Journal of Oil Palm Research Vol. 33 (1) March 2021 p. 46-55
DOI: https://doi.org/10.21894/jopr.2020.0061

ESTIMATING THE YIELD LOSS OF OIL PALM DUE TO *Ganoderma* BASAL STEM ROT DISEASE BY USING BAYESIAN MODEL AVERAGING

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ABSTRACT

It is very crucial to planters to estimate the yield loss due to Ganoderma *basal stem rot (BSR) disease in oil palm. However, currently there is a limited mathematical model available that can be used for that purpose. Therefore, this empirical study was conducted to build a mathematical model which can be used for yield loss estimation due to the disease. Three commercial oil palm plots with different production phases (*i.e. *steep ascent phase, plateau phase and declining phase) were selected as the study sites. The yield and disease severity of the selected palms in the three study sites were recorded for the duration of 12 months. Model averaging approach using Bayes theorem was used to build the model. This is also known as Bayesian Model Averaging (BMA). The BMA model revealed that planting preparation technique was the most important predictor of oil palm yield loss, followed by disease progress (measured using area under the disease-progress curve, AUDPC), disease severity, number of infected neighbouring palms, and two interaction terms. By using the developed BMA model, it was estimated that the economic loss can be up to 68% compared to the attainable yields of all the infected palms.*

Keywords: yield loss, oil palm, *Ganoderma* basal stem rot, total bunch weight, Bayesian model averaging.

Received: 21 December 2019**; Accepted:** 9 July 2020**; Published online:** 11 September 2020.

INTRODUCTION

Ganoderma basal stem rot (BSR) disease is the most widely studied oil palm disease in Malaysia (Idris, 2012). The disease is caused by the white rot fungi, *Ganoderma* species (Flood *et al.*, 2000; Mercière *et al.*, 2017). *Ganoderma boninense* was identified as the main species that causes the disease (Ho and Nawawi, 1985; Wong *et al.*, 2012; Siang *et al.*, 2013). In the region of South-east Asia, especially in Malaysia and Indonesia, it is considered as the most devastating disease. Cases of the disease were also reported in several oil palm producing countries such as Angola, Cameroon, Ghana, Nigeria, Zambia, San Tome and Principe, Tanzania, Zimbabwe, and the Republic of Congo in Africa, Honduras in the region of Central America, and Papua New Guinea in the Oceania region (Ariffin *et al.*, 2000). The disease can reduce the yield of the infected palms either from total yield loss by killing the infected palms (called direct loss) or by reducing the weight or the number of fresh fruit bunches (FFB) of the infected palms but still living palms (or indirect loss) (Roslan and Idris, 2012).

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Despite the fact that the disease has been present for many years, information on the relationship between disease severity and yield loss is still very limited (Assis *et al*., 2016). There is no specific study that has been conducted to model the relationship between the *Ganoderma* BSR disease development (*i.e*. disease incidence and disease severity) and oil palm yield loss by taking into account the growth of oil palm. This means that the information on the relationship between the disease progress and oil palm yield is still lacking. A study conducted by Roslan and Idris (2012) is the latest effort to estimate the yield loss due to *Ganoderma* BSR disease, but the study did not take into account the severity of the disease. Furthermore, there is a limited mathematical model available to estimate the loss. The economic loss assessment was only based on the infected dead palms. In other words, the economic loss was underestimated since the loss in yield had already occurred even before the infected palms collapsed. The same goes with the study conducted by Singh (1991) where the yield loss estimation was only based on the disease incidence without considering the disease severity and no mathematical model was developed to estimate the loss. Both of these studies had estimated the yield loss but the estimations were not based on the individual palm level which can give more accurate loss estimation.

This relationship must be quantified, developed, modelled and validated based on empirical data which are collected through observation or experiment, as opposed to relying solely on theory. By having this mathematical disease-yield loss relationship, it will be very helpful especially to the management team of oil palm producers in determining the effectiveness of their practical disease managements and also to researchers and by extension to workers in evaluating their experiments (Savary *et al*., 2006). The oil palm producers can accurately determine their yield loss and therefore economics of applying any treatments. The predicted loss will then play a very important role in guiding the management to formulate their future programme, such as proposed low-input and environmental-friendly strategies to the epidemic development of the disease in order to decrease the yield losses and reduce their consequences.

MATERIALS AND METHODS

Study Sites

The data were collected based on the statistical approach where the level of disease occurred naturally in the fields of study without any intervention. FAO (1983) calls this approach as an individual plant comparison approach. The advantages of this statistical approach are the yield loss-disease relationship is based on the natural disease epidemic and there will also be no side effects of treatments on the yield which possibly can affect the yield loss-disease relationship. Based on this design or approach, all the study sites must have a certain level of disease incidence.

A single-plant method was used in this study. In this method, each plant was considered as a single datum point for regression analysis (Gaunt, 1990), *i.e.* the sampling unit was the individual palm. The individual palms studied include infected palms and uninfected palms (*i.e*. healthy palm). All the infected palms in the studied sites were sampled and monitored for the duration of 12 months starting from the first disease census. For the uninfected palms, only the selected palms were monitored. A simple random sampling using a uniform distribution was therefore used to select certain number of palms as a control. This is due to the fact that the spatial distribution of the disease is random (Assis *et al*., 2015). This random sampling was conducted based on the identification number which has been assigned for every single palm planted in the study sites.

There were three study sites selected as shown in *Table 1*. These sites were selected from three different estates but owned by the same company located in Tawau division, Sabah, Malaysia. The main criterion used in selecting the study sites was the growth phases of oil palm. These three study sites covered three production phases of oil palm; which are steep ascent phase (3-10 yr after planting) where the yield is in increasing phase, plateau phase (10-15 yr after planting) where the yield is in flat or maximum phase, and declining phase (older than 15 yr after planting) where the yield is in declining phase (Amstrong, 1999). The age of oil palm is among the most important confounding factor of *Ganoderma* BSR disease in affecting the yield (Ariffin *et al*., 2000). Besides, any disease assessment data must be qualified by the growth stage of the crop at the time of assessment (Brown and Keane, 1997). Other criterion of selecting these study sites was the *Ganoderma* BSR incidence must be considerably significant to study the relationship between yield loss and disease (Cooke, 2006). All the study sites were managed under the same plantation company. This was done to ensure similarity in terms of the effect of agronomic practices that could also affect the yield loss-disease relationship (Virdiana *et al*., 2010; Chung, 2011). The study sites used in this study is the same with Assis *et al*. (2016) but different in terms of disease census data (disease census at month 6 *vs*. month 12), time frame (6 months *vs*. 12 months), and also modelling approach (single model *vs*. model averaging approach).

TABLE 1. DESCRIPTIONS OF THE STUDY SITES

Description	Study site 1	Study site 2	Study site 3
ID	MBE0702	SKE0224	MDE8717
Location	Latitude 4° 25′ 53.76″ N; Longitude 117° 45′ 8.64″ E	Latitude 4° 19′ 24.96″ N; Longitude 118° 05′ 26.88″ E	Latitude 4° 46′ 19.35″ N; Longitude 118° 8′ 18.67″ E
Production phase	Ascent phase	Plateau phase	Declining phase
Year of planting (age)	2007 (8 yr after planting)	2002 (13 yr after planting)	1987 (28 yr after planting)
Total area	13.47 ha	10.75 ha	6.8 ha
Number of palms	2042	1462	999
Soil type	Lumisir	Lumisir	Bulanat/Lating
Previous crop	Oil palm	Oil palm	Forest
Generation	2nd generation	2nd generation	1st generation
Planting technique	Zero burning with evenly spread chip	Zero burning with evenly spread chip	Jungle to oil palm clearing

Source: Sawit Kinabalu Sdn Bhd (2013).

Variables of Study

The predict and or dependent variable in this study was yield loss in total bunch weight (TBW) of oil palm due to *Ganoderma* BSR disease. The predictors were disease severity, area under the disease progress curve (AUDPC), number of infected neighbouring palms, age of palm, previous crop, soil type and planting preparation technique. Even though nutrient availability in the soil is also one of the predisposing factors of the disease (Ariffin *et al.*, 2000), this factor was not considered in the yield loss model building. This factor was assumed to be constant since all the study sites were using the same agronomic practices (*i.e.* all the study sites were under the same plantation company).

By following the standard measurement of yield loss used by FAO (1983), the yield loss (YL) in TBW for each individual palm studied was calculated by using Equation (1) (Savary and Willocquet, 2014).

$$YLTBW_i = Y_a - Y_i \qquad \text{Equation (1)}$$

where Y_a denotes the average attainable TBW in 12 months for the uninfected palms and Y_i denotes the actual TBW in 12 months for ith palm (i is the sampling unit). The Y_a was calculated using Equation (2) (Teng, 1990).

$$Y_a = \frac{\sum_{i=1}^{n} Y_{i_{\text{uninfected}}}}{n} \qquad \text{Equation (2)}$$

where $\sum_{i=1}^{n} Y_{i_{\text{uninfected}}}$ refers to the total actual TBW of the selected uninfected palms in the three study sites and n denoted the number of selected uninfected palms. The normality of the $Y_{i_{\text{uninfected}}}$ data distribution was first checked by using statistical as well as graphical methods before calculating the Y_a. This was done to ensure that the Y_a is an unbiased estimate for representing the average yield of uninfected palms.

Disease severity was measured by using visual method instead of non-visual method which is time-consuming and very costly. This visual method was conducted by following the standard procedures used by the Malaysian Palm Oil Board (MPOB) in conducting *Ganoderma* BSR disease census (Idris *et al.*, 2016). A standard procedure of measurement must be used to ensure consistency in terms of measurement between observers and simplicity for speed of operation (Cooke, 2006). The disease severity was labelled as R1 (uninfected), R2 (mild infection), R3 (moderate infection), R4 (severe infection), and R5 (dead). This variable was considered as categorical data, thus dummy transformation was performed. The R1 was chosen as the reference category since it represented uninfected palms. The disease census was conducted quarterly to monitor the disease development progress.

AUDPC was used to measure the disease progress. AUDPC has been found as one of the important predictors that can predict the yield loss of crops due to diseases or pests (Wolf and Verreet, 2009; Lal *et al.*, 2014). The AUDPC for each palm was calculated by using Equation (3) (Brown and Keane, 1997).

$$AUDPC = \sum_{i=1}^{n} \frac{DS_i + DS_{i+1}}{2} + (t_{i+1} - t_i) \qquad \text{Equation (3)}$$

where DS_i is the disease assessment at time i, n is the number of disease assessments, and $(t_{i+1} - t_i)$ is the interval between two consecutive assessments. The AUDPC takes into consideration of the amount of disease (*i.e.* $\frac{DS_i + DS_{i+1}}{2}$) as well as the duration of the disease (*i.e.* $t_{i+1} - t_i$).

Root to root contact has been found to be the main spread mode of *Ganoderma* BSR disease (Sanderson, 2005; Cooper *et al*., 2011; Naher *et al*., 2013). This means that there is a possibility that infection occurs due to the infected neighbouring palms. Therefore, this study considered the number of infected neighbouring palms as one of the possible predictors to estimate the yield loss due to the disease. In this study, the neighbouring palms were limited to the eight nearest palms to the studied palms. The minimum and maximum numbers of infected neighbouring palms for each of the studied palm were therefore 0 (if no infected neighbouring palms) and 8 (if all the neighbouring palms are infected), respectively. The calculation of the number of infected neighbouring palms was based on the first disease census which was during the first month of monitoring.

Age of palm is one of the predisposing factors of *Ganoderma* BSR disease (Idris *et al*., 2011). Older palms are more susceptible to be infected by the disease (Idris *et al*., 2010). Due to the limited resources, there were only three different palm ages covered in this study (*Table 1*). However, it covered all the three production phases of oil palm (*i.e*. ascent phase, plateau phase, and declining phase). Additionally, there is also a difference of FFB weight according to the age of oil palm. There is positive correlation between the weight of FFB and age of palm (Breure and Menendez, 1990; Corley and Tinker, 2016).

Type of previous crop has been confirmed to be one of the predisposing factors of *Ganoderma* BSR disease (Singh, 1991). The previous crop for MBE0702, SKE0224, and MDE8717 were oil palm, oil palm, and forest respectively (Sawit Kinabalu Sdn Bhd, 2013). Since this variable was a categorical variable, hence, dummy transformation was also performed.

Another predisposing factor of the disease is type of soil. Previous studies have found that the disease is most serious in coastal areas as compared to inland areas (Lim *et al*., 1992; Suriya Rao *et al*., 2003). The disease incidence is also high especially in areas with low water levels (*e.g*. more than 75 cm from the peat surface). On peat areas, therefore it is important to maintain a water level of 50-75 cm from the peat surface to minimise the *Ganoderma* BSR disease infections and spread of this deadly disease on oil palms planted on peat (Roundtable of Sustainable Palm Oil, 2012; Supriyanto *et al*., 2020). In this study, there were two types of soil involved, which are Lumisir and Bulanat/Lating. The major particle for Lumisir is sand. However, there was no clear picture of the major particle for Bulanat/Lating (The Malaysian Society of Soil Science, 1977). Therefore, there was no clear guideline whether the effect of soil type on YLTBW is positive or negative.

Availability of inoculum source is one of the important factors of *Ganoderma* BSR disease distribution (Chung, 2011). Planting preparation technique can potentially determine the availability of inoculums. Burning crop residues including diseased materials is an effective way of sanitation during replanting especially in areas where the BSR incidence is increasing in second and third generation oil palm planting (Chung, 2011). However, permission from the authorities is required for this replanting technique. Currently, zero burning with evenly spread chip is the standard practice by big oil palm companies in land preparation. Zero burning is considered as one of the best management practices in oil palm (Roundtable of Sustainable Palm Oil, 2012). In this study, there were two planting preparation techniques involved, namely zero burning with evenly spread chip (*i.e*. for MBE0702 and SKE0224 study sites) and jungle clearing (*i.e*. for MDE8717 study site). Zero burning with evenly spread chip can reduce the inoculum source of *Ganoderma* BSR disease, thus this category of planting technique was set as the reference category in this study.

Large number of potential predictors causes large number of possible models. One of the solutions to reduce the number of potential predictors is by removing predictors that demonstrate multicollinearity (Bush, 2012). Besides, one of the assumptions of multiple linear regression model estimated by ordinary least square (OLS) is not an exact linear relationship (*i.e.* multicollinearity) among the predictors. There were two methods used in identifying the main source of multicollinearity, namely the correlation-based and the variance-based method. This screening, however, involved only the main effects because multicollinearity is not a serious issue when involving interaction effects (Gujarati, 2003). It is clear that there will be high collinearity between the main effects and the interaction effects. The main effects include disease severity of R2 (labelled as R2), disease severity of R3 (labelled as R3), disease severity of R4 (labelled as R4), number of infected neighbouring palms (labelled as N), age of palm (labelled as AGE), type of previous crop (labelled as PREVIOUSCROP), soil type (labelled as SOILTYPE), and planting technique (labelled as PT), while the interaction effects include AUDPC, AUDPC*N, AUDPC*AGE, AUDPC*PREVIOUS, AUDPC*SOILTYPE, and AUDPC*PT. The AUDPC was considered as an interaction effect (*i.e*. integral variable) since it was calculated based on the disease severity (*i.e*. R1, R2, R3, R4, and R5) [Equation (3)]. The disease severity is one of the main effects in this study.

Bayesian Model Averaging

Bayesian Model Averaging (BMA) is an alternative to estimation-post-selection approach. The basic idea of this approach is that there may be more than one possible model can fit into the data well and give accurate predictions of the quantity of interest. Combining these possible models by averaging the parameters of the selected predictors can give higher accuracy of prediction as compared to a single 'best' model. Besides incorporating model selection uncertainty, this approach also incorporates other forms of uncertainty such as predictor selection, transformations, outliers and model form (Clyde, 2003). Furthermore, model averaging approach also integrates two main problems in model selection; which are model search and model selection criterion by averaging or combining the information from all the possible models or from a subset of the possible models during the estimation, inference, or prediction (Hoeting, 2002). In many cases, models developed by BMA have better predictive performances as compared to any single model (Wang *et al.*, 2004; Prost *et al.*, 2008; Genell *et al.*, 2010; Hayden *et al.*, 2010; Zou *et al.*, 2013; Morozova *et al.*, 2015).

In this study, each model considered in BMA was a linear regression model. The main principles of BMA are explained as follows (Montgomery and Nyhan, 2010). Let Y be the dependent variable, β_0 denotes the constant term, β_j denotes the coefficients of k predictors (or also called as limiting factors in yield gap studies), X_j, and μ denotes the error term with normal distribution, $\mu \sim N(0,\sigma^2)$, then

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \mu = X\beta + \mu \qquad \text{Equation (4)}$$

BMA estimates this model by taking into consideration all the possible combinations of $\{X\}$. The problem arises when there is a large number of possible predictors, k, to consider. If there is k possible variables, then there will be 2^k possible models. The aim of BMA is to compute the posterior distribution of β. Let β in Equation (4) is estimated by $\hat{\beta}$, then

$$P(\hat{\beta}|D) = \sum_{i=1}^{n=2^k} P\ (\hat{\beta}|D,M_1)\ P(M_1|D) \qquad \text{Equation (5)}$$

where M_1, M_2,..., M_n is the set of possible models, D denotes the data set, and $P(.|.)$ denotes a conditional density probability function. The $P(\hat{\beta}\,|\,D)$ is the sum of the posterior distributions [or posterior model probability (PMP)], $P(M_i \mid D)$, under each of the models, weighted by their PMP. The $P(\hat{\beta} \mid D)$ is also called the posterior inclusion probabilities (PIP). PIP is the probabilities that each variable belongs to the final model. In this study, Bayesian information criterion (BIC) approximation was used to obtain approximate posterior model probabilities. The approximate posterior model probabilities using BIC was calculated as

$$P(M_i|D) = \frac{P(M_i)\ \exp[-.5BIC(M_i)]}{\sum_{i=1}^{n} P(M_j)\ \exp[-.5BIC(M_j)]} \qquad \text{Equation (6)}$$

where $BIC\ (M_i)$ is

$$BIC\ (M_i) = \text{-2log (maximum likelihood} \,|\, M_i) + q_k \log\ (N) \qquad \text{Equation (7)}$$

The q_k is the dimension of model M_i and N is the number of cases. The estimated posterior means and standard deviations of $\hat{\beta} = \hat{\beta}_1, \hat{\beta}_2, ..., \hat{\beta}_k$, were then constructed as Equation (8) and Equation (9) respectively.

$$E[\hat{\beta}|D] = \sum_{j=1}^{n=2^k} \hat{\beta} P(M_n|D) \qquad \text{Equation (8)}$$

$$V[\hat{\beta}|D] = \sum_{j=1}^{n=2^k} (Var\ [\hat{\beta}|D, M_n] + \hat{\beta}^2)\ P(M_n|D) - E[\beta|D]^2 \qquad \text{Equation (9)}$$

The R package or specifically 'library(BMA)' was used to develop model using BMA approach. The function of 'bicreg' of the BMA library was used to compute the posterior parameter means using the simple BIC approximation to the posterior model probabilities (Raftery *et al.*, 2015). It implements Occam's window algorithm for linear regression (Raftery, 1995).

RESULTS AND DISCUSSION

Yield Loss Model

Table 2 shows the summary of the BMA model showing 10 selected best models. It was clear that the first model which is labelled as model 1 is the best model among all the 256 possible models since it has the lowest BIC and the largest PMP (*i.e.* of being the correct model). This model includes R2, AUDPC and PT, which is the same with the best model selected under best-subset selection. But the estimation of yield loss in BMA was not only based on this single model, but it considered all the 10 selected best models.

Based on the PIP, PT was the most important predictor with PIP value of 100. This means that this predictor was 100% included in all 10 models selected. The second important predictor is AUDPC (with the PIP value of 72.1), followed by R2 (with the PIP value of 69.2), R4 (with the PIP value of 34.8), R3 (with the PIP value of 33.6), N (with the PIP value of 15.5), AUDPC_N (with the PIP value of 8), and AUDPC_PT (with the PIP value of 2.8). But both of R2 and AUDPC_PT had negative effects on the oil palm yield loss. But all of these eight predictors were included in the final model of BMA regardless of the sign of effect and contribution of the predictors. This means that there was no subset selection as in backward stepwise subset selection and also in best-subset selection. Based on the posterior distribution mean for each coefficient, the BMA model can be written as

$$
\begin{aligned}
YLTBW = & -24.632 - 18.307(R2) + 13.456(R3) + \\
& 21.531(R4) + 2.346(AUDPC) + 0.551(N) \\
& + 35.11(PT) + 0.014(AUDPC\_N) - \\
& 0.011(AUDPC\_PT)
\end{aligned}
$$

The identification of the main sources of multicollinearity was performed based on correlation-based analysis (Pearson product-moment correlation coefficient) and also variance-based analysis (variance inflation factor, VIF). The results of these two analyses show that three variables; age of palm, type of previous crop, and soil type caused multicollinearity problems. Hence, these variables were removed from the model. Residual analysis on the BMA model was performed to check whether this model violated the assumptions of zero mean of errors, normality, homoscedasticity, and no outliers. The mean and standard deviation of the standardised residual of the model were zero and close to 1 (*i.e.* 0.997 ≈ 1) respectively. The result of Kolmogorov-Smirnov test shows that the distribution of the errors was also normal (statistic value = 0.045, df = 378, p = 0.061) (Dhamu and Ramamoorthy, 2012) and the scatterplot also reveals that no extreme values or outliers were detected in the errors of the model where all the standardised residual fall within the range of ±3 (Field, 2009).

The constant value in the model represents the average yield difference of healthy palms which were not surrounded by any infected palm and also planted in the area with the planting preparation technique of zero burning with evenly spread chip. The negative value means that any healthy palm that fulfilled all the criteria mentioned above will produce higher TBW per year as compared to the average TBW of reference palms (*i.e.* R1) with the difference is approximately 24.632 kg yr^{-1}.

If a palm is infected with disease severity of R3 (moderate) or R4 (severe), there will be a reduction in TBW of about 13.455 kg or 21.531 kg respectively within one year as compared to the average yield of the reference palms' (*i.e.* R1) TBW by assuming other predictors are constant. However, the model also suggested that if a palm is infected with disease severity of R2 (mild), there will be no reduction in TBW. Instead, the TBW will be higher than the average yield of the reference palms' (*i.e.* R1) by 18.307 kg yr^{-1}.

One additional neighbouring palm infected will cause the central palm a loss of approximately 0.551 kg within one year. If there is a positive increase in disease progress (AUDPC) by one unit, it will cause a loss of 2.346 kg of FFB in 12 months' time if other predictors are still unchanged. For planting preparation technique, zero burning with evenly spread chip will reduce the loss by 35.113 kg of FFB one year after the disease census as compared to the jungle clearing planting technique. Planting preparation technique was the most influencing predictor in the model. The coefficient of this predictor was significantly different from zero in all the selected 10 best models (*Table 2*).

For the two interaction effects, the disease severity with the number of infected neighbouring palms (AUDPC_N) and the disease severity with the planting preparation technique (AUDPC_PT), their effects on the YL in TBW were only 0.014 kg and 0.011 kg yr^{-1} respectively. Every unit increase in the interaction between disease severity and number of infected neighbouring palms will cause the YL in TBW to increase by 0.014 kg yr^{-1}. However, this interactions term will have no effect on the YL if a palm is healthy or not surrounded by any infected neighbouring palms. For the interaction between the disease severity and the planting preparation technique, every unit increase in this interaction term will cause the YL in TBW to decrease by only 0.011 kg yr^{-1}. And again, this interactions term will also have no effect on the YL if a palm is healthy or planted in the area with the planting preparation technique of zero burning with evenly spread chip.

Economic Loss Estimation

Table 3 shows how the economic loss was estimated. Based on the first disease census conducted, there were 461 infected palms from the three study sites. Specifically, a total of 78 palms, 98 palms, 71 palms, 214 palms were rated as R2, R3, R4, and R5, respectively. Based on the attainable yield (*i.e.* 118 kg of TBW yr^{-1}) estimated in this study, all the 461 infected palms attainably can produce in total 54 398 kg of FFB yr^{-1} [*i.e.* (78 x 118 kg = 9204) + (98 x 118 kg = 11 564) + (71 x 118 kg = 8378) + (214 x 118 kg = 25 252) = 54 398]. Unfortunately, due to *Ganoderma* BSR disease, there were some reductions in TBW. The YL model developed in this study was used to estimate the reductions (or losses). Based on the BMA model, the total YL due the infected palms with disease severity of R2, R3, R4, and R5 were approximately 590.68 kg, 5811.73 kg, 5734.52 kg, and 25 252 kg respectively. In total, the yield loss was 37 388.93 kg. When converted into monetary value with the exchange rate of RM 1 = USD 0.2576 (*i.e.* the average exchange rate in 2015), the total economic loss was USD 4112.78 yr^{-1} (*i.e.* 37 388.93 kg x USD 0.11 = USD 4112.78). The price per kilogram was the average monthly FFB price (mill gate) for Sabah region in 2015 (MPOB, 2015). This economic loss is equivalent to 68.73% of the attainable yield of 461 palms if not infected by the disease.

TABLE 2. SUMMARY OF THE BEST 10 MODELS IN BAYESIAN MODEL AVERAGING (BMA)

Predictor	PIP	EV	SD	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Cumulative
Intercept	100.0	-24.632	11.226	-30.836	-8.421	-34.024	-30.389	-11.331	-28.592	-16.319	-31.139	-32.997	-9.536	-
R2	69.2	-18.309	13.260	-26.536	-	-26.476	-26.301	-	-24.246	-27.869	-27.869	-27.221	-	-
R3	33.6	13.455	20.893	-	45.405	-	-	45.013	-	-4.663	-4.663	-	42.728	-
R4	34.8	21.531	31.921	-	70.387	-	-	70.471	9.673	-	-	-	67.029	-
AUDPC	72.1	2.346	1.545	3.372	-	3.373	3.188	-	3.071	3.472	3.472	3.562	-	-
N	15.5	0.551	1.513	-	-	3.617	-	3.380	-	-	-	-	-	-
PT	100.0	35.113	5.643	36.491	32.852	34.400	34.903	30.953	36.368	36.841	36.841	42.353	31.387	-
AUDPC_N	8.0	0.014	0.060	-	-	-	0.171	-	-	-	-	-	0.178	-
AUDPC_PT	2.8	-0.011	0.125	-	-	-	-	-	-	-	-	-0.415	-	-
No. of predictors	-	-	-	3	3	4	4	4	4	4	4	4	4	-
R^2	-	-	-	0.395	0.392	0.400	0.397	0.397	0.397	0.396	0.395	0.395	0.395	-
BIC	-	-	-	-171.932	-170.468	-169.227	-167.706	-167.336	-167.173	-166.560	-166.484	-166.428	0.166.416	-
Posterior probability	-	-	-	0.432	0.208	0.112	0.052	0.043	0.040	0.029	0.028	0.028	0.027	1.000

Note: The column 'PIP' indicates the probability that the coefficient for a given predictor is not zero, among the 10 models returned. The column 'EV' displays the BMA posterior distribution mean for each coefficient and the column 'SD' displays the BMA posterior distribution standard deviation for each coefficient.
R2 - mild infection, R3 - moderate infection, R4 - severe infection, AUDPC - age under the disease progress curve, N - number of infected neighbour palms, PT - planting technique, AUDPC_N - disease severity with the number of internal neighbour palms, AUDPC_PT - disease severity with the planting preparation technique, BIC - Bayesian information criterion.

TABLE 3. YIELD LOSS DUE TO REDUCTION IN TOTAL BUNCH WEIGHT (TBW)

Disease severity (after 12 months)	Field data				Modelling results			
	8 years after planting	13 years after planting	28 years after planting	Total infected palms	Attainable yield (kg yr^{-1})*	Attainable economic yield (USD yr^{-1})**	Estimated yield loss kg yr^{-1})***	Estimated economic loss (USD yr^{-1})*
Mild infection	9	36	33	78	9 204.00	1 012.44	590.68	64.97
Moderate infection	14	22	62	98	11 564.00	1 272.04	5 811.73	639.29
Severe infection	9	13	49	71	8 378.00	921.58	5 734.52	630.80
Dead	169	32	13	214	25 252.00	2 777.72	25 252.00	2 777.72
Total loss	-	-	-	461	54 398.00	5 983.78	37 388.93	4 112.78
Percentage of loss as compared to the attainable level	-	-	-	-	-	-	68.73%****	68.73%*****

Note: *Calculated based on the average attainable yield of healthy palms (*i.e.* R1) which is 118 kg $palm^{-1}$ yr^{-1}
**Estimated by using the model developed which is Bayesian model averaging (BMA) model.
***Estimated by using the fresh fruit bunch (FFB) price of USD0.11 kg^{-1} (MPOB, 2015).
**** (37 388.93 kg/54 398 kg) x 100.
***** (USD 4112.78/USD 5983.78) x 100.

This is considered as a huge loss to the planter since it represents 68.73% of the attainable yield per year which is higher compared to the estimated loss by Assis *et al*. (2016), 43.32% per six months. But these two studies are not perfectly comparable since the approach used (*i.e*. single model approach versus model averaging approach) to develop the YL model as well as the time frame used (*i.e*. 6-month *vs*. 12-month) are different. The loss estimation using this BMA model is also more detailed as compared to the loss estimation done by Roslan and Idris (2012) and Singh (1991). The loss estimation in this present study considered dead palms as well as infected but still productive palms.

CONCLUSION

By using the YL model developed, it was estimated that the economic loss due to the disease was equivalent to 68.73% of the attainable yield of all the infected palms (*i.e*. 461 palms) after 12 months observation. This model has the potential to be used by oil palm planters including estate and smallholders in helping them to estimate the potential YL as well as economic loss due to *Ganoderma* BSR disease. However, the model developed still needs to be validated in different setting, such as different plantation companies, areas, *etc*. Once the model is validated, it can potentially be used to estimate the potential loss as a baseline data in deciding the right time to carry out replanting especially in the hot spot areas of *Ganoderma* BSR disease. Additionally, the potential loss estimated from the model can also be used to compare the effectiveness of any preventive or control measures taken to reduce the economic loss due to the disease.

ACKNOWLEDGEMENT

We would like to acknowledge MPOB for funding this project and also Sawit Kinabalu Sdn Bhd for allowing us to conduct the study in their selected oil palm estates in Tawau, Sabah. We would also like to thank all the field assistants especially to Jumain Sinring, Mohd Irwan Salleh and Sutrisno Sumarno for their assistance.

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