Journal of Food Science and Agricultural Technology

International peer-reviewed scientific online journal

Published online: http://rs.mfu.ac.th/ojs/index.php/jfat

Original Research Article

Application of artificial neural networks in the prediction of fruit damages and hand weight in Cavendish banana

Johnson Ogunsua, Rattapon Saengrayap, Habib Ullah, and Saowapa Chaiwong*

Program in Postharvest Technology, School of Agro-Industry, Mae Fah Luang University, Chiang Rai 57100, Thailand

ARTICLE INFO

Article history:
Received 31 July 2018
Received in revised form 31 December 2018
Accepted 08 January 2019

Keywords:
Artificial neural networks
Banana production
Temperature
Visual appearance

ABSTRACT

The research study estimated the impact of season, maturity and temperature inside different material covers in predicting defect on banana peel from hand weight (HW), pulp per peel ratio (PPR), sunburn (SB) as well as thrips damages (TD) score of Cavendish banana in Chiang Rai. The banana bunch covers were conducted in summer (May to June 2017) and in rainy (August to October 2017). A one hidden layer feed forward backpropagation artificial neural network (ANN) was developed by varying the hidden node in a hidden layer for 2-20 nodes. Four separately ANN models were performed for Cavendish banana to predict qualities by using R and RStudio programs. Data input variables were rate of heat energy transmitted (Qx), hand location, and temperature profiles. The results showed that the 4-18-1, 6-16-1, 5-8-1, and 5-12-1 architectures were the most suitable model for HW, PPR, SB and TD score, respectively. The model performance presented the relatively high R^2 of 0.76, 0.96, 0.86, and 0.88 for HW, PPR, SB and TD score, respectively. Moreover, the selected model provided root mean square error (RMSE) of 1,157.62g, 0.252, 8.407, and 1.310 for HW, PPR, SB and TD score, respectively. The computational model ANN was used for the prediction of hand weight, pulp per peel ratio (maturity), sunburn, and thrips damages for Cavendish banana production in Thailand.

* *Corresponding author*: Tel.: -+66-5391-6737; fax: +66-5391-6737
E-mail address: saowapa@mfu.ac.th

Published by School of Agro-Industry, Mae Fah Luang University

ISSN: 2408-1736

INTRODUCTION

Bananas (Musa spp.) being a tropical fruit belong to the family of Musaceae and are originated from Southeast Asia (Ravi & Vaganan, 2016). Banana is classified as one of the economic fruits in Thailand. In the hierarchy of banana production globally, Thailand is ranked in fifteenth position and continentally (Southeast Asia) in third position with annual production volume of about 1.7 million tons (FAOSTAT, 2016). Chiang Rai, a Northern Province in Thailand, commercially produces Cavendish banana (Musa (AAA group) 'Kluai Hom Khieo') in a large area (190 hectares) for export market, particularly China. According to export market, high quality and quantity of banana fruits for international market with visual acceptability, optimum horticultural maturity and good postharvest quality attributes are required.

Some environmental factors particularly temperature plays a very significant role in crop growth and development which directly influence fruit yield and quality (Ushada & Murase, 2006). However, the relationship of temperature especially with tropical fruit like banana greatly influence its fruit growth and development during bunch emergence (Santosh et al., 2017). In addition, high temperature around 36-38^{o}C could cause sunburn (SB) in summer season (Nakasone & Paul, 1999) as well as temperature increase around (33°C) during rainy season has been reported to aid thrips activities which could cause thrip damage (TD) on Cavendish banana (Ogunsua, 2018). However, SB and TD posed as major problems of Cavendish banana plantation in Chiang Rai in summer and rainy seasons, respectively. These serious problems cause visual blemishes and defects on its peel in both seasons which consequently lead to quality reduction and economic losses particularly at export market.

Banana bunch covers are widely used across the commercial banana growing areas globally (Muchui et al., 2010). They are used to reduce defects on banana peels, improve appearance of banana peel, reduce use of insecticide and pesticide, and increase yield and fruit quality (Harvey, 2005; Soto Ballestero, 1992; Stover & Simmonds, 1987). Cavendish banana cover in Chiang Rai contains a 3-layers material for banana covering which are thin nonwoven, paper and blue perforated PE to reduce the problem of SB and TD as well as improving fruit maturity and increasing hand weight in summer and rainy seasons, respectively.

Recently, mathematical modelling has shown to be one of the tools which could be used to develop useful information to predict the outcome of fruit such as qualities yield, weight, size etc., right from the planting period to harvesting (Soares et al., 2013). This modelling only requires equation development that covers production phase and the calculation of the required parameters. Among mathematical modelling being used is artificial neural networks (ANNs). Artificial neural networks (ANNs) is one of the mathematical modelling used in analysis prediction and thus has found its usefulness in the field of agriculture especially in predicting fruit quality such as yield, weight, size. Recently, Soares et al. (2013) reported the use ANNs in predicting 'Tropical' banana bunch weight only. This indicates a need to understand the various perception of ANNs as relate to predicting other fruit quality such as hand weight (HW), fruit maturity as pulp per peel ratio (PPR) and fruit defects as sunburn (SB) and thrip damage (TD) score in Cavendish banana.

Therefore, the aim of this study was to establish a method based on study with ANNs to allow the prediction of HW, PPR, SB and TD score in Cavendish banana fruit.

MATERIALS AND METHODS

Plant material and treatment

24-uniform Cavendish banana trees (Musa (AAA group) 'Kluai Hom Khieo') 9-months-old were selected in the experimental plantation at, Phaya Meng Rai district, Chiang Rai province. The experiment was designed as completely randomized design (CRD) with six replicates (one bunch for each replicate) for summer and rainy seasons. Banana bunch with six hands of same maturity were selected and covered with four treatment covers as applied to summer and rainy seasons as follows; perforated blue bag (PE), nonwoven material (NW), coated non-woven (CNW), and aluminum foil (ALF) while water-proof nonwoven (WPNW) was used to replace CNW during rainy season trial with six replicates per treatment in each season. The treatment covers were applied on Cavendish banana around 20 days AIE during late summer and rainy seasons between (May 14th and June 26th, 2017) and (August 26th and October 22nd, 2017), respectively. The banana trees received regular cultural practices until the harvesting at mature stage (around 9 weeks and 11 weeks AIE) on 26th June 2017 for summer season and 22nd October 2017 for rainy season. The first, third and fifth hands of the bunch were selected for quality evaluation.

Temperature monitoring

Air temperature was monitored both outside and inside bunch covers of the four treatments in summer and rainy seasons at intervals of 20 minutes, using temperature data logger (Tinytag Talk 2:TK-4023-PK, UK). Temperature data generated by the data loggers for both seasons were analyzed and calculated from six and eight weeks respectively, based on average, maximum, minimum, day time (7.00-18.59) and nighttime (19.00-6.59).

Physical characteristics determinations

For mature green stage, twelve banana fruits from each hand in both seasons were randomly sampled for hand weight, by weighing on digital weight scale (PB4001-S, Mettler Toledo, Switzerland). Pulp to peel ratio were determined using four fingers from each selected hand in each season were weighed by digital weighing scale and the ratio was determined by using following equation as applied to both seasons (Pathak et al., 2016).

$$\text{Pulp per peel ratio} = \frac{\text{Weight of pulp (g)}}{\text{Weight of the peel (g)}}$$

Fruit damage assessment

Fruit sunburn assessment: The percentage of sunburn as applied to summer season only was determined and calculated as following formula by counting only number of fruits with sunburn above 10% of total area in each fruit.

$$\text{Sunburn (\%)} = \frac{\text{Number of fruit with sunburn occurrence above 10\%}}{\text{Total number of fruits in a hand} \times 100}$$

Fruit thrips damage assessment: Thrips damage (TD) percentage (%) as applied to rainy season only on each banana hand was determined by adapting Lakshmi et al. (2011) and scored as following;

0-10% = 1 (No thrips damage)
11-20% = 2 (Low thrips damage)
21-50% = 3 (Medium thrips damage)
>50% = 4 (High thrips damage)

Selection parameters procedure

Banana fruit quality selection procedure was conducted by selecting hand weight (HW) to represent the fruit yield due to its importance in fruit worth and cost evaluation among banana farmers. While, pulp per peel ratio (PPR) was selected to represent fruit maturity. In addition, sunburn (SB) and thrips damage (TD) score were selected to represent the fruit defect in summer and rainy seasons, respectively. These selected parameters were firstly analyzed by using Pearson's correlation coefficient (*r*) to determine their correlations with five temperature profiles in each season (Average (Tav), Maximum (Tmax), Minimum (Tmin), Daytime (Tday) and Nighttime (Tnight)) before ANN modelling was performed to predict the banana quality.

Statistical analysis

Pearson's correlation coefficient was used to study the relationship among the fruit quality and temperature profile at 99% and 95% level of confidence.

Artificial neural networks (ANNs) modelling

ANN was performed for Cavendish banana to predict fruit yield, maturity and defect using R (version, 64bit × 3.5.0) and RStudio (version, 1.1.447) programs. The feed-forward one hidden layer architectures were used as explained as follows; in terms of fruit yield (HW), consisted of four neurons as the first layer which were regarded as input variables (quantity of heat transfer through the material covers (Q_x), maturity stage (MS), minimum temperature (T_{min}) and nighttime temperature (T_{night}); fruit maturity (PPR), consisted of six neurons as input variables (Q_x, MS, T_{max}, T_{min}, T_{night}, and T_{day}) while, fruit defect (SB and TD score), five neurons as input variables which consisted of (Q_x, MS, T_{av}, T_{max} and T_{day}) with SB and TD score as output variable with respect to summer and rainy seasons, respectively. The second layer represented the hidden layer which the number of the hidden nodes were tested from 2 to 20 nodes with the increment of two while (HW, PPR, SB and TD score) as third layer served as the output layer (Figure 1 A, B, C and D). The selected input variables were trained with non-linear functions to predict HW, PPR, SB and TD score. Ninety datasets were used for developing ANN. All datasets were randomly selected for training (60%) and testing (40%). In terms of the validation, k-fold validation method was used to validate the model. Mean prediction error (MPE), root mean square error (RMSE) and coefficient of determination (R^2) were used as the criteria for the most suitable model for predicting banana.

RESULTS AND DISCUSSION

The correlation between temperature profile and fruit quality

Table 1 shows the correlation results obtained between the temperature profiles and the selected fruit quality parameters (HW, PPR, SB and TD score). In terms of HW, although, there was no significant difference found in correlation coefficient (*r*) in both seasons; however, *r* values were observed to be higher at T_{min} (0.447, -0.386) and T_{night} (0.458, 0.388) when compared with other temperatures in summer and rainy seasons, respectively (P>0.05). In terms of PPR, *r* values were found to be higher at T_{max}, T_{min} and T_{night} (-0.369, 0.418 and 0.420) in summer season while in rainy season r values were observed to be higher only at T_{max} and T_{day} (-0.484 and -0.421), respectively. As regard fruit defect, there was no significant difference found in *r* values in SB, although, the range of *r* values were found to be higher (0.392 to 0.500) at T_{av}, T_{max} and T_{day}, in summer season (P>0.05). However, in rainy season, the range of *r* values at T_{av}, T_{max} and T_{day} (0.831 to 0.740) were found to have highly significant correlations (P<0.01) (Table 1). Therefore, based on these above observations, HW, PPR, SB and TD score were found to have high correlation with the selected temperature profiles and thus were selected as output data in ANN analysis for the fruit quality prediction in Cavendish banana.

Artificial neural network for predicting hand weight, pulp per peel ratio, sunburn and thrips damage score in Cavendish banana

Figure 1 A, B, C and D present the neural network architectures which were developed through 'feed-forward back propagation' process to predict HW, PPR, SB and TD score, respectively in Cavendish banana. The models were trained by using the selected experimental data that represented quantity of heat transfer through the material covers, maturity stage, field temperature (T_{av}, T_{max}, T_{min}, T_{day}, and T_{night}). The results from both summer and rainy seasons of this method are explained below. Each training sections was performed and evaluated separately according each output parameters, HW, PPR, SB and TD score, by increasing the node in the hidden layer after the other until relatively lower mean prediction error (MPE) with highest coefficient of determination (R^2) value which indicates prediction percentage accuracy, were recorded and the corresponding hidden node with the relatively lower MPE was selected in each case as shown in Table 2, 3, 4 and 5.

According to Table 2, which showed the HW in terms of fruit yield, the model that produced the best result was 4-18-1 architecture which represented the network with 4 inputs layer, 18 hidden nodes in a hidden layer and 1 outputs layer. This model recorded a relatively lower MPE (0.811) with tolerable RMSE (1157.62) and highest R^2 value (0.76) for HW when compared with other networks with different hidden layer, respectively. As regard the PPR in terms of fruit maturity, architecture model 6-16-1 produced the best result with lowest MPE (0.581), RMSE (0.252) and the highest R^2 value (0.96) (Table 3). However, with respect to fruit defect, model 5-8-1 produced best result for SB which represented the network with 5 inputs layer, 8 hidden nodes and 1 output layer with relatively lower MPE (0.412), RMSE (8.407) and R^2 value (0.86) (Table 4). While, in TD score, 5-12-1 architecture model recorded the best result which represented the network of 5 inputs layer, 12 hidden nodes and 1 output layer with lower MPE (0.450), RMSE (1.310) and R^2 value (0.88) (Table 5).

The lower the MPE and the higher the R^2 recorded in ANN the better the accuracy in the data prediction (Soares et al., 2014). The relatively lower MPE (0.811, 0.581, 0.412 and 0.450) and R^2 (0.76, 0.96, 0.86 and 0.88) selected in this study suggests better accuracy in predicting HW, PPR, SB and TD score, respectively, in Cavendish banana. These results support Soares et al. (2014), who selected (10-10-1) with relatively lower MPE (0.014) and R^2 (0.91) as the best prediction model among ANN architectures analysed in their study to predict 'Tropical' banana bunch weight. Similarly, Kaul et al. (2014) reported that lower MPE and higher R^2 in ANNs could accurately estimate corn and soybeans production forecast more than other model multiple linear regressions model. Furthermore, the previous study conducted with olive trees reported the lower standard error (0.137) recorded from ANNs architecture of (80-10-10) as the best parameters statistically to predict contents of olive oil (Ram et al., 2010). The predictive model would give the banana producer better conditions for planning and transporting the cargo, maximizing the efficiency of the business without losses. In addition, the developed model would allow the producer to estimate the profitability of the current crop and forecast their final product quality by using only the forecast temperature from local meteological agency and bunch covering properties.

Table 1. Correlation coefficient (*r*) between fruit quality of Cavendish banana and temperature in summer and rainy seasons

Season/Fruit quality	$T_{av.}$	$T_{max.}$	$T_{min.}$	$T_{day.}$	$T_{night.}$
Summer					
HW	0.326	-0.215	0.447	0.021	0.458
PPR	0.186	-0.369	0.418	-0.114	0.420
SB	0.392	0.441	-0.133	0.500	-0.130
Rainy					
HW	-0.250	-0.167	-0.386	-0.100	-0.388
PPR	-0.201	-0.484	0.278	-0.421	0.224
TD score	0.831**	0.786**	0.535	0.740**	0.638*

Note. **, * denotes significant correlation coefficients at (P<0.01) and (P<0.05) levels, respectively by using Pearson's correlation.

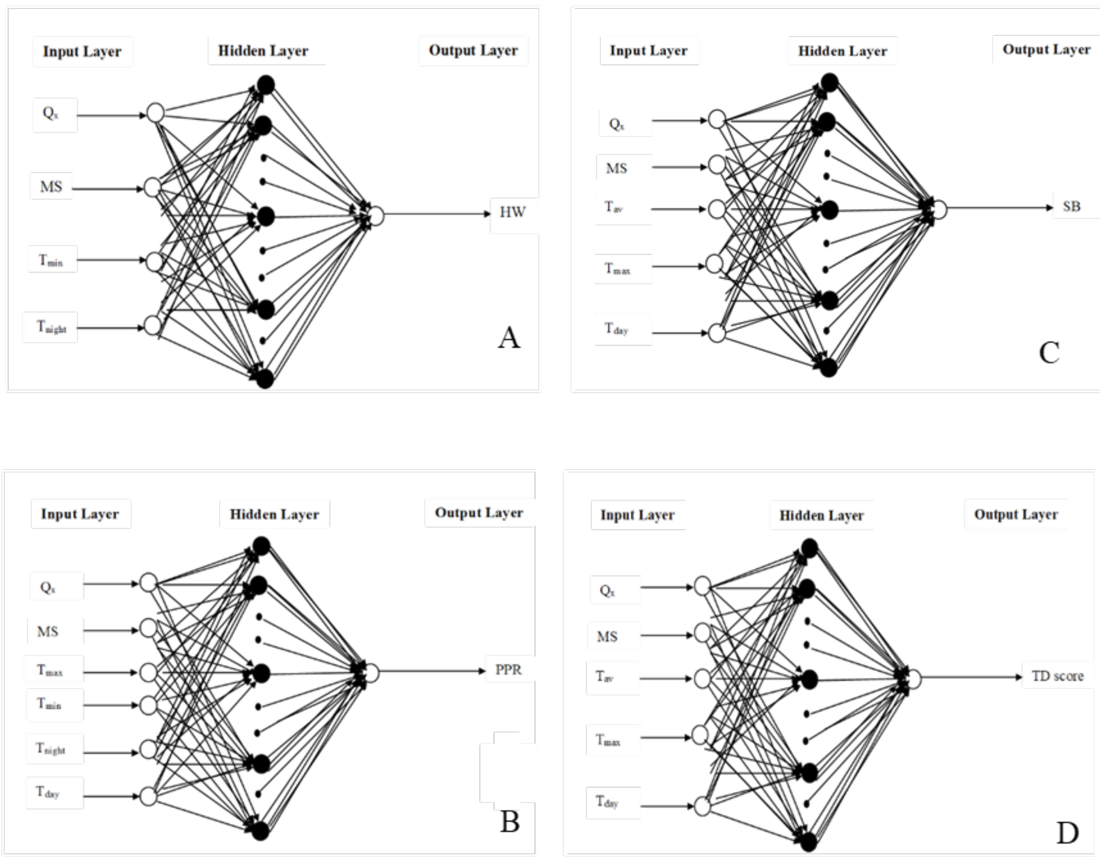

Figure 1. A typical feed-forward one-hidden layer ANN model for the prediction of the hand weight (HW) (A); Pulp per ratio (PPR) (B); Sunburn (SB) (C) and Thrips damage (TD) score (D) in Cavendish banana. (Q_x) Quantity of heat energy transfer; MS, maturity stage; T_{av}, Average temperature; T_{max}, Maximum temperature; T_{min}, Minimum temperature; T_{day}, Daytime temperature; and T_{night}, Nighttime temperature.

Table 2. Architecture and statistical parameters for the developed ANNs for hand weight (HW)

Hidden node	Error	Steps	RMSE (HW)	R^2	R^2_{adj}
2	1.393	66	807.76	0.14	0.11
4	1.111	1559	904.62	0.07	0.04
6	0.941	2670	1043.30	0.43	0.41
8	0.811	3894	1319.15	0.29	0.26
10	1.084	1453	969.18	0.23	0.20
12	0.789	3697	1053.74	0.46	0.44
14	0.794	3849	1031.09	0.40	0.38
16	0.804	3045	1135.96	0.69	0.68
18	**0.811**	**4603**	**1157.62**	**0.76**	**0.75**
20	0.798	3055	1117.51	0.64	0.63

Note. MPE: mean prediction-error, RMSE: root mean square error, R^2: coefficient of determination and R^2_{adj}: adjusted R^2
Values in bold represent the best values for number of hidden layer, error, steps, RMSE, R^2 and R^2_{adj}.

Table 3. Architectures and statistical parameters for the developed ANNs for pulp per peel ratio (PPR)

Hidden node	Error	Steps	RMSE (HW)	R^2	R^2_{adj}
2	0.858	650	0.199	0.23	0.20
4	0.782	583	0.217	0.46	0.59
6	0.623	3299	0.256	0.01	0.01
8	0.612	2757	0.256	0.02	0.01
10	0.621	3172	0.310	0.09	0.06
12	0.605	2299	0.238	0.75	0.74
14	0.620	2396	0.245	0.85	0.84
16	**0.581**	**2861**	**0.252**	**0.96**	**0.96**
18	0.615	2455	0.237	0.74	0.73
20	0.609	2162	0.251	0.94	0.94

Note. MPE: mean prediction-error, RMSE: root mean square error, R^2: coefficient of determination and R^2_{adj}: adjusted R^2
Values in bold represent the best values for number of hidden layer, error, steps, RMSE, R^2 and R^2_{adj}.

Table 4. Architectures and statistical parameters for the developed ANNs for sunburn (SB)

Hidden node	Error	Steps	RMSE (HW)	R^2	R^2_{adj}
2	0.864	410	4.897	0.34	0.32
4	0.548	2789	6.385	0.07	0.04
6	0.457	2146	7.614	0.53	0.51
8	**0.412**	**4450**	**8.407**	**0.86**	**0.85**
10	0.378	2200	7.567	0.51	0.49
12	0.373	4549	7.813	0.61	0.60
14	0.492	4244	7.648	0.54	0.52
16	0.403	1899	6.917	0.26	0.23
18	0.445	2300	7.200	0.37	0.35
20	0.402	3743	6.783	0.21	0.18

Note. MPE: mean prediction-error, RMSE: root mean square error, R^2: coefficient of determination and R^2_{adj}: adjusted R^2
Values in bold represent the best values for number of hidden layer, error, steps, RMSE, R^2 and R^2_{adj}.

Table 5. Architectures and statistical parameters for the developed ANNs for thrips damage (TD) score

Hidden node	Error	Steps	RMSE (HW)	R^2	R^2_{adj}
2	0.575	1568	0.827	0.25	0.22
4	0.577	234	0.852	0.20	0.17
6	0.541	385	0.880	0.15	0.12
8	0.461	2168	0.942	0.03	0.01
10	0.353	2605	1.083	0.29	0.26
12	**0.450**	**2768**	**1.310**	**0.88**	**0.88**
14	0.571	103	0.848	0.21	0.18
16	0.575	105	0.864	0.18	0.15
18	0.567	218	0.860	0.19	0.16
20	0.542	266	0.883	0.14	0.11

Note. MPE: mean prediction-error, RMSE: root mean square error, R^2: coefficient of determination and R^2_{adj}: adjusted R^2
Values in bold represent the best values for number of hidden layer, error, steps, RMSE, R^2 and R^2_{adj}.

CONCLUSIONS

In this study, 2 to 20 hidden nodes with 4 variables (HW, PPR, SB and TD score) were tested separately using 90 datasets. The results showed that 18, 16, 8 and 12 neuron-hidden layer recorded the lower mean predicting error MPE (0.811, 0.581, 0.412 and 0.450) with tolerable RMSE (1157.62, 0.252, 8.407 and 1.310) and R^2 (0.76, 0.96, 0.86 and 0.88) when compared with other networks with different hidden layer, respectively. The significance of this model is that, commercial banana farmers could apply the model to forecast fruit yield, maturity and defect in terms of hand weight, pulp per peel ratio, sunburn and thrips damage, respectively, on Cavendish banana provided that parameters such as data on quantity of heat transfer rate through material cover, temperature records in terms of average, maximum, minimum, daytime, nighttime temperatures as well as banana fruit maturity stage are available.

ACKNOWLEDGEMENTS

The authors are grateful to Thailand International Cooperation Agency (TICA), Mae Fah Luang University (MFU) and the management of Phaya Meng Rai Agriculture Limited Partnership for the financial supports and provision of experimental site for this research study, respectively.

REFERENCES

FAOSTAT. (2016). Bananas. Retrieved July 3, 2018, from FAO http://www.fao.org/faostat/en/#data/QC

Harvey, B. V. (2005). Mild Chilling Injury of Banana (Cavendish cv. Williams) and Its Control In The Field. PhD Thesis, The University of Adelaide.

Kaul, M., Hill, R. L., and Walthall, C. (2005). Artificial Neural Networks for Corn And Soybean Yield Prediction. AGSY Agricultural Systems, 85(1), 1-18.

Lakshmi, B. K. M., Reddy, P. N., and Prasad, R. D. (2011). Cross-infection Potential of *Colletotrichum gloeosporioides* Penz. Isolates Causing Anthracnose in Subtropical Fruit Crops. Tropical Agricultural Research, 22(2), 183-193.

Muchui, M. N., Mathooko, F. M., Njoroge, C. K., Kahangi, E. M., and Kimani, E. M. (2010). Effect of Perforated Blue Polyethylene Bunch Covers on Selected Postharvest Quality Parameters Of Tissue-Cultured Bananas (Musa spp.) cv. Williams in Central Kenya. Journal of Stored Products and Postharvest Research, 1(3), 29-41.

Nakasone, H.Y, and Paull, R.E (1999). Tropical fruits. Banana. Wallingford, UK. CAB Publishing, 103-131.

Ogunsua, J. M. (2018). Influence of Bunch Covers on Fruit Quality and Defect of Cavendish Banana in Summer and Rainy Seasons in Thailand. MSc Thesis. Mae Fah Luang University, Thailand.

Pathak, P., Baruah, K., Kalita, P., and Baishya, K. P. (2016). Influence of Bunch Covers on Appearance and Maturity of Banana cv. Jahaji under High Density Planting System. International Journal of Current Research, 8(3), 28143-28146.

Ram, H. Y. M., Ram, M., and Steward, F. C. (1962). Growth and Development of the Banana Plant. Annals of Botany, 26(4), 657-673.

Ravi, I., and Vaganan, M. M. (2016). Abiotic Stress Tolerance in Banana. In N. K. Srinivasa Rao, K. S. Shivashankara & R. H. Laxman (Eds.), Abiotic Stress Physiology of Horticultural Crops (pp. 207-220). India: Springer.

Santosh, D. T., Tiwari, K. N., and Reddy, R. G. (2017). Banana Bunch Covers for Quality Banana Production – A Review. International Journal of Current Microbiology and Applied Sciences, 6(7), 1275-1291.

Soares, J. D. R., Pasqual, M., Lacerda, W. S., Silva, S. O., and Donato, S. L. R. (2013). Utilization of Artificial Neural Networks in the Prediction of Bunches Weight in Banana Plants. Scientia Horticulturae, 155, 24-29.

Soares, J. D., Pasqual, M., Lacerda, W. S., Silva, S. O., and Donato, S. L. (2014). Comparison of Techniques Used in the Prediction of Yield in Banana Plants. Scientia Horticulturae, 167, 84-90.

Soto Ballestero, M. (1992). Banana: Cultivation and Commercialization. Litografia yImprensa, San Jose, 170-204.

Stover, R. H., and Simmonds, N. W. (1987). Bananas: Longman Scientific & Technical.

Ushada, M., and Murase, H. (2006). Identification of a Moss Growth System Using an Artificial Neural Network Model. Biosystems Engineering, 94(2), 179-18.