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Five Lessons for Closing the Last Mile: How to Make Climate Decision Support Actionable

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Key Points:

- As weather shocks become more frequent and severe, building trust, honing collaborations, and refining decision support tools are crucial
- Increasingly sophisticated models predict weather and crop production but often have little impact on users of agro-climatic forecasts
- We identify five lessons for decision-support systems to enable climate services to be more actionable and effective for last-mile users

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Abstract Climate shocks are increasing, threatening global agricultural production and food security. But a more extreme climate allows for improved predictions and enables advisory services that allow farmers, ranchers and consumers to respond effectively. To date, there is limited uptake of forecasts. How can we make sure these predictions are valued by and valuable for users of agro-climatic forecasts? Over the past two years, we held over 40 interviews with food system stakeholders to identify their needs and shortcomings of existing decision support. In this Commentary, we combine these findings and nascent modeling efforts with existing literature to characterize five lessons for improving the uptake and utilization of predictive tools for last mile users in the agrifood system. Given the explosion of machine learning prediction efforts across many applications, we believe our lessons are broadly applicable to forecasting models intended for decision support. Improved accuracy alone does not necessarily lead to improved decision support, and the trust required to motivate action.

Plain Language Summary Extreme weather events threaten the global food system. As climate change increases the severity of these events, they are also becoming more predictable. Yet, many end users working in the agrifood system report that existing predictions do not support action. We propose five lessons that can help transform forecasts into useful proactive interventions. First, by prioritizing and integrating the needs of users from the very beginning of model development, that is, in the first mile, models are more likely to deliver benefits to last-mile users. In particular, we heard that models need to move beyond predicting weather to predicting weather impacts. Second, modelers need to balance uncertainty and timeliness of predictions to enable response. Third, models need to be transparent and communicate uncertainty to users. Fourth, during the joint model development process, modelers need to respect the capacity constraints of end users. And fifth, modelers need to have a plan for what happens when they are wrong. As extreme weather becomes more common, it is vital that we translate the increased predictability of these extremes into impact risk assessments that last mile users can use to guard against food insecurity.

1. Introduction

Climate volatility is increasing, with global ramifications for farmers, ranchers and people vulnerable to food insecurity (Funk et al., 2019; ICPAC, 2022; Sengupta in New York Times, 2024). Poor households spend up to 70% of their income on food, which makes them highly sensitive to production shortfalls and resulting price increases (Funk et al., 2019). As climate events become more extreme, the number of food insecure people is also rocketing upward to staggering levels. Since 2015, the number of people facing starvation has increased from 35 million to 129 million in 2023. To mitigate these increases, we need to provide farmers and ranchers and food aid providers with actionable information on the impacts of weather so that they can proactively mitigate these shortfalls.

Fortunately, correlated climate shocks have become more predictable. Our ability to forecast extreme heat, drought and heavy rains associated with warming sea surface temperatures and events like El Niños and La Niñas has increased dramatically over the past two decades. As climate change warms the oceans, we see more extreme eastern and western Pacific sea surface temperatures (Figure 1), and these extremes offer opportunities for

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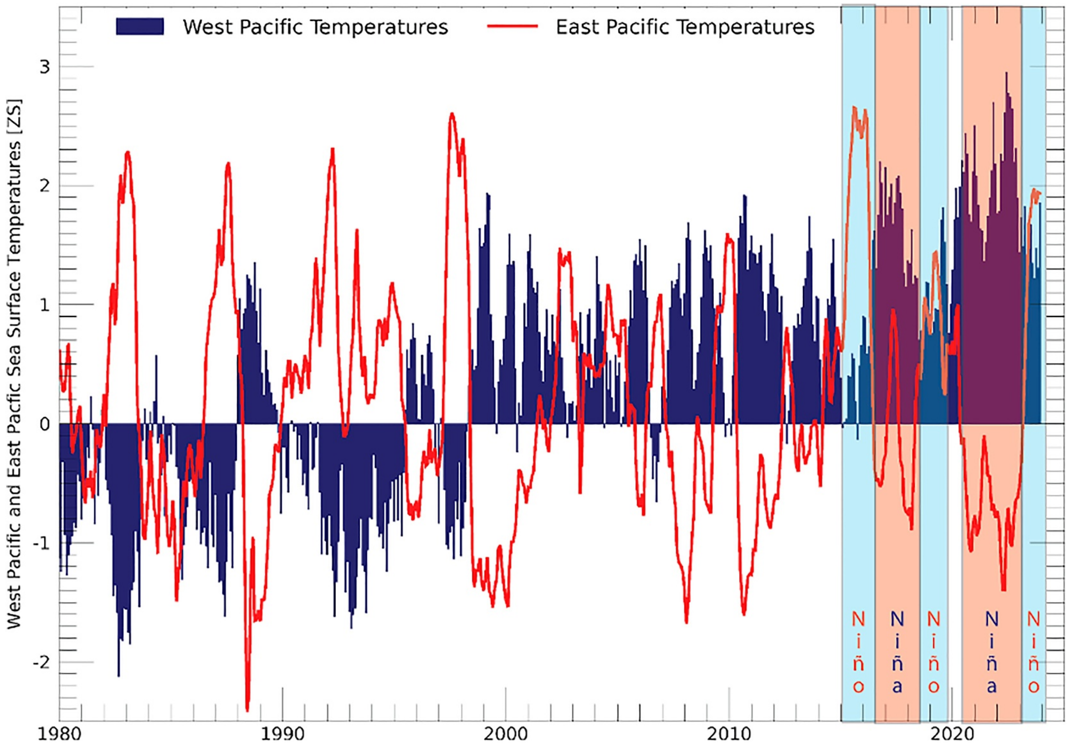

Figure 1. Time series of monthly standardized sea surface temperatures for the west and east Pacific. Since the middle of 2015, there has been an unremitting sequence of El Niño and La Niña events. Data available at https://www.chc.ucsb.edu/data.

accurate long-lead climate forecasts and proactive interventions (Funk et al., 2023). Further, compound extremes can be very hazardous, and difficult to attribute (King et al., 2023), but they are predictable when events like droughts, heat extremes, and precipitation deficits reinforce each other, as was the case in southern Africa in 2024 (SADC 2024, (2016)). Second, our modeling toolset has dramatically expanded. For example, AI tools hold the potential for forecast models to be tailored to specific end-users and their settings, enabling us to combine those weather forecasts with additional information to generate context-specific impacts for last-mile users (Becker-Reshef et al., 2019; Shukla et al., 2024). However, to date, our respondents report that these forecasts often fail to enable action.

In this Commentary on bringing impact-based forecasts to last-mile users of agro-climatic information, we examine why these forecasts are not being used and suggest some lessons to improve their impact on decision-making. We believe these lessons are generally applicable to the broader scientific community working on decision support problems.

2. Approach

We interviewed stakeholders involved in food production and food assistance to identify the demand and need for co-produced actionable weather and climate decision support for users of agro-climatic predictions.

In 2022 and 2023, we held 40 interviews with members of three different stakeholder groups—Gulf Coast food bank staff ($n = 6$); ranchers, ranch service providers and climate information providers in southwestern US ($n = 7$, including one group of 8) and northern Kenya ($n = 27$ including 52 individuals), we heard repeatedly that current climate information did not lend itself to decision-making. Particularly US ranchers and pasture managers, Kenyan pastoralists and local food-aid providers - who we refer to as last mile users - reported that much of our existing decision support does not reach or meet their needs. We found that forecasts are not at the necessary scale, precision, or time frame, nor are they bundled with the other information needed for the decisions people can make.

Respondents from all user groups reported "playing it safe" or being reactive in part because climate services are not meeting their needs and can create confusion about what to do. Such confusion may result in severe damage when weather outcomes are bad or a loss of opportunities when weather outcomes are good (Funk et al., 2023a). A Southwest US rangeland manager explained that understanding the impact of drought on rangelands is hard because available greenness measures include inedible plants. Therefore, the Pueblo community he works with prefers to "play it safe," operating as if it were in drought every year, even though this limits production. A focus group of pastoralists in arid northern Kenya reported their perception that available forecasts were right only four out of 10 times; once they were right eight out of 10 times, they would start using them. An employee of Houston Food Bank explained that without knowing where flooding is likely to be prolonged and whether that overlaps with populations at risk of food insecurity, they cannot prioritize where to respond with additional food aid. Thus, to bring decision support across the last mile, we need to integrate the needs of users from the start, beginning with the very first mile.

We identify five components of decision-support systems that would enable climate services to be more actionable and effective. These include: (a) co-producing models of weather impact, (b) identifying tradeoffs between forecast windows and uncertainty, (c) being transparent about uncertainty, (d) respecting the needs and capacity of users, and (e) having a plan for when models are wrong.

Other researchers have identified several of these lessons for either weather forecasts or for uptake of decision support tools in the agrifood system. Many decision-support tools exist in the climate hazards space (see Weber, 2019) and a rich literature identifies the need for the co-production of weather forecasts (e.g., Cash & Belloy, 2020; Cvitanovic et al., 2019; Fleming et al., 2025; Leitch et al., 2019; Stolz et al., 2023; Vincent et al., 2018). Further, in the agrifood system space, increasingly sophisticated models predict weather, crop production and food security (Anderson et al., 2024; Elliott, 2022; Wang et al., 2022; Zhou et al., 2022). These models are often co-produced with local meteorological offices and higher-level extension actors but our last-mile users report these models are often not fit for their purpose (see also: Findlater et al., 2021; Fleming et al., 2025; Hansen et al., 2019; IPCC, 2023; Lentz & Maxwell, 2022).

We propose that the lessons ought to be considered in conjunction with one another, alongside methodological advances and extended beyond weather to the food system. With careful attention to last mile user needs, vulnerable communities will be better able to mitigate the harm and harness the potential benefits of often predictable weather extremes.

3. Discussion: Five Lessons

3.1. Lesson 1: For Weather Information to Be Actionable, It Needs to Be Converted to Potential Agro-Climatic Impacts, Co-Produced With Stakeholders

To make long-range forecast information usable, we need to understand their impacts and how affected people can change those impacts with the decisions that they make.

Two examples underscore how last mile users in the agrifood system are currently underserved by weather products. First, one community partner working in the livestock agrifood system in Kenya asked: "What do we do when we hear there will be 20 mm of rain?" For this respondent, knowing weather forecasts were not enough for them to make decisions about livestock. They also need to know, for example, how prices and weather forecasts are expected to affect the price of both cattle and feed. Second, when describing the food security threats from flooding, stakeholders with the Houston Food Bank informed us that the problem was frequent floods, not necessarily the large events associated with substantial downpours that occur during tropical storms. Thus, disruptions in food bank operations were the result of more mundane weather events than is often assumed, and to be able to respond to these disruptions, the foodbank needs to know where and when those events will translate to localized flooding. Stakeholders hold context-specific knowledge that can help modelers make predictions useful and actionable. Local knowledge might be critical to understanding how specific weather outcomes affect food production and impacts.

To produce actionable output, decision-support systems need to be co-produced with stakeholders from the beginning. Co-production is defined as the "iterative and collaborative processes involving diverse types of expertise, knowledge and actors to produce context-specific knowledge and pathways" (Norström et al., 2020, p. 183). While co-production is becoming more common in climate services (Cash & Belloy, 2020; Cvitanovic

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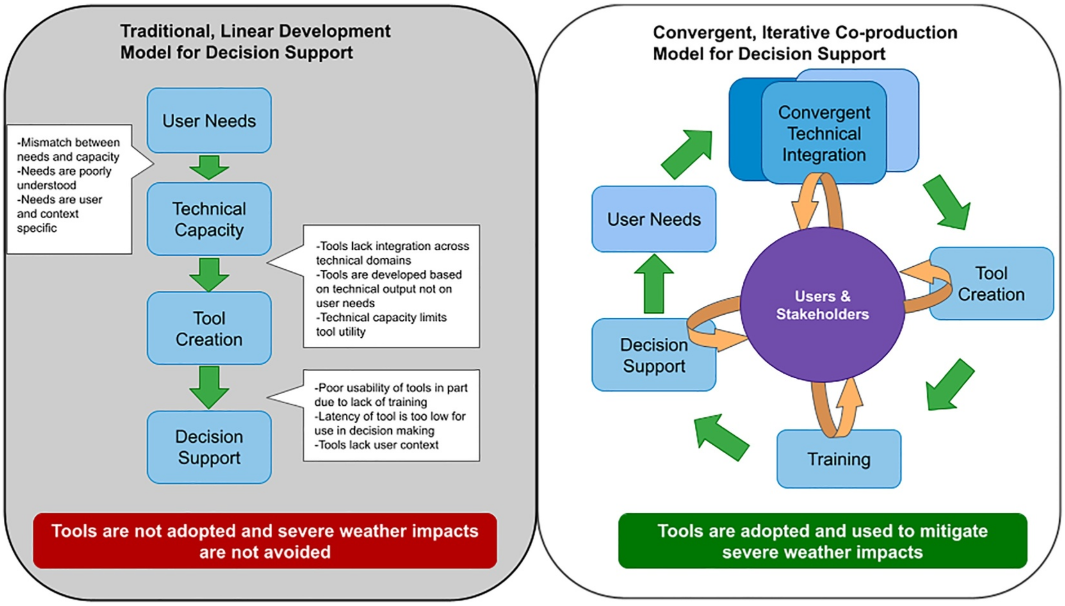

Figure 2. Traditional, linear approaches to model development versus convergent, co-production of decision support that highlights the literature approach to model development. Authors' own figure.

et al., 2019; Stoltz et al., 2023; Vincent et al., 2018), it is not widely adopted by the broader food system modeling community, leading decision-makers to express confusion about how to use model-based predictions (Coyle & Weller, 2020; Lentz & Maxwell, 2022; Maxwell et al., 2021).

Co-production offers several advantages compared to traditional, linear approaches, illustrated in Figure 2, panel a. (Cash & Belloy, 2020; Cvitanovic et al., 2019; Vincent et al., 2018). Co-production can help (Figure 2, panel b) by: (a) identifying the timing of key decision points, (b) assessing tradeoffs on timing and certainty, (c) determining which measures are valuable and (d) creating buy-in (Lu et al., 2022) and build trust among users (Chambers et al., 2021; Norström et al., 2020), among other benefits.

It is crucial for the last-mile users to be collaborators in developing and refining models, both adding new information and adjusting optimization criteria (Zhou et al., 2022) for several reasons. First, the fitness of a forecast model for a specific problem will depend on the needs of decision-makers and on the feasible set of possible decisions. Understanding the degree to which the data available address the needs of the stakeholders is an important first step and what outcomes they care most about should shape the model. For example, food bank respondents requested highly spatially disaggregated information on flooding, which had not been previously available, in order to better respond to neighborhood-level impacts. In some cases, the most needed data may not be available; conversations on expectations can help modelers and stakeholders assess whether and how the model is useful.

When identifying what outcome the model is geared to predict and what tradeoffs exist for end users, stakeholder input is critical. For example, stakeholders may care more about mitigating the risk of a particularly bad result than knowing the most likely outcome. Pastoral women in Kenya described wanting information - even several hours in advance - of sudden onset of seasonal downpours that kill unsheltered and drought-emaciated livestock. This event and its impact calls for a unique and specific trigger. Thus, different needs of end users ideally drive model outcomes and performance (Zhou et al., 2022).

Second, coproduction is best thought of as an ongoing process (see Figure 2, panel b). Stakeholders need to be involved in the development of information products, to improve the product design, develop trust and ensure buy-in for the advisors (Coyle & Weller, 2020). As part of this process, one can work with stakeholders to train them in the model capacity, and use their feedback in terms of model accuracy and relevance to further train the model. This ongoing training of both people and models implies that these decision support services require continual connection and operational support once the tool is developed. Continual modifications of the predictive models using stakeholder input will ensure models are adapted to the needs of end users. Crossing the last mile requires investing in community dialog, outreach, and education.

Third, to develop models that go beyond forecasting weather to forecasting impact requires input from a wide range of scientific disciplines along with contextual knowledge (Mariotti et al., 2024; McClure et al., 2024; Webber, 2019). For example, to understand how a drought will affect feed and cattle prices, we need to couple weather models with economic models, incorporating stakeholder input to ensure that the combined model can reflect users' specific contexts. As another example, weather events (particularly those associated with global ENSO events) may be correlated over space and therefore we need to model not only the direct effects of these weather events on a specific location, but their spillover effects.

Accounting for these interlinkages requires a multidisciplinary convergence-science approach, bringing together climatologists, hydrologists, sociologists, economists, statisticians and policy experts to appropriately model both the weather and its potential impacts. Expertise in different areas is needed to help reduce confusion or misunderstanding (Bojovic et al., 2021; Findlater et al., 2021; Fundel et al., 2019). A co-production mindsight can move science from a siled delivery of technical capacity, which can result in a lack of integration across technical domains, to convergent technical integration, which can result in tools that better match the needs of users and that integrate findings across multiple disciplines (In Figure 2 see technical capacity in panel a and convergent technical integration in panel b). A truly cross-disciplinary approach requires researchers who can articulate and explain how various assumptions are incorporated into the model to one another and to end users. While this does require time and other investments in collaboration, this approach helps ensure that the factors included in each model component are carefully combined to produce trusted insights needed for decisions.

3.2. Lesson 2: Recognize the Tradeoffs Between Decision Timing and Forecast Windows and How This Tradeoff Influences the Portfolio of User Options

Information needs to be timely to be actionable. The challenge, though, is that timely information can often be less accurate and this varies across different portfolios of user decisions. But both climate and agricultural systems have their cycles, and convergent science, science that studies people, plants and climate processes, can explore and exploit linkages between the timing of user needs and the potential for anticipating shocks, as well as opportunities for benefiting from favorable weather.

As an example of the tradeoff between timing and model uncertainty in both the southwest US and East Africa, forecasts are forward-looking, but uncertain and spatially imprecise. Over the course of the monsoon rains (or their failure), more information about moisture stress becomes available, making predictions more accurate (Turner et al., 2025). Thinking through how improvements in information interact with user decision-points can highlight opportunities and barriers. With enough advance notice, long-lead forecasts can inform farmer seed selection decisions about livestock purchases or sales. Various statistical and machine learning models can be effectively applied for short-term forecasts, whereas building reliable models for long term forecasts for a half-year to a year often require variable selection and integrating disparate information potentially at different spatio-temporal scales (Dinku et al., 2018). Some responses are constrained by the timing of model forecasts and some are constrained by the time needed to implement a response (Hansen et al., 2019). Stakeholders may face decision deadlines that may come before adequate forecast certainty, which might suggest the need for no-regrets programming.

Seasonal calendars and decision trees provide a set of tools that can help describe timing of information needs and how they relate to decision-making (Haigh et al., 2015; Prokopy et al., 2017; Takle et al., 2014). Forecasters need user input to understand when an early, uncertain forecast is better than a later, more precise one. This will vary by agricultural process and ecological location. Agricultural producers (and others) make decisions at multiple timescales ranging from today's operational decisions to long-term strategic decisions. For longer-term decisions, climate information lead-time is crucial, and there are trade-offs between lead-time and forecast skill. Forecast skill varies throughout seasons and inter-annually, requiring forecast providers to more fully engage with end-users to identify windows of opportunity for matching forecasts with critical forecast lead-times. The process of co-creating calendars of cyclical and recurring decisions made by decision-makers helps forecast producers and end-users identify those windows of opportunity.

The value of information provided to decision-makers varies by livelihoods and locations. In one interview, a Pueblo rangeland manager indicated that stocking rate decisions are made early in the season and there is a preference to stock conservatively rather than ask ranchers to remove animals later in the grazing season. Farmers may have a great deal of flexibility to respond to information before they decide what crop to plant and when, but their set of choices narrows after the crop is in the ground. In contrast, pastoralists in Samburu County, Kenya described making a series of ongoing adjustments to where they pastured their livestock, suggesting a more continuous need for weather forecasts. Donors seeking to address food insecurity face yet another decision-tree of interventions that have different timeframes, costs, and efficacy (Lentz & Maxwell, 2022; Zhou et al., 2022). Delivering fodder to drought-affected areas for livestock is low cost but requires more time to set up than starting a livestock offtake program. When severe drought is forecast with limited certainty, intervening earlier at a lower cost may make sense rather than waiting for more certainty and facing higher cost intervention options. Thus, climate prediction information needs to fit decision-makers' windows of opportunity.

At the same time, the longer the time horizon of a forecast, the less certainty there will be. Clearly indicating timing-certainty tradeoffs can help decision makers understand the relative risks and benefits associated with their decisions, and timing of their actions.

Each end user is unique and we are not (yet) at a point where forecasts can be tailored to individuals. Nonetheless, we found stakeholders facing similar decisions within livelihoods and agrifood system production areas reported similar needs. For example, in arid and semi-arid areas in Kenya, large scale commercial ranchers care more about profitability and are willing to offtake animals preceding drought warnings. In contrast, smaller pastoralists reported wanting to avoid distress sales. They wanted information about fodder sources, and warnings about pests and diseases that could harm weakened animals.

3.3. Lesson 3: Model Developers Need to Consider User Priorities, Including Transparency and Model Uncertainty

Developers face a long list of choices when developing forecasting models (Zhou et al., 2022). These choices should reflect what users need. e.g., different users might have different objective functions: one group of users may care about precision, while others may want to understand the probability of a particularly bad outcome. This may suggest different criteria for the machine learning algorithms in and across different settings. In conversations with policymakers, we heard that predicting classifications was more useful than predicting continuous outcomes, since it fit better with their existing targeting system (i.e., go-no go interventions).

Modelers also face decisions around what inputs to use and what specific outputs to predict. When modeling spatial-temporally dependent outcomes, fast and efficient variable selection can be crucial to determine the inputs needed to model the outcome in each space-time coordinate. Incorporating stakeholder needs in these decisions is critical for usability. Kenyan pastoralists preferred predictions based on analog years (e.g., this year is predicted to be similar to an identifiable prior year) than predictions of specific weather outcomes, because analogs reflect local context. Alternative prediction targets may require different modeling choices throughout the design and training phase.

When providing predictions to stakeholders, there is often a focus on point prediction (Zhou et al., 2022). Yet reliable uncertainty estimates may be equally important, as it allows the users to identify scenarios in which the model becomes inaccurate. A lack of communication on uncertainty of predictions contributes to "data confusion" among stakeholders, often resulting in delayed or no responses (Lentz & Maxwell, 2022). Effective decision support systems need to be able to estimate and communicate appropriate levels of uncertainty, especially regarding severity and spatial extent (Fundel et al., 2019; Handmer & Proudley, 2007).

A probabilistic framework approach offers a coherent way of obtaining uncertainty quantification (Gu et al., 2024). Furthermore, having a probabilistic generative model of data enables the user to better understand the underlying assumptions of the model, and allows modelers to develop improved approaches to represent reality (Storm et al., 2024). By focusing not only on point estimates but on the potential distribution of outcomes that may result from correlated shocks, modelers and users have the potential to identify risks and key components of the food system that could be bolstered to improve resilience.

Given the increased power and prevalence of machine learning tools in prediction models, modelers may be tempted to tackle some of these tricky forecast problems by throwing algorithms at it, which can hamper uptake

(Findlater et al., 2021). Transparency in modeling and attending to interpretability can help to decrease data confusion by helping end users understand the model and build trust in its results (Zhou et al., 2022). Often understanding why a model produces a given forecast and its certainty is just as important as the prediction itself.

3.4. Lesson 4: Understand and Respect Different User Capacities When Designing Decision Support Systems

In lesson 1, we argued that co-production is vital. This might suggest that one would want to have frequent meetings with stakeholders to get detailed feedback on modeling efforts and outputs. But, some stakeholders may not have the capacity or personnel to participate. These differences will have implications for how information needs to be communicated and how to integrate stakeholders in the modeling efforts.

Different user communities will have different abilities to incorporate the information into their decision-making processes and may need information tailored to their capacity and cultural context. The technical capacity of decision makers differs across scales and institutions (Wilby & Lu, 2022). For example, some of the food banks we were working with had their own research teams, whereas others have skeleton staff only focused on program delivery. Remote communities may need quick loading, lower resolution graphics or communication in local languages. One respondent, a radio host in a local language in northern Kenya, explained that reaching out to community members about forecasts in local languages was better received by his audience when delivered conversationally between hosts and meteorologists rather than delivered as a news-report. As a second example from Kenya, respondents described low uptake of a smart-phone app that was user-friendly but only reached those with smartphones and cellular coverage. SMS and radio remain far more accessible. While bespoke information delivery is not yet at hand, to be useful for different types of users, decision support systems need to vary in terms of complexity, granularity, and mode of expression (Wilby & Lu, 2022).

Further, while there are many strategies for explaining models to stakeholders, we found respondents with more familiarity with forecasting most enjoyed sharing feedback following demonstrations of mock-ups and opportunities to "test-drive" innovations while other people were more comfortable talking through major decisions linked to paper-based seasonal calendars following Haigh et al. (2015).

Thus, who the "stakeholders" are, their ability to respond to information and what information they need will shape the approach to co-production and its outputs. In other words, the last mile might look very different depending on who the users are. Further, intermediaries and advisors, such as extension agents, can play an important role in aiding the adoption of the models or translating them for users (Lemos et al., 2014; Lu et al., 2021; Safford et al., 2017).

3.5. Lesson 5: Have a Plan for What Happens When the Decision Support Is Wrong

By definition, there is always a chance that a forecast will be wrong. A Kenyan county agricultural officer explained that based on an unclear understanding of the low certainty of the 2023 March-April-May forecast, his office had recommended planting a high-yielding maize variety that was susceptible to drought. When drought hit, many subsistence farmers in his county lost their crops. We should not downplay this characteristic of forecasts. We can, however, plan ahead by pairing no regrets programming and risk mitigation products (e.g., weather insurance) with forecasts to protect populations when models yield projections that are off by a meaningful amount. This is especially important because both increasing climate extremes means that vulnerable communities will face more shortfalls and that few vulnerable communities can take on increased risk.

To help prepare communities for shortfalls, we need to first clearly communicate the uncertainty associated with our models in ways that are accessible to end users (Gustafson & Rice, 2020). Research on maps that communicate hurricane risk describe one approach to identifying effective communication strategies (Millet et al., 2020. See also Fundel et al., 2019; Handmer & Proudley, 2007). Second, and crucially, we need de-risk opportunities related to climate clemency - expectations for good weather. While much of the climate forecasts have focused on better predicting adverse extreme events, we also need to help communities capture benefits from good seasons (Funk et al., 2023). When a good year is forecasted, there is an opportunity for agricultural systems to benefit. But to be able to benefit from potential good years, decision-makers need to be in a position to handle the risk if things go wrong.

As we roll out these decision-support services, it is important to communicate both the potential risks of being wrong and ideally pair the forecasts with no-regrets programming and risk mitigation tools (e.g., weather insurance) with forecasts to protect affected populations when models are incorrect.

4. Conclusions

Extreme weather and climate events increase agricultural production costs, decrease incomes, and raise the price of food, making food less affordable with particularly strong consequences for vulnerable persons. Despite tremendous advances in early warning, the magnitude of climate-induced humanitarian disasters continues to grow. Increased predictability should empower actions that address food insecurity, but this predictability is not being effectively translated into decision support. As one respondent explained "If you are not planning for drought, drought will plan for you." More accurate, accessible, and useful forecasts of weather impacts can help households mitigate the risk of extreme weather for agricultural production and food insecurity. Yet, while we have focused on modeling impact, a retired Kenyan policymaker warned "It is fine to tell people to plan early. But, only if they have the seeds available and the capacity." In other words, without an enabling environment, better early warning can only do so much. As our abilities to develop complex, sophisticated predictive models expand, modelers working on different problems across different sectors have an opportunity to learn from one another and from their user communities. While our case focuses on the intersection of climate and food security, the learning is applicable to other arenas as well.

In sum, focusing on co-produced climate information is not enough to go the last mile. Decision support tools need to be accessible, transparent, and actionable; co-production is vital to ensure that these decision support tools serve their intended purposes (and users). As weather and climate shocks become more frequent, opportunities for building trust, honing collaborations, and refining decision support tools also become more frequent and more needed.

5. Inclusion in Global Research Statement

We are thankful for and benefited from the insights from a range of stakeholders, including meteorologists based in the US and Kenya, Pueblo members, community members in Samburu Kenya, and US-based food banks. Conversations hosted by the Kenya Meteorological Department and IGAD Climate Predictions and Applications Center helped inform our conclusions.

Data Availability Statement

Underlying data to generate Figure 1 is available at https://www.chc.ucsb.edu/data.

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Erratum

The originally published version of this article contained a typographical error. Coauthor C. Gundersen's name was misspelled as C. Gunderson. The error has been corrected, and this may be considered the authoritative version of record.