WEATHER-BASED FORECASTING MODEL FOR THE PRESENCE OF *Metisa plana* IN OIL PALM PLANTATION USING FEATURE SELECTION IN ARTIFICIAL NEURAL NETWORK

Mohammad Zafrullah Salim[1*], Mohammad Hilmi Mohd Zahir[1], Farrah Melissa Muharam[1], Nur Azura Adam[2], Dzolkhifli Omar[2], Nor Azura Husin[3] & Syed Mohd Faizal Syed Ali[4]

[1]Department of Agriculture Technology,
Faculty of Agriculture,
Universiti Putra Malaysia,
43400 UPM, Serdang, Selangor, Malaysia.
[2]Department of Plant Protection,
Faculty of Agriculture,
Universiti Putra Malaysia,
43400 UPM, Serdang, Selangor, Malaysia.
[3]Department of Computer Science,
Faculty of Computer Science and Information Technology,
Universiti Putra Malaysia,
43400 UPM, Serdang, Selangor, Malaysia.
[4]TH Plantations Berhad,
Level 31-35, Menara TH Platinum,
No. 9 Persiaran KLCC,
50088 Kuala Lumpur, Malaysia.
*Corresponding author: *zafrullahsalim@gmail.com*

ABSTRACT

Bagworm is the most important insect defoliator of oil palm. The bagworm larvae scrape off the leaflets' epidermis while the older larvae chew the leaflets and leaving multiple holes and causes the palm to lose its photosynthetic capability. A bagworm census should be carried out quickly to determine the extent of damage. However, the conventional practices are heavily dependent on in-situ data collection, which is destructive, less efficient, laborious, and costly. Recently, many studies have incorporated machine learning analysis such as artificial neural network (ANN) in agricultural fields especially in the development of pest prediction model. Therefore, this study was conducted to develop a weather-based bagworm prediction model using ANN-Feature Selection method. Bagworm censuses were done by identifying *Metisa plana*'s larval stage 1 (L1) to 7 (L7) from 13 random palms by cutting off frond number 17 biweekly and weather data was recorded by installing weather station in an oil palm plantation belongs to TH Plantation Berhad in Muadzam Shah, Pahang, Malaysia from July 2016 to June 2017. The results revealed that the significant weather parameters were frequent at time-lag 12. All the larval stage prediction models from ANN-Feature Selection were able to produce satisfactory R^2 values ranging from 0.526 to 0.995. The best model was the L1 model with R^2 value of 0.985 and the accuracy of more than 90 %.

Keywords: Bagworm, artificial neural network, feature selection

ABSTRAK

Ulat bungkus merupakan serangga pemakan daun yang paling penting ke atas pokok sawit. Larva ulat bungkus mengikis epidermis anak daun manakala larva yang lebih tua mengunyah anak daun dan meninggalkan banyak lubang dan menyebabkan pokok sawit kehilangan kemampuan fotosintesisnya. Bancian ulat bungkus harus dilakukan dengan segera untuk mengenal pasti tahap kerosakan. Namun, amalan lazim ini sangat bergantung pada pengumpulan data in situ yang memusnahkan, kurang efisien, menjerihkan dan menelan kos yang tinggi. Kebelakangan ini, banyak kajian telah menggabungkan analisis pembelajaran mesin seperti rangkaian neural buatan (ANN) dalam bidang pertanian terutamanya dalam pengembangan model ramalan perosak. Oleh itu, kajian ini dilakukan untuk mengembangkan model ramalan ulat bungkus berdasarkan cuaca menggunakan rangkaian neural buatan-pemilihan ciri. Bancian ulat bungkus dilakukan dengan mengenal pasti tahap larva *Metisa plana* iaitu tahap 1 (L1) hingga 7 (L7) dari 13 pokok sawit secara rawak dengan memotong pelepah ke-17 pada setiap dua minggu manakala data cuaca direkodkan dengan memasang stesen cuaca di ladang sawit kepunyaan TH Plantation Berhad di Muadzam Shah, Pahang, Malaysia bermula Julai 2016 hingga Jun 2017. Hasil kajian menunjukkan bahawa parameter cuaca yang signifikan sering berlaku pada sela waktu ke 12. Semua model ramalan tahap larva dari rangkaian neural buatan-pemilihan ciri dapat menghasilkan nilai R^2 yang memuaskan antara 0.526 hingga 0.995. Model terbaik adalah model L1 dengan nilai R^2 0.985 dan ketepatan lebih daripada 90 %.

Kata kunci: Ulat bungkus, rangkaian neural buatan, pemilihan ciri

INTRODUCTION

In 1960, 54,700 ha of oil palm were planted in Malaysia. Since then, oil palm hectarage has been expanded rapidly to 641,791 ha in 1975. By 2019, oil palm became the primary agriculture crop of this country with 5.9 million ha planted, making Malaysia the 2nd largest exporter of crude palm oil in the world (Malaysian Palm Oil Board 2019). The oil palm is the most productive crop compared to other oil crops with 3.30 tonne per ha of oil produced per year. Rapeseed oil comes in the second place with 1.33 tonne of oil per ha per year, followed by sunflower oil with 0.66 tonne per ha per year and soybean oil with 0.46 tonne per ha per year (Basiron & Chan 2004). The productivity of oil palm is 3 to 8 times higher than the other oil crops mentioned. In addition, oil palm is also able to supply 20% of world demand for oil and fats consumption with less areas planted (Wahid et al. 2005). Oil palm takes up the least percentage of world areas of oil crops (7.52%) compared to soybean (63.48%), sunflower (16.72%) and rapeseed (12.26%) (Basiron & Chan 2004). Despite having big potential towards Malaysia's economy, the oil palm industry has been battling with leaf eating pests since 1981. Bagworm is the most important defoliator of Malaysian oil palm as reported by Halim et al. (2017). The bagworms are more problematic than nettle caterpillar with 37,102 ha being infested by bagworm over 1981 to 1985 compared to 538 ha infested by nettle caterpillar over 1981 to 1990 due to its ability to cause outbreaks through successful dispersion owing to their nature of ballooning (Kevan & Basri 1995). Three common and problematic species of bagworm associated with oil palm were identified: *Pteroma pendula, Metisa plana,* and *Mahasena corbetti* (Wood & Kamarudin 2019). Scraping off the leaflets is the predominant mode of damage by *M. plana.* The young bagworm larvae scrape off the leaflets' epidermis while the older larvae chew through the leaflets leaving multiple holes. Ho (2002) listed the total mean leaf area damaged by *M. plana* larva at each instar: L1 (n = 100) = 18.49 mm^2, L2 (n = 93) = 92.48 mm^2, L3 (n = 90) = 108.00 mm^2, L4 (n = 80) = 118.16 mm^2, L5 (n = 70) = 124.90 mm^2, L6 (n = 49) = 109.48 mm^2, L7 (n = 21) = 108.95 mm^2. Leaf damage was the least during L1 but increased at L2 and remained relatively consistent from L3 to L7 despite having different number of samples. The common symptom for bagworm attack is the necrosis of the leaf tissue. If this is left untreated, the leaves will eventually become skeletonised. From that point onwards, the palm will lose its photosynthetic efficiency and will have to fight a long battle for its recovery.

Artificial neural networks (ANN) are a powerful computational device that mimics the human brain in term of information processing. It is composed of several interconnected nodes that receive an input signal, processes it and produces transformed output signal to other nodes. According to Reilly & Cooper (1995), the individual node is imperfect but collectively it can perform various tasks efficiently. Due to its advanced way of computing and processing information, ANN can develop higher accuracy of the prediction model and capture non-linear relationships, unlike the regression analysis. The structure of ANN comprises three main layers: input, output, and hidden layer (Kim & Park 2009). The input layer is the layer that represents the independent variables, the output layer represents the dependent variables, and the hidden layer represents the relationships developed between both independent and dependent variables. The relationship between the input and output layer is developed through a network of iterative training. Each input carries weight into the network and each training set will produce estimated output values that will be compared to the actual output values. The comparison between output values produces errors that will be used in network training and the iterative training will be conducted repeatedly until a minimum error is achieved. Currently, ANN is being used in many different fields including pest management in agriculture. Recent application of ANN in pest management has been widely used to forecast pest outbreak that is the foremost cause of the reduction in crop yield (Bejo et al. 2014).

Feature selection has become the focus of much research in areas of application for which datasets with tens or hundreds of thousands of variables are available. These areas include text processing of internet documents, gene expression array analysis and combinatorial chemistry. The objective of feature selection is three-fold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data. Examples of feature selections are Genetic Algorithm (GA), Backward Stepwise and Forward Stepwise. Generally, GA is stochastic search methods relying on the principles of natural genetic systems; every possible feature is considered as a population, and it does not rank variables individually (Wlodarczak 2019). On the other hand, forward stepwise uses an iterative method where it starts with no feature in the model and keeps adding feature that best improves the model until it is exhausted (Savorani et al. 2013). On the other hand, the backward stepwise works contradict with the forward stepwise: it starts with all the features and sequentially removes the least significant feature until no improvement of the model is observed (Walczak & Massart 2000).

Time-lag is a fixed amount of passing time, where one set of observations in a time series is plotted against a later set of data. This notion can be applied in an insect study where the effects of abiotic factors towards insect population can either be immediate or delayed. Therefore, the immediacy of the population dynamic's response towards abiotic factors should be well understood to develop a precise and accurate prediction model where time-lag analysis is applicable. In a study to predict the bagworm population utilizing remotely sensed derived relative humidity, Ruslan et al. (2019) assessed the accuracy of different individual and combined time-lags. The results showed that the combined time-lag of 1 to 3 weeks were able to produce the highest adjusted R^2 value with the accuracies above 95% in comparison to individual time-lags (T1, T2, T3, T4, T5 and T6) and combined time-lags (T4, T5 and T6, and T1, T3, T4 and T6). They concluded that the model was able to predict instar one to four, one to three weeks earlier during the reproductive stage of *M. plana*. Given the limited study conducted on the delayed effects of weather parameters on bagworm population, this study was conducted to develop a prediction model between *M. plana* and weather parameters at different time-lags under field condition using ANN.

MATERIAL AND METHODS

Study Site

This research was carried out in an oil palm plantation in Pahang, Malaysia from June 2016 to July 2017. The site belongs to Tabung Haji Plantation Berhad. It consists of two thousand hectares of oil palm crops ranging from 10 to 20 years old that is divided into 26 blocks. This plantation management practices Integrated Pest Management (IPM) with pesticides being applied through trunk injection to suppress bagworm's infestation under the economic threshold. Two oil palm fields were chosen (Figure 2): A 15-year-old palm, Block 16 (2°59'53.63" N and 102°54'24.31" E) and a 12-year-old palm, Block 21 (3°0'46.64" N and 102°57'58.84" E). Since oil palm plantations are hardly planted simultaneously throughout the estates, to obtain palms of same age, topography, growth, and ground conditions are an arduous task. Therefore, the criteria of selection for the fields were limited to similar age, topography, and ground conditions such as the cover crops, beneficial plants and their location that is far from the main road.

Under the estate management, both blocks are managed under the mature age group (Alam et al. 2015). Block 16 has a severe infestation of bagworm while Block 21 has a mild infestation of bagworm. The severity level was based on the estate's economic threshold for bagworm infestation which is 10 alive bagworms per frond. Exceeding this threshold will be considered severely infested and vice versa. Generally, the topography of both sites has a similar steep slope with deep valleys at the bottom, at the high peak is flat and undulating. Both blocks were located next to the main road and the distance between both blocks was approximately 4km apart. The temperature ranges from 24°C to 35°C with the average monthly rainfall of 43 mm to 54 mm and average relative humidity of 59% to 65%. In both blocks, an area of one hectare consists of 138 standing palms was marked for this study.

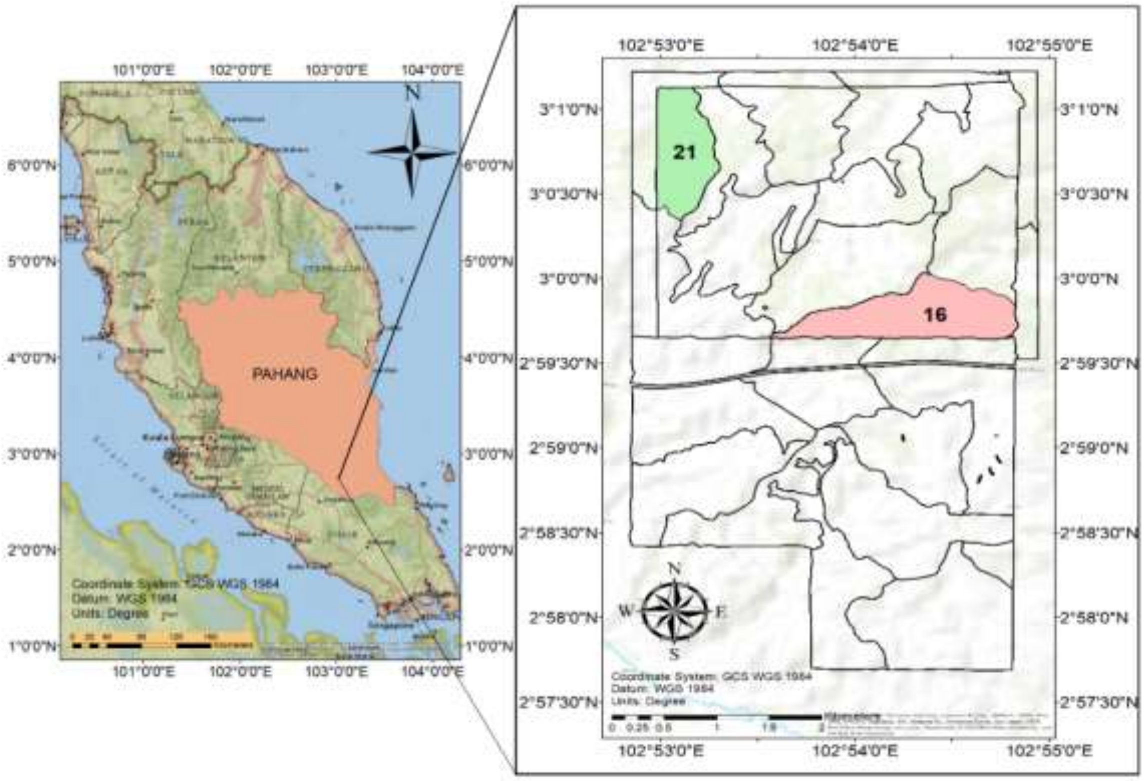

Figure 1. Map of Sungai Mengah' estate, Kota Bahagia (Bl6: Severe infestation; B21: Mild infestation)

Data Collection

Bagworm Census

Starting from July 2016 to July 2017, the counting and grouping of bagworm was carried out by cutting the frond number 17. This frond 17 was chosen because of its reliability to portray the bagworm population (Rhainds et al. 1996) and often, the highest larval population could be achieved between frond 15 to 25 (Ang et al. 1997). Bagworm has seven larval stages which were different in sizes. The bagworms found were grouped to its larval stage by measuring the size of its bag. The size of the first larval stage (L1) ranges from 1.3 to 2.5 mm, second larval stage (L2) is 2.2 to 3.2 mm, third larval stage (L3) is 3.5 to 4.4 mm, fourth larval stage (L4) is 4.4 to 6.5 mm, fifth larval stage (L5) is 7.3 to 8.8 mm, sixth larval stage (L6) is 7.6 to 10.1 mm, and seventh larval stage (L7) is 9.3 to 11.0 mm (Kevan & Basri 1995; Kok et al. 2011). The census was carried out biweekly with 13 palms chosen randomly for both blocks. The accumulated bagworm numbers were then totalled for each larval stage to produce totalled bagworms for every biweekly measurement. This sampling method was based on the agronomic practices carried out in the estate

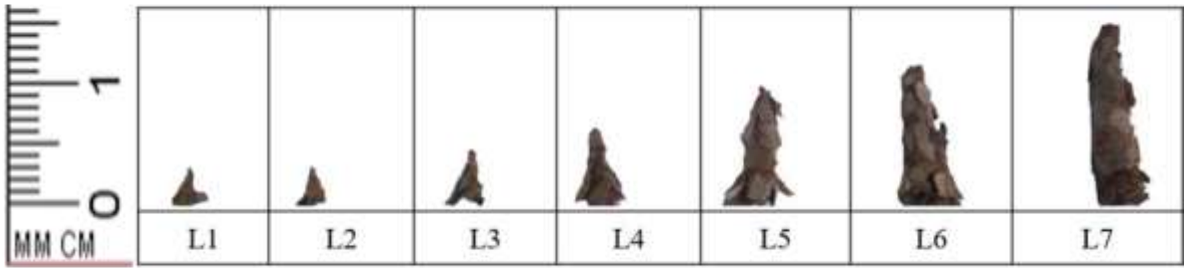

Figure 2. Larval stages of bagworm; (a) L1, (b) L2, (c) L3, (d) L4, (e) L5, (f) L6, and (g) L7

Weather Data

Both blocks have a unit of Davis WeatherLink Vantage Pro2 weather station installed in the middle of the marked one hectare. The Vantage Pro2 weather station consists of an anemometer, a rain gauge, air temperature, relative humidity and solar radiation sensors, and a solar panel. Seven weather parameters that were collected by the weather stations are tabulated in Table 1. The weather stations recorded the measurements of the weather parameters every 30 minutes.

Table 1. Specification of weather parameters collected by the weather stations

Parameter	**Range**	**Accuracy**
Temperature (˚C)	-40°C to 75°C	+/-0.5°C
Rainfall (mm)	0 to 6553 mm	+/- 4 %
Relative humidity (%)	1 to 100%	+/- 3%
Solar radiation (Wm^{-2})	0 to 1800 Wm^{-2}	+/- 5%
Wind speed (ms^{-1})	1 to 80 ms^{-1}	+/- 5%
Wind direction	0 degree to 360 degree	+/- 3 degree
Heat Index	-40°C to 74°C	+/- 1°C

The data collected by the weather stations were retrieved weekly via Universal Serial Bus (USB) cable. The weather data were then transferred to Microsoft Excel sheet and calculated the mean for each parameter by a 15-day interval except for rainfall, to produce biweekly mean temperature (MT), mean relative humidity (RH), mean solar radiation (SR), mean wind speed (WS) and mean heat index (HI). Only rainfall readings were accumulated for the two-weeks duration to produce total rainfall (RF) values.

Data Analysis

The bagworm census data were paired with the weather data at pre-determined time-lags of 2 (T2), 4 (T4), 6 (T6), 8 (T8), 10 (T10) and 12 (T12) weeks prior to model development. The maximum time lag of 12 weeks was chosen considering that the life cycle of *M. plana* takes 76 days to complete under field condition as reported by Ho (2002) and given that the sampling was conducted biweekly. The time-lag analysis was conducted since authors such as Karpakakunjaram et al. (2002), Ruslan et al. (2019) and Wood and Foot (1981) found that the effect of abiotic factors on insect population was not immediate.

Alyuda NeuroIntelligence 2.2 (Alyuda Research LLC, Cupertino, CA) was used to develop a forecasting model for this study. There are three main layers that characterize the architecture of the neural network: the input, output, and hidden layers. The input layer represents the independent variables, the output layer represents the dependent variables, and the hidden layer represents the relationship developed between input and output variables. The relationship between the input and the output variables will be established by the hidden layers through the adjustment of weightage that is performed iteratively by network training. The hidden and output layers connection is activated using the logistic (sigmoid) function.

The number of bagworms and all the time-lagged weather parameters were directly imported to the software to undergo feature selection process. Three options of feature selection available: Backward Stepwise, Forward Stepwise (Beale 2018) or Genetic Algorithm (Yordanova et al. 2013). The feature selection method was applied only to Block 16 as Block 21 did not meet the requirement of input values to be further analysed due to its low number of bagworms. The network architectures in this method were represented by *w*-*x*-1. The input layer or *w* was determined after the feature selection process, while the hidden layer or *x* was later determined by having the best fit line and the highest correlation value of the network architecture.

The selected network was then trained using the following algorithms until the best models were produced: Quick Propagation (Chehreh Chelgani et al. 2018), Conjugate Gradient Descent (Hestenes & Stiefel 1952), Quasi-Newton, Limited Memory Quasi-Newton (Broyden et al. 1973), Levenberg-Marquardt (Levenberg 1914; Marquardt 1963), Online Back Propagation, and Batch Back Propagation (Rumelhart et al. 1986). During the training process, the data fed to the network was analysed and the weights were tweaked according to their impact towards the dependent variables through a series of iterations. The weights were modified through the validation process of the neural network where the number of hidden units were determined and the declination of predictive ability of the neural network was detected. The ANN predictions were then evaluated for their testing accuracy where the perfect accuracy is 100%.

RESULTS

Table 2 tabulates all the models generated by feature selection and followed by the ANN. Firstly, the best feature selection for L1 predictor was Genetic Algorithm that consisted of multiple variables: mean temperature at time lag 10, total rainfall at time lag 2, 4, 10 and 12, mean relative humidity at time lag 2 and 12, mean wind speed at time lag 2 and 8, mean solar radiation at time lag 6, and mean heat index at time lag 2, 6 and 8. This model utilized Conjugate Gradient Descent as the training algorithm and had a network architecture of [13-12-11]. The model achieved R^2 value = 0.985, with the highest test accuracy of 99.63%. The L2 model also used the same training algorithm as for the model L1 but was trained with Backward Stepwise feature selection. It comprised mean relative humidity, mean wind speed and mean heat index at time lag 12. This L2 model achieved moderate R^2 = 0.526 and accuracy of 41.66%. For the model L3, L4, L5 and L6, all of them illustrated a similar pattern of accuracy; they achieved high R^2 values but relatively low accuracy. For example, the R^2 value for the model L3 was 0.931 but only achieved 30.59% test accuracy. This was followed by the L4, L5, and L6 model with R^2 = 0.995, 0.980 and 0.873, but the test accuracy was 18.48%, 42.11% and 10.54%, respectively. The L3 model comprised mean temperature at time lag 4 and 12, total rainfall at time lag 6, mean relative humidity at time lag 6, mean heat index at time lag 8 and 10, mean solar radiation at time lag 12 and mean wind speed at time lag 8. For the L6 model, significant parameters were mean temperature at time lag 6, total rainfall at time lag 4, 8, 10 and 12, mean relative humidity at time lag 6 and 10, mean solar radiation at time lag 2, 4, 6 and 12, mean wind speed at time lag 2 and 10, and mean heat index at time lag 8. Both models were developed with Genetic Algorithm as the feature selection and utilized training algorithm of Limited Memory Quasi-Newton and Quick Propagation with a network architecture of [11-6-1] and [14-2-1], accordingly. Both L4 and L5 model used Backward Stepwise feature selection and have the same variables: mean solar radiation and mean heat index at time lag 12. However, the L4 model used the Levenberg-Marquardt as the training algorithm with a network architecture of [2-6-1] while L5 used Quasi-Newton as the training algorithm and [2-2-1] network architecture. The L7 model consisted of only one variable i.e., mean heat index at time lag 2, used Backward Stepwise for feature selection, trained by Conjugate Gradient Descent, and had a network architecture of [1-5-1]. The model achieved the least R^2 value of 0.266 but the test accuracy was the second highest amongst other models that was 79.90%.

Table 2. ANN models with feature selection for Block 16

Model	**Input layers**	**Network Architecture**	**Training Algorithm**	$\mathbf{R^2}$	**Training Accuracy (%)**	**Validation Accuracy (%)**	**Test Accuracy (%)**
L1 Genetic Algorithm	RF, RH, WS, HI at T2 RF at T4 SR, HI at T6 MT, WS, HI at T8 MT, RF at T10 RF, RH at T12	[13-12-1]	Conjugate Gradient Descent	0.985	99.20	99.30	99.63
L2 Backward Stepwise	RH, WS, HI at T12	[3-3-1]	Conjugate Gradient Descent	0.526	79.67	99.15	41.66
L3 Genetic Algorithm	MT at T4 RF, RH at T6 HI at T8 HI at T10 MT, WS, SR at T12	[8-6-1]	Limited Memory Quasi-Newton	0.931	96.63	3.48	30.59
L4 Backward Stepwise	HI, SR at T12	[2-6-1]	Levenberg-Marquardt	0.995	99.53	78.49	18.48
L5 Backward Stepwise	HI, SR at T12	[2-2-1]	Quasi-Newton	0.980	86.71	59.91	42.11
L6 Genetic Algorithm	WS, SR at T2 RF, SR at T4 MT, RH, SR at T6 RF, HI at T8 RF, RH, WS at T10 RF, SR at T12	[14-2-1]	Quick Propagatio n	0.873	97.23	80.91	10.54
L7 Backward Stepwise	HI at T12	[1-5-1]	Conjugate Gradient Descent	0.266	99.99	6.02	79.90

DISCUSSION

Metisa plana's prediction models were generated using ANN-Feature Selection. Overall results show that the R^2 values were obtained ranging from 0.526 to 0.995 (Table 2). Other researchers such as Tonnang et al. (2010) also preferred the ANN approach in developing insect prediction models, since the ANN was able to produce prediction models for Diamond Black Moth (DBM) and *D. semiclausum* population with R2 value up to 0.91 and 0.89, respectively. Fedor et al. (2008) also found out that a simple ANN architecture i.e., multilayer perceptron (MLP) with a single hidden layer produced a 97% correct simultaneous identification of 18 common European species of Thysanoptera from four genera.

ANN could produce high R^2 values since it can cater to non-linear datasets. Essentially, the common regression analysis predicts the relationship between dependent and independent variables by assuming the linearity of the relationship when producing models (Stangierski et al. 2019). This is the principle that limits the ability of regression analysis to predict the non-linear relationship efficiently. The ANN, alternatively, possess the capability to capture the non-linear relationship and thus, is more efficient in predicting the relationship between the dependent and independent variables in this study, which uses real-life data that are known to be non-linear. This principle allowed ANN to be more flexible in terms of producing models, which then lead to the identification of complex patterns. In addition, it has been reported that ANN is better in handling the large class-imbalance inherent in the data set and can better generalize its predictions (Kim et al. 2018).

For instance, in a bagworm prediction study utilizing satellite-derived relative humidity, Ruslan et al. (2019) reported that MLP ANN models were far superior to the MLR, with the latter illustrated R^2 values ranging from 0.08 to 0.57 while latter depicted much lower R^2 values ranging from 0.00 to 0.05. The superiority of ANN against MLR analysis was also confirmed by Saxena et al. (2014) who stated that an MLP ANN model improved the R^2 value obtained from the MLR regression from 0.44 to 0.63. They agreed that the MLP prediction was closer to the observed data and concluded that ANN was a recommended tool for predicting the aphid population outbreak. Skawsang et al. (2019) also demonstrated that the RMSE of ANN in comparison to the random forest and MLR models for predicting BPH population were the lowest i.e., 1.686 versus 1.737 and 2.015, respectively. Finally, in a study to predict mosquito abundance in urban areas, Lee et al. (2016) illustrated that the ANN was able to predict the abundance of mosquito better than MLR with RMSE of 14.38 versus 17.53.

When examining the relationship between time-lag weather parameters and bagworms, the results suggested that the ANN has a greater sensitivity in detecting the favourable range of weather condition for bagworm to outbreak. Parts of the reason observed for this is that the ANN has a better ability to predict nonlinear patterns contained within the dataset compared with MLR (Lee et al. 2016). The ANN models the non-linear function as the sigmoid or S-shaped curve that has the upper and lower boundary of 1 and 0, respectively. On the other hand, Lactin et al. (1995) reported that linear regression can only estimate lower threshold temperature but not the upper threshold temperature for insect development. This finding is also supported by Briere et al. (1999).

Nonetheless, it was found that the ANN-Feature Selection model for L1 was the best out of all the models. For the L1 model, the significant weather parameters selected through the GA were RF, RH, WS, HI at T2, RF at T4, SR, HI at T6, MT, WS, HI at T8, MT, RF at T10, and RF, RH at T12. The L1 model produced high accuracies above 99% for the training, validation, and testing accuracy. However, for the rest of the prediction models showed much lower accuracies than the L1 model despite having high R^2 value i.e., L3, L4, L5 and L6. This can be credited to the 13 significant weather parameters in the L1 model. While the rest of the models had less than 10 significant parameters, the L6 model which had 14 significant weather parameters does not have similar accuracy as in the L1 model despite having more significant weather parameters. GAs are efficient search methods based on the paradigm of natural selection and population genetics. It is a general optimization method that has been applied to many problems including neural network training (Jensen et al. 1999). The usefulness of the genetic algorithm highly depends on the representation of the solution and some form of trial-and-error tuning that is necessary for each instance of a problem (Jones 2005).

The accuracies for the L2 larval stage model and onwards were too low to qualify as prediction models. In these models, for each larval stage, either the training, testing or validation accuracy was exceptionally low i.e., below 42.11 %. This finding implied that having more significant weather parameters in a model does not guarantee high accuracy. It was also observed that the time-lag 12 was dominant followed by other time-lags such as time-lag 6, time-lag 2, time-lag 8, time-lag 10. This finding suggested that certain weather parameters had a delay effect on bagworm larvae. Furthermore, the fact that ANN feature selection could only produce reliable prediction model for L1 suggested that early larval stages were significantly influenced by weather parameters. This result implied that the prediction of bagworm at its earliest stage could be conducted using appropriate modelling tools and time-lag analysis to properly plan necessary mitigation, considering that the L1 to L4 is the most damaging stage to oil palm (Ho et al. 2011; Kok et al. 2011).

CONCLUSION

The prediction models developed using ANN feature selection in this study demonstrated that the significant weather parameters mostly occurred at time-lag 12 and the prediction model was able to predict the L1 bagworm larval stage with R^2 value of 0.985 and the training, validation, and test accuracy of more than 90%.

ACKNOWLEDGEMENTS

We acknowledge Ministry of Science, Technology, and Innovation Malaysia (MOSTI) for providing a research grant (04- 01-04-SF2158), Tabung Haji Plantation Berhad for providing study area and Universiti Putra Malaysia (UPM) for awarding Graduate Research Fellowship (GRF) to support this work.

REFERENCES

Alam, A.F., Er, A.C. & Begum, H. 2015. Malaysian oil palm industry: Prospect and problem. *Journal of Food, Agriculture & Environment* 13(2): 143-148.

Ang, B.N., Chua, T.H., Chew, P.S., Min, M.M. and Saserilla, Y. 1997. Distribution of *Darna trima* (Moore) and *D. bradleyi* (Holloway) larvae (Lepidoptera: Limacodidae) in oil palm canopy, in a single species and a double species infestation. *Planter* 73: 107–118.

Basiron, Y. & Chan, K.W. 2004. The oil palm and its sustainability. *Journal of Oil Palm Research* 16(1): 1–10.

Beale, A.E.M.L. 2018. American Society for Quality Note on Procedures for Variable Selection in Multiple Regression American Society for Quality Stable *Technometrics* 12(4): 909–914.

Bejo, S., Mustaffha, S. & Wan Ismail, W. 2014. Application of artificial neural network in predicting crop yield: A review. *Journal of Food Science and Engineering* 4(1): 1–9.

Briere, J.F., Pracros, P., Le Roux, A.Y. & Pierre, J.S. 1999. A novel rate model of temperature-dependent development for arthropods. *Environmental Entomology* 28(1): 22-29.

Broyden, C.G., Dennis, J.E. & Moré, J.J. 1973. On the local and superlinear convergence of quasi-newton methods. *IMA Journal of Applied Mathematics (Institute of Mathematics and Its Applications)* 12(3): 223–245.

Chehreh Chelgani, S., Shahbazi, B. & Hadavandi, E. 2018. Support vector regression modeling of coal flotation based on variable importance measurements by mutual information method. *Measurement: Journal of the International Measurement Confederation* 114(2): 102–108.

Fedor, P., Malenovský, I., Vaňhara, J., Sierka, W. & Havel, J. 2008. Thrips (Thysanoptera) identification using artificial neural networks. *Bulletin of entomological research* 98(5): 437-447.

Halim, M., Muhaimin, A.M.D., Syarifah Zulaikha, S.A., Nor Atikah, A.R., Masri, M.M.M. & Yaakop, S. 2017. Evaluation of infestation in parasitoids on *Metisa plana* Walker (Lepidoptera: Psychidae) in three oil palm plantations in Peninsular Malaysia. *Serangga* 22(2): 135-149.

Hestenes, M.R. & Stiefel, E. 1952. Methods of conjugate gradients for solving linear systems. *Journal of Research of the National Bureau of Standards* 49(6): 409.

Ho, C.T. 2002. Ecological studies on *Pteroma pendula* Joannis and *Metisa plana* Walker (Lepidoptera : Psychidae) towards improved integrated management of infestations in oil palm. Ph.D Dissertation, Universiti Putra Malaysia.

Ho, C.T., Ibrahim, Y. & Chong, K. 2011. Infestations by the bagworms *Metisa plana* and *Pteroma pendula* for the period 1986-2000 in major oil palm estates amanged by Golden Hope Plantation Berhad in Peninsular Malaysia. *Journal of Oil Palm Research*

23*:* 1040-1050.

Jensen, C.A., Reed, R.D., Marks, R.J., El-Sharkawi, M.A., Jung, J.B., Miyamoto, R.T., Anderson, G.M. & Eggen, C.J. 1999. Inversion of feedforward neural networks: Algorithms and applications. *Proceedings of the IEEE* 87(9): 1536–1549.

Jones, K.O. (2005). Comparison of genetic algorithm and particle swarm optimisation. International Conference on Computer Systems and Technologies, 1–6 January 2005.

Karpakakunjaram, V., Kolatkar, M.D. & Muralirangan, M.C. 2002. Effects of abiotic factors on the population of an acridid grasshopper, Diabolocatantops pinguis (Orthoptera: Acrididae) at two sites in southern India: A three-year study. *Journal of Orthoptera Research* 11(1): 55–62.

Kevan, P. & Basri, M.W. 1995. Life history and feeding behaviour of the oil palm bagworm, *Metisa plana* Walker (Lepidoptera: Psychidae). *Elaeis* 7(1): 18–35.

Kim, J.S., Merrill, R.K., Arvind, V., Kaji, D., Pasik, S.D., Nwachukwu, C.C., … & Cho, S.K. 2018. Examining the ability of artificial neural network machine learning models to accurately predict complications following posterior lumbar spine fusion. *Spine* 43(12): 853.

Kim, K. & Park, J. 2009. A Survey of Applications of Artificial intelligence algorithms in eco-environmental modelling. *Environmental Engineering Research* 14(2): 102–110.

Kok, C.C., Eng, O.K., Razak, A.R. & Arshad, A.M. 2011. Microstructure and life cycle of *Metisa plana* Walker (Lepidoptera: Psychidae). *Journal of Sustainability Science and Management* 6(1): 51–59.

Lactin, D.J., Holliday, N.J., Johnson, D.L. & Craigen, R. 1995. Improved rate model of temperature-dependent development by arthropods. *Environmental Entomology* 24(1): 68-75.

Lee, K.Y., Chung, N. & Hwang, S. 2016. Application of an artificial neural network (ANN) model for predicting mosquito abundances in urban areas. *Ecological Informatics* 36: 172-180.

Levenberg, K. 1914. Brown University. *Journal of Education* 80(14): 367–368.

Malaysian Palm Oil Board. (2019). Overview of the Malaysian Oil Palm Industry. *Malaysian Palm Oil Board* January: 1–4.

Marquardt, D.W. 1963. An algorithm for least-squares estimation of nonlinear parameters. *Journal of the Society for Industrial and Applied Mathematics* 11(2): 431–441.

Reilly, D.L. & Cooper, L.N. 1995. An overview of neural networks: early models to real world systems. *How We Learn; How We Remember: Toward an Understanding of Brain and Neural Systems: Selected Papers of Leon N Cooper* 10: 300-321.

Rhainds, M., Gries, G., & Chinchilla, C. 1996. Development of a sampling method for first instar *Oiketicus kirbyi* (Lepidoptera: Psychidae) in oil palm plantations. *Journal of Economic Entomology* 89(2): 396–401.

Rumelhart, D.E., Hintont, G.E. & Williams, R.J. 1986. Learning represntations by back-propagating errors. *Nature*, 323(6088): 533-536.

Ruslan, S.A., Muharam, F.M., Zulkafli, Z., Omar, D. & Zambri, M.P. 2019. Using satellite-measured relative humidity for prediction of *Metisa plana*'s population in oil palm plantations: A comparative assessment of regression and artificial neural network models. *PLoS ONE* 14(10): 1–15.

Savorani, F., Rasmussen, M.A., Rinnan, Å. & Engelsen, S.B. 2013. Interval-based chemometric methods in NMR foodomics. *Data Handling in Science and Technology* 28: 449-486.

Saxena, P.N., Gupta, S.K. & Murthy, R.C. 2014. Comparative toxicity of carbaryl, carbofuran, cypermethrin and fenvalerate in Metaphire posthuma and *Eisenia fetida* - A possible mechanism. *Ecotoxicology and Environmental Safety* 100: 218-225.

Skawsang, S., Nagai, M., K Tripathi, N. & Soni, P. 2019. Predicting rice pest population occurrence with satellite-derived crop phenology, ground meteorological observation, and machine learning: A case study for the Central Plain of Thailand. *Applied Sciences* 9(22): 4846.

Stangierski, J., Weiss, D. & Kaczmarek, A. 2019. Multiple regression models and Artificial Neural Network (ANN) as prediction tools of changes in overall quality during the storage of spreadable processed Gouda cheese. *European Food Research and Technology* 245(11): 2539-2547.

Tonnang, H.E., Nedorezov, L.V., Owino, J.O., Ochanda, H. & Löhr, B. 2010. Host–parasitoid population density prediction using artificial neural networks: Diamondback moth and its natural enemies. *Agricultural and Forest Entomology* 12(3): 233-242.

Wahid, M.B., Abdullah, S.N.A. & Henson, I.E. 2005. Oil palm - Achievements and potential. *Plant Production Science* 8(3): 288–297.

Walczak, B., & Massart, D.L. 2000. Calibration in wavelet domain. *Data Handling in Science and Technology* 22(C): 323-349.

Wlodarczak, P. 2019. *Machine Learning and its Applications*. Boca Raton, Florida: CRC Press.

Wood, B.J. & Kamarudin, N. 2019. Bagworm (Lepidoptera: Psychidae) infestation in the centennial of the Malaysian oil palm industry - A review of causes and control. *Journal of Oil Palm Research* 31(3): 364–380.

Wood, F.H. & Foot, M.A. 1981. Graphical analysis of lag in population recation to environmental change. *New Zealand Journal of Ecology* 4: 45–51.

Yordanova, M., Evstatieva, Y., Chernev, G., Ilieva, S., Denkova, R. & Nikolova, D. 2013.

Enhancement of xylanase production by sol-gel immobilization of *Aspergillus awamori* K-1. *Bulgarian Journal of Agricultural Science 19*(Suppl. 2): 117–119.