

Long-Term Forecasting of Crop Water Requirement with BP-RVM Algorithm for Food Security and Harvest Risk Reduction



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ABSTRACT

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Cropping pattern planning is important to avoid crop failure. Meanwhile, cropping patterns are affected by climate change, which is constantly shifting and erratic. Mistakes in determining the planting schedule will affect the risk of crop failure. Hence, climate forecast using long-term hydro-climatological data must be conducted as cropping patterns are mapped for a multi-year period. Data was collected from the Meteorology, Climatology, and Geophysics Agency in Lombok Island. This paper discusses the combination of backpropagation and relevance vector machine with RBF kernel. We utilized BP-RVM architecture with three hidden layers to improve the performance of the network. This combination is utilized because of the BP algorithm's ability to simplify data pattern recognition and RVM to speed up and reduce the number of iterations for each data training-testing process. The evapotranspiration of each crop was then calculated using the FAO24 Blaney-Criddle method. Based on the forecasting, the average MAPE was below 20%, which indicates "good forecasting". The evapotranspiration values of CGPRT and horticultural crops were almost the same with an average of 2.79 mm/day and 2.78 mm/day. These values are lower than the evapotranspiration values of tobacco and rice. Finally, based on the calculation of each crop's water requirement throughout the year, it was recommended to start the first planting season at the end of October. The results of this study can be recommended to the government to apply the BP-RVM algorithm in forecasting hydro-climatological data and optimizing cropping patterns to avoid crop failure and maintain the stability of national food security.

1. INTRODUCTION

Land is important for people whose lives depend on the agricultural sector. A developing country always makes strategies to improve food security for its people. Therefore, some areas are designated as national food estates [1]. Muthayya et al. [2] mentioned that Indonesia is one of several countries with the largest rice production in the world. Together with China, India, Bangladesh, Vietnam, Myanmar, Thailand, the Philippines, Japan, Pakistan, Cambodia, the Republic of Korea, Nepal, and Sri Lanka, Asian countries account for 90% of the world's total rice production [3].

Policies on climate change are crucial to maintain the stability of food security because climate change affects an area's water availability as well as environmental, social, and agricultural systems. Therefore, Riptanti et al. [4] stated that information on climate change and water availability is required to increase crop productivity, especially in drylands. The climate change in question is closely related to the annual trend of hydro-climatological data. Therefore, hydro-climatological data is very important in planning planting schedules, which are part of a good cropping pattern. A proper planting schedule must follow the interval of water availability based on climate change throughout the year. The positive impact is to improve national food security.

One of the purposes of hydro-climatological forecasting is to predict climate change and determine farmers' cropping pattern [5]. Hydro-climatological data include rainfall (mm), temperature (°C), humidity (%), sunshine duration (hours), and wind speed (knots). From time to time, these data change and shift, especially rainfall. It affects the timing and pattern of planting, which farmers should change accordingly. The process of determining planting patterns cannot be separated from the optimization of irrigation systems, land area, agricultural production, and other indicators in agriculture. There are various studies on irrigation system optimization for determining irrigation water requirement [6-14]. The implementation of irrigation system is limited to wetlands, which have reservoirs used to meet water requirements. Therefore, cropping pattern planning should be applicable in both wetlands and drylands, which can only be planted with rainfall overflow.

In addition, on average, farmers realize that using local technology causes low crop productivity as well as low income. These problems generally occur due to the lack of institutional support from the government for farmers' activities [15]. Meanwhile, food production index has a significant and positive impact on poverty reduction [16, 17].

Modeling or forecasting of hydro-climatological data has been widely applied in the fields of economics, planning,

construction, transportation, and agriculture. Bathia and Rana [18] used linear programming to determine the allocation and combination of crops in each growing season. Villagrán [19] made a greenhouse simulation for fruit and vegetable production by taking into account wind speed and temperature data. Ramli et al. [20] used linear regression with a log transformation to predict rainfall data, rainfall, total of rainy days, temperature, humidity, duration of irradiation, and wind speed for 29 years to forecast climate change. The model found was only able to predict with an R-square value of 24.61% and RMSE value of 57.676. Therefore, they recommended that the forecasting of hydro-climatological data should use non-linear methods for better data pattern recognition. The utilization of linear methods is sometimes only able to be trained on a relatively small amount of data. Therefore, a method that is capable of training a large amount of data and is more complex is needed.

A forecasting method with non-linear functions is artificial neural network backpropagation (ANN-BP). ANN have been widely used for hydro-climatological data forecasting and the most popular data predicted is rainfall [21-24]. This is done because rainfall has an important role to determine weather and climate changes. ANN-BP algorithm with two hidden layers was used by Irawan et al. [25] to predict hydro-climatological data for determining crop water requirement and planning planting patterns. Architecture with two hidden layers was also used by Syaharuddin et al. [26] to forecast inflation data with the training function is trainrp and the activation function of each layer is logsig. The process of increasing the number of hidden layers in the ANN-BP architecture will certainly make it easier for the network to recognize data patterns. Furthermore, the experimental results of Vera et al. [27], using the activation function and the training function, found that the results of training data using a backpropagation architecture with three hidden layers are better than two hidden layers. The MSE and MAPE values are 0.0382 and 0.1954, respectively, when using two hidden layers, while when using three hidden layers, the MSE and MAPE values are 0.0375 and 0.1936, respectively.

The forecasted hydro-climatological data can be used to calculate evaporation, evapotranspiration (potential and actual), effective rainfall, and crop water requirement. Generally, researchers use the Penman method (1948) to determine the potential evapotranspiration value if the station recording hydro-climatological data provides complete data. However, at some locations or actual data recording stations, the data is sometimes unavailable or limited. This means that one or more of the five hydro-climatological data is incomplete or the data recording unit is not daily. Thus, scientists developed other methods such as Thomthwaite (1948), Makkink (1957), Blaney-Criddle (1959), Turc (1961), Hamon (1961), Rohwer (1962), Jensen-Haise (1963), Penman-Monteith (1965), Priestley-Taylor (1972), Hargreaves (1975), Doorenbos-Pruitt (1977), Kharrufa (1985), Linacre (1977), and Abtew (1996) [28-32]. These methods have been redeveloped according to Food and Agriculture Organization (FAO) standards; among them are Penman-Monteith, Blaney-Criddle, Turc, Jensen-Haise, Jensen, Priestley-Taylor, and Hargreaves [33-38].

Researches continuously experiment with the methods that have been modified in order to determine a reliable method to obtain evapotranspiration values. Chiew et al. [39] analyzed climate characteristics in 16 Australian locations and found that the FAO24 radiation, FAO24 Blaney-Criddle, and

Penman-Monteith gave similar monthly ET, estimates. This result is reinforced by the results of research [40-43], which showed that the Blaney-Criddle method gave good calculation results of evapotranspiration values, which was close to the results found using the FAO Penman-Monteith method as a basic method. This finding is an important basis for researchers in determining evapotranspiration and crop water requirement when hydro-climatological data are incomplete at a location.

The results of of hydro-climatological data forecasting and calculation of evapotranspiration and crop water requirement need to be integrated due to the multi-year nature of the cropping pattern planning procedure. It has still been done by many other researchers, where forecasting is only done for one current year. Meanwhile, cropping pattern planning is multi-year. Hence, long-term forecasting must be carried out to obtain hydro-climatological data of the coming year. In addition, many researchers only focus on rice as the staple food although in one heterogeneous land, other crops such as CGPRT crops (coarse grains, pulses, roots and tubers), horticultural crops, and even tobacco must also be planted. Therefore, the purpose of this research is to explain the implementation of artificial neural network backpropagation and relevance vector machine (BP-RVM) for long-term forecasting of hydro-climatological data. Furthermore, we calculate evapotranspiration values, effective rainfall, and irrigation water requirements, and crop water requirements during the cropping process based on the forecasting results. The results of this research are expected to be useful in planning optimal cropping patterns and serve as a basis for the government in devising policies on agriculture.

2. ARTIFICIAL NEURAL NETWORK

Climatological data such as wind speed, temperature, humidity, and sunshine duration are needed to determine evapotranspiration value, crop management water requirement, and cropping pattern. Cropping pattern is planned for three growing seasons (a multi-year period), thus the data must be predicted based on long-term forecasting with Eq. (1):

$$y_{k+1} = NN(y_k, y_{k-1}, y_{k-2}, y_{k-3}, \dots) \quad (1)$$

with NN as backpropagation neural network and y_k as forecasting result in year k obtained using Eq. (2) as follows:

$$y(x) = f(w_{0k} + \sum_{j=1}^p w_{jk} \cdot f(v_{0j} + \sum_{i=1}^n v_{ij} \cdot x_i)) \quad (2)$$

with $x_1, x_2, \dots, x_i, \dots, x_n$ are an input layer determined by the amount of input data, $y_1, y_2, \dots, y_k, \dots, y_m$ are an output layer, $z_1, z_2, \dots, z_j, \dots, z_p$ are hidden layers of multi-layer nature, v_{0j} is the initial weight matrix on the hidden layer that initializes randomly between 0 and 1, w_{0k} is the initial weight matrix on the output layer, while $f(\cdot)$ is an activation function that converts input data into external data between layers in intervals of -1 and 1, depending on the activation function given at each layer [44]. This architecture requires a long training duration. Therefore, the relevance vector machine (RVM) algorithm is needed to build a faster algorithm when compared to the ANN-BP algorithm only. Furthermore, the radial basis function kernel will help in the data recognition process in the first hidden layer. While the 2nd and 3rd hidden

layers use binary sigmoid function (Sub-heading 4.3).

3. CALCULATION OF CROP WATER REQUIREMENT

Generally, the growing requirements of each crop depends on climatic indicators such as rainfall (mm/month), temperature (°C), and humidity (%). The growing requirements of each crop are different (Table 1), thus affecting the crop planting schedule for each season. Therefore, these needs must be taken into account in planning a good cropping pattern, especially water requirement.

Rainfall is the main indicator for all crops. In planning cropping patterns, hydro-climatological data must be considered, especially in the data forecasting process. Initially, forecasting data is used to determine the evapotranspiration value and water requirement of each crop during the pre-planting, planting, and harvesting (including post-planting) processes. Evapotranspiration is the evaporation of the surface

of a field overgrown with plants, which is a combination of evaporation and transpiration stages [45]. Meanwhile, crop water requirements are generally determined by evapotranspiration and effective rainfall [46, 47]. The actual crop evapotranspiration value (mm/day) can be determined using Eq. (3):

$$Et_c = K_c \cdot Et_o \quad (3)$$

with K_c indicating crop coefficient (Table 2) [48] and indicating potential evapotranspiration (mm/day) [49]. Crop coefficients are characteristics of crops used to predict evapotranspiration values and have different values according to the length of planting of food crops. Meanwhile, potential evapotranspiration is a value that describes the need for the environment, a set of vegetation, or an agricultural area to evapotranspire which is determined by several factors, such as sunlight intensity, wind speed, leaf area, air temperature, and air pressure.

Table 1. Growing conditions and crop harvest time

Types of Plants	Rainfall (mm/month)	Temp. (°C)	Humidity (%)	Harvest Time (days)
Rice (C1)	200	23-27	50-80	100-115
Corn (C2)	85-100	23-27	55-80	85-115
Peanut (C3)	100-150	25-32	50-80	85-110
Green Bean (C4)	50-200	25-27	50-89	51-80
Soybean (C5)	100-200	23-30	60-70	70-100
Cassava (C6)	50-90	25-28	60-65	215-320
Sweet Potato (C7)	60-125	25-27	50-60	90-150
Tobacco (C8)	50-125	22-33	50-70	120-150
Red Onion (C9)	100-200	25-32	50-70	60-90
Watermelon (C10)	40-50	25-30	50-70	70-100

Table 2. K_c value according to the food and agriculture organization (FAO)

10-days	Rice	CGPRT Crops						Tobacco	Horticulture	
		Corn	Soybean	Green Bean	Peanuts	Sweet Potato	Cassava		Red Onion	Watermelon
1	1.1	0.5	0.5	0.5	0.51	0.50	0.5	0.50	0.50	0.40
2	1.1	0.51	0.63	0.59	0.59	0.51	0.51	0.51	0.51	0.58
3	1.1	0.59	0.75	0.67	0.66	0.51	0.51	0.52	0.51	0.75
4	1.08	0.78	0.88	0.98	0.76	0.59	0.59	0.61	0.60	0.88
5	1.05	0.96	1.0	1.003	0.85	0.66	0.66	0.70	0.69	1.00
6	1.05	1.01	1.0	1.025	0.9	0.76	0.76	0.90	0.80	1.00
7	1.05	1.05	1.0	0.97	0.95	0.85	0.85	1.10	0.90	1.00
8	1	1.04	0.91	0.84	0.95	0.90	0.90	1.12	0.93	0.85
9	0.95	1.02	0.82	0.7	0.95	0.95	0.95	1.13	0.95	0.70
10	0.95	0.99	0.64		0.75	0.95	0.95	1.13	-	-
11	0.95	0.95	0.45		0.55	0.95	0.95	1.12	-	-
12	0.95	0.95	0.45		0.55	0.55	0.75	1.07	-	-
13-15	-	-	-	-	-	0.55	0.95	0.84	-	-
16-18	-	-	-	-	-	-	0.55	-	-	-
Average	1.03	0.86	0.75	0.81	0.75	0.69	0.68	0.86	0.71	0.8

Table 2 shows that each crop has a different coefficient value (K_c), which affects the evaporation and evapotranspiration values of each crop [50, 51]. Et_o value can be determined with various methods according to the types of available data, such as rainfall, temperature, wind speed, humidity, and sunshine duration. In this study, the authors used the FAO24 Blaney-Criddle method as shown in Eq. (4) [36]:

$$Et_o = a + bp(0.46T + 8.13)(1 + 0.0001E) \quad (4)$$

with T is temperature (°C); p is empirical coefficients based on

latitude ($^{\circ}$) (see Figure 1); E is elevation (m) [52]; a and b are calibrated constants obtained using Eq. (5) and Eq. (6):

$$a = 0.0043(RH_{min}) - \left(\frac{n}{N}\right) - 1.41 \quad (5)$$

$$b = 0.88165 + 0.857596 \left(\frac{n}{N}\right) - 0.00454((RH_{min}) + 0.093803(U_d)) - 0.00405((RH_{min}) \left(\frac{n}{N}\right) - 0.00087(RH_{min})(U_d)) \quad (6)$$

with RH_{min} as the lowest daily relative humidity (%); n/N as

the average ratio of actual to possible sunshine duration (%); and U_d as wind speed. Furthermore, the p-value in Eq. (4), shown in Figure 1, was taken from the position of Kediri station, which is close to a latitude of 10^0 (see Figure 2).

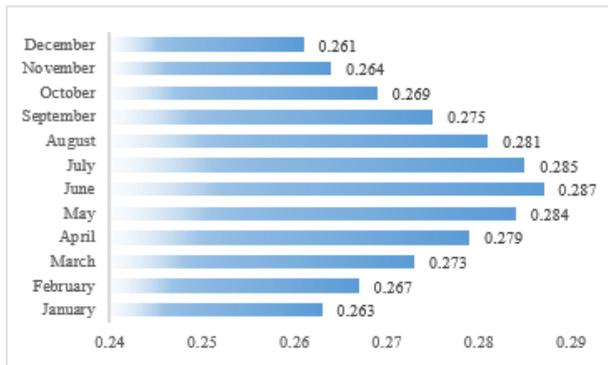


Figure 1. P-value based on blaney-criddle method

Et_o value can be used to calculate water requirement for rice production or irrigation water requirement (IR) with Eq. (7):

$$IR = \frac{Me^k}{e^{k-1}} \quad (7)$$

with $e=2.7182$; $M = 1.1 Et_o + 3$; $k = \frac{3M}{25}$.

Furthermore, the effective rainfall (R_{eff}) for rice (Eq. (8)) is different from that for CGPRT crops (Eq. (9)).

$$R_{eff} = 0.7 \frac{R_{80}}{10} \quad (8)$$

$$R_{eff} = 0.7 \frac{R_{50}}{10} \quad (9)$$

R_{80} and R_{50} are the mainstay rainfall determined from all data used as input for making forecasting using the BP-RVM

architecture. Furthermore, Eq. (3) and Eqs. (8)-(9) were used to determine crop water requirement with Eqs. (10)-(11).

$$NFR = Et_c + P - R_{eff} + WLR, \text{ (for rice)} \quad (10)$$

$$NFR = Et_c + P - R_{eff}, \text{ (for CGPRT crops, horticulture, etc)} \quad (11)$$

P is the location that shows soil infiltration; in this study, the P -value was 3 mm/day. WLR is the turnover of subsoil water carried out twice a month (semi-monthly according to the fertilization schedule); each was 50mm (3.3 mm/day for 15 days).

4. METHOD

4.1 Study area and dataset

There are two sources of data used in this research. The first source was the Agriculture and Plantation Office that provided data on crop coefficients, plant growth requirements, and several standard parameters in calculating crop water requirements, such as location Eqs. (10)-(11), elevation Eq. (4), p -coefficient based on the Blaney-Criddle method (Figure 1), 30-day land preparation period, water requirements for saturation and a water layer of 200mm. The second source was the Meteorology, Climatology, and Geophysics Agency in Lombok Island, Indonesia that provided hydro-climatological data consisting of rainfall, wind speed, humidity, temperature, and sunshine duration data taken from 3 stations, namely Kediri station, Gunung Sari station, and Lembar station. The agricultural data is standardized based on direct observation and the results of statistical calculations by agricultural experts. Meanwhile, hydro-climatological data is 10 daily data so that 36 data are obtained in a year. The data is normalized using the Z-score method that has been constructed in the BP-RVM computing system. The distribution of stations is shown in Figure 2.

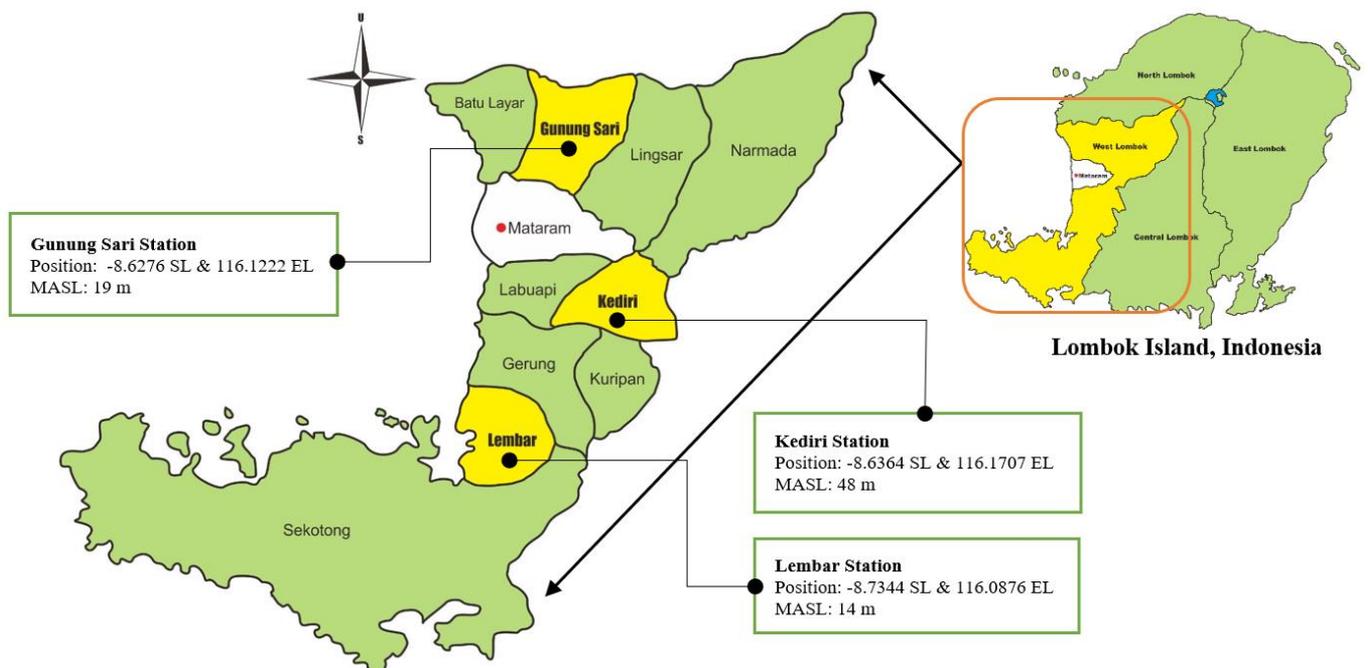


Figure 2. Study area and data selection

4.2 Research procedure

In the initial stage, hydro-climatological data were predicted using a backpropagation neural network. Long-term forecasting was used because a cropping schedule is generally prepared for three growing seasons (a multi-year period). Furthermore, the results of this data forecasting were used to calculate the values of evaporation, radiation, evapotranspiration, effective rainfall, and water requirements for crop management.

In this study, a backpropagation architecture with three hidden layers was used. The number of neurons in the input layer, hidden layer, and output layer was 36-73-37-19-1. This architecture is in accordance with the research results of Syaharuddin et al. [53] who carried out training-testing on rainfall and temperature data from Lombok International Airport station. Furthermore, Syaharuddin et al. [44, 54] also tested several parameters of the backpropagation architecture with three hidden layers. Moreover, the relevance vector machine (RVM) algorithm with radial basis function (RBF) kernel was combined with backpropagation to improve network performance and minimize the number of epochs. On the input layer and hidden-1 layer, **radbas** function (RBF) was utilized, while **logsig** function was utilized on the hidden-2 layer and hidden-3 layer. We use accuracy parameters, namely mean square error (MSE) and mean absolute percentage error

(MAPE), which show that the smaller the value, the more accurate the forecasting results. We utilize the MSE and MAPE values as a standard that supports each other in seeing the error rate or accuracy of the BP-RVM algorithm. In this research, we use the maximum value standard according to Lewis (1982), namely the MAPE value of <10% indicates high accurate forecasting, $10\% \leq \text{MAPE} < 20\%$ indicates good forecasting, $20\% \leq \text{MAPE} < 50\%$ indicates reasonable forecasting, and $50\% \geq \text{MAPE}$ indicates inaccurate forecasting. Furthermore, the number of epochs is used to see the number of iterations generated with a maximum target of 100 epochs in each architecture performance. The flowchart of the BP-RVM-RBF architecture is shown in Figure 3.

Hydro-climatological forecasting data (rainfall, temperature, wind speed, humidity, and sunshine duration) were used to determine evapotranspiration values (Eqs. (3)-(4)), treatment or irrigation water requirements (Eq. (7)), effective rainfall (Eqs. (8)-(9)), and crop water requirements (Eqs. (10)-(11)). In Figure 2, there are three stations recording rainfall data, so the effective rainfall was determined after determining the average rainfall in the area around the three stations. In addition, the calculation in Figure 3 was done to analyze the availability of water required by crops in each month based on the forecasting data. Thus, the suitable time to plant each crop according to the provisions in Table 1 would be found.

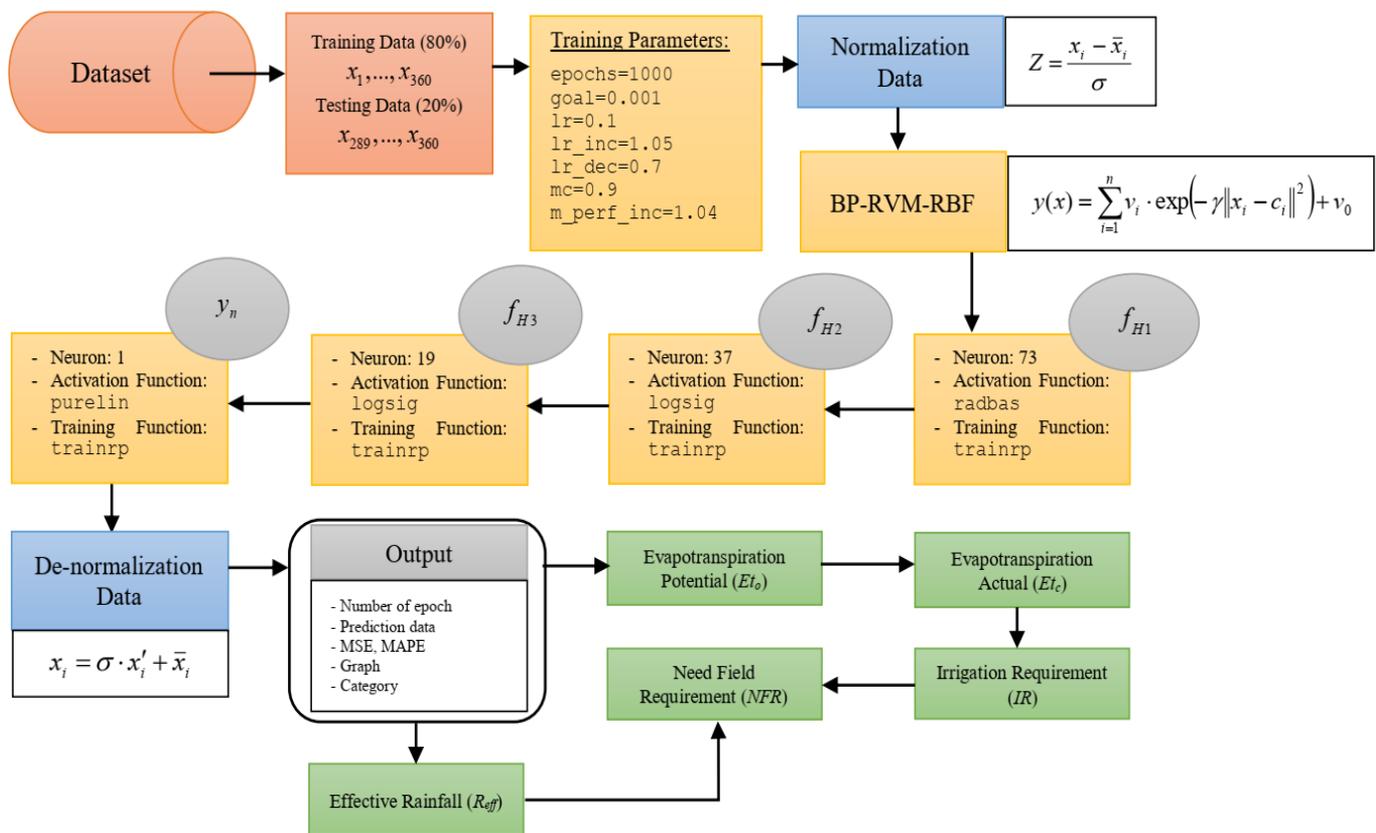


Figure 3. Algorithm of BP-RVM with radial basis function kernel

5. RESULTS AND DISCUSSION

5.1 Hydro-climatological data forecasting results

Based on Figure 2, there are three rainfall stations, namely Gunung Sari Station, Lembar Station, and Kediri Station. The

forecasting results from these three stations are averaged before calculating the effective rainfall value. We utilized average statistics because cropping pattern planning is global for the West Lombok district. This has an impact on government calculations in determining the amount of food crop seed and fertilizer supplies before distribution. The

results of the average rainfall calculation will not significantly affect the calculation of effective rainfall and other parameters. While the temperature, wind speed, humidity, and sunshine duration data still use data from Kediri station. This is due to the climatology data recording tool only being available at

Kediri station. The architecture in Figure 3 is used for data in long-term forecasting using Eq. (1), meaning that 2012-2021 data is used for 2022 data forecasting, then 2012-2021 data and 2022 forecasting results are used for 2023 data forecasting. The forecasting results are shown in Table 3.

Table 3. Descriptive results of hydro-climatological data forecast

Data	Years	Maximum	Minimum	Average	Epoch	MSE	MAPE
Rainfall-Kediri Station	2022	202,82	0	64,07	34	1643,35	-
	2023	165,9	0	64,77	41	950,617	-
Rainfall-Lembar Station	2022	218,51	0	49,84	52	1312,75	-
	2023	249,14	0	48,20	40	1249,45	-
Rainfall-Gunung Sari Station	2022	182,18	0	63,04	28	2839,21	-
	2023	174,39	0	68,49	27	899,269	-
Temperature	2022	27.75	24.72	26.55	33	0.37	1.83
	2023	28.13	24.38	26.46	42	0.25	1.52
Humidity	2022	88.48	78.65	84.20	33	7.75	2.68
	2023	89.34	79.4	84.38	37	6.62	2.64
Wind Speed	2022	5.03	1.2	3.02	48	1.23	27.51
	2023	5.17	1.13	2.96	40	0.53	23.62
Sunshine	2022	89.99	38.69	69.15	35	188.22	17.24
	2023	93.25	39.24	71.46	36	175.14	17.10

Table 3 indicates that the number of epochs generated is between 27 and 52. When predicting rainfall data, the smallest number of epochs was found from data obtained from Gunung Sari station, while the highest was found from data taken from Lembar station. Furthermore, the highest average of rainfall was found in the Kediri station area. Geographically, this station is located in a flat area, whereas Gunung Sari and Lembar areas which are in mountainous areas. In addition, the MSE value of each data could be found. A higher value indicates that the data have high fluctuations and vice versa. For example, temperature data that is relatively static has an average MSE value of 0.31. The forecasting results also showed that the maximum average rainfall in 2022 and 2023 would be 172.53 mm and 178.33 mm, respectively. Overall, taking into account the MAPE value based on Lewis' classification [55], the average forecasting results fall into the "good forecasting" category. The distribution of forecasting data based on long-term forecasting is shown in Figures 4-8.

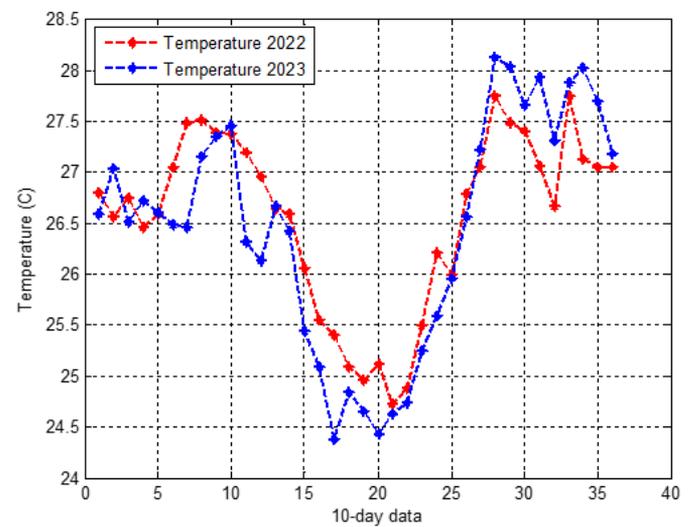


Figure 5. Forecasting data of temperature

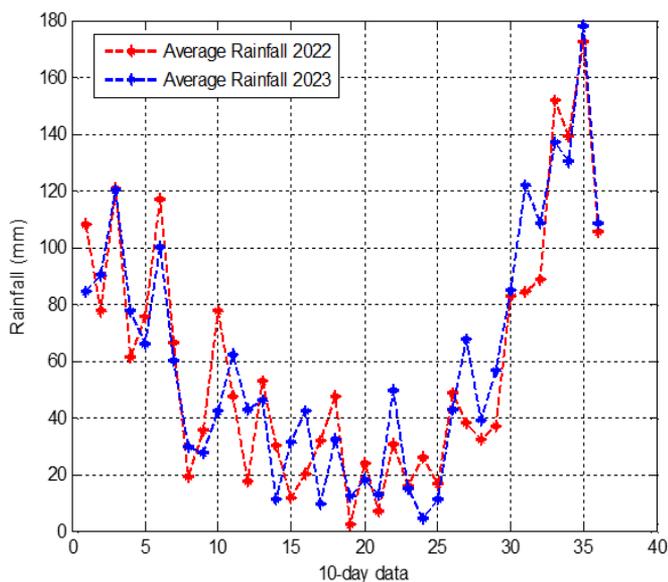


Figure 4. Forecasting data of rainfall

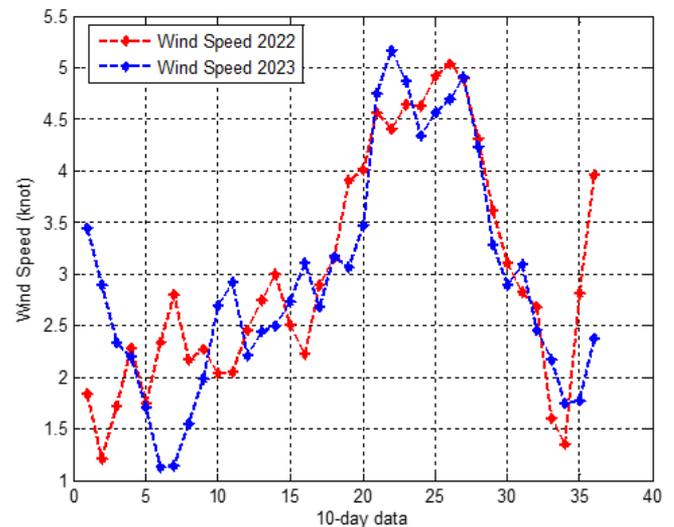


Figure 6. Forecasting data of wind speed

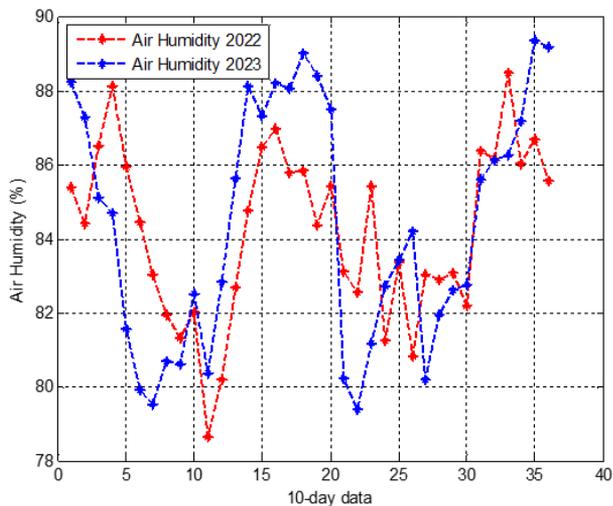


Figure 7. Forecasting data of humidity

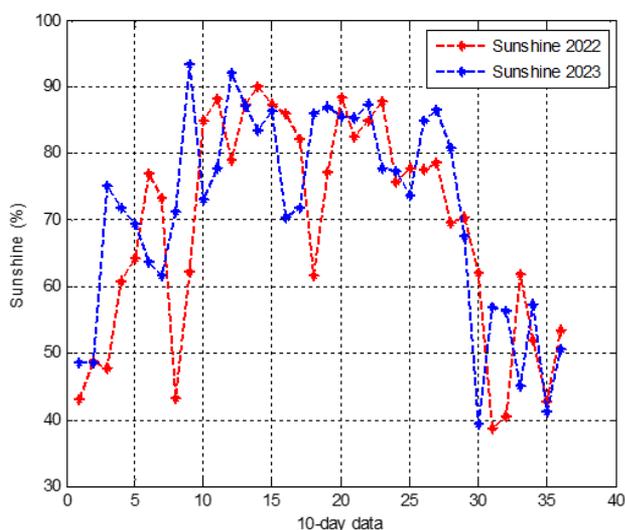


Figure 8. Forecasting data of sunshine duration

Generally, Figures 4-8 demonstrate that the trend of each data is relatively stable. The forecasting data of the year 2023 does not appear to have different fluctuations from the forecasting data in 2022. Rainfall forecasting data in Figure 4 show that rainfall in 2023 tends to increase compared to 2022 with a peak occurring in December 2022 of 417.01 mm and starting to decline at the end of February 2023.

Furthermore, the temperature forecasting data in Figure 5 show that there would be an increase in temperature in September-October every year, reaching more than 28°C as the rainy season would begin in this period. Wind speed forecasting data in Figure 6 show that the maximum wind speed would occur in July-August, reaching 5 knots. The speed would increase again in early January, reaching more than 4 knots. The humidity forecasting data in Figure 7 show an increase at the beginning, middle, and end of the year with an average of 84.28%. Finally, the forecasting data of sunshine duration in Figure 8 show that there would be an increase at the end of March and decrease at the end of August. Humidity would be between 79% and 89%. Humidity is strongly influenced by temperature, wind speed, rainfall, sunshine duration, and vegetation density [56, 57]. This means that high rainfall will increase the density of plant vegetation, which can increase humidity in an area with high vegetation.

The amount of water, temperature, and humidity suitable for each crop shown in Table 4 were calculated based on the criteria in Table 1 and the results of data forecasting. These values can be used as a reference to determine the appropriate planting season (PS) for each crop.

Table 4. Rainfall suitability for crops

PS	Month	R (mm)	T (°C)	Crops
PS-1	October	204.45	27.31	C1, C2, C4, C5, C9
	November	379.47	27.18	C1, C2, C4, C5, C9
	December	362.51	26.89	C1, C2, C4, C5, C9
	January	287.77	26.75	C1, C2, C4, C5, C9
PS-2	February	226.48	26.51	C1, C2, C4, C5, C9
	March	99.66	27.32	C2, C4, C6, C7, C8, C10
	April	151.49	26.37	C2, C3, C4, C5, C9
	May	85.01	25.65	C2, C4, C6, C7, C8, C10
PS-3	June	54.94	24.62	C4, C6, C8, C10
	July	81.15	24.59	C4, C6, C7, C8
	August	30.20	25.59	-
	September	150.20	27.30	C2, C3, C4, C5, C9

Based on the rainfall forecasting in Figure 4, rainfall in 2022 would start to increase in October 2022, meaning that the planting season (PS-1) could begin that month. Therefore, Table 4 shows that almost all crops are suitable to be planted between late October and February, except peanut, cassava, sweet potato, tobacco, and watermelon. Generally, these crops could be planted in the dry season (PS-2 and PS-3). Table 4 also shows that there would be very little rainfall in August, so it would not be suitable to plant any of the crops that month.

5.2 Effective rainfall and irrigation water requirements

The forecasting results of hydro-climatological data were used to calculate the potential evapotranspiration value (Eq. (4)), water requirement for rice production or irrigation water requirement (Eq. (7)), and effective rainfall (Eqs. (8)-(9)). The calculation results are shown in Figure 9.

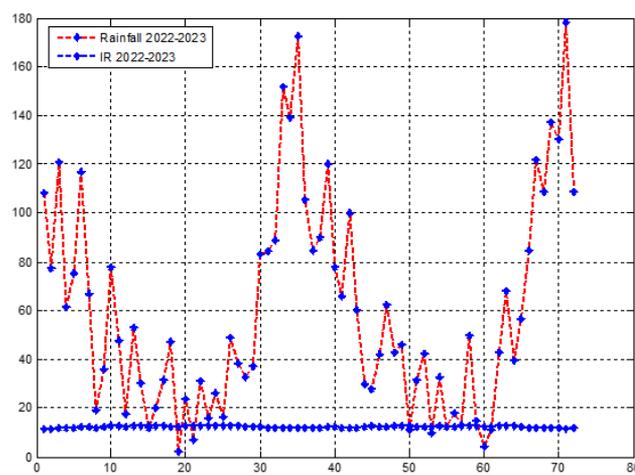


Figure 9. Rainfall conditions and water requirements for rice production

Irrigation water requirement is the amount of water needed to meet the needs for crop evaporation, water loss, water requirements by taking into account the amount of water provided by nature through rainfall and beneath the ground. Figure 9 illustrates that the ratio of rainfall to water requirement for rice production is normal. The average

irrigation water requirement throughout 2022-2023 would be 12.36mm. It would be met by rainfall except in July 2022, June 2023, and August 2023 because the dry season (PS-3) with very low or zero rainfall intensity would take place in these months.

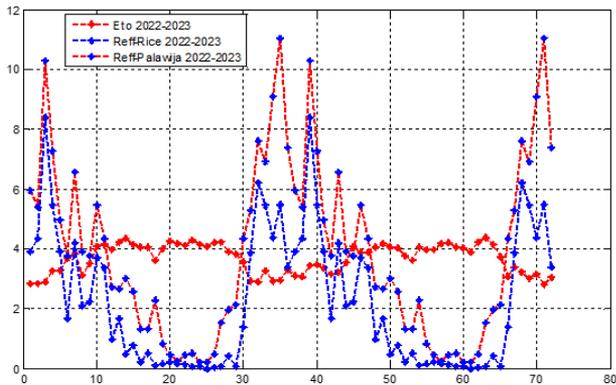


Figure 10. E_{t_o} value and effective rainfall

Based on Figure 10, it can be seen that the potential evapotranspiration value throughout 2022-2023 would be between 2.82mm/day and 4.38 mm/day with an average of 3.6 mm/day and a maximum of 4.38mm/day at the end of September 2023. Meanwhile, effective rainfall for both rice and CGPRT crops would be very high in the December-January-February (DJF) period with a maximum value of 8.4mm/day for rice and 11.06mm/day for CGPRT crops. In the March-April-May (MAM) period, the value would decrease since this period occurs in the dry season and the beginning of PS-2.

5.3 Actual evapotranspiration and crop water requirements

The actual crop evapotranspiration value (Eq. (3)) and crop water requirement (Eqs. (10)-(11)) were determined according to the planting schedule in a year. Figure 4 shows that the rainfall data at the end of October 2022 would reach more than 50mm. This means that the planting season (PS-1) for rice and crops that meet the growing requirements could begin. Thus, the suitable planting season should begin between late October 2022 and early October 2023. Hence, in the interval of the growing season, the value of E_{t_c} and NFR can be determined according to Figure 11 and Figure 12.

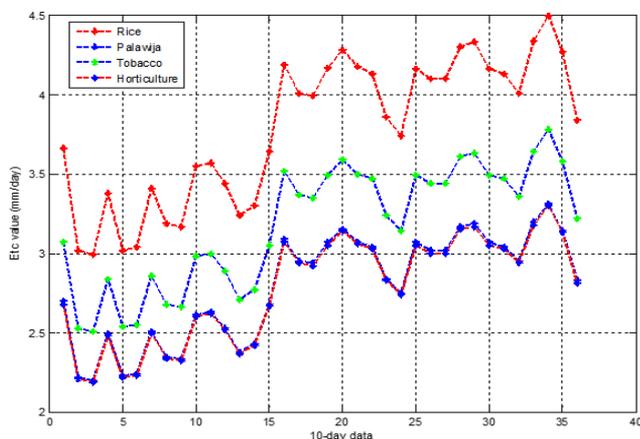


Figure 11. Average value of E_{t_c}

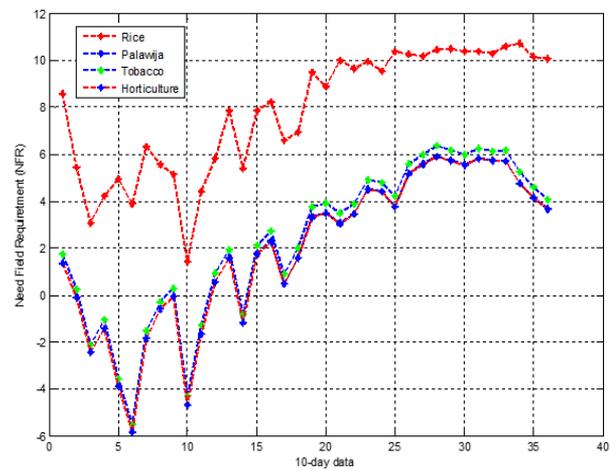


Figure 12. Average value of NFR

The evapotranspiration value of rice was higher than that of CGPRT crops, tobacco, and horticultural crops. The maximum E_{t_c} value of rice was 4.5 mm/day, the minimum value was 2.99 mm/day, with an average of 3.79 mm/day. Figure 11 also presents the high evapotranspiration value of tobacco. This high value was obtained due to the relatively long harvest time of tobacco with an average coefficient (K_c) of 0.86. This value was higher than the coefficient of CGPRT crops and horticultural crops (see Table 2). Finally, the evapotranspiration values of crops and horticulture were almost the same with an average of 2.20 mm/day (CGPRT crops) and 2.19 mm/day (horticultural crops). This occurred because the morphology and coefficient of CGPRT and horticultural crops are almost the same, namely 0.76 and 0.75 respectively.

Crop water requirements are dominantly influenced by the actual evapotranspiration value of and the effective rainfall for each crop [58, 59]. Figure 12 shows that rice has the highest water requirement compared to CGPRT crops, tobacco, and horticultural crops. Meanwhile, the crops suitable to be planted in the dry season (PS-2 and PS-3) statistically have the same water requirements.

6. CONCLUSIONS

The combination of backpropagation algorithm and relevance vector machine (BP-RVM) with three hidden layers demonstrated a good performance in forecasting hydro-climatological data. The data forecasting results are categorized as “good forecasting” with a MAPE value of 11.77% (<20%). Based on the results of rainfall forecasting, the determination of the beginning of the growing season (PS-1) would begin in late October 2022 with rainfall reaching 82.96 mm (>50 mm). The water requirement for rice production throughout the year would be met except in July 2022, June 2023, and August 2023 (PS-3 period). Furthermore, the calculation results of the FAO24 Blaney-Cridde method provide information that the evapotranspiration value of CGPRT crops was almost the same as that of horticultural crops with an average of 2.79 mm/day and 2.78 mm/day. These values are lower than the evapotranspiration of tobacco and rice. Throughout the season, the average water requirements were 7.88 mm/day for rice, 1.94 mm/day for CGPRT crops, 2.33 mm/day for tobacco, and 1.93 mm/day for horticultural crops. The results of

evapotranspiration, crop water requirements, and crop suitability (rice, CGPRT crops, tobacco, and horticultural crops) for each growing season can be used as an initial policy in preparing the amount of food crop seed and fertilizer supplies to be distributed. In addition, we recommend other researchers to use FAO24 Blaney-Criddle in calculating evapotranspiration values if incomplete data is found at a hydro-climatological data recording station.

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