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Assessing the Economic Value of Seasonal Climate Forecasts for Corn-based Farming Systems in Leyte, Philippines

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Abstract

Corn is considered the most important crop next to rice in the Philippines. It is highly valued as human food, animal feed, and as raw materials for industry. While corn is an important commodity for the Philippine economy, corn farming still remains a risky investment largely because it is dependent on a highly variable climate. Like in many parts of the world, climate variability is one of the main sources of uncertainty and risk in many agricultural systems in the Philippines. Agriculture has been described as the most weather-dependent of human activities, and for this reason there is a need for this factor to be considered directly or indirectly in most production decisions.

The application of seasonal climate forecast (SCF) provides rainfed corn farmers greater ability to manage climatic risk. This study estimates the economic value of SCF for corn-based farming in Leyte, Philippines. Specifically, it aims to: (i) present a brief description of dominant cropping patterns and corn production practices in the study area; (ii) review and present a valuation framework for estimating the economic benefits of SCFs information under various assumptions of risks and uncertainty; (iii) quantity the potential economic value of SCF information to corn farmers; and (iv) draw policy implications on the usefulness of SCF to corn farmers in the Philippines.

The CERES-Maize model within DSSAT V4 is used to estimate the consequences of meteorological differences of different ENSO (EL Niño Southern Oscillation) phases on crop yield. The value of seasonal climate forecasts is determined as the difference in economic returns from optimal decisions based on ENSO (‘with forecast’) and optimal decisions based on historic climatology (‘without forecasts’). A forecast has value if the ‘with forecast’ scenario leads to different decisions and improved outcomes over the decisions and outcomes of the ‘without forecast’ scenario.

Results show that SCF is valuable for particular forecast types at certain periods of the year. The average return for particular forecast types was higher when averaged over the years of forecast period than using entire climatology. This suggests that corn farmers can gain additional benefits from skillful climate forecasts in corn production for particular cropping decision. Policy implications and recommendations were discussed.

Keywords: climate variability, risk, ENSO, seasonal climate forecast, corn, farming systems
1. Introduction

In the Philippines, corn is considered the most important crop next to rice. It is highly valued as human food, animal feed, and as raw materials for industry. In the 1991 census there were 1.7 million corn growers in the Philippines covering an area of 2.7 million hectares, 41% of growers (53% of the area) were in Mindanao and 27% of growers in the Visayas (18% of the area). Recent statistics reveal that the P27 billion corn industry employs about 30% of Filipino farmers (Caraos 2002) while about 20% of the country’s population depends on corn as staple food, especially in the Visayas, Cagayan Valley, and Mindanao (The National RDE Network for Corn, 2003). The commodity is classified into white and yellow corn, with the former being used primarily as food and the latter as feed. Approximately 27% of Philippine corn production is used as staple food and 70% as feed. Corn is also used in the manufacture of starch, gluten, and alcohol.

While corn is an important commodity for the Philippine economy, corn farming remains a risky investment largely because it is dependent on a highly variable climate. As in other parts of the world, climate variability is one of the main sources of uncertainty and risk in many agricultural systems in the Philippines. Agriculture has been described as the most weather-dependent of human activities (Oram 1989), and for this reason weather is a factor to be considered in most production decisions. Unfavourable weather remains a major cause of crop failure (Lansigan 2001). During the 1997-1998 El Nino occurrence for instance, the Philippines lost more than P3.2B in corn production which primarily affected the two major corn growing provinces of Isabela and South Cotabato (Lansigan et al. 2002).

Advances in the science of seasonal climate forecast (SCF) give rainfed corn farmers greater ability to manage risk brought about by highly variable climate conditions. Corn production is
effected by climatic extremes such as either flooding during wet seasons, and drought during dry seasons, hence skillful seasonal climate forecasts information could become important to corn farmers’ production decisions. According to Pingali and Pandey (2001), drought at any stage of crop development affects production, but maximum damage is inflicted when it occurs around flowering stage. Farmers may respond to drought at the seedling stage by replanting their crop, but drought at flowering stage can be mitigated only by irrigation. It is in this context that skillful seasonal climate forecasts may prove valuable since corn growing areas in the Philippines are all non-irrigated or dependent on rainfall for water supply. However the application of SCF to cope with climate variability may also be valuable for decisions in less extreme conditions including (i) the choice of crop to grow in the coming season, (ii) the timing of cropping period, and (iii) the level of input use.

This paper aims to estimate the potential economic value of seasonal climate forecasts (SCF) for corn-based farming systems in Eastern Visayas region of the Philippines. Specifically, this study aims: (i) to present a brief description of dominant cropping patterns and corn production practices in the study areas; (ii) to review and present a valuation framework for estimating the economic benefits of SCFs information under various assumptions of risks and uncertainty; (iii) to quantity the potential economic value of SCF to corn farmers in Leyte; and (iv) to conduct policy analysis and draw policy implications on the usefulness of SCF to corn farmers in the Philippines.

2.0 Description of the Study Area and the Corn Farming System

The municipality of Mahaplag in Leyte was chosen as the study of this study because on-farm trials of corn production have been conducted previously in the area (Balbarino, 2003).
The municipality of Mahaplag is located in the central part of the island of Leyte and situated between two mountain ranges. It has an area of 19,550 ha of agricultural and forest lands. It is 29 km east of Baybay, 30 km southwest of Abuyog, and 35 km north of Sogod, southern Leyte. The municipality has 28 barangays covering its agricultural lands. The total cultivated area devoted to agricultural production is 4,643 ha. The major crops grown in the study area are coconut, rice, and corn. The corn crop occupies a larger area compared to coconut and rice. For some farmers the corn areas are also used for rice production during rainy season (Balbarino, 2003). The soil types dominating in the site are clay in the hillside and sandy loam to silt loam in the corn and rice areas. The soil has the following characteristics: pH = 5.0-7.0; organic matter content (OM) = 0.50-1.93% which is far from the ideal value of 5%; phosphorus (P) = 22-35 ppm; exchangeable K = 0.44-1.21 me/100gm. This indicates that the soil is slightly acidic, very low in organic matter, adequate in phosphorus and slightly deficient in potassium.

Mahaplag has a Type II climate which is characterized by above average rainfall in the months of November, December and January. The onset of rainy season usually starts in the month of September but the heaviest rainfall is in November and December. The dry season months are April, May and June. The average and median annual rainfall is 2,452 mm and 2,409 mm, respectively (Tacloban synoptic station) over a period of 77 years while the mean monthly rainfall is 202 mm (see Figure 1).

In Mahaplag, corn production follows twice a year cropping pattern. For the first cropping, corn is usually planted in the months of April and May and during August and September for the second cropping season. Some farmers intercrop peanuts with corn while others intercrop mungbean with corn or sweet potato with corn to offset low production of corn in the second season (Balbarino et al. 2000).
Native varieties of white corn remain the most widely grown in the locality. This is followed by open-pollinated varieties and the least preferred are hybrid varieties. Seed of native varieties is cheaper than open-pollinated and hybrid varieties. Most often farmers acquire seed from farmers in the locality or in neighboring municipalities.

This analysis focused on the Mahaplag study site using rainfall data and other climatic information from Tacloban synoptic station of PAGASA, which is the nearest rainfall station with relatively longer available weather and climatic data.

3. **Methodology**

3.1 **Overview of Decisions Affected by Climate Forecast**

The crop choice aspect of the corn case study can be represented as follows (Figure 2). There are two cropping seasons for corn for most farmers (but a few farmers sometimes plant a 3rd crop of rice). In each season fallow is an option which is characterized by no return. Thus the choices are between corn and fallow for both 1st and 2nd cropping seasons.
If the decision is made to grow corn either in the 1st or 2nd cropping period then there are further decisions to be made relating to choice of variety, planting time and nitrogen rate application (see Figure 3). In the choice of variety, farmers may choose to plant either native, open-pollinated or hybrid varieties. There are three sowing dates considered in the analysis and two nitrogen fertilizer rate application if the farmers decide not to plant a native corn variety.

3.2 Economic Valuation Framework for Seasonal Climate Forecast Information

This section briefly discusses the theoretical framework used to estimate the value of an ENSO forecast. Following Crean et al. (2005), the economic value of seasonal climate forecasts can be assessed within the framework of Expected Utility Theory (EUT) using a Bayesian approach to the revision of probabilities of particular climatic states as indicated by SCFs.
(Marshall et al. 1996). In this framework, the additional information provided by forecasts is treated as another factor in the decision process (Johnson and Holt 1997).

For climate sensitive decisions, the process of valuing climate information requires the following key theoretical assumptions of EUT and Bayesian learning: (i) decision makers hold prior probabilities about the likelihood of climatic states (the majority of studies assume knowledge of the full climatological record); (ii) there are consequences or payoffs arising from taking certain actions under each state; (iii) decision makers are able to rank alternative outcomes according to their own set of preferences (measured in utility); and (iv) the availability of forecast information leads to a revision of prior probabilities to create posterior probabilities.

In the context of EUT as outlined by Anderson, Dillon and Hardaker (1996) and a Bayesian decision making process, a decision maker faces a choice between alternative acts, $A_j$. The particular outcome $x_{ij}$ occurs after taking act $A_j$ and is affected by the state $S_i$. The prior probability of the occurrence of state $S_i$ is denoted by $P(S_i)$. The utility of the outcome $x_{ij}$ is denoted by $U(x_{ij})$. The utility of the prior optimal act $U^*$ (without forecast) is:

$$U^* = U(A_j^*) = \max_j U(A_j) = \max_j \left[ \sum_i U(x_{ij})P(S_i) \right]$$

A forecast $z_k$ of the occurrence of the state $S_i$ becomes available at a cost of $c_k$. Given knowledge about the conditional distribution of $z_k$ relative to $S_i$, Bayes theory is used to find the posterior distribution $P(S_i|z_k)$. In light of the forecast, the decision maker revises the strategy and the utility of posterior optimal act $U^{**}$ is:

$$U^{**} = U(\{A_{jk}^*\}) = \max_j U(A_{jk}) = \max_j U(A_j | z_k) = \max_j \left[ \sum_i U(x_{ij} - c_k)P(S_i | z_k) \right]$$

The utility of forecast is the difference between the posterior and prior optimal acts:

$$U(z_k) = U^{**} - U^*$$
The value of the climate forecast is the change in expected utility from the more informed decision. This framework is used in the empirical section of the study. A key attraction of EUT is its empirical tractability, particularly if risk neutrality is assumed. However, there are also challenges to EUT as the standard theory of choice under uncertainty (Schoemaker 1982; Machina 1987; Hammer et al. 1996; Buschena 2003).

3.3 Estimation of the Value of Seasonal Climate Forecast

Assessing the value of seasonal climate forecasts at the farm level requires historical data on crop yield under various ENSO phases. Since this information is usually not available, an alternative is the use of crop biophysical simulation model to estimate the consequences of different ENSO phases on crop yields. We used the CERES-Maize model within the Decision Support System for Agrotechnology Transfer (DSSAT v4) (Hoogenboom et al. 2004) to generate corn yields over time under various climate scenarios (see Figure 4). A brief description of DSSAT model is provided in succeeding section.

The model was calibrated for corn production using existing parameters, secondary biophysical (soil and crop) and management input data, observed daily rainfall, temperature, and solar radiation at PAGASA synoptic station near the study area. Crop yield and consequently the yield probability distribution function was estimated for both with and without SCF scenarios. The expected payoff or returns from each scenario was derived by combining crop yields with economic parameters such material input and labor requirements for the corn farming system, input and output prices, discount rate and other economic assumptions. The expected returns or payoff with and without SCF was subjected to a stochastic dominance analysis with respect to a
function. The value of seasonal climate forecast information was derived from the difference between the expected return with and without SCF as follows

\[ V(SCF) = E(NR)_{wcf} - E(NR)_{woef} \]

where: \( V(SCF) \) is the value of SCF information, \( E(NR)_{wcf} \) and \( E(NR)_{woef} \) is the expected net returns with and without climate forecast, respectively.

### 3.4 Data Sources and Crop Simulation

A combination of secondary data (both published and unpublished reports, field experiment results), expert judgement, personal communication, observed farmers’ cropping practice and focus group discussion provided the soil, genetic, and management factors used in parameterizing the CERES-Maize DSSAT model for local corn varieties. This model simulates corn growth and yield taking into account processes such as phenological and morphological development, biomass accumulation and partitioning. Variety-specific coefficients and local daily weather data (i.e., solar radiation, rainfall, minimum and maximum temperature) covering the period from planting to harvesting are used to simulate corn yields over time under various ENSO phases.

The simulated crop yields from the DSSAT model were used in the economic assessment of SCF.
3.5 Seasonal Climate Forecast Systems Used in Economic Assessment

The spatial analysis capabilities in RAINMAN software package ACIAR Special edition 4.1 (Clewett et al. 2002) were used to evaluate the seasonal forecasts based on the planting calendar dates in Mahaplag, Leyte. In the absence of longer climate data set in the study area, data in Tacloban synoptic station was used since both sites have the same climate type. Chance of rainfall for the station was computed using the SST Forecast Phase System (Pacific Effects) and the Average SOI forecast system through the RAINMAN International version 4.1 (Clewet et al. 2002). The SST Phase Forecasting System uses sea surface temperature data from the Pacific
Ocean. The SST menu options in RAINMAN enable the SST Phase analyses to be done as follows: The Pacific Phase System enables the main effects of the Pacific Ocean to be tested namely: Cooler Pacific Ocean pattern (La Niña): Phases 1,4,7 are combined, Neutral Pacific Ocean pattern (Neutral): Phases 2,5,8 are combined and the Hotter Pacific Ocean pattern; Phases 3,6,9 (El Niño) are combined. Phases 3,6,9 are associated with below the median rainfall conditions while Phases 1,4,7 are associated with above median rainfall.

The SOI Forecasting system was also used to evaluate the forecasts in the study area. The basis of this forecast system are historical records of SOI which are stratified into three groups based on the average value of the SOI during the forecast period with default SOI boundary values to form the groups of SOI below −5 (El Niño), -5 to +5 (neutral group), and SOI above +5 (La Niña).

4.0 Results

4.1 Relationships of Seasonal Climate Forecasts and Rainfall

There must be a statistically significant relationship between forecast types and growing season rainfall in order for the seasonal climate forecasts to be useful in making crop choice and timing of planting decisions. Such a relationship may also be useful for deciding the corn variety to plant and the rate of nitrogen fertilizer application. For this purpose, the significance of the different ENSO phases has been assessed using the Kruskal-Wallis (KW) and the Kolmogorov-Smirnov (KS) test. These are both non-parametric tests and are preferred tests for rainfall data which usually are not normally distributed. The KW test is used to determine whether at least one of the forecast groups is different. The KS test measures the maximum difference between
two cumulative distribution functions of forecast types. The tests were undertaken through the RAINMAN software package (Clewett et al 2002).

Seasonal rainfall forecasts were done based on the planting dates in the Province of Tacloban for both the SST Phase Forecasting System and the Average SOI (Figures 7 & 8). Results revealed that there is significant skill using both the Average SOI Forecasting and the SST Phase Forecasting Systems during the months of JFM, AMJ and OND. However, it was found out that there is a predictability barrier during the month of JAS. It can be noted that JAS is the peak of the southwest monsoon and there are many factors affecting the rainfall pattern during this period.

The LEPS score showed that it is greater than 7.6 during the months of September to April (Figure ) indicating results are statistically significant and imply that the forecast system being tested has skill (forecasts with values below 7.6 are not sufficiently skilful and forecasts with skill scores below 0.0 have no skill) Rainman v4 - DPI&F.

Furthermore seasonal forecast skill (KW) also showed that when the SOI > 0.5 or SOI < -0.5, the KW test is greater than 0.90 (Fig__) during the months tested. When the KW is greater than 0.9 there is statistical evidence that at least one group has a distribution that is different from the other groups although it does not specify which group is different. If the KW test is less than 0.90, it is recommended that the long-term climatology (i.e. the data in the ‘all years’ column) be used to assess climate risks. (Rainman v4 - DPI&F).
Figure

Figure __ shows the percent chance of rainfall in Tacloban showing different values of SOI. When the SOI >+ 5 the chance of getting above the median rainfall increases ( ) and when the SOI < -5 the chance of below the median rainfall decreases ( ). The further apart the lines, the greater the influence of the predictor (SOI or SST).

The pie-chart divides rainfall into terciles (upper third, middle third or lower third) for all years. Different pies can be selected by phases or average of the SOI or by the average or trend of the SST. For example, under a negative SOI (Figure 3) there may be only a 52% chance of receiving rainfall in the upper tercile (Figure 4) but a 72% chance of being in the lower tercile).