Topic 4: On the potential value of seasonal climate forecasts for index insurance

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The modern era of seasonal climate forecasts began in the late 1980s with the first successful retrospective predictions of the large 1982–83 El Niño/Southern Oscillation event using a dynamical model (Cane et al., 1986). Today, seasonal predictions are issued routinely at many national and international centers including IRI, based on both dynamical and statistical models (see Goddard et al., 2003). The purpose of this contribution is to provide some background into seasonal forecasting techniques, and to raise key issues regarding their potential value to index insurance contract design. This is a nascent field, but one poised for rapid development in view of the potential quantitative value of forecast information.

Insurance design issues

Interventions for dealing with climate risk and adapting to anticipated climate change for smallholder agriculture include seasonal climate forecasts (Howden et al. 2007) and innovative financial instruments such as weather index insurance (Barrett et al. 2007). While there may be benefits to smallholder farmers from integrating seasonal forecasts with weather index insurance (Carriquiry and Osgood 2008), this has not yet happened in practice, in part because of non-trivial hurdles to implementing integrated products, and lack of demonstrated benefits in the smallholder farming context.

Both damaging and beneficial interactions between insurance and forecasts are possible. Even with an index-based contract, adverse selection can create problems for the financial viability of insurance (Luo et al.,1994), as farmers could use private information to purchase insurance only in years with enhanced drought risk and probability of payout. Alternately, acquiring seasonal forecasts may prove too expensive for some small-holder farmers allowing insurers to take advantage of the farmers.

Skees et al. (1999) proposed that adjusting index insurance premiums based on seasonal climate forecasts may reduce adverse selection. The potential benefits of seasonal climate prediction has received some attention for the weather derivatives market (Jewson and Brix 2005) and in the context of common crop insurance contracts and U.S. agricultural policy (Mjelde et al. 1996; Cabrera et al. 2006; Mjelde and Hill 1999), but little has been done to formally study the benefits of seasonal forecasts on index-based weather insurance schemes for small-holder farmers in less-developed countries. In theory, forecasts and insurance are exact compliments. Insurance that incorporates the forecast in essence insuring against forecast skill potentially allows the appropriate response to noisy forecasts. Carriquiry and Osgood (2008) used a stylized theoretical presentation of the relationship between insurance, forecasts and input use, to argue for the benefits of forecast-based pricing without explicitly addressing the issues of lenders, implementation constraints or real-world evidence of potential benefits.

Osgood et al. (2008) provides an illustration of the potential relationship between forecasts and insurance in an applied setting. They use the contracts, data, and design constraints from the Malawi index insurance implementation to examine whether there may be real-world benefits from incorporating simple forecasts based on ENSO conditions into an insurance scheme. They note that knowledge of ENSO states could be used strategically by farmers to undermine the insurance project in Malawi unless forecasts are accounted for. For example, if farmers were to only purchase insurance in El Nino years, they could undermine the financial stability of the insurance unless the system was modified.

Simulation results suggest that the integration of forecasts and the financial package substantially increases cumulative gross revenues. The resulting wealth accumulation can reduce long-term vulnerability, supporting adaptation to climate variability and change. Basing insurance price on ENSO state more than doubled mean gross margins, and increased the maximum gross margin by a factor of more than five relative to fixed insurance pricing. The figure (from Osgood et. al. 2008) illustrates the differences across seasons in gross margins between one ENSO-adjusted and the fixed price package, showing that the gains result from very high gross margins in a small number of La Niña years (shaded in the figure). In El Niño years, the gross margin is slightly smaller for the ENSO-adjusted scheme because of the smaller area planted. The variability of annual gross margin that the farmer faces is much higher because the farmer has the opportunity to earn substantially more in years with abundant rains.

Because this work was based simply on ENSO states, it is merely illustrative. Work must be done to understand the utility of state of the art seasonal forecasts in index insurance, develop the tools to design and price insurance considering the forecast, and detect when even weak forecasts have enough skill to undermine naïve insurance schemes.

Seasonal forecasting

The physical basis of seasonal forecasting rests largely on the memory of the upper ocean whose thermal capacities and motions are much larger/slower than those of the atmosphere, together with sensitivity of the atmosphere to underlying sea surface temperatures. The most pronounced phenomenon with seasonal predictability is the El Niño/Southern Oscillation (ENSO), which involves a coupling between ocean and atmosphere over the tropical Pacific Ocean, and it is ENSO that often provides a large fraction of seasonal forecast skill; ENSO exhibits statistically robust associations with precipitation anomalies over 20%–30% of the land in any one season (Mason and Goddard 2001). Atmospheric “teleconnection” patterns are responsible for transmitting the ENSO signal to other regions across the globe, and it is the details of these patterns, together with the local seasonality of rainfall that determine whether or not there is seasonal predictability in rainfall and temperature at a particular location at a given time of year (Ropelewski and Halpert, 1987,1996). Thus, seasonal forecasts are only possible because in some parts of the world and at some times of the year, tending to work best in tropical regions.

Although the oceans can impact the average weather conditions over a period of a few months, the effects of day-to-day weather variability still remain fairly strong so that it is not possible to predict with any high degree of accuracy exactly what the average weather conditions are like. Thus, although in theory an estimate of the average rainfall for the next three months, for example, could be made, the errors in this forecast are likely to be large. Instead, forecasters communicate the uncertainty along with the forecast, by issuing the forecasts in a probability format, typically in terms of the probabilities of forecast categories, such as below-normal, near-normal and above-normal.

State-of-the-art seasonal climate forecasts are made using multi-model ensembling approaches, because the skill of the individual models has been shown to be improved by averaging ensemble forecasts made by several different models together (Rajagopalan et al., 2002; Palmer et al., 2005). Complex coupled ocean-atmosphere global climate models (GCMs) represent the equations of motion of air and water on grids of 100–300 km resolution, and parameterize smaller scale motions and rainfall processes; these models are run in ensembles with 10's of members to bracket the unpredictable element of daily weather in the seasonal forecast.

Tailoring of forecasts for risk management

Climate risk management generally requires climate information at local scale, and often it is the statistics of daily weather that matter most. These needs conflict with the customary coarse-graining of seasonal forecasts into tercile categories of seasonal averages. While this coarse-graining is designed to reduce the uncertainty in low-resolution GCM forecasts, it nonetheless often proves possible to extract finer scale information of daily weather properties, through statistical bias correction using fine-scale data records, (e.g. Tippett et al., 2003; Robertson et al., 2004), or through nesting high-resolution dynamical regional climate models to capture the effects of complex land-surface heterogeneity (e.g. Sun et al., 2005). This is called "downscaling" or "tailoring" of the GCM output to the specific application at hand, and can sometimes reduce the uncertainty by isolating the predictable aspect that may be smeared out in the coarse-grained forecast.

For example, frequency or persistence of daily rainfall is often found to be more predictable than the seasonal rainfall total in the tropics (Moron et al. 2006), and may be more relevant that the seasonal rainfall total for agriculture; the onset of the monsoon season is also sometimes predictable (Moron et al., 2008b,c), and may help planners anticipate when farmers will plant their crops, while knowledge of the probability of a "false start" to the rains may help minimize the cost of wasted seeds. Ensembles of stochastic daily weather sequences enable crop-yield simulation to explore decision making strategies (Hansen et al., 2006). In this context, seasonal forecasts can be thought of as conditioning climatological likelihoods of particular sequences. The climate forecast can, in principle, be incorporated as a smaller or larger force on the system. It then becomes imperative that this conditioning be unbiased, so that the resulting forecast probabilities are correct on average (Mason et al., 2007).

A central tenet of IRI's "demand driven" approach is that the forecast system cannot be optimized for managing climate-related risks without close interaction between forecasters, sectoral models and end-users, to identify the critical forecast variables and relevant aspects of the probability distribution. Thus, the dialog at the core of this workshop becomes essential from a climate forecast perspective as well.

Climate indices

Indices have long been created by meteorologists to study regional climate variability and large-scale atmospheric teleconnection patterns (Walker and Bliss 1932; Wallace and Gutzler 1981). The concept of indices thus forms a natural way to connect insurance models with climate forecasts in a quantitative way. Climate indices range from indicators of large-scale see-saw pressure patterns, especially the Southern Oscillation and North Atlantic Oscillation, through regional indices of monsoon strength, down to indices of local station rainfall. Large-scale indices may be useful in insurance when they describe geographical see-saws that allow for the spreading of risk (see topic paper #7); regional indices such as the All-India rainfall can characterize aggregate conditions over India, even when the monsoon is typically associated with droughts in some regions and floods in others. In cases where a single spatially-coherent atmospheric phenomenon controls a rainfall season, an index can be used to characterize the potentially predictable component, and to quantify local deviations from it. For example, recent studies have shown that the monsoons over the Philippines and Indonesia contain large-scale spatially-coherent climate signals in onset-date (Moron et al., 2008b,c). These signals are substantially related to ENSO, and thus partially predictable, while the nature of post-onset rainfall has been found to be much less so. At local scale, these signals are variously contaminated by small-scale unpredictable noise that is essential to quantify. An ENSO index based insurance for floods has been proposed for Peru (Khalil et al., 2007).

Linking seasonal forecasts with index insurance

Climate indices can be classified according to their predictability, and their associations with local, regional, and large-scale weather and climate, see Table 1. Quantitative treatment requires both aspects to be characterized using probabilistic models. Predictability and current forecastability must ultimately be described in terms of the full probability density function, conditional on the forecasts. Several decades worth of forecasts made retrospectively are required to construct such products, and to ensure that they are properly calibrated.

Given forecasts and an index insurance scheme, it is a daunting technical task to reflect all of the information in the forecast in the insurance package, both to fully utilize the forecast and to prevent it from undermining the insurance. It is likely that rainfall simulation (see topic paper # 5) is the fundamental tool to connect these two pieces. If rainfall simulators are trained including forecasts as conditioning variables, then the resulting rainfall simulations could be generated for different forecasts. Contract design optimization and pricing could then be performed on the forecast-modified simulations to quantitatively capture the forecast in insurance contracts and pricing. Several approaches have been explored for conditioning stochastic daily rainfall simulation on seasonal forecasts, including: (1) stochastic disaggregation of monthly GCM rainfall (Hansen and Ines, 2005); (2) K-nearest neighbor resampling of observed daily rainfall according to GCM simulated daily circulation fields (Moron et al., 2008a); (3) conditioning of stochastic weather generator parameters on GCM output (Wilks, 2002); (4) non-homogeneous hidden Markov models (Robertson et al., 2004, 2006).

Different strategies might be developed to address the issue of seasonal forecasts, depending on the ability of clients to respond to the information in seasonal forecasts. If clients have no potential for improved activities in response to forecasts, the strategies include closing contract sales before forecasts are available, multiple year contracts, or selling options on the right to purchase the insurance. If the forecasts have information that could allow small-scale farmers to make better decisions, then other strategies might be appropriate. The insurance package could be built to take advantage of the forecast information, encouraging a farmer to take advantage of more profitable options when climate risks are lower, while using forecasts of bad years to provide incentives for more protective activities to prevent losses. When credit is connected to the insurance through an insurance–loan package (as for example in Malawi), the bundle could be designed to provide financial resources for the production package that are appropriate for the forecast, while still providing insurance protection in case the anticipated weather does not occur.

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Table

Climate index	Spatial scale	Temporal range	Predictabiity
ENSO (SOI, Nino-SST, MEI)	near-global	seasonal-interannual	relatively high
North Atlantic Oscillation	northern hemisphere	all	low
Madden-Julian oscillation	tropics	intra-seasonal	moderate
Indian summer monsoon rainfall	India	seasonal-interannual	low
Indonesian monsoon onset	Indonesia	seasonal-interannual	high

Table 1: Examples of climate indices.

Figure

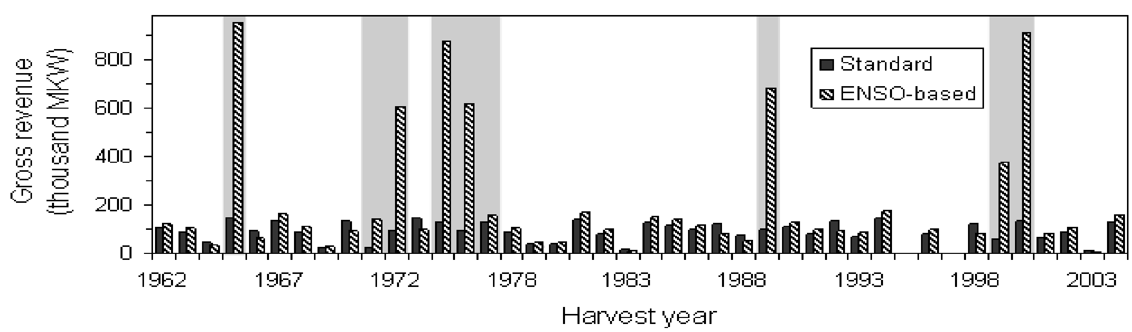

Figure 1: Gross margins for the ENSO-scaled ENSO-scaled and fixed insurance pricing packages using simulated yields in a hypothetical farm that plants only the hybrid maize given by the bundled scheme. Shading shows La Niña years.