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Contextualising seasonal forecasts to accelerate their uptake for agricultural decision-making

Ignacio Saldivia Gonzatti[1,*], **Wouter Smolenaars**[1], **Christian Siderius**[2], **Hester Biemans**[1,3] and **Spyridon Paparrizos**[1]

[1] Water Systems and Global Change Group, Wageningen University & Research, Wageningen, The Netherlands
[2] Uncharted Waters, Sydney, Australia
[3] Wageningen Environmental Research, Wageningen, The Netherlands
[*] Author to whom any correspondence should be addressed.

E-mail: ignacio.saldiviagonzatti@wur.nl

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1. Introduction

Seasonal climate forecast capability continues to advance, with promising gains in forecast skill from enhanced physical models and machine-learning methods [1, 2]. As these advancements create new opportunities for agricultural decision support in rainfed systems [3], realising the potential of seasonal forecasts depends on how information is contextualised and communicated to farmers and agricultural planners. Currently, seasonal forecasts are mostly delivered as climate signals, such as rainfall and temperature anomalies, which offer a general understanding of climatic conditions, but rarely connect to concrete choices these actors must make before and during the growing season [4]. We argue that contextualisation has emerged as a major challenge to forecast uptake. By contextualisation, we mean translating climate signals into decision-focused agro-climatic indicators aligned with local thresholds and the periods when farmers and planners can still modify their choices (the decision windows). Here, we present a forecast-to-decision chain that highlights contextualisation as the critical bottleneck, and outline improvements needed to strengthen this link. Focusing on the realities of rainfed food systems, we point to actionable steps to integrate forecast information into everyday decision-making.

Seasonal forecasts shape strategic choices for farming. They inform cultivar selection, planting date, fertiliser applications, and labour requirements [5]. They also inform decision-makers beyond the farm, including agricultural advisors and planners who use seasonal forecasts for logistics, contingency planning, and food availability outlooks [6]. The complexity of smallholder livelihoods makes such decision-ready information especially critical. Farmers manage several crops on overlapping calendars, often alongside livestock, and allocate limited household resources between farm and off-farm activities [7], requiring decisions on when to plant, which varieties to use, and how much labour or input to commit. Where forecasts are sharp and reliable, farmers can take calculated risks [8], and planners can allocate resources more effectively and stabilise markets [9].

Effective seasonal forecasts help agricultural decision-makers navigate these choices. However, several challenges complicate their uptake in rainfed agricultural systems. Sparse and discontinuous in situ records make it hard to calibrate and validate forecasts, yielding coarse products that smooth over local rainfall patterns relevant for planting and critical growth stages [10]. Limited connectivity and literacy faced by farmers further impede access and interpretation. Even when forecasts reach users, they are often out of context, require technical expertise, and do not match local realities [7, 11].

These challenges have reinforced the use of climate signals in seasonal climate services, such as tercile rainfall and temperature maps and seasonal totals [12]. Although computed against local climatology, they are typically coarse in space and time and not framed around agronomic thresholds [4, 12]. A 'near-normal' season may still be too dry for maize in a semi-arid district, whereas a 'below-normal' season in a humid district may still provide enough water. As a result, climate signals rarely guide decisions across the season [13]. By contrast, translating the same signals into decision-focused indicators aligned with actionable windows can highlight operational risks and opportunities, such as the chance that rains begin by a given date or that a two-week dry spell occurs during a crop's sensitive stage [14].

Additional operational constraints complicate the development of contextualised indicators. Predictability varies by location, season, and metric, requiring careful selection of indicators with demonstrated skill [4]. Forecasts issued at grid scale are interpreted at farm and district scales, creating mismatches when local notions of 'normal' differ from regional forecast categories [5]. Furthermore, operational workflows must deliver information before decision windows and be updated as conditions evolve throughout the season. Success depends on timely use through trusted communication channels, requiring responsive, locally-relevant information systems.

In this perspective, we present a forecast-to-decision chain framework that highlights the required links to translate seasonal forecasts into actionable advisories. We focus on contextualisation as the critical link and outline the reinforcements needed now to accelerate forecast uptake. Although several studies have advanced individual elements, such as presenting the full forecast distribution or integrating forecasts with crop models, clear and simple guidance is still lacking on how to go from primary seasonal forecast data to decision-relevant information. We fill this gap by bringing these advances together within a single, iterative framework that links ensemble forecasts to decision-focused indicators, communication, and evaluation.

2. The forecast-to-decision chain

The success of seasonal forecast services has often been judged mainly by their accuracy and skill, with less emphasis on decision usefulness [15]. The proposed chain treats forecasting as a design process in which each link must produce an output that the next user can act on. Forecast information moves from national agencies and research centres, which generate and process ensemble forecasts, to meteorological offices and regional planners, who translate them into operational indicators, and finally to extension services that interpret and apply these indicators with farmers at the local scale. Information at each stage must be tailored to the users' decision horizon, technical capacity, and institutional mandate. Success is therefore measured not only by accuracy but also by timeliness, usability, and actionability. The chain is iterative, with links feeding back into one another as data, indicators, and delivery are refined through co-evaluation with end users.

The chain sets out four links for forecasts to become actionable advisories, as illustrated in figure 1.

1. It begins with a **technical foundation** that ensures forecast ensembles are available on schedule, bias-corrected, and downscaled to the relevant service area.
2. Forecast data is then **contextualised** into decision-focused indicators that align with local decision windows and thresholds, and their skill is tested individually.
3. The indicators are **delivered** through trusted channels, supported by **capacity building** for users to interpret them and link them to actions.
4. The indicators' effectiveness, usability, equity, and value are **co-evaluated** to ensure they are understood and trusted, prompt timely action, reduce losses, and provide equitable benefits that match the different needs and capacities of users.

This chain implies a shift in the field of seasonal forecast services, where improving services is not only about more accurate data but about designing for decisions. We now turn to the crucial link to accelerate the uptake of seasonal forecasts.

3. Contextualisation: the crucial link

Reinforcing the contextualisation link requires four key improvements. First, tailoring indicators to decision windows that support when actions must be taken. Second, exposing the full ensemble distribution with user-defined thresholds. Third, validating reliability at the indicator level, meaning evaluating how accurately each indicator has performed in past forecasts rather than only assessing the underlying climate signal. Fourth, leveraging the potential of crop models to capture complex interactions of the agricultural system. Below, we explain how each improvement addresses different barriers that limit action on seasonal forecasts.

3.1. Build indicators around decision windows

Indicators must be tied to context- and time-specific critical climate-stress moments that determine decision windows when farmers and planners can still modify their choices [16, 17]. These decision windows occur at different phases throughout the growing season, from before planting, when farmers choose varieties based on expected season length, to near harvest, when post-harvest rainfall determines storage decisions. Although specific indicators will vary depending on the decision window, region, and crop, most fall into an established family of three agro-climatic indicator categories: hydrological balance (often via Standardised Precipitation-Evapotranspiration Index (SPEI) windows), wetness (wet-day counts), and temperature stress (heat and cold) [14]. The relevance of these indicators clearly depends on co-creation processes that validate local practices, crop varieties, and calendars. As climate change alters the length and timing of seasons and climate baselines continue to shift, co-creation becomes

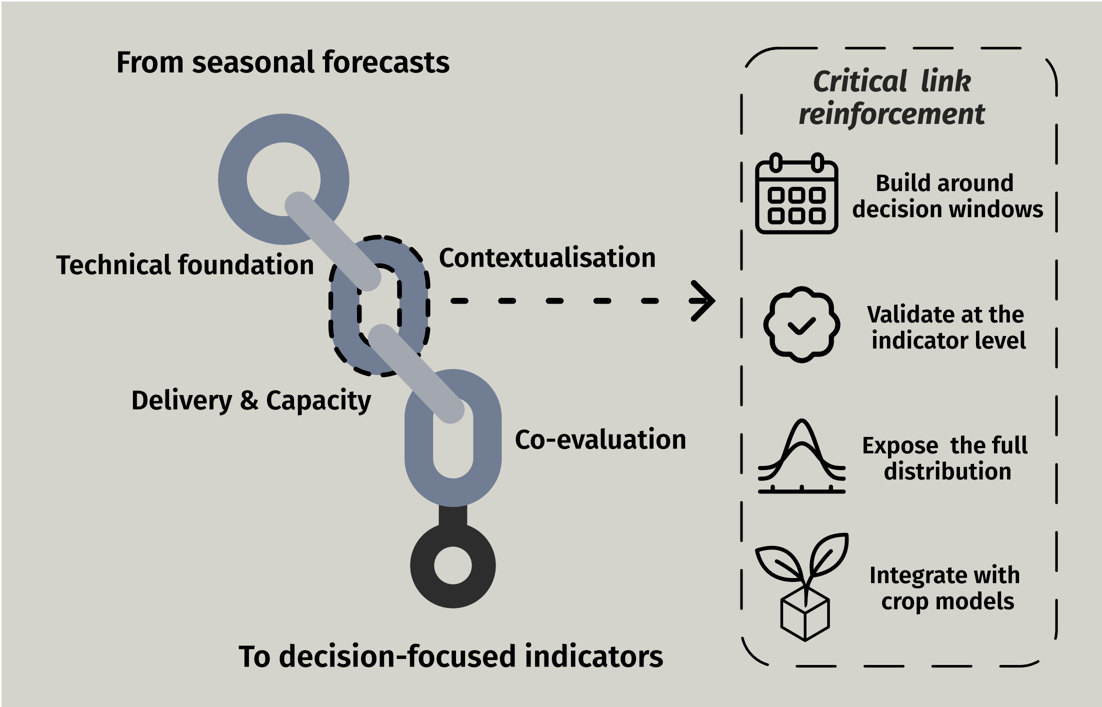

Figure 1. The forecast-to-decision chain translates seasonal forecasts to decision-focused advisories. The four links (and their outputs) are: (1) technical foundation (scheduled, bias-corrected, downscaled ensembles); (2) contextualisation (co-produced decision-focused indicators); (3) delivery and capacity building (actionable advisories); and (4) co-evaluation (usability assessment and feedback). The right-hand side illustrates the improvements to strengthen the contextualisation link: building indicators around decision windows, exposing the full forecast distribution, validating at the indicator level, and integrating into crop models.

critical to ensure indicators remain relevant to local decision windows [18]. Beyond initial development, the co-evaluation link should comprehensively and equitably determine the value of indicators [19].

3.2. Expose the full forecast distribution

Exposing the full forecast distribution addresses fundamental limitations in how seasonal forecasts are currently communicated. In forecast systems, ensemble members are designed as equally likely representations, making it impossible to consistently select individual skilful members across different initialisation periods. This design requires communicating the forecast as probabilities rather than deterministic outcomes. However, tercile maps, dominant in forecast services, constrain decision-making by using arbitrary statistical thresholds that rarely align with agronomic realities, and by obscuring critical information about forecast uncertainty [12]. The solution lies in presenting the complete forecast ensemble distribution alongside local climatology, allowing users to select thresholds relevant to their decisions. Using cumulative distribution functions to show probability-of-exceedance, or probability-density functions that compare forecast and climatological distributions, makes both the forecast signal and its uncertainty explicit [12]. This approach enables decision-makers to assess, for example, the probability that rainfall will meet crop water requirements or that the growing season will be long enough for a specific crop variety, rather than interpreting the generic below-, near-, or above-normal categories that may have little relevance to their choices.

3.3. Validate at the indicator level

Contextualising indicators raises requirements for the reliability link. Once thresholds and decision windows are tailored to specific decisions, reliability must be established for each indicator, not only for the climate signal behind it. 'Dangerously useless' indicators, where higher forecast probabilities and observed occurrence of events have an inverse relation, should be excluded from operational services [20]. Nevertheless, reliability alone may not justify action when forecasts lack sharpness (i.e. distributions remain spread out) [8]. Contextualisation also reveals predictability contrasts across event types: temporally aggregated hydrologic-balance windows (e.g. SPEI) smooth daily noise and often show stronger reliability at seasonal lead times than wet-day counts, which depend on local daily processes that models handle poorly [9]. Because lead time and season phase influence reliability, some indicators are only suitable for certain decision windows [4]. Overall, contextualisation improves interpretation but increases demands on verification

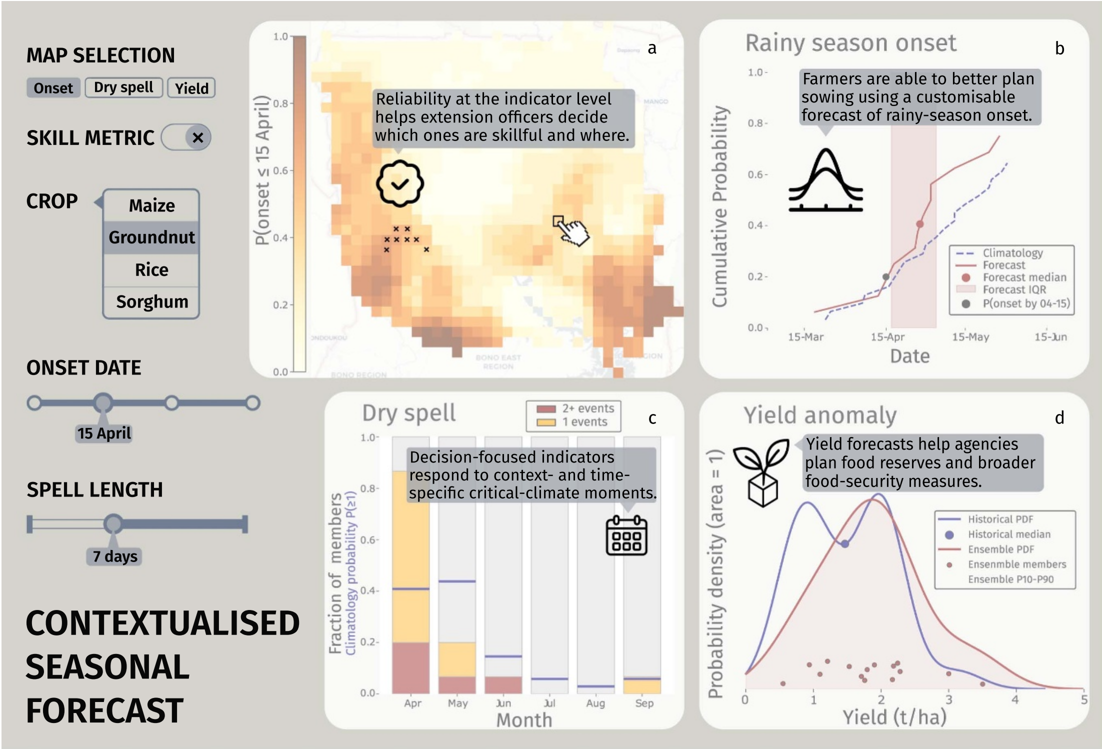

Figure 2. Example of contextualised seasonal forecast using decision-focused indicators. (a) Map view showing forecast probability that rainy-season onset will occur by a selected date, with skill overlay available to highlight areas with unreliable forecasts. (b) Rainy-season onset panel displaying the full forecast and climatology probability distributions for the selected grid cell, along with the probability of onset occurring by the chosen date. (c) Dry-spell panel showing the fraction of ensemble members predicting different numbers of dry spells per month for a specified spell length, with climatological probability of at least one dry spell shown for reference. (d) Yield anomaly forecast panel presenting the distribution of forecast ensemble members and historical yield data for the selected grid cell. Red dots representing individual ensemble members are vertically spaced to avoid overlap, and their y-axis positioning carries no quantitative meaning.

and communication, making reliability assessment critical to the contextualisation link.

3.4. Integrate into crop models

Integrating seasonal forecasts into crop models can offer additional and more precise information for specific crops, enabling targeted variety recommendations and management decisions. Crop models simulate the interaction between local environmental conditions (e.g. soil texture, CO_2), climate variables, and crop-specific responses (e.g. sensitivity to heat stress during flowering, harvest index). Therefore, they capture non-linear effects on crop growth and yield that climate indicators cannot. They can also generate stage-specific indicators, such as the probability of dry spells during flowering, based on predicted phenological stages rather than fixed cropping calendars. Additionally, they can test the implications of different sowing dates and varieties on expected yields [14]. Yield forecasts are also more directly relevant for crop insurance and food security planning than climate indicators. Despite their advantages, crop models require local calibration and high-quality data, with performance varying by location and crop. Their uncertainties, stemming from model structure, calibration, and data availability [21] must be communicated alongside forecasts. Currently, the integration of seasonal forecasts into crop models is concentrated in specific regions and crops, showing potential for broader application [22].

A strong contextualisation link produces indicators that align with local decision windows, expose the full forecast distribution and skill, and allow users to select thresholds relevant to their choices. Figure 2 illustrates an example of such a workflow for Northern Ghana. A user can select an area, toggle a skill overlay, and inspect rainy season onset and dry-spell panels that display forecast and climatology distributions together with probabilities for user-defined thresholds. For instance, an agricultural advisor might check the likelihood that rains will begin by 15 April and whether a 7 d dry spell is probable during the flowering phase of groundnut. The dashboard also includes a crop-yield panel that summarises the forecast ensemble and historical yield distribution, linking climate indicators directly to expected agronomic outcomes. This example shows how the framework enables advisors to translate forecast information into practical planting guidance while highlighting decision windows, uncertainty, indicator-level skill, and potential yield implications.

4. Conclusion

Until now, contextualisation of seasonal forecasts has been constrained by technical limitations, reinforcing reliance on generic climate signals. As forecast skill continues to improve, contextualising forecasts into decision-focused indicators should become a priority to accelerate the uptake of seasonal forecast services. Realising this potential requires coordinated action across the forecast-to-decision chain, with government and nongovernmental actors aligning policies and operations. While the proposed framework applies broadly to climate-agriculture services, its immediate users are national and regional agencies responsible for seasonal advisories and extension services that deliver forecast information to smallholder farmers.

Clarifying these user roles strengthens the targeted design of the forecast-to-decision chain. Therefore, we recommend that national meteorological and hydrological services and agriculture ministries adopt common standards that express guidance as probabilities of exceedance and report indicator-level reliability. Also, co-creation processes to validate local decision windows and thresholds with users are critical, as is integrating indigenous and scientific forecasts. We also recommend seasonal co-evaluation cycles to assess the usability and value of the forecast indicators. Finally, we call on the scientific community and service providers to open-source tools and maintain openly accessible hindcast archives that enable reproducibility and learning. Taken together, these commitments reinforce the forecast-to-decision chain, making indicators timely, trusted, and actionable.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors have no conflict of interest to declare.

Ethics statement

No ethical statement required.

ORCID iDs

Ignacio Saldivia Gonzatti 0000-0002-9684-2434
Wouter Smolenaars 0000-0003-0511-7905
Christian Siderius 0000-0002-2201-9728
Hester Biemans 0000-0001-8750-2553
Spyridon Paparrizos 0000-0002-4226-8043

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