Evapotranspiration Prediction Using ARIMA, ANN and Hybrid Models for Optimum Water Use in Agriculture: A Case Study of Keiskammahoek Irrigation Scheme, Eastern Cape, South Africa

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Abstract: Evapotranspiration is the main limitation for irrigation development in developing countries and semi-arid regions. Proper prediction of this variable is key for proper planning and positively contribute to daily management of irrigation schemes. This study used 18 years (2001-2018) of remotely sensed data extracted at Keiskammahoek Irrigation Scheme, Eastern Cape province of South Africa, a province that has been declared drought disaster region forcing many irrigation schemes in this region to close some irrigated sections in order to deal with reduced dam levels. This study used three prediction models, namely Auto-Regressive Integrated Moving Average (ARIMA), Artificial Neural Networks (ANN), and Hybrid (ARIMA-ANN) to predict ET for optimal water use in this irrigation scheme. The prediction models were evaluated using four model performance statistics, namely Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and the Pearson's correlation of coefficient (R). The results show that the hybrid (ARIMA-ANN) model outperformed both the ARIMA and ANN consecutively with less values of the statistical performance evaluation showing RMSE = 33.80, MAE = 27.02, MAPE = 17.31, and R = 0.94 compared to higher values of ARIMA and ANN. In general, these prediction results show the dominance of the Hybrid (ARIMA-ANN) model over ARIMA and ANN. These results will assist water managers at Keiskammahoek Irrigation Scheme to plan effectively.

1 INTRODUCTION

The estimation and understanding of the terrestrial water balance are part of viable water administration systems. Considering the recent patterns of the impact of climate change, these estimates will be of increasing importance. One of the primary water-balance calculation parameters is the reliable estimation of evapotranspiration (ET). Therefore, understanding of energy and water vapor fluxes in certain sites is vital, particularly in a perspective of authenticating climate change forecasting (Gwate, Mantel, Pailmer, Gibson, & Munch, 2018). Thus, precise prediction of ET flux is important for agricultural development and water resource management. However, in developing countries, like South Africa, it is very difficult to obtain all the relevant data to use in a widely applied Penman-Montheith approach, therefore alternative reliable and powerful prediction approaches are used to examine the non-linear trends related to the predictor variables for ET rate (Ghorbani, Kazempour, Chau, Shamshirband, & Ghazvinei, 2018).

This study predicts evapotranspiration for optimal water use in Keiskammahoek irrigation scheme located in the Eastern Cape province of South Africa. This province has been declared a drought disaster region (Mahlalela, Blamey, Hart, & Reason, 2020, Botai, et al., 2020, Graw, et al., 2017), which led to Keiskammahoek Irrigation Scheme closing other section of its irrigated site in order to deal with

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reduced water levels on water reserves. This study, therefore, used three widely used prediction tools namely, ARIMA, ANNs and Hybrid (ARIMA-ANN) model to predict ET and in order to assist Keiskammahoek water managers to plan and manage the irrigation scheme effectively.

According to (Ziervogel, et al., 2014), the increase in annual temperatures in South Africa by at least 1.5 times of the average 0.65 degrees has led to climate being a key concern. They further suggested that it was posing a vital treat to South Africa's water reserves, food security, health, infrastructure, as well as ecosystem services and biodiversity. The growing impact of climate change has key consequences for South Africa, particularly for the poor even though there are programmes supporting an ambitious renewable energy program, South Africa's response to climate change is hindered by hesitation in policies(Chersich, et al., 2018). In the province of Eastern Cape, South Africa livestock farming is very crucial for livelihood and is considered as a wealth by famers despite their education status (Mandleni & Anim, 2011). According to the conclusion of (Todaro & Smith, 2012), livestock farmers suffer a greater impact from climate change. South Africa suffers from scarcity of water as the demand for water resources increases with the increase in population. If the country wants to sustain economic development, urgent needs must be in place to protect the quality of the resources whilst striving to meet the problem of water scarcity (Todaro & Smith, Economic development, 2020).

Most of the land in this province is used for agriculture with around 35% of households being involved in agricultural activities, however the extreme drought conditions over the past decades have negative impact on these famers (Graw, et al., 2017). In South Africa, irrigation accounts for over 55% of the total available consumptive freshwater (Mishra & Singh, 2011). South Africa falls within the semi-arid region where the evaporation rate is more than the precipitation rate (Nkondo, Zyl, Keuris, & Shrener, 2012).ET is one of the crucial elements of the hydrological cycle; hence, it expedites the furtherance of precipitation through the process of condensation. It is also crucial for the transportation of minerals and nutrients necessary for plant growth, and it creates a favorable cooling method to plant canopies in many climates through its direct relationship with the Latent heat flux (LE) effect on earth energy and water balance (Calzadilla, Zhu, Rehdanz, Richard, & Ringler, 2014).

Therefore, ET remains to be one of the major constraints for irrigation development in developing countries and in semi-arid regions of the world (Traore, Wang, & Kerh, 2008). Accurate prediction of ET is key for agriculture as it informs proper planning and contributes positively to the daily management of the irrigation scheme. Moreover, determining the perfect timing and amount of water needed for irrigation is important for effective management of water used by crops (Kishore & Pushpalatha, 2017). Therefore, scheduling becomes very critical in agriculture, as ET estimation will give an assurance of the reliable daily run of the irrigation scheme, design, and project planning (Kishore & Pushpalatha, 2017). It is therefore crucial to effectively predict ET in agriculture in order to attain a comprehensive picture of the water cycle. (Dutta, Smith, Grant, Pattey, & Desjardins, 2016) and for effectively managing scarce resources for crop production (Anapalli, Fisher, Reddy, Rajan, & Pinnamaneni, 2019).

2 MATERIAL AND METHODES

2.1 The Study Area

Keiskammahoek Irrigation scheme is in Keiskammahoek, a small town situated in the Eastern Cape province of South Africa and located at Latitude S 32°41′14″ E 27°07′48″. The average temperature ranges from 6.5º C in winter to 26.7º C in summer. and an average rainfall of 502mm (Sanral, Gibb, & Eoh, 2016).

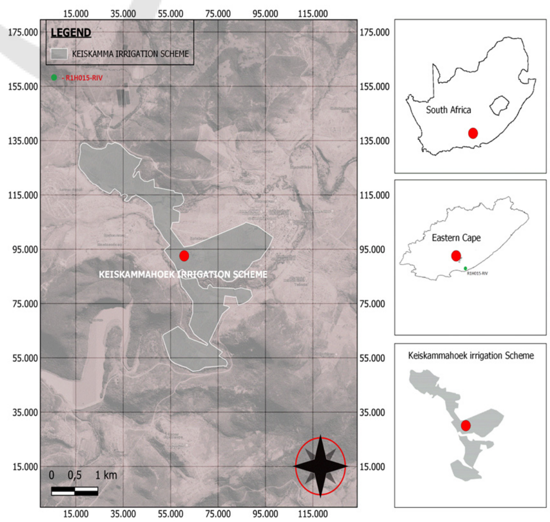


Figure 1: Map of Keiskammahoek Irrigation Scheme.

2.2 Autoregressive Integrated Moving Average (ARIMA) Model

Autoregressive integrated moving average (ARIMA) is one of the most widely used models because of its statistical properties, and it can be used in different ways, such as pure autoregressive (AR), pure moving average, and combined ARIMA series (Kishore & Pushpalatha, 2017). It is also called the Box-Jenkins modeling approach and it is one of the most used time series because of its flexibility, even though it cannot predict nonlinear relationships as its linear correlation structure is presumed among the time values (Zhang, Zhang, & Li, 2016). In their study, Zhang, Zhang, & Li, (2016) define ARIMA as the model that can be decomposed into two parts, with the first part being the "Integrated (I) component (d)", representing the quantity of distinguishing to be achieved on the sequence to make it constant; the second is the ARIMA model sequence that is rendered constant through variation. ARIMA is regarded the most effective forecasting tool, and it is widely used in social science and for time series; it also depends on the historical data as well as its past error relations for predicting (Adebiyi, Adewumi, & Ayo, 2015). In the study by Gautam & Sinha, (2016), ARIMA is reported as the most appropriate modeling tool for examination and predicting hydrological events. They further explain the model as explaining the linear mixture of the earlier state of a variable "(pure AR component), and previous forecast error (pure MA component)". Therefore, in this study, the ARIMA model will be one of the forecasting techniques applied to this study to assist seek accurate prediction of evapotranspiration at the Keiskammahoek Irrigation scheme. The ARIMA model can be mathematically explained as follows:

$$y = θ0 + ∅1\ yt\text{-}1 + ∅2yt\text{-}2 + \ldots\ldots\ ∅pyt\text{-}p \tag{1}$$

$$+\ εt - ∅1εt\text{-}1 - ∅2\ εt\text{-}2\ \ldots\ldots ∅qεt\text{-} \tag{2}$$

Where the terms y_t and ε_t are the actual value and the random error at a given time t. The model parameters are $\emptyset_i(1,2,\cdots,p)$ $\theta_j(0,1,2,\cdots,q)$..

The model parameters p and q are integers and are normally explained as orders of the model. The model random errors ε_t, are predicted to be independently and identically distributed with a mean of zero and a constant variance of σ^2. The above equation is a general equation that represents and necessitates several essential special cases of the ARIMA family of models. For example, if $q = 0$, then this ARIMA model becomes an AR model of order p. On the other hand, when parameter $p = 0$, this model reduces to an MA model of order q. Therefore, the most important part of designing the ARIMA model is to determine the appropriate model order (p, q).

2.3 Artificial Neural Networks (ANN) Model

ANN is a family of artificial intelligence techniques which can predict any time series, including the geophysical time series. ANNs are non-linear data-driven networks that were designed and inspired by the theory of neuroscience (Morimoto, Ouchi, Shimizu, & Baloch, 2007), hence the name 'neural'. These are mathematical models based on the capabilities of the human brain to predict and classify problem domains. Khanna, Plyus, & Bhalla, (2014) describe ANN as "the information processing paradigm that is inspired by the way biological nervous systems such as a brain process information". ANNs are fundamentally a semi-parametric regression method with the capacity to estimate any quantifiable function up to an unrestrained degree of correctness (Parasuraman, Elshorbagy, & Carey, 2007). They have been widely adopted for predicting and forecasting in diverse fields of research such as finance, medicine, engineering, and sciences as well as to solve an extraordinary range of problems (Maier & Dandy, 2000). ANNs are specifically useful when the relationships between both input and output variables are discrete (Jha, 2007). These models have been commended as favorable models in cases where the variety of data is excessive and the relationship among those variables is mainly unclearly understood (Jha, 2007).

In this study, the single hidden layer feedforward network was used as one of the techniques to predict ET. Schultz, Wieland, & Lutze, (2000) explains a single hidden feedforward network as the widely used models for forecasting models for modelling and for predicting time series. The model has three processing layers which are linked by its acyclic and distinguished by its connection between output (yt) and inputs (y_{t-1}. y_{t-2},.., y_{t-p}. Schultz, Wieland, & Lutze, (2000), gives the following model's mathematical association between input and output:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} \sum_{i=1}^{p} \beta_{ij} y_{t-1}\right) + \varepsilon_t, \tag{3}$$

Where $\alpha_j\ (j = 0,1,2,\cdots,q)$ and $\beta_{ij}\ (i = 0,1,2,\cdots,p; j = 1,2,\cdots,q)$ are model limits which are called the joining weights; p and q are the number of inputs nodes and the number of the hidden nodes, respectively. When designing these types of ANN, the logistic function is often employed as the hidden layer transfer function that is given by:

$$g(x) = \frac{1}{1 + \exp(-x)} \quad (4)$$

It should be noted though that the ANN model presented above performs a nonlinear functional mapping from the past observations $(y_{t-1}, y_{t-2}, \cdots, y_{t-p})$ to the future value y_t i.e.;

$$y_t = f(y_{t-1}, y_{t-2}, \cdots, y_{t-p}, w) + \varepsilon_t \quad (5)$$

Where w is a vector of all parameters and f is a function determined by the network structure and connection weights (Schultz, Wieland, & Lutze, 2000).

- Training the Artificial Neural Networks

A multilayer perceptron (MLP) type of network was used; hence, it is the most used form of a neural network. Provided sufficient data, sufficient hidden units, and sufficient time, an MLP can learn to estimate almost any function to a precise degree (Jha, 2007).

2.4 Hybrid (ARIMA-ANN) Model

To ensure the accuracy of the results obtained from two models that have already been used, namely Auto Regressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN), a hybrid (ARIMA-ANN) model was used. As much as both models can be satisfactory in modelling and forecasting using time series, ARIMA are able to detect linearity of the time series whilst the ANNs are capable of detecting nonlinearity of the time series. Therefore, each model alone cannot adequately handle linear and nonlinear patterns; thus, by using joint models, multifaceted autocorrelation structures in data can be modelled precisely (Zhang G. P., 2003). As an example, a study by Mallikarjuna & Prabhakara, (2019), used Zhang hybrid model and reported that neither ARIMA nor ANN is completely appropriate for prediction of all the time series because the real-world time series have both linear and nonlinear correlation structures between observations. Thus, in this study, they followed a study by (Zhang G. P., 2003) and used both ARIMA and ANN and developed a hybrid system which is given by:

$$y_t = L_t + N_t \quad (6)$$

Elwasify, (2015) described what each of these values represents as follows:

- y_t - represents the observation of time series at the time t,
- L_t - represents the linear part of ARIMA models, and
- N_t- represents the nonlinear part of the ANN models.

According to Zhang G. P., (2003), the first step is to model using ARIMA for the linear component, and the residual left from the liner data will contain the nonlinear relationship and letting ET donate the residual at time t from the linear model then et is presented as follows:

$$e_t = y_t - L_t \quad (7)$$

Where L_t is the prediction value of time *t* from the predicted relationship of the original ARIMA formula. This residual is very crucial in the diagnosis of the adequate linear models; hence, the linear model is not adequate should there still be linear correlation structures remaining on the residual. Currently, there is no statistic for nonlinear autocorrelation connection diagnosis and that causes that even when models have been accepted by the diagnosis examination, it may still be accurate enough for a nonlinear relationship to be properly modelled and that means every nonlinear pattern cannot be modelled by ARIMA. Modeling the residual using ARIMA will assist to discover the relationship in nonlinear correlation. Zhang G. P., (2003), suggests the models for residual as follows:

$$e_t = f(e_t - 1, e_t - 2, \ldots\ldots, e_{t-n}) + \varepsilon_t \quad (10)$$

ε_t is the random error whilst f is determined by the nonlinear function using neural network, and if f is not adequate, the error is not certainly random. It is very crucial to determine the perfect model. Therefore, by donating forecast from the residual model, the combined forecast will be

$$\hat{y} = L_t + N_t \quad (11)$$

This simply means that the first step will be to utilise the ARIMA model to examine the linear part, and the second step of the hybrid will be to develop the models using the residual from the first ARIMA model; hence, the residual from ARIM will be having nonlinear patterns and the results obtained from neural networks will be used to estimate the model error for ARIMA terms. The Hybrid model will therefore have different features and will have much power of ARIMA and ANN, which will determine different patterns (Zhang P. G., 2003).

2.5 Model Performance

Normally, there are no standard norms for evaluating the forecasting performance of a model and appraisal with other benchmark models (Mbatha & Bencherif, 2020). To evaluate the performance of the three models used in this study, namely ARIMA, ANNs, and Hybrid, we compared the forecasted ET values with their corresponding measured ET values obtained from the study site using typical performance metrics. According to Lewis C. D., (1982), there are many alternative models used over the years to forecast the time series; therefore, one needs to consider specific conditions in choosing the appropriate model to be employed. For the purpose of this study, It is crucial to check the model accuracy to select the most appropriate model based on the ET forecasted results. Below are the performance measures used for RMSE, MAPE and MAE as explained by (Lewis C. D., 1982). The Root Mean Square Error was used in order to evaluate the difference between the predicted ET results and the original ET data. According to (Chai & Draxler, 2014), the RMSE model has been widely used in many studies to examine the model performance. Because of uncertainties reported by Willmott & Matsuura, (2005), other models were applied. The Mean Percentage Error (MAPE) statistic measure was also applied in order to evaluate the quantity of error in the forecasted values of ET.

This widely used Measure is used when the amount of the predicted values remain higher than zero (Myttenaere, Golden, Grand, & Rossi, 2016, Khair, Fahmil, Hakim, & Rahim, 2017). The Mean Absolute Error (MAE) was also applied. This measure is calculated from an average error, and it is frequently used to examine the vector to vector models (Willmott & Matsuura, 2005). The model accuracy was checked by the use or Pearson's correlation of coefficient. This model is explained by Mukaka, (2012), as the method that is used to evaluate the likely two-way linear connection between two continuous variables. Zero value of the Correlation coefficient indicates that there is no linear association between the two variables. However, between +1 or -1 indicate a perfect correlation and this strength can be found anywhere between +1 and -1. The positive value indicates the direct relationship between two values and the negative value indicates that there is an inverse relationship between two values. Results and discussion.

3 RESULTS AND DISCUSSION

3.1 ARIMA Model Selection

The data from 2001 to 2018 was fitted to AUTOARIMA using "R" and a portmanteau test called Ljung-Box was done to test the excellence of the time series model. According to Burns, (2002), this test is mostly used, and should the significant autocorrelation not be found on model residuals, the model is considered perfect. If the values of correlation of residuals for various time lags is not significantly different from zero, the model is then considered adequate for use in forecasting. On one hand, Figure 2(a &b) shows the Akaike's Information Criteria (AIC) graph that indicates that there is no significant correlation because all the bars do not exceed the dotted line 95% confidence levels and

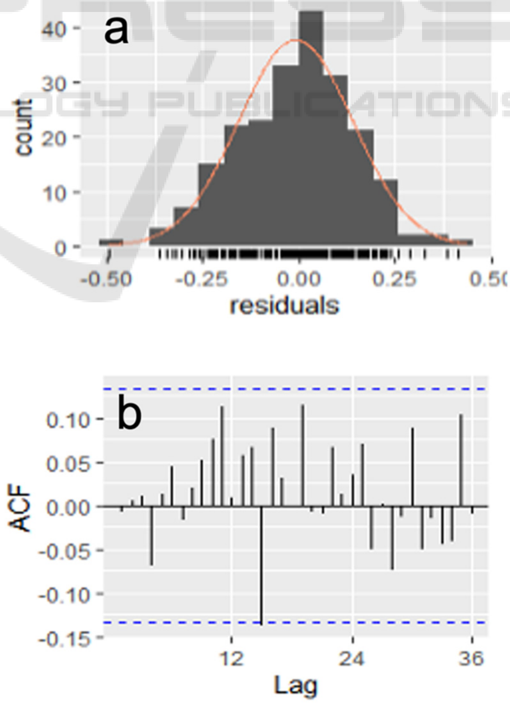


Figure 2: Autocorrelation Function (ACF) and Histogram of residuals of residual of Keiskammahoek Irrigation Scheme as a ideal fitted model for data series of ET from 2001 to 2018.

according to (Widowati, Putro, Koshio, & Oktaferdian, 2016), and (Gautam & Sinha, 2016) the residue is random. The best selected ARIMA model to forecast ET is ARIMA (1,0,0). On the other hand, Figure 9(b) presents residuals which are evenly dispersed. The normal distribution of residuals indicates that the selected ARIMA model is free of overfitting (Reza & Debnath, 2020).

3.2 ARIMA Model Training

The training of the ARIMA model was done by selecting data from 2001 to 2015 as a training set of data. One of the important aims of slitting data to training and testing is to use the testing part of the time series to check the sign of the variable's parameters, and to investigate whether they are significant or not

3.3 ARIMA Forecasting

In this study, the training of the ARIMA model was done by selecting data from 2001 to 2015 as a training set of data. One of the important aims of slitting data to training and testing is to use the testing part of the time series to check the sign of the variable's parameters, and to investigate whether they are significant or not.

Figure 3(a-c) depicts the prediction results using ARIMA, ANN and Hybrid models. After the training of the models was done using 15 years time series data from 2001 to 2015, the next step was to predict ET using the remaining 3 year data from 2016 to 2018. Thus, the data set from 2016 to 2018 was used as the testing part of the time series Prediction. This was important in forecasting because the testing part is forecasted and then forecasting results are compared with the actual results. The black line represents the training part of the time series data (2001 to 2018) and the ET forecasted results (2016 to 2018) indicated by the blue line with the dark grey and light-grey shadings, indicating the 80% and 95% confidence levels of the forecasted time series. The ARIMA model constructed for this data is the ARIMA (1,0,0) and NNAR (1,1,2)(12) for ANNs.

The Zhang P. G., (2003) proposed this model shown by figure 3(d) because of its the ability to forecast both linear and nonlinear underlying processes. The Kaiskammahoek irrigation scheme is no exception to real world time series contains both linear and nonlinear correlation structures. The black line indicates the training data set for a 15-year period (2001 to 2015); the blue line indicates the forecasted ET results, and the grey shading indicating the 95% confidence levels for the three year period (2016 to 2018).

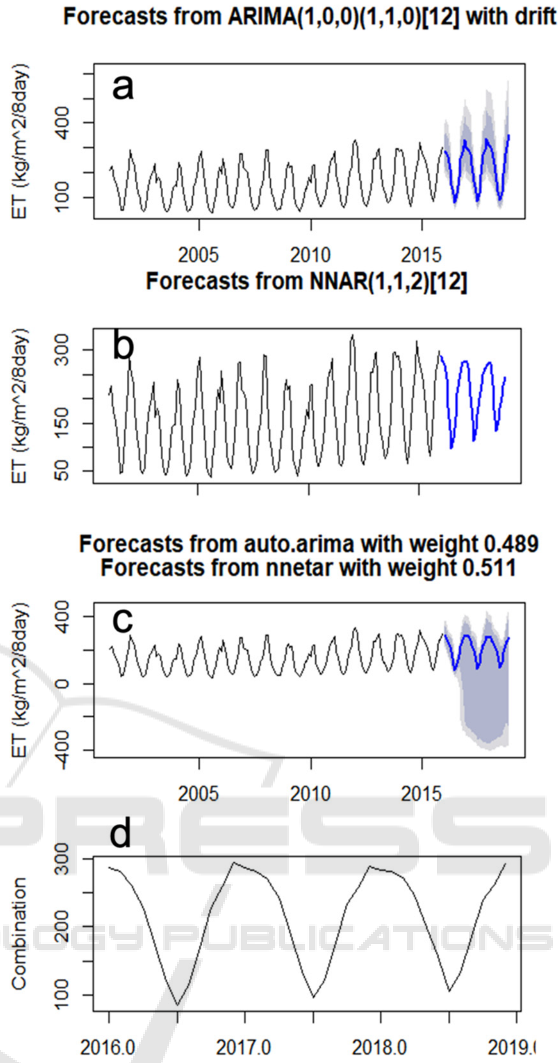
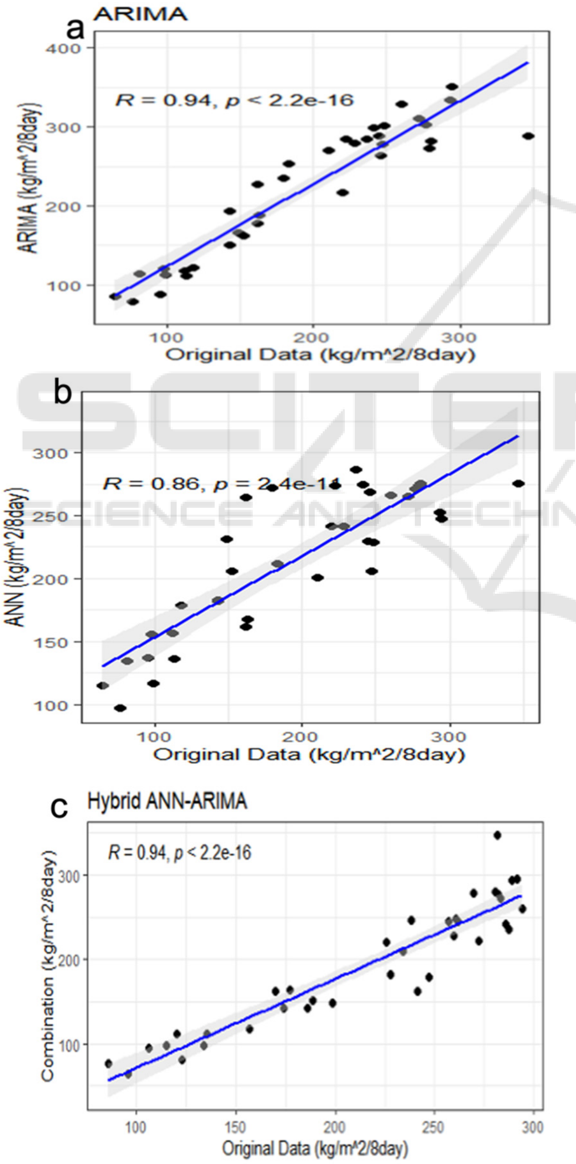


Figure 3: Forecasted ET for 3-year period from 2016 to 2018 using the ARIMA (a), ANN (b), Hybrid (ARIMA-ANN) (c) and the ever-aged models (d). The black line in Figure 3 (a-c) represents the data from 2001 to 2015 and the blue line presents the 3 year forecast, with 95% confidence levels grey lines (a &c) and figure 3(d) with a black line representing 3 years averaged (ARIMA, ANN and Hybrid) models.

Consecutively Figure 3(d) shows the prediction of 3 combined ARIMA, ANN and Hybrid models averaged using the summation methods. The black line shows combined prediction part from 3 models used from 2016 to 2018. This was done to see if the 3 averaged models could improve the forecast as such has been proven by other researchers. This study has employed 3 different model systems and showed its performances in terms of the correlation coefficient "R". However, it is always important to also average the forecast in order to improve the forecast accuracy (Bates & Granger, 2017, Clemen, 1989).

3.4 Correlation Statistics

To check the correlation of the prediction portion person correlation (Lin, 1989), was employed with ET predicted variables against the ET observed variables. Figure 3 (a-d) depicts the scatter diagram of the original ET and forecasted ET, represented by the black dots falling on the 45 line through the origin.



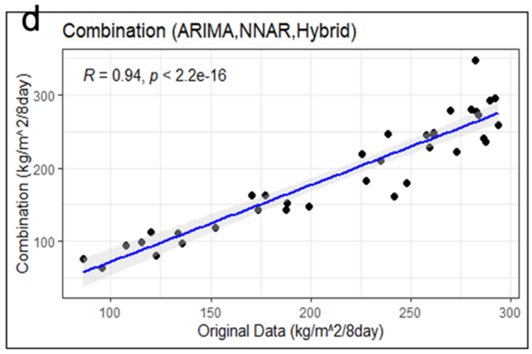


Figure 4: Scatter plot between observed and forecasted ET show diagram of the actual ET versus the forecasted annual ET using ARI-MA (1,0,0)(1,1,0)[12] (a), NNAR(1,1,2)[12] (b), Hybrid (ARIMA-ANN's) (c) and the averaged (d) models (with validation period, 2016 to 2018).

The correlation of the forecasted for all the 4 forecasting models applied shows a strong correlation coefficient with ARIMA (R = 0.94), ANN (R= 0.86), Hybrid (R = 94) and the averaged models with (R = 0.94). Based on the R values for all the 3 models and the averaged model, it is evidence that there is higher linear relationship between the forecasted results and the original time series data. Correlation Coefficient suggest other 3 used forecasting modelling ARIMA and Hybrid to be more correlated compared to lower value of ANN (0.86).

3.5 Model Comparison

Table 1 below shows the three models employed in this study to forecast ET at Keiskammahoek Irrigation Scheme, namely ARIMA, ANNs and Hybrid (ARIMA-ANN), and average of the three models. The model forecast capabilities are compared by using model performance statistics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Correlation Coefficient (R). The results presented in this table indicate that Hybrid model outperforms other models with RMSE = 33.80, MAE = 27.02, MAPE = 17.31 and R = 0.93. It is also noticeable that the Mean Absolute Percentage Error-values for ARIMA and Hybrid seem similar, considering ARIMA (MAPE = 17.26) and Hybrid (MAPE = 17.31). Since the hybrid model is made up of a combination of ARIMA and ANNs, it is possible that this model will perform better than the other models because it is expected to be capable of capturing both linearity and non-linearity in the time series. In terms of the correlation coefficient, ARIMA seems to outperform the others models, with a correlation coefficient of R = 0.94.

Table 1: Comparison of the ARIMA, ANN, Hybrid and Combined Models: RMSE, MAE, MPE, and R.

Models	RMSE	MAE	MAPE	R
ARIMA	37.58	32.37	17.26	0.94
ANN	44.18	35.88	24.35	0.86
Hybrid	33.80	27.02	17.31	0.94
Combined	34.68	28.00	18.15	0.94

These results are interesting as they agree with results found by (Zhang P. G., 2003), who archives higher accuracy of time series prediction through use of Hybrid (ARIMA-ANN) models.

The three utilized models were further averaged to see if prediction accuracy could be reached. It has been shown in previous studies that combination of multiple forecasting methods leads to increase of the forecasting accuracy (Clemen, 1989). Therefore, in this study, the predictions obtained from the three models used were combined by using the summation method. The results of the COMBINED models indicated in Table 1 show better results of ARIMA and NNAR. These observations are encouraging as they are consistent with results of studies on the combination of several time series forecasting methods. Similar what is obtained in this study, Hyndman & Athanasopoulos, (2018), also pointed out that combining forecasts often lead closer to, or better than, the best component method.

4 CONCLUSIONS

The possibility to predict evapotranspiration (ET) is essential as it can affirm perfect planning, design and operation of any irrigation scheme. Thus, the main aim of this study was to predict evapotranspiration (ET) at Keiskammaheok, Irrigation Scheme located in the province of Eastern Cape of South Africa using 3 time series forecasting models, namely (ARIMA), (ANN), and the Hybrid (ARIMA-ANN) models. The 18 years (2001-2018) remotely sensed ET data was extracted from a cloud-built software called Moderate Resolution Imaging Spectroradiometer (MODIS) Tera/ Aqua 16-day dataset. Using four model models performance measures, namely, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Correlation Coefficient (R). It could be concluded that the Hybrid (ARIMA-ANN) guarantees the steadfast ET prediction for Keiskammahoek irrigation Scheme. The model outperformed other models with less values (RMSE =33.80, MAR = 27.02, MAPE = 17.31 and R = 0.94). This indicates that the combination of ARIMA and ANN is a better option because such hybrid models are able to capture both linearity and non-linearity in the time series of ET, which in turn produce better results. This work will assist the Keiskammahoek irrigation scheme management to plan effectively.

Future work may include further checking other variables in order to assess whether these reported drought in this region like Normalized Different Vegetation Index (NDVI) to assess vegetation state, Normalized Deference Water Index (NDWI) which is the availability of water in plants and Normalized Difference Different Index (NDDI) in order to check the drought state in the study site.

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