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Monitoring the Response of Bulacan Rice Yield to Environmental Indicators using a Bayesian Framework

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Abstract: The Climate Change Commission (CCC) through its National Climate Change Action Plan calls for the development of models that could help in determining how crops respond to the changes in the climate and the environment in general. This study was therefore created in hopes to contribute in addressing such research gaps. A Bayesian Framework was used to determine the impacts of 11 selected natural and anthropogenic factors to the rice yield of Bulacan. The quarterly data from 1993 to 2018 was divided into training set and test set to generate the model and forecasts. The result shows that rainfall and windspeed have negative effects. The rising levels of concentration of carbon dioxide, methane, and nitrous oxide in the atmosphere have moderate impacts. On the other hand, minimum and maximum temperature has contrasting effects whereas the other global indices have negligible impacts. This paper provides contribution to the call of the CCC and could extend further as an early warning tool in monitoring how the crop of the province would react to environmental variabilities. Moreover, the two-year forecasts show that the seasonality of the yield will still be evident with the potential lower limit consistent to the previous years. This could be an area of further investigation since the population is steadily increasing while resources and land conversion is unpredictable. Lastly, the relatively easy application of the proposed model may be used by policymakers for future applications.

Key Words: Rice Yield; Climate and Environment; Bayesian Structural Time Series; Forecasting

1. INTRODUCTION

Various studies provide evidences that warming effects worldwide is expected as the greenhouse gases (GHG) in the atmosphere gets accumulated (Yohannes, 2016). This could take toll in producing crops in developing countries including the Philippines as changes in temperature, precipitation, and extreme weather events are the foreseen outcomes of the rising GHG levels.

Crop yields directly reacts to the variabilities in temperature as well as the length of time the heat or cold waves hits. These waves could be modified by extreme weather activities and growth period of plants may be affected (Hoffman, 2013; in Yohannes, 2016). As GHG emissions increase, direct effects in agricultural systems could be observed. Herein, agricultural yield under controlled conditions may increase but seasonal alterations in precipitation and temperature may bring adverse impacts (Rosegrant et al., 2010).

The most important crop for the Filipinos is rice (*Oryza sativa*) which is domestically known as *palay*. Its importance to the nutrition and economy are well-documented (Briones et al., 2017; in Pantolla and Arcilla, 2020). Being cultivated in the fields, the susceptibility of rice to changes in the environment is predictably high. Typhoons, and impacts to the Philippines of climate change that is identified to be the third most vulnerable to it, may bring further damages in rice production (Briones et al., 2017; Radtke et al., 2018; in Pantolla and Arcilla, 2020)

Studies which are specific to smaller areas are recommended to address this situation (Sajise et al., 2012; Cruz et al., 2017; in Pantolla and Arcilla, 2020). Climate change effects are also urged to be part of policies and actions for review and development according to United Nations Sustainable Development Goals (Tiongco, 2019). On the local scene, the Climate Change Commission (CCC) listed crucial research gaps in the National Climate Change Action Plan (NCCAP) pertaining to food security (CCC, 2013). Among these gaps is a call for studies that aim to advance the knowledge in determining how agricultural crops (and fisheries) react to the variability of climate and the environment in general. Moreover, uncertainty in variable selection for models arises as complexity and interactions between environmental variables are always present. This study is therefore developed to contribute in addressing such research gap.

The main objective of this study is to identify the effects of selected environmental variables, both local and global, to the rice yield of Bulacan that would serve as the dependent variable. The province was selected to be more site-specific compared to an existing regional econometric model (Pantolla and Arcilla, 2020). The dependent variable is an aggregation of both the irrigated and rainfed types. Some global indices were also included to determine how those lesser-known variables which have influences on the climatic system of the country impacts the rice yield of the province. Herein, a Bayesian Framework was applied to discriminate the importance of the variables through weighting and corresponding magnitude via averaged coefficients in modeling the rice yield.

2. METHODOLOGY

2.1 Data

The dependent variable used is the calculated quarterly data of rice yield in kilograms per hectare (kg/ha) from Bulacan from 1993 to 2018 which were downloaded from the website of the Philippine Statistics Authority (PSA, n.d.). A total of 104 quarters was used in this study. The predictors used were collected from different local and global sources. The daily datasets of rainfall in millimeters (mm), maximum (Maxtemp) and minimum (Mintemp) temperature in degrees Celsius (in °C), humidity in percent (in %), and windspeed in kilometers per hour (in kph) data were requested from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). The atmospheric concentration of the three most abundant GHG composed of carbon dioxide (CO_2) in parts per million (ppm), methane (CH_4), and nitrous oxide (N_2O) both in parts per billion (ppb), where downloaded from the website of Commonwealth Scientific and Industrial Research Organization (CSIRO, n.d). The data of sea surface temperature anomaly (SSTA) was downloaded from the website of the Climate Prediction Center (CPC) of National Oceanic and Atmospheric Administration (NOAA, n.d.). The data of Madden-Julian Index (MJO) were extracted from the website of Earth and Science Research Laboratory (ESRL) of NOAA (n.d.) while that of the Pacific Decadal Oscillation (PDO) was taken from the website of Japan Meteorological Agency (JMA, n.d.). These global indicators which were originally on a monthly basis were averaged into a quarterly frequency and have no formal units. Appropriate conversions were done to all the variables to achieve consistent quarterly data set. Every dataset matches at the first quarter of 1993 and ends at the last quarter of 2018. The data was divided into modeling and forecasting sets to evaluate its predictive performance. The first 96 quarters were used for modeling purposes while the remaining 8 was used for forecasting.

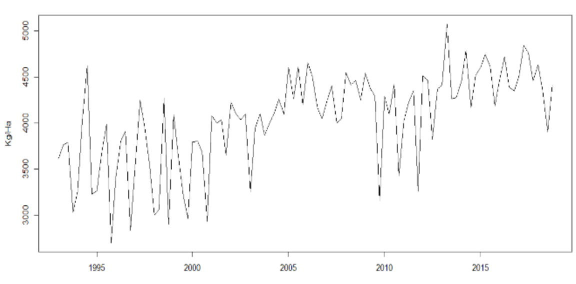

Fig. 1. Line plot of the rice yield of Bulacan.

Figure 1 shows the yield of rice of Bulacan for the selected time frame. The quarterly behavior is apparent. The increasing trend can be observed as well. These characteristics of the plot is useful in adding the appropriate components for the multivariate modeling.

Using local weather variables accounts for possible spatially or spatiotemporally changes for the chosen location. These weather variables may be influenced by larger weather or climatic systems. Thus, GHG, both anthropogenic and not in nature, were plugged in to the model. Moreover, the STA, MJO, and PDO which are identified to be related to rainfall in the country were also included (Cruz et al., 2018). The uncertainty in variable selection as predictors of the rice yield of Bulacan, at least those that are of environmental types, are aimed to be reduced in this study.

2.2 Bayesian Structural Time Series Model

This study applied the Bayesian Structural Time Series (BSTS) Model. The statistical tool matches the data as it draws results from an ensemble of forecasts averaged in an entire collection of regressors that could be very large. In turn, it addresses model and variable selection uncertainty. A short-term forecasting could also be done which could identify how the selected variables influence the behavior of the dependent valuable in a few quarters. Furthermore, the BSTS Model features a robust and automatic regressor selection procedure (Scott and Varian, 2013).

Consider the *observation* equation

$$y_t = \underline{Z}_t^T \underline{\alpha}_t + \varepsilon_t;\ \varepsilon_t \sim N\left(0, \underline{H}_t\right) \qquad \text{(Eq. 1)}$$

where y_t is an observation for a t real valued time series and $\underline{\alpha}_t$ is a vector of latent state variables. Take also the *transition* equation that defines the behavior of the latent state over time given by

$$\alpha_{t+1} = \underline{T}_t \underline{\alpha}_t + \underline{R}_t \eta_t;\ \eta_t \sim N\left(0, \underline{Q}_t\right). \qquad \text{(Eq. 2)}$$

In Eq. 1 and Eq. 2, $\underline{Z}_t$, $\underline{T}_t$, and $\underline{R}_t$ are matrices that could be usually a combination of clearly-defined values which are often 0s or 1s and unknown parameters. These matrices consequently lead to having $\underline{Q}_t$ as a full rank variance matrix. $\underline{H}_t$ on the other hand, is a positive scalar. Any model that follows Eq. 1 and Eq. 2 is contained in the *state space form.*

Now for this dataset where trend and seasonality are clearly manifested as seen in Figure 1 and would use a set of multiple regressors, model is extended to

$$y_t = \mu_t + \tau_t + \underline{\beta}^T \underline{X}_t + \varepsilon_t \,. \qquad \text{(Eq. 3)}$$

In Eq. 3, μ_t and τ_t are the trend and seasonal components respectively while $\underline{\beta}$ stands for the parameter estimates for the vector $\underline{X}_t$ that may contain trends verticals, needed lags, and other transformations among others (Scott and Varian, 2013).

For the forecasting part, the BSTS Model has a built-in Bayesian Model Averaging (BMA) algorithm (Hoeting, Madigan, Raftery, and Volinsky, 1999; in Scott and Varian, 2013). BMA applies the Monte Carlo Markov Chain sampling process for smoothing the forecasts and weights of each regressor in modeling. The modeling weight is also known as the Posterior Inclusion Probability (PIP).

2.3 Methods

Every data matched from the 1st quarter of 1993 to the last quarter of 2018 for a total of 104 data points. The yield was calculated as the ratio of estimated rice volume multiplied to 1,000 and land area. The daily weather data were all averaged except for rainfall which was aggregated to have a quarterly frequency. Every global data is on a monthly frequency and therefore averaged as well. This study applied the bsts package in R thereafter (Scott, 2019). Linear trend, seasonality, and regression components were all added in the model. The first 96 of the 104 quarters were used as training set while the remaining data points were used as test set for the forecasting. The coefficients (Posterior Mean), PIP of each variable, and forecasts were all calculated and shown too. Tthe coefficients and PIP were generated after setting the effect size of the model to 8. This was done to determine which among the regressors could be identified with high probability of model entry. This strategy is one of the three prior specifications techniques that can be done in applying the BSTS Model (Scott, 2013).

3. RESULTS AND DISCUSSION

3.1 Summary Statistics

The first 96 quarters used for modeling. For this period, the mean Yield of rice for Bulacan is 4004.50 kg/ha with a standard deviation (SD) of 514.85 kg/ha. Its Rainfall volume has a mean of 706.87 mm with an SD of 620.03 mm. The Maxtemp has a mean of 32.12°C and SD of 1.23°C while the Mintemp has a mean and SD of 23.52°C and 1.25°C respectively. The average Humidity is 78.67% which has an SD of 5.91%. For the GHG, the mean CO_2 concentration is 376.10 ppm with an SD of 13.52 ppm. On the other hand, the concentration of CH_4 is 1,735.09 ppb with an SD of 29.30 while that of the N_2O is 318.10 ppb on the average with an SD of 5.62 ppb. For the other climate indicators, the SSTA, has a mean of -0.02 with an SD of 0.89. The MJO has a mean of 1.24 with an SD of 0.41 whereas PDO has a mean of -0.15 with an SD of 0.94.

3.2 BSTS Modeling Outputs

The averaged coefficients and PIP over every model considered is presented in Table 1. The model has an R^2 value of 0.7102. Hence, around 71% of the variability in the rice yield of Bulacan can be explained by the model while the remaining close to 29% could be caused by external factors. Moreover, Table 1 shows that Rainfall has a negative impact and has the highest PIP. The coefficient is -0.2803 with a PIP of 0.7844. Hence, every 1 mm increase in Rainfall may decrease the yield by 0.2803 kg/ha on the average and it will inevitably be part of modeling the dependent variable at 78.44% as the PIP denotes. This also means that although Rainfall could reduce the yield quite lowly, it should always be included in modeling the rice yield of Bulacan. In contrast, Humidity on the average has the highest contribution to the yield. Every unit increase in percent of Humidity may increase the rice yield by around 1,087.9015 kg/ha and its weight in an ensemble of modeling for the dependent variable is almost 58%. Furthermore, increased Windspeed per kph could be detrimental to the rice yield of Bulacan as it could cause a decline of 50.2264 kg/ha on the average may be expected.

Table 1. BSTS Model for the rice yield of Bulacan

Variable	Coefficient	PIP
Rainfall	-0.2803	0.7844
CH_4	-0.4242	0.6389
N_2O	0.0515	0.6257
CO_2	-0.5787	0.6230
Humidity	1,087.9015	0.5767
Maxtemp	-2.0253	0.5026
Mintemp	12.6012	0.4868
Windspeed	-50.2263	0.2209
MJO	2.2104	0.0608
PDO	1.0421	0.0384
SSTA	1.1953	0.0384

Table 1 also shows that the GHG are almost identical in terms of PIP with at least 62%. These GHG has moderate inclusion probabilities. However, based from the averaged coefficients of the GHG, N_2O is the only one with a positive contribution to the Yield yet the effect is minimal. The increase in N_2O concentrations in the environment may promote growth in the Yield by 0.0515 kg/ha on the average. Additionally, the Mintemp and Maxtemp have been found to have contrasting impacts in terms of averaged coefficients. The PIPs of both variables are quite similar at around 50% but the difference in coefficients is evident. Every unit increase in °C of Maxtemp could lessen to the rice yield if Bulacan by 2.0253 kg/ha on the average while the same case for Mintemp may contribute to the dependent variable by a mean of 12.6012 kg/ha. Lastly, the global indices of MJO, PDO, and SSTA, are negligible in modeling the dependent variable as revealed by both the averaged coefficients and PIPs. Therefore, these climatic indicators may not be directly influential to the Yield.

The forecasts with 95% confidence band is shown in Figure 2. The perforated lines represent the confidence band limits. On the other hand, the line at the middle of the limits is the median on each quarter. Unsurprisingly, the seasonality is still expectedl. The forecasts have a Mean Absolute Percentage Error of 7.07%, Moreover, the contrasting potential increase or decrease in the rice yield of Bulacan in the future is evident. There are slight chances that the projected yield for the province would increase. However, the yield could possibly be lower on the same level of the previous quarters.

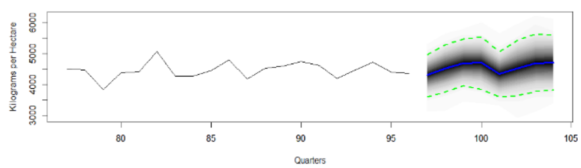

Fig. 2. Two-year forecasting for the yield

4. CONCLUSIONS

This study was able to determine how the yield of rice Bulacan responds to the 11 selected local and global environmental systems. It was found out that Rainfall and windspeed have negative effects to the dependent variable where the latter is more profound. Moreover, while every GHG has moderate impacts, only N_2O has positive effects but is still marginal. It was also determined that Humidity is the biggest contributor to the yield. The Mintemp and Maxtemp have opposing contributions yet the former has a relatively large and positive effects. Therefore, separating these variables instead of using the average of the two may avert the potential loss of valuable information. The rice yield of Bulacan responds negatively to increased Rainfall and Windspeed which may have supported further that strong typhoons are detrimental to it. Additionally, the MJO, PDO, and SSTA were found to be negligible and may be dropped in modeling the same dependent variable in the future.

Specific to the lower limit of the forecasts, the extreme lows are comparable to the previous actual estimates. This could be investigated deeper since the population is steadily increasing, GHG emissions that could lead to extreme weather events are still on an increasing trend, and land use or conversion is unpredictable.

Lastly, the considerably less tedious and fairly robust BSTS technique in modeling the rice yield may be beneficial for forecasters and policymakers alike. Some variables including farm management practices may be included in the future for modeling purposes. The selected statistical method could also be used in other agricultural commodities or areas.

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