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The Use of Artificial Neural Networks to Estimate Reference Evapotranspiration

Abdul Haris[1,4], Marimin[2], Sri Wahjuni[1], Budi Indra Setiawan[3]

[1] Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University
[2] Department of Agro-Industrial Technology, Faculty of Agricultural Engineering, IPB University
[3] Department of Civil and Environmental Engineering, Faculty of Agricultural Engineering, IPB University
[4] Department of Informatics, Faculty of Energy Telematics, Institut Teknologi PLN

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Correspondence:
Abdul Haris
Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University
Email: abdulharis@apps.ipb.ac.id

ABSTRACT

Evapotranspiration is defined as the loss of water from soil and vegetation to the atmosphere, driven by weather conditions. It reduces the availability of water for agricultural purposes, which affects the amount of irrigation water, particularly during the dry season. The objective of this paper is to present a comparative analysis of the estimated reference evapotranspiration value based on artificial neural networks (ANN) with backpropagation bias 1 (BP-1) and backpropagation bias 0 (BP-0) architectures. The model was fed with data of air temperature, relative humidity, and solar radiation. The model is utilized to calculate the evapotranspiration using the Hargreaves method as the training data. The performance of ANN model was evaluated using the mean square error (MSE), root mean square error (RMSE), and coefficient determination (R^2). Our results showed that both ANN models performed well as indicated by low error (MSE < 0.01) and high R^2 (>0.99). Also, we found that air temperature and relative humidity determine the optimal prediction. Further, this proposed model can serve as a reference for other models seeking to determine the most appropriate computational model for evapotranspiration value estimation.

KEYWORDS
agriculture, computational models, error evaluation, Hargreaves method, water requirements

1. INTRODUCTION

Water is one of the important aspects for agriculture and has become one of the main factors in the country development. Under hot climate, more evaporated water is expected, which makes water management in precision agriculture practices more challenging. Evapotranspiration is one of the most important variables in the hydrological cycle (Liu, 2022) and in precision irrigation system (Nocco et al., 2019). In rainfed agriculture, limited water availability during dry season reduces the utilization of farmland (Srihartanto and Widodo, 2020).

Irrigation system is proposed to deal with water problem over agriculture land, as it provides adequate water to support optimal plant growth (Ahmed et al., 2023). The water requirements of an irrigation system are largely influenced by the process of evapotranspiration from soil and plants into the atmosphere (Gong et al., 2019). Therefore, evapotranspiration plays a pivotal role in determining the optimal irrigation system for agricultural land.

Models have been developed earlier to estimate evapotranspiration, such as Hargreaves, Penman-Monteith FAO, Blaney-Criddle, Makkink, and Linacre. Each model has its own pro and cons that depends on various aspects (Hernández-Bedolla et al., 2023). This research focuses on the estimated evapotranspiration based on the Hargreaves approach. The choice of Hargreaves model is based on its simplicity and compatibility with limited parameters (Althoff et al., 2019).

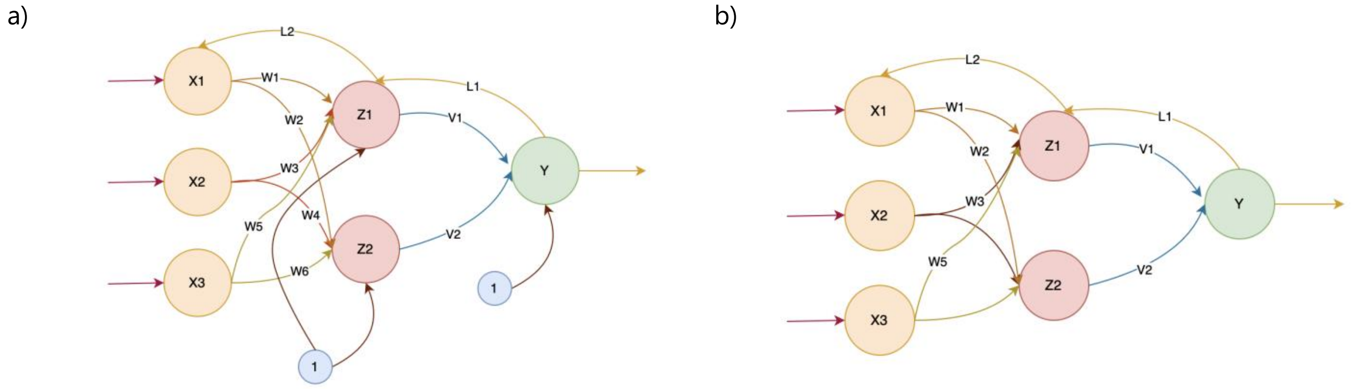

Figure 1. (a) ANN-backpropagation architecture using bias 1 (BP-1) and (b) ANN-backpropagation architecture without bias (BP-0). x is the input value, w is the weight of the input value x, while z is the output value of the multiplication of x and w and becomes the input for y, and v is the weight of z. While L, the loss value is the evaluation result of each network.

In this paper, the backpropagation ANN model is used as a computational model due to its suitability for use on devices with limited processing power (Abdolrasol et al., 2021). The benefit of using ANN model relates to its simple architecture, which does not require the use of processing devices that are capable of high-speed and high-capacity data processing (Wang et al., 2023). ANN has also been widely used in various types of data, especially for classification (Lin et al., 2022; Muñoz-Zavala et al., 2024; Salmayenti et al., 2017).

Two scenarios of ANN backpropagation are tested namely backpropagation bias and no-bias approach. The scenario is used to see the effect of the tolerance value given in the ANN model on the reference evapotranspiration value for a precision irrigation system (Dasgupta et al., 2017). The research aims to quantify evapotranspiration using ANN algorithm. The outputs of research will be benefit for development of a precise, intelligent irrigation system for agricultural land.

2. RESEARCH METHODS

2.1 Data

In this research, the reference evapotranspiration for irrigation systems on open land has been tested. The weather data were obtained from the Automatic Weather Station (AWS) for March 7, 2023 to May 14, 2023, which was installed in the laboratory of SIL IPB. We measured air temperature, relative humidity, and solar radiation at 10-minute interval.

2.2 Model Pre-Processing

We calculated daily evapotranspiration using Hargreaves according to Equation 1 (Feng et al., 2017; Hargreaves and Allen, 2003; Wu et al., 2021).

$$\mathrm{ET_o} = 0.0023 \text{ x } \mathrm{R_a} \text{ x } (\mathrm{T_a}) + 17.8) \text{ x } (\mathrm{T_m} - \mathrm{T_n})^{0.5} \qquad (1)$$

where ET_o is the daily reference evapotranspiration value, $\mathrm{T_a}$ is the average daily air temperature, $\mathrm{T_m}$ and $\mathrm{T_n}$ are the daily maximum and minimum temperatures,

$\mathrm{R_a}$ is the daily extraterrestrial radiation. $\mathrm{R_a}$ value depends on geographic location, which changes daily according to sun movement as in Equation 2.

$$\mathrm{R_a} = \int_0^{24} \mathrm{S(t)}.\cos\big(\theta(\mathrm{t})\big)\,\mathrm{dt} \qquad (2)$$

where $\mathrm{S(t)}$ is the solar radiation flux at time t and $\theta(\mathrm{t})$ is the elevation angle of the sun at time t. The modeling is used to obtain values that are used to obtain training data to train input data on the computational model.

Then we used a computational model process based on the Artificial Neural Network (ANN) algorithm with a backpropagation approach (Figure 1) to predict Hargreaves' evapotranspiration. This algorithm is used to obtain data from the computing results of each algorithm. The training was carried out with scenarios by reducing the variables used. In the first test, we used the combination variables of temperature, relative humidity, and solar radiation. Then, we carried out comparison tests by reducing the number of combination variables used and so on. By using the metrics, we obtained the optimal combination model with the lowest error. In addition, we measured the training length of each algorithm and the speed of the process per-epoch data.

2.3 Computational Model Architecture

The computational model was divided into two backpropagation algorithms, namely backpropagation using bias 1 (BP-1) and backpropagation using bias 0 (BP-0). These two architectures were used to see the effect of reducing variables from all the variables used. It is expected that optimal results with low errors can be achieved despite the number of variables is minimal. The architectural scenario is as shown in Figure 1. In the mathematical equations, the ANN backpropagation algorithm is still presented in this paper, but in implementation, the bias value will be reduced for architectures that do not use bias.

In the architecture of Figure 1, x_1 to x_3 are input values, which were determined from the temperature and relative humidity variables. w_1 to w_6 are weight values for networks x_1 to x_3, and v_1 and v_2 are weights for networks z_1 and z_2. These weight values were determined randomly. Meanwhile, the values z_1 and z_2 are the output values obtained from multiplying the input value with the weight in network x, while the y value is the output value obtained from multiplying the y value with the weight in network z, while the value 1 in the architecture is the bias value.

After obtaining the Hargreaves ETo using Equation 1, the ANN was tested using backpropagation by comparing the BP results using bias 1 (BP-1) and without using bias (BP-0) according to the proposed architecture. This condition is expected to see the effect of reducing the variables obtained from the model. In addition, the test measured the length of the training process to find the lowest error value, the speed of the epoch process in seconds, and the value of the determinant coefficient. From this architecture, the ANN BP-1 and BP-0 models used Equation 3, which was used to find the output layer value from the input layer to the next layer. The activation layer of ANN algorithm is a sigmoid form Equation 4 derived from the Equation 3.

$$\mathrm{Out_i} = \mathrm{b_i} + \sum_{i=1}^{n} \mathrm{x_i w_i} \quad (3)$$

Outputs of Equation (3) act as an input to activate function in Equation 4. This is the value obtained from the multiplication of the input and weight prior to the application of the sigmoid activation function.

$$\acute{y}_i = \frac{1}{1+e^{-x}}(\mathrm{Out_i}) \text{ or } \acute{y}_i = \sigma\ (\mathrm{Out_i}) \quad (4)$$

$$\delta_i^L = \frac{1}{n} \sum_{i=1}^{n} (y_i - \acute{y}_i)^2 \quad (5)$$

The next step was evaluation process computation for each neuron starting from the output layer to the initial layer using Equation (6).

$$\delta_j = \sigma\,(w_i^{j+1} . \delta_i^{j+1}) \quad (6)$$

Then we evaluate the error value of each model layer using $\frac{\partial L}{\partial w^i} = \delta_i^L . \mathrm{out_i}$. Furthermore, we also use $\frac{\partial L}{\partial b^i} = \delta_i^L$ to evaluate the bias value of each layer. L is the error evaluation network for each layer. The w and b are used to calculate changes in bias and changes in weight for the next iteration process repeatedly until optimal weight was met.

Next, the weight changes are made to carry out the input process using Equation 7 and the bias is changed for BP-1 using Equation 8.

$$w_{new}^j = w_{old}^j - \alpha . \frac{\partial j}{\partial w^j} \quad (7)$$

$$b_{new}^j = b_{old}^j - \alpha . \frac{\partial L}{\partial b^i} \quad (8)$$

2.4 Computational Model Evaluation

To evaluate the computational model, several statistical metrics were used to see the errors of each algorithm architecture, both using the BP-1 model and using BP-0 from several variables used. The model error was evaluated using Equations (9-15). The evaluation, which is used to find out the best model evaluation in this algorithm comparison, was carried out to achieve minimal error based on seven statistical metrics, such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), logarithmic root means square error (LOG), relative error (RE), and squared relative error (RR). This is done. In addition, using these seven model evaluations can be a reference in model development to determine the best evapotranspiration reference value if reducing or adding further variables. The MSE (mean square error, Equation 9) is a statistical measure used to quantify the discrepancy between the actual and predicted values in a computational model. In this context, a_i represents the actual value, while p_i denotes the predicted value as estimated by the model.

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (a_i - p_i)^2 \quad (9)$$

Root means square error (RMSE) is defined as the square root of the mean of the squared differences between the predicted and measured outcomes in the model (Hodson, 2022).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (a_i - p_i)^2} \quad (10)$$

The mean absolute error (MAE) is a metric employed to ascertain the mean absolute discrepancy between the predicted and actual values.

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} |a_i - p_i| \quad (11)$$

The mean absolute percentage error (MAPE) is a statistical measure employed to assess the precision of forecasting or prediction. This model is one of the metrics utilized to evaluate the accuracy of predictions derived from its computational model.

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{a_i - p_i}{a_i} \right| \mathrm{x}100 \quad (12)$$

Log or Log RMSE is a metric frequently employed to assess the efficacy of a predictive model when confronted with data exhibiting a considerable range of values or a logarithmic distribution.

$$\mathrm{LOG} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\log a_i - \log p_i)^2} \quad (13)$$

$$\mathrm{LOG} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log a_i - \log p_i)^2} \quad (13)$$

RE (Relative Error) is a measure that indicates the magnitude of the discrepancy between a predicted or measured value and its true or reference value.

$$\mathrm{RE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|a_i - p_i|}{a_i} \quad (14)$$

The Squared Relative Error, or Relative Squared Error (RR), is an error metric that calculates the discrepancy between the predicted value and the actual value in squared form, then normalizes it against the square of the actual value. where a is the observed data, p is the predicted data from the model, n is the amount of observed data, and i is the number of data iterations for which error calculations are carried out.

$$\mathrm{RR} = \frac{1}{n}\sum_{i=1}^{n}\frac{(a_i - p_i)^2}{a_i^2} \quad (15)$$

For temperature and relative humidity, three variables were identified i.e. minimum, maximum, and average values, which made the total variables used were 7. The tests were conducted using Excel and the Python programming language.

3. RESULTS

The performance of ANN model for bias and non-bias propagations were presented in Table 1. Based on MSE metric, the error was comparable for both i.e. 0.0056 and 0.0060 for BP-1 and BP-0 all variables, respectively. Similar result was observed for R^2 metric, indicating that both algorithms were a very good performance. Table 1 explains the results of model comparison using accuracy metrics.

For combination of T-RH, by excluding variable of solar radiation, the model performance declined. MSE and RMSE values were 0.19% higher compared to all variables (Table 1), while the R^2 value reduced by 0.14 by reducing the number of variables for prediction, there was a tendency that the performance model declined, as expected from combination Ta-RHa as well. Generally, combination variables of temperature (variable T, Table 1) were performed well compared to the RH only. The error value testing yielded slightly different results. For instance, in the test using Squared Relative Error (SRE), BP-0 performed better than BP-1, with BP-0 achieving a value of 0.0111 compared to BP-1's value of 0.0120. Additionally, the test results using Relative Error (RE) showed a value of 0.0839 for BP-0 and 0.0845 for BP-1. Meanwhile, testing with Logarithmic RMSE yielded a value of 0.0810 for BP-0 and 0.0823 for BP-1.

The duration of the training process was a significant factor distinguishing these two conditions. For BP-0, the training time required to achieve the smallest error was 7,600 seconds, whereas for BP-1, it took 16,500 seconds to reach the minimum error. This indicated that the use of temperature and relative humidity variables in BP-0 was more effective than in BP-1. The results of the tests carried out using all variables can be seen as shown in Figure 2. From the comparison results of the second test, good error values were obtained, as stated above. During measurements using RMSE, the results obtained for BP-0 were 0.0922 and the BP-1 value was 0.0919. Details can be seen in Table 1. From the results of the tests carried out, the value of the determinant coefficient (R^2) was also calculated for both algorithmic conditions, which produced the same value. This can be understood because in the computing process, the BP-1 value has a tolerance value for errors that occur in the computing process.

4. DISCUSSION

The results of the tests conducted on all variables without the inclusion of solar radiation (Rs) were presented in Table 1. The comparison results obtained

Table 1. Performance metrics of ANN models using different combinations of variables, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Logarithmic Root Mean Square Error (Log RMSE), Mean Absolute Percentage Error (MAPE), Relative Error (RE), and Squared Relative Error (SRE).

Model ANN	MSE	RMSE	MAE	LOG	MAPE	RE	RR	R^2
BP-0 All Variable	0.0060	0.0922	0.0719	0.0155	1.5187	0.015	0.0004	0.9940
BP-1 All Variable	0,0056	0.0919	0.0707	0.0150	1.4683	0.015	0.0003	0.9940
BP-0 Variable T - RH	0.1996	0.4586	0.3758	0.0810	8.3892	0.0839	0.0111	0.8509
BP-1 Variable T - RH	0.1996	0.4580	0.3708	0.0823	8.4501	0.0845	0.0120	0.8513
BP-0 Variable Ta-RHa	0.8884	0.9466	0.7521	0.1774	18.460	0.1846	0.0771	0.3647
BP-1 Variable Ta-Rha	0.7964	0.8828	0.7140	0.1657	17.237	0.1724	0.0608	0.4475
BP-0 Variable T	0.2993	0.5471	0.4567	0.0964	10.190	0.1019	0.0159	0.7878
BP-1 Variable T	0.3036	0.5510	0.4550	0.0958	9.9817	0.0998	0.0150	0.7848
BP-0 Variable RH	0.4248	0.6518	0.5228	0.1174	11.981	0.1198	0.0240	0.6988
BP-1 Variable RH	0.4135	0.6431	0.5258	0.1166	12.035	0.1203	0.0239	0.7068

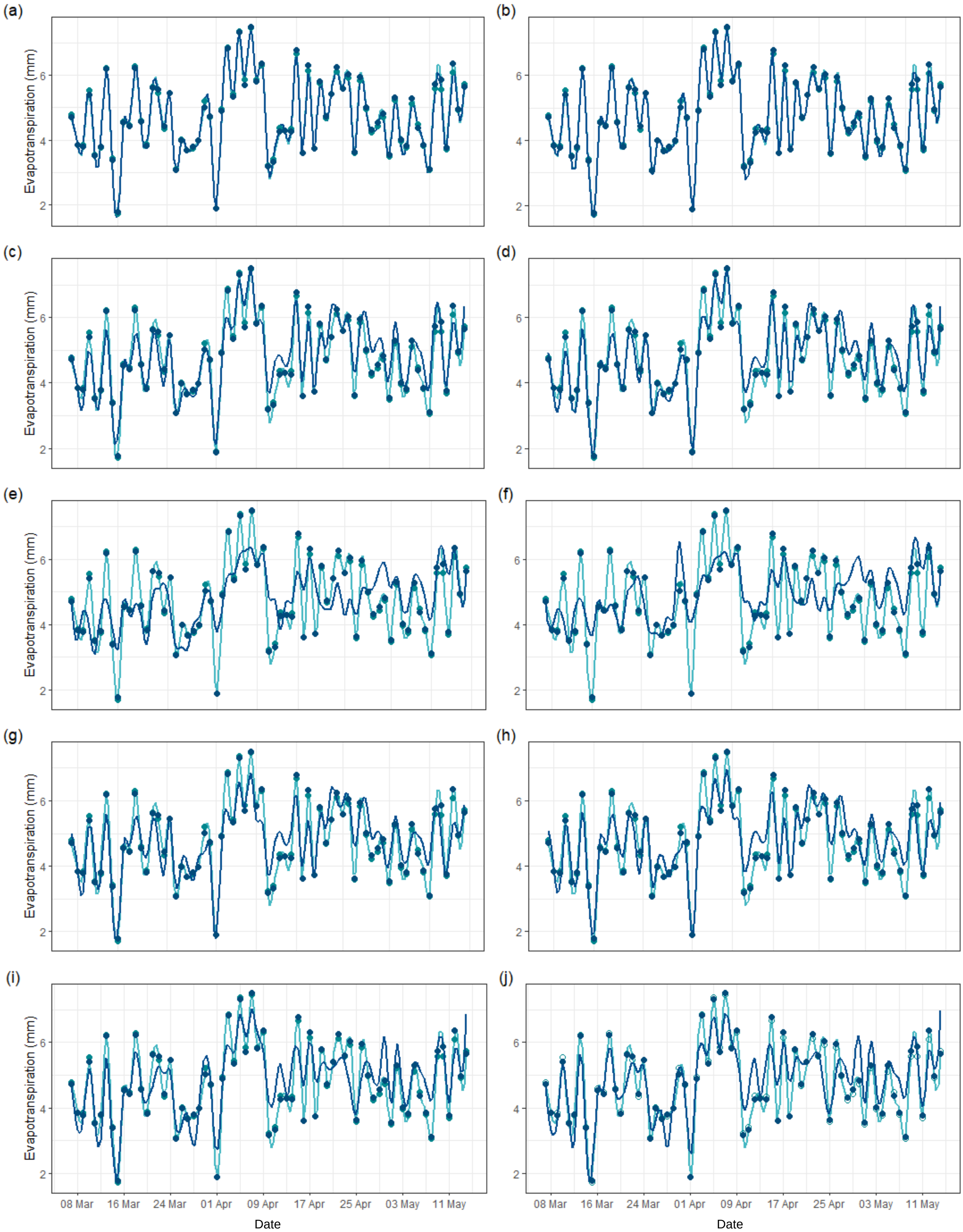

Figure 2. Comparison of modeled evapotranspiration (darker blue) with observed values (light blue) under two different backpropagation bias settings: BP-1 (left column) and BP-0 (right column). Panels (a-b) represent the model using all variables, (c-d) use temperature and relative humidity, (e-f) use average temperature and average relative humidity, (g-h) use only temperature, and (i-j) use only relative humidity.

for BP-0 and BP-1 as a whole were not significantly different, and the results were almost the same when using all variables, including the solar radiation value (Rs). The findings reveal that the use of relative humidity or temperature alone is still under performed for evapotranspiration estimate (Figure 2). By excluding solar radiation from predictor of ETo, the model performance significantly declines. The result was consistent for both scenarios (BP-0 and BP-1).

In case of limited data of solar radiation, our findings showed that model predictors based on temperature only or humidity only is still acceptable as supported by relatively high of R^2 (Table 1). When compared with research that has been carried out previously, such as that carried out in Malaysia, it uses several variables to determine evapotranspiration values, such as temperature, relative humidity, wind speed, sunlight duration, and pressure. Thus, requiring the use of quite expensive technology (Hou et al., 2023).

Its study, a machine learning vector autoregression (VAR) model was used, and the root mean square error value was obtained of 1.1663; this value is much higher than the BP model used in this paper. Furthermore, research has been conducted in Egypt with the objective of determining the reference value of evapotranspiration using minimum and maximum temperatures, relative humidity, and wind speed. This is employed to discern alterations in the reference evapotranspiration through the utilization of the Penman-Monteith methodology. This is considered a relatively complex process due to the necessity of a lengthy statistical analysis (Yassen et al., 2020).

In this study, we determined the reference value of evapotranspiration using the temperature variables Ta, Tn, Tx, RHa, RHn, and RHx, and achieved optimal error results. The process was relatively straightforward: first, the ETo value was calculated using the Hargreaves method as training data, as previously described; then, it was processed using the ANN computational algorithm. This study demonstrated that optimal values could be achieved using a limited set of variables. For future research, other methods or approaches, such as the FAO Penman-Monteith method, could be used for comparison to obtain more comprehensive insights.

5. CONCLUSIONS

The results of the research and testing that have been carried out can be concluded that the estimation of the reference value of evapotranspiration using the Artificial Neural Network (ANN) computational model BP-1 model is better than using the BP-0 model. This is reasonable because BP-1 has a tolerance value for errors. In the calculation of the reference value of evapotranspiration using the variables of temperature, air humidity, and solar radiation, optimal values can be produced.

If these variables are reduced, such as using only the temperature variable without using other variables, the reference value of evapotranspiration does not get an optimal value. This can be seen from the R2 value, which has reached 0.7878 for BP-1 and 0.7848 for BP-0. However, the weakest is only using the average temperature (Ta) and average air humidity (RHa) variables. This variable obtains a high error value and has a very low R2 value of 0.3647 for BP-0 and 0.4475 for BP-1. From this study, it can be concluded that using temperature and relative humidity variables, the ANN BP-1 computational model is best used to model the reference value of evapotranspiration if ignoring the value of solar radiation, so it is recommended to determine the reference value of evapotranspiration with variables that can use at least two variables, namely temperature and relative humidity.

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