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Climate Forecasts: Emerging Potential to Reduce Dryland Farmers' Risks

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ABSTRACT

Agricultural management strategies are needed to improve lives of people in harsh, dryland regions. If the upcoming season's climate was predictable, farmers could tailor practices to match anticipated climate, reducing risks during adverse seasons, while investing more to benefit from favorable seasons. Such a possibility has long been a dream, but there is reason for optimism that our ability to predict climate is improving. In this paper we describe climate forecasts and discuss potential applications at the farm level. Climate forecasts include local early indicators of future climate, correlation of local climate to global processes, and dynamic modeling of climate processes. Operational forecasts offer potential to guide production decisions, such as crop species or cultivar selection, fertility management, area to be planted, pest management, intensity and timing of grazing and purchase, sale, or movement of animals. Management decisions related to marketing, labor, and diversification, and regional decisions relating to input supply, markets, transportation, storage, or community health services could also be guided by climate forecasts. Forecasts have sufficient utility to guide decision-making in some regions for some seasons. To move forward, continued improvement and evaluation of forecasts skill are needed. Improvements in forecasting tools for regions that gain little from current forecasts and forecasts of extreme events should be a focus for further work. Uncertainty analysis for scenario simulation, tools to assess tradeoffs within a whole farm context, and better methods to communicate probabilistic outcomes are needed. Perhaps most critical is engaging farmers as partners in development of new tools to support decision-making on-farm and using seasonal climate forecasts within the context of overall risk analysis and management of an agricultural system.

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Abbreviations: CLIGEN, a stochastic generator that produces daily time series estimates of weather parameters; ENSO, El Niño-Southern Oscillation; GCM, global circulation model; IOD, Indian Ocean Dipole; NWS, National Weather Service; NOAA/CPC, National Oceanic and Atmospheric Administration, Climate Prediction Center; SOI, Southern Oscillation Index; SST, sea surface temperature; WEPP, Water Erosion Prediction Project.

INTRODUCTION

The arid and semiarid dryland regions of the world provide some of the harshest environments for human sustenance and multiple investments are needed to improve lives of people in these regions (Steiner et al., 1988). One investment that may have potentially large payoff is in the area of development, adaptation, and implementation of climate forecasting systems for agricultural management in dryland regions. Because these regions have marginal and unreliable precipitation, prevailing agricultural systems are highly conservative. Farmers in these regions must minimize risk of crop loss or loss of the costs of agricultural inputs. Such losses can jeopardize economic and food security of the household. The conservative systems, however, do not allow the farmers and rural communities to maximize benefits during more favorable years. If the upcoming season's climate was more predictable, farmers could tailor practices to match anticipated climate, reduce economic and crop failure risks during adverse seasons, while investing in higher production inputs to benefit from more favorable seasons.

While knowing the next season's climate has long been a dream of people in harsh dryland regions of the world, today there is reason for optimism that our ability to predict future seasonal climates is improving. A comprehensive summary of research and applications related to seasonal climate forecasts with application to agriculture and natural resource management were reported in Hammer et al. (2000); readers are referred to this resource for more detailed information. In this paper, our objective is to present an overview of operational climate forecasts and discuss evaluation and interpretation of these forecasts for relevance at the farm scale. We then illustrate potential forecast applications for farm management decisions within the context of cropping/grazing systems in the Southern Great Plains of the US.

OVERVIEW OF CLIMATE FORECASTING

Climate forecasting is an age-old concept, and initiatives to improve and use such forecasts are underway in many regions of the world. For example, brightness of stars in the Pleiades constellation near winter solstice was used traditionally as an indicator of variation in summer rainfall and autumn harvest in the Andes. Orlove et al. (2000) recently reported that poor visibility of the Pleiades in June was caused by increased sub-visual high cirrus clouds. This phenomenon was observed during El Niño years, and was often associated with low rainfall during the subsequent growing season. This finding provided a different perspective of traditional knowledge about the climate system and presents an opportunity to extend traditional knowledge into modern technologies. Climate forecasts will be discussed in terms of local early indicators of future climate, correlation of regional climate to global processes, dynamic modeling of climate processes, and available operational climate forecast systems.

Early Indicators in Local Climate Records

Pioneering research conducted in the 1970's by J. I. Stewart and others (Stewart and Hash, 1982; Stewart and Kashasha, 1984; Stewart and Faught, 1984; and Stewart, 1988) developed the concept of response farming. The basis of response farming was the identification of correlations between date of onset of the rainy season with both the length of the growing season and total seasonal precipitation. Such relationships gave an early indication of the type of season to be expected. Management responses were then developed to match the most probable

Table 1. Probability of seasonal rainfall based on April precipitation in Mildura, Victoria, Australia. (V. Sadras, 2002, personal communication).

Seasonal Rainfall	"DRY" April[†]	"WET" April
mm	%[‡]	%
50	4	0
100	16	4
150	40	8
200	60	36
250	96	68
300	100	88
350		96
400		96
450		100

[†] "Dry" indicates April rainfall < 13 mm, the median rainfall for this location, and "Wet" indicates April rainfall > 13 mm.
[‡] Based on a 25 year precipitation record, each year represents 4% probability.

type of growing season. With early onset, and in anticipation of a good rainy season, longer growing season crops could be planted and higher level of inputs could be purchased. With late onset indicating higher probability of low rainfall, a conservative management system could be followed to ensure food security and minimize economic risks. The approach was originally developed in Kenya and was later extended to Sub-Saharan West Africa, the Mediterranean region, and parts of Asia. Response farming is generally most applicable to Mediterranean and monsoonal climates, where virtually all of the annual precipitation comes in the rainy season; it is less applicable to continental climates where precipitation may come in any season, though usually there are months or seasons with higher and more reliable precipitation. Mediterranean, monsoonal, and continental climate patterns are illustrated in Steiner et al. (1988). McCown et al. (1991) evaluated response farming in Kenya and found that while some economic benefit and risk reduction could be realized through variable management under response farming, the benefit was smaller than that realized by adoption of a few simple fixed management changes, relative to prevailing practices.

Stewart's work provided the basis for later research by Sadras et al. (2003) who developed systems for the southeast Australia Mallee region to adjust seasonal management based on April precipitation. The participatory research identified April precipitation as relevant to farmers' decision-making. Sadras (2002) developed correlation relationships between April precipitation and growing season precipitation (Table 1) for subregions, and simulated profitability for "conservative" and "risky" strategies across a forty-year climate record (Fig. 1). The figure presents profit differences of "conservative" vs. "risky" strategies in such a way that a positive difference indicates benefit to the conservative strategy while a negative difference indicates benefit to the riskier strategy. In many years, the profit difference between the two systems was relatively modest, but a manager following a set, rather than responsive strategy, would miss the opportunity for much larger profit to the intensive system during several of the wet forecast years or would miss the far higher profit for the conservative

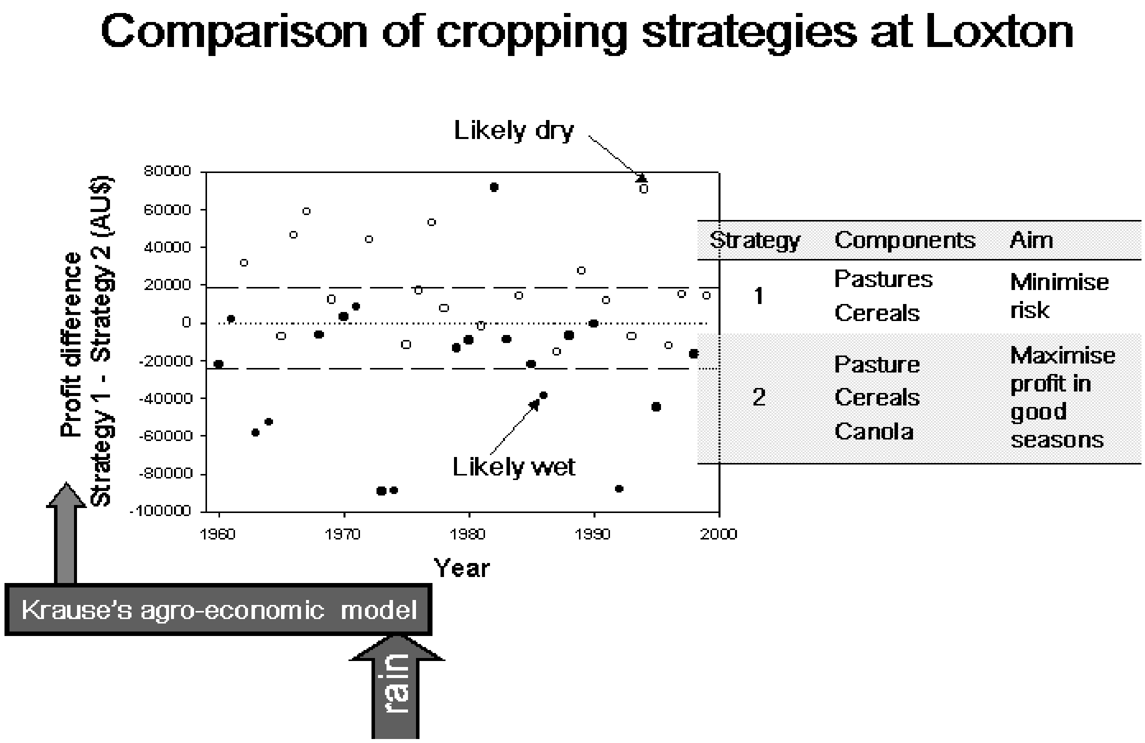

Fig. 1. Estimated impact of cropping strategy on profitability in wet and dry forecast seasons. (Source: Sadras et al., 2003).

system in several of the dry forecast years. The "conservative" and "risky" systems varied by subregion and by soil type, allowing farmers to focus on the systems most relevant to a particular location. Particularly for drier sites, adoption of a dynamic cropping strategy by selecting a conservative regime when April precipitation was below the median and a riskier (more intensive) regime when April precipitation exceeded median indicated overall improved economic return (simulated), particularly during the most extreme years.

Correlation of Regional Climate to Global Processes

Another body of research has explored correlation of historic climate at a particular location or region to ocean-atmosphere patterns observed elsewhere on the globe. Tropical Pacific Ocean patterns have exhibited numerous and diverse links with weather and climate in many parts of the globe. Such linkages across large distances in the earth: atmosphere system are often called "teleconnections".

One such teleconnection described early in the 20th century was the Southern Oscillation, based on the difference in atmospheric pressure at Darwin, Australia, and Tahiti. This pattern was shown to be correlated to Indian monsoonal rainfall and later to precipitation in many parts of Australia and other parts of the globe. For example, Hutchinson (1992) described how the

Southern Oscillation Index (SOI) was correlated with year-end rainy season precipitation in Somalia, with an absence of high precipitation seasons in years with a high SOI, but great variability of precipitation in low SOI years. Stone et al. (1996a) described five phases of the SOI and developed correlations between SOI and precipitation patterns in various regions of Australia. A more recently described atmospheric pressure pattern is the North Atlantic Oscillation that shows correlations with temperature and precipitation patterns in eastern North America, northern Europe, and northern Asia.

The best-known teleconnection is linkage of sea surface temperature (SST) in the equatorial Pacific with global precipitation and temperature patterns. This phenomenon is called El Niño during times when the SST is high relative to the long term average, and La Niña when SST is lower than average. These SST patterns are correlated to temperature and precipitation patterns in many parts of the world (e.g., Phillips and McIntyre, 2000). Because the SST and atmospheric pressure patterns are linked phenomena, the term El Nino-Southern Oscillation (ENSO) is commonly used.

More recently, the Indian Ocean Dipole (IOD) was described which might provide better insight into the monsoonal precipitation on the Indian subcontinent or Western Australia. The correlation of the IOD and the ENSO to monsoonal precipitation in India is of opposite sign, so the impacts of both must be considered in forecasting precipitation for that region.

Although this paper focuses most strongly on precipitation, forecasting temperature is also important in reducing risk in many agricultural systems. Stone et al. (1996b) described SOI correlation with frost dates in the Australian spring wheat [*Triticum aestivum,* (L.)] belt, with the potential that later planting dates or varieties with greater frost tolerance could be selected when the risk of a late frost was above average. Lobell and Asner (2003) reported that US corn and soybean yields across major production regions were correlated with maximum temperature during the past two decades. Generally negative correlations of yield to temperature were found in the Southeastern US and much of the Midwestern corn-soybean belt while positive correlations were seen further west and north in the Great Plains. Such correlations have management and marketing implications for farmers who could select different options based on forecasts of higher or lower than normal temperature.

Dynamic Climate Models

Increasing knowledge of atmospheric and global processes is leading to rapid improvements in dynamic global circulation models (GCM) that simulate the global system and can reproduce many of the patterns observed through the years. Climate forecasting is a rapidly advancing field of research and operation, based on the rapid advances in basic knowledge of oceanic and atmospheric processes, improved remote sensing and environmental monitoring technologies, and increased computing power. Forecasts can utilize GCMs in two ways, either for direct forecast of precipitation and climate patterns in particular regions, or in a hybrid format. The hybrid format forecasts sea surface temperature and atmospheric pressure patterns (as a forecast of the ENSO phase) and then uses statistical correlations of ENSO patterns to forecast precipitation and temperature patterns for various parts of the world. Whether in the GCM or hybrid mode, incorporation of other ocean temperature and atmospheric signals, as well as land surface moisture and snow cover impacts, may improve forecasts in the future for regions of the globe that have weak or undetectable correlation to the ENSO signal.

Operational Climate Forecasts

Operational forecasts are being made by various groups around the world. A widely utilized forecast of global and regional climate is made by the International Research Institute for Climate Prediction (http://iri.columbia.edu/climate/). In Australia, the Queensland Department of Primary Industry and the Commonwealth Bureau of Meteorology release seasonal climate forecasts based on ENSO and SOI signals for Queensland and the Australia continent (http://www.bom.gov.au/climate/ahead), or globally (http://www.longpaddock.qld.gov.au/index.html). The U.S. National Oceanic and Atmospheric Administration's Climate Prediction Center (http://www.noaa.gov/climate.html) releases 3-month seasonal climate forecasts covering the coming year for the US.

All of these forecasts are statements of probability of future climate states, relative to the normal distribution of climate for that particular region and that particular season. The forecasts are not a prediction of one particular future climate pattern, but a statement of probability of a range of possible outcomes across a season. Regardless of whether the forecast is above or below normal, any outcome within the probability distribution may be realized. Additionally, because of high variability within seasons, wet seasons may exhibit short-term, dry periods or *vice verse*. Because of the inherent uncertainty, economic value of a forecast increases as the skill of the forecast increases and varies depending on what application is made with the forecast (e.g., Gadgil et al., 1995).

Hammer et al. (1996) reported that tactical management based on five phases of the SOI increased profit and reduced risk compared to fixed management in Australian wheat regions. The tactical responses included selection of cultivar maturity and N–fertilization strategy based on forecast frost dates and seasonal precipitation. In simulation studies focused on Zimbabwe, Phillips et al. (1998) emphasized the relative importance of forecasting favorable seasons and managing for enhanced productivity, compared to forecasting adverse seasons. This may be a reflection of the risk-adverse management systems developed to avoid total crop failure during drought years. Because forecasts are a relatively new product, and the forecasts are being released to new user groups outside the traditional meteorology community, new methods for evaluation are needed. Schneider and Garbrecht (2003a, 2003b) developed indices to evaluate seasonal forecasts for agricultural applications. In their system, "usefulness" addresses the question of how often, and by how much, the forecasts predict departures from normal. The "dependability" index assesses how often the forecasts predict the direction of precipitation departures from normal, and is assessed separately for wet and dry forecasts. "Effectiveness" combines "usefulness" and "dependability" to define the frequency of forecasts offering dependable predictions of useful departures, answering the question "How often can I do better using these forecasts?". Their "effectiveness" index for the NOAA/CPC forecasts for the continental US (Fig. 2) is highest in the Desert Southwest and Florida, with good results in the Pacific Northwest, northern Rocky Mountains, and along the Gulf Coast from Texas to the coastal Carolinas. The forecasts are available for 3-12 months out, but the skill level declines rapidly after 6-months out. For the regions with high "effectiveness", these forecasts may have considerable water resource and agricultural implications. Given increasing forecast skills for some regions and seasons, the question remains of how to downscale and interpret the impact of forecasts for applications at a local level. As illustrated in Fig. 3, the probability distribution of forecast precipitation, relative to normal, will usually **not** exhibit the same deviation from

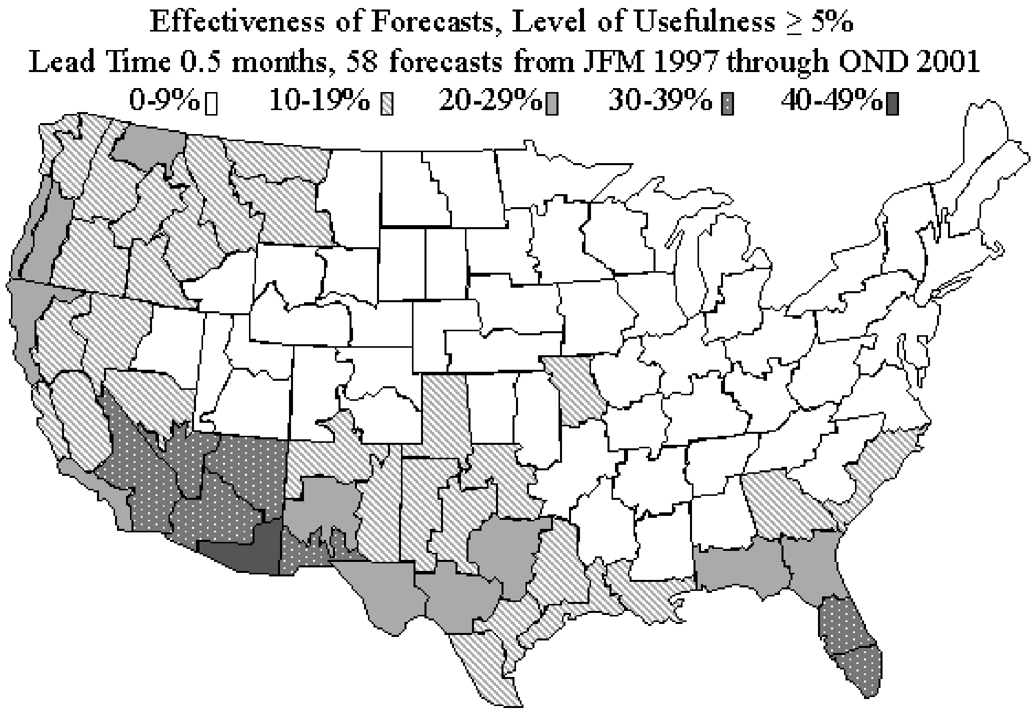

Fig. 2. Effectiveness index for NOAA/CPC forecasts for 3-month total precipitation

normal as the probability distribution of an outcome simulated for forecast and normal climate scenarios.

APPLICATIONS TO AGRICULTURE

Climate forecasts are based on average precipitation across relatively large regions (e.g., in the contiguous US, the forecasts are made for 102 climate divisions). For application to decision-making at a farm level, it is important to know how climate at that particular location relates to the climate in the forecast division (Fig. 4). If the local climate distribution differs significantly from the forecast division, then the seasonal forecast may need to be interpreted relative to the local normal, rather than the regional normal. A critical early step in this process is engaging the user community to determine their understanding of climate and weather, and find out how they might want to apply climate forecasts to their system (e.g, Letson et al., 2001).

Because a climate forecast is a probabilistic statement, interpretation must deal with the uncertainty associated with the forecast. A climate forecast for precipitation is a surrogate for information about the likely amount of crop water use (Fig. 5), which is associated with large impacts on yield (Stewart and Steiner, 1990). There is considerable uncertainty in the relationship between crop yield and soil water content due to amount and distribution of growing season precipitation (Fig. 5b). Uncertainty also exists in the relationship between crop yield and growing season precipitation due to differences in precipitation effectiveness and soil water supply (Fig. 5c).

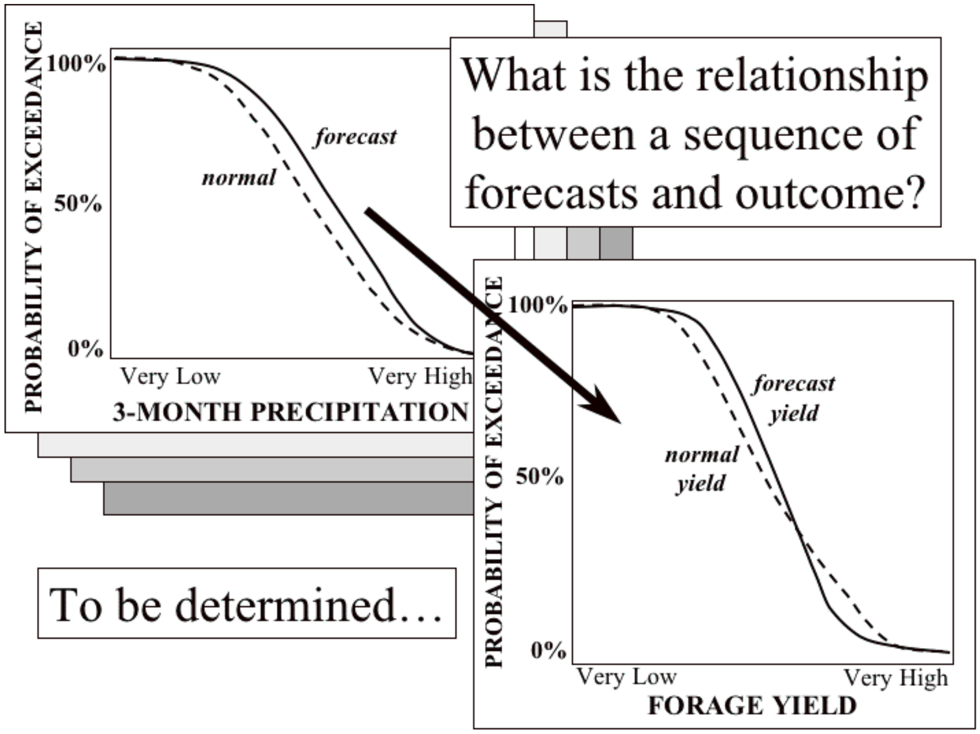

Fig. 3. Interpreting the impact of seasonal climate forecasts for farm-level management decision remains an area of uncertainty. (Source: Schneider, 2002)

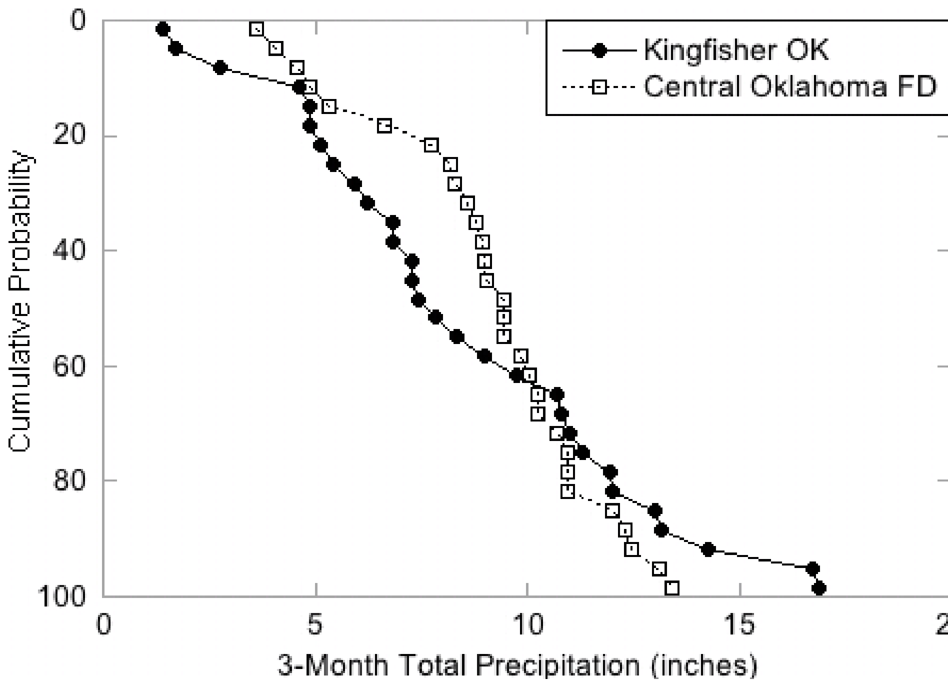

Fig. 4. Differences between the 30-year July-August-September precipitation distribution averaged across the Central Oklahoma Forecast Division and for a single station within that division, Kingfisher, Oklahoma.

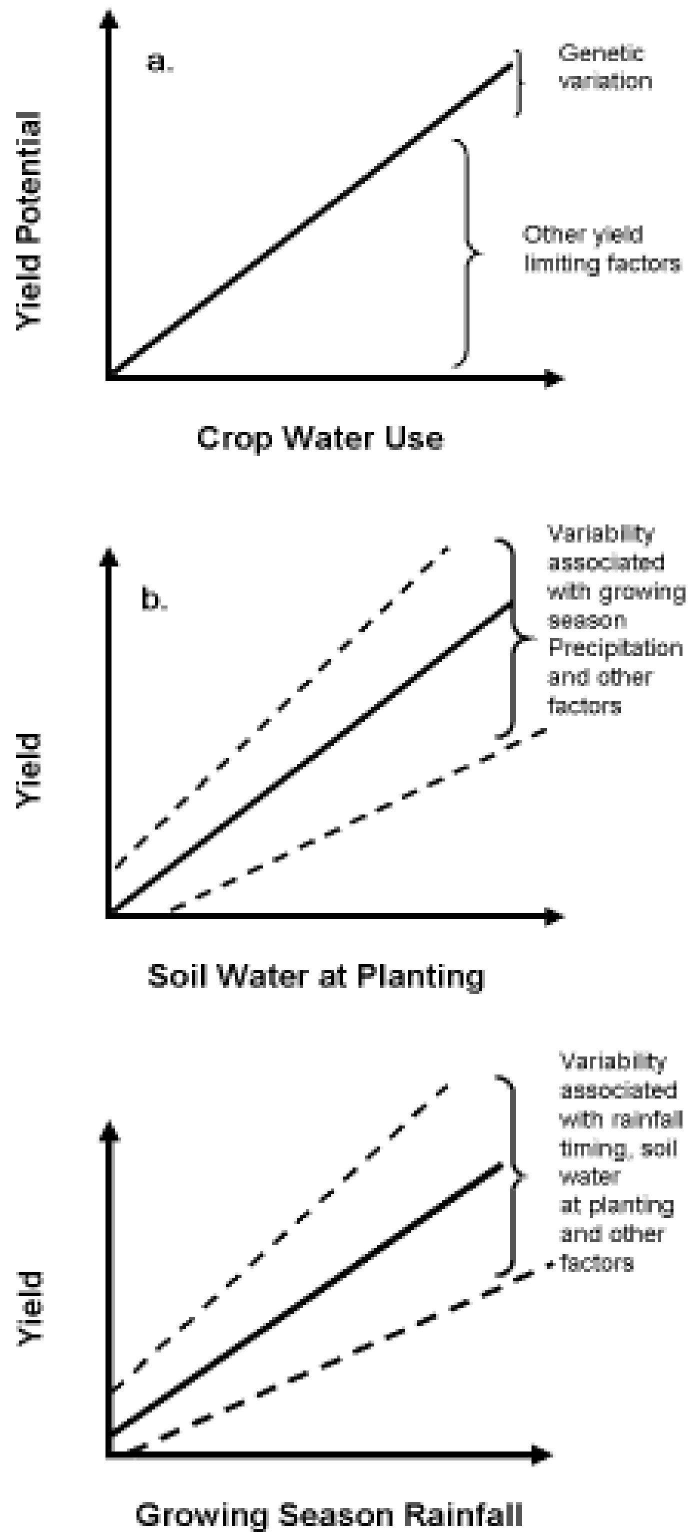

Fig. 5. Conceptional relationship of crop yield to a) crop water use, b) soil water at planting, and 3) growing season precipitation.

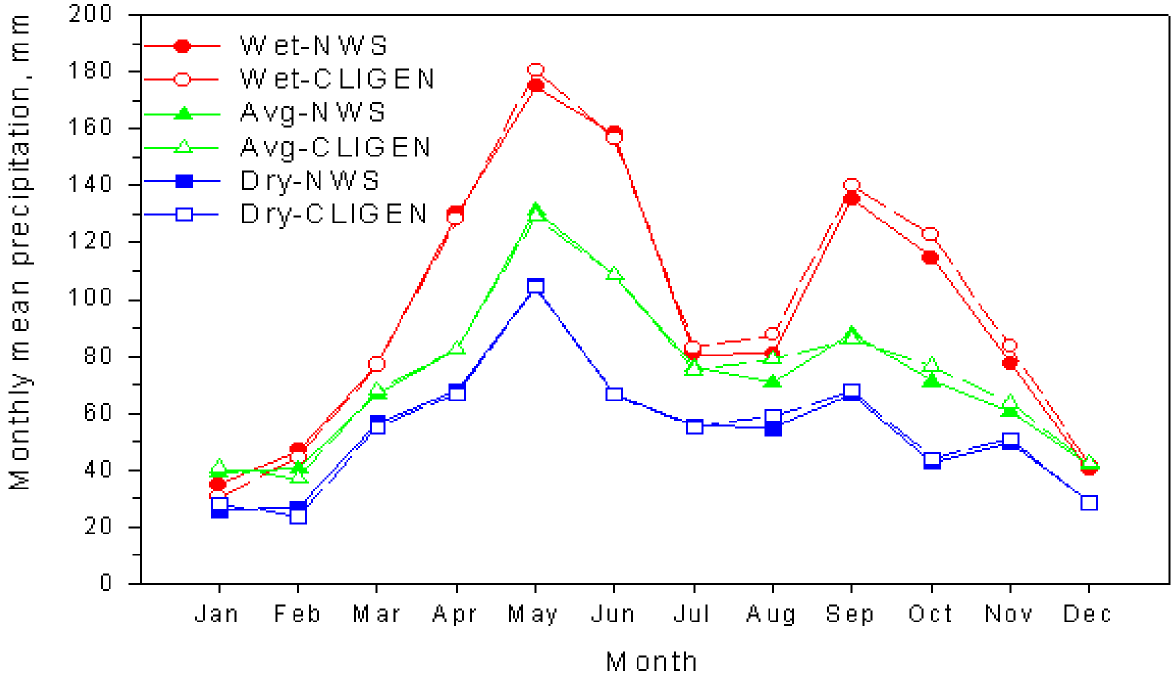

Fig. 6. Tercile precipitation for a station in central Oklahoma illustrating the ability of CLIGEN to replicate National Weather Service (NWS) monthly mean observed precipitation. (Source: Zhang, 2003)

Since soil water depletion is a major component of crop water use and is highly variable at planting time in many regions, opportunities to integrate measurement of soil water content at planting with use of climate forecasts should be investigated. Robinson et al. (2002) found that pre-plant soil water content provided the best forecast of dryland crop yields in the northern Australian grainbelt, but relatively few farmers accurately measured soil water content prior to planting. Prior to turning to seasonal climate forecast to reduce risks, there usually will be greater return to first analyzing risks associated with the current management system, adopting good agronomic practices, and implementing relatively straightforward monitoring (such as soil water or soil nutrient contents) into decision-making processes. Good farm managers who have done this may realize additional risk reduction through use of seasonal climate forecasts.

Crop growth models are often used to simulate probable production or profitability outcomes associated with a climate forecast. Most crop models require daily weather data. For analysis of performance of a management scenario in a variable climate, crop models are run over a number of years in order to determine a range of outcomes associated with a range of climate conditions. Researchers generally use long-term historical weather data or weather generators that produce daily values based on the mean and standard deviation of historical climate records for a location.

To describe the system response to a management scenario in a variable climate, some researchers have utilized tercile analysis. To do this, alternative scenarios are contrasted for the driest, average, and wettest one-third of the climate years on record. If a climate forecast was available, a farmer might select the scenario that performed best for the driest tercile when the forecast was for higher probability of below-normal conditions and the scenario that provided the best outcome for the wettest tercile when the forecast was for a higher probability of above-normal precipitation. Zhang (2003) showed that the CLIGEN weather generator produced the same distribution of monthly mean precipitation as historical climate data in Oklahoma (Fig. 6). Subsequent analyses utilizing the generated climate years and the WEPP model showed that yield distribution of winter wheat was responsive to dry, average, and wet precipitation regimes, but was only responsive to initial stored soil water in central Oklahoma in the driest years (Fig. 7). While this simulation approach demonstrates crop yield sensitivity to annual wet or dry climate conditions, the potential of the tercile approach is more limited for risk-based decision-making based on seasonally issued forecasts and seasonally sensitive agronomic productivity. Also, the selection of climate conditions associated with one tercile limits the flexibility to reflect the risk of the full range of possible outcomes provided by the forecasts.

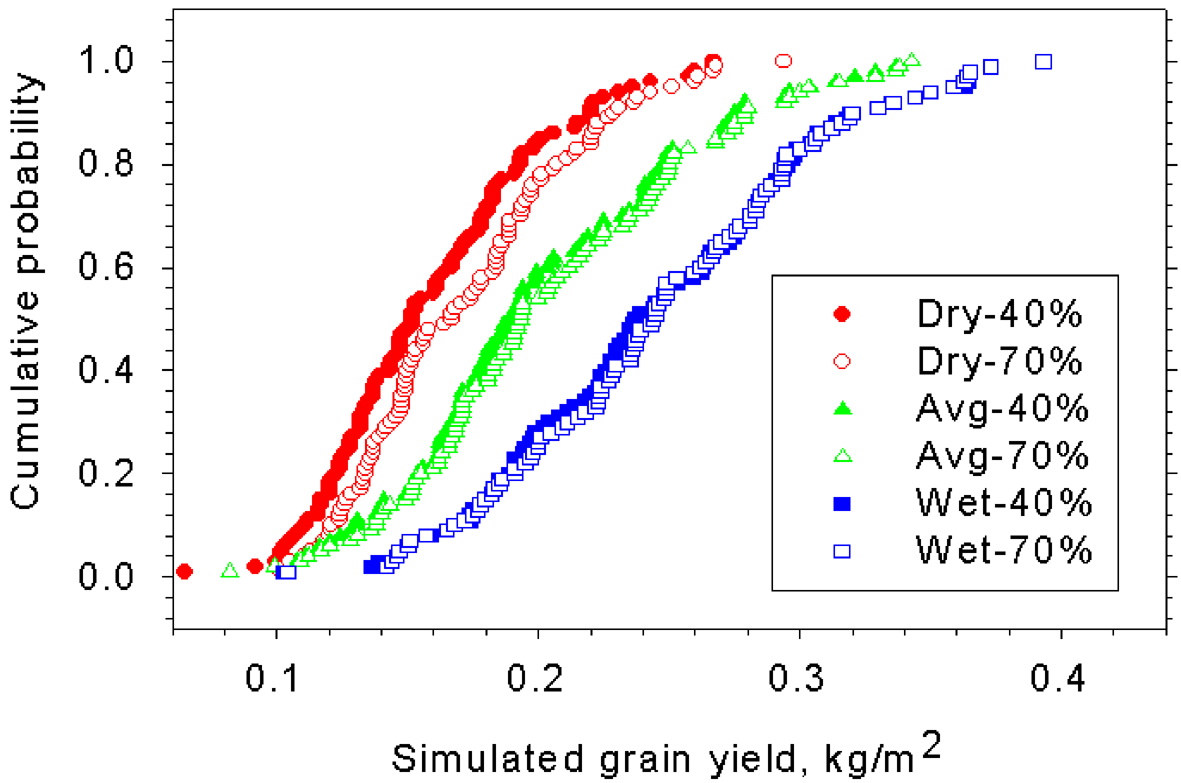

Fig. 7. Tercile analysis of probability distribution of WEPP-simulated yield in dry, average, or wet years, with either 40% or 70% stored soil water at planting. (Source: Zhang, 2003)

Another approach uses analog climate years, based on a climate indicator. For instance, the Queensland Center for Climate Applications contrasted scenarios for the five phases of the SOI index (Stone et al., 1996a) by selecting all years in the historical record that match the current phase of the SOI as analogs for the probable climate for the upcoming season. A third approach that is currently under consideration by the authors is modification of weather generators to produce a full range of possible climate sequences that reflect the frequency distribution of the seasonal climate forecast. These generated alternative climate sequences are then fed into an agronomic model to estimate the range of agronomic responses that correspond to the seasonal climate forecasts. The frequency distribution of the agronomic responses then provide the necessary information to establish the production risk associated with that forecast, which can be used in crop enterprise budgets to compare alternative crops or assess the profitability of a certain scenario. Carberry et al. (2002) have worked with Australian farmers who have had some successes in using of seasonal climate forecasts in farm level decision-making. Their system, FARMSCAPE, combined soil monitoring and simulation with the climate forecasts, and involved farmers, advisors, and researchers working together closely. Their experience indicated that seasonal climate forecasts without the other tools provided little benefit.

Management Decisions Impacted by Climate Variability

There are numerous levels of decision-making that could be guided by climate forecasts. These include agronomic, crop/livestock, household economic or business decisions, as well as regional-level decisions. Agronomic decisions may include things such as crop selection, e.g., maize vs. sorghum vs. millet as a summer crop depending on the probability distribution of growing season precipitation. For a given species, selection of a long vs. short season cultivar could be guided by precipitation or temperature forecasts. Greater planting density and narrow rows have the potential to capture more radiation and potentially produce higher yields in good seasons, but may be more drought prone due to more rapid depletion of stored soil water. Fertility levels can be adjusted based on anticipated precipitation to reduce risks associated with yield reduction and economic loss. In some regions, the amount of area to be planted may be adjusted based on seasonal forecasts, or crops could be planted in heavier soils if the forecast is for dry conditions or on more freely draining soils if a wet season is anticipated. There is also potential to anticipate the pressure associated with some crop pests based on forecasts [e.g., Maelzer and Zalucki (2000) reported correlation of *Helicoverpa* species infestation with SOI, up to 6-15 months in advance].

In crop/livestock systems, decisions may relate to planning for future stocking rates; management of a particular forage crop for grazing, haying, or in some instances grain harvest; intensity and timing of grazing on different areas; the need for supplemental feed; and to guide purchase, selling, or movement of animals based on anticipated forage/feed availability.

At the household level, business decisions could include marketing or hedging based on climate forecasts in the local area as well as in major global production areas for a particular crop. Forecast of unfavorable seasons might lead to decisions to diversify farm enterprises. In some cases, climate forecasts might influence decisions about the need for off-farm income relative to the need for on-farm labor and food security.

At the regional level, climate forecasts could guide decisions such as anticipated need for inputs (fertilizers, seeds of different crop species and varieties), market capacity, storage, and transportation needs; community health service requirements associated with climate variability (e.g., Bi et al., 1998); or drought preparedness planning and implementation (Dilley, 2000; Finan and Nelson, 2001).

Decision Points in a Cropping/Grazing System in the Southern Great Plains

To illustrate potential applications of climate forecasting to agricultural decision-making, we have selected a major cropping/grazing system common to the Southern Great Plains of the

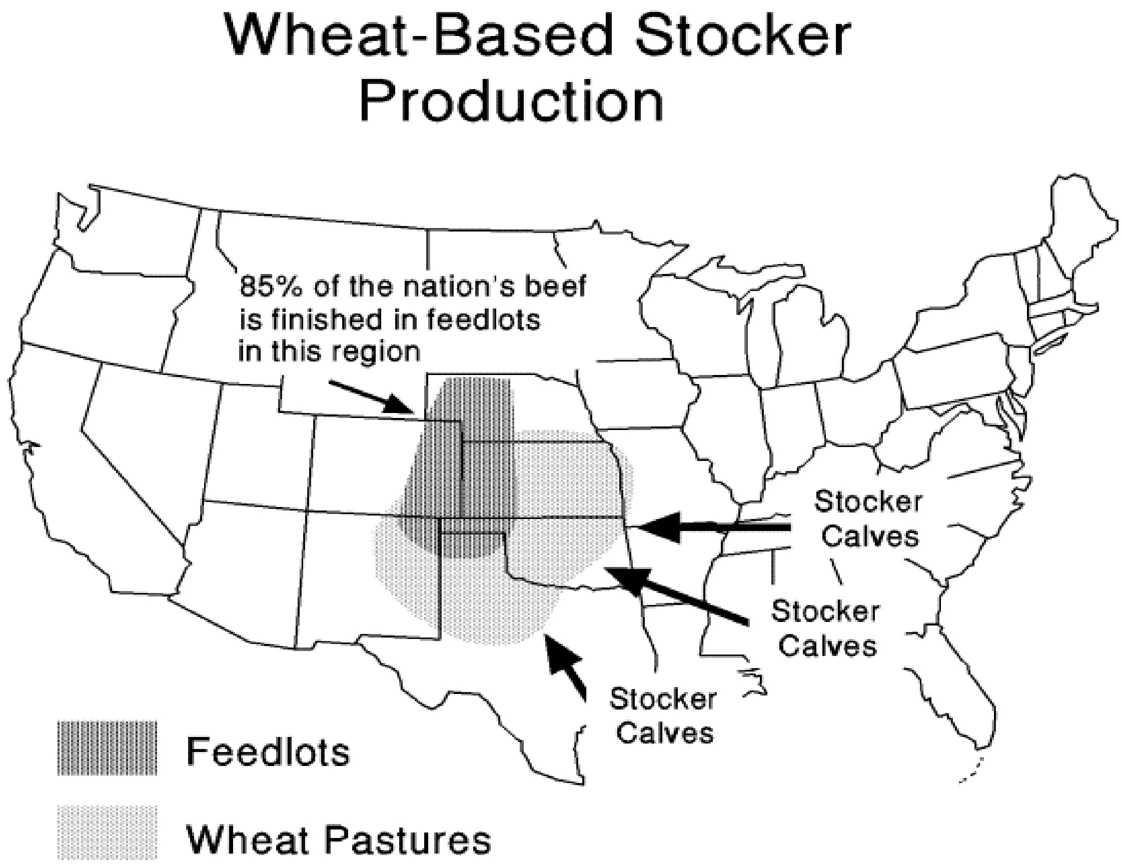

Fig. 8. Beef production systems in the USA, including cow/calf production, stocker grazing, and confined finishing.

US, with winter wheat, cold- and warm-season perennial grasses, summer annual crops, and beef cattle (*Bos taurus*) as major components. The beef cattle system we will discuss is the "stocker" phase of beef production in the US. The beef system in the US dominantly consists of three phases: cow/calf production, stocker growth, and feedlot finishing. These phases often occur with different owners for each phase and often take place in geographically separate regions (Fig. 8). Cow/calf production is predominantly located in the southeastern US, but is also important in rangelands of the semiarid and arid west. Stocker animals are weaned at about eight months of age and frequently are transported to other regions for additional weight gain, utilizing perennial grasses and other forages. The Southern Great Plains is the destination for large numbers of these animals, generally being shipped into the area in the fall. The stocker cattle are grazed on native and introduced perennial grasses as well as annual forages. An important forage in the Southern Great Plains is winter wheat, often grown as a dual-purpose crop that provides fall and winter forage for grazing as well as a subsequent grain crop. The economic return to wheat farmers from stocker grazing can equal the economic returns of the grain crop.

The Great Plains is a sub-humid to semi-arid region that extends from central Canada to central Texas. There is a strong east-west annual average precipitation gradient of approximately 100 mm decrease with each 160 km from roughly the 100th meridian toward the Rocky Mountains. The climate at El Reno, Oklahoma, in the sub-humid region illustrates year round

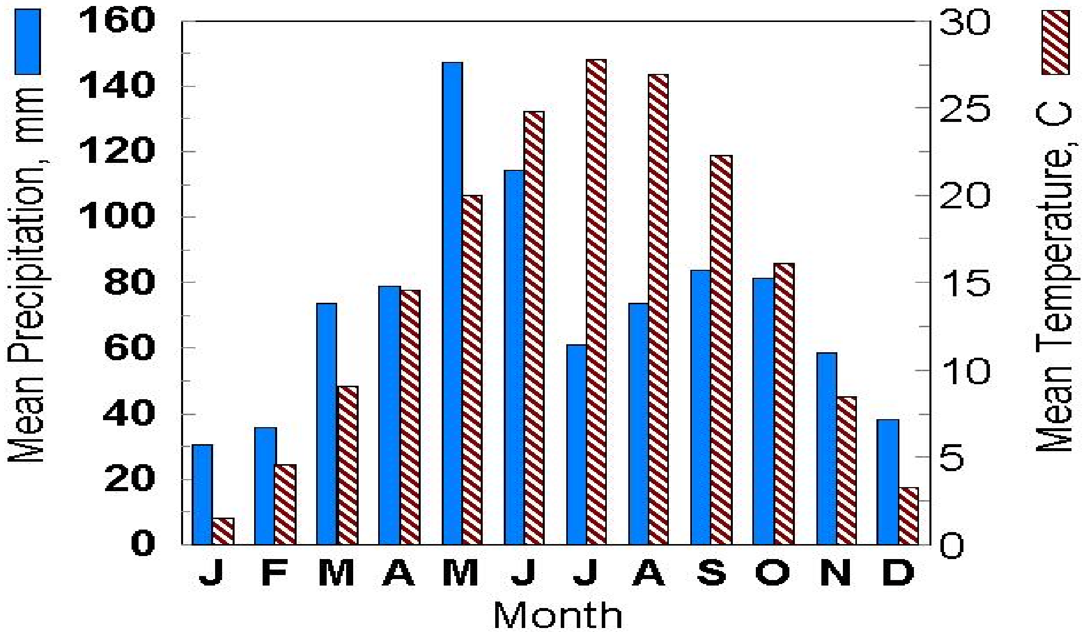

Fig. 9. Monthly mean precipitation and temperature for Canadian County, Oklahoma. 1971-2000.

distribution of precipitation with the peak in May and June, and relatively low precipitation in the hottest months of July and August, when potential evapotranspiration greatly exceeds precipitation (Fig. 9). The dominant native prairie species are warm season grasses, but considerable opportunity exists to grow cool season perennials and annual crops. Winter temperatures can present favorable or unfavorable conditions for plant growth, with extreme variability within and between years.

This system is summarized in Table 2 which identifies numerous decisions that are required throughout the year, often with multiple, complex factors involved and tradeoffs across five major enterprises that comprise the system. Some decisions could be strongly impacted by a seasonal climate forecast (see underlined decisions in Table 2) but even those would also be influenced by additional factors. Some of the climate-sensitive decisions might be guided using existing crop models (e.g., decision whether or not to plant a summer annual following wheat harvest), while others would require whole farm models that incorporate crop, livestock, and marketing issues. Additional factors that have a large impact on economic viability or quality of life for a farm family may not be largely influenced by climate.

Continuous mono-culture of winter wheat is fairly common in much of the Southern Great Plains. These lands, often intensively tilled, have low organic carbon level soils and the surface is often left bare in the summer when intensive convective storms present a great risk of erosion. The soils are also subject to erosion by wind, further degrading the soil and presenting air quality and visibility problems in the region. The farmers chose continuous wheat cropping because of their reliance on the dual purposes of the wheat to maintain economic returns. Planting a short season summer annual following harvest of wheat grain in June would provide cover to protect the soil from erosion as well as providing carbon and potentially nitrogen to the soil. Additionally, it would provide a high quality forage in August and September to supplement warm season perennial pastures that have low forage quality at that time. The feasibility of double cropping depends on availability of soil water for germination and establishment. Additionally, July and August are the least reliable months for rainfall in this region. If summer cropping is implemented, there is a need for precipitation in September or October to recharge the soil water for planting and establishment of the next wheat crop. The likelihood of success would be enhanced by recharge of soil water in late May and early June when the wheat crop was maturing and using little water. At wheat harvest in June, soil water content could be measured and seasonal climate forecasts for summer and fall would be available. The summer forecasts for this region have very low utility at this time (Schneider and Garbrecht, 2003b) so crop models using normal precipitation distributions might be most suited for evaluating alternative scenarios (plant a summer annual or don't plant a summer annual). However, the fall climate forecasts have better skill, particularly in El Niño years, so a forecast of higher than normal odds of high fall precipitation might increase confidence in the decision to plant a summer annual. A seasonal forecast for fall precipitation that is above or below normal odds might also influence decisions about stocking rates and delivery dates of stockers for fall/winter grazing.

Based on the acceptable dependability of seasonal forecasts in some regions and some types of seasons (Schneider and Garbrecht, 2003b), as well as the rapidly advancing state of knowledge in the ocean:atmosphere:climate arena, we believe these forecasts are good enough to help guide management decision-making to reduce risks associate with climate variability. In our research, we're focusing on how to apply these climate forecasts to tactical decision-making at the farm level. This will require a broad approach to evaluating and managing risks, such as described by Carberry et al. (2002). The wheat-stocker-grass system described above is one of the initial systems we will examine. Additional applications are being explored in the area of soil and water conservation and water resource management.

NEXT STEPS TOWARD APPLYING CLIMATE FORECASTS TO DRYLAND FARMING

The state of knowledge in the ocean:atmosphere:climate arena is rapidly growing and evolving so people focusing on applications of seasonal forecasts for decision-making will need to stay apprised of developments in this field of science, and how the new knowledge is feeding into operational forecasts. The forecasting skill of current technologies varies greatly by region and it will require ongoing research to develop effective forecasting tools for regions that currently gain little from forecasts. The strength of teleconnectic signals, as well as directions of the phases, can have large influences on the magnitude and regional distribution of the climate impacts (Izaurralde et al., 1999) The potential economic gain from improved climate forecasting indicates that investment in such research is justified (Petersen and Fraser, 2001; Jones et al., 2000). As forecasts rely more and more on dynamic models, the variability of both the initial values of driving variables as well as uncertainty within the model formulation must be considered (Palmer, 2000).

Another area that needs additional research attention is forecasting climatic extremes. Forecast of probability distributions of future climates contains the most reliable information in the middle 80% of the distribution. The distributions have little reliability in the upper or lower

10% probability. However, impacts of extreme cases are often the most critical, particularly in the areas of food security risks during drought and natural resource/environmental risks associated with either drought or floods.

Integration of climate forecasts with historical data bases and crop simulation models will allow risk-based analyses of alternative management scenarios. Two immediate tasks include 1) development of techniques to temporally and spatially downscale the climate forecasts to daily time series for particular locations needed to drive crop models, and 2) quantify the uncertainty of climate forecasts and uncertainties of crop models including those associated with input variables, model parameters, and the models themselves. Without such uncertainty analysis reliable crop forecasts are impossible. In addition, since many management decisions involve a multitude of issues, single crop models will have limited application to many of the assessments. Advances in tools to evaluate alternatives and tradeoffs in terms of the whole farm system are needed.

Perhaps the most critical need is engagement of farmers as partners in development of new tools to support tactical decision-making on-farm and using seasonal climate forecasts in the context of overall risk analysis and management. This will require development of better methods to communicate probabilistic outcomes for farm decision-making (Perry, 1994). It will also require assessment of climatic risks as only one of many factors that might impact decision-making. Whether at the farm level, or rural community level, uncertainty in the socioeconomic and policy arenas can inhibit adoption of climate forecasts (e.g., Eakin, 1999) or other new technologies.

Table 2. Decision points in an agricultural management calendar for Southern Great Plains (USA) cropping/grazing system (Decisions that are underlined may be influenced by seasonal climate forecast).

Month	**Enterprises within the System** †					**Tactical Decisions to be Made** ***Issues That May Influence Decision***
	Winter Wheat	Summer Perennial	Winter Perennial	Summer Annual	Stocker Cattle	
January	graze					Is wheat growth adequate to support feed requirements of the cattle on the pasture? Are alternative forages available? Is supplemental feeding needed to maintain animal body weight?
February	graze				sell first set of stockers	Grow wheat to grain? If so, remove cattle prior to growing point emergence aboveground. *Decision impacted by cattle and grain futures markets, forage availability, and* ***precipitation forecast.*** Spring fertilizer? *What is status of soil fertility, stored soil water and* ***prospects for seasonal precipitation****?*
March	graze out		graze			Bale wheat in May? If so, remove cattle prior to jointing/heading.
April	graze out		graze			
May	end graze out or cut hay	fertilize? weed control? burn?	graze			As temperatures warm, monitor cool season perennial growth and forage quality to determine end of grazing season.

Month	Enterprises within the System †					Tactical Decisions to be Made ***Issues That May Influence Decision***
	Winter Wheat	Summer Perennial	Winter Perennial	Summer Annual	Stocker Cattle	
June	grain harvest	graze	end grazing	sow?		<u>Summer double crop following wheat harvest</u>? *What is the soil water storage and* ***seasonal precipitation forecast?*** *Is there adequate forage available elsewhere on the farm for anticipated needs?* Do you need to fix nitrogen with a summer crop or is there a need to build soil organic matter with a cover crop?
July		graze? hay? forage quality dip		graze? based on need for greater forage quantity or quality	contract for cattle?	<u>What is the anticipated carrying capacity of stocker cattle in the upcoming season</u>, *based on current forage conditions, cropping plans for the autumn/winter season, and* ***climate forecasts***? What is the purchase price for cattle and what are future prices for cattle when I want to sell? Will there be adequate return to justify supplemental feeding or would a lower stocking rate with minimal supplemental feed requirement be better? <u>Would early or late delivery be better</u>, *based on anticipated sowing date of wheat, and anticipated condition of fall perennial forages, given the* ***climate outlook for fall and winter***?
August		poor forage quality		graze? hay?	sell or deliver to feedlot?	Is forage quality adequate to sustain gain? Is supplemental protein needed or grazing of summer annual? If forage is greater than anticipated, is there benefit in holding these cattle longer than planned, or is there more benefit in selling and stockpiling available forage for the next animals?

Month	Enterprises within the System †					Tactical Decisions to be Made *Issues That May Influence Decision*
	Winter Wheat	Summer Perennial	Winter Perennial	Summer Annual	Stocker Cattle	
September	sow for grazing		graze	harvest	start to buy cattle delivery	Determine area to plant wheat, which fields first, variety, seeding rate, fertilizer amount, *as influenced by plans for cattle enterprise and* ***climate outlook***. As temperatures cool, monitor cool-season perennial growth to determine when grazing can start.
October	sow for grain		graze			
November			graze			Is fall growth of the wheat adequate to begin grazing; are there other fall forages that should be utilized?
December	graze					Is wheat growth adequate to support feed requirements of the cattle on the pasture? Are alternative forages available? Is supplemental feeding needed to maintain animal body weight?

† Approximate seasons for:

Winter wheat	October to early June, for grain production
Summer perennials	
Native	June to August, forage quality dip in late July to August
Introduced	Late May to early September, forage quality dip in late July to August
Winter perennials	March to June, September to November or later with low stocking density or delayed grazing start
Summer annual	If double cropped with wheat, mid-June to early July planting.
Grazing	July-September
Hay	August or September
Cover	Terminate in August to allow recharge of September rains for wheat
Grain	August to late September, depending on species and cultivar

Stocker cattle	In general, delivered, following weaning, in mid to late fall and grazed until ~ August. However, management is highly variable. Land area per animal for spring/summer grazing is ~25% of the area required for fall/winter grazing. The area not needed for summer grazing can be harvested for hay or grain. Additional cattle can be purchased in late winter and/or mid spring as forage availability increases.

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