Title

The Development of Seasonal Climate Forecasting for Agricultural Producers

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Body (7634 words)

1 Introduction

Seasonal climate forecasts are used by crop producers for long-term decisions, for example planting and harvest timing, field fertilization, or water management, among others. To review the literature, the main methods used were keyword searches in publisher-unaffiliated databases such as Web of Knowledge and in publication libraries of institutions known for their interdisciplinary work in climate forecasting and agriculture, such as the Southeast Climate Consortium and the International Research Institute for Climate and Society. Section 1 outlines a brief history on the topic. Section 2 explores single-model and ensemble forecasts. Section 3 reviews measures of skill and utility to assess the value of seasonal climate forecasts. Section 4 puts seasonal climate forecasts in context with other agricultural decision factors. Section 5 looks at tailored seasonal climate forecasts and seasonal climate forecasts from an agricultural perspective, while exploring communication challenges between forecast provider and forecast user, and highlights how agricultural decision-making differs depending on the crop type and planning horizon. Lastly, section 6 explores end-to-end concepts.

1.1 Historical Overview

The benefits of weather and climate monitoring for agricultural purposes have been recognized for several centuries. Thomas Jefferson, third president of the United States (U.S.) (1801-1809), planned farming operations based on local climate conditions (Changnon, 2007). From 1776 to 1816, he kept an almost continuous record of daily weather conditions (Fiebrich, 2009). Long-range weather forecasts date back to at least 1793, the first publication of the Farmer's Almanac, an annual general interest magazine containing descriptive weather forecasts for the coming calendar year (Hale, 1991). Forecasts in the Farmer's Almanac were based on reoccurring weather patterns and proxy data, such as the thickness of the skin of onions, width of the stripes on the woolly caterpillar, or moon phases; however, the exact forecasting method remains unpublished (Hale, 1991). A survey of agricultural advisors to midwestern U.S. corn growers found that 95 percent of participants knew of the Farmer's Almanac, but only 18 percent indicated using it (Prokopy et al., 2013).

Native American Tribes were recognized for their long-term forecasts, as a 1950-to-1952 letter by Senator Robert S. Kerr (D-Oklahoma) reveals. Despite having access to U.S. Weather Bureau (predecessor of the National Weather Service, NWS) forecasts, Kerr wanted to "know what some of the Indians in the various sections of the nation think about our coming winter probabilities" (Peppler, 2010: 200). Much like the Farmer's Almanac, Tribes appeared to base their predictions on natural phenomena,

such as the thickness of corn shuck and how many spider webs were in the air and in trees (Peppler, 2010).

Other authors reviewed the then-current status of long-term weather predictions and seasonal forecasting. For example, Namias (1968) summarized historical developments and important literature on long-range forecasting, while Nicholls (1980) gave an historical overview of seasonal forecasting methods, such as analogs, teleconnections, cosmic cycles, time series, and early numerical modeling. Goddard et al. (2001) reviewed predictability and prediction of seasonal to inter-annual forecasts, including statistical and dynamical forecast methods and forecast performance, and Goddard et al. (2012) compared seasonal forecasting to decadal forecasting. None of these summaries, however, focused on the usefulness of seasonal forecasts to agricultural producers.

In 2006, the World Meteorological Organization (WMO) set production and verification standards for seasonal climate forecasts that are currently followed by 12 national and multinational forecast centers on five continents, so-called Global Producing Centers (GPC) (WMO, 2015). According to these standards, nations must forecast air temperature (2-m height), precipitation, sea-surface temperature, mean sea-level pressure, 500hPa height, and 850hPa temperature, issued at least every three months with minimum lead-times between zero and four months (WMO, 2015).

1.2 Recent Efforts in Seamless and Extreme Events Forecasting

With improvements in supercomputing and advances in understanding of physical processes both in the atmosphere as well as between atmosphere, oceans, and land surfaces, modelers can apply techniques from numerical weather prediction to numerical climate prediction. “[S]cientifically, predicting weather at shorter ranges, or its various statistics at longer time ranges, is based on the same laws of physics” as forecasting for longer time scales (Toth et al., 2007: 1427). This transition to longer time scales is desirable in an effort to provide seamless, skillful forecasts from hourly to seasonal time scales (Toth et al., 2007). In practice, several programs have been initiated to work towards seamless forecasting. From 2006 to 2016, THORPEX (“The Observing system Research and Predictability EXperiment”), a WMO program supervised by the U.S. National Oceanic and Atmospheric Administration (NOAA), developed procedures and devised research priorities to extend the 7- to 10-day limit of numerical weather prediction out to 14 days. THORPEX was also intended to develop intraseasonal forecasts of up to 60 days lead-time (Toth et al., 2007). DEMETER (“Development of a European Multimodel Ensemble system for seasonal to inTER-annual prediction”), a European project from 2000 to 2003, used downscaling techniques to produce high-resolution global seasonal climate forecasts from an ensemble of

European seasonal forecast models (three or seven models, depending on the length of the hindcast period) as input for other prediction models, for example for crop yields or the distribution of diseases like malaria (Palmer et al., 2004).

DEMETER's successor, ENSEMBLES ("ENSEMBLE-based predictions of climate changes and their impacts"), ran from 2004 to 2009 and improved DEMETER's seasonal forecast performance (for example in the northern midlatitudes, and in lead-times of 4 to 6 months) by using an ensemble of nine updated forecast models (Weisheimer et al., 2009; Alessandri et al., 2011). From 2012 to 2016, EUPORIAS ("EUropean Provision of Regional Impact Assessment on a Seasonal-to-decadal timescale"), another European, multi-institutional program, developed probabilistic forecasts of high-risk events for Europe and parts of Africa for seasonal to decadal timescales (Hewitt et al., 2013). EUPORIAS facilitated 24 national and multinational European forecast centers with expertise in seasonal forecasting, impacts assessment, and new media communication, as well as climate-sensitive industries such as agriculture, energy, and tourism, to create decision-support tools for these industries and to increase their competitiveness (Hewitt et al., 2013).

In 2013, the S2S (Sub-seasonal to Seasonal) prediction project was initiated by the World Weather Research Programme (WWRP), World Climate Research Programme (WCRP), and THORPEX as a five-year project to foster international research collaboration and to fill the forecast gap between medium-range weather forecasts (up to 2 weeks) and seasonal forecasts of 3 to 6 months (Robertson et al., 2015). S2S objectives, science plans, and descriptions of individual sub-projects can be viewed on www.s2sprediction.net. Most recently, ICON ("ICOsahedral Non-hydrostatic general circulation model") was developed by the German Weather Service and the Max Planck Institute for Meteorology as a numerical modeling framework for forecasting on several temporal and spatial scales (Zängl et al., 2014). Therefore, ICON could also benefit seasonal forecasting, for example for agriculture. In addition to government products, many long-range forecasts are being produced by commercial providers, as overviewed by Hartmann et al. (2002).

2 Seasonal Forecasts and Their Application in Agriculture

After highlighting scientific achievements towards seasonal and seamless forecasting, the following sections will focus on the development of two seasonal climate forecast efforts carried out by the U.S. Climate Prediction Center and illustrate how these products can be applied to agricultural decision-making.

2.1 Seasonal Tercile and POE Forecasts

The U.S. Climate Prediction Center (CPC) has been issuing long-range forecasts for the contiguous U.S. since 1946 (Kerr, 2008), for example for crop producers or natural gas suppliers (Kerr, 1989: 30). Until 1981, these forecasts had no lead-time (i.e., the forecast started with the issue date), and forecasts were three-month aggregated and based on three probabilistic categories (above, below, and near the long-term average) (O'Lenic et al., 2008). Better understanding of El Niño in the 1980s and 1990s (e.g., Rasmusson and Carpenter, 1982) led to advances in the skill of seasonal forecasts such that, in 1995, CPC changed the forecast format into a series of 13 consecutive, overlapping 3-month periods, issued every month, starting at lead-times of 0.5 month (Fig. 1), and ending at 12.5 months (O'Lenic et al., 2008). The 0.5 minimum lead-time was to avoid redundancy with daily weather forecasts (van den Dool, 1994) while 12.5 months was long enough to cover an entire crop year while not significantly losing forecast skill (van den Dool, 1994). Agricultural producers and related industries embraced these improvements and started using seasonal forecasts more frequently (Changnon, 2004). In 2006, CPC started using a new forecast model, the Climate Forecast System version 2 (CFSv2) which has improved predictive skills over its predecessor (O'Lenic et al., 2008; Peng et al., 2013; Saha et al., 2014).

There are two major ways in which CPC's probabilistic seasonal forecasts are displayed: tercile maps and probability of exceedance (POE) graphs. Tercile maps (Fig. 1) indicate which regions will most likely experience above-, below-, or near-normal conditions for temperature and precipitation. Although terciles are the most commonly used format, they have a number of disadvantages. They do not contain much spatial detail, and they have been criticized by users for not being communicated in an "obvious, user-friendly format" (Barnston et al., 2000: 1272) and for not having enough skill to be considered in decision-making (Barnston et al., 2000). They also lack information on forecast uncertainty (Barnston et al., 2000) and cannot quantify the amount of deviation in temperature or precipitation from normal, reducing their utility for agricultural producers (Garbrecht et al., 2010).

Barnston et al. (2000) argue that seasonal climate forecasts would be considered more seriously by users "if more plentiful and detailed information were offered both in the forecasts themselves and in descriptions of their expected accuracy" (Barnston et al., 2000: 1272). POE graphs (Fig. 2) are less common but provide more information than tercile maps. They show the probability (on the y-axis) that a given temperature (on the x-axis) will be exceeded during a particular time period (e.g., May-July 2015), both for that period (black line in Fig. 2) and for the historic average (red line in Fig. 2). POE graphs can be viewed as "a backward cumulative probability density function" (Barnston et al., 2000: 1273) because the probability of exceeding a certain temperature threshold decreases with increasing temperature. CPC calculates POE graphs for each of the 102 NWS forecast divisions in the U.S. (see also Fig. 4), and thereby provide more spatial detail than their tercile maps. POE graphs also provide information on

forecast uncertainty, a feature often requested by agricultural producers. Seasonal climate forecasts in POE graph format have been used to create a forecast precipitation index for water managers in the southeastern U.S., resulting in potential benefits for the state of Georgia estimated between \$30 million and \$350 million per year (Steinemann, 2006). These products have also been used to estimate surface runoff in the U.S. (Garbrecht et al., 2006), and to estimate the utility of seasonal forecasts for U.S. agricultural producers (Schneider and Garbrecht, 2003a; Schneider and Garbrecht, 2003b; Schneider and Garbrecht, 2006).

2.2 Multimodel Ensemble Seasonal Forecasts

Increased multinational collaboration and nearly four decades of research into the origins of seasonal predictability brought two major advances in seasonal forecasting in the early 2000s: inclusion of quantitative information about uncertainty, and recognition that multi-model ensembles are a viable option to reduce forecast uncertainty (over single model approaches as used by CPC), both of which help serve end users with better decision-support (Kirtman et al., 2014). An implementation of these advances is exemplified in the North American Multimodel Ensemble (NMME), which went operational in 2012. It creates global seasonal forecasts by averaging forecasts from several individual seasonal forecast models, each of which is run with a range of different initial conditions.

Averages of ensemble forecasts are considered more skillful than single-model forecast averages because multiple models can average out errors of individual models (Stockdale et al., 2010; DelSole and Tippett, 2014). Tests with NMME in Kirtman et al. (2014) also came to this conclusion, in particular with respect to comparing sea and land-surface temperature and precipitation forecasts between NMME and CFSv2 from 1982 to 2009. Furthermore, Infanti and Kirtman (2014) found low error and high skill in NMME temperature and precipitation forecasts for the southeastern U.S. during the El Niño-affected winter of 2006/2007.

NMME produces forecasts in one- and three-month aggregates, with lead times of one to seven months for mean temperature and total precipitation anomalies (Kirtman et al., 2014). Fig. 3 exemplifies an NMME forecast for North America for October 2015, issued one month earlier. In 2015, forecasts for additional variables became available: global geopotential height at 200hPa atmospheric pressure, global and U.S. maximum and minimum temperature, U.S. soil moisture, and U.S. runoff. The spatial resolution of the forecasts is 1° latitude by 1° longitude (Infanti and Kirtman, 2014). To determine the forecast skill of the ensemble, hindcasts were compared against observations using anomaly correlation, root-mean square error, reliability, and the ranked-probability skill score (Kirtman et al., 2014). As of 2016, seasonal

forecasts and forecast skill are available in map and table formats at <http://www.cpc.ncep.noaa.gov/products/NMME/>.

2.3 Applications and benefits for agriculture

Agricultural producers and related industry users (e.g., seed manufacturers, fertilizer producers, cooperative extension, weather insurance) have long had interest in climate forecasts for decision support (Sonka et al., 1992; Boulanger and Penalba, 2010; Frisvold and Murugesan, 2012). Crop and livestock producers use weather and climate data for irrigation, planting, and harvest timing, selection of crop type and/or crop variety, decisions related to grazing, moving and selling of livestock, and decisions related to crop storage and purchase of crop insurance (Frisvold and Murugesan, 2012). Yet, producers also remain skeptical of seasonal climate forecasts (Changnon et al., 1988) because of individual negative experiences in the past (Hu et al., 2006), for example. Agribusinesses use climate forecasts to develop new crop varieties (seed producers), to scout for locations for new plant sites (food processors), and to schedule production of fungicides and pesticides (agrochemical companies) (Changnon et al., 1988).

Although agribusinesses in the U.S. use climate forecasts, they also state that forecast accuracy and insufficient prediction lead-time were major impediments for using them for specific decisions (Sonka et al., 1992) which is why most of these applications were mainly restricted to historical climate records, rather than actual forecasts (Changnon et al., 1988). Year-to-date information (e.g., calendar year, crop year, or water year to the current date) and seasonal forecasts were found potentially useful by users and were valued higher than historical records (Changnon et al., 1988; Haigh et al., 2015), suggesting that agribusinesses would incorporate forecasts if they provided economic benefits through increased reliability. Indeed, between 1981 to 2002, the value and usage of climate predictions for agribusinesses grew (Changnon, 2004). This increase largely resulted from skill improvements in CPC's seasonal forecasts, more private firms that provided climate services based on these improved forecasts, new corporate orientations within seed producers and food processing companies, such as geographic diversification which allowed for hedging and lowered their overall weather- and climate-related risks, as well as increased competition and economic pressure, better understanding of climate predictions, improved information access, and more timely forecasts (Sonka et al., 1992; Changnon, 2004; Templeton et al., 2014).

Decision experiments related to hedging weather risks show, forecast accuracy levels of only 50% had “considerable financial value” (Changnon, 2004: 611), and forecast accuracy of 65% or more “offered quite sizable corporate benefits” (Changnon, 2004: 611). Crane et al. (2010), meanwhile, describe risk management of Georgia family farmers as a mix of “planning and performance” rather than

risking losses due to short-term adjustments: “The rationale for this approach is that consistency eventually pays off and that, in the long run, it is safer than trying to adjust cropping patterns seasonally to maximize short-term gain” (Crane et al., 2010: 50).

Seasonal climate forecasts are also used as input for numerical crop models to produce or improve crop yield estimations. Mishra et al. (2008), for example, incorporated seasonal rainfall forecasts into the System of Agro-climatological Regional Risk Analysis version H (SARRA-H) crop model and improved sorghum yield predictions in Burkina Faso (for more information about SARRA-H, see Bontkes and Wopereis, 2003). Roel and Baethgen (2007) tested warm, neutral, and cold El Niño Southern Oscillation (ENSO) phases in a crop simulation model for rice yield prediction in Uruguay for respective El Niño, La Niña, and neutral years. Although their crop model generally underestimated productivity, results from three different simulations had high correlations ($r = 0.78$ to 0.90 ; $p = 0.0001$) to observed yields (Roel and Baethgen, 2007). Zinyengere et al. (2011) used five different ENSO phases (positive, neutral, negative, rising, and falling) to feed Rainman, a climate analysis tool, to produce monthly climate forecasts for these ENSO categories for a region in Zimbabwe. The resulting output was then used as input for a crop model, AquaCrop, to estimate maize yields and to serve as a starting point for a maize production decision-support tool.

Although crop models can help estimate yields using operational seasonal climate forecasts, steps need to be taken to merge the spatial and temporal scales in which crop models and climate models operate (Hansen and Indeje, 2004). Hansen and Indeje (2004) point out that crop models usually operate on field-scale and daily resolution, while operational seasonal climate forecasts are often aggregated over three-month periods, to reduce noise and to increase forecast skill, and have a spatial resolution “on the order of $10,000 \text{ km}^2$ ” (Hansen and Indeje, 2004: 144), multiple times larger than what is suitable for crop models (see Flato et al., 2013: 854-866 for spatial resolutions of different climate models). To bridge those differences, Hansen and Indeje (2004) discuss two pathways: (1) using daily-resolution weather input directly from climate models or from stochastic weather generators, and (2) applying crop yield models that operate on the basis of climatic predictor variables, such as ENSO. Takle et al. (2014) also argue that higher spatial resolution is required to allow management decisions on a field-scale. “Decisions on crop and cultivar selection, tillage and conservation practices, fertilizer and chemical application, and planting and harvesting options require climate information that, ideally, is at the field scale” (Takle et al., 2014: 4).

3 Skill and utility as measures of forecast value

In this section, forecast value as a function of forecast skill, predictability, and effectiveness of seasonal climate forecasts will be explored.

3.1 Forecast skill

By definition, climate models are a simplification of the earth's climate system and calculate atmospheric, land surface, and oceanic processes in a simplified way (NRC, 2010). As a result, model predictions form an incomplete and imprecise picture of atmospheric processes, and they can also deviate substantially from each other because the research groups that assembled them used different algorithms, numerical techniques, and observational data for model initialization, calibration, and validation. Climate models and climate forecasts also have inherent errors because of the limitations of point measurement representing an entire area, measurement errors, and limited computing resources for processing at higher resolutions and with more complex physics (NRC, 2010; IPCC, 2013). Skill scores can quantify these model errors, for example, by comparing a number of years of observations against a retrospective forecast for the same time period produced by the climate model or climate model ensemble of interest (Wilks, 2011). By using hindcast predictions, one can assess how many of the ensemble realizations made “correct” predictions (i.e., how many were within a defined margin of error around the actual observation) and the magnitude of the total difference between forecast and observation (Richardson, 2001; Kirtman et al., 2014). Skill information is an important metric to assess and compare in terms of accuracy of forecasts and climate models; and knowledge about past forecast skill is valuable for crop and livestock producers in assessing and managing forecast uncertainty (Hansen, 2002: 319). More (less) skill may reduce (increase) the need to diversify grain crops or even change what livestock species are produced (Stern and Easterling, 1999: 64).

In many areas of the world, prediction skill and predictability of seasonal climate are determined by two factors: (1) the strength of dominant climate signals, like ENSO, in the region of interest, and (2) predictability of the ENSO signal itself, which reoccurs quasi-periodical (Latif et al., 1998). Via teleconnections, climate signals like ENSO determine weather and climate in many regions, such as Uruguay (Roel and Baethegan, 2007), Paraguay (Ramirez-Rodrigues et al., 2014), Argentina (Jones et al., 2000), Mexico (Adams et al., 2003), the southeastern U.S. (Hansen et al., 1998; Jones et al., 2000; Hansen et al., 2001), or the U.S. Gulf Coast (Polade et al., 2013). Skill in seasonal climate forecasts in the U.S. is strongest for winter, weakest in summer, with spring and fall in between (van den Dool, 1994; Lau et al., 2002; Saha et al., 2014) which is related to the so-called spring barrier, a phenomenon of lower forecast skill for ENSO sea surface temperatures (SST) in the Equatorial Pacific for spring and summer

conditions compared to fall and winter conditions (Barnston et al., 1994; Balmaseda et al., 1995; Wen et al., 2012; Beraki et al., 2014). Skill also varies geographically, depending on the time and location of occurrence of the dominant atmospheric signals, for example ENSO, North Atlantic Oscillation (NAO), or Pacific Decadal Oscillation (PDO) (Barnett et al., 1993; Davies et al., 1997; Muller et al., 2005; Jin et al., 2008; Polade et al., 2013). ENSO is widely assumed to have an important if not the most important impact on U.S. climate (e.g., Ropelewski and Halpert, 1986). However, its impact is inhomogeneous across seasons and regions (Peng et al., 2012) which is reflected in the accuracy of forecasts for different regions. Kerr (2008) studied CPC's tercile forecasts and found that temperature forecasts were correct in more than 85 percent of cases "across much of the eastern [U.S.] out to more than eight months" (Kerr, 2008: 900) when an ENSO signal existed, compared to only 13 percent without an ENSO signal. Kerr (2008) also found that precipitation forecasts "along the southern tier states and up the West Coast" (Kerr, 2008: 900) were correct in 50 to 85 percent of cases "about half a year into the future" (Kerr, 2008: 900) during El Niño or La Niña phases, compared to 3 percent in years without a significant signal.

Skill maps and data accompanying NMME's ensemble forecasts for the U.S. often show low skill for much of the U.S. Great Plains, especially for precipitation. "High skill is evident in the central and eastern tropical Pacific Ocean, as well as portions of the tropical Atlantic and Indian Oceans and some isolated regions in the extra-tropics" (Kirtman et al., 2014: 589). Wintertime extreme precipitation, which can be devastating to grain crops, is correlated to ENSO signals in the southeastern U.S., the Gulf Coast, central Rocky Mountains, and the Ohio-Mississippi River valleys and responds strongly enough to make it predictable (Gershunov and Barnett, 1998). The ENSO signal itself (i.e. the occurrence of El Niño, La Niña, and neutral phases in the tropical Pacific) is quasi-periodical with dominant peaks occurring about every four years and minor peaks every two years (Latif et al., 1998). Jin et al. (2008) tested a multimodel ensemble and found an overall strong correlation (0.86) between predicted and observed ENSO state at six months lead, which was higher than any single model in their test. Jin et al. (2008) also found that strong ENSO events are better predicted than weak ENSO events, neutral phases are predicted worse than warm (El Niño) or cold (La Niña) phases, and the skill of predictions that start in spring decreases faster than skill of predictions that start in fall.

3.2 Forecast effectiveness

Forecast value can also be expressed as a function of its value in management practices. Seasonal forecasts are useful for agricultural producers if they allow them to adjust crop- or livestock-related management decisions according to the forecast (Stern and Easterling, 1999). Schneider and Garbrecht (2003a; 2003b; 2006) designed a method to assess the effectiveness of seasonal forecasts. In their context,

effectiveness is a function of the deviation of the forecast from the long-term average. It represents the percentage of forecasts in a region that are considered above or below average and are forecasted in the correct direction (e.g., forecasted warmer than average when observations are warmer than average, too). Schneider and Garbrecht (2003a; 2003b; 2006) assumed that forecasts had more value to agricultural producers the more they deviated from climatology while being correct. They argued that decisions would have greater positive financial impacts (i.e., larger profits or smaller losses) the more that the forecasts deviated from the long-term average — an alternative basis for farm decision-making (Schneider and Garbrecht, 2003a; Schneider and Garbrecht, 2003b). From 1997 to 2005, effectiveness for CPC's 0.5-month lead-time temperature outlooks was highest in the southwestern U.S., and high in the Pacific Northwest, parts of Texas, and the Florida Peninsula, as Fig. 4 (top) shows. For much of the remaining U.S., including most of the Great Plains, effectiveness was less than 20%. The 0.5-month precipitation outlooks show a similar pattern but an overall lower effectiveness, in particular across the agricultural regions of the Great Plains and the Midwest (Fig. 4, bottom). Garbrecht et al. (2010) conclude that such low occurrence of forecasts with large deviations from climatology, especially in agricultural states like Oklahoma, discourage the development of decision-support tools for stocking rate selection in winter-wheat grazing operations.

4 Seasonal climate forecasts in the context of other farm decision factors

Agricultural decisions are in large steered by weather and climate conditions, but other factors play an important role, too, such as markets, costs, land constraints, or production goals (Klockow et al., 2010). Jones et al. (2000) show that potential benefits from climate forecasts also depend on wealth and risk aversion of producers. Higher risk aversion is commonly associated with higher crop diversification, which in Jones et al. (2000) for the southeastern U.S., leads to reduced average annual farm income but also lower fluctuation in income. In other words, a crop mix that is adapted to the respective forecast slightly reduces average farm income but also substantially reduces potential financial losses while creating more planning security for producers. Forecast value increased with increasing risk aversion, particularly in cases of low initial wealth (Jones et al., 2000).

Meinke et al. (2003) suggest a systems approach by including crop simulation results, climate science, and systems analysis into discussions about risk mitigation and adaptation with stakeholders. Meinke et al. (2003) conducted a case study in India in which growers either adjusted plant density or crop type (i.e. planted sorghum or peanuts instead of cotton) in response to seasonal climate forecasts. The majority of farmers responded by adjusting in one way or the other and still made a harvest, but “ca. 20% of farmers, who took the risk and planted cotton [a crop with higher potential profits than sorghum

or peanuts but less suited for the forecasted climate conditions] had to abandon their crops by August, losing all their input costs” (Meinke et al., 2003: 4).

Harwood et al. (1999) found that changes in laws and regulations, decreases in crop or livestock production, and uncertainty regarding commodity prices are the biggest concerns of agricultural producers. While irrigation, crop insurance, enterprise diversification, or production contracting are ways to alleviate risk in crop production (Harwood et al., 1999; Barham et al., 2011), they are not always without drawbacks, like reduced income, additional costs, or loss of entrepreneurial freedom (see examples in Harwood et al., 1999: 2-3). Other studies add to a broader picture of risks in farming and ranching, such as risks in human resources (e.g., lack of necessary farm labor) or marketing (variations in commodity prices and/or quantities that can be marketed), together with finance (maintaining income, avoiding bankruptcy), production (variations in yields due to weather, pests, and diseases), and legal actions (law suits over contractual agreements, government regulations about pollution and farm practices), which influence farmers’ decision-making and suggest mitigation measures (Musser and Patrick, 2002).

Meinke and Stone (2005) argue that probabilistic forecasts and proactive farming practices allow farmers to capitalize on beneficial seasonal conditions and buffer against detrimental ones. Choi et al. (2015) support this idea in an economic study from Spain on cotton, two vegetable crops, two grain crops, and animal calories. They concluded that revenue increases not only were positive for almost all crops using proactive measures, but were also remarkably higher (between 1.5 and 5 times) compared to conservative approaches, which also often had revenue losses (Choi et al., 2015).

Dual-purpose production of winter wheat and cattle is a common practice in the U.S. Southern Great Plains, as it provides a second source of income and spreads risks (Colorado State University, 2010). It provides two management scenarios: growing winter wheat (1) solely as cattle feed or (2) for grain production with the option of cattle grazing during winter (in the early stages of crop growth) as nutritious hay supplement for cattle during this part of the year. Deciding which scenario to opt for is in large determined by market prices for cattle meat and wheat grain, but also by climate forecasts for the growing season. Differences in regional precipitation amounts or timing can translate into different crop yields for wheat and thus live weight gain for cattle. This means that depending on market prices for grains and livestock and the amount of growing season precipitation (November to March), either grain production or meat production offers the highest return-on-investment. For example, a study in northern Texas by Mauget et al. (2009) used different market prices and climate forecasts to show how market price conditions can dominate decision-making over using seasonal climate forecasts. If a respective climate forecast was not significantly different from normal such that best management practices would not change, then that seasonal forecast had no economic value (because it did not foster changes in practice).

This concept of critical threshold was also used in studies mentioned earlier by Schneider and Garbrecht (2003a; 2003b; 2006) and Garbrecht et al. (2010) who found that for large parts of the Great Plains and the Midwest, seasonal climate forecasts for temperature only rarely deviated substantially from the long-term average and therefore provided only small additional value for decision-makers in this region (see Fig. 4). Mauget et al. (2009) also showed that depending on market conditions, best management practices did not always benefit from more localized seasonal climate forecasts. This meant that forecasts with higher spatial resolutions did not necessarily translate into higher forecast values for decision-makers.

5 Forecast demands and forecast communication

In line with the development and improvement of operational seasonal climate forecasts, climate services have also evolved over the past decades. The field of climate services focuses on two areas: (1) measuring, recording, and providing climate data, and (2) interpreting data to generate climate information (Changnon, 2007). Climate information for U.S. agricultural producers can be communicated through agricultural advisors like the Cooperative Extension Service (CES), a network of state headquarters at land-grant universities and subordinate networks of county offices affiliated with the headquarters in their state (USDA, 2015a). CES extension agents provide research-based advice for crop and livestock producers, such as weather- and climate-based information and agricultural practices (USDA, 2015c). For agricultural producers, failing to adapt to a more variable future climate could result in lower yields (Meinke et al., 2003). To allow producers to benefit from favorable climate conditions and to reduce losses from unfavorable ones, it was proposed to develop tailor seasonal forecasts to specific user groups (e.g., Meinke et al., 2003; Lamb, 2011), and numerous modeling studies and user surveys were conducted to determine current shortcomings and to explore user needs in more detail (e.g., Hansen and Indeje, 2004; Fraisse et al., 2006; Schneider and Wiener, 2009; Prokopy et al., 2013). Effective forecast communication is also discussed internationally. In a special issue of the WMO Bulletin on the “Global Framework for Climate Services”, Tall (2013) proposes an interactive, five-step method to deliver tailored climate services to end users: 1) understanding the demand side, 2) bridging the gap between climate forecasters and sector expertise, 3) co-producing climate services to address end-user climate service needs, 4) communicating to reach ‘the last mile’, and 5) assessing and re-assessing.

5.1 Forecast demands from producers and agricultural advisors

Schneider and Wiener (2009: 100A) list nine forecast requests based on a survey of agricultural producers and water managers:

1. forecasts of up to one year for long-term planning
2. forecasts for regions regarded as competitors
3. better warnings of anomalous events such as snow storms in spring or flash floods
4. more clear explanations and documentation of the accuracy and reliability of data and forecasts
5. information provided in a “now versus last year versus normal” format
6. what weather patterns and storm tracks commonly recur in the region
7. the need for simple procedures to “calibrate” large-scale forecasts and warnings to local areas
8. better information to improve decision-making related to wildfires
9. observations and forecasts on soil moisture and relative humidity

Most producers use seasonal climate forecasts to improve planting schedules, for irrigation and nutrition management, and to select crop type and crop variety (Cabrera et al., 2006; Templeton et al., 2014). They request seasonal climate forecasts of both direct meteorological variables (e.g., air temperature and precipitation) and derived information from these and other variables (e.g., humidity, growing degree-days, soil moisture, or evaporative loss) (Schneider and Wiener, 2009; Frisvold and Murugesan, 2012)¹. Table 1 links some of these variables with agricultural decisions.

Different crops, such as winter wheat, cotton, sugarcane, or corn, are planted and harvested in different months, and require different precipitation patterns, different management practices, and different decisions at certain times of the year (Steiner et al., 2004: 16-17). Tailored climate forecasts should therefore be crop-specific and depend on time of year and decision lead-time (e.g., days or months) (Meinke et al., 2003; Steiner et al., 2004; Meinke and Stone, 2005; Haigh et al., 2015). Crop-specific calendars (Tab. 2, Tab. 3, Fig. 5) reflect this need, inform about critical crop stages, and highlight when weather and climate information can be particularly helpful in making crop-related decisions. For example, Table 3 and Figure 5 show that soil temperature information is particularly important for corn producers during winter when fertilizer is applied that could volatilize if temperatures are too high (Takle et al., 2014). Table 3 shows how production and marketing decisions for corn differ depending on lead-time and season. Likewise, Table 4 shows how decision lead-times differentiate between short-term (operational) and long-term (strategic) crop-related decisions, such as sowing depth, planting time frame, crop type and variety, or decisions on equipment purchase (Hudson, 1972). Finally, Mavi and Tupper (2004) illustrate the benefits of seasonal forecasts for farm management decisions. Table 5 lists key

¹ Frisvold and Murugesan present results from a subsample of the 2005/2006 National Agricultural, Food, and Public Policy Preference Survey. The complete survey was published by LUBBEN, B., BILLS, N. L., JOHNSON, J. B. & NOVAK, J. L. (2006) The 2007 Farm Bill: U.S. producer preferences for agricultural, food and public policy. Farm Foundation, Oak Brook, IL.

management decisions for livestock and various grain crops, demonstrating why seasonal climate forecasts are important and what management decisions can help mitigate unfavorable conditions.

A growing number of publications call for comparisons to previous years (e.g., Schneider and Wiener, 2009) and the need for seamless short-term weather to seasonal climate forecasts (NOAA, 2011; Tall, 2013). Information on forecast reliability and accuracy are also requested by producers (Schneider and Wiener, 2009; Takle et al., 2014) and thus are needed to communicate predictability to the users. Unclear accuracy levels and perceived inaccuracy are top barriers for producers, scholars, extension agents, and consultants to use seasonal climate forecasts (George et al., 2007). To overcome these barriers, survey respondents suggested more localized and more accurate forecasts with higher degrees of certainty, information about past accuracy, and provision of skill scores (George et al., 2007).

5.2 Communication Challenges

Mismatched terminology, unrealistic expectations, and disordered integration of information into the decision process create a communication barrier between scientist and stakeholder (Lemos and Rood, 2010; Briley et al., 2015). In order to satisfy end users, scientists need to do research with the end user in mind (Hartmann, 2002). Education of researchers about decision-making in agriculture could increase the applicability of forecast products for agricultural producers (Takle et al., 2014).

To explain the value that a user perspective can add to providing forecast advice, Hubbard (2007: 2) gives a hypothetical dialogue between a crop producer (client) and a public service employee (expert), for example an agricultural extension agent:

Client: I need temperature data, do you have a station near Westbend?

Expert: What is the question you are trying to answer?

C.: I want to know the length of the freeze free season so I can decide whether to buy the new corn hybrid offered by my seed dealer.

E.: We can provide the average length of the growing season but, we also can provide information on the variability. So we can provide answers to the question 'How many years out of 10 would the growing season exceed 175 days?'. Would you be interested in this analysis?

C.: Yes, I knew that each growing season was different but, I didn't know how to include that in addressing my problem.

E.: We can also show that years with the same number of growing season days often have a difference in heat available, or GDDs [Growing Degree Days], to move the crop to maturity. We can assess the GDDs by year and give you information to answer how many years out of 10 does the accumulated GDD exceed a threshold, e.g. 2800.

C.: That would be great.

This dialogue illustrates the importance of a common mindset among expert and client (compare Schneider and Wiener, 2009). Hubbard (2007) emphasizes that the expert in this example not only answers the initial question but points out additional information to answer the client's request. The expert's language resembles that of the client when communicating advice.

To improve the value of forecasts, Takle et al. (2014) list questions that forecast developers should know the answers to:

- What meteorological variables are needed to improve the climate-related decisions? Is there linkage of this information to remote, slow time-varying forcing such as ENSO, the Atlantic multi-decadal oscillation (AMO), the Pacific decadal oscillation (PDO), and soil moisture?
- At what points in the annual or inter-annual decision cycle are these variables needed?
- How can past information best be collected and archived for effective data mining?
- Who makes the decisions and when; what is the lead-time?
- Are combinations of meteorological conditions important in certain cases, such as consecutive days of extreme rainfall and high winds followed by drought, which could lead to toxins in crops, e.g., aflatoxins in corn, that can be harmful if consumed by livestock or humans (compare Vincelli et al., 1995).
- What ancillary biological or soil information is needed — such as crop development stage, plant physiology, soil fertility, terrain slope, weeds, insects, and diseases — to allow evaluation of both biotic and abiotic impact on the crop?
- What else could help translate meteorological data into decision aids, e.g., crop growth/yield model, soil compaction model, soil erosion model, and calculation of days per week suitable for field work?
- What is the best way to convey uncertainty metrics: graphs, tables, PDF, or terciles of skill?

Intermediary organizations that act between scientists and stakeholders can help bridge the various gaps in language and mindset. Examples for these intermediaries are the Department of the Interior (DOI) Climate Science Center network (DOI, 2009), the U.S. Department of Agriculture Regional Climate Hubs (Allen and Stephens, 2016), and the NOAA Regional Integrated Sciences and Assessments (RISA) teams (Lemos and Morehouse, 2005; Miles et al., 2006), such as the Climate Assessment for the Southwest (CLIMAS), the Southern Climate Impacts Planning Program (SCIPP) or the Great Lakes Integrated Sciences and Assessment (GLISA) program (Briley et al., 2015).

Recently, much effort is put into web-based applications and services that presume computer and internet access among the agricultural community (e.g., Pasteris et al., 2004; Fraisse et al., 2006; Breuer et al., 2008). However, while internet access is common among farmers (70% in 2015), only about 43% of all U.S. farmers use computers in their farm business (USDA, 2015b). This biennial survey is based on about 28,000 responses from farmers and represents all sizes and types of farms within the contiguous U.S. (USDA, 2015b). Although smartphone use is not assessed in the survey, web-based applications may miss a large portion of the U.S. agricultural community.

6 End-to-End Concept

Traditionally, climate forecast products have been developed in two ways: (1) by using existing forecast information for practical uses (top-down approach), such as CPC's categorical seasonal forecast, or (2) by taking user demands and finding niches for climate forecasts to assist in decision-making, such as the NMME seasonal multimodel ensemble forecast for soil moisture, runoff, as well as skill information (bottom-up approach) (Goddard et al., 2001). Both approaches are restricted in their potential because they emphasize some components while neglecting others. An end-to-end concept encompasses the entire work process, from forecast production, tailoring and communicating the forecast, to forecast application by end users, while also considering social behavior, institutional constraints, or sector system models (Agrawala et al., 2001; Goddard et al., 2001; Power et al., 2007). Fig. 6 illustrates the end-to-end concept. End-to-end forecast development is being spurred by existing relationships between climate science and various other fields, such as agriculture, food security, disaster management, disease incidence, and disease risk (Coelho and Costa, 2010). Development of end-to-end products is achieved by interacting and collaborating with user groups, conducting workshops and surveys in order to understand their needs, learning their vocabulary, and framing the limits of their understanding when it comes to weather and climate (Bales et al., 2004). Coelho and Costa (2010) present a "simplified framework" for an end-to-end forecast system, consisting of three key elements: (1) the underlying climate forecast information ("climate science"), (2) the impacts of climate on human and natural systems ("systems science"), and (3) decision-making that is "performed on the basis of forecast information jointly produced by climate and systems sciences" (Coelho and Costa, 2010: 318). Shafiee-Jood et al. (2014) apply an end-to-end approach in a case study of corn farmers in Illinois, studying the value of seasonal climate forecasts during an extreme drought in the summer of 2012. Garbrecht and Schneider (2007) review the top-down and participatory end-to-end approach for agriculture-focused climate forecasts and discuss a hybrid method of forecast development using a participatory approach and forecast dissemination following a top-down approach.

Once an end-to-end forecast system is established, a recurring dialog between forecast users and forecast producers needs to take place to continually improve climate information and its use (Bales et al., 2004; Roncoli et al., 2009). Within the U.S., RISA (Lemos and Morehouse, 2005), administered by the NOAA Climate Program Office, facilitates this discussion through regional initiatives that provide actionable science for a range of decision types, from agriculture to natural hazards mitigation. RISA initiatives with an agricultural focus include CLIMAS (Bales et al., 2004), GLISA (Briley et al., 2015), and the Southeast Climate Consortium (SECC; Fraisse et al., 2006). Similarly, an international example for (trans-disciplinary) integration of scientific knowledge and user input to assist decision-making is the work of the International Research Institute for Climate and Society (Mason et al., 1999; Barnston et al., 2003; Lyon et al., 2014).

7. Conclusion

Seasonal climate forecasting has come a long way over the last centuries and improved substantially in recent decades. Thanks to a better understanding of atmospheric processes, advances in computing, and improved prediction models, seasonal forecasts of temperature and precipitation are now a standard forecast product available in the U.S. and many other countries around the world. A new challenge of making these forecasts more valuable to specific users, like agricultural producers, is now being approached by integrating social science and climate science. Researchers found an increasing appreciation of seasonal climate forecasts by producers despite still essential shortcomings, and they are beginning to understand farmers' decision-making processes and decision-timing. As a result, forecast developers are able to better transform basic forecast data into tailored forecast products for specific sets of decisions and degrees of comprehension, in order to improve the value of seasonal forecasts. The current state of the science are end-to-end concepts of continuous development and feedback loops, integrating both the development of prediction models and tailoring forecasts according to user needs.

Acknowledgements

The authors thank two anonymous reviewers for their critiques and comments, which enhanced this paper. This work was funded by the Office of the Dean of the College of Atmospheric and Geographic Sciences and by the Office of the Vice President for Research at The University of Oklahoma, and by the Oklahoma EPSCoR project through the Oklahoma State Regents for Higher Education and the National Science Foundation under NSF grant no. OIA-1301789.

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Figure 1: CPC three-month temperature forecast for June/July/August 2015, issued on May 21, 2015 (0.5 months lead-time). Source NOAA CPC

Figure 3: NMME ensemble forecast for precipitation deviation from normal for October 2015, issued in September 2015. Source: NOAA CPC

Table 1: Agricultural decisions connected to different types of meteorological variables. Source: Frisvold and Murugesan (2012)

Type of weather data	Agricultural Decision
Temperature	Planting, harvesting, defoliation, crop modeling, disease risk, shelter animals, pest control, sheep shearing
Precipitation	Planting, harvesting, fertilizer applications, cultivation, spraying, irrigation, disease risk, livestock and poultry protection
Soil Moisture	Planting, harvesting, fertilizing, transplants, spraying, irrigation, monitoring of growing conditions, measuring plant stress
Soil Temperature	Planting, pest overwintering conditions, transplanting, fertilizing
Frost	Pest overwintering conditions, Protect crops from damage, animal sheltering, irrigation (to avert crop damage)
Degree Days	Planting, irrigation, pest control
Relative Humidity	Harvesting, pollination, spraying, drying conditions, crop stress potential
Wind Speed	Defoliation, harvesting, freeze potential/protection, animal sheltering, shelter, pest control, pruning, spraying or dusting, pollination, dust drift, pesticide drift
Wind Direction	Freeze potential/protection, cold or warm air advection over crop areas, pesticide drift, dust drift

Table 2: Summer and winter crop stage calendar for the US. Source: USDA (2015b).

Month	Crop and Stage (summer crop)	Crop and Stage (winter crop)
January	Sugarcane: harvesting	Grains: dormant
February	Sugarcane: harvesting	Grains: dormant
March	Sugarcane: harvesting Cotton: planting	Grains: vegetative
April	Corn, small grains, cotton: planting	Grains: vegetative
May	Corn, small grains, cotton, sorghum: planting	Grains: heading
June	Small grains: heading Soybeans: planting Corn, cotton, sorghum: vegetative	Grains: maturing to harvesting
July	Small grains: filling to maturing Corn: silking Soybeans: flowering Sorghum: heading Cotton: blooming	Grains: harvesting
August	Small grains: harvesting Corn, soybeans, sorghum, cotton: filling	-
September	Small grains: harvesting Corn, soybeans, sorghum, cotton: maturing	Grains: planting
October	Corn, soybeans, cotton: harvesting	Grains: vegetative
November	Corn, soybeans, cotton, sugarcane: harvesting	Grains: hardening
December	Cotton, sugarcane: harvesting	Grains: dormant

Table 3: Corn growers' needs for forecast information at specific times of the crop year. Source NOAA (2011)

Production	March - May	June, July	August - October	November - February
Corn Producer Decision	Field work, planting	Pest/disease/weed/irrigation management	Harvest, grain drying	Seed variety, fertilizer, crop insurance
	Forecast Elements			
Real-time Monitoring	Soil moisture, soil temperature	Wind, humidity, soil moisture	Soil moisture	
1-3 days	Soil moisture, wet days	Humidity, wind, rainfall	wet days	
1-3 weeks		Spring soil moisture, summer humidity, summer drought, flood	Fall freeze	Rain (fall), Snow (winter)
1-6 months		Summer drought, extreme daytime heat, fall freeze, fall wet days		spring drought, flood, soil moisture, temperature
6-12 months				summer drought/flood

Marketing	March - May	June, July	August - October	November - February
Corn Producer Decision	Purchase/selling of corn in storage	Purchase/selling of corn in storage	Purchase/selling of corn in storage	Purchase/selling of corn in storage
	Forecast Elements			
Real-time Monitoring	Spring freeze	Global drought, flood, extreme daytime/nighttime heat, hail/wind damage	Fall wet days	
1-3 days				
1-3 weeks	Late spring freeze, spring flood	Soil moisture, drought, flood, extreme daytime/nighttime heat		
1-6 months	Summer drought, flood, extreme daytime/nighttime heat	Summer drought, extreme daytime/nighttime heat, fall freeze, fall wet days		spring drought, flood, soil moisture, temperature
6-12 months				Summer drought, flood, extreme daytime/nighttime heat

Table 4: Farm management decisions related to different forecasts lead-times. Source: Hudson (1972)

Time frame	Agricultural aspects to consider
5-day Forecast	<ul style="list-style-type: none"> • which depth to plant the seeds • whether to sow a crop or not • deciding whether or not to irrigate • deciding whether or not to harvest crop • time spray programs to ensure maximum efficiency against pests and diseases affected by weather • frost protection of crops • increase efficiency of herbicides • decide on supplementary pollination due to poor weather
5-week Forecast	<ul style="list-style-type: none"> • extend the time of seeding to cover successional sowings of crops like peas, to ensure a steady flow to the processing plant • harvest crops for short-term storage in cases when conditions might interfere with lifting (e.g. frozen soil) or prevent harvesting (e.g. soil soft and saturated with water) • put perishable goods in short-term storage, or on the market, based on estimates of demand and supply • decide on water use, based on the probability of non-moisture-stress days • decide on dates for sowing crops sensitive to frost, to maximize the chance of achieving a large leaf-area index by the time light conditions are optimal • deciding on straying, depending on whether or not diseases and pests will affect crops
5-month Forecast	<ul style="list-style-type: none"> • decide on growing marginal crops depending on upcoming seasonal temperatures, e.g. tomatoes, which are highly profitable in a hot summer but fail entirely in a cool summer • managing scarce water resources • employing and scheduling labor for handling crops, determining cropping schedules • match fertilizer application to expected yields • planning timely measures against diseases and pests likely to affect crops based on seasonal forecast • choose crop varieties based on seasonal forecast • estimate acreage for a required tonnage of crop
5-year Forecast	<ul style="list-style-type: none"> • lay out long-term path of crop choices and alternatives based on expected weather and climate shifts • plan long-term investments for special equipment, e.g. for harvesting, irrigation, frost protection, short-term storage, grain drying • (for policy-makers) determine national policy of support and development of marginal crop areas

Table 5: Farm management decisions related to seasonal climate forecasts. * indicates decision that are also influenced by forecasts of shorter time scales, such as extended weather forecasts or short-term weather forecasts. Source: Excerpt from Mavi and Tupper (2004)

Key Decision	Why seasonal climate information is important	Strategies to reduce losses/increase profits
Management		
Investment in new machinery	Purchase/hire of high-cost machinery requires good weather for maximum income to ensure easy repayment.	Make large purchases in seasons when the outlook is normal or better than normal.
Seasonal planning	Warmer weather conditions may cause crops to mature early. Excessively wet season requires planning for control of weeds, insect pests, and diseases.	Book labor and contractors earlier to harvest crops.
Cropping		
Crop variety to plant	Most crop species have a number of varieties available that vary in their length of growing season or resistance to heat, cold, frost, water logging, or disease.	Choose a crop variety that best suits the seasonal conditions. Plant varieties that mature before the possibility of late frost. Plant a long-season variety of rainfall is likely to be evenly spread and a short-duration variety of probability is of less rainfall.
Fertilizing	Fertilizing with nitrogen can increase crop yields potential but only if there is sufficient rainfall.	Fertilize at the optimum rate only if the outlook for the season is favorable.
Disease control	Many crop diseases are affected by weather. As an example, yellow spot in wheat can become prevalent in wet years, causing reduced production.	Be prepared for disease control of the outlook is for a wet season. Monitor the crop and undertake a spray application when the first symptoms of disease become apparent.
Weed control*	Wetter years or wetter than average seasons may cause an increase in the number of crop weeds.	Spray earlier to ensure weeds don't get too large, and if using ground spraying, spray when damage to soil by machinery is least.
Sugarcane		
Replant or retain old ratoon	New plantings culminate in poor stands and stunted growth in dry seasons	New planting should take place only in a favorable season. Maintain old ratoon if conditions are unfavorable.
Trash blanket	Cover ground with trash in dry weather to preserve soil moisture.	Do not burn trash in dry years; harvest green.
Viticulture (the cultivation of grapevines)		
Harvesting*	Warm temperatures enhance growth and harvesting is easier	Plan to harvest earlier if seasonal outlook is of warm weather.
Water / Irrigation		

Key Decision	Why seasonal climate information is important	Strategies to reduce losses/increase profits
Water allocations	Weather will determine if storage or water source is replenished	Crop smaller areas when outlook is for dryer conditions and water allocation is low. Adopt water-saving practices.
Stock water*	Hot, dry weather increases stock water intake and increases evaporation from the stored water	If the seasonal outlook is for lesser rain, use water sparingly and budget water allocation between animals and paddocks.
Grazing / Pasture		
Optimum stocking rates*	Climate determines the type and amount of grass and herbage growth.	If seasonal forecast is favorable, stocking rates can remain at current levels.
The number of stock to carry during the dry season	Weather determines how much stock feed will be available.	Lower stock numbers before dry conditions set in to avoid cost of feeding or sale of stock at low market prices.
Burning pasture for weed control*	Weather affects the effectiveness and safety of using fire as a tool. In the longer term, burning before a dry period may mean a shortfall in feed supplies.	Burn grass only on days with low fire danger; burn only small areas if the outlook is poor, so that there will be extra feed for dry periods.
Fire breaks*	Weather can affect the severity of the fire season leading up to fire occurrences.	Maintain fire breaks early in the season and increase preparedness on potentially dangerous days.
Feeding and supplements	Dry periods result in little or no plant growth	Budget to feed or supplement stock; buy and stockpile feed.
Pasture improvement*	Pasture improvement is a costly program, and the aim is to maximize establishment of pasture. Ideal climatic conditions are required for pasture improvement.	Undertake pasture improvement if seasonal forecast is favorable.
Haymaking		
Marketing	Hay prices are usually low in good seasons and high in poor seasons.	Stockpile hay if the outlook is for a dry season and sell in the dry seasons at better prices.
Sheep and Wool		
When to shear*	Choose a time of year to shear when newly shorn sheep are not subject to extreme weather changes.	Shear when rainfall is less likely or when major temperature changes do not occur. Increase area under cover for sheep.
Supplementary feeding	Lack of rain may necessitate early feeding of costly supplements to maintain growth and minimize production losses.	Decrease stock numbers; buy feed supplements earlier at lower prices. Feed early to minimize losses.
Treatment for fly control*	Warm humid weather increases incidence of sheep becoming struck/infested with flies.	Treat sheep with chemical before problems occur, or monitor sheep carefully in susceptible periods.
Footrot*	Wet conditions favor spread of footrot in sheep.	Plan to have sheep in paddocks where they are less susceptible to prolonged wet conditions.
Parasite control	Wet conditions allow an increase in the level of internal parasites.	Pasture sheep in paddocks with less possibility of wet soil; drench sheep to decrease worm numbers coming into a wet season.

Key Decision	Why seasonal climate information is important	Strategies to reduce losses/increase profits
Cattle		
Restocking	After drought, producers often buy stock to take advantage of extra paddock feed.	Restock only if seasonal outlook is favorable. A break in the season may not last long, necessitating early sale or feeding of stock, causing losses.
Weaning	Calves may need to be weaned off their mothers earlier if there is a dry period and then sold or fed.	Weaning calves early in dry weather stops stress on cows and allows them to go into calf for the following season.
Parasite control	In wet conditions internal worms are more likely to increase in numbers.	Treat stock early to avoid buildup of parasites, or pasture in areas where parasites are not such a problem.

Figure 4: Effectiveness of seasonal temperature (top) and precipitation (bottom) forecasts for 0.5 months lead-time, for each of the 102 climate forecast divisions. Percentage values indicate what portion of forecasted values were above or below normal and in the same tercile category as the observed values. Source: Schneider and Garbrecht (2006)

Figure 5: Climate-based decision cycle for corn. The outer calendar identifies the time of year management decisions are made. The inner calendar depicts the soil or crop impact, and the label on the arrow identifies the weather or soil conditions relevant to the impact. Length of the arrow gives the lead time of climate forecasts that links the specific agricultural decisions to soil or crop impacts. Source: Takle et al. (2014)

Figure 6: Schema of the end-to-end concept. Actionable outcomes require interaction and feedback from societal, biological, and physical elements. Source: Goddard et al. 2001