Seasonal Climate Forecasts and Agricultural Risk Management: Implications for Insurance Design

Miguel A. Carriquiry[a], and Walter E. Baethgen[b]

[a]Corresponding author

Instituto de Economía

Facultad de Ciencias Económicas y Administración

Universidad de la República

mcarrriquiry@iecon.ccee.edu.uy

Joaquin Requena 1375

Montevideo, Uruguay

Tel: (598) 24000466

Fax: (598) 24089586

[b]International Research Institute for Climate and Society,

The Earth Institute at Columbia University

61 Rt. 9W, Monell Bldg

baethgen@iri.columbia.edu

Palisades, New York 10964

Tel: (845) 680-4459

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Abstract

Seasonal climate forecasts and insurance are two instruments with potential to help manage risks in agricultural production. While both instruments play a distinct role in practice, they interact among themselves and with other production decisions. In particular, we contend that the progress in climate science in providing increasingly accurate seasonal forecasts has implications for the design of agricultural insurance. Early information regarding likely growing conditions will result in shifts in the expected distribution of crop yields, and the payouts associated with an insurance contract. The magnitude of these effects is illustrated using a combination of crop simulation models, and Monte Carlo techniques.

Key words: agricultural risk, index insurance, insurance, seasonal climate forecast

Resumen

Pronósticos climáticos estacionales y seguros son dos herramientas con potencial para ayudar a manejar riesgos en la producción agrícola. Mientras ambos instrumentos juegan un rol diferente en la práctica, interaccionan entre ellos y con otras decisiones de producción. En particular, proponemos que el progreso en la ciencia del clima a la hora de generar pronósticos que mejoran en cuanto a su precisión tiene implicancias para el diseño de seguros agropecuarios. Información temprana sobre las condiciones de crecimiento más probables resulta en cambios en la distribución esperado de rendimientos de cultivos, y las indemnizaciones asociadas a contratos de seguros. La magnitud de esos efectos es ilustrada usando una combinación de modelos de simulación de cultivos y técnicas Monte Carlo

Palabras Clave: riesgo agropecuario, seguro sobre índices, seguros, pronósticos climáticos estacionales.

Clasificacion temática orientativa: 3. Economia de los sistemas agropecuarios

Seasonal Climate Forecasts and Agricultural Risk Management: Implications for Insurance Design

1. Introduction

Many decisions in agricultural production that depend on climate need to be made several months before the climate conditions materialize. A complicating factor is that some of the decisions about production practices interact in complex ways with the prevailing climate during the growing season in determining the economic performance of the enterprise. Therefore, critical choices such as crop mix, planting dates, and fertilizer applications, might turn out to be erroneous (or at least non-optimal) in an ex-post sense. The impacts of these "mistakes" may be serious, especially for farmers engaged in subsistence agriculture. Faced with uncertainty regarding climate conditions, decision makers tend to use production practices that reduce losses in adverse conditions at the expense of foregoing profitable activities in good years and in some cases accelerated environmental degradation (Hansen, 2002). Reducing climatic uncertainty should help producers make better decisions and improve their performance.

Scientists have made remarkable progress in the last few decades at predicting seasonal climate fluctuations months in advance (Goddard et al., 2001). The growing ability to deliver timely and skillful seasonal climate predictions introduces the possibility to improve decision making, to either intensify activities and investments when favorable conditions are expected or prepare in advance when higher chances of adverse events are announced (Hansen, 2002). Moreover, it should be recognized that the forecasts are probabilistic, hence, even when they indicate that a given season is likely to be propitious for a given activity the realization may still fall in the low probability scenario. The remaining risks may limit producer responses (both for intensification or increase preparedness) to climate information, highlighting the importance of complementing forecasts with other risk management tools such as agricultural insurance.[1]

However, the same expanding ability by climate scientist can harm some members of society if they are not aware of the information provided, the impacts it has on their activities, or are simply constrained to react to it (Pfaff et al., 1999). Agricultural insurance is among the activities that can be potentially affected by information on expected climate conditions (Ker and Mc Gowan, 2000; Luo et al., 1994; Skees et al., 1999; Hess and Syroka, 2005). Insurance products are most commonly priced considering expected payouts based on long-term historical records, used either directly or as input for simulation models to conduct Monte Carlo-based analysis (Goodwin and Mahul, 2004, Jewson and Brix, 2005). Any information that implies a modification of the expected payouts will induce a change in the value of the insurance (or the price of risk) that should be reflected in the premium if known before the contract is transacted (Skees et al., 1999). Failure to incorporate the information will put one of the parties involved at a disadvantage. The contract will be relatively over-priced in years when favorable conditions are expected diminishing the incentives of potential buyers to seek protection. On the other hand, the insurance will be relatively under-priced when poor conditions are expected providing incentives for potential buyers to increase their purchases. The dynamic of modifying the purchases in response to mismatches between the risk and its price is known as inter-temporal

[1] Even if producers react fully to the information provided, and the forecasts are always correct, there are some scenarios (e.g. drought) where it is best not to engage in agricultural activities. Insurance might be a tool to prevent bankruptcies or famines.

adverse selection. The financial sustainability of the insurance will be compromised in the presence of opportunities to engage in this type of behavior. In situations where producers rely heavily on external financing to conduct their activities, the extent of intertemporal adverse selection can be limited by a policy linking the insurance to rural credit. However, this measure will not be effective when a significant number of producers can choose whether to use external or internal resources to finance their operations. Moreover, the policy will force producers to borrow in order to have access to the risk management tool. Another possible way to avoid adverse selection is to establish multiannual contracts, i.e., purchase insurance for a number of consecutive years at a pre-established price. This option has important limitations in developing country settings.

Even in the absence of opportunities to engage in inter-temporal adverse selection, the effectiveness with which relevant risks are protected might change under different forecast scenarios. The seasonal forecast may not indicate a shift in expected payouts, but may modify the relationship between the insured variable and the risk from which protection is being sought. The latter is especially relevant in the case of index insurance, where the protection is crucially dependent on the relation between the index (rainfall, temperature, etc) and the variable of interest (e.g. yields, net income, etc).

In summary, seasonal climate forecast will be relevant for an insurance contract if; a) the variable upon which the product is written responds in a predictable way to the information provided (e.g., likelihood of rainfall events in critical growth stages); and b) the relationship between the insured variable and the risk the insurance is designed to protect is modulated by the forecast's content.

The goal of this paper is to explore the implications of climate forecasts for an agricultural insurance product that pays when either yields, or an index correlated with yields fall below a trigger level. In the first section we establish the relationships between climate variables and yield. Clearly, if yields and climate variables are not associated, climate information will not interact with the insurance scheme. The analysis is based on the relationship between rainfall and maize (*Zea mais*) yields. The second section discusses the seasonal tercile forecasts such as those available from the International Research Institute for Climate and Society (IRI) and assesses what information they contain about crop yields. The implications for insurance programs are covered in the following section. The paper ends with a set of final remarks.

2. Establishing a Relationship Between Rainfall and Yields

To establish the impact of climate variables, in particular rainfall on yield variability time series of national level maize yields for Uruguay were obtained. The data, spanning the 1900-2004 period was obtained from the Direction of Agricultural Statistics of the Ministry of Agriculture of Uruguay (DIEA, 2008) and is presented in Figure 1. Two main sources of year to year variability are present. First, yields appear to have a time trend, which accelerates markedly since about 1975. The yield trend, which is fitted using locally weighted regression (loess; Cleveland et al., 1988) is attributed to technological improvement. The second source of variability is year to year fluctuations around that trend, which is attributable at least in part to climate variability.

Since the focus of this article is on yield variability induced by climate variables, the time trend was removed. The procedure to express year's t yield in terms of the base year (2004) yields consist in multiplying the yield by a factor given by the ratio of the predicted yield for the base year to the predicted yield at year t (Goodwin and Ker, 1998, Goodwin and Mahul, 2004). For example, let y_t, and $\hat{y}_t$ be the observed and predicted yields at time t respectively and let $\hat{y}_{base}$ be the predicted yield for the base year. Then the detrended yield observation is given by $y_t^d = y_t * \hat{y}_{base} / \hat{y}_t$. Figure 2 show the detrended yields data.

<FIGURE 1 ABOUT HERE>
<FIGURE 2 ABOUT HERE>

A linear regression model was then fitted to explore whether the year to year variability is associated with differences in seasonal rainfall amounts. The time scale was chosen to match the scales at which seasonal forecasts are issues in practice. The season that showed the highest association with national corn yields was December-January-February (DJF). This is expected since given the most common planting date in the country (mid September to October), the DJF period includes flowering, a growth stage in which the crop is highly sensitive to water stress. Results of two models are presented in Table 1. The table shows that the seasonal DJF rainfall total and the square of that variable explain almost 40% of the variance of yields. As expected, yields increase at a decreasing rate with seasonal rainfall. Perhaps surprisingly, little gain in explanatory power was obtained by increasing the temporal resolution of rainfall. Replacing seasonal by monthly rainfall amounts (for January, the month with highest explanatory power) increased the proportion of the variance explained by only 5% to 0.43 (data not shown).

<TABLE 1 ABOUT HERE>

The analysis conducted thus far, is based on yields aggregated to the national level. As such, they aggregate yields produced under very different conditions, in terms management practices, soil types, and climate. The mentioned aggregation masks the variability of individual producers or regions. Since this article is concerned with farm level variability, and given that long time series of farm-level data are not available, yields were simulated using the CERES-Maize model from the Decision Support System for Agrotechnology Transfer (DSSAT) model (Jones et al., 1998).

The crop models included in DSSAT (including CERES and CROPGRO) are detailed biological simulation models of crop growth and development that operate on a daily time step. The models simulate dry matter production as a function of climate conditions, soil properties and management practices. The dry matter produced on any given day is partitioned between the plant organs that are growing at that time. Crop development in DSSAT models is driven by the accumulation of daily thermal time or degree days and by photoperiod sensitivity. The inputs required to run the models are daily weather variables, management information (planting date, fertilizer use, irrigation, etc.), cultivar characteristics and soil profile data. Output from the models includes final grain yield, total biomass, and biomass partitioning between the different plant components at harvest. The maize model used in this research was calibrated and tested using data from several field experiments established in INIA (National Agricultural Research Institute of Uruguay) during 1992-2000 (Baethgen, 1993; Baethgen, 2006 unpublished).

3. Effect of Management Practices on Yields

Nine different management practices (treatments) for an agricultural soil representative of southwestern Uruguay were simulated, using forty years of daily weather data. The treatments resulted from the combination of 3 different hybrids, and 3 planting dates feasible for the growing conditions of the country. Hybrids were chosen to represent short, medium, and long cycles. The planting dates were defined as early season, mid-season, and late season. To avoid potentially extreme results from a specific day, the yields for each planting season (early, mid and late) are the average of yields from three planting dates spread over a three-week period. The planting dates were September 8, 15, and 22 for the early season, October 18, 25, and November 1 for the mid season, and December 8, 15, and 22 for the late season. Fertilization practices were held constant across the 9 treatments, with application of urea at a rate of 40kg N/ha at planting and 60 kg N/ha when the crop had 6-8 leaves. Table 2 summarizes the treatments and yield simulation results.

<TABLE 2 ABOUT HERE>

Table 2 highlights the importance of a limited set of management practices. Varying only the hybrid and planting dates, expected mean yields changed from 3129kg/ha to 5353kg/ha. The variability (as measured by the standard deviation) of yields is also highly dependent on management practices. Expected yields were highest for a short hybrid planted early, but producers could, by sacrificing some expected yields, significantly reduce their risks by planting the same hybrid late in the season.[2] Simulated results indicate that planting late in the season has the potential of reducing yield variability, and in general increasing expected yields. The main reason is that the maize growth stages that are most sensitive to water deficits (tasseling) escape the periods with highest evaporative demand (December, and January). Clearly, the present discussion confirms that interactions between forecasted season and management practices such as planting dates should be considered. In general, more differences in yields in response to alternative forecasts should be expected when the crop's most sensitive stages to the climate variable coincide with the forecasted season.

Before evaluating the implications of the information contained in tercile forecasts for an insurance that would produce a payout whenever simulated yields fall below a fixed level (here a proportion of the expected yield in the absence of a forecast), some features of the distributions of yields are compared under alternative forecasts for different seasons.

4. Seasonal Tercile Forecasts: What Information Do They Contain About Yields?

As mentioned before, seasonal climate forecast will be relevant for an insurance contract if the variable upon which the product is written responds in a predictable way to the information provided. This section evaluates the implications of the information contained in seasonal tercile forecasts for expected yield levels, risks, and in general the distribution of yields. The terciles format was chosen to represent one of the ways in which forecasts are more commonly available.[3] In this form, the forecast provide probabilities that precipitation or temperature will be in the highest one-third of the climatological distribution, the middle one-third, or the lowest one-third.

[2] A similar trade-off is obtained if the producer plants a hybrid of medium cycle late in the season.
[3] Seasonal tercile forecasts for the globe are publicly available from the International Research Institute for Climate and Society (http://portal.iri.columbia.edu/portal/server.pt).

For the purpose described in the previous paragraph, yield samples of size 1000 were created by sampling with replacement the pool of 40 years for each treatment, in accordance with the climate forecast. Specifically, years with observed seasonal rainfall amounts for the November-December-January (NDJ) to January-February-March (JFM) seasons were classified into terciles (assigned by season). When the forecast was for a 45-30-25 percent of probabilities of rainfall in NDJ falling in the upper, middle, and lower tercile, 45-30-25 percent of the years in the sample came from years classified in the upper, middle and lower terciles respectively according to the relevant season. The same procedure was followed for all the season from NDJ to JFM, and different forecasts.

As stated before the maize growth stage most sensitive to water stress is flowering: grain yields are greatly affected around the time of tasseling. Consequently, the rainfall seasonal forecasts are especially relevant during that growth stage. We therefore assessed the impact of climate forecasts with different probability levels for the seasons where flowering occurred in each of the 9 treatments (see Table 3).

<TABLE 3 ABOUT HERE>

Figure 3 shows the expected yields for the nine treatments, and how they differ from the no forecast information scenario (climatology) and under two alternative forecasts for the season centered in flowering. The two forecasts considered differed in the probabilities of assigned to each tercile (above normal, around normal and below normal): one represents an expected wet season (45-30-25) and the other represents an expected drier season (25-30-45). For this region of the world, forecasts that depart from climatology more than the ones considered in figure 3 are not very frequent. However, we also considered more skillful forecasts in figure 4 to assess the expected shifts when they are issued.

<FIGURE 3 ABOUT HERE>

The expected yield responses to forecasts that deviate from climatology (33-33-33) are represented by the vertical distance between the dots and the 45 degree line in the figures. Notice that expected yields under the dry (wet) forecast are in general lower (higher) than those in the absence of information. That is, the observed deviations occur in the expected direction. Figure 3 makes clear that the tercile forecasts with the assumed departures from climatology do not result in significant changes in expected yields. However, it is apparent that the forecast will imply distinct deviations from expected yields for different treatment. Seasonal forecasts seem to provide more information regarding expected yields for some treatments (e.g. 1, 2, 4, 5, 7 and 8) than for others (e.g., 3, 6, and 9). The results imply that the forecasts provided little information regarding changes in expected yield of maize crops planted late (treatments 3, 6, and 9). A potential hypothesis is that planting late places the flowering stage in a period of expected lower evaporative demand. This would in turn imply that a given deviation of seasonal rainfall would have lower impacts on yield than for earlier dates.

In general, the ranking of treatments in terms of expected yields remains largely unchanged under different forecasts. However, some useful information for risk management can be obtained from figure 3. While similar yields should be expected from the short cycle hybrid planted early or late (treatments 1, and 3 respectively) in the absence of forecast information, a dry forecast would indicate that late planting should be preferred. The opposite is true in the case of a wet forecast.

Figure 4 shows the same graphs but under forecasts that differ more from climatology. The new scenarios are given by the following terciles; 55-30-15 for a wet forecast, and 15-30-55 for a dry forecast.

<FIGURE 4 ABOUT HERE>

As expected, yields tended to differ more from long term mean yields as forecasts become more different from climatology (more skillful). Additionally, the ranking of treatments now differs more than for the other set of forecasts. Under a dry forecast figure 4 makes clear that the treatment with highest expected yields is no longer the one that yielded more under climatology (treatment 1). It is also clear that under the dry forecast, the difference among the expected yields of treatments that rank in the middle in the climatology forecast (treatments 2, 4, 5, 9) is reduced.

Expected yields, though clearly important, do not provide an indication of the risks faced by producers under different treatments and forecasts. For that purpose, the yield samples constructed through the procedures outlined above were used to obtain the empirical distribution of yields for each treatment under the alternative forecasts. To save space, only the distributions for the medium planting date and DJF forecast are presented in figure 5. The other treatments (not presented) show similar patterns. The distributions of yields obtained indicate that forecasts will provide meaningful information on the risk profile of the different treatments. Non-parametric statistical tests (Kolmogorov-Smirnov) confirmed that for each treatment, significantly different yield distributions (p-value< 0.05) are associated with different forecasts.

<FIGURE 5 ABOUT HERE>

Of particular interest from a risk management perspective is the lower tail of the yield distributions under different forecasts. Table 3 shows some sample quantiles for the yield distributions under selected forecasts for the season centered around flowering for each treatment. The table shows that forecasts placing more weight in lower rainfall terciles are associated with lower yield quantiles. The forecast does not seem to provide information about the 30% quantile for the hybrids planted late (treatments 3, 6, and 9). However, the forecast information is reflected in the lower quantile considered for all treatments.

<TABLE 4 ABOUT HERE>

Figure 5 and table 3 indicate that for the treatments and seasons considered, forecasts that place more weight on the upper precipitation tercile result in first-order stochastically dominating shifts in the yield distribution. In other words, relatively wetter forecasts will be associated with rightward shifts in the cumulative density function of yields. This has direct implications for risk management instruments such as insurance, which are explored next.

5. Implications for Insurance

Consider a hypothetical insurance product that makes an indemnity payment if yields fall below a guarantee $\alpha\mu$ that is proportional to the producer's expected yield μ. In the case in which a payout is triggered, its size is given by the difference between the yield guarantee and the realized yield.[4] The payout function for the described insurance is given by

$$P_t = \max\left(\alpha\mu - y_t, 0\right), \tag{1}$$

where P_t denotes payouts in year t, and y_t represents realized yields on the same year. In general, the price of the contract in equation (1), or equivalently the premium for the insurance can be represented by

$$Premium = E(P_t) + Risk\ Margin \tag{2}$$

where $E(\cdot)$ denotes the mathematical expectations operator. The appropriate risk margin in equation (2) depends on the risk preference of the insurer, and is in the end a highly subjective choice.[5] To avoid making unnecessary assumptions, and since the focus of this article is on expected payouts, the risk margin will not be considered.

The previous section established that different seasonal forecasts are associated with shifts in the distribution of yields. As such, seasonal forecasts provide early indication on expected yield losses and hence on expected payouts. An actuarially fair insurance that ignores the link established here is not financially sustainable. The risk loading (usually contained in the risk margin term of equation 2) might off-set the potential losses in the presence of intertemporal adverse selection, but payouts will ultimately exceed these anticipated by the insurer. Figure 6 presents the expected payouts under different seasonal forecasts.

<FIGURE 6 ABOUT HERE>

Figure 6 shows that for all treatments, expected payouts are different under alternative relevant forecasts. Clearly, higher payouts are expected as the weight placed on lower seasonal precipitation terciles increases. For treatment 2 (short cycle planted in the mid-season) the expected payout from the contract is about 200 kg/ha under the 55-30-15 DJF forecast, whereas the same variable is three times as much under a 15-30-55 forecast for the same season. Similar results are observed for other treatments (e.g. 1, 4, and 5). The treatments showing the least changes in expected payout under different forecast are as expected, those planted late. Figures 3 and 4, together with table 3 already revealed that late plantings were the least sensitive to changes in seasonal rainfall at the flowering stage.

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[4] In the simulations scenarios presented in this article, the outcomes of the model can be seen as actual yields, or as an index for them. Under the second interpretation, the insurance analyzed here is index-based. Since it integrates information about water and nutrient balances with genetic characteristics of the crop, an insurance based on a well calibrated model of yields should provide better risk protection than the most common indexes based on precipitation and or temperatures (World Bank 2005).

[5] For a review of different approaches see Henderson (2002).

The results presented in figure 6 are consistent with the changes in yield distributions shown in figure 5.[6] In fact, the latter figure is simply translating the implication of the shifts of the yield distribution illustrated in the previous figure to changes in insurance expected payouts. The shifts in yield distributions imply that expected payouts will be lower (for any fixed yield guarantee) under forecast placing higher probabilities in the upper tercile compared to relatively dryer forecasts. The change in expected payouts is explained by two forces acting in the same direction; a) the shift in the distributions imply that probability of yields falling below any given level decreases as more weight is placed on the upper tercile of precipitations, and b) given that a yield shortfall (compared to the guarantee) occurs, it is expected to be lower.

6. Final Remarks

The discovery of the pervasive influence of the El Niño/Southern Oscilation (ENSO) phenomenon on rainfall and temperatures over many parts of the world in the late 1970s unleashed the development of new generation of numerical climate models. The improved understanding of ENSO as a coupling between the oceans and the atmosphere combined with the increasingly accurate climate models are resulting in better prospects for seasonal climate predictions. However, while the climate science community expected this progress would be rapidly incorporated into agricultural risk management and decision making, adoption proved to be slow.

Many reasons may be behind the slow incorporation of seasonal climate forecasts on agricultural decision making. An often cited barrier is the mismatch between the specific information farmers are seeking and the information that can be provided by climate scientists. While farmers might be interested on deterministic forecasts of climate phenomena (e.g., about the amount of rainfall or duration of dry spells in a critical stage of crop growth), the current state of knowledge only allow scientists to provide forecasts for variables such as temperature or rainfall aggregated at a seasonal scale and in probabilistic terms. The demonstrated gains of providing forecast information of climate characteristics that are more relevant for crop production such as dry spell duration (Baethgen et al., 2009) has recently promoted promising advances in the forecasting of such climate variables (Robertson et al., 2010).

In this article we contend that tercile-based, probabilistic seasonal climate forecasts contain useful information for both decision making and risk management in agriculture. The analysis of the specific example of maize yields in Uruguay showed that probabilistic seasonal climate forecasts contain information about likely shifts in the distribution of yields. This in turn would be reflected on expected returns and the risk associated with different decisions in terms of crop/hybrid selection and planting dates. For example, while a producer might be largely indifferent between planting a short hybrid early or late in the season (treatments 1 and 3) for the average year, she/he could take advantage of a relatively wet forecast by planting early. On the other hand, if the forecast indicates that the season is likely to be relatively dry, planting late is her/his best option in terms of yield prospects.

We also point out that seasonal climate forecasts and agricultural insurance are two risk management tools that interact in practice. The study shows that the information currently

[6] Notice that only hybrids planted in the middle of the season (treatments 2, 5, and 8) are shown in figure 5.

provided in probabilistic seasonal forecasts has implications for insurance products designed to manage agricultural risks as expected changes in payouts can be inferred from the forecasts. The main implication is that ignoring the forecasts may provide opportunities for inter-temporal adverse selection and hinder the viability of insurance as a risk management tool. Increasing the premium to compensate for the losses induced by adverse selection may render the product ineffective or unaffordable. We showed that even within a given hybrid and planting dates, the payout that is expected might vary by a factor of three under alternative forecasts.

There are at least two ways to take into the account the presence of seasonal forecasts on the design of agricultural insurance. First, insurance might be traded before a skilled forecast becomes available. In this way the information contained in the forecast is sidestepped. A potential problem with this practice is that farmers would sometimes need to buy insurance months before planting the crop. Early commitment of resources may limit the ability of farmers to wait and form more accurate expectations regarding the relative prices of alternative crops before deciding which one to plant. Financing constraints might also limit advance purchases.

A second way to consider the presence of forecast is to make the price of the insurance contingent on the information provided. In this manner, the insurance would be reflecting relative risks. An upside of this practice is that it sends information embedded in the forecasts regarding risks to farmers. Potential downsides are that a price varying insurance introduces another source of variability into the farmer's operation, and that the insurance may become unaffordable when it is needed the most. This strategy would work best if the producer has choices regarding what to plant or whether to participate in agricultural activities in the season.

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Table 1. Regression of Yields (kg/ha) on Total Rainfall (mm) in the December-January-February (DJF) Season.

	Model 1	Model2
	$y_t = \beta_0 + \beta_1 DJF_t + \varepsilon_t$	$y_t = \beta_0 + \beta_1 DJF_t + \beta_2 DJF_t^2 + \varepsilon_t$
β_0	3336**	1418**
β_1	3.4**	16.2**
β_2	-	-0.018**
R^2	0.19	0.38

**Significant at 1%

Table 2. Simulated treatments and summary of statistics for the 40 years of simulated yields.

Treatment	Hybrid's Cycle	Planting Date	Average Yield	St. Dev.
			(Kg/ha)	(Kg/ha)
1	Short	Early	5353	1971
2	Short	Middle	4648	1723
3	Short	Late	5211	1429
4	Medium	Early	4848	2134
5	Medium	Middle	4431	1681
6	Medium	Late	5051	1460
7	Long	Early	3593	1807
8	Long	Middle	3129	1339
9	Long	Late	4180	1447

Table 3. Mean maize anthesis (flowering) and maturity dates for the nine treatments, trimester centered in the flowering month.

Treatment	Hybrid	Sowing	Anthesis	Maturity	Trimester
1	Short	15-Sep	6-Dec	30-Jan	NDJ
2		25-Oct	30-Dec	22-Feb	DJF
3		15-Dec	10-Feb	13-Apr	JFM
4	Medium	15-Sep	17-Dec	8-Feb	NDJ
5		25-Oct	7-Jan	2-Mar	DJF
6		15-Dec	18-Feb	27-Apr	JFM
7	Long	15-Sep	25-Dec	16-Feb	NDJ
8		25-Oct	15-Jan	11-Mar	DJF
9		15-Dec	25-Feb	11-May	JFM

Table 4. Two sample quantiles in the lower tail of the yield distribution for different forecasts centered at the flowering season for each treatments. Yields for the 9 treatments are in Kg/ha.

		Treatments								
Forecast	Quant.	1	2	3	4	5	6	7	8	9
25-30-45	0.10	2311	1934	2711	1273	2023	2534	1143	1269	1862
33-33-33		2975	2080	2711	2077	2257	2600	1265	1382	1862
45-30-25		3153	2612	2883	2495	2283	2977	1319	1382	2156
25-30-45	0.30	3303	2950	4260	3011	2612	4230	2098	2183	3058
33-33-33		4268	3127	4260	3555	4015	4230	2429	2410	3058
45-30-25		4633	4307	4260	4066	4135	4230	2559	2826	3058

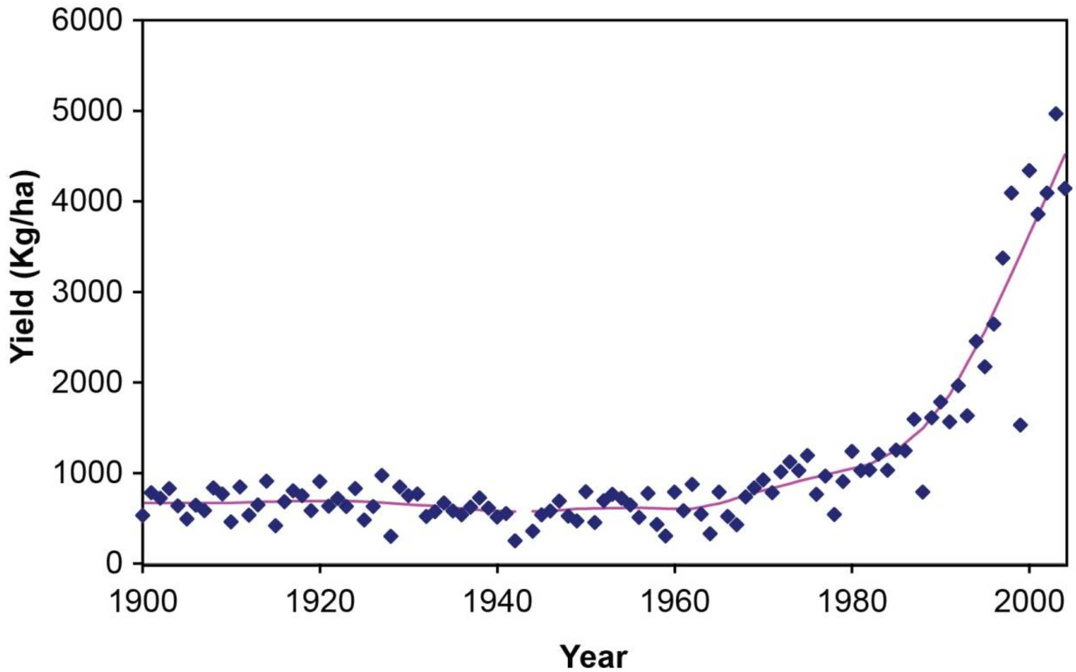

Figure 1. Time series of Country-Level Maize Yields for Uruguay.

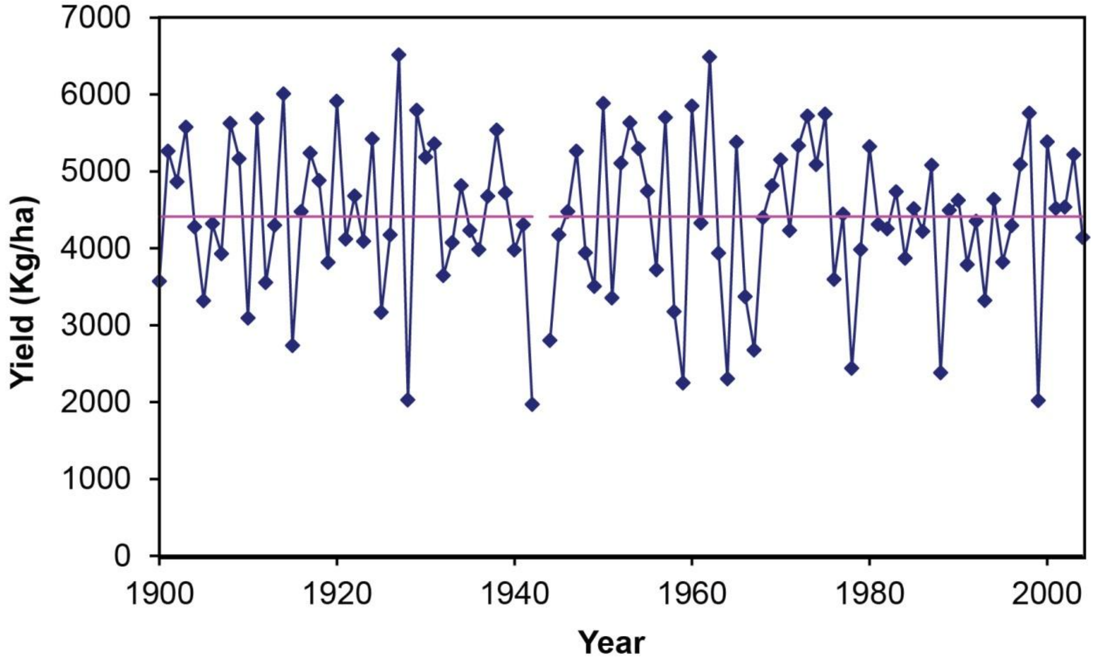

Figure 2. Variability of National Level Maize Yields (Detrended).

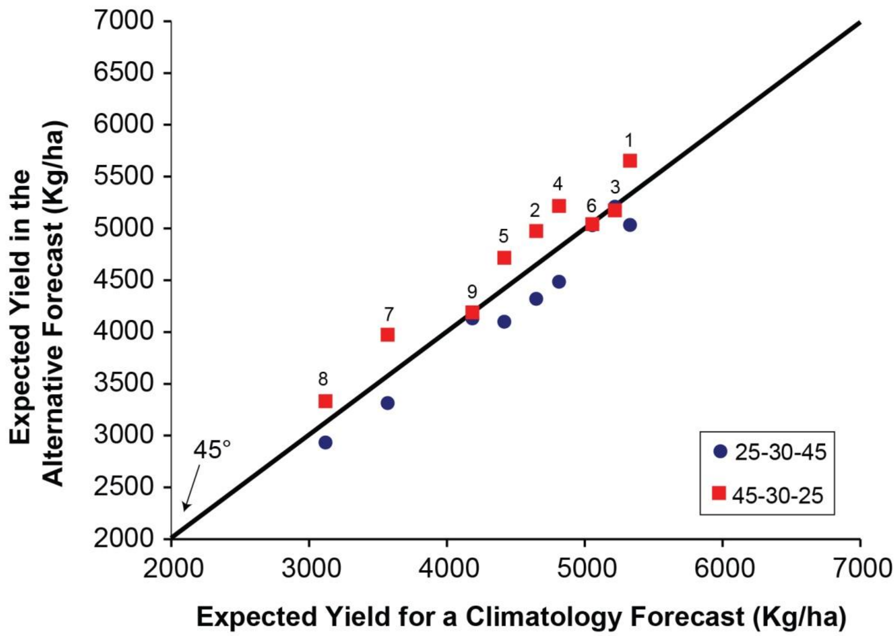

Figure 3. Expected yield responses for the 9 simulated treatments under relatively wet (45-30-25) and dry (25-30-45) scenarios for forecasts corresponding to the seasons centered around the crop flowering stage. Numbers in the figure correspond to treatments.

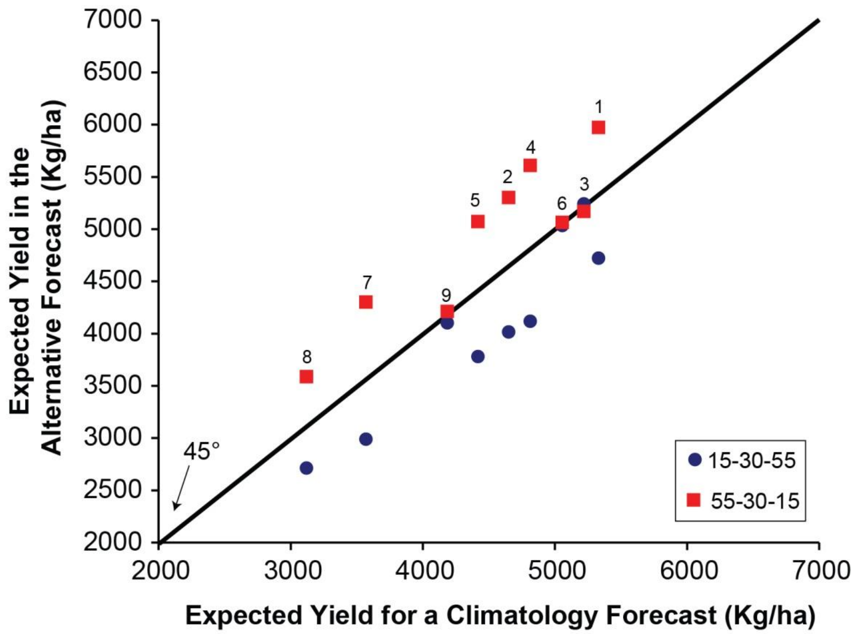

Figure 4. Expected yield responses for the 9 simulated treatments under relatively wet (55-30-15) and dry (15-30-55) scenarios for forecasts corresponding to the seasons centered around the crop flowering stage. Numbers in the figure correspond to treatments.

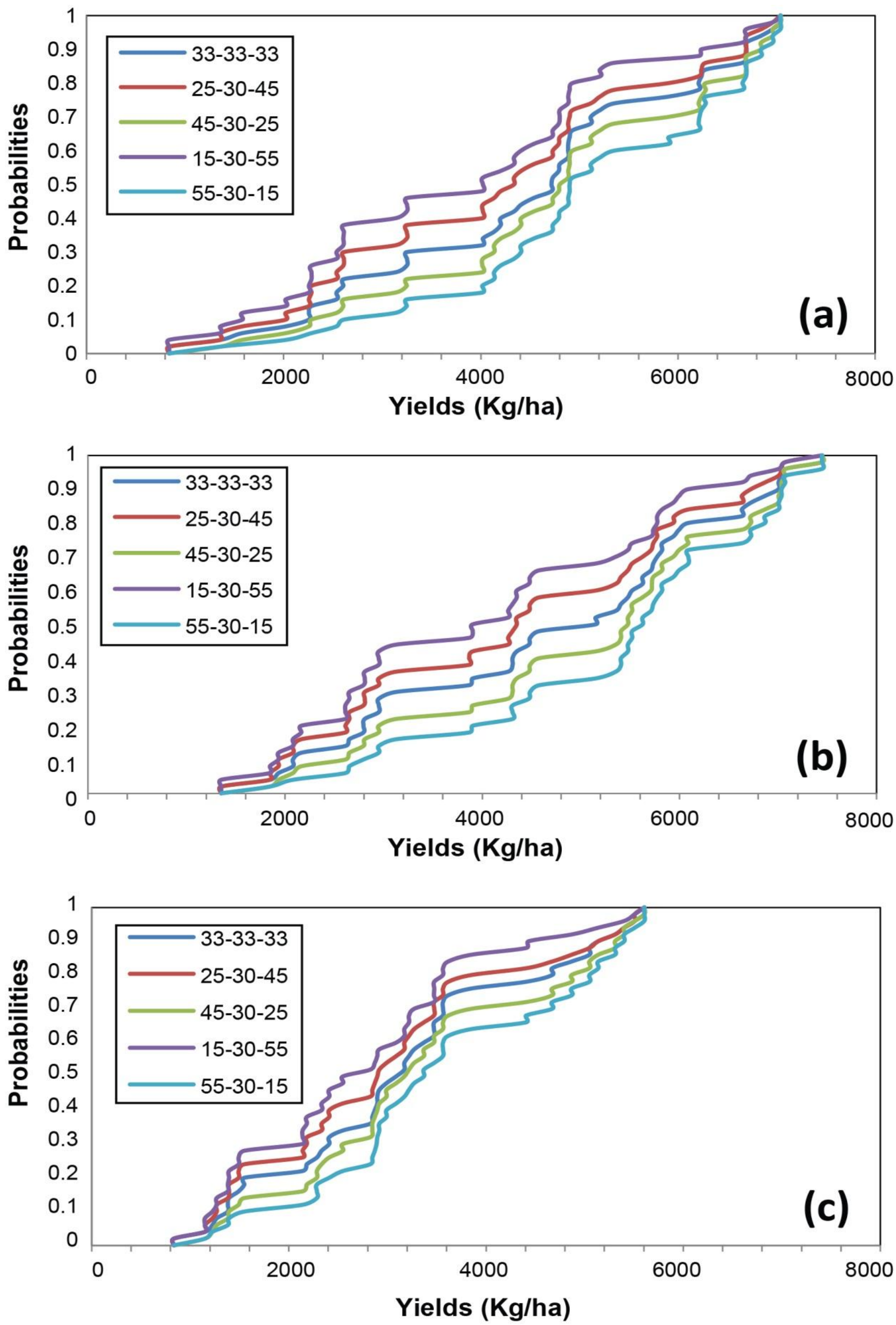

Figure 5. Empirical cumulative distribution functions of yields under different DJF forecasts for short (a), medium (b), and long (c) hybrid cycles planted at mid-season.

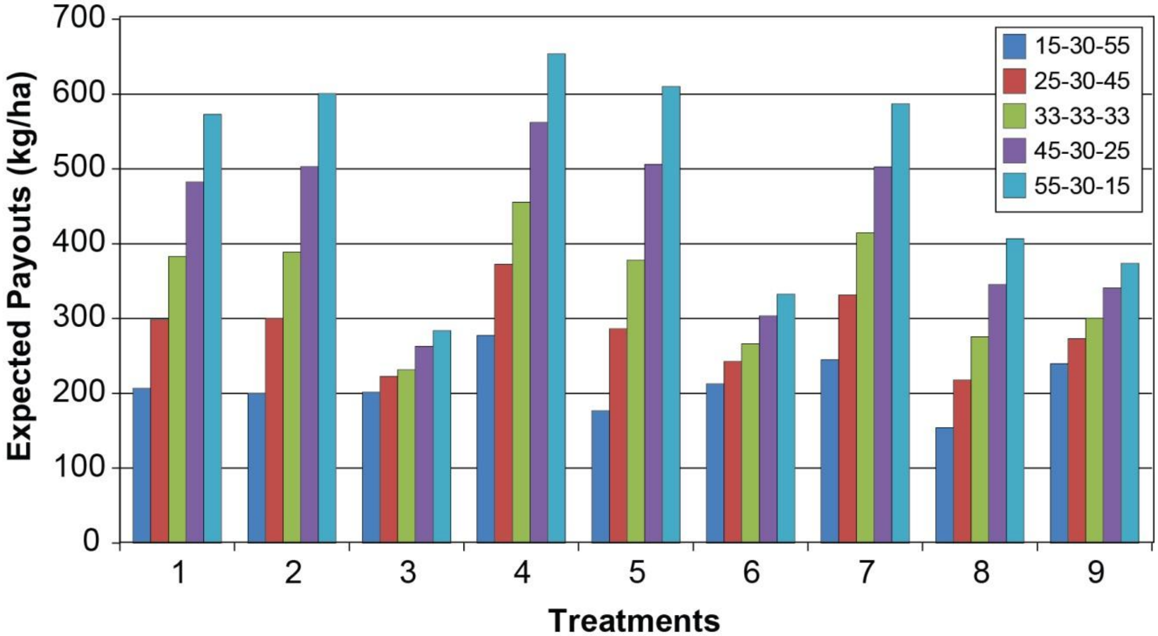

Figure 6. Expected payouts under 5 different tercile forecasts for the 9 treatment. Forecasts are for the season centered around the flowering stage for each treatment (see table 3.