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Incorporating Regional Rice Production Models in Rice Importation Simulation Model: A Stochastic Programming Approach*

Celia Reyes[1], Christian Mina[2], Jason Crean[3], Rosalina De Guzman[4], and Kevin Parton[5]

Abstract

In the Philippines, importation has remained as one of the most feasible options for the government to meet the growing demand for rice. It is thus imperative for the government to develop a strategy that would ensure adequate supply and minimum importation costs. One of the critical factors in import decisionmaking is rice production. The Inter-Agency Committee on Rice and Corn (IACRC), where the National Food Authority (NFA) and Bureau of Agricultural Statistics (BAS) are members, decides on importation when there is an impending production shortfall in the coming season. However, because Philippine agriculture is vulnerable to extreme climate events and climate change is believed to further intensify the effects of seasonal climate variability, rice production forecast is becoming more uncertain. Inaccurate production forecasts could lead to incorrect volume and ill-timing of rice imports, which in turn could result in either a waste of resources for the government or a burden to consumers. Contraction of rice imports in the early 1990's, ill-timing of imports in 1995, and over-importation in 1998 illustrate how inaccurate forecasts of volume and timing of rice importation, especially during El Niño and La Niña years, could result in substantial economic costs such as higher rice prices due to rice shortages, higher storage costs, among others.

This paper evaluates the significance of SCF information, among other things, in rice policy decisions of the government, particularly on importation. It presents an alternative method of forecasting the level of rice production through regional rice production models. The rice production models systematically incorporate SCF and could be used in support of the current practice of forecasting rice production based on planting intentions. The paper also demonstrates how SCF, together with these production estimates, could be incorporated in the rice import decisions of the government through the Rice Importation Simulation (RIS) model, which was developed using a Discrete Stochastic Programming (DSP) modelling approach. The RIS model, which recommends a set of optimal rice import strategies, could serve as guide for the government in its rice import decisions in the face of seasonal climate variability and could be used in estimating the potential value of SCF.

Key words: rice, seasonal climate forecast (SCF), importation, production models, Discrete Stochastic Programming (DSP), Inter-Agency Committee on Rice and Corn (IACRC), National Food Authority (NFA), Bureau of Agricultural Statistics (BAS), El Niño, La Niña

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1. Introduction

Seasonal climate variability exposes crop production to different kinds of risk. These production risks include lack of water supply during critical crop growth stage due to an El Niño-induced drought, submerging of seedlings in flood water because of typhoons caused by La Niña, and any other perils attributable to extreme climate events. This is particularly true for the Philippines as it is often and severely affected by these extreme climate events primarily due to its geographical location. (Fraisse et al. 2007; Lansigan 2004; Dawe et al. 2006) Also, irrigation system in the Philippines has not yet been fully developed as there are still many areas that need to be irrigated and a number of existing national irrigation facilities have to be rehabilitated (Reyes et al. 2009). Recent climate change studies predict that there would be an overall change in global climate patterns (Lansigan 2004). This is believed to further intensify climate variability and its associated effects not only on rice but on agricultural production in general. In fact, rice and onion farmers in Nueva Ecija related that scheduling of farm operations had been a lot easier decades ago because climate patterns were more predictable then.

The adverse effects of extreme climate events on rice production, which significantly affected the rice supply and demand in the Philippines, could be exemplified by what had happened in the 1990's. The prolonged El Niño episodes from the third quarter of 1990 to the first quarter of 1995 had led to consistent decline in rice production (Intal and Garcia 2005). However, based on the reports of the farmers, as reflected in the results of Palay[6] Production Survey (PPS) of the Bureau of Agricultural Statistics (BAS), rice production during those times would be sufficient to meet the local demand. In order to protect farmers' income, the government had tightened rice importation during the period. This then resulted in what has been known as the rice crisis. In 1997 and 1998, the worst episodes of El Niño and La Niña, respectively, were experienced by the Philippines. This had resulted in significant shortfall

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[6] paddy rice

in production, amounting to around 2 million metric tons as estimated by the Department of Agriculture. Learning from the 1995 rice crisis, the government decided to import more than what was required in 1998.

Rice production is indeed a major deciding factor of importation. The Inter-Agency Committee on Rice and Corn (IACRC), where the National Food Authority (NFA) and BAS are members, decides on importation when there is an impending production shortfall in the coming season. The rice production forecast is made by BAS based on the estimates of the farmer-respondents, which are captured by quarterly PPS. Unfortunately, this production forecasting system does not systematically incorporate seasonal climate forecast (SCF). Moreover, the IACRC does not systematically link SCF with rice import decisions, which could result in optimal volume as well as timing of rice importation. Contraction of rice imports in the early 1990's and over-importation in 1998 illustrate how inaccurate forecasts of the volume and timing of rice importation, especially during El Niño and La Niña years, could result in substantial economic costs such as higher rice prices due to rice shortages, higher storage costs, among others. (Kajisa and Akiyama 2003; Ramos 2000; Unnevehr 1985) In recent years, rice imports of the Philippines continue to exceed the required limit resulting in increasing level of stock inventory. While it may be safe to always import more than what the country needs, substantial amount of money could be saved by the government if optimal volume of imports could be determined.

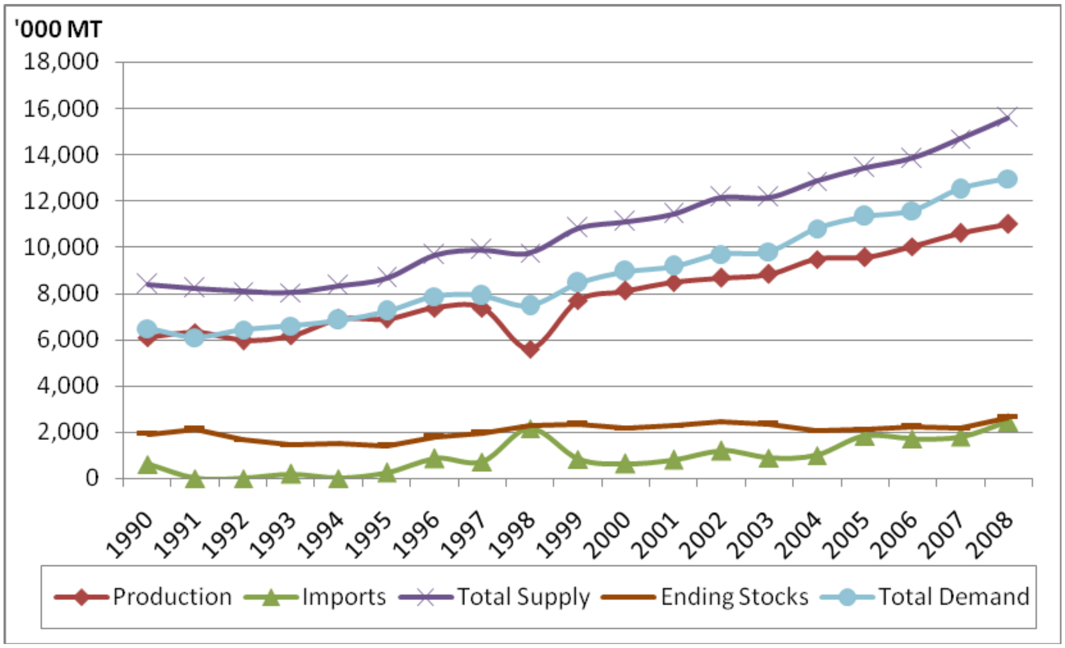
This paper primarily aims to evaluate the significance of climate forecast information, among other things, in rice policy decisions of the government, particularly on importation. Specifically, it presents a methodology that would show how climate forecast information can be systematically linked with rice importation decisions of the government and then demonstrate an approach in estimating the potential value of SCF for such decisions. It also introduces an alternative method of forecasting the level of rice production using climate forecast information. This paper will form part of the rice policy level study under the ACIAR-funded project titled "Bridging the gap between seasonal climate forecast (SCF) and decision makers in agriculture".

2. The Philippines as a Net Rice Importer

The Philippines has been a net importer of rice due to a number of reasons. Dawe et al. (2006) stressed that geography is the primary reason why the Philippines has been a net importer of rice for a long time now. The Philippines, like other importing countries such as Indonesia and Malaysia, is an island country, which has little arable land suitable for growing rice and lacks those large river deltas, which are present in traditional exporting countries. Also, being located off the eastern edge of Asia, it is not unusual that the Philippines is severely affected by typhoons and other extreme climate events, which have adverse effects not only on rice, but on agricultural production in general. Apart from natural endowments, Filipino farmers devote a relatively small proportion of their land to rice cultivation, resulting in relatively lower production of rice that falls short of the local demand. In addition, few farmers are adopting hybrid rice (which is believed to have greater promise in terms of yield than regular rice varieties), apply sufficient quantities of fertilizer (particularly during dry season when it is most needed), spend less labor in operating farm activities, and have good access to irrigation (Dawe et al. 2006; David 2006; Reyes et al. 2009). On top of these, land conversion and other population pressures were also believed to have contributed much on the deceleration of production growth (David and Inocencio 1995).

Historical data on rice supply and demand provides concrete evidence why the Philippines has to remain a net importer of rice. Figure 1 shows that for the period 1990-2008, domestic production could hardly meet the local demand. Clearly, the gap between total demand and domestic production had been increasing over the eighteen-year period. The most notable gap is when the country had experienced the impact of the 1997-1998 back-to-back episodes of El Niño and La Niña. But upon adding imports into the equation, it can be observed that supply could already meet the demand. Indeed, imports have been playing a very significant role in the supply-demand situation of the country. This is particularly true after the country had experienced the 1995 rice crisis. As can be seen from the graph, imports had been increasing from 1996 to 2008. In 1998, the government imported around 2 million metric tons (MT) in response to the occurrence of El Niño and La Niña and partly, in an attempt to avoid a crisis like what happened in 1995.

Moreover, because the Philippines is exempted from rice tariffication during the period 1995-2004 under the Special Treatment Clause or "Rice Clause" of the General Agreement on Tariffs and Trade-Agreement on Agriculture (GATT-AoA), the World Trade Organization (WTO) forced the country to import, regardless of necessity, a minimum access volume (MAV) which is equivalent to around 1 to 4 percent of domestic consumption. Within the period, import levels had gone far beyond the MAV requirements, which caused the country to pay 100 percent out-quota tariff. (Intal and Garcia 2005) In 2005, the government negotiated for another 10-year extension of the exemption and it can be seen from the graph that imports had been relatively much higher during and after this period.



Source of basic data: BAS

Figure 1. Rice supply and demand in the Philippines, 1990-2008

3. The NFA

3.1. Mandates

The National Food Authority (NFA) is the national government agency tasked to ensure the food security of the country and stability of supply and price of the staple grains for the benefit of farmers, consumers and other grains sector stakeholders. On food security in cereals in times and places of calamity or emergency, either natural or man-made, staple food requirements in calamity/emergency-stricken areas shall be made available within 48 hours. On the stabilization of grains supplies and prices, both at the farm-gate and consumer levels, farm-gate prices shall be kept at levels that provide farmers a reasonable return on their investment while retail prices shall be kept at reasonable levels for the benefit of the consumers. (Tolentino et al. 2002; Reburiano 2005)

3.2. Rice Marketing Activities

In order to carry out the objectives of the agency, various marketing activities on rice are being implemented. One of these is the procurement of paddy rice from the farmers at a support price that is relatively lower than the prevailing price in the market and is applicable across the country, regardless of locations and conditions. The objective of implementing this support price is primarily to protect farmers from price fluctuations, especially during peak harvest months while assuring them of a ready market that guarantees a fair return on investments (Ramos 2000). This support price is currently set at a uniform price of 17 pesos per kilogram of paddy rice, or 26.98 pesos per kilogram of well-milled rice[7], plus a 40-centavo incentive if some conditions are satisfied.

Another major activity of the NFA is distribution of milled rice to consumers, regardless of income and expenditure capacity, at a price that is usually lower than the prevailing market price across regions and seasons. This activity is regularly implemented by the agency in order to address the mandate of stabilization of grains supplies and prices at the consumer level. At present, the NFA is selling at 18.25 pesos per kilogram of well-milled rice to identified consumer-beneficiaries and at 25 pesos per kilogram to non-beneficiaries.

[7] one kilogram of paddy rice is equivalent to 0.63 kilogram of well-milled rice

In order to ensure food security in the country, the NFA also maintains buffer stocks that serve as protection during cases of emergency (Ramos 2000). Specifically, the NFA is mandated to maintain buffer stocks that are equivalent to a 30-day level during lean months and 15-day level at any given time in all its warehouses nationwide. Because of the 1995 rice crisis, the NFA was mandated also to ensure a food security buffer that is equivalent to 90 days at the end of June or on July 1st of every year; 30-day level should be with the NFA, 15-day level should be with the commercial sector, and 45-day level must be in the hands of the households (Reburiano 2005). Moreover, given that the national average of stock requirement is good for 15 days, the required level of stocks varies by province according to their classification: 5 days for "self-sufficient" (if the production of the province is just enough for consumption); 2 days for "surplus" (from the level of production, the province can still supply to private traders outside the province); 15 days for "less critical" (the province still has production but is less than the food requirement and has to be supplied), and; 30 days for "very critical" (the province has no production and totally dependent on the inflow delivered by the NFA).

Moreover, because domestic production is usually not sufficient to meet the local demand as well as the mandated buffer stock requirements, importation of rice is being carried out to avoid rice shortage and thus, escalation of domestic prices. In the Philippines, the NFA is vested with the exclusive authority to import rice based on the recommendation of the IACRC on the volume and timing. Importation is viewed as one of the tools for stabilizing the supply as well as price of rice in the market, making it one of the most influential forms of government intervention in the rice sector (Ramos 2000). While this is true, it is also one of the most expensive. Thus, decisions on the volume as well as timing of rice importation are among the most important policy decisions of the government. [For more information on the NFA marketing activities, refer to Reyes and Mina (2009).]

3.3. Importation Process

Importation is resorted to after the IACRC has identified that a production shortfall would exist and there is a need for additional stocks to stabilize supply and prices. The IACRC is the authorized body that decides on the volume and timing of importation based on its assessment of rice and corn situation. In assessing the supply-demand situation for rice and corn, the following inputs are needed:

(1) Results of the Rice and Corn Production Survey (RCPS)[8] conducted by BAS every quarter, which include:

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[8] which includes the Palay Production Survey or PPS

(a) final production estimates for the last quarter;

(b) production forecasts for the next quarter based on the standing crops; and,

(c) production forecasts for the quarter after the next quarter based on planting intentions;

(2) Assessment of the NFA accomplishments, which include stock inventories and procurement volume (both domestic and international);

(3) Forecast of PAGASA;

(4) Other relevant information provided by the different IACRC member-institutions such as the National Irrigation Administration (NIA), Farmers' Groups and the DA Programs

The Committee meets quarterly (or as often as needed) to assess the supply-demand situation for rice and corn and, based on this, recommends the volume as well as the timing of importation, if necessary. This passes through the Secretary of the Department of Agriculture (DA) and then to the NFA Council, which in turn inform the President. (Refer to Figure 2 for the whole process)

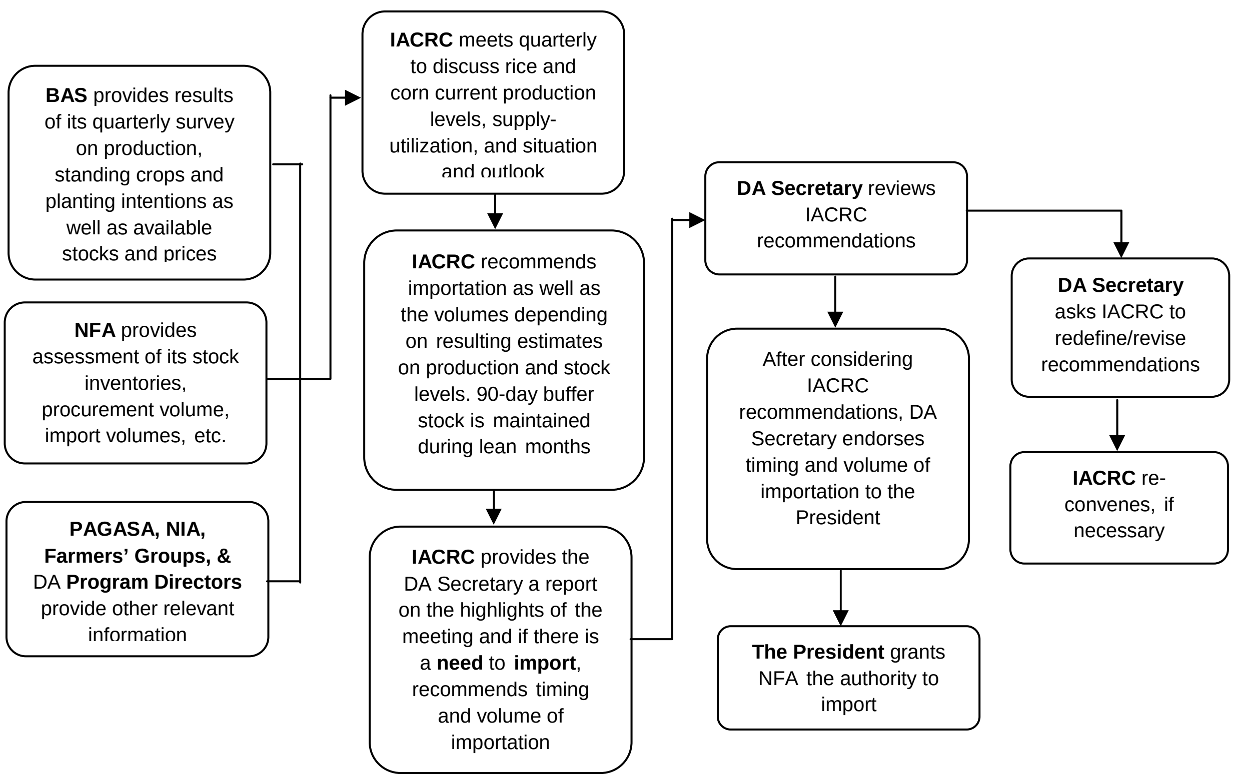

Figure 2. IACRC Assessment of Rice and Corn Situation

The IACRC, during its December meeting, decides on whether to import rice or not. During this period, information that are critical for import decisionmaking such as production estimates from the main cropping season (through the 4th round of the PPS survey of BAS; which account for about 70 percent of the total production for the year), amount procured by the government, and the remaining stock inventory at the end of the year, are available. If importation is recommended, there must be a final decision on the volume of importation as early as January. This is to give enough time for the whole importation process, which usually takes around 3 months because of the new procurement law (known as R.A. 9184). (Reburiano 2005) Imports are expected to arrive in March until around June. Together with carry-over stocks from the previous season (including the rice produced from the main cropping season which are harvested and procured during the last quarter of the year) and the rice produced from the second cropping or "Palagad" season (which are harvested and procured from March to May), imports comprise the stocks for the lean season. Sufficient level of stocks should be positioned before the end of June or start of the lean season. This is to avoid the high cost of transporting rice during this period since this is also the rainy season. In addition, because this period coincides with the growing period for rice, supplies are low and thus, prices are expected to be relatively higher. (Refer to Figure 3 for the timeline of activities for rice)

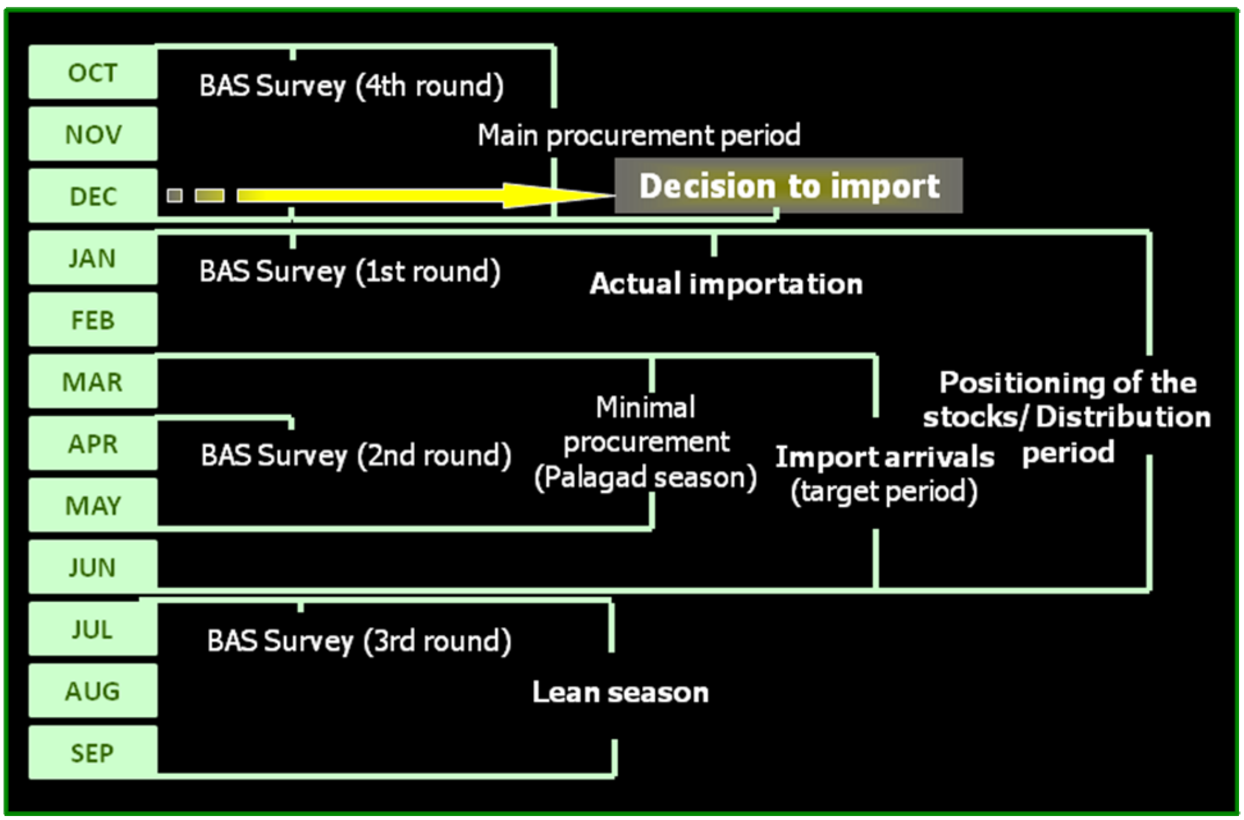

Figure 3. Timeline of activities for rice

4. Importance of SCF in Rice Import Decisions

Rice production is indeed a major deciding factor of importation. The IACRC, where the NFA and BAS are members, decides on importation when there is an impending production shortfall in the coming season. Currently, the rice production forecast is made by BAS based on the estimates of the farmer-respondents, which are captured by quarterly PPS. Unfortunately, this production forecasting system does not systematically incorporate SCF. Moreover, the IACRC does not systematically link SCF with rice import decisions, which could result in optimal volume as well as timing of rice importation. Contraction of rice imports in the early 1990's, ill-timing of imports in 1995, and over-importation in 1998 illustrate how inaccurate forecasts of the volume and timing of rice importation, especially during El Niño and La Niña years, could result in substantial economic costs such as higher rice prices due to rice shortages, higher storage costs, among others. (Kajisa and Akiyama 2003; Ramos 2000; Unnevehr 1985)

First is the under-importation during the first half of the 1990's. Starting the third quarter of 1990 up to the end of 1991, a warm episode of El Niño Southern Oscillation (ENSO) was experienced by the country. It then worsened in the first quarter of 1992 up to the second quarter. But it did not end there. The warm episode continued until the end of 1993, then returned in the second half of 1994 up to the first quarter of 1995. During that time, importation was crucial because the increase in local demand was 5.8 percent while the increase in production from 1994 to 1995 was only 0.03 percent (an almost negligible value) (Intal and Garcia 2005). However, because of the mandate of Magna Carta of Small Farmers (that importation is to be implemented only if the shortage situation was determined upon consultation with farmer representatives and other industry actors, instead of the IACRC), importation was postponed, which resulted in the 1995 rice crisis (Ramos 2000). Should the government had incorporated SCF systematically in their production forecasts and import decisions during the first half of the 1990's, the crisis would have not occurred.

Because of what happened in 1995, larger volumes of rice were imported during the period 1996-1998. Since 1996 is considered a normal year, it seems that the volume of imports during that time was unreasonably high. The total supply less imports for that period was far greater than the demand. Thus, when the worst El Niño occurred in 1997, there were large stocks in the hands of the government. In fact, what happened during the late 1990's was over-importation, perhaps because the government did not want to experience a rice crisis again. (Intal and Garcia 2005) Over-importation could have been avoided should SCF had been strongly considered in planning for the level of importation in the second half of the 1990's.

From 2000 onwards, the total supply has consistently been higher than the total demand, resulting in an ending stock inventory of around 2 million MT maintained over the period. This is primarily due to the continuously growing level of rice imports, which are very much higher than the consumption requirements of the country. While it may be safe to always import more and keep a positive level of stock inventory, substantial amount of money could be saved by the government if optimal volume and timing of importation could be determined. This could be done by systematically incorporating SCF in rice production forecasts and import decisions of the government.

5. Rice Production Models

Production forecast is an important input to the rice import decisions of the government. However, the government currently relies on the production forecasting system of BAS, which is based on farmers' estimates as captured by the PPS. An alternative method of forecasting the level of production, which systematically incorporates SCF, is through the development of the rice production models.

5.1. Review of Rice Production Models with Climate-Related Factors

Climate is considered as one of the major determinants of rice production or yield. Many studies were able to find significant relationship between climate-related factors and rice production/yield using econometric models. Some of these investigated the impact of climate-related factors on rice production in addition to other farm inputs such as fertilizer and labor. Kaul (n.d.) developed a number of econometric bio-models to examine the impact of climatic variables, together with farm inputs, on rice production in India. Agricultural variables included in the model are fertilizer and labor inputs. Climatic variables, on the other hand, include the following: actual rainfall, normal rainfall, deviation from normal rainfall, maximum temperature, and minimum temperature. Data on climatic variables covered the growing period for rice. They noted that climate conditions during the critical growing period of rice are important in influencing the level of rice production at the end of the season. The models were estimated using linear regression both at the national and district levels. The major finding of the study is that rice production is significantly affected by fertilizer use and some climatic variables such as actual rainfall, maximum temperature, and minimum temperature. Excessive rains and very high temperature were found to be detrimental to rice production.

Meanwhile, Abedullah and Pandey (2007) estimated a heteroskedastic quadratic production function using panel data gathered from 46 rice farmers in Tarlac, Philippines for the period 1990-1995. The independent variables included in the model are total labor, fertilizer, total rainfall during the rice production period, quadratic terms of these three variables, and interactions among them. The resulting model indicated highly significant relationship between each of the following variables and rice production: fertilizer; quadratic terms of labor, fertilizer and rainfall; interaction between labor and fertilizer, and; interaction between fertilizer and rainfall. This finding implies that aside from farm inputs, rainfall and its interaction with farm inputs (especially fertilizer) also have significant effects on rice production.

Other existing models examined only the effects of climate-related factors on rice production. Sarma et al. (2008) established an agroclimatic model to investigate the effects of rainfall, growing degree day units (which is derived using daily minimum and maximum temperatures as well as threshold temperature for a crop), satellite-derived vegetation index, sea surface temperature (SST) of Niño 3 region, and southern oscillation index (SOI) on rice yield in Andhra Pradesh, India. Using data from 1950 to 2002, the model was estimated using a multiple linear regression. In addition, correlation analyses between rice yield and each of the independent variables were also employed. The study found that rice yield was relatively lower in El Niño than in La Niña years. The study also noted that rice yield and rainfall were not significantly correlated. One plausible explanation for this is the presence of irrigation, which weakens the relationship between rice yield and rainfall. Moreover, SST was found to be more significantly related with rice yield than with SOI.

Tao et al. (2008), on the other hand, examined the relationships between rice yields and growing season climate in the main production regions of China over the period 1951-2002. Climatic variables include maximum and minimum temperatures, diurnal temperature range, and rainfall. One of the major findings of the study is that rice yield was significantly influenced by the growing season climate. In particular, growing season temperature, which had a generally significant warming trend, had increased rice yields in northeast China over the period.

Furthermore, Zubair (2002) noted that ENSO conditions have varying significant effects on rice yields in Sri Lanka, depending on the cropping season. In this study, the following variables were analyzed for the 'Maha' (October to March) and 'Yala' (April to September) cropping seasons from 1952 to 1997 using correlation analysis: SST-based ENSO index of Niño 3.4; rainfall, and; departure of rice production from long-term trends. The results showed that the 'Maha' rice production is significantly correlated with the average SST-based ENSO index and aggregate rainfall, both for the current season (October to December). 'Yala' rice production, on the other hand, was found significantly related with ENSO index for the current season (April to September) and the rainfall for the previous season (October to December).

Some studies further limited their analyses to investigating the effects of ENSO indices on rice production. Falcon et al. (2004) measured the effects of ENSO on paddy rice yield, area harvested and production in Indonesia. Simple econometric models were estimated, both at the national and provincial levels, with August Niño 3.4 SST anomaly (SSTA), time and its quadratic term as independent variables. Better models had been established by using production data on a crop-year basis, rather than data on a calendar-basis. Using crop-year data from 1983 to 2002, the estimated models were able to find significant relationship between August SSTA and paddy rice output.

Similarly, Naylor et al. (2001) measured the impact of ENSO on rice production in Java, Indonesia. Using data on rice production and Niño 3.4 SSTA for the period 1971-1998, both correlation and regression analyses were employed. In order to allow direct analysis of year-to-year variability in rice production and at the same time, address the possible problem of serial correlation, the variables were converted into first-differences before conducting a regression analysis. Regression results revealed that ENSO-related climate variability causes fluctuations both in rice plantings and production.

Moreover, Delos Reyes and David (2009) analyzed the effects of El Niño on rice production, yield and area harvested in the Philippines for the period 1970-2005 for normal and for all (including El Niño) years. Regression was employed to estimate the effect of an index of El Niño-induced drought magnitude on the deviations in rice production over the period, at the provincial level. Results of the analysis indicated that the annual growth rate in rice production is linearly related with El Niño-induced drought. Further, the deviations in rice production were found to be dependent on the strength and time of occurrence of the warm episode. In particular, the dry-season production had significantly declined by about 22 percent, 6 percent and 0.2 percent during strong, moderate and weak El Niño episodes, respectively.

5.2. Model Variables

Utilizing the readily available data, the variables considered in developing the rice production models are as follows: rainfall, ENSO classification, area planted, irrigated area, fertilizer usage, and relative price of rice. Because 1991 is the earliest year for which data on area planted is available, data on all variables used in developing the rice production models only covered the period 1991-2008. Refer to Table 1 for variable definition.

Table 1. Variables used for the regional production models

Variable	Description
Dependent	
prod	Rice production (in metric tons)
Independent	
rain_dry	Dummy for 'below normal' rainfall
rain_avg	Dummy for 'near normal' rainfall *(base category)*
rain_wet	Dummy for 'above normal' rainfall
enso_dry	Dummy for El Niño
enso_avg	Dummy for Neutral *(base category)*
enso_wet	Dummy for La Niña
irrig	Proportion of area planted to paddy rice that is irrigated (in hectare)
aplanted	Area planted to paddy rice (in hectare)
fert	Average fertilizer applied (in metric ton per hectare)
relprice	Relative price of rice (domestic price over world price)

Dependent Variable: Rice Production

The dependent variable is rice production (**prod**). Data on production is based on the volume of total paddy rice production (measured in metric tons) collected quarterly by BAS through its PPS. The quantity refers to paddy rice harvested from all farm types or ecosystem (i.e., irrigated, rainfed, and upland). It includes those harvested but damaged, stolen, given away, consumed, given as harvester's share, reserved, etc., and excludes those produced but not harvested due to low price, lack of demand and fortuitous events, etc. (BAS 2008) Paddy rice production was then converted to rice production by multiplying it with a conversion factor equal to 0.63. While BAS assumes that about 65.4 percent of the total volume of paddy rice remain after regular milling, 63 percent is assumed as the milling recovery rate for well-milled rice. Well-milled rice (formerly known as special rice) is considered as the most popular type of variety among the rice consumers nowadays.

Generally, there are two rice cropping seasons in the Philippines, namely: wet season (May-October), and; dry season (November-April). During the wet or main cropping season, most of the farmers commence rice planting in June and the operations usually end in August, although others end in early September. Because many areas do not have access to irrigation facilities, most of the rice farmers in many regions depend mainly on rain water for their farming operations. Considering that farmers plant either early- or late-maturing rice varieties, harvesting period usually occurs three to four months after; that is, from September up to December. Production during this period accounts for about 70 percent of the total rice production for the year. During the second or dry cropping season, however, the planting period typically starts in December and ends in February. The produce from this season are harvested from March to May, although bulk of the harvesting operations take place in April. The second, or the so-called "summer", crop comprises 30 percent of the total production for the year.[9]

In developing the rice production models, data used for the rice production variable were disaggregated by cropping season. As noted in the preceding paragraph, those harvested during the months of September until December represent the rice production for the main cropping season while those harvested from March to May make up the rice production for the second cropping season. It is assumed in this study that the periods considered for both cropping seasons already incorporated the planting delays which might be caused by extreme climate events.

Independent Variables

The independent variables[10] used in developing production models are a combination of agricultural and climatological data. Apparently, most of the agricultural data were sourced from BAS through the Bureau's nationwide surveys while climatological data were sourced from PAGASA.

ENSO Classification

ENSO classification is based on the operational definitions of the National Oceanic and Atmospheric Administration (NOAA) for El Niño and La Niña. El Niño is said to occur when Oceanic Niño Index or ONI met or exceeded +0.5 ^{o}C for a period of at least 5 consecutive months. On the other hand, a full-fledged La Niña is considered when ONI is less than or equal to -0.5 ^{o}C for at least 5 consecutive months. ONI is actually a 3-month running-mean values of Sea-Surface Temperature (SST) departures from the average in the Niño 3.4 region (5N-5S, 120-170W), which is calculated with respect to the 1971-2000 base period using the Extended Reconstructed SST version 3 (or, ERSST.v3). (NOAA, 2008) The ENSO states or categories are as follows: El Niño (if ONI is greater than or equal to +0.5 ^{o}C); Neutral (if ONI is less than the absolute value of 0.5 ^{o}C, or; if ONI is less than +0.5 ^{o}C but greater than -0.5 ^{o}C), and; La Niña (if ONI is less than or equal to -0.5 ^{o}C).

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[9] This cropping calendar is based on the first-hand observation of Mr. Jovino De Dios (Supervising Science Research Specialist, Agronomy and Soils Division, Philippine Rice Research Institute) through their interactions with rice farmers nationwide; Ms. Ma. Dolores Fernandez (Division Chief, Operations and Planning Division, Department for Marketing Operations, National Food Authority) supported this observation.

[10] interchangeably used with 'predictors' in this paper

With respect to the observed rice cropping calendar in the Philippines, the periods that were considered relevant for the ENSO variable (**enso_dry**, **enso_avg**, **enso_wet**) are those that cover both planting and harvest periods. Although the growing period of a crop is usually considered, this study assumes that determining the ENSO state during both the growing and harvest periods of a crop would give a better idea on how much volume of production to expect at the end of the season. In the Philippines, an ENSO event may trigger extreme climatic effects such as drought, floods, among others, which could have adverse effects on rice production in certain regions (SCF Project Team 2005). El Niño is manifested by drier weather conditions such as prolonged dry season, early termination of rainy season, less number of typhoons and higher-than-normal temperature (Verceles 2005). Prolonged drought condition brought about by El Niño, for instance, could inhibit the growth of the dry season rice crop in certain areas, resulting in lower volume of production. In other areas, however, such condition might cause the delay in the planting of wet season crop, particularly those in rainfed areas. (David, n.d.) On the other hand, La Niña is characterized by wetter weather conditions such as short dry season, early onset of rainy season, higher number of typhoons, and lower-than-normal temperature. This could be beneficial to some rice areas where irrigation system is inaccessible but could also be devastating to some which are flood-prone.

Rainfall

The dummy variables for rainfall (**rain_dry**, **rain_avg**, **rain_wet**) are based on the data on percentage deviation from normal rainfall, which was estimated by PAGASA using the following formula:

$$\%N = \left(RR/N \right) \times 100,$$

where: $\%N$ = percentage deviation from normal rainfall

RR = amount of observed rainfall (in millimetres)

N = normal rainfall, or the average amount of rainfall for the period 1971-2000 (in millimetres)

Based on these figures, the amount of rainfall can be assessed whether it is below, near or above the normal amount of rainfall for a 30-year period. This classification results in a *rainfall tercile*, which is actually a form of a seasonal rainfall forecast regularly issued by PAGASA. The levels of this categorical rainfall variable are as follows: below normal (0-80%); near normal (81-120%), and; above normal (above 120%).

These rainfall dummy variables may also reflect the effect of ENSO on the amount of rainfall (e.g., an El Niño episode is expected to result in a below normal amount of rainfall). However, perhaps due to Philippine geography, the expected impact of ENSO on rainfall patterns for a particular region is not often realized and varies across regions. This then implies that inclusion of both ENSO and rainfall dummy variables in the model may not lead to a problem of perfect collinearity. Meanwhile, like the ENSO variables, the periods considered for the rainfall dummy variables are those covered by both the planting and harvest periods.

Proportion of Area Planted to Paddy Rice that is Irrigated

To be able to capture the effect of irrigation, the 'proportion of area planted to paddy rice that is irrigated' (named as **irrig**) was used as a proxy to irrigated area. Data on irrigated area (served by the national, communal and private irrigation facilities) were not utilized due to unavailability of data that are disaggregated by cropping season. The variable is defined as follows:

$$\boldsymbol{irrig} = \frac{area\ planted_{irrig}}{area\ planted_{total}},$$

where: $area\ planted_{irrig}$ = area planted to paddy rice that is irrigated (in hectares)

$area\ planted_{total}$ = total area planted to paddy rice (in hectares)

The data used for the irrigation variable were taken from the same period of the rice planting operations, namely: June-September (for the main cropping season), and; December-February (for the secondary cropping season). However, available data from BAS (collected through PPS) are by semester only prior to 2007, and no monthly percentage distribution is available. Starting 2007, the survey on area planted and fertilizer use became a rider to PPS, making data on these variables available on a quarterly basis. At the end of the semester/quarter, the farmers were asked to estimate their total area planted and total fertilizer use for the past semester/quarter. In order to estimate the proportion of area planted that is irrigated for the June-September period, weighted average of the data for the first and second semesters of the year were used. Data for the June-September period, however, were estimated using weighted average of the data for the second semester of the year and first semester of the following year. Moreover, because there is no disaggregation of area planted by ecosystem or farm type (e.g., irrigated, rainfed) before 1991, the historical data used in developing the rice production models cover only the period 1991-2008.

Area Planted to Paddy Rice

Area planted to paddy rice (**aplanted**) refers to all areas planted with paddy rice (measured in hectares), regardless of farm type or ecosystem (i.e., irrigated, rainfed, upland) for a particular period. The data were also obtained from BAS through its PPS. Like the 'irrig' variable, the data used for area planted are those for June-September (for the main cropping season) and December-February (for the secondary cropping season). Again, the figures for June-September and December-February were estimated using the approach used for the 'irrig' variable.

Average Fertilizer Applied

Average fertilizer applied (**fert**) is defined as follows:

$$\boldsymbol{fert} = \frac{fertilizer\ used}{area\ applied},$$

where: *fertilizer used* = total quantity of fertilizer applied (in 50-kilogram bags); includes all types of fertilizer such as urea, ammosul, ammophos, complete, and others

area applied = total area applied with all types of fertilizer (in hectares); includes both farm types or ecosystem (i.e., irrigated and rainfed)

The data for this variable (measured in 50-kilogram bags per hectare) cover the planting periods for rice. Because the available data from BAS on quantity of fertilizer applied and total area applied are also by semester (prior to 2007) or quarter (starting 2007) and monthly percentage distribution for each is not available, the approach used in coming up with figures for area planted for June-September and December-February was used.

Relative Price of Rice

Relative price of rice (**relprice**) is defined as follows:

$$\boldsymbol{relprice} = \frac{domestic\ price_{rice}}{world\ price_{rice}},$$

where: $domestic\ price_{rice}$ = retail price of rice (in PhP per kilogram)

$world\ price_{rice}$ = price of Thai rice, 5% broken (expressed in PhP per kilogram)

The data used for domestic price of rice are the average monthly retail price of well-milled rice (in PhP per kilogram) sourced from BAS. Aside from being the most popular, its price data has relatively longer time series compared to other types. The data used for world price, on the other hand, are the average monthly export price of Thai rice (5% broken; milled white rice) (in US$ per metric ton free-on-board (FOB)). Although developing countries like the Philippines usually procure (in bigger volumes) the relatively lower grade such as 25% or 15% broken, price of 5% broken is considered as the benchmark for the world price of rice. Aside from this, its price data are usually the most readily available with considerably longer time series. The data on world price were sourced from the World Rice Statistics of the International Rice Research Institute (WRS, IRRI). In order to allow comparability between the domestic price and world price, the export price of Thai rice was expressed in terms of PhP per kilogram using the average monthly figures of PhP/US$ exchange rate and a conversion factor (metric ton to kilogram) of 0.001. The data on exchange rate were sourced from the *Bangko Sentral ng Pilipinas* (BSP).

5.3. Model Estimation

Historical data on the identified variables from the first cropping period of 1991 up to the first cropping period of 2008 were used. Using a Multiple Linear Regression (MLR) technique, a number of candidate rice production models for each of the sixteen regions[11] were developed. Diagnostic tests were employed on these candidate models and the necessary adjustments were done to ensure that the basic assumptions in regression modelling were satisfied. All of the continuous variables were transformed logarithmically in attempt to satisfy the basic assumptions in simple regression (such as normality and constancy in variance) and time series modelling (such as constancy in variance caused by serial correlation and non-stationarity). Also, lags of the production variable were included in the models to correct for serial correlation. Below is the final specification of a rice production model for a particular region:

$$\begin{aligned} ln\_prod_t = {} & \alpha + ß_1 * rain\_dry_t + ß_2 * rain\_wet_t + ß_3 * enso\_dry_t + ß_4 * enso\_wet_t + ß_5 * ln\_irrig_t + \\ & ß_6 * ln\_aplanted_t + ß_7 * ln\_fert_t + ß_8 * ln\_relprice_t + ß_{9[t-j]} * ln\_prod_{[t-j]}, \end{aligned}$$

where:

ln_prod: natural logarithm of rice production

rain_dry: dummy for ‘below normal’ rainfall

rain_wet: dummy for ‘above normal’ rainfall

enso_dry: dummy for El Niño episode

[11] excluding the National Capital Region (NCR) due to non-existence of rice area

enso_wet: dummy for La Niña episode

ln_irrig: natural logarithm of proportion of area planted to paddy rice that is irrigated

ln_aplanted: natural logarithm of total area planted to paddy rice

ln_fert: natural logarithm of average fertilizer applied per hectare

ln_relprice: natural logarithm of relative price of rice

ln_prod[t-j]: natural logarithm of rice production for the past *j* period

α: constant term

$ß_i$: regression coefficient of variable *i*, *i* = 1, 2, 3, ..., 9

[t-j]: lag term; current period *t* less *j* period, *j* = 1, 2, 3, ...

Agriculture-related variables (i.e., area planted, proportion of area planted that is irrigated, fertilizer use, relative price) were hypothesized to have positive effect on production. This study hypothesizes that increasing the level of inputs (e.g., area of land devoted to rice, volume of seeds planted, recommended amount of fertilizer, and water supply from irrigation facilities) translates into a higher level of output, *ceteris paribus*[12]. Also, an increase in the price of domestically-produced rice relative to that of rice in the world market induces local farmers to augment their produce to take advantage of a relatively higher price and thus, a higher profit. On the other hand, climate-related variables such as ENSO and rainfall were assumed to have either positive or negative effect on production, depending on the geographical location. In the Philippines, impact of ENSO varies across regions.

The final production models satisfied the following set of criteria: (i) residuals are normally distributed; (ii) perfect collinearity among the independent variables does not exist; (iii) serial correlation (or correlation among observations from different time periods) is not present, and; (iv) signs of the estimated model coefficients are consistent with the hypothesized relationships between production and the independent variables. However, not all of the final 16 regional rice production models were able to satisfy the constancy-in-variance assumption. Thus, a Robust Regression was employed in order to achieve a relatively higher degree of confidence with the model estimates albeit such moderate departures from homoskedasticity[13].

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[12] holding other things constant

[13] constancy in variance

5.4. Model Results

The final set of production models have considerably high R-squares; ranging from 0.5510 to 0.9677 with a high mean value of 0.7833. (Refer to Table 2 for the regional rice production models) On the average, more than 75 percent of the variation in production data could be explained by the final set of predictors in the model. This implies that the developed production models might be adequate in predicting the volume of future rice production of the country. Among the regional models with highest R-squares are the following: Region I (Ilocos Region) – 0.9677; Region VI (Western Visayas) – 0.9449; ARMM – 0.9263, and; CAR – 0.9149. Those regions whose models got the lowest R-squares include: Region V (Bicol Region) – 0.5510; Region IV-A (CALABARZON) – 0.5795, and; Region VII (Central Visayas) – 0.5823. Meanwhile, the estimated models for two of the largest rice growing regions in Luzon, Region III (Central Luzon) and Region II (Cagayan Valley), respectively, have R-squares that are slightly lower than the mean value.

Among the model predictors, the lagged variables of production came out to be the most significant, followed by area planted and then proportion that is irrigated (refer to Table 2). Lagged variables, particularly 'lag 2', were found to have positive significant relationship with production variable in all of the models, implying that seasonality is really inherent in rice production data. In particular, the present level of production is significantly affected by the level of production two seasons ago, which is the dry season of the previous year. Rice production was also found to be elastic to area planted and irrigated area in some of the regions. This implies that as the area planted increases, expected volume of production also increases. In the top rice-producing regions, namely Regions III and VI, only area planted and past level of production can significantly explain the trends in production. In Region VI, however, production was found to be very responsive to changes in area planted. Similar observation applies to Region X, as evidenced by the estimated coefficient that is greater than 1. Moreover, if the irrigated portion of area planted increases, production level also increases. In fact, production tends to be very elastic to proportion of irrigated area in Regions IV-A, V, XI (Davao Region), and VII, respectively. It seems that access to irrigation in these regions helps a lot in augmenting their produce.

Table 2. Regional rice production models

Region	Rainfall tercile:		ENSO classification:		Ln of proportion of area planted to palay that is irrigated	Ln of total area planted to palay	Ln of average fertilizer applied per hectare	Ln of relative price of rice	Lagged of ln of rice production:		Constant term	**R-square**
	dry	wet	El Niño	La Niña					lag 1	lag 2		
	(rain_dry)	*(rain_wet)*	*(enso_dry)*	*(enso_wet)*	*(ln_irrig)*	*(ln_aplanted)*	*(ln_fert)*	*(ln_relprice)*	*(ln_prod[t-1])*	*(ln_prod[t-2])*	*(α)*	***(R^2)***
CAR	-0.2151*	-0.1050	-0.1029	0.0269	0.2519	0.1392	0.0306			0.9029**	-0.0344	**0.9149**
Region 1	0.0032	-0.0306	0.0484	0.1958**	0.1107		0.5369			0.9949**	0.8193	**0.9677**
Region 2	-0.0111	0.0323	-0.0624	0.1249		0.3508				0.6880**	-0.0264	**0.6997**
Region 3	-0.0389	-0.0892	-0.0527	0.0140	0.7747	0.3632**				0.7730**	-1.0643	**0.7720**
Region 4A	-0.0680	-0.2406**	-0.1383*	0.0223	2.1407**	0.6503**				0.7640**	-3.1178	**0.5795**
Region 4B	-0.0730	-0.2057**	-0.1010	0.1066		0.3692	0.9540**			0.7328**	0.8399	**0.8949**
Region 5	-0.0462	0.0212	-0.0630	-0.0656	1.4654**	0.6499**	0.0084			0.4801**	-0.2226	**0.5510**
Region 6	0.0183	-0.0721	-0.1749	0.0969		1.2033**		0.2228		0.6780**	-10.4950	**0.9449**
Region 7	-0.8557**	-0.1072	0.0722	0.2471	1.2797**	0.7337**	0.0774		0.3315**		0.9699	**0.5823**
Region 8	-0.0359	0.1322*	0.0716	-0.0354		0.4663		0.2263		0.8770**	-3.7935	**0.7483**
Region 9	-0.1035	-0.0300	-0.0579	0.0372		0.9349**				0.4589**	-3.7665	**0.8637**
Region 10	-0.0706	-0.0011	0.1196	0.0025		1.0536**	0.0426			0.2414**	-2.3673	**0.7186**
Region 11	-0.0882	0.1476**	-0.0116	0.0817**	1.3841**	0.3471**	0.1137			0.6227**	1.1799	**0.8578**
Region 12	-0.1794	-0.0414	0.0693	0.0200		0.6996				0.5660**	-2.6416	**0.8455**
ARMM	-0.4043*	-0.0109	0.0062	-0.0179	0.4283	0.9379**				0.4684**	-3.6057	**0.9263**
CARAGA	-0.0700	0.0014	-0.1258	-0.0091			0.2630			0.7412**	3.5089	**0.6652**

** significant at 5% level; * significant at 10% level

Fertilizer use and relative price, on the other hand, appeared to be not very significant in explaining the movement of rice production from season to season. Only in Region IV-B (MIMAROPA) where fertilizer application was found to have positive significant influence on production level. However, rainfall and ENSO variables were also found to be significant predictors of rice production in some regions. ‘Below normal’ rainfall was found to have negative effect on production levels of Regions VII, ARMM and CAR. Interestingly, these regions are among those which are less irrigated (see Figure 4). In times when rainfall amount is below the normal level, volume of rice production tends to be lower in regions where irrigation system is hardly accessible. On the other hand, production in Regions IV-A, IV-B, VIII and XI tend to be responsive to ‘above normal’ rainfall. The effect of too much rainfall on production in Region IV is negative while positive in other two regions. Moreover, ENSO state appeared to be not very significant in determining the volume of rice production, particularly the El Niño. In Regions I and XI, La Niña tends to have positive effect on production. On the other hand, El Niño was found to have negative effect on production although it is not highly significant.

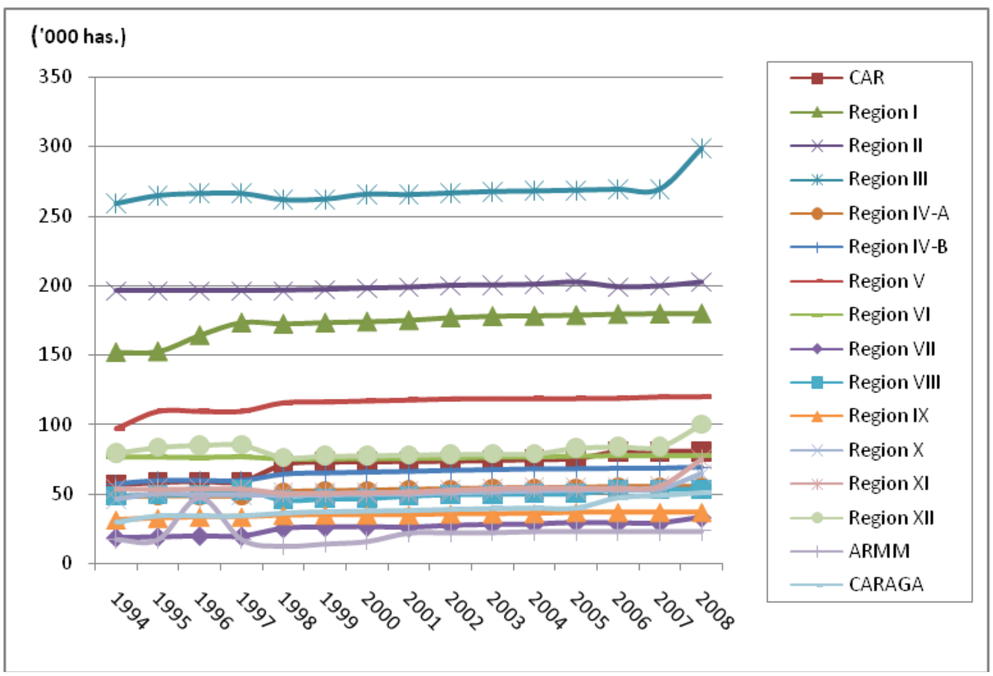

Figure 4. Irrigated area served by the national, communal and private irrigation systems, by region, 1994-2008

5.5. Model Validation

In order to evaluate the model fit and predictive ability of the models, both in-sample and out-of-sample forecasting were conducted. In 'in-sample forecasting', estimation data or data used in developing the production models were used (i.e., data for 1993-2007). On the other hand, 'out-of-sample forecasting' made use of a new set of data that were not included in model estimation (i.e., data for 2008). Because there are three possible levels of production for different climate states[14], the one which corresponds to the observed climate state was compared with the actual. This was done for all regions and for all years considered in this study.

In order to determine how far the predicted levels are from the actual, Mean Absolute Percentage Error (MAPE) was computed for each of the regional models. Among the scale-independent statistics that are commonly used in measuring the forecasting ability of the models, MAPE is considered as the most versatile, self-evident, and simplest to determine. It indicates, on the average, the percentage error a given forecasting model produces for a specified period. Basically, it is the sum of the absolute value of the difference between the actual and predicted values divided by the actual values, expressed as a percentage, divided by the total number of periods. (Chatfield 2000; ITSMF-NL 2006; Frechtling 1996) The formula used in calculating MAPE is as follows:

$$MAPE = \frac{1}{n}\left[\sum_{t=1}^{n}\left|\frac{e_t}{A_t}\right| \times 100\right] = \frac{1}{n}\left[\sum_{t=1}^{n}\left|\frac{(A_t - P_t)}{A_t}\right| \times 100\right],$$

where: A_t = actual value at time t

P_t = predicted value at time t

e_t = forecast error

n = total number of periods

t = time period

ITSMF-NL (2006) noted that the forecasting model with MAPE below 40 percent might be considered reasonably reliable. This is supported by the rules of thumb presented in Frechtling (1996), which were basically the suggested interpretation of MAPE values in Lewis (1982) (Refer to Table 3).

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[14] i.e., climate states during the planting period

Table 3. Rule-of-thumb for MAPE values

Interpretation	Range of MAPE values
Highly accurate forecasting	less than 10 percent
Good forecasting	between 10 and 20 percent
Reasonable forecasting	between 20 and 50 percent
Inaccurate forecasting	greater than 50 percent

Table 4 displays the computed MAPEs for each of the estimated regional rice production models. In-sample MAPEs show that half of the models are considered reasonable while others are found to have good forecasting ability. Out-of-sample MAPEs indicate that four of the models are inaccurate, four are reasonable, four are good, and four are highly accurate. Generally, the estimated regional rice production models have reasonably good forecasting ability, as indicated by the average MAPEs less than 50 percent.

Table 4. Computed MAPEs for each of the regional rice production models

Region	In-sample MAPE	Out-of-sample MAPE
CAR	20.54	8.48
Region I	20.67	33.41
Region II	10.77	8.19
Region III	13.27	14.84
Region IV-A	16.13	21.77
Region IV-B	16.44	12.35
Region V	12.55	32.19
Region VI	25.50	68.36
Region VII	40.98	181.66
Region VIII	23.41	15.93
Region IX	25.13	76.26
Region X	10.40	2.90
Region XI	12.53	32.81
Region XII	26.22	50.50
ARMM	32.53	11.37
CARAGA	11.05	2.37
Average	19.88	35.84

Further refinements on the models, however, are deemed necessary to further improve their predictive performance. Some of these may include: further classification of ENSO states to take into account the degree/intensity; exploration of nonlinear forms of the models through the use of interaction terms, e.g., rainfall and irrigation, etc.; inclusion of temperature and other relevant variables (if they are available already or they could be disaggregated by region and by cropping season); among others. But then, one possible source of problem here is the limited number of observations due to unavailability of longer time series for some of the variables included in the model.

6. Rice Importation Simulation (RIS) Model

Because the Philippines is a perennial rice importer and is often affected by extreme climate events, incorporation of SCF in rice import decisions of the government (through the NFA) is considered a viable solution in minimizing the importation cost incurred by the government. In order to realize this, a Rice Importation Simulation (RIS) model was developed using a Discrete Stochastic Programming (DSP) modelling approach.

6.1. Overview of DSP Modelling

This section provides background information on DSP modelling, which is heavily drawn from Crean (2009).

DSP modelling approach is an extension of the standard Linear Programming (LP) approach with a second-period decision. The general feature of the two approaches is the two-stage model formulation where time is simply divided into 'present' and 'future'. While the order of events in static LP model is in $x \rightarrow s$ format, the format in DSP model is $x \rightarrow s \rightarrow z(s, x)$, where: x is a vector of stage 1 decisions; s is the state of nature, and; $z(s, x)$ is a set of stage 2 decisions, contingent upon earlier stage 1 decisions and the state of nature.

The objective function of the DSP model is comprised of returns in each of these stages and can be written as:

$$
\begin{aligned}
\text{Max } Y &= c^T x + E_s Q(x,s) \\
\text{subject to } \quad Ax &= b \\
x &\geq 0
\end{aligned}
$$

where:

$$
\begin{aligned}
E_s Q(x,s) &= \max \sum_{s=1}^{S} \pi_s e^T{}_s z_s \\
\text{subject to } \quad T_{sx} + W_s &= b_s \\
z_s &\geq 0
\end{aligned}
$$

In the first equation, $c^T x$ is the stage 1 return, which is just a product of a net revenue vector (c^T) and the level of stage 1 activities (x). The decisions are made prior to determination of the state of nature. The constraints relating to stage 1 are the same as those for the general LP model and concern a matrix of resource requirements (A) and a vector of resources (b). The stage 2 return function (also known as 'recourse function'), $E_s Q(x,s)$, on the other hand, is an expected return which is summed over all states. The return in each state is a product of a stage 2 net return vector (e^T) and the level of stage 2 activities (z_s). The probability of each state (π_s) gives different weights to the outcomes in each state. The constraints of stage 2 consist of a technology matrix, (T_{sx}), a recourse matrix, (W_s), and a vector of state-contingent resource supplies (b_s).

The structure of the model for a two stage-three state problem is illustrated in matrix form in Figure 5. The first group of columns refers to stage 1 strategic activities. The second group (columns 2 to 4) refers to the stage 2 tactical activities. The last group refers to constraints. The top row of sub-matrices is multiplied by the sub-matrices in all other rows to determine the solution to the problem.

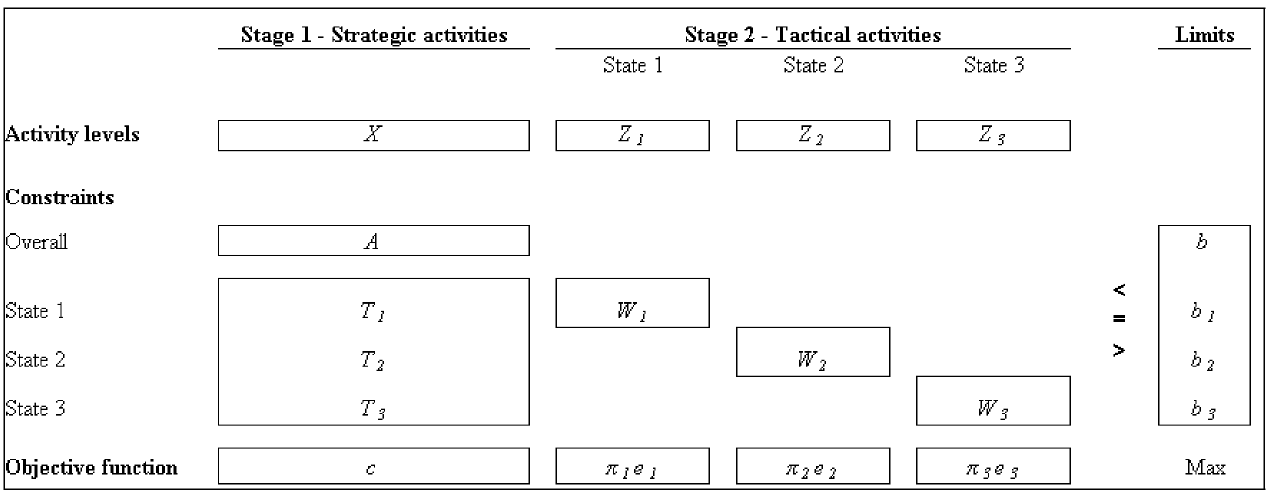

Figure 5. Structure of a DSP Model

6.2. Operational Framework

Following the general framework of the DSP model, the RIS Model was developed to aid the government in its rice import decisions in the face of seasonal climate variability. The ultimate objective of the model is to come up with the optimal set of strategies with regard to rice importation (particularly on the volume and timing) and their associated costs under different climate forecast scenarios. This is basically a minimization problem which seeks to minimize the potential importation costs of the government under climate uncertainty.

Objective Function

The objective function of the RIS model is as follows:

$$Min\ Z = c_1^* x_1 + \left[\sum_{i=1}^{3} p_{S_i|F_i} c_{2S_i}^b y_{2S_i}^b + \sum_{i=1}^{3} p_{S_i|F_i} c_2^h v_{2S_i}^h + \sum_{i=1}^{3} p_{S_i|F_i} c_2^d z_{2S_i}^d \right]$$

subject to:

$$\begin{array}{lllll} x_1,\ y_{2S_i}^b & & & & \geq 0 \\ x_1 + & y_{2S_1}^b & & & \geq n_1 \\ x_1 + & & y_{2S_2}^b & & \geq n_2 \\ x_1 + & & & y_{2S_3}^b & \geq n_3 \\ x_1 & & & & \leq b \end{array}$$

As mentioned earlier, the objective function aims to minimize the potential cost of importation. The total cost of importation is composed of two components, namely: costs of pre-season buying and storing rice, or the stage 1 costs, and; combined costs of in-season buying, storing and distributing rice, or the stage 2 costs. The first component is just the product of volume of rice purchased pre-season (x_1) and all costs associated with it (c_1^*), which is the sum of the price of rice pre-season, other import-related costs, and cost of holding it up to the in-season.

The second component, on the other hand, is the sum of all costs associated with in-season buying, storing and distributing rice, weighted by the probabilities of occurrence of each state. The total cost of in-season buying is the weighted sum of in-season costs of buying rice for all three different states (S_i), namely: S_1 = 'dry' or rainfall is 'below normal'; S_2 = 'average' or rainfall is 'near normal', and; S_3 = 'wet' or rainfall is 'above normal'. This is estimated by first getting the product of volume of rice purchased in-season ($y_{2S_i}^b$), all costs associated with it (which include the seasonal price of rice plus other import-related costs ($c_{2S_i}^b$)), and probability of occurrence of a particular state ($p_{S_i|F_i}$; which is dependent on the forecast skill and forecast type) for each state, and then summing all these three. Similarly, the total costs of in-season storage and distribution are the weighted sums of in-season costs of storing and distributing rice, respectively, for all states. The total cost of in-season storage is estimated by getting the product of volume of rice stored in-season ($v_{2S_i}^h$), cost of in-season storage (c_2^h, which is constant across all states), and probability of occurrence of a particular state ($p_{S_i|F_i}$) for each state, and then getting the sum of these products. The total cost of in-season distribution is estimated by getting the product of volume of rice distributed in-season ($z_{2S_i}^d$), cost of in-season distribution (c_2^d , which is constant across all states), and probability of occurrence of a particular state ($p_{S_i|F_i}$) for each state, and then getting the sum of these products.

To be able to solve this cost-minimization function, a number of constraints should be taken into account. First, the volume of rice purchases in either period should always be non-negative, as they indicate net rice imports. Second, the total volume of rice purchases in both periods may be greater than or equal to the identified volume of net import demand. Alongside the objective of minimizing the total importation cost of the government is for the expected supply to meet the expected demand for rice in the country. Thus, the total volume of rice imports during the year should never fall short of the identified net import demand. Third, the total volume of rice purchased pre-season should not exceed the specified rice storage capacity (b). One of the assumptions of the model is that the volume of rice purchased in-season which is equivalent to the net import demand would be distributed right away during that same period. Thus, only excess purchases (which are estimated as the difference between the total volume of rice purchases for the two periods and net import demand) need to be stored in-season. Consequently, only pre-season storage needs to be constrained by the rice storage capacity.

Based on the pre-season and in-season estimated costs of importation (price of rice plus other relevant costs) and probabilities of occurrence of different states, together with net import demand, the model will then produce a set of optimal import strategies and their associated costs. These strategies, which provide suggestions on the optimal timing and volume of importation, are composed of the following: how much to buy and store pre-season; how much to buy in-season, for each state; how much to store in-season, for each state, and; how much to distribute in-season, for each state. The associated costs of all of these strategies will also be estimated for each state.

The model is an example of a stochastic programming model with recourse. It decides on a set of optimal import strategies prior to knowing the state of nature since the government only knows the probabilities of occurrence of the rainfall states for the coming season. Once the state has been realized, the government can then make a recourse decision. For instance, if the season turned out to be dry, the NFA might need to buy additional volume of rice but at a higher cost relative to the pre-season price. If the season turned out to be wet, the NFA might need to store some of the rice they bought pre-season. Either way, there is a cost associated with not knowing the real state; either the NFA buys too much pre-season (which is associated with higher storage cost) or too little (which might be associated with higher in-season price). In other words, the model only serves as guide to decisionmakers when the real state is still unknown but once the state is known already, the decisionmakers can then make adjustments on their earlier decisions.

Value of Forecasting System

The decisionmakers are given the choice of whether to use or not to use the forecast. The value of the forecasting system can be estimated by comparing the estimated costs of importation for each forecast scenario. The estimated costs of importation are based on the optimal import strategies and costs produced by the model under different forecast scenarios. The formula used in estimating the potential value of forecasting system is as follows:

$$V_F = Z^*_{F_0} - \sum_{i=1}^{3} q_{F_i} Z^*_{F_i}$$

(such that: $p_{S_i|F_i}$ are used in calculating $Z^*_{F_0}$, instead of p_{S_i}),

where:

$Z^*_{F_0}$ = estimated cost of importation if the forecast is not used

$Z^*_{F_i}$ = estimated cost of importation if the forecast is used

q_{F_i} = forecast frequency

The estimated cost of importation if the forecast is not used ($Z^*_{F_0}$) is basically the weighted sum of the optimal costs for different states under the 'No Forecast' scenario. ['No Forecast' means that no forecast is used, or the forecast is available but is not used.] The weights used are the posterior probabilities ($p_{S_i|F_i}$) to allow a valid comparison between the 'use' and 'not use' forecast estimates. The estimated cost of importation if the forecast is used ($Z^*_{F_i}$), however, is the average of the estimated costs for the three forecast scenarios (i.e., dry, average, wet), weighted by forecast frequency. The forecast frequency is just a simple weight assigned to a particular forecast based on the total number of states to be forecasted. In this case, each q_{F_i} is equivalent to 1/3 or 0.33.

6.3. Model Parameters and Data

Based on the items discussed in the preceding section, two sets of data are needed in running the RIS model. The first set consists of forecast type and hit rates, or the climate data. The second set is composed of rice supply and demand as well as import-related costs, or the agricultural data. In order to check the capability of the model, a simulation exercise had been conducted. In particular, the exercise aimed to evaluate whether systematically incorporating SCF in rice import decisions of the government could lead to determination of the optimal import policy strategies and thus, minimization of the costs of importation in the future. In this exercise, data pertaining to rice importation in 2008 were utilized.

<u>*Climate Forecast and Forecast Skill*</u>

Forecast Types

There are four (4) types of forecast used in the RIS model, which represent 4 different bases under which the model is being run. As mentioned earlier, these are as follows: (1) No Forecast; (2) Forecast – dry; (3) Forecast – average; (4) Forecast – wet. As mentioned earlier, ‘no forecast’ means that a forecast is available but is not used. The three other types, on the other hand, correspond to the different rainfall categories used in the forecasts issued by PAGASA, or the so-called terciles, namely: below normal (or ‘dry’); near normal (or ‘average’), and; above normal (or ‘wet’). Terciles are used to represent three broad sectors of the probability distribution that are equally likely climatologically. Forecasts are expressed in terms of the likelihood terciles because of the typically large amount of uncertainty in the forecasts. The use of tercile probabilities provides both the direction of the forecast relative to climatology as well as the uncertainty of the forecast.

Posterior Probabilities

Posterior probabilities were computed using the Bayes’ formula, which uses both the definition of conditional probability and the law of total probability (Hogg and Craig 1995). Below is the formula used in this study:

$$p_{S_i|F_i} = \frac{p_{S_i} p_{F_i|S_i}}{\sum_{i=1}^{3} p_{S_i} p_{F_i|S_i}},$$

where: $p_{S_i|F_i}$ = *posterior probability* = probability of observing a certain rainfall state (S_i) given a certain rainfall forecast (F_i)

p_{S_i} = *prior probability* = probability of receiving a certain rainfall state (S_i) prior to new information

$p_{F_i|S_i}$ = *conditional probability* = probability that a certain rainfall forecast (F_i) will be obtained given that a certain rainfall state (S_i) occurs; an indication of accuracy of forecast

i = rainfall category (1 = dry or 'below normal'; 2 = average or 'near normal'; 3 = wet or 'above normal')

As mentioned already in the preceding section, these probabilities would serve as weights in the computation of optimal costs of importation and as inputs in determining the optimal volume and timing of importation. The main requirement in the calculation of posterior probabilities is the forecast skill, which is computed based on hit rates.

Forecast Skill

The forecast skill is computed as follows:

$$\textit{Forecast Skill} = S = \frac{A - A_0}{A_p - A_0},$$

where: A = % of correct forecasts = hit rates

A_0 = % of correct forecasts by chance

A_p = maximum number of correct forecasts

This formula implies that forecasts with hit rates that are close to 0.33 have zero skill.

Hit Rates

From the viewpoint of the government, it is important to determine whether there is some degree of confidence in predicting the rainfall state for the December-February planting period so that they can make decisions accordingly. For instance, the reported hit rate for 'below normal' rainfall is considerably high. When PAGASA forecasted that the coming season would be drier than normal, then it might be rational for the government to consider importation because production shortfall might be possible.

Hit rates were derived from the contingency tables of the observed and forecast rainfall that are provided by PAGASA. Given the observed monthly rainfall amount (in millimetres) from 1990 to 2008, cumulative running seasonal rainfall values for the period December-February for all years were calculated by station. Using these seasonal rainfall values per station, interpolation through the so-called 'kriging'[15] method using ArcView[16] software was done to come up with regional figures. On the other hand, seasonal rainfall forecasts (also for December-February period) were generated per station using Rainman[17] software based on historical data and SST anomaly values of the Niño 3.4 region. These values were actually 'hindcasts' since estimates were based on historical records. Like in observed rainfall, regional estimates of these seasonal rainfall forecasts (in millimetres) were interpolated through 'kriging'.

Terciles for each region were generated using actual rainfall ranges for each location and season based on the set of historical observations (i.e., 1951-2008). Terciles are used to represent three broad sectors of the probability distribution that are equally likely, climatologically. To help determine the three tercile ranges, the historical rainfall data were ranked from highest to lowest. The highest value was tagged as rank 1, the second highest was rank 2, and so forth. In defining the terciles, what is really necessary are the two boundaries, namely the borderline between the upper and the middle tercile, and that between the middle and the lower tercile. Observed and forecast rainfall values were each compared with the estimated boundaries and then came up with rainfall tercile for each region. Rainfall terciles for the observed were then compared with those for the forecast, resulting in a 3x3 contingency table. Using this contingency table, events falling under each cell were counted. Table 5 shows a schematic of a 3x3 contingency table indicating the common nomenclature of the individual cells of the table. The letters in the table represent the total events from the sample which fit the indicated forecast-observed combination. Hit rates were then calculated based on the entries in the contingency table:

A/D = percentage of correct forecasts of 'below normal' rainfall (relative to the total number of observed 'below normal' rainfall) = hit rate for 'dry' or 'below normal'

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[15] Kriging is a geostatistical interpolation method used to estimate values for unmeasured location points by getting the weighted linear combination of the surrounding measured points. The weights are based on the distance between the measured and unmeasured points as well as on the overall spatial arrangement among the measured points and their values, wherein the spatial autocorrelation is being quantified (ESRI, 2001).

[16] ArcView is geographic information system (GIS) software for visualizing, managing, creating, and analyzing geographic data (ESRI, 2001).

[17] Rainman International software is an integrated package about rainfall information and allows analyses of rainfall data for better management decisions (Clewett et al. 2002).

F/H = percentage of correct forecasts of ‘near normal’ rainfall (relative to the total number of observed ‘near normal’ rainfall) = hit rate for ‘average’ or ‘near normal’

K/L = percentage of correct forecasts of ‘above normal’ rainfall (relative to the total number of observed ‘above normal’ rainfall) = hit rate for ‘wet’ or ‘above normal’

After coming up with regional hit rates, national average was estimated. The average hit rates used in the RIS model are as follows: dry – 0.3868; average – 0.3823; wet – 0.4231.

Table 5. 3x3 contingency table of the observed and forecast rainfall

Observed/Forecast Rainfall	Forecast – below normal (or ‘dry’)	Forecast – near normal (or ‘average’)	Forecast – above normal (or ‘wet’)	Total
Observed – below normal (or ‘dry’)	A	B	C	D
Observed – near normal (or ‘average’)	E	F	G	H
Observed – above normal (or ‘wet’)	I	J	K	L
Total	M	N	O	P

Rice Supply and Demand

In this study, the general assumption is that the lean season (which covers the third quarter or the months of July, August, and September) is referred to as the ‘in-season’. In the Philippines, lean season is the period when the main crop is growing and potential shortages may be expected. This is perhaps the rationale behind the NFA mandate of positioning 90-day level of stocks from all sectors (i.e., government, commercial, household) by the end of June, in time for the lean season. This 90-day stock inventory usually comprised of any of the following: stocks carried over from the previous season; rice harvested from the second or dry cropping season, and; imports. The carry-over stocks include the production from the main or wet cropping season, which are harvested during the last quarter of the year. The rice planted during the second cropping season (which is usually from December to February), as noted earlier, are expected to be harvested from March up to May (since most rice varieties grow from about 3 to 4 months). The imports, on the other hand, are expected to arrive before the end of June. Because of the new procurement law (known as R.A. 9184), the importation process usually takes around 3 months now. Taking all these things into consideration, this study considered December as the most ideal time to finalize decisions on importation so as to give enough time for bidding, arrival, warehouse positioning, among others. All the necessary information needed for import decisions should be gathered during this period. Meanwhile, since the importation decision is made on December, the 'pre-season' period is assumed to cover the period January-June.

Expected Supply[18]

Expected supply has been equated to expected volume of rice production during the second cropping season, which is the last production prior to the in-season period. At this point, it is important to note that the expected rice supply refers to the expected paddy rice production for the second cropping season (estimated using the regional rice production models) less those that would be used for non-human consumption such as seeds, feeds and wastes, and for non-food processing. The amount left was then converted to well-milled rice since, as indicated in the earlier section, it is the most popular rice variety to consumer nowadays. The basic data used in estimating the expected supply were sourced from BAS.

For the simulation exercise, the estimated rice supply was based on predicted production for the second/dry cropping season or during the period March-May 2008 (using the regional production models; without any adjustment). Table 6 displays the expected rice supply for three different states.

[18] definition was based on suggestions of Ms. Fernandez of NFA, who is also attending IACRC meetings regarding rice importation

Table 6. Expected supply of rice* for 2008, in MT, by state and by region

Region	Dry	Average	Wet
NCR	0	0	0
CAR	56,360	81,743	74,740
Region I	113,674	106,982	129,684
Region II	479,814	522,582	625,376
Region III	629,318	698,056	641,122
Region IV-A	61,012	77,575	60,152
Region IV-B	170,689	207,005	185,538
Region V	150,961	171,386	162,792
Region VI	125,398	148,951	153,043
Region VII	32,099	83,138	97,252
Region VIII	252,165	242,000	270,418
Region IX	40,266	48,490	48,885
Region X	77,732	73,434	73,550
Region XI	80,320	90,167	116,881
Region XII	136,527	153,606	150,132
ARMM	40,565	64,879	62,776
CARAGA	96,950	121,592	120,534
PHILIPPINES	2,543,847	2,891,586	2,972,875

* based on production from the second or dry cropping season (March-May 2008)

Expected Demand

Expected demand is equivalent to estimated human consumption from the time the import decisions are made up to the end of the lean season. Thus, the data on expected demand cover the period December up to September. The human consumption requirements were derived by multiplying the estimated per capita consumption of rice (from BAS) by the population estimates (of the National Statistics Office, or NSO) for the period. Because data on rice supply and utilization accounts (SUA) released by BAS are not available at the regional level, estimates of rice per capita consumption from the Food Consumption Survey of Food and Nutrition Research Institute (FNRI) in 2000 were used since it is available down to the provincial level. Meanwhile, the expected demand would also include some buffer in addition to the estimated consumption requirements.

For the simulation exercise, the expected demand used was merely composed of the estimated consumption requirements for the period December 2007 to September 2008. Adding the mandated buffer requirements (which are equivalent to 30-day level for lean months and 15-day level for all other months) would blow up the estimates for the total import requirements, which are substantially higher than the actual importation in 2008.

Table 7. Expected demand for rice for 2008^, in MT, by region

Region	Per capita consumption (kg.)*	Population estimates for 2008**	Consumption (MT)	Expected Demand (MT)
NCR	6.92	11,252,700	778,687	778,687
CAR	7.88	1,625,600	128,162	128,162
Region I	9.16	4,974,000	455,631	455,631
Region II	7.18	3,250,100	233,494	233,494
Region III	8.48	9,770,100	828,686	828,686
Region IV-A	7.94	11,402,800	904,972	904,972
Region IV-B	8.99	2,865,800	257,555	257,555
Region V	8.50	5,497,200	467,519	467,519
Region VI	9.21	7,289,900	671,643	671,643
Region VII	4.84	6,754,200	327,190	327,190
Region VIII	8.67	4,273,000	370,555	370,555
Region IX	4.03	3,351,300	135,037	135,037
Region X	7.15	4,174,100	298,440	298,440
Region XI	7.47	4,222,800	315,435	315,435
Region XII	6.59	3,903,800	257,198	257,198
ARMM	8.71	3,395,900	295,946	295,946
CARAGA	8.55	2,453,900	209,716	209,716
PHILIPPINES		90,457,200	6,935,865	6,935,865

^ specifically, for the period December 2007 to September 2008
* monthly estimates; based on 2000 Food Consumption Survey by FNRI
** based on projection of NSO

Current Stocks Held

Currents stocks held refers to the total quantity of rice stored by all sectors (i.e., government, household, and commercial) at the time when the import decisions are made. Since December is considered as the most ideal time for making import decisions, the available data on stock inventory is the beginning stock inventory for December (i.e., as of December 1). It is assumed that the remainder of the harvest from the main or wet cropping season (which are either procured by the NFA or private traders, or just kept by the farming households for their own consumption) is already reflected in this stock inventory. Data on total rice stock inventory came from BAS. The national estimate for beginning stock inventory as of December 1, 2007 (or when the import decision is made) is 2,291,500 MT.

Net Import Demand

The net import demand reflects the rice supply and demand situation in the country. If there is a rice production shortfall in the country and the stock inventory handled by the three different sectors (i.e., NFA, household, commercial) are not enough to meet the demand for rice, importation is deemed necessary. However, if production and stocks held by the different sectors are sufficient, importation need not be conducted, considering that it is a very costly intervention.

Net import demand is defined as follows:

$$Net\ import\ demand = \begin{cases} 0,\ if\ \ current\ stocks + expected\ supply > expected\ demand \\ \\ (\text{expected demand - current stocks - expected supply}), \\ if\ \ current\ stocks + expected\ supply < expected\ demand \end{cases}$$

The resulting estimates for the net import demand are as follows:

Table 8. Estimates for net rice import demand for 2008, in MT, by state

State	Current stocks held (MT)	Expected supply (MT)	Expected demand (MT)	Net import demand (MT)
Dry	2,291,500	2,543,847	6,935,865	2,100,518
average	2,291,500	2,891,586	6,935,865	1,752,779
Wet	2,291,500	2,972,875	6,935,865	1,671,490

Although the estimated import requirements are still higher than the actual importation (which is equivalent to 1,220,952 MT[19]), these estimates are still the closest.

<u>Rice Import Prices and Other Import-Related Costs</u>

Rice Import Prices

Export price of Thai rice (5% broken) was used as the benchmark for the world price of rice because of the following reasons: (i) Thailand is now one of the leading rice exporters in the world; (ii) data on price of Thai rice (5% broken) are the most readily available among the Thai rice varieties.

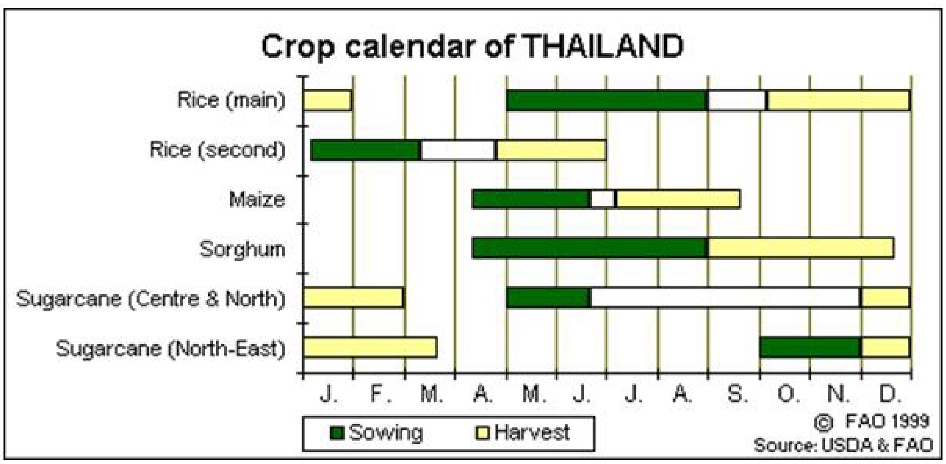
The pre-season price used is the export price of Thai rice (5% broken) for December. The in-season price, on the other hand, is the expected July price which was made dependent on the rainfall state. Thus, in-season rice prices were estimated for three different states. This was done by first grouping the years in which historical data on December and July prices are available based on ENSO state during the December-February planting period. Climate condition during this period greatly affects the supply, and

[19] excludes balance of 2007 contract and PL-480 (both for 2007 and 2008)

thus the prices, during the lean months. Justifications for the use of ENSO state during the December-February planting period are as follows:

(i) The Philippines and Thailand have almost similar rice cropping calendars. The planting period for the second or dry cropping season in the Philippines is from December to February and the harvest period is usually from March to May. In Thailand, the second crop is planted from January to early March (bulk are from January to February) and harvested from late April up to end of June (Refer to Figure 6). Thus, it is assumed in this study that the rice imported by the Philippines from Thailand during the lean season mostly (if not all) came from the latter's produce during the second crop.

(ii) Classification of the years should have been based on the rainfall state during the planting period in Thailand but data are not readily available. A good proxy for it is information on ENSO state during the planting period for the second crop since this is readily available at the NOAA website.



Note: This chart was taken directly from USDA-FAS (2009).

Figure 6. Rice cropping calendar in Thailand (first two lines)

After grouping the years, the percentage difference between the July and December prices were calculated and then averaged per group. The averages for the three groups were then incorporated to the pre-season price to come up with the estimates of the in-season prices for three different states.

The pre-season as well as the estimated in-season prices were only in Free On Board (F.O.B.) prices. Freight and marine insurance were then added to these prices to come up with Cost, Freight and Insurance (CIF) prices. Meanwhile, 50 percent of CIF were further added to incorporate tariff on imports.

Other Import-Related Costs

On top of the rice import prices in CIF plus the 50 percent tariff, other import-related costs were also included in the list of cost items in the model. These include the following: interest cost (10 percent per annum but payable only in 6 months); unloading expenses such as trucking and handling from disport up to the first warehouse (weighted by disport[20]); storage cost, and; distribution cost (assumption: from first warehouse up to the next warehouse only).

All import-related costs, including the pre- and in-season rice prices, used in this simulation exercise are shown in Table 9.

Table 9. Estimated rice import prices and other import-related costs, in PhP/MT

Item	Unit cost
Pre-season price[a/]	24,857.27
Other importation expenses[b/]	643.12
Storage cost	
- 3 months	187.32
- 6 months	374.64
Interest cost[c/]	0.05
Distribution cost[d/]	261.51
In-season prices[a/]	
- dry	28,445.78
- average	20,000.00
- wet	24,441.11

[a/] CIF + 50% tariff
[b/] unloading expenses (weighted by disport); also includes trucking and handling from disport up to 1st warehouse
[c/] 10% per annum; payable in 6 months
[d/] trucking and handling from 1st warehouse up to the next warehouse

Storage Capacity

Because the NFA can always lease additional warehouses when NFA warehouses cannot accommodate additional stocks (especially when the total volume of imports is larger than usual), storage capacity has been set to 3.0 million MT, which is far greater than the net import demand.

[20] Major disports in the country are located in the following areas: La Union (for Region I and Benguet); Subic (for Regions II and III, plus the rest of provinces in CAR); Metro Manila (for NCR); Batangas (for the whole Region IV); Tabaco/Legaspi (for Region V); Negros Occidental/Iloilo (for Region VI); Cebu (for Regions VII and VIII); Zamboanga City (for Region IX); Cagayan de Oro (for Region X); Surigao City (for CARAGA), and; Davao City/General Santos City (for Regions XI, XII and ARMM).

6.4. How RIS Model Works

The RIS model has been set up using the software called What's*Best!*, which was developed by LINDO Systems. This solver is an add-in to Microsoft Excel that could perform linear and non-linear optimization models in a range of applications such as resource allocation, financial planning, production, among others, in various fields like business, finance, science, etc. (LINDO Systems 2008)

Figure 7 shows how the RIS model works. This basically summarizes the discussions in the preceding sections through a diagram. Using the regional rice production models, the level of rice production can be predicted for three different states. These production estimates will be added to the current stocks held to make up the expected supply. Meanwhile, the expected demand can be estimated using per capita consumption and population estimates for the period. The expected supply will then be compared with the expected demand. If the difference between the expected supply and expected demand is positive, net import demand would be zero. If the difference is negative, it means that the government has to import rice and the net import demand is equivalent to the estimated difference. Net import demand varies across states, namely: dry, average, wet.

Another important parameter in the model is the set of in-season import rice prices. Aside from net import demand, the model takes into account also the in-season prices in determining how much and when to import rice. To estimate these in-season prices, the years in which historical data on December and July world prices are available were grouped based on ENSO state during the December-February planting period. After grouping the years, the percentage difference between the July and December prices were calculated and then averaged per group. The averages for the three groups were then incorporated to the pre-season price to come up with the estimates of the in-season prices for three different states.

These two parameters – together with pre-season rice price, other import-related costs, hit rates, and forecast type – were entered into the RIS model. The model will then solve the cost-minimization function and come up with a set of optimal importation policy strategies and their associated costs. Based on the optimal strategies and costs for different forecasts, the model will also estimate the potential value of SCF by getting the difference between the estimated cost of importation if the forecast is not used and the estimated cost of importation if forecast is used.

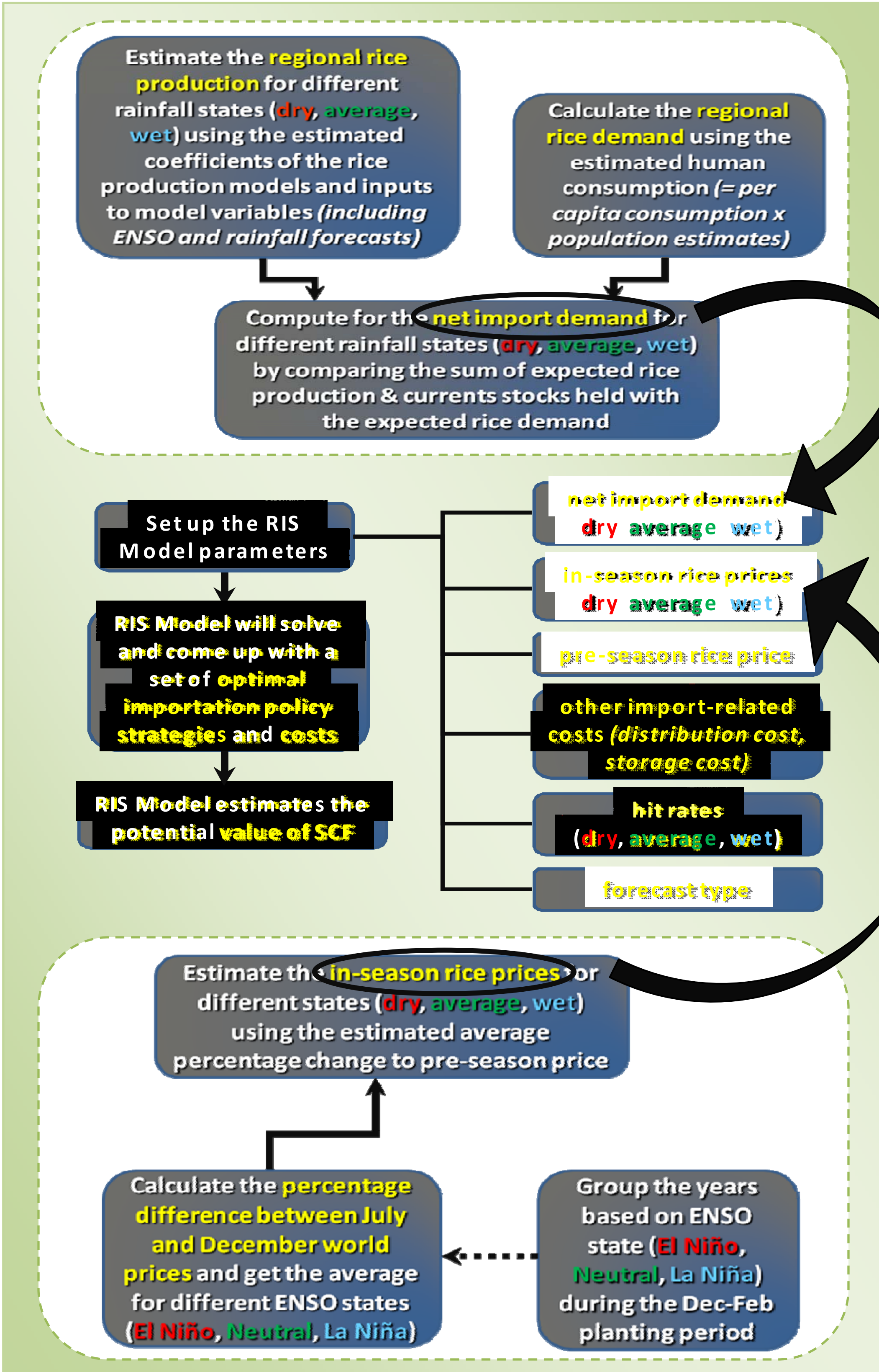


Figure 7. How RIS model works

6.5. Simulation Results

Using the preliminary estimates of PAGASA hit rates, the RIS model had shown that the potential importation cost when the forecast is used is not different from the cost when the forecast is not used. This is perhaps due to the fact that these hit rates are close to climatology (0.33) and are almost equivalent to zero forecast skill. This means that if there is a forecast, for instance, that the coming season would be drier than normal, the government will tend to be conservative in buying pre-season because it has not enough confidence which of the estimated in-season prices will prevail; whether the one that is lower or higher than the pre-season price. As shown in Table 10, the set of optimal import policy strategies under the 'No Forecast' scenario is the same as those under the 'With Forecast' scenarios. Under all of these scenarios, the model recommends pre-season buying which is equivalent to the net import demand for wet state. This result may be affected by the following: (1) hit rates under 'With Forecast' scenarios are not significantly higher than 0.33 and thus, each scenario yields the same set of optimal strategies; (2) the pre-season price is lower than the estimated in-season prices for the two states (i.e., dry and average) and thus, on the average, it might be more efficient to purchase higher volume during the pre-season than during the in-season, and; (3) net import demand for wet state is the lowest among import requirements for all states while the hit rate for this particular state is the highest, making it the most optimal volume to be purchased pre-season. Based merely on this set of results, it can be noted that indeed, the most critical parameters in RIS model that significantly affect the set of optimal import policy strategies and costs are the *hit rates*, *import rice prices (both pre- and in-season)*, and the *net import demand*. A series of sensitivity analyses were then carried out to further evaluate the effects of these input parameters on the outputs of the model, which include the set of optimal import policy strategies and costs as well as the potential value of SCF.

Table 10. Simulation results using preliminary estimates of PAGASA hit rates

Rainfall state/Hit rate	Dry	0.3868		
	Avg	0.3823		
	Wet	0.4231		
Forecast	No Forecast	Forecast - dry	Forecast - avg	Forecast - wet
Posterior probability				
- dry	0.3333	0.3868	0.3088	0.2884
- avg	0.3333	0.3066	0.3823	0.2884
- wet	0.3333	0.3066	0.3088	0.4231
Policy strategy	Rice	Rice	Rice	Rice
Buy pre-season	1,671,490	1,671,490	1,671,490	1,671,490
Buy in-season				
- dry	429,028	429,028	429,028	429,028
- avg	81,290	81,290	81,290	81,290
- wet	0	0	0	0
Store in-season				
- dry	0	0	0	0
- avg	0	0	0	0
- wet	0	0	0	0
Distribute in-season				
- dry	2,100,518	2,100,518	2,100,518	2,100,518
- avg	1,752,779	1,752,779	1,752,779	1,752,779
- wet	1,671,490	1,671,490	1,671,490	1,671,490
Policy cost	Million	million	million	million
- dry	Php58,966.74	Php58,966.74	Php58,966.74	Php58,966.74
- avg	Php48,169.85	Php48,169.85	Php48,169.85	Php48,169.85
- wet	Php45,764.39	Php45,764.39	Php45,764.39	Php45,764.39
Estimated Mean Value (EMV)	Php50,966.99	Php51,608.57	Php50,761.40	Php50,266.20
Forecast is not used		Php51,608.57	Php50,761.40	Php50,266.20
Forecast is used		Php51,608.57	Php50,761.40	Php50,266.20
Value of single forecast		Php0.00	Php0.00	Php0.00
Value of forecasting system	**Php0.00**			

The first sensitivity analysis was done using hit rates as the input variable. Under the 'Forecast-dry' scenario, the model recommends pre-season buying that is equivalent to net import demand for wet state if hit rate for dry state ranges from 0.3868 (preliminary estimate of PAGASA hit rate) to 0.75, holding the hit rates for average and wet states constant at preliminary estimates of PAGASA hit rates. When the hit rate is increased to 0.80 or 0.85, the recommended volume increased moderately to the net import demand for average state (which is slightly higher than that for wet). When forecast skill becomes closer to 100 percent (i.e., 90-100%), that is the time when the model recommends pre-season buying that is equivalent to net import demand for dry (which is the highest among all import requirements). Similar set of observations were found under the ‘Forecast-average’ scenario. If the forecast is an average state, the government is only advised to buy pre-season the volume of imports required for that state if the hit rate for such state is 0.85 or higher. These observations indicate that the government should only buy pre-season the volume equivalent to total import requirements for a particular state if such state has a very high probability of occurrence and if the estimated in-season price for this state is higher than the pre-season price. If the forecast is wet, on the other hand, the model stops buying pre-season (or delays importation) when the hit rate reaches 0.80. Because the estimated in-season price for wet is lower than the pre-season price, the government is more confident in buying the total import requirements during the in-season because it would definitely give great savings.

The sensitivity analysis using hit rates as the input variable revealed that there is such a threshold level for skill of the forecast before it becomes reliable and thus, affects the policy strategies of the government. Specifically, SCF starts to have a value if hit rates for dry, average and wet are set to 0.80, 0.85 and 0.80, respectively. Accordingly, the threshold levels for the skill of the forecast for dry, average and wet states are 0.70, 0.775 and 0.70, respectively. Both Table 11 and Figure 8 summarize the results. The slope of the curves in the graph also indicates that the marginal increase in the hit rates for dry and wet states gives higher SCF value compared to that for average state. This implies that correctly forecasting an extreme climate condition (either dry or wet state) would be very important for the government in terms of minimizing the amount required for importation. Table 12 and Figure 9, meanwhile, display the simulation results when hit rates are equal for all states. It can be observed from the results that 0.70 is the threshold level for forecast skill (equivalently, 0.8 for hit rate) if they are equal for all states. Assuming that all of the parameters in the model are reasonable and realistic, all the above results imply that an increase of around 50 percent in the preliminary estimates of PAGASA hit rates is required in order for the SCF to become useful for the government in terms of achieving efficiency in rice importation.

Table 11. SCF value at varying hit rates for a particular state (holding two others constant at PAGASA hit rates)

Hit rate	SCF Value (in million)		
	Dry	Average	Wet
0.3333	Php0.00	Php0.00	Php0.00
0.4500	Php0.00	Php0.00	Php0.00
0.5000	Php0.00	Php0.00	Php0.00
0.5500	Php0.00	Php0.00	Php0.00
0.6000	Php0.00	Php0.00	Php0.00
0.6500	Php0.00	Php0.00	Php0.00
0.7000	Php0.00	Php0.00	Php0.00
0.7500	Php0.00	Php0.00	Php0.00
0.8000	Php5.56	Php0.00	Php49.46
0.8500	Php27.16	Php2.35	Php150.14
0.9000	Php86.25	Php21.54	Php250.83
0.9500	Php285.76	Php40.74	Php351.51
1.0000	Php485.27	Php59.93	Php452.20

Note: Hit rates are for a particular rainfall state, holding two others constant at preliminary estimates of PAGASA hit rates

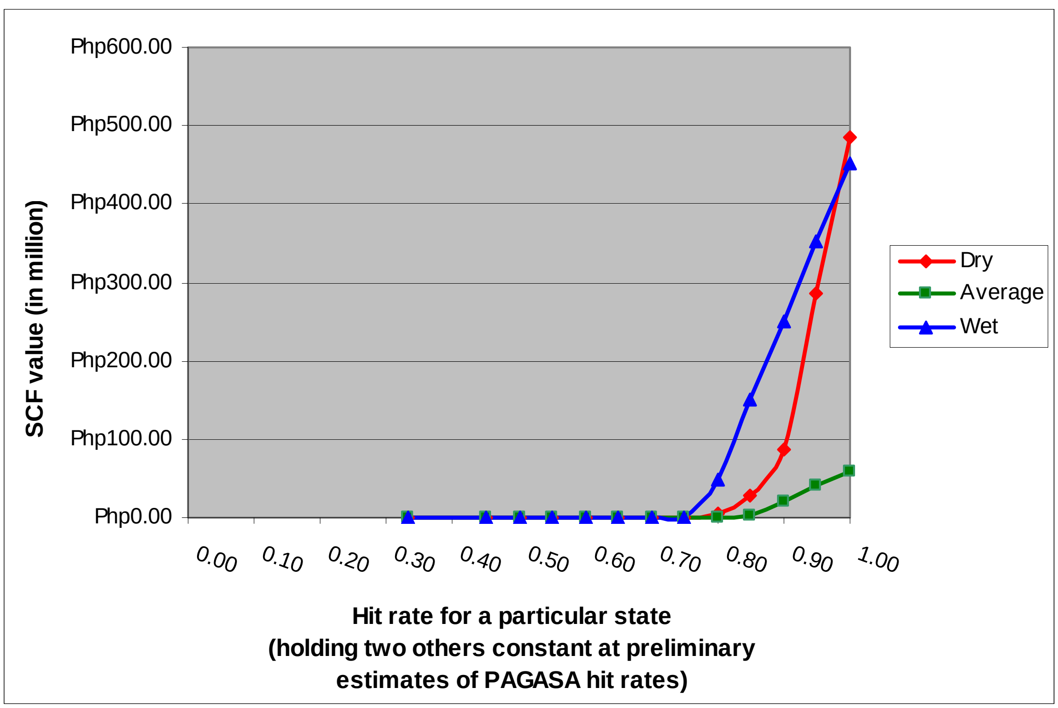


Figure 8. SCF value at varying hit rates for a particular state (holding two others constant at PAGASA hit rates)

Table 12. SCF value at varying hit rates for all states

Hit Rate			SCF Value (in million)
Dry	Average	Wet	
0.3333	0.3333	0.3333	Php0.00
0.3868	0.3823	0.4231	Php0.00
0.4500	0.4500	0.4500	Php0.00
0.5000	0.5000	0.5000	Php0.00
0.5500	0.5500	0.5500	Php0.00
0.6000	0.6000	0.6000	Php0.00
0.6500	0.6500	0.6500	Php0.00
0.7000	0.7000	0.7000	Php0.00
0.7500	0.7500	0.7500	Php0.00
0.8000	0.8000	0.8000	Php55.02
0.8500	0.8500	0.8500	Php179.65
0.9000	0.9000	0.9000	Php358.62
0.9500	0.9500	0.9500	Php678.01
1.0000	1.0000	1.0000	Php997.40

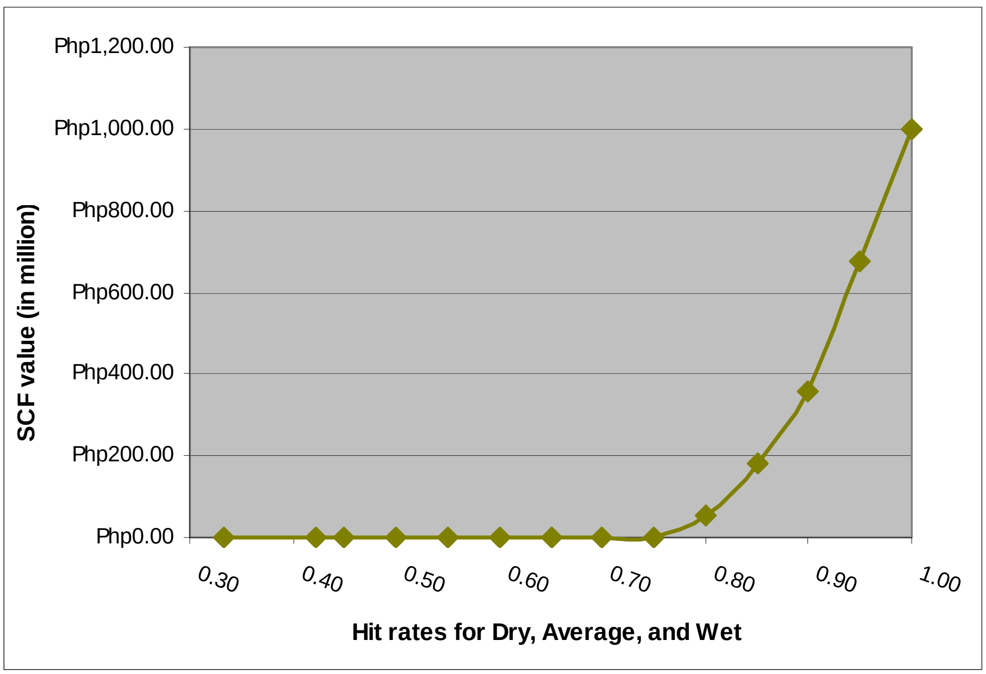


Figure 9. SCF value at varying hit rates for all states

In doing sensitivity analyses using in-season prices and net import demand as input variables, hit rates for all states were fixed at 0.80 because SCF starts to have a value only at this level. To determine the effect of in-season prices on SCF value, prices for all states were varied from PhP25,000 to PhP35,000, holding hit rates constant at 0.80 and net import demand at their estimated values. Table 13 and Figure 10 summarize the results of price sensitivity analysis. Generally, increasing the in-season price (away from the pre-season price) simultaneously for all states increases the SCF value. SCF starts to have a value when the in-season prices for all states were increased to PhP29,000, which is around 4,000-peso higher than the pre-season price. Because the expected level of rice production varies minimally across states, such gap between the pre-season and in-season price marks the minimum price difference that could induce decisionmakers (who are forecast users) to opportunistically vary the distribution between the pre-season and in-season volume of importation which in turn could result in positive SCF value. Clearly, as the price difference becomes larger, SCF value increases further.

To determine the effect of net import demand on SCF value, import requirements for all states were varied from 1.0 million to 3.0 million MT, holding hit rates constant at 0.80 and in-season prices at their estimated values. Table 14 and Figure 11 show the results of sensitivity analysis using net import demand as input variable. The results indicate that SCF value increases as net import demand for all states increases. Optimal set of import strategies remained the same across different values of net import demand. Because in-season prices for dry and average states are relatively higher than the pre-season price, pre-season buying is recommended if the forecast is either dry or average. If the forecast is wet, however, in-season buying is recommended since pre-season price is lower. Thus, as the net import demand increases, the estimated gains from using SCF in coming up with a set of optimal import strategies also increases.

Table 13. SCF value at varying in-season rice prices for all states
(using hit rates of 0.80 for all states)

In-season rice prices	SCF Value (in million)
Php25,000	Php0.00
Php26,000	Php0.00
Php27,000	Php0.00
Php28,000	Php0.00
Php29,000	Php45.91
Php30,000	Php97.12
Php31,000	Php148.34
Php32,000	Php227.27
Php33,000	Php375.85
Php34,000	Php524.43
Php35,000	Php673.01

Note: In-season rice prices are equal for all states

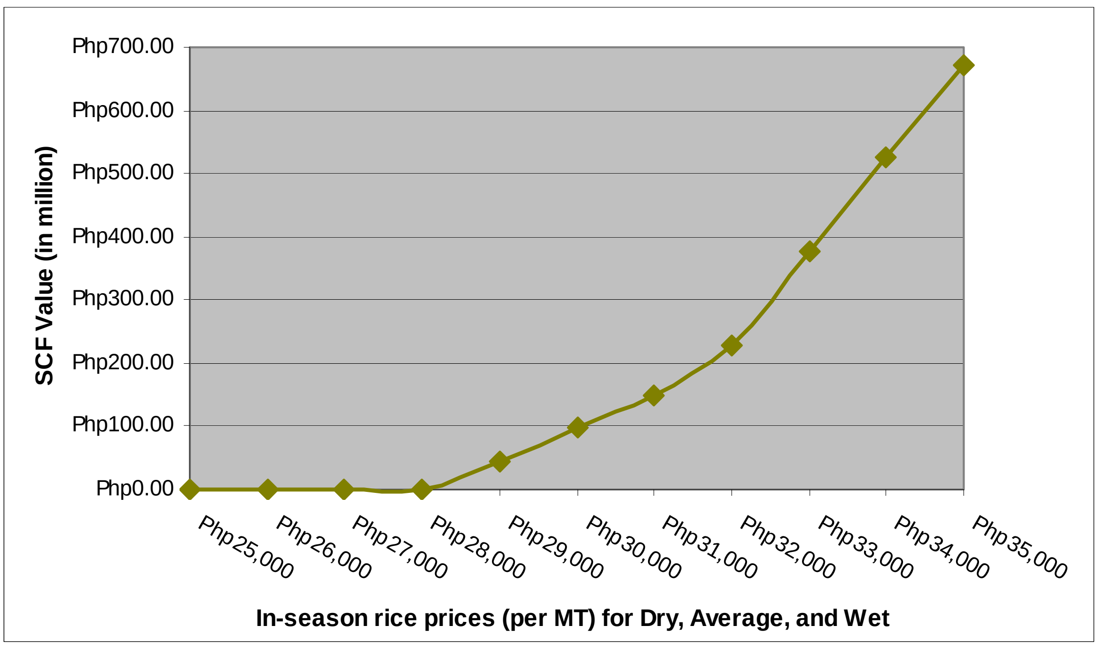


Figure 10. SCF value at varying in-season rice prices for all states
(using hit rates of 0.80 for all states)

Table 14. SCF value at varying net import demand for all states
(using hit rates of 0.80 for all states)

Net import demand (in MT)	SCF Value (in million)
1,000,000	Php29.59
1,500,000	Php44.38
2,000,000	Php59.18
2,500,000	Php73.97
3,000,000	Php88.77

Note: Net import demand are equal for all states

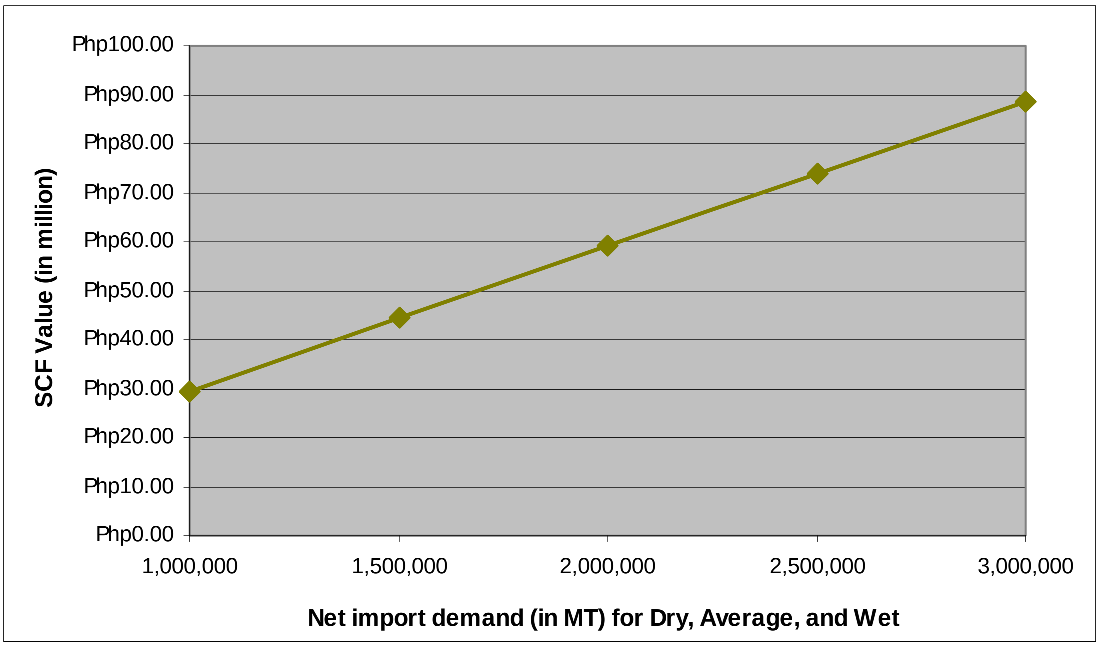


Figure 11. SCF value at varying net import demand for all states
(using hit rates of 0.80 for all states)

7. Summary, Conclusions and Recommendations

This study had demonstrated an approach that systematically links SCF with rice import decisions. In particular, it had shown that SCF can be incorporated in rice production models to predict the total supply of rice. Together with the estimated total demand for rice, the rice production models can be used to forecast the required level of importation. Using the import demand estimates, estimated prices and climate forecast information, the RIS model was able to determine the optimal level of rice to be imported pre-season and in-season. The model was also used to estimate the potential value of SCF based on the optimal volume and timing of rice importation under different forecast scenarios. The initial simulations suggest that the value of SCF is sensitive to both the skill of the forecast and attributes of the decisionmaking environment. In this context, assumptions about rice production and prices have key and complex influence on the value of the forecast. Simulation results indicate that there is a threshold for forecast skill to have a positive value of SCF. Specifically, the skill should be at least 70 percent (equivalent to 80 percent hit rate) for dry and wet states and 77.5 percent (equivalent to 85 percent hit rate) for average state. The simulations also found that skillful forecasts for dry and wet states translate into relatively higher SCF value. This implies that the government would benefit enormously from using SCF if it can correctly forecast the occurrence of an extreme climate event. Aside from hit rates, in-season prices and net import demand were also found to have significant influence on the set of import policy strategies and SCF value. Price sensitivity analysis indicates that SCF value increases as the difference between the in-season and pre-season price of rice gets larger. The results also revealed that there is a minimum price difference required to opportunistically vary the distribution between the pre-season and in-season volume of importation. Similarly, SCF value increases with net import demand. The results of the sensitivity analysis imply that as the import demand increases, the estimated gains from using SCF in coming up with a set of optimal import strategies also increases.

Moreover, the potential value of SCF had been estimated at the national level. Because this does not reflect how the NFA coordinates regional rice stocks, the approach might have underestimated the true value of SCF. The NFA has the opportunity to re-distribute rice between regions, but this had not been modeled yet. The optimum decision is likely to be climate-sensitive. This opportunity adds value because re-distribution decision could be made in response to forecast. Another is that there could be a localized forecast skill at the regional or local level that had not been taken into account. Further refinements in the RIS model could also be done by making the in-season prices dependent on climate forecasts. Meanwhile, refinements in the rice production models could also be considered to be able to get better estimates of the total supply, which would be essential inputs in the rice import decisions of the government.

Notwithstanding the limitation of the current version of the model, the rice production estimates of the model could already be used in support of the current practice of forecasting rice production based on planting intentions. Together with these production estimates, SCF could also be incorporated in the RIS model to be able to come up with a set of optimal rice import strategies that would serve as guide for the government in its rice import decisions.

References

Abedullah and S. Pandey. 2007. "The Value of Rainfall Forecasts in the Rainfed Rice Areas of the Philippines". *The Lahore Journal of Economics* 12(2): 69-81 (Winter 2007).

Amien, I., P. Redjekiningrum, B. Kartiwa, and W. Estiningtyas. 1999. "Simulated Rice Yields as Affected by Interannual Climate Variability and Possible Climate Change in Java". *Climate Research* 12: 145-152.

Bureau of Agricultural Statistics (BAS). 2008. "Metadata of BAS Statistics". Retrieved on 10 July 2008 from: <http://countrystat.bas.gov.ph>.

Chatfield, C. 2000. *Time-Series Forecasting*. Boca Raton, FL: Chapman and Hall/CRC.

Clewett, J. F., O. S. Hwang, D. T. Owens, D. A. George, and I. J. Partridge. 2002. "Rainman International Version 4: An Integrated Software Package of Rainfall Information for Better Management". QI02023, Department of Primary Industries, Queensland.

Climate Prediction Center, National Centers for Environmental Prediction (NCEP), National Oceanic and Atmospheric Administration (NOAA), United of States Department of Commerce (USDA). 2008. "ENSO Cycle: Recent Evolution, Current Status and Predictions" (15 June 2009).

Crean, Jason. 2009. "The Economic Value of Seasonal Climate Forecasts in Central West New South Wales (NSW)". Doctoral thesis (unpublished), Charles Sturt University, Orange, New South Wales, Australia.

Das, H. P., D. M. Rase and M. P. Shewale. 2006. "Dependence of Rice Yield in Orissa on Rainfall and Sea Surface Temperature Anomalies over Equatorial Pacific SST". *Vayumandal* 32 (1-2): 28-32.

David, C. 2006. "The Philippine Hybrid Rice Program: A Case for Redesign and Scaling Down". *Research Paper Series* No. 2006-03. Makati City, Philippines: Philippine Institute for Development Studies.

David, W. P. (n.d.). "El Niño Southern Oscillation (ENSO): Its Impact on Philippine Agriculture".

David, C. C. and A. B. Inocencio. 1995. "Comparative and Competitive Advantage of Philippine Rice Production: 1966-1990". *PIDS Discussion Paper* Series No. 95-03 (October). Makati City, Philippines: Philippine Institute for Development Studies.

Dawe, D., P. Moya and C. Casiwan (eds). 2006. "Why Does the Philippines Import Rice?: Meeting the Challenge of Trade Liberalization". Los Baños, Laguna and Sciency City of Muñoz, Nueva Ecija, Philippines: International Rice Research Institute (IRRI) and Philippine Rice Research Institute (PhilRice). 166 pp.

Delos Reyes, M. L. F. And W. P. David. 2009. "The Effect of El Niño on Rice Production in the Philippines". *The Philippine Agricultural Scientist* 92(2): 170-185 (June).

Environmental Systems Research Institute, Inc. (ESRI). 2001. Using ArcGIS™ Spatial Analyst. Retrieved on August 2009 from: <http://www.gis.unbc.ca/help/software/esri/Tutorials/Using_ArcGIS_Spatial_Analyst_Tutorial.pdf>.

Falcon, W. P., R. L. Naylor, W. L. Smith, M. B. Burke, and E. B. McCullough. 2004. "Using Climate Models to Improve Indonesian Food Security". *Bulletin of Indonesian Economic Studies* 40(3): 355-377.

Foreign Agricultural Service (FAS), United States Department of Agriculture (USDA). 2009. "Thailand: Drought Affects 2004/05 Rice Crop". Retrieved on 5 May 2009 from: <http://www.fas.usda.gov/pecad/highlights/2004/12/Thai04/index.htm>.

Frechtling, D. C. 1996. *Practical Tourism Forecasting*. Linacre House, Jordan Hill, Oxford: Butterworth-Heinemann.

Fraisse, C. W., J. O. Paz and C. M. Brown. 2007. "Using Seasonal Climate Variability Forecasts: Crop Yield Risk". *CIR1498* (January). Florida: Institute of Food and Agricultural Sciences (IFAS), University of Florida.

Hogg, R. V. and A. T. Craig. 1995. *Introduction to Mathematical Statistics* (5th ed.). Upper Saddle River, New Jersey: Prentice Hall, Inc.

Ignacio, J. 2005. "Trading-off Philippine Rice: Implications of the Proposed Removal of Quantitative Restriction (QR)". Quezon City: Integrated Rural Development Foundation of the Philippines.

Intal, P. and M. Garcia. 2005. "Rice and Philippine Politics". *PIDS Discussion Paper* Series No. 2005-13. Makati City, Philippines: Philippine Institute for Development Studies.

ITSMF-NL. 2006. *Metrics for IT Service Management*. Zaltbommel, Netherlands: Van Haren Publishing.

Kajisa, K. and T. Akiyama. 2003. "Evolution of Rice Price Policies over Four Decades: Thailand, Indonesia, and the Philippines". Tokyo, Japan: Foundation for Advanced Studies on International Development.

Kaul, S. (n.d.). "Bio-Economic Modelling of Climate Change on Crop Production in India". New Delhi, India: Indian Agricultural Statistics Research Institute.

Lansigan, F. P. 2004. "Coping with Climate Variability and Change in Rice Production Systems in the Philippines". In *Rice is Life: Scientific Perspectives for the 21st Century*. Proceedings of the World Rice Research Conference held in Tsukuba, Japan, 4-7 Novermber 2004, pp. 542-45.

Lewis, C. D. 1982. *Industrial and Business Forecasting Methods* (2nd ed.). London: Butterworths.

LINDO Systems. 2008. "What'sBest!". Retrieved on 25 July 2008 from: <http://www.lindo.com>.

Naylor, R. L., W. P. Falcon, D. Rochberg, and N. Wada. 2001. "Using El Niño/Southern Oscillation Climate Data to Predict Rice Production in Indonesia". *Climate Change* 50:255-265.

Ramos, C. G. 2000. "State Intervention and Private Sector Participation in Philippine Rice Marketing". Quezon City, Philippines: Management and Organizational Development for Empowerment, Inc.

Reburiano, M. P. 2005. "NFA Rice Importation". Presentation during the First Consultation Meeting ACIAR-funded project *Bridging the gap between seasonal climate forecasts and decisionmakers in agriculture*, 8 July 2005, NEDA Building, Makati City, Philippines.

Recide, R. S. 2005. "Inter-Agency Committee on Rice and Corn (IACRC)". Presentation during the First Consultation Meeting on ACIAR-funded project *Bridging the gap between seasonal climate forecasts and decisionmakers in agriculture*, 8 July 2005, NEDA Building, Makati City, Philippines.

Reyes, C. M., S. N. Domingo, C. D. Mina, and K. G. Gonzales. 2009. "Policy Options for Rice and Corn Farmers in the Face of Seasonal Climate Variability". *PIDS Discussion Paper Series* No. 2009-11 (April). Makati City, Philippines: Philippine Institute for Development Studies.

Reyes, C. M. and C. D. Mina. 2009. "Profitable Use of SCF in a Policy Context: The Case of Rice Stockholding in the Philippines". *PIDS Discussion Paper Series* No. 2009-09 (March). Makati City, Philippines: Philippine Institute for Development Studies.

Sarma, A. A. L. N., T. V. Lakshmi Kumar and K. Koteswararao. 2008. "Development of an Agroclimatic Model for the Estimation of Rice Yield". *Journal of the Indian Geophysical Union* 12(2): 89-96 (April).

Satake, T. And S. Yoshida. 1978. "High Temperature Induced Sterility in Indica Rices at Flowering". *Japanese Journal of Crop Science* 47: 6-17.

SCF Project Team. 2005. "Understanding the ENSO Phenomenon and Its Implications". *Economic Issue of the Day* 5(1) (July 2005). Makati City, Philippines: Philippine Institute for Development Studies.

Tao, F., M. Yokozawa, J. Liu, and Z. Zhang. 2008. "Climate-Crop Yield Relationships at Provincial Scales in China and the Impacts of Recent Climate Trends". *Climate Research* 38: 83-94.

Tolentino, B., B. de la Peña, E. Noveno, B. Rayco, and I. L. Villapando. 2002. "101 Facts about the NFA". DA-DOF-ADB TA 3429 (10 May 2002).

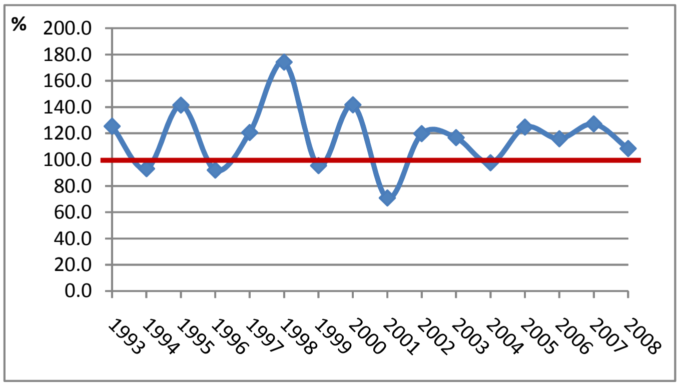
Unnevehr, L. J. 1985. "The Costs of Squeezing Marketing Margins: Philippine Government Intervention in Rice Markets". *The Developing Economies* 23(2): 159-172.

Verceles, E. R. 2005. "Basics of El Niño Southern Oscillation (ENSO)". Presentation during the Pulong Saliksikan, 21 April 2005, NEDA Building, Makati City, Philippines.

Zubair, Lareef. 2002. "El Niño Southern Oscillation Influences on Rice Production in Sri Lanka". *International Journal of Climatology* 22: 249-260.

Annex A. Predicted as percentage of actual levels of production, by region, 1993-2008

CAR



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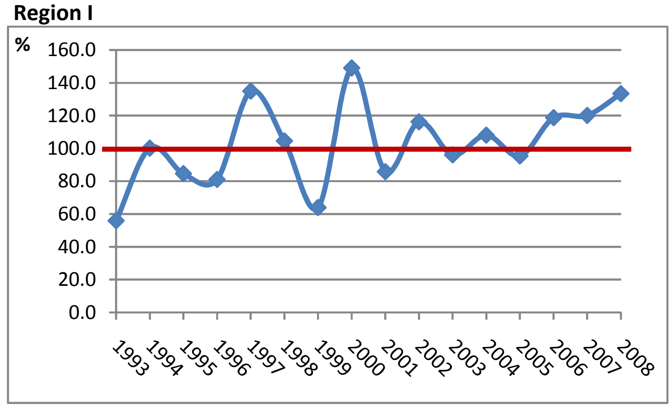

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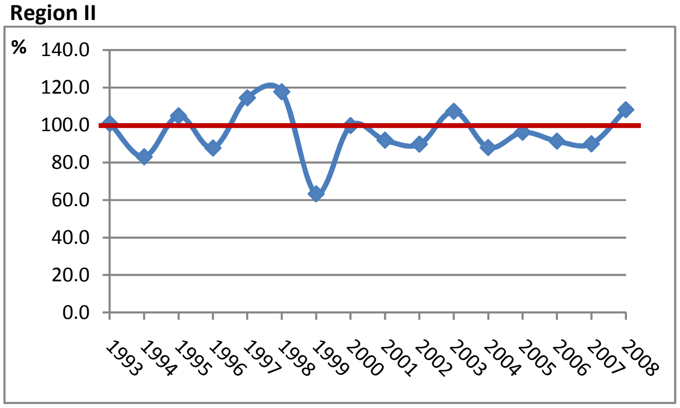

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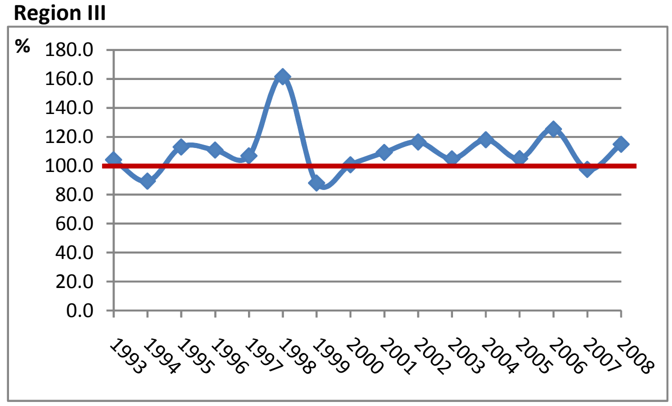

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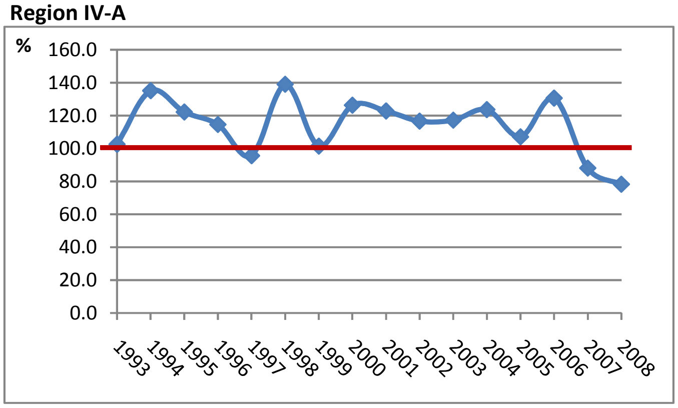

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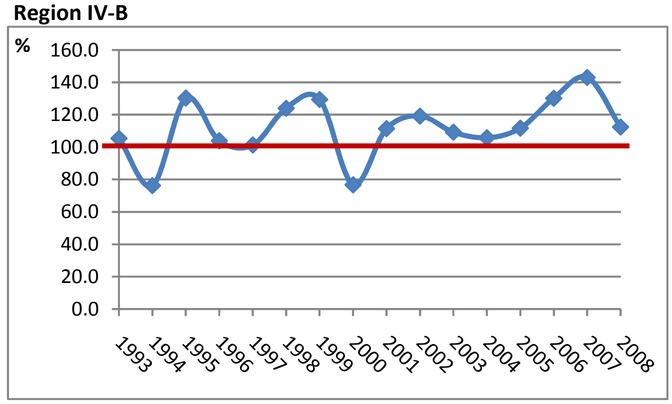

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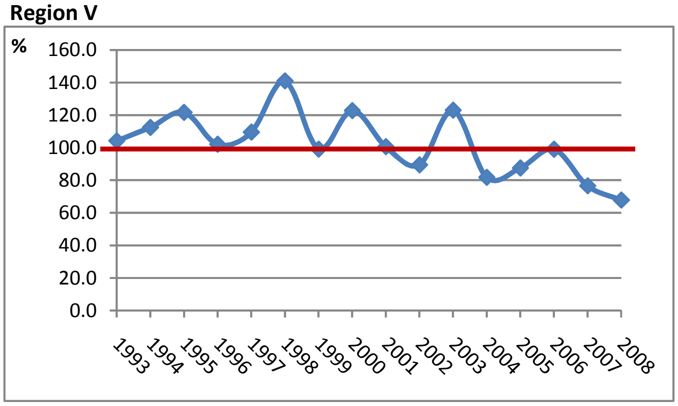

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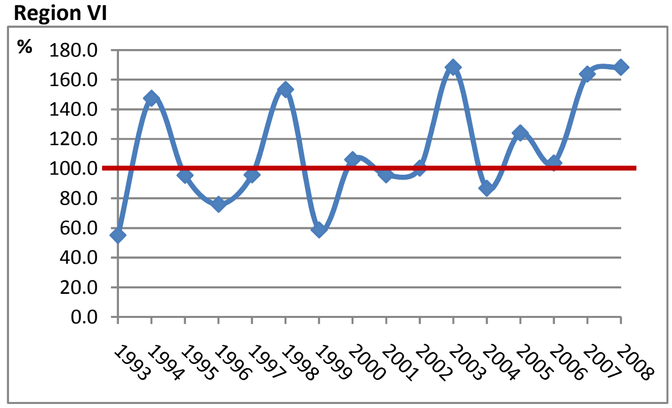
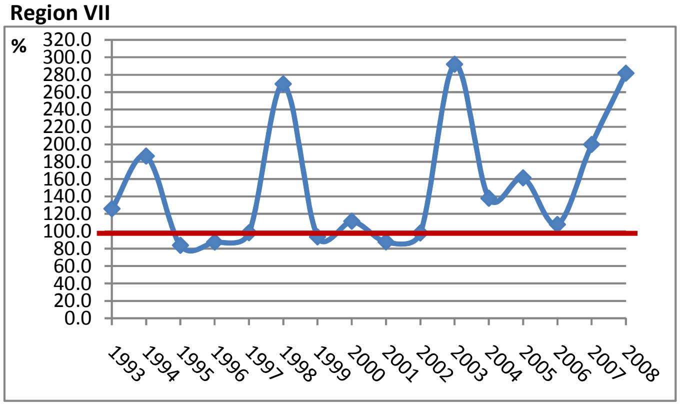


Annex A. (continued)

Region VII



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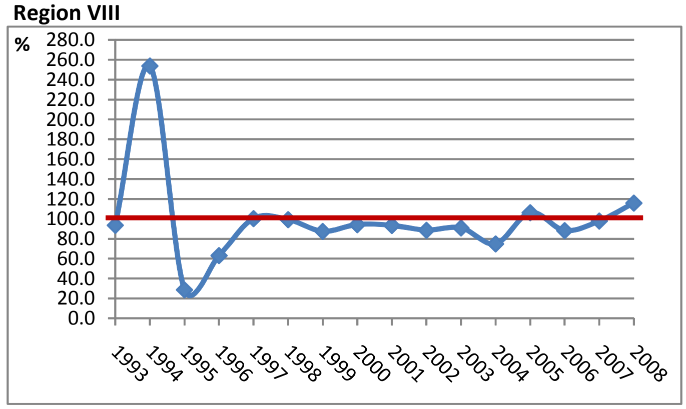
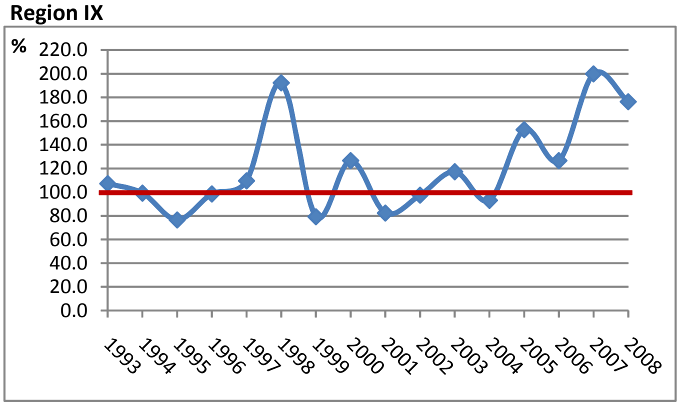


Region IX



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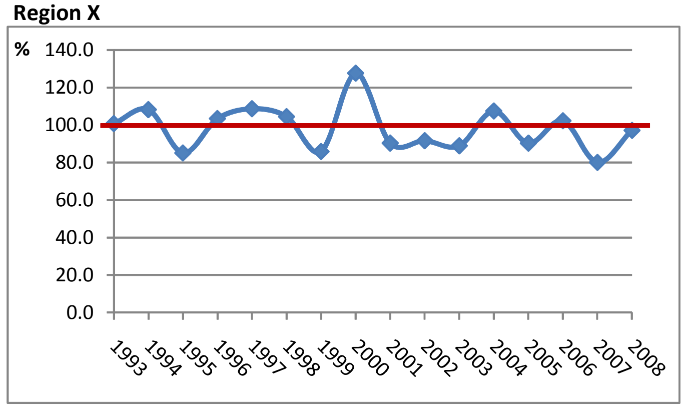

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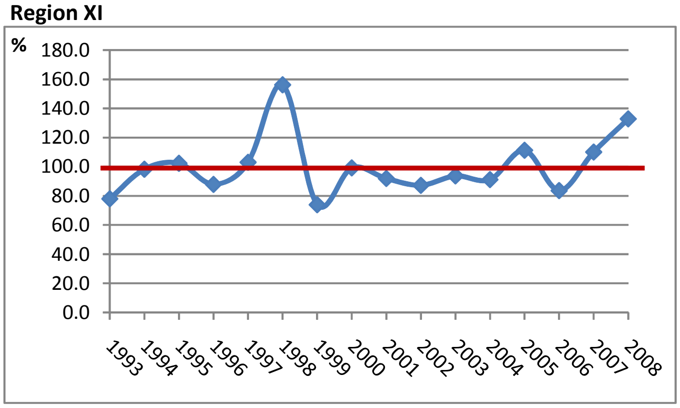

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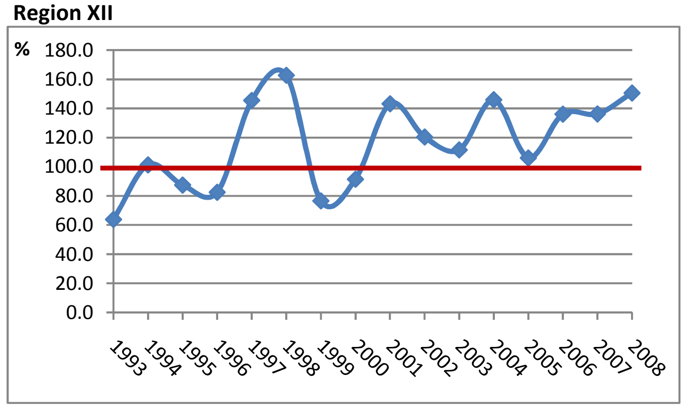

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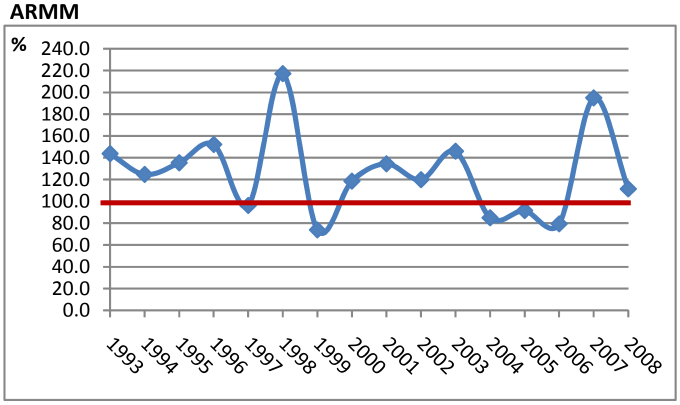
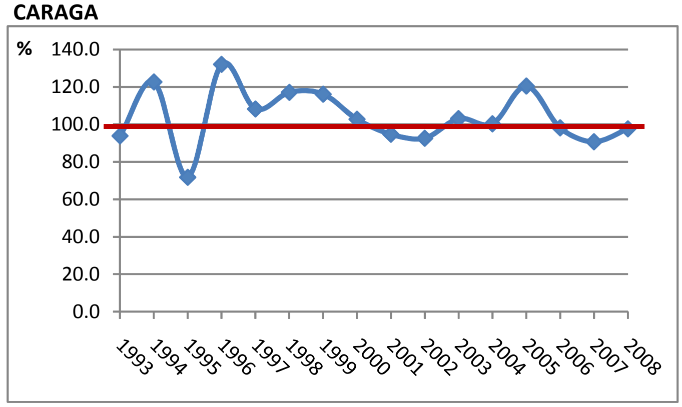


CARAGA



Annex B. El Niño vulnerability map for rice