Sains Malaysiana 47(2)(2018): 409-417
http://dx.doi.org/10.17576/jsm-2018-4702-24

Meteorological Multivariable Approximation and Prediction with Classical VAR-DCC Approach

(Penghampiran Berbilang Pemboleh Ubah Meteorologi dan Jangkaan dengan Pendekatan Klasik VAR-DCC)

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ABSTRACT

The vector autoregressive (VAR) approach is useful in many situations involving model development for multivariables time series. VAR model was utilised in this study and applied in modelling and forecasting four meteorological variables. The variables are n rainfall data, humidity, wind speed and temperature. However, the model failed to address the heteroscedasticity problem found in the variables, as such, multivariate GARCH, namely, dynamic conditional correlation (DCC) was incorporated in the VAR model to confiscate the problem of heteroscedasticity. The results showed that the use of the VAR coupled with the recognition of time-varying variances DCC produced good forecasts over long forecasting horizons as compared with VAR model alone.

Keywords: Dynamic conditional correlation; forecast; meteorology; vector autoregressive

ABSTRAK

Pendekatan vektor autoregresif (VAR) adalah berguna dalam pelbagai keadaan yang melibatkan pembangunan model berbilang siri masa pemboleh ubah. Model VAR digunakan dalam kajian ini dan diaplikasi dalam pemodelan dan peramalan empat pemboleh ubah meteorologi. Pemboleh ubah ini adalah data hujan n, kelembapan, kelajuan angin dan suhu. Walau bagaimanapun, model ini gagal untuk menangani masalah heteroskedastisiti yang ditemui dalam pemboleh ubah, justeru, multivariat GARCH iaitu kolerasi dinamik bersyarat (DCC) telah dimasukkan pada model VAR untuk merampas masalah heteroskedastisiti. Keputusan menunjukkan bahawa penggunaan VAR ditambah pula dengan pengiktirafan daripada variasi perbezaan masa DCC menghasilkan peramalan yang baik ke atas peramalan panjang berbanding model VAR semata-mata.

Kata kunci: Korelasi dinamik bersyarat; meteorologi; ramalan; vektor autoregresif

Introduction

Climate change or global warming is deemed as the most atrocious environmental issue in the 21st century (Calvin et al. 2012). Extreme or severe weather is devastating and can lead to a more harmful natural disaster. A disaster is typically caused by the climate changes and can cause to a more serious disruption to the societies involving human, material, economic and environmental losses. It also affects the ways individuals cope with natural resources. Since, 1950s, global warming has been unequivocal and many researchers have observed the fact that the changes will be unprecedented over decades. The atmosphere and ocean have warmed, the amount of ice has diminished and the sea level has risen. The data that are needed in measuring the climate change include temperature, rainfall and precipitation solar radiation (IPCC 2014).

Time series analysis is an essential measurable instrument that investigate the behaviour of time dependent records and forecast future values and these are dependent on the historical backdrop of the information variation. A time series is a sequence of observations measured over time which can be of discrete or continuous time unit. A more thorough understanding can be acquired by investigating distinct variables that are pertinent to each other. A multivariate time series comprise successions of estimations of a few concurrent factors that are revised with time (Chakraborty et al. 1992). A vital case is the point at which the factors being measured are fundamentally related, for instance, when comparable characteristics are measured at various areas. In estimating new values for every variable, better expectation capacities are accessible if varieties in alternate factors are additionally considered. A powerful estimation must depend on every single accessible relationship and exact inter-dependencies among various worldly successions. Numerous accessible strategies for time-series studies accept linear correlations among the factors (Box & Jenkins 1971). However, in this present reality, temporal varieties that are present in the information do not show basic regularities and it is a challenge to investigate and anticipate precisely. Linear recurrence relations their mergers depict the conduct of such information are regularly observed to be insufficient. It appears to be important, therefore, that nonlinear models be utilised for the investigation of true transient information. In a study, Tong (1983) described several disadvantages of linear modelling for time-series analysis. One of the disadvantage is that it is incapable to show sudden blasts of an expansive amplitude at sporadic time interval. Research that was conducted after Tiao and Tsay's (1989) study has also acknowledge the issue and suggested linear time series models for multi variables to solve the issue. To accommodate such failures, nonlinear models, for example, the threshold and bilinear models, proposed and highlighted Tong (1990) while the utilisation of nonlinear transformation of the initial information before conducting the 'normal' linear modelling was recommended by Granger and Newbold (1986). Most of the meteorological data are influenced by the nonlinear characteristic of the variance which usually known as time-varying variance or volatility. This can be captured by the generalised autoregressive conditional heteroscedasticity (GARCH) models developed by Engle (1982). GARCH is one of the most reliable tools to seize the change in variance. Yusof and Kane (2013) modelled the volatility of the rainfall using the hybrid of ARIMA-GARCH method while Benth and Benth (2007) modelled the seasonal volatility of the time dynamics of the daily average temperatures using an Ornstein-Uhlenbeck process.

There are many works related to weather forecasting and most of the works focus on temperature forecasting that analyses financial weather derivatives as the prime application. Besides atmospheric models, models attempting to capture these dynamics using time-series models, examples of the works includes; Benth et al. (2007), Campbell and Diebold (2005), Oetomo and Stevenson (2004), Svec and Stevenson (2007) and Taylor and Buizza (2006, 2004). According to Oetomo and Stevenson (2004), although a model that relies on auto-regressive moving average processes exhibits a better goodness-of-fit than Monte Carlo simulation models, such models do not necessarily generate better forecasts. Another important issue which Campbell and Diebold (2005) and Taylor and Buizza (2006) discussed was point and density forecasting. While time-series model is more popular for wind and temperature forecasting, these techniques are not as widely used for the combination of multi-variable weather forecasting. Heinemann et al. (2006) and Remund et al. (2008) stipulated that comparing the forecasts of different methods is useful in providing comparative statistics to validate a forecasting model. Wind speed is typically forecasted several minutes to several days ahead, typically using statistical methods. For example, Erdem and Shi (2011) used auto-regression moving average-based approaches whereas Li and Shi (2010) used artificial neural networks. Other works, such as Chen et al. (2013) and Traiteur (2011), combined multiple numerical techniques to produce ensemble wind forecasts. Giebel et al. (2011) provided a thorough analysis of the feasible technique for wind speed forecasting. Meanwhile, Liu et al. (2014) used vector autoregressive method to models and forecast solar radiation, temperature and wind speed.

This paper used a combination of multivariate time-series methods to model and generate 12 months of rainfall, temperature, humidity and wind speed forecasts at Alor Star station in Malaysia. The four-weather variables were response variables in a vector autoregressive (VAR) model and the residuals of the estimated variables were then modelled using dynamic conditional correlation (DCC). Other than model estimation, an out-of-sample validation to test the quality of the forecasts had also been conducted. This study improved on Norrulashikin et al. (2015) where the authors investigated the suitability of vector autoregressive model towards the multivariable meteorological data.

DATA AND METHODS

The data used were collected from Alor Star station. It is situated in the north-western of Peninsular Malaysia at the edge of Malacca Strait which isolates Malaysia and Indonesia with coordinates $6°7'N$ and $100°22'E$. The city includes a territory of 424 km² and is encompassed by essential waterway frameworks, for example, the Anak Bukit River, Kedah River, Alor Merah, River Langgar, Alor Malai and Tajar River. Similar to a majority parts of Peninsular Malaysia, Alor Star highlights a tropical rainstorm atmosphere under the Koppen atmosphere categorisation. Alor Star has a exceptionally extensive wet season. As is basic in a few locales with this atmosphere, rainfall is seen notwithstanding amid the short dry season. Temperatures are moderately predictable over the span of the year, with normal high and low temperatures of about 32 °C and 23 °C, respectively. Alor Star receives approximately 2300 mm of precipitation for each year.

VECTOR AUTOREGRESSIVE (VAR) MODEL

Selection of lag

The Akaike (AIC), Schwartz (SC) and Hannan-Quinn (HQC) information criterias decides the length of lag for VAR p order, (Misztal 2010). The associated criterias are:

1. $AIC = \ln \frac{1}{T} \sum_{t=1}^{T} (\hat{u}_t^{(p)})^2 + m\frac{2}{T}.$
2. $SC = \ln \frac{1}{T} \sum_{t=1}^{T} (\hat{u}_t^{(p)})^2 + m\frac{\ln T}{T}.$
3. $HQC = \ln \frac{1}{T} \sum_{t=1}^{T} (\hat{u}_t^{(p)})^2 + m\frac{2 \ln(\ln T)}{T},$

where $\hat{u}_t^{(p)}$ is the estimated residuals of the AR(p) process and m is the quantity of estimated parameter.

STATIONARITY TESTING

In this paper, we concentrated on the Augmented Dickey-Fuller (ADF) test. An ADF test analysing on the invalid speculation of unit root against the option of stationarity (Dickey & Fuller 1979). The formulation of an ADF test is as follows:

$$X_t = \alpha X_{t-1} + y_t\delta + \beta_1\Delta X_{t-1} + \beta_2\Delta X_{t-2} + ... + \beta_p\Delta X_{t-p} + \varepsilon_t.$$

The hypothesis: H_0: $\alpha = 0$ (There exist unit root in the series)
H_1: $\alpha \neq 0$ (The series is stationary)
The test statistics: $t_\alpha = \hat{\alpha}/se(\hat{\alpha})$,

where ΔX_t is the differenced series; X_{t-1} is the immediate previous observation; y_t is the optional exogenous regressor; α and δ are the parameter to be estimated, $(\beta_1, ..., \beta_p)$ is the coefficients of the lagged difference term up to lag p and e_t is the error term. The null hypothesis is rejected if t_α is less than asymptotic critical values.

MODEL ESTIMATION

A VAR model specification was utilised to model each variable as an element of all the lagged endogenous variables in the framework. Johansen (1988) examined that the procedure e_t is characterised by an unrestricted VAR system of order (p):

$$y_t = \delta + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + ... + \Gamma_p y_{t-p} + u_t,\ t = 1, 2, 3, ..., T,$$

where y_t is independent $I(1)$ factors; the Γ's are estimable parameters; and $u_t \sim$ iid $(0, \Sigma)$ is vector of impulses which represent the unforeseen developments in y_t. Nevertheless, such a model is just suitable if each of the arrangement in y_t is integrated to order zero, $I(0)$. It implies that each arrangement is stationary (Wong et al. 2007).

STRUCTURAL ANALYSIS

Granger causality test is an approach used to figure out if the one-time series is appropriate in predicting. Granger (1969) defined the concept of causality as a cause that cannot come after the impact. Along these lines, if a variable x influences a variable y, the previous ought to help in enhancing the expectations of the latter variable (Lütkepohl 2005). The causality model is defined as follow :

$$x_t = c + \sum_{t=0}^{2} \alpha_i x_{t-i} + \sum_{t=0}^{2} \beta_j x_{t-j} + u_t\,.$$

The hypothesis: H_0: $B_1 = B_2 = 0$ (x do not Granger cause y)
H_1 = at least one, $\beta_\text{i} \neq 0$, i = 1, 2 (x Granger cause y)

The test statistics:

$$F = \frac{(SSE_r - SSE_{ur})/q}{SSE_{ur}/(T-k)} \sim F((df_r - df_{ur}), (T-k)),$$

where SSE_r is the sum of squares of residual from the restricted model and SSE_{ur} is the sum of squares of residual from unrestricted model, $k = (1 + 4p)$ and $q = (1 + p)$. Failed to reject the null hypothesis if the p-value is more than the significance level, else we reject the null hypothesis if the p-value is fewer than the significance level.

DYNAMIC CONDITIONAL CORRELATION (DCC)

The models of multivariate GARCH are devised with main goal to investigate the volatilities and correlations co-movements between variables This is done for it to provide better decision tools in modelling and forecasting techniques (Sclip et al. 2016). The literature provides several multivariate GARCH models, for example, the VECH, BEKK, CCC and DCC models. Of all the multivariate models, the DCC model of Engle (2002) was decided to be used as VECH and BEKK is unsuitable for more than three variables. In addition, DCC offers better execution in terms of portfolio designation among the families, pertinent to extensive panel models. Therefore, it is more powerful than the constant correlation estimator initiated by Bollerslev (1990).

This model exploit the way that correlation matrices are less demanding to handle than the covariance matrices. Indeed, the DCC models concepts is fascinating and engaging. It split up the multivariate volatility modelling into two stage. The initial stage is to acquire the volatility series $\{\sigma_{it,t}\}$ for $i = 1, ..., k$. In practical estimation of DCC models, we consider a k-dimensional innovation a_t to the residuals series z_t. Univariate GARCH models are used to acquire estimates of the volatility series $\{\sigma_{it,t}\}$. Let $F_{t-1}^{(i)}$ denote the σ-field generated by the former information of a_{it}. That is, $F_{t-1}^{(i)} = \sigma[a_{i,t-1}, a_{i,t-2}, ...\}$. Univariate GARCH models obtain $Var(a_t|F_{t-1}^{(i)})$. Then again, the multivariate volatility $\sigma_{it,t}$ is $Var(a_t|F_{t-1})$.

The last stage is to model the dynamic dependence of the correlation matrices ρ_t. Let $\Sigma_t = [\sigma_{ij,t}]$ be the volatility matrix of a_t given F_{t-1}, which represents the information accessible at time $t - 1$. Then, the conditional correlation matrix is

$$\rho_t = F_t^{-1}\Sigma_t D_t^{-1},$$

where $D_t = diag\{\sigma_{11,t}^{1/2}, ..., \sigma_{kk,t}^{1/2}\}$ is the diagonal matrix of the k volatilities at time t. Let $\eta_t = (\eta_{it}, ..., \eta_{kt})'$ be the marginally standardized innovation vector, where $\eta_{it} = a_{it}/\sqrt{\sigma_{it,t}}$. Then, ρ_t is the volatility matrix of η_it. The DCC models is projected by Engle (2002) and is defined as:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 Q_{t-1} + \theta_2 \eta_{t-1}\eta'_{t-1} \qquad (1)$$

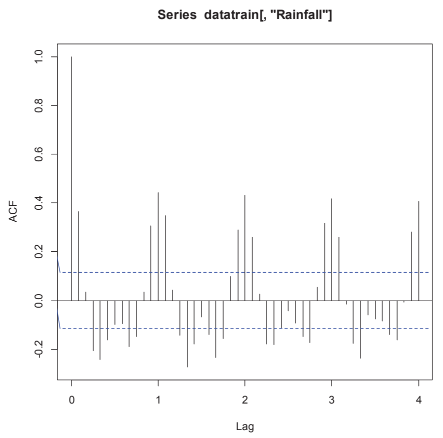
$$\rho_t = J_t Q_t J_t,$$

where for η_t, $\bar{Q}$ is the unconditional covariance matrix, θ_1 are non-negative real numbers fulfilling $0 < \theta_1 + \theta_2 < 1$ and $J_t = diag\{\sigma_{11,t}^{-1/2}, ..., \sigma_{kk,t}^{-1/2}\}$, with $q_{ii,t}$ denotes the (i, i)th component of Q_t. From the delineation, Q_t is a positive-definite matrix and J_t is just a normalisation matrix. The correlations dynamic dependence is administered by (1) with parameters θ_1 and θ_2 (Tsay 2014).

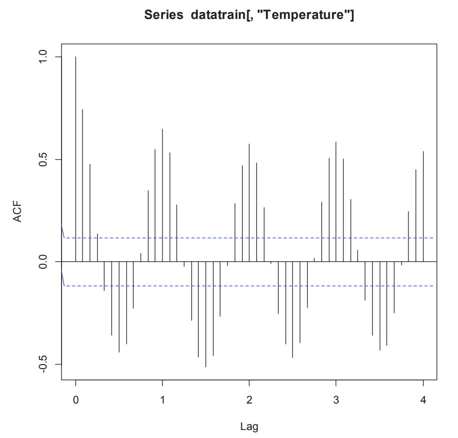
RESULT AND DISCUSSION

STATIONARITY TEST

Figure 1 displays the autocorrelation function (ACF) for each series of the data. From the figure, it is found that all series shows yearly seasonal pattern, depicting that all series will repeat the same pattern every 12 months. ADF test was piloted to determine the integrated order of the series. The outcomes of the ADF test was reported in



1(a)



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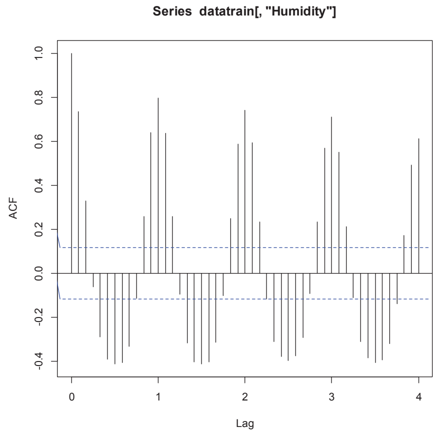

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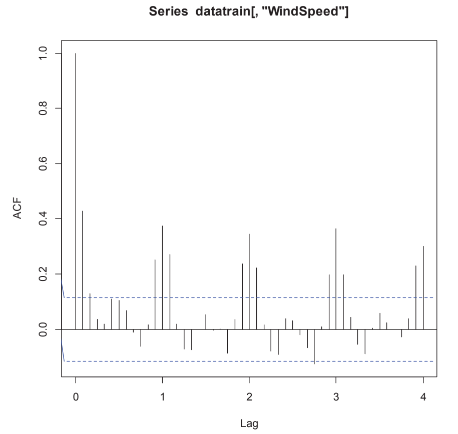

1(d)

FIGURE 1(a)-1(d). The autocorrelation function for each series

TABLE 1. The ADF stationarity test

Variable	Level	Seasonal difference
Rainfall (R)	–4.3431***	–10.3289***
Temperature (T)	–0.2173	–5.8769***
Humidity (H)	–0.622	–6.8221***
Wind Speed (W)	–0.7918	–7.3766 ***

** indicates the null hypothesis rejection of unit root at 5% significance. The 5% critical value is –1.95

TABLE 2. Information criteria for model estimation

	p=1	p=2
AIC	9.1268	**9.0384**
SC	9.3367	9.4582
HQ	9.2110	**9.2069**

Table 1. Seasonal differencing was needed rather than first differencing since the ACF shows seasonal pattern. These result showed that unit root can be rejected for the seasonal difference but not the levels for all factors at 5% level of significance, except for rainfall data where rainfall data are already stationary in level, however because of the seasonal pattern in the ACF, then the seasonality should be removed. Thus, the meteorological data are integrated of the order twelve, namely I(12).

Vector Autoregressive and Granger Causality Lag length order is a standout amongst the most imperative viewpoints that ought to be incorporated into VAR modelling in light of the fact that on the off chance that we had picked an alternate request of lag length, we would experience diverse result that could prompt misdirecting interpretation. In this study, AIC, SC and HQC were used as a criterion procedure as a part of request to recognize the right number of lag of VAR order, p. AIC proposed that an ideal lag length, p=2 is fitting for the modeling time series data while SC and HQC suggested p=1. In the wake of recognizing the lag order for VAR model, the estimation procedure of VAR modeling was performed. The parameter estimation of VAR (1) and VAR (2) went through model comparison using AIC, SC and HQC again as shown in Table 2. VAR (2) was chosen as it shows smaller values from AIC and HQC criterion. Equation 2 reports the vector autoregressive estimates for each meteorological variable.

$$\begin{bmatrix} R \\ T \\ H \\ W \end{bmatrix}_t = \begin{bmatrix} 1.5738 \\ 0.0035 \\ -0.0131 \\ -0.0227 \end{bmatrix} + \begin{bmatrix} 0.0467 & 2.842 & 0.2932 & -0.6448 \\ 0.0008 & 0.396 & -0.0210 & 0.0178 \\ -0.0030 & -0.320 & 0.4116 & 0.0073 \\ -0.0004 & 0.132 & -0.0039 & 0.2091 \end{bmatrix}$$

$$\begin{bmatrix} R \\ T \\ H \\ W \end{bmatrix}_{t-1} = \begin{bmatrix} -0.0192 & -0.879 & 0.7783 & 0.8063 \\ 0.0010 & 0.230 & -0.0093 & 0.0262 \\ -0.0019 & 0.253 & 0.1452 & -0.3281 \\ -0.0009 & -0.224 & -0.0210 & 0.1124 \end{bmatrix} \begin{bmatrix} R \\ T \\ H \\ W \end{bmatrix}_{t-2} . \tag{2}$$

The VAR estimation was utilised to test the Granger causality of the explanatory variables. For x Granger-cause y, Granger causality does not claim that, x is the reason for y, for example, y moves because x moves. It just says that x is helpful in forecasting y. The outcomes of the Granger-causality tests was displayed in Table 3. F-test and null hypotheses where the independent variables do not Granger-cause the explanatory variable can be rejected at 5% level of significance. From the result displayed, it can be concluded that the capability to improve the forecast of weather variables based on the histories of all observable variables is unaffected by the omission of the rainfall's history. However, the history of all variables are needed to improve the forecast of rainfall. The cumulative sum (CUSUM) test was applied to examine the stability parameter of the short-run VAR model as proposed by Brown et al. (1975). The CUSUM of the recursive errors falls within the 5% significance levels, showing that the assessed coefficients are stable over the sample time frame, as presented in Figure 2. The residual analysis of the VAR model was done and found out that the autocorrelation test using Breusch-Godfrey LM test shows the residuals are uncorrelated. However, Breusch-Pagan test and Goldfred-Quandt test for heteroscedastic analysis shows that there exist heteroscedasticity effect on the residuals (Table 5). Hence, DCC modeling is necessary to remove the heteroscedastic effect on the residuals.

TABLE 3. Granger causality test

Null hypothesis	F-test	p-value	Conclusion
Rainfall do not Granger-cause Temperature, Humidity and Wind speed	1.6394	0.0088	Failed to reject null hypothesis
Temperature do not Granger-cause Rainfall, Humidity and Wind speed	1.0906	0.3267	Reject null hypothesis
Humidity do not Granger-cause Rainfall, Temperature and Wind speed	1.1074	0.3025	Reject null hypothesis
Wind speed do not Granger-cause Rainfall, Temperature and Humidity	0.9257	0.6020	Reject null hypothesis

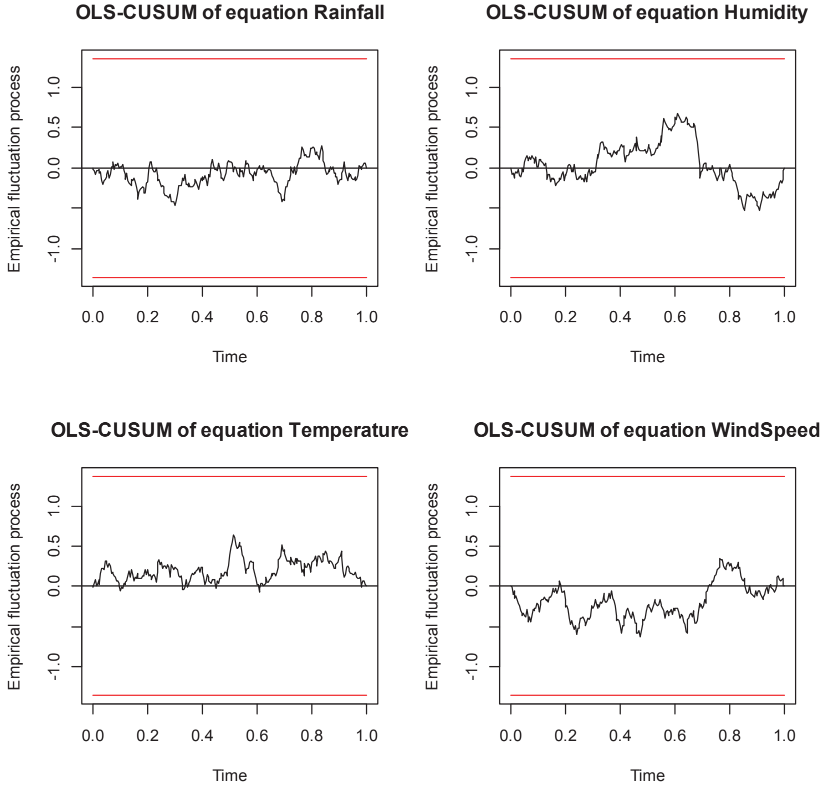

FIGURE 2. The Ordinary Least Square Cumulative Sum (OLS-CUSUM) test

VAR-DCC Hybrid estimation Since VAR model was unable to capture the volatility dynamics of the data, DCC model was introduced to the residuals of VAR (2) to capture the remaining heteroscedastic effect in the model. Table 4 shows the parameters of the fitted DCC models as described in Section 2. The sum of α and β measures the extent to which the variance of current volatility remains significant for long periods into the future. When the sum of α and β is equal to one, then any variance to volatility is permanent and the unconditional variance is infinite. The volatility is said to be explosive if the sum of α and β is greater than one, as such the higher the volatility, the riskier the security.

TABLE 4. VAR-DCC estimation

		Estimates	Standard error	Probability
Parameter	α	8.828e-10	0.0125	0.9999
	β	0.9312	3.245	0.7741
Information criteria	Akaike		14.998	
	Bayesian		15.315	
Log-likehood			–2030.783	

Diagnostic checking Numerous analytic tests on the residuals of the DCC model were carried out to detect if there is any substantial departure from the usual assumptions of model adequacy. These include the Breusch-Godfrey Lagrange multiplier test for residuals autocorrelation, Breusch-Pagan and Goldfred-Quandt test for the heteroscedasticity in the residuals and for model misspecification, the Anderson Darling and Shapiro-Wilk test for normality of the residuals. Table 5 displays the outcomes of the demonstrative tests and the results showed that the residual from the estimated VAR model happens to have heteroscedastic problem where it did not pass the 5% significance level of both test. However, VAR-DCC model passed the tests at 5% significance level, demonstrating that there is no significant departure from the standard assumptions.

TABLE 5. Diagnostic checking for each model

	VAR model	VAR-DCC model
Autocorrelation :		
Breusch-Godfrey LM test	0.342	0.9315
Heteroscedasticity :		
Breusch-Pagan test	0.00041	0.8064
Goldfred-Quandt test	0.00046	0.4025
Normality :		
Anderson Darling test	0.3175	0.3252
Shapiro-Wilk test	0.2601	0.4107

Forecasting ability The predictive adequacy of VAR-DCC model was further assessed by comparing the forecasts with the real meteorological data over the ex post estimating period, which is from January 2008 to December 2008. The mean absolute percentage error (MAPE) was utilised to quantitatively gauge how intently the forecasted variable tracks the real data. The forecast rate error of both VAR and VAR-DCC model is consistent within the acceptable limit of 10%, giving a genuinely low MAPE, except for rainfall series for both models, as shown in Table 6. However, in this study, we are focussing on the VAR-DCC model since VAR model is not able to capture the heteroscedasticity effect and time varying volatility in the residuals. Figure 3(a) to 3(d) that representing the rainfall, temperature, humidity and wind speed variable illustrates vividly the fitted generated from the forecasting model and the real data, demonstrating satisfactory goodness-of-fit of the newly developed VAR-DCC model. The red line represents the observed data while the blue line represents the modeling and forecasting of the VAR-DCC model. Henceforth, the after effects of the analytics tests and the assessment of forecasts prove that the developed VAR-DCC model is satisfactorily effective and powerful to conjecture the climate in Malaysia in the future.

Summary and Conclusion

This study was propelled by the requirement for a meteorological analysis for the determinants of the climate change in assisting the meteorologists to plan for the future climate. For this purpose researcher established and estimated a forecasting model from the monthly meteorological variables. Applying vector autoregressive (VAR) methods and the basic method of multivariate time-series analysis, it was found that the rainfall variable and other related variables namely temperature, humidity and wind speed are interrelated. A VAR was then developed for forecasting purposes but the model did not pass the heteroscedasticity diagnostic statistical criteria. The residual of the model was then being modelled using the time-varying volatility model named dynamic conditional correlation (DCC) to capture the heteroscedasticity effect. A hybrid model, VAR-DCC was then developed and checked against various diagnostic statistical criteria.

The outcomes and the technique implemented in this study may contribute as a source of perspective for other tropical climate nations. The techniques utilised and the outcomes displayed as a part of this paper likewise give experiences into the impacts of these factors on the meteorological forecasting. This paper discovered that when ignoring conditional heteroscedasticity, the VAR model did not give a good forecast performance. However, when conditional heteroscedasticity model was incorporated into the model, researcher obtained the best forecasting performance. The results showed that the use of the VAR coupled with the recognition of time-varying variances DCC produced better forecasts over long forecasting horizons as compared with VAR model alone. The important contribution of this paper is that the forecasting was done at once and the performance is good for all the four meteorological variables. It can be used to predict future behaviour of all the variables. Whether the

3(a)
3(b)
3(c)
3(d)

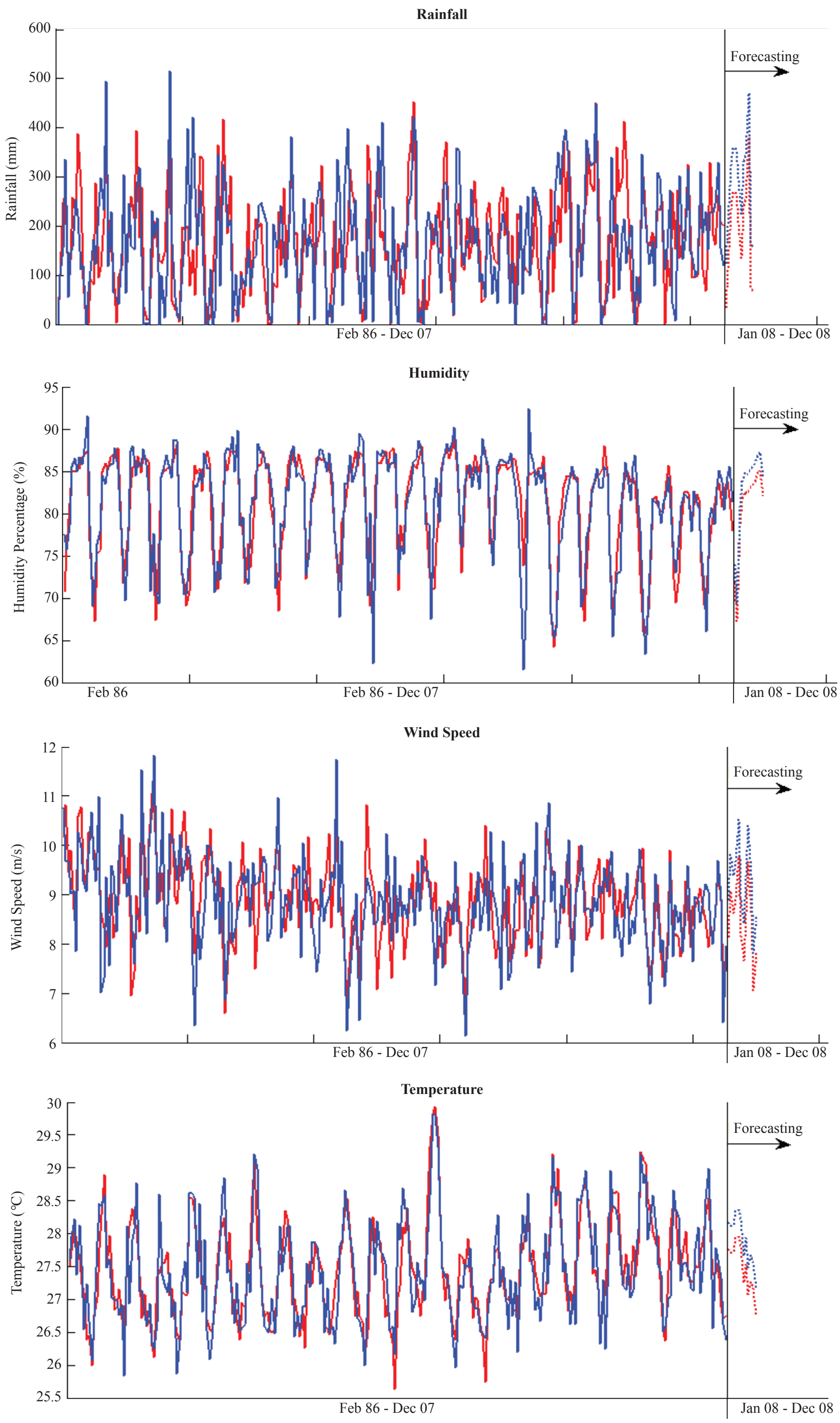

FIGURE 3(a)-(d). Graph of observed and fitted data

TABLE 6. In-sample and out-sample accuracy checking

		Rainfall	Temperature	Humidity	Wind speed
VAR model	In-sample	2.2642	0.0137	0.0280	0.0797
	Out-sample	0.8891	0.0189	0.0313	0.1019
VAR-DCC model	In-sample	2.1240	0.0134	0.0295	0.0808
	Out-sample	0.9011	0.0163	0.0315	0.1040

results can be further substantiated with other data is a topic for future research.

ACKNOWLEDGEMENTS

The authors want to express gratitude toward Universiti Teknologi Malaysia (UTM) and grant vote no. 14H00 for the financing assistance.

REFERENCES

Benth, F.E. & Benth, J.S. 2007. The volatility of temperature and pricing of weather derivatives. *Quantitative Finance* 7(5): 553-561. doi:10.1080/14697680601155334.

Benth, J.Š., Benth, F.E. & Jalinskas, P. 2007. A spatial-temporal model for temperature with seasonal variance. *Journal of Applied Statistics* 34(5): 823-841. doi:10.1080/02664760701511398.

Bollerslev, T. 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalized arch model. *The Review of Economics and Statistics* 72(3): 498-505.

Box, G.E.P. & Jenkins, G.M. 1971. Time series analysis forecasting and control. *Operational Research Quarterly* 22(2): 199-201.

Brown, R.L., Durbin, J. & Evans, J.M. 1975. Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society* 37(2): 149-192.

Calvin, K., Clarke, L., Krey, V., Blanford, G., Jiang, K., Kainuma, M., Kriegler, E., Luderer, G. & Shukla, P.R. 2012. The role of Asia in mitigating climate change: Results from the Asia modeling exercise. *Energy Economics* 34(Suppl. 3). Elsevier B.V.: S251-60. doi:10.1016/j.eneco.2012.09.003.

Campbell, S.D. & Diebold, F.X. 2005. Weather forecasting for weather derivatives. *Journal of the American Statistical Association* 100(469): 6-16. doi:10.1198/016214504000001051.

Chakraborty, K., Mehrotra, K., Mohan, C.K. & Ranka, S. 1992. Forecasting the behavior of multivariate time series using neural networks. *Neural Networks* 5(6): 961-970. doi:10.1016/S0893-6080(05)80092-9.

Chen, N., Qian, Z., Meng, X. & Nabney, I.T. 2013. Short-term wind power forecasting using Gaussian processes. In *23rd International Joint Conference on Artificial Intelligence*. Beijing, China.

Dickey, D.A. & Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association* 74(366): 427-431.

Engle, R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics* 20(3): 339-350. doi:10.1198/073500102288618487.

Engle, R.F. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50(4): 987-1007.

Erdem, E. & Shi, J. 2011. ARMA based approaches for forecasting the tuple of wind speed and direction. *Applied Energy* 88(4): 1405-1414. doi:10.1016/j.apenergy.2010.10.031.

Giebel, G., Brownsword, R., Kariniotakis, G., Denhard, M. & Draxl, C. 2011. The state-of-the-art in short-term prediction of wind power. In *Development of a Next Generation Wind Resource Forecasting System for the Large-Scale Integration of Onshore and Offshore Wind Farms*. Project ANEMOS. pp. 1-36.

Granger, C.W.J. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37(3): 424-438. doi:10.2307/1912791.

Granger, C.W.J. & Newbold, P. 1986. *Forecasting Time Series*. New York: Academic Press.

Heinemann, D., Lorenz, E. & Girodo, M. 2006. Forecasting of solar radiation. In *Solar Energy Resource Management for Elitricity Generation from Local Level to Global Scale*. pp. 83-94. doi:10.1016/j.solener.2006.09.009.

Intergovernmental Panel on Climate Change. 2014. *Climate Change 2014: Synthesis Report*.

Johansen, S. 1988. Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control* 12(2-3): 231-254. doi.org/10.1016/0165-1889(88)90041-3.

Li, G. & Shi, J. 2010. On comparing three artificial neural networks for wind speed forecasting. *Applied Energy* 87(7): 2313-2320. doi:10.1016/j.apenergy.2009.12.013.

Liu, Y., Roberts, M.C. & Sioshansi, R. 2014. A vector autoregression weather model for electricity supply and demand modeling. http://spotidoc.com/doc/1341173/a-vector-autoregression-weather-model-for-electricity-sup.

Lütkepohl, H. 2005. *New Introduction to Multiple Time Series Analysis*. New York: Springer.

Misztal, P. 2010. Foreign direct investments as a factor for economic growth in Romania. *Review of Economic and Business Studies (REBS)* 3: 39-53.

Norrulashikin, Siti Mariam, Fadhilah Yusof & Ibrahim Lawal Kane. 2015. An investigation towards the suitability of vector autoregressive approach on modeling meteorological data. *Modern Applied Science* 9(11): 89-100. doi:10.5539/mas.v9n11p89.

Oetomo, T. & Stevenson, M. 2004. Hot or cold?: A comparison of different approaches to the pricing of weather derivatives. *Journal of Emerging Markets Finance* 4(2): 101-133.

Remund, J., Perez, R. & Lorenz, E. 2008. Comparison of solar radiation forecasts for the USA. In *European PV Conference* 2: 3-5. http://www.task34.iea-shc.org/data/sites/1/publications/Comparison_of_USA_radiation_forecasts.pdf.

Sclip, A., Dreassi, A., Miani, S. & Paltrinieri, A. 2016. Dynamic correlations and volatility linkages between stocks and *sukuk*: Evidence from international markets. *Review of Financial Economics*. 31: 34-44. doi:10.1016/j.rfe.2016.06.005.

Svec, J. & Stevenson, M. 2007. Modelling and forecasting temperature based weather derivatives. *Global Finance Journal* 18(2): 185-204. doi:10.1016/j.gfj.2006.04.006.

Taylor, J.W. & Buizza, R. 2006. Density forecasting for weather derivative pricing. *International Journal of Forecasting* 22(1): 29-42. doi:10.1016/j.ijforecast.2005.05.004.

Taylor, J.W. & Buizza, R. 2004. A comparison of temperature density forecasts from GARCH and atmospheric models. *Journal of Forecasting* 23(5): 337-355.

Tiao, G.C. & Tsay, R.S. 1989. Model specification in multivariate time series. *Journal of the Royal Statistical Society* 51(2): 157-213.

Tong, H. 1990. *Non-linear Time Series: A Dynamical System Approach*. Oxford: Oxford University Press.

Tong, H. 1983. *Threshold Models in Nonlinear Time Series Analysis*. New York: Springer-Verlag.

Traiteur, J.J., Callicutt, D.J., Smith, M. & Roy, S.B. 2011. A short-term ensemble wind-speed forecasting system for wind power applications. American Meteorological Society. doi:10.1017/CBO9781107415324.004.

Tsay, R.S. 2014. *Multivariate Time Series Analysis with R and Financial Applications*. *Statewide Agricultural Land Use Baseline 2015*. Vol. 1. New York: John Wiley & Sons. doi:10.1017/CBO9781107415324.004.
Wong, J.M.W., Chan, A.P.C. & Chiang, Y.H. 2007. Forecasting construction manpower demand: A vector error correction model. *Building and Environment* 42(8): 3030-3041. doi:10.1016/j.buildenv.2006.07.024.
Yusof, F. & Kane, I.L. 2013. Volatility modeling of rainfall time series. *Theoretical and Applied Climatology* 113(1-2): 247-258. doi:10.1007/s00704-012-0778-8.

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Received: 7 February 2017
Accepted: 5 July 2017