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

ASSIS KAMU*; CHONG KHIM PHIN**; IDRIS ABU SEMAN‡; DARMESAH GABDA* and HO CHONG MUN*

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 twelve 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.

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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).
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 management practices 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 programmes, such as proposed low-input and environmentally 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 versus model averaging approach).
Variables of Study

The predictand 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).

\[ YLTBW = Y_a - Y_i \]

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 \( i \)th palm (*i* is the sampling unit). The \( Y_a \) was calculated using Equation (2) (Teng, 1990).

\[ Y_a = \frac{\sum_{i=1}^{n} Y_{\text{uninfected}}}{n} \]

where \( \sum_{i=1}^{n} Y_{\text{uninfected}} \) 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 \( Y_{\text{uninfected}} \) data distribution was first checked by using statistical as well as graphical methods before calculating the \( Y \). 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 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).

\[ \text{AUDPC} = \frac{\sum_{i=1}^{n} DS_i + DS_{i+1}}{2} + (t_{i+1} - t_i) \]

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.* \( DS_i + DS_{i+1} \)) 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 area, 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 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 (BMA)**

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; Zoia 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, $\beta_0$ denotes the constant term, $\beta_j$ denotes the coefficients of $k$ predictors (or also called as limiting factors in yield gap studies), $X_j$ and $\mu$ denotes the error term with normal distribution, $\mu \sim N(0,\sigma^2)$, then

$$ Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \mu = X\beta + \mu $$

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, there will be $2^k$ possible models. The aim of BMA is to compute the posterior distribution of $\beta$. Let $\hat{\beta}$ in Equation (4) is estimated by $\hat{\beta}$, then

$$ P(\hat{\beta}|D) = \sum P(\hat{\beta}|D,M_i) P(M_i|D) $$

Equation (5)

where $M_i$, $M_{j,\ldots,M_n}$ is the set of possible models, $D$ denotes the data set, and $P(.)$ denotes a conditional density probability function. $P(\hat{\beta}|D)$ is the sum of the posterior distributions [or posterior model probability (PMP)], $P(M_i|D)$, under each of the models, weighted by their posterior model probabilities. $P(\hat{\beta}|D)$ 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

$$ P(M_i|D) = \frac{P(M_i) \exp[-5BIC(M_i)]}{\sum P(M_j) \exp[-5BIC(M_j)]} $$

Equation (6)

where $BIC(M)$ is

$$ BIC(M) = -2\log(\text{maximum likelihood}|M) + q_i \log(N) $$

Equation (7)

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

$$ E[\hat{\beta}|D] = \sum \hat{\beta} P(M_i|D) $$

Equation (8)

$$ E[\hat{\beta}|D] = \sum [\text{Var}[\hat{\beta} (M_i, D)] + \hat{\beta}^2] P(M_i|D) - E[\hat{\beta}|D]^2 $$

Equation (9)

R package or specifically ‘library(BMA)’ was used to develop model using Bayesian model averaging approach. The function of ‘bicreg’ of the BMA library was used to compute the posterior parameter means using the simple BIC (Bayesian Information Criterion) 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:

\[
Y_{LTBW} = -24.632 - 18.307(R2) + 13.456(R3) + 21.531(R4) + 2.346(AUDPC) + 0.551(N) + 35.11(PT) + 0.014(AUDPC_N) - 0.011(AUDPC_PT)
\]

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 will cause the yield loss in TBW to decrease by only 0.011 kg yr⁻¹. And again, this interactions term will also have no effect on the yield loss 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 yield loss in TBW to decrease by only 0.011 kg yr⁻¹. However, this interactions term will have no effect on the yield loss if a palm is healthy or not surrounded by any infected neighbouring palms.

**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] kg. Unfortunately, due to Ganoderma BSR disease, there were some reductions in TBW. The yield loss model developed in this study was used to estimate the reductions (or losses). Based on the BMA model, the total yield loss 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 25252 kg respectively. In total, the yield loss was 37 388 kg. When converted into monetary value with the exchange rate of RM1 = USD0.2576 (i.e. the average exchange rate in 2015), the total economic loss was USD4112.78 yr⁻¹ (i.e., 37 388.93 kg x USD0.11 = USD4112.78). The price per kilogram was the average monthly FFB price (Mill gate) for
TABLE 2. SUMMARY OF THE BEST 10 MODELS IN BAYESIAN MODEL AVERAGING (BMA)

<table>
<thead>
<tr>
<th>Predictor</th>
<th>PIP</th>
<th>EV</th>
<th>SD</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
<th>Model 10</th>
<th>Cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2</td>
<td>69.2</td>
<td>18.309</td>
<td>13.260</td>
<td>-26.536</td>
<td>-26.301</td>
<td>-24.246</td>
<td>-27.869</td>
<td>-27.869</td>
<td>-27.221</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td></td>
</tr>
<tr>
<td>R3</td>
<td>33.6</td>
<td>13.455</td>
<td>20.893</td>
<td>45.405</td>
<td>45.013</td>
<td>4.663</td>
<td>4.663</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>42.728</td>
<td></td>
</tr>
<tr>
<td>R4</td>
<td>34.8</td>
<td>21.531</td>
<td>31.921</td>
<td>70.387</td>
<td>70.471</td>
<td>9.673</td>
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<td>-</td>
<td>-</td>
<td>67.029</td>
<td></td>
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</tr>
<tr>
<td>AUDPC</td>
<td>72.1</td>
<td>2.346</td>
<td>1.545</td>
<td>3.372</td>
<td>3.373</td>
<td>3.188</td>
<td>3.071</td>
<td>3.472</td>
<td>3.472</td>
<td>3.562</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
<tr>
<td>N</td>
<td>15.5</td>
<td>0.551</td>
<td>1.513</td>
<td>3.617</td>
<td>3.380</td>
<td>3.961</td>
<td>3.095</td>
<td>3.095</td>
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<td>3.095</td>
<td>0.035</td>
<td>0.035</td>
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<tr>
<td>PT</td>
<td>100.0</td>
<td>35.113</td>
<td>5.643</td>
<td>36.491</td>
<td>32.852</td>
<td>34.400</td>
<td>30.935</td>
<td>36.368</td>
<td>36.841</td>
<td>42.353</td>
<td>31.387</td>
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<td>-</td>
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</tr>
<tr>
<td>AUDPC_N</td>
<td>8.0</td>
<td>0.014</td>
<td>0.060</td>
<td>-</td>
<td>0.171</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.178</td>
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<tr>
<td>AUDPC_PT</td>
<td>2.8</td>
<td>-0.011</td>
<td>0.125</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.415</td>
<td></td>
</tr>
<tr>
<td>No. of predictors</td>
<td>3  3  4  4  4  4  4  4  4  4  4  4</td>
<td>3  3  4  4  4  4  4  4  4  4  4  4</td>
<td>0.432 0.208 0.112 0.052 0.043 0.040 0.029 0.028 0.028 0.027 1.000</td>
<td>0.395 0.392 0.400 0.397 0.397 0.397 0.396 0.395 0.395 0.395</td>
<td>-171.932 -170.468 -169.227 -167.706 -167.336 -167.173 -166.560 -166.484 -166.428 0.166.416</td>
<td>BIC</td>
<td>31.387</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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)

<table>
<thead>
<tr>
<th>Disease severity (After 12 months)</th>
<th>Field data</th>
<th>Modelling results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>8 years after planting</td>
<td>13 years after planting</td>
</tr>
<tr>
<td>Mild infection</td>
<td>9</td>
<td>36</td>
</tr>
<tr>
<td>Moderate infection</td>
<td>14</td>
<td>22</td>
</tr>
<tr>
<td>Severe infection</td>
<td>9</td>
<td>13</td>
</tr>
<tr>
<td>Dead</td>
<td>169</td>
<td>32</td>
</tr>
<tr>
<td>Total loss</td>
<td>461</td>
<td>54 398.00</td>
</tr>
</tbody>
</table>

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 BMA model
***Estimated by using the FFB price of USD0.11 kg⁻¹ (MPOB, 2015)
**** (37 388.93 kg / 54 398.00 kg) x 100
***** (USD4112.78 / USD5983.78) x 100
Sabah region in 2015 (Malaysian Palm Oil Board, 2015). This economic loss is equivalent to 68.73% of the attainable yield of 461 palms if not infected by the disease.

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 yield loss 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 yield loss 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 yield loss 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.

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