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ASSESSING USER NEEDS AND MODEL ACCURACY OF SEASONAL CLIMATE FORECASTS FOR WINTER WHEAT PRODUCERS IN THE SOUTH-CENTRAL UNITED STATES

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ASSESSING USER NEEDS AND MODEL ACCURACY OF SEASONAL CLIMATE FORECASTS FOR WINTER WHEAT PRODUCERS IN THE SOUTH-CENTRAL UNITED STATES

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BY

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Für meine Eltern

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"Now to him who is able to do immeasurably more than all we ask or imagine, according to his power that is at work within us, to him be glory in the church and in Christ Jesus throughout all generations, for ever and ever! Amen." (Ephesians 3.20-21, NIV)

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Abstract

The research presented in this dissertation highlights ways in which seasonal climate forecasts can be tailored to better serve the needs of winter wheat producers in the south-central United States (U.S.) and presumably in other regions, and address previously raised criticism of these forecasts by the agricultural community. It applied a collaborative, interdisciplinary approach and conducted a quantitative online survey of agricultural advisors to determine decision timing and seasonal forecast needs in winter wheat production in Texas, Oklahoma, Kansas, and Colorado. These results were used to create a ranking that showed forecast elements most requested are related to precipitation and consist of information directly modeled, such as average total precipitation or average temperature, and data derived from such information, such as connective days without precipitation or chances of extreme precipitation. A subsequent analysis used this ranking to conduct a error comparison of a high-resolution seasonal climate model and a persistence forecast derived from observational data. Survey results show that current seasonal climate forecast omit several forecast elements important in winter wheat production, which current seasonal forecast models are capable of producing, such as the number of consecutive days without rainfall or the chances for extreme rainfall. Results of the seasonal forecast analysis showed that the seasonal climate forecast model used had a greater absolute error than a seasonal persistence forecast for all forecast elements across most of the study region and most of the year.

Results contribute significantly to the current body of knowledge in tailored seasonal climate forecasting and highlight the fact that both model and persistence forecast can be more accurate, depending on the forecast element, time of year, geographic location, and

lead-time, and that in some cases, both model and persistence forecasts may be very inaccurate.

Chapter 1 - Introduction

Agriculture is a highly weather- and climate-dependent industry. Unseasonal warm or cold periods and extreme events like drought or extreme rainfall can severely impact agricultural production and have serious societal impacts as a result of food shortage and/or food price fluctuations. As seen in recent years in the United States (U.S.), East Africa, and Syria, severe drought and heat can lead to severe crop damage and crop failure (NRDC 2013), affect regional economies (Cargill 2015), cause spikes in insurance payments (U.S. Department of Agriculture 2017), affect food security and food prices (USDA ERS 2013), and contribute to famine and violent conflicts, such as recently in East Africa (Marthews et al. 2015) and Syria (Gleick 2014).

Seasonal climate forecasts, forecasts with lead-times of one to 12 months issued monthly as one- or three-month averages or totals, can help mitigate and reduce these negative impacts. Proactive farm decision making that adapts to uncertain weather and climate conditions has been shown to stabilize crop yields, reduce revenue fluctuations, provide a more stable income over time compared to conservative, business-as-usual practices, and even increase yields by taking advantage of more favorable conditions (Meinke et al. 2003, Meinke and Stone 2005, Nicholls 1980). Seasonal climate forecasts, forecasts with monthly or seasonal averages and lead-times of one to 12 months, have been issues for the contiguous U.S. since 1946 (O'Lenic et al. 2008) and have been used by agricultural producers for decades, however not without criticism (Changnon, Sonka and Hofing 1988, Sonka, Hofing and Changnon 1992). Among other factors, producers critiqued the lack of relevant information and the disconnect between forecasters and users (Schneider and Wiener 2009), what informally is called the “loading dock approach” by the National Weather Service (NWS)(Cash, Borck and Patt 2006), issuing forecasts without tracking who uses them and without feedback or initial input from users. In response, Cash et al. (2006) proposed science co-production across disciplinary boundaries, scales, and knowledges, to produce "to create information that is salient, credible, and legitimate to multiple audiences" (Cash et al. 2006), a task that in the past, due to its cross-disciplinary, applied nature seemed particularly suited for geographers (Moser 2010).

Over the past decades, advances in the understanding of atmospheric, land, and ocean processes and their interaction have led to substantial skill improvements in seasonal climate forecasting in many parts of the worlds (Delworth et al. 2006, Delworth et al. 2012, Goddard et al. 2001, Jia et al. 2015, Kirtman and Min 2009, Kirtman et al. 2014). In order to translate this progress (and many other advances) into improved decision making and societal applications in the U.S., several programs, such as the National Oceanic and Atmospheric Administration (NOAA) Regional Integrated Sciences and Assessment (RISA) program (Lemos and Morehouse 2005), the Department of the Interior Climate Science Centers (DOI 2009), and the U.S. Department of Agriculture Regional Climate Hubs (Allen and Stephens 2016) were initiated between the late 1990s and early 2010s. Major goals of these programs were to provide climate-related decision support by bringing together scientists and stakeholders and building lasting relationships across disciplines, moving from the loading dock approach towards "deliberate coproduction, which involves explicitly planning coproduction into research processes and applying the best practices in collaborative research to achieve usable science" (Meadow et al. 2015). The result of these efforts are end-to-end approaches, more holistic and collaborative approaches to science production, which are aimed at considering the entire forecast production cycle, from developing models to tailoring information for specific decisions in collaboration with users (Bales, Liverman and Morehouse 2004, Lyon et al. 2014, Roncoli et al. 2009, Shafiee-Jood et al. 2014).

Despite efforts to derive applications from long-term climate information, recent research often focused solely on the assessment of user needs, in particular with regards to the agricultural community (Takle et al. 2014, Schneider and Wiener 2009, Cabrera et al. 2006), while intra-seasonal to inter-annual forecasts are being improved with the potential of seasonal climate forecast products tailored in ways requested by users. The research presented in the following chapters embraces the collaborative, interdisciplinary efforts outlined in the previous paragraph and intended to move one step further towards operational tailored forecasts. The work presented here is built on the idea of combining current knowledge in seasonal forecast development and methods in science co-production and attempt to move forecast production and user needs closer together.

This research was intended to focus on one single crop and explore ways in which seasonal climate forecasts can be tailored to help producers improve their decision making. The crop chosen for this research was winter wheat, a strain of wheat and the largest crop by acreage in the south-central U.S., grown on 21.1 million acres (in 2016), twice the area of the second largest crop, corn (Han et al. 2012). Winter wheat also contributes about 71 percent to the total U.S. harvest of wheat, which itself is the third largest U.S. field crop behind corn and soybean (USDA 2012). With this, the goal of this work was to answer two research questions:

1. How can seasonal climate forecasts be tailored to serve the needs of winter wheat growers in the south-central United States?

2. Can existing seasonal forecast models provide meteorological variables as requested by winter wheat farmers with better skill than a persistence forecast?

The following three chapters are three publications from this research, which have been published, are currently under review, or are in draft. Chapter two gives a historic review of the development of seasonal climate forecasts for agricultural producers, predominantly since the year 2000. Chapter three presents a survey study conducted in 2016 in Texas, Oklahoma, Kansas, and Colorado, to assess decision timing of major farm practices in winter wheat production in the south-central U.S. and to determine seasonal forecast needs of winter wheat producers. Chapter four presents a forecast model analysis that used results from chapter three to feed a statistical comparison of a high-resolution seasonal forecast model and a persistence forecast for the survey study domain, determining whether a model forecast or a persistence forecast are more accurate in providing forecasts as requested by winter wheat producers in the study area. Finally, Chapter five summarizes all results and draws an overall conclusion.

Chapter 2 - The Development of Seasonal Climate Forecasting for Agricultural Producers

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Abstract

This review summarizes advances in seasonal climate forecasting with a focus on agriculture, predominantly since the year 2000. The main research 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. Crop and livestock producers use seasonal climate forecasts for management decisions such as planting and harvest timing, field fertilization, or grazing. Agricultural users have often criticized lack of forecast skill and usability as well as a lack of understanding of user needs among forecast developers. Recently, interdisciplinary studies started exploring agricultural decision-making and integrating social science and climate science in order to improve the value of seasonal forecasts. Producer requests include direct and derived forecast products, such as total rainfall and consecutive dry days, information on uncertainty, and comparisons to previous years. The review explores single-model and ensemble forecasts, describes different measures of forecast value, and highlights economic and other agricultural decision factors besides weather and climate. It also examines seasonal climate forecasts from an agricultural perspective, explores communication challenges and how to overcome them, and delves into end-to-end forecast concepts that span forecast production to forecast application by end users.

1 Introduction

Seasonal climate forecasts, forecasts with lead-times of one to 12 months issued monthly as one- or three-month averages or totals, are used by crop producers for management 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. (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, Peña and Vintzileos 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, Buontempo and Newton 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. Ringler et al. (2008) and Hoskins (2013) point out that forecasts on different time-scales, from days to centuries, can be affected by distinct phenomena and components of the natural world that need to be researched and taken into account for skillful forecasting, such as fronts and convective systems, ocean circulation, or vegetation cover. Seamless forecast model development included the Model for Prediction across Scales (MPAS) (Ringler et al. 2008) developed at the National Centers for Atmospheric Research (NCAR) and ICON ("ICOsahedral Non-hydrostatic general circulation model"), developed by the German Weather Service and the Max Planck Institute for Meteorology (Zängl et al. 2014). Both MPAS and 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

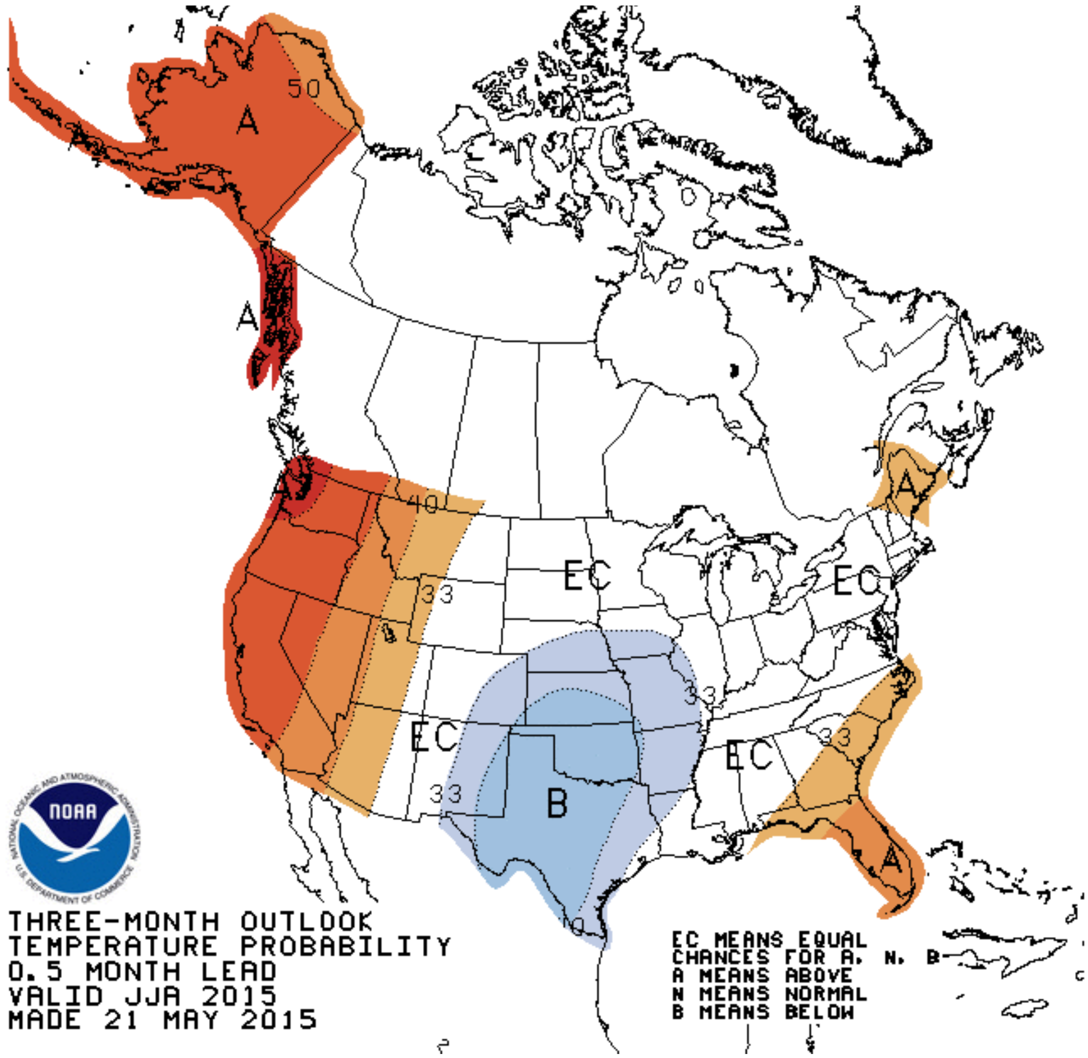

Fig. 1: CPC three-month temperature forecast for June/July/August 2015, issued on May 21, 2015 (0.5 months lead-time). Source NOAA CPC.

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

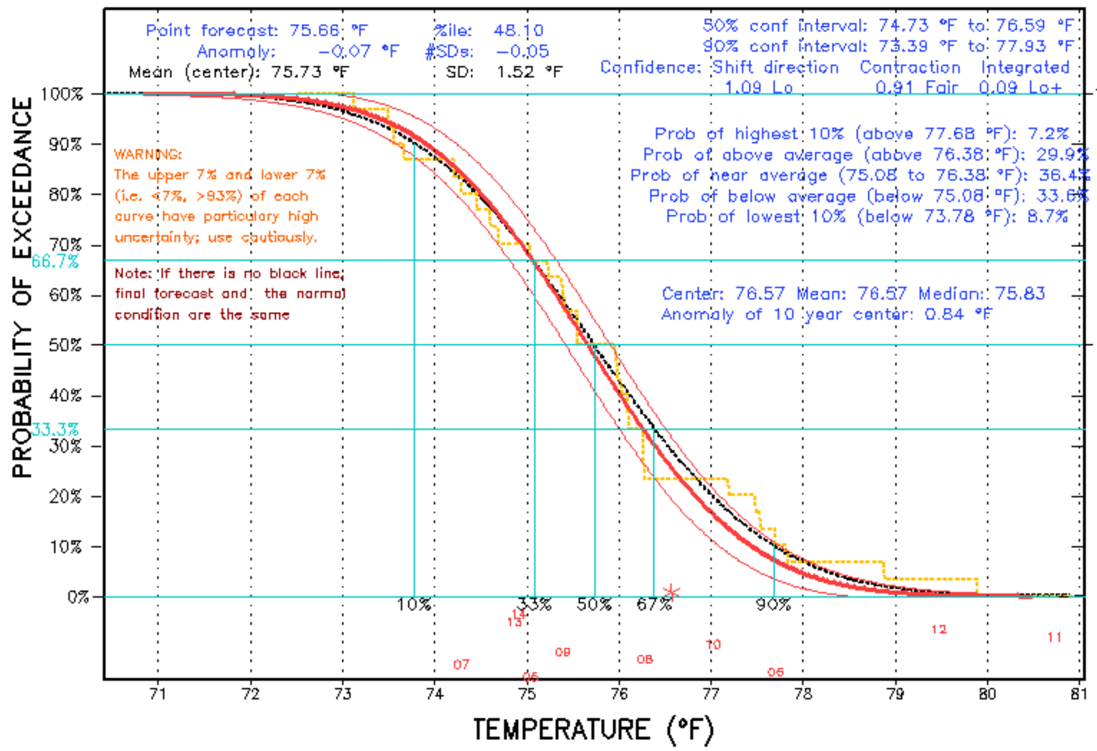

Fig. 2: Probability of Exceedance (POE) curve for average temperature forecast in central Oklahoma (forecast division 53) for May to July 2015, issued April 16, 2015. Source: NOAA CPC

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, Schneider and Van Liew 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

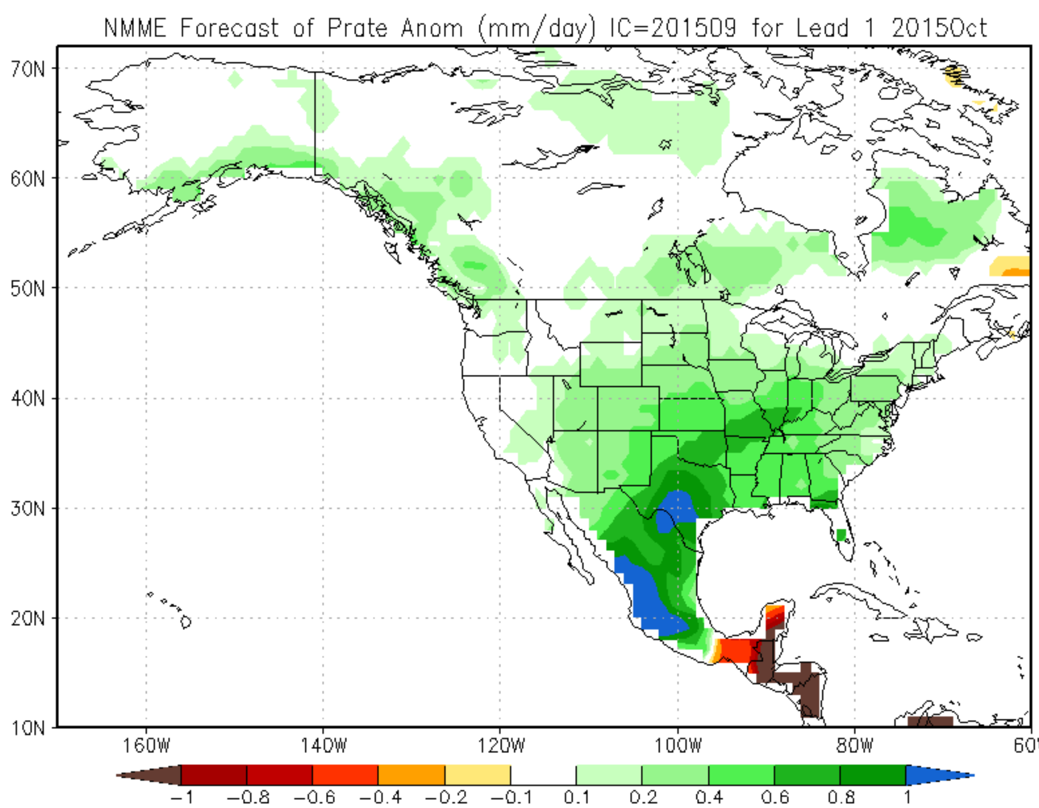

Fig. 3: NMME ensemble forecast for precipitation deviation from normal for October 2015, issued in September 2015. Source: NOAA CPC

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).

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 Baethegan 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 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). Another skill-limiting factor is the inherent chaos of the weather system in which minute changes, undetectable by measuring devices and indescribable in equations, can have major effects on the development of future conditions (Lorenz 1969, Slingo and Palmer 2011). 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, Hodges and Jones 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, Kim and Shen 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, Davey and Anderson 1995, Wen, Xue and Kumar 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, Rowell and Folland 1997, Muller, Appenzeller and Schar 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 (Kirtman et al. 2014). "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 devastative 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 multi-model 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.

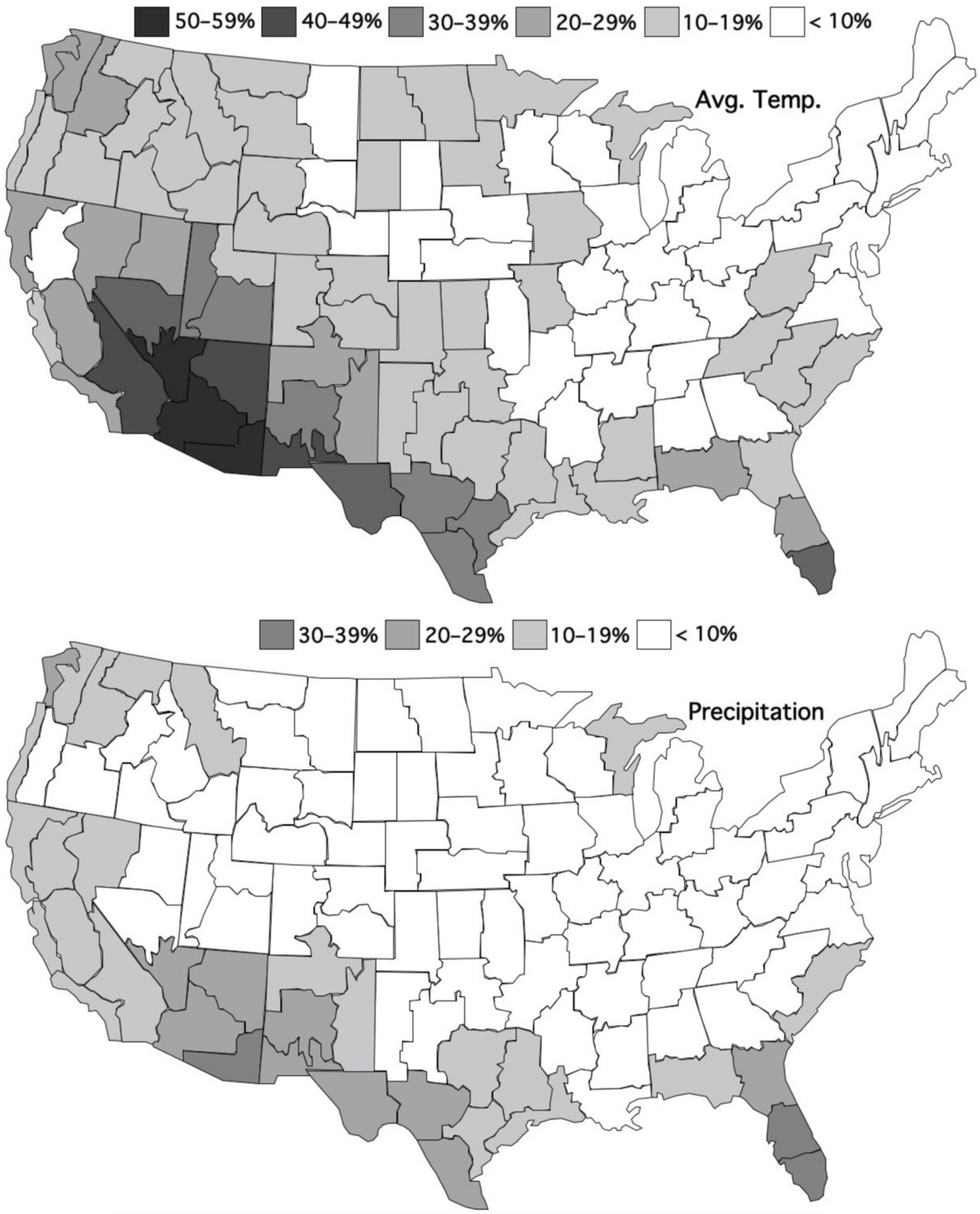

Fig. 4: Effectiveness of seasonal temperature (top) and precipitation (bottom) forecasts for 0.5 months lead- time, for each of the 102 climate forecast divisions. Percentage values indicate what portion of forecasted values were above or below normal and in the same tercile category as the observed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

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, McPherson and Sutter 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 (Barham et al. 2011, Harwood et al. 1999), 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, Timmer and Lélé 2011), and numerous modeling studies and user surveys were conducted to determine current shortcomings and to explore user needs in more detail (Prokopy et al. 2013, Schneider and Wiener 2009, e.g., Fraisse et al. 2006, Hansen and Indeje 2004). 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). Tab. 1 links some of these variables with agricultural decisions.

Tab. 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

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). 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, Fig. 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). Tab. 3 shows how production and marketing decisions for corn differ depending on lead-time and season. Likewise, Tab. 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 key management decisions for livestock and various grain crops, demonstrating why seasonal climate forecast are important, and what management decisions can help mitigate unfavorable conditions.

Tab. 5 lists key 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

Tab. 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

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).

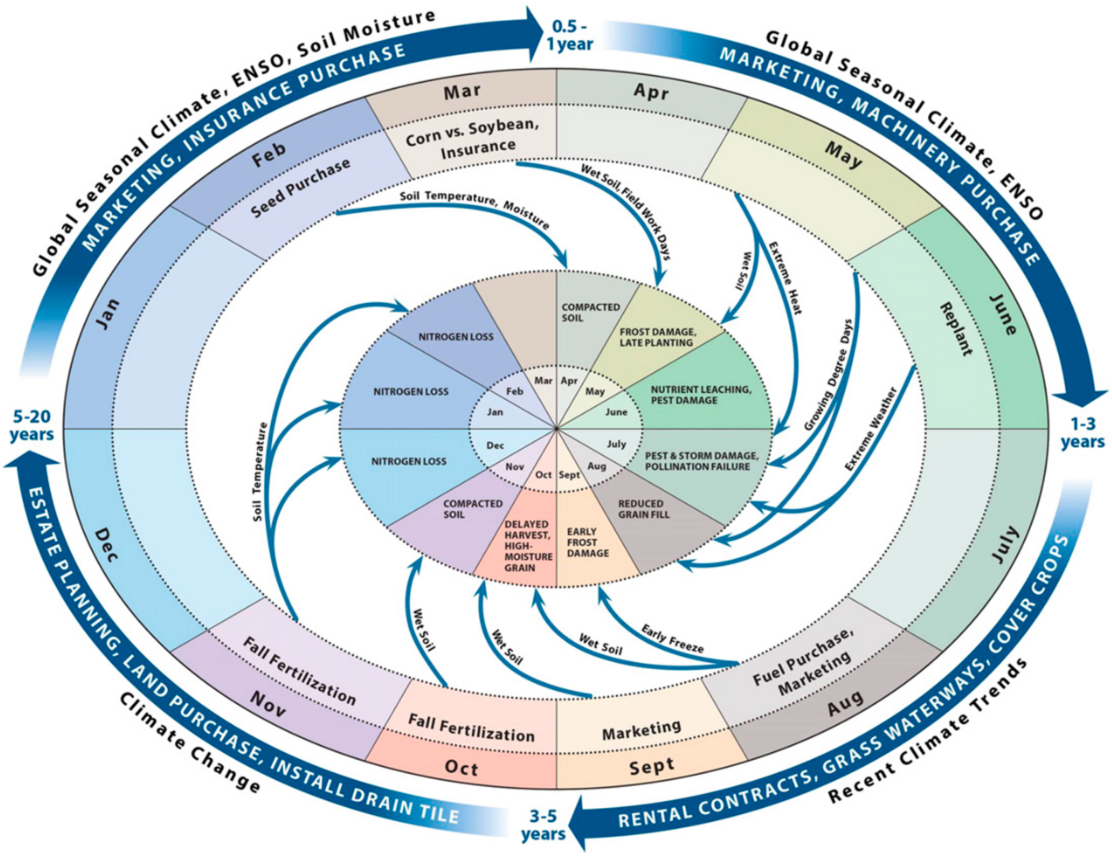

Fig. 5: Climate-based decision cycle for corn. The outer calendar identifies the time of yea management decisions are made. The inner calendar depicts the soil or crop impact, anc the label on the arrow identifies the weather or soil conditions relevant to the impact Length of the arrow gives the lead-time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

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

	March – May	June, July	August – October	November – February
Production				
Decision	Field work, planting	Pest/disease/weed/ irrigation management	Harvesting, grain drying	Seed variety, fertilizer, crop insurance
Real-time Monitoring	Soil moisture, wet days	Wind, humidity, soil moisture	Soil moisture	
1-3 days	Soil moisture, soil temperature	Humidity, wind, rainfall	Wet days	
1-3 weeks		Spring soil moisture, summer humidity, summer drought, flood	Fall freeze	Rain (fall), Snow (winter)
1-6 month		Summer drought, extreme daytime heat, fall freeze, fall wet days		Spring drought, flood, soil moisture, temperature
6-12 months				Summer drought/flood
Marketing				
Decision	Purchase/sell corn in storage	Purchase/sell corn in storage	Purchase/sell corn in storage	Purchase/sell corn in storage
Real-time monitoring	Spring freeze	Global drought, flood, extreme daytime/ nighttime hear, hail/wind damage	Fall wet days	
1-3 days				
1-3 weeks	Late spring freeze	Soil Moisture, drought, flood, extreme daytime/ nighttime heat		
1-6 months	Summer drought, flood,	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

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

Time frame	Agricultural aspects to consider
5-day forecast	• 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	• 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	• 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	• 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

Tab. 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.

Tab. 5: Continued

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		
Harvesting	Warm temperatures enhance growth and harvesting is easier	Plan to harvest earlier if seasonal outlook is of warm weather.
Water / Irrigation		
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.

Tab. 5: Continued

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 in 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 footnote 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.
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.

Tab. 5: Continued

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.

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, Brown and Kalafatis 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, Parker and McNeill 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., Breuer et al. 2008, Fraisse et al. 2006, Pasteris, Puterbaugh and Motha 2004). A biennial survey by the U.S. Department of Agriculture (USDA), based on about 28,000 responses from farmers and represents all sizes and types of farms within the contiguous U.S. (USDA 2015b), found that internet access is common among farmers (70% in 2015). However, it is unclear from the survey how the internet is accessed. In 2015, only 43% of all U.S. farmers use computers in their farm business (USDA 2015b). While smartphone use is not assessed in the survey, web-based applications that require computers could 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

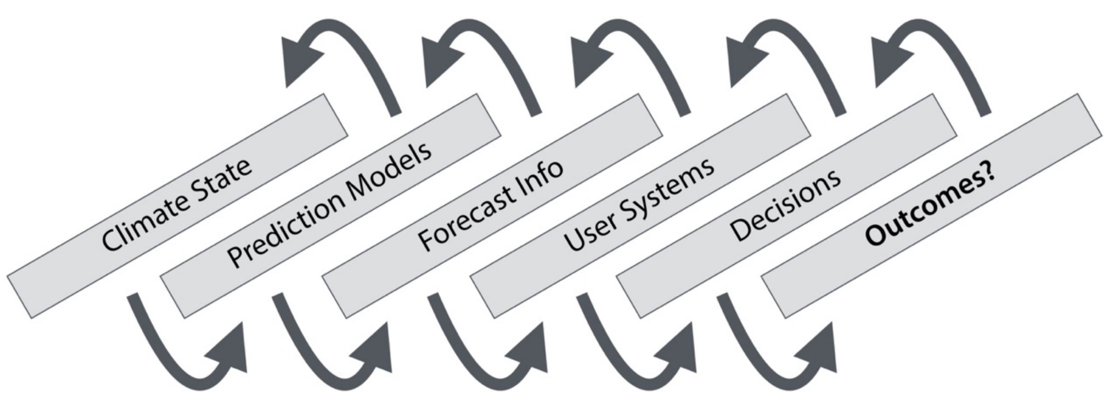

Fig. 6: Schema of the end-to-end concept. Actionable outcomes require interaction and feedback from societal, biological, and physical elements. Source: Goddard et al. (2001)

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, Broad and Guston 2001, Goddard et al. 2001, Power, Plummer and Alford 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.

8. Acknowledgements

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9. Conflict of Interest Statement

The authors have no conflicts of interest to declare for this study.

Chapter 3 - Assessing Decision Timing and Seasonal Climate Forecast Needs of Winter Wheat Producers in the South-Central United States

Submitted as:

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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 advisors in Oklahoma, Kansas, Texas, and Colorado was conducted that 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. Winter wheat growers were not only interested in directly modeled variables, such as total monthly rainfall, but also derived elements, such as consecutive number of dry days. Extension agents perceive that winter wheat producers needed seasonal climate forecasts to cover one to three months in advance — the planning lead-time for major farm practices, like planting or applying fertilizer. We created a forecast calendar and monthly rankings for forecast elements that can guide forecasters and advisors as they develop decision tools for winter wheat producers and can serve as a template for other time-sensitive decision tools developed for stakeholder communities.

1. Introduction

Droughts, floods, heat waves, extreme rainfall, 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 (U.S.), 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 — three times the annual average from 2001 to 2010 (USDA 2016a, USDA 2016b) — 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 (van den Dool 1994, O'Lenic et al. 2008). 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 U.S. but worldwide. 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, CPC issues monthly seasonal climate forecast ensembles based on eight individual models, with up to seven months lead-time 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 et al. 1988, Sonka et al. 1992, Changnon 2004). 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 2012, 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 co-production 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 (Takle et al. 2014). Our study 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; 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 agricultural extension agents to study decision-making patterns in winter wheat production and the specific forecast needs of these producers. This study also explored the specific role of agricultural advisors 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.

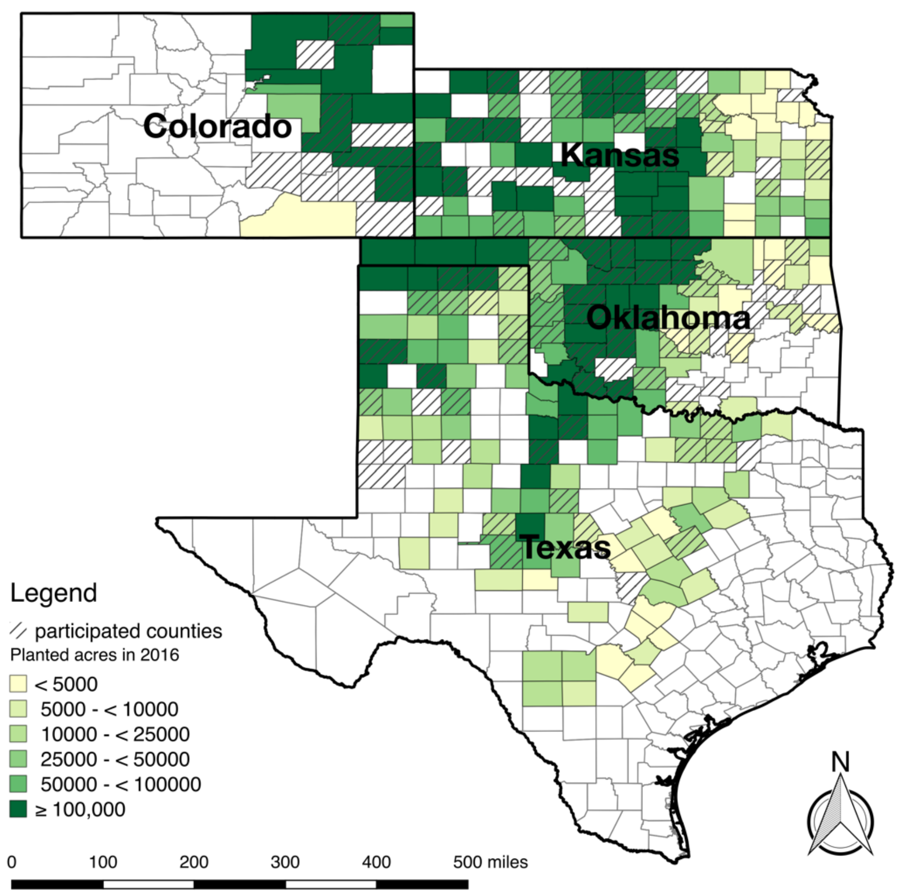

Fig. 7: The study region. Extension agents from counties with diagonal lines participated in the survey. Yellow/green shaded counties show the acreage of planted winter wheat in 2016. Acreage data source: USDA National Agricultural Statistics Service

2.1 Why winter wheat?

This study focused on one particular crop type (as opposed to all grain crops) because decision making, and especially the timing of decisions, is different from one crop to another. Winter wheat is the dominant crop in the Southern Great Plains of the U.S.. In the study region, the states of Colorado, Kansas, Oklahoma, and Texas (Fig. 7), winter wheat is grown on 21.1 million acres (in 2016), 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 U.S., wheat is the third-largest crop after corn and soybeans, and winter wheat contributes about 70 percent to the total wheat harvest in the U.S. (USDA 2012). Because of its overall contribution to the national wheat harvest and its role in the study region, winter wheat was chosen as focus crop for this study.

2.2 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 advisors, specifically cooperative extension agents associated with land grant universities in the study domain (Fig. 7). Approximately 360 cooperative extension agents were contacted and 119 unique responses (ca. 33 percent response rate, average for online surveys, according to Nulty (2008)) were received. 10 of these responses stated no winter wheat was grown in their jurisdiction and were discounted. 109 were eventually used in the analysis. Extension agents are agricultural advisors 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 homogenous group regarding educational background and access to email 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 our results represent the aggregate views of the producer community.

Online surveys have been shown to be more efficient than phone or in-person interviews for quantitative or binary (yes/no) questions (Babbie 2014), such as those used in this survey. Survey distribution is inexpensive, easy, and fast via email, and survey responses are available in electronic format, eliminating transcription errors and post-processing time. Survey sponsors, people known in the extension community (i.e., extension district directors and state climatologists), helped distribute the survey. They received email address lists and text templates, including the survey URL and a one-page summary about the survey. Some survey sponsors did not use the email list but instead sent the invitation/reminder via their own mailing lists. The authors were copied on all emails to record send dates and times and to get confirmation about the sending. After initial survey invitations were distributed, two to four reminder emails were sent out, with intervals of three to four weeks in between each reminder.

Procedures by Dillman et al. (2014) were adopted to increase survey responses and to enhance the quality of the responses. "Survey sponsors" (Dillman et al. 2014) sent initial survey invitations and later reminders to extension agents in their jurisdictions. After pretesting the survey with three extension agents, incorporating revisions, and receiving Institutional Review Board approval, initial survey invitations were sent between 19 January 2016 (Oklahoma) and 2 March 2016 (Colorado). The survey closed on 6 May 2016.

2.3 Survey design

The survey time was estimated to take 10-15 minutes to complete. Median response time was 12 minutes. 130 individual responses were received. After eliminating double and triple responses (only the first responses were kept) and empty forms, and responses from 10 agents who stated no winter wheat was grown in their jurisdiction, 109 responses were used in the analysis (see Tab. 6). Eighteen respondents did not include state or county information. Those responses were used in all analyses except to examine regional differences in responses.

Tab. 6: Number of survey responses by state and number of responses without location information.

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

Location data based on IP addresses for these responses were available; however, it was found these data to match the actual locations poorly in the cases that included state and county information, and therefore IP addresses was not used. 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. Thus, the regional analysis sample was comprised of responses from 99 individuals who provided location information (state and county, or region). To geo-locate these 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 (Appendix 1) 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 timescales 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 and climate variability and extremes, with responses to this question describing the needs of their 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 (section 3.4). 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. Lastly, the final two questions requested voluntary contact information for follow-up interviews (which were not conducted due to time constraints) and additional comments. See the appendix 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 (Mavi and Tupper 2004, Cabrera, Letson and Podestá 2007, Schneider and Wiener 2009, Prokopy et al. 2013, Takle et al. 2014) and seasonal forecast model development (Jia et al. 2015, Jia et al. 2016, 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.

3. Results

3.1 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 zero to 42 years). Forty-two percent of respondents indicated that 1–49 percent of producers in their county grew predominantly winter wheat; 48 percent of agents said that percentage was 50 or higher. Nine percent responded that no one grew predominantly winter wheat; these participants did not take part in the remaining survey. One percent did not know. The majority of advisors (87 percent) answered that producers grew predominantly unirrigated winter wheat, and about half (46 percent) answered that 50 percent 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.

Extension agents indicated that current conditions and 1-7 day forecasts were the most relevant lead-times for their advice to farmers, with 56 percent and 50 percent of

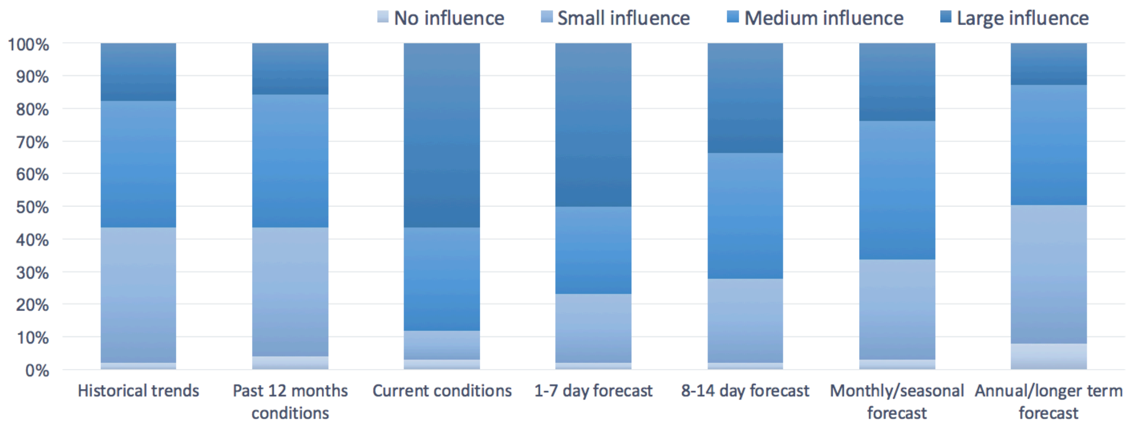

Fig. 8: Survey responses from extension agents about the level of relevance of different weather or climate forecast information for their advice to crop producers.

responses, respectively (Fig. 8). The longer the lead-time, the less influential the forecasts were, agents responded. Monthly and seasonal lead-times had "large influence" for 24 percent 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 percent on a daily or weekly basis) and least often with state climatologists and the State Department of Agriculture, with whom some agents have never interacted at all. Between these extremes and at comparable levels are seed producers, farm chemical dealers, other advisors, 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 percent of extension agents agreed or strongly agreed that "In the last five years, I've seen more variability (e.g., more extremes) in the climate across my county." Only 4 percent disagreed or strongly disagreed with this statement. Fifty-five percent of agents agreed or strongly agreed that "Climate variability hurts my growers more than it benefits them" while 2.5 percent 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. Thirty-three percent disagreed or strongly disagreed with the statement that "Current seasonal forecasts are insufficient for winter wheat producers," while 26 percent agreed or strongly agreed.

3.2 Decision timing

Planning patterns for most decisions were unimodal or bimodal (Fig. 9) meaning that agents indicated specific decisions were made only once or twice per year (Tab. 7 and Fig. 10). For example, August 30 was noted as the peak time for planning to plant winter wheat, May 28 for harvest planning, and July 24 for purchasing a specific crop variety.

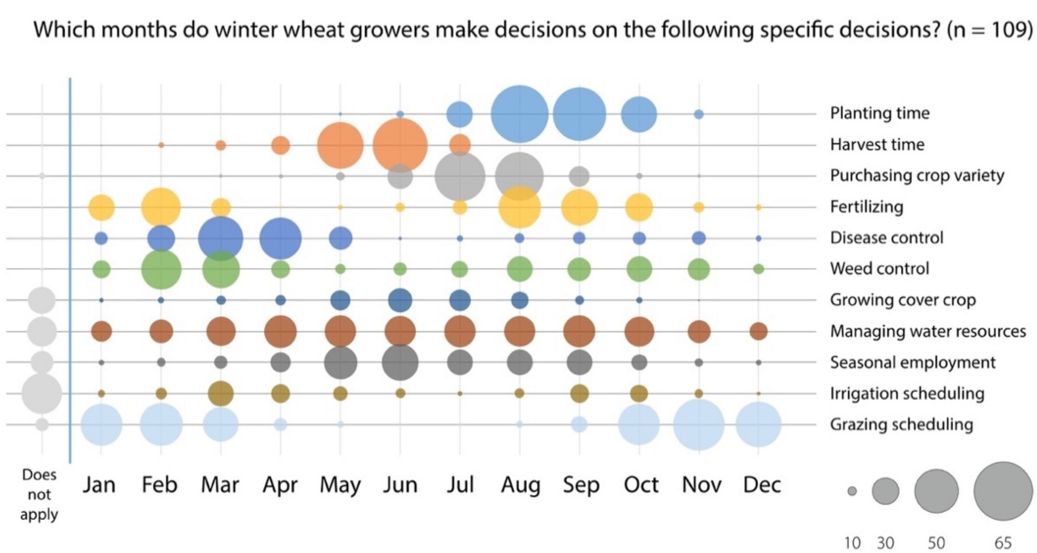

Fig. 9: This matrix shows when winter wheat growers plan for certain agricultural practices. The calendar months are listed on the x-axis, labeled at the bottom; practices are listed on the y-axis, labeled on the right. The size of the bubble represents how often a given practice was selected for that 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.

Bimodal decision peaks during spring and fall referred to practices that are conducted twice a year; for example, planning peaks for fertilizing occur on February 12 and September 5. To determine the average planning dates for bimodal planning decisions, the respective distribution was split at its minima into two sub-distributions, then calculated the peak time and time range for each of the two resulting unimodal sub-distributions. The sub-distributions did not always have the same lengths. Following this process, peak times were March 23 and October 4 for disease control planning, March 4 and September 17 for weed control, and April 1 and September 26 for irrigation scheduling. As Fig. 9 shows, planning for water resource management showed no particular peak but appeared relevant all year round. For this reason, it was excluded

From Fig. 10 and from some of the further analyses.

Regional differences in the timing of decision peaks or decision time spans were calculated by splitting all responses into roughly equal-sized subgroups, four by latitude

Tab. 7: 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	August 30, 1.35 months	
Harvest timing	May 28, 1.1 months	
Purchase crop variety	July 24, 1.45 months	
Fertilizer application	Spring: February 12, 0.71 months	Fall: September 5, 1.08 month
Disease control	Spring: March 23, 1.27 months	Fall: October 4, 1.09 month
Weed control	Spring: March 4, 0.93 months	Fall: September 17, 1.58 months
Growing cover crops	June 11, 1.95 months	
Managing water resources	No peak, year round	
Seasonal employment	June 20, 3.7 months	
Irrigation scheduling	Spring: April 1, 1.68 months	Fall: September 26, 1.52 months
Grazing scheduling	December 15, 3.55 months	

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 May 11 to June 8. Peak decision timing for fall fertilizing shifted by 35 days from south to north, from September 29 to August 25. Peak decision timing for spring disease control shifted by 37 days from south to north, from March 5 to April 11. And for seasonal employment, the decision time span increased by 93 days from west to east across the study area, from 66 days 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 example, planting for winter wheat takes place between early September and early October (Colorado State University 2010, Kansas State University 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 May 28, on average about 1.5 months before harvest time. Taking into account the time range in responses, the preferred lead-time for forecasts to inform harvest planning is zero to 2.5 months.

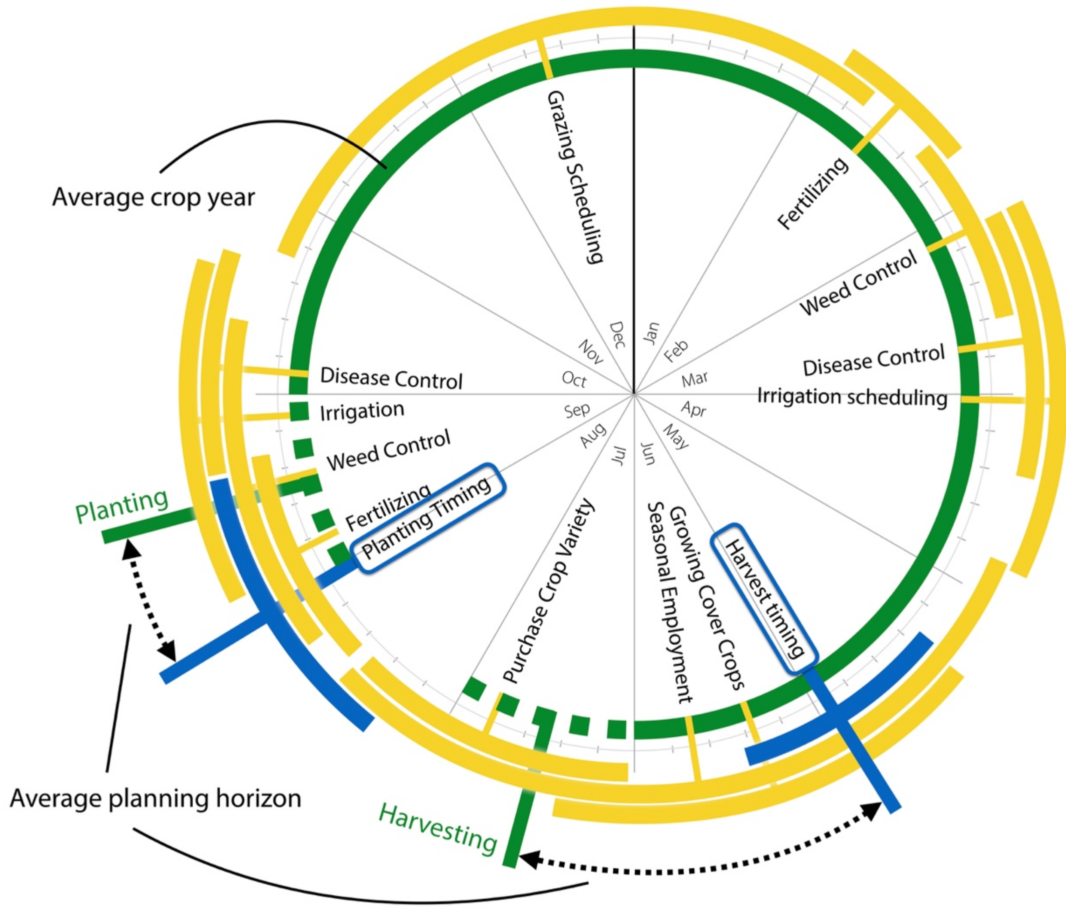

Fig. 10: This diagram, based on the responses shown in Fig. 9 and Tab. 7, represents the timing of when survey participants expected winter wheat producers to make key decisions (e.g., application of weed control) for their farm. Calendar months are represented as pie slices, labeled near the center of the diagram. Light gray ticks on the circle denote one fifth of each month. Average decision periods 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. 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 zero to 2.5 months. Water resource management is not included because it did not show a particular seasonality.

3.3 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. 11). (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 threats than others. For example, planning for harvest timing was most sensitive to unseasonal weather conditions overall, followed closely by planting timing. Least affected were planning for growing cover crops and seasonal employment. Fig. 11 also shows that drought and heat were considered greater threats during planting timing as compared to harvest timing, likely because seeds need moist soil

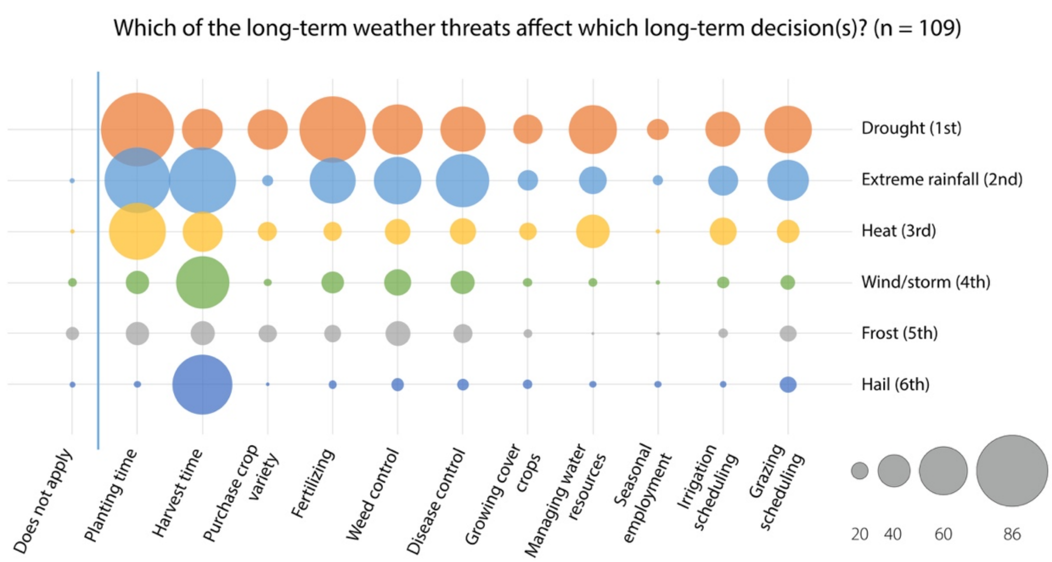

Fig. 11: This matrix shows what management practice decisions are impacted by which weather and climate threats. The practices are listed on the x-axis, labeled at the bottom; threats are listed on the y-axis, labeled on the right. The size of the bubble represents how often a given practice was selected for that given month by extension agents, with larger bubbles representing more responses. The ranking of threats is based on the total number of times they were associated with a practice. 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, e.g., hail impacts harvest time more than any other listed practice.

to germinate. 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.

3.4 Forecast preferences

Lastly, extension agents were asked what forecast information can help improve what 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. 12). Average precipitation ranked highest, followed by consecutive days without rainfall, deviation from average precipitation, and chances for extreme rainfall. In fifth place, 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 9th out of 11.

Finally, to ensure that products were tailored for south-central U.S. wheat producers, requests for specific forecast elements (e.g., average monthly precipitation) were ranked by month (Tab. 8). For each calendar month, this ranking was calculated by multiplying the number of survey responses per month for each management decision (i.e., the

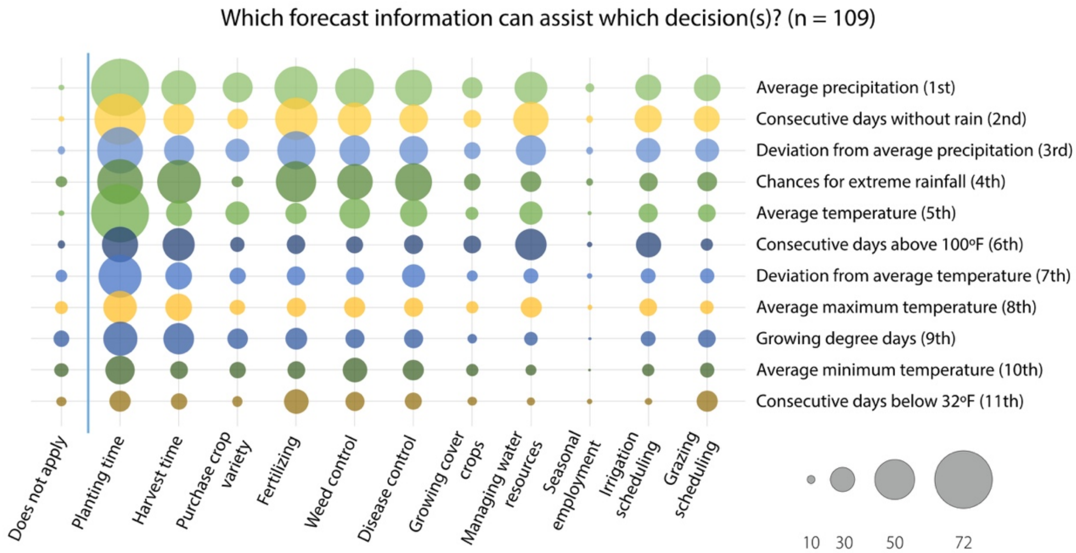

Fig. 12: This matrix shows which forecast elements help producers plan for which practices. The practices are listed on the x-axis, labeled at the bottom; forecast elements are listed on the y-axis, labeled on the right. The size of the bubble represents how often a given practice was selected for that given month by extension agents, 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 to 11 relate to temperature.

underlying data for Fig. 9) by the associated number of responses per forecast element for each management decision (i.e., the underlying data for Fig. 12). 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, and the forecast-element totals were ranked for each calendar month, as shown in Tab. 8. Average precipitation ranked first and consecutive days without precipitation ranked second throughout the year. The ranking of the remaining forecast elements varied from month to month.

Tab. 8: Ranking for forecast elements based on monthly decision-timing and forecast preferences for each decision.

	Ranking												
Forecast Element	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 above 100°F	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 below 32°F	11	9	10	11	11	11	11	11	11	11	11	10	7

4. Discussion and Conclusion

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 management decisions addressed by the survey occurred with a distinct seasonality once or twice per year, and they peaked from one to three months before the respective practice was conducted. 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.

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 others changed ranks from month to month. Comparing the northern (eastern) vs. southern (western) part of the study region, 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 suggested that winter wheat producers plan for the surveyed subset of management decisions (e.g., planting, harvesting) only one to 2.5 months before operationalizing those plans (Kansas State University 1997, Colorado State University 2010). These lead-times are well within the capabilities of current models in seasonal forecasts, such as the North American Multimodel Ensemble, with up to 7 months lead-time (Kirtman et al. 2014), or the Geophysical Fluid Dynamic Laboratory's Forecast-oriented Low Ocean Resolution (FLOR) model, with up to 12 months lead-time (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 our 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 U.S. (Barnston et al. 1994, van den Dool 1994, Balmaseda et al. 1995, Lau et al. 2002, Wen et al. 2012, Beraki et al. 2014, Saha et al. 2014). 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 et al. 1988, Sonka et al. 1992, Changnon 2004, Schneider and Wiener 2009).

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. 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). In addition, survey respondents only represented growers who actually interact 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 our participants had about their clients. The survey was also unable to say whether the preference for a zero to 2.5 month decision lead-time was caused by the limited forecast skill of current seasonal climate forecasts or because of other management issues. In other words, would the decision lead-time have been longer if producers thought that more skillful forecasts were available? As a result, we recommend ongoing 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 (Kansas State University 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 have fundamental value in communicating user needs to forecasters and forecast model developers. The results provide insights into the timing of major long-term 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.

5. Acknowledgements

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Chapter 4 - Assessing Model Accuracy of Seasonal Climate Forecasts for Winter Wheat Producers in the South-Central United States

To be submitted as:

Klemm, Toni & Renee A. McPherson: Assessing Model Accuracy of Seasonal Climate Forecasts for Winter Wheat Producers in the South-Central United States.

Abstract

Seasonal climate forecasts have been used by the agricultural community for decades in decision planning and have been critiqued, for example, for their lack of skill or lack of relevant information. This study analyzed whether a high-resolution, single-model seasonal climate forecast, tailored to the needs of winter wheat producers in the south-central United States, is more accurate than a 5-year seasonal persistence forecast.

Average monthly temperature, surprisingly, was almost never forecasted more accurately by the model, and the model error was particularly high in summer at long lead-times. Model forecasts for average monthly precipitation showed strong seasonality and were more accurate than persistence during winter across in large parts of Texas for all lead-times (zero through 11). On the other hand, the number of dry days and the number of days with extreme precipitation per month were forecasted more accurately by the model compared to persistence for summer across large parts of the study area and less accurately than persistence in winter. Overall, both extreme precipitation amounts and the number of dry days per month were vastly underestimated by model and persistence forecasts.

1. Introduction

For decades, the agricultural community has been using long-term weather and climate forecasts to inform decision making and to warn for unseasonal conditions (Klemm and McPherson 2017), for example, for decision planning on irrigation, planting, harvesting, or trading of livestock (Frisvold and Murugesan 2012). However, despite using these forecasts, producers raised critiques about numerous shortcomings, such as low accuracy, not enough forecast lead-time (Sonka et al. 1992), or a general lack of understanding in user needs (Schneider and Wiener 2009); thus, they often preferred to use historical records, year-to-date information, or other observation-based information for decision making (Changnon et al. 1988, Haigh et al. 2015). Moreover, Klemm and McPherson (2017) pointed out that publicly available seasonal forecast information by the National Weather Service's Climate Prediction Center (CPC) is not tailored to specific user needs, such as those of agricultural producers.

As a result, numerous studies addressed existing shortcomings by improving seasonal forecast models (O'Lenic et al. 2008, Delworth et al. 2012, Kirtman et al. 2014, Saha et al. 2014, Jia et al. 2015). Other studies explored forecast needs through collaboration with users and decision makers, for example in the southeastern United States (U.S.) (Breuer et al. 2006, Cabrera et al. 2006), the Midwest (Takle et al. 2014, Haigh et al. 2015), or the south-central U.S. (Klemm and McPherson in review), and how to improve communication pathways to decision makers (Dilley 2000, Hansen 2002, Lemos, Kirchhoff and Ramprasad 2012, Taylor, Dessai and de Bruin 2015, Allen and Stephens 2016). Qualitative studies described the complexity of decision processes in cattle production (Wilmer and Fernández-Giménez 2015, Wilmer et al. 2016). In addition, boundary organizations were created in the U.S. to build relationships with climate information users and to provide capacity and expertise for this type of research, such as the National Oceanic and Atmospheric Administration (NOAA) Regional Integrated Sciences and Assessment (RISA) teams (Miles et al. 2006, Lemos and Morehouse 2005), the Climate Science Center network of the U.S. Department of the Interior (DOI 2009), or the U.S. Department of Agriculture Climate Hubs network (Allen and Stephens 2016).

The study presented here is a continuation of a survey conducted by Klemm and McPherson (in review) about decision timing and forecast needs of winter wheat producers in the south-central United States (U.S., see chapter 3). We used their results (see Tab. 2) to set priorities in an analysis of the accuracy of a numerical climate model compared to a persistence forecast of the same spatial resolution (50 km by 50 km). Our intention was to explore the capability of a forecast model to provide tailored information of both averages and extremes requested by producers, according to the survey. Existing literature (see above) described general skepticism of the accuracy and quality of seasonal climate forecasts and the preference of users for historical and observed data. This study was intended to compare accuracy of a model forecast and a persistence forecast, which is derived from observational data, to assess if a model forecast could be a more accurate alternative to a persistence forecast for forecast elements of interest to winter wheat producers in our study area.

2. Study area, data, and methods

In this section, we address our dataset choices and explain our data processing procedures, including how and why we chose certain criteria and thresholds.

2.1 Study area climatology

Generally, monthly total average precipitation in the study area, a four-state region in the south-central U.S. comprised of Texas, Oklahoma, Kansas, and Colorado, ranges from 34 mm (January) to 85 mm (May); average monthly temperature ranges from 4 °C (January) to 26 °C (July) (Fig. 13). From October to March, precipitation is highest in eastern Texas and the Colorado Rocky Mountains and lowest in western Texas and eastern Colorado. From April to September, the precipitation peaks over the eastern half of the study area, especially eastern Oklahoma and Kansas, and decreases westwards. Temperature follows a south-north gradient all year, with maxima being observed in southern Texas and minima being observed in the Colorado Rocky Mountains.

2.2 Observational and model datasets

For our analysis we used a total of six temperature (monthly) and precipitation (daily and monthly) datasets: three gridded, observational datasets and three model datasets, all of which had the same temporal and spatial resolutions and same time period (Tab. 9). Using the National Oceanic and Atmospheric Administration (NOAA) Earth System

Tab. 9: Description of the observational and model datasets used in the study.

Dataset	Variables	Spatial Resolution	Temporal Resolution	Time period	Lead time
GHCN CAMS	Air temperature	0.5° x 0.5°	monthly	1980-2014	-
CPC Global Unified Precipitation	Total Precipitation	0.5° x 0.5°	daily	1980-2014	-
NOAA PREC/L	Total Precipitation	0.5° x 0.5°	monthly	1980-2011	-
GFDL FLOR B01	Air temperature	0.5° x 0.625°	monthly	1980-2014	0-11 months
GFDL FLOR B01	Total Precipitation	0.5° x 0.625°	daily	1980-2014	0-11 months
GFDL FLOR B01	Total Precipitation	0.5° x 0.625°	monthly	1980-2011	0-11 months

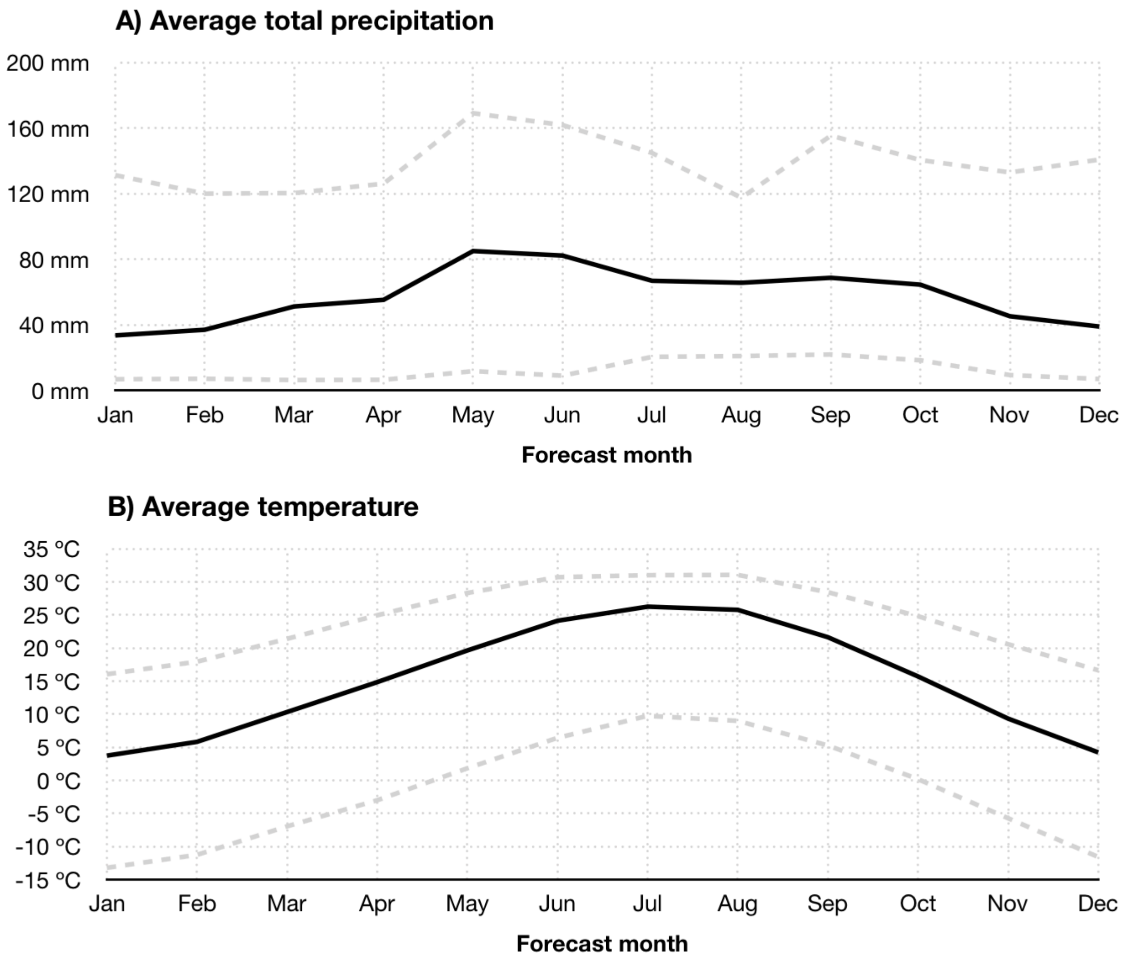

Fig. 13: Observed averaged for (A) monthly total precipitation and (B) monthly average temperature across the study area. Solid lines represent averages, dashed lines represent minima and maxima.

Research Laboratory Physical Science Division dataset catalogue, we selected the Global Historical Climatology Network CAMS dataset for average monthly air temperature (Fan and van den Dool 2008), the CPC Global Unified Precipitation dataset for daily total precipitation (Xie et al. 2007, Chen et al. 2008), and NOAA's Precipitation Reconstruction over Land dataset for monthly precipitation (Chen et al. 2002).

Using the National Center for Atmospheric Research Earth System Grid data catalogue (www.earthsystemgrid.org), we obtained corresponding model temperature (monthly) and precipitation (daily and monthly) hindcast data from the Geophysical Fluid

Dynamics Laboratory (GFDL) Forecast-oriented Low Ocean Resolution (FLOR) model, variation B01. This non-flux-adjusted climate model output 12 historical simulations, all of which use identical model physics but were initiated with different initial conditions (Vecchi et al. 2014, Jia et al. 2015, Jia 2017). Seasonal forecasts are issued every month for the coming 11 months, starting with the month of issuance (lead zero) to 11 months out (lead 11). For example, the seasonal forecast issued in January 2010 covered January 2010 to December 2010. Issuing forecasts in the case of our study ended in December 2010. This, however, means that for every month in 2011 the number of forecasts decreased from January to December.

A seasonal persistence forecast (hereafter simply called persistence forecast) was used to compare against the monthly model forecasts. It was calculated as the unweighted average of the preceding five years for the respective month of interest. For example, the persistence forecast for December 1985 was the average of observations in December 1980, December 1981, December 1982, December 1983, and December 1984. For the analysis of daily data, the same was done in a daily fashion. As a result, the comparison period started in 1985 and ended one year prior to the end of the data record (2010 for monthly precipitation and 2013 for all other forecast elements).

2.3 Survey data input

The forecast elements prioritized for this study were based on survey data collected by Klemm and McPherson (in review) from 109 agricultural advisors in Texas, Oklahoma, Kansas, and Colorado. The study focused on decision timing and seasonal forecast preferences of winter wheat producers in the south-central United States (U.S.), where winter wheat is the dominant crop type. The researchers found that decisions on practices like planting, harvesting, or fertilizing had a strong seasonality and were planned for only in certain times of the year, specifically about one to three months before they were carried out. Klemm and McPherson calculated a ranking of 11 forecast elements and found that producers' decisions most often required forecasts of average total precipitation, consecutive days without precipitation, the deviation from average precipitation, chances for extreme precipitation, and average temperature (Tab. 8). We analyzed model performance on four of the top five forecast elements for each month: average precipitation, consecutive days without precipitation, chances for extreme precipitation, and average temperature. Because of our method of analysis, we decided to leave out deviation from average precipitation.

Our goal was to evaluate model accuracy for forecast elements most relevant to winter wheat producers in the south-central U.S. while also accounting for basic forecast abilities of a seasonal forecast model. Therefore, we decided to interpret "consecutive days without precipitation" and "chances for extreme precipitation" as "number of days per month with no precipitation" and "number of days per month with extreme precipitation" because (1) it is highly unlikely that on a daily resolution with lead-times of several months, extreme precipitation occurrence or no precipitation occurrence will be forecasted correctly, and (2) knowing months in advance exactly when extreme precipitation will occur with unknown skill levels does not provide producers with actionable information.

In the past, various definitions have been applied to define extreme precipitation and no precipitation. Groisman et al. (2005) considered the top 0.3% of daily rainfall events in a study of Northern Hemisphere changes in intense precipitation. Zhai et al. (2005) used the 95th percentile of days with rainfall of all weather stations for a trend analysis of extreme precipitation frequency in China between 1951 and 2000. Higgins et al. (2011)

took into account the top 50 daily events when studying the frequency of extreme precipitation events between 1950 and 2009. Villarini et al. (2013) analyzed extreme precipitation over the U.S. Great Plains using a peak-over-threshold approach with the 95th percentile of non-zero precipitation values for each of the 447 weather stations in their study, accounting for regional differences in the absolute values of the threshold. Schoof and Robeson (2016) used a percentile classification developed by the Expert Team on Climate Change Detection and Indices (ETCCDI) under the umbrella of the World Meteorological Organization Commission for Climatology/World Climate Research Programme project on Climate Variability and Predictability; these values are commonly referred to as ETCCDI indices (Schoof and Robeson 2016).

In our analysis, we used ETCCDI indices on a grid-cell basis, rather than a fixed precipitation threshold (e.g., 50 mm/day) or a predetermined number of extreme events (e.g., the 100 highest precipitation days) as "they are easy to interpret and are directly related to impacts in agriculture and other sectors" (Schoof and Robeson 2016, p. 29). Defining threshold by grid cell also acknowledged the strong precipitation gradient across the study region, from the Gulf of Mexico in the southeast to the Rocky Mountains in the northwest (see PRISM Climate Group). In accordance with ETCCDI, we chose the 95^{th} (99^{th}) percentile of all days (January 1^{st} 1985 to December 31^{st} 2013) with precipitation equal or greater than 1 mm as the threshold for very (extremely) wet days, and days with less than 1 mm of daily precipitation as dry days (Tab. 10).

2.4 Data preparation and processing

All data processing was done using the NCAR Command Language (NCL), netCDF Operators (NCO), and bash shell scripting, with the occasional use of Microsoft Excel for

Tab. 10: Definitions or precipitation thresholds used in the study.

Classification	Definition
very wet days	95th percentile of days with ≥ 1 mm precipitation
extremely wet days	99th percentile of days with ≥ 1 mm precipitation
dry days	days with < 1 mm precipitation

testing and verifying procedures. Model and observational data were obtained for a global domain for the time periods of interest. Observations were subset using a shapefile of the four-state study region (Texas, Oklahoma, Kansas, and Colorado) created in QGIS with data from Global Administrative Areas (GADM, www.gadm.org), a web portal for geographic shapefile datasets. Model data was first subset to a latitude-longitude rectangle around the study region with about 1.5° buffer around the four states and then regridded using bilinear interpolation in NCL ("linint2") from its original 0.5° x 0.625° grid to a 0.5° x 0.5° grid that matched the observational datasets in location and spatial resolution. After bias correcting the model data (see next section), we calculated the differences between each forecast dataset and its observational counterpart for each forecast month, lead-time, and model run. We also calculated the difference between each persistence forecast and its associated observations for a given month. For example, the persistence forecast for December 1985 is the average of observations in December 1980, December 1981, December 1982, December 1983, and December 1984. Finally, we compared the absolute differences between model and observations (absolute model error) and persistence and observations (absolute persistence error) to assess whether forecast or persistence had smaller errors. This approach is similar to calculating a skill score.

We used a factor-based bias correction for precipitation and a difference-based bias correction for temperature, as described by Maraun et al. (2010) and Crochemore et al. (2016), respectively, to correct systematic model biases. We calculated the bias at lead zero for each calendar month and removed this monthly bias from all lead times (zero to 11) for the respective month. Biases were computed for each grid cell and forecast month (January to December) by comparing the lead zero forecast for each month and year to their observational counterparts and then averaging the differences by forecast month. For precipitation, we *divided* each lead zero forecast value for every grid cell by its corresponding observational measurement; a quotient greater (smaller) than one meant over-prediction (under-prediction). These quotients were averaged by forecast month and represented the relative bias at lead zero for a particular forecast month, which we subsequently used for bias correction. For temperature, we *subtracted* monthly, individual observations from their lead-zero model counterpart before averaging these error by forecast month to obtain the lead-zero bias for every month, subsequently used for bias correction.

Graphs in Fig. 14 show minimum, maximum, and average values for precipitation and temperature bias for every forecast month. Precipitation bias showed two distinct patterns. From November to April, over-prediction of precipitation prevailed throughout most of the study region, with maxima in the western part of the domain and minima in the southeast that became an under-prediction during November and December. From

May to September, the model ensemble under-predicted precipitation across large parts of the region, in particular the eastern half.

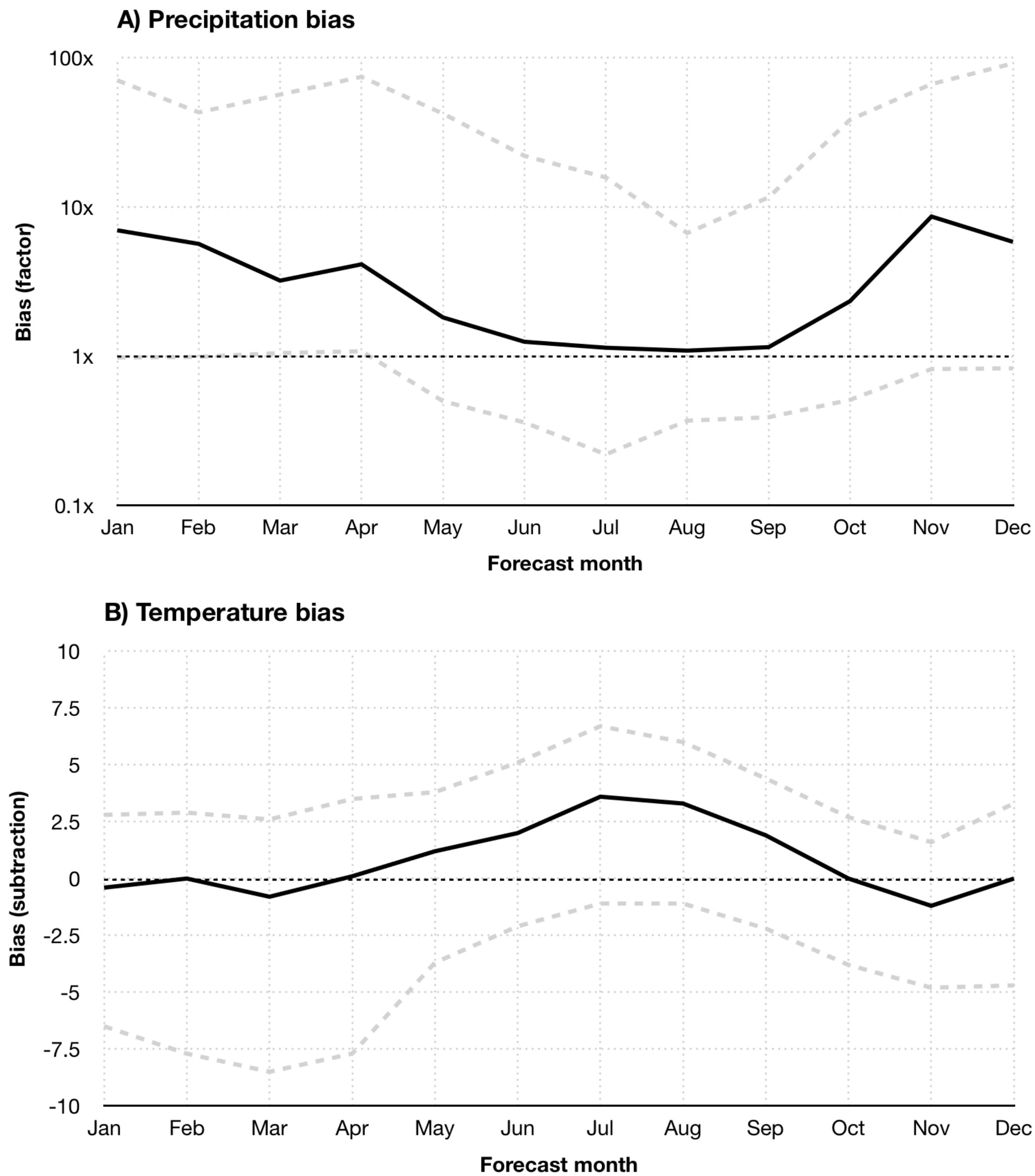

Fig. 14: Biases at lead zero for (A) monthly total precipitation and (B) monthly average temperature by forecast month. Note that the y axis in (A) is logarithmic. Errors above one (zero) indicate overestimation of the model for precipitation (temperature); errors below one (zero) indicate underestimation of the model for precipitation (temperature). Solid lines represent monthly averages, dashed lines represent minima and maxima across the study region.

Temperature biases showed three patterns. From December to April, over- and under-prediction occurred across roughly equal portions of the study region, with over-prediction covering Kansas and Oklahoma and parts of Colorado and Texas, and under-prediction occupying the remaining study region. From May to October, temperatures across most of the study region were over-predicted, except for parts of southern Texas and Colorado. In November, temperatures across most of the study region were under-predicted, with the exception of northwestern Kansas, eastern Colorado, and isolated spots in Texas and Oklahoma.

After determining monthly biases, we used linear scaling (Maraun et al. 2010, Crochemore et al. 2016) with precipitation forecasts, dividing each forecast datasets by their corresponding biases to create a bias-corrected precipitation. To correct temperature forecasts, we used a delta method (Maraun et al. 2010) and subtracted the bias from forecasts for corresponding months.

We also applied the factor-based method to correct *daily* precipitation. However, the patterns of these were very different from those of the monthly precipitation. The bias calculation determined that most of the model data at lead zero vastly overestimated precipitation, and correction therefore resulted largely in reducing the modeled values. This reduction, however, changed the model forecast values so much that for some grid cells all data were below 1 mm. Consequently, these data became unusable for creating thresholds for the 95th and 99th percentile (see below), because 1 mm was the threshold above which the 95th and 99th percentile were calculated. As a result, daily precipitation data were not bias-corrected.

3. Results

In this section we present and describe the results of the comparison of absolute model forecast error and absolute persistence forecast error to answer our research question: "Can existing seasonal forecast models provide meteorological variables as requested by winter wheat farmers with better accuracy than a persistence forecast?" We present results first for monthly total precipitation, then average air temperature, the number of days per month with extreme precipitation, and finally the number of days per month less than 1 mm of precipitation (dry days).

3.1 Total monthly precipitation

Observed average monthly precipitation between 1985 and 2011 had a bimodal distribution in our study area, with a seasonal pattern of local maxima in spring and fall and local minima in summer and winter. This result is in agreement with other datasets, e.g., from the National Centers for Environmental Information. The pattern was also

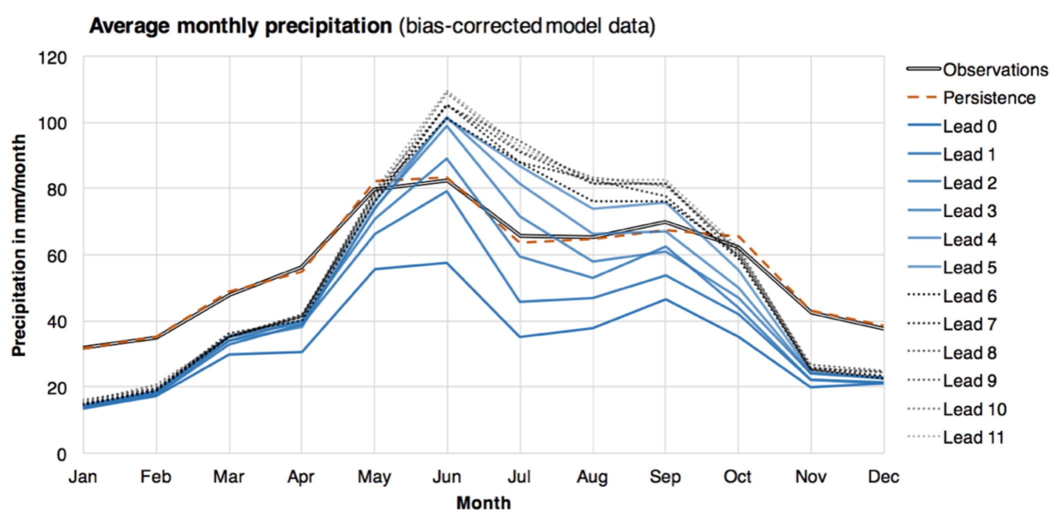

Fig. 15: Average total precipitation per calendar month for 1985 to 2011, for observations (black double line), persistence forecast (red dashed line), and leads zero to 11 of the bias-corrected model forecast (lead zero to five: blue solid lines, lead six to 11: dotted grey lines). Note: The differences between observations and forecasts do not reflect the absolute errors described in the text. The persistence forecast in this case is essentially a climatological average.

present in both persistence and model forecast (Fig. 15). Monthly averages of the persistence forecast were roughly equal to observations, due to the way they were calculated.

The bias-corrected model forecast generally underestimated precipitation at shorter lead-times in all months and over-estimated it at longer lead-times during summer. We also found that the uncorrected data over-estimated monthly summer precipitation, albeit not as much as the bias-corrected data. It should be noted that the differences between average observations and average forecasts in Fig. 15 are different from the absolute errors and absolute error differences discussed in the following sections. While differences between model forecasts and observations in Fig. 15 reflected averages of the actual model error that included magnitude and direction of the error, averages of the absolute errors only included the magnitude, but not the direction of the error.

The following analysis was done using model data that was not bias-corrected. Comparing absolute model and absolute persistence errors, shown in Fig. 16, two distinct patterns emerged: in summer and early fall (June to September), the absolute persistence error was smaller nearly throughout the study area (green shaded areas in Fig. 16). In late fall and winter (November to February), considerable parts of the study area showed smaller model error (blue shaded areas in Fig. 16: Maps showing the differences between absolute model and absolute persistence forecast errors for every target month, averaged for all lead-times. Green (blue) shaded areas indicate smaller persistence (model) error.). Spring and fall were transition periods. Fig. 16 shows that during summer, averaged over all lead-times, the absolute error of the persistence forecast was smaller across the entire study area, especially in June and July over the western parts of Texas, Oklahoma, and

Kansas. In winter, particularly in November and December, the model error was smaller in parts of Texas, Oklahoma and Kansas.

Differences in the spatial distribution and magnitudes of error differences between absolute persistence error and absolute model error, averaged by target month, were similar across different lead-times (Fig. 17), suggesting a seasonal character of the model

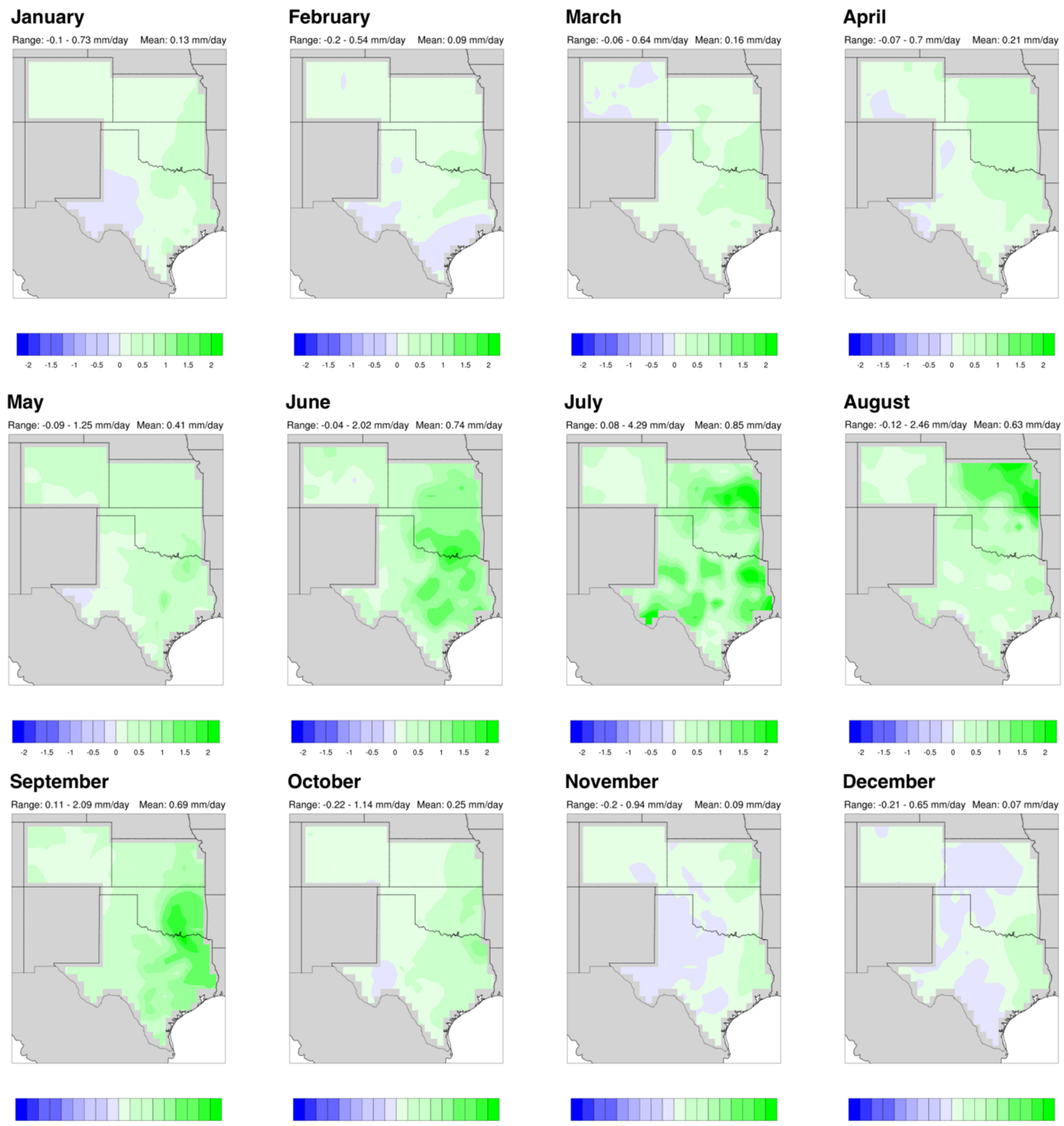

Fig. 16: Maps showing the differences between absolute model and absolute persistence forecast errors for every target month, averaged for all lead-times. Green (blue) shaded areas indicate smaller persistence (model) error.

forecast. This result suggests that the absolute model error is more dependent on the target month than on the forecast lead-time. An exception in our analysis was the lead-zero forecasts for summer, when the error differences across the study area were considerably smaller compared to other leads of the same month (Fig. 17, bottom). This result could be due to two reasons: (1) large parts of the study area were generally under-predicted by the model forecast at lead zero but over-predicted at lead-times longer than four months, or (2) our bias correction method (see section 2.4), which generally reduced the model error at lead zero, but generally increased model errors at longer lead-times, especially in summer. One possible reason for this abnormal error at short lead-times is initialization shock (Jia 2017), which can occur in non-flux-adjusted models like GFDL's FLOR model, whereby energy fluxes of atmospheric and ocean components of a coupled forecast model are not in sync at initiation (Diro 2015, Mulholland et al. 2015). Consequently, using lead zero as a basis for bias correction of all lead-times would increase the error of the remaining lead-times. Fig. 18 shows that error differences were similar for leads zero through 11 for forecasts for November to May, with average differences fluctuating by less than 0.1 mm/day between lead zero and lead 11 in these months. Forecasts for June to October had larger average changes (0.16 to 0.46 mm/day) and a larger increase in error difference with increasing lead-time.

Time series from 1985 to 2011 showed year-to-year variations in error differences but no clear pattern across months or multi-year trend (Fig. 19). Some years stood out by having very small or even negative error differences at lead zero and lead 11 (for example February 1988, April 1998, or October 1999, 2001, and 2003) while pre- or succeeding years had considerably larger differences. Fig. 19 also illustrates how dissimilar the absolute error differences were are at lead zero and lead 11 for summer and early fall as compared to forecasts for winter and early spring.

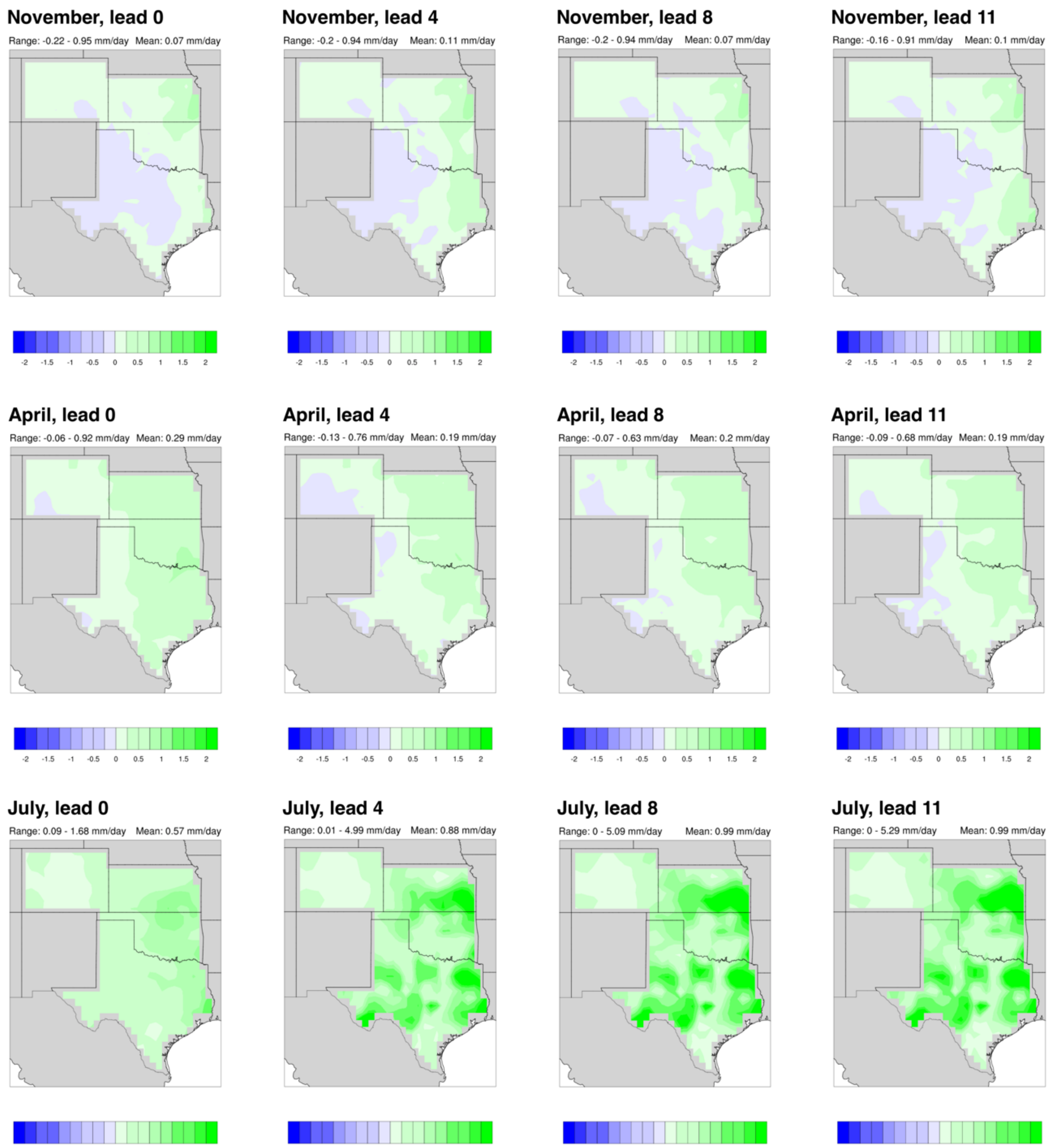

Fig. 17: Maps showing the differences between absolute model and absolute persistence forecast errors for forecasts for November, April, and July at lead zero, four, eight, and 11. Green (blue) shaded areas indicate smaller persistence (model) error.

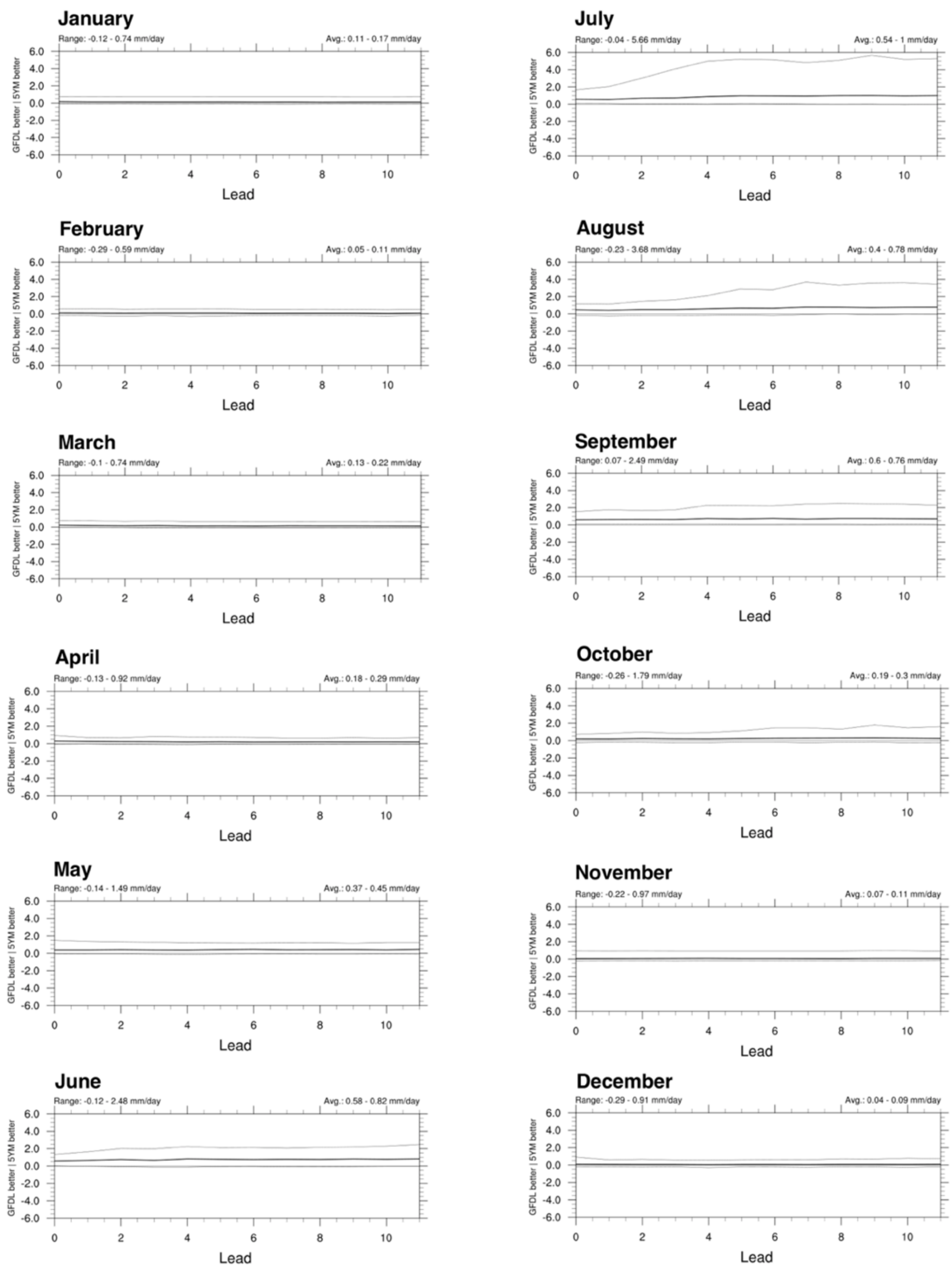

Fig. 18: Time series showing the differences of absolute model and absolute persistence forecast errors from January to December from lead zero to 11. The thick line represents the average, thin lines the minima and maxima across the study area for a respective lead-time. Values above (below) zero indicate smaller absolute persistence (model) error.

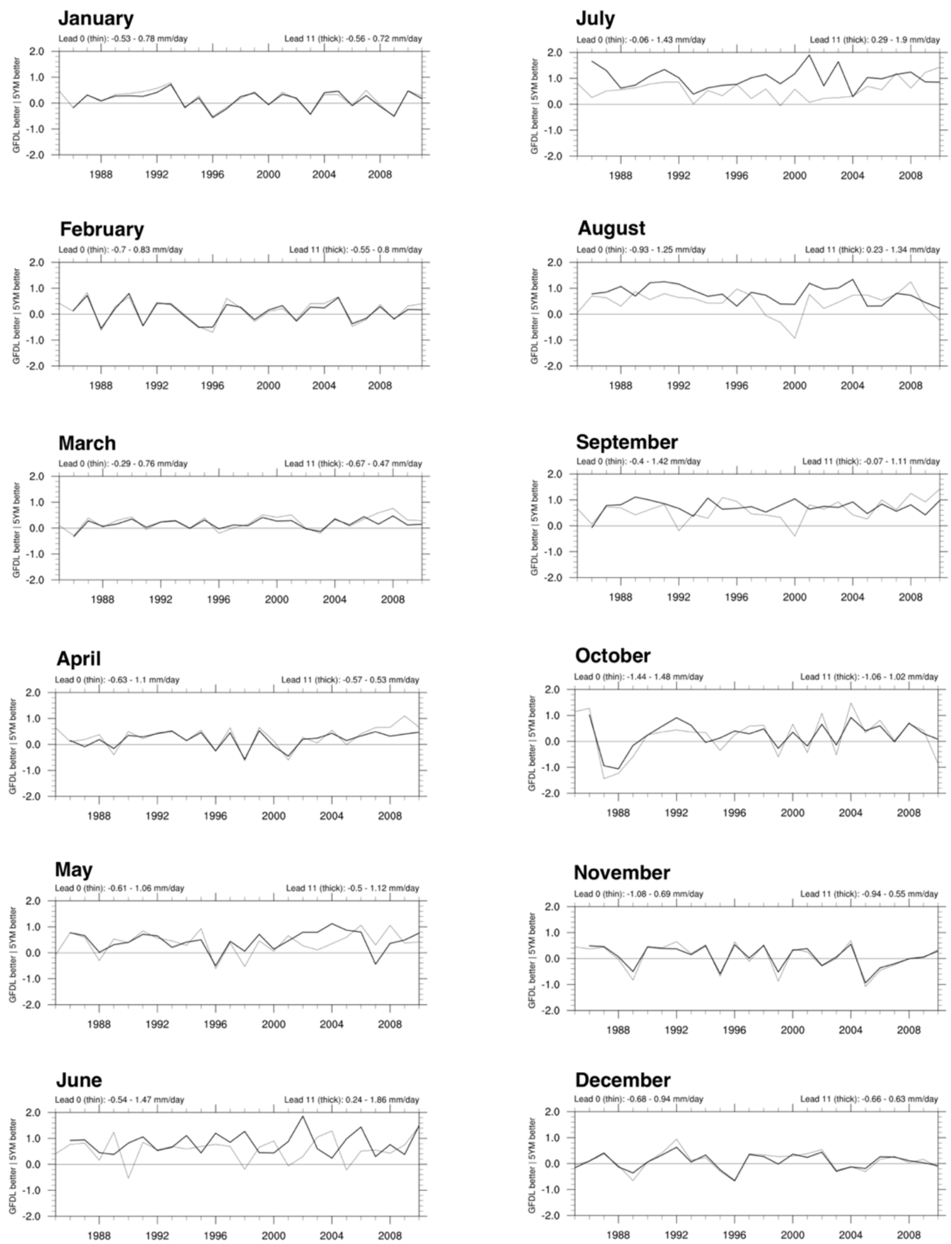

Fig. 19: Precipitation time series from 1985 to 2011 comparing averages of absolute model and absolute persistence forecast errors for every target month. Graphs show the difference between absolute model and absolute persistence error at the shortest (thin line) and longest lead (thick line). Values above (below) zero indicate smaller model (persistence) error.

3.2 Average monthly air temperature

Observed average monthly temperature had a unimodal pattern in our study area between 1985 and 2013, with a maximum in summer and minimum in winter. Like average total precipitation, this climatological pattern agreed with other datasets, e.g., from the National Centers for Environmental Information. The pattern was replicated by both persistence and bias-corrected model forecasts (Fig. 20). Similar to monthly precipitation (section 3.1 and Fig. 15), monthly averages of the persistence forecast for temperature were also similar to monthly averages of observations. The bias-corrected model forecasts generally underestimated temperature at shorter lead-times in all months and over-estimated it at longer lead-times during summer. It should be noted that the error differences shown in Fig. 20 between average observations and average forecasts are not the same than the differences in absolute error discussed here.

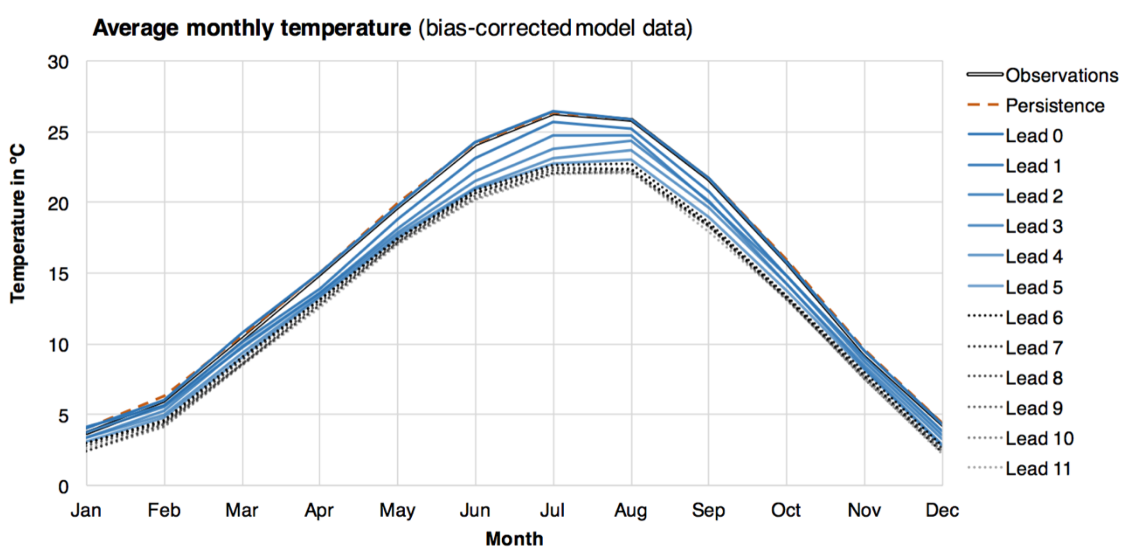

Fig. 20: Average temperature per calendar month for 1985 to 2013, for observations (black double line), persistence forecast (red dashed line), and leads zero to 11 of the bias-corrected model forecast (lead zero to five: blue solid lines, lead six to 11: dotted grey lines). Note: The differences between observations and forecasts do not reflect the absolute errors described in the text.

The following analysis was done with bias-corrected model data. Similar to monthly total precipitation, differences between absolute model error and absolute persistence error for monthly average temperature were lowest in winter and highest in summer when averaged by target month across lead zero to lead 11 (Fig. 21). Unlike for precipitation, however, the error difference was almost always above zero throughout the year, meaning that the absolute persistence error was smaller overall in the vast majority of months across the study area. When averaged by target month and lead-time (Fig. 22), negative error differences (i.e. smaller absolute model error than absolute persistence error) occurred only very rarely on very small number of grid cells along the Texas Gulf Coast (not shown) for forecasts for May (lead zero), July (leads two and three), and August (leads zero to two and four to 11), with error differences between -0.01 and -0.08 ºC. Individual years had more pronounced differences than the overall lead and target year average (Fig. 23), suggesting a minimal advantage for the model forecast over a persistence forecast, mostly for small parts of the Texas Gulf Coast for May, June, and July. In all other month-lead averages the absolute persistence error was smaller.

Comparisons of lead-times leading to the same target month, as shown in Fig. 24 for November, April, and July forecasts at leads zero, four, eight, and 11 (Fig. 22 and Fig. 23) for all months, suggest that, unlike precipitation (Fig. 17), error differences in temperature are considerably dependent on lead-time. Differences during summer increased considerably with lead-time (Fig. 24), due to an overall greater absolute model error at longer lead-times (not shown).

Time series from 1985 to 2013 (Fig. 23) showed that the increase in error difference with lead-time varied considerably from year to year, and often increased with lead-time during summer and early fall (June to September), but to a much smaller extent in winter.

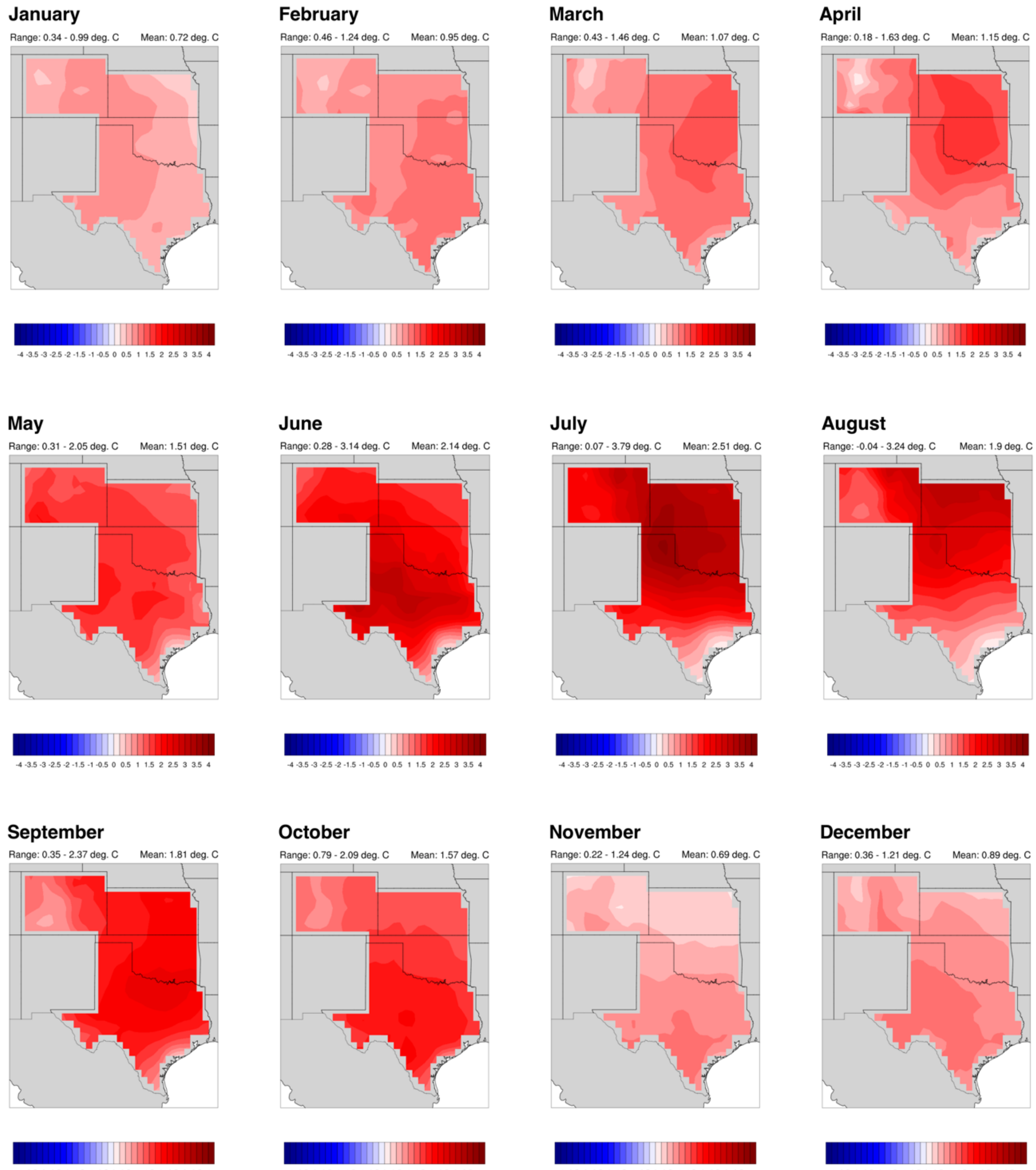

Fig. 21: Air temperature maps comparing absolute model and absolute persistence forecast errors for every target month, averaged for all lead-times. Red (blue) shaded areas indicate smaller persistence (model) error.

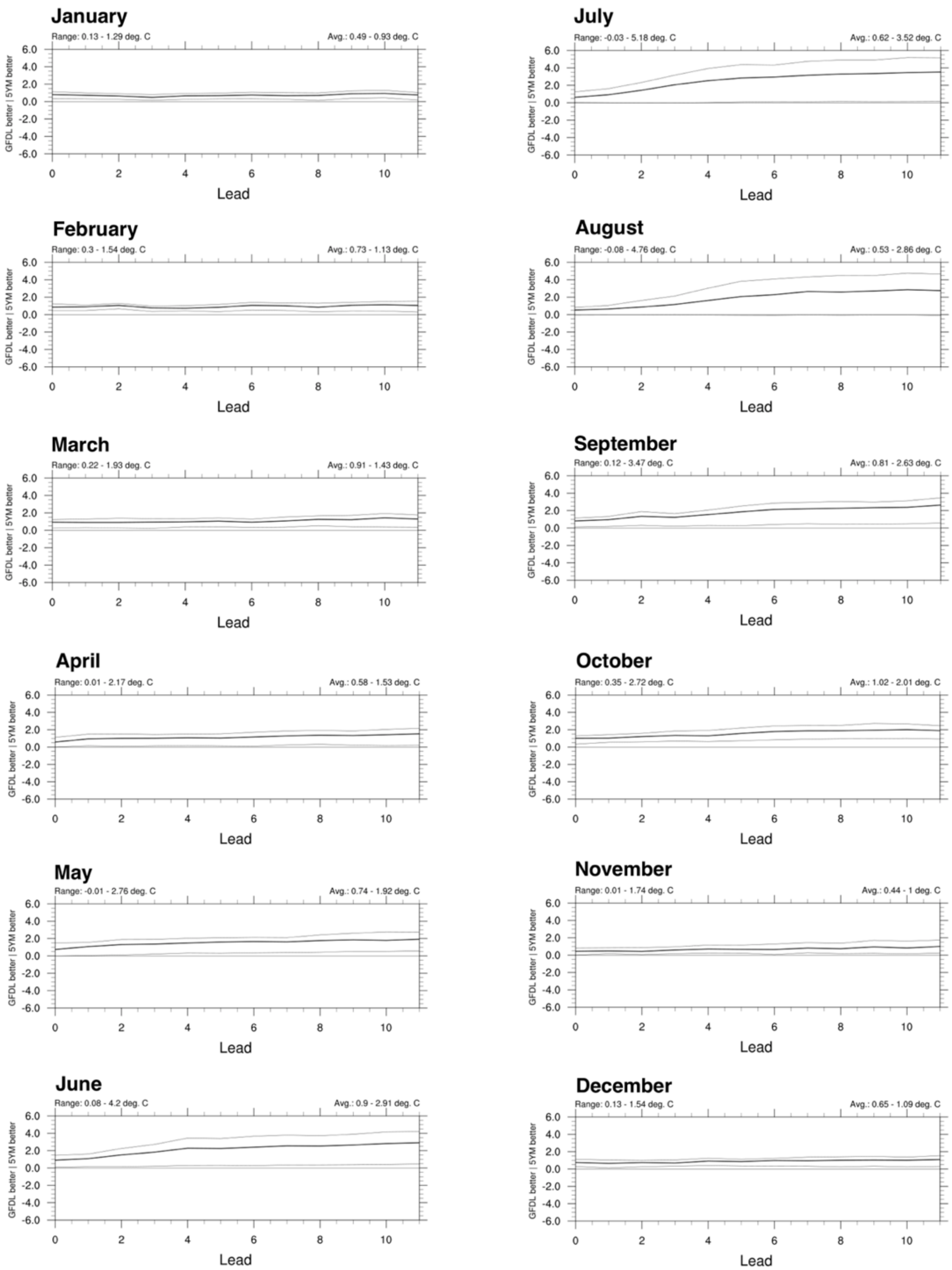

Fig. 22: Time series for temperature for January to December comparing averages of absolute model and absolute persistence forecast errors for lead 0 to 11. Graphs show the difference between absolute model and absolute persistence error. Values above (below) zero indicate smaller model (persistence) error.

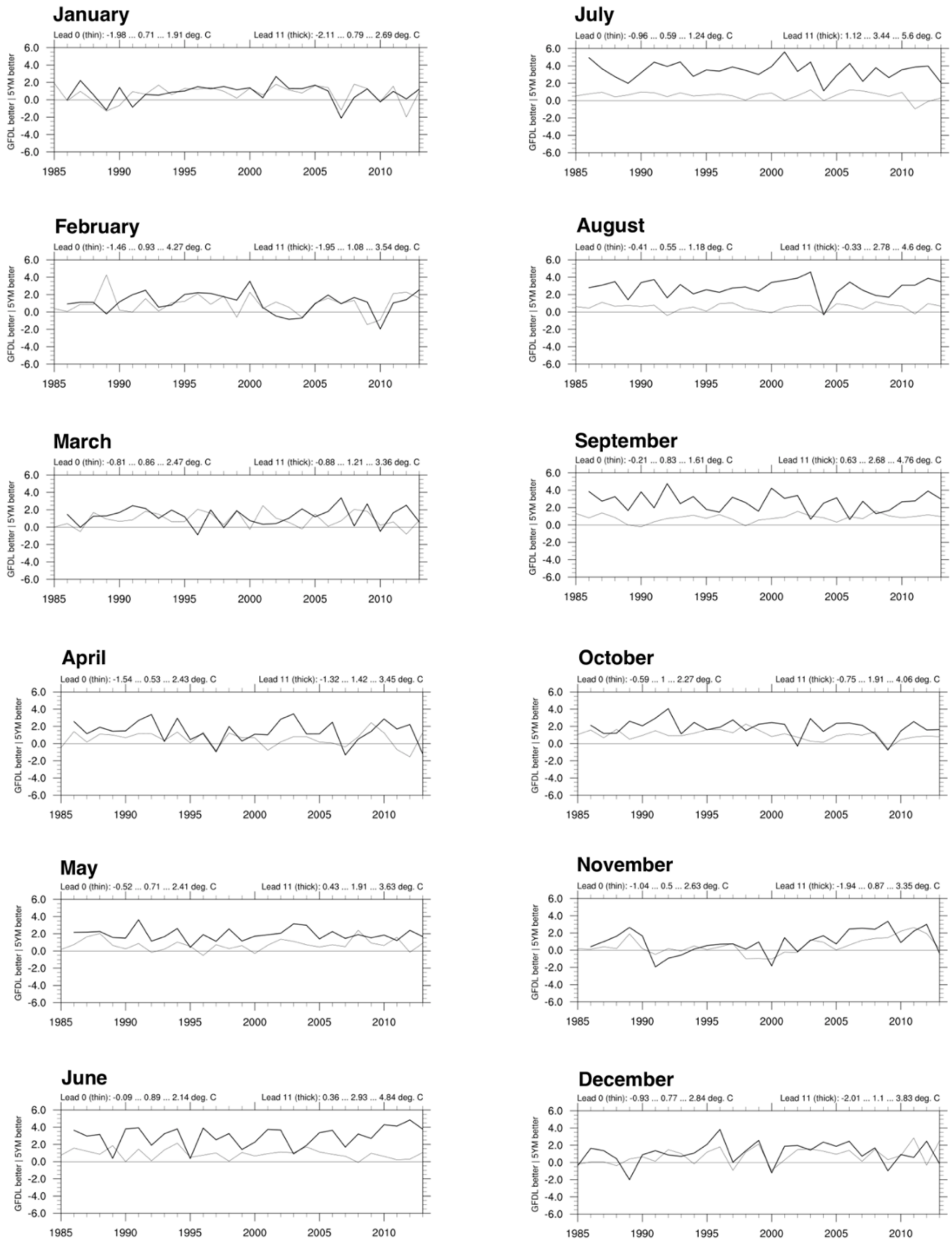

Fig. 23: Temperature time series from 1985 to 2013 comparing averages of error differences for forecasts for January to December (lead zero and lead 11). Graphs show the difference between absolute model and absolute persistence error at lead zero (thin line) and lead 11 (thick line). Values above (below) zero indicate smaller model (persistence) error.

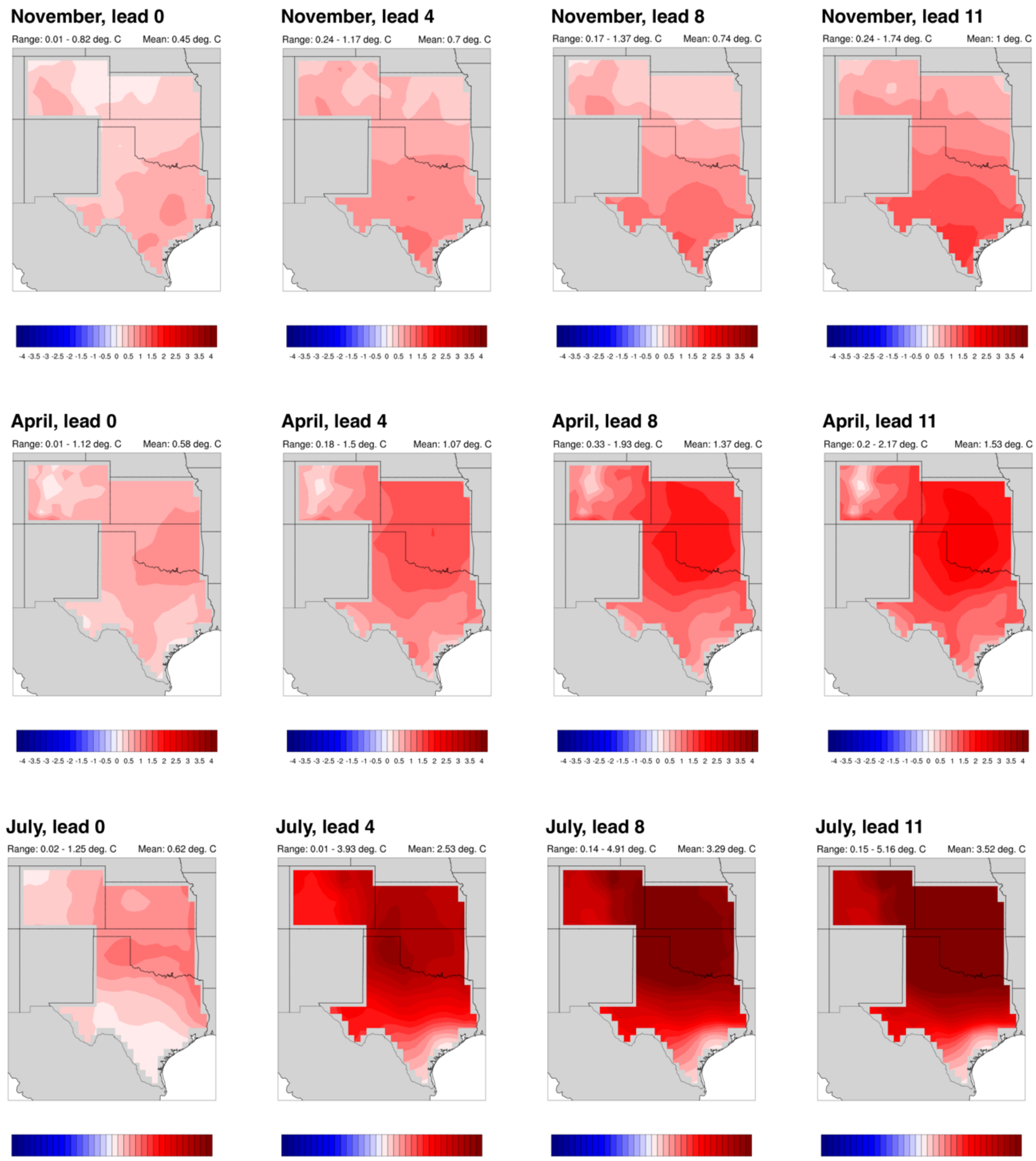

Fig. 24: Air temperature maps comparing error differences between absolute model and absolute persistence errors for November, April, and July at leads 0, 4, 8, and 11. Red shaded areas indicate smaller persistence error.

3.3 Number of days per month with extreme precipitation

For this part of our analysis, we deviated from the survey results that drove this study, which asked for a measure of the "chances for extreme rainfall." Since we used a single model forecast (with 12 runs driven by different initial conditions) instead of an ensemble forecast with different individual models, the resulting autocorrelation between the 12 model runs would have created a false level of confidence in the forecast as compared to an ensemble that used models with independent model structure and physics. Therefore, we decided to study the number of days per month with extreme rainfall as a proxy to quantify the forecast accuracy of extreme rainfall. In our view, this measure could still provide agricultural producers with a useful long-term decision support product, assuming the accuracy was sufficient.

We used daily observations and daily model forecasts for total precipitation from 1985 to 2013. We also used the observational dataset (1980-2012) to calculate a daily persistence forecast for 1985 to 2013 in a way similar to the monthly persistence forecast, with the difference that the persistence forecast was the average of the same calendar day (not month) from the previous five years. We defined extremes thresholds using two indices from the Project to Develop Datasets for Indices of Climate Extremes (CLIMDEX), an initiative by the World Meteorological Organization (WMO) Expert Commission on Climate Change Detection and Indices (ETCCDI). CLIMDEX provides 27 extremes indices for various variables (http://www.climdex.org/indices.html). CLIMDEX extreme precipitation indices have recently been used in various studies analyzing extremes in weather and climate models over North America, e.g., Bennett and Walsh (2015), Mutiibwa et al. (2015), Curry et al. (2016), Werner and Cannon (2016), Schoof and Robeson (2016), or Sobie and Murdock (2017). We used the 95th and 99th percentile of days with precipitation of at least 1 mm as threshold for very wet days and extremely wet days respectively, as defined by CLIMDEX. Tab. 11 defines the observational and model datasets as well as CLIMDEX indices we used. Our bias correction caused a reduction of daily precipitation, which for some grid cells resulted in no precipitation above 1 mm, which would have rendered this analysis useless. Therefore, we conducted our analysis (as well as the analysis of dry days in section 3.4) on uncorrected data.

Tab. 11: Precipitation datasets and extremes indices used.

	Precipitation datasets
Observations	CPC Global Unified Gauge-Based Analysis of Daily Precipitation
Model	GFDL Forecast-oriented Low Ocean Resolution (FLOR) version B01
	CLIMDEX indices
R95pTOT	95th percentile of precipitation on days with ≥ 1 mm precipitation
R99pTOT	99th percentile of precipitation on days with ≥ 1 mm precipitation

Generally, both persistence and model forecasts underestimated high daily precipitation amounts and overestimated low daily precipitation amounts, but the geographic distribution of minima and maxima across the study region was similar to the monthly precipitation results. These phenomena of over- and under-prediction of low and extreme precipitation are a known problem in forecasting (Chakraborty 2010, Fernandez-Gonzalez et al. 2015, North et al. 2013, Rodwell et al. 2010, Zhou and Wang 2017) and had an effect on the thresholds of the 95th and 99th percentiles and their respective counts, shown in Fig. 25 (95th percentile) and Fig. 26 (99th percentile). The 95th percentile thresholds (Fig. 25, top) for observations, for example, ranged from 7.9 mm/day to 43.1 mm/day; the 95th percentile thresholds for model and persistence forecasts ranged from 3.3 mm/day to 8.5 mm/day and 3.4 mm/day to 15.5 mm/day respectively. Therefore, applying the observational thresholds to the model data would have resulted in a vast under-estimation of extreme values in the model data. To account for the underestimation of extreme precipitation in model and persistence forecasts, individual thresholds for observations, model forecast, and persistence forecast were used, and the number of days per month exceeding the respective thresholds were normalized with the respective overall totals of values exceeding the 95th and 99th percentile per grid cell (Fig. 25 and Fig. 26, bottom). After normalizing, monthly totals of days exceeding the 95^{th} and 99^{th} percentile were calculated for observations as well as model and persistence forecasts, and model and persistence errors were calculated for each grid cell. After making these errors absolute, we calculated the difference in absolute model and persistence error. Values below zero meant smaller absolute model error, values above zero meant smaller absolute persistence error. Lastly, the errors were averaged by lead-time (0 to 11), target month (January to December), and year (1985 to 2013).

Overall, for the number of days per month exceeding the 95th (99th percentile), shorter leads showed greater model accuracy in most of the study area, while longer leads showed greater persistence accuracy in most of the study area (Fig. 27). More specifically, leads one to four (five) showed smaller absolute model errors in more than 50 percent of the study area, whereas leads five (six) to 11 showed smaller persistence errors in more than 50 percent of grid cells. An exception for both the thresholds is lead zero, in which the model forecast strong over-estimated the number of days with extreme precipitation, compared to leads one to four (five). The underlying cause for this is an abnormally high model error during the winter half year at lead zero for both the 95th and the 99th percentiles (see Fig. 28). The reason for this could be the low and relatively consistent winter precipitation, which might be captured more accurately by a persistence forecast

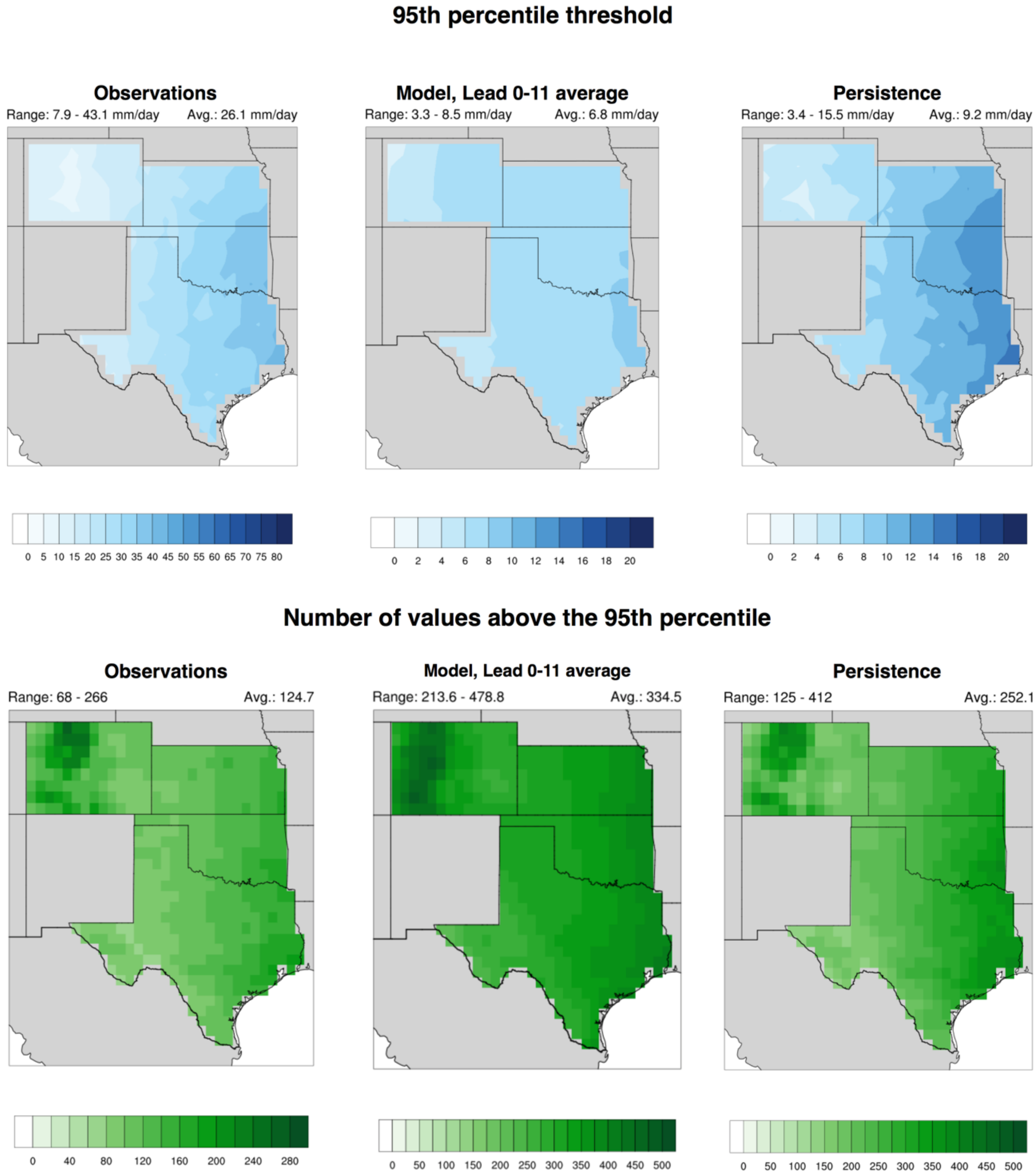

Fig. 25: 95th percentile thresholds (top) and the total number of daily values (1985-2013) that exceeded the threshold in each grid cell (bottom) for observations (left), model forecasts (center), and persistence forecast (right).

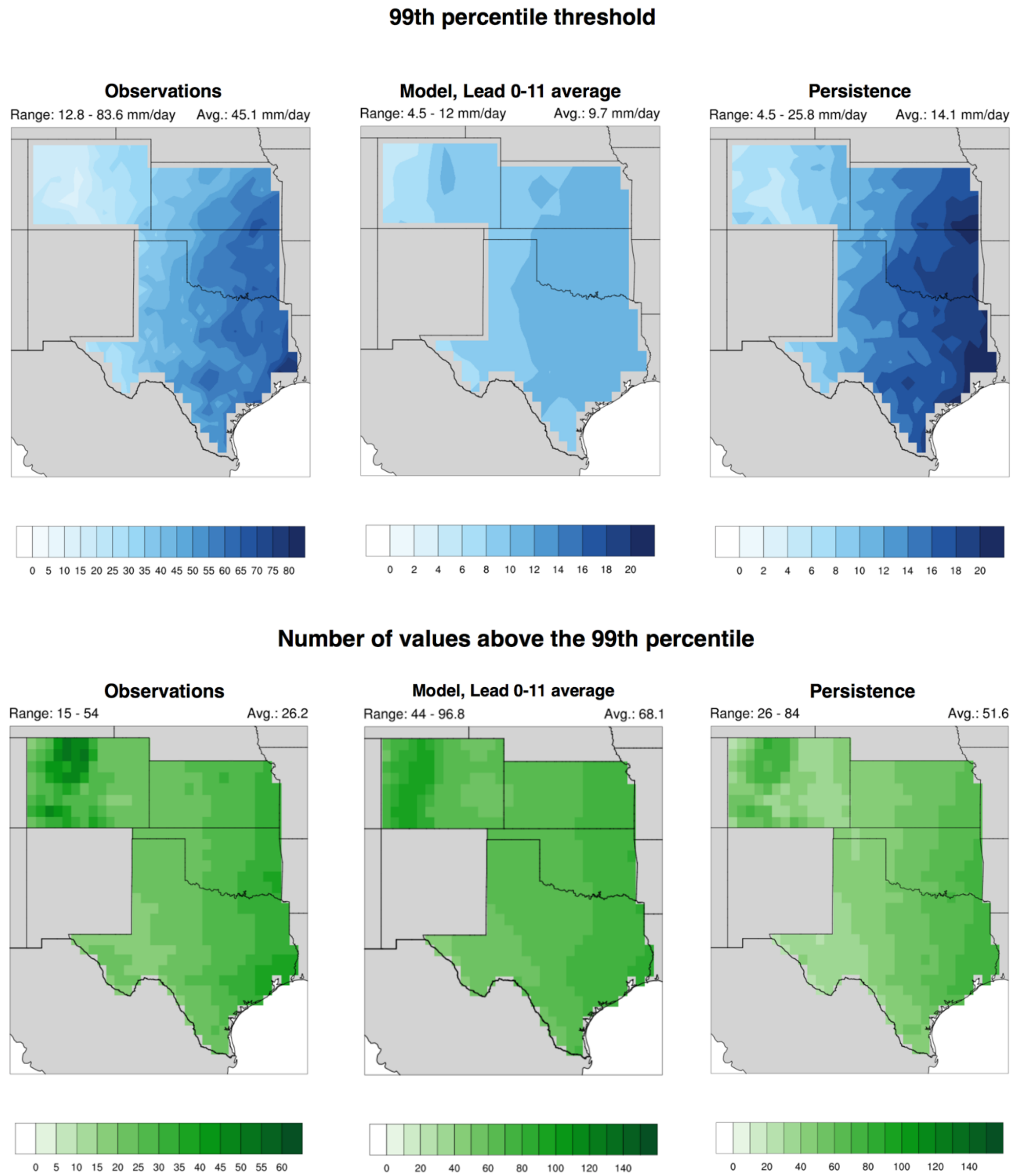

Fig. 26: 99th percentile thresholds (top) and the total number of daily values (1985-2013) that exceeded the threshold in each grid cell (bottom) for observations (left), model forecasts (center), and persistence forecast (right).

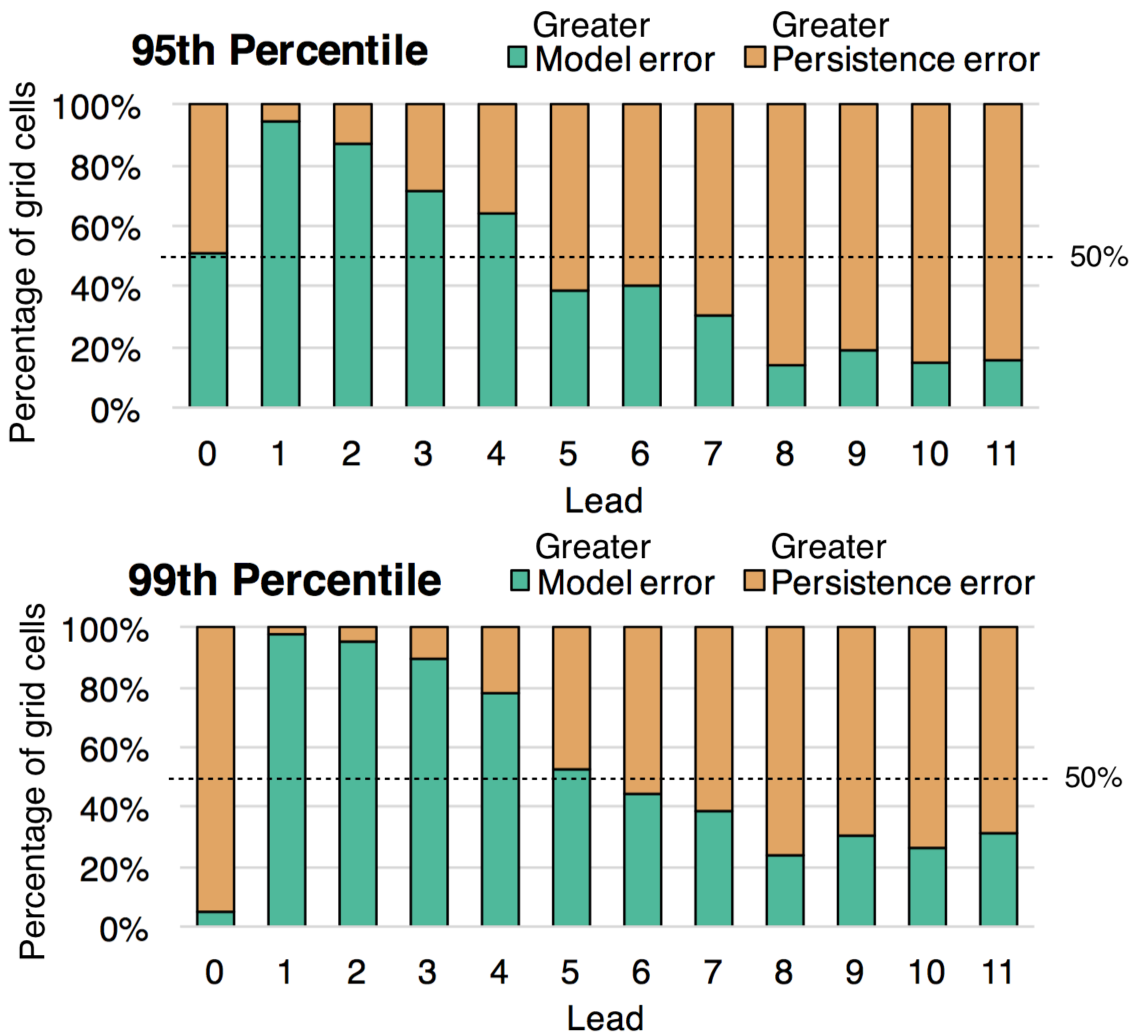

Fig. 27: Lead-time comparison of model and persistence error (across months January to December and years 1985 to 2013) for number of days per month above the 95th and 99th percentile. Bars indicate the portion of the study region with greater absolute model or persistence error.

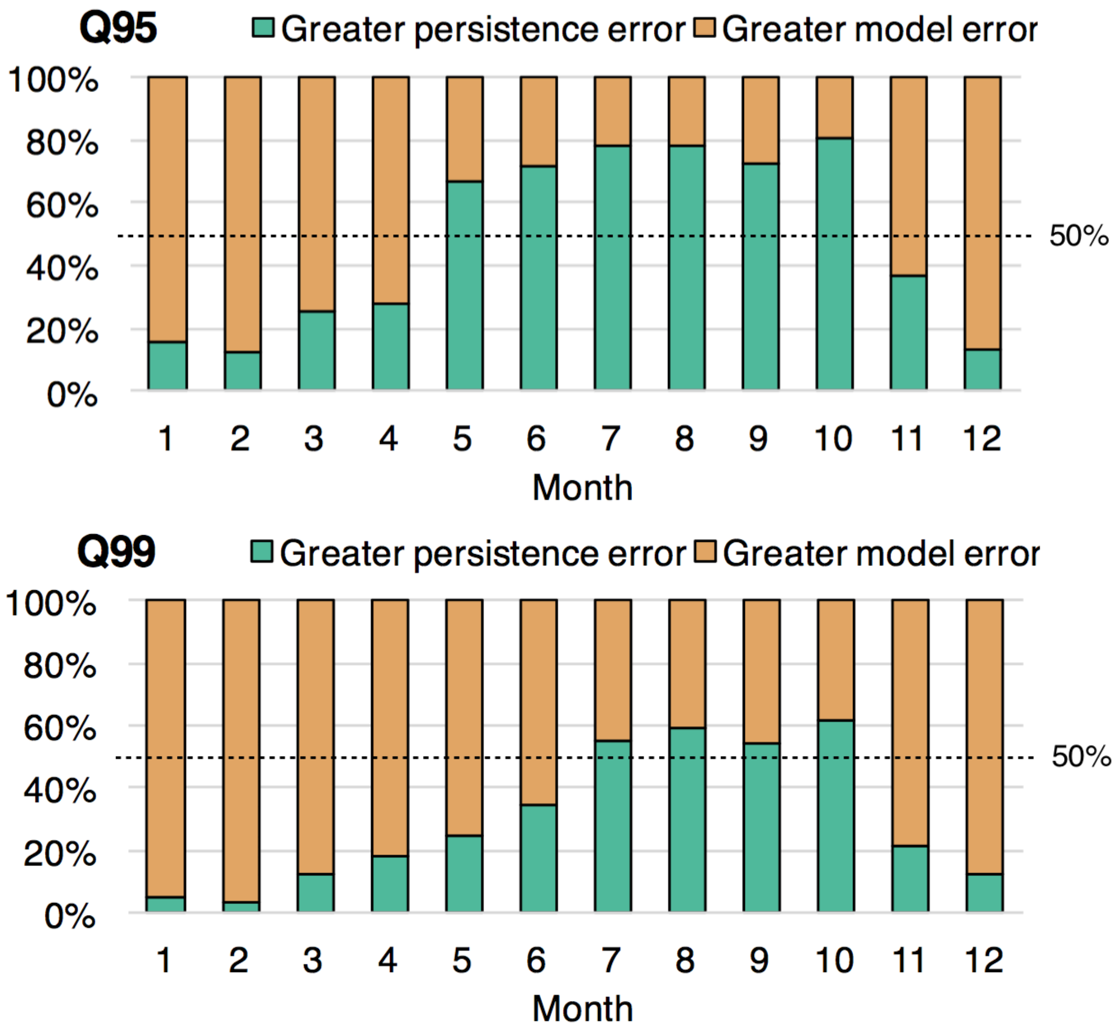

Fig. 28: Detail on the lead zero bars in Fig. 27. Percentage of grid cells within the study region that show higher absolute model error or higher absolute persistence error for the number of days per month with precipitation above the 95th/99th percentile. The average percentages for model and persistence error in both charts roughly equal the respective lead zero bars in Fig. 27.

and was generally over-predicted by the model at lead zero due to initialization shock (see also footnote in section 3.1). On the other hand, precipitation extremes in summer caused by convective events might be less accurately captured by a persistence forecast, therefore a higher relative persistence error during summer compared to the model forecast. The transition from less than 50 percent model error to less than 50 percent persistence errors was gradual. Neither the geographic distribution in different lead-times nor the transition from short to long leads followed a spatial pattern, except an area with low model accuracy across most leads and target months were the Rocky Mountains in central Colorado, where the absolute model error was generally larger than the persistence error for both the number of days above the 95th and 99th percentile (Fig. 29).

A monthly comparison (across all lead-times and years 1985 to 2013), shown in Fig. 30, places the lowest model accuracy (highest persistence accuracy) between November and April, with a gradual increase (decrease) in accuracy from April to October. This pattern is evident for most lead-times (not shown).

A year-by-year comparison (across all months and lead-times), displayed in Fig. 31, shows that model (persistence) error was greater in more than 50 percent of grid cells for 17 (12) years. It is worth noting that in 2011, a year with severe summer drought in much of the Southern Great Plains, on average 84 (82) percent of grid cells showed smaller absolute model error than persistence error for days above the 95th (99th) percentile, more than in any other year, especially during the summer months (not shown) when the drought had the greatest spatial extent and was most severe in the Southern Great Plains (Svoboda et al. 2002, Southern Climate Impacts Planning Program 2018). The reason for this is likely because the five previous years (which went into the persistence forecast) did not have such unseasonal conditions and were thus unable to represent the drought year.

Meanwhile, 2011 was a La Niña year, with the Ocean Niño Index (ONI), a three month average of sea surface temperatures in the Niño 3.4 region, smaller than -0.5 in nine of 12 month (http://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php). The year also had a stronger-than-average correlation between ONI and absolute model error for days per month exceeding the 95th percentile (however, not for the 99th percentile), as shown in Fig. 32. Therefore, it could be assumed that 2011 was more predictable than other years, and while the model forecast for 2011 also showed high errors (not shown), the year might have been somewhat more predictable by model compared to persistence.

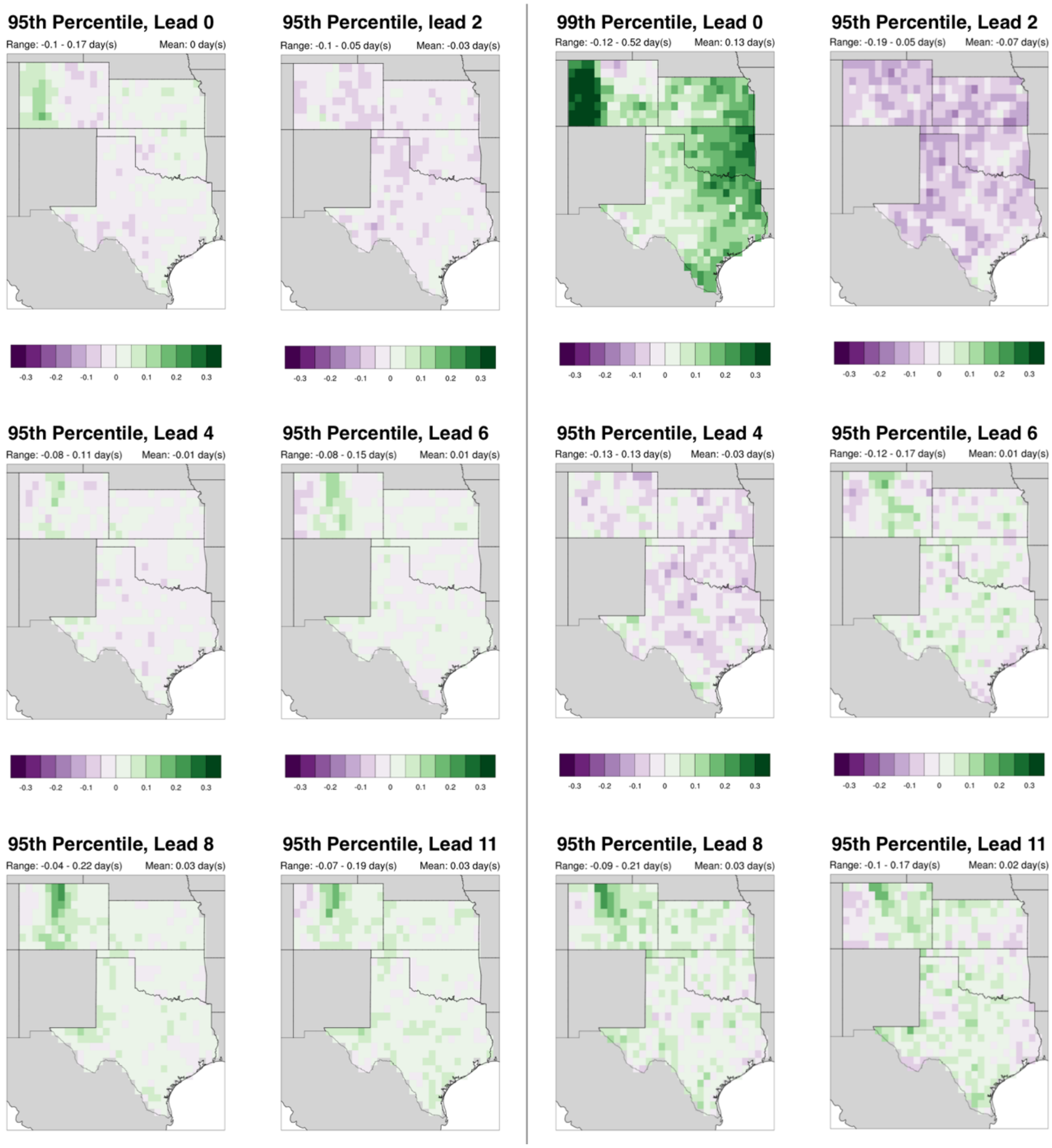

Fig. 29: Distribution of differences between the absolute model error and absolute persistence error in estimating the number of days per month with precipitation above the 95th (left) and 99th (right) percentile of daily precipitation. Purple (green) grid cells represent smaller absolute model (persistence) errors.

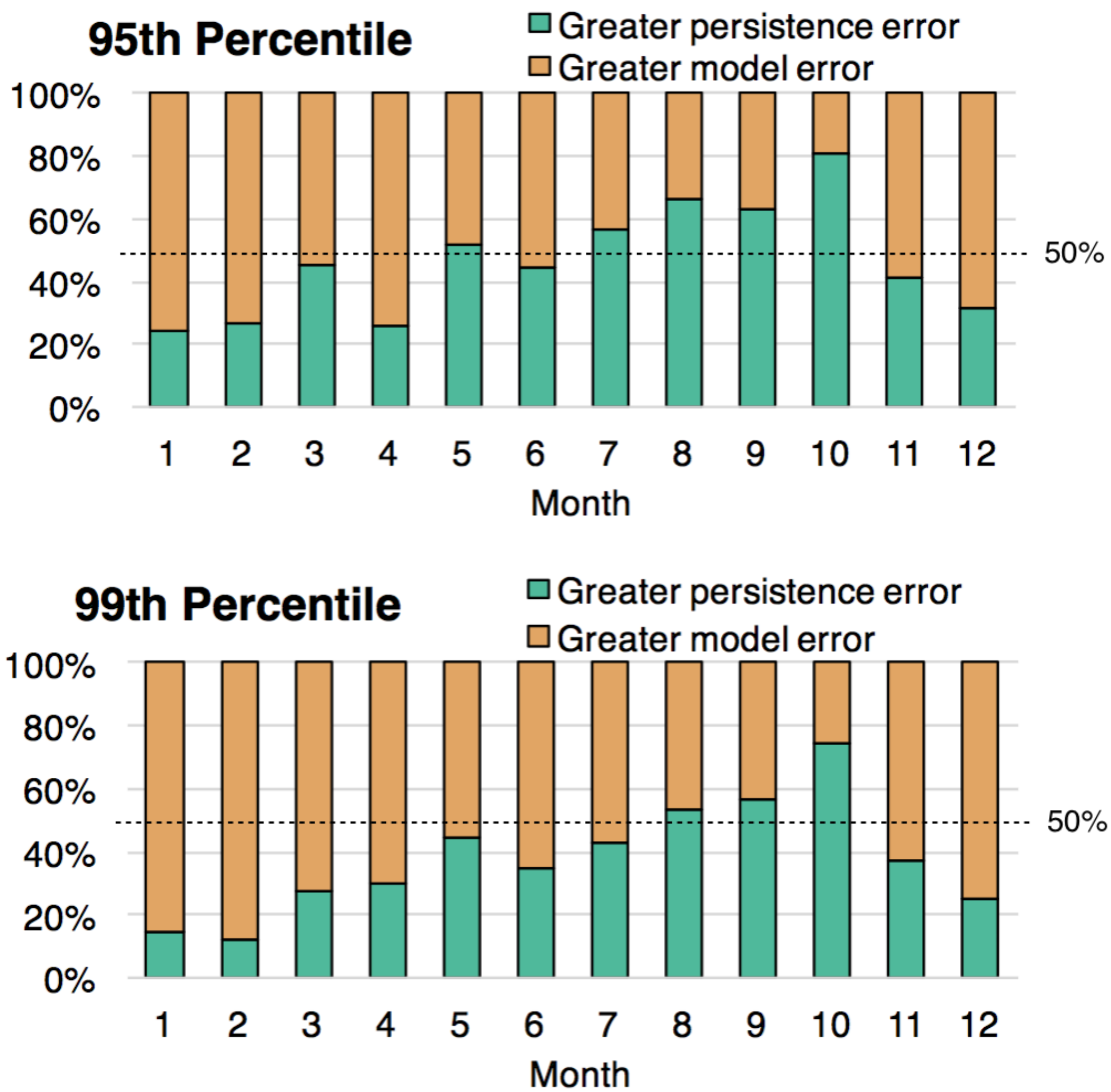

Fig. 30: Monthly comparison of model and persistence error (average of leads zero to 11 and years 1985 to 2013) for number of days per month above the 95th and 99th percentile. Bars indicate the portion of the study region with greater absolute model or persistence error.

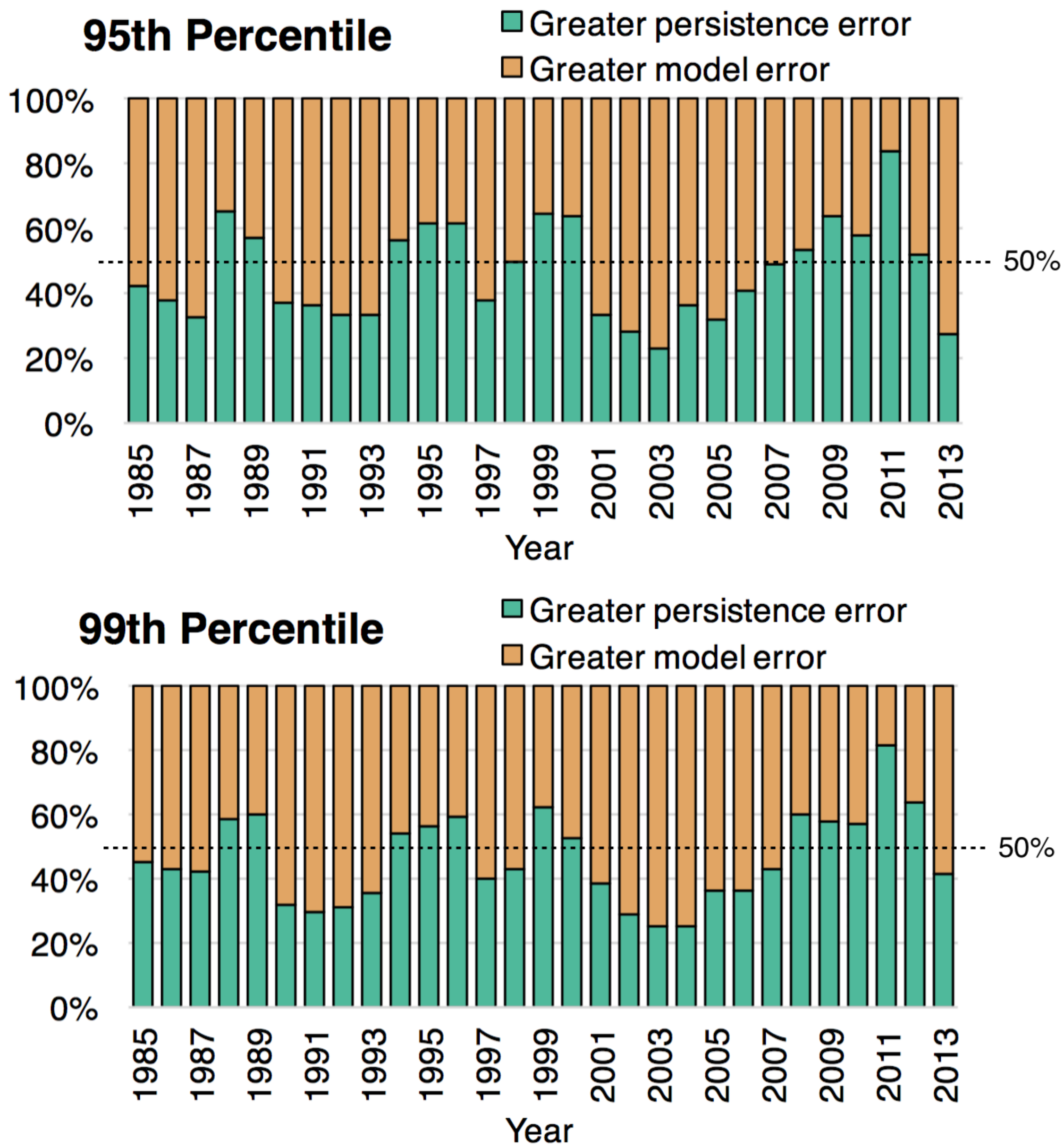

Fig. 31: Yearly comparison of model and persistence error (across leads zero to 11 and months of January to December) for number of days per month above the 95th and 99th percentile. Bars indicate the portion of the study region with greater absolute model or persistence error.

3.4 Number of dry days per month

For this section, we compared model and persistence forecasts in their ability to correctly predict the number of days per month with less than 1 mm of precipitation. We chose this threshold because we have also used it in the previous section as threshold to define wet days (days with at least 1 mm daily precipitation) in accordance with WMO standards, and it is also used as threshold in other ETCCDI indices. As in the previous analysis, we decided to deviate from the extension survey informing this study, for feasibility and practicality reasons. The survey requested a forecast for the number of consecutive days with no precipitation per month, which means the forecast skill received a penalty for forecasting the incorrect amount of precipitation *and* for forecasting precipitation on the wrong day. This test was difficult, even in the short term, and it appeared to be information that farmers would unlikely use for long-term decisions because of uncertainty in other decision factors, such as market prices (see Klockow et al.

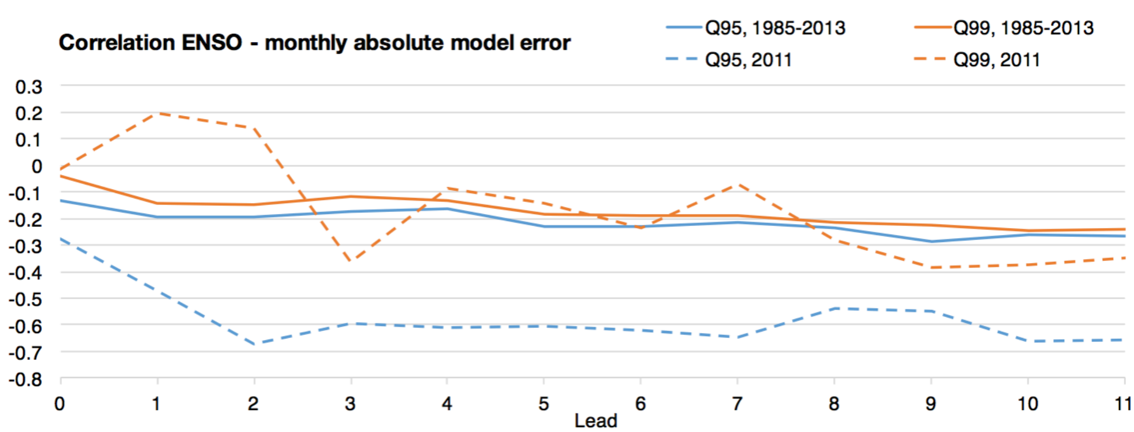

Fig. 32: Pearson correlation between ENSO 3.4 index (3-month average deviation from the long-term normal) and monthly absolute model error for the number of days above the 95th and 99th percentile for lead zero to 11. Solid lines show the correlation between ENSO and all absolute errors. The dashed blue (red) line shows the correlation for 2011 for the absolute error for days/month exceeding the 95th (99th) percentile for lead zero to 11.

2010 for details). Therefore, as a more feasible and practical proxy to the forecast element requested in the survey, we analyzed the total number of dry days per month.

Both model and persistence forecasts considerably under-predicted the average number of dry days per month observed between 1985 and 2013 in our study area (Fig.

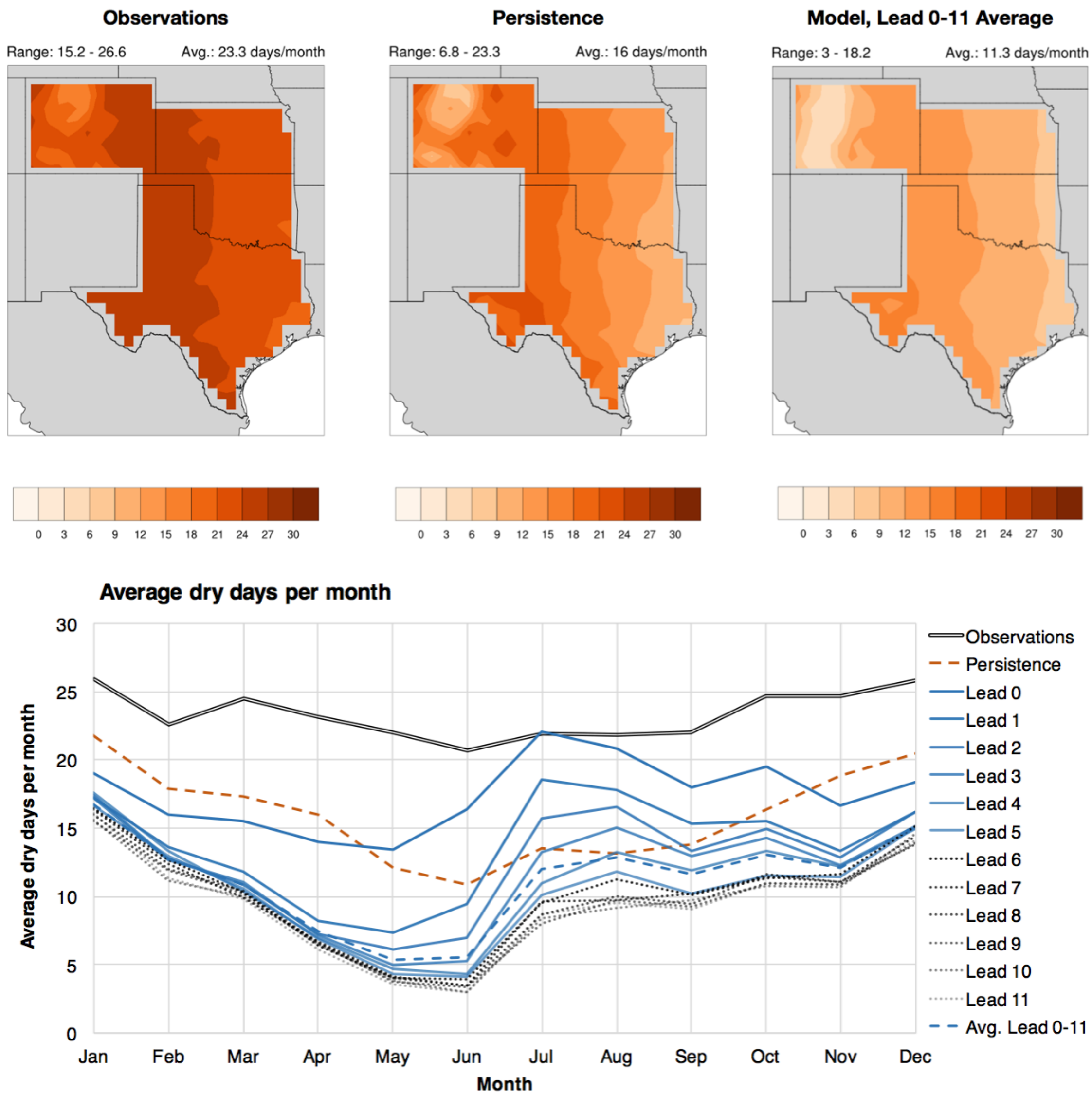

Fig. 33: Average number of dry days per month from 1985 to 2013 for observed daily precipitation (top left) and predicted by persistence forecast (top center) and model forecast (top right). Range and Averages state the average number of days per month on the respective maps. The graphs (bottom) show the average number of dry days per calendar month, for observations (black double line), persistence (red dashed line), and leads zero to 11 of the model forecast (lead zero to five: blue solid lines, lead six to 11: dotted grey lines, lead zero to 11 average: blue dashed line).

33, top). On average, 23.3 days per month recorded precipitation of less than 1 mm. The persistence forecast estimated an average of 16 days per month, and the model forecast averaged 11.3 days per month. As a result, the persistence forecast under-predicted on average by 7.3 days per month, and the model forecast under-predicted on average by 12 days per month. Note: These errors reflect the average raw errors, meaning averages of over- and under-prediction. For the remainder of this section we analyzed averages of absolute errors, meaning the magnitude but not the direction. Therefore the following average errors will not be exactly the same as the ones just mentioned.

The observed spatial distribution of minima and maxima in average monthly dry days was maintained in persistence and model forecasts, as shown in Fig. 33 (top), with minima in all three cases located in western Colorado as well as eastern Oklahoma and Texas, and maxima located in a band from western Texas to eastern Colorado. The temporal distribution of minima and maxima throughout the year, shown in Fig. 33 (bottom), was different between model forecast, observations, and persistence forecast. While observations and the persistence forecast have minima in June and maxima in December and January, the model forecast predicts local maxima during the summer (lead zero and lead one even have their highest overall averages in July) and minima in May and June for lead zero to lead three and lead four to lead 11, respectively.

Despite the temporal mismatch between model forecast and observations, in parts of the study area for several months and lead-times the model forecast had smaller absolute errors than the persistence forecast. Fig. 34 compares the average absolute errors of model and persistence forecasts of dry days per calendar month. While the absolute model error generally increases with lead-time, it is smaller than absolute persistence error in at least one, and as many as six calendar months. For example, between May and October at lead zero (Fig. 35, top left), 73 to 90 percent of the study area (mainly the entire study area except for parts of Colorado) had smaller absolute model errors compared to persistence errors. This percentage decreased with longer lead-times; however, certain regions maintained the smaller absolute model errors through lead 11. For example, Fig. 36 shows that in the month of August most of the study region had smaller absolute model error in more than 50 percent of the area at shorter leads zero to four, and even up to lead 11, the

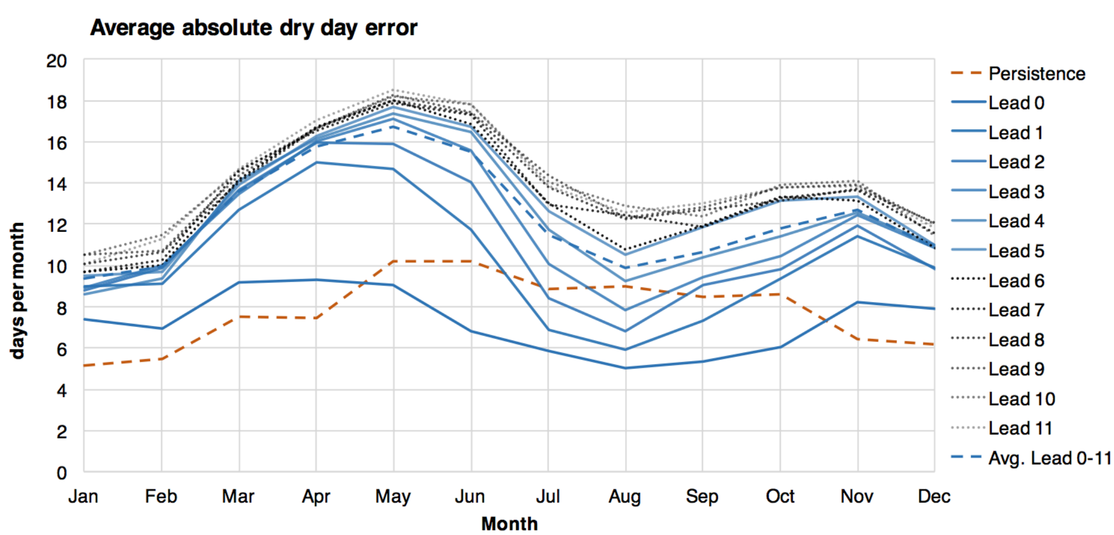

Fig. 34: Average absolute persistence and model forecast errors. The dashed red line shows the average persistence error, the blue shaded solid lines and grey shaded dotted lines show the model error for leads zero to five and six to 11 respectively, the blue dashed line shows the lead zero to 11 average.

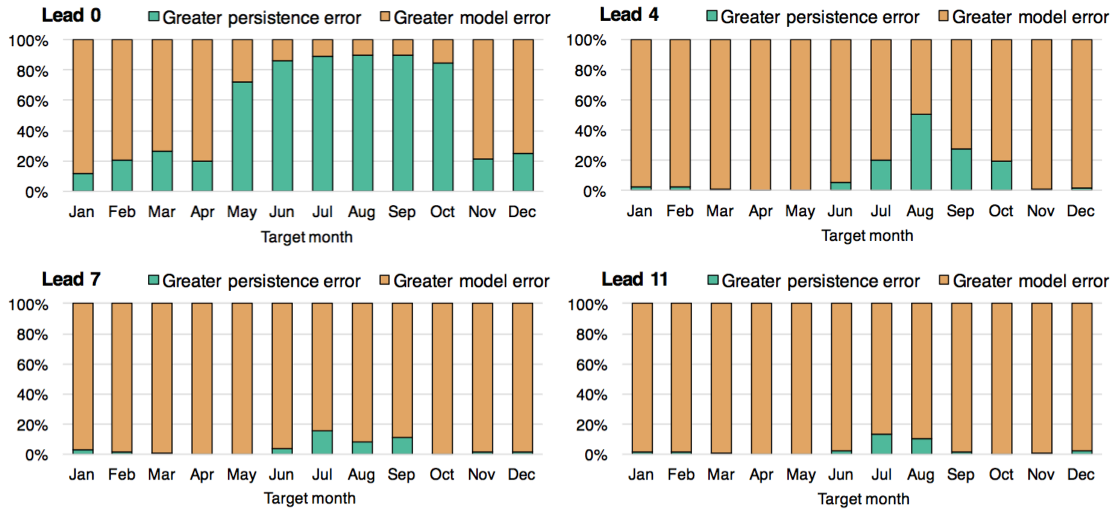

Fig. 35: The percentage of study area with smaller absolute persistence error (green) and smaller absolute model error (red) for forecasts at lead zero, four, seven, and 11.

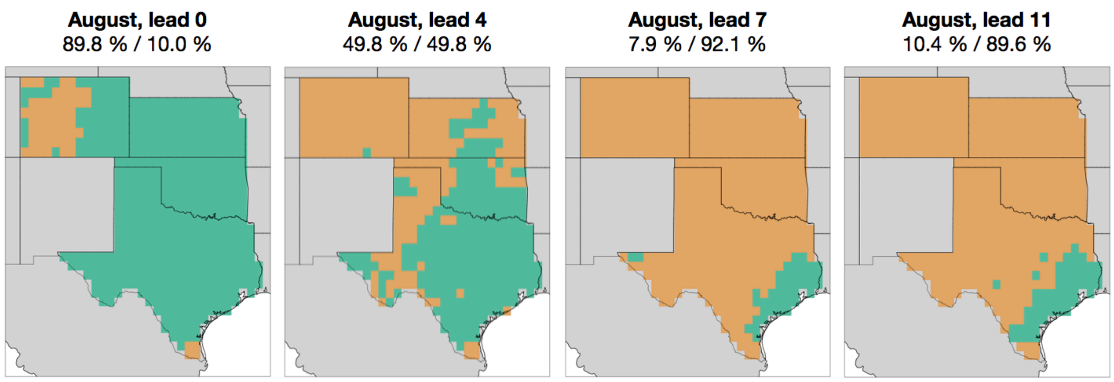

Fig. 36: The spatial distribution of areas with smaller absolute model errors (green) and areas with smaller absolute persistence errors (red) for leads zero, three, seven and 11 forecasts for forecasts for the month of August. Numbers above the maps show the percentage of grid cells in green (left) and red (right). Sums different from 100 percent are due to rounding.

Texas Gulf Coast, the absolute model error remained smaller than the absolute persistence error. This spatial distribution and temporal change was similar in June, July, and September (not shown).

Although model and persistence forecasts performed better or worse relative to each other in some months and geographic areas, neither of them performed particularly well compared to observations, as shown in Fig. 33 and Fig. 34 and described earlier. The absolute persistence error, averaged for all calendar months, was 7.8 days per month; the average absolute model error, averaged for all calendar months at lead zero, was 7.3 days per month and nearly doubled to 14 days per month at lead 11 (not shown). The average absolute model error for May to October at lead zero was 6.4 days per month (14.9 days per month at lead 11). Fig. 37 compares for each calendar month and lead-time how many percent of observed dry days per month were predicted by model and persistence forecast. The persistence forecast predicted, on average, 68 percent of observed dry days per month. The model forecast at lead zero predicted 75.3 percent of the observed number of dry days per month (39.7 percent at lead 11). From May to October, the model forecast predicted, on average, 82.7 percent of observed dry days per month at lead zero (33.1 percent at lead 11). The lowest percentages by both persistence and model forecast occurred between April and June; the lowest persistence forecast was 52.2 percent (June).

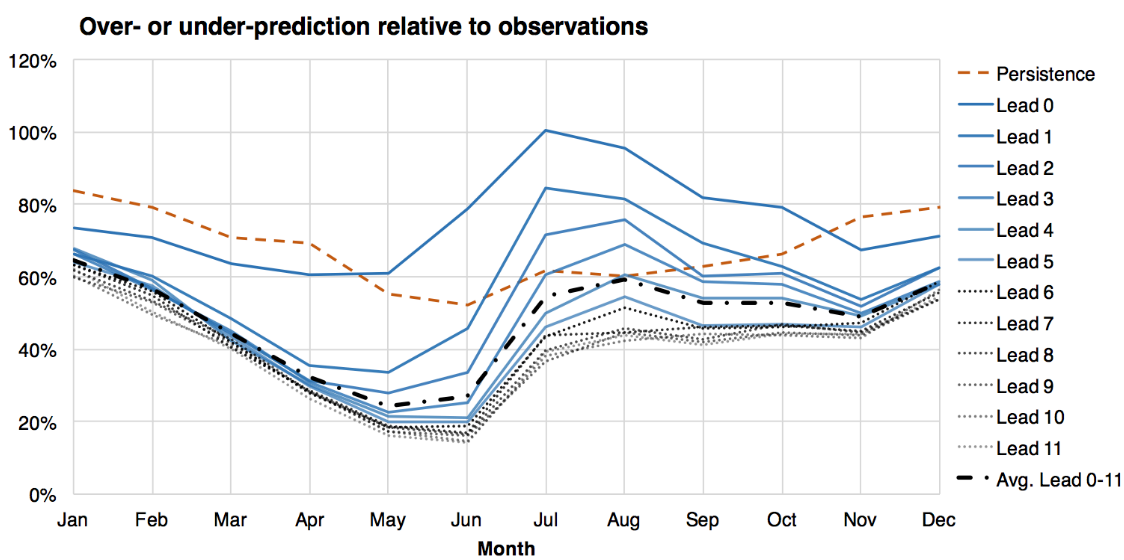

Fig. 37: Percentage of the numbers of dry days/month as predicted by persistence and model forecast. The dashed red line shows the average persistence error, the blue shaded solid lines and the grey shaded dotted lines show the model error for leads zero to five and six to 11 respectively. The black dash-dotted line shows the model lead zero to 11 average. Note: The underlying absolute numbers are based on averages of the raw data (the same data that was used in Fig. 27 and Fig. 28); therefore, the percentages here do not match the absolute forecast errors of the respective month (and lead-time).

The lowest model forecast ranged between 60.5 percent at lead zero (occurred in April) to 14.2 percent at lead 11 (June).

4. Summary and discussion

In the previous section we compared the accuracy of model and persistence forecasts related to four forecast elements: total monthly precipitation, average monthly air temperature, number of days per month with extreme precipitation, and number of dry days per month. The thought behind this analysis was to compare model accuracy against an alternative forecast product (a persistence forecast) that farmers might create from publicly available weather observations and use in lieu of an actual model forecast. In this section, we summarize our findings and put them in context by reviewing and comparing them to existing literature.

Average total monthly precipitation was more accurately forecasted by the persistence forecast in most months and across most of the study area, especially in summer. However, forecasts for November to February for all lead-times across central and western Texas and Oklahoma, showed greater accuracy in the model forecast. Accuracy of average precipitation had considerable seasonality and depended overall more on the target month rather than the forecast lead-time. This disagreed with previous studies by Schneider and Garbrecht (2006), who studied probabilistic seasonal outlooks by CPC and found that forecast skill for wetter- and dryer-than-average forecasts existed mainly along the Texas coast and dropped considerably after lead zero, in addition to longer lead-times having a strong tendency towards the long-term average. Our results found that no model forecast improvement over time, which agreed with Krakauer et al. (2013), with the caveat that they studied CPC seasonal outlooks that were created with a different model than the GFDL FLOR. The seasonal character of precipitation accuracy was also found by van den Dool (1994) and Peng et al. (2013), albeit also studying CPC's seasonal outlooks.

Accuracy of average monthly temperature, unlike precipitation, was very dependent on lead-time. For virtually all months and lead-times, but especially in summer at longer lead-times, model accuracy was lower than persistence accuracy. This result also contradicts Schneider and Garbrecht (2006), who found that forecast skill for warmer-than-average forecasts in our study area existed throughout all lead-times, but with a tendency of forecasts closer to climatology at longer lead-times. Cooler-than-average forecasts, meanwhile, rarely differed from climatology in their study. These results also contrast with other studies that generally showed that seasonal temperature forecasts had higher skill than seasonal precipitation forecasts (Schneider and Garbrecht 2003b, Schneider and Garbrecht 2006, Kerr 2008).

Analyzing daily extremes, we found that while dry days were underestimated by model and persistence forecast, our data suggested that low precipitation amounts were actually overestimated and high precipitation amounts were underestimated by both model and persistence forecasts. We attributed this result to the fact that individual model and persistence forecasts were averages of several datasets (preceding years for the persistence forecast, 12 model runs for the model forecast), which meant that single extreme values (both dry and wet) present in one dataset could be smoothed with data from other datasets. Thus, low precipitation values could be overestimated and high precipitation could be underestimated, which is a problem also discussed in other studies, with similar conclusions (Knutti et al. 2010, Barnston and Mason 2011, Huang and Gao 2017). The number of days with extreme precipitation was estimated more accurately by the persistence forecast at longer lead-times and lead zero across most of the study area during most of the year. However, the model forecast was more accurate in most of the region during summer at shorter lead-times, with the exception of lead 0, suggesting the highest model accuracy at these lead-times.

The number of dry days per month was more accurately forecasted by the model than by the persistence forecast in summer across most of the study area at short lead-times, including lead zero, and along the Texas Gulf coast at all lead-times in summer. However, both persistence and model forecasts vastly underestimated the number of dry days per month. The persistence forecast predicted between 52 and 84 percent, the model forecast (lead zero to 11 average) predicted between 24 and 65 percent of the observed dry days per month. Interestingly, forecasting dry days and extreme precipitation days, the model was most accurate compared to persistence in months when it was least accurate in predicting average precipitation.

Using a single-model approach over a model ensemble approach to create tailored forecasts (or any forecasts for that matter) has advantages and disadvantages. Computationally, running a single model reduces cost and time over running multiple forecast models; however, model ensembles are generally seen as more skillful than single models in predicting average temperature and precipitation (Knutti et al. 2010, Stockdale et al. 2010, DelSole and Tippett 2014, Kirtman et al. 2014). For the purpose of cost-effective yet skillful seasonal forecasts, further research should be conducted in model comparison.

5. Conclusion

Our analysis answered our initial research question, whether or not the model forecast is more accurate than a persistence forecast for forecast elements requested by winter wheat producers in our study area. In closing, we would like to leave the reader with two considerations: (1) Although the model forecast is more accurate than persistence at times, it might not be accurate enough to serve actual decision making, and future studies should explore ways and thresholds to determine this answer. (2) Depending on time and location, a model forecast might not always be the best basis for decision making, and the decision maker may instead (also) consider a persistence forecast, as it might be able to better inform about future conditions. Future work should include improving forecast models' ability to predict extremes and other variables relevant to agricultural producers. Studies should also explore ways to assess and communicate uncertainty of the forecast, such that user can determine how much to trust and whether to use the forecast.

6. Acknowledgements

We thank Dr. Esther Mullens for help writing the NCL scripts for our analysis, and to Drs. Derek Rosendahl and Adrienne Wootten for advice on our analysis. We would also like to thank Mark Stacy, Tyler Pearson, and the support staff at the University of Oklahoma's Supercomputing Center for Research and Education (OSCER) for troubleshooting help during our analysis, and we thank the South Central Climate Science Center for providing computing power and data storage for this study.

7. Conflict of interest statement

The authors have no conflicts of interest to declare for this study.

Chapter 5 - Summary and Conclusion

1. Summary

Extreme weather and climate, such as drought, heat, or extreme rainfall, can have a destructive impact on agricultural productivity, with severe consequences. In recent years world events, such as the famine at the Horn of Africa or the civil war in Syria, have shown that given the “right” (or rather, wrong) political, societal, and economic circumstances, failing agricultural systems can contribute to economic disruption, food insecurity, famine, and even conflicts. In the U.S., the 2011 to 2014 drought in the Great Plains, the Midwest, and California has demonstrated how vulnerable agricultural systems are even in highly developed countries.

For several decades in the U.S., forecast information has been issued by the National Weather Service following a loading-dock approach (Cash et al. 2006), issuing forecast information without user input or feedback and without analyzing who is using the forecasts. Without involvement from users, such as forest managers, policy makers, city planners, or agricultural producers, and without coordinated planning and incorporation of user needs these forecasts can leave recipients uninformed or even misinformed, potentially causing more problem than they solve (Cash et al. 2006, Meadow et al. 2015).

The research conducted in this dissertation examined the seasonal forecast needs of producers of winter wheat and compared the accuracy of a high-resolution seasonal climate forecast model in providing forecasts elements as requested in the survey for the Southern Great Plains. In collaboration with the agricultural community, this research intended to answer two questions:

1. How can seasonal climate forecasts be tailored to serve the needs of winter wheat growers in the south-central United States?

2. Can existing seasonal forecast models provide meteorological variables as requested by winter wheat farmers with better skill than a persistence forecast?

Survey data collected from 109 surveys submitted by cooperative extension agents working in Colorado, Kansas, Oklahoma, or Texas highlighted that:

- Decision planning occurred about zero to 2.5 month before the respective practice (e.g., planting, harvesting) was carried out, suggesting a strong seasonality and timing closely tied to the timing of the practice.

- Drought and extreme rainfall are the overall most relevant weather threats with regard to long-term decision timing. However, relevance of threats differs from one decision to another. For example, while drought, extreme rainfall, and heat most affect planning for planting time, extreme rainfall, wind/storm, and hail are most closely tied to the decision about when to harvest, and drought and heat play a less important role.

- Overall, forecast elements related to precipitation ranked higher in importance than forecast elements related to temperature, which is consistent with existing literature. In particular, average precipitation and consecutive days without precipitation ranked highest and second highest in every month and overall. Deviation from average precipitation and chances for extreme precipitation ranked third and fourth overall. Average temperature followed in fifth place and was followed by six other temperature-related forecast elements.

- Of all ranked forecast elements, only the first, third, fifth, and seventh (average precipitation, deviation from average precipitation, average temperature, and deviation from average temperature) are currently provided through seasonal forecasts issued by the NWS for the U.S.

Unexpected survey analysis results included the required forecast lead-time of zero to 2.5 months, and the low ranking of growing degree days, a decision-support tool specifically developed for agricultural and horticultural users. This suggested that on a seasonal timescale, winter wheat producers do not require this tool as much as they do on shorter forecast timescales, as found by Haigh et al. (2015) for corn producers in the U.S. Midwest.

Following the survey, a quantitative analysis was conducted to compare a high-resolution seasonal climate forecast model with a persistence forecast regarding accuracy of monthly forecasts for four of the five forecast elements ranked highest in the survey: average precipitation, average temperature, chances for extreme rainfall, and consecutive days without rainfall. The model that was chosen is developed and operated by the NOAA Geophysical Fluid Dynamics Laboratory (GFDL) and produces daily and monthly forecasts on a 50 by 50 km grid with lead-times from zero to 11 months, zero being the month the forecast is issued. The model consists of 12 model runs with differing initial conditions, which were averaged (unweighted) for the analysis. In the process, two of the elements were changed for reasons of feasibility, from chances for extreme precipitation to the number of days per month with extreme precipitation, and from consecutive days without precipitation to the number of days per month without precipitation. The persistence forecast for a particular calendar month (day) was calculated by averaging the observational values of the same calendar month (day) from the preceding five years. Absolute forecast and persistence errors were created using monthly air temperature observations from the Global Historical Climatology Network as well as daily and monthly precipitation observations from CPC and NOAA, respectively. Finally, these absolute errors were compared for each calendar month and lead-time. The following results are worth mentioning:

- On average, average precipitation was forecasted more accurately by the model forecast between November and February for all lead-times in large parts of the study area, and more accurately by the persistence forecast between June and September nearly throughout the study area. October and March to May were transition months. This dependence of model accuracy on season rather than lead-time is consistent with existing literature.

- On average, monthly air temperature was forecasted more accurately by the persistence forecast in almost every month and lead-time, and in particular during summer at longer lead-times.

- Model accuracy of monthly temperature and precipitation forecasts for summer has likely been decreased due to bias correction in combination with the fact that the model used was not flux-adjusted.

- On average, the number of days with extreme precipitation was estimated more accurately by the persistence forecast at longer lead-times and lead zero across most of the study area during most of the year. However, the model forecast was more accurate in most of the region during summer at shorter lead-times, with the exception of lead 0.

- On average, the number of dry days per month was forecasted more accurately by the model across most of the study area between May and October at lead-times of one to up to four. Along the Texas gulf coast from June to September, the model forecast was more accurate at all lead-times. Generally though, longer lead-times and forecasts for November to April were more accurately forecasted in most of the study region by the persistence forecast.

- Overall, both persistence and model forecasts greatly underestimated the number of days per month with extreme precipitation and underestimated the number of dry days per month. This is presumably caused by the described averaging of observations and model runs.

Unexpected was the low absolute model accuracy of average monthly temperature relative to absolute persistence accuracy, which, unlike the comparison of forecasts for total monthly precipitation, was lower almost throughout the year and across the entire study area for every lead-time. This was surprising considering that temperature forecasts are generally more accurate than precipitation forecasts. Unexpected were findings that model forecasts for precipitation averages were more often more accurate than persistence forecasts during winter, but model forecasts for precipitation extremes were more accurate than persistence forecasts in summer.

This research focused on one crop type instead of multiple crop types or crop production in general in order to taking into account the different decision-making processes that distinguish winter wheat production from other crop types, for example, corn, cotton, or soybean production. Winter wheat is the dominant crop type by planted acreage in the study region (Texas, Oklahoma, Kansas, and Colorado), grown on 21.1 million acres (in 2016), twice the area of the second largest crop, corn (Han et al. 2012). As a strain of wheat, it also contributes 71 percent to the U.S. wheat harvest (USDA 2012). Wheat itself is the third largest crop by harvested acreage in the U.S., after corn and soybean. Therefore, because of its overall contribution to the national wheat harvest and its role in the study region, compared to other crops, it was chosen as focus crop for this research.

The goal of this research was to help forecasters provide better decision support for agricultural producers generally and winter wheat producers in particular, to provide model developers with insights into model performance regarding specific user needs, and to highlight the advantages of and continued need for collaborative, interdisciplinary efforts towards a better understanding of decision-making processes in agricultural production systems.

2. Conclusion

This research, broadly speaking, illustrated some of the benefits of co-produced research over (previous) research that was produced in "academic silos" with little or no interaction with and/or input from users. It showed ways in which seasonal climate forecasts can be improved to serve as better decision tools in winter wheat production, and it highlighted shortcomings of a current seasonal climate forecast model in producing such tailored forecasts. The results, produced in a collaborative, cross-disciplinary way, add to the existing body of knowledge by highlighting decision processes and forecast needs for a specific crop type. They pointed out several forecast elements relevant to winter wheat producers that could currently be provided by seasonal forecast models. However, due to the complex nature of farm decision making, it should be emphasized that even if a forecast was perfect producers may choose not to act upon them due to other limitations, such as risk, market conditions, or other climatic factors.

The forecast comparison highlighted three aspects. Discounting model forecast data out of skepticism in favor of observation-based data, such as seasonal persistence forecasts (Changnon et al. 1988, Sonka et al. 1992), or vice versa, might put decision makers at a disadvantage, because they may rely on more inaccurate information. However, while both model and persistence forecasts were more or less accurate relative to each other at certain times across the study region, both were also very inaccurate in certain instances to begin with. Lastly, past research showed that model ensembles are in many cases more accurate than single models due to the smoothing effect of averaging several datasets which reduces overall errors. The analysis of extremes, however, suggested that this smoothing can cause considerable misrepresentation of extreme values, such as dry days or extreme precipitation days.

This work is an important stepping stone in lifting research out of the metaphorical silos of academia and closer to the literal silos of agricultural production. Scientific research often takes place isolated from the real world and is often taught that way. While not all research needs practical context, real-world urgency, such as the increasing impacts of climate variability and climate change on various aspects of everyday life, can make it necessary to go a step further and explore ways in which scientific knowledge can have real-world use. While the research presented here is likely incomplete and in only a few years outdated, it is a step towards helping society adapt to and mitigate climate variability and change by producing knowledge and developing decision tools that can help secure wellbeing and prosperity, and by advancing ways of collaboration between scientists and decision makers.

3. Future work

Identifying user needs has been done for other agricultural commodities in different parts of the U.S. and internationally (Unganai et al. 2013, Haigh et al. 2015, Takle et al. 2014, Goddard et al. 2010, Klemm and McPherson 2017), but more work is necessary to connect these puzzle pieces to a more complete picture and to provide guidelines for best practices. The development and testing of forecast models can benefit from these user-inspired results, too, for example, by making model evaluation and comparison more practically relevant. The value of scientist-stakeholder relationships and science co-production as it exists, for example, within the Climate Science Center network, should to be promoted among and shared with other agencies that are not following these practices yet or are struggling to adopt them. Qualitative and quantitative metrics to evaluate the success of collaborative projects should be developed to accurately, truthfully, and comprehensively describe the value of this research to funding agencies, policy-makers, natural and cultural resource managers, and researchers (Wall, McNie and Garfin 2017). Research frameworks also need to be developed, improved upon, and standardized to assure compatible and quality results (Meadow et al. 2015, Buizer, Jacobs and Cash 2016). Last but certainly not least, college coursework is necessary to train future researchers in understanding, appreciating, and incorporating scientific findings from multiple disciplines (Evans et al. 2015, Hill et al. 2014).

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