## Contributions of Agricultural Systems Modeling to Weather Index Insurance

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Climate exerts a profound influence on the lives of rural populations, particularly the rural poor, who depend on agriculture for livelihood and sustenance, who are unprotected against climate-related diseases, who lack secure access to water and food, and who are vulnerable to hydrometeorological hazard. Climate shocks such as drought and flooding lead not only to loss of life, but also long-term loss of livelihood through loss of productive assets, impaired health and destroyed infrastructure. The uncertainty associated with climate variability is a disincentive to investment and adoption of agricultural technologies and market opportunities, prompting the risk-averse farmer to favor precautionary strategies that buffer against climatic extremes over activities that are more profitable on average. Weather index insurance is one of several promising interventions for overcoming the negative impacts of climate risk on rural livelihoods and food security.

The field of *Agricultural Systems* began with early efforts (1960s-1970s) to model response of crop and livestock systems to the environment and to model interactions between farmer decision making and biological and ecological processes in farming systems. Since then, it has evolved into an integrative, trans-disciplinary approach to dealing with the complexities of agriculture and its relationship with the natural and human environment across scales. Agricultural systems methodology and insights have much to offer to the challenges identified for scaling up applications of weather index insurance for agricultural development and food security (Barrett et al., 2007). We discuss the potential role of agricultural systems modeling in three areas: (a) designing indices that manage basis risk in its various forms; (b) identifying and quantifying the right risk, and (c) understanding and evaluating potential incentives, management responses, and benefits associated with index insurance and its interaction with advance information.

### 1. Crop-Weather Models: from Statistics to Water Satisfaction to Processes

Seasonal averages of single climate variables such as rainfall accumulation often correlate poorly with crop yield, even in environments that are strongly water limited. Crop production is a function of dynamic, nonlinear interactions between weather, soil water and nutrient dynamics, management, and the physiology of the crop. The same amount of rainfall will have different impacts on the crop growth and final yield depending on the characteristics of wet and dry spells and on the crop stage when a deficit occurs. As a simple example, spring wheat in Moree (Northern NSW, Australia) is grown as a dryland crop in winter. ENSO contributes to extreme rainfall variability with seasonal (May to August) totals varying from near zero to more than 400mm. District yields correlate weakly with seasonal rainfall (Fig. 1a, $R^2 = 0.22$). A simple district yield model that takes soil water balance and antecedent soil

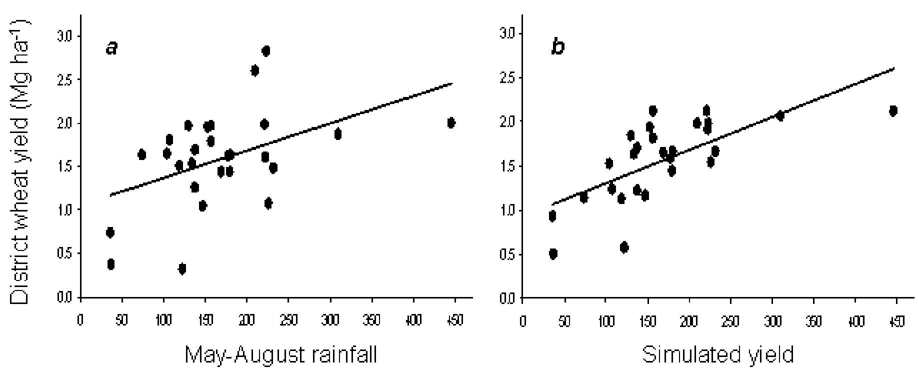


**Figure 1. Seasonal rainfall (May-August) at Moree, NSW, Australia against (a) district wheat yields from 1975 to 2001 and (b) simulated wheat yields for the same period.**

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moisture into account (Potgieter et al., 2002, 2005), improves the correlations considerably (Fig. 1b, $R^2$ = 0.46). Parallel developments in agricultural systems modeling and agrometeorology have greatly improved our ability to model the response of crops and forage to weather.

In contrast to statistical modeling, agricultural systems models establish a functional relationship between causes and effects based on understanding of mechanisms. The early evolution of crop modeling in the 1960s and 1970s paralleled *levels of production* (perhaps more appropriately, "levels of analysis") defined by the factors that limit production (Fig. 2, Rabbinge 1993). *Potential production* is limited only by crop genetic characteristics, solar radiation, temperature, day length and $CO_2$. Yields decrease from potential, to *water-limited*, to *N-limited*, to *actual production* because each successive level involves additional constraints. Models capable of simulating *potential production* processes (i.e., photosynthesis, respiration, partitioning and phenology) were developed first, then expanded to incorporate models of the soil water balance and the physiology of water stress response, and later N dynamics and use. Complexity and data requirements grow as crop models incorporate additional processes. With increasing complexity, there is a tradeoff between the reduction of uncertainty from capturing additional determinants of actual production, and the additional uncertainty from the need to estimate increasing numbers of parameters (Fig. 3). The optimum level of complexity depends on the determinants of yield and the uncertainty of the parameters required for the particular context and scale. No model simulates the full range of determinants of *actual production*, but there has been progress in addressing some relevant determinants beyond water and nitrogen.

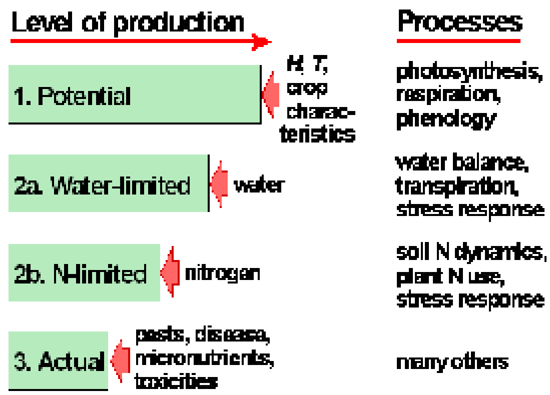


**Figure 2. Levels of crop production (after Rabbinge, 1993).**

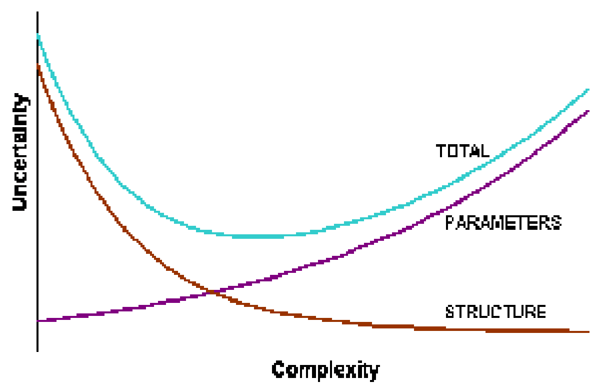


**Figure 3. Stylized relationship between model complexity and uncertainty due to model structure and parameters.**

Agrometeorology took a pragmatic approach to the goal of improving prediction of water-limited crop yields. The FAO water requirement satisfaction index (WRSI) and its variants incorporate a simple dynamic soil water balance model, fixed crop development calendar, and seasonally-integrated ratio of actual (limited by the smaller of evaporative demand or supply in soil) to potential evapotranspiration (Frère and Popov, 1979, 1986; Doorenbos and Kassam, 1979). Yield loss due to water stress can be estimated by weighting this ratio by crop sensitivity during the various growth stages. In this form, WRSI can be considered an index of seasonal rainfall that is integrated in a manner that is consistent with how crops respond instead of by an arbitrary summation. The WRSI concept attempts to capture the water-limited level of production without modeling potential production. Since WRSI is related to proportional yield reduction due to water stress, yield estimation requires an independent estimate of potential yield.[2] The WRSI concept is embedded in process-oriented models of water-limited crop production that use

[2]"Potential yield" in this case refers to yield without water stress, and is not equivalent to the potential production concept in agricultural systems modeling (Rabbinge, 1993).

evapotranspiration ratio to modify processes such as carbon assimilation, partitioning and leaf expansion. A convention of calculating WRSI on a dekadal (10-day) time step, adopted in the 1970s to accommodate manual calculation and data storage constraints, is still widely used but no longer justified. Calculating WRSI on a daily time step can presumably better capture water stress from dry spells within a dekad and hence better predict yield response to rainfall particularly under conditions of low soil water-holding capacity and high evaporative demand, but we are not aware of efforts to test this assumption.

## 2. Agricultural Models as Insurable Indices of Production and Economic Loss?

Basis risk – the gap between an insured index and the risk it is meant to target – is regarded as the price paid for removing moral hazard, adverse selection and their resulting transaction costs as barriers to insuring vulnerable farmers against climate-related risk. Basis risk results from (a) the imperfect relationship between the index and the targeted loss, (b) the differing scales of risk faced by insurers (at an aggregate scale) and clients (e.g., farmers, input providers, at a local scale), and (c) distance from a meteorological station. Correlation of an index with the targeted loss is crucial if index insurance is to be an effective alternative to indemnity insurance, but transparency and acceptability to the clients and other stakeholders, vulnerability to manipulation, data requirements, and robustness in the face of sparse data are also important considerations. Can an agricultural simulation model serve as an insurable index of production or economic loss? How would it compare to alternatives such as cumulative rainfall during portions of the growing season, joint precipitation and temperature thresholds, official area-average yield statistics, or remotely-sensed vegetation (e.g., NDVI)? The suitability of area-averaged yields depends critically on the quality of official production statistics and vulnerability of the estimation process to manipulation. A cursory look at country-level yield statistics in FAOSTAT reveals widespread problems in many developing countries.

A properly used agricultural simulation model will generally have lower basis risk than precipitation or temperature averaged over portions of the growing season. It will also be more readily extrapolated than a statistical relationship between weather and yields. While the reported performance of crop models is quite variable, coefficients of determination ($R^2$) on the order of 0.7-0.9 between observed and simulated yields can be expected when (a) weather data and soil hydrological properties are measured where yields are measured; (b) cultivar parameters are measured experimentally or calibrated with adequate data; (c) the observed yields vary substantially in response to some combination of genetics, water availability and nitrogen supply; and (d) either production is managed at close to the ***attainable level***, or damage from other stresses such as pests or disease is measured and incorporated into the simulation. "Proper use" assumes that the model is used with understanding of its capabilities and limitations, understanding of the system being modeled, adequate consideration of the levels of accuracy needed, evaluation of model performance for the given application, and appropriate calibration if needed. We also assume that the choice of model is appropriate considering the balance between adequacy to capture the important determinants of yield, and data availability and uncertainty issues associated with model complexity.

Remote sensing vegetation products such as NDVI are considered an alternative to weather indices for agriculture and food security-related insurance applications. Food security institutions such as FAO, WFP and FEWSNET treat rainfall (raw or integrated into WRSI) and NDVI as independent, complementary pieces of information. With advances in model data assimilation, an alternative is to optimally integrate remotely sensed vegetation indices into agricultural systems models to improve accuracy. Updating crop model state variables within the simulation period with sequential data assimilation (e.g., Evensen, 1994) minimizes the cumulative effects of model structural uncertainty, initial/boundary conditions and data input errors in the simulation of crop growth, and hence yield. We expect that a model-based index that integrates multiple sources of information, including satellite remote sensing, will often provide the best information about weather-related production losses and hence result in the lowest basis risk.

Crop-weather models are typically developed and tested for the scale of a homogeneous plot. Yet the plot is not necessarily the scale of risk that is most relevant to the insurer or lender. Insurance for food crisis management is concerned with weather impacts at aggregate scales that incorporate considerable heterogeneity. If heterogeneity of the environment (soils, climate) or management is not sampled adequately, a model will produce poor and potentially biased simulations of aggregate production or average yields. Methods for reducing error when simulating at an aggregate scale (reviewed in Hansen and Jones, 2000) include sampling input variability in geographic or probability space, or by calibrating either model inputs or outputs.

Relative to a purely meteorological index, using a process-based model as an index would increase data requirements and the need for technical expertise or training. Difficulty in understanding a complex model could be an obstacle to acceptance if it affects transparency and allows at least the perception of vulnerability to manipulation. Although an agricultural model is more complex than cumulative rainfall, using an integrated estimate of the target loss as an index would result in a simpler and perhaps more transparent contract than rainfall totals for multiple periods or combinations of precipitation and temperature. Restricting an index to time-averaged meteorological variables shifts the responsibility for relating them to production-related losses onto the intuition of the various stakeholders. Quite complicated contracts can result if local experts impose ad-hoc adjustments, such as upper limits to dekadal rainfall to account for runoff. We propose that the decision about choice of an index for agricultural or food security applications should recognize and seek to balance the tradeoffs between basis risk and the communication challenges associated with a given model, and not assume either that communication challenges are insurmountable or that basis risk is trivial.

## 3. Quantifying the Right Risk

For index insurance to be effective, it must target the right risk and the index must capture a sufficient portion of that risk. Pricing depends on quantifying that risk. Risk for agriculture is often classified as *production risk* (i.e., uncertain crop yields or livestock production), *market* or *price risk* (i.e., uncertainty in commodity and input prices, including influence from currency exchange rates), *institutional risk* (i.e., risk of unfavorable changes in institutional services and policy at various levels), *business* or *income risk* (which aggregates production, market and institutional risk), and *financial risk* (resulting from the degree and terms of borrowing). This classification overlooks *consumption risk* – a more important measure in subsistence-oriented agriculture.

Weather is most closely related to the production component of risk. Weather index insurance initiatives we are aware of emphasize crop yields – typically for a single crop – or the productivity or mortality of livestock. A standard method to characterize production risk is to run a suitable, well-validated crop, forage or livestock model with many realizations of weather data either from historic observations or a stochastic weather model parameterized from observations. This simple procedure carries a few potential pitfalls beyond the general warning about misuse of agricultural models. First, many stochastic weather generators systematically under-represent year-to-year variability (Kats and Parlange, 1998; Wilks, 1999). Second, using many realizations from a stochastic weather model may mask an inadequate sample of observed weather (used to parameterize the weather generator), giving a false sense of confidence in the resulting distribution. Third, if initial conditions (e.g., soil water or nutrient content) are not reset prior to simulation with each weather data sample, the resulting distribution will not represent the climate component of risk. Fourth, established methods assume that weather risk is stationary (i.e., central tendency, dispersion and other statistics do not change significantly over time), which does not hold in the face of (multi−)decadal climate variability and anthropogenic climate change. Finally, the scale of the model and the targeted risk must be consistent, as variability of crop or forage yields tend to decrease with increasing scale of aggregation (Hansen and Jones, 2000).

The yield distribution of a given crop is not necessarily the best measure of the climate-related risk that a farm household faces. First, market risk adds a level of variability and uncertainty. Yet where local markets are weakly integrated with the regional or global economy, the yields and prices of a given crop tend to move in opposite directions in response to climate variations, and gross margins (i.e., income from sales minus variable costs of production) may be more stable than yields of the crop. Capturing market response to weather variability through economic equilibrium modeling is feasible but daunting. A simpler approach incorporates a stochastic price model (e.g., Fereyra et al., 2001) conditioned if necessary on yields. Second, because income from different farm and possibly non-farm enterprises is imperfectly correlated, the economic (business or consumption) risk that a farm household faces is often quite different than crop yield variability would suggest. The more diversified the household's livelihood system, the less it is affected by weather impacts on any particular farm enterprise. Agricultural insurance programs tend to target a single crop or livestock commodity, but the risk covered may be only weakly related to the economic risk farmers face. Realistic characterization of climate-related risk within a diversified farming system requires analysis at the farm level, which adds a level of complexity, and sensitivity to heterogeneity of resource endowment and the physical environment.

## 4. Evaluating Management Incentives and Responses

As with any development intervention, ex-ante analysis of the potential impacts of index insurance can improve the design and targeting of packages with the greatest potential benefit and lowest risk of negative consequences. Where index insurance seeks to remove barriers to access to credit and production technology, agricultural systems modeling can be used to estimate the potential benefits of the improved access to resources, and to estimate optimum levels of production inputs and hence target levels of credit. Realistic evaluation may require analysis at the farm level informed by in-depth understanding of farmers' goals, resources and constraints. Integration with market-level analysis may be needed if insurance will be implemented on a scale that is sufficient to impact prices of agricultural commodities or inputs. Yet simpler enterprise-level analyses may still yield useful insights.

Advance information in the form of seasonal climate forecasts, often seen as a threat to weather index insurance, appears to have potential to enhance the benefits of insurance if the forecast information is incorporated into the contract (Carriquiry and Osgood, 2008). The potential to incorporate seasonal climate forecast information into contract design and pricing is raising particular interest in evaluating the implicit hypothesis that forecast information can be transmitted through market (insurance or credit) prices in a manner that is consistent with the way farmers would respond to that information (i.e., intensifying production under anticipated favorable climatic conditions while being more conservative under anticipated adverse conditions). Model-based methods used to estimate the potential value of seasonal climate forecasts for agricultural management (reviewed by Meza et al., 2007) are directly applicable to evaluating management responses and resulting shifts in demand for credit in response to forecast information.

In the context of an ongoing pilot bundled insurance-credit scheme for farmers in Malawi, Osgood et al. (submitted) illustrate how basing insurance premium on climate forecasts in the form of ENSO phase might improve the income of farmers without jeopardizing the insurer. Their analyses assumed that farmers would respond to changes in credit supply due to forecast-based pricing by adjusting the area under a fixed intensified maize technology package. Figure 4 illustrates the logical next step to assess how forecasts would change optimum input levels and hence the demand for credit under more realistic assumptions. The profit-maximizing combination of seed and N fertilizer inputs for maize vary with ENSO conditions. A risk-averse farmer would likely select lower input levels, but would still benefit from intensifying management during climatically-favorable neutral years while remaining conservative with borrowing and input use during adverse El Niño years. Such analyses (ongoing) provide insight into the influence of climate on demand for credit. However, the design of insurance packages to support farm management that exploits advanced information about climatic conditions should be informed by more complete farm-level risk analysis that considers the full range of options, and accounts realistically for farmers' goals, risk attitudes, constraints, and must therefore involve farmer participation.

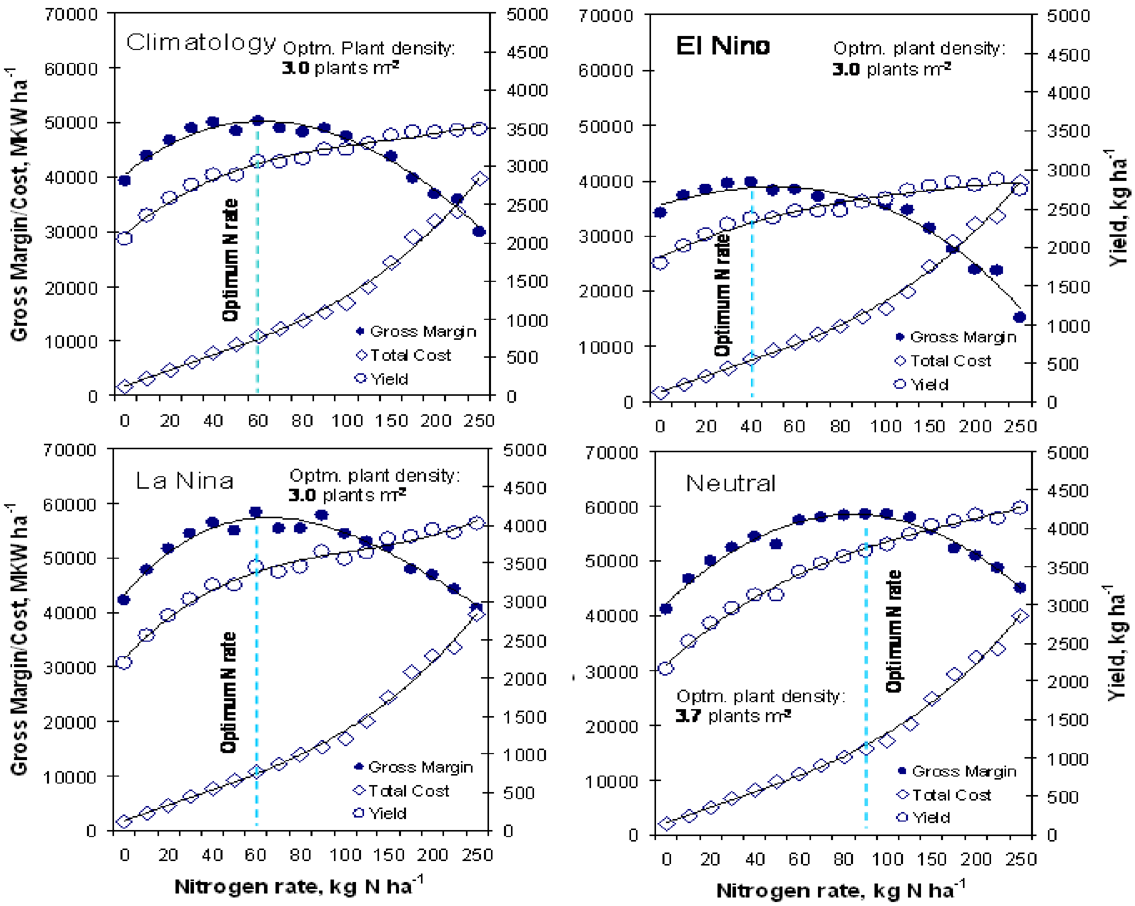


**Figure 2. Maize yield simulated with CERES-Mize and gross margin as functions of applied N fertilizer, and optimum fertilizer levels for all years and each ENSO phase, Chitedze, Malawi.**

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