FORECAST APPLICATIONS IN AGRICULTURE: APPROACHES, ISSUES, AND CHALLENGES

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Abstract

We discuss the path along which agricultural applications research has evolved, and current approaches that attempt to meet the challenge of utilizing seasonal forecasts in farm management. Approaches used have evolved over the period since they first become available in the mid 1980's. From an early phase of searching for locations around the world where predictable inter-annual variability influenced crop outcomes and improving our understanding of the physical interactions between climate and crop growth, our current interest rests more in the human-oriented issues of perception of probabilistic information and implications for decision making. For small-scale and commercial farmers alike, we argue that improving the comprehension of uncertainties associated with climate outcomes and their implications holds the largest hope for successful applications of forecasts to farm management.

1. Introduction

Applications of seasonal climate forecasts have been contemplated for a number of years now in many places around the world, with the agricultural sector considered one of the most likely to receive benefits. Approaches to the promotion and improved use of forecasts in farm management have evolved over that time, yet a number of obstacles remain. From an early stage of optimism about "revolutionizing" agriculture, when anticipated benefits to dryland agricultural production were heralded as "the next Green Revolution" (Cusack, 1983; Sah, 1987), we now have a more realistic understanding of the opportunities and limitations to applying seasonal forecasts, and have more clearly identified the challenges.

Given the ubiquitous nature of the farming enterprise, experience can be drawn from a wide range of farming systems applications, across many continents, cultures, and levels of development. Although details of the uses of seasonal forecasts may differ from system to system, we will argue here that many of the challenges are common to all. All farmers are faced with managing a complex production system under a range of constraints. Decisions are made with imperfect information regarding future states of a number of variables, often dominated by the uncertainty regarding weather outcomes. Seasonal climate forecasts *constrain* the distribution of possible outcomes of weather more narrowly than the climatological distribution in the absence of forecasts. Yet the decision-making process remains the same (or should remain the same, as we argue), if the new information is correctly understood. One of the biggest challenges, then, is ensuring that decision

makers have a solid understanding of the expected distribution of climate outcomes and its implications for their production options.

In this paper, we present some background on the path that has led us to the current focus of research, then expand on the issue of communication and approaches being developed to address the technology transfer challenge.

2. Early Approaches in Agricultural Applications

Early insights into the potential ramifications of El Niño-related inter-annual climate variability were discovered through simple correlation analysis. Given the large-scale nature of the influence of Pacific sea-surface temperatures (SSTs) on global climate, teleconnections with seasonal variation in precipitation at the regional or national scale could easily be detected through straightforward statistical tools. The earliest, and now famous, example of this was Sir Gilbert Walker's work attempting to understand the causes of the massive drought and ensuing famine in India at the end of the 19th century. Walker was the first to make the connection between inter-annual oscillations in sea-level atmospheric pressure in the southern Pacific and the episodic failure of the Indian monsoon.

Since then, many others have confirmed the ocean-atmosphere links, but the next step toward understanding implications for crop production was slow in coming. Early correlation work between SSTs and crop production in the United States (Handler and Handler, 1983) and Australia

(Nicholls, 1985), went unnoticed until late 1980's and early 1990's, when evidence of predictability of ENSO was confirmed (Cane, Zebiak and Dolan, 1986). In 1994, Mark Cane recognized the ENSO signal in a time series of national maize yields in Zimbabwe, gaining international attention with a publication in the journal *Nature* (Cane et al., 1994). If future states of ocean surface temperature were predictable, then crop production (and by extension food shortfalls) would also be predictable, with large implications for food security management.

In that early phase of applications work, such analyses were used mainly as an exploratory tool, looking for ENSO impacts where they were not easily found by looking only at the meteorological records (Hansen et al., 2000), or to identify areas of potential ENSO forecast applications (e.g. Carlson et al., 1996; Posestá et al., 1999; Zubair and Somasundea, 2000). It has been argued (e.g., Rosenzweig, 1994), somewhat successfully, that examination of ENSO signals in monthly or seasonal mean climate statistics can miss agriculturally-important climatic responses to ENSO. This is because plant growth can integrate precipitation and temperature sequences thereby revealing impacts of global circulation anomalies through regional yields that might otherwise go undetected. This turned out to be useful both for revealing regions where ENSO has an influence, and also for pointing out some of the complexities of plant-environment-human interactions (e.g. the difficulties of finding a "signal" in the yields of paddy rice). In order to move beyond descriptive studies to understanding implications for management, other tools were needed.

3. Experimenting with Decision Scenarios Using Crop Simulation Models

Approaches originally developed in the context of climate change impacts on agriculture using crop simulation modeling were soon adopted by the research community interested in inter-annual climate prediction. At the simplest level, crop models could be driven with historical time series of observed climate data and results sorted by ENSO phase to gain insight into the mechanisms of ENSO impacts. For example, Phillips et al. (1999) combined statistical and modeling approaches to investigate the impacts of El Niño and La Niña phases on maize yields in the United States Cornbelt. The statistical analysis revealed an association between regional maize yields and Pacific SSTs ($R^2 = 0.39$), but mapping of the district-level yields by ENSO phase showed high spatial variability in the response. The use of crop growth simulations revealed that lower maize yields in La Niña years were associated with both accelerated development resulting from higher temperatures in July and August, and also with water stress during grainfill. As a number of other studies have pointed out (e.g. Meinke and Hochman, 2000), soil type, depth, and initial soil moisture influence the severity of the impact. Studies of this sort carried implications for management but were not explicitly designed to test decision alternatives.

Other studies have taken this approach one step further, using simulation models explicitly to investigate potential management strategies. This approach has been used extensively in Australia to assess alternative cropping strategies (e.g., Meinke et al., 1996 (peanut); Hammer et al., 1996

(wheat); Meinke and Hochman, 2000 (wheat and sorghum)). One important conclusion from this body of work is that variation in a number of factors, from the temporal distribution of rainfall to spatial distribution of soil type or initial moisture conditions, lead to a wide range of yield outcomes within any given ENSO phase. This recognition has helped to foster awareness of the importance of the probabilistic nature of forecasts to making appropriate farm management decisions (e.g. Meinke and Hochman, 2000; Ferreyra et al., 2001).

In additional to the ability to investigate production outcomes as a function of ENSO phase and alternatives such as planting date (Phillips et al., 1998), cultivar (Phillips and Rajagopalan, 1999), or land allocation (Messina et al., 1999), simulation allows for cost/benefit analysis and risk assessment. Hansen (2000) shows the importance of identifying one's risk tolerance in evaluating outcomes of alternatives under a range of climate scenarios. Using the example of farm land allocation between maize, soybean, and sunflower based on the work of Messina et al. (1999), he compares the risk-adjusted value of forecast information between risk neutral decision makers and those that are risk averse, varying their perception of the uncertainty in the forecast. He shows that for risk averse farmers who interpret the forecast deterministically – that is, assuming the mean tendency of an ENSO phase is the expected outcome - the value of forecast information is negative over the long run due to exposure to excessive income risk. In comparison, a risk averse farmer correctly considering the probabilistic nature of the forecast information responds with decisions that result in a net positive value over the long run.

4. Communicating Forecast Uncertainty and Implications for Farm Decision Making

Analyses of historic agricultural data, simulation experiments with decision scenarios, and experience working with farmers has clearly highlighted the importance of (1) the variability of impacts of climate fluctuations both in space and time, and (2) understanding the resulting forecast uncertainties associated with any skillful but imperfect forecasts, and their implications for how forecast information is used in farm management (Phillips et al., 2001; Hansen, 2000; Jones et al., 2000; Hammer et al., In press).

With respect to forecast uncertainty, the issue is not one of "poor" forecasts – we are assuming that forecast quality is high. Rather, it is the intrinsically probabilistic nature of the forecast, and of climate in general, that is crucial to the decision making process. We have found that the concept of a "prediction" is often taken to mean a deterministic indication of a future event (Letson et al., 2000; Phillips et al, 2001); this interpretation is what often leads to poor decisions. Farmers are generally concerned not only with averages, but with the stability of production and reliability of income. This is particularly true of smallholder, resource-poor farmers in climate-sensitive environments. Farmers employ a range of risk management strategies to reduce their vulnerability to consequences of a poor year, generally at the cost of some reduction of average production, resource use efficiency, and sometimes sustainability of natural resources. In the absence of seasonal climate forecasts, farmers clearly factor into their decisions some mental representation of the distribution of

possible weather outcomes derived from their understanding of local climate. Although there is evidence that this mental representation can be distorted from the "real" distribution (Weber, 1997), it none the less considers a range of outcomes rather than a single expected event. Thus, in order to support the appropriate use of seasonal climate forecasts, our task is to present them clearly as shifts from the climatological distribution.

Regarding variation in impacts across space and time, it can be argued that prescriptive advice regarding the "correct" usage of a forecast may be difficult to provide (Jones et al., 2000). More importantly, conveying the range of possible climate outcomes, and implications for the potential impacts on crop response may be the most effective aspect to communicate. Helping farmers become aware of the importance of climate variability, and equipping them with the tools to analyze and assess their own farm condition, preferences and risk tolerance will help them make use of probabilistic climate forecasts and manage climate variability.

Although most of the crop simulation studies mentioned above are based on scenarios depicting large-scale commercial farmers, the points of greatest concern are arguably relevant to all scales of farming. While some argue that large-scale, better-endowed farmers are likely to reap most of the benefit from seasonal forecasts because they have greater access to resources and information, and hence, greater decision capacity (e.g., Broad and Agrawala, 2000), others argue that resource-poor smallholder farmers will potentially benefit more due to their greater vulnerability to impacts of climate variability, leading perhaps to greater motivation to use forecast information (e.g.,

Barrett, 1998). The issue of risk may be of greater importance for small-scale, resource-limited farmers, who appropriately tend to be more risk averse than relatively wealthy farmers. Where conditions allow, resource-poor farmers seek to spread risk by cultivating a wider variety of crops and utilizing off-farm employment more frequently than large-sale farmers, making their decision environment even more complex. A focus on communicating the probabilistic nature of the information seems therefore to be particularly critical in the case of smallholder farmers.

Communicating a basic understanding of the uncertainties in forecast information is a current focus of research on applications of seasonal climate forecasts to agricultural management at the IRI. To achieve this we are developing hands-on training materials that address the topic of understanding climate variability in general, decision making in the face of climate uncertainty, and the implications of seasonal forecasts within that probabilistic framework. Crop simulation modeling is seen as one of the tools that can help convey this understanding by making potential crop management outcomes explicit. Moving beyond simple ENSO-based climate scenarios, we are working on developing methods to express model-based forecasts of seasonal climate in the format necessary to drive crop simulations (see IRI, 2000). Understanding how people perceive uncertainty and make decisions under risk is a necessary ingredient in developing training programs to help people use seasonal forecasts wisely.

5. Summary

Research on the application of seasonal climate forecasts has progressed from a focus on the physical impacts of inter-annual climate variability on crop production to a more human-centered consideration of how farmers can incorporate this probabilistic information into decisions to minimize production risks. It has become clear over the last few years of working in this field that misinterpretation of what the forecast represents can actually lead to poorer decisions and increased exposure to risk. However, it can be shown that correct interpretation of forecasts, and their wise use in farm management will lead to improvements in overall agricultural productivity, with likely benefits to resource use efficiency and environmental sustainability. The greatest task before us is to learn, along with the farm community, how to express forecast information in such a way that the full range of possible outcomes of various decision alternatives are made explicit, and that farmers have the tools to apply that information to their own specific decision context. Increasing awareness of climate interactions with the farming enterprise will help farmers better manage climate variability with or without a strong forecast. A partnership between climate scientists, the agricultural research community, and farmers on the ground will be necessary to achieve this goal.

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