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Approaches in Forecasting Cereals Production

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ABSTRACT

We assess the forecasting abilities of transfer function model and spatial autoregression, along with the possible benefits from deseasonalization. When the deterministic seasonal components are set aside, the structural dynamics in a time series model of the remaining stochastic components are better understood, hence empirically fitted well, facilitating forecasting. However, a model that best incorporates the interactions among different agents of seasonality is still superior to that of the model that only sets aside seasonality, not making it an integral part of the model. When there is a pronounced, stable seasonality usually occurring when deterministic seasonality dominates the stochastic seasonality, deseasonalization becomes beneficial for forecasting in transfer function models.

Spatial autoregression provides an alternative modeling framework when there is a constraint on available explanatory variables. Spatial and temporal autoregressions can account for spatial externalities and temporal accumulations that explain a large part of the fluctuations in a time series forecasting situation. Using rice and corn production data for the Philippines, forecast errors can be reduced by at least half with the inclusion of a spatial autoregressive term in the model.

Keywords: ARIMA models, transfer function models, deseasonalization, spatial autoregression, backfitting

I. INTRODUCTION

The Philippines is an agricultural country. Rice and corn are the two of the major cereal commodities that significantly affect the country's economy and politics. These crops are the most economically and politically important crops monitored by a wide spectrum of stakeholders. Supply levels of these crops have to be maintained at a certain level to ensure food security. Timmer (2004) points out that food security and economic growth interact in a mutually reinforcing process over the course of development. For developing countries, government interventions are deemed vital since records show that these interventions can lift the threat of hunger and famine for enhanced food security. Forecasts of production are therefore essential to help policy makers formulate mitigating measures in the event of a shortage, price volatility, and other socio-economic disturbances.

Ruttan (2002) notes that one of the leading resource and environmental constraints faced by the world's farmers include impact of climate change among other factors. Changes in temperature, rainfall and sunlight may also alter agricultural productivity, although the effects will vary greatly across regions. These changes can be very well linked to El Niño Southern Oscillation (ENSO), indexed by the Southern Oscillation Index (SOI) in this paper. BOM (2008) includes a wide variety of information on SOI. Ruttan (2002) further added that

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prior to the start of the twentieth century, almost all increases in crop production occurred as a result of increases in the area cultivated. Then, by the end of the century, most increases are attributed to increases in land productivity.

It is thus regarded important to look into the effects of both area planted/harvested and Southern Oscillation Index (SOI) in forecasting production levels of rice and corn. The efficient utilization of inputs by the farmers and other agronomic endowments including environmental integrity can provide better insights on the dynamics of cereal production. However, due to the limited access to measurable indicators of these factors, quantification into the model will be impossible. We propose a modeling strategy (spatial autoregression) that can serve as a proximate measure of other production inputs. Comparison of forecast accuracy will be done using ARIMA models as a benchmark and transfer function models as a possible structural model alternative. The possible roles of the very basic factors of production like area planted/harvested and Southern Oscillation Index are explored. Deseasonalization is also assessed to determine the potential benefits that forecasting can derive from.

II. SOUTHERN OSCILLATION INDEX AND AGRICULTURE

Climate is one of the primary determinants of agricultural production. Weather remains to be one of the most important uncontrollable factors in an agricultural production system. To understand the production dynamics, it is essential to have a clear understanding of these weather fluctuations such as those irregularities caused by El-Niño Southern Oscillation (ENSO).

The El-Niño Southern Oscillation (ENSO) can be described broadly as an anomalous oceanic and atmospheric phenomenon during which unusually warm ocean condition appears along the western coast of Ecuador and Peru causing climatic disturbance of varying severity. It has to be realized that ocean and atmosphere form one intricately interrelated system. The ocean supplies heat and water vapor to the atmosphere to drive large-scale wind circulation. Winds, in turn, power ocean currents. The key manifestation of Southern Oscillation is a seesaw exchange of air between eastern Southern Pacific and the equatorial Indian Ocean around Indonesia. The Southern Oscillation always starts and disappears about the same time in the following year so that comparable events are likely to occur in the same season. In particular, when the pressure measured at Darwin is compared with that measured at Tahiti, the differences between the two can be used to generate an "index" of the magnitude of the oscillation, called Southern Oscillation Index (SOI). The SOI can provide a good picture of the weather condition of a country. This can be used as an indicator of the overall amount of rainfall expected in the country. In the Philippines, a large positive SOI indicates La Niña or severe rainfall (eastern tropical Pacific ocean cooling) and a large negative number SOI indicates El Niño or less rain (or ocean warming). See BOM (2008) for further details.

Several studies stress the strong dependence of many agricultural activities on weather. Some try to establish the influences and effects of ENSO on agriculture. Naylor et al (2002) note that climate patterns associated with El Niño and La Niña episodes exert dominant influence on agricultural productivity and food security in Southeast Asia. In Indonesia, the production of rice and corn is especially vulnerable to climate variability with ENSO events. The authors examine two intermediate linkages to model the impacts of climate variability on grain area and production – the relationships between ENSO and rainfall and the direct association between ENSO and rice area planted and harvested. They also measure the direct connection between ENSO and rice output in the wet season. Another study looks into the crops that are vulnerable to ENSO-related weather variability and therefore likely to benefit from application of ENSO-based climate forecasts. Hansen et al (1998) point out that ENSO phase significantly influenced corn and tobacco yields, the areas of soybean and cotton harvested, and the values of corn, soybean, peanut and tobacco.

Adams et al (1999) develop estimates of the economic consequences of ENSO phenomena on US agriculture using stochastic economic model of the US agricultural sector. Both El Niño and La Niña result in economic damages to US agriculture. The paper likewise stresses that forecasts of ENSO events have potential economic value because they can stimulate actions that mitigate adverse consequences or take advantage of potential gains for an ENSO phase.

Harris and Robinson (2001) study the economy-wide effects of ENSO in Latin America. Results show that improved forecasting techniques can help mitigate agricultural losses. ENSO events harm some regions, particularly Central, Pacific South, and South East regions, more than others. Since these regions are the ones with higher poverty level, they should be targeted by poverty alleviation programs incorporating the effects of ENSO events.

III. TRANSFER FUNCTION MODELS

Modeling time series data requires capturing more data characteristics (e.g. autocorrelation and seasonality) compared to modeling cross section data. Regression analysis is a convenient tool that often serves the purpose of understanding the dynamics between the dependent variable and a set of determinants. There are however, many complications that contradict the distributional assumptions when time series data is used. The most common among these is the dependence among the error terms. Many of the optimal properties of the ordinary least squares estimates will not be satisfied. Although regression with autocorrelated errors can be considered, since it includes models with AR, MA or ARMA errors, it assumes only linear relationship between the dependent and independent variables.

Transfer function models are generalized version of the regression model with autocorrelated errors. The dependent variable called the output may assume a more general functional relationship with the independent variable called the input. Relationships can be linear or nonlinear and the model can allow for lagging of the effects of the input to the output. Transfer function models can be more effective than nonstructural models if one or more time series can be found to be closely related to the time series to be forecasted, Bowerman (1989).

In the Box-Jenkins methodology, the term transfer function model refers to a model that predicts future values of a time series based on the past values of the time series as well as on the past values of one or more related time series time series, see Box et al (1994). One of the assumptions of transfer function models is that there is unidirectionality in the relationship between the input and output series, no feedback mechanism (output towards input) is present. Prior to modeling, if the output and input series are stochastic, these are centered and differenced, if necessary, to attain stationarity. Seasonal differencing and deaseasonalization may also lend an instrument to simplify the modeling process.

The general transfer function model with input series has the form

$$w_t = \mu + \sum \frac{\omega_i(B)}{\delta_i(B)} B^{k_i} x_{i,t} + \frac{\theta(B)}{\phi(B)} a_t \tag{1}$$

Where w_t is the output series or the differenced or transformed series which is stationary

μ is the constant term

$X_{i,t}$ is the i^{th} input series or the difference of the i^{th} input series at time t

k_i is the pure time delay for the effect of the i^{th} input series

$\omega_i(B)$ is the numerator polynomial of the transfer function for the i^{th} input series

$\delta_i(B)$ is the denominator polynomial of the transfer function for the i^{th} input series

B is the backshift operator

$\phi(B)$ is the autoregressive operator defined by $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$

$\theta(B)$ is the moving average operator defined as $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$

a_t is the independent disturbance, also called random error

The model can also be written more compactly as

$$w_t = \mu + \sum_i \psi_i(B) X_{i,t} + \eta_t \tag{2}$$

Where $\psi_i(B)$ is the transfer function weight for the i^{th} input series modeled as ratio of two polynomials as $\psi_i(B) = \frac{\omega_i(B)}{\delta_i(B)} B^{k_i}$, and η_t is the error series: $\eta_t = \frac{\theta(B)}{\phi(B)} a_t$. This model expresses the response series as a combination, which could be linear or nonlinear, of past and present values of the random shocks and other input series. Wei (2005) presents a summary of the theoretical foundations of the transfer function model.

Transfer function models are used in a wide variety of forecasting problems. In economics, transfer function models of leading indicators are used in forecasting business cycles. A transfer function model can show how a change in net import is affected by a change in exchange rate. In marketing, these models are used to determine the factors, such as advertisement, competition, or economic conditions that may affect the sales of certain products. Transfer function models are also frequently used in environmental studies where we may be interested on how air and water pollution are affected by various environmental factors. We can then determine, among other things, the effectiveness of pollution control policy by using such models.

In terms of forecasting, transfer function models require more values of the input variables. For example, if there is a lag of say, 6 months between the movement of the input and output, this implies that one can predict at most 6 future observation of the output. Unless forecasts for the input series are available, we cannot have longer forecast lead using the transfer function. Since most of the input variables are exogenous, it can be projected independently, before fitting the model for the response series to generate independent forecasts that are then used in the transfer function to generate forecasts in the longer horizon.

Box et al (1994) notes that an advantage of dealing with transfer function models is that in some situations this approach can lead to a considerable reduction in the errors of the forecasts. It also lends itself to a better understanding of the response series by incorporating other relevant time series that can help predict values of the desired time series with improved accuracy.

IV. SPATIAL AUTOREGRESSION MODEL

Cereal production is to a large extent a function of many spatial endowments and externalities. Soil fertility, agricultural programs, cultural practices of the farmers, and technological innovations are just a few of many such factors. They can lend a better explanatory power to characterize the dynamics of cereal production, but data is very scanty even for proximate indicators. In a regression model, the error term is a composite summary of all the effects of other determinants that are not explicitly accounted into the model in addition to pure error. Pace and Barry (1997) introduced sparse spatial autoregression that attributes certain portion of the residuals to spatial externalities. The model was able to reduce the amount of residuals, but in estimating the contributions of spatial externalities, some proximate measures of "neighborhood" will be needed. Landagan and Barrios (2007) study various measures of neighborhood indicators that best explains spatial externalities in cereal production setting. An estimation procedure that is a hybrid between the Cochranne-Orcutt procedure and the backfitting algorithm was also introduced along with a generalized spatial-temporal model.

Cereal production will be postulated as a sparse spatial autoregression model given by:

$$y_t = \beta_0 A_t^{\beta_1} + \delta D\left(y_t - \beta_0 A_t^{\beta_1}\right) + \varepsilon_t \qquad \varepsilon_t = \rho\varepsilon_{t-1} + a_t \quad a_t \sim N\left(0, \sigma_a^2\right) \tag{3}$$

where y_t is the measure of cereal production at time t and A_t is area harvested at time t. The factors of production are represented by area harvested, SOI, and the autoregression of the error term. SOI is incorporated into the model through the autoregression component.

D is an indicator of spatial correlations. In this paper, we define a neighborhood as characterized by weather similarities. Natural agronomic endowments, technology, agriculture programs and other inputs are easily "enhanced" or "neutralized" by weather conditions. Thus, the notion of neighborhood over time is defined in terms of weather conditions. Barrios (2004) observed that when SOI is lower than -10, there is usually a drought in the Philippines (El Niño), while when the values exceed +10, there is unusually more rains than normal (La Niña). When SOI ranges from -10 to +10, this episode is usually considered as "normal" weather conditions. Following similar argument, this paper segmented the time points based on the SOI values, those with less than -10 as one neighborhood, those with SOI from -10 to +10, as another neighborhood, and those with +10 as another neighborhood. Assuming that production in the same neighborhood are exposed in the same spatial externalities, the matrix of spatial distance D can be defined as a block diagonal, nonzero values for the elements are assigned with units in the rows and columns are in the same neighborhood, zero otherwise. This will result to averaging the residuals for units in the same neighborhood and used as regressor in the third component of equation (3).

The parameters are estimated using the hybrid of the Cochranne-Orcutt procedure and the backfitting algorithm proposed by Landagan and Barrios (2007).

V. THE DATA

The data used in this paper are obtained from the Rice and Corn Production Survey (RCPS) of the Bureau of Agricultural Statistics (BAS). This is a quarterly survey that covers provinces as its domain. Although provincial data are available, the aggregated regional data is used in this paper to illustrate the relative advantage of spatial autoregression when there are limitations on data availability. The time series from first quarter of 1990 to fourth quarter of 2005 of production and area harvested are used.

Production of cereals (rice and corn) in the Philippines is characterized by marked seasonality. In irrigated rice paddies, there are two complete production cycles in a year, three for some. In upland areas however, only one production cycle is completed in a year, planting only happens during the rainy season. Corn is planted less frequently in a year, one cycle is completed for many farmers, and two cycles a year for the more efficiently planning farmers. Rice production peaks very 4th quarter of the year while it is usually on the 3rd quarter for corn production. In the time plots in Figures 1 and 2, there is a striking drop in production in 1998 when the world experienced a severe El Niño event (a global weather anomaly whose effect in the Philippines is prolonged dryspell). This shows that the effects of drought provide the clearest evidence of vulnerability of the agricultural sector.

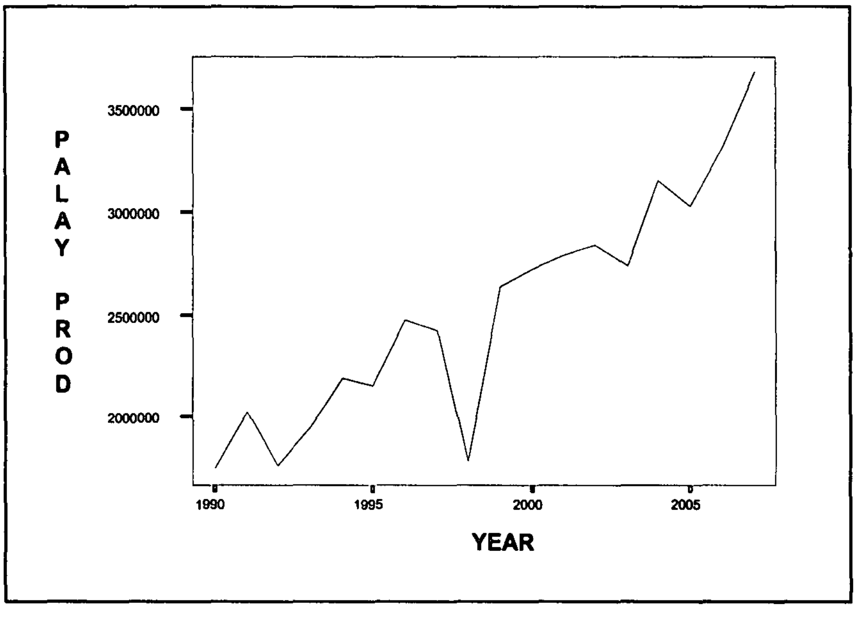

Figure 1. Rice Production in the Philippines (1990-2005)

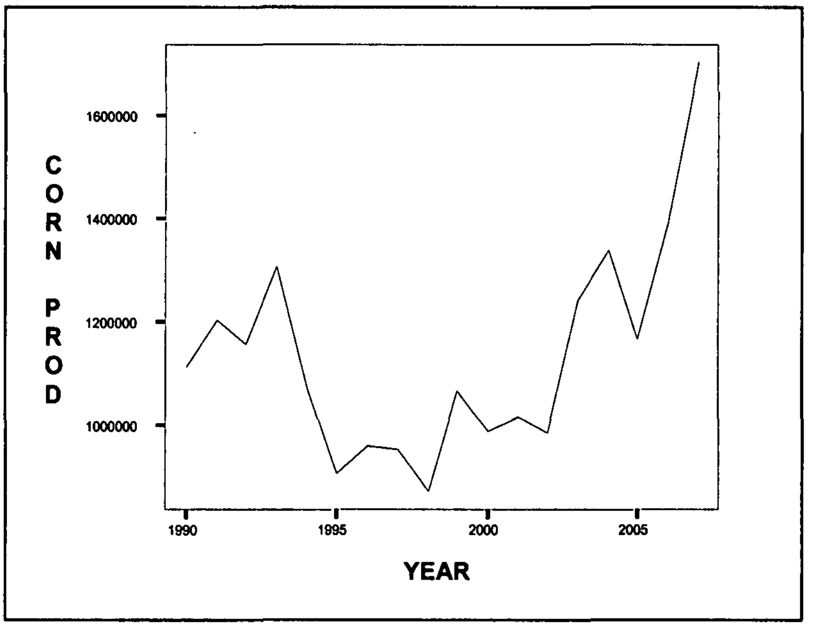

Figure 2. Corn Production in the Philippines (1990-2005)

The monthly SOI data used was downloaded from BOM (2008). Monthly data for SOI was aggregated (average) into quarterly summaries for compatibility with other indicators.

VI. RESULTS AND DISCUSSION

In modeling rice and corn data, quarterly breakdown from 1990 to 2005 are used in the estimation of forecasting models. There are many measures of predictive accuracy like the Diebold-Mariano Test Diebold and Mariano (1995), but the simplest measure, mean absolute prediction error (MAPE) is used since the goal of the study is to address the limited data problem in forecasting time series data.

The univariate ARIMA models are fitted initially for both series. A nonstructural model like ARIMA is convenient to use in forecasting since it does not require information on other time series. This shall serve as a benchmark in assessing the three strategies namely deseasonalization, transfer function modeling, and spatial autoregression in forecasting rice and corn production.

6.1. Rice Production

ARIMA (Original Data)

A deterministic seasonal pattern will cause the series to be nonstationary since the expected value of the series will not be constant for all time periods. Persistent repetition of high or low values can recur as stimulated by the seasonal fluctuations, causing the mean and variance to exhibit dynamic behavior in the entire realization of the time series. Since rice production exhibit persistent seasonal patterns, it is seasonally differenced at a lag corresponding the length of the cycles of the season. Even after seasonal differencing, a seasonal autoregressive model turns out to be the best, indicating that both a deterministic and a stochastic seasonal behavior are contained in the series. After doing seasonal differencing, the model includes an autoregressive component with lag of 4. The final model is given by:

$$\left(1-B^4\right)\left(1-0.2728B^4\right)y_t = 88959 + a_t \qquad (4)$$
$$(p < 0.037) \qquad (p < 0.026)$$

The model exhibits a MAPE of 13.17% (sd=15.35).

ARIMA (Deseasonalized)

Because of the deterministic seasonality observed in rice production, deaseasonalization was done to pave the way for a better understanding of the stochastic characteristics of the time series. A stable seasonality ($p<0.001$), using F-test for presence of seasonality assuming stability, is indeed confirmed in the course of deseasonalizing the series. The average quarterly seasonal indices are 94.92, 72.67, 66.36 and 165.67, for the first, second, third and fourth quarter, respectively.

First differencing is still needed to achieve stationarity of the deseasonalized rice production. The final model is given by:

$$(1-B)(1-0.3304B)y_t = a_t \qquad (5)$$
$$(p < 0.0088)$$

Note that deseasonalization affected in the way the nonstationarity of the model is interpreted in the empirical model-fitting work. The deterministic seasonal component can potentially mask other nature of nonstationarity that the time series may exhibit. The model in equation (4) yield a MAPE of 8.85% (sd=9.85), much better than the MAPE in equation (3). In this case, the improvement in MAPE that can be attributed to deaseasonalization is approximately 4.32%.

Transfer Function Models

In using transfer function, three models are determined varying only the inputs included in the model. The first model includes both rice area harvested and SOI. The second and third models separately include only one of the input series. A separately modeling exercise for single and multiple input transfer function will empirically assess the implications in forecasting when inputs are correlated, as in the case of SOI and area harvested. The estimation results are shown in Appendix 1.

When the two input series are included in the transfer function model, seasonal differencing is required for both rice production and area harvested to achieve stationarity. The resulting model is autoregressive with both input variables significant.

Simultaneous inclusion of area harvested and SOI may pose a question on the possibility that the two are correlated. Thus, models are determined including only one of the inputs. First, only area harvested is considered to influence rice production. The results show a seasonal moving average model with area harvested as a significant input, is appropriate for the data. When SOI is considered to be the input variable, again a seasonal autoregressive and a significant SOI appear in the model.

Spatial Autoregression

There is an evidence of diminishing returns to scale in rice production in the Philippines, a 1% increase in rice production area can only result to a 0.99% increase in actual rice production ($p<0.000$). There is also an evidence of competition for the limited area planted to rice and corn, a 1% increase in corn production area can mean a 0.12% reduction in palay production. There is also a very strong correlation between production in consecutive time points ($\rho=0.71$), reflecting the overlapping production cycles among all farmers across the country. Production cycle varies according to the weather pattern that significantly varies from the northern to the southern parts of the country. The spatial autoregression term also contribute significantly in explaining the behavior of palay production ($p<0.006$). The portions of the fluctuations in rice production that cannot be explained by area are accounted by both the spatial autoregression and the temporal autoregression terms. The spatial autoregression term accounts for the externalities that are associated/related to weather endowments since SOI is used in defining the spatial neighborhood. The temporal autoregression, on the other hand, explains the accumulation of inputs that is improving over time, e.g., technology, agriculture programs, etc.

Discussion

With the original rice production data, it seems that the simultaneous inclusion of SOI and harvest area is beneficial for forecasting. Since SOI drives primarily the seasonal movements of the agriculture sector in general, and harvest area in particular, the fact that seasonality represented by SOI and its implication, represented by area harvested, can best explain the dynamics in rice production. When area alone or SOI alone is included in the model, the benefits over ARIMA does not add up to (lesser) the gains in MAPE when both inputs are included in the model.

The display of a strong seasonality in rice production leads to the deseasonalization of the series before modeling. The X12 procedure is employed to remove the seasonal component of the series. The seasonal part accounts for 90.87% of the stationary portion of the variance in the original rice production series. The final seasonal indices are given in Appendix 5. These can be used both in deseasonalization of future values and in converting the forecasts back to its original level.

Following the same procedure on deseasonalized series as in the original series, both area and SOI are included initially. For the input series, only area requires seasonal differencing since SOI is already stationary. First differencing of the deseasonalized rice production series is found necessary since the correlogram does not die off quickly. A seasonal moving average with both inputs significant turns out to be the best with both inputs lagging by 1 quarter.

The model considers only area harvested as input variable. Area harvested is seasonally differenced to attain stationarity. The final model includes a seasonal moving average with a significant input variable.

Only SOI serves an exogenous variable. There is no need to difference SOI as it is already stationary. The final model is a moving average and SOI lags by 1 quarter.

If instead, SOI is used as the basis in defining spatial neighborhood and a spatial autoregression model is fitted, there is a dramatic improvement in the forecast ability of the model with harvest area alone as the available indicator of production input.

The summary of forecast accuracy of the models above is presented Table 1.

Table 1. MAPE for Rice Production Models

Model	**Palay**	
	Original	Deseasonalized
ARIMA	13.17	8.85
Transfer Function		
Both Inputs	3.73	7.75
Area only	11.87	6.51
SOI only	11.57	7.34
Spatial Autoregression	2.83	

For palay production, the forecast from ARIMA modeling benefits from deseasonalization. Transfer function models also generally benefits from deseasonalization. When the deterministic seasonal components are set aside, the structural dynamics in a time series model of the remaining stochastic components are better understood, hence empirically fitted well, facilitating forecasting. However, a model that best incorporates the interactions among different agents of seasonality is still superior to that of the model that only sets aside seasonality, not making it an integral part of the model. The spatial and temporal autoregressions can adequately account for the absence of other indicators of inputs of production.

6.2 Corn Production

ARIMA (Original Data)

Corn production is first analyzed using univariate ARIMA with no input. This serves as a benchmark for the structural models that are also fitted. To determine if the forecasts will benefit from deseasonalization, X12 procedure is also used.

For the original corn production data, the fitted model is given by

$$\left(1-B^4\right)\left(1-0.2622B^4\right)y_t = a_t \qquad (6)$$
$$(p < 0.0475)$$

There is also a strong deterministic seasonality in corn production data, needing both seasonal differencing and seasonal component into the model. The model however, exhibits weak forecasting ability since the MAPE is quite large at 17.50% (sd=29.015).

ARIMA (Deseasonalized)

For deseasonalized corn production, first differencing is still needed to achieve stationarity. The final model yields better forecasting ability with MAPE at 13.22% is given by:

$$(1-B)y_t = (1+0.79942)a_t \qquad (7)$$
$$(p<0.001)$$

Transfer Function Models

A scatterplot of corn production and area harvested for corn shows a strong positive linear relationship between the two time series. It is thus hypothesized that area harvested may have an influence on corn production. Using area harvested for corn and SOI as input variables, the transfer function model indicates a moving average component with both input variables showing significance. The effect of SOI lags by 1 quarter.

With area harvested only as an input to corn production, the model includes a moving average and the effect of area is found significant. On the other hand, another model is determined by including only SOI as an influence to corn production. A seasonal ARMA model fits the data and SOI is likewise found significant.

Since corn production displays pronounced seasonality, the series is deseasonalized using X12 procedure. Strong seasonality is indeed found in the time series. The relative contribution of the seasonal component to the overall behavior of the data is 89.17%.

Utilizing the same procedure on deseasonalized corn production, all models include a seasonal moving average term and all inputs whether treated together or monadically are significant. A look on the forecast accuracy of all models yields a conclusions that transfer function models are superior (smaller MAPE) although the discrepancies are not that large but there seems to be an indication that inclusion of other exogenous variable may prove helpful in coming up with good forecasts.

Spatial Autoregression

While palay production in the Philippines already exhibits diminishing returns to scale, corn production exhibit the reverse, a 1% increase in production area can result to a 1.03% increase in production ($p<0.000$). Palay production area is not a threat to corn production since increasing palay production area will not significantly influence corn production ($p<0.552$). Many corn production areas in the Philippines are not viable for palay production while many palay production areas can still be converted into corn production areas. There is strong temporal dependence of corn production among consecutive months ($\rho=0.75$), indicating the varying production cycle adopted by different farmers across the country. The spatial autoregression component also contributes significantly in explaining corn production ($p<0.001$). Production inputs interacting with weather conditions (summarized by SOI) are indeed, important determinants of corn production.

Discussion

An important application of transfer function is in forecasting. If there is a dynamic relationship between the input and output variables then past values for those time series can be used in forecasting the output variable. In some conditions, this approach can lead to a considerable reduction in the errors of the forecasts (Box et al, 1994). This is supported by the smaller MAPE for all transfer function models compared to ARIMA models. Forecasting production of rice and corn appears to have benefited from using a set of other time series. In addition to these, an examination of Appendix 5 shows that seasonal indices for rice production are more variable compared to those of corn production. This suggests that the seasonal component for rice production is better accounted by deseasonalization. This means that when there is a pronounced, stable seasonality usually occurring when deterministic seasonality dominates the stochastic seasonality, deaseasonalization becomes beneficial for forecasting. Corn production data also illustrates the usefulness of spatial autoregression in forecasting time series data with limited data on other determinants. In this case, prediction error has been reduced tremendously, up to about 50%.

Table 2. MAPE for Corn Production

Model	**Corn**	
	Original	Deseasonalized
ARIMA	17.50	13.22
Transfer Function		
Both Inputs	15.06	10.12
Area only	17.38	10.44
SOI only	15.75	11.78
Spatial Autoregression	7.53	

VIII. CONCLUSION

Modeling production data based on its past values as well as the past values of other pertinent variables such as area harvested and SOI proves helpful. The use of transfer function models provides a clearer insight on rice and corn production and optimizes the use of information available. Since it is known that area and SOI have an influence on production, it is valuable using this information to have better forecasts.

Deseasonalization in general offers a reduction in mean absolute percentage errors. Rice production benefited more from deseasonalization since seasonality is more pronounced. This variability is better captured by deseasonalization than by simply incorporating seasonal differencing in the model.

In lieu of other factors of production that may not be easily measured/collected, spatial and temporal autoregressions can be used. It can account for a large part of spatial externalities and temporal accumulation that help explain fluctuation in production.

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