesia sees increases in rainfall, while the EHoA often experiences sequential dry conditions in OND and MAM[3-7]. While the OND teleconnections (Fig. 1C) are well-appreciated, the strong MAM "teleconnections" implicit in Fig. 1D are not as well-appreciated.

Gradient indices provide a convenient short-hand to describe Indian and Pacific Basin SST patterns. While gradients are commonly used in the Indian Ocean[41], there remains a tendency to only describe the Pacific with equatorial eastern Pacific SSTs[46]. Such a focus can miss important interactions with climate change and lead to missed opportunities for skillful predictions[5,6].

We define two gradients useful for such predictions. For OND, we describe the Pacific via the "West Pacific Gradient" (WPG)[3]: the difference between standardized equatorial western and eastern Pacific SSTs (Pacific boxes in Fig. 1C). For MAM, we use a similar "Western V Gradient" (WVG), based on the difference between NINO3.4 and Western V temperatures (boxes in Fig. 1D). During MAM, there are important extratropical interactions with the northern and southern hemisphere subtropical westerly jets over the Pacific Ocean, which link warm extra-tropical northern and southern Pacific SST to La Niña-like climate impacts[6,7].

Following the 1997/98 El Niño, the western Pacific warmed substantially, and WPG and WVG values decreased dramatically (Fig. 1E). This set the stage for numerous, often sequential, EHoA dry seasons (noted with short vertical lines). This trend towards more frequent strong gradient events has been attributed to a combination of natural ENSO variability and human-induced warming in the western Pacific[6,7,47,48]. Strong upward SST trends in the equatorial west

Pacific[3], the western North Pacific[6], and the "Western V" region[7] have been formally linked to human-induced warming[6,7]. Warming in the already very warm west Pacific has enhanced observed La Niñas[3,6] in ways similar to climate change projections[49,50]. These exceptional Pacific gradient events have arisen alongside an exceptional number of 1998-2022 La Niña events—thirteen events in twenty-five years since 1998. Historically, La Niña events occur every three-to-five years[24,25]. Hence, very frequent La Niñas, a lack of a warming trend in the eastern Pacific[47,48], and rapid warming in the west Pacific have created a large increase in Pacific SST gradients (Fig. 1E), setting the stage for sequential droughts, especially during multi-year La Niñas[51]. However, wet EHoA rainy seasons, associated with exceptionally warm western Indian Ocean and eastern Pacific conditions, are also expected[29-36].

We briefly assess the role of climate change in recent extremely warm SST hot spots (Fig. 1F). The extremity of SST hot spots during recent extreme EHoA rainfall seasons is clear when compared to the past ~70 years, while climate model SST simulations highlight the very likely role of climate change. During the droughts in OND 2016/2020/2021 and MAM 2017/2021/2022, and the flooding in OND 2019[39], either the western Pacific or the western Indian Ocean was exceptionally warm. In Fig.1F, the observed SST anomalies for these seasons, represented as vertical black lines, are compared with CMIP6 ensemble PDFs for 1950-1979 and 2016-2022. The observed hot spots were +0.5 to 1°C above the 1950-2021 baseline. In a cooler world with less climate change (1950-1979), climate models indicate that the observed anomalies during these seasons were virtually impossible in such a world without climate change (Fig. 1F). The large offset between modeled SST in the recent period and historically much cooler conditions reflects a strong climate change signature in these areas. Diagnostic studies link EHoA rainfall extremes to these very warm SSTs[3,4,6,7,39]. Climate change helped produce these extreme WPG, WVG, and IOD values, and associated EHoA rainfall extremes. Can these warm ocean conditions be predicted well, offering opportunities for improved decision-making?

Results 2. The latest generation of climate models can predict these extreme ocean states well at eight month leads

Figure 2 presents exciting new examples of how climate change is interacting with natural variability to produce opportunities for long lead prediction. Each scatterplot shows NMME ***eight-month*** lead forecasts and actual outcomes: OND forecasts (left panels) were made in May, while MAM forecasts (right panels) were made in September. The first row presents the WPG and WVG indices, the western region component of the WPG and WVG indices. The second row displays equatorial west Pacific and Western V SSTs. Since mid-2020, such scatter plots have been used operationally[11] to inform FEWS NET's Food Security Outlook process[52]. These plots convey information about the predictability (high R^2) of the SSTs, as well as the potential association between extreme SST states and observed EHoA dry and wet rainy season outcomes (circle color).

At long leads, the WPG and WVG are predicted well (Fig. 2A), with R^2 values of greater than 70%. The uncertainty surrounding these forecasts are shown with 80% confidence intervals. These 80% confidence intervals can be used to assess the probability of being within a strong gradient season. In May, the models robustly anticipated strong negative WPG values associated with eight OND La Niña events. When such forecasts were made, there were below-normal EHoA seasons ***seven times out of eight***. These dry seasons are shown with orange circles in the left of 2A. When forecast MAM WVG values have been less than -0.4Z, as was anticipated in September 2023, dry seasons occurred ***nine times out of thirteen*** (orange circles, right side Fig.

2A). In late 2016, 2020, and 2021, WVG forecasts helped anticipate dry outcomes the following MAM[11,12]. Used in concert, WPG/WVG forecasts can anticipate sequential droughts (Fig. 1B).

Extreme West Pacific SST predictions, alone, are also useful drought indicators. Forecasts of exceptionally warm west Pacific SST clearly indicate strong tendencies for dry EHoA outcomes (Fig. 2B), and diagnostic studies have explained how these warm conditions modify winds in ways that reduce EHoA rains[6,7]. This information builds on the information contained in more traditional predictors, such as equatorial eastern Pacific (NINO3.4) SST forecasts. Knowing, with a high degree of certainty at long leads, that the western Pacific will be extremely warm allows us to bracket future drought events with higher confidence. These extreme SSTs are associated with climate change (Fig. 1F).

Results 3. Climate change simulations anticipate more 2020-2050 strong gradient La Niñas

Should we anticipate more WPG and WVG events in the future? To address this question, we examine the 1920-2050 OND and MAM Pacific SST gradients, derived from 152 CMIP6 SSP2-4.5 SST simulations[22]. For each year, for all of the simulations, we count the number of strong gradient events (WPG or WVG values less than -1Z) and translate those counts into a summary time-series (Fig. 3A). Due to warming in the west Pacific, all of the models indicate substantial (>30%) event frequency increases between 2020-2030 and 1920-1979. There is very consistent agreement on these changes across all the models (inset in Fig. 3A). The simulations (Fig. 3A), like the observations (Fig. 1E), suggest a strong tendency towards more frequent strong gradient events, such that in the 2020s, we expect strong gradient La Niña-like conditions about 50% of the time. This tendency is related to a strong anthropogenic ENSO-residual trend mode[53] that is closely related to the west Pacific warming, and will almost certainly increase over the next several decades (Fig. 3A) as the west Pacific continues to warm. This creates both an opportunity and a need for improved forecast information.

Results 4. Exploring spatially-explicit WVG-based MAM forecasts

If WPG/WVG events do become even more frequent, then enhanced forecast systems will be a critical tool for managing risk. One challenge associated with improving forecasts is the difficulty in linking research-based attribution studies[6,7,51] with the operational "consolidated" forecast system used by groups such as ICPAC (https://www.icpac.net/seasonal-forecast/). These forecasts use spatially explicit maps and are presented at seasonal Climate Outlook Fora in East Africa. The OND and MAM seasons differ in that MAM rains are not predicted well by climate models[54], because these rains are less spatially homogeneous[55] and can have non-linear relationships to SSTs, with more coherent links during droughts (e.g., Fig. 1D). ICPAC scientists, however, are now exploring the use of logistic regression, in conjunction with WVG forecasts, to produce experimental MAM forecast maps at long-leads (Fig. 3B), and such predictions are being used to support long-lead alerts[17]. Preliminary results from such approaches appear promising. Unlike Fig. 3B, the scatter plot-based forecasts shown in Fig. 2 lack the spatial dimension required to fit into ICPAC's map-based forecast streams. If gradient events become more frequent (Fig. 3A), these novel forecasting techniques may help capture the predictability inherent in extremely warm SST (Fig. 2A).

Discussion 1. Implications of these advances in the predictability: challenges

While Ethiopia, Kenya, and Somalia face many barriers to increased food security[56-59] and agricultural development[9] better climate predictions can support relief planning, policy, agricultural advising, and adaptation decisions. Yet, translating prediction to action is not straightforward[9]. Most east Africans are small-scale farmers with little mechanization and often nutrient-depleted soils[60]. These farmers are typically poor and risk-averse[9], which limits their ability and willingness to change farming practices. There is very limited uptake of innovative farming practices, crop insurance, and advisory services[9]. Since 2015, extreme climate has contributed to large increases in food insecurity[61,62].

While research has demonstrated that combinations of investment in resilience and early action can both protect lives and livelihoods and save money on humanitarian response in EHoA[63], research has also explored why humanitarian relief responses have often been inadequate[56-59]. The latter work has identified barriers associated with **limited funding**, **uncertain tradeoffs**, and **inertia**[56-59]. Adequate relief funding is always a challenge. Organizations face a financial trade-off: "*do I use these limited resources for real, known needs now, or do I devote them to mitigating future problems?*" This barrier also incorporates uncertainty and the fear that resources might be squandered, especially if the information is contradictory or confusing. Social inertia within national or international agencies provides another barrier. Relief agencies design their programs, identify their partners and beneficiaries, and make security arrangements. Changing these plans is difficult and slow because the plans are complex, and involve many partners.

Governments operate within limited budgets. Uncertain tradeoffs involve multiple stakeholders, the media, and competing goals. Will national insurance schemes reduce incentives for households to adapt? While traditional models assume that individuals make fully reasoned choices, decision-making itself is cognitively costly, individuals often employ "fast and frugal" heuristics[64,65]. These rules support decisions in the absence of full information. Despite some encouraging signs, there remain inconsistent findings in research on associations between farmers' perceptions of climate variability and the likelihood of them using weather and climate information services[66-68]. Decisions involve tradeoffs. Forecasts provide information on the probability of an adverse event, but they are silent on the risk of moving from the status quo. Yet, moving from the status quo also involves risk: adopting a new practice, crop, technology, or livelihood mix that may increase short-term resilience but prove to be maladaptive, resulting in negative impacts on crop yields, ecological health, or socioeconomic systems in the long run. For example, switching from a water-demanding crop like maize to drought-tolerant cassava often involves a tradeoff between lower risk and lower returns. A heuristic that mimics neighbor behaviors under conditions of covariant risk exposure and thin markets can lead to suboptimal outcomes, such as deflated prices for the livestock everyone is simultaneously selling to cope with a shock. Better predictions do not always translate into better decisions, as individuals tend to favor the known over the unknown, including known risks over unknown risks[69]. The risk-perception literature finds that individuals systematically overestimate the size of risks that are small, unfamiliar, involuntary, and uncertain, and contrastingly underestimate the size of risks that are larger, more certain, more familiar, or, over which they have some control[70-72]. The risk of extreme climate events in the EHoA is growing, unfortunately familiar, and now more predictable, but certainly not voluntary.

Discussion 2. Implications of these advances in the predictability of East African rains: opportunities

In theory, improving EWS may be one of the most cost-effective mechanisms for reducing food insecurity[73]. In practice, individual behavior change may never be sufficient to offset the negative consequences of catastrophic, covariant risks without public investment in large-scale insurance schemes and rural infrastructure. However, within that context, improving EWS and the distribution of related advisories is a crucial component in improving resilience.

The availability and influence of agricultural advisories remains very low in Africa[9]. Furthermore, such advisories may not respond to the unique needs of farmers: a recent survey[74] found that "*most climate services have been developed using a 'loading dock model', whereby products are designed by information suppliers with little input from … users."* In contrast, co-developed services involve engagement and discussion between data providers, advisory service developers, and farmers. Table 1 provides some good examples of co-developed participatory agricultural advisory systems in Ghana, Rwanda[75], and Senegal[76,77]. In some non-African La Niña-impacted countries like Colombia, agro-advisories have helped maize farmers[78] and rice farmers[79,80] increase profits. Modest expenditures on improved advisories can improve yields by 30% or more.

In Ethiopia, multi-agency collaborators have developed the Ethiopian Digital AgroClimate Advisory Platform[81] (EDACaP, advisory.ethioagroclimate.net). EDACaP uses climate and weather forecasts in conjunction with soil and crop data to develop local language advisories that are distributed to development agents and farmers via text messages and radio.

In Kenya, collaboration between the Kenya Meteorological Department, PlantVillage, Shamba Shape Up, and the Climate Hazards Center is providing text and television-based advisories to more than 9 million Kenyans. These advisories incorporate high-resolution rainfall observations[19], weather forecasts[82], and WPG/WVG-based climate outlooks (Fig. 2). In addition to outreach, PlantVillage is piloting innovative strategies that promote drought resilience via labor-intensive cultivation practices that involve the digging of moisture retaining "Zai" pits and the introduction of biochar. Zai pits can hold up to nine seeds of maize and can be filled with organic manure, biochar, or dry plant biomass. Derived from local organic waste, biochar attracts and maintains nutrients and water in the soil. Despite the dry MAM 2022 rains, a pilot project based in Kilifi county in eastern Kenya (Fig. 3C) demonstrated the potential benefits. While control plots exhibited very low maize yields (< one ton per hectare), harvests in the test plots ranged from three-to-four tons per hectare. While more research and evaluation are required, WVG-based forecasts (Fig. 3B) hold the promise of supporting increased resilience, even in the face of severe droughts, as suggested by the pilot from Kilifi.

These advisory services are not costless, but are relatively inexpensive when compared to post-impact, response-based alternatives such as humanitarian assistance and/or funding safety-net programs. In Kenya, the cost of getting a single SMS-advisory into the hands of a farmer is $0.006, and a farmer might typically receive 15 advisories per season. To reach 6-8 million farmers per week on TV is approximately $3,000. Reaching 50 million farmers each year via SMS might cost $4.5 million dollars. Localizing climate information, however, to agro-ecological and social contexts will require a considerable increase in resources.

From a policy perspective, the potential costs of EWS-empowered advisory systems might be compared to the >$2 billion USD in humanitarian relief being provided in 2022 to Ethiopia, Kenya, and Somalia. Investments in advisory systems might save millions of dollars a year in east Africa alone, if they reduced the need for very expensive emergency relief while supporting resilience and autonomy.

Pilot studies (Table 1) suggest that ~30% increases in yields are plausible. In terms of historical variations, a 30% increase is a substantial increase. For example, in Kenya, poor MAM rains typically appear in association with a ~15% reduction in national maize yields. A 30% increase in national maize production (~1MT), represents a large sum of money, when valued at 2022 wholesale Kenyan maize prices (~US $320 million). In addition to increased economic outcomes, increased crop production can reduce price volatility.

Discussion 3. Can long-lead forecasts be used to improve decision-making and increase resilience?

As sequential droughts become more common during La Niña events, responding to the first drought, which consistently arises in OND, may be a low-regret intervention, especially since MAM dry seasons often follow. Social protection via safety nets and insurance programs can support more effective resilience building at scale by integrating early action and preparedness[83]. Guaranteed funding before a shock can enhance the scalability, timeliness, predictability, and adequacy of social protection benefits. In 1998, 2010, 2016, 2020, 2021 and 2022, June forecasts of extremely warm west Pacific SSTs clearly indicated OND droughts (Fig. 2B) that led to widespread livestock loss and plummeting livestock prices. Index-Based Livestock Insurance (IBLI) is another promising intervention strategy that targets pastoralists and agropastoralists who face some of the most-extreme risks from drought[84]. Climate forecasts (Fig. 3B) might be combined with Predictive Livestock Early Warning Systems (PLEWS)[85] to improve predictions of forage conditions. More extreme precipitation may be recharging deep aquifers[86]. Accessing this water via boreholes might help buffer rainfall deficits.

There are opportunities to better link EWS with adaptation research. For example, the Evidence for Resilient Agriculture (ERA, https://era.ccafs.cgiar.org/) project provides data and tools that pinpoint what agricultural technologies work where. Resources like the Adaptation Atlas (http://adaptationatlas.cgiar.org/riskmap) allow decision-makers to examine climate change-related risks alongside potential solutions. Agroforestry, micro-credit, insurance, digital advisories, improved breeds, crops, forages and diets, fertilizer, intercropping, irrigation, mulch, trees, planting decisions, stress-adapted varietals, and water harvesting—the list of potential adaptations is long. African-led efforts that link EWS to appropriate local solutions can help us anticipate and adapt to more extreme climate.

Conclusion: recommendations vis-à-vis calls for improved early warning systems

In November 2022, at COP27, the UN Secretary-General unveiled the "Early Warnings for All Plan"[23] which provides $3.1 billion USD to support EWS in developing countries. The plan supports four disaster-risk reduction[84] pillars: 1) Disaster-risk knowledge, 2) Observations and Forecasting, 3) Preparedness and response, and 4) Dissemination and communication. EWS "*are a proven, effective, and feasible climate adaptation measure, that save lives, and provide a tenfold return on investment,"*[73] which have been recognized by the IPCC as a key adaptation strategy[87]. Within Africa, ICPAC, FEWS NET and the Kenyan and Ethiopian Meteorological Departments provide some of the most sophisticated EWS. This sophistication, the long-standing climate volatility, and food insecurity in the Horn, in addition to the many years of collective research and practical experience represented by the authors, provide us a vantage point from which to provide ten recommendations related to effective EWS development and implementation in the context of climate change. These recommendations are relevant for many regions linked to Indo-Pacific SSTs:

1. Realize that climate change is happening now and offers opportunities for prediction.
2. Realize that climate change contributed to recent extreme SSTs and associated EHoA droughts and floods, and that many of these extremes were predictable.
3. Realize that extreme SST gradients provide opportunities for forecasts.
4. Pay attention to extremely warm SSTs, these can drive predictable droughts and floods.
5. Be concerned about increasing aridity and declining per capita resources.
6. Work towards integrated observation/forecast systems.

7. Invest in building capacity. Utilize local expertise.
8. Look for places or seasons where conditions will likely be clement. Teleconnections will produce droughts, but also areas with bountiful rains.
9. Leverage agricultural adaptation resources to build resilience. Link EWS to the latest agricultural adaptation science.
10. Pay attention to barriers to climate information use, and learn from them.

Trust, **urgency**, and **accuracy** can enable action, helping overcome barriers associated with **funding**, **uncertain tradeoffs,** and **inertia**. Trust and urgency involve a shared understanding of how climate change is interacting with natural variability to produce frequent climate extremes, now. Trust also involves developing (and investing in) co-developed participatory advisory services: localized, culturally appropriate flows of information. Accuracy arises when we carefully combine domain-specific insights with the best-available information. For example, satellite observations and numerical model predictions are tremendous sources of information, but transforming this information into accurate rainfall estimates[19] or forecasts (Fig. 2, 3B) demands expertise. Predictions of exceptionally warm west Pacific SSTs (Fig. 2B) help anticipate the influence of climate change. While still evolving, inter-disciplinary collaboration is leading to first-in-kind long-lead alerts[16,17]. But the development of effective EWS in developing countries will require large investments in human capacity. "Loading dock" approaches to climate services can fail to provide locally appropriate advisory services[74] just as "raw" climate model forecasts may miss important teleconnections and opportunities for prediction, such as those shown in Fig. 2. Especially for MAM, long-lead drought outlooks would be substantially less skillful if they were just based on climate model rainfall forecasts[54] or equatorial east Pacific

SST predictions. Skill matters. For OND La Niña-related droughts, which the models capture well, effective actions based early alerts can build resilience in the face of sequential droughts.

Urgency arises from the long-term implications of extreme SST gradients (Fig. 3A), warming air temperatures, population growth, income gaps, and other socioeconomic and political stressors. Strong negative WPG/WVG gradients have become common (Fig. 1E). Climate change contributed to extreme gradients in 2016/17 and 2020/22 (Fig. 1F). These gradients helped produce an unprecedented five-season drought in the Horn. Given that the serial correlation of EHoA MAM and OND rains is very close to zero, the chance of a five-season drought sequence happening randomly is extremely low ($0.333^5 \approx 0.4\%$).

The frequency of strong gradient events is expected to increase dramatically (by >50%) by mid-century (Fig. 3A), which will likely increase in the frequency of poor EHoA rainy seasons. More frequent dry seasons may also be accompanied by more frequent El Niños and positive IOD events and extreme precipitation[30,31,50]. Increasing air temperatures contribute to both droughts and floods. Under dry conditions, warmer air draws more moisture from plants. Under wet conditions, warmer air holds more water vapor, leading to more extreme precipitation. Such influences contribute to "wet-getting-wetter" and "dry-getting-drier" tendencies in the Horn[88]. Observed EHoA crop water requirements are also trending upward during dry seasons, and these influences appear preferentially in hot-arid lowland areas[10,89]. Importantly, the spatial signature of these impacts largely aligns with the footprint of WPG/WVG-related drought tendencies.

Finally, increases in population and water scarcity are also likely to expand insecurity. UN projections suggest that between 2022 and 2050, the population of Ethiopia, Kenya, and Somalia, will increase by 70%. Holding other factors constant, population-driven per capita water availability projections for 2050 indicate the potential for severe water stress and scarcity[61]. Population-driven projections of Kenyan per capita maize production also indicate 40% reductions by 2050[89]. Planning for more frequent and severe extremes by enhancing EWS and advisory services can help mitigate these climate shocks.

The long-term implications of these compound stresses are very concerning, especially for the hot, dry EHoA lowlands. Yet, there is also hope that crop productivity can be increased in humid areas. Many areas of Ethiopia, and substantial portions of Kenya, are climatically secure. Some of these areas (most of Ethiopia) tend to experience rainfall increases during La Niña-like seasons. Closing yield gaps in humid regions would create wealth and lower food prices, and there is growing evidence that climate-enhanced advisories can contribute (Table 1). But achieving this promise will require much greater investments in African experts, experts who can improve and interpret forecasts, link to agricultural ministries, extension programs, and agricultural research centers, and, ultimately, farmers and pastoralists.

Data Availability:

The time series data supporting the primary results of this study are available via Dryad. Funk, Chris (2022), Data - Tailored forecasts can predict extreme climate informing proactive interventions in East Africa, Dryad, Dataset, https://doi.org/10.25349/D9MC8Z.

For now, the data is available at:

https://datadryad.org/stash/share/PxI2GIJv-4Q_C51wiHw-gySoI72xjRpl9_2euUONcM4

Code Availability: The bulk of the analysis presented in this paper are based on simple time-series manipulations, and are presented in the excel file in the Dryad link above. The most salient results can be recreated without coding, using the time series provided in the Dryad repository. Time-series extraction and the simple SST composite plots shown in Fig. 2C,D were done using Interactive Data Language version 8.7, and the related code is contained with the Dryad Repository. Zip files in that directory also contain NOAA extended reconstruction version 5 gridded SST data, NMME SST forecasts from May and September, and regionally averaged CMIP6 SSP245 SST time-series. For the convenience of the reviewers, the contents of the data repository are also available at: https://data.chc.ucsb.edu/people/chris/DataRepository.zip.

Table 1 | Exemplar case studies demonstrating the benefits of co-production and social networks in scaling climate-informed advisories.

Location	**Agriculture decision affected**	**Benefit**	**Scaling potential**	**Behavior science for scaling**	**Distribution channel**
Senegal	Crop varieties, field location, intercrop, crop type, crop mix, timing of sales, harvest & weeding, fertilizer use, water harvesting	Crop income increased between 10 and 25%	PICSA and WMG approaches can be easily scaled.	Multidisciplinary Working Groups (WMG) increase farmer's awareness of forecasts by 18%, access by 12% and uptake by 10%.	SMS, phone, Interactive radio, farmers share information word of mouth.
Rwanda	Crop type, Crop varieties, Timing of planting and land preparation, When and how to prepare land	With PICSA +24% production +36% income With PICSA+RLC +47% production +56% income	-PICSA and RLC approaches can be easily scaled.	Participatory Integrated Climate Services for Agriculture (PICSA) approach. Radio Learning Clubs (RLC) address disparities.	Radio, Phone, TV (43:11:7%) With RLC (81:37:9 %)
Ghana	Land preparation planting & harvest dates, crop varieties, fertilizer scheduling	+35% sorghum yields +6% technical Efficiency	Easily replicated. Requires mobile access. $35 subscription plus training costs	The most significant factor in forecast use was training.	Mobile (Voice Message, SMS, Call Centre)
Colombia, Guatemala, Honduras	Sowing & harvesting dates, rainwater harvesting, pest prevention, crop rotations, variety changes	Avoided income loss of 20%. +20-to-50% yield gain for rice, maize, bean	Government and local stakeholder uptake of LTAC approach enables scaling	Local Technical Agro-Climatic Committees (LTACs) where stakeholders discuss forecasts and develop recommendations.	Agroclimatic bulletin, radio, TV, newspaper, extension service, social networks

Figures

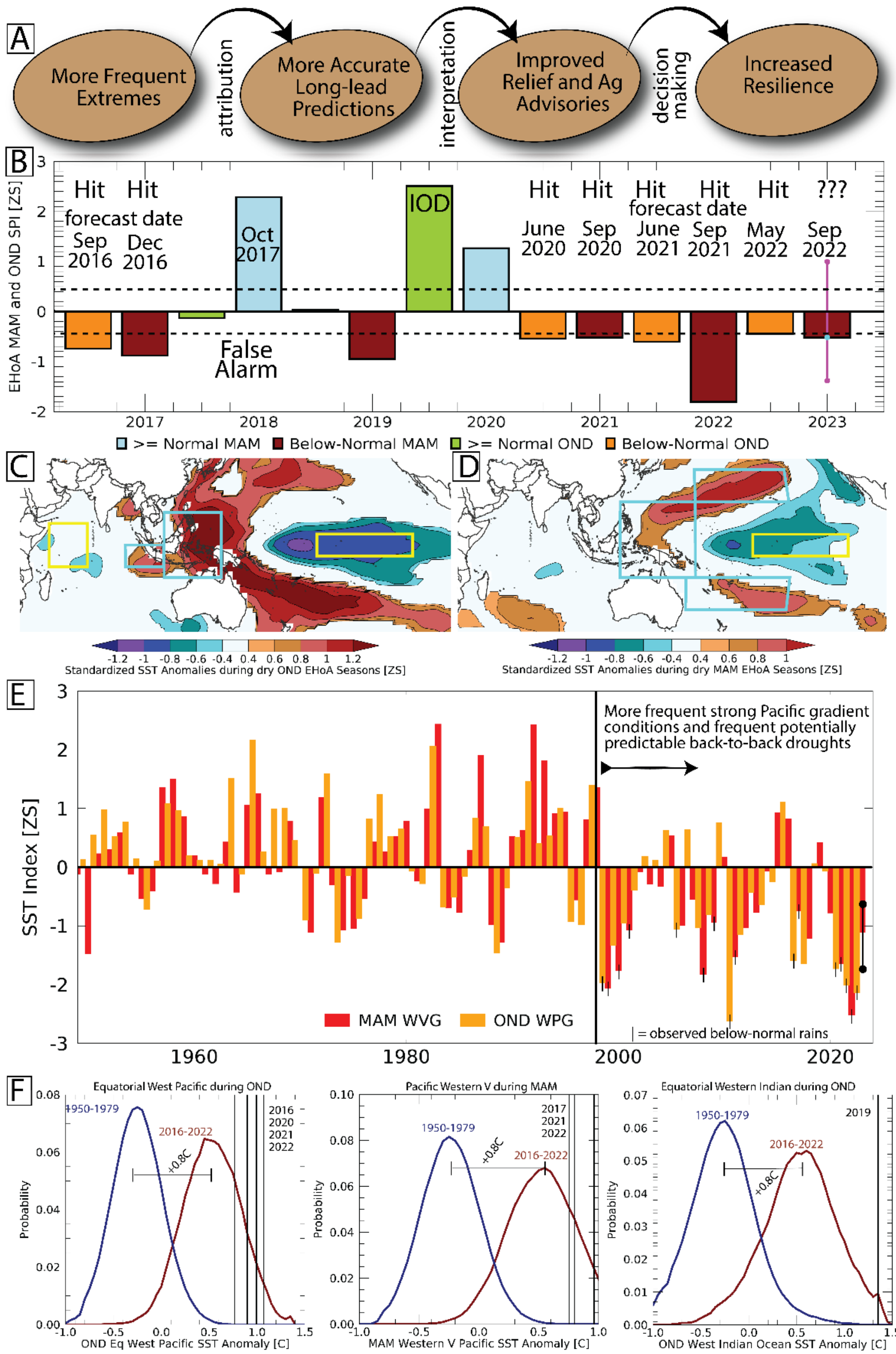

Figure 1. A. Schematic diagram describing the links between climate attribution, prediction and improved interventions. **B**. Barplot showing 2016-2023 regionally averaged EHoA MAM and

OND Standardized Precipitation Index values. Western Pacific Gradient (WPG) and Western 'V'-Gradient (WVG)-based drought forecast dates are noted for La Niña-related dry seasons, along with hit or false alarm outcomes. MAM 2023 result is a forecast, shown with 80% confidence intervals. **C**. Standardized OND SST composites for post-1996 dry EHoA OND seasons. Screened for significance at p=0.1. Boxes denote the western and eastern IOD regions, the equatorial west Pacific (110°E-140°E, 15°S-15°N), and the NINO3.4 region. **D**. Same for MAM EHoA dry seasons. Boxes denote the Western V (blue) (110°E-140°E, 15°S-15°N, 160°E-160°W, 20°N-35°N, 155°E-160°W, 15°S-30°S) and NINO3.4 (yellow) regions. **E**. SST index values for the observed MAM WVG and OND WPG. Anomalies calculated using a 1950-2020 baseline. The Pacific gradients associated with droughts (**1C,D**) are becoming more frequent (**1E**). Recent below-normal EHoA rainy seasons are marked with short vertical lines. The 2023 MAM WVG values are based on forecasts in Fig. 2. The black circles denote the associated 80% confidence intervals. The associated question mark conveys our concerns for a 6th dry season, based on the 2023 WVG forecast in Fig. 2. **F**. Equatorial OND western Pacific, MAM Western V, and OND western Indian Ocean CMIP6 SSP245 SST anomalies for 1950-1979 and 2016-2022, along with observed SST anomalies for selected drought seasons. Anomalies based on a 1950-2020 baseline.

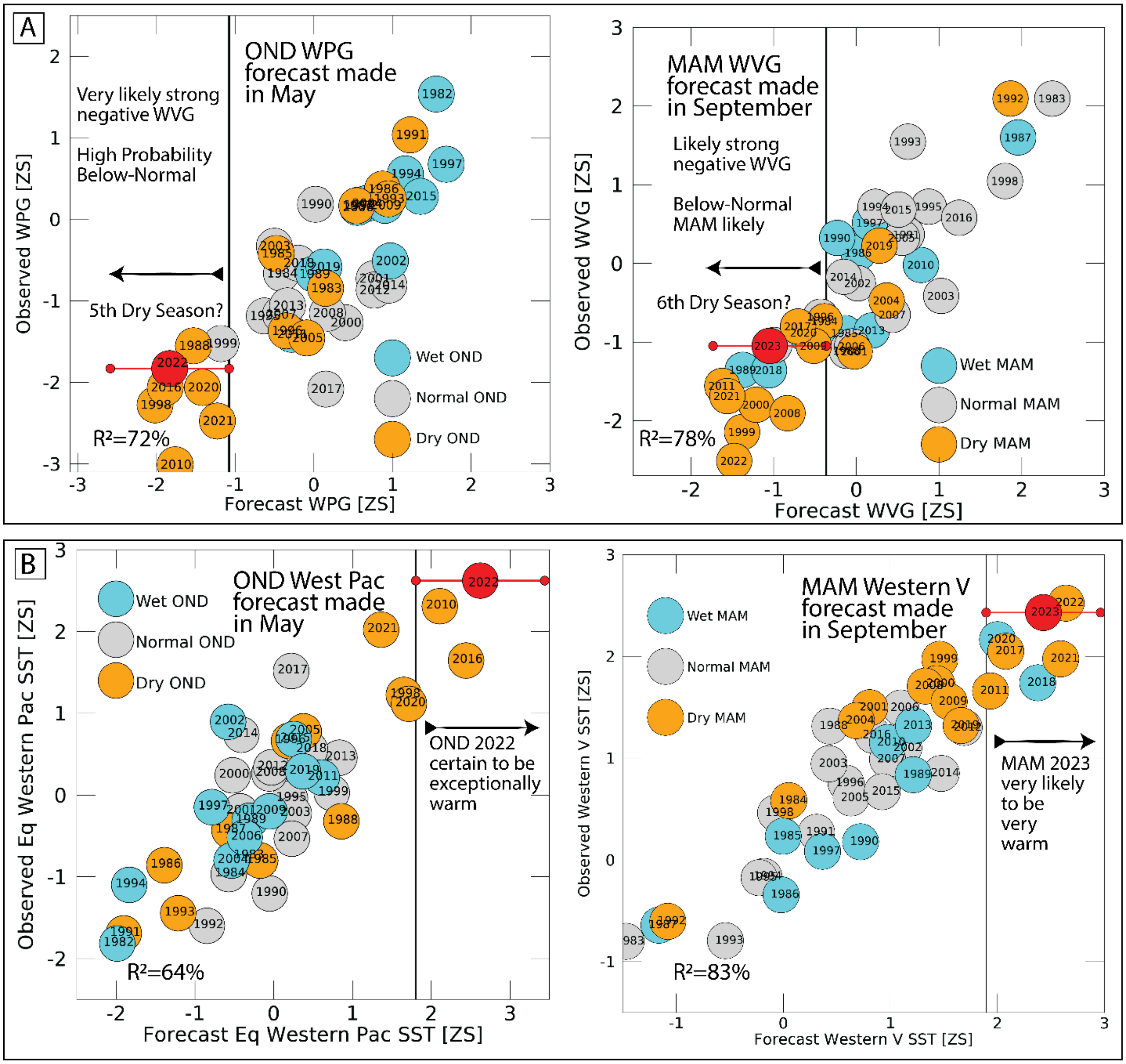

Figure 2. **A.** Scatterplots of forecast and observed WPG and WVG values. Left panels show 1982-2022 OND forecasts made in May. Right panels show 1983-2023 MAM forecasts made in September. OND 2022 and MAM 2023 'observations' are assumed to equal the forecasts. Vertical bars indicate 80% confidence intervals. Blue, gray and red circles denote the EHoA rainfall outcomes for each OND or MAM season. **B.** Same but for regionally averaged SST in equatorial western Pacific and Western V regions. Regions described in Fig. 1C,D.

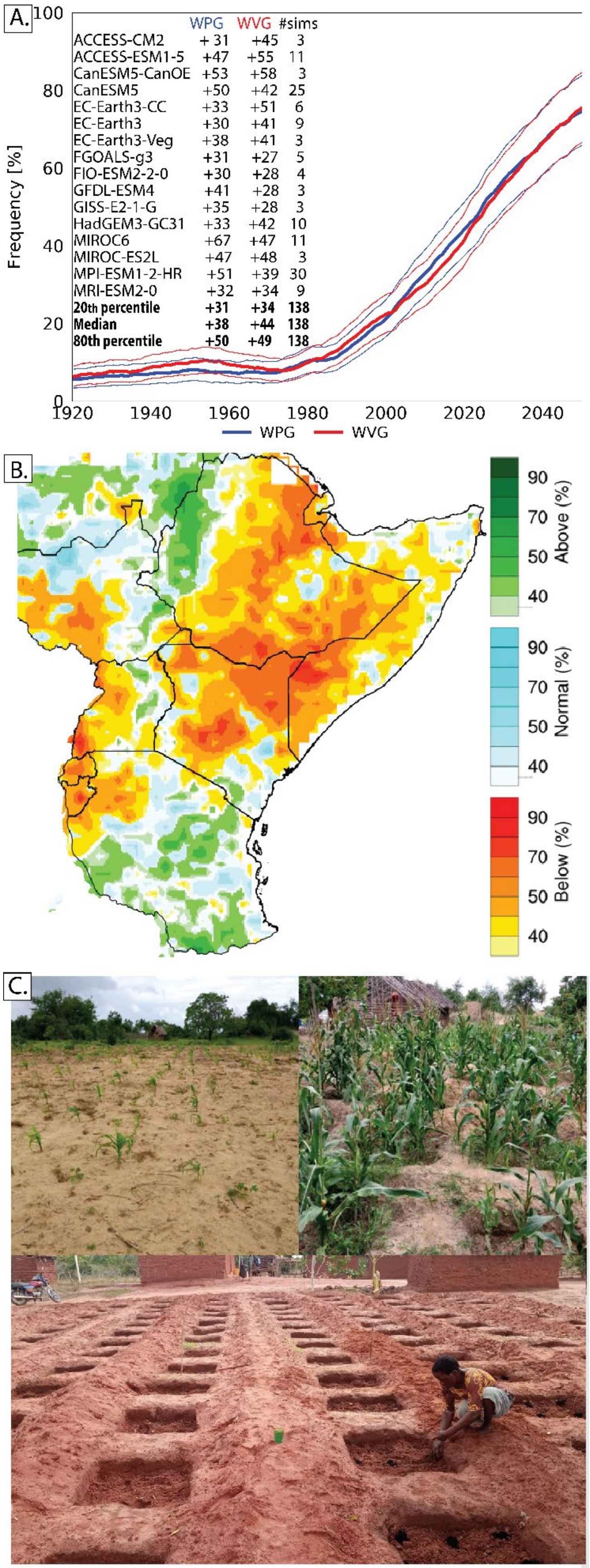
A.
WPG WVG #sims
ACCESS-CM2 +31 +45 3
ACCESS-ESM1-5 +47 +55 11
CanESM5-CanOE +53 +58 3
CanESM5 +50 +42 25
EC-Earth3-CC +33 +51 6
EC-Earth3 +30 +41 9
EC-Earth3-Veg +38 +41 3
FGOALS-g3 +31 +27 5
FIO-ESM2-2-0 +30 +28 4
GFDL-ESM4 +41 +28 3
GISS-E2-1-G +35 +28 3
HadGEM3-GC31 +33 +42 10
MIROC6 +67 +47 11
MIROC-ES2L +47 +48 3
MPI-ESM1-2-HR +51 +39 30
MRI-ESM2-0 +32 +34 9
20th percentile +31 +34 138
Median +38 +44 138
80th percentile +50 +49 138
Frequency [%]
0
20
40
60
80
100
1920 1940 1960 1980 2000 2020 2040
WPG WVG
B.
Above (%)
Normal (%)
Below (%)
90 70 50 40
C.

Figure 3. **A**. Time-series showing the median frequency of extreme OND WPG and MAM WVG events, based on standardized time-series from the CMIP6 SSP245 climate change ensemble, along with 95% confidence intervals. The WPG and WVG are calculated using SSTs from the Pacific boxes in Fig. 1A and 1B, respectively. Extreme negative OND WPG and MAM WVG events are associated with values less than -1Z. Change in extreme event frequencies (# of events per 100 years) were calculated by taking the frequency differences between 2020-2030 and 1920-1979, and are reported in the inset table for each model with at least three simulations. The 20^{th}, 50^{th} and 80^{th} percentile values of the per-model changes are shown in the last three columns. Time series were standardized using a 1950-2020 baseline. Human-induced warming in the western Pacific results in strong inter-model agreement on more frequent WPG and WVG events, in line with the observed gradient values shown in Fig. 1C. **B**. Experimental ICPAC forecasts for MAM 2023, based on localized logistic regressions and WVG forecasts. **C**. Test plot results in eastern Kenya from MAM 2022. Upper-left and right panels show adjacent control and test plots. Bottom panel shows field preparation using Zai pits and biochar.

References

1 Funk, C. *et al.* Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. *Proc Nat Acad Sci USA* **105**, 11081-11086 (2008).

2 Williams, P. & Funk, C. A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. *Climate Dynamics* **37**, 2417-2435 (2011).

3 Hoell, A. & Funk, C. The ENSO-Related West Pacific Sea Surface Temperature Gradient. *Journal of Climate* **26**, 9545-9562 (2013).

4 Hoell, A. & Funk, C. Indo-Pacific sea surface temperature influences on failed consecutive rainy seasons over eastern Africa. *Climate Dynamics* **43**, 1645-1660 (2013).

5 Funk , C. *et al.* Predicting East African spring droughts using Pacific and Indian Ocean sea surface temperature indices. *Hydrology and Earth System Sciences Discussions* **11**, 3111-3136 (2014).

6 Funk, C. *et al.* Examining the role of unusually warm Indo-Pacific sea surface temperatures in recent African droughts *Quart J Roy Meteor Soc* **144**, 360-383, doi:10.1002/qj.3266 (2018).

7 Funk, C. *et al.* Examining the potential contributions of extreme 'Western V' sea surface temperatures to the 2017 March-June East African Drought. *Bull. Amer. Meteor. Soc.* **100**, S55-S60 (2019).

8 Tadesse, T. Strategic framework for drought risk management and enhancing resilience in Africa, in *African Drought Conference.* 15-19 (2016).

9 Hansen, J. *et al.* Climate risk management and rural poverty reduction. *Agricultural Systems* **172**, 28-46 (2019).

10 Funk, C. *et al.* An Agro-Pastoral Phenological Water Balance Framework for Monitoring and Predicting Growing Season Water Deficits and Drought Stress. *Frontiers in Climate* **3**, doi:10.3389/fclim.2021.716568 (2021).

11 CHC/FEWSNET. in *blog.chc.ucsb.edu* (Climate Hazards Center, University of California, Santa Barbara, 2022). blog.chc.ucsb.edu/?p=10, blog.chc.ucsb.edu/?p=94, blog.chc.ucsb.edu/?p=283, blog.chc.ucsb.edu/?p=757, blog.chc.ucsb.edu/?p=868, blog.chc.ucsb.edu/?p=991, blog.chc.ucsb.edu/?p=1030, blog.chc.ucsb.edu/?p=1192, https://blog.chc.ucsb.edu/?p=1240.

12 Voosen, P. The hunger forecast. *Science* **368**, 226-229, doi:DOI: 10.1126/science.368.6488.226 (2020).

13 Yang, W., Seager, R., Cane, M. A. & Lyon, B. The East African Long Rains in Observations and Models. *Journal of Climate* **27**, 7185-7202, doi:10.1175/JCLI-D-13-00447.1 (2014).

14 Lyon, B. & DeWitt, D. G. A recent and abrupt decline in the East African long rains. *GEOPHYSICAL RESEARCH LETTERS* **39** (2012).

15 Lyon, B. Seasonal Drought in the Greater Horn of Africa and its Recent Increase During the March-May Long Rains. *Journal of Climate* **27**, 7953-7975 (2014).

16 ICPAC, C., FEWS NET, CHC, FAO, WMO, OCHA, IRI, WFP, Mercy Corps, UK Met Office, UKAID, UNHCR, Islamic Relief. The Threat of Starvation Looms in East Africa After Four Failed Rainy Seasons. *Multi-Agency Drought Alert* (2022). <https://www.fao.org/3/cc0312en/cc0312en.pdf>.

17 ICPAC *et al.* Immediate global action required to prevent Famine in the Horn of Africa. *Multi-agency Drought Alert* (2022). <https://fews.net/sites/default/files/Joint%20Alert%20on%202023%20MAM%20Rains%20Final_0.pdf>.

18 Funk, C. *et al.* The Centennial Trends Greater Horn of Africa precipitation dataset. *Scientific Data* **2**, doi:10.1038/sdata.2015.50 (2015).

19 Funk, C. *et al.* The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data* **2** (2015).

20 Huang, B. *et al.* Extended Reconstructed Sea Surface Temperature, Version 5 (ERSSTv5): Upgrades, Validations, and Intercomparisons. *Journal of Climate* **30**, 8179-8205, doi:10.1175/JCLI-D-16-0836.1 (2017).

21 Becker, E. J., Kirtman, B. P., L'Heureux, M., Muñoz, Á. G. & Pegion, K. A Decade of the North American Multimodel Ensemble (NMME): Research, Application, and Future Directions. *B Am Meteorol Soc* **103**, E973-E995 (2022).

22 Eyring, V. *et al.* Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development* **9**, 1937-1958 (2016).

23 WMO. *Early Warnings for All Action Plan unveiled at COP27*, <https://public.wmo.int/en/media/press-release/early-warnings-all-action-plan-unveiled-cop27> (2022).

24 Diaz, H. F. *El Niño and the Southern Oscillation: multiscale variability and global and regional impacts*. (Cambridge University Press, 2000).

25 Glantz, M. H. *Currents of change: impacts of El Niño and La Niña on climate and society*. (Cambridge University Press, 2001).

26 Barnston, A. G., Tippett, M. K., Ranganathan, M. & L'Heureux, M. L. Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. *Climate Dynamics* **53**, 7215-7234 (2019).

27 L'Heureux, M. L. *et al.* Observing and predicting the 2015/16 El Niño. *B Am Meteorol Soc* **98**, 1363-1382 (2017).

28 Tippett, M. K., Ranganathan, M., L'Heureux, M., Barnston, A. G. & DelSole, T. Assessing probabilistic predictions of ENSO phase and intensity from the North American Multimodel Ensemble. *Climate Dynamics*, doi:10.1007/s00382-017-3721-y (2017).

29 Cai, W. *et al.* Increasing frequency of extreme El Nino events due to greenhouse warming. *Nature Clim. Change* **4**, 111-116, doi:10.1038/nclimate2100 (2014).

30 Cai, W. *et al.* Increased ENSO sea surface temperature variability under four IPCC emission scenarios. *Nature Climate Change* **12**, 228-231, doi:10.1038/s41558-022-01282-z (2022).

31 Cai, W. *et al.* Increased frequency of extreme Indian Ocean Dipole events due to greenhouse warming. *Nature* **510**, 254-258 (2014).

32 Cai, W. *et al.* ENSO and greenhouse warming. *Nature Climate Change* (2015).

33 Cheng, L., Abraham, J., Hausfather, Z. & Trenberth, K. E. How fast are the oceans warming? *Science* **363**, 128-129 (2019).

34 Cai, W. *et al.* Opposite response of strong and moderate positive Indian Ocean Dipole to global warming. *Nature Climate Change* **11**, 27-32 (2021).

35 Ihara, C., Kushnir, Y. & Cane, M. A. Warming trend of the Indian Ocean SST and Indian Ocean dipole from 1880 to 2004. *Journal of Climate* **21**, 2035-2046 (2008).

36 Abram, N. J., Gagan, M. K., Cole, J. E., Hantoro, W. S. & Mudelsee, M. Recent intensification of tropical climate variability in the Indian Ocean. *Nat Geosci* **1**, 849-853 (2008).

37 Cravatte, S., Delcroix, T., Zhang, D., McPhaden, M. & Leloup, J. Observed freshening and warming of the western Pacific warm pool. *Climate Dynamics* **33**, 565-589 (2009).

38 Roxy, M. *et al.* Twofold expansion of the Indo-Pacific warm pool warps the MJO life cycle. *Nature* **575**, 647-651 (2019).

39 Nicholson, S. E., Fink, A. H., Funk, C., Klotter, D. A. & Satheesh, A. R. Meteorological causes of the catastrophic rains of October/November 2019 in equatorial Africa. *Global and Planetary Change* **208**, 103687 (2022).

40 Park, S., Kang, D., Yoo, C., Im, J. & Lee, M.-I. Recent ENSO influence on East African drought during rainy seasons through the synergistic use of satellite and reanalysis data. *ISPRS Journal of Photogrammetry and Remote Sensing* **162**, 17-26 (2020).

41 Saji, N. H., Goswami, B. N., Vinayachandran, P. N. & Yamagata, T. A dipole mode in the tropical Indian Ocean. *Nature* **401**, 360-363 (1999).

42 Saji, N. & Yamagata, T. Possible impacts of Indian Ocean dipole mode events on global climate. *Clim Res* **25**, 151-169 (2003).

43 Behera, S. K. *et al.* Paramount impact of the Indian Ocean dipole on the East African short rains: A CGCM study. *Journal of Climate* **18**, 4514-4530 (2005).

44 Indeje, M., Semazzi, F. H. & Ogallo, L. J. ENSO signals in East African rainfall seasons. *International Journal of Climatology* **20**, 19-46 (2000).

45 Wainwright, C. M. *et al.* 'Eastern African Paradox'rainfall decline due to shorter not less intense Long Rains. *npj Climate and Atmospheric Science* **2**, 1-9 (2019).

46 Trenberth, K. E. The definition of el nino. *B Am Meteorol Soc* **78**, 2771-2778 (1997).

47 Seager, R., Henderson, N. & Cane, M. Persistent discrepancies between observed and modeled trends in the tropical Pacific Ocean. *Journal of Climate*, 1-41, doi:10.1175/jcli-d-21-0648.1 (2022).

48 Seager, R. *et al.* Strengthening tropical Pacific zonal sea surface temperature gradient consistent with rising greenhouse gases. *Nature Climate Change* **9**, 517-522, doi:10.1038/s41558-019-0505-x (2019).

49 Cai, W. *et al.* Increased frequency of extreme La Niña events under greenhouse warming. *Nature Climate Change* **5**, 132-137 (2015).

50 Cai, W. *et al.* Increased variability of eastern Pacific El Niño under greenhouse warming. *Nature* **564**, 201-206 (2018).

51 Anderson, W. *et al.* Multi-year La Niña events and multi-season drought in the Horn of Africa. *Journal of Hydrometeorology* (2022).

52 Magadzire, T., Galu, G. & Verdin, J. How climate forecasts strengthen food security. *World Meteorological Organisation Bulletin - Special Issue on Water* **67** (2017). <https://public.wmo.int/en/resources/bulletin/how-climate-forecasts-strengthen-food-security>.

53 Funk, C. & Hoell, A. The leading mode of observed and CMIP5 ENSO-residual sea surface temperatures and associated changes in Indo-Pacific climate. *Journal of Climate* **28**, 4309-4329 (2015).

54 Shukla, S. *et al.* Assessing North American multimodel ensemble (NMME) seasonal forecast skill to assist in the early warning of anomalous hydrometeorological events over East Africa. *Climate Dynamics*, 1-17, doi:10.1007/s00382-016-3296-z (2016).

55 Nicholson, S. E. Climate and Climatic Variability of Rainfall over Eastern Africa. *Reviews of Geophysics*, doi:10.1002/2016RG000544 (2017).

56 Lentz, E. & Maxwell, D. G. Anticipating, Mitigating, and Responding to Crises: How Do Information Problems Constrain Action? *International Journal of Disaster Risk Reduction*, 81, 103242, https://doi.org/10.1016/j.ijdrr.2022.103242 (2022).

57 Maxwell, D. & Hailey, P. Towards anticipatory information systems and action: Notes on early warning and early action in East Africa. (Tufts University, Feinstein International Center, Friedman School of Nutrition Science and Policy, Boston, MA, 2020).

58 Maxwell, D. G. *Famine in Somalia*. (Oxford University Press, 2016).

59 Sarkar, A., Spatz, B. J., de Waal, A., Newton, C. & Maxwell, D. The Political Marketplace Framework and Mass Starvation: How Can Humanitarian Analysis, Early Warning and Response Be Improved? *Journal of Humanitarian Affairs* **3**, 43-55 (2021).

60 Giller, K. E. *et al.* Small farms and development in sub-Saharan Africa: Farming for food, for income or for lack of better options? *Food Sec* **13**, 1431-1454 (2021).

61 Funk, C. & Shukla, S. *Drought early warning and forecasting: theory and practice*. (Elsevier, 2020).

62 ICPAC *et al.* Unprecedented drought brings threat of starvation to millions in Ethiopia, Kenya, and Somalia. *Multi-Agency Drought Alert* (2022). <https://fews.net/sites/default/files/Joint%20Statement%20Horn%20of%20Africa%209%20June%202022.pdf>.

63 Venton, C. C., Fitzgibbon, C., Shitarek, T., Coulter, L. & Dooley, O. The economics of early response and disaster resilience: Lessons from Kenya and Ethiopia. *Final report* (2012).

64 Dosi, G., Napoletano, M., Roventini, A., Stiglitz, J. E. & Treibich, T. Rational heuristics? Expectations and behaviors in evolving economies with heterogeneous interacting agents. *Economic Inquiry* **58**, 1487-1516 (2020).

65 Luan, S., Reb, J. & Gigerenzer, G. Ecological rationality: Fast-and-frugal heuristics for managerial decision making under uncertainty. *Academy of Management Journal* **62**, 1735-1759 (2019).

66 Djido, A. *et al.* To what extent do weather and climate information services drive the adoption of climate-smart agriculture practices in Ghana? *Climate Risk Management* **32**, 100309 (2021).

67 Diouf, N. S. *et al.* Factors influencing gendered access to climate information services for farming in Senegal. *Gender, Technology and Development* **23**, 93-110 (2019).

68 Owusu Danquah, E. *et al.* Monitoring and modelling analysis of maize (Zea mays L.) yield gap in smallholder farming in Ghana. *Agriculture* **10**, 420 (2020).

69 Ellsberg, D. Risk, ambiguity, and the Savage axioms. *The quarterly journal of economics*, 643-669 (1961).

70 Cullen, A. C., Anderson, C. L., Biscaye, P. & Reynolds, T. W. Variability in cross-domain risk perception among smallholder farmers in Mali by gender and other demographic and attitudinal characteristics. *Risk analysis* **38**, 1361-1377 (2018).

71 Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S. & Combs, B. How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy sciences* **9**, 127-152 (1978).

72 Slovic, P. Perception of risk. *Science* **236**, 280-285 (1987).

73 Global Commission on Adaptation. Adapt now: A global call for leadership on climate resilience. (World Resources Institute, 2019).

74 Born, L., Prager, S., Ramirez-Villegas, J. & Imbach, P. A global meta-analysis of climate services and decision-making in agriculture. *Climate Services* **22**, 100231 (2021).

75 Ingabire, C. Closing Gender Gaps in Farmers' Access to Climate Information: The Case of Radio Listeners Clubs (RLCs) in Rwanda: Preliminary results of a mixed-method analysis. (2021).

76 Chiputwa, B., Blundo-Canto, G., Steward, P., Andrieu, N. & Ndiaye, O. Co-production, uptake of weather and climate services, and welfare impacts on farmers in Senegal: A panel data approach. *Agricultural Systems* **195**, 103309 (2022).

77 Chiputwa, B. *et al.* Transforming climate science into usable services: The effectiveness of co-production in promoting uptake of climate information by smallholder farmers in Senegal. *Climate Services* **20**, 100203 (2020).

78 Jimenez, D. *et al.* A scalable scheme to implement data-driven agriculture for small-scale farmers. *Global Food Security* **23**, 256-266 (2019).

79 Case, C. O., America, L. & Läderach, P. Cracking patterns in big data saves Colombian rice farmers' huge losses. *Tropical Agriculture (CIAT)* (2014).

80 Delerce, S. *et al.* Assessing weather-yield relationships in rice at local scale using data mining approaches. *PloS one* **11**, e0161620 (2016).

81 Seid, J., Demissie, T., Tesfaye, K., Tamene, L. & Solomon, D. Ethiopian Digital AgroClimate Advisory Platform (EDACaP) Technical Working Document| Brief version. (2020).

82 Harrison, L. *et al.* Advancing early warning capabilities with CHIRPS-compatible NCEP GEFS precipitation forecasts. *Scientific Data* **9**, 1-13 (2022).

83 Costella, C. *et al.* Scalable and sustainable: How to build anticipatory capacity into social protection systems. (2017).

84 Syll, M. M. A. Willingness to Pay for Index-Based Livestock Insurance by Pastoralists and Agropastoralists: Evidence from Senegal. *Int. J. of Innovative Science and Research* (2021).

85 Matere, J. *et al.* Predictive Livestock Early Warning System (PLEWS): Monitoring forage condition and implications for animal production in Kenya. *Weather and Climate Extremes* **27**, 100209 (2020).

86 Adloff, M. *et al.* Sustained water storage in Horn of Africa drylands dominated by seasonal rainfall extremes. *Geophysical Research Letters*, e2022GL099299 (2022).

87 Pörtner, H.-O. *et al.* Climate change 2022: Impacts, adaptation and vulnerability. *IPCC Sixth Assessment Report* (2022).

88 Haile, G. G. *et al.* Projected Impacts of Climate Change on Drought Patterns Over East Africa. *Earth's Future* **8**, e2020EF001502, doi:https://doi.org/10.1029/2020EF001502 (2020).

89 Funk, C., Way-Henthorne, J. & Turner, W. Phenological Water Balance Applications for Trend Analyses and Risk Management. *Frontiers in Climate* **3**, doi:10.3389/fclim.2021.716588 (2021).