Assessing the Forecasting Accuracy of the Multivariate ARMA Model in Predicting the Weather of Nueva Ecija, Philippines

Juan Carlos Tamayo
De La Salle University
jctamayo17@yahoo.com

Executive Summary

In the Philippines, most researchers rely on NWP models such as the WRF model in order to predict future weather conditions. In this study, however, the possibility of using a purely statistical multivariate model that does not rely on any NWP model is explored. This study focuses on using a multivariate ARMA model that assumes different AR and MA orders for each series in order to model the 2001 - 2015 precipitation, minimum, and maximum temperature data of Nueva Ecija. The data that was used in the analysis came from the two weather stations of PAGASA in the province which are the Cabanatuan and CLSU Munoz stations. Thus, there is a total of six series included in the analysis. In this study, forecasts were generated and their forecasting accuracy were subsequently measured. Results showed that the forecasts of the model had yearly MAPE and MASE values ranging from about 2.8% to about 3.2% and about 0.8448 to about 1.0307, respectively, which are attributes of "good" forecasts according to their respective "rules-of-thumb". A comparison of numerical measures for the multivariate ARMA model and their counterparts with the WRF model was then performed for three different scenarios. These scenarios detail the performance of the two models for monthly forecasting and extreme event and non-extreme event forecasting. Results revealed that the multivariate ARMA model had smaller values for almost all yearly and monthly numerical measures with substantial differences present in some of these measures. The same result was also found for the majority of the numerical measures under the non-extreme event scenario. For the extreme event case, results showed that neither the multivariate ARMA forecasts nor the WRF forecasts may be considered as good forecasts. Thus, for this scenario, it was concluded that the use of both the multivariate ARMA and WRF forecasts was deemed to be more appropriate as compared to using just one of them.

Keywords: multivariate linear parametric time series model, weather forecasting, precipitation, minimum temperature, maximum temperature

Assessing the Forecasting Accuracy of the Multivariate ARMA Model in Predicting the Weather of Nueva Ecija, Philippines

by
Juan Carlos Tamayo
De La Salle University

I. Introduction

In modern society, weather forecasting has become a very useful tool since it helps provide information regarding future weather conditions. The application of weather forecasting is numerous. For example, it could be used in agricultural planning since it provides estimates of future weather conditions which could be used for crop planting. For policy making, the same information could be used to make better and timelier decisions; for example, politicians may use it in order to determine if a particular area should be evacuated or not.

For this study, it is of interest to forecast future weather conditions for the Philippine province of Nueva Ecija. Nueva Ecija is situated in Region III, which is acknowledged as the "Rice Granary of the Philippines", and is very important to the country since it is one of its biggest producers of paddy rice (Department of Trade and Industry, n.d.). In this area, weather forecasting is particularly useful since it helps provide information that concerns rice production. It is well known that the weather of any particular area has a strong effect on the capability of that area to produce rice (Lansigan, de los Santos, & Colladilla, 2000; Lansigan & Salvacion, 2007; Koide, Robertson, Ines, Qian, DeWitt, & Lucero, 2013). Numerous studies have shown, such as that of Lansigan, de los Santos, and Coladilla (2000), that weather and climate directly affect plant yield and that any fluctuations in these two will greatly affect crop growth and yield. Due to this, performing weather forecasting in this province may also help in ascertaining food security.

In this study, three weather variables are of interest; which were chosen due to their importance in crop production. These three are precipitation, minimum temperature, and maximum temperature. Forecasting these weather variables may be performed in numerous ways. However, only objective weather forecasting was focused on in this study. In this field, there are two predominant methods that are commonly used. The first being the Numerical Weather Prediction (NWP) method and the second being the statistical weather forecasting method.

In the Philippines, the weather forecasting techniques that the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) employs are either NWP models, such as the Weather Research and Forecasting (WRF) model, or are mixtures of NWP models and statistical models. However, there are many complications that may be encountered when using such methods; which have already been pointed out by numerous authors. First, Ihshaish, Cortes, and Senar (2012) and Wilks (2011) pointed out that the initial condition of the atmosphere that is used in NWP models is "estimated only within a certain accuracy" and that the assumed initial state may differ from the true initial state of the atmosphere. Wilks (2011) explained this by saying that these NWP models "do not contain complete and true representation of the governing physics" that explain the atmosphere. Malone (1955) also affirmed the same sentiments and further discuss that these NWP models are used even though there is “an incomplete marshaling and even understanding of all the factors” that are important in weather forecasting. This entails that the forecasts of these NWP models are already subject to error starting at the initialization stage. This problem, however, could be easily solved by the calibration of these NWP models (F. Lansigan, personal communication, December 12, 2017). Nevertheless, Wilks (2011) pointed out that the assumed state of the atmosphere will almost never be the same as the true state of the atmosphere since the information regarding the true state of the atmosphere is always incompletely observed.

Furthermore, Ihshaish, Cortes, and Senar (2012) declared that the forecast skill of these NWP models is sensitive to the specified initial condition. Wilks (2011) further explained this by discussing the concept of dynamical chaos. The concept of dynamical chaos mainly revolves around the idea that a deterministic dynamical system, such as the dynamic models used in the NWP approach, is very sensitive to the assumed conditions the system is initialized from. The author explains further and supposes that there are two possible realizations of the initial conditions that may be used to represent the atmosphere: one of which is the condition of the real atmosphere and the other is a perfect mathematical model of the physics governing the atmosphere. The author explained that if there are even slight differences in these two realizations, then their “time evolutions will diverge markedly”.

Finally, Wilks (2011) also discussed that these dynamical models may not be able to cover the “small-scale effects (e.g. of topography or small bodies of water) that may be important to local weather forecasting”. That is, these models are not able to explicitly represent the effect of variables such as location, gradual elevation of the terrain, proximity to bodies of water, etc. in the forecasting procedure. This problem may be amplified when used for the Philippines due to the island topography of the country and its weather conditions may be “very poorly represented by coarse GCM models” (Robertson, Qian, Tippett, Moron, & Lucero, 2012).

These problems may all be encountered when using NWP models. Due to this possibility, other methods should be considered so as to mitigate the risk of committing errors. Additionally, the comparison of multiple weather forecasts may also be useful as it can help verify the credibility of such forecasts. This study, therefore, proposes the use of a purely statistical model in forecasting future weather conditions to circumvent these problems. This could potentially be useful since it could provide an alternative method for weather forecasting in the Philippines; one that does not rely on the results of dynamic models to do so.

The primary objective of this paper is to investigate the use of a multivariate ARMA model in modelling Nueva Ecija weather data. Specifically, it was of interest to study the forecasting accuracy of the developed multivariate ARMA model. It was also of interest to determine the practical use of the developed forecasts by comparing its accuracy with the accuracy of the official PAGASA WRF forecasts.

This paper concentrated on generating forecasts using the classical statistical weather forecasting approach. This means that the forecasts that were made in this study solely relied on statistical modeling and absolutely refrained from the use of any information provided by NWP models. The only data that was used in this study that came from NWP models is the PAGASA generated WRF forecasts. These forecasts were only used in this study in order to compare its performance to the performance of the developed multivariate ARMA model.

An inherent weakness that is present for most time series models, including the one developed in this study, is its inaccuracy when performing long-term forecasting. Time series models only reproduce historical patterns of the data and may be unable to properly represent any significant long term changes, such as climate change, in its forecasts. As a result, this study is not concerned in long term forecasting and, therefore, is not broached upon.

II. Overview of Methods

Two models were initially focused on in this study. The first of these models is the Multivariate Autoregressive (MAR) model initially developed by Matalas (1967). This model is simply the multivariate extension of the univariate AR (p) or the univariate ARMA (p,q) model. In this framework, the present value of any series is modelled as a function of its past p values as well as the past p and q values of other series. Due to this form, the MAR model is able to demonstrate the statistical relationships present among the variables and among the different time lags that are used in the model. However, this model assumes that each series would be modelled using the same p- and q- orders. Thus, it may be inappropriate to use if it is found that each series shall be modelled by different univariate ARMA models.

The second model that was initially focused on in this study was the multivariate ARMA model detailed in Salas et al. (1980). In this approach, it is assumed that not all series may be modelled using the same p- and q- orders of the ARMA model. This poses some difficulties in building the theoretical multivariate model. Instead, the results of the univariate ARIMA models are used and the correlations in space of the series are incorporated into the multivariate model through the residuals of these univariate models. Thus, this model is still able to incorporate the multivariate relationships present between each series but is not as functional as the MAR model since it is unable to include the past values of the other series as regressors.

III. Methodology

The data used in this study came from the weather stations maintained by PAGASA for the province of Nueva Ecija in the Philippines and covers the years 2001 to 2016. PAGASA has two weather stations in Nueva Ecija. They have one synoptic station located in Cabanatuan City and one agromet station located in Central Luzon State University. Precipitation, minimum, and maximum temperature data were taken from these two stations. Precipitation readings were recorded in millimeters (mm) while temperature readings were recorded in Celsius (°C). Observations starting from January 1, 2001 up to December 31, 2015 were used for the model building procedure. These observations were deseasonalized first using seasonal decomposition to ease the model building procedure. Meanwhile, observations starting from January 1, 2016 up to December 31, 2016 were withheld and were used to compute for the forecasting accuracy of the model. SAS and R were used to perform the statistical analysis in this paper.

For the data that was collected, it was found that the most appropriate multivariate model is the one detailed in Salas et al. (1980). Thus, a model of this form was fitted and forecasts for the year 2016 were generated from the resulting model. These forecasts coincide with the withheld data set and would only have a lead time of one day. These forecasts were then seasonalized by integrating back their seasonal indices. All temperature forecasts were then rounded off to the ones digit while all precipitation forecasts were rounded off to the tenths digit.

To visually inspect the performance of each set of forecasts, their time plots were constructed and were superimposed on the time plot of the original series. Meanwhile, numerical measures of forecasting accuracy were generated to quantitatively measure the accuracy of each model. For this, the Mean Absolute Deviation (MAD), the Residual Standard Error (RSE), the Mean Percentage Error (MPE), the Mean Absolute Percentage Error (MAPE), and the Mean Absolute Scaled Error (MASE) were computed. These measures were computed for both the multivariate ARMA and WRF forecasts. Further comparison of the forecasting capabilities of the two models was also performed. For this, the performance of the two models for yearly forecasting, monthly forecasting, and extreme event and non-extreme event forecasting were inspected.

IV. Results and Discussion

Yearly Forecasting

To help visualize the difference in performance between the multivariate ARMA and the WRF models, a plot of their forecasts is given. Each graph contains three time plots: the time plot of the historical values of each series, the time plot of the multivariate ARMA forecasts, and the time plot of the WRF forecasts. These graphs are given in Figure 1.

Upon inspection of Figure 1, it can easily be seen that the forecasts of the multivariate ARMA model are able to follow the pattern set by the historical series. That is, its forecasts are generally able to follow the increases or decreases of the historical series for, roughly, the same time points. However, there is a limit to the volatility that the multivariate ARMA forecasts can reproduce. In the same figure, it is shown that the aforementioned forecasts were not able to properly forecast the historical series whenever there is an extreme increase or decrease in its value. This is especially evident when inspecting the two precipitation series since there are numerous sudden peaks and dips in its values. In these instances, the multivariate ARMA forecasts are simply not able to generate these extreme leaps in its values.

On the other hand, it can be seen that the forecasts generated by the WRF model were also able to generally follow the pattern of the actual series. However, it is not as good as that of the multivariate ARMA forecasts since there are instances where the WRF forecasts create its own patterns that are not in line with what has happened in the historical series. An example of this may be seen from the two precipitation series since the WRF forecasts differed markedly from the actual series. Despite this, however, it is clear that the WRF model better replicates the extreme variability present in the historical series as compared to the multivariate ARMA model.

Based on these visual findings, it would be very hard to determine which between the two models is more accurate and is more precise. Thus, to help objectively determine which between the two models has produced a better set of forecasts, numerical measures of forecasting accuracy were computed. These values are given in Table 1.

Inspecting the values of these numerical measures, it may be seen that the MAPE of both the WRF and multivariate ARMA forecasts are below 10%. This is important since, according to a well-established rule-of-thumb, it implies that both sets of models may be considered as good models. Take note that this previous statement is only applicable to the four temperature series since only their MAPE values may be computed. The MAPE cannot be computed for the two precipitation series since most of their historical values are zero. It may also be seen that the MASE values of the multivariate ARMA forecasts are below or are near the value of one (Table 1). This is important since a set of forecasts whose MASE values are less than one are said to be better than a one-period-ahead forecast from the naïve method (Hyndman, 2006). The same cannot be said, however, for the WRF forecasts since the same table clearly shows that all of its MASE values are above one.

Upon comparing the values given in Table 1, it may clearly be seen that the multivariate ARMA model has smaller values for almost all numerical measures. The only numerical measure of forecasting accuracy that is smaller for the WRF forecasts is the RSE for the Cabanatuan maximum temperature series. Noticeably, some of these differences may even be considered as substantial. For example, it may be seen that the differences in the MAPE values of the two sets of forecasts range from about 0.5% to about 4%. This may be considered as a huge disparity which could indicate a substantial difference in the errors between the multivariate ARMA and WRF forecasts. This then suggests that the errors of the multivariate ARMA forecasts are substantially lower as compared to the WRF forecasts. Thus, it may be said that the former set of forecasts are more accurate as compared to the latter. This claim is further strengthened by inspecting the MASE values of these forecasts since all multivariate ARMA MASE values are lower as compared to their corresponding WRF counterparts. This is especially true for the two precipitation series since there is a huge disparity between their MASE values.

The aforementioned results also suggest that most of the multivariate ARMA errors are less volatile as compared to the WRF errors. This is due to the fact that most of the RSE values for the multivariate ARMA forecasts, a number which measures the spread of the errors, are less than that of the WRF forecasts which implies that they vary less. Thus, based on these two findings, it may be said that the multivariate ARMA forecasts are more accurate and more precise as compared to the WRF forecasts for the entirety of 2016.

Monthly Forecasting

The information given in the previous section of this paper summarizes the forecasting accuracy for the whole of 2016 but does not, however, reveal any information regarding the monthly performance of the model. Inspecting the monthly performance of the developed model would be useful in practice and is, thus, performed. The results of this investigation are detailed in Figures 2 through 7.

Inspecting the results of this investigation, it may be seen that the majority of the numerical measures for the multivariate ARMA forecasts are smaller as compared to their WRF counterparts (Figures 2 – 7). In fact only 31 out of the 312 numerical measures were smaller for the WRF forecasts; 18 of which were found in the two maximum temperature series. In the majority of these 31 instances, it may be seen that the difference in the numerical measure values between the multivariate ARMA and WRF forecasts were actually minimal. This leads to the conclusion that, for these instances, the performance of the two sets of forecasts are comparable.

Closer inspection of the monthly numerical measures for the two maximum temperature series also reveals an interesting similarity (Figures 3 and 6). In both of these figures, it may be seen that both sets of forecasts performed comparably from the months of May to September. This finding is interesting since these months mainly come from the wet season of the country. As such, the WRF forecasts were expected to have a decisively better performance due to its ability to better replicate the volatility of the series; which is highest during these months. Nevertheless, it may be seen from these results that this was not the case.

Further study of the monthly numerical measures for the four temperature series reveals that the instances where the multivariate ARMA forecasts had higher numerical measure values are the months that have the highest monthly standard deviation values (Figures 2, 3, 5, and 6). The months of May, June, July, August, and September are the 2nd, 1st, 3rd, 4th, and 5th highest standard deviation values, respectively, for the Cabanatuan maximum temperature series. The months of December, January, and February are the 1st, 2nd, and 3rd highest standard deviation values, respectively, for the Cabanatuan minimum temperature series. The months of May, June, July, and September are the 3rd, 1st, 2nd, and 5th highest standard deviation values, respectively, for the CLSU Muñoz maximum temperature series. All of these months are where the values of the numerical measures for the multivariate ARMA forecasts are slightly higher as compared to their WRF counterparts. This hints at the possibility that, whenever high variability is expected, the WRF model may outperform the multivariate ARMA model.

Based on these findings, it may be concluded that the monthly multivariate ARMA forecasts are at least comparable to the monthly WRF forecasts; with the majority of the results suggesting that the former is more accurate and precise as compared to the latter. Furthermore, it was also found that the instances where the multivariate ARMA model was slightly outperformed by the WRF model were actually the months with the highest variability. This could indicate that, for such scenarios, the multivariate ARMA model may perform poorly. To determine if this is the case, the performance of the two models for forecasting extreme and non-extreme events was investigated.

Extreme and Non-Extreme Event Forecasting

For this investigation, all observations that were found to be within two standard deviations from the mean were deemed to be non-extreme events while the rest were deemed to be extreme events. For the non-extreme event case, it may be seen that all numerical measures are substantially lower for the multivariate ARMA forecasts, as evidenced by the disparity in their values, as compared to their WRF counterparts (Figure 8). From this, it may be said that the multivariate ARMA model was able to produce more accurate and more precise forecasts for the non-extreme events case as compared to the WRF model. This is unsurprising since the multivariate ARMA model is known to produce forecasts that generally hover around the mean of a series. As such, it is usually a good model for non-extreme scenarios.

The results presented for the extreme case, on the other hand, are not as straightforward (Figure 9). The only aspect that is easily seen is that the MAPE and MASE values for the two sets of forecasts are more than 10% and 1.0, respectively, which indicates that the two models are not good extreme event models. It may even be seen that the MAPE reaches a value of about 129%; which highlights just how bad these forecasts are for extreme events. These results, however, are unsurprising since these models were calibrated to account for the entire series and not just its extreme events.

To better understand the results presented for the extreme events scenario, consider summarizing and grouping together all numerical measures by the series for which they belong to. If this was performed, it would reveal that the multivariate ARMA forecasts had a lower value only for the following numerical measures: (1) the MPE for the Cabanatuan minimum temperature series, (2) the RSE for the Cabanatuan maximum temperature series, (3) the RSE, MAD, MAPE, and MASE for the two precipitation series, (4) the RSE, MAD, MPE, MAPE, and MASE for the CLSU Muñoz minimum temperature series, and (5) none for the CLSU Muñoz maximum temperature series.

These results confirm an earlier conjecture that the multivariate ARMA model could potentially perform poorly as compared to the WRF model for instances when high variability is expected. This is exactly what has happened for the Cabanatuan minimum temperature series and the two maximum temperature series. For these three series, the majority of numerical measures suggest that the WRF extreme events forecasts are more accurate and are, mostly, more precise as compared to their multivariate ARMA counterparts. However, these results also show that this conjecture is not true for all cases as there are extreme event scenarios where the multivariate ARMA model performed better than the WRF model.

What is interesting about these results is that the multivariate ARMA forecasts outperform their WRF counterparts for the extreme occurrences of the two precipitation series. For both series, four out of the five numerical measures all suggest that the multivariate ARMA forecasts were more accurate and precise as compared to the WRF forecasts (Figure 9). This is quite surprising since the WRF forecasts were expected to perform much better due to their ability to replicate the extreme variability of these precipitation series (i.e. the sudden peak in values) as compared to the multivariate ARMA model. However, as was shown by these results, this is not the case and, in fact, it was shown that the multivariate ARMA model had more accurate and precise forecasts as compared to the WRF model.

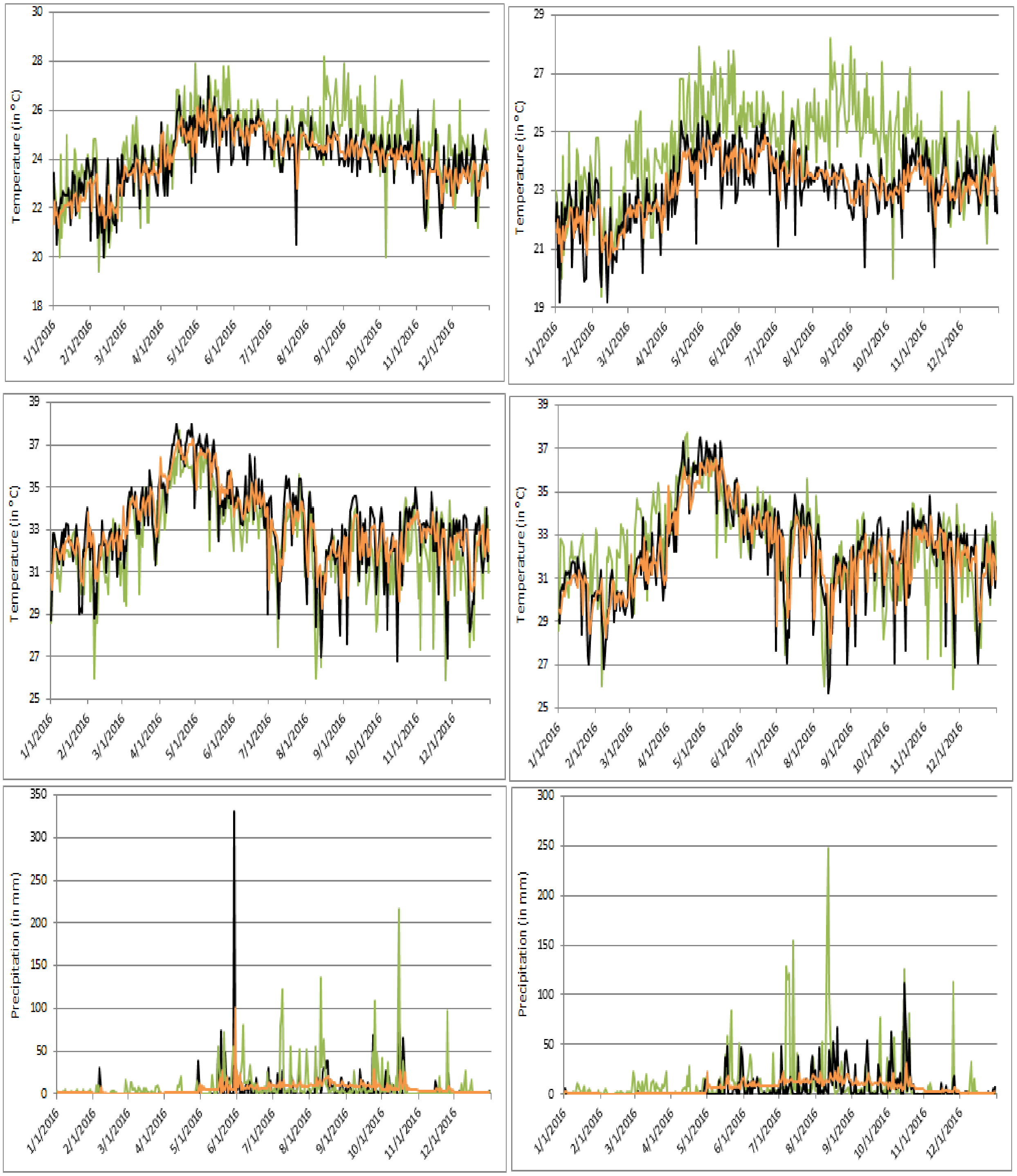
Lastly, results also showed that the multivariate ARMA forecasts for the extreme events of the CLSU Muñoz minimum temperature series were also more accurate and more precise as compared to the WRF forecasts. Evidence of this may be seen in all five numerical measures as all five of them have lower values for the multivariate ARMA forecasts. From these findings, it may be said that no one model is better for forecasting the extreme events of all six series. Thus, these results suggest that, for extreme events, it would be best to consider both sets of forecasts rather than just one.

V. Conclusion

In the Philippines, the most commonly used approach to weather forecasting all revolve around the use of a NWP model. This paper has brought up some problems that may be encountered when using these types of models and, thus, proposed a possible alternative by using a purely statistical model. The paper proposes that certain weather conditions, such as temperature and precipitation, may be better forecasted by developing a model using a multivariate statistical approach; to be specific, by modelling them using a multivariate ARMA model. To study this possibility, data from Nueva Ecija was taken and was fitted with a multivariate ARMA model of the form given in Salas et al. (1980).

The developed model was then used to produce forecasts for 2016 and its accuracy was compared to the accuracy of the WRF forecasts. Visually, it was shown that the multivariate ARMA model was better able to replicate the general pattern of the historical series but the WRF model was better able to replicate the variability of the historical series. Numerical measures of forecasting accuracy were also used to compare the two sets of forecasts. These were then computed for three scenarios: yearly forecasting, monthly forecasting, and extreme and non-extreme event forecasting. Results from the yearly forecasting showed that the multivariate ARMA model is a good forecasting model since both its MAPE and MASE values are less than or near 10% and 1.0, respectively. In fact, the MAPE values of the multivariate ARMA forecasts only ranged from about 2.8% to about 3.2% and their MASE values only ranged from about 0.85 to about 1.03.

Results from these investigations revealed that the multivariate ARMA model generally had a better performance in yearly, monthly, and non-extreme event forecasting. It also revealed that no one model is better for forecasting extreme events for all six series. Instead, the forecast from both the multivariate ARMA and WRF models should be considered and should be taken into consideration. Overall, the results of this study suggest that the multivariate ARMA does have practical use for weather forecasting in the Philippines.



Legend: - *Actual Series* *Multivariate ARMA* *WRF*

Figure 1. Historical series along with the multivariate ARMA and WRF forecasts for minimum temperature (top row), maximum temperature (middle row), and precipitation (bottom row) of the Cabanatuan (left) and CLSU Muñoz (right) stations.

Table 1.
Measures of forecasting accuracy for the WRF and multivariate ARMA one-step ahead forecasts for the whole of 2016

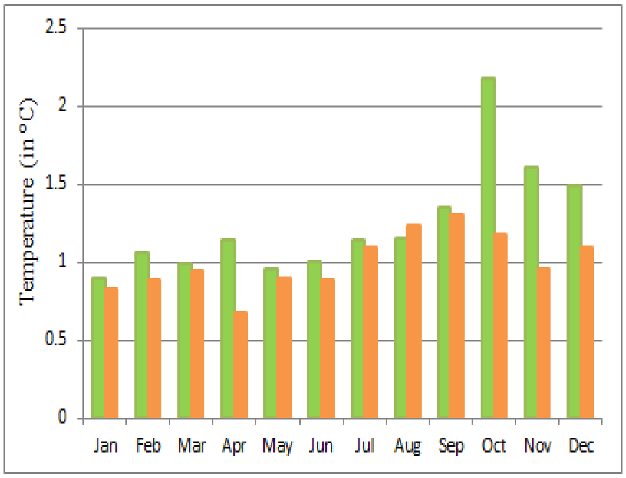
Series \ Measure	MAD	RSE	MPE	MAPE	MASE
Z_1	1.0438 °C	1.2587 °C	2.1041%	4.3964%	1.3769
	0.6713 °C	0.8607 °C	0.0339%	2.8340%	0.8855
Z_2	1.1553 °C	1.2489 °C	-2.0945%	3.5141%	1.0662
	0.9951 °C	1.3200 °C	-0.2406%	3.0853%	0.9183
Z_3	9.2719 mm	24.5857 mm	N/A	N/A	1.2394
	7.0079 mm	20.6742 mm	N/A	N/A	0.9387
Z_4	1.5825 °C	1.3640 °C	5.9602%	6.9159%	2.0161
	0.6631 °C	0.8599 °C	-0.0054%	2.9018%	0.8448
Z_5	1.2986 °C	1.6442 °C	0.9403%	4.1375%	1.1871
	1.0148 °C	1.3702 °C	-0.1222%	3.2345%	0.9276
Z_6	10.0082 mm	24.2795 mm	N/A	N/A	1.5924
	6.4350 mm	11.6943 mm	N/A	N/A	1.0307

Legend: - *WRF Forecasts* - *Multivariate ARMA Forecasts*

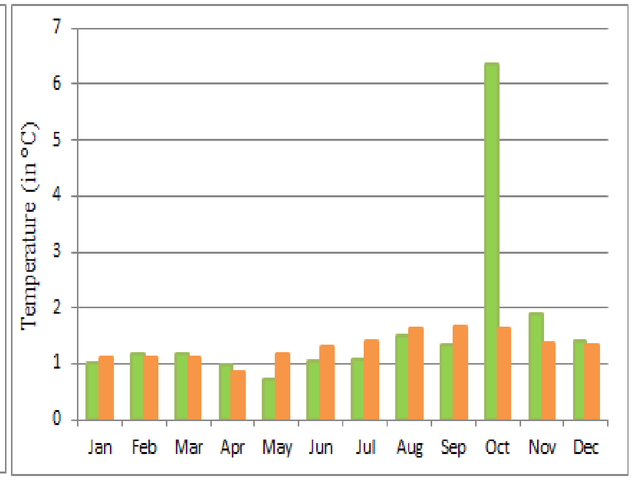
Z_1- *Cabanatuan minimum temperature series,* Z_2- *Cabanatuan maximum temperature series,* Z_3- *Cabanatuan precipitation series,* Z_4 - *CLSU Muñoz minimum temperature series,* Z_5- *CLSU Muñoz maximum temperature series,* Z_6- *CLSU Muñoz precipitation series*

Legend: - *Multivariate ARMA* *WRF*

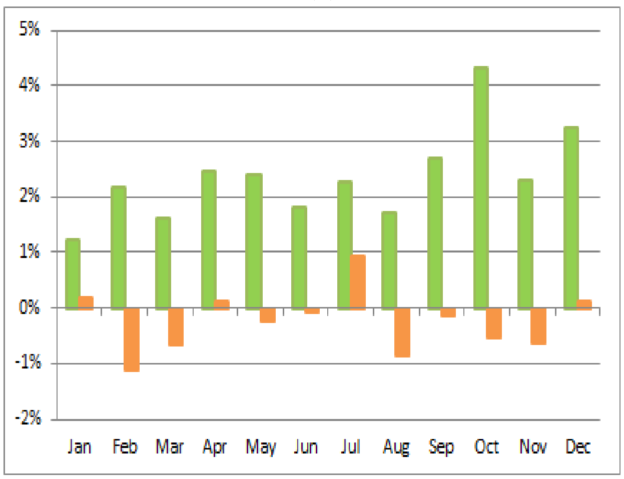
Figure 2. Monthly MAD (a), RSE (b), MPE (c), MAPE (d), and MASE (e) values of the multivariate ARMA and WRF forecasts for the Cabanatuan minimum temperature series.



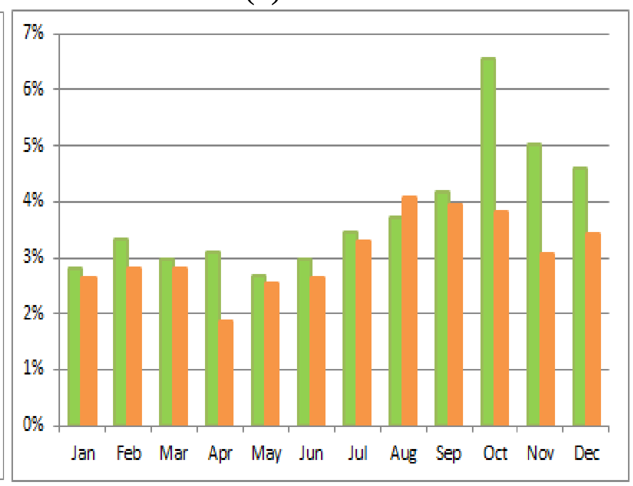
(a)



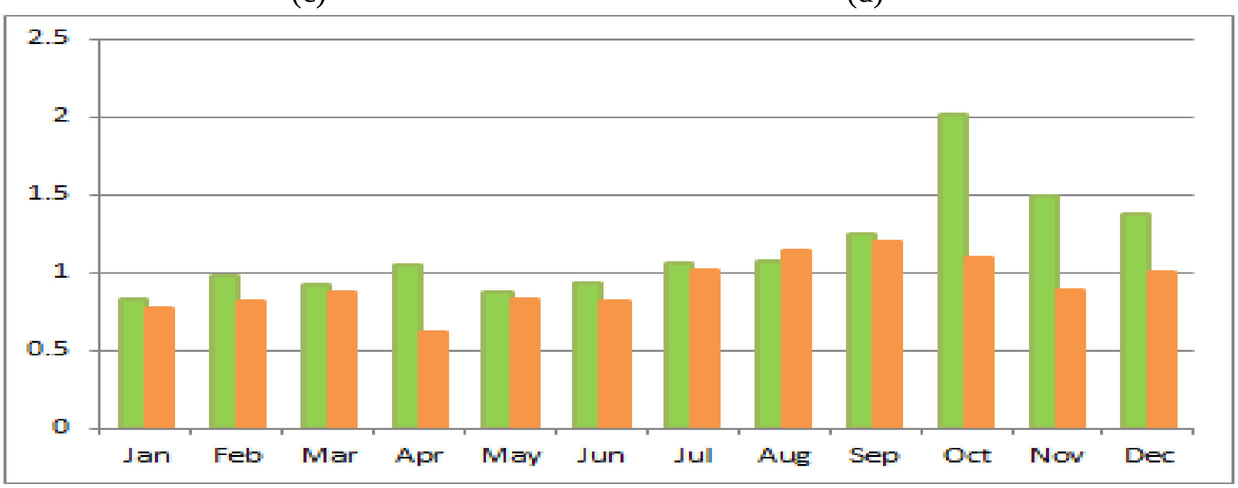
(b)



(c)



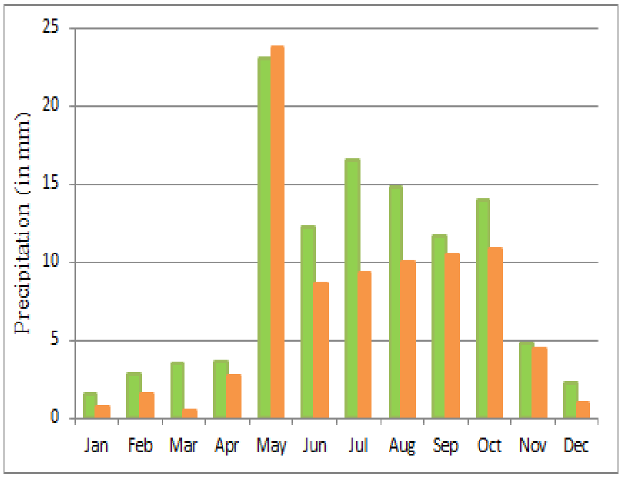
(d)



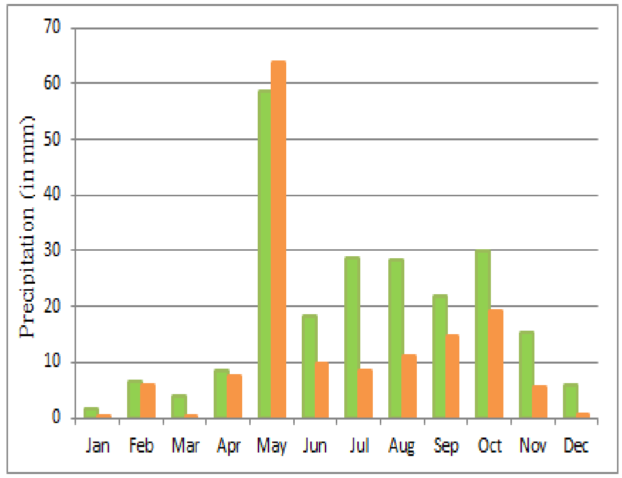
(e)

Legend: - *Multivariate ARMA* *WRF*

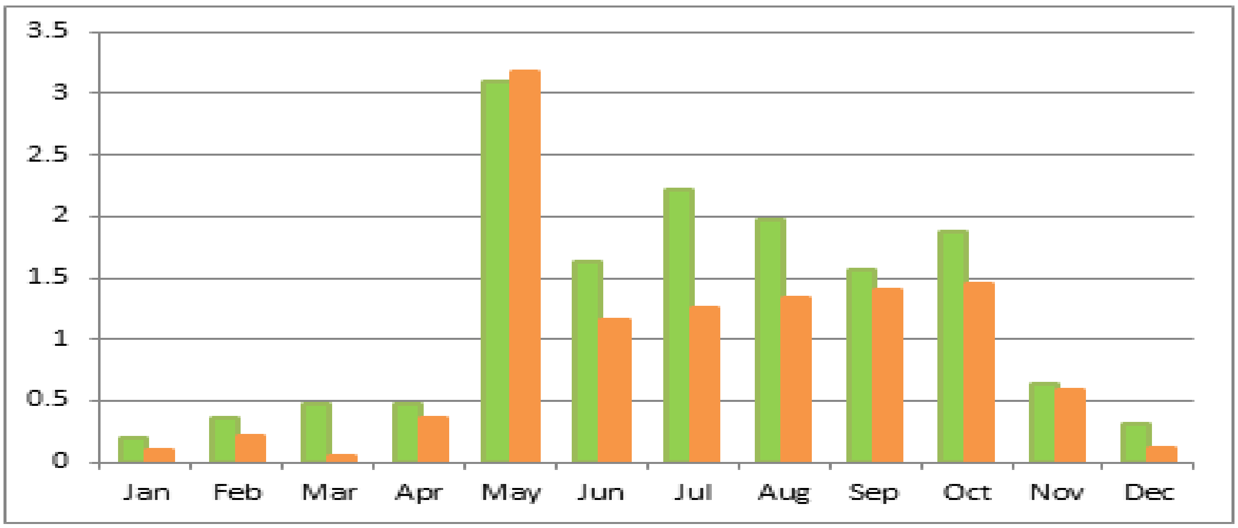
Figure 3. Monthly MAD (a), RSE (b), MPE (c), MAPE (d), and MASE (e) values of the multivariate ARMA and WRF forecasts for the Cabanatuan maximum temperature series.



(a)



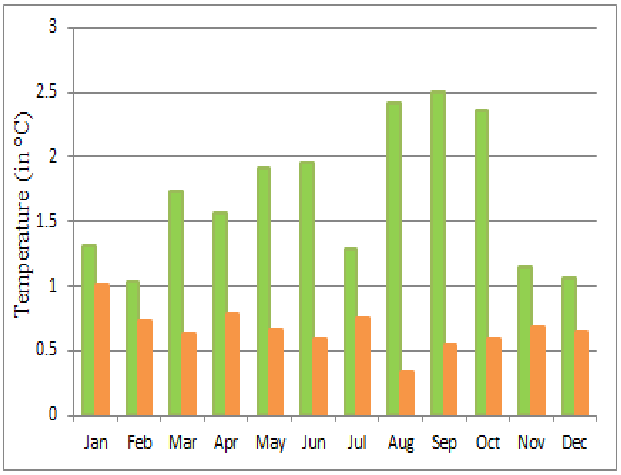
(b)



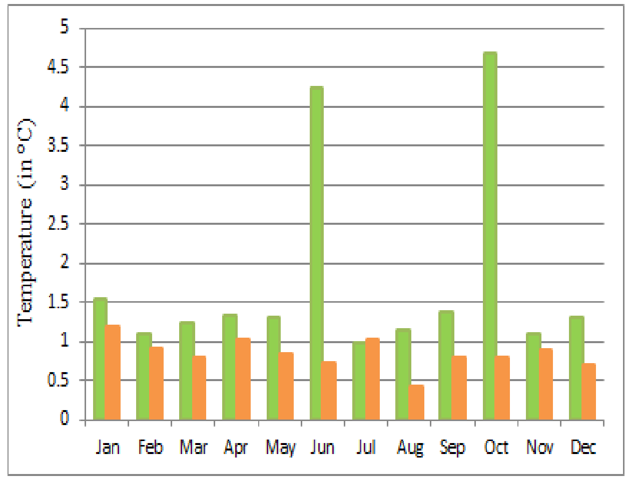
(c)

Legend: - *Multivariate ARMA* *WRF*

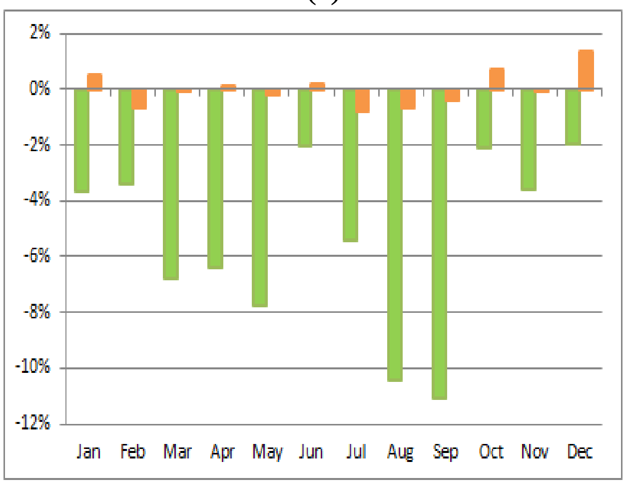
Figure 4. Monthly MAD (a), RSE (b), and MASE (c) values of the multivariate ARMA and WRF forecasts for the Cabanatuan precipitation series.



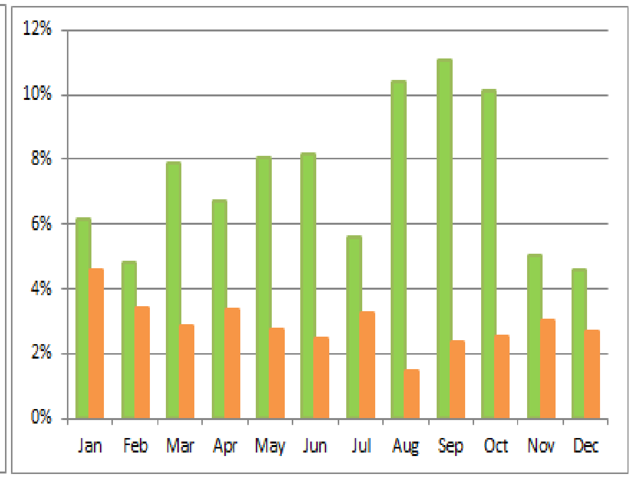
(a)



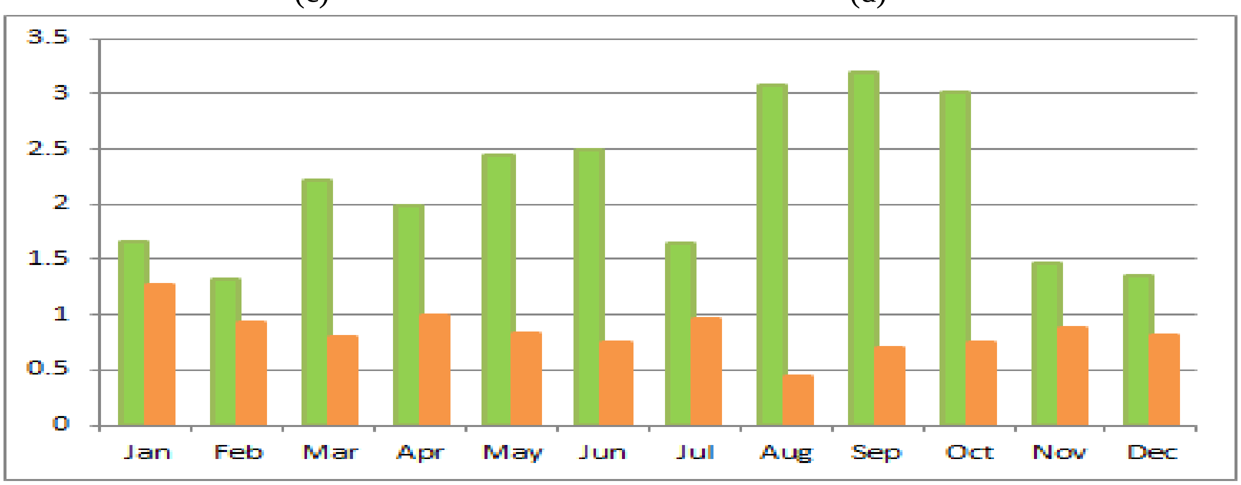
(b)



(c)



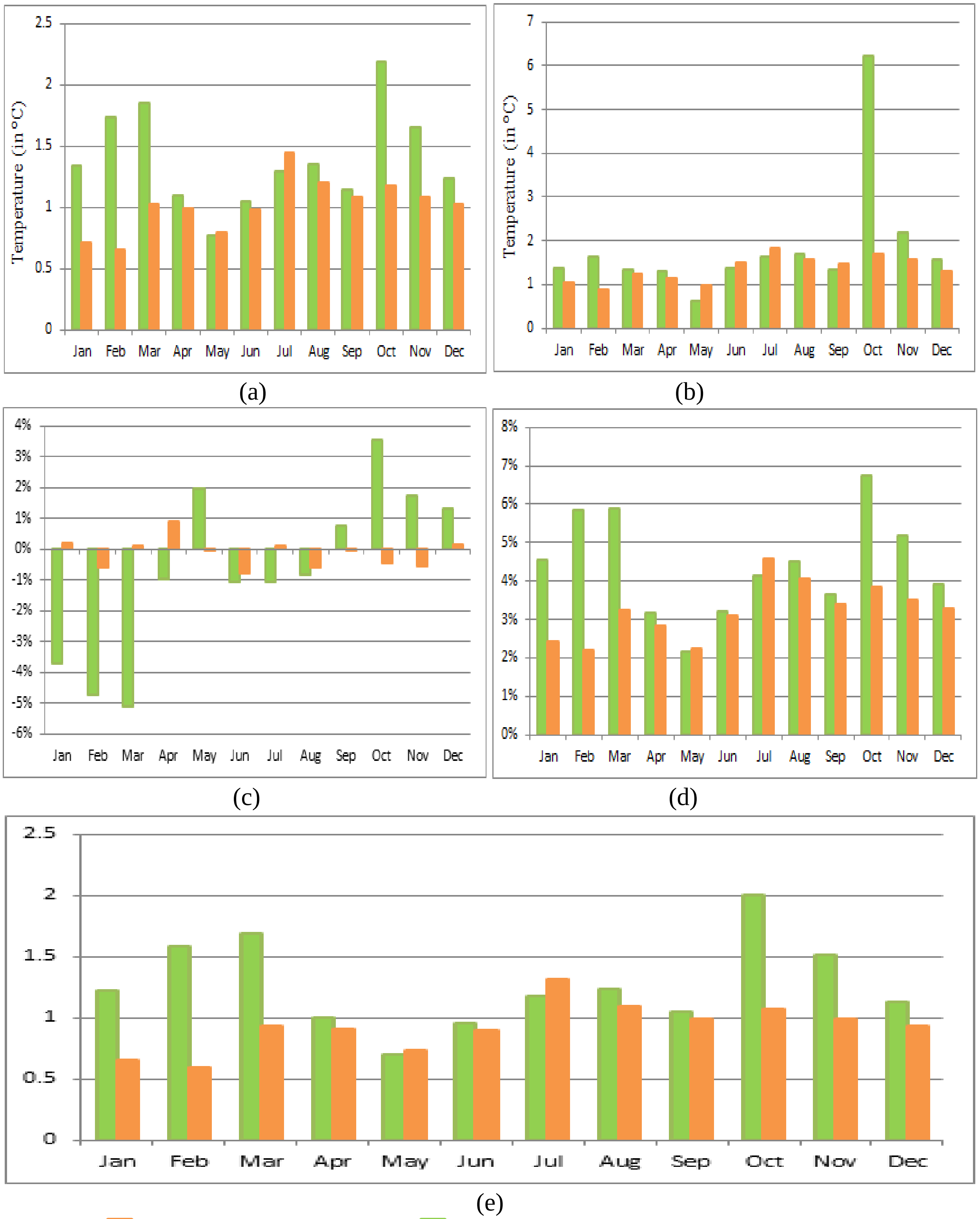
(d)



(e)

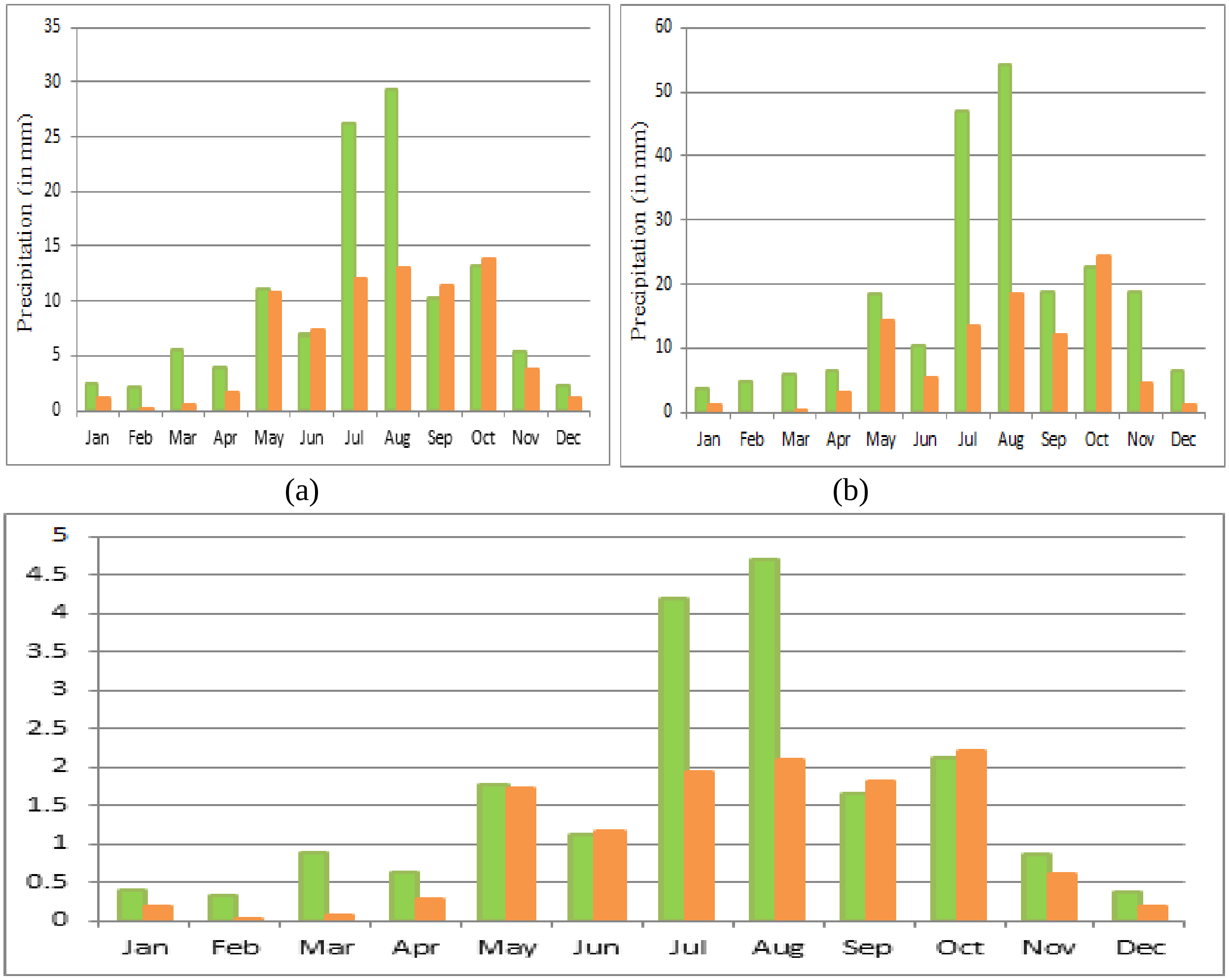
Legend: - *Multivariate ARMA* *WRF*

Figure 5. Monthly MAD (a), RSE (b), MPE (c), MAPE (d), and MASE (e) values of the multivariate ARMA and WRF forecasts for the CLSU Muñoz minimum temperature series.



Legend: - *Multivariate ARMA* *WRF*

Figure 6. Monthly MAD (a), RSE (b), MPE (c), MAPE (d), and MASE (e) values of the multivariate ARMA and WRF forecasts for the CLSU Muñoz maximum temperature series.



(c)

Legend: - *Multivariate ARMA* *WRF*

Figure 7. Monthly MAD (a), RSE (b), and MASE (c) values of the multivariate ARMA and WRF forecasts for the CLSU Muñoz precipitation series.

Legend: - *Multivariate ARMA* *WRF*

Figure 8. MAD (a), RSE (b), MPE (c), MAPE (d), and MASE (e) values of the multivariate ARMA and WRF forecasts for non-extreme events.

Legend: - *Multivariate ARMA* *WRF*

Figure 9. MAD (a), RSE (b), MPE (c), MAPE (d), and MASE (e) values of the multivariate ARMA and WRF forecasts for extreme events.

REFERENCES

Ihshaish, H., Cortes, A., Senar, M.A. (2012). Towards Improving Numerical Weather Predictions by Evolutionary Computing Techniques. *Procedia Computer Science, 9,* 1056 – 1063. Retrieved February 10, 2017 from http://www.sciencedirect.com/science/article/pii/S1877050912002359.

Koide, N., Robertson, A.W., Ines, A.V.M., Qian J., Dewitt, D.G., & Lucero, A. (2013). Prediction of Rice Production in the Philippines Using Seasonal Climate Forecasts. *Journal of Applied Meteorology and Climatology, 52,* 552 – 569. Retrieved February 15, 2017 from http://www.pagasa.dost.gov.ph/images/climate_and_agromet_files/climate_studies/RICE-PRODUCTIONS-AMS.pdf.

Lansigan, F.P., de los Santos, W.L., & Coladilla, J.O. (2000). Agronomic Impacts of Climate Variability on Rice Production in the Philippines. *Agriculture, Ecosystems and Environment, 82*(1-3), 129 – 137.

Lansigan, F.P. & Salvacion, A.R. (2010, October). *Assessing The Effect of Climate Change on Rice and Corn Yields In Selected Provinces in the Philippines*. Paper presented at 10th National Convention on Statistics, Mandaluyong City.

Malone, T.F. (1955). Applications of Statistical Methods in Weather Prediction. *Proceedings of the National Academy of Sciences of the United States of America, 41*(11), 806 – 815. Retrieved February 10, 2017 from http://www.jstor.org/stable/89159.

Matalas, N.C. (1967). Time Series Analysis. *Water Resource Research, 3*(3), 817 – 829, doi: http://dx.doi.org/10.1029/WR003i003p00817.

Matalas, N.C. (1967). Mathematical Assessment of Synthetic Hydrology. *Water Resource Research, 3*(4), 937 – 945, doi: http://dx.doi.org/10.1029/WR003i004p00937.

Robertson, A.W., Qian J., Tippet, M.K., Moron, V., & Lucero, A. (2012). Downscaling of Seasonal Rainfall over the Philippines: Dynamical versus Statistical Approaches. *Monthly Weather Review, 140,* 1204 – 1218. Retrieved February 15, 2017 from http://www.pagasa.dost.gov.ph/images/climate_and_agromet_files/climate_studies/DOWNSCALING_SEASONAL_RR.pdf.

Salas, J.D., Delleur, J.W., Yevjevich V., & Lane, W.L. (1980). *Applied Modeling of Hydrologic Time Series*. Colorado, USA: Water Resource Publications.

Wilks, D.S. (2011). *Statistical Methods in the Atmospheric Sciences* (3rd Edition). Oxford; Waltham, MA: Academic Press.