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Information Value of Climate Forecasts for Rainfall Index Insurance for Pasture, Rangeland, and Forage in the Southeast United States

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In this article, possible use of climate forecasts in rainfall index insurance of hay and forage production is considered in a geographical area (southeast United States) relatively heavily impacted by the El Nino Southern Oscillation (ENSO). Analysis of the stochastic properties of rainfall, yields, and the ENSO forecasts using the copula technique shows that the forecast impact depends on the proximity to the Gulf Coast where the impact of the ENSO is more pronounced and earlier in the year. Stochastic modeling shows that the use of skillful long-term climate forecasts by the insured producers creates intertemporal adverse selection that can be precluded by offering forecast conditional premiums. The impacts on the efficiency of the rainfall index insurance and results of sensitivity analysis with respect to model parameters are discussed.

Key Words: copulas, ENSO forecasts, rainfall index insurance

JEL Classifications: Q14, Q51, R51, R11, R38

Over the past two decades, several alternative designs of agricultural crop insurance have been tried in an attempt to increase participation rates and improve actuarial performance of the program. However, reducing moral hazard and adverse selection inherent in insurance contracts is frequently associated with reduction in the risk covered by insurance (Glauber, 2004). One example is the index-based agricultural insurance that largely avoids the moral hazard issues and can be especially applicable for crops and areas with limited yield/revenue records and where agriculture is more rainfall-dependent (Skees, 2008).

In 2007, the U.S. Risk Management Agency (RMA) introduced a pilot program to offer Pasture, Rangeland, and Forage (PRF) insurance that provides protection against losses of forage produced for grazing or harvested for hay (RMA, 2012). Two types of PRF insurance contracts are currently available under the pilot program, both of which are designed to indemnify producers when yield-reducing drought conditions arise. Rainfall Index (RI) contracts indemnify policyholders based on gridded 0.25° latitude by 0.25° longitude rainfall data published by the National Oceanic and Atmospheric Administration Climate Prediction Center. Vegetation Index (VI) contracts indemnify

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policyholders based on gridded 4.8 mile × 4.8 mile Normalized Difference Vegetation Index (NDVI) data published by the U.S. Geological Survey Earth Resource Observation Center. In the 2011 crop year, RI insurance was offered in 16 states and VI insurance in nine states.

Both types of PRF contracts are examples of index insurance. Index insurance differs from the conventional insurance in that it indemnifies policyholders based not on verifiable individual producer losses, but rather on realization of a variable or an "index" that is highly correlated with these losses. Index insurance is generally considered to be free of the moral hazard problems that have undermined the actuarial performance of traditional crop insurance (Halcrow, 1949). However, with index insurance, it is possible for a policyholder to suffer a loss without receiving an indemnity as a result of the basis risk caused by imperfect correlation between the index and the losses. Properly designed index insurance products can minimize basis risk although not completely eliminate it. The benefits, limitations, and optimal design of agricultural index insurance have been thoroughly studied in the literature. Miranda (1991) was the first to analyze the demand for agricultural index insurance in a stylized setting, demonstrating that the optimal quantity of index insurance that a producer should purchase is generally proportional to the correlation between the index and the producer's yields. Mahul (1999, 2001) and Mahul and Wright (2003) extended Miranda's results, examining practical design issues and revenue insurance. Carriquiry and Osgood (2012) developed a theoretical model looking specifically at the impact of climate (weather) forecast availability on producer welfare and demand for index insurance.

Currently, the U.S. Risk Management Agency calculates PRF insurance premiums using all available historical rainfall and NDVI time-series data ("pooled" data) without regard to interannual climate variations. Climate research, however, has established that rainfall in the southeastern United States is heavily influenced by El Niño-Southern Oscillation (ENSO) cycles (Agroclimate.org, 2012; Gershunov, 1998; Hansen, Hodges, and Jones, 1998; Royce, Fraisse, and Baigorria, 2011).

The ENSO cycles are driven by central Pacific sea surface temperature (SST) anomalies with significant positive anomalies classified as El Niño events and significant negative anomalies classified as La Niña events. A peculiarity of the ENSO phenomenon is that central Pacific sea surface temperatures observed in late Fall usually persist for 6–10 months, making them useful in predicting the onset of El Niño or La Niña conditions.

As such, central Pacific sea surface temperatures (or any other index reflecting ENSO phases) may be used to predict rainfall in the southeastern United States and, thus, the payouts expected from a PRF insurance contract, which has a late November sales closing date. This gives rise to the possibility of "intertemporal" adverse selection, the practice among producers of purchasing more insurance coverage when expected payouts are high and purchasing less insurance coverage when expected payouts are low. Unless a corrective action is taken by the insurer, such intertemporal adverse selection would increase the long-term loss ratio of the contract (i.e., the indemnities policyholders expect to receive per unit of premium), thus undermining its actuarial soundness.

This article analyzes the potential impact of long-range climate forecast availability on the risk-reducing effectiveness of the RI PRF insurance in the southeastern United States. The analysis is based on stochastic simulation of rainfall, yields, and ENSO indices. Copula approach is used to model joint distribution of the relevant random variables.

The rest of the article is organized as follows. Section one discusses the theoretical model. Section two describes data and statistical methods and presents the estimation results. Section three presents the simulation results under varying assumptions about farmer purchasing decisions and crop insurance rating methods. The last section provides concluding remarks.

Modeling Framework

As mentioned before, index-based insurance relies on the fact that the insured index is correlated with the loss variable (e.g., yield).

Previous research suggests that the demand for index-based insurance (or demand for coverage) is generally proportional to the correlation between the index and the yield (Mahul, 1999; Miranda, 1991).

An implicit assumption behind pricing of any index insurance contract is that the insurer can sell roughly the same number of contracts over any time period so as to break even in the long run. However, availability of a skillful or accurate (i.e., better in terms of predictive power) forecast reduces the demand for coverage when low probability of a loss is predicted ("good" year) and vice versa.[1] Under such circumstances, the insurer may not be able to collect enough premiums in "good" years to offset payoffs in "bad" years. To compensate for such an intertemporal adverse selection, the insurer can either offer a menu of multiperiod contracts or make the premiums conditional on the forecast.

With this in mind, we specify the model as follows. A risk-neutral insurer with zero costs offers an RI-based contract with the coverage equal to 100% of E[RI].[2] The indemnity is defined as a positive deviation of the RI index from the coverage multiplied by the value coefficient b, the county base value (CBV) representing the marginal impact of precipitation on yields and thus the level of indemnification. This coefficient is obtained by regressing county yield on RI, i.e. Y = a + b*RI.[3]

Given forage yield y, rainfall index r, coverage C, premium P, initial wealth W_0, and joint density of f(r,y), the expected utility of the producer is

$$\text{(1)} \quad \mathrm{E[U]} = \int_{R_{min}}^{\mathrm{R}_{max}} \int_{\mathrm{Y}_{min}}^{\mathrm{Y}_{max}} U(\mathbf{W_0} + \mathbf{y} + \boldsymbol{\delta}(\mathrm{b} * \max(\mathbf{0}, \mathrm{C} - \mathrm{r}) - \mathrm{P}))\mathrm{f(r,y)dr\,dy}.$$

where $\delta = 1$ indicates purchase of insurance, whereas $\delta = 0$ corresponds to the case of no insurance. The insurer sets the premium P of the index insurance contract to be actuarially fair so that

$$\text{(2)} \quad P = \mathbf{E}[loss] = \int_{R_{min}}^{C} b(C - r) f_R(r)\, dr$$

where $f_R(r) = \int_{Y_{min}}^{Y_{max}} f(r,y)\, dy$ is the marginal density of the rainfall index.

In this model, the insurer and the insured compute the expectations based on their subjective perceptions of the index and yield distributions. If the relevant information is fully available, then the distributions f(r, y) used by both parties are the same, the insureds perceive the contract as actuarially fair, purchase it on an annual basis, and allow the insurer to break even in the long run as implied by the premium calculations, which implies zero expected income transfer from the insurer to the insured.

However, if the ENSO phases affect the realizations of rainfall, then the bivariate joint distribution f(r, y) of rainfall and yield is in fact a marginal distribution derived from a more general trivariate distribution f(r, y, E) of the rainfall, yield, and ENSO ∞ index forecast so that $\mathrm{f(r,y)} = \mathrm{f}_E(\mathrm{r,y}) = \int_{\mathbf{0}}^{\infty} \mathrm{f}(\mathrm{r,y},E)\mathrm{d}E$.

Availability of the ENSO forecast essentially allows the agents to use the conditional distribution of rainfall and yields instead of the marginal (unconditional) one. In this regard, there are four possible scenarios of climate information availability (asymmetry) that can be constructed (both the insurer and insureds either are aware of the forecast or not). We focus on the three that seem to be the most

[1] Formally, forecast skill in meteorology is defined as one minus the ratio of mean squared error (MSE) of the forecast in question and MSE of a reference forecast (Glossary of Meteorology). This measure does not accommodate different forecasting and forecast variables (ENSO index and rainfall index in our case) and, additionally, requires a reference forecast that we do not have. Because the forecast skill is closely related to the correlation between the forecast and its realization, we use simple correlation between the forecast (MEI from November of the previous year) and the rainfall index realization in a bimonthly interval as a measure of forecast accuracy (Murphy, 1988).

[2] We use the 100% coverage level for the sake of simplicity of exposition. The analysis can be extended to any other coverage level in a straightforward fashion.

[3] With corr(RI,yield) ranging between 0.4 and 0.7, the coefficients are statistically significant in all counties.

interesting and realistic.[4] The implications of each scenario discussed subsequently are based on the theory of informational asymmetry going back to the works of Rothschild and Stiglitz (1976) and Wilson (1977). More formal derivation supporting these statements can be found, for example, in Mas-Colell, Whinston, and Green (1995).

1) Baseline scenario: the forecast information is unavailable or is of no interest to both the insured and the insurer. All expectations are then based on the marginal joint distribution of yields and RI. The demand for insurance is based on comparing the expected use of the end-of-season wealth with and without the contract.
2) The insurer does not know about the value of the forecast, but the insured recognizes the forecast accuracy (predictive capability). The former still computes the expectations based on the marginal joint distribution of yields and RI, whereas the latter uses the conditional distribution $f(y, r|E_t) = \frac{\partial^2 F(y, r, E)}{\partial y \partial r}\Big|_{E=Et}$, where ϵ_t is the forecast of ENSO index. Advance knowledge of the realization of conditioning variables leads to intertemporal adverse selection, i.e., an incentive not to buy the contracts in "good" years predicted to have high values of rainfall (and thus yield) and vice versa. Note that the contract pricing continues to be actuarially fair based on the insurer's evaluation of risk, but not actuarially sound (E[loss] > P) as a result of the intertemporal adverse selection. This situation leads to the expected income transfer from the insurer to the insured, E[loss] − P, in addition to the insured's risk reduction in "bad" years. The net gain (benefit) is made of the insured's expected use gain expressed in terms of certainty equivalent revenue described in Section 2.1 and the insurer's losses resulting from expected income transfer. The net gain is different from zero because the insured is risk averse, whereas the insurer is not.
3) Both the insurer and the insured are aware of the forecasting value of the ENSO index realization. If the premiums are originally set based on the unconditional marginal distribution of rainfall index and yields, then the insured has an incentive to intertemporally adversely select as described in Scenario 2. However, the insurer can now respond by making the premiums conditional on the forecast. The contract again is both actuarially fair and actuarially sound. Given nonnegative index–yield correlation, the demand will remain positive because of actuarial fairness and no discrepancy in subjective perceptions of joint distributions. However, the insured's would be worse off relative to the baseline scenario because the contract would now only insure a portion of the rainfall risk not explainable by the ENSO index and thus provide lower level of risk reduction.

Methods, Data, and Estimation Results

Statistical Methods

To quantify the effects of long-range climate forecasts on performance of RI insurance in the scenarios outlined previously, we need to analyze the relationship between the climate (ENSO phases), RI, and yield. A significant relation between climate forecast and insured variable (e.g., index) is indicative of the forecast accuracy that is generally valuable in risk management. The marginal distributions of the RI, forage yield, and end-of-last-year ENSO index representing the climate forecast are estimated from the historical data using the maximum likelihood method. The joint density of the ENSO index, RI, and yield are then constructed using the estimated marginals and the copula approach.

To accommodate seasonal differences in rainfall, we construct annual series for each insurable bimonthly period. The best fits for the marginal distributions of rainfall index, yield,

[4] The fourth possible scenario corresponds to the situation in which the insurer is aware of the forecast but the insureds are not. However, this case is trivial and reduces to one of the two analyzed scenarios. Indeed, if the insurer has reasons to believe that the producers do not intertemporally adversely select, it can choose to ignore the forecast thus leading to Scenario 1. Alternatively, the insurer can introduce the forecast-conditional premiums. In this case, the insurer would have to educate the producers as to the reasons behind the differences in premium, thus leading to Scenario 3.

and ENSO index are chosen from several alternative distributions (beta, gamma, log-normal, normal, and Weibull). Copulas are functions that combine the marginals of jointly distributed variables into their joint distributions. The connection between copulas and probability distributions is established by the Sklar's Theorem (Nelsen, 2006). The latter states that for any group of jointly distributed variables, there exists a unique copula function $C(\cdot)$ such that the joint distribution function $H(x_1, x_2, \ldots, x_n)$ with marginals $\{H_i(x_i)\}$ can be represented as

$$(3) \qquad H(x_1, \ldots, x_n) = C(H_1(x_1), \ldots, H_n(x_n))$$

Equation (3) can also be rewritten to relate the joint and marginal probability densities so that

$$(4) \qquad \boldsymbol{h}(x_1, \ldots, x_n) = C(H_1(x_1), \ldots, H_n(x_n)) \cdot \boldsymbol{h_1}(x_1) \cdot \ldots \cdot h_n(x_n)$$

where $\boldsymbol{h}(x_1, \ldots, x_n) = \frac{\partial^n H}{\partial x_1 \ldots \partial x_n}$, $C(\cdot) = \frac{\partial^n C(u_1, \ldots, u_n)}{\partial u_1 \ldots \partial u_n}$, **and** $h_i(x_i) = H'_i(x_i)$.

Copulas can be instrumental in constructing joint distributions by combining variables with different marginals. The usefulness of copulas comes from the fact that, once a copula is estimated, it can be used to construct joint distributions by combining variables with different marginals (Tejeda and Goodwin, 2008). Importantly, the copula approach allows for better use of available data when data series are of different lengths. In our case, the yield data series are much shorter (approximately 25 observations per location and insurable bimonthly interval) than the RI and ENSO data (approximately 50 observations per location and insurable interval). Although estimation of the dependency structure in equation (4) still needs matching data points, the marginal distributions for each variable can be estimated individually using all available data.[5] The conventional estimation of a full joint distribution, on the other hand, would only use the matching observations.

For the purposes of this analysis, we use Gaussian and *t*-copulas. These copulas are commonly used in the literature and are characterized by a symmetric dependence structure, which is consistent with the dependence observed in our data.[6]

Marginal densities of the three variables (ENSO index, RI, and yield) were computed on a three-dimensional grid of Simpson quadrature nodes. The trivariate joint density at the nodes was then calculated according to equation (4) and used in computing the expected utilities (equation [1]) and contract premiums (equation [2]) under the three scenarios of information availability outlined previously.

To reflect possible imprecision in ENSO forecasts, we partitioned the range of ENSO index into a number of intervals of equal length (10 or more to approximate a continuous index measure) and calculated rainfall distributions conditional on the ENSO index belonging to each interval. Any consistent patterns in ENSO-conditioned premiums would then indicate predictable differences in the volatility of rainfall and therefore of a potential value of climate forecast information.

Commonly found in financial literature are several measures of performance of risk-reducing contracts that include value at risk, mean root square loss, and certainty equivalent revenues (CER). In production analysis, comparison of certainty equivalent revenues is a good indicator of net benefits from risk reduction, because agricultural producers are normally viewed as risk-averse and the level of aversion matters (Schnitkey, Sherrick, and Irwin, 2003). The constant absolute risk aversion utility function of the form

$$(5) \qquad U(R;A) = 1 - \exp(-A \cdot R).$$

was used for the analysis with the results expressed in terms of certainty-equivalent wealth (CEW given $W_0 = 0$ becomes CER). Following Babcock, Choi, and Feinerman (1993), we

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[5] For a brief technical description of copulas, see Vedenov (2008). For a detailed discussion, see Nelsen (2006).

[6] Currently, there is no common approach to the copula selection in the literature and this topic goes outside of the scope of the present article. We relied on visual inspection of data to select these two copulas for our analysis.

calibrated the risk aversion coefficient A based on assumptions about the risk premium level, i.e., the share of the expected income an individual would be willing to give up to eliminate all risk. For a given risk premium θ, the risk aversion coefficient A can be calculated by numerically solving a fixed point problem $U([1 - \theta]ER; A) = EU(R; A)$.

The net gain from insurance to both the insured and the insurer is made of the difference in certainty equivalent revenues with and without insurance, $CER_{Ins} - CER_{NoIns}$, minus expected income transfer from the insurer to the insured, E[loss] – premium, which can be positive in case of intertemporal adverse selection.

Data

The states that are currently fully or partially covered by the RI-based PRF insurance are Alabama, Colorado, Idaho, Missouri, Montana, North Dakota, Pennsylvania, and South Carolina.[7] The geographical scope of this research is limited to locations in Alabama, Georgia, and the Florida Panhandle representing a variety of regions ranging from coastal to inland. This variety is important, because the ENSO impact on rainfall is usually the strongest in the coastal areas.

Rainfall data were collected from the Climate Prediction Center (CPC) and local meteorological sources.[8] The RI used by the RMA reflects precipitation received in an area relative to the long-term average and is highly correlated with monthly rainfall data, available from the National Oceanic and Atmospheric Administration's climate data inventory, for the same weather station locations. We use the RMA's RI data collected from the RMA online database as more suitable for our research purposes (RMA, 2012).

Four ENSO indices are commonly used by climatologists and agronomists, namely the Nino 3.4, the Oceanic Nino Index (ONI), the Japan Meteorological Agency (JMA) index, and the Multivariate ENSO Index (MEI). The SST anomalies in the Nino 3.4 region of the Pacific Ocean are believed to be the most suitable for explaining climate variations in the southeastern United States (CPC; Hansen, Hodges, and Jones, 1998). The ONI and the JMA indices are highly correlated with the Nino 3.4 index but represent 5-month moving averages emphasizing the persistence of the phenomenon.

The MEI is a composite ENSO index based on six main observed variables over the tropical Pacific, viz. sea surface temperature, sea-level pressure, zonal and meridional components of the surface wind, surface air temperature, and total cloudiness fraction of the sky. Because of its composite nature more fully reflecting the complex atmospheric processes, the MEI index scores best as a predictor of corn, cotton, and peanut yields in the Southeast (Royce, Fraisse, and Baigorria, 2011). Monthly and weekly data on these indices are available from the National Aeronautics and Space Administration online database (NASA, 2012). Because the stated deadline for signing the RI insurance contracts is November 30, we used the reported November values of the MEI as a proxy for the next year's forecast.

Monthly hay yield data come from the Agricultural Experiment Station yield performance reports. The latter cover the period of 1999–2010 (with some variations) and summarize field trial yields of different ryegrass varieties recorded continuously from September to October to April to June at the rate of three to six annual measurements (approximately 40 observations for each location). To account for irregular measuring intervals, the reported incremental yields averaged across varieties (mostly ryegrass) were converted to daily averages. The correlation between these daily averages and precipitation is significant and varies between 0.4 and 0.7.[9]

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[7] The PRF insurance is also available in Texas, Kansas, Nevada, New York, North Carolina, Oklahoma, Oregon, South Dakota, Virginia, and Wyoming, but there it uses the vegetation index (VI) for indemnity determination.

[8] Precipitation and yield data collected at experiment stations were chosen as the most reliable.

[9] Annual forage yield data are not used in this analysis because the bimonthly yield distributions necessary for our analysis are sufficiently different from the annual yield distributions.

Table 1. Correlation between Forecast (Multivariate El Nino Southern Oscillation Index [MEI] in November previous year) and Rainfall Index in February to March

Locations in Alabama			
Coastal (Fairhope)	Further from Coast (Headland)	Further from Coast (Chilton)	Inland (Belle Mina)
MEI Rainfall Index Correlation (p value)			
0.569 (0.065)	0.368 (0.086)	0.255 (0.279)	–0.199 (0.981)

Impact of the El Nino Southern Oscillation Forecast on Rainfall and Premiums

Table 1 shows typical correlations between the RI in February to March and the lagged (November$_{-1}$) ENSO index (MEI) representing forecast at four Alabama experiment stations ranked by their proximity to the coast. The forecast accuracy appears to be highly dependent on the proximity to the Gulf Coast.

Because we are interested in the insurance implications of climate information and therefore its effect on downward volatility (losses) of the insured variable, we also ran quantile regressions of the rainfall index on the lagged values of the MEI, Nino 3.4, and JMA indices. A sample of results reported in Table 2 indicates that most of the impact is on the lower to mid-quantiles of rainfall distribution and that, at least for the coastal regions, the impact is significant for the index lagged up to 6 months.[10]

Tables 3, 4, and 5 show typical results of expected utilities and certainty equivalent revenues calculated under the three scenarios discussed in the previous section. Gaussian copula is used to construct estimates of trivariate densities of the RI, lagged ENSO index (MEI) representing the forecast, and ryegrass yields. The ENSO forecast takes on one of 10 values reflecting the interval into which the lagged ENSO index falls. Table 3 shows typical results for a coastal location (Mobile County, AL). As expected, the mean of the rainfall index is positively related to the ENSO forecast value, i.e., the lagged MEI index showing the strength of the ENSO (El Nino) signal (Table 4, column 2). Even more notably, the relationship between the forecast and expected losses of the RI insurance is almost monotonic with the losses (Table 4, column 3) increasing with the forecast up to its upper range, albeit slightly falling at the end. The premiums conditioned on the forecast (Table 4, column 4) are inversely related to the forecast value.

Of greatest interest is the impact of the forecast availability on the risk reducing effectiveness of the insurance contract under the alternative scenarios described earlier. If the unconditional distributions are used in equations (1) and (2), the benefit from the RI insurance (as measured by the change in CER) is quite small and amounts to only approximately 6% of the CER of the uninsured yield (Table 3, row 3). As expected, the RI insurance with premiums not conditioned on climate forecasts is always preferred to that with forecast-conditional premiums, although the difference is not very large. The small magnitude of the losses from conditioning premiums on forecast could be attributed to a relatively small impact of the forecast on the insured index.

When the producers make insurance purchasing decisions based on skillful forecasts but the contract offers premiums based on unconditional distribution (Tables 4 and 5, Scenario 2), the producers benefit the most as a result of their ability to intertemporally adversely select across time. Close to the coast and in Winter/early Spring, purchasing the insurance is optimal only under three most pessimistic forecasts (1–3) out of 10 as evidenced by comparing the unconditional premium (unconditional expected losses) with the expected

[10] Mixture models are a better methodology for ascertaining ENSO impact on weather at distributional extremes because they eschew any arbitrary subpopulation classification. However, the use of mixture models is outside the scope of this article as a result of space limitations and the focus on modeling index insurance contracts.

Table 2. Quantile (q) Regression Coefficients for Monthly Rainfall on Forecast (Multivariate El Nino Southern Oscillation Index [MEI] in November of previous year)

MEI, November$_{-1}$	November–December$_{-1}$	January–February	February–March	March–April	April–May	May–June	June–July	July–August
Fairhope (coastal)								
q10	0.183*	0.223**	0.633***	0.485***	0.269	0.247	0.383**	0.478***
q30	0.381**	0.364*	0.631***	0.627***	0.443**	0.320	0.473**	0.503**
q50	0.545***	0.434***	0.482***	0.444***	0.461***	0.412**	0.395***	0.375
q70	0.410	0.274	0.301	0.364	0.269	0.134	0.153	0.109
q90	0.950***	0.657*	0.502	0.778**	0.663	0.584	0.721	0.495
Headland (further from coast)								
q10	0.0579	0.0794	0.148	0.208	0.118	0.132	0.132	0.191
q30	0.315**	0.421**	0.626***	0.542**	0.316*	0.118	0.121	0.163
q50	0.589***	0.508***	0.536***	0.612***	0.630***	0.317	0.338	0.372*
q70	0.511**	0.507***	0.491**	0.578***	0.452	0.271	0.340	0.353
q90	0.182	0.383	0.357	0.313	0.308	0.331	0.280	0.452
Chilton (further from coast)								
q10	0.313**	0.173	0.262*	0.312*	0.375**	0.163	0.132	0.265
q30	0.307***	0.263*	0.370***	0.418***	0.225	0.213	0.0309	0.168
q50	0.271	0.184	0.303	0.251	0.165	–0.015	–0.020	0.016
q70	0.373**	0.206	0.216	0.197	0.225	0.101	0.0183	0.079
q90	0.641	0.141	0.074	–0.194	–0.413	–0.513	–0.556	–0.840
Belle Mina (inland)								
q10	–0.197	–0.194*	–0.054	–0.070	–0.172*	–0.203	–0.195	–0.126
q30	0.054	0.048	0.070	0.123	0.131	0.111	–0.0323	0.060
q50	–0.025	–0.145	–0.113	–0.101	–0.127	–0.145*	–0.141	–0.113
q70	–0.275	–0.269	–0.205	–0.100	–0.459*	–0.53***	–0.376	–0.059
q90	–0.126	–0.076	–0.032	0.010	0.069	0.006	0.239	0.300

Note: asterisks define significance (1%, 5%, and 10%).

Table 3. Benefits from Insuring December–February Rainfall Insurable Interval (Mobile County, AL)

Scenario	CER
No insurance	2152.7
	Δ CER from no insurance:
Scenario 1 Unconditional premiums Producer benefit = net benefit	129.3
Scenario 2 Unconditional premiums, intertemporal adverse selection Producer benefit	145.9
Scenario 2 Unconditional premiums, intertemporal adverse selection Net benefit	101.6
Scenario 3 Forecast conditional premiums Producer benefit = net benefit	122.8

CER, certainty equivalent revenue.

losses conditional on the ENSO forecast in Table 4. The net benefit from insurance—calculated as the producer benefit (CER) minus expected income transfer from the insurer resulting from intertemporal adverse selection—is always smaller relative to the forecast-conditional situation (Scenario 3). The higher the forecast accuracy, the smaller the net benefit.

These results reinforce the intuitive and expected conclusion that, in the absence of positive forecast impact on management practices, which is more likely to be the case in forage than in crop production, climate forecast information does not have a positive value for the insurance. However, as the correlation between the forecast and the insurable index in subsequent insurable intervals (further in the year) decreases, the forecast information translates into smaller differences in benefits when incorporated into contract design. For maximizing the efficiency of the RI insurance, defined as the net gains equal to difference in certainty equivalent revenues with and without insurance, $CER_{Ins} - CER_{NoIns}$, minus expected income transfer from the insurer to the insured, E[loss] – premium, it is (almost) always better to offer forecast-conditional contracts than to allow intertemporal adverse selection under contracts with premiums based on unconditional distributions (pooled contracts).

The effect of forecast accuracy on the risk-reducing effectiveness of the RI insurance is demonstrated in Table 5, which presents the CER results under the three scenarios of

Table 4. Expected Losses Conditional on Forecast Insuring December–February Rainfall Insurable Interval (Mobile County, AL)

Forecast value (ENSO index interval)[a]	E[RI|forecast]	E[loss|forecast][b]	E[loss/RI|forecast][b]
1	66.28	9.93	0.15
2	81.04	11.83	0.15
3	95.26	12.89	0.14
4	109.53	13.51	0.12
5	124.16	13.89	0.11
6	139.30	14.10	0.10
7	154.98	14.15	0.09
8	170.95	14.01	0.08
9	187.00	13.43	0.07
10	201.03	11.63	0.06
Unconditional premiums (Scenario 2)	99.84	14.13	0.14

[a] Higher intervals correspond to stronger ENSO signal (higher index values).
[b] Expected loss computed according to equation (2) using conditional densities.
ENSO, El Nino Southern Oscillation Index; RI, insurable rainfall index.

Table 5. Results Summary for All Insurable Intervals (Mobile County, AL)

Insurable Interval (bimonthly, starting January)			Scenario	CER[a]
1	corr(forecast, RI)	0.53	Scenario 1. Unconditional premiums	129.31
	Demand, % of forecast[b]	0.40	Scenario 2. Unconditional premiums, intertemporal adverse selection, producer benefits	145.87
	Insurer's loss[c]	−44.24	Scenario 2. Unconditional premiums, intertemporal adverse selection, net benefits	101.62
			Scenario 3. Forecast conditional insurance	122.79
2			Scenario 1. Unconditional premiums	119.10
	corr(forecast, RI)	0.26	Scenario 2. Unconditional premiums, intertemporal adverse selection, producer benefits	119.76
	Demand, % of forecast	0.50	Scenario 2. Unconditional premiums, intertemporal adverse selection, net benefits	108.01
	Insurer's loss	−11.75	Scenario 3. Forecast conditional insurance	110.68
3			Scenario 1. Unconditional premiums	105.06
	corr(forecast, RI)	0.19	Scenario 2. Unconditional premiums, intertemporal adverse selection, producer benefits	105.08
	Demand, % of forecast	0.60	Scenario 2. Unconditional premiums, intertemporal adverse selection, net benefits	99.52
	Insurer's loss	−5.56	Scenario 3. Forecast conditional insurance	99.15
4			Scenario 1. Unconditional premiums	114.47
	corr(forecast, RI)	0.08	Scenario 2. Unconditional premiums, intertemporal adverse selection, producer benefits	114.47
	Demand, % of forecast	1.00	Scenario 2. Unconditional premiums, intertemporal adverse selection, net benefits	114.47
	Insurer's loss	0.00	Scenario 3. Forecast conditional insurance	111.80
5	corr(forecast, RI)	−0.04		
6	corr(forecast, RI)	0.04		

[a] CER refers to certainty equivalent revenues corresponding to a scenario (1, 2, and 3) in each insurable interval (1–6, bolded).
[b] Percent of forecasts under which insurance is purchased.
[c] Expected income transfer to the insured.
RI, rainfall index.

information availability for all six insurable bimonthly periods for a coastal location in Alabama (Mobile County). As the forecast accuracy declines over the subsequent periods, the forecast information makes less and less difference between the benefits from the insurance with and without using the forecast information (between Scenario 1 and Scenario 3), becoming irrelevant in mid-Summer when the ENSO usually transitions from one phase to another. Similarly, lower forecast accuracy in locations further inland makes forecast information almost completely irrelevant for the RI insurance. The results for Georgia and Florida are very similar and are not shown as a result of space limitations.

Sensitivity Analysis

To evaluate the sensitivity of our results to assumptions and modeling choices, we vary several factors including forecast accuracy and precision, correlation between the yield and the index, producer's risk aversion, and the county

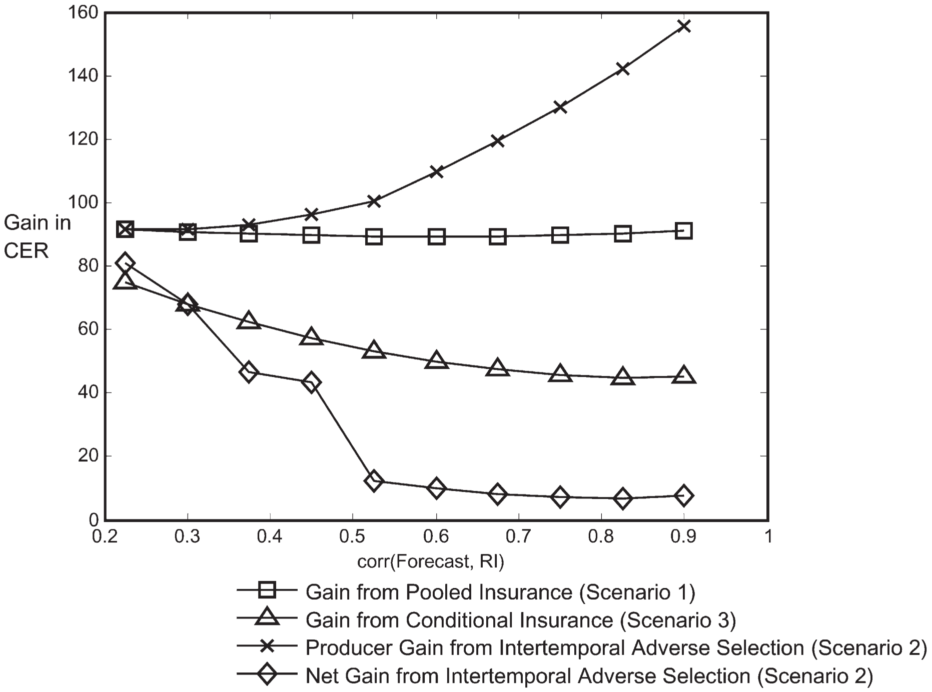

Figure 1. Benefits (gains) from Insurance Relative to No Insurance (as measured by certainty equivalent revenues [CERs]), Sensitivity to Forecast-Index Correlation

base values (the conversion factor between the index and the yield in equation [1]).[11]

For all reasonable parameter ranges, demand for the RI contract based on the unconditional distribution remains the same: it is optimal to buy the actuarially fair insurance at the maximum available coverage (100% of the expected RI). This result agrees with the theory, because the correlation between the RI and yield is high enough to justify demand for coverage at the mean of the RI.

The impact of the forecast accuracy (i.e., the correlation between the forecast and the RI) on welfare and demand for insurance can be traced by comparing results for coastal (higher correlation) with inland (lower correlation) areas. However, such comparisons may be obscured by the differences in marginal distributions across the intervals. Therefore, we varied the correlation between the forecast and the RIs directly. The results of the simulations are shown in Figure 1.

Increasing forecast accuracy, ceteris paribus, has two major impacts on the effectiveness of RI insurance. On the one hand, it reduces producer benefits from the insurance (as measured by CER) under the forecast-conditioned contracts (Scenario 3). Intuitively, better forecast reduces the insurable portion of the rainfall risk and thus the producers are left bearing a higher portion of the risk.

On the other hand, higher forecast accuracy results in a higher degree of intertemporal adverse selection under Scenario 2. In other words, under the asymmetric information scenario, better forecast leads to more selective purchase of insurance, thus leading to higher transfer of expected income from the insurer to the producer. The kink in the net gains (net benefits) from insurance (insured's gains minus expected income transfer) is explained by the discrete specification of forecast intervals. The insured's benefits increase more smoothly because of simultaneously losing the benefits of consumption smoothing.

[11] Existing analytical models of index insurance that provide comparative statics are based on a set of restrictive assumptions (Cariquiry and Osgood, 2012; Mahul, 2001; Miranda, 1991). We use sensitivity analysis to focus on a set of local empirical estimates.

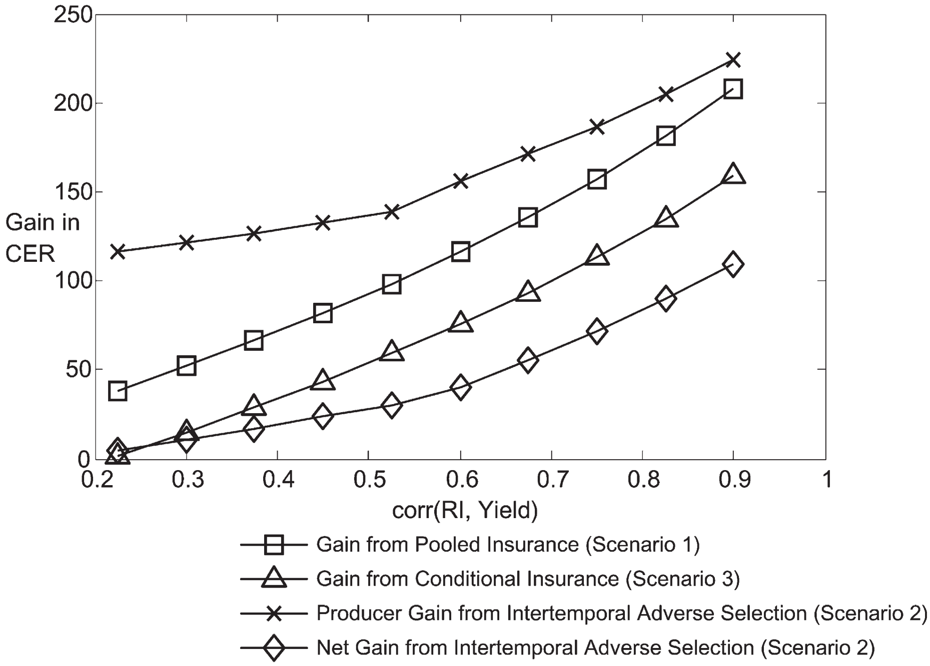

Figure 2. Benefits (gains) from Insurance, Sensitivity to Index–Yield Correlation

In our analysis, the range of ENSO index was divided into intervals on which the premiums were conditioned. This modeling setup approximated the forecast precision (as opposed to the forecast skill).[12] Decreasing the number of intervals—making the forecast more "crude"– reduces the informational content of the forecast, no matter how skillful or accurate. This brings Scenarios 1 and 3 closer together and reduces the degree of intertemporal adverse selection. For small variations in the number of intervals, the impact is minimal. The results are not reported here for brevity sake.

Higher correlation between the index and the yield improves producers' well-being in all three scenarios (Figure 2). Intuitively, higher index–yield correlation means higher risk reduction in terms of the CER regardless of the premium structure. As the correlation increases, intertemporal adverse selection decreases (insurance is purchased under a wider range of forecasts). However, the impact on the expected income transfer is indeterminate because producer benefits under the intertemporal adverse selection scenario increase with the correlation. Our estimates suggest that expected income transfer becomes smaller with greater index–yield correlation as insurance, even under more favorable forecasts, becomes more valuable to the producer. Conversely, expected income transfer under the intertemporal adverse selection scenario is inversely related to the index–yield correlation: the lower the correlation, the more indifferent the insured is between buying and not buying the insurance, which reduces demand even under the bad, but now less relevant, forecasts.[13]

Correlation between the forecast and the yield also affects the effectiveness of insurance contract, albeit indirectly. As shown in Figure 3, increasing correlation leads to greater divergence

[12] Precision is a measure of exactness; it is negatively correlated with random error (as in measurement).

[13] On a side note, an interesting observation is that, under the assumptions of forecast use and premiums based on unconditional distribution, higher index–yield correlation causes smaller changes in demand for insurance and thus increases both the producer's welfare and net welfare.

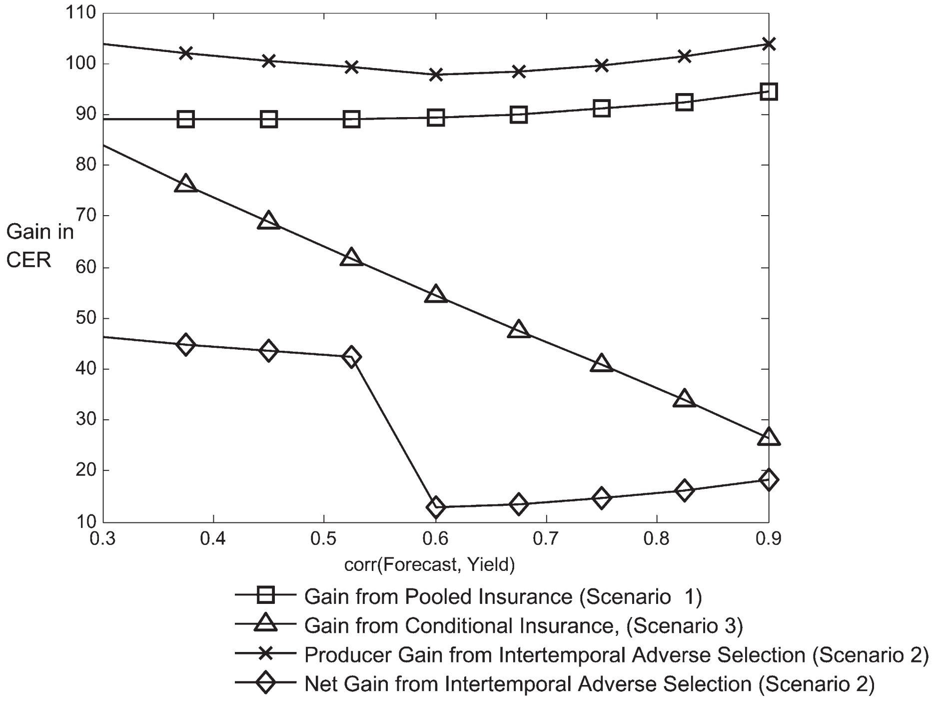

Figure 3. Benefits (gains) from Insurance Relative to No Insurance, Sensitivity to Forecast–Yield Correlation

between the CERs in Scenarios 1 and 3. Intuitively, for a given forecast accuracy (forecast–index correlation), higher forecast–yield correlation implies higher index–yield correlation. Therefore, the same reduction in the insurable portion of the index risk (occurring in Scenario 3) leads to higher reduction in insurable portion of the yield risk and thus lower overall effectiveness of the insurance contract with the forecast-conditioned premiums. Furthermore, as the forecast–yield correlation increases, the intertemporal adverse selection in Scenario 2 becomes more severe (fewer contracts are purchased) and benefits the producer less. At the lower levels of the correlation values, the insurance is purchased only 50% of the time. As the correlation increases, the demand falls even further without benefitting the producer much because most of the gain is expected income transfer from the insurer that is largely offset by the losses from not insuring under intertemporal adverse selection.

Increasing risk aversion has different impacts under different scenarios (Figure 4). On the one hand, it leads to greater divergence between the contracts with premiums based on unconditional distribution (Scenario 1) and the forecast-conditional premiums (Scenario 3). Indeed, higher risk aversion means that the uninsurable portion of the rainfall risk results in higher loss of use.

On the other hand, increasing risk aversion in Scenario 2 eventually leads to the situation in which the contract appears to be "overpriced" relative to the risk protection provided and the expected use of the contract begins to decrease. Given that producers in Scenario 2 only purchase insurance in "bad" years, the frequency of such high loss events does not seem to be high enough to justify purchase of the contract.

The CBVs represent the marginal impact of precipitation on yields and thus the level of indemnification. As shown in Figure 5, gains (benefits) from the insurance are maximized under Scenarios 1 and 3 when the base values represent the actual coefficient from regressing yields on bimonthly rainfall indices as described in the "Methodology" section. Under Scenario 2, the benefit of insurance also reaches

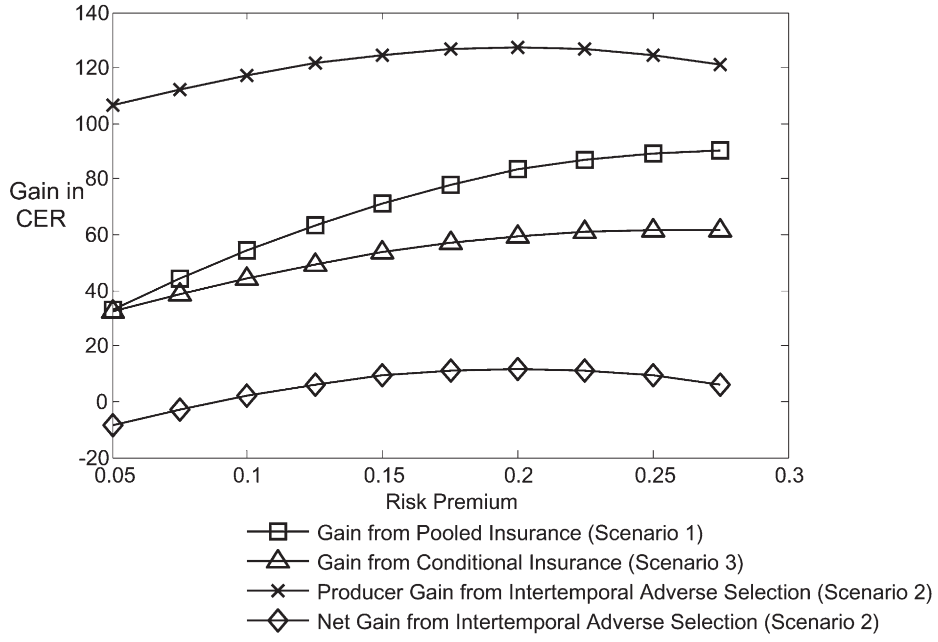

Figure 4. Benefits (gains) from Insurance, Sensitivity to Risk Aversion (risk premium)

a maximum although at a higher level of CBV (outside of the graph range). The difference is explained by the higher levels of the expected income transfer from the insurer, because it is scaled by the CBV.

Conclusions

This article analyzes the effect of long-term climate forecasts on RI insurance for hay and forage production in a geographical area where the climate is relatively heavily impacted by the ENSO phases (southeastern United States). The copula approach is used to model the joint distribution of the RI, hay yields, and the ENSO forecast. The forecast impact appears to be dependent on the proximity to the Gulf Coast where the impact of the ENSO is more pronounced. Both the mean of the RI and the contract indemnities increase with the forecast (stronger El Niño signal), whereas the premiums decrease with the forecast.

The effectiveness of insurance contracts is measured by the certainty equivalent wealth of an insured producer under three different scenarios reflecting forecast use by the insurer and the insureds. In the baseline case (Scenario 1), neither the insurer nor the insureds use the forecast, and the contract is priced based on the unconditional distribution of index and yield. In this case, the actuarially fair contract is perceived as such and is always purchased.

Producers benefit the most in the Scenario 2 in which the premiums are set based on unconditional distribution, but the producers use the forecast to selectively purchase insurance only in years with higher expected losses. This results in intertemporal adverse selection and income transfer from the insurer to the insureds. The contract is essentially mispriced and the premiums are not actuarially sound. In Scenario 3, both the insurer and the insureds are aware of the forecast and the insurer offers contracts with forecast-conditioned premiums. In this case, the forecast reduces the insurable portion of the index risk, and the producers are relatively worse off because they have to internalize this uninsurable risk. Stochastic modeling shows that the efficiency loss from using the forecast-conditioned premiums is relatively small in the southeastern United States but the effect is sensitive to the parameters and assumptions.

The main results of sensitivity analysis are that forecast accuracy (correlation between the

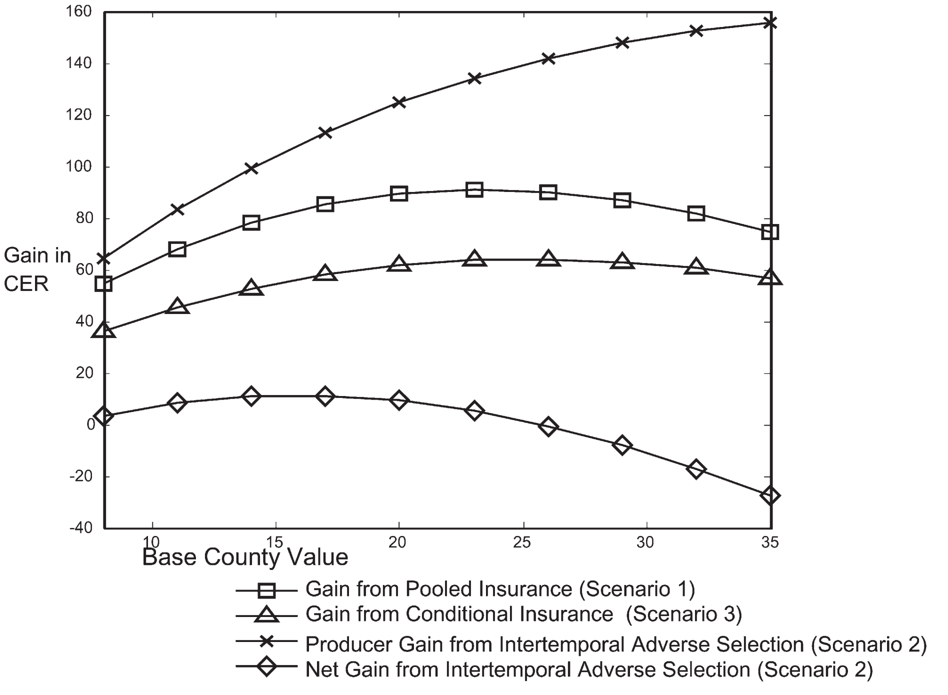

Figure 5. Benefits (gains) from Insurance, Sensitivity to Base Values (index value in terms of yield)

forecast and the RI) increases intertemporal adverse selection in Scenario 2. However, in most cases, higher correlation between the RI and the yield improves the efficiency of the RI insurance defined as the net gains equal to difference in certainty equivalent revenues with and without insurance minus expected income transfer from the insurer to the insured.

Currently, the RMA does not condition the premiums of RI insurance contracts on ENSO forecast. At this point, the lack of relevant data does not allow us to determine whether the producers are aware of the value of ENSO forecasts or use those to intertemporally adversely select against the RMA (i.e., whether the current situation corresponds to Scenario 1 or 2). Further research would be required to definitively answer this question.

If the evidence of intertemporal adverse selection is found, then the RMA would need to introduce the forecast-conditioned premiums to maintain the actuarial soundness of the program. The effect of such an action would be an overall decrease in risk-reducing effectiveness of the RI contracts, because the producers will have to bear the uninsurable (predictable) portion of the RI risk. Note, however, that the problem does not necessarily lie in the predictability of ENSO phases, but rather in the advance availability of the forecast. A possible solution in this situation would be to introduce the ENSO insurance which can be purchased before the forecast becomes available (or accurate) and can provide protection against the ENSO-driven variability in the rainfall and thus yield.

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