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Evaluations of Soil Resistivity in Relation to Basal Stem Rot Incidences Using Soil Moisture Sensor

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ABSTRACT

Basal stem rot (BSR) caused by *Ganoderma boninense* is a major disease attacking the oil palm plantation in Malaysia, and incur big losses in palm oil industries. The disease is spread mostly by root either through spore availability in soil or roots contacts. Soil properties were reported to have significant influence on the growth of fungi. Meanwhile, the value of soil resistivity is influenced by soil properties. This paper presents a new approach of BSR detection by using soil moisture sensor which measures resistivity of soil in unit ohm (Ω) at 15 cm surrounding the basal stem of oil palm trees. The study was conducted on 39 oil palm trees at different healthiness levels. The sensor was embedded approximately 4.7 cm deep in the soil at eight different points for each palm. The results showed that healthy oil palm trees significantly have higher mean ($ER_{MEAN} \geq 400$) of electrical resistance (ER) readings compared to infected trees ($ER_{MEAN} < 400$). More specifically, ER readings at points without symptoms (i.e. fruiting bodies and/or hollow) were significantly higher compared with ER readings at points where

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symptoms appeared even though the points of measurements were on the same palm. This finding has brought to the introduction of a new index to detect *Ganoderma* infection, named as K-index. Combination of ER_{MEAN} taken from eight points of measurement and its K-index gave better results of detection and a new model was developed based on these two parameters (i.e. ER_{MEAN} and K-index). The developed model has accuracy rates of 82% and gained 100% successful rate during validation. This research showed that soil resistivity can contribute to *Ganoderma*-infected detection in oil palms with a high degree of accuracy.

Keywords: Basal stem rot, electrical resistance, ganoderma boninense, soil moisture sensor, soil resistivity

INTRODUCTION

The oil palm production in Malaysia is threatened by basal stem rot (BSR) disease caused by the wood-rotting fungus named *Ganoderma boninense,* which reduces the oil palm production (Liaghat et al., 2014). Primary route of infection appears to be through root contact with inoculum sources in the soil (Rees et al., 2009). Previous studies indicated that occurrence of BSR was higher in coastal areas and in areas previously planted with coconuts (Turner, 1965). High incidence was recorded in locales where an old stand of oil palm had been felled and the stumps left in the ground. This gives advantages to fungi to grow as there is a wounded host in the soil. Subsequently, the disease spreads from plant to plant by roots or by spores (Paterson, 2007).

Available techniques of *Ganoderma* detection can be classified into three main approaches i.e. human inspection, lab-based and remote sensing. The difficulty of detecting this disease at early stage of infections is due to its less external symptoms appearance (Su'ud et al., 2007). *Ganoderma* detection based on remote sensing approach can be classified into three scopes i.e. ground-based, space borne and airborne (Khosrokhani et al., 2016). The use of space borne images is limited where the images are not always available when needed or sometimes the resolutions of available images are too coarse to be used. Meanwhile, a manned airborne platform has disadvantages on operational complexity, high costs and lengthy product delivery.

The advanced technologies in electronics and computation have widely been used to resolve present day challenges. Microcontroller is leading the electronics revolution. Various sensors had been used together with microcontroller to measure and control physical quantities such as heat, light, humidity and temperature (Abbasi et al., 2014). For instance, electrical resistance-based sensor is a common sensor used in agriculture as a means of soil moisture content measurement. The electrical resistance of a medium is a measure of the difficulty to pass an electric current through that medium. Larsson et al. (2004) proposed point resistivity measurements to detect decay in living trees. The results of their study showed that healthy trees gave a higher voltage difference than those with decay. The electrical properties of the trees changes with the decay (Larsson et al., 2004). Accordingly, trees having decay showed a lower resistivity than sound trees. According to Shigo and Shigo (1974), when wood decays, cations will increase, and resistance will decrease. There are more free ions in the decayed wood than in non-decayed wood, thus causing a drop of resistivity (Moore, 1999). As the fungi consume the cell structure, metallic ions, in particular potassium are released (Jartti, 1978). These ions are mobile in the humid trunk of the decay. Nurnadiah et al. (2014) studied the potential use of electrical resistance to detect the infection of *Ganoderma boninense* in oil palm tree. Land Mapper ERM-2 (Landviser, LLC, USA) was used to detect the diseases by collecting ER data at eight positions surrounding the trunk at three different levels of height for each tree. The infected trees gave low ER readings. Paglis (2013) studied the potential use of electrical resistance tomography (ERT) in order to detect the root biomass in coffee trees. The results showed that soil resistivity was quantitatively related to root biomass. Borges et al. (2012) studied the possibilities of using Electrical Impedance Spectroscopy (EIS) to detect plant disease by recording changes in amplitude and phase of the current as it passed through the sample. In the study, a young pine specimen revealed some discrimination between healthy specimens and those infected with nematode diseases. The preliminary tests demonstrated that the EIS system was a promising technique to diagnose plant diseases.

Based on the literature, the use of electrical sensors to detect disease is promising. However most of the detections were done at the tree trunk. Since the spread of the BSR disease was reported through root (Paterson, 2007; Rees et al., 2009), an observation of root growth or health is crucial. Roots play an important role in plants and are responsible for several functions; nutrient and water absorption (Fitter, 2002). Soil properties including moisture content (Chang, 2003), pH (Nawawi & Ho, 1990) and nutrient content of soil (Bivi et al, 2016) were reported to have significant influence on the growth of *Ganoderma boninense* and the tendency of the tree to be infected with the BSR disease. The value of soil resistivity is influenced by soil properties such as moisture content, chemical content and temperature. Thus, the same concept has been used in our study by manipulating soil moisture sensor in the soil as an electric conductor allowing the current to flow through the soil medium. This paper suggests the use of Arduino soil moisture sensor to investigate soil resistivity related to BSR incidence.

MATERIALS AND METHODS

Arduino Soil Moisture Sensor

The properties of healthy and infected oil palm trees were evaluated based on the output given by the Arduino soil moisture sensor. The sensor measures the soil moisture by measuring its soil resistivity in unit ohm (Ω). The measuring systems consist of YL-69 soil moisture sensor **(**Shenzhen JiexingWeiye Electronic Co. Ltd, China**)**, Arduino Uno microcontroller (Adafruit Industries, USA) and a Windows 8 platform laptop (Asus, Taiwan). There are two sensor probes, set in the soil to pass current through the soil and then record the resistance value to get the moisture level. At higher water content in the soil, the sensor detected less resistance due to the soil conducting electricity easier. The dry soil conducted electricity poorly due to more resistance. The Arduino Uno is a microcontroller board based on the ATmega328. It contains everything needed to support the microcontroller. In this research, the Arduino Uno board would received an analogue data converted from the electronic signal recorded by the soil moisture sensor. The analogue data interpreted by the processor and the value of ER appeared at the LCD display of the computer in real time.

Data Collection

The study was conducted in the oil palm plantation located at Teluk Intan, Perak, Malaysia (4.112169°, 100.890208°) from 16th to 20th of January 2017**.** Soil type of the plantation area is coastal compacted peat soil. The oil palm trees (10 years old palms) were categorized into four healthiness levels i.e. T0: healthy, T1: mild (with fruiting body but no foliar symptom), T2: moderate (with fruiting body and less 50% foliar symptom) and T3: severe (with fruiting body and more than 50% foliar symptom). The identification of the healthiness condition of the palm was done by expert from Malaysian Palm Oil Board (MPOB). The data were collected during day time period, i.e. between 8 am to 5 pm. In this preliminary study, environmental factors such as temperature, humidity and sunlight were not discussed. A total of 39 palms were randomly selected with 8 palms were taken from T0, 11 palms from T1, 12 palms from T2 and 8 palms from T3. The measurement was conducted on eight points around the tree trunk with distance (d) 15 cm from the tree.

RESULTS AND DISCUSSION

ER Readings at Each Point

Figure 1 shows example of eight points of ER readings for T0, T1, T2 and T3. The ER values of the eight points varied especially at infected oil palm trees. For healthy oil palm tree, the ER values of T0 for the eight points were above 400 Ω ranging from 414 Ω to 534 Ω. Meanwhile, for infected palms, the ER values of T1, T2 and T3 ranged from 231 Ω to 558 Ω, 296 Ω to 474 Ω and 195 Ω to 484 Ω, respectively. There were five points with ER values less than 400Ω and three points with ER values above 400 Ω for T1 and T2, respectively. Most of the ER values of T3 were less than 400 Ω, where only one point with ER value greater than 400 Ω.

A low variation of ER value was obtained on healthy palm with standard deviation of 38.97 Ω. Standard deviation of infected palms varies between 69.75 Ω to 125.04 Ω.

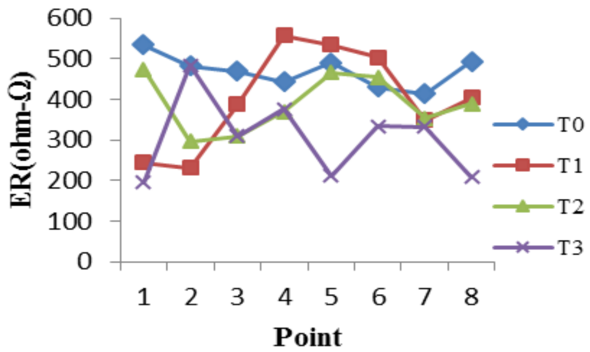

Figure 1. Eight points of ER readings for T0, T1, T2 and T3

Based on detail investigation, the fluctuation value of ER at infected palms depended on the existence of fruiting body or hollow around the palm. For instance, the values of ER at the same palm were higher (≥ 400 Ω) at points which had no hollow and fruiting body. The values of ER were lower (≤ 200 Ω) when there were hollow and fruiting body at the point. Previous work conducted by Nurnadiah et al. (2014) showed that ER values of oil palm tree infected with *Ganoderma* at base positions with appearance of fruiting bodies were lower than healthy palms. The data was collected using Land Mapper ERM-2 (Landviser, USA).

Based on the ER readings taken at eight point positions, it has clearly shown that a single point cannot be used to indicate the healthiness condition of the palm. Results from all eight points gave clear indicator where the higher the severity level, the higher number of points with less ER values. Thus, the detection of healthiness condition should consider the eight points measurement instead of using only a single point measurement.

Model Development

Average value of ER (ER_{MEAN}) for each palm has been calculated by averaging ER readings taken from eight points. The distribution of the results is presented in Figure 2. It can be seen that all healthy palms have ER_{MEAN} above 400 Ω. While for unhealthy palms, the ER_{MEAN} ranged from 232 Ω to 581 Ω. Therefore, a value of 400 Ω was set as ER_{MEAN} threshold value (t-value) to roughly differentiate between healthy and unhealthy palms based on ER_{MEAN} value. Some of the infected palms recorded ER_{MEAN} higher than 400 Ω. This is due to the influence of point with very much larger ER values than most of the values. This has already been proven as explained in previous section where the standard deviation for infected palm is larger than healthy palm. Thus, based on this trend, a new index (K-index) for each palm has been developed based on the value of ER_{MEAN} and ER standard deviation (ER_{STDEV}) of ER taken from eight points at each palm calculated as in equation [3]. The healthy palm is expected to have K-index value of nearly one due to low value of ER_{STDEV}.

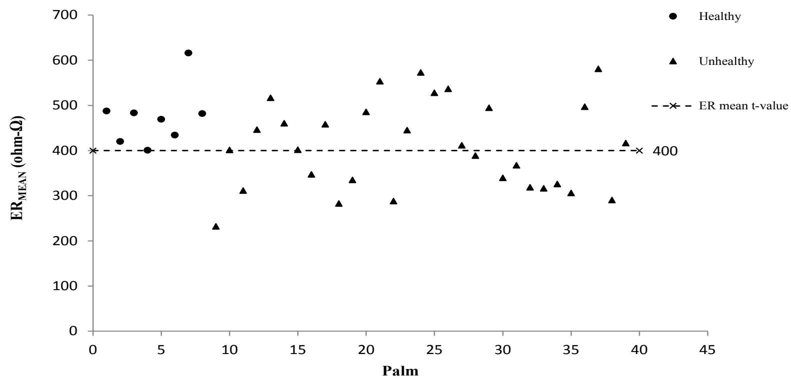

Figure 2. ER_{MEAN} for each palm

$$ER_{MEAN} = \frac{\sum_{i=1}^{n} x_i}{n} \quad [1]$$

$$ER_{STDEV} = \sqrt{\frac{\sum(x-\bar{x})^2}{n}} \quad [2]$$

$$K-\text{index} = \frac{(ER_{MEAN} - ER_{STDEV})}{ER_{MEAN}} \quad [3]$$

n = number of sample points for each palm

Figure 3 shows K-index of 39 palms. For healthy palms, values of K-index ranged from 0.706 to 0.918 with mean value of 0.847.While for unhealthy palms, values of K-index ranged from 0.280 to 0.888 with mean value of 0.727. As expected, the values of K-index for healthy palms were higher than the infected palm. A t-value to differentiate between healthy and unhealthy palms was determined based on following consideration; (mean of K-index of healthy palms + mean of K-index of unhealthy palms)/2 i.e. (0.847+0.727)/2 = 0.787.

Two ANOVA test were carried out to see possibility of ER_{MEAN} and K-index to differentiate between healthy and infected palms. For ER_{MEAN} analysis, there is no significant difference between healthy and infected palms as F value (3.232) is smaller than F critical (4.105). However, analysis for K-index showed significant difference between healthy and infected palms as F value (5.861) is larger than F critical (4.105). A graph of K-index versus ER_{MEAN} (Figure 4) was plotted to best describe the relationship between these two parameters. An x-axis intersection line and y-axis intersection line with value of 400 and 0.787 respectively, act as separator line between healthy and unhealthy palms. Thus, four different regions were formed represented as A, B, C and D. Region A, B and C represent unhealthy regions, where plotted dots for unhealthy palms should fall, while region D

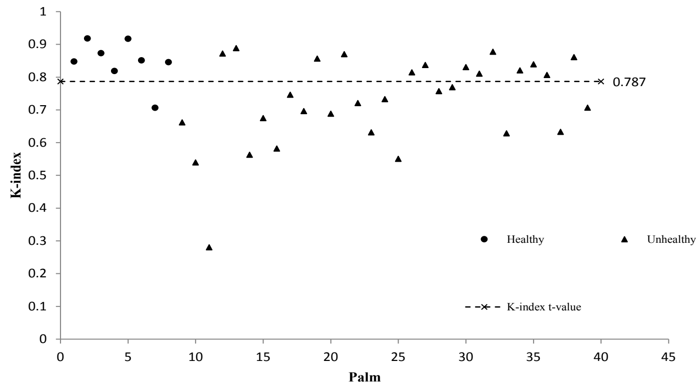

Figure 3. K-index for each palm

is for healthy palms. Based on Figure 5, one unhealthy palm was in region C. While, six infected palms were in region D. This indicates that a total of seven palms were not correctly categorized according to its actual healthiness condition. Other than moisture, soil compaction rate also affects sensor readings. This contributed to the error of the actual value which should measure the value of the soil ER. In summary, this model successfully categorizes the healthy and unhealthy palms with accuracy rate of 82 %.

Model Validation

Ten palms with a total of 80 points were taken to validate the developed model which consists of four T0 palms, two T1 palms, two T2 palms and two T3 palms. The graph of

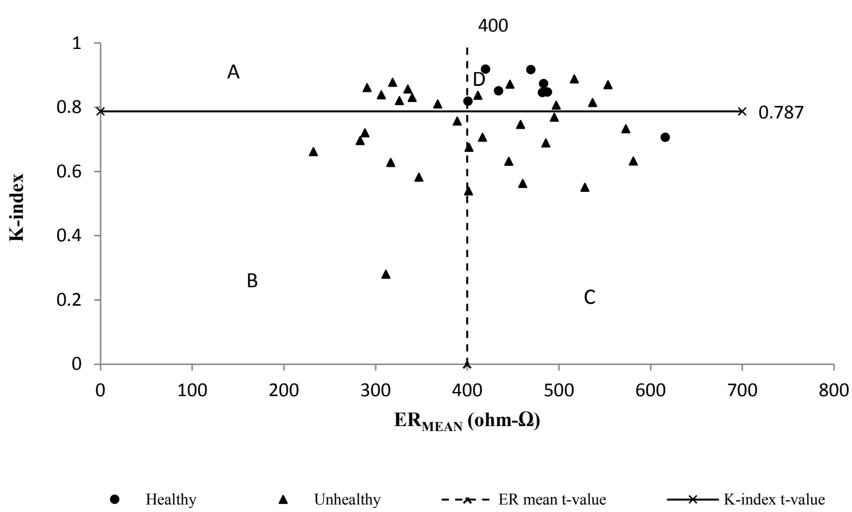

Figure 4. K-index versus ER_{MEAN} of 39 palms for development of the model

K-index versus ER_{MEAN} was plotted and the result is shown in Figure 5. It can be seen that all palms were correctly categorized to healthy (D) and unhealthy (B) regions. All T0 palms plotted dots are in D region categorized as healthy palms while another six palms (two palms for each T1, T2 and T3) are in B region categorized as unhealthy palms. The successful rate of the validation process was 100 %. Lelong et al (2009) also successfully obtained 100% accurate result when detecting *Ganoderma* using hyperspectral remote sensing data by applying partial least square regression (PLS) and discriminant analysis (DA). Shafri and Hamdan (2009) had shown that Lagrangian interpolation red edge technique gave better results than vegetation indices (Khairunniza-Bejo et al., 2015) to identify *Ganoderma*-infected oil palm, however it only gave 84% accuracy.

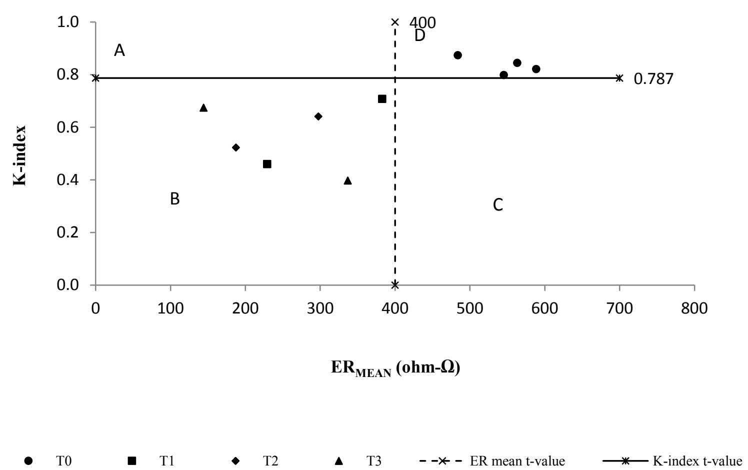

Figure 5. K-index versus ER_{MEAN} of 10 palms for validation of the model

CONCLUSIONS

The ER readings obtained from soil using soil moisture sensor were feasible to identify healthy and infected oil palm trees. Healthy oil palm tree gave higher ER reading (≥ 400 Ω) compared to infected tree (< 400 Ω) especially at the position with the existence of fruiting bodies and/or hollow. However, a single point ER reading could not be used to indicate the healthiness condition of the palm. Result had shown that the higher the severity level, the higher the number of points with less ER values. Combination of average value of ER taken from all eight points and its standard deviation led to the introduction of a new parameter to detect *Ganoderma* infection, named as K-index. A new model was later developed using K-index and ER_{MEAN}. The model gave accurate results of detection, with 82% accuracy during testing and 100% accuracy during validation. Although the proposed method showed promising results, however, there is still room for improvement. Currently the model is only applicable to differentiate between healthy and infected palms, not to the level of basal stem rot severities (i.e. T1, T2 and T3). Therefore, further investigation needs to be done in the future to improve the method especially on the severity level of detection. This process needs detailed analysis and might require other parameters and different type of sensors. Besides that, environmental factors such as temperature, humidity and sunlight are also recommended for further investigation.

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