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A global meta-analysis of climate services and decision-making in agriculture

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ABSTRACT

Harmonizing the supply of climate information with the type of information needed by next-users is crucial for effective weather and climate services (CS). Understanding of information demand could help reshape supply-side based CS that have dominated the field over the last few decades. Most CS have been developed using a 'loading dock' model, whereby products are designed by information suppliers with little input from or consultation with users of climate services. Notably, a focus on climate modelling and prediction has largely resulted in a lack of consideration of the demand-side when producing climate services. Here, we contribute to understanding of CS demand by presenting a global *meta*-analysis – a 'decision matrix' - of farmers' climate-influenced decisions. We identify 41 studies that encompass 186 decisions, three forecast timescales (weather, dekadal, seasonal), and five forecast variables (precipitation, temperature, wind, soil moisture and soil temperature). Several insights were offered by this literature review into the value of climate services and the way forward in considering users' needs. We find that the seasonal precipitation is the most frequently used forecast variable for decision-making, particularly of crop sowing date. Forecasts such as temperature, soil moisture and soil temperature appeared to be less used by farmers, according to the decision matrix. It is apparent that more investigation is necessary into how farmers use climate information in their decision-making to better establish the value of CS. We suggest that different sectors should make their respective decision matrices to explore decision spaces and engage with users of climate information in various sectors.

Practical implications

This *meta*-analysis examines the available literature and systematizes how climate services support decision-making related to farm management and agricultural livelihoods. A principle finding of this work is the need for more evaluations that aim to establish the impact of forecast use on farmers' livelihoods. We find a wide and varied range of climate forecasts that are relevant to farmers' decisions, depending on crop, location and timescale. This implies the need for further investigation of the role of decision context, with implications related to the ongoing development of climate services for agriculture.

One challenge in the existing body of literature is that many papers on climate services in agriculture do not fully describe how forecasts influence decision-making. The literature generally recognizes that farmers use climate forecasts to support decisions regarding crop choice, sowing date, and insurance purchases (amongst others), but the specific information chain, context, and mitigating factors between climate information and farming decisions is not sufficiently explored. By systematically characterizing the decision space in which farmers may use climate information, this work offers both new insights into the potential use of climate information in agriculture decision making, as well as an understanding of how different demands for climate services may affect the design thereof.

Building the structured approach of the "decision matrix" presented here, this work offers a systematic basis for cataloguing

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climate services in other sectors. The results of this study, when combined with similar reviews in other sectors will support increased opportunities for leveraging shared resources and aligning sector goals to optimize climate services value and use, in line with the objectives associated with the Global Framework for Climate Services.

One last implication is the nature of how we define the success of climate services interventions. Farmers may choose to diversify their income with non-agricultural activities for a season or several if forecasts are unfavourable for crop production. The choice to invest in alternative livelihoods should be recognized as a valid response to climate risk and should be understood as a possible way to measure the 'success' of CS interventions. Unfavourable climate conditions can result in severe losses but climate information may prove useful in avoiding losses. Farmers can choose to move in and out of agriculture as investments tend to dip and rise for a season or longer. The role of CS in such decisions should be identified as an impact on farmer decision-making.

Introduction

This paper aims to address a persistent opportunity associated with efforts for better understanding the demand for climate services (CS) in an agricultural context. While there is abundant literature on specific CS implementations (for example: Falloon et al., 2018; Miles et al., 2006; Mudombi and Nhamo, 2014) and a similar abundance related to the broader conceptual issues associated with weather and climate services (see: Brooks, 2013; Vaughan et al., 2016), there is less work synthetizing specific CS related decision making at the sectoral level (see: Clements et al., 2013; Soares et al., 2018). We thus see an opportunity in terms of the general characterization and comparison of the decision space in which CS are applied, and specifically, need for CS related decision making in agriculture. Here we delve into understanding how agricultural users may leverage climate information for agricultural decision making by constructing a 'decision matrix' that systematically characterizes the decision space that CS literature currently addresses. In evaluating the demand side of climate services, we outline several important concepts underpinning the use of climate and weather information in agriculture. We detail how the climate services field has evolved over the decades and explore the effects of a pervasive supply side bias. Through better understanding of users' needs and the demand side perspective, we then offer a decision matrix to contribute to the understanding of the patterns of forecast use for the support of continued development of more demand driven and user-oriented approaches. For the purposes of clarity in this paper, both agro-climatic services and climate services as well as weather services fall under the umbrella of "climate services (CS)".

Climate services to address risk in agriculture

Climate services involve the provision of scientific information for informed decision-making. These services support climate-sensitive decision-making in environments where not having this type of information could have an adverse impact on livelihoods, although the value of information is subject to debate, depending on context (Vaughan et al., 2018a). CS encompass the (co)production, translation, transfer and use of climate information to enable and inform decision-making (Vaughan et al., 2016; Vaughan and Dessai, 2014). Weather services provide weather forecasts on the timescale of hours to days while climate services aim to enable decisions typically 3–6 months in advance in agriculture, or longer timescales in other sectors. Seasonal forecasts typically associated with CS are a climate risk management (CRM) tool used in several sectors known to be sensitive to climate variability and change (White et al., 2017). CRM strategies in agriculture are intended to aid in preparing for climate events that may damage crops and livelihoods as well as capitalizing on opportunities that might otherwise be forfeited in climatically favourable years (Hansen, 2007). CS have the potential to be particularly valuable in agriculture as climate variability is an inherent challenge for farmers, who frequently make agricultural decisions in advance of the growing season (Roudier et al., 2012) with the assumption that certain climatic conditions will occur (Eakin, 2000). The risk of climate variability often results in farmers making decisions that protect against loss rather than taking advantage of opportunity and can result in avoidance of employing new technologies or assets (Hansen, 2007).

A key challenge in agricultural settings is that the decision-making landscape is highly heterogonous and complex, and farmers need to account for numerous livelihood objectives while balancing different risk factors in addition to climate (Wallace and Moss, 2002). CS thus supports more informed decision-making by providing relevant and salient information to farmers. Tall et al. (2014a) define salient information as tailored content that considers format and lead time in the context of farm-level decision-making. CS in the agricultural sector typically aim to promote specific recommendations for the growing season such as the choice of planting dates, cultivars, or irrigation and fertilization schedules (Capa-Morocho et al., 2016)). Although not the primary focus of CS, longer scale forecasts are useful for longer-term decisions such as those based on land purchase, investment in infrastructure and breeding of cultivars.

Evolution of climate services

Supply-side advances are an essential factor supporting the production of weather and climate services that are more accurate and reliable. Climate data collection, resolution, and prediction have improved over the years because of improved inputs, model skill, and understanding of climate processes and teleconnections (Sivakumar and Hansen, 2007). Vaughan et al. (2019) surveyed experts in the field of CS to find that continuous development and maintenance of the climate observational network is critical supply-side element supporting climate research. Accurate atmospheric observations are also critical for the production of skilful short-term climate forecasts (Collins, 2002). Advances on the supply-side of climate services should be continually pursued along with investment in approaches to engage with end-users to address their needs.

Climate services were characterized for many years by a supply-side bias (Feldman and Ingram, 2009; Lourenço et al., 2016) based on the available forecasting science that resulted in a "loading dock" approach (Cash et al., 2006). This caused some degree of neglect of the demand side of CS, where users' needs did not feature as strongly in endeavours to produce climate information (Dutton, 2002). Such a supply-side emphasis resulted in an improvement loop that produced more of the same information, with limited relevance to end-users (Dilling and Lemos, 2011; Lourenço et al., 2016). Users' needs and perspectives have been recognised as integral for salient, accessible and legitimate climate services (Tall et al., 2014a). Efforts to better integrate the demand side through coproduction of climate services have been ongoing for many years (Cash et al., 2006; McNie, 2007), although the focus of literature tends to be on the models that would most effectively implement coproduction as an approach (Palutikof et al., 2019), rather than empirical evidence from research in the field. The “uneven progress” towards coproduction (Vaughan et al., 2018a) reflects the current state of climate services and the difficulty of scaling demand-centred approaches. A contributing factor in the continued persistence of the supply-side is the increasing availability and accessibility of climate data and forecasts, particularly as the private sector has become more involved in the CS production process (Singh et al., 2018). The information age has opened up many sources of data, often at little to no cost, and has encouraged the production and supply of forecasts from many varied sources, with little guarantee of relevance, legitimacy or salience (Cash et al., 2006). The plethora of available data and forecasts of unknown validity in some regions highlights a persistent negligence of users’ needs and a necessity to more meaningfully engage with end-users of climate services (Vogel and O’Brien, 2006; Vogel et al., 2017).

Why demand-centred approaches? unpacking the demand for climate services

The focus of CS in recent years has shifted to better include users in production and promote active partnerships across stakeholders in the information value chain. CS have experienced limited effectiveness overall as seen by the somewhat limited uptake of CS endeavours (Haigh et al., 2015; Lourenço et al., 2016; Singh et al., 2018). This may have contributed towards the paradigm shift from viewing CS as a matter of supplying climatic information to a process involving the end-users in design and production. This shift is clear in the study conducted by Vaughan et al. (2016) where the international CS community identified the improvement of the connection of climate information to users as a research priority in the field. There are several methods to achieve this end, including the approach called coproduction, which has gained recognition over the past few decades (Vaughan et al., 2018b; Meadow et al., 2015; Prokopy et al., 2017). The advantages of demand-driven approaches are numerous, including that user-centred approaches could help to develop end-users’ capacity to use and effectively demand climate information (Hansen et al., 2011a). Additionally, incorporating users’ needs from early priority setting and design stages would likely increase the effectiveness of CS and their uptake (Hewitt et al., 2017). Salient, relevant climate information is more likely to be used for making future decisions. In a study on drought planning, Lemos et al. (2012) state that an improved understanding of how climate information is used would increase its usability. Centring end-users’ needs in climate services has gained recognition as a vital factor for impact to be achieved, although there remains a legacy of supply-side bias that pervades due to a lag in scaling user-centred approaches. This is a similar challenge in scaling subscription-based models for digital extension in an agricultural context (Fabregas et al., 2019).

Coproduction, translation and communication of CS

The translation of climate information into actionable knowledge requires CS to link to real-world decision and contexts. In agriculture, climate services must be co-produced in a manner that is user-orientated (Meinke et al., 2006), and assures agricultural relevance and potential for impact (Takle et al., 2014). Coproduction is one amongst several approaches in the creation of CS that strives to improve collaboration between experts and non-experts (Crane et al., 2010). Co-production takes a demand-led approach and uses co-design and co-learning to engage scientists and decision-makers in collaborative knowledge creation (Meadow et al., 2015). The approach has gained recognition as an effective strategy to produce CS that is useful and provides value for end-users.

Table 1
Key words used to source literature for constructing the decision matrix.

Dimension	Search terms	Dimension	Search terms
Climate services	Weather and climate forecast	Agricultural/pastoral management	Farmer decision-making
	Decision support tool		Agricultural adaptation
	Climate information		Start of the season
	Soil moisture		Planting date
	Soil temperature		Decision calendar
	Rainfall forecast		Climate risk management
	10-day forecast		Pastoral decision-making
	Seasonal forecast		
	Forecast skill		
	Climate risk management		
	Climate prediction		

While the call for CS development strategies that emphasize iterative feedback between producers and users of climate information is being well received and could increase the usefulness of climate services, evidence is somewhat sparse. There have been few studies which have established the value of coproduction for CS (Carr et al., 2020) due to the challenging nature of implementation (Carr et al., 2017), relative novelty of the approach and potential cost of conducting post hoc evaluations beyond the project timeline. The USAID Learning Agenda (Carr et al., 2017) was created to better understand how to identify users of climate information and their needs. In this assessment, co-production is found to be necessary but in need of further research that discovers the barriers and opportunities of the approach. Beyond the need for evidence on coproduction of CS, there are also several barriers to its use. It is a process that is continuous and time-intensive to conduct (Carr et al., 2017). There are obstacles on both the demand and supply sides that could compromise the efficacy of participatory processes or make them difficult to predict when addressing farmers’ needs (Carr et al., 2020). Nonetheless, as in the field of climate adaptation, it is essential to engage with stakeholders in climate services beyond consultation to include explicit attempts to understand stakeholders’ knowledge, political interests and values (Eriksen et al., 2021). Given these challenges, Oliver et al. (2019) suggest that researchers should stipulate specific motivations for implementing coproduction approaches to research, and evaluate whether outcomes were achieved to track usefulness. Taken together, these issues highlight some of the key challenges with assuming coproduction is appropriate and scalable in all contexts.

A central facet of coproduction is co-exploration by producers and users of the decision space. Vincent et al. (2018) highlight the importance of understanding which decisions can be addressed by which climate services when identifying the potential need for CS. The identification of the decision space is partially addressed by the analysis that we have conducted, which explores how forecasts are used in agricultural decision-making. This compendium of forecast-influenced decisions allows for a more nuanced understanding of the decision context and highlights potential gaps between information supply and demand in the CS landscape. The decision matrix is a *meta*-analysis of the available literature that describes how climate information is used to make agricultural and livelihood decisions.

GFCS and the CS value chain

The WMO’s Global Framework for Climate Services (GFCS) is a global partnership designed to mainstream climate services into primary sectors for the "better management of the risks and opportunities of climate variability and change in climate-sensitive productive sectors" (WMO, 2018). The GFCS focuses on integrating five pillars for developing climate services value chains across the sectors; observations and monitoring; climate services information system; research, modelling and prediction; user interface platform; and capacity development. The GFCS is established in-country through the National Framework for Climate Services (NFCS), which is a co-ordinating mechanism for enabling the development and delivery of climate services. Co-production and co-design are key facets of the NFCS for the co-ordination and collaboration of institutions along the CS value chain (WMO, 2018), which encompasses the networks of stakeholders that perform data generation, translation, delivery and use of climate information. This structured approach to ensuring that users are at the centre of CS endeavours requires exploring the context of usable climate information. The NFCS intends for climate services to be co-designed, co-produced, delivered and used by other climate-sensitive socioeconomic sectors, including agriculture (WMO, 2018). Conducting our analysis in these socioeconomic sectors may contribute to this goal by improving coordination between institutions and understanding end-users' decision-making.

Materials and methods

This paper aims to establish the potential value of climate services to farmers and patterns of climate information use in an agricultural context. We do so by systematically characterizing the farmer decision space in which weather and climate services are used. We recount the steps involved in creating a reproducible methodology for a thorough account of the literature as far as possible. Every effort was made to include all relevant literature but due to the time intense and laborious process of examining articles for specific pieces of information, there are likely numerous relevant papers that have not been included. With this in mind, the total number of articles amounted to comparatively few in the arena of *meta*-analyses.

The first step is to identify the relevant literature for inclusion in the *meta*-analysis. Our sources for literature searches included Google, Google Scholar, CG Space and Web of Science using keywords listed in Table 1. The CG Space allowed for material from the CGIAR's Climate Change, Agriculture and Food Security (CCAFS) research around climate services use in partner countries. Papers were relevant if they met the following criteria for inclusion into the analysis:

1) A specific type of weather or climate information is used or could be used by a stakeholder in agriculture or pastoralism
2) A specific agriculture-related decision is or could be altered by the use of the aforementioned climate information
3) A benefit of some sort is expected from the use or potential use

The specificity of the criteria results in many papers being excluded by default, as oftentimes a paper will describe a general impact of forecasts on decision-making with no specific decision mentioned. For example, stating that seasonal forecasts affect crop choice does not fulfil the criteria as a specific crop choice is not described. While analysing papers for meeting the criteria, citations for further papers are investigated as well. This snowball method results in hundreds of papers being identified, which ultimately narrowed down to 41 articles that fulfil the criteria. We analyse the articles for the decisions described in each study according to the type of weather or climate information influencing decisions, the region, the crop or livestock pertaining to the decision, the expected or experienced benefit of the decision, and if applicable, the forecast skill. These descriptive data of each forecast-influenced decision allows for an in-depth analysis of the types of studies in this paper and various other trends such as emphasis on particular countries or crops. We use these data to construct our compendium, or 'decision matrix', which has two axes corresponding to agricultural decisions (x axis) and forecasts (y axis). We describe a decision as a specific agricultural or pastoral action described in relation to the use of specific forecast information. These categories were chosen because their specificity allows for the identification of studies that are based on evidence, such as decision models, farmer surveys or consultations with experts. Such information offers the opportunity to gain insight, into patterns of climate information use and the role of context.

Table 2
Types of agriculture-based actions taken with weather or climate information.

Action type	Sub-category	Number of decisions (%)
Sowing	Sowing date	24 (13%)
	Sowing density	7 (3.8%)
	Sowing depth	1 (0.5%)
	Staggering	3 (1.6%)
Planting regime	Cover crop	2 (1.1%)
	Crop choice	42 (22.5%)
	Fallow land	3 (1.6%)
	Land preparation	29 (15.6%)
Crop inputs	Fertilizer and manure use	23 (12.4%)
	Herbicide and insecticide use	6 (3.2%)
Agricultural practices	Weeding method	2 (1.1%)
	Marketing strategy	4 (2.2%)
	Conservation agriculture	1 (0.5%)
	Tillage	2 (1.1%)
	Water conservation techniques	11 (5.9%)
	Harvest date	8 (4.3%)
	Labour	3 (1.6%)
	Asset purchase	2 (1.1%)
Livelihood actions	Livelihood strategy	7 (3.8%)
Livestock	Livestock management	6 (3.2%)
Total decisions		**186**

Results

The studies in this *meta*-analysis are based on quantitative simulations, qualitative surveys, or a combination of both. There are no studies that systematically followed farmers' or pastoralists' decision-making from receiving forecasts until the end of the growing season to establish how real-world forecast-informed decisions. In this sense, results from the matrix may not be true reflections of on-the-ground forecast use. Nevertheless, due to the wide geographies, farming systems, and end-users of CS in this analysis, it is intended as an indication of the potential value of climate information and the need for more systematic evaluations of CS.

The *meta*-analysis yielded 41 articles that identified 186 decisions supported by weather and climate information, covering 32 crops in 15 countries. The literature sourced in this analysis came from several different fields of study, some not focusing on climate services themselves but rather on farming calendars or household adaptation strategies. As such, climate-informed decisions are rarely described beyond the type of forecast and agricultural decision. We found two types of studies, or some combination of both; the first being qualitative and based on presenting farmers with a hypothetical forecast and asked how they would change their management practices; the second being quantitative and using climate and agronomic data in simulations to

Table 3
Forecasts described in the decision matrix and the number of decisions influenced by each forecast.

Forecast influencing decision in the Decision Matrix	Timescale of forecast	Number of decisions influenced
Precipitation forecast	Daily	6
	Dekadal (10 day)	19
	Seasonal	129
Temperature and precipitation forecast	Seasonal	16
Temperature forecast	Seasonal	5
Soil moisture and precipitation forecast	Dekadal (10-day)	6
Precipitation, temperature and wind forecast	Daily	1
Soil temperature forecast	Seasonal	2
Soil moisture	Dekadal (10-day)	1
	Seasonal	1
Total		**186**

show how management decisions could be optimized. It was uncommon for a paper to study how a climate services end-users responded to a real-world weather or climate forecast

Crop type and country are frequently undescribed in papers, which we have classified as "unspecified". Repetitions are evident in the matrix as several articles may mention the same application of forecasts to decision-making. For example, when a 'wet' season was forecast, one of the decision applications was to apply more fertilizer than a 'normal' season, which was mentioned in three articles. The frequency of decisions in the decision matrix is described in parentheses after the description of the decision. The matrix itself is an enormous representation of specific data that cannot be easily simplified or reduced. As such, it has not been included in the article, and is instead uploaded onto dataverse, with some graphics relating to smaller sections of the matrix being presented in this analysis. Seasonal precipitation forecasts (Fig. 2) and 10-day forecasts (Fig. 3) encompass the majority of the data in the matrix.

In the studies documented in the matrix, there were numerous different ways in which authors measured qualitative activities; household surveys, focus group discussions, simulation modelling, individual interviews, workshops, expert interviews, and role-play exercises and model simulations. Studies found concentrate in Africa (21 out of 41 papers) and the United States (7 out of 41). Results in Asia came from India (2 papers), Australia (6), and South America (2 from Argentina). Two papers did not specify in which country were the forecast-based decisions relevant.

Table 2 shows the type of agricultural decisions in the studies analysed which can be further divided into several sub-categories that cover almost all farm management decisions from planting to harvesting. Other decisions include livelihood alternatives and livestock actions. Out of a total of 186 decisions reported, the most frequent were crop choice (22%), followed by land preparation (17%), sowing date (13%) and fertilizer and manure use (12%). The decisions that appeared to be least affected by forecast, or were least documented in the literature, were conservation agriculture techniques, asset purchase, and sowing depth. It could be that conservation agriculture and asset purchase are long-term decisions that require the consideration of many other factors beyond weather and climate forecasts, while sowing depth could be a decision that tends not to be the focus of simulation studies, nor interviews with farmers perhaps due to the high-tech nature of considering this decision on a farm.

Table 3 illustrates the frequency of agricultural decisions and related forecast type in the analysis. Precipitation forecasts appear to be the most frequently studied forecast, according to the literature in the matrix. Precipitation forecasts of all timescales account for 145 of the 175 total decisions. Specifically, seasonal precipitation forecasts are those that are most frequently associated with farmers' decision-making across the globe, according to the analysis. These forecasts are applied across many of the decision sub-categories listed in Table 3 (17 out of 20 sub-categories). Dekadal, or 10-day, precipitation forecasts, and seasonal temperature and precipitation forecasts are the next most frequently studied, accounting for 16 decisions each in the decision matrix. By contrast, several forecasts apply to very few categories of agricultural decisions. A forecast of precipitation, temperature and wind together is documented once in the analysis, with reference to a "hot, dry and windy summer". Soil moisture forecasts are also documented twice, once each on dekadal and seasonal timescales, influencing harvest date and land preparation respectively.

There are instances in the matrix where climate forecasts appear to be solely applied to one agricultural decision, one of which is the application of soil temperature forecasts to fertilizer application decisions. Furthermore, forecasts description in studies varied from general statements ('a dry season is forecast') to specific descriptions, for example, on hit and false alarm rates of forecasts.

The decision space in which farmers operate is complex and the role of climate information is difficult to establish. The matrix is a simplified representation on a global level of how farmers may make decisions, according to the literature described (Fig. 1; also see Appendix 1 for an extract). The visualization of the matrix in Fig. 2 shows the timescale of forecast types, which decisions they may influence and at which time in the season the forecasts might be useful. The colours depict the different types of forecast (e.g. soil, precipitation or temperature forecast). The numbers in each coloured cell describe how many decisions relate to the forecasts that are described in the decision matrix (the relative frequency of papers mentioning the forecast-influenced decision). We found that certain forecasts are most useful before the growing season has begun, for what we call "step decisions" that often cannot be reversed such as leaving land fallow or divesting from agriculture. Other forecasts appear to be more useful during the season for "continually adjusted decisions" such as harvest date and use of inputs.

The decision matrix and its visualizations offer valuable insights into which climate information may be useful in which agricultural or livelihood circumstance. Most obvious at first glance is that forecasts appear to be most applicable before, rather than during, the season. Furthermore, decisions seem to be concentrated around particular forecast timescales and variables, indicating that specific forecasts may be more broadly applied to various different decisions than others. To some extent, this may also reflect levels of data and knowledge availability for particular forecast variables. For instance, seasonal precipitation forecasts are the most populated in the matrix, indicating their applicability to virtually all of the step and continually adjusted decisions identified. The high frequency of precipitation forecasts in the matrix is likely a result of the fact that roughly half (54%) of the studies focus on Africa, where agriculture is primarily rainfed, but also of forecast and observation data availability. Soil moisture forecasts, on the other hand, were only described in the literature with reference to harvest times.

The complexities and nuances of decision-making are, however, under-represented in Fig. 2. All decisions examined in this review relate to the use of short-term climate information and mostly focus on annual crops in monoculture systems (with no representation of highly diversified, silvo-pastoral or agro-forestry systems). In the below subsections, we first present a general overview of how forecasts may influence decision-making, and then expand on the types of forecasts, or forecast simulations, found in the literature, namely, seasonal precipitation

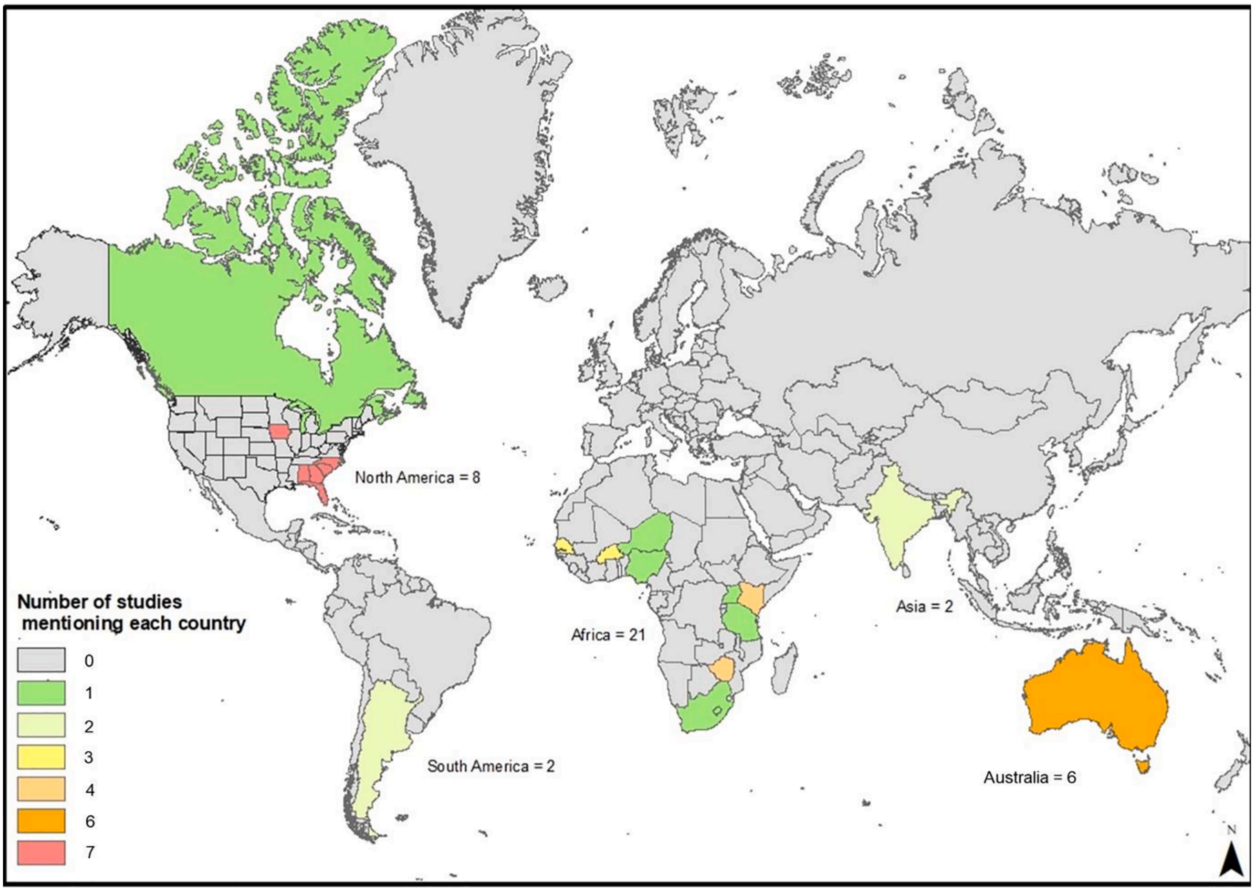

Fig. 1. Number of studies that mention each country from the articles documented in the decision matrix. 8 papers in North America, 21 in Africa, 2 in South America, 2 in Asia, 6 in Australia and 3 papers with unspecified locations for climate influenced decisions adds up to a total of 41 papers. The USA has been split into states in this map to illustrate which areas of the country are the focus of climate services articles relevant to the decision matrix. The legend goes from 0 to 7, omitting 5 as there are no countries with 5 papers in the matrix.

forecasts, dekadal precipitation, and seasonal temperature forecasts. Dekadal forecasts refer to those that are 10 days long.

Can forecasts influence decision-making?

The decision matrix shows that many different forecasts and combinations of forecasts can influence decision making on different timescales. This is partly because farmers make spontaneous decisions based on their embodied knowledge (Crane et al., 2011), not simply rational expertise, and this creates a complex decision space. Consistent with this, the decision matrix shows that one forecast may influence several different agricultural or livelihood decisions and vice versa (Fig. 2). Different meteorological variables may influence decisions according to timescale and nature of the decision (relating to crop growth, household goals, policy landscape, external environment etc.). One decision type that is typically impacted by several different forecast types is fertilizer application (see Fig. 2). The choice to apply fertilizer is heavily dependent on rainfall. From the matrix, we can see that several different types of precipitation forecast affect fertilizer application at different stages in the season. Above normal rainfall forecast at planting may lead farmers to apply more than their usual amount of fertilizer at planting to capitalize on 'good' conditions (Ingram et al., 2002). If rainfall is forecast to increase during the season, farmers may apply more nitrogenous fertilizer (Hochman et al., 2009). By contrast, if dry conditions are forecast for the season, farmers may choose to use more slow-release nitrogen than usual (Fraisse et al., 2006).

Responses to forecasts assessed through farmer interviews may also seem conflicting. For example, a forecast of above normal rain around the time of planting can lead farmers to sow either earlier or later, depending on their motivation. An earlier planting would allow for crops to establish themselves and withstand heavy rains (Ingram et al., 2002) while a later planting could avoid early loss of crops (O'Brien et al., 2000). In our analysis, two vastly different decisions are documented as a response to a forecast of flooding for the season. Rasmussen et al. (2014) found from surveying farmers that a flooding forecast may result in the decision to increase cultivated area because some fields will be lost to flooding. On the contrary, O'Brien et al. (2000) surveyed farmers to find that a viable decision for flooding is to stop farming and go into commercial business. This serves to illustrate how farmers must consider numerous possible outcomes in their decision-making and that establishing a single meteorological variable as a sole influencer of decisions is difficult.

The decision matrix also shows that end-users can use climate information to make livelihood decisions that involve divesting from

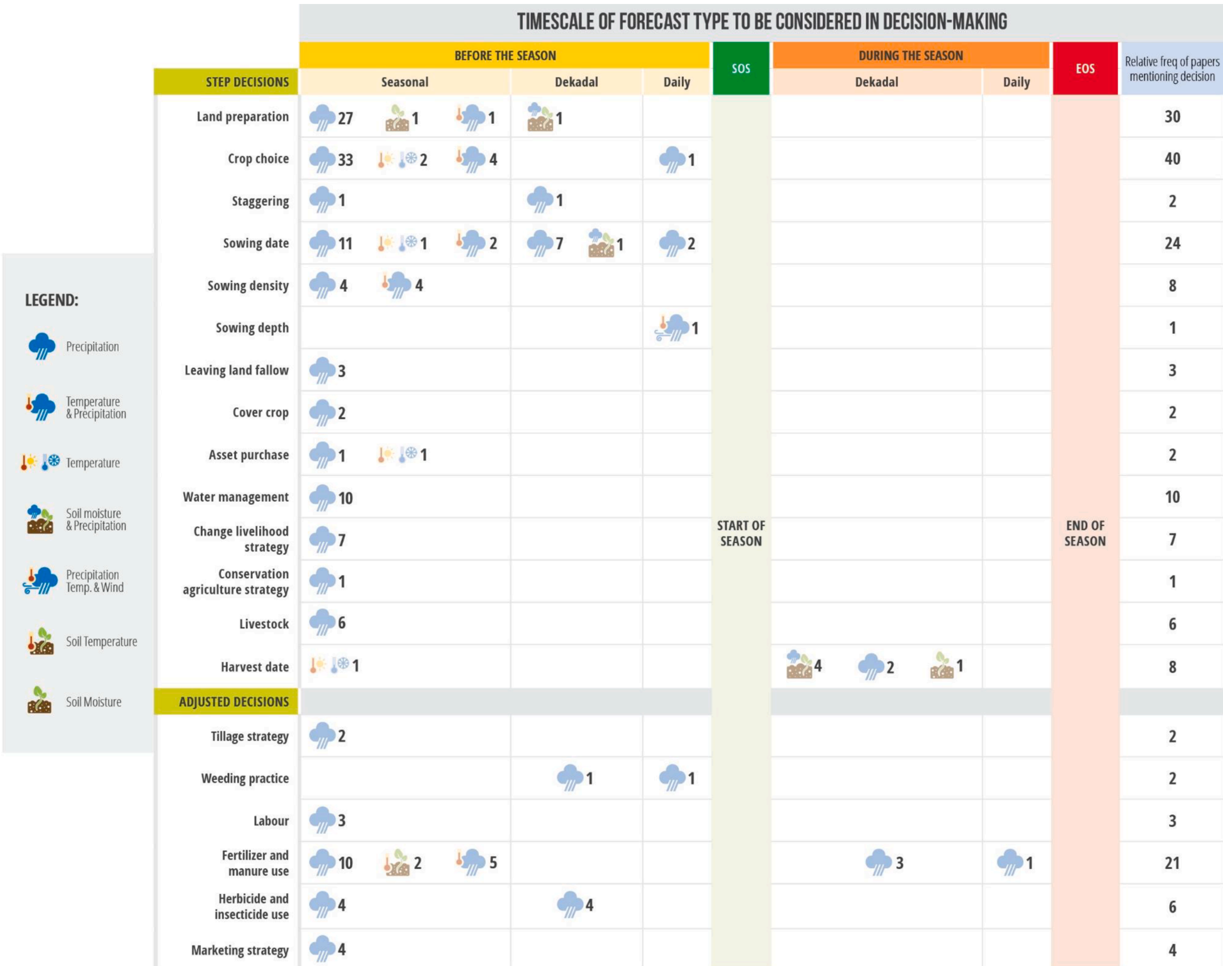

Fig. 2. Step and continually adjusted decisions that farmers may encounter during the growing season, categorized according to the timescale of the forecasts that influence decisions. Symbols show which type of forecast while numbers indicate how often the decision is described in the decision matrix.

agriculture. The papers in the matrix outlining responses related to alternative livelihoods activities (other than farming) are based on survey methods that document farmers' responses to seasonal forecasts. Responses generally involve some level of divestment without completely abandoning agricultural practices. The livelihood security of farmers may depend to differing degrees on small-scale mining, trade, crafts, or seasonal migration work (Roncoli et al., 2009; Ingram et al., 2002) in addition to continued agricultural practices. For example, farming households in the Central Plateau of Burkina Faso use labour migration to Côte d'Ivoire as a livelihood strategy (Ingram et al., 2002). Seasonal climate information appears to be the forecast type that would be most pertinent to broader livelihood decisions. (Crane et al., 2010; Ingram et al., 2002; Nyamwanza et al., 2017; O'Brien et al., 2000; Thomas et al., 2007). For many, full or partial divestment from agriculture is a risky decision and a seasonal forecast offers some indication as to whether or not an alternative crop or an alternative livelihood strategy is a better decision.

While our understanding of the role and value of CS is developing quickly, there remain several steps to improving how we judge CS to be successful and how this will aid in evaluating CS (Vaughan and Dessai, 2014). We have examined why it is difficult to identify the specific benefits of climate services in agriculture however, a closer look needs to be taken at evaluation criteria for CS. Determining what defines successful climate services requires a value judgement and associated criteria. For example, the number of next- and end-users that access a particular climate service is a metric often used to measure success. While this gives an indication of reach, there is no indication of whether farming decisions are altered in response to climate information. Other metrics could be considered for a broader assessment of the value of climate services, such as end-users' choice to divest. Impact assessments and monitoring and evaluation could further improve our understanding of the value of climate information, although these are seldom implemented as they require activities beyond a project's lifetime.

The value of weather and climate information

Of the matrix papers that employ simulations in their analyses all use yield as a metric of the potential value of climate information. Simulations typically use crop models to establish how yield would likely respond to management decisions based on climatic conditions. While such studies are not intended to provide exact recommendations to farmers, they do provide an indication of how climate information may alter decisions and impact yield. These studies are still valuable to the analysis due to the context specificity and expert input that is involved in

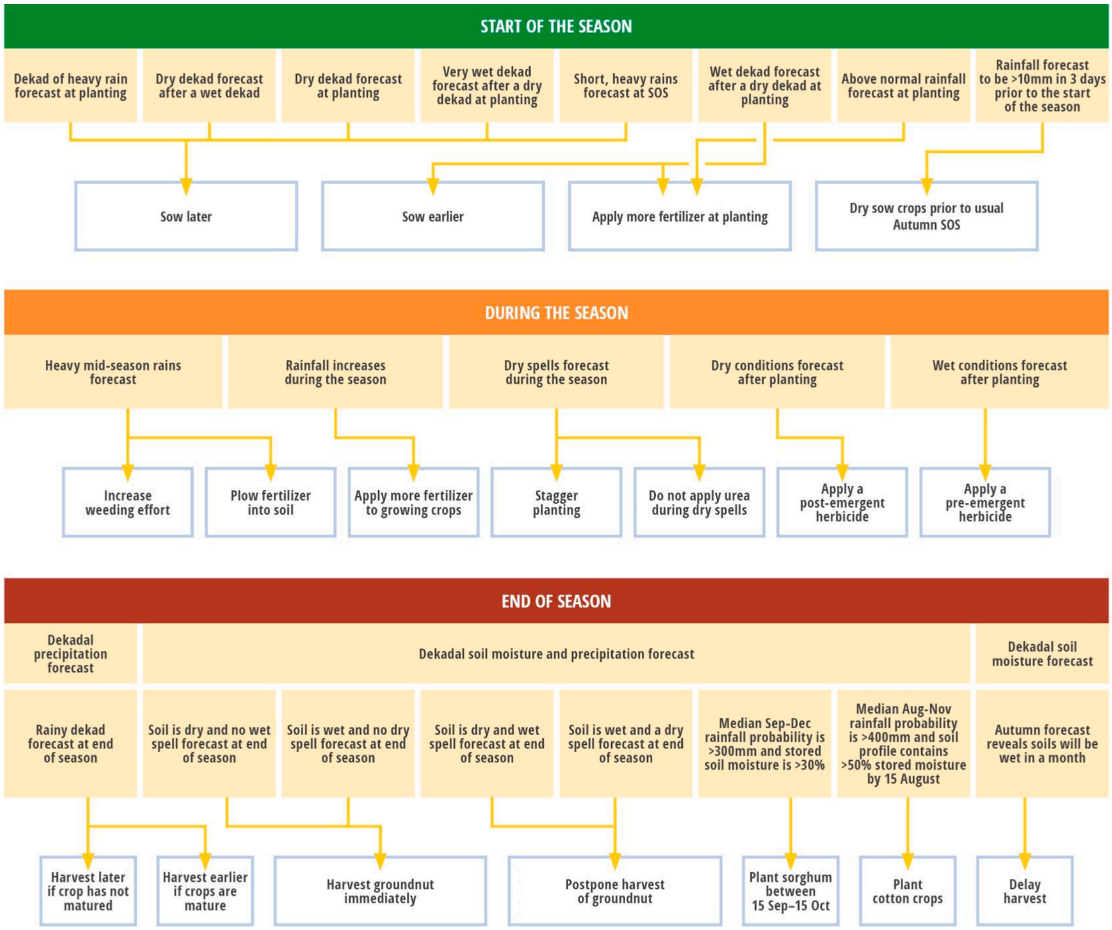

Fig. 3. A visualisation of the decision matrix showing how dekadal (10-day) forecasts may influence agricultural decision before, during and after the growing season.

simulations. Studies that tracked farmers' forecast use throughout the growing season were uncommon, possibly due to limited resources availability. This serves to highlight the dearth of evaluations and assessments aimed at establishing how farmers may value climate information in their decision-making. Although there are no studies in the matrix that describe a realized yield benefit for farmers using climate services, Tarchiani et al. (2018) conducted a study over two growing seasons that quantified how yield changed with forecast use. They found that average sorghum yields from 2015 and 2016 increased by 64% in Mauritania with the use of agrometeorological services. The paper did not fulfil the criteria to be included in the matrix, as decision descriptions were more general than specific. Quantitative studies on the impact of CS use on crop yield are key to furthering understanding of forecast value. New methods need to be developed for understanding how seasonal climate forecasts are useful for farmers' decision-making, as concluded in a study assessing farmers' use of 3-month outlooks on climate (Falloon et al., 2018).

Seasonal precipitation forecasts

The decision matrix reveals patterns in the literature regarding climate-informed decision-making that infers how climate information may affect on-farm decisions. The high frequency of seasonal precipitation forecasts in the matrix reflects the large number of climate-sensitive agricultural decisions that are made before the growing season begins (Roudier et al., 2012). Seasonal precipitation forecasts are the tool most often used to plan the upcoming season, with most decisions revolving around crop choice, land preparation, conservation agriculture techniques, water conservation strategies, tillage, sowing date and alternative livelihood choices. Seasonal precipitation forecasts have typically been the focus of climate information for agriculture, with sub-seasonal forecasts (2–3 week lead time) receiving less attention than longer (seasonal) or shorter (10-day and daily) forecasts (Kolachian and Saghafian, 2019; Vitart, 2014). The origin of this lack of attention can be partially attributed to a supply-side problem, where the sub-seasonal timescale is less predictable than seasonal or daily timescales, although has recently gained recognition as forecasting techniques have evolved (Kolachian and Saghafian, 2019).

Dekadal precipitation forecasts

The dekadal (10-day) precipitation forecast was rarely mentioned in reference to planting regime decisions, with only one entry; staggering planting of crops when dry spells are forecasting during the season. Other planting regime decisions such as crop area and choice, crop rotation, land use and land preparation appear to be more frequently mentioned in the matrix in reference to seasonal forecasts. Dekadal precipitation forecasts are more often mentioned for step decisions taken during the season such as fertilizer application, sowing date and harvest date (Fig. 3). Dekadal temperature forecasts were absent in the matrix.

Seasonal temperature forecasts

Seasonal temperature forecasts were mentioned twice in the matrix; a forecast of a hot summer may lead farmers to plant tomatoes as a marginal crop (Klemm and McPherson, 2017); and a warm seasonal forecast could result in farmers planning to harvest their crops earlier (Mavi and Tupper, 2004). However, neither paper specifies to which country or crop system it is pertinent Such farming decisions are naturally specific to certain region and crop systems. We can thus gain some insight into how temperature may influence decisions, rather than specific, universally applicable farming decisions. Seasonal precipitation forecasts appear to be more pertinent to decision-making than seasonal temperature forecasts which seems counter-intuitive considering how important both meteorological variables are to crop growth. However, as stated earlier, this is likely because roughly half of the studies identified here are from Africa, where variability at inter-annual timescales is generally greater for precipitation than for temperature, and where precipitation is the more limiting factor compared to temperature.

Soil moisture and soil temperature forecasts

Both soil moisture and soil temperature are infrequently mentioned in the decision matrix, covering 2 and 4 decisions respectively. The specificity of soil moisture forecasts compared to seasonal precipitation forecasts may offer some guidance on where to invest in climate services. It is possible that seasonal precipitation forecasts apply to more decisions, however, it could be that there is a gap in supply of other types of forecasts, resulting in apparent differences in usefulness. Potentially a barrier to using soil moisture forecasts is the difficulty in collecting such data at scale due to the expense associated with sensors and laboratory tests to calibrate sensors (Dubois et al., 2021). Nevertheless, soil moisture is an important indicator of drought and is often used to determine planting dates at the beginning of the season.

Daily precipitation forecasts

Decisions related to fertilizer use and sowing date are the most frequently mentioned in relation to daily precipitation forecasts. The accuracy of weather forecasts compared to seasonal forecasts allows for more precise decisions on shorter timescales which typically include crop inputs, sowing dates and harvesting dates. Weather forecasts for other meteorological variables seem to be absent from the decision matrix. This may be representative of a general bias towards particular forecast types such as seasonal precipitation forecasts, which permeates into the literature centred on yield simulations and climate information.

Discussion

We discovered several patterns in forecast use from the decision matrix that may prove useful in CS initiatives. The apparent usefulness of seasonal precipitation forecasts may present a starting point for implementing CS in a given context. Seasonal precipitation forecasts give a probabilistic outlook of temperature and precipitation several months in advance in tercile categories; above normal, normal and below normal, based on the previous 30 or so years of precipitation data. This shows how probable it is that the upcoming season will be climatologically different (Singh et al., 2018) which potentially offers direction for farmers in their decision-making. Dekadal, or 10-day, precipitation forecasts are most suitable for step decisions due to the changeable nature of these decisions and their short time horizon. Temperature forecasts were rarely found to be useful for end-users, according to the literature reviewed. Weather forecasts, on the other hand, are less uncertain as they perform better due to the shorter timescale of less than two weeks (Takle et al., 2014). Weather forecasts are useful for continually adjusted decisions that are resolved in the next few days such as when to apply inputs to crops or when to weed. Step decisions are better addressed by seasonal climate forecasts, although the uncertainty associated with a probabilistic forecast has been cited as a barrier by users of climate information in several studies (Haigh et al., 2015; Sivakumar and Hansen, 2007; Soares et al., 2018).

Furthermore, the trends in potential forecast use identified here may prove useful in establishing what farmers consider their objectives when using climate information to make decisions. Typically, it is with the intent of achieving a resource allocation that maximizes the utility of labour, capital and land (Wallace and Moss, 2002). CS tend to be tailored for maximizing yield as the primary way to achieve maximum utility. However, farmers may pursue different livelihood objectives to the expected yield improvement. McConnell and Dillon (1997) highlight that farmers may pursue objectives such as economic return, yield stability, crop diversity, flexibility of practices, labour productivity or environmental sustainability. These objectives, or some combination thereof, could better align with household resources than solely yield improvement. Farmers may also pursue objectives on different timescales to climate forecasts, adding further uncertainty to decision-making (Kniveton et al., 2014). It is thus imperative to consider different objectives and timescales of farmers' decision-making when tailoring climate services. "Successful" climate services should include efforts towards increasing population resilience (Carr et al., 2017) and prioritizing livelihood pursuits such as household resource allocation (Tall et al., 2014) or potentially migrating to the city instead of farming for the season (Ingram et al., 2002).

The decision matrix contributes to the literature highlighting the need for more numerous and detailed evaluations of real-world applications of climate forecasts. The importance of user-centred approaches has long-since been established in the field of climate services and progress towards scaling is ongoing. However, the supply-side legacy remains partially intact while initiatives and endeavours are being scaled. One such initiative is the Local Technical Agroclimatic Committees (LTACs) that are currently being scaled in Latin America through the CGIAR's CCAFS research programme. The LTACs create dialogue between farmers and researchers to provide farmers with relevant choices responding to climate variability (Loboguerrero et al., 2018). Since the inception of two LTACs in Colombia, the approach has scaled to 23 LTACs across Latin America, with more in the pipeline. Another user-centric initiative that is scaling is the Participatory Integrated Climate Services for Agriculture (PICSA) approach. PICSA places particular emphasis on engaging with end-user communities and understanding their context prior to establishing which risk management practices are most appropriate for their livelihoods (Dayamba et al., 2018). PICSA embodies the notion put forward by Hansen et al. (2011b), that agricultural extension services should incorporate climate information where possible. Farmers have affirmed that PICSA has encouraged them to consider and implement agricultural innovations suitable to their contexts (Dayamba et al., 2018) which is integral to effective CRM. The matrix offers insight into forecasts of different scales and their potential to contribute to choices of climate risk management strategies. In seasons that forecasts suggest might be favourable, farmers may be willing to invest in new technologies or assets previously considered to be too risky. For example, one entry in the matrix states that farmers may plan to make large purchases when rainfall is forecast to be evenly spread throughout the season (Mavi and Tupper, 2004). Another entry states that farmers might build dams for water storage in seasons where above normal rainfall is forecast (Ndiaye, 2011). Additionally, the matrix offers researchers and practitioners the opportunity to efficiently identify relevant factors pertaining to the impact of their climate services initiatives.

Agriculture is one amongst several sectors that depends directly on the climate. Weather and climate services are useful to sectors that experience vulnerability due to climate variability or extreme events (Alexander and Dessai, 2019; WMO, 2017). The GFCS aims to mainstream climate information into decision-making in several primary sectors of countries and is currently being implemented in 41 countries. We suggest that the construction of a decision matrix in each sector may offer an opportunity to better understand the decision space where end-users are using CS. This would be a step towards supporting the GFCS to identify entry points, information needs and synergies across sectors for the scaling of CS. Additionally, opportunities to leverage shared resources and maximize knowledge sharing could be realized by constructing decision compendiums. Access to climate and weather forecasts is a measure that could increase the resilience of the agricultural sector (Robinson et al., 2013) and could be used to increase resilience in other sectors as well. There is promise that the integration of climate forecasting into different sectors could reduce the cost of adapting to climate variability (Feldman and Ingram, 2009).

Conclusions

The decision matrix of forecast-influenced agricultural decisions offers a counter to the supply side approach that has previously dominated the CS perspective. The analysis is somewhat limited by the nature of the relevant literature which focuses largely on simulating decisions through models or surveys with farmers. As such, the patterns in the value of forecasts offered by the decision matrix are interpreted through a lens of potentiality and context-setting. Seasonal precipitation forecasts appear to have inherent utility based on the frequency of matrix entries, while other forecasts appear to be less valued. Potentially underutilized or undervalued forecasts for agricultural decision-making include temperature, soil moisture, soil temperature and wind forecasts. As complex as farmer decision-making for climate risk management might be, understanding the decision space allows for the identification of potentially useful information and potential gaps in information provision. This helps CS practitioners in the future to move strategically to develop climate services for impact.

The matrix also provides a starting point by exploring the decision space in which climate forecasts are used in agriculture. This encourages dialogue that could bring together climate and agriculture expertise, and expedite the process of two-way communication in CS production. Linking the supply and demand sides early in climate services production may help in establishing opportunities and gaps in the CS landscape (Hoogenboom et al., 2007). Evaluating the CS value chain also offers the opportunity to gauge the socio-technical capacity of different stakeholders, institutions and end-users of climate services. It is a process that can offer value to all players involved in CS production, and may prove valuable to CS practitioners.

Further identified by this analysis is the need for impact studies focusing on climate services to establish tangible benefits that are replicable. Coproduction should continue to be evaluated as well in this vein. Recent work suggests that there is a dearth of impact assessments or evaluations that determine whether coproduction in CS has increased outcomes and impacts (Vogel et al., 2017). While the barriers to coproduction are well-established, evidence of the approach improving the usability of CS is scant (Hansen et al., 2019), as is evidence of its scalability (Vaughan et al., 2019). There is a need for more monitoring and evaluations efforts to establish how climate services are used by stakeholders in agriculture and pastoralism.

The benefits of the decision matrix that have been highlighted may be applied to other climate-sensitive sectors with the construction of their own sector-specific matrices. Sectors that may benefit include health and safety, water and sanitation, urban planning, rural development, telecommunications, tourism and trade. It is possible that constructing decision matrices for these sectors could allow for better alignment of weather and climate services initiatives at both national and regional scales, in line with the GFCS. Capacity development is one of five pillars of focus of the NFCS and is an all-encompassing endeavour as capacity of all stakeholders involved is important for useful, valuable climate services. Establishing decision matrices in each sector may also help the process of co-production in sectors as stakeholder and institution mapping can be shared.

CRediT authorship contribution statement

Lorna Born: Data curation, Writing - original draft, Visualization, Investigation, Methodology, Formal analysis. **Steven Prager:** Conceptualization, Supervision, Validation, Project administration, Funding acquisition, Writing - review & editing, Methodology. **Julian Ramirez-Villegas:** Writing - review & editing. **Pablo Imbach:** 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.

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Appendix

Table A1
Extract from the decision matrix.

Forecast			Agricultural action								
			For Sowing Actions				For Planting Regime Actions				
Meteorological variable forecast	Timeline of forecast	Forecast of event	Sowing date	Staggering	Sowing density	Sowing depth	Crop choice	Staggering	Cover crop	Fallow land	Land use and preparation
Precipitation	Daily	Rain forecast for the following few days during the season									
		Start of the rains are forecast in the next few days	Sow as the rains begin (1)								
		10mm of rain forecast in 2 days at SOS in June	Sow crops (1)								
		SOS is forecast to be later than usual					Switch from maize to beans and root crops (1)				
	Dekadal	Rainy dekad forecast at the end of season									
		Dry spells forecast during the season		Stagger planting to avoid periods of water deficits							
		Heavy mid-season rains forecast									
		Rainfall increases during the season									
		Above normal rainfall forecast at planting	Sow earlier so that plants can withstand heavy rains (maize) (1)								
		Wet dekad forecast after a dry dekad	Sow earlier (millet) (1)								
		Very wet dekad forecast after a rainy dekad	Sow later (maize) (1)								
		Dry dekad forecast after a wet dekad	Sow later (maize and peanut) (1)								
		Dry dekad forecast at the start of the season	Sow later (maize and peanut) (1)								
		Short, heavy rains are forecast at SOS	Plant crops later to avoid harsh conditions (maize)								

Full decision matrix available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:https://doi.org//10.7910/DVN/UDDTXE

Table A2
Table of crops, decisions and forecasts that are described in the decision matrix, classified by country.

Country	Crops	Decisions	Forecasts
Argentina	Maize	Sowing date, crop choice, sowing density, fertilizer	Dekadal and seasonal precipitation forecasts, ENSO forecasts
Australia	Wheat, sugarcane	Sowing time, land preparation, fertilizer application, herbicide application	Dekadal and seasonal precipitation forecasts
Burkina Faso	Sorghum, millet, maize, rice and cotton	Crop choice, labour, land use, sowing date, fertilizer, diversification, sowing date	Dekadal and seasonal precipitation forecasts, soil moisture forecasts
Canada	Corn, beans	Crop choice	Temperature forecasts
Kenya	Maize, beans, sorghum, millet, livestock	Alternative livelihoods, fertilizer, labour, land use, crop choice, sowing density, sowing date	Dekadal and seasonal precipitation forecasts
India	Groundnut, cotton, sorghum	Sowing date, harvest date, crop choice	Soil moisture, dekadal and seasonal precipitation forecasts
Lesotho	Maize, sorghum, wheat	Crop density, crop choice	Seasonal precipitation forecasts
Niger	Millet	Sowing date	Daily precipitation forecast
Nigeria	Maize	Planting date	Daily and seasonal precipitation forecasts
Senegal	Maize, millet, peanut	Crop choice, labour, fertilizer, sowing date, harvest date	Dekadal and seasonal forecasts
South Africa	Unspecified	Alternative livelihoods	Seasonal precipitation forecasts
Tanzania	Maize, beans, rice	Alternative livelihoods, sowing date	Dekadal and seasonal precipitation forecasts
Uganda	Livestock	Alternative livelihoods, land use	Seasonal precipitation forecasts
Unspecified	Unspecified	Sowing depth, asset purchase	Precipitation, temperature and wind daily forecasts
USA	Corn, wheat, tomato	Fertilizer application, sowing date, land use, crop choice, harvest date	Soil temperature, soil moisture, dekadal and seasonal precipitation forecasts
Zimbabwe	Maize, cotton	Alternative livelihoods, crop choice, land use, sowing date	Dekadal and seasonal precipitation forecasts, temperature forecasts

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