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Seasonal seed scenario planning: co-design of a generic framework for matching seed supply and demand using seasonal climate forecasts

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ABSTRACT

To cope with interannual climate variability, many farmers in tropical and sub-tropical regions choose crop varieties that fit seasonal climate conditions. Therefore, seed demand for different varieties, such as early- or late-maturing cultivars, varies between years. Resulting mismatches between relatively constant supply and variable demand create losses for both seed suppliers and farmers. Because demand for seed of different varieties is influenced by seasonal climate, however, probabilistic seasonal rainfall forecasts could help seed suppliers better anticipate upcoming seed demand. To explore this idea, we engaged decision-makers from seed supply organizations in Zimbabwe and Ethiopia. Through a participatory design process, we identified opportunities and challenges for using seasonal rainfall forecasts to inform seed supply decisions. In a case study of maize seed sales in Zimbabwe, we tested our assumptions and iteratively devised a systematic procedure for forecast-based planning in seed supply, relying on free online data sources and expert deliberations. We found that currently accessible rainfall forecasts could indeed be useful for prioritizing likely high-demand varieties during the stages of seed treatment, packaging, and logistics. In practice, though, more flexible and adaptive management of seed supply pipelines might be required to make use of seed demand forecasts. In the future, targeting farmers with climate forecasts along with recommended variety portfolios may strengthen the association between seasonal climate and farmers' variety demand, increasing the accuracy of demand anticipation. This study highlights opportunities for increased case-specific collaboration between climate scientists and the seed sector to make seasonal forecast information operational.

Practical implications

To maximize productivity, farmers in topical and sub-tropical regions need reliable access to seed of locally suitable crop varieties. But climate outcomes, especially rainfall quantities, generally vary between years. This means that a different set of varieties may be optimal every year. For example, farmers typically demand more early-maturing varieties in drought years than in rain-abundant years. Seed suppliers (including commercial enterprises, public bodies, and NGOs) have an interest in aligning their variety portfolios to farmers' demand. This is because both over-supply of certain varieties (more seed offered than farmers demand) and under-supply (too little seed offered, farmers turn to alternative seed sources) create costs. Therefore, both farmers and seed suppliers would benefit from an increased ability to anticipate farmers' seed demand at the variety level. This information could be used to adapt seed supply operations in a way that minimizes the mismatch between supply and demand. This study explores how this idea could work out in practice.

Because farmers' demand for different seed varieties is influenced

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by seasonal climate, seasonal climate forecasts create opportunities to anticipate seed demand. Using freely available climate forecasts and real data on maize seed demand in Zimbabwe, this study demonstrates that this is possible in principle. Based on engagements with seed supply practitioners, we point out opportunities and conditions for employing seed demand forecasts in the management of seed supply chains. We do not present a ready-made decision-making tool, but a general proof-of-concept and prototype validated by seed supply practitioners from two sub-Saharan countries. For further operationalization of the concept, this study highlights opportunities for future development, including case-specific collaboration between the seed supply sector and climate researchers. Our results are an encouraging base of evidence to motivate further investigation around the use of seasonal climate forecasts for improving seed supply in tropical and sub-tropical regions.

Data availability

The data that has been used is confidential.

1. Introduction

In many tropical and sub-tropical regions, marked year-to-year climate variability creates uncertainty for decision-making in smallholder agriculture. In parts of Eastern Africa, for example, annual rainfall anomalies of 50 % above or below the long-term annual mean are common (Kotir 2011, Tierney et al. 2015, Nicholson 2017). This variability has implications for the livelihoods of farmers, who make up large parts of the population in many low- and middle-income countries. Any given farm configuration (e.g., choice of crops, crop varieties, and other inputs) is likely to show different levels of productivity under different seasonal climates (Challinor et al., 2014, Rowhani et al. 2011, Thornton et al. 2014). To mitigate risks from weather and climate variability and optimize farm performance, a key strategy is an appropriate choice of crop varieties to fit seasonal climate conditions. For key food security crops such as maize, smallholder farmers' variety demand can be more strongly determined by supply-side factors than by farmers' choices (Chivasa et al. 2022; Rutsaert et al. 2021; Waldman et al. 2017). But farmer perceptions of intra- and interannual climate variability also influence seed demand. For example, some farmers decide to plant, on the whole, later-maturing varieties when rainfall conditions are favorable (Lacy et al. 2006) or prioritize traditional over modern varieties in shorter rainy seasons (Almekinders et al. 2021).

Variable seed demand increases the risk of mismatches between seed supply and demand. Often, farmers take seed sourcing decisions as late as the very onset of planting, or even later, in cases where the farm must be replanted (Lacy et al. 2006, Burer et al. 2008). Yet at these points in time, major seed supply decisions – which amounts of which varieties get multiplied, distributed, promoted, etc. – have already been made. Faced with the unpredictability of exact seasonal seed demand, suppliers in open seed markets (commercial enterprises, not-for-profit organizations, or public institutions) plan and prepare for average demand patterns based on past experiences (Burer et al. 2008). Consequently, outstandingly high demand can contribute to the unavailability of preferred varieties for some farmers (Shiferaw et al. 2008, Shiferaw et al., 2015). In this case, farmers may need to buy alternative, less preferred varieties and accept lower yield potential or increased production risk. Due to lower willingness-to-pay for less preferred varieties and carry-over of unsold seed, mismatches between seed supply and demand are costly for seed suppliers (Burer et al. 2008, Teferi et al. 2020).

Despite the frequent *ad-hoc* nature of seed purchasing decisions, seed demand can be anticipated to some extent, due to its association with seasonal climate and other factors, such as crop prices or the availability of credit. Zhu et al. (2019), for example, demonstrated that demand for horticultural seeds in Shanghai can be forecasted up to five months into the future using data on climate, market prices, and seed inventories, at practically meaningful levels of accuracy. In the (non-agricultural) manufacturing and retail industry, demand forecasting is a widely established practice for supply chain coordination (Fildes et al. 2022, Petropoulos et al. 2022). Seasonal forecasts of seed demand could help reduce the degree of mismatch between seed supply and demand, likely translating into better overall outcomes for both seed suppliers (lower market share lost to competitors, lower share of unsold seed) and farmers (more reliable access to suitable, preferred varieties).

Since climate variability influences seed demand, seasonal climate forecasts could inform forecasts of seed demand. Seasonal climate forecasting is made possible due to the influence of slowly moving boundary conditions of the climate system on atmospheric phenomena (Troccoli 2010). For example, variability in tropical Pacific sea surface temperature, associated with El Niño-Southern Oscillation (ENSO), is predictable up to one year ahead. This allows long-lead prediction of seasonal rainfall anomalies, given the influence of ENSO on them (Ham et al. 2019, Taschetto et al. 2020). One widely used approach for producing seasonal forecasts is the use of numerical climate model simulations. These models provide predictions for a range of variables, such as temperature and precipitation, typically up to six months into the future. Seasonal forecasts are now provided free of charge through national and supranational initiatives such as Copernicus (the European Union's earth observation program) or NOAA (the US climate science department). The potential of seasonal climate forecasts to support farmers' decision-making has been explored extensively, both in high-income and smallholder context (Hansen 2002, Hansen et al. 2011, Klemm and McPherson 2017, Chisadza et al. 2020, Ceglar and Toreti 2021, Alexander and Block 2022). Experimental access to seasonal forecast information can positively influence farmers' agronomic decisions, for example, about sowing dates and variety choice (Roudier et al. 2014). In practice, however, available seasonal forecast products are rarely inclusive to the needs and capacities of resource-poor smallholder farmers (Hansen et al. 2019, Vogel et al. 2019). Staff of seed supply organizations are likely to face lower technological and cognitive access barriers than farmers, but to our knowledge, the potential use of seasonal climate forecasts for decision-making in seed supply has not been widely studied.

2. Opportunities for scenario planning

Operational seasonal climate forecasts often provide probabilistic forecasts of rainfall terciles, i.e., they give the likelihood of a rather dry (lower tercile), average (middle tercile), or rather wet season (upper tercile), relative to historical rainfall variability at a particular location. If seed suppliers can assess the most likely implications of these rainfall outcomes on seed demand, seed supply operations can be planned ahead in a way that minimizes the risk of mismatches. This type of anticipating the future and defining optimal operational adjustments under uncertainty is commonly referred to as 'scenario planning'. Scenario planning is used by organizations, such as businesses and governments, to strategically pre-plan their responses to alternative, possible combinations of future events and circumstances – i.e., scenarios (Reilly and Willenbockel 2010, Amer et al. 2013). For example, the existence of stringent pandemic preparedness plans, developed through earlier scenario planning exercises, has been crucial for effective and rapid responses to the COVID-19 health crisis (Richmond et al. 2021, Villa et al. 2020).

In contrast to stochastic modelling approaches used by insurance companies, which can consider the probabilities of numerous factors for determining the probability of an outcome of interest, scenario planning is driven by human deliberation. Scenario planning supports decision-making by identifying a small number of discrete, plausible futures that call for different responses. As a first step, this implies identifying key uncertainties that may affect the future performance of a policy or enterprise. Then, based on the most relevant factors of uncertainty (usually 3 to 8), planners define a manageable number of scenarios (typically 3 to 4) through different, plausible combinations of the uncertainty variables (Amer et al. 2013). This way, even without estimating the probability of each scenario, decision-makers can already define an optimal response to each scenario, usually through qualitative deliberations.

Seed supply in low- and middle-income countries may benefit from systematic use of scenario planning and strategic foresight. Climate variability exposes seed supply to high uncertainty. There is strong public interest in risk mitigation, as the efficiency of seed supply affects rural livelihoods and food security. Here we assess how seasonal climate forecasts can be employed by seed supply decision-makers in scenario planning exercises to better meet farmers' seed demand. Through an open-ended co-design process with seed supply stakeholders in Zimbabwe and Ethiopia, we co-developed a generic decision-support procedure that harnesses seasonal forecasts for informing risk-minimizing decisions on seed supply. Two main objectives guided our study: First, to co-develop a concept of forecast-based seasonal scenario planning together with practitioners and evaluate its potential for seed supply management. Second, to create a replicable procedure for implementing the concept in practice, as a starting point for further methodological development.

In the following, Section 3 describes the concept we devised and the co-design process with seed sector stakeholders in Zimbabwe and Ethiopia. Results from a case study are reported, and we present the tentative implementation of the generic seed scenario planning tool. Section 4 presents the main insights from our exploratory proof-of-concept study, including on likely use cases and recommended further development. Section 5 concludes with key lessons learned and an outlook.

3. Exploring the use of seasonal scenario planning for seed supply management

3.1. Concept of seasonal seed scenario planning

Seasonal seed scenario planning intends to support seed supply organizations' anticipation of seed demand at crop variety level. Based on this anticipation of upcoming seed demand, planners can adapt decision-making, increasing their ability to respond to farmers' demand and minimize economic loss. The idea here is to use historical data to associate different seasonal climate conditions with seed demand, in a statistical model. This information can then be integrated with anticipated climate variability from numerical seasonal forecast models to estimate upcoming seed demand. Finally, this demand forecast can be used to inform decision-making along the seed supply chain. As a decision support process, the concept comprises five key stages.

(i) *Identifying drivers of seed demand variability.* The first step consists of understanding which factors generally influence farmers' demand for different seed varieties in the target context. Seasonal rainfall is an example, but depending on context, also elections (distorting open-market demand, as political campaigns may distribute free seed of certain varieties) or disasters such as droughts or floods (increasing demand, as farmers need to replant) might play a role.

(ii) *Envisioning plausible, alternative scenarios.* Based on different, coherent combinations of the identified drivers of seed demand variability, agricultural seasons are categorized into a low number of stereotypical scenarios. An example would be 'high overall rainfall, no election, no disaster'.

(iii) *Assessing scenario probabilities.* For the upcoming season, the probability of each scenario is estimated. This can be done using available data (e.g., electoral calendar), expert heuristics, or scientific forecasts (e.g., seasonal climate forecasts). Some scenarios may have a probability of 0 %. For example, when no election is scheduled to take place, all scenarios involving an election may be disregarded. The probabilities of all considered scenarios add up to 100 %.

(iv) *Defining an overall risk-minimizing strategy.* Under each scenario, matching supply and demand requires a different set of actions by the seed supply organization. As decision-makers cannot know for sure which seasonal scenario will eventually occur, however, an overall risk-minimizing behavior can be identified. This overall optimal strategy is defined by identifying the scenario-specific optimal strategies and weighting them by the respective scenario probabilities.

(v) *Preparing an action plan for each scenario.* The overall risk-minimizing strategy balances the different scenario probabilities and their respective risks, using best available knowledge prior to the agricultural season. Nonetheless, this strategy is unlikely to perfectly suit the actual seasonal outcome. Thus, for each individual scenario, an action plan can be prepared. These action plans consider that the overall risk-minimizing strategy will be adopted. Then, for each scenario, they outline actions that help to better respond to actual seasonal demand and reduce economic loss.

3.2. Co-design process

3.2.1. Design criteria

Our goal was to co-design with seed sector stakeholders a user-friendly procedure for seasonal scenario planning in seed supply, combining digital and non-digital features as appropriate. To ensure the resulting procedure fits the targeted decision-making context and considers the needs, habits, preferences, and capacities of seed supply stakeholders, we facilitated a process of participatory design (see Stitzlein et al. 2020, Eastwood et al. 2022, McCampbell et al. 2022, Steinke et al. 2022). Participatory design intends to generate context-aware solutions without predetermining any features or characteristics of the eventual solution. While we adopted this open-ended approach, the research team agreed on multiple design criteria. These are requirements that the scenario planning procedure should fulfill to be widely applicable beyond the immediate design context and case study. We considered the following design criteria:

Low cognitive effort. Seasonal seed scenario planning should avoid the need for advanced technical know-how in statistics or climate science, but instead use simple indicators and heuristics that seed sector stakeholders are generally familiar with. The procedure should not require the use of complex software that would require users to invest significant time into learning.

Low access barriers. All features of seasonal seed scenario planning should be immediately accessible (online), without requiring individual registration, affiliation to a certain organization, or payments.

Low time investment. The procedure should require minimal time commitment by the decision-makers involved.

Actionable output. The output of seasonal seed scenario planning should provide a practically meaningful input into adaptive decision-making in seed supply chains.

Universal application. Although we created and tested the procedure in a specific case study, our goal was to design a decision-support tool that can be used across regional contexts and crops.

3.2.2. Explorative interviews with seed sector experts

To understand current practices of demand assessment and to identify the practical potential of influencing decisions with seasonal demand forecasts, we conducted semi-structured interviews with production and marketing managers of *Seed Co Limited* in Zimbabwe. Seed Co is a major commercial breeder and supplier of cereal and legume seed, serving both large- and small-scale farmers across multiple countries in sub-Saharan Africa. In addition, we were interested in understanding the major drivers of farmers' seed choice in the case study area, Zimbabwe. Due to travel restrictions in the face of the COVID-19 pandemic, two individual interviews and one focus group discussion with three participants were conducted via video conferencing software.

As a starting point for prototyping the tool, we mapped current decision-making procedures within Seed Co, as well as along the wider seed value chain (see Table 1). Production decisions – how many tons of each variety will be produced by contract farmers – are influenced by multiple considerations: first, production is driven by a long-term plan for market positioning, determined by senior management. Second, production managers estimate demand for different varieties based on previous seed sales and feedback from seed retailers, but also considering expected effects from advertising specific varieties. On top of this estimated seed demand, a fixed percentage of surplus seed eventually gets produced. This is because – although seed carry-over has a cost in terms of logistics, storage, and administration – Seed Co prioritizes ensuring customer loyalty by avoiding running out of stock. Bulk seed is then distributed to regional depots according to the regional demand estimates. For further distribution, Seed Co staff collects initial orderings from seed retailers. During the season, these local agro-dealers regularly order seed batches from the regional depots to restock their shelves.

3.2.3. Prototyping a decision-support tool for seasonal seed scenario planning

During a prototyping phase, we collected feedback from climate scientists and seed sector decision-makers to progressively specify our initial design idea. This also involved insights gained through the interactions under Sections 3.3 and 3.4 (see below).

As a first step, we conceptualized a possible procedure for forecasting seed demand based on our insights about drivers of variety demand in Zimbabwe, available seed sales data, and current decision-making processes around seed supply in Seed Co, our case study. To obtain feedback from potential users of seasonal seed scenario planning, we presented the concept to decision-makers at Seed Co via an online workshop and jointly discussed potential use cases as well as perceived challenges around its different components.

Our concept involved three steps: (1) Past growing seasons are individually categorized by two scenario factors that are known to influence seed demand: seasonal rainfall (dry/medium/wet tercile), and whether the season was preceded by a national election (yes/no). This results in six possible seasonal scenarios. (2) Data on historic seed demand is used to estimate the statistical association between scenario factors and demand for individual varieties, using linear regression models. The fitted regression coefficients are then used to predict average seed demand patterns under each scenario. (3) The probability of each scenario in the next season is assessed using a seasonal climate forecast and the electoral calendar. An overall demand forecast is then generated by weighting the different scenario-specific average demand patterns by the respective forecasted scenario probabilities.

To implement this concept in practice, we first searched for a suitable source of historic rainfall data that could be used to categorize past seasons. We identified the CHIRPS dataset, which has global coverage and is open access (Funk et al., 2015). CHIRPS daily rainfall estimates are derived from geostationary infrared satellite retrievals of cloud top temperature, merged with available rain gauge data. Data can be accessed through a global map interface at ClimatSERV[1], a data service jointly offered by NASA and USAID, allowing users to download daily rainfall estimates at country and sub-country levels.

Next, we identified a seasonal climate forecast product that best serves our design criteria. We chose the Copernicus Climate Change Service (C3S) multi-model forecast[2] because it provides a probabilistic rainfall forecast (probabilities of a rather dry, average, or rather wet season) and visualizes these forecasts as global maps. In addition to being globally applicable and freely accessible online, our evaluation showed that a probabilistic map was understood by seed sector decision-makers.

In stakeholder consultations with Seed Co, and to address our design criteria, we decided to implement all analyses in one Microsoft Excel workbook, with embedded weblinks to ClimatSERV (to download rainfall data) and C3S (to obtain the most recent seasonal climate forecast). The workbook comprises six sheets:

Sheet 1: Enter sales data. The user is asked to provide data on historic seed demand by variety and per annum (seed sold or distributed in the region of interest). Data can be supplied for up to 50 years and up to ten different crop varieties (cf. Step 1 in Fig. 1).

Sheet 2: Get rainfall data. This sheet includes the weblink to ClimatSERV. The user is asked to click this link, which will open in a browser, outside Excel. The rest of the sheet includes screenshots from the ClimatSERV interface to guide the user towards downloading historical daily rainfall estimates from the region of interest.

Sheet 3: Insert rainfall data. The user is asked to paste the recently downloaded daily rainfall estimates (cf. Step 2 in Fig. 1). A bar chart of monthly rainfall averages is automatically generated. This allows the users, who are expected to be familiar with their target region's climate chart, to verify whether any errors in downloading or pasting the data have occurred.

Sheet 4: Get seasonal forecast. This sheet includes the weblink to the C3S seasonal rainfall forecast and shows screenshots to guide the user through this online resource. The user is asked to generate the forecast maps for the upcoming agricultural season, i.e., the probabilities for rainfall in the lower, middle, and upper tercile category (a rather dry, average, or rather wet season). The user is asked to focus on their region of interest and retrieve the respective forecasted probabilities (cf. step 4 in Fig. 1). C3S forecast maps provide a spatial resolution of $1^\circ \times 1^\circ$, equivalent to roughly 111 km × 111 km at the equator, and smaller grid cells towards the poles. In cases where forecasted probabilities are shown to vary across a larger region of interest, the user may choose to focus on the dominant probability across the region of interest. Ideally, though, separate analyses should be carried out for smaller sub-regions.

Back in the Excel sheet, the user then supplies these forecasts in three drop-down cells. For use in further calculations, the user also specifies the forecast period of interest, i.e., the three-month agricultural season (for example, October-November-December).

Sheet 5: Calculations. All calculations are automated in this background sheet, which is hidden from view and password protected to prevent accidental edits. Section 3.3 (see below) and Fig. 1 provide a detailed overview of calculations with example data (cf. steps 3 and 5 in Fig. 1).

Sheet 6: Results. Two types of results are generated. The first result is a forecast of overall seed demand, across all varieties. The forecast is provided in the form of relative statements, comparing forecasted seed demand to both the long-term average and, as a direct reference, to last year's demand. The result can take five levels, from 'much lower' (more than two standard deviations, SD, below long-term average) to 'lower' (at least one SD below average), 'about average' (within one SD around average), 'higher' (at least one SD above average), and 'much higher' (more than two SDs above average). The second result resembles the first but provides statements for each individual variety (cf. step 6 in Fig. 1).

We created a first prototype of this Excel workbook and refined its design in multiple iterations of user testing. We performed user evaluations by presenting early versions to decision makers at Seed Co and collecting qualitative feedback. We also performed independent tests with two users previously unfamiliar with the entire concept, using the think aloud method (Jaspers et al., 2004). These test users (one woman, one man) were a geographer and a biologist based in Germany, with no pre-existing expertise on smallholder seed systems. These interactions

[1] https://climateserv.servirglobal.net/.

[2] Created by the European Centre for Medium-Range Weather Forecasts (ECMWF).

Table 1
Schematic representation of major decision-making opportunities for mitigating risks along the commercial seed value chain.

Row no.	Approximate number of months before sowing	Seed supply operation	Decisions to be made	Risks to be mitigated	Decision-making agent
1	24	Parent seed production	What quantities of parent seed of which varieties to produce	Insufficient supply of high-demand varieties	Seed supplier
2	12	Seed multiplication	What quantities of certified seed of which varieties to multiply	Insufficient production of high-demand varieties Overproduction of low-demand varieties	Seed supplier
3	9	Post-harvest management: sorting, grading, quality control	What quantities of which varieties to prioritize, and which to shelve for later processing	Investments into post-harvest processing of seed that will eventually be sold as grain, if farmer demand is low	Seed supplier
4	6 to 1	Preparation of seed batches: cleaning seed, chemical treatment, packaging, labelling	What quantities of which varieties to process into small batches, and which to shelve in bulk storage	Investments into seasonal preparations for seed that will eventually be sold as grain or feed Destruction of chemically treated seed, which cannot be sold as grain or seed	Seed supplier
5	3 to 1	Bulk shipping to regional depots	What quantities of which varieties to allocate in each region	Local under-supply, requiring supplementary shipments between regional depots	Seed supplier
6	3 to 1	Shipping to local agro-dealers	What quantities of which varieties to allocate at local agro-shops	Preferred seed varieties sold out too soon, farmer customers turning to competitors Costly return shipment of unsold seed	Seed supplier, local agro-dealers
7	1 to 0	Last-minute advertisement	Which varieties to promote to farmers to increase demand for varieties in stock	Seed demand diverts substantially from expectations, leading to local under- or over-supply	Seed supplier, local agro-dealers
8	1 to 0	Seed purchase by farmers	What quantities of which varieties to purchase	Use of suboptimal varieties leading to disappointing yields Inaccessibility of preferred seed in case of replanting needs	Farmers
9	3 after sowing	Shipping unsold seed back to central warehouse	None	None	Seed suppliers
10	6 after sowing	Reprocessing of returned seed	What quantities of which varieties to sell as grain, and which to retain for renewed sale as seed What quantities of which varieties to export for upcoming sale on other national markets	Foregone profit due to lower sales price of grain or costs of exporting seed Over-supply of seed in next season	Seed suppliers

were especially helpful for simplifying the language (avoiding jargon) and adding instructions to the prototype. After each test, we adapted features of the Excel workbook. The eventual design is appended to this article as a supplementary file.

3.3. Case study with Seed Co (Zimbabwe)

To understand the usefulness and define potential use cases of our prototype, we explored it in practice and with real world data, together with decision-makers at Seed Co in Zimbabwe. This case study was carried out in mid-2020, aiming at forecasting seed demand in the November-December-January (NDJ) season 2020/21. We compiled historic sales data on five Seed Co maize varieties with different times to maturity (ranging from 'ultra-early' to 'late'). For each variety, sales records were aggregated per calendar year across all of Zimbabwe, covering the years 2012 through 2019. Because Zimbabwe has one planting season typically centered on NDJ, aggregated seed sales recorded in a calendar year can be expected to be associated with the agricultural season starting that same year.

We downloaded daily precipitation estimates, averaged over Zimbabwe, from ClimatSERV (see previous Section) for the period of 1993–2019. For each year in the reference period, cumulative rainfall over the forecast season was calculated (i.e., November 1 to January 31). Because the reference period used by the C3S seasonal forecast to calculate tercile thresholds is 1993–2016 by default, we used this 24-year period to calculate tercile thresholds for Zimbabwe, too. Using these thresholds (346 mm and 441 mm), each of the seasons 2012–2019 (for which seed demand data were available) was classified as either dry, average, or wet. In addition, seasonal rainfall for a 'typical' dry, medium, and wet season was calculated by taking the median of the eight reference seasons per tercile: 315 mm (dry), 388 mm (medium), and 506 mm (wet).

To link seasonal scenarios and seed demand, a linear regression was calculated for each maize variety. Annual seed demand was the dependent variable, and independent (explanatory) variables included seasonal rainfall, seed demand in the previous year, and an 'election' dummy. Although not part of the scenario definition, seed demand in the previous year was added since this variable has been shown to be an important predictor of future demand (see Zhu et al. 2019). Previous experiences with agricultural technologies, such as seed varieties, are an important determinant of subsequent adoption decisions and willingness to pay (e.g., Mastenbroek et al. 2021). Expected seed demand per variety in a 'typical' dry, medium, or wet season was then calculated using the regression coefficients of the three explanatory variables. The resulting seed demand estimates highlighted links between seasonal scenarios and seed demand:

- Overall seed demand, adding up all varieties, increased with increasing seasonal rainfall. Predicted seed demand in a 'typical' wet season exceeded demand in a 'typical' dry season by 33 %. Two factors are likely to contribute to this observation: first, in anticipation of a wet season, farmers are likely to buy larger quantities of certified seed than in drier years, as these investments are more likely to pay off (see Almekinders et al. 2021). Second, Seed Co staff observed that in rain-abundant seasons, some commercial farmers with access to supplemental irrigation switch from one cropping cycle (typically using a late variety) to two successive cropping cycles (using ultra-early seed), effectively requiring the double amount of seed.
- Total seed demand in election years was higher than in non-election years regardless of seasonal rainfall. This increase was primarily explained by higher sales of very-early seed, the main variety used by

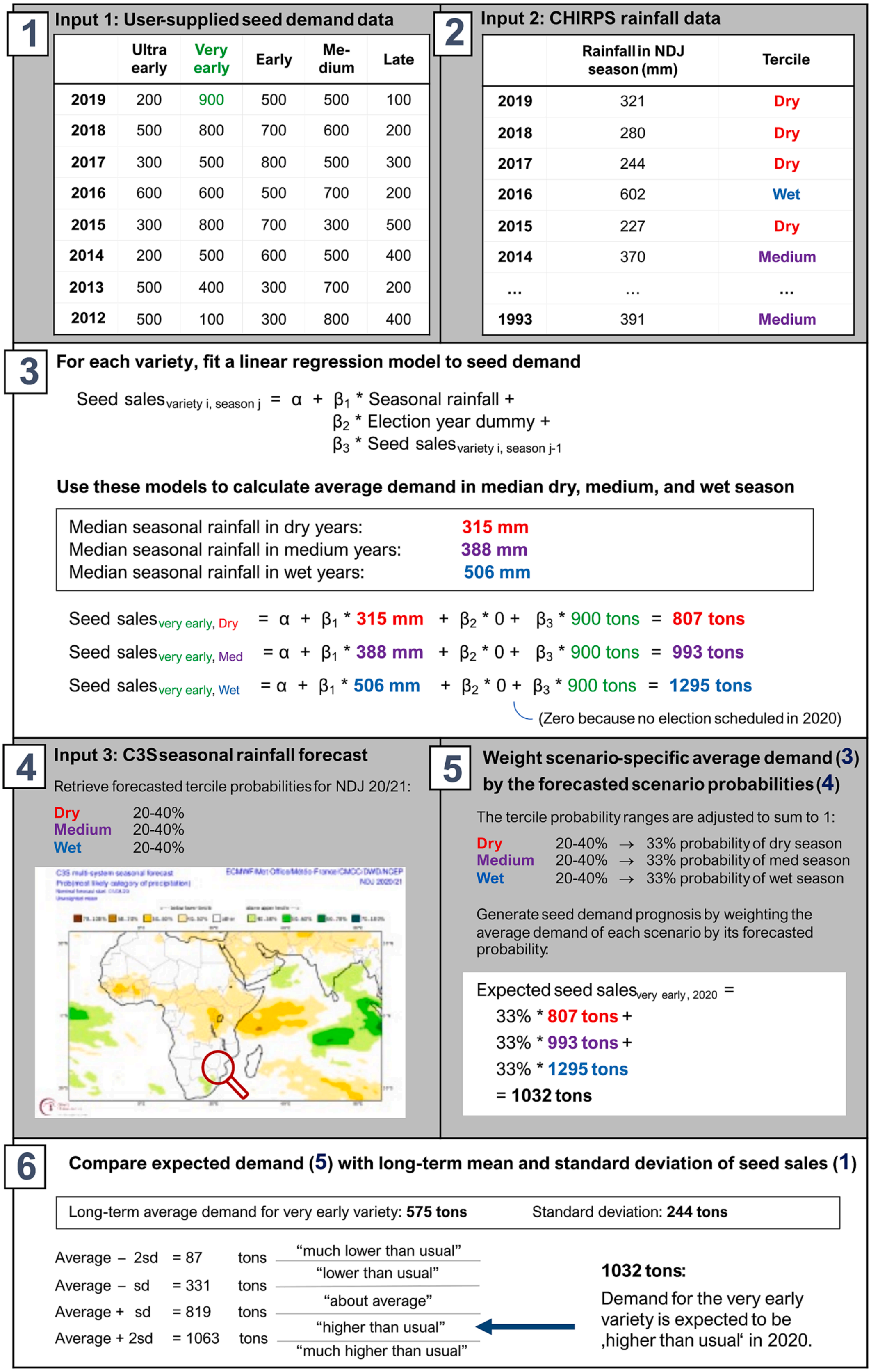

Fig. 1. Flowchart of inputs, calculations, and outputs of seasonal seed scenario planning. Maturity classes in facet 1 and rainfall data in facet 2 reflect the Seed Co case study. Facet 1 does not show the actual demand data due to a confidentiality agreement with Seed Co.

smallholder farmers in rain-fed conditions. It is assumed that these sales are due to seed handouts acquired by electoral campaigns.

× Increasing seasonal rainfall implied a shift towards later-maturing varieties. From dry to medium to wet season, the predicted relative shares of very-early and early decreased, whereas the share of medium increased. Contradicting our original expectations, however, increasing seasonal rainfall was associated with more ultra-early, and less late. This can be explained by the fact that both varieties are mainly used by commercial farmers with access to irrigation, who tend to use the ultra-early varieties for double cropping in wet seasons (see above).

× Goodness-of-fit of the seed demand regressions was highest for the ultra-early variety ($R^2 = 0.70$). This indicates that the demand for this extreme maturity class responds more strongly to variations in climatic conditions than the demand for other maturity classes (R^2 ranging between 0.11 and 0.20). This may be because commercial farmers have better access to seasonal climate forecasts than smallholder farmers, and thus their varietal choice is more strongly influenced by seasonal climate.

To generate foresight on seed demand in the 2020/21 NDJ season, we used the C3S online interface (see previous Section). We retrieved a seasonal rainfall forecast for Africa in August 2020 (nominal forecast start August 1, 2020). We focused on Zimbabwe and recorded the probabilities for a dry, average, and wet NDJ season. These probabilities were "20–40 %" for all three seasonal outcomes. Lastly, seed demand in the upcoming season was forecasted. For each variety, the 'typical' seed demand quantities in the three seasonal scenarios were weighted by the forecasted scenario probabilities. In our case study – where all scenarios were forecasted to have same probability – this was the same as taking the mean of the three 'typical' demand quantities.

Eventually, results statements were generated by comparing the predicted seed demand with historic seed demand records (for the 2012–2019 period). Overall seed demand as well as demand for individual varieties were forecasted to be "about average", i.e., within one standard deviation around the average of the 2012–2019 period.

These results statements suggested the overall risk-minimizing strategy: in this (unspectacular) case, maintaining seed supply of all varieties at average levels balances the risks of under- and over-supply. Had the seasonal forecast suggested, for example, a drier-than-usual season, then the overall risk-minimizing strategy may have involved more meaningful changes, such as supplying more seed of the very-early variety.

3.4. Validation exercise with Oromia Seed Enterprise and Ethiopia Seed Enterprise (Ethiopia)

To ensure the scenario planning procedure can be used by users previously unfamiliar with the concept, we facilitated a one-day workshop with decision-makers from two public seed enterprises in Ethiopia. Rather than gradually implementing and iteratively improving the decision support procedure, as we did with Seed Co in Zimbabwe, we aimed at carrying out the entire procedure in one go. Three decision-makers from each Oromia Seed Enterprise (OSE) and Ethiopia Seed Enterprise participated, and the exercise used seed demand data from the East Wellega zone, provided by OSE. During this test, we continuously collected qualitative feedback from participants. We recorded their assumptions and expectations around the procedure and its outputs. We also sought for challenges in understanding the concept, the underlying calculations, and the Excel or online interfaces. Another emphasis consisted in understanding participants' views on potential use cases in Ethiopian seed supply context. This feedback was used to improve the design of our procedure and the Excel decision support tool.

3.5. Replicable implementation of the procedure for seasonal seed scenario planning

The Seed Co case study (see Section 3.3) demonstrated that the strength of statistical links between seasonal scenarios and seed demand can vary considerably. Depending on the maturity class, the regression models explained between 9 % and 73 % of the year-to-year variation in varietal seed demand (mean R^2 values from leave-one-out cross-validation, Hastie et al. 2009). Low explanatory power for some maturity classes may have different reasons. One potential limiting factor is the rather low number of years for which seed sales data were available. To ensure that seed demand anticipation is backed by adequate statistical power, future applications of our concept may need to rely on more observations. Under the conditions of our case study, for example, ten seasons of demand data would provide acceptable statistical power for a variety with a relatively high $R^2 = 0.7$, but at least 20 observations are needed for a lower $R^2 = 0.4$.

Other drivers of seed demand, not included in the statistical models, might also play a role. For example, seed purchasing decisions can be influenced by the availability of cash, which may vary with yields and market prices of cash crops (Almekinders et al., 2021). Along with the inherent uncertainty of climate forecasts, this means that presenting the demand forecasts to decision-makers as 'predictions' could insinuate a certainty that is unwarranted. Therefore, we decided to embed the use of the Excel tool as part of an expert workshop. The seed demand prognoses were kept deliberately tendential ("lower than average", etc.) to avoid insinuating deterministic accuracy and to serve as mere information inputs into qualitative expert discussions and decision-making.

Another important insight from the validation exercise with seed supply decision-makers in Ethiopia (see Section 3.4) was the need for well-prepared, competent facilitation. Therefore, we created detailed support materials for workshop facilitators to lead participants through the collective decision-making process. In addition to the Excel tool that is to be filled and used jointly by workshop participants, the procedure is supported by a detailed workshop guide (aiming for around 3 h) and a PowerPoint presentation. Using these support materials, a facilitator can autonomously prepare and implement a seasonal seed scenario planning workshop. The workshop comprises the following stages (intended duration in minutes in parentheses): Welcome and clarify objectives (5′), Explain background and motivation for scenario planning (10′), Simple exercises to familiarize with the concept of scenario planning (15′), Introduction to the Excel tool (20′), Coffee/tea break (15′), Joint use of the Excel tool (60′), Joint discussion of implications of results for seed supply decision-making (60′).

4. Insights and methodological learnings

4.1. Potential use cases

Seed sector stakeholders involved as co-designers and test users agreed that seed demand forecasting and scenario planning would be most useful before seed production. However, decisions on seed production are typically made at least a year before the season of interest (see Table 1). Climate forecasts with 12-month lead times exist, but usually lack skill and are not widely publicized. Thus, seasonal seed scenario planning is more likely to be useful for influencing post-production decisions. Reasonable use cases include decision-making at the stages of seed pre-treatment, packaging, and distribution, which take place within few months or weeks before the beginning of the season (i.e., rows 4 to 7 in Table 1). Scenario planning could be used by seed suppliers to adapt the respective quantities of each seed variety that are cleaned, treated, packaged, and allocated to different regions or warehouses. For example, chemically treated, but unsold seed cannot be relabeled as food grain and in some cases needs to be destroyed. Scenario planning could help to minimize this type of loss, by better adapting (initial) treatment and packaging to forecasted demand.

Logistics is another use case. In advance of the planting season, big seed suppliers typically stock multiple regional depots with different quantities of seed, according to expected demand. Regionally explicit demand forecasts could be valuable to plan initial stocking, reducing both shortage of high-demand seed and carry-over and return shipments of less demanded seed (see Alemu and Bishaw 2016).

Interactions with seed suppliers in Zimbabwe and Ethiopia highlighted, however, that current, rather linear seed supply pipelines do not easily accommodate flexible, adaptive decision-making based on scenario planning. Current business practice does not allow for significant deviation from a standard sequence of steps in seed supply (e.g., production, packaging, distribution), for example, by prioritizing some varieties over others, or shelving a share of certain varieties for a while, to avoid unnecessary treatment/packaging/shipping. An effective use of seasonal seed scenario planning would require moving away from a predetermined linear succession of operations in seed supply, towards increased agility. For example, while great amounts of seed could originally be shelved based on a forecasted low demand, they could be treated, packaged, and shipped later in response to an unfolding high-demand scenario. This would also require quick and accurate feedback about demand from distribution points, as well as available labor force to implement treatment, packaging, and shipping in successive 'instalments'.

Seasonal seed scenario planning requires that seed demand is influenced by predictable phenomena (such as seasonal rainfall or elections). In our Zimbabwean case study, we found that the regressions, based on our scenarios, had stronger predictive power for some varieties than for others. Without expert validation (judging whether results are plausible), generating demand foresight based on weak statistical links risks leading to wrong conclusions. As a solution, the Excel tool could apply a threshold for the strength of association between seasonal scenarios and demand (for example, $R^2 \geq 0.40$ in the regression models) as a condition for generating any results. This way, users would focus on those varieties where demand forecasts can be made with more certainty. In future applications, empirically identifying additional determinants of variable seed demand and including them in the regression models could lead to more accurate predictions.

4.2. Compliance with design criteria

Across the co-design process, our design decisions aimed at considering five design criteria (see Section 3.2.1). Here, we discuss how these criteria were addressed.

Low cognitive effort: Our case study and validation exercise showed that seed supply decision-makers generally can understand all steps of analysis and discuss potential implications. Familiarity with key concepts such as cumulative seasonal rainfall, seasonal climate forecasts, variability of demand, probabilities and uncertainty, or statistical association can be assumed. Nonetheless, a prepared facilitator seems necessary to guide participants through the process and keep discussions focused on the scenario planning exercise.

Low access barriers: Daily rainfall data as well as seasonal climate forecasts can be freely accessed online. While there are relevant resources that require registration, our procedure was built around using CHIRPS rainfall estimates and the C3S rainfall forecast, which are free and immediately accessible.

Low time investment: Some time commitment for becoming familiar with the Excel tool and the online resources, as well as for compiling the seed demand data seems inevitable for applying the procedure properly. However, we minimized overall time requirement by suggesting the assignment of a workshop facilitator. We estimate the facilitator needs about two hours for preparing the workshop, and additional time for compiling and cleaning seed demand data, which will depend on the level of data standardization and curation within the seed supply organization. The other participants (about 3–5 persons) should spend about three hours in the workshop.

Actionable output: Feedback from decision-makers in Zimbabwe and Ethiopia suggested that results are well understood and are perceived as useful inputs to discussions around the prioritization of varieties in post-production treatment, as well as in allocation to different warehouses or depots. Until now, however, the relatively rigid, linear succession on operations in seed supply limits the scope for using the outputs of seasonal seed scenario planning in adaptive decision-making.

Universal application: We deliberately focused on a near-global rainfall dataset (CHIRPS) and a global climate forecast (C3S) to ensure our implementation of seasonal seed scenario planning can be easily applied in any regional context. There are, however, also continental, regional, or national climate forecasts, which often provide higher resolution than C3S. One example is the seasonal forecast generated by ICPAC[3] for the greater Horn of Africa. If users prefer, alternative forecasts can be used instead of C3S, and forecasted tercile probabilities can easily be entered in the Excel tool.

To come up with the seasonal seed scenario planning procedure, we applied a participatory design process. This process was open-ended regarding the type of solution that would be generated. The design assignment, however, made relatively strong assumptions on the usefulness of seasonal climate forecasts for seed supply management. As a result, the generated procedure does not reflect the major information needs of targeted stakeholders – prioritizing varieties at the production stage – and cannot be easily 'plugged in' with current business practices of seed suppliers. Effective use of seasonal seed scenario planning likely requires institutional adjustments toward more flexible operations in seed supply (see previous Section). The relative difficulty of immediately implementing our procedure under current conditions challenges a claim of participatory design – that it generates context-specific, fit-for-purpose solutions – and highlights the need for even less prescriptive design assignments (Steinke et al. 2022).

4.3. Future development

Along the co-design process, multiple needs and opportunities for further development of the seasonal seed scenario planning concept and its practical implementation emerged. One challenge noticed in both the case study and the rapid replication exercise was the difficulty of compiling data on seed distribution at variety level. In both cases, aggregating data from different in-house sources, verifying variety names, and removing duplicated entries required considerable effort and time. In practice, the challenge of accessing reliable data on historic variety demand might discourage decision-makers from using seasonal seed scenario planning. Seasonal seed scenario planning relies on seed distribution data in a specific format (seed quantity of each variety distributed in a defined area across a defined time period). This may require seed supply organizations to first systematize seed distribution records correspondingly.

Seed supply stakeholders also highlighted that, for scenario planning to unfold its full potential, farmers themselves may require greater access to seasonal climate forecasts. In our study regions, some farmers already receive seasonal forecast information from extension agents or local input dealers. Many farmers, however, lack access to seasonal forecasts and thus cannot easily align their seed demand with forecasted seasonal rainfall (see also Waldman et al. 2017). This may, in part, explain the relatively weak statistical link between climate and seed demand observed especially for the varieties targeting smallholders in Zimbabwe. Large-scale dissemination of seasonal climate forecasts, along with concrete recommendations on suitable, risk-minimizing variety portfolios, is expected to strengthen these statistical links, as farmers' demand may better align with seasonal climate. To date, seed

[3] ICPAC is the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre, see https://www.icpac.net/seasonal-forecast/.

demand is strongly supply-side driven even in countries with relatively competitive private seed markets, such as Kenya (Rutsaert et al. 2021, Chivasa et al. 2022). Thus, seed suppliers might minimize the economic risks of mismatches – costly carry-over or foregone profits (when farmers have lower willingness to pay for less-preferred varieties or buy seed from competitors) – by deliberately promoting seasonally adapted variety portfolios. Promotion efforts, for example, via collaborating agro-dealers, might more strongly influence farmer demand than the dissemination of seasonal forecasts (see Rutsaert and Donovan 2020). Through improved farm performance, promoting seasonally adapted variety portfolios may also enhance farmers' trust in seed suppliers' brands, potentially leading to increased customer loyalty and future revenue.

By generating a generic, globally applicable solution, our experimental proof-of-concept study has demonstrated the general feasibility and potential usefulness of seasonal scenario planning for matching supply and demand in the seed sector. In future practice, more case-specific implementations may be possible. Collaborations between climate scientists and seed supply organizations could lead to the development of highly practice-oriented decision-support tools that consider locally relevant climate phenomena – going beyond seasonal rainfall – possibly at longer lead times. Rather than focusing on cumulative seasonal rainfall alone, climate science could help estimate seasonal risk for scenarios that combine different extreme weather events (e.g., drought spell during germination phase + elevated heat during grain filling). Moreover, identifying climatic boundary conditions, such as tropical sea surface temperatures, that influence seasonal rainfall could help increase the lead time of forecasts (Lehmann et al. 2020). An improved understanding of the climatic conditions relevant for seed demand (beyond rainfall alone) can help increase prediction skill, but requires in-depth regional analyses.

The scenario planning approach relies on assessing the probabilities of different outcomes, yet in our implementation of seasonal seed scenario planning, the output insinuates a deterministic prediction: for each variety, expected seed demand is calculated and users receive a single results statement. This was a deliberate design decision to keep the output simple and to limit information load for users. But future co-design exercises with seed sector decision-makers could explore alternative realizations of the trade-off between simplicity and a more accurate representation of uncertainty in the results. For example, it would be possible to assign a probability to each of the five results statements, rather than just reporting one statement. For users, receiving more detail on uncertainty increases the challenge of interpreting results. Hence, participatory research could evaluate what types of additional detail on results that better represent uncertainty are perceived as useful and actionable.

Our low-tech approach to the decision-support tool, consisting of an Excel workbook with embedded weblinks, has generated valuable insights on user needs, but also brings challenges. In our case, future modifications in the user interfaces of ClimatSERV or C3S could make the user instructions obsolete. Requiring users to navigate back and forth between Excel and the web browser risks attrition and distraction. Eventually, offering a decision-support tool for seasonal seed scenario planning as a freely accessible one-stop website would likely provide a more inclusive, streamlined user experience. Through Application Programming Interfaces (APIs), such an online tool could conveniently import and display CHIRPS data, as well as a range of different climate forecasts. Another implication of our emphasis on technological simplicity is the use of linear regression models, using only three predictor variables. This type of model can be implemented in Excel, but advanced machine learning approaches, accounting for non-linear effects, could yield more skillful demand forecasts (see Zhu et al. 2019). Future research could explore the design of user interfaces that allow seed sector decision-makers to train and use more sophisticated prediction systems.

Lastly, seasonal seed scenario planning could be useful not only to seed suppliers interested in meeting farmers' demand for existing varieties. Exploring the principle of seasonal scenario planning could also be useful in other parts of the seed sector, such as breeding pipelines. A good understanding of seed demand and crop performance under different seasonal scenarios could, for example, enable breeding programs to evaluate not only individual varieties and their performance under future scenarios, but also the overall varietal portfolio that is available to farmers and evaluate the complementary value of different varieties (see Condori et al. 2014).

5. Conclusion

This study explored the practical potential of using seasonal climate forecasts for anticipating farmers' seed demand and informing risk-minimizing seed supply decisions. Our findings suggest that by implementing 'seasonal seed scenario planning', decision-makers at seed supply organizations could meaningfully reduce the risk of mismatches between seed supply and demand at variety level. Establishing statistical links between seasonal (climate) scenarios and empirical seed demand allows anticipating near-future seed demand. This information can be useful for adapting certain operations at seed supply organizations, such as bulk seed logistics. This may help minimize economic risks faced by seed suppliers, such as costly carry-over of unsold seed, while improving farmers' access to seed of preferred varieties.

To be implemented in practice, however, more agile decision-making mechanisms and more flexible operations management may be needed within seed supply organizations. Also, our case study on maize seed demand in Zimbabwe shows that links between seasonal scenarios and farmers' seed demand for most varieties are relatively weak. In the future, improving farmers' access to skillful and timely seasonal climate forecasts may increase the strength of association between seasonal climate and farmers' variety choices, allowing more accurate prediction of demand. Active promotion of seasonally adapted variety portfolios, informed by scenario planning, may also help align supply and demand in a way that minimizes risk for both seed suppliers and farmers.

The co-design process highlighted diverse needs and opportunities for future joint efforts of climate scientists, agricultural researchers, and seed sector practitioners to make climate forecast information operational for mitigating climate-related risk in seed supply. Future research should explore how seasonal scenario planning can be effectively integrated in decision-making at seed suppliers, and how it affects seed business and farm performance on the long run.

CRediT authorship contribution statement

Jonathan Steinke: Conceptualization, Methodology, Investigation, Software, Writing – original draft. **Berta Ortiz-Crespo:** Conceptualization, Methodology, Investigation, Software, Writing – review & editing. **Jacob van Etten:** Conceptualization, Supervision, Writing – review & editing. **Gareth Denis Borman:** Conceptualization, Funding acquisition, Writing – review & editing. **Mohammed Hassena:** Methodology, Investigation, Validation. **Marlene Kretschmer:** Methodology, Writing – review & editing. **David A. MacLeod:** Methodology, Writing – review & editing. **Dean Muungani:** Conceptualization, Investigation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

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