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Modelling the Canopy Conductance of Cocoa Tree Using a Recurrent Neural Network

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Abstract: Direct measurement of crop water use is difficult and labour intensive. In some cases, the technicalities involved can only be exploited by well-trained researchers. Therefore, estimating this important crop parameter from readily available climatic data by way of modelling will ease the burden of direct measurement. The aim of the study is to parameterize models of canopy conductance of rain-fed cocoa tree, suitable for inclusion in physically-based model for predicting water use of cocoa trees. To do this, Sap flow density was monitored in three cocoa trees (Forestaro cultivar group) at the eight (8) year old cocoa plantation of the Federal University of Technology, Akure, Nigeria (7° 18' 15.9"N, 5° 07' 32.3"E), from 8th March 2018 to 7th March 2019, covering the two seasons of the region. Cocoa tree transpiration was determined from the measured sap flow and fitted into a physically based model (PM) to derive canopy conductance used for modelling. To choose the best model that predicts canopy conductance (the stomata control of water transport) in cocoa trees, Vector Autoregressive Models (VAR), a multivariate time series model, and Long Short-Term Memory (LSTM) network, an Artificial Intelligence (AI) model were employed. The prediction power of the VAR model was assessed and visualized using the vars R package, while the LSTM model, a Recurrent Neural Network (RNN) algorithm was implemented using Python programming within Google COLAB jupyter notebook. Before modelling, data were tested for stationarity using the Augmented Dickey-Fuller test. While two-thirds of the data were used to train the models, the remaining one-third of the data were used to test the trained model. As VAR models were evaluated using R-squared and Root Mean Squared Error (RMSE), LSTM was evaluated by comparing the train loss and test loss, and also RMSE. VAR (with Adjusted R-Squared=0.11) is found not to be suitable to model the complex relationship between canopy conductance and climatic variables. Further iteration to exclude insignificant climatic variables from the VAR model did not also improve the model. However, LSTM with RMSE of 0.026 and having the test loss not dropping below the training loss was observed to perform better in modelling the canopy conductance of Cocoa. The result of the research further revealed that temporal dynamics of transpiration is complex and difficult to be defined by traditional regression. LSTM with a prediction accuracy of 97.4% could therefore be used for the prediction of cocoa canopy conductance.

Keywords: Cocoa, Canopy Conductance, Sap Flow, Transpiration, Recurrent Neural Network

1. Introduction

Basically, water use characteristics data are time-series in nature, meaning that they are time-dependent and chronological. Thus, best models that suit water use characteristics research should be one that can explain and model time series data, resulting into better understanding of the stochastic mechanism that gives rise to the observed data and good forecast of future value of the series based on the nature of that series and possibly other factors.

For the past few years, different models have been extensively used in analysing time series data similar to water use characteristics [1, 2], and such models can be categorised into three, namely, traditional time series models, econometric models, and artificial intelligence models.

Traditional time series models describe a variable in respect of its own historic variation and pattern, with key focus on seasonality. Based on this characteristic, future predictions can be made. Example of traditional time series models include ARIMA [3, 4], SARIMA [5, 2], Naïve 1, Naïve 2 and exponential smoothing models [6]. In looking further at the performance of these models, ARIMA and SARIMA have been found inconsistent in their prediction performance, and thus, researchers have in recent times sought for alternative models [6]. Naïve 1, naïve 2 and exponential smoothing models have also been employed in research but in many of the studies, they have been used as mere yardsticks for predicting error [6]. Key feature of most of these time series model is that they are univariate in nature, and may not be suitable in predicting crop water use that are determined by multiple factors. In the present study, traditional time series model was not used because crop water use needs to be explained by the factors influencing it.

In contrast to traditional time series models, econometric models are useful in description and prediction, using factors influencing it [7]. Such approach to forecasting is of great interest to crop water use research because it provides information on the extent to which crop water use is influenced by determining factors. Econometric models such as Autoregressive Distributed Lag Model (ADLM) [8], Error Correction Model (ECM) [9], Time Varying Parameter (TVP) [10] and Vector Autoregressive (VAR) models [11] have been used commonly in literature in recent time. However, in the present study, VAR was adopted as the model of choice, being a model that has evolved over the years as a standard model to analyse multivariate time series data [12]. One important feature of VAR is that it is stable, meaning that it can create stationary time series that has time invariant means, variances and covariance structure, assuming there are sufficient starting values [13].

In addition to traditional time series models and econometric models, artificial intelligence (AI) models are other models that have been employed in research involving time series data. AI technique has been applied in various disciplines in recent times [14]. Its advantage is that prior information such as probability and distribution of data are not needed [15]. Examples of AI models in use are Artificial Neural Network (ANN), Support Vector Regression (SVR), Fuzzy Time Series (FTS) [16]. ANN model, which is based on simulation of human brain using a computer model is composed of interconnected processing elements called neurons, which are trained by adjustments of weights connecting the neurons such that the difference between the predicted and the observed outputs minimised as much as possible [17]. A commonly employed algorithm in the training is the back-propagation algorithm [18]. It is such that a neuron output is computed by joining a transfer function to the weighted sum of its input, which later serves as input to other neurons. ANN model is reported to be better than traditional time series model due to its flexibility in modelling non-linearity events [17]. The SVR is based on Support Vector Machine (SVM) procedure. The SVM is a nonlinear generalisation of the Generalized Portrait algorithm developed in Russia in the 1960s [19]. In real sense, SVM algorithm is deeply rooted in statistical machine learning and has wide real-world applications [20]. SVM has been applied to nonlinear regression modelling, such as in support vector regression (SVR) [21, 22]. SVR has been adjudged to be more powerful and flexible than traditional time series model like ARIMA when used in the field of social science [12]. Wen *et al.* [23] evaluated ET_o estimate of SVM models by comparing the output with the ET_o calculated using Penman–Monteith FAO 56 equation (PMF-56) and found that the ET_o estimated using SVM with limited climatic data was in good agreement with those obtained using the conventional PMF-56 equation employing the full complement of meteorological data. In the case of FTS model, it has the advantage of analysing short time series with few historical data. However, the drawback of FTS is that it is not good enough in terms of accuracy. There are suggestions for more research geared towards improving the accuracy and ascertaining its consistency [24].

Water use characteristics and climatic data are time series events that are difficult to predict accurately using traditional regression. Unlike regression predictive modelling, time series also imposes the complexity of a sequence dependence among the input variables. A powerful type of ANN designed to handle sequence dependence is known as recurrent neural networks. The Long Short-Term Memory (LSTM) network is a form of recurrent neural network used in deep learning because very large architectures can be effectively trained [25, 26]. LSTMs (or long-short term memory networks) allow for analysis of sequential or ordered data with long-term dependencies present [25]. A special advantage of LSTMs compared to other time series models such as ARIMA and VAR, is that data does not need to be stationary (i.e. constant mean, variance, and autocorrelation), in order for LSTM to learn [27] for this reason LSTM was employed as a modelling tool in the study.

2. Materials and Methods

2.1. Sap Flow Measurement

Sap flow density of three cocoa trees was measured, following Granier [28] thermal dissipation design. The study was conducted at 8 years old cocoa plantation of the Federal University of Technology, Akure, Nigeria (7° 18' 15.9"N, 5° 07' 32.3"E), from 8th March 2018 to 7th March 2019, covering the two seasons of the region. Cocoa tree transpiration was determined from the measured sap flow and fitted into a physically based model (Penman-Monteith) to derive canopy conductance used for modelling.

2.2. Analysis of Canopy Conductance

The analysis of cocoa canopy conductance in this research was based on the formulation of Penman-Monteith (PM) in equation (1) [29]:

$$\lambda E_c = \frac{\Delta(R_n - G) + \rho_a C_p D_e \, g_a}{\Delta + \gamma\left(1 + \frac{g_a}{g_c}\right)} \quad (1)$$

where, λ (J kg^{-1}) the latent heat of water vapourization, E_c (kg m^{-2} s^{-1}) the canopy transpiration, g_a (ms^{-1}) is the canopy conductance, Δ (kpa K^{-1}) the rate of change of vapour pressure with temperature, γ (kpa K^{-1}) the psychometric constant, ρ_a (kg m^{-3}) the dry air density, C_p (J kg^{-1} K^{-1}) the specific heat capacity of the air, D_e (kpa) the vapour pressure deficit, g_a (ms^{-1}) the aerodynamic conductance, R_n (W m^{-2}) the net radiation at the canopy level and G (W m^{-2}) is the soil heat flux that will be taken as 10% of R_n [30]. Aerodynamic conductance- g_a was derived following the formulation of [31] in equation (2):

$$g_a = \frac{K^2 u_z}{ln\frac{(z-d)}{z_o} ln\frac{(z-d)}{(h_c-d}} \quad (2)$$

where, K is von Karman constant (0.41), z (m) is the height of wind speed measurement, d (m) the zero plane displacement estimated as d=0.67 h_c, with h_c (m) as the tree mean height, z_o (m) is the roughness length taken as $0.1h_c$, and u_z (m s^{-1}) is the wind speed at height z.

Canopy conductance (g_c) representing the integrated behaviour of the leaf stomata conductance [32], is the key crop parameter reflecting its physiological response to changing atmospheric conditions. Inversion of the Penman-Monteith equation (equation 1) has been used successfully to derive canopy conductance [33]. It was estimated by rearranging equation 1 to give equation 3 and substituting the sap-flow transpiration values.

$$g_c = \frac{\gamma \lambda E_c g_a}{\Delta(R_n - G) + \rho_a C_p D_e \, g_a - \lambda(\Delta + \gamma)E_c} \quad (3)$$

2.3. Modelling Canopy Conductance

In this study, Vector Autoregressive Models (VAR) and Long Short-Term Memory (LSTM) networks were used to simulate cocoa canopy conductance and predict the stomata conductance of the cocoa tree. The process of VAR is defined in equation 4:

$$y_t = A_y y_{t-1} + \ldots\ldots\ldots\ldots A_p y_{t-p} + u_t \quad (4)$$

where, A_i are (K X K) coefficient matrices for i=1, ……, p and u_t is a K-dimensional process with E(u_t)=0 and the invariant positive definite covariance matrix $E(u_t u_t^T) = \Sigma_u$(white noise) (Saigal and Mehrotra, 2012). VAR model in this study was implemented using *vars* R package, while LSTM model, a Recurrent Neural Network (RNN) algorithm was implemented using Python programming within Google COLAB jupyter notebook. The approach followed in employing the models in the modelling is as stated below:

2.3.1. Splitting of Datasets

In total, the sap flow data covered about 12 months out of which the first eight (8) months (between March and October) was used as the training data set to build the model, while the latter four months (between November and February) was used as the testing data set for the model, meaning that the training data set accounted for about 67% of the data set while the testing data set accounts for about 33% of the data. For model optimization and cross-validation, the data was divided into two equal sets. The first data consists of all the odd days of measurement, while the second set of data was all the even days of measurement. The second set of data was used to validate the model that will be fitted on the first set of data and *vice versa*. This type of validation has been used by [34, 35].

2.3.2. Checking Data for Non-stationary Component

Before subjecting the data to vector autoregression, there is a need to check if the data is stationary because standard errors from non-stationary data are unreliable. If the data is non-stationary, stationarity needs to be achieved by differencing before subjecting the data to vector autoregression [36]. Thus, data were tested for stationarity using the Augmented Dickey-Fuller test.

2.3.3. Selection of the Order of Model

Before vector autoregression, the optimum number of lags needed to be known and this was done using the VARselect function of the *R vars* package. Optimum lag for the VAR model was selected based on the Schwarz Criterion (SC) of the VARselect function. SC was preferred to the popular Akaike Information Criterion (AIC) because AIC tends to choose the lag number of lags which is inappropriate for VAR models [37].

2.3.4. Estimation of Model Coefficients

Basically for a set of endogenous variables $y_1 \ldots\ldots\ldots\ldots y_T$, coefficients of VAR are computed effectively [13]. Once VAR model coefficients were estimated, further tests such as autocorrelation, forecasting, and dynamic behaviour of model (impulse response functions) were carried out. These processes were implemented using the VAR function of the *R vars* package based on the optimum lag chosen by SC. To assess the fitness of the models, the significance of regression and adjusted R^2 was used. Adjusted R^2 was used instead of R^2 because it is more reliable and unbiased when comparing models with an unequal number of explanatory variables [38]. Models that are not significant at the 5% level, and whose R^2 is less than 50% were discarded.

2.3.5. Diagnostics Test

It is typical of time series data that the variable value observed in the current time can be influenced by values of that variable in previous periods. Thus, it is very common to have autocorrelation of residuals when fitting time series models [37]. Models with autocorrelation may have prediction intervals that are large and unreliable. In the present study, for a model to be recommended to be used for prediction, it must show evidence of no autocorrelation, no overfitting, high fitness and high accuracy. Therefore, VAR models were tested for autocorrelation using Portmanteau test implemented in *R* *portes* package [39], LSTM on the other hand was tested using line plot of train and test loss.

2.3.6. Prediction and Model Evaluation

VAR model was implemented by R programming using vars *R* package and the algorithm of LSTM model was implemented by Python programming ran in Google COLAB jupyter notebook. In order to select the best model to recommend, fitness of the VAR model was evaluated using R-squared. For the LSTM, its evaluation was done by comparing the train loss and test loss, and also RMSE.

2.3.7. Impulse Response Analysis

The impulse response analysis is a type of analysis that can show the extent to which a response variable will react to the effect of shocks in the explanatory variables [13]. Impulse response analysis, which is implemented by impulse response function (irf) function of *var* R package is a moving average representation of VAR in equation 5. Equation 5 represents an orthogonal representation of impulse response function [40]:

$$Y_t = \sum_{i=0}^{\infty} \emptyset_i \, U'_{t-i} \qquad (5)$$

where U'_t and $\emptyset_i$ signify impulse response functions, because they can explain the behaviour of Y_{it} as influenced by shocks U'_t. Impulse response analysis results are useful in that it shows how long the effect of shocks will be.

3. Results and Discussion

Figure 1 shows the correlation matrix of cocoa canopy conductance (g_c) with air temperature, Solar Radiation, Reference Evapotranspiration, Rainfall, and Relative humidity. Correlation of g_c with all the environmental variables was observed to be poor and as a result the dependence of g_c on the combined climatic variables could not be established. Oguntunde and van de Giesen [41] obtained a similar result in the *Anacardium occidentale* plantation. From the foregoing, the use of traditional simple or multiple linear regression models for predicting g_c a time series variable may not likely yield a good result. Before employing the time series model, the stationarity test conducted on the data using the Augmented Dickey-Fuller test shows that the g_c data and the climatic variables were stationary and therefore suitable for the time series model. The result of the test is presented in Table 1.

The result of Vector Autoregressive Models (VAR) presented in Table 2 revealed that the Adjusted R-squared of 0.1139 (11%) is very low. This imply that only about 11% of cocoa canopy conductance (g_c) was explained by the variation in the climatic data. Further iteration to exclude insignificant climatic variable from the model did not also improve the model.

For the LSTM model, the line plot of train and test loss in Figure 2 strongly suggests no evidence of overfitting because the test loss does not drop below training loss. On the whole, the Root Mean Squared Error (RMSE) value of 0.026 and prediction accuracy of 97.4% strongly indicate that LSTM is far better than VAR model in predicting canopy conductance. This is further corroborated by the result presented in Figure 3.

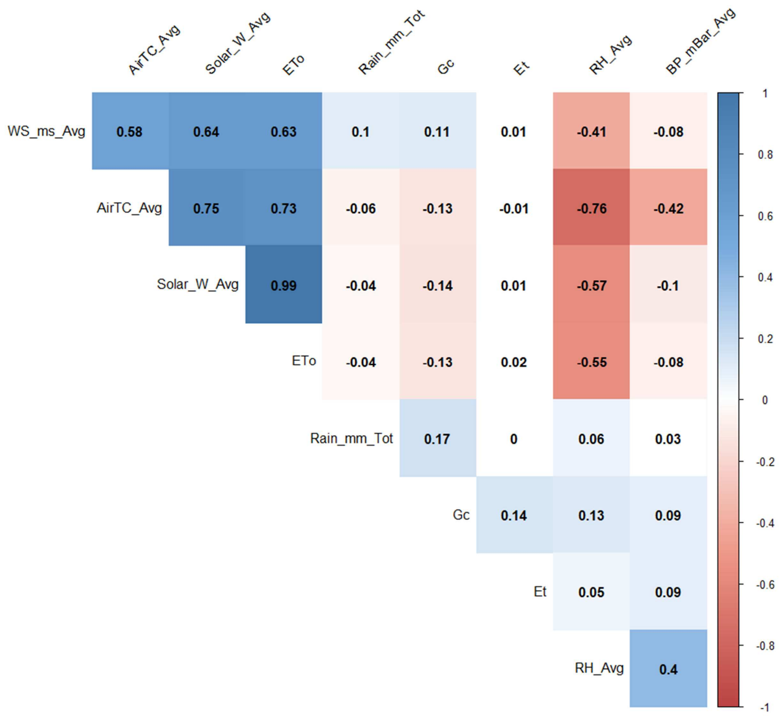

Figure 1. *Correlation matrix of Canopy Conductance(Gc) and climate variables.*

Legend: Air temperature (AirTc_Avg); Solar Radiation (Solar_W_Avg): Reference Evapotranspiration (ETo): Rainfall (Rain_mm_Tot): Relative humidity (RH_Avg)

Table 1. *Augmented Dickey-Fuller Test on Stationarity.*

Variable	P-value	Dickey Fuller	Comment
Rainfall	0.01	-16.261	Stationary
Relative Humidity	0.01	-8.983	Stationary
Wind Speed	0.01	-13.509	Stationary
Solar Radiation	0.01	-20.482	Stationary
Reference Evapotranspiration	0.01	-20.427	Stationary
Atmospheric Pressure	0.01	-4.8103	Stationary
Air Temperature	0.01	-12.338	Stationary
Canopy Conductance	0.01	-15.265	Stationary

Table 2. *VAR Modelling result.*

	Estimate	Std. Error	t value	Pr(>|t|)
Rain_mm_Tot.11	1.78e-04	7.43e-04	0.239	0.810767
RH_Avg.11	5.95e-04	8.59e-04	0.693	0.488358
WS_ms_Avg.11	1.51e-02	4.26e-03	3.533	0.000414 ***
Solar_W_Avg.11	-1.90e-04	7.39e-05	-2.566	0.010325 *
ETo.11	1.97e-01	9.09e-02	2.172	0.029922 *
BP_mBar_Avg.11	-3.25e-03	2.55e-03	-1.274	0.202848
AirTC_Avg.11	-1.31e-03	2.94e-03	-0.447	0.654615
Gc.11	2.26e-01	1.48e-02	15.287	< 2e-16 * **
Rain_mm_Tot.12	9.65e-05	7.55e-04	0.128	0.898256
RH_Avg.12	4.91e-04	1.22e-03	0.402	0.687364
WS_ms_Avg.12	1.11e-03	5.20e-03	0.213	0.831094
Solar_W_Avg.12	2.57e-04	7.37e-05	3.482	0.000502 ***
ETo.12	-4.09e-01	9.17e-02	-4.456	8.55e-06 ***
BP_mBar_Avg.12	-3.93e-04	4.28e-03	-0.092	0.926932
AirTC_Avg.12	4.81e-03	4.25e-03	1.131	0.257907
Gc.12	7.50e-02	1.51e-02	4.961	7.25e-07 ***
Rain_mm_Tot.13	3.13e-03	7.28e-04	4.304	1.71e-05 ***
RH_Avg.13	-7.79e-05	8.53e-04	-0.091	0.927269
WS_ms_Avg.13	-6.79e-03	4.19e-03	-1.621	0.105098
Solar_W_Avg.13	-3.79e-05	6.99e-05	-0.542	0.587667
ETo.13	1.17e-01	8.76e-02	1.331	0.18336
BP_mBar_Avg.13	5.50e-03	2.58e-03	2.131	0.033114 *
AirTC_Avg.13	-1.51e-03	2.93e-03	-0.515	0.606665
Gc.13	3.92e-02	1.49e-02	2.638	0.008374 **
const	-1.98e+00	7.70e-01	-2.581	0.009868 **

Signif. codes: 0	'***' 0.001	'**' 0.01	'*' 0.05 '	.' 0.1 '
Residual standard error: 0.08536 on 4846 degrees of freedom				
Multiple R-squared: 0.1182, Adjusted R-squared: 0.1139				
F-statistic: 27.07 on 24 and 4846 DF, p-value: < 2.2e-16				

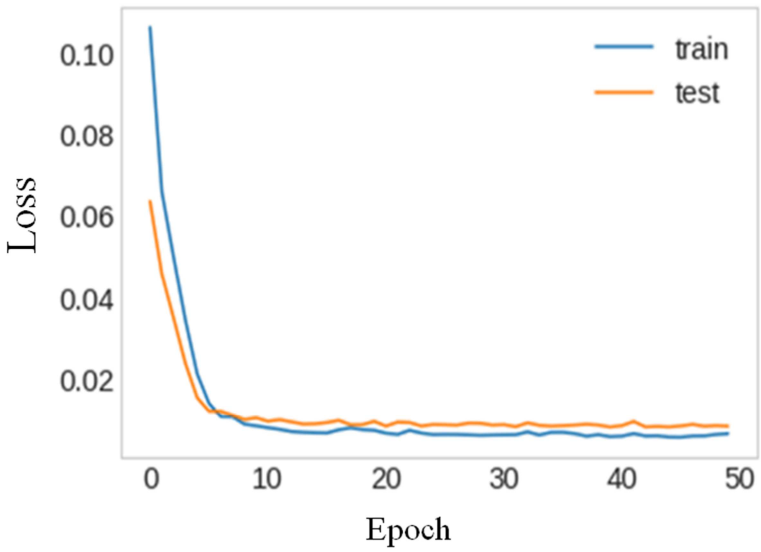

Figure 2. *Diagnostic Line Plot of LSTM Model.*

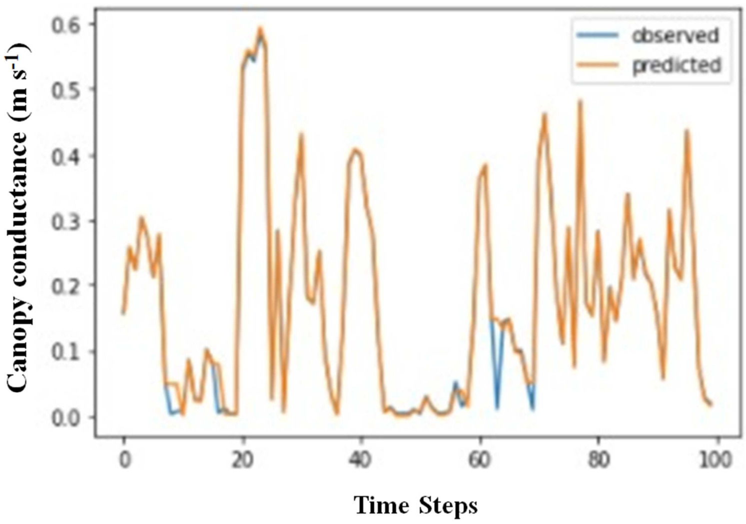

Figure 3. *LSTM Modelling: Observed versus Predicted (RMSE=0.026).*

4. Conclusion

Crop water-use modeling is a complex non-linear time-series task. In the past, some of the models formulated to predict water use characteristics of cocoa in the tropics did not usually take into consideration the time-series nature of the climatic data and the crop water-use characteristics. Having acknowledged the time-series nature of the water-use characteristics of cocoa and the multivariate nature of climatic inputs contributing to crop evapotranspiration, we compared the suitability VAR and LSTM in predicting cocoa canopy conductance, and LSTM was found to be better. The reason why LSTM model performs better than VAR model is its ability to model non-linear relationships and time-series sequence. In general, the proposed LSTM model to predict cocoa canopy conductance can as well be applicable to sites with ecological conditions. In addition, our result also demonstrated the advantage of deep learning techniques over traditional statistical models in predicting crop water use characteristics that are time-series in nature.

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