Lizlei Valdez

DEVELOPING AN INDEX SYSTEM FOR US IN WEATHER INDEX-BASED INSURANCE

ABSTRACT

The Philippines is one of the top 16 countries that are vulnerable to climate change and one of the industries highly affected by this phenomenon is agriculture. According to the World Bank, the said sector accounts for 12% of the Philippine's economy and employs 37% of the Filipino workforce in 2012—conditions that expose the country and its constituents further to additional risks.

One of the financial instruments that most countries use to mitigate the risks of their farmers is crop insurance. However, with the administrative and miscommunication problems that arise from traditional crop insurance, other alternatives have been explored; one of which is by using weather as an index for insurance.

This study introduces a new methodology for creating a weather index and a corresponding strike level for use in index-based insurance using time series analysis techniques. The researchers used daily weather data provided by PAGASA and quarterly palay yield data from the Bureau of Agricultural Statistics for the province of Nueva Ecija, Philippines for the years 1988 to 2013. The index was formed using the coefficients generated from the AutoRegressive Moving Average with Exogenous variables (ARMAX) model that could describe most of the variation in crop yield while taking into account the effects of different weather variables. An appropriate corresponding strike level which tempers the shocks but captures the trend, seasonality, and cyclical component of the palay yield was also determined. Furthermore, the suggested methodology were subjected to forecast evaluation tests in order to assess its accuracy. Finally, a method to calculate basis risk using time series data has also been proposed.

Keyword/s: ARMAX, Weather-based index insurance, WIBI, basis risk, ARMA

I. INTRODUCTION

A. Background of the Study

Asia has been tagged as the most vulnerable continent to the damages that climate change has and will be bringing upon (McKie 2014). It has been reported that people living in the continent are four times more likely to be affected than those who are in Africa and 25 times more likely than those in Europe and Africa (Lohani 2012). With an increased frequency and intensity of flooding and a higher rate of drought (IPCC 2007), it has been expected that there would be an increased number of weather-induced diseases and deaths and a substantial decrease in crop yields (TERI 2014).

Moreover, 10 out of the top 16 most vulnerable countries to climate change are Asian and unfortunately, the Philippines is one of them (New Scientist 2010). This does not come as a surprise considering the number of strong typhoons that has devastated the country for the last five years: Typhoon Ondoy*(Ketsana)* caused losses amounting to PhP 11.121 billion mostly in Metro Manila, CALABARZON, and Central Luzon (Alojado and Padua 2010); Typhoon Pepeng*(Parma),* left damages which summed to approximately PhP 27.195 billion, mostly in Northern Luzon and Cordillera (Alojado and Padua 2010); and Typhoon Yolanda *(Haiyan),* the strongest storm that hit the Philippines, left Leyte and Samar needing more than PhP361 billion pesos to rehabilitate and reconstruct the affected villages (Xinhua 2013).

Along with the plans to minimize the causes of climate change, certain actions regarding the farmers' livelihood must be formulated and implemented since agriculture is highly dependent on the weather conditions. The Philippines, being an agricultural country (Advameg, Inc. n.d.), has its economy hinged on the outputs that farmers produce. Furthermore, inability to help them recover from financial shocks might lead to food scarcity as they will not have any means to buy what is necessary to produce crops. It has been reported that rice and corn production have already had a yield reduction of 15-27 and 12-19 percent, respectively (Vista 2014) which coincides with the worldwide reduced food production growth of 2 per cent per decade (Gillis 2013). With the anticipated rise of global food demand to 50 per cent by the year 2030 (UNDESDA 2014), methods to support and empower the poorest people of this country must become a priority.

One of the best ways to help farmers recover during times of unexpected weather phenomena is through crop insurance. Crop insurance is defined as the legal commitment between the farmer who "agrees to insure all the eligible acreage of a crop planted in a particular county" and the insurance provider who agrees to protect the farmer against the losses that may be incurred during the cropping year. (United States Department of Agriculture n.d.)

The case of the corn producers and farmers in Midwest America during the great drought of 2012 (Walsch 2012) is an illustration of how crop insurance could be of assistance. Similarly, this financial tool has provided a motivation for rice farmers in Tamil Nadu, India to focus on crop specialization which contributed greatly to their economic returns from agriculture (Varadan and Kumar 2012).

These two countries used and had been assisted by traditional crop insurances; however, there are some perils regarding this, as pointed out by Ramirez and Colson (2013). One of which is it may cause moral hazards on the farmers' side. Since they are already assured of their payoffs in the case that something happens to their crops, they may adaptto various cultivation processes and plant riskier plants. Another concern is that it is difficult to assess fair premiums for the farmers. Agriculture is not just a function of the farmers' efforts; it is also dependent on weather variability, changes in technology, and unforeseen pests problems. Ultimately, it may favor certain crops and regions systematically. Scientific research have shown that the geographic location and loss patterns differences are predictable as they have a certain degree of correlation and those patterns could be observed by the significant aspects of historically-used rating methodologies (Woodard cited in Ramirez and Colson (2013)).

In this light, weather-index based insurances (WIBI) have been introduced. According to World Bank (2011), a weather-based index must (i) identify the critical weather risks at various stages of the crop cycle, (ii) quantify the value of exposure to weather risks at different phases during cycle, (iii)provide information for assigning weights to given weather risks, and (iv)quantify the farmer's weather exposure per unit of the defined index, and (v) quantify the yield volume lost per unit index. Aside from making the farmers risk-neutral, it also saves on costs as there is no need for field-level assessments (Binswanger-Mkhize 2012). Furthermore, the indices' objective nature lessens the problem of information asymmetry (Berg and Schmitz cited Heimfarth 2012) and eases the creation of insurance design as the index could be modeled diversely through a single weather variable (Heimfarth 2012).

There have been various methods on how to compute for the index and this study aims to introduce an alternative methodology for developing such here in the Philippines. Using palay yield data from Bureau of Agricultural Statistics *(BAS)* andweather data from the Muñoz weather station of Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA),this research aims to address the following objectives:

- To develop a weather index that could describe most of the variation in crop yield while taking into account the effects of different weather variables through the use of an AutoRegressive Moving Average with Exogenous Covariates (ARMAX) model
- To determine an appropriate corresponding strike level[1] that captures the trend, seasonality, and cyclical component of palay yield time series to estimate the conditional mean while tempering the effects of shocks
- To assess the accuracy of the suggested methodology through forecast evaluation tests.
- To calculate the basis risk which is defined as (i) the risk of not getting paid when the insured has suffered great loss or (ii) the risk of the insurer mistakenly giving out payoffs

[1] This is the The attachment level (or strike) at which the weather protection begins and financial compensation is received (World Bank 2011)

B. Significance of the Study

Since it is a Filipino trademark to frequently include rice in their meals, it is no wonder that 11.5 million farmers primarily depend on the rice industry and 33 per cent of the agricultural lands are allocated to planting such (John J. Carroll Institute on Church and Social Issues 2009). Palay production contributed 21 percent to the share of agriculture on the country's Gross Domestic Product (GDP) as shown by the 18.44 million metric tons of palay produced last year (Bureau of Agricultural Statistics 2013). This is a figure 2.26 percent higher than the statistics recorded during 2012 (Bureau of Agricultural Statistics 2013), suggesting that there might be an increasing demand for rice in the Philippines.

Unfortunately, the number of Filipino farmers are declining. According to Asterio P. Saliot, the current director of the Department of Agriculture – Agricultural Training Institute, the average age of the Filipino farmer is 57 (IRIN 2013), implying that there will be fewer farmers in the near future.

The children and grandchildren of the farmers have good reasons for not pursuing their father's line of work. Agriculture is highly dependent on the country's climate and it has already been shown through various studies that the Philippines will experience heavier rains and longer dry periods (Anglo cited in John J. Carroll Institute on Church and Social Issues 2009). Also, it has already been stipulated that the quality of crops will change (IRIN 2009) in response to this situation; making agriculture a riskier business than usual.

Moreover, the PhP20, 000.00 average annual income is clearly not sufficient to raise and support a family (BAS cited in Alave 2011). According to Senator Francis Pangilinan, the chairman of the Senate committee on agriculture and food, it appears that to the younger generations, farming is not a way out of poverty. They would rather migrate or go to the cities to pursue a more profitable career (Alave 2011).

This then raises the urgent need to improve the living conditions of the farmers who, together with the fishermen, comprise approximately 70 percent of the rural poor (BAS cited in IRIN 2013). One way of inspiring the Filipinos to continue to turn into this line of work is to create policies and certain measures that would assure them of their future finances.

II. METHODOLOGY

A. Data Collection

Six weather variables measured daily for all days from 1988 to 2013 were collected from the Climate Data Section of the Philippine Atmospheric Geophysical and Astronomical Services Administration (PAGASA). Five weather variables were gathered from the Central Luzon State University PAGASA Agromet Station in Muñoz, Nueva Ecija—minimum temperature, maximum temperature, open pan evaporation, minutes of sunlight, and amount of rainfall—while daily wind speed was gathered from the Cabanatuan PAGASA Weather Station in Cabanatuan City, Nueva Ecija. Data on quarterly irrigated palay yield in tons per hectare of land for the province of Nueva Ecija were collected from the Bureau of Agricultural Statistics website for the same period, 1988 to 2013.

The collected daily weather data were aggregated into quarterly summaries. The variable names and descriptions of the data aggregation methods used are given by:

Variable Name	**Description**
$EVAP\_CUM_t$	Cumulative amount of evaporation when pan is open at period t
$RAIN\_DEF10_t$	Sum of the amount of daily rainfall below 10mm at period t
$RAIN\_EXC20_t$	Sum of the amount of daily rainfall exceeding 20mm at period t
SUN_CUM_t	Cumulative amount of minutes of sunlight at period t
$TEMP\_TRESH20_t$	Sum of the amount of daily minimum temperature below 20 degrees Celsius at period t
$TEMP\_TRESH35_t$	Sum of the amount of daily maximum temperature above 35 degrees Celsius at period t
$SPEED\_AVE_t$	Average daily wind speed at period t

B. Index System Development

1. Strike Level Determination

Let $YIELD_t$ be the palay yield in tons per hectare at period t. Appropriate differencing on $YIELD_t$ is done based on the conclusions of the Augmented Dickey-Fuller Tests for Unit Root (ADF Test) and Test for Seasonality. After the necessary differencing, the ARMA specification to be used for forecasting is derived by modelling the stationary $YIELD_t$ using all the data points, first quarter of 1988 to the fourth quarter of 2014, as an ARMA process. Diagnostic measures for the ARMA model are done until all the errors are white. The strike levels of the proposed index system are the respective one-quarter ahead ARMA forecasts of $YIELD_t$ for the first quarter of 2008 up to the fourth quarter of 2013. In-sample forecasts are also determined for all time points for use in forecast evaluation procedures.

2. Weather Index Determination

Appropriate differencing is done on all weather variables—$TEMP\_TRESH35_t$, $TEMP\_TRESH20_t$, $RAIN\_EXC20_t$, $EVAP\_CUM_t$, SUN_CUM_t, $RAIN\_DEF10_t$, and $SPEED\_AVE_t$—based on the conclusions of ADF Tests and Tests for Seasonality. After the necessary differencing, the ARMAX specification to be used for forecasting is derived by using the ARMA specification used in forecasting the strike levels and by retaining the significant exogenous contemporary weather covariates using all data points, first quarter of 1988 to fourth quarter of 2014. The realized index values of the proposed index system are the respective one-quarter ahead ARMAX forecasts of $YIELD_t$ for the first quarter of 2008 up to the fourth quarter of 2013. In-sample forecasts are also derived for all time points for use in forecast evaluation procedures.

C. Index System Assessment

To assess whether the proposed weather index determination procedure—ARMAX—is more accurate, and thus, better captures the dynamics of $YIELD_t$, than the commonly used index determination procedure—classical linear regression through least squares estimation (CLR)—descriptive measures are of accuracy are computed and hypothesis tests for equal forecast accuracy are undergone. The CLR model is defined by regressing $YIELD_t$ on the significant aggregated weather variables.

The mean absolute percentage errors (MAPE) of both the ARMAX model and the CLR model are computed for both the in-sample and the out-of-sample forecasts. The MAPE is given by:

$$MAPE = \frac{1}{T}\sum_{i=1}^{T}\frac{abs\left(Y_t - \hat{Y}_t\right)}{Y_t}$$

$$where\ Y_t = actual\ value\ of\ t^{th}\ observation\ of\ the\ series$$

$$\hat{Y}_t = predicted/forecasted\ value\ of\ the\ t^{th}\ observation\ of\ the\ series$$

However, mere comparison of MAPE may not be enough to ascertain that one index determination procedure is better than the other, therefore, to determine whether the proposed index determination procedure—ARMAX—is indeed more accurate than the common index determination procedure—CLR—Diebold-Mariano Test for Equality of Forecast Accuracy is carried out to determine whether the ARMAX forecasts are significantly more accurate than the CLR forecasts out-of-sample.

Basis risk is the central and integral theme of WIBI, therefore, estimating the basis risk of the proposed index system is imperative not only because minimizing the basis risk is the main goal of WIBI but also to provide a comparison value of risk for future studies. Basis risk can be defined as:

$$Var_t(Basis\ Error)$$
$$= Var_t(Actual\ Losses - Predicted\ Losses)$$
$$= Var_t\left[(Strike_t - Y_t) - \left(Strike_t - \hat{Y}_t\right)\right]$$
$$= Var\left(Y_t - \hat{Y}_t\right)$$
$$where\ Strike_t\ is\ the\ strike\ level\ at\ time\ t$$
$$Y_t = actual\ value\ of\ t^{th}\ observation\ of\ the\ series$$
$$\widehat{Y_t} = predicted/forecasted\ value\ of\ the\ t^{th}\ observation\ of\ the\ series$$

The basis risk can also be viewed as the conditional heteroscesdasticity at time t. Define $d_t=(Y_t-\hat{Y}_t)^2$ as the squared errors. Treating the squared errors as the basis errors, the conditional heteroscedasticity—basis risk— at time t can be estimated using a GARCH process.

Also, the probability of payouts and payout misclassifications among the different index systems namely, using ARMA forecasts as the strike, using the long-term average as the strike, and using seasonal averages as the strike are computed to provide comparisons between varying payout schemes.

III. DISCUSSION OF RESULTS

Model Building

The ADF Test concludes that $YIELD_t$ follows a single stochastic trend. Subsequent regression of the first difference of $YIELD_t$ to seasonal dummy variables resulted in a significant F-statistic at 10% level of significance, thereby concluding that $YIELD_t$ has both stochastic trend and seasonality. Let $\Delta YIELD_t$ be the detrended and deseasonalized series of $YIELD_t$. The best ARMA model based on goodness-of-fit and satisfaction of model assumptions is given by:

$$\Delta YIELD_t = \beta_0 + \phi_1 \Delta YIELD_{t-7} + \phi_2 \Delta YIELD_{t-4} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \quad \Delta YIELD_t \sim ARMA(7,1)$$

The ARMA model specification estimated using the whole sample is given by:

$$\Delta \widehat{YIELD}_t = \widehat{\beta_0} + \widehat{\phi_1} \Delta YIELD_{t-7} + \widehat{\phi_2} \Delta YIELD_{t-4} + \widehat{\theta_1} \Delta \widehat{\varepsilon_{t-1}}$$

$$\Delta \widehat{YIELD}_t = 0.0004427 - 0.278683 \Delta YIELD_{t-7} - 0.248154 \Delta YIELD_{t-4} - 0.992224 \widehat{\varepsilon_{t-1}}$$

Table 3.1 Model Fit Summary of the final ARMA Model Specification

R-squared	**0.575144**	AIC	**1.24641**
Adjusted R-squared	0.56066	**SIC**	1.356053

Table 3.2 Summary of Results of ADF Tests and Seasonality Tests

VARIABLE	**UNIT ROOT**	**ORDER OF INTEGRATION**	**SEASONALITY**
TEMP_TRESH35	NO	0	YES
TEMP_TRESH20	NO	0	YES
RAIN_EXC20	NO	0	YES
EVAP_CUM	NO	0	YES
SUN_CUM	NO	0	YES
RAIN_DEF10	NO	0	YES
SPEED_AVE	YES	1	YES

Necessary differencing were done to all weather variables based on the conclusions of ADF Tests and Tests for Seasonality (See Table 3.2). The ARMAX model uses the ARMA model specification used for strike level with all the appropriately differenced weather variables as the exogenous covariates. The initial ARMAX model is given by:

Table 3.3 Initial ARMAX Model Specification

Variable	**Coefficient**	**Std. Error**	**z-statistic**	**p-value**
Constant	-0.056612	0.114701	-0.493559	0.6216
$\Delta EVAP\_CUM_t$	-0.00061	0.00014	-4.369997	0
$\Delta RAIN\_DEF10_t$	3.92E-05	0.000145	0.269307	0.7877
$\Delta RAIN\_EXC20_t$	3.63E-04	1.49E-04	2.439991	0.0147
$\Delta SPEED\_AVE_t$	0.077868	0.058147	1.339167	0.1805
$\Delta TEMP\_TRESH20_t$	-0.002002	0.000856	-2.337679	0.0194
$\Delta TEMP\_TRESH35_t$	0.001679	0.000744	2.257373	0.024
$\Delta YIELD_{t-7}$	-0.251761	0.103438	-2.433917	0.0149
$\Delta YIELD_{t-4}$	-0.349865	0.12962	-2.699167	0.007
Δe_{t-1}	-0.971757	0.020943	-46.39913	0

Some of the coefficients of the exogenous covariates are insignificant. Backward selection of covariates until all covariates remaining have significant coefficients reduces the model to:

Table 3.4 Final ARMAX Model Specification

Variable	**Coefficient**	**Std. Error**	**z-statistic**	**p-value**
Constant	0.029438	0.086134	0.341775	0.7325
$\Delta RAIN\_DEF10_t$	-0.000215	0.000118	-1.820877	0.0686
$\Delta RAIN\_EXC20_t$	0.000387	0.000103	3.747293	0.0002
$\Delta TEMP\_TRESH35_t$	0.002017	0.000601	3.354638	0.0008
$\Delta YIELD_{t-7}$	-0.351686	0.087218	-4.032277	0.0001
$\Delta YIELD_{t-4}$	-0.22002	0.118693	-1.85368	0.0638
Δe_{t-1}	-0.977447	0.00919	-106.3578	0
PULSE_1999Q4	1.094191	0.195243	5.604252	0

Note that the coefficients of the variables $\Delta RAIN\_EXC20_t$ and $\Delta TEMP\_TRESH35_t$ follow a positive sign, which contradicts most studies in literature. This is not unusual considering the crudeness of the procedure for quarterly aggregation of daily data used by the researchers.

Table 3.5 Model Fit Summary Statistics

R-Squared	0.650249	**AIC**	1.123828
Adjusted R-Squared	0.621103	**SC**	1.480167

Table 3.6 Actual Yield with the Out-of-Sample Strike Level (ARMA Forecasts) and Realized Index Value (ARMAX Forecasts)

Date	Actual	Strike Level	Realized Index Value
2008Q1	5.444279	5.024022625	4.849546559
2008Q2	5.640998	5.457898217	5.326307764
2008Q3	4.456715	5.142226066	4.909111331
2008Q4	4.633428	4.969467383	4.736437863
2009Q1	6.025666	5.335363863	5.237588424
2009Q2	5.849722	5.732105969	5.536151246
2009Q3	4.607059	4.891829751	4.504259623
2009Q4	3.709998	4.723682735	4.623318501
2010Q1	6.042604	5.833943553	5.993483375
2010Q2	5.825989	6.024249314	6.038491579
2010Q3	4.895665	4.624750702	4.648248322
2010Q4	3.868984	3.826867819	3.623799235
2011Q1	5.705165	6.062835847	6.010957738
2011Q2	5.949709	5.757751618	5.870774548
2011Q3	4.683721	5.123657365	5.379680202
2011Q4	3.470163	3.755922077	3.852479148
2012Q1	5.718845	5.695893422	5.757794461
2012Q2	6.115102	5.757024767	5.772938087
2012Q3	4.810306	4.632276212	5.044954528
2012Q4	4.964642	3.61925093	3.736623011
2013Q1	5.785951	5.713806038	6.237804175
2013Q2	6.192371	6.217055586	6.56268936
2013Q3	5.81168	4.935817645	5.44274184
2013Q4	4.669362	5.311265625	5.234630748

Index System Assessment

Table 3.7 MAPE of ARMAX and CLR Forecasts

		MAPE
In-sample	ARMAX	7.342%
	CLR	12.667%
Out-of-Sample	ARMAX	7.946%
	CLR	15.962%

Both in-sample and out-of-sample forecasts of the ARMAX model have a lower percentage of error when compared to the CLR forecasts. In-sample ARMAX forecasts are approximately 40% more accurate than CLR forecasts while out-of-sample forecasts yield better results since ARMAX forecasts are about 50% more accurate than CLR forecasts. The DM Test (See Table 3.4) rejects the null hypothesis at even less than 1% level of significance. This validates the claim that indeed, the proposed weather index determination procedure—ARMAX—produces more accurate forecasts than CLR forecasts.

Table 3.8 Diebold-Mariano Test for Equality of Forecast Accuracy (Out-of-Sample)

Diebold-Mariano Test Statistic	-3.844851175
p-value	6.03128E-05

Table 3.9 Basis Risk GARCH Model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	-0.00547	0.044455	-0.12294	0.9022
RESID(-1)^2	-0.20048	0.115577	-1.73463	0.0828
GARCH(-1)	1.273742	0.473956	2.687468	0.0072

The conditional heteroscedasticity of the series d_t is modelled using a GARCH(1,1) process (See Table 3.9). The basis risk per out-of-sample period is found on Table 3.10. The period where there is the greatest risk of losses is on the fourth quarter of 2012, while the period where there is least amount of risk is on the first quarter of 2013. On the average, this proposed index system has an average basis risk of 0.13545. This means that 0.368034 tons of palay per hectare of land is at risk on the average under this proposed index system.

Table 3.10 Basis Risk per Out-of-Sample Period

Date	**Basis Risk**
2008Q1	0.094019
2008Q2	0.089208
2008Q3	0.106196
2008Q4	0.121404
2009Q1	0.149149
2009Q2	0.107181
2009Q3	0.129117
2009Q4	0.158974
2010Q1	0.057527
2010Q2	0.067808
2010Q3	0.080495
2010Q4	0.096313
2011Q1	0.116488
2011Q2	0.141157
2011Q3	0.174325
2011Q4	0.169545
2012Q1	0.206208
2012Q2	0.25719
2012Q3	0.319381

2012Q4	0.400735
2013Q1	0.049037
2013Q2	0.048637
2013Q3	0.052715
2013Q4	0.057966

Table 3.11 Basis Risk Summaries

	Basis Risk	**Time**
Max	0.400735	2012Q4
Min	0.048637	2013Q1
Mean	0.135449	

Table 3.12 Percent of Payout and Misclassification under varying Strike Levels

	Strike Used	**Actual**	**Predicted**
Percent of Payout	Long Term Averages	12.5%	12.5%
	Seasonal Averages	8.33%	4.17%
	ARMA Forecasts	41.67%	45.83%
Percent of Misclassification	Long Term Averages	8.33%	
	Seasonal Averages	12.5%	
	ARMA Forecasts	37.5%	

In literature, the strike levels used are mostly long term averages. However, using long term averages as the strike level provide a naïve way estimating the agricultural conditions which are inherently volatile. Long term averages as strike ignores the fact that a time series may follow a specific trend, has seasonality, and has a cyclical component. On the other, using seasonal averages as the strike provide a better alternative to long term averages since seasonal averages take into account the inherent seasonality of a time series. However, the trend and the cyclical component of the time series is neglected under this strike level scheme. Percent of misclassification is low when using long term averages and seasonal averages since both of these strike level schemes undervalues the conditional mean for most periods. Also, the percent of payout under the two naïve schemes are extremely low; again, this is caused by the tendency of long term averaging to undervalue or overvalue the conditional means, especially under the presence of extreme observations.

IV. SUMMARY AND CONCLUSION

The researcher proposed a novel methodology to develop an index system using various time series techniques. The methodology is applied to data from Nueva Ecija, Philippines wherein the strike level, weather index, and corresponding basis risk were determined. The researcher propose to use ARMA forecasts (with interventions) to model the conditional mean of yield. This is a different methodology when compared to most studies in literature since the strike levels at a particular period t is determined using the conditional mean of the outcome variable at the same period t in contrast to most studies that use long term averages as their strikes which ignore the inherent trend, seasonality, and cycle of a particular time series. The researcher determined the index through an ARMAX model with various weather variables as the exogenous covariates. Most of the exogenous covariates were deemed insignificant and some of the significant variables yielded signs that contradict most studies in literature; this is caused by the unsophisticated way of aggregating the daily weather variables into quarters. The researcher has no knowledge about the crop cycles and the planting seasons in Nueva Ecija, and thus, specific data aggregation was not possible. Although this study underwent problems with regard to the data aggregation procedure, the proposed weather index determination methodology still yielded good results. It was concluded that the proposed index determination methodology—ARMAX—has better forecast accuracy than the CLR model, the most prevalent index determination procedure.

A methodology to estimate the basis risk was also proposed by the researcher by modelling out-of-sample squared forecast errors as a GARCH process. Conditional heteroscedasticity at time t can be viewed as the basis risk at time t. Based on the results of the GARCH(1,1) model, basis risk were determined for quarters of 2008 to 2013. The proposed methodology and the subsequent estimation of basis risk now provides future researchers a novel methodology to model basis risk; this implies that comparative studies of this nature, that is, development of index systems for use in weather index-based insurance using time series data is now possible.

Although the accuracy of the suggested methodology is better than the accuracy of studies in literature that use CLR, a high percent of misclassification of payout is present (37.5%). This suggests that the ARMAX model still does cannot account for a large portion of the variation of palay yield in tons per hectare of land; this problem can be solved through the use of better aggregated weather variables and more accurate weather data in order to add more significant variables to the model.

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