

Earth's Future



COMMENTARY

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Key Points:

- Climate change and La Niña are producing extreme Pacific sea surface temperature (SST) gradients, which can be predicted very far in advance
- These Pacific SST forecasts provide robust opportunities for predicting well wet and dry outcomes in East Africa
- *Trust, urgency and accuracy* can overcome barriers due to *limited funding, uncertain tradeoffs, and inertia* by improving advisory services

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Tailored Forecasts Can Predict Extreme Climate Informing Proactive Interventions in East Africa

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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, 23 million east Africans faced starvation in 2022, 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 dynamical models to predict droughts at 8-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 “Early Warning for All” Executive Action 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. In Africa and beyond, climate change brings increasingly extreme sea surface temperature (SST) gradients. Using climate models, we can often see these extremes coming. Prediction, therefore, offers opportunities for proactive risk management and improved advisory services, if we can create effective societal linkages via cross-silo collaborations.

Plain Language Summary Eastern East Africa is extremely food insecure. Millions of farmers and pastoralists rely on two meager rainy seasons that arrive twice a year. In the 13 seasons since late 2016, the region experienced eight droughts and three exceptionally wet seasons. Seven droughts were linked to very strong Pacific sea surface temperature (SST) gradients, which arose through an interaction between climate change and La Niña. Climate change will bring more extreme Pacific and Indian Ocean SST gradients. Here, 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, agriculture, 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 creates 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. Investing now in collaborative African climate systems, participatory advisory services and proactive risk management will help counter these threatening climate extremes.

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1. 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 (Figure 1a). The team includes scientists from the IGAD Climate Prediction and Applications Center (ICPAC), the Famine Early Warning Systems Network (FEWS NET), the Ethiopian and Kenyan Meteorological Departments, and scientists engaged in agricultural development, advisory services, and humanitarian relief efforts. Updating previously published climate attribution studies (Funk et al., 2008, 2014, 2018, 2019; Hoell & Funk, 2013a, 2013b; Williams & Funk, 2011), 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 (Figure 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 (8-month) lead-times (Figure 2). Finally, given that climate change is likely to increase the frequency of these events (Figure 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 (Tadesse, 2016), in practice, millions of poor households remain vulnerable to climate shocks (Hansen et al., 2019). Could improved forecasts, EWS and advisory services be useful to agricultural and food security decision-makers?

The schema in Figure 1a lays out the logic of this Commentary. We first describe how climate change attribution leads to a tailored forecast process that produces more accurate long lead time forecasts. We then discuss how these forecasts might improve agricultural outcomes, humanitarian relief planning, and food security if decision-makers are able to translate predictions into effective practice. For many smallholder farmers, uncertainty and risk aversion lead to low adoption rates for innovations. Accurate forecasts, communicated effectively via localized and trusted advisories, might decrease the uncertainty associated with trade-offs. For example, the fact that seasonal rains are *not* likely to be below-normal might reduce farmer's reasonable aversion to risk and innovation. Conversely, forecasts for regional drought, and increased cereal prices, might motivate farmers in climatically-secure areas or countries to increase production by investing more capital or labor. Such production increases might reduce regional price shocks. Hence, tailored forecasts, in conjunction with trusted and localized advisory systems, can motivate feasible cost-effective responses that address 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.

2. 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 (Figure 1b). Below-normal rains are inadequate to support productive crops and rangeland (Funk, Turner, et al., 2021).

Seven of the eight dry seasons in Figure 1b were anticipated with operational “tailored” forecasts (CHC/FEWS-NET, 2022), 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 [CHC/FEWSNET, 2022]). Hits, that is, droughts that were accurately forecasted, included the back-to-back drought sequence in 2016/2017 (Voosen, 2020) 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 (a) attributes droughts to extreme SST states, which arise through the interaction of natural variability and climate change (Figure 1), then (b) predicts these states using the latest state-of-the-science climate forecast ensembles (Figure 2).

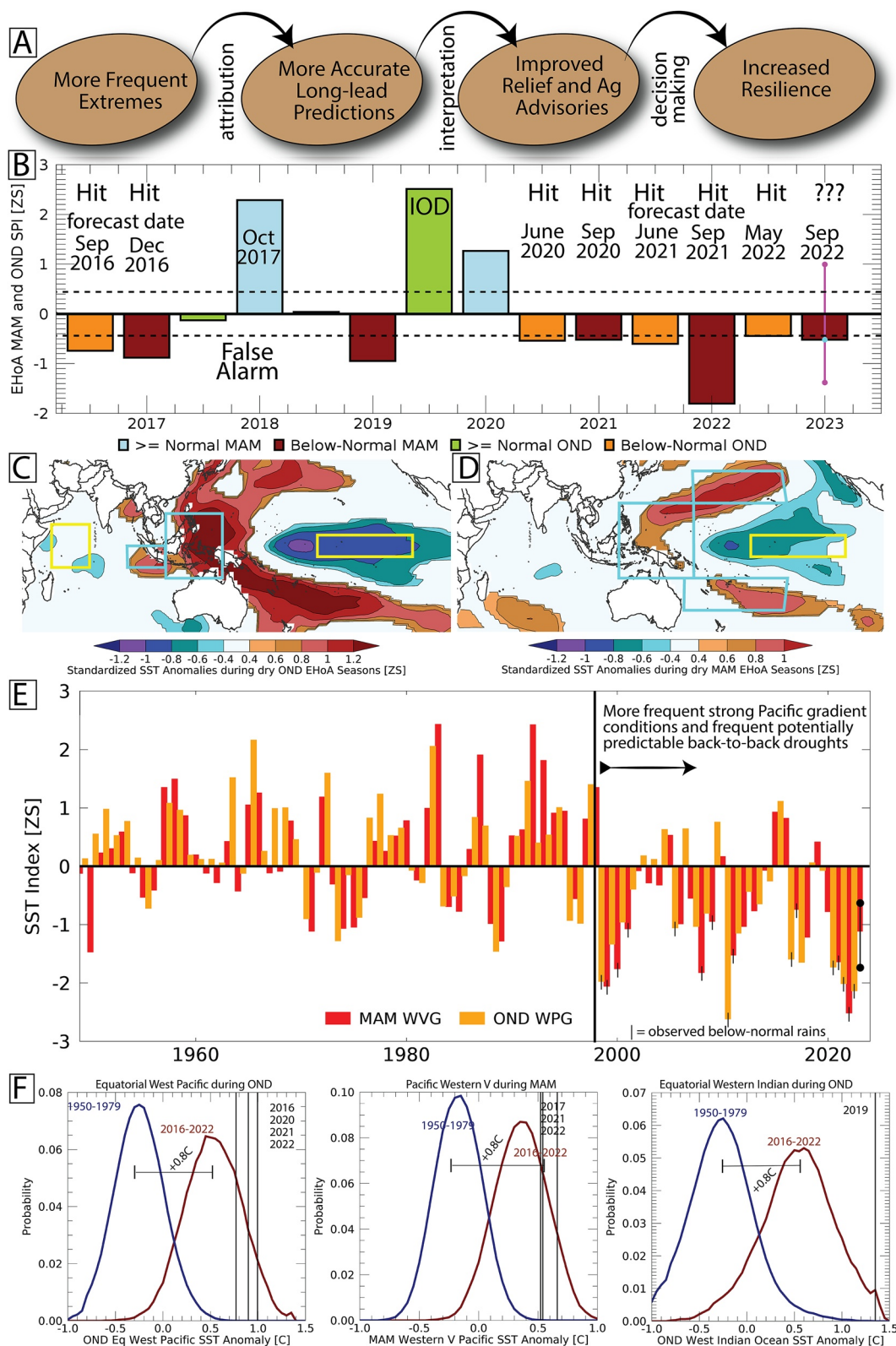


Figure 1.

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 Ocean, 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 (Lyon, 2014; Lyon & DeWitt, 2012; Yang et al., 2014), and hence, largely unpredictable. However, many FEWS NET studies (Funk et al., 2008, 2014, 2018, 2019; Hoell and Funk, 2013a, 2013b; Williams & Funk, 2011) 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, supported five successful long-lead forecasts in a row (CHC/FEWSNET, 2022). Eight months before the end of OND and MAM, strong Pacific SST gradients can often be accurately predicted. In May (ICPAC et al., 2022a) and November (ICPAC et al., 2022b) 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 (ICPAC et al., 2022b). 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 (Figure 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 (Figure 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 dialog, 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.

3. Data and Methods

This study relies on widely used Climate Hazard Center rainfall data sets (Funk et al., 2015a, 2015b) and NOAA Extended Reconstruction SST data (Huang et al., 2017). 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) (Becker et al., 2022). 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) (Eyring et al., 2016). The attribution analyses, detailed in our first results section and presented in Figure 1, are updates of climate attribution studies focused on the 2016/2017 droughts (Funk et al., 2018, 2019). These results (Funk et al., 2018, 2019) informed accurate tailored forecasts (CHC/FEWSNET, 2022) (Figure 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 (Figure 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 World Meteorological Organization (WMO) “Early Warning for All” project (WMO, 2022).

Figure 1. (a) Schematic diagram describing the links between climate attribution, prediction and improved interventions. (b) Barplot showing 2016–2023 regionally averaged Eastern Horn of Africa (EHOA) March–April–May (MAM) and October–November–December (OND) Standardized Precipitation Index values. West 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 sea surface temperature (SST) composites for post-1996 dry EHOA OND seasons. Screened for significance at $p = 0.1$. Boxes denote the western and eastern Indian Ocean Dipole (IOD) regions, the equatorial west Pacific (110°E–140°E, 15°S–15°N), and the Niño 3.4 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 Niño 3.4 (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 (c, d) are becoming more frequent (e). Recent below-normal EHOA rainy seasons are marked with short vertical lines. The 2023 MAM WVG values are based on forecasts in Figure 2. The black circles denote the associated 80% confidence intervals. The associated question mark conveys our concerns for a sixth dry season, based on the 2023 WVG forecast in Figure 2. (f) Equatorial OND western Pacific, MAM Western V, and OND western Indian Ocean Coupled Model Intercomparison Project Phase 6 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.

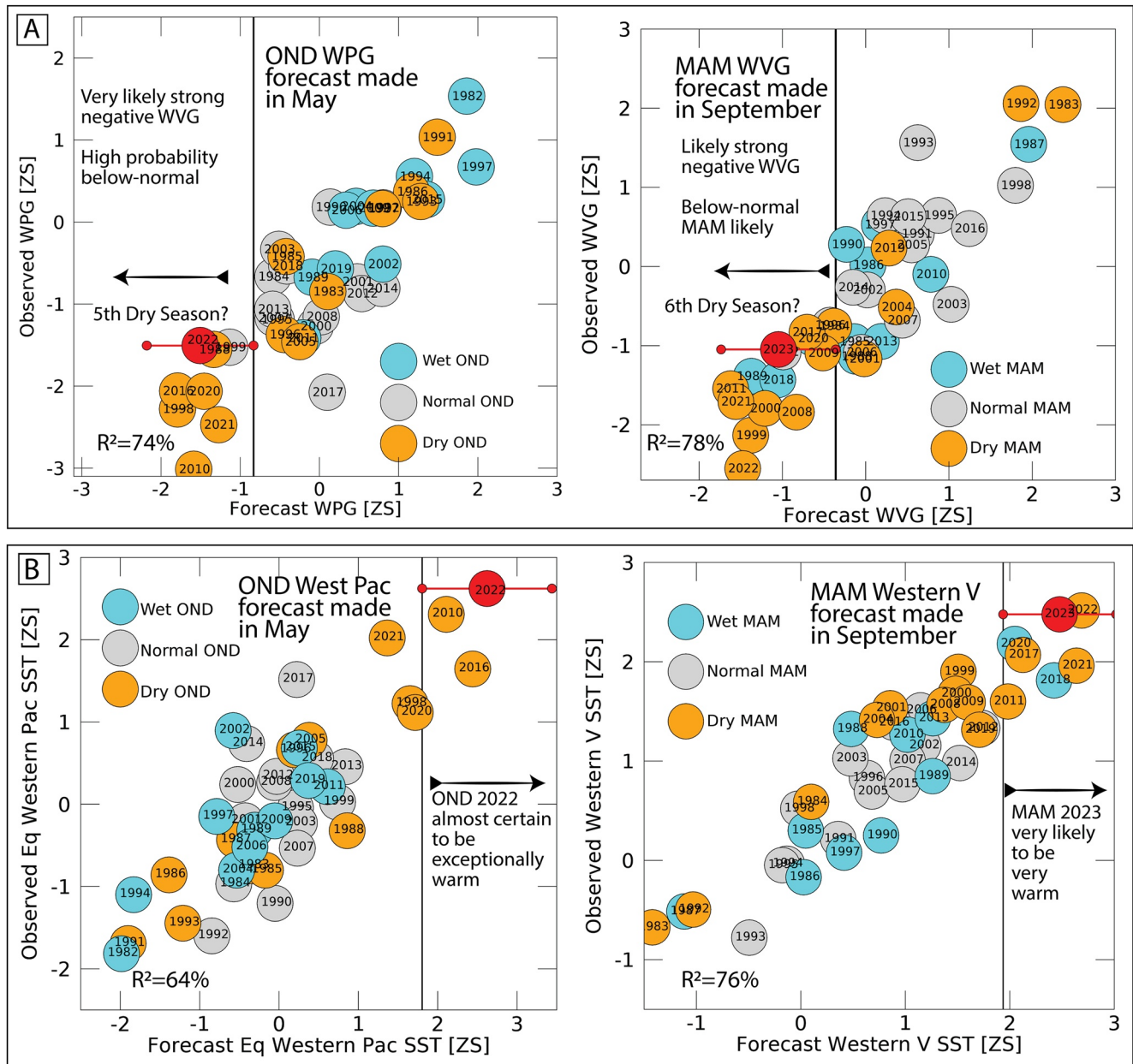


Figure 2. (a) Scatterplots of forecast and observed West Pacific Gradient (WPG) and Western V Gradient (WVG) values. Left panels show 1982–2022 October–November–December (OND) forecasts made in May. Right panels show 1983–2023 March–April–May (MAM) forecasts made in September. OND 2022 and MAM 2023 “observations” are assumed to equal the forecasts. Vertical bars indicate 80% confidence intervals. Blue, gray and red circles denote the Eastern Horn of Africa (EHOA) rainfall outcomes for each OND or MAM season. (b) Same but for regionally averaged sea surface temperature (SST) in equatorial western Pacific and Western V regions. Regions described in Figures 1c and 1d.

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.

3.1. Results 1—Linking Recent Droughts to Extremely Warm Pacific SSTs and Climate Change

Scientists have long emphasized the societal dangers (Diaz, 2000; Glantz, 2001) associated with predictable (Becker et al., 2022; Barnston et al., 2019; L'Heureux et al., 2017; Tippett et al., 2017) El Niños and La Niñas and

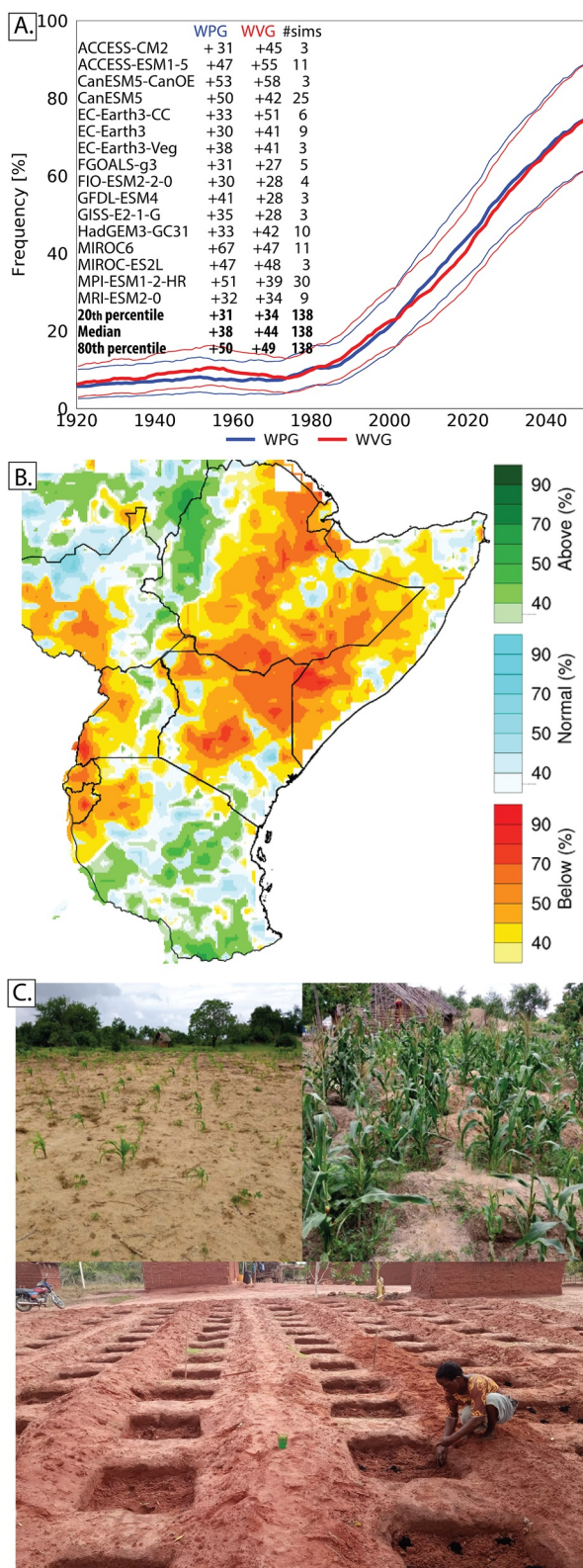


Figure 3.

that climate change is expected to increase the frequency of strong ENSO and IOD events (Cai et al., 2014a, 2014b, 2015a, 2022). What is less appreciated is that the interaction of climate change and ENSO is creating opportunities for prediction—now. As climate change rapidly warms (Cheng et al., 2019) dynamically important regions in the Indian (Abram et al., 2008; Cai et al., 2021; Ihara et al., 2008) and Pacific Oceans (Cravatte et al., 2009; Roxy et al., 2019), exceptionally warm ocean conditions can produce potentially predictable droughts and wet seasons (Funk et al., 2018, 2019; Nicholson et al., 2022). For EHOA, this may be especially important for MAM, due to a strengthening connection to La Niña (Park et al., 2020). Figures 1c–1f updates attribution studies that identified how extremely warm west Pacific SST contributed to droughts in 2016/2017 (Funk et al., 2018, 2019). Composites of standardized contemporaneous SSTs during recent OND and MAM dry seasons (Figures 1c and 1d) can help identify predictor zones. OND rains are influenced by IOD (Behera et al., 2005; N. H. Saji et al., 1999; N. Saji & Yamagata, 2003), ENSO/Niño 3.4 SSTs (Indeje et al., 2000), and the SSTs in the equatorial west Pacific (Funk et al., 2018; Hoell and Funk, 2013a, 2013b). The MAM rains are linked to SSTs in the southern Indian Ocean (Wainwright et al., 2019), and the Pacific “Western V” and equatorial eastern Pacific regions (Funk et al., 2018, 2019). 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 (Funk et al., 2014, 2018, 2019; Hoell and Funk, 2013a, 2013b). While the OND teleconnections (Figure 1c) are well-appreciated, the strong MAM “teleconnections” implicit in Figure 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 (N. H. Saji et al., 1999), there remains a tendency to only describe the Pacific with equatorial eastern Pacific SSTs (Trenberth, 1997), often summarized exclusively with the Niño 3.4 region (5°N–5°S, 170°–120°W). Such a focus can miss important interactions with climate change and lead to missed opportunities for skillful predictions (Funk et al., 2014, 2018).

We define two gradients useful for such predictions. For OND, we describe the Pacific via the “West Pacific Gradient” (WPG) (Hoell & Funk, 2013a): the difference between standardized equatorial western and eastern Pacific SSTs (Pacific boxes in Figure 1c). For MAM, we use a similar “Western V Gradient” (WVG), based on the difference between Niño 3.4 and Western V temperatures (boxes in Figure 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 (Funk et al., 2018, 2019).

Following the 1997/1998 El Niño, the western Pacific warmed substantially, and WPG and WVG values decreased dramatically (Figure 1e). This set the stage for numerous, often sequential, EHOA dry seasons (noted with short vertical lines). This trend toward more frequent strong gradient events has been attributed to a combination of natural ENSO variability and human-induced warming in the western Pacific (Funk et al., 2018, 2019; Seager et al., 2019, 2022). Strong upward SST trends in the equatorial west Pacific (Hoell & Funk, 2013a), the western North Pacific (Funk et al., 2018), and the “Western V” region (Funk et al., 2019) have been formally linked to human-induced warming (Funk et al., 2018, 2019). Warming in the already very warm west Pacific has enhanced observed La Niñas (Funk et al., 2018; Hoell & Funk, 2013a) in ways similar to climate change projections (Cai et al., 2015b, 2018). These exceptional Pacific gradient events have arisen alongside an exceptional number of 1998–2022 La Niña events—13 events in 25 years since 1998. Historically, La Niña events occur every 3-to-5 years (Diaz, 2000; Glantz, 2001). Hence, very frequent La Niñas, a lack of a warming trend in the eastern Pacific (Seager et al., 2019, 2022), and rapid warming in the west Pacific have created a large increase in Pacific SST gradients (Figure 1e), setting the stage for sequential droughts, especially during multi-year La Niñas

Figure 3. (a) Time-series showing the median frequency of extreme October–November–December (OND) West Pacific Gradient (WPG) and March–April–May (MAM) WVG events, based on standardized time-series from the Coupled Model Intercomparison Project Phase 6 (CMIP6) SSP245 climate change ensemble, along with 95% confidence intervals. The WPG and WVG are calculated using SSTs from the Pacific boxes in Figures 1a and 1b, respectively. Extreme negative OND WPG and MAM WVG events are associated with values less than -1σ . 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 20th, 50th and 80th 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 Figure 1c. (b) Experimental IGAD Climate Prediction and Applications Center 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.

(Anderson et al., 2022). However, wet EH_oA rainy seasons, associated with exceptionally warm western Indian Ocean and eastern Pacific conditions, are also expected (Abram et al., 2008; Cai et al., 2014a, 2014b, 2015a, 2021, 2022; Cheng et al., 2019; Ihara et al., 2008). Modes of intraseasonal variability, such as the Madden–Julian oscillation, will also continue to produce impactful rainfall extremes, but the time scales these operate on make these anomalies hard to predict at long lead times.

We briefly assess the role of climate change in recent extremely warm SST hot spots (Figure 1f). The extremity of SST hot spots during recent extreme EH_oA 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 (Nicholson et al., 2022), either the western Pacific or the western Indian Ocean was exceptionally warm. In Figure 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 +0.5–1°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 (Figure 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 EH_oA rainfall extremes to these very warm SSTs (Funk et al., 2018, 2019; Hoell and Funk, 2013a, 2013b; Nicholson et al., 2022). Climate change helped produce these extreme WPG, WVG, and IOD values, and associated EH_oA rainfall extremes. Can these warm ocean conditions be predicted well, offering opportunities for improved decision-making?

3.2. Results 2. The Latest Generation of Climate Models Can Predict These Extreme Ocean States Well at Eight-Month Lead Times

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 8-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 (CHC/FEWSNET, 2022) to inform FEWS NET's Food Security Outlook process (Magadzire et al., 2017). 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 EH_oA dry and wet rainy season outcomes (circle color).

At long leads, the WPG and WVG are predicted well (Figure 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 EH_oA 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 Figure 2a). In late 2016, 2020, and 2021, WVG forecasts helped anticipate dry outcomes the following MAM (CHC/FEWSNET, 2022; Voosen, 2020). Used in concert, WPG/WVG forecasts can potentially anticipate sequential droughts (Figure 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 EH_oA outcomes (Figure 2b), and diagnostic studies have explained how these warm conditions modify winds in ways that reduce EH_oA rains (Funk et al., 2018, 2019). This information builds on the information contained in more traditional predictors, such as equatorial eastern Pacific (Niño 3.4) 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 (Figure 1f).

3.3. 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 (Eyring

et al., 2016). 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 (Figure 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 Figure 3a). The simulations (Figure 3a), like the observations (Figure 1e), suggest a strong tendency toward 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 (Funk & Hoell, 2015) that is closely related to the west Pacific warming, and will almost certainly increase over the next several decades (Figure 3a) as the west Pacific continues to warm. This creates both an opportunity and a need for improved forecast information.

3.4. 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 (Anderson et al., 2022; Funk et al., 2018, 2019) 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 (Shukla et al., 2016), because these rains are less spatially homogeneous (Nicholson, 2017) and can have non-linear relationships to SSTs, with more coherent links during droughts (e.g., Figure 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 (Figure 3b), and such predictions are being used to support long-lead alerts (ICPAC et al., 2022b). Preliminary results from such approaches appear promising. Unlike Figure 3b, the scatter plot-based forecasts shown in Figure 2 lack the spatial dimension required to fit into ICPAC's map-based forecast streams. If gradient events become more frequent (Figure 3a), these novel forecasting techniques may help capture the predictability inherent in extremely warm SST (Figure 2a).

3.5. Discussion 1. Increased Trust, Urgency and Accuracy Can Help Overcome Barriers Associated With Limited Funding, Uncertain Tradeoffs, and Inertia by Supporting Improved Advisory Services

Improving food security outcomes in Africa is challenging, given that costly and momentous decisions must be made in a setting of uncertain tradeoffs (Lentz & Maxwell, 2022; D. G. Maxwell, 2016; D. Maxwell & Hailey, 2020; Sarkar et al., 2021). Most east Africans are risk-averse (Hansen et al., 2019) small-scale farmers with little mechanization and often nutrient-depleted soils (Giller et al., 2021). Uptake of innovative farming practices, crop insurance, and advisory services is limited (Hansen et al., 2019) and food insecurity is increasing (Funk & Shukla, 2020; ICPAC et al., 2022c). While acting earlier can save money, lives and livelihoods (Venton et al., 2012), decision making under uncertainty is difficult (Dosi et al., 2020; Luan et al., 2019). However, developing a shared appreciation of the *urgency* associated with climate change impacts (Figure 3a) and the *accuracy* of climate forecasts (Figure 2) can open the door for forecast utilization. But, achieving that goal requires the development of *trusted* advisory services linking stakeholders with climate forecast services.

Building trust is challenging. Despite some encouraging signs, there remain inconsistent findings in research examining associations between farmers' perceptions of climate variability and the likelihood of them using weather and climate information services (Diouf et al., 2019; Djido et al., 2021; Owusu Danquah et al., 2020). 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. 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 (Ellsberg, 1961). 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 (Cullen et al., 2018; Fischhoff et al., 1978; Slovic, 1987).

As the risks associated with predictable extreme SST gradients grow more urgent, trusted EWS advisories may be a cost-effective means of reducing poverty (Global Commission on Adaptation, 2019).

Increased farmer innovation, combined with public investment in large-scale insurance schemes and rural infrastructure, can help manage climate risk. Unfortunately, the availability and influence of agricultural advisories remains very low in Africa (Hansen et al., 2019). Furthermore, unless co-developed, such advisories may not respond to the local needs of farmers (Born et al., 2021). It is important, however, to acknowledge examples of effective services. Table 1 provides some good examples of co-developed participatory agricultural advisory systems in Ghana, Rwanda (Ingabire, 2021), and Senegal (Chiputwa et al., 2020, 2022). In some non-African La Niña-impacted countries like Colombia, agro-advisories have helped maize farmers (Jimenez et al., 2019) and rice farmers (CCAFS, 2014; Delerce et al., 2016) 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 (Seid et al., 2020) (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 (Funk 2015b), weather forecasts (Harrison et al., 2022), longer sub-seasonal weather predictions and WPG/WVG-based climate outlooks (Figure 2).

Trusted advisories can motivate innovations that help manage climate shocks. For example, 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 (Figure 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, spatially-explicit WVG-based forecasts (Figure 3b) hold the promise of supporting increased resilience, even in the face of severe droughts, as suggested by the pilot from Kilifi (Figure 3c).

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 (~1 MT), 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.

3.6. Discussion 2. 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

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 Center)
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

by integrating early action and preparedness (Costella et al., 2017). 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 correctly indicated OND droughts (Figure 2b) that led to widespread livestock loss and plummeting livestock prices. Index-Based Livestock Insurance is another promising intervention strategy that targets pastoralists and agro-pastoralists who face some of the most-extreme risks from drought (Syll, 2021). Climate forecasts (Figure 3b) might be combined with Predictive Livestock Early Warning Systems (Matero et al., 2020) to improve predictions of forage conditions. More extreme precipitation may be recharging deep aquifers (Adloff et al., 2022). 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 varieties, 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.

4. 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” (WMO, 2022) which provides \$3.1 billion USD to support EWS in developing countries. The plan supports four disaster-risk reduction (Syll, 2021) pillars: (a) Disaster-risk knowledge, (b) Observations and Forecasting, (c) Preparedness and response, and (d) Dissemination and communication. EWS “*are a proven, effective, and feasible climate adaptation measure, that save lives, and provide a tenfold return on investment,*” (Global Commission on Adaptation, 2019) which have been recognized by the IPCC as a key adaptation strategy (Pörtner et al., 2022). 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 10 recommendations related to effective EWS development and implementation in the context of climate change. These recommendations are relevant for many regions linked via teleconnections 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 toward 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 (Funk et al., 2015b) or forecasts (Figures 2 and 3b) demands

local expertise, capacity building, and tailored communication systems (cf. Table 1). Predictions of exceptionally warm west Pacific SSTs (Figure 2b) help anticipate the influence of climate change. While still evolving, inter-disciplinary collaboration is leading to first-in-kind long-lead alerts (ICPAC et al., 2022a, 2022b). 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 (Born et al., 2021) just as “raw” climate model forecasts may miss important teleconnections and opportunities for prediction, such as those shown in Figure 2. Especially for MAM, long-lead drought outlooks would be substantially less skillful if they were just based on climate model rainfall forecasts (Shukla et al., 2016) 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 (Figure 3a), warming air temperatures, population growth, income gaps, and other socioeconomic and political stressors. Strong negative WPG/WVG gradients have become common (Figure 1e). Climate change contributed to extreme gradients in 2016/2017 and 2020/2022 (Figure 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 (Figure 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 (Cai et al., 2014b, 2018, 2022). 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 (Haile et al., 2020). Observed EHoA crop water requirements are also trending upward during dry seasons, and these influences appear preferentially in hot-arid lowland areas (Funk, Turner, et al., 2021; Funk, Way-Henthorne, et al., 2021). 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 (Funk & Shukla, 2020). Population-driven projections of Kenyan per capita maize production also indicate 40% reductions by 2050 (Funk, Way-Henthorne, et al., 2021). 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 Statement

The time series data supporting the primary results of this study are available via Dryad. Funk (2022), Data—Tailored forecasts can predict extreme climate informing proactive interventions in East Africa, Dryad, Dataset, <https://doi.org/10.25349/D9MC8Z>. *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 Figures 2c and 2d 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.

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