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ANNEX

Index insurance and climate risk:

Prospects for development and disaster management

IRI Technical Report 10-10

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Index-based financial risk transfer mechanisms are being tested in the context of development and climate change adaptation. These instruments show the capacity to dramatically reduce conditions of chronic underdevelopment by both enabling investment and reducing shocks in agricultural livelihoods. However, important issues have been raised, including the potential for scaling up and the role of climate-informed science to help overcome some of the challenges to scale up.

This document is an annex to the Climate and Society Volume 2 "Index insurance and climate risk: Prospects for development and disaster management" (http://iri.columbia.edu/csp2/download), which was a joint effort by IFAD, WFP, Oxfam America, UNDP, Swiss Re and NOAA. This annex focuses specifically on identifying and distilling key technical issues, rather than covering broader issues such as climate risk management strategies or how to implement index insurance as a tool to reduce poverty.

This annex is the end result of a process intended to link practitioners with the appropriate scientific communities in a practical dialog. A key component of this process was the Workshop on Technical Issues in Index Insurance in October 2008 at the International Research Institute for Climate and Society (IRI) in Palisades NY. The IRI convened experts from fields as diverse as reinsurance, climate science, economics and food security to participate in the workshop, in an effort to gain insight on how innovative tools and research can best serve development, today.

This workshop was built around the set of short papers technical papers written by teams of experts, with a structure with heavy emphasis on input and synthesis from workshop participants. Topics focused on the current state of the art technologies and its potential use to support the scaling up of index insurance identifying priority actions and research areas. The topics include agricultural systems, communicating index insurance to farmers, satellite rainfall estimates, remote sensing of vegetation, water resources, rainfall modeling and simulation, seasonal forecasts, risk spreading, and climate changes, one decade at a time.

Institutions from outside of Columbia University that are represented in the writing team include Cornell, Duke, FAO, IIASA, Le Centre Européen de Recherche et d'Enseignement des Géosciences de l'Environnement, NASA, Partner Re, Red Cross, Oxfam, University of Florida, UCSB, University of Reading (UK), Wageningen University (NL), WFP. Institutions from outside of Columbia University that were represented by workshop registrants include Cornell University, GEF, Green Ink, Harvard Business School, IFAD, IIASA, Jawaharlal Nehru University (New Delhi), Liverpool School of Tropical Medicine, MIA, Millennium Promise, Mississippi State University, NASA Goddard Space Flight Center, NOAA, OECD, Oxfam America, PartnerRe, Penn State University, Purdue University, Rockefeller, U Miami/RSMAS, UCSB, UNDP, UNEP, University of Florida, USGS/UCSB Geography, WFP, World Bank, Yale University, and YellowJacket.

Following the workshop, the documents were finalized through a follow up writeshop and author exchange. The process informed the conclusions of Climate and Society Volume 2, with each topic summarized in a technical box in the volume and the full expert papers presented in this Annex.

Connecting scientists to decision makers not only informed practitioners on the capabilities and limitations of each technology, but it allowed for introspection on whether or not scientists areasking the best research questions.

Hopefully, both research and practice on index insurance can be better informed through the products and relationships developed through this process.

Contents

CONTRIBUTIONS OF AGRICULTURAL SYSTEMS MODELING TO WEATHER INDEX INSURANCE

Baethgen W., Hansen J.W., Ines A.V.M., Jones J.W., Meinke H. and Steduto P.

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.

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 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.

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[1]. The WRSI concept is embedded in process-oriented models of water-limited crop production that use 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.

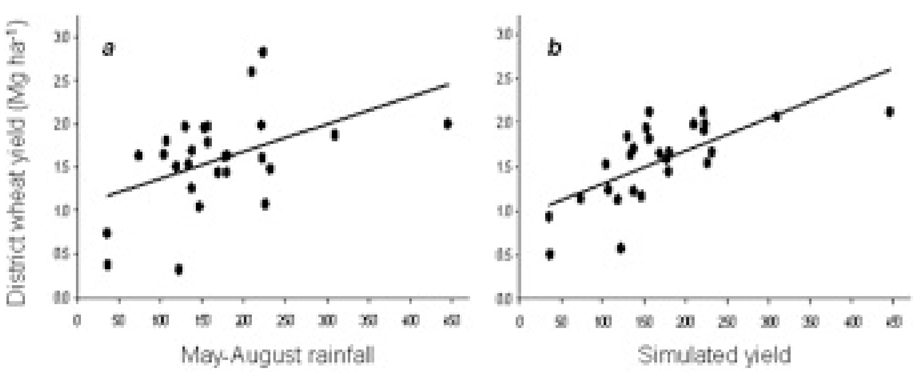

Figure 0 - Seasonal rainfall (May-August) at Moree, NSW, Australia against (a) district wheat yields from 1975 to 2001 and (b) simulated wheat yields for the same period.

1 *"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).*

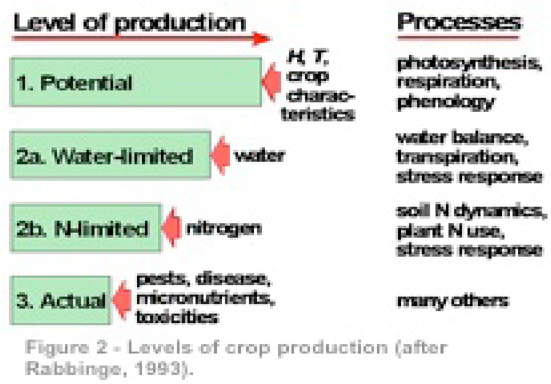

Figure 2 - Levels of crop production (after Rabbinge, 1993).

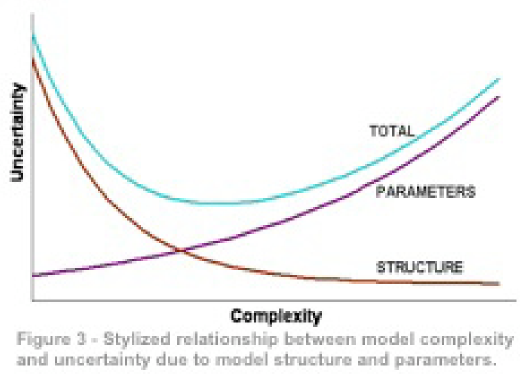

Figure 3 - Stylized relationship between model complexity and uncertainty due to model structure and parameters.

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.

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.

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.

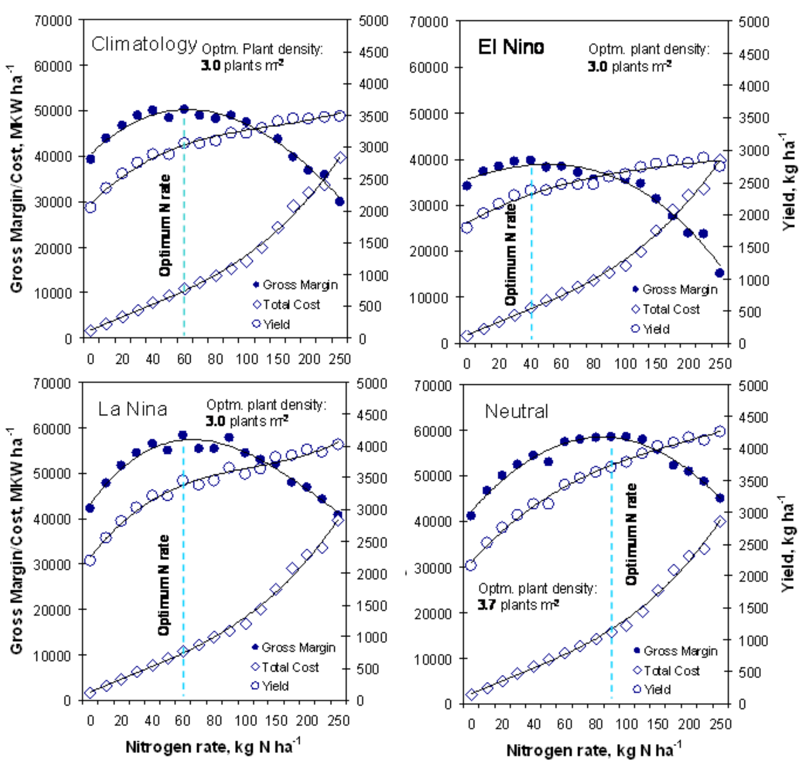

Figure 0 - Maize yield simulated with CERES-Mize and gross margin as functions of applied N fertilizer, and optimum fertilizer levels for all years and each ENSO phase, Chitedze, Malawi.

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.

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MAKING INDEX INSURANCE ATTRACTIVE TO FARMERS

Patt A., Peterson N., Velez M., Pfaff A., Suarez P. and Hess U.

Introduction

There is reason to believe that index insurance could stimulate rural development. For insurance markets to function well and be sustainable, however, it is important that farmers understand how they operate well enough to be able to make informed decisions about whether or not to purchase insurance, and to trust that choice even if it seems, *ex post*, to have been a waste of money. Concerns about a lack of understanding go in two directions. The first is that farmers will forego the choice to purchase insurance, and will fail to realize the benefits that it offers. The second is that farmers will purchase insurance that is not right for them, and thus be harmed by having done so.

Background

Whether or not farmers purchase insurance is contingent on a number of factors. As rational actors in the strict economic sense, they will purchase it if it increases their expected utility or welfare, which depends on its net average cost to them, the likelihood and extent to which it shields them from losses, and their personal level of risk aversion. As social actors, they will purchase insurance based on whether they trust the people who are selling it, and whether they observe other members in their community doing the same. As real people, their decision is probably predicated on a number of factors, most importantly their personal prior experience with insurance.

The economic calculus requires some ability to work with probabilities. There is an extensive literature, based largely on experimental methods, demonstrating that individuals display certain biases in the appraisal of likelihood (Kahneman and Tversky, 1979; Tversky and Kahneman, 1974). Another set of studies have shown that people's probability perceptions, and how those perceptions influence their judgments, depends on whether it is born out of their own experience, or from information that others have given them, and in the latter case, the vividness of the explanation (Patt, 2007; Weber, 2006). This could be quite relevant in the context of index insurance, because it would suggest that prior experience purchasing insurance, being exposed to its often complicated payout likelihoods, could work differently than a verbal explanation. Studies of people's willingness to pay for flood insurance in developed countries have yielded results consistent with the presence of behavioral biases (Johnson et al., 1993; Kunreuther, 1996).

A special concern has arisen with respect to subsistence farmers: that they lack the educational background and mathematical skills to be able to understand and use probabilistic information. Research has demonstrated this concern to be nuanced, but by and large unfounded. First, subsistence farmers perform qualitatively the same as westerners on tests of probability understanding, and their quantitative performance improves when decisions are framed not in the abstract but in familiar terms, such as what crops to plant given different probabilities of different amounts of rain (Patt, 2001). Second, farmers who receive probabilistic information coupled to specific advice are significantly more likely to trust and use the advice, compared to farmers who receive the advice alone (Patt et al., 2005).

Relevant for the social calculus, there is also a growing literature on trust, and the ways to enhance or destroy it both in different cultural contexts (Bohnet and Zeckhauser, 2004; Herrmann et al., 2008), and among subsistence farmers in particular. Much of the latter comes out of work on seasonal forecast communication and responding to climate variability. In the state of Ceará in northeast Brazil, for example, there was a highly successful programme to communicate forecasts, coupled with distributing lower yielding but drought tolerant seeds in years where rainfall was anticipated to be slight. The programme enjoyed high levels of trust, until one year when farmers planted the drought tolerant seeds, rainfall turned out to be good, and harvests were lower than they otherwise would have been (Glantz, 2000; Lemos et al., 2000). A similar story emerged in Zimbabwe, but here the result was more nuanced: it appeared that who farmers had received the forecast from influenced the degree to which trust fell (Patt et al., 2007). In a set of comparative case studies, theoretically informed by a wider literature on knowledge brokering institutions, researchers have observed that organizations with identifiable accountability to farmers were more trusted when communicating forecasts, especially after perceived forecast error (Cash et al., 2006). A related study observed a similar increase in trust in the context of a controlled experiment, set up as a decision-making game (Patt et al., 2006). For more background on these topics, please refer to Patt et al., 2009.

Case Studies

The recognition that many people may not only have difficulties understanding index insurance, but also that their decisions about whether to purchase it or not may be sensitive to how the concept is presented to them, has led a number of researchers to explore ways of improving that presentation. Much of this has been built around the use of role-playing games, both as a research tool, and as a way of giving farmers an experience similar to that of actually buying insurance over several years.

Worksheets and Workshops in Malawi and Ethiopia

Nicole Peterson and other researchers from the IRI worked with farmers in Malawi and Ethiopia, as part of efforts to introduce pilot index insurance schemes. In Malawi, the researchers had the task, during the second year of the pilot, of ensuring that farmers understood the index insurance contracts. Importantly, banks and insurance companies wanted to avoid any misunderstandings about payouts in the coming year. The researchers developed a worksheet that included the key characteristics of the previous year's contract, including the amount of rainfall needed for a payout, and what the payout would be under different amounts of rainfall. They also presented the information to farmers graphically, and included data on what payouts would have been with this contract in previous years. They held several workshops with local farmers, and asked them to calculate, using the graphs, how much of a payout they would receive under different amounts of rainfall. The participants in these workshops had very few problems understanding and using the worksheet tool, and even made suggestions on how to change the slope of the graph to represent their losses better.

Throughout these workshops and in a separate set of focus groups and surveys in Ethiopia, several important issues arose for these types of insurance projects. First of all, the relationships with farmer organizations or development groups were crucial for establishing and maintaining these programs, for reasons of trust, experience with the communities, and the connections to organizational networks. In some cases, it seems that agriculturalists are interested in these projects for the sole reason of maintaining these important relationships.

Second, these communities have often developed risk-mitigating strategies, such as cattle or communal sharing of unforeseen expenses. While insurance programs may be useful supplements to these systems, there is also the possibility that they will replace these local strategies, leaving participants unprepared to deal with uninsured risks. Third, banks, insurers, and others often underestimate the ability of the farmers to articulate their needs and preferences, limiting the potential to create programs that provide useful benefits. Insurance programs thus have the potential to meet the needs of various participants, but should be considered one strategy among others for mitigating climactic risks. Altogether, the interaction between researchers and farmers suggested that farmers' ideas about relationships, risk, and expected benefits were crucial to the success of the pilot schemes. The workshops also provided the researchers with insights into how particular concepts might be communicated, such as the rain gauge and contract-specific time periods. These insights have been collected in a training manual for program representatives.

An Abstract Game in Brazil

Maria Velez and other researchers from Columbia University's Center for Research on Environmental Decisions (CRED) conducted decision-making experiments with cash payments to test individual understanding and behavior facing an offer of basic index insurance, in Ceará, Brazil, The region and state are characterized by low rainfall but high rainfall variance, and is where seasonal climate forecast credibility had fallen so dramatically many years before. Uncertainty is a central feature of agriculture decisions. A total of 266 subjects participated, from both the urban and rural area.

The games to this point have framed the probabilistic decision in the abstract, rather than drawing specific reference to rainfall and crop yields. Participants played a game in which they won a prize, depending on a two stage random process. The first stage was to assign them randomly to one of two boxes (A or B), while the second stage was to draw a random ball from the box they had been assigned. The balls were either red or blue—Box A always had more red balls than blue, while Box B had more blue balls—and blue balls provided a higher prize. Participants' only decision was whether to pay a small amount of money for a contract, which would in turn pay them a larger amount of money back if Box A (the one with more bad red balls) was assigned to them in the first stage. Individuals decided whether to buy or not for each of 20 contract prices, in each of several scenarios featuring different probabilities of being assigned Box A and different distribution of balls within each box. The analogy to index insurance is straightforward. Whether one is assigned Box A or B is equivalent to the value of the index. Whether one draws a blue or red ball is equivalent to having a good yield or bad. Basis risk is the risk of drawing a red ball from Box B, the one with more blue ones.

At this point there are preliminary results based on exit surveys, but not yet hard analysis of the game playing strategies. The surveys demonstrate the challenges of explaining and understanding experiments of this type with this kind of abstract framing. Without a connection to a real context, the rules seemed arbitrary, and participants had difficulty understanding the difference between different elements of the setting. "Luck" was a common answer when explaining individual decisions, and about 20% of participants in each session switched decisions back and forth between prices (which would not appear to be rational although some explained this behavior as indifference at low prices). Moreover, price levels appeared to be more important determinants of decisions than information about the probability of being assigned Box A, or the composition of the balls in the two boxes. The upcoming analysis will, most likely, back up these insights with statistical significance.

Insurance Games in Peru, Malawi and Ethiopia

Finally, several researchers have conducted games very similar to the ones in Brazil, except that the two-stage random process was framed specifically in terms of community rainfall and individual luck, and the decision was framed specifically in terms of whether to purchase index insurance.

Michael Carter and his research collaborators[2] have devised and implemented two index insurance simulation games: one for cotton farmers in Peru and a second for pastoralists in Kenya[3]. Both games were devised after the design and pricing of index insurance contracts for each location. The contract design work included estimation of the probability distribution of both the insurance index and of the residual basis risk farmers would face. This information allowed the games to be framed in terms most familiar to the participants. The Peruvian cotton game, which was designed to mimic an area based yield contract that is now under sale in Peru, was cast in terms of the land areas, units of measure and cost structures that constitute the daily lives of farmers in this region. Indeed, farmers were at ease discussing (and in some cases disputing) the accuracy of the information used in the game.

The researchers' expectation is that farmers are more prone to take such a precisely framed game seriously, as an analogue to their reality, rather than a mere 'game.' In addition, researchers were able to use such a precisely framed game to explore farmer preferences over contractual options (e.g., contract strike points) as well as to obtain information on sensitivity to price (farmers played the game at both actuarially fair prices as well as prices marked up by standard loading factors). In the case of Peru, the final contract design was based on farmer feedback obtained during early versions of the game. The final game, based on the market price and other characteristics of the real contract, was played with nearly 450 cotton farmers. Just under two thirds of those farmers 'purchased' the insurance in the game. Research is currently underway to determine if these game findings accurately predict real world transactions.

A second critical design issue in the Peru and Kenya insurance games concerns how to capture intertemporal incentives in the games. For example, Peruvian cotton farmers risk losing their land and future credit market access if they are unable to repay loans in any given year. A potentially important advantage of insurance is not only that it insulates current income from shocks, but also that it protects individuals against these inter-temporal or future period penalties. In the Peru game, farmers played a sequence of simulated crop years. If any year they were unable to repay a loan based on random outcomes of the game, then in all future game years they were excluded from the credit market and could only employ a low return strategy. In addition, farmers were paid the value of their land at the end of the game. Farmers who had defaulted during the game were given a lower per-hectare payment for their land. Participant farmers appeared to find these penalties sensible and they definitely appeared to shape play within the game.

In Kenya, the participant pastoral population is much less commercially oriented than the Peruvian cotton farmers and production credit is almost unknown. However, research in that region suggests that pastoralists are subject to non linear, poverty traps dynamics. Any pastoralist who falls below a critical minimum herd size threshold is likely to collapse to a low level, poverty trap equilibrium. Such poverty traps thresholds potentially give a huge advantage to insurance that protects individuals from falling below that threshold.

To capture these intertemporal incentives for insurance, the game was designed such that expected net herd growth was positive above the threshold and negative below the threshold. While potentially complicated to implement in the field, a simple fixed cost mechanism was used to implement the non-

2 Carter's work in Peru is joint with Stephen Boucher (University of California Davis), Carolina Trivellis (Instituto de Estudios Peruanos and graduate students Francisco Galarza (Wisconsin) and Conner Mullally (Davis). The Kenya project is joint with John McPeak (Syracuse University), Chris Barrett (Cornell University), Andrew Mude (international Livestock Research Institute) and graduate student Sommarat Chantarat (Cornell).

3 Additional details on the games can be found in BASIS Brief no. 2008-06 "Insuring the Never-before Insured: Simulation Games to Explain Index Insurance and Determine Demand" (http://www.basis.wisc.edu/publications_ama/ama_publications.html) linear dynamics. Each individual in the game maintained a stock of chips representing their herd in tropical livestock units (TLU). At the beginning of each year of the game, each individual had to pay 0.5 TLUs to cover necessary cash expenses for the family. A growth rate was then determined for each person (based on a common draw for a covariant shock and an individual draw for an idiosyncratic shock). With an expected herd growth rate of 7% per-annum, any herd below about 7 TLUs would actually shrink in size following payment of the 0.5 TLU fixed cost. Preliminary tests of the game (with the insurance priced at an actuarially fair premium) revealed that nearly 100% of the pastoralists purchasing insurance with most individuals buying protection for their entire herd. While still under development, the game is being used to explore the sensitivity of demand to herd size (wealthier herders seem to buy slightly less coverage) and other contract parameters. The actual insurance contract is currently slated to be sold in advance of the short rains in mid-2009.

Pablo Suarez and Anthony Patt, consultants working for the World Food Programme, have played similar games with farmers in Ethiopia and Malawi. Like Carter, they framed the game in terms of rainfall, yields, and insurance, but the probabilities and prices were not tied to local conditions. After playing the game, the participants filled out a survey, structured as a series of true/false questions, which tested whether they understood some of the basic concepts of insurance. Another group of farmers (i.e. a control group, selected randomly from the entire pool of participants), filled out the same survey, but instead of having first played an insurance game, a facilitator explained to them all of the basic ideas about index insurance. Thus the experiment yielded two sets of data. The first was how farmers played the game, and the second was the relative effects of game playing and verbal explanation on comprehension. The researchers have not yet analyzed the data from the game itself, although anecdotal evidence suggests that here, as in Peru, farmers playing a game framed explicitly in terms of rainfall, yields, and insurance seemed to make reasonable decisions. The researchers have, however, analyzed the survey, and these results are more pessimistic. First, the results suggest that participants had very little understanding of the basic concepts underlying index insurance, and were essentially guessing in order to answer most of the survey questions. Second, compared to the control group, game participants did perform slightly better on some of the survey question. But the differences were slight, and across all survey questions, even with 278 survey takers, statistically insignificant.

Conclusion

There is a substantially literature grounded in a number of disciplines that offer reasons to worry that farmers will make poor insurance decisions, and also reasons to believe that gaining practical experience could help. A number of studies have attempted to test these hypotheses. Survey results from two studies support the first of the two: farmers do poorly understanding the probability problems present in making economic decisions about insurance. There has not yet been analysis of data relevant to the second, but preliminary evidence suggests that farmers playing role-playing games do make good decisions in the context of the game, and that this could translate into good decision-making in actual insurance markets. If the upcoming statistical analysis supports the second of these findings, then there is potentially a contradiction. The resolution of the contradiction may indeed be that decision-making is not explicitly or exclusively rational, but rather depends on a combination of factors, at both the conscious and subconscious levels. In this case, games may help people to make good decisions, even if they themselves do not know the reasons why.

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THE POTENTIAL OF SATELLITE RAINFALL ESTIMATES FOR INDEX INSURANCE

Dinku T., Funk C. and Grimes, D.

Introduction

Most agricultural index-based insurance schemes are triggered by rainfall data rather than crop data. This is because it is preferable to trigger with objectively measurable weather events as it reduces the 'moral hazard' associated with subjective assessments of crop failure and allows evenhanded dealing with marginal and successful farms (Osgood et al., 2007; Skees et al., 2005). The traditional source of rainfall data has been rain gauge measurements. In many developing countries (such as those in sub-Saharan Africa) index-based agricultural insurance would be extremely useful because of the high dependence on subsistence agriculture in marginal crop growing conditions. However, precisely in these areas, the number of rain gauge stations is often very limited and the distribution of rain gauges very uneven, with most stations located in the main cities. As a result, the gauge data may not represent the rainfall over the farmers' plots where the information is needed most. Even where gauge data exist, there are other limitations including short historical time series, missing data, reading errors and poor representation of growing conditions because of poorly sited gauges.

The alternative to surface rainfall measurement is satellite rainfall estimation (RFE). RFE is the technique of obtaining rainfall information from data collected by environmental satellites. Different techniques exist to estimate rainfall from satellite thermal infrared (TIR) and passive microwave (PMW) sensors and combinations of the two. The main advantages of RFE, particularly with regards to index insurance, are:

i. it can provide spatially continuous data over most of the globe;

ii. it is ideal for scaling-up; and

iii. it is tamper-proof.

The two main constraints on using RFE are

i. the uncertainty involved in the estimation of the rainfall; and
ii. the short period of record typically associated with newer satellite derived time series.

With regard to uncertainty, it is important to realize that satellites do not measure precipitation directly; rather rainfall amounts are inferred from microwave and/or thermal infrared brightness temperatures. Often no attempt is made to quantify the uncertainty of the satellite estimates over the region where RFE is needed most. With regard to the limited period of record, TIR data archives go back at most to the late 1970's and microwave archives to the late 1980s. Although these data sets are now becoming sufficiently long, most commonly used satellite-based rainfall archives make use of data inputs which differ significantly from year to year. While this is often done to improve the accuracy of individual measurements, it can result in a loss of homogeneity in the long term time series making it difficult to extract the necessary statistics for the calculation of agricultural risk. Furthermore, the use of data from multiple sensors limits the time series to those years for which all sensors were operating.

However, recent research shows that it is possible to overcome these constraints. It is possible to quantify the uncertainty of the satellite-based rainfall estimates and also that long, homogeneous rainfall time series can be generated for critical areas such as sub-Saharan Africa. This makes satellite-based rainfall indices an attractive proposition, given the other advantages of good spatial coverage, relatively long time series, and the fact that they are tamper proof.

Satellite Rainfall Estimation

A brief summary of the science of satellite rainfall estimation is given here. For more detail the reader may referred to, among many others, two publications (Levizzani et al., 2002; Gruber and Levizzani, 2008). Unfortunately, no satellite yet exists which can reliably identify rainfall and accurately estimate the rainfall rate in all circumstances. However, satellites carry sensors which can 'see' the Earth in a variety of different ways. Some sensors can make indirect estimates of rainfall by measuring cloud thickness or cloud top temperature. Geosynchronous satellites are preferable to polar orbiting satellites because of their more frequent observations. From the sensors available on geosynchronous satellites, the visible and thermal infra-red (TIR) wave bands provide useful information about storm clouds. Storm clouds show up as very bright to the visible sensor while the infra-red sensor can identify storm clouds by their low temperature. Passive microwave (PMW) sensors are attractive because they contain information about rainy areas rather than clouds, but they are not available on geosynchronous satellites. Almost all current rainfall estimation techniques are based on TIR and/or PMW. Most TIR rainfall estimation methods are based on the assumptions that rainfall comes mainly from convective storm clouds, these clouds only rain when their tops have reached a certain minimum height which can be identified by its temperature on TIR image. At a given location, the quantity of rainfall can be calculated from the length of time the cloud top has been below a given temperature threshold.

Limitations of TIR-based rainfall estimates

Local variations in rainfall

Rainfall intensity varies from place to place beneath the cloud. The satellite sees only the top of the cloud, and it cannot pick up this variation in intensity. Thus, the images produced by the satellite do not provide a precise estimate of rainfall for a particular spot on the ground at a particular time.

Effect of warm rain processes

TIR images are used to distinguish raining cloud from non-raining cloud on the basis of their observed cloud top temperature. However, regions near coasts or in mountainous areas may experience rainfall from clouds which do not reach high enough into the atmosphere to register as 'cold' clouds. In such cases rainfall would indeed occur but would not appear in the satellite rainfall estimate image.

Effect of Cirrus clouds

Cirrus clouds are high enough in the atmosphere composed of ice crystals rather than water drops. Such clouds appear as very cold to the satellite and therefore would indicate the presence of rain, although in fact the clouds are not deep enough for rainfall to develop.

Limitations of PMW-based rainfall estimates

The main limitations of PMW include background emission from the land surface which varies significantly depending on vegetation type and soil water content (Morland et al., 2001), low repetition rate (typically twice per day) which makes aggregation over daily time periods impossible, and coarser spatial resolutions than that of TIR-based approaches.

Merging satellite rainfall estimates from different sensors and blending with gauge observations

A logical route to optimizing RFE is to merge the information from PMW and TIR, combining the better rainfall identification of PMW with the higher spatial and temporal frequency of the TIR images. Various statistical techniques are employed by different agencies to accomplish this. Another approach towards better satellite rainfall products is blending the satellite rainfall estimates with available gauge measurements. The quality of the final product depends on the quality, number, and distribution of the gauges used.

Future directions for satellite research

The satellite rainfall estimation community is currently working towards the improvement and consistency of PMW algorithms and improving the quality of global climate data sets using PMW inputs. Most of all, this community is excited about a significant future development, which is the Global Precipitation Mission (http://gpm.gsfc.nasa.gov/). This is a satellite mission that will consist of constellation of satellites with advanced PMW and radar instruments. It is expected to increase PMW repeat frequency to three-hourly, and thus improve satellite rainfall estimation significantly. However, this may not be relevant to index insurance immediately. The most relevant research in this respect is the attempt being made to produce historical time series from single and combined instruments. One such example is a project by IRI, University of Reading in UK and National Meteorological Agency of Ethiopia. This project will produce 30-year (1979-2008) time series of locally calibrated rainfall estimates from Meteosat TIR at high spatial and temporal resolution. It will also produce 30-year time series of gridded gauge data and corresponding RFE-gauge blended product. This will offer consistent and homogenous RFE time series as well as improved, but possibly less homogenous, blended product.

Another example is the use of high resolution grids of long term monthly mean rainfall, to substantially enhance the accuracy of RFE retrievals (Funk et al., 2007). These high resolution grids can also be used to downscale coarse long time series satellite estimate products like the 2.5o 1979–near present Global Precipitation Climatology Project dataset (Adler et al., 2003). When blended with gauge data, these down-scaled data create long and accurate depictions of hydrologic conditions (Funk et al., 2007), although it is important to note that for homogeneous time series, the blending must make use of the same set of gauges throughout the series. It is also possible to use block kriging with spatially varying target regions that correspond to desired administrative units (Funk et al., 2008). Block kriging can blend station observations and satellite estimates to provide estimates of the mean rainfall (Grimes et al., 1999). This procedure also produces estimates of the standard errors of the mean estimates (Fig. 1). Teo and Grimes (2007) have shown how district-based area rainfall averages and their associated uncertainties can be used in the context of crop-yield analysis in Africa. A geostatistical framework of this nature could be used to assess optimal scales for index insurance programs. Larger spatial units will have lower standard errors, but the insurance triggers will be less geographically refined. Smaller spatial units will target affected populations more precisely, but at the cost of more missed droughts and false alarms.

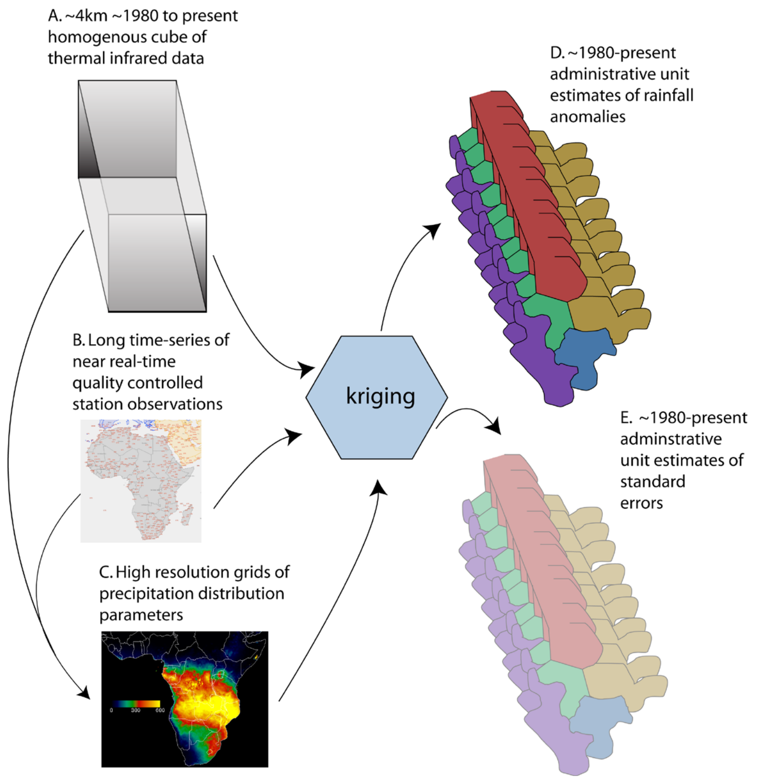

Figure 1 - Schema for gauge-enhanced satellite rainfall estimation process based on block kriging. A long high resolution time series of homogeneous TIR data (A) would be combined with gauge observations (B), elevation and slope fields to produce high resolution grids of monthly statistical rainfall parameters (mean rainfall, rainfall frequency, rainfall variance, C). These multiple sources of information can be used to translate satellite and gauge rainfall amounts into relative amounts. Block kriging with a background can then be used to blend the satellite and gauge estimates, producing district level estimates of rainfall (D), complete with associated standard error fields (E).

Summary

While trends in rainfall, population, and agricultural capacity are placing increasing numbers of Africans at risk of under-nourishment (Funk et al., 2008), the relatively novel use of index insurance offers another tool for mitigating weather-related risks (Osgood et al., 2007; Skees et al., 2005). Satellite RFE fields offer 'tamper proof' spatially extensive estimates with high repeat rates. Short data records and large systematic and random errors may limit use of many standard algorithms, but these obstacles may be overcome by the use of local tuning, high resolution climatologies, additional gauge data, and the retrieval and processing of archived TIR data. While no 'best' system exists at present, the routine use of satellite RFE fields by the early warning community bears a salient testimony to the utility of satellite RFE. Much of the error in satellite retrievals tends to be related to systematic distortions in retrievals. Local tuning and the use of high resolution climatologies can reduce these biases. Thus RFE fields, even where they perform quite poorly, such as within regions of complex terrain (Dinku et al., 2007), can still provide reliable measures of relative rainfall amounts. While more research, and more data (both TIR and gauge), can strengthen RFE systems, these satellite fields offer an exciting basis for index insurance products.

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REMOTE SENSING - VEGETATION

Ceccato P., Brown M., Funk C., Small C., Holthaus E., Siebert A. and Ward N.

Index Insurance and Remote Sensing

Index insurance is a financial product contracted on an index used as a surrogate for yield failure instead of being contracted directly on yield loss. The index is usually based on rainfall, vegetation status or other types of surrogates for crop production (*e.g.* evapotranspiration, water requirement satisfaction index). Retrieval of rainfall and vegetation indices from remotely sensed data has been extensively studied and operational products have been available for more than 25 years. Rainfall and vegetation products derived from remotely-sensed data provide independent measurement across large areas around the world and are available in near real-time. Thanks to the development of the internet, satellite images and derived products are becoming easier to access and their precision regarding spatial resolution has reached new levels at sub-meter precision. This easy access and the capacity to monitor crops around the world with independent measurements are attractive features upon which to base the development of new insurance products.

State of the Art

The primary index for monitoring vegetation status as a surrogate for pasture and crop production is the Normalized Differential Vegetation Index (NDVI), a satellite derived indicator of the amount and vigor of vegetation. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general, higher values of NDVI indicate greater vigor and amounts of vegetation (Tucker, 1985).

Index insurance contracts based on vegetation are generally designed to insure against a decline in NDVI over a designated area (called a grid) and are primarily intended for use by producers whose crop production tends to follow the average vegetation patterns for that designated area (Rasmussen, 1997). Losses are calculated using the vegetation index and producers are indemnified based on the deviation from normal within the grid and index interval(s) selected.

For pastures, monitoring vegetation vigor and biomass during the growing season provides a good estimation of what the final pasture production will be. This assumption is based on statistical correlations found between vegetation greenness and forage production (Fuller, 1998). Vegetation greenness, however, does not directly predict forage production. For crop production such as maize, soybean, millet, and wheat, the relationship between vegetation vigor/biomass during the growing season and final crop production (in terms of seeds produced) is not as simple. Although the vigor and biomass can be used as a proxy for final seed production in some cases (Fuller, 1998, Fischer, 1994, Maselli *et al.*, 1993, Rasmussen, 1992) , the exact relation of NDVI to crop yield depends on a range of factors (*e.g.* nutrients, solar radiation, water stress during critical stages such germination, growing and flowering).

NDVI decrease is often used as a surrogate for monitoring stress due to drought. Because drought is typically a spatially coherent phenomenon, NDVI datasets with a spatial resolution (grid) of 1km to 8km are generally considered adequate to capture the evolution of drought episodes. In many index insurance applications, payouts are based on an individual met station. NDVI may be helpful in quantifying the distance from the met station for which the contract is useful. It may also be useful in the case of a relative new met station where NDVI might provide information on past droughts. In regions where crops are grown on a large industrial scale such as the USA and Canada, NDVI can provide a measure of crop health directly. In regions where crops are mixed with natural vegetation, such as in Africa, monitoring crop status directly is a challenge. In this case, NDVI decrease is measured after the harvest, providing an estimation of drought that affected both crops and natural vegetation.

Pioneering Projects

To date, pilot projects have been developed to provide insurance to farmers based on vegetation status products derived from satellite observations. This section gives a few examples of programs that have used satellite-derived payout triggers.

Index Insurance for Rangeland and Pasture

- United States Department of Agriculture (USDA) Risk Management Agency (RMA) issues insurance programs for pasture, rangeland, and forage using two indices to determine pasture conditions (rainfall index and NDVI) (http://www.rma.usda.gov/policies/pasturerangeforage/). The Vegetation Index Plan of Insurance is designed as a risk management tool to insure against a decline in the vegetation index in a designated area of roughly 4.8-miles (8km) square grid.

Index Insurance for Crops

- The Agriculture Insurance Company (AIC) in India proposes a wheat insurance policy based on satellite images to capture crop vigor (biomass) and assess claim payouts to farmers (Financial Daily, Dec 05 2005). The Wheat Insurance Policy is a unique technology-based insurance product which provides risk management to wheat producers who are likely to be impacted by poor growth of the crop arising out of non-preventable natural factors (AIC, Wheat Insurance Policy)

- The Millennium Villages Project (Earth Institute Columbia University and UNDP) in partnership with Swiss Re has developed and implemented a drought index insurance program in a number of rural villages in 10 countries in Africa. To date, three drought insurance contracts, two of which are solely based on NDVI, have been implemented. Preliminary results point toward optimism in the ability for NDVI to reliably pick out most of the major drought years in many locations, particularly in regions with high seasonal NDVI variance such as the semi-arid Sahel region of Africa (Ward *et al*. 2008).

- In Ethiopia, crop insurance has recently been extended to more than six million people (IRIN NEWS, September 16, 2008[4]). This project, co-developed by WFP, the World Bank, and FAO, is working with the Ethiopian government to implement drought indices based on crop water requirement models, gauge-enhanced satellite rainfall and vegetation index at 1km^2 spatial resolution.

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4 *http://www.irinnews.org/Report.aspx?ReportId=75865*

Opportunities and Challenges in Using NDVI

Opportunities

Many NDVI products are available through the internet, produced by several national space agencies. Daily observations of global vegetation dynamics have been made since 1981. NDVI datasets derived from several different satellites at spatial resolutions varying from 1km to 8km (grid size) are available.

Data from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) meteorological satellites have been used to create twenty-six year datasets by a number of different organizations, including NASA Global Monitoring and Modeling Systems (Tucker *et al.*, 2005), NOAA NESDIS (Jiang *et al.*, 2008), and NOAA EROS (Eidenshink and Faundeen, 1994). In addition, new investment in the global AVHRR data record has enabled the reprocessing using improved techniques that have improved the resolution of the data to 4km globally since 1981 (Pedelty *et al.*, 2007). This long-time period allows the identification of local and sub-regional drought and enables identification of the worst drought years in order to establish insurance policies.

Recently, sensors with higher spatial resolution than 1km are becoming available. Currently, sensors with spatial resolution ranging from 100m to below 10m are available allowing the identification of very precise areas with pasture or crop problems.

NASA's MODIS (the MODerate Resolution Imaging Spectroradiometer) is a source of extremely high quality NDVI data and now has an 8 year long data record. Recent investments by the US Department of Agriculture will soon result in a global NDVI product with 9 hour latency and 500 m resolution which will enable rapid analysis of crop conditions (Huete *et al.*, 2002).

Challenges

There are a number of challenges for using NDVI data in a crop insurance scheme that have been taken into account to establish pilot contracts. These include:

- Low spatial resolution of 4- 8km for long term data records is a problem for monitoring crops in regions where agricultural production occurs at spatial scales finer than 1km. This low resolution is however superior to that of many ground-based rain gauge networks in the developing world.

- NDVI values vary from one sensor to another. NDVI values can differ over the same area depending on the sensor used (Brown *et al.*, 2006).

- Change in quality of a dataset over time because of calibration and data correction, particularly when comparing real time data to historical datasets that may have a different processing scheme (Brown, 2008).

- For crops, NDVI measures greenness not seed productivity. NDVI is used as a surrogate for monitoring stress conditions due to drought.

- Cloud contamination poses a very real obstacle. 'False alarms' due to cloud contamination could trigger insurance payouts in above normal years.

Possible Improvements and Research Priorities

- Low spatial resolution for monitoring crops at finer spatial scale: **Solutions**: i) Monitor the crop and vegetation within the grid and investigate the relationship between phenology of agriculture and native vegetation. ii) Investigate the use of higher spatial resolution data.

- NDVI consistency between sensors and change in quality of a dataset over time: **Solutions**: i) Use statistical approaches that incorporate multiple sensors and normalize the actual measured NDVI according to standard deviations and variance ii) Use new methods to optimize retrieval of vegetation status independently of the sensors (use a new optimized index: FAPAR, Gobron *et al.*, 2000) iii) Develop new metrics that enable a quantification of the relationship with crop production for each sensor (see Funk and Budde, 2008 and Brown and De Beurs, 2008).

- Measurement of greenness and crop production problems. **Solution**: In each location where the insurance program will be implemented, collect production and yield statistics for the past and estimate relationship between vegetation and crop production.

- Role of other factors (*e.g.* disease, nutrient depletion, pests, wind, and hail) in yield outcomes: **Solution:** Use ground measurement to understand non-productivity related factors in widespread production declines, and to use this knowledge to establish a clause in insurance contracts specifying these exceptions.

- Cloud contamination: **Solution**: Improve algorithms to identify and mask clouds.

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APPLICATION OF INSURANCE MECHANISMS IN WATER RESOURCES

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Introduction

Urbanization, economic development, and climate variability and change present major challenges to water resources managers, including increasing competition between users, and increasing financial, human and economic losses from extreme hydroclimatic events. Managed water resources are an essential component of growth, social and economic development, poverty reduction and equity. Although droughts and floods are the principal risks typically associated with water management, frequently taxing the limits of existing infrastructure or water policy, year to year fluctuations may also prove challenging. Managing this variability (streamflow, precipitation, etc.) is becoming increasingly difficult given the high and diversified demand on water and inflexible design of system infrastructure (Brown and Carriquiry 2007). Current climate variability and weather extremes already severely affect economic performance, with the poor often carrying the largest burden; their livelihoods are most deeply affected and they posses fewer resources to help them manage climate risks. The need for a mechanism to hedge against these risks in an effort to manage extreme events and help buffer impacts without having to implement costly (and sometimes controversial) infrastructural adjustments is rapidly gaining attention and momentum. This brief discusses the applicability of index-based and traditional insurance as risk transfer mechanisms within the field of water resources.

Financial insurance provides a means for regularizing the impact of extreme climate events. The design of insurance contracts typically requires long, high-quality datasets through which the likelihood of an extreme event, the level of vulnerability and exposure, and the losses incurred may all be reliably estimated. Such datasets rarely exist in the field of hydrology, especially in developing countries. Another shortcoming of traditional insurance is its susceptibility to moral hazard; it is not infeasible that the insured may tamper with or alter the system to attain a higher payment from the insurer. Index insurance attempts to circumvent these deficiencies by basing the insurance contract on a timely observable, easily measured, stable, and sustainable variable (Dick 2006). Rather than being based on the variable insured, as in traditional insurance, it is traditionally based on a highly correlated variable – the index. Ideally indexes are objective, transparent, independently verifiable, and reported in a timely manner (Dick 2006).

Reservoir Index Insurance

In Brown and Carriquiry (2007) insurance indexed on reservoir inflows is proposed as a mechanism for smoothing variable costs associated with water market provisions. Within the proposed framework, these variable costs have been mapped from the hydrologic space to the financial space through option contracts. This option contract – reservoir index insurance framework was designed for the case of two bulk water users: an urban water supplier and irrigated agriculture near Manila in the Philippines. In dry years, the urban water supplier has the option of restricting flows to the agriculturalists for monetary compensation. Without the index insurance piece of the proposed framework, the urban water supplier is left exceptionally vulnerable to highly variable year-to-year costs. The proposed index insurance consequently smoothes the variability by requiring the urban water supplier to pay a relatively stable annual premium, eliminating the risk of large unforeseen compensations. The proposed insurance is designed for total coverage of the in-season cost of water supplied through the option contract. Alternatives include covering only a portion of the full cost at a reduced insurance premium, in which case the urban water supplier would retain a larger portion of the supply cost risk.

An alternative reservoir management insurance scheme is proposed by Skees and Leiva (2005) for a reservoir in the Rio Mayo irrigation district in Sonora, Mexico, to mitigate the adverse impact of uncertain irrigation supply. For one reservoir, a double-trigger contract is devised in which payments may be discounted under occurrences of “bonus” inflows in each Fall/Winter season. The design attempts to take advantage of the natural hedging provided by these inflows. An intermediary farmer group is suggested to coordinate premium and indemnity payments among farmers vis-à-vis the insurance company. During water scarcity periods, indemnity payments would provide the liquidity needed to spur water market transactions. Thus, in some fashion, this contract would not only mitigate the losses to the irrigation district as a whole, but would also encourage the development of water markets that lead to an efficient use of the resource.

Many reservoirs are designed as multi-purpose reservoirs, covering water supply, hydropower generation and flood control. Traditionally, reservoir storage is "allocated" to each of these uses, and rules based on a risk analysis using a relatively short record or stochastic models are used to operate the system. A combination of insurance, forecasting and adaptive operation strategies has the potential for improving the efficiency of reservoir operation for all the purposes. Such applications need to be researched at this point. The use of reservoir inflows as indices for insurance is actually problematic, especially for multiple reservoir systems, or for insuring against low flow in regions where there is likely to be significant diversion of upstream flow. In these settings, alternate indices or proxies need to be developed and tested to ensure that the conditions outlined by Dick (2006) are met.

Disaster Management

Index insurance has also been advocated as a useful risk transfer tool for disaster management situations where rapid fiscal relief is desirable and where estimating insured losses may be difficult, time consuming, or subject to manipulation and falsification. Governments and relief agencies would be likely candidates for acquiring this type of insurance. For climate-related hazards, a rainfall or temperature index may be proposed, however rainfall may be highly spatially variable relative to the gauge network, and in many locations data are inadequate to develop an index because of short time series and the spatial dispersion of stations. In such cases, it may be helpful to consider a climate proxy index as a regional rainfall index. This is particularly useful if a long record is available for the climate index through an independent source and it is well correlated with the regional rainfall hazard. Khalil et al. (2007) suggest utilizing the El Nino–Southern Oscillation (ENSO) as a proxy to extreme rainfall/regional floods in one of the districts of Peru, Piura. Crop losses in the region are highly correlated with floods but are difficult to assess directly. Basic infrastructure is destroyed during the most severe events, disrupting trade for many microenterprises.

The use of the ENSO-based index provides access to a much longer historical record to verify exceedance probabilities and payout frequency attributes. Since the index data is provided by an agency outside the country, it is not subject to manipulation by those who may seek such insurance. The index insurance product could be purchased by a microfinance authority or local state or district authority to facilitate rapid loans and relief in the event of a disaster that matches the triggered event, or be purchased directly by individual farmers.

Some issues with the implementation of the proxy ENSO index need be explored, including assessment of the reliability of the index at different levels of probability of exceedance of maximum seasonal rainfall, quantifying the effect of sampling uncertainties and the strength of the proxy's association to local outcome, and estimating the potential for clustering of payoffs. Potential adjustments for the increased volatility due to climate change or non-stationarity will be necessary, and the Khalil et al (2007) procedures for estimating and pricing the impact of these uncertainties and clustered payouts need to be further developed and demonstrated.

Compared to index insurance designed for droughts (slow onset over expansive areas), flood index insurance may pose an additional technical challenge due to the nature of flooding, namely being more acute in both space and time. For a number of reasons (e.g. data availability), developing models and indexes that strongly correlate with streamflow and/or flooding extent at specific points in the basin may prove exceptionally difficult. Alternatively, a strategy targeting models and techniques to provide an aggregate flood probability (e.g. over an entire basin) based on an index, when coupled with other complimentary tools, may prove attractive.

Pizarro (2006) suggests that a hierarchical risk management strategy for managing the impact of floods is needed. Depending on the spatial scale of the region or the entity of interest, a combination of index insurance, structural mitigation, catastrophe bonds, and other innovations may be useful. He also advocates considering a spatial correlation structure for flood insurance, regardless of whether it is of an index or traditional type, to reduce issuing and premium costs. An approach that recognizes the correlation matrix of the entire set of locations insured, and the probability distribution of losses, would be needed. Pizarro claims that if a diversified natural hazards cat bond market were to evolve, countries could set up individual insurance programs. Then, countries whose flood risks are negatively correlated (e.g., those located at the opposite ends of the tropical Pacific) could seek to be a part of a reinsurance pool that could in turn offer Cat bonds that are more attractively priced than individual Cat bonds.

Future Directions

In spite of the technical challenges highlighted above, applications of index-based and traditional insurance to water resources applications is a rapidly emerging field. This is largely due to the encouraging performance of other types of index insurance, which has led to increasing knowledge, capacity and experience. Perhaps the largest obstacle to implementation is the need for a paradigm change in decision making at high levels and amongst water managers. Concerted and creative research, in addition to pilots/demonstrations, is required to better recognize avenues for buffering against costs and losses associated with hydrologic extremes, and to gain practical experiences. This may require bundling multiple contracts (e.g. traditional insurance for flooding and index insurance on reservoir contents in single basin) or designing a framework for dealing with multi-owner scenarios (e.g. transboundary rivers with dams in series.) These innovations would work best if they were linked to clearly defined operating rules for the water systems, and the corresponding assessment of the residual climate risk, its predictability and variation over time and across the elements of the water system. A particularly promising area for such applications is the use of index insurance with a strategy for conjunctive use of surface and groundwater. Such a strategy would consider increased pumping in drought years and groundwater recharge in wet years. The index insurance or traditional insurance strategy could then mitigate the associated increase or volatility in energy costs. However, a systematic analysis of such an option is needed to assess how best the premiums could be structured considering both the correlated climate risk, and the separate jurisdictions of the users who are likely to be insured.

Likewise, research needs to be directed towards how best operation and insurance strategies can be balanced for a multi-purpose reservoir. An interesting example is that for the Folsom-Shasta reservoirs above Sacramento, CA. Sacramento has one of the highest vulnerabilities to floods in the United States, and these reservoirs and a levee system were designed to handle the estimated 500-year flood. However, there have been 7 events in the last 50 years that have approached a critical level. At the same time the reservoirs hold water to meet much of San Francisco and the Central Valley's domestic and irrigation needs. Drawing down the reservoir to mitigate flood risk, given a flood forecast, exposes the risk of subsequent water shortfalls. The opportunity to cover both risks using insurance and forecast based operation is an interesting and challenging research problem.

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RAINFALL MODELING AND SIMULATION

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Introduction

The payout and price of a rainfall-based index insurance contract are both functions of rainfall, which is a random process. In order to design and price these contracts, therefore, the buyers and the sellers of the contracts must both have a satisfactory understanding of the rainfall process, and must be able to communicate their beliefs to each other in order to negotiate the design and price of the contract. Rather than base a contract design on the empirical (historical) distributions of various rainfall statistics, such as the 10th percentile of seasonal rainfall, or the length of the longest dry spell in the season, which can be sensitive to individual, unusual historical events and further limited by sparse or missing data, the designers of insurance contracts can use statistical models trained on historical data to more accurately estimate the distributions of various rainfall-based statistics. A statistical model for rainfall has at least two useful properties: (1) it can describe the relationship between rainfall at a given location and other weather-related variables, such as large-scale climate variables and rainfall observed at other nearby locations, in order to reduce the unexplained variation in rainfall amounts, and (2) it provides a principled way to quantify the uncertainty that accompanies rainfall processes, which is crucial to the efficient design of insurance contracts.

This document will review and discuss different statistical models used for rainfall, and different strategies for evaluating these models and simulating rainfall from them. We pay particular attention to the way in which low rainfall events are modeled, because the main purpose of these contracts is to allow farmers to hedge their risk of poor yields due to drought. Many of the models we discuss, though, could also be used to investigate properties of floods, or be used to simulate rainfall time series as inputs to crop growth models. We believe that there is currently a gap in the knowledge between how rainfall simulators generally work, and how they work specifically in the context of index insurance. We recommend that further research be focused on filling in this knowledge gap, and we provide some guidelines in Section 3 for how this can be done.

Rainfall Models

We will review four basic types of rainfall models that have been the focus of most of the recent research on rainfall modeling: (1) Generalized linear models (GLMs), (2) Hidden Markov models (HMMs), (3) Nonparametric models, and (4) "Mechanistic" models. The first three types are reviewed in Wilks and Wilby (1999), and the first and fourth types are reviewed in Chandler, et al. (2007).

GLMs

Coe and Stern (1982) and Stern and Coe (1984) first introduced the use of GLMs to model a daily time series of rainfall measurements at a single site. These types of models are the simplest example of stochastic weather models, and were the first to be widely used. GLMs are parametric models that have the structure to condition the outcome variable, daily rainfall, on observed covariates, such as sine and cosine functions of time, to account for seasonality, climatological variables such as sea surface temperature, and regional forecasts. Multiple sites can be modeled this way using multivariate time series methods, where correlations across space are modeled, and rainfall outcomes at locations that were not observed can be imputed. The marginal distribution of daily rainfall data has a point mass at zero (dry days), so it is common for these models to be comprised of two parts: (1) a model for dependent binary data - such as a two-state Markov chain model - to model the occurrence of rainfall on a given day, conditional on previous rainfall occurrence, and (2) a right-skewed distribution, such as the exponential, gamma, or mixed exponential distribution, to model the intensity of rainfall on wet days. Sine and cosine functions of different periods can be included or excluded according to formal tests such as likelihood ratio tests; the most obvious source of seasonality is the yearly rotation of the earth, although lower and higher-frequency sources of seasonality drive rainfall processes as well, such as ENSO state, which occurs at a period of 3-7 years, and various local atmospheric conditions, which can occur on periods of one month or shorter. One of the strengths of GLMs is that they can account for climate change over a long time scale through their incorporation of covariate effects. Most GLMs are fit using maximum-likelihood methods (McCullagh and Nelder, 1989), although Bayesian methods can also be used.

HMMs

The second type of model is an HMM, which is also fit to discrete data in time and space, but differs from a GLM in that it models autocorrelation and spatial correlation through some number, K, of discrete, unobserved hidden states, which correspond to different "weather states" that result in different patterns of rainfall. In an HMM, the hidden states change through time according to a first-order Markov chain, and the outcomes are modeled as independent draws from distributions conditional on their corresponding hidden states. Basic HMMs, which are stationary in time, have been extended to model non-stationary processes by incorporating time-varying covariates (i.e. sine and cosine functions of time, seasonal forecasts, etc.); these models are called non-homogeneous HMMs, or NHMMs. The first NHMMs for rainfall data, introduced by Hughes and Guttorp (1994a,b) and extended in Hughes et al. (1999), allowed for seasonality in the rainfall occurrence process, whereas more recent work (Bellone et al., 2000, Robertson et al., 2004, 2006) has allowed for seasonality in the rainfall amounts process (i.e. the conditional distributions) as well. NHMMs can be fit using the EM algorithm or Bayesian methods; in either case, they are fit given a pre-determined value of K, the number of hidden states. The choice of K can be guided in part by (1) out-of-sample predictive error measured via cross-validation, and (2) scientific grounds in which the hidden states have specific interpretations in the context of the application. The autocorrelation structure of HMMs can be made richer by allowing higher-order dependence in the hidden state sequence, or by relaxing the conditional independence of observations. The strength of NHMMs for rainfall data lies in their ability to reflect real scientific phenomena, like regional atmospheric conditions, with the hidden states.

Nonparametric Models

Nonparametric models for rainfall represent an interesting alternative to GLMs and HMMs, because their lack of dependence on parametric distributions to describe the data gives them flexibility to model certain features of the rainfall process better than other models. The key feature of most nonparametric models is a resampling algorithm, in which daily time series of rainfall are simulated by resampling the observed data in a way that accounts for the autocorrelation of observed rainfall as well as the relationships between rainfall and other weather variables. Such models have been developed and fit by Young (1994), Lall et al. (1996), Rajagopalan & Lall (1999), and Moron et al. (2008). Nonparametric models generally can more flexibly describe nonlinear relationships between variables, but are sometimes limited in that they can only reproduce values that have already been observed, which limit their ability to incorporate the effects of long-term climate changes into the rainfall process.

Mechanistic Models

The fourth type of model in current use is one that models the physical process of rainfall using radar data collected at a high resolution in time and space. These models describe a process by which 'rain events' occur randomly, and spawn smaller 'storms' at random times and locations within their interiors (which are typically regions of over 1000 km^2), which in turn are comprised of 'rain cells' which also arise at random times and locations within the storm. The entire rain event moves across space at a random velocity. The resolution of data to which these models are fit is typically high with respect to both space (2 km^2 regions) and time (5 minute intervals) (Chandler, et al., 2007). These models are stationary in time, and are usually fit with the goal of describing floods in catchment areas. Two drawbacks of these models with respect to index insurance applications are that (1) they are not well-suited to incorporating covariates that could explain variation in rainfall over long time periods, and (2) they require high-resolution radar data to be fit, and this data is unavailable for most developing countries in which index insurance is being used. For these reasons, we don't focus on mechanistic models in this report.

Rainfall Simulation

No matter what type of model is fit, a common goal is to simulate rainfall from the fitted model. Such simulations should be produced by incorporating two sources of variation: (1) variation built into the model, and (2) variation associated with the uncertainty with which the parameters of the model are estimated during the training phase of the data analysis. This second source of variation is often overlooked. (A third source of variation could be considered: the choice of the model itself - but we don't discuss this issue here). Although Bayesian methods are not widely used in rainfall modeling thus far, they offer a natural and convenient way to simulate rainfall while incorporating both of the above sources or variability by sampling from the posterior predictive distribution of the outcome variable (Gelman, et al. 2004).

A crucial fact about index insurance design is that the payout and price are complicated, but deterministic, functions of rainfall. The payout, for example, is a random variable which is realized once per year, and its distribution depends entirely on the parameters of the rainfall model (and the parameters of the contract, which we treat as fixed, for now). The goodness-of-fit of rainfall models is usually checked with respect to monthly means and variances, and the lengths of runs of wet and dry spells. Mavromatis and Hansen (2001) compare a group of stochastic weather generators, paying special attention to their goodness-of-fit with respect to the interannual variability of rainfall, which is known to be somewhat difficult to capture with statistical models. In this section we will outline steps needed to be taken in order to evaluate the goodness-of-fit of rainfall models with respect to the particular characteristics of rainfall that influence the payout of an index insurance contract illustrated in Osgood, et al. (2007).

Consider an index insurance contract for a single site with the following design: Dekadal sums of rainfall are calculated, and then, based on a sowing condition that stipulates that the growing season starts in the first dekad to receive more than s mm of rainfall, 3 contract phases are determined, each of which lasts 2-4 dekads and corresponds to a different part of the growth of the specific crop for which the contract is designed. In each phase, the payout function is a piecewise linear function of the sum of rainfall during the phase, such as the one illustrated in Figure 1(a). Given the parameters of the contract (sowing condition, phase definitions, and the parameters of the piecewise linear phase payout functions), the payout for a given year is a random variable that we observe: the sum of the payouts from each phase. If we have N years of data, then we observe N realizations of payouts, where N is typically between 5 and 50 for sites that implement index insurance. Considering that efficient insurance designs only pay out approximately 10-20% of the time, then even for a relatively long time series, such as a 50-year series, we may only observe 5 to 10 non-zero payouts: many too few observations to estimate the mean or 99th percentile of a distribution, which are critical factors in the price of insurance (Osgood, et al., 2007).

To estimate the distribution of payouts more accurately we fit a model to daily data and simulate thousands of years of data. Before we check these simulated payouts against the observed payouts, we recommend performing a series of intermediate goodness-of-fit model checks of statistics that are components of the insurance payout. These statistics to check include:

1. Dekadal sums. Check that the model produces dekadal sums with approximately the same distribution of the observed dekadal sums, for each dekad of the year.

2. The onset of the growing season. Check that the model-based estimates of the start of the growing season are in line with the observed sowing dekads.

3. Phase sums. The phase sum is the sum of 2-4 dekads of rainfall. Dekadal sums may be correlated within the growing season, so even a good model for dekadal sums may be bad for phase sums if it ignores correlations between dekads.

4. The lower tail of phase sums. Most contracts are designed to pay out in approximately 10-20% of years. In other words, the triggers for each phase of most contracts are set to low quantiles of the phase sum distributions. We must pay special attention to the fit of models with respect to these low quantiles of the phase sum distributions to ensure that the payout distributions are well-estimated.

Using Bayesian methods, the formal name for an analysis of these kinds is a posterior predictive check (Gelman, et al. 1996). Note that one must check the goodness-of-fit of not only statistics that are explicitly modeled, but also of those that aren't. Generally speaking, if the residuals from a rainfall model are spatially clustered, or are related to other observable weather variables, then a buyer or seller of a rainfall contract based on such a model could factor in these additional variables and "game the system" to his advantage.

In conclusion, we stress that developing a model for rainfall from which we can make accurate inferences about low-rainfall events, for the purpose of designing and pricing an index insurance contract, is a challenging process that has received much attention already, and deserves still more.

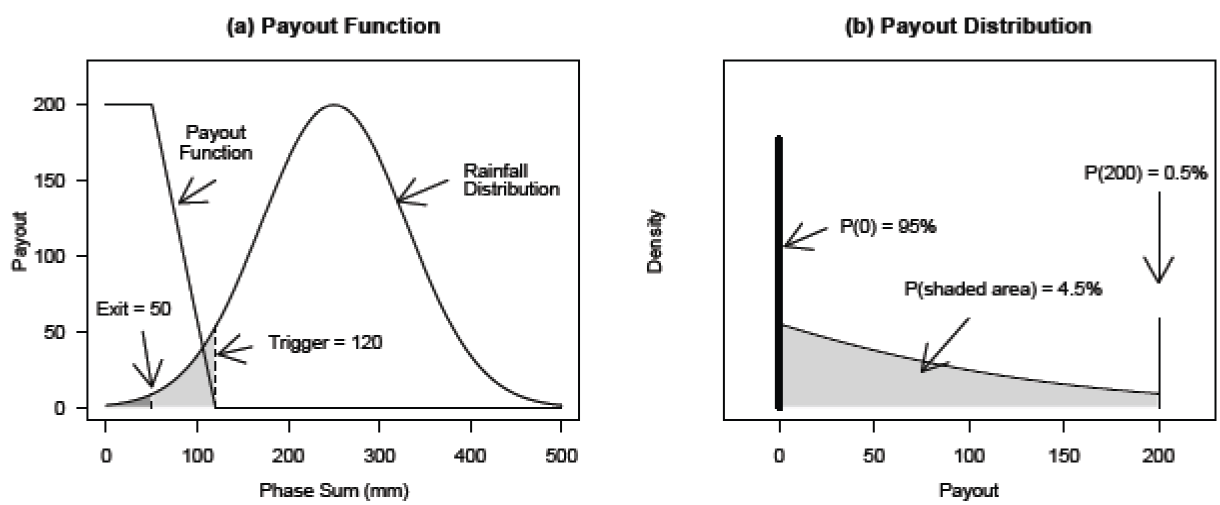

Figure 1: The payout function and distribution for a hypothesized distribution of rainfall by phase. (a) The left plot shows a (normal) distribution of rainfall, with the payout plotted on the y-axis as a function of the rainfall, plotted on the x-axis. The shaded area is the proportion of years in which there is a payout for this phase, and the darkly shaded area is the proportion of years in which there is a maximum payout for this phase. (b) In the right plot, the hypothetical distribution of the payout is depicted. There is a point mass at zero and at the maximum payout (200). The interior of the distribution is a truncated normal distribution.

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ON THE POTENTIAL VALUE OF SEASONAL CLIMATE FORECASTS FOR INDEX INSURANCE

Robertson A.W., Barnston A.G.,Hansen J.W., Lall U., Moron V., Osgood D.E. and Sun L.

Introduction

Seasonal climate forecasts and innovative financial instruments such as weather index insurance offer new opportunities for dealing with climate risk in agriculture and water resource management, and for adapting to anticipated climate change (Howden et al. 2007; Barrett et al. 2007) 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 seasonal forecast information.

Both beneficial as well as damaging 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 complements. Insurance that incorporates the forecast has the potential to provide the appropriate response to seasonal forecasts—in essence insuring against the uncertainty inherent in probabilistic forecasts.

Seasonal Forecasting

The physical basis of seasonal forecasting derives in part from the long 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 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 effective 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 generally not possible to predict with a high degree of accuracy exactly what the average weather conditions will be 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 rainfall.

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 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 atmosphere and ocean on grids of 100–300 km resolution, and parameterize smaller scale motions and rainfall processes; these models are each themselves run in ensembles with 10's of members to bracket the unpredictable element of daily weather in the seasonal forecast. The use of forecast ensembles enables estimates of the forecast distribution of seasonal climate, from which probabilistic forecasts are derived. Figure 1 shows a schematic of a probabilistic forecast, in which the historical probability distribution of the index is predicted to be shifted to the right and reduced in spread. Also shown are the tercile categories, computed from the historical observations; shifting the mean by half a standard-deviation and reducing the variance by 20% changes the probability of the below-normal category to 15% and of the above-normal to 53%.

To be useful to real-world decision-making, the probabilities issued by the forecasts need to be correct on average, so that they are reliable in the long run. The process of forecast verification and model calibration are essential parts of developing seasonal forecasts, and make use of forecast performance assessed retrospectively over several decades (Stephenson and Jolliffe, 2003; Mason et al., 2007).

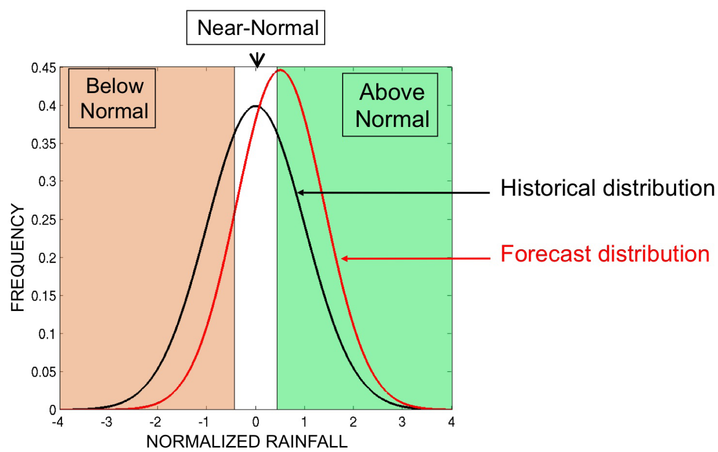

Figure 1 - Schematic of a seasonal forecast of an index, showing how the historical climatological distribution of the index computed over all years is modified in the forecast – here a shift in the odds toward wetter conditions. Also shown are the observed historical "climatological" tercile categories, and how their probabilities are shifted in the forecast.

Tailoring 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 across the season 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 predictable in some regions (Moron et al., 2009a,b), 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. A range of methods (reviewed in Hansen et al., 2006) have been developed for integrating seasonal climate forecasts with crop simulation models to forecast yields prior to planting or within the growing season. These methods include the use of stochastic daily weather sequences, conditioned on seasonal forecasts.

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 modelers 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.

Linking Seasonal Forecasts with Index Insurance

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.

As mentioned above, the use of insurance has the potential to provide the appropriate decision-making response to seasonal forecasts, because the latter are probabilistic by nature. For example, a strong seasonal precipitation forecast for a location in Africa might be expressed as [15%, 32%, 53%] for the dryer-than-normal, near-normal, and wetter-than-normal tercile categories respectively, as in Fig. 1. In this case there is a shift in the odds toward wetter conditions (compared to the [33%, 33%, 33%] climatological odds), but the forecast is still predicting a 15% chance of the season turning out to be dryer than normal. For a decision maker to plan in anticipation of wetter conditions, it might be crucial to insure against the 15% chance of drought.

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 an index insurance implementation in Malawi, southern Africa, 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. Figure 2 (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 Fig. 2). 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 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.

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. Stochastic rainfall simulation (see topic paper # 5) provides options 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) constraining a rainfall simulator to reproduce monthly GCM rainfall (Hansen and Ines, 2005); (2) *K*-nearest neighbor resampling of observed daily rainfall conditioned on GCM simulated daily circulation fields (Moron et al., 2008); (3) conditioning of stochastic weather generator parameters on GCM output (Wilks, 2002); and (4) non-homogeneous hidden Markov models (Robertson et al., 2004, 2006, 2009).

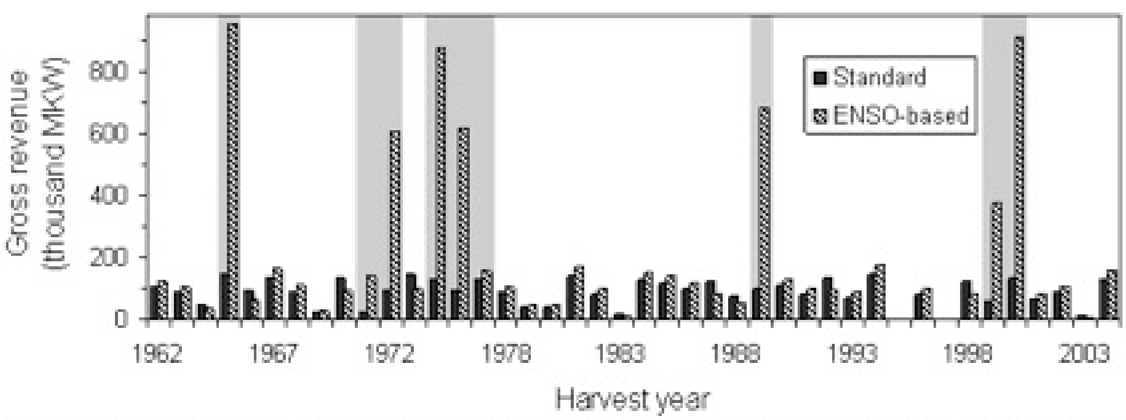

Figure 2 - Gross margins for the ENSO-scaled ENSO-scaled and fixed insurance pricing packages using simulated yields in a hypothetical farm that plants only the hybrid maize given by the bundled scheme. Shading shows La Niña years.

Seasonal climate forecasts are relevant to index insurance because they change expected probabilities of the targeted loss, through an appropriate index. The index can be purely meteorological, or it may be tailored to the targeted loss by addressing crop or forage yield, farm income, reservoir inflow or flood damage. Large-scale climate indices may be useful in insurance when they describe geographical see-saws that allow for the spreading of risk (see topic paper #7); an ENSO index based insurance for floods has been proposed for Peru (Khalil et al., 2007). 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 (Moron et al., 2008, 2009a,b). Indeje et al. (2006) showed that a remote sensing vegetation index (NDVI), which is commonly used to represent forage conditions and has been used as an index for insurance, can be predicted directly from dynamical seasonal climate forecast models. With a few exceptions, seasonal forecasts are not yet expressed in terms directly relevant to risk management or insurance on an operational basis. Such value-added climate forecast products may become more attractive to index insurance applications if and when the management of basis risk leads to the use indices that are more directly related to the targeted risks.

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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INTERTEMPORAL AND GEOGRAPHIC RISK SPREADING

Vicarelli M., Giannini A., Lall U., Lyons B., McLaurin M., Osgood D.E., Ropeleski C., Robertson A.W. and Turvey C.

Scaling up insurance programs both in space and time would expand risk-spreading opportunities at the insurance and reinsurance level. Spatial scale up would allow to pool together contracts from different areas with anticorrelated or non-correlated seasonal climate signals, thus reducing the cost of insurance programs. Scaling up in time translates into intertemporal risk spreading strategies using climate proxies and forecasts to design insurance (reinsurance) contracts in (between) regions with observed interannual climate variability patterns. By reducing potential losses over time, geographic and intertemporal risk spreading through insurance and reinsurance is potentially valuable for national (or regional) adaptation and mitigation planning to cope with climate variability and change.

At this stage, current precipitation-indexed insurance programs do not actively use climate proxies (e.g. ENSO indexes) and forecasts in their contract designs. However, interannual climate variability is an important component in modulating the rainfall regime in several regions of the world and the possible use of proxies and forecasts is receiving more and more attention. The available literature on the potential integration of seasonal forecasts in index-based weather insurance schemes is still very limited. Mjelde and Hill (1999) explored the farm value of ENSO-based forecasts in the context of common crop insurance contracts. Cabrera et al. (2006) studied the interactions between conventional crop insurance and ENSO-based climate information for increasing farm income stability in a hypothetical Florida farm, and concluded that for high risk-averse farmers the best insurance strategy depends on the ENSO phase. ENSO indexes have also been explored for use as proxies of extreme rainfall in one district of Peru (Khalil et al., 2007).

In collaboration with IIASA Risk and Vulnerability Group we developed an exploratory exercise to study the potential for integrating forecasts in indexed-insurance contracts for regions with opposite climate patterns. In our exercise we analyzed payouts associated to contracts for maize, with respect to ENSO index NIÑO 3.4, in Malawi, Kenya and Tanzania. ENSO signals, generated in the Pacific basin, are an important factor in determining inter-annual precipitation variability in Southern and Eastern Africa both directly via an atmospheric bridge – *atmospheric teleconnection*5 – (Glantz et al. 1991; Wallace et al. 1998) and indirectly, via the response of the Indian and the Atlantic Oceans (Klein et al. 1999; Alexander et al. 2002). Ropelewski and Halpert (1987, 1989) suggested two areas of ENSO related precipitation effects: equatorial eastern Africa (which includes Kenya and Tanzania) and south-eastern Africa (including Malawi). A bipolar precipitation pattern is associated to these two regions: la Niña events are associated with dry climate in eastern Africa and wet climate in Southern Africa. In other words, la Niña phase (also called Cold Episode) increases the likelihood for stronger and more frequent storms in Southern Africa, and is thus associated with an increased probability for above normal rainfall in that season. During El Niño (or Warm Episode) the precipitation dipole is inverted (Halpert and Ropelewski, 1992).

As a first step of our experiment we simulated possible payouts using historical precipitations data and analyzed the differences between years with different ENSO states –from 1961 to 2005. The results obtained from historical precipitation data indicate that more abundant rainfalls reduce payouts and the risk of loan default during El Niño in Kenya and Tanzani, and during La Niña in Malawi. Figure 1 shows the distributions and value of payouts for three Malawi villages: Kasungu, Lilongwe and Chitedze. The vertical colored bands indicate the ENSO state associated to each payout with pink, blue and green indicating respectively La Niña, El Niño and neutral years.

The relatively short precipitation time series available represent a limitation of this preliminary simulation. So, as a second step, we chose to apply the Monte Carlo method in order to analyze the statistical distribution of payouts using a larger sample of precipitation data. More specifically, we modeled precipitations by a gamma distribution the parameters of which were deducted from the historical precipitations. Then, the Monte Carlo approach allowed us to extract large random samples from the precipitation distribution. Finally, we used the simulated precipitations distributions in each location to calculate the mean and variance of payouts associated to different ENSO states. The results of the Monte

Carlo simulations confirm our preliminary findings for Kenya and Tanzania but they are more ambiguous for Malawi (Vicarelli, 2007).

This exploratory study illustrates that despite the technical constraints associated to upscaling over different regions and over multiple time periods (e.g. taking into considerations interannual climate variability and forecasts) new opportunities emerge.

Let's focus first on the challenges to be faced. A first group of constraints includes limitations related to climate data, simulations and forecasts: (i) larger scales and the use of climate proxies translate into the necessity for reliable climate data distributed over large areas. However, sparse stations and short data series (especially in developing countries) can compromise reliability of rainfall measures. This is an intrinsic limitation in the simulation of rainfall distributions in both space and time; (ii) spatial and temporal scale up is not feasible for heterogeneous regions characterized by several microclimates; (iii) scaling up insurance contracts in time up to 10-30 years allows integrating climate variability in the insurance/reinsurance design, however, the uncertainty related to seasonal forecasts could be a limitation to insurance planning; (iv) longer timescales also require taking into account precipitation and temperature trends associated to our changing climate. However, disagreement between models in simulating local trends represents a further source of uncertainty in insurance planning and contract design; (v) even when the climate data is satisfactory and the forecast is solid, the very timing of the forecast might not be compatible (thus useful) with respect to the agricultural calendars, planning decisions, and thus with the insurance contract calendar.

The second group of limitations is related to the existing economic and institutional framework especially in developing countries where index-insurance projects are currently under implementation. (i) Local commercial banks are not always able to participate as source of funding for large scale microfinance or microinsurance programs (volatility, illiquidity of local currencies). (ii) Linking micro-insurance contracts in different countries in an effort to spread risk geographically might not be feasible because of different currencies in use and/or regulatory systems. Moreover, the very risk of political instability, especially in developing nations, is a further major constraint in the implementation of insurance programs. (iii) Last but not least, institutional mediators for "regional risk-sharing" planning are still missing in the international framework.

Besides these challenges new opportunities for innovative tools and strategies emerge, representing also new directions for research. From a technical point of view, by scaling up insurance programs, the use of climate proxies and remote sensing, for both rainfall and vegetation, might help to overcome the problems related to sparse stations and short data series. The use and applications of such tools is just at a pioneering stage and needs to be refined. From a strategic planning and institutional point of view: (i) while shorter time scale and local spatial scale are difficult to model, timescales of 10-30 years over large areas are more relevant for mitigation planning at a regional level and could increase the ability of insurance markets to intertemporally diversify risk; (ii) geographic and intertemporal risk spreading might translate into a scaling up of the institutions involved; national governments could emerge as public partners of the insurance sector in developing regional strategies to reduce risk exposure; (iii) forms of regional cooperation between neighboring nations could also take shape in an effort to maximize risk spreading; (iv) and finally from a regulatory perspective, new challenges but also new opportunities for micro-insurance regulation and supervision institutions would arise.

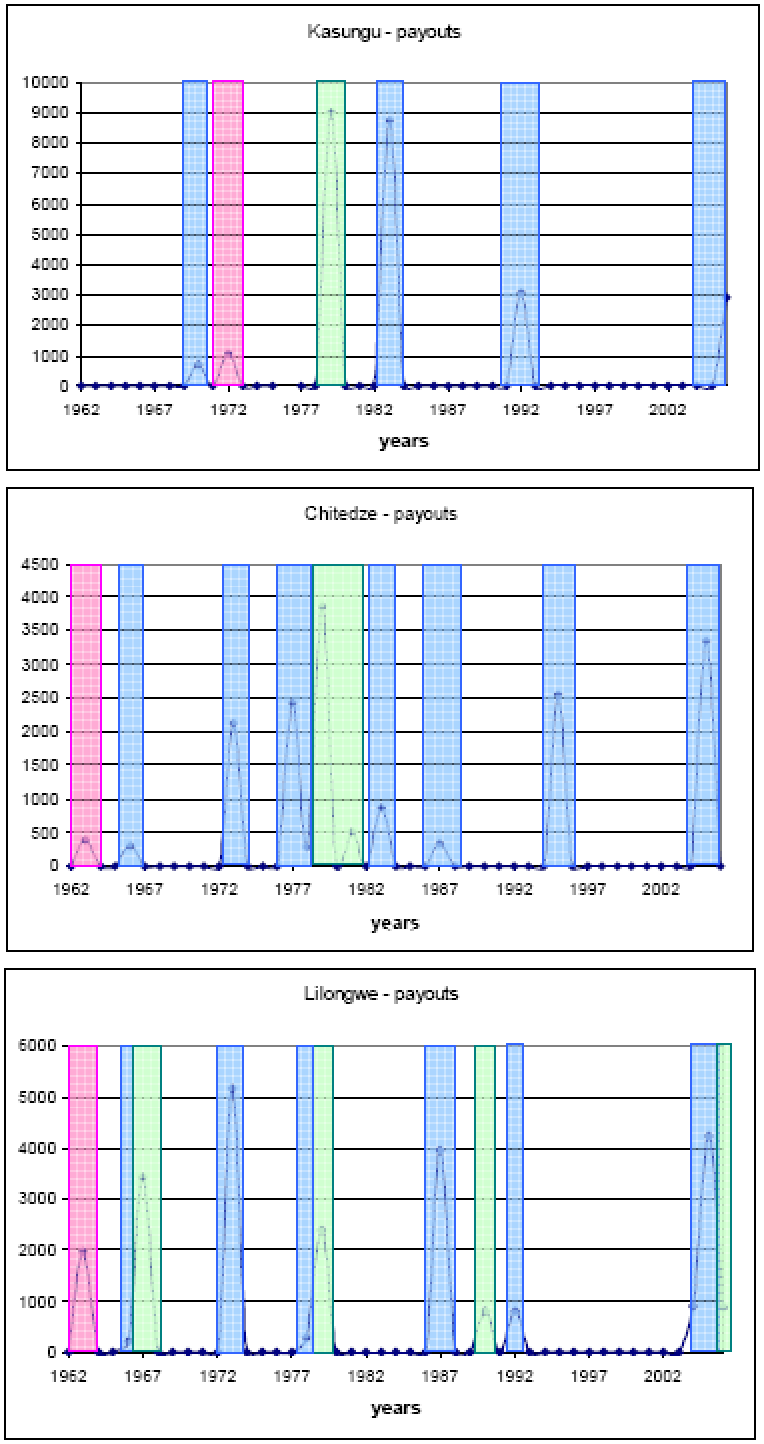

Figure 1 - Distribution of payouts for different ENSO states in three Malawi villages (Vicarelli, 2007)

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CLIMATE CHANGE, ONE DECADE OF A TIME

Greene A.M., Goddard L., Ward N., Siebert A., Hellmuth M. and Baethgen W.

Climate change is happening now, and further changes during the next decades are inevitable (IPCC, 2007). During the last century, the global climate warmed by about 0.7°C. At the same time, there were distinct changes in rainfall patterns, an increase in both frequency and severity of extreme weather events, and a rise in sea levels. The impacts of these changes are already being felt, and will intensify as further changes take place. Another 2–4°C rise is projected for the current century, mostly as a result of greenhouse gases that have already been emitted. This means that, although aggressive mitigation of greenhouse gas emissions is crucial to prevent longer term, potentially catastrophic changes, most of the changes projected for the coming decades cannot be avoided.

On the one hand, index insurance is being promoted as a useful tool for climate change adaptation[5], because it helps farmers and governments (amongst others) to mitigate and better respond to climate related risks. On the other hand, climate change, by changing the frequency and occurrence of risk over time, has an important implication for the long-term affordability and profitability of index-based financial products (and hence for the willingness of the industry to invest in new markets). Indeed, a recent analysis from Hochrainer et al (2008) demonstrates that it may be worthwhile for index insurance projects to adapt as climate change unfolds. Climate science and information can potentially help to better understand and manage these concerns.

To ensure sustainability of index insurance over time, two important questions need addressing: how well does index insurance buffer against climate change, and how can we better design index insurance products given climate change. Both questions rely on understanding the future climate. Here we focus on the "near term" climate change (over one or more decades, usually involving predictions over the next 10–30 years), which lies at the intersection between year-to-year climate variability and climate change. In contrast to climate change, this timescale has immediate relevance to strategic planning, and is consequently the subject of much ongoing research.

"Near Term" Climate Change

In the modeling community, climatic fluctuations occurring over the next few decades are often referred to as "decadal variability," and the distinction between it and climate change is more than academic. Decadal variability implicitly refers to a set of climate *processes* that effectively differ from those of climate change as discussed in IPCC assessments. Climate changes experienced over the next few decades can in fact be thought of as a *superposition,* of the centennial-scale trends forced by increasing concentrations of greenhouse gases that mankind has added (and continues to add) to the atmosphere, and decadal variations that arise from natural processes internal to the climate system.

It is important to make a distinction between these two components of near-term climate change, because they have differing implications with respect to predictability: While the climate tendencies resulting from so-called anthropogenic forcing have been extensively studied and are relatively well understood (though modeling the intermediary processes is still far from perfect), the same cannot be said about the processes underlying decadal variations. Most, if not all, such processes are lacking satisfactory theoretical explanations, limiting predictive capacity. Attempts to assess the potential of decadal forecasts, using climate models in which the climate system – most importantly the subsurface ocean - is initialized (i.e., brought to a quasi-realistic state) are just now being undertaken for the first time (Smith et al., Keenlyside

5 i.e. see for example, the Bali Action Plan, which will help frame the post-Kyoto Protocol agreement under the UNFCCC, calling for ""…Enhanced action on adaptation, including, inter alia, consideration of risk management and risk reduction strategies, including risk sharing and transfer mechanisms such as insurance" (UNFCCC, 2007).

et al.) Decadal variability will be a focus of the fifth (i.e., next) assessment report of the IPCC; it presently remains very much an emerging science.

Currently, GCMs generally perform poorly at reproducing decadal modes of variability. Over the next few decades, this information is particularly relevant if the decision maker is interested in acting on these variations. An example of the relative magnitude of climate variability at different time scales is shown in Figure 1. The figure was constructed by partitioning the total variability observed in annual rainfall in the Sahel for the period 1900-2006. Panel (a) shows the rainfall variability at the long-term (linear trend in the last 100 years), the scale that is usually called "climate change". The second panel (b) shows the variations of rainfall measured at the decadal scale (after removing the linear trend), and reveals decades when rainfall tended to be above average (e.g., the 1950's and the early 1960's) and decades when rainfall tended to be below average (e.g., the 1970's and 1980's). Finally, panel (c) shows the variability of rainfall in the year-to-year time scale that remains after removing the linear and the decadal trends. The figure shows the relative magnitude of the rainfall variability at these three temporal scales as measured by the percent of the total variance explained by each temporal scale. The proportion of total variance explained by the short-term (interannual) variability is 3 times greater than the corresponding to the long-term variability ("climate change"), and 2 times greater than that of the decadal variability.

Thus, a possible approach to introduce the issue of "adaptation to climate change" into the policy and development agendas is to consider the longer-term variations ("climate change") as part of the continuum of the total climate variability, from seasons to decades to centuries, and generate information at the temporal scale that is relevant and applicable for the particular time frames or planning horizons of the different decisions. This approach allows considering "climate change" as a problem of the present (as opposed to a problem of the future) and aims to inform the decision-making, planning and policy-making processes, in order to reduce current and potential future vulnerabilities to climate variability and change.

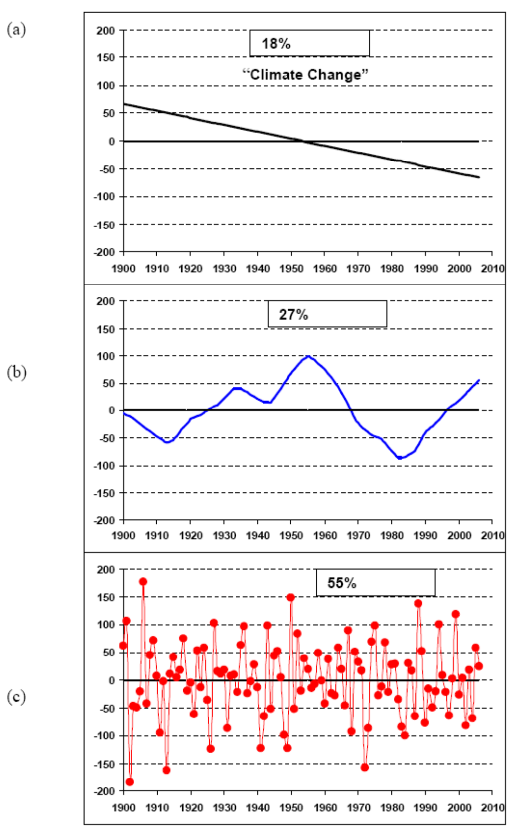


Figure 1 - Partition of the total observed rainfall variability in the Sahel. Rainfall is expressed as anomalies (i.e., deviations from the mean annual rainfall of 1900-2006). (a) long-term variability (linear trend), (b) decadal variability (after removing the linear trend), (c) inter-annual variability (after removing the linear and decadal trends)

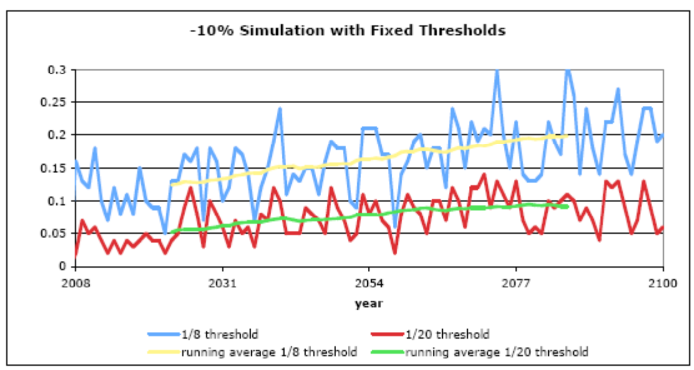
Implications for Index Insurance

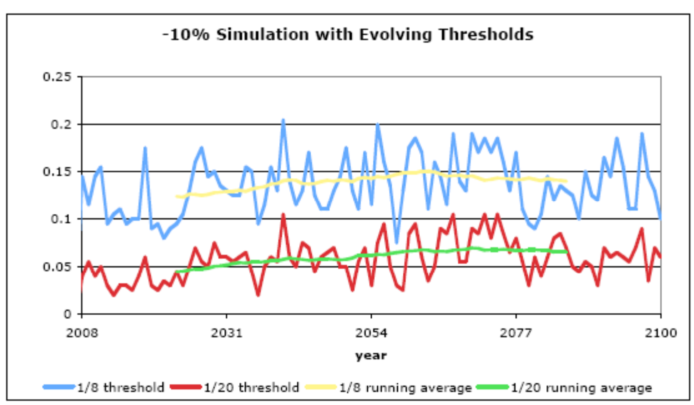
Near-term climate change, including both anthropogenic and internal components, comes to bear on our expectations about climate during the next few decades, and it is these expectations, in one form or another, on which index insurance is based. But since decadal forecasts do not yet exist, how can such information be utilized in the insurance setting? A possible answer lies in attempting to *characterize* decadal fluctuations in regional historical records: Do such fluctuations exist? What is their amplitude, relative to expected climate trends over the next few decades? What can paleorecords tell us about this component in the spectrum of regional climate variability? With such information in hand it may be possible to better estimate the envelope of uncertainty surrounding climate projections based on the response to anthropogenic forcing.

Application of Different Temporal Scale Analysis to Index Insurance

Preliminary research is currently underway at IRI exploring how hypothetical index insurance contracts might respond to decadal changes in climate. In this study, rainfall-based drought index insurance contracts are explored under several climate change scenarios, with the resulting trends in precipitation being added to simulated inter annual climate variability to 2100. In one set of simulations, the thresholds for contract payout are fixed at values determined from the historical record, and the payout frequency proves to be quite responsive to the trend in rainfall created by the climate change scenario. In another set of simulations, the thresholds themselves evolve over time on the basis of a roughly 30 year long sliding window of time that serves as the reference point for an individual year's threshold calculation. Under this construction, the payout frequency is considerably more stable and less sensitive to the systematic shifts in climate, although some small trends in payout frequency remain. Figures 2a and 2b provide an illustration of these points under the assumption of a simulated 10% decline in rainfall for the period from 2009-2100 for Dertu, Kenya. The proposed contract has a twotiered structure with a smaller payout for events that cross the 1/8 drought threshold and a larger payoutfor events that cross the 1/20 drought threshold.

Figures 2A and 2B - A steady decrease in seasonal rainfall over the 21st century would have a profound impact for livelihoods in Sub-Saharan Africa. However, ongoing research at the IRI shows that index insurance can still be a robust risk management tool even in a changing climate. The simulation below shows the effects of an anticipated 10% decrease in rainfall on an index insurance contract for a village in Eastern Kenya. If the thresholds agreed upon for a 2008 contract are held constant through 2100 (a), a 1 in 20 threshold pays out twice as frequently (1 in 10), and a 1 in 8 threshold pays out nearly twice as often (1 in 5). If thresholds are instead allowed to change with the most recent 30 years of data (b), the increase in payout frequency is not as severe.





Scaling Up (or Down)

It is axiomatic that climate projections are more reliable for larger spatial scales. This idea underlies the emphasis, in IPCC assessments, on regions of continental or subcontinental scale. If information is sought for much smaller areas – a watershed, catchment or valley – available climate projections will almost certainly have to be downscaled in order to infer it. Given the very large-scale nature of the forcing, probabilities of an expected impact typically will not differ between neighboring localities. Specific amounts and characteristics of variability may be better quantified locally; however, uncertainties will increase. So although interventions may begin at the smallest spatial (or social) scales, for climate information the situation is reversed. It is possible to conduct analyses on records from particular weather stations, but such records often have low signal-to-noise ratios, particularly for rainfall; it is for this reason that such records are often aggregated. It may also be possible to combine information across a range of spatial scales in order to generate some sort of optimal projection. This would be a research question deserving of investigation.

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