Assessing Decision Timing and Seasonal Climate Forecast Needs of Winter Wheat Producers in the South-Central United States

TONI KLEMM AND RENEE A. MCPHERSON

*Department of Geography and Environmental Sustainability, University of Oklahoma, and
South Central Climate Adaptation Science Center, Norman, Oklahoma*

(Manuscript received 5 September 2017, in final form 17 June 2018)

ABSTRACT

Agricultural decision-making that adapts to climate variability is essential to global food security. Crop production can be severely impacted by drought, flood, and heat, as seen in recent years in parts of the United States. Seasonal climate forecasts can help producers reduce crop losses, but many nationwide, publicly available seasonal forecasts currently lack relevance for agricultural producers, in part because they do not reflect their decision needs. This study examines the seasonal forecast needs of winter wheat producers in the southern Great Plains to understand what climate information is most useful and what lead times are most relevant for decision-making. An online survey of 119 agricultural advisers, cooperative extension agents in Oklahoma, Kansas, Texas, and Colorado, was conducted and gave insights into producers' preferences for forecast elements, what weather and climate extremes have the most impact on decision-making, and the decision timing of major farm practices. The survey participants indicated that winter wheat growers were interested not only in directly modeled variables, such as total monthly rainfall, but also in derived elements, such as consecutive number of dry days. Moreover, these agricultural advisers perceived that winter wheat producers needed seasonal climate forecasts to have a lead time of 0–2.5 months—the planning lead time for major farm practices, like planting or harvesting. A forecast calendar and monthly rankings for forecast elements were created that can guide forecasters and advisers as they develop decision tools for winter wheat producers and that can serve as a template for other time-sensitive decision tools developed for stakeholder communities.

1. Introduction

Droughts, floods, heat waves, or other unseasonable weather and climate conditions can have considerable impact on agricultural productivity and farm revenues, and they are costly for the taxpayer. From 2011 to 2014, when large portions of the United States, in particular the Great Plains and the Midwest, were hit by severe drought and flood, federal crop insurance paid an average of \$12.4 billion—3 times the annual average from 2001 to 2010 (USDA 2018a,b)—to compensate farmers for losses in crop yields. Seasonal climate forecasts can help crop producers make better educated decisions (Carberry et al. 2000; Meinke et al. 2003) that are more appropriate for expected conditions. These forecasts can

lead to decisions that reduce or prevent revenue losses due to unseasonably warm, cold, dry, or wet conditions or even allow producers to capitalize on these conditions and increase yields and revenues (Carberry et al. 2000; Jones et al. 2000; Meinke and Stone 2005).

The U.S. Climate Prediction Center (CPC) has been producing seasonal climate forecasts since the 1940s, constantly improving forecast skill and increasing forecast lead time (O'Lenic et al. 2008; van den Dool 1994). A better understanding of atmospheric and oceanic processes, like El Niño (e.g., Ropelewski and Halpert 1986), and improvements in computing power have also advanced seasonal forecasting, not only in the United States but worldwide as well. Currently, 12 countries and multinational organizations around the world issue global seasonal climate forecasts for environmental variables that include air temperature, sea surface temperature, and precipitation, following standards set by the World Meteorological Organization (WMO 2015). For example, each month, CPC issues seasonal climate forecast ensembles based on eight individual models, with a lead time of

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/JAMC-D-17-0246.s1>.

Corresponding author: Toni Klemm, toni-klemm@tamu.edu

up to 7 months for average, maximum, and minimum air temperature, precipitation, and soil moisture, as well as other variables (Kirtman et al. 2014).

For decades, seasonal climate forecasts have been of interest to the agricultural industry for decision support (Changnon 2004; Changnon et al. 1988; Sonka et al. 1992). Farmers and ranchers use these forecasts to improve key decisions, such as irrigation scheduling, planting, harvesting, fertilizing, or selecting crop type and crop variety (Cabrera et al. 2006; Frisvold and Murugesan 2013; Templeton et al. 2014). Although usage of seasonal climate forecasts by agricultural producers has increased, complaints regarding lack of skill and lack of lead time were common (Changnon 2004). A comprehensive review of the development of seasonal climate forecasting for agricultural producers, including examples of knowledge coproduction and communication challenges between forecasters and forecast users, can be found in Klemm and McPherson (2017). Schneider and Wiener (2009) concluded that there is a lack of mutual understanding between the forecast and user community, leading to a lack of relevance of produced forecasts for decision-making of farmers and ranchers. Recent studies pointed out that crop-specific seasonal forecasts, for example, for corn farmers, could improve farm decision-making related to weather- and climate-related risks (Haigh et al. 2015; Takle et al. 2014). This study, through a survey of agricultural extension agents, tackles these challenges for a single crop and region so that the detailed timing of production decisions can be documented as they relate to weather and climate impacts.

2. Methods

The goal of this study builds upon forecast limitations and needs previously identified (Klemm and McPherson 2017; Schneider and Wiener 2009); it can be summarized by this research question: “How can seasonal climate forecasts be tailored to serve the needs of winter wheat growers in the south-central United States?” To answer this question, an online survey was sent to extension agents to study decision-making patterns in winter wheat farming and the specific forecast needs of these producers. This study also explored the specific role of these agricultural advisers in the decision-making process of winter wheat growers. Ultimately, the intent was to create a foundational understanding from which to develop decision-support tools based on the needs, timing, and professional network of the user, rather than the capabilities of the provider.

a. Why winter wheat?

This study focused on one particular crop type (as opposed to all grain crops) because decision-making,

FIG. 1. The study region. Extension agents from counties with diagonal lines participated in the survey. Some agents represented several counties, depending on their assigned jurisdiction. Yellow to green shaded counties show the acreage of planted winter wheat in 2016 (National Agriculture Statistics Service 2018).

and especially the timing of decisions, is different from crop to crop. Winter wheat is the dominant crop in the southern Great Plains of the United States. In the study region, the states of Colorado, Kansas, Oklahoma, and Texas (Fig. 1), winter wheat is grown on 21.1 million acres (2016 value), more than twice the acreage of the second largest crop, corn (Han et al. 2012). Wheat itself, used for both food and livestock feed, is the world's largest crop by harvested acreage (FAO 2014). In the United States, wheat is the third-largest crop after corn and soybeans, and winter wheat contributes about 70% to the total wheat harvest in the United States (USDA 2012). Because of its overall contribution to the national wheat harvest and its role in the study region, winter wheat was chosen as the focus crop for this study.

b. Survey population and distribution

Data for this study were collected via an online survey using the Qualtrics survey platform. The survey was distributed to agricultural advisers, specifically cooperative extension agents associated with land-grant universities in the study domain (Fig. 1). Approximately 360 cooperative extension agents were contacted and 119 unique responses [~33% response rate, average for online surveys, according to Nulty (2008)] were received. Of these responses, 10 stated no winter wheat was grown in their jurisdiction and were discounted. Thus, 109 responses were eventually used in the analysis.

Extension agents are agricultural advisers with academic backgrounds who work on a county level and advise producers on best practices.

Extension agents were chosen as survey participants rather than winter wheat producers themselves because the former represented a more homogeneous group regarding educational background and access to e-mail and Internet, reducing representation bias and the risk of using unfamiliar terminology. Each agent also works with a large number of farmers in their jurisdiction; thus, the results represent the aggregate views of the producer community.

Procedures by [Dillman et al. \(2014\)](#) were adopted to increase survey responses and to enhance the quality of the responses. To distribute the survey, the authors worked with “survey sponsors” ([Dillman et al. 2014](#)), people known in the extension community (i.e., extension district directors and state climatologists), who sent out initial survey invitations and later reminders. After pretesting the survey with three extension agents, incorporating revisions, and receiving Institutional Review Board approval, initial survey invitations were sent out between 19 January 2016 (Oklahoma) and 2 March 2016 (Colorado). The survey closed on 6 May 2016.

Online surveys have been shown to be more efficient than phone or in-person interviews for quantitative or binary (yes or no) questions ([Babbie 2014](#)), such as those used in this survey. Online survey distribution is inexpensive, easy, and fast via e-mail, and survey responses are available in electronic format, eliminating transcription errors and postprocessing time. Survey sponsors received e-mail address lists and text templates, including the survey URL and a one-page summary about the survey. Some survey sponsors did not use the e-mail list but instead sent the invitation/reminder via their own internal mailing lists to extension agents in their region. The authors were copied on all e-mails to record send dates and times and to get confirmation about the sending. After initial survey invitations were distributed, 2–4 reminder e-mails were sent out, with intervals of 3–4 weeks in between each reminder.

c. Survey design

The survey time was estimated to take 10–15 min to complete. Median response time was 12 min, and 130 individual responses were received. After eliminating all but the first response from participants who participated in the survey multiple times (the first responses were kept), empty forms, and responses from agents who stated no winter wheat was grown in their jurisdiction, 109 responses were used in the analysis (see [Table 1](#)). It should be mentioned that not every respondent answered every question.

TABLE 1. Number of survey responses by state.

State	Number of responses
Colorado	3
Kansas	23
Oklahoma	37
Texas	28
No location information	18
Total	109

Of the 109 responses, 18 did not include state or county information. Those 18 responses were still used, but not in the analysis of regional differences in responses. All responses included IP addresses, which can be used to georeference responses. However, when state and county information was included also, it was found that IP addresses poorly matched the stated locations. Thus, IP addresses were not used for locating participants. As a result, the regional analysis sample consists of responses from 91 individuals who provided location information (state and county, or region). For nine responses, agents entered more than one county as their area of responsibility. For these cases, their jurisdiction was treated as a single, large region as opposed to separate responses for every county they stated. To geolocate responses, the center coordinate of the respective county or region was calculated using QGIS, an open-source geo-analysis software, using the *centroid* function. Using this center coordinate, responses were sorted by latitude and longitude to examine regional differences. All further statistical analysis was done in Microsoft Excel for Mac.

The survey consisted of 16 questions that were developed to answer the research question—How can seasonal climate forecasts be tailored to serve the needs of winter wheat growers in the south-central United States?—and to provide insights into the farming communities in the study region. The first seven questions collected general information about the extension agents and the winter wheat producers they serve. The next two questions asked about their familiarity with producers’ information needs and the level of influence of weather and climate information on the advice that extension agents give to their winter wheat producer clientele. Both questions helped determine the importance of monthly and seasonal forecast time scales for agents’ advice overall. Question 10 described the agents’ professional communication network. Question 11 measured agents’ levels of agreement with various statements related to seasonal forecasting, climate variability and extremes, and the recognition of agents’ expertise by peers. Some of the responses to this question described the needs of producers. Questions 12 and 14 asked about agents’ knowledge of *when* farmers

make decisions on specific farm practices and their perception of *what* forecast elements could assist which decisions. These responses were used to create a tailored forecast calendar (see [section 3d](#)). Question 13 asked agents about weather threats affecting producers' long-term decisions, information that can be used to tailor forecasts to inform specifically about extreme conditions like drought, late frost, or heat, which can negatively affect crop growth. The final two questions requested voluntary contact information for follow-up interviews (which were not conducted because of time constraints) and additional comments. See the online supplemental material for the full survey.

Prior to designing the survey, a short list was created of forecast elements desired by agricultural producers and feasible to be provided by current forecast models. The authors consulted with agricultural educators from the Oklahoma Mesonet ([McPherson et al. 2007](#)) and extension employees prior to survey design. In addition, relevant literature related to agricultural surveys ([Cabrera et al. 2007](#); [Mavi and Tupper 2004](#); [Prokopy et al. 2013](#); [Schneider and Wiener 2009](#); [Takle et al. 2014](#)) and seasonal forecast model development ([Jia et al. 2016, 2015](#); [Kirtman et al. 2014](#); [Vecchi et al. 2014](#)) was examined in order to ask questions that explored user needs while also recognizing current seasonal forecast capabilities. In addition, questions 12–14 included text boxes for agents to enter additional decisions, threats, and forecast elements. These boxes registered a total of only five entries for question 12 (management decisions): crop marketing, insect control, fungicide applications, equipment needs, and insecticide applications, entered by three agents. Question 13 (threats) listed one additional item: snow. Question 14 (forecast elements) listed two additional items: high wind/wind duration and first frost/last frost, entered by one agent. Although some of these entries appeared similar to our listed items, they were disregarded in the analysis.

3. Results

a. General survey statistics

On average, participants in the extension agent survey had been working in their current state for about 15 years (the range was 0–42 years). Of the respondents, 42% indicated that 1%–49% of producers in their county grew predominantly winter wheat; 48% of agents said that value was 50% or higher. Among the respondents, 60% (40%) indicated this percentage varied (did not vary) from year to year. As mentioned above, 9% responded that no one grew predominantly winter wheat; these participants did not take part in the remaining survey. The remaining 1% of respondents did

not know (they remained in the survey). The majority of advisers (87%) answered that producers grew predominantly unirrigated winter wheat, and about half (46%) answered that 50% or more of their producers grow dual-purpose winter wheat, which, unlike grain-only winter wheat, is also used as feed supplement for cattle in winter. Of the respondents, 65% (35%) indicated this percentage varied (did not vary) from year to year. When asked about their familiarity with winter wheat producers' general information needs, 98% of agents stated they are very or somewhat familiar with it. When asked about their familiarity with producers' weather and climate forecast information needs, 87% stated they are very or somewhat familiar with it. The remaining agents for these two questions, 2% and 13% of agents, respectively, said they were unfamiliar with these information needs.

Extension agents indicated that current conditions and 1–7-day forecasts were the most influential lead times for their advice to farmers, with 56% and 50% of responses, respectively ([Fig. 2](#)). The longer the lead time, the less influential the forecasts were, agents responded. Monthly and seasonal lead times had “large influence” for 24% of agents. It is unclear, however, if this result is because of a greater importance of shorter lead times or because of the lack of confidence in forecasts with longer lead times. Weather data for the past 12 months and historical weather trends fared second lowest in priority, behind all but annual to longer-term forecasts. In their efforts to network, extension agents are most often in contact with farmers (90% on a daily or weekly basis) and least often with state climatologists and the state Department of Agriculture, both of which some agents have never interacted with at all. Between these extremes and at comparable levels are seed producers, farm chemical dealers, other advisers, and farm organizations such as the Farm Bureau.

Agents were asked about their level of agreement with two statements about climate variability. For the first statement, 70% of extension agents agreed or strongly agreed that “in the last five years, I've seen more variability (e.g., extremes) in the climate across my county.” Only 4% disagreed or strongly disagreed with this statement. Of agents, 55% agreed or strongly agreed that “climate variability hurts my growers more than it benefits them,” while 2.5% disagree or strongly disagree. Interestingly though, in the former question, the rate of agreement increased with an increase in the years of work experience, even though the question only asked about the past five years. A similar trend of increasing agreement with increasing work experience was detected in the latter question. Of agents, 33% disagreed or strongly disagreed with the statement that

FIG. 2. Survey responses from extension agents about the level of influence of different weather or climate forecast information for their advice to crop producers.

“current seasonal forecasts are insufficient for winter wheat producers,” while 26% agreed or strongly agreed.

b. Decision timing

Planning patterns for most decisions were unimodal or bimodal (Fig. 3), meaning that agents indicated specific decisions were made only once or twice per year (Table 2; Fig. 4). Average decision time span was the average of the lengths of time from first to last month (i.e., the range) recorded for all decisions. Decision peak is defined as the middle point of the average decision period. For example, 30 August was noted as the peak time for planning to plant winter wheat, 28 May for harvest planning, and 24 July for purchasing a specific

crop variety. Bimodal decision peaks during spring and fall referred to practices that are conducted twice a year; for example, planning peaks for fertilizing occur on 12 February and 5 September. To determine the average planning dates for bimodal planning decisions, the respective distribution was split at its minima into two subdistributions. Peak time and time range were then calculated separately for each of the two resulting unimodal subdistributions. The subdistributions did not always have the same lengths. Following this process, peak times were 23 March and 4 October for disease control planning, 4 March and 17 September for weed control planning, and 1 April and 26 September for irrigation scheduling. As Fig. 3 shows, planning for water

FIG. 3. This matrix shows when winter wheat growers plan for certain agricultural practices. The calendar months are labeled on the bottom x axis; practices are labeled on the right y axis. The size of the bubble represents the number of times a given practice was selected for a given month by extension agents, with larger bubbles representing more responses. Overall, the graph depicts the seasonality of important, climate-related decisions in winter wheat production. “Other” entries are not shown.

TABLE 2. Date of peak planning times and average decision time span calculated by creating the average of the last month extension agents selected for every decision and subtracting it from the average first month agents selected for every decision.

Decision	Decision peak and average decision time span	
Planting timing	30 Aug, 1.35 months	
Harvest timing	28 May, 1.1 months	
Purchase crop variety	24 Jul, 1.45 months	
Fertilizer application	Spring: 12 Feb, 0.71 months	Fall: 5 Sep, 1.08 months
Disease control	Spring: 23 Mar, 1.27 months	Fall: 4 Oct, 1.09 months
Weed control	Spring: 4 Mar, 0.93 months	Fall: 17 Sep, 1.58 months
Growing cover crops	11 Jun, 1.95 months	
Managing water resources	No peak, year-round	
Seasonal employment	20 Jun, 3.7 months	
Irrigation scheduling	Spring: 1 Apr, 1.68 months	Fall: 26 Sep, 1.52 months
Grazing scheduling	15 Dec, 3.55 months	

resource management had no particular peak but appeared relevant all year round. For this reason, it was excluded from Fig. 4 and from the analyses on decision timing.

Regional differences in the timing of decision peaks and decision time spans were calculated by splitting all responses into roughly equal-sized subgroups, four by latitude and four by longitude. A *t* test was conducted to test for statistical significance at the 95% level of differences in decision timing. In most cases, differences in decision timing were insignificant and/or inconsistent. However, in four cases, decision peak time or decision time span shifted statistically significantly. For harvest timing, peak decision time shifted by 28 days from south to north, from 11 May to 8 June. Peak decision timing for fall fertilizing shifted by 35 days from south to north, from 29 September to 25 August. Peak decision timing for spring disease control shifted by 37 days from south to north, from 5 March to 11 April. And for seasonal employment, the decision time span increased by 93 days from west to east across the study area, from 66 to 159 days.

As expected, these planning time patterns aligned with the timing and seasonality of the actual decisions. Unexpectedly, however, survey results suggested a relatively short lead time for climate information ahead of the decisions for planting and harvesting. Planting for winter wheat takes place between early September and early October (Peairs and Armenta 2010; Shroyer et al. 1997). With the planning time peak for planting in late August and an average time span of 1.35 months, the required average lead time for climate forecast products was about 0.5 months. Similarly, harvest planning peaks on 28 May, on average about 1.5 months before harvest time (Fig. 4). Taking into account the time span in responses, the preferred lead time for forecasts to inform harvest planning is 0–2.5 months. This study only refers to planting and harvesting when estimating planning

lead times, because the timing of other management decisions, such as disease or weed control, is dependent on when the crop is planted, which itself is dependent on whether the crop is used for grain or forage production (Hunger et al. 2012).

FIG. 4. This diagram, based on the responses shown in Fig. 3, represents the timing of when survey participants expected winter wheat producers to make key decisions (e.g., application of weed control) for their farm. Calendar months are represented as pie slices, labeled near the center of the diagram. Light gray ticks on the circle denote one-fifth of each month. Average decision time spans and decision peaks for farm practices are highlighted by yellow and blue circle segments; words within the circle and yellow or blue bars mark peak times. Average decision time span was the average of the lengths of time from first to last month (i.e., the range) recorded for all decisions. Decision peak is defined as the middle point of the average decision period. The average winter wheat growing season is included in green for comparison. It starts in September (planting) and ends in July (harvest). The dotted green circle segments indicate average time of planting and harvesting. The figure suggests that average planning horizon for decisions (and thereby lead time for seasonal climate forecasts) is 0–2.5 months. Water resource management is not included because it did not show a particular seasonality.

FIG. 5. This matrix shows which management practice decisions are impacted by which weather and climate threats. The practices are labeled on the bottom x axis; threats are labeled on the right y axis. The size of the bubble represents how often a given threat was associated by extension agents with a given practice, with larger bubbles representing more responses for a given combination. The ranking of threats is based on the total number of times each threat was associated with all practices. It shows that the most impactful threat is drought, followed by extreme rainfall. The matrix also highlights that some threats impact some practices more than others; for example, hail impacts harvest time more than any other listed practice. “Other” entries are not shown.

c. Weather and climate threats

Survey results suggested that drought was the number one weather or climate threat overall, and it was connected to more decisions than any other listed threat (Fig. 5). (Threats were ranked by counting how many “yes” responses they received.) Drought was followed by extreme rainfall, heat, wind/storm, frost, and hail, in that order. Some decisions were more affected by some threats than others. For example, planning for planting timing was most sensitive to drought, but least sensitive to hail (see Fig. 5, second column). On the other hand, harvest timing was much more affected by the threat of hail, but less so by the threat of drought (Fig. 5, third column). Figure 5 also shows that drought and heat were considered greater threats during planting timing as compared to harvest timing, because seeds need moist soil and a certain soil temperature range to germinate well (Peairs and Armenta 2010; Mavi and Tupper 2004). Storms and hail, on the other hand, were greater problems during harvest planning, when the matured wheat plant can be easily damaged by either. Extreme rainfall was a major concern for both planting and harvesting, because it can make fields inaccessible for the necessary planting and harvest machinery. “Does not apply” was least selected, suggesting that all listed threats were, in some way, relevant for these decisions. At the same

time, the extension agents did not use the text boxes for entering additional threats.

d. Forecast preferences

Last, extension agents were asked what forecast information can assist a specific decision or decisions. The intent was to diagnose 1) what forecast information is most and least important to wheat farmers and 2) what seasonal forecast elements should be provided by seasonal climate forecasts. Overall, all forecast elements related to precipitation were ranked higher than elements related to temperature (Fig. 6). Average precipitation ranked highest, followed by consecutive days without rainfall, deviation from average precipitation, and chances for extreme rainfall. In fifth place overall, average air temperature was the highest-ranked temperature-related forecast information. Perhaps surprisingly, growing degree-days, used to estimate plant growth and maturation based on air temperature in horticulture and agriculture (Bonhomme 2000), only ranked ninth out of 11. One agent made two entries in the text boxes provided, which, however, were not included in the analysis: “high wind/wind duration” and “first frost/last frost.”

Finally, to ensure that products were tailored for south-central U.S. wheat producers, requests for specific forecast elements (e.g., average precipitation) were

FIG. 6. This matrix shows which forecast elements help producers plan for which practices. The practices are labeled on the bottom x axis; forecast elements are labeled on the right y axis. The size of the bubble represents how often a given practice was associated by extension agents with a given forecast element, with larger bubbles representing more responses. The ranking of forecast elements is based on the total number of times they were associated with a practice. Average precipitation is the most helpful forecast element overall, and the top four forecast elements all relate to precipitation. Ranks 5–11 relate to temperature. “Other” entries are not shown.

ranked by month (Table 3). For each calendar month, this ranking was calculated by multiplying the number of survey responses per month for each management decision (i.e., the underlying data for Fig. 3) by the associated number of responses per forecast element for each management decision (i.e., the underlying data for Fig. 6). By doing so, the relative importance of each

forecast element was calculated for each calendar month. These calculations were summed by calendar month and forecast element across all management decisions, and the resulting forecast-element totals were ranked for each calendar month, as shown in Table 3. Average precipitation ranked first, and consecutive days without precipitation ranked second throughout the

TABLE 3. Ranking for forecast elements based on monthly decision timing and forecast preferences for each decision. Rankings indicate how important a forecast element was in a particular calendar month relative to all other forecast elements in the same month. Ranks were calculated by combining results from questions 12 (Fig. 3) and 14 (Fig. 6). A detailed description of the calculation can be found in section 3d.

Forecast element	Ranking												
	Avg	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average precipitation	1	1	1	1	1	1	1	1	1	1	1	1	1
Consecutive days without precipitation	2	2	2	2	2	2	2	2	2	2	2	2	2
Deviation from average precipitation	3	3	4	4	4	4	4	3	3	3	3	3	3
Chances for extreme precipitation	4	4	3	3	3	3	3	4	5	4	4	4	4
Average temperature	5	5	5	5	5	6	6	5	4	5	5	5	5
Consecutive days >100°F (~38°C)	6	6	6	6	6	5	5	6	6	6	6	6	6
Average maximum temperature	7	8	7	7	7	7	7	9	9	8	8	9	9
Growing degree-days	8	7	8	8	8	8	8	8	8	9	9	7	8
Deviation from average temperature	9	10	9	9	9	9	9	7	7	7	7	8	10
Average minimum temperature	10	11	11	10	10	10	10	10	10	10	10	11	11
Consecutive days <32°F (0°C)	11	9	10	11	11	11	11	11	11	11	11	10	7

year. The ranking of the remaining forecast elements varied from month to month.

4. Discussion and conclusions

This paper summarized results from an online survey of extension agents in the southern Great Plains about decision timing and seasonal forecast needs in winter wheat production in their jurisdiction. It was found that most planning decisions addressed by the survey occurred with a distinct seasonality once or twice per year. With regard to planting and harvesting, they had a planning lead time of 0–2.5 months before planting and harvesting are carried out. In agreement with existing literature (Mavi and Tupper 2004), it was found that forecast elements based on precipitation were more relevant to producers than those based on temperature. Somewhat surprisingly, forecasts for growing degree-days, specifically developed for farming and horticulture, did not rank highly at all. Decision timing varied across the study region, but apart from four cases, it occurred without statistically significant spatial trend. South to north shifts (i.e., for harvest timing, fall fertilization, and spring disease control) likely were dominated by growing degree-day thresholds that occur later in the year in the north as compared to the south. It is unclear why decisions for seasonal employment were made substantially earlier in the west than the east of our domain.

Despite the seasonality of most management decisions, the two most requested forecast elements—average precipitation and consecutive days without precipitation—remained as the highest priorities throughout the year, while other forecast elements changed ranks from month to month. Comparing the northern (eastern) versus southern (western) part of the study region (using the same subgroups as in the analysis of regional differences in decision timing; section 3b), some of the rankings changed, indicating that forecast providers should keep forecasts regionally relevant. That said, though, the authors suggest that operational seasonal forecasts be designed for existing administrative regions, such as the National Weather Service forecast areas, to better fit into existing distribution networks and to minimize additional operational expenses for issuing these forecasts.

Overall, results suggest that winter wheat producers planned for the surveyed subset of management decisions (e.g., planting, harvesting) 0–2.5 months before operationalizing those plans (Peairs and Armenta 2010; Shroyer et al. 1997). These lead times are well within the capabilities of current models in seasonal forecasts, such as the North American Multimodel Ensemble, with a lead time of up to 7 months (Kirtman et al. 2014), or the

Geophysical Fluid Dynamic Laboratory's Forecast-Oriented Low Ocean Resolution (FLOR) model, with a lead time of up to 12 months (Jia et al. 2015; Vecchi et al. 2014). In many cases, shorter forecast lead times have higher forecast skill than longer lead times (Kirtman et al. 2014), particularly for precipitation-related forecast elements, which ranked highest in priority in the study. An exception to this rule is the so-called spring barrier, which limits the skill of seasonal summer forecasts regardless of lead time because of higher uncertainty in forecasting the equatorial Pacific conditions that control summer climate variations in many parts of the world, including the United States (Balmaseda et al. 1995; Barnston et al. 1994; Beraki et al. 2014; Lau et al. 2002; Saha et al. 2014; van den Dool 1994; Wen et al. 2012). The desire for shorter lead times also suggests that tailored seasonal forecasts may have sufficient skill at time scales relevant for decision-making, helping to address producers' complaints of the past (Changnon 2004; Changnon et al. 1988; Schneider and Wiener 2009; Sonka et al. 1992).

Surveying extension agents has advantages, as explained in section 2, but also some limitations. Extension agents, as all human respondents, might have been biased in their responses and based their answers on recent memories or on interactions with peers, for example (Nadeau and Niemi 1995). Extension personnel were also one step removed from the decision-makers (i.e., winter wheat producers) themselves and therefore have limited knowledge. For example, extension agents can say little about the rationale for individual farm management decisions and the factors that contributed to it, such as the timing of a decision, why they preferred one forecast element over another, or how important weather and climate forecasts were relative to other decision factors, such as markets, costs, or production goals (Klockow et al. 2010), or the use of crop insurance. Depending on the expected price of wheat and beef, winter wheat farmers can decide to prioritize using their crop for cattle forage over grain production. This means the crop is planted earlier to allow it to grow larger before cattle are grazing on it over the winter (Hunger et al. 2012). In addition, survey respondents only represented growers who actually interacted with their local extension officials, which might have created bias and potentially left out a considerable part of the winter wheat community. Thus, the analysis and insights were limited by the knowledge that participants had about their clients. Future studies should explore decision-making of winter wheat producers who do not regularly interact with local extension agents. The survey was also unable to say whether the preference for a 0–2.5-month decision lead time was caused by the lack of forecast skill of current

seasonal climate forecasts (or perception thereof) or because of other management issues. Existing studies, for example, McCrea et al. (2005), Sherman-Morris (2005), or Crane et al. (2010), generally suggest that users' trust in and comprehension of forecast information does affect its use, but the question in this case remains whether decision lead time would have been longer if producers thought that more skillful forecasts were available. Further, it must be acknowledged that survey responses are sensitive to wording (Borgers et al. 2004; Rasinski 1989; Warnecke et al. 1997), and despite pretests, it cannot be ruled out that participants misinterpreted survey questions. As a result, the authors suggest continued research in these areas. It is also recommended to establish and maintain communication between the climate forecast community, the agricultural extension community, and the producer community so that forecast improvements can be incorporated effectively into decision tools, and decision tools can be adjusted based on decision-making and forecast availability.

Regardless of how good the tailored seasonal climate forecasts are or can be, growers may choose not to apply them because of conflicts with other decision factors, including other climatic factors. For example, winter wheat growers can delay planting in case of dry soil when rain is forecasted soon; however, planting cannot be delayed too much or otherwise the plant might not mature enough to survive the cold winter. Likewise, if planting occurs too early (because of suitable conditions earlier than normal), increased growth before winter dormancy can deplete soil moisture too much, which jeopardizes growth in spring and eventually a good harvest (Shroyer et al. 1997). Finally, the findings of this study apply strictly to winter wheat farming in the southern Great Plains. Different crops, such as cotton or corn, or different winter wheat regions around the world can have very different decision calendars and, therefore, require different tailored forecasts.

Despite these limitations, these results can provide climate forecasters with information that can help address criticism of seasonal forecasts from the agricultural community mentioned at the beginning of this paper. The results provide insights into the timing of major management decisions in winter wheat farming and suggest ways in which forecasters can adjust or create seasonal forecasts to serve the needs of these producers and assist them in making proactive management decisions to reduce crop losses as a result of unseasonal weather and climate conditions.

Acknowledgments. We thank the USDA Cooperative Extension Services of Texas, Oklahoma, Kansas, and Colorado, and the state climatologist of Texas for

participating in this survey and for their invaluable help pretesting and distributing it. Thanks also to Drs. Mike Langston and Jean Steiner for connecting us to the extension community and to Al Sutherland and Gary McManus for their feedback on early versions of the survey. We also thank Drs. Derek Rosendahl, Duncan Wilson, Elinor Martin, Esther Mullens, Jason Slemmons, Joe Ripberger, and Travis Gliedt, as well as Benjamin Ignac and Braden Owsley for their help with our analysis and visualization. Finally, we thank three anonymous reviewers for their excellent comments and suggestions, which made this a much stronger paper. This work was funded by the Oklahoma EPSCoR project through the Oklahoma State Regents for Higher Education and the National Science Foundation under NSF Grant OIA-1301789, with additional support from the Office of the Vice President for Research of the University of Oklahoma (OU) through the South Central Climate Adaptation Science Center and the Dean of the College of Atmospheric and Geographic Sciences through the OU Department of Geography and Environmental Sustainability.

REFERENCES

- Babbie, E. R., 2014: *The Basics of Social Research*. 6th ed. Cengage, 542 pp.
- Balmaseda, M. A., M. K. Davey, and D. L. T. Anderson, 1995: Decadal and seasonal dependence of ENSO prediction skill. *J. Climate*, **8**, 2705–2715, [https://doi.org/10.1175/1520-0442\(1995\)008<2705:DASDOE>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<2705:DASDOE>2.0.CO;2).
- Barnston, A. G., and Coauthors, 1994: Long-lead seasonal forecasts—Where do we stand? *Bull. Amer. Meteor. Soc.*, **75**, 2097–2114, [https://doi.org/10.1175/1520-0477\(1994\)075<2097:LLSFDW>2.0.CO;2](https://doi.org/10.1175/1520-0477(1994)075<2097:LLSFDW>2.0.CO;2).
- Beraki, A. F., D. G. DeWitt, W. A. Landman, and C. Olivier, 2014: Dynamical seasonal climate prediction using an ocean–atmosphere coupled climate model developed in partnership between South Africa and the IRI. *J. Climate*, **27**, 1719–1741, <https://doi.org/10.1175/JCLI-D-13-00275.1>; Corrigendum, **27**, 5670, <https://doi.org/10.1175/JCLI-D-14-00318.1>.
- Bonhomme, R., 2000: Bases and limits to using 'degree.day' units. *Eur. J. Agron.*, **13**, 1–10, [https://doi.org/10.1016/S1161-0301\(00\)00058-7](https://doi.org/10.1016/S1161-0301(00)00058-7).
- Borgers, N., D. Sikkell, and J. Hox, 2004: Response effects in surveys on children and adolescents: The effect of number of response options, negative wording, and neutral mid-point. *Qual. Quant.*, **38**, 17–33, <https://doi.org/10.1023/B:QUQU.0000013236.29205.a6>.
- Cabrera, V. E., N. E. Breuer, J. G. Bellow, and C. W. Fraisse, 2006: Extension agent knowledge and perceptions of seasonal climate forecasts in Florida. Southeast Climate Consortium Tech. Rep. 06-001, 15 pp.
- , D. Letson, and G. Podestá, 2007: The value of climate information when farm programs matter. *Agric. Syst.*, **93**, 25–42, <https://doi.org/10.1016/j.agry.2006.04.005>.
- Carberry, P., G. Hammer, H. Meinke, and M. Bange, 2000: The potential value of seasonal climate forecasting in managing cropping systems. *Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems*, G. L. Hammer, N. Nicholls, and C. Mitchell, Eds., Springer, 167–181.

- Changnon, S. A., 2004: Changing uses of climate predictions in agriculture: Implications for prediction research, providers, and users. *Wea. Forecasting*, **19**, 606–613, [https://doi.org/10.1175/1520-0434\(2004\)019<0606:CUOCPI>2.0.CO;2](https://doi.org/10.1175/1520-0434(2004)019<0606:CUOCPI>2.0.CO;2).
- , S. T. Sonka, and S. Hofing, 1988: Assessing climate information use in agribusiness. Part I: Actual and potential use and impediments to usage. *J. Climate*, **1**, 757–765, [https://doi.org/10.1175/1520-0442\(1988\)001<0757:ACIUIA>2.0.CO;2](https://doi.org/10.1175/1520-0442(1988)001<0757:ACIUIA>2.0.CO;2).
- Crane, T. A., C. Roncoli, J. Paz, N. Breuer, K. Broad, K. T. Ingram, and G. Hoogenboom, 2010: Forecast skill and farmers' skills: Seasonal climate forecasts and agricultural risk management in the southeastern United States. *Wea. Climate Soc.*, **2**, 44–59, <https://doi.org/10.1175/2009WCAS1006.1>; Corrigendum, **2**, 168, <https://doi.org/10.1175/2010WCAS1075.1>.
- Dillman, D. A., J. D. Smyth, and L. M. Christian, 2014: *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. John Wiley and Sons, 528 pp.
- FAO, 2014: World crops ranked by harvested area, 2014. FAO, accessed 19 October 2016, <http://faostat.fao.org>.
- Frisvold, G. B., and A. Murugesan, 2013: Use of weather information for agricultural decision making. *Wea. Climate Soc.*, **5**, 55–69, <https://doi.org/10.1175/WCAS-D-12-00022.1>.
- Haigh, T., E. Takle, J. Andresen, M. Widhalm, J. S. Carlton, and J. Angel, 2015: Mapping the decision points and climate information use of agricultural producers across the U.S. Corn Belt. *Climate Risk Manage.*, **7**, 20–30, <https://doi.org/10.1016/j.crm.2015.01.004>.
- Han, W., Z. Yang, L. Di, and R. Mueller, 2012: CropScape: A web service based application for exploring and disseminating US continuous geospatial cropland data products for decision support. *Comput. Electron. Agric.*, **84**, 111–123, <https://doi.org/10.1016/j.compag.2012.03.005>.
- Hunger, B., J. Edwards, T. Royer, and K. Giles, 2012: Effect of planting date and seed treatment on diseases and insect pests of wheat. Oklahoma State University Rep. CR-7088, 4 pp.
- Jia, L., and Coauthors, 2015: Improved seasonal prediction of temperature and precipitation over land in a high-resolution GFDL climate model. *J. Climate*, **28**, 2044–2062, <https://doi.org/10.1175/JCLI-D-14-00112.1>.
- , and Coauthors, 2016: The roles of radiative forcing, sea surface temperatures, and atmospheric and land initial conditions in U.S. summer warming episodes. *J. Climate*, **29**, 4121–4135, <https://doi.org/10.1175/JCLI-D-15-0471.1>.
- Jones, J. W., J. W. Hansen, F. S. Royce, and C. D. Messina, 2000: Potential benefits of climate forecasting to agriculture. *Agric. Ecosyst. Environ.*, **82**, 169–184, [https://doi.org/10.1016/S0167-8809\(00\)00225-5](https://doi.org/10.1016/S0167-8809(00)00225-5).
- Kirtman, B. P., and Coauthors, 2014: The North American Multi-model Ensemble: Phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bull. Amer. Meteor. Soc.*, **95**, 585–601, <https://doi.org/10.1175/BAMS-D-12-00050.1>.
- Klemm, T., and R. A. McPherson, 2017: The development of seasonal climate forecasting for agricultural producers. *Agric. For. Meteorol.*, **232**, 384–399, <https://doi.org/10.1016/j.agrformet.2016.09.005>.
- Klockow, K. E., R. A. McPherson, and D. S. Sutter, 2010: On the economic nature of crop production decisions using the Oklahoma Mesonet. *Wea. Climate Soc.*, **2**, 224–236, <https://doi.org/10.1175/2010WCAS1034.1>.
- Lau, K.-M., K.-M. Kim, and S. S. P. Shen, 2002: Potential predictability of seasonal precipitation over the United States from canonical ensemble correlation predictions. *Geophys. Res. Lett.*, **29**, 1097, <https://doi.org/10.1029/2001GL014263>.
- Mavi, H. S., and G. J. Tupper, 2004: *Agrometeorology: Principles and Applications of Climate Studies in Agriculture*. CRC Press, 447 pp.
- McCrea, R., L. Dalglish, and W. Coventry, 2005: Encouraging use of seasonal climate forecasts by farmers. *Int. J. Climatol.*, **25**, 1127–1137, <https://doi.org/10.1002/joc.1164>.
- McPherson, R. A., and Coauthors, 2007: Statewide monitoring of the mesoscale environment: A technical update on the Oklahoma Mesonet. *J. Atmos. Oceanic Technol.*, **24**, 301–321, <https://doi.org/10.1175/JTECH1976.1>.
- Meinke, H., and R. C. Stone, 2005: Seasonal and inter-annual climate forecasting: The new tool for increased preparedness to climate variability and change in agricultural planning and operations. *Climatic Change*, **70**, 221–253, <https://doi.org/10.1007/s10584-005-5948-6>.
- , S. M. Howden, W. Baethgen, G. L. Hammer, R. Selvaraju, and R. C. Stone, 2003: Can climate knowledge lead to better rural policies and risk management practices? *Insights and Tools for Adaptation: Learning from Climate Variability*, NOAA, 7 pp.
- Nadeau, R., and R. G. Niemi, 1995: Educated guesses: The process of answering factual knowledge questions in surveys. *Public Opin. Quart.*, **59**, 323–346, <https://doi.org/10.1086/269480>.
- National Agricultural Statistics Service, 2018: 2016 winter wheat production, planted acreage. USDA, accessed 5 February 2018, <https://quickstats.nass.usda.gov/results/8D2E8AF6-8D42-33FC-91D9-A437A360228E>.
- Nulty, D. D., 2008: The adequacy of response rates to online and paper surveys: What can be done? *Assess. Eval. Higher Educ.*, **33**, 301–314, <https://doi.org/10.1080/02602930701293231>.
- O'Lenic, E. A., D. A. Unger, M. S. Halpert, and K. S. Pelman, 2008: Developments in operational long-range climate prediction at CPC. *Wea. Forecasting*, **23**, 496–515, <https://doi.org/10.1175/2007WAF2007042.1>; Corrigendum, **23**, 1044, <https://doi.org/10.1175/WAF2222190.1>.
- Pears, F., and R. Armenta, Eds., 2010: *Wheat Production and Pest Management for the Great Plains Region*. Colorado State University Extension, 188 pp.
- Prokopy, L. S., and Coauthors, 2013: Agricultural advisors: A receptive audience for weather and climate information? *Wea. Climate Soc.*, **5**, 162–167, <https://doi.org/10.1175/WCAS-D-12-00036.1>.
- Rasinski, K. A., 1989: The effect of question wording on public support for government spending. *Public Opin. Quart.*, **53**, 388–394, <https://doi.org/10.1086/269158>.
- Ropelewski, C. F., and M. S. Halpert, 1986: North American precipitation and temperature patterns associated with the El Niño/Southern Oscillation (ENSO). *Mon. Wea. Rev.*, **114**, 2352–2362, [https://doi.org/10.1175/1520-0493\(1986\)114<2352:NAPATP>2.0.CO;2](https://doi.org/10.1175/1520-0493(1986)114<2352:NAPATP>2.0.CO;2).
- Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System version 2. *J. Climate*, **27**, 2185–2208, <https://doi.org/10.1175/JCLI-D-12-00823.1>.
- Schneider, J. M., and J. D. Wiener, 2009: Progress toward filling the weather and climate forecast need of agricultural and natural resource management. *J. Soil Water Conserv.*, **64**, 100A–106A, <https://doi.org/10.2489/jswc.64.3.100A>.
- Sherman-Morris, K., 2005: Tornadoes, television and trust—A closer look at the influence of the local weathercaster during severe weather. *Global Environ. Change*, **6B**, 201–210, <https://doi.org/10.1016/j.hazards.2006.10.002>.
- Shroyer, J. P., D. Whitney, and D. Peterson, 1997: *Wheat Production Handbook*. Kansas State University, 42 pp.

- Sonka, S. T., S. A. Changnon Jr., and S. L. Hofing, 1992: How agribusiness uses climate predictions: Implications for climate research and provision of predictions. *Bull. Amer. Meteor. Soc.*, **73**, 1999–2008, [https://doi.org/10.1175/1520-0477\(1992\)073<1999:HAUCPI>2.0.CO;2](https://doi.org/10.1175/1520-0477(1992)073<1999:HAUCPI>2.0.CO;2).
- Takle, E. S., and Coauthors, 2014: Climate forecasts for corn producer decision making. *Earth Interact.*, **18**, <https://doi.org/10.1175/2013EI000541.1>.
- Templeton, S. R., M. S. Perkins, H. D. Aldridge, W. C. Bridges Jr., and B. R. Lassiter, 2014: Usefulness and uses of climate forecasts for agricultural extension in South Carolina, USA. *Reg. Environ. Change*, **14**, 645–655, <https://doi.org/10.1007/s10113-013-0522-7>.
- USDA, 2012: Census of agriculture. USDA Rep. AC-12-A-51, 695 pp.
- , 2018a: Federal crop insurance corp: Summary of business report for 1995 thru 2004. USDA, accessed 5 February 2018, https://www3.rma.usda.gov/apps/sob/current_week/sobrpt1995-2004.pdf.
- , 2018b: Federal crop insurance corp: Summary of business report for 2005 thru 2014. USDA, accessed 5 February 2018, https://www3.rma.usda.gov/apps/sob/current_week/sobrpt2005-2014.pdf.
- van den Dool, H. M., 1994: New operational long-lead seasonal climate outlooks out to one year: Rationale. *Proc. 19th Annual Climate Diagnostics Workshop*, College Park, MD, NOAA, 405–407.
- Vecchi, G. A., and Coauthors, 2014: On the seasonal forecasting of regional tropical cyclone activity. *J. Climate*, **27**, 7994–8016, <https://doi.org/10.1175/JCLI-D-14-00158.1>.
- Warnecke, R. B., T. P. Johnson, N. Chávez, S. Sudman, D. P. O'Rourke, L. Lacey, and J. Horm, 1997: Improving question wording in surveys of culturally diverse populations. *Ann. Epidemiol.*, **7**, 334–342, [https://doi.org/10.1016/S1047-2797\(97\)00030-6](https://doi.org/10.1016/S1047-2797(97)00030-6).
- Wen, C., Y. Xue, and A. Kumar, 2012: Seasonal prediction of North Pacific SSTs and PDO in the NCEP CFS hindcasts. *J. Climate*, **25**, 5689–5710, <https://doi.org/10.1175/JCLI-D-11-00556.1>.
- WMO, 2015: Global producing centres for long range forecasting. WMO, http://www.wmo.int/pages/prog/wcp/wcasp/clips/producers_forecasts.html.