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Statistical Analysis between Soil Properties and Fusarium Wilt Disease in Banana

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Abstract Soilborne Fusarium wilt disease is a disastrous constraint that has a detrimental effect on banana agronomic performance. Climates and soil characteristics play significant roles in the occurrence and severity of Fusarium wilt disease in bananas. This study aimed to present statistical tools for direct and reflective information on the Fusarium wilt disease occurrence by including the soil environmental factors such as moisture, pH, and electrical conductivity. There are numerous opinions regarding the interaction between soil attributes and Fusarium wilt disease in bananas. Yet, the knowledge of how soil properties influence Fusarium wilt occurrence in bananas and otherwise remains unresolved. Therefore, this study was conducted by including different statistical tools such as t-test, MANOVA and binary logistic regression to explore the potential relationship between Fusarium wilt disease incidence and soil properties. The present study also consists of a reversed interaction of soil attributes and Fusarium wilt disease incidence. Though not all soil attributes were included, the preliminary findings revealed that soil moisture and soil pH have relationship with the development of Fusarium wilt disease in banana plantation. Although this statistical analysis does not prove the existence of genuine biological interaction between characteristics, it significantly suggests its possibility. Therefore, more experimental and statistical data are needed to document the right direction of the critical elements for the Fusarium wilt disease incidence.

Keywords Fusarium Wilt Banana, Statistics, *Fusarium Oxysporum* f. sp. *Cubense*

1. Introduction

Fusarium wilt banana (FWB hereafter) or Panama disease caused by *Fusarium oxysporum* f. sp. *cubense* (Foc) has been the most terrifying and devastating threat in the banana plantation for many years [1]. For instance, local banana growers in Malaysia are frequently curtailed by pests and diseases, which can negatively affect the banana industry [2]. The most prevalent Foc is Tropical Race 4 (TR4), which threatens a wide *Musa* spp [2]. Diseased banana typically encounters wilting and yellowing leaves resulting from blocked xylem and no water transportation [3-4]. The Foc enters the vascular tissues and rapidly produces a high volume of chlamydospores, microconidia, and macroconidia across the entire banana plant [5]. In recent decades, the phytopathological interest in the FWB has increased, especially in the country that planted a wide area of bananas. Despite the overwhelming FWB research, there is still a dearth of effective and trustworthy control information based on biogeographical and agro-environmental, which limits the management of Fusarium wilt disease.

Numerous abiotic soil characteristics have been associated with the Fusarium wilt disease incidence [6]. Thus, both plant pathologists and statisticians continue to provide insight into the relationship between soil environments and plant disease occurrence. This information would be relevant to a more comprehensive understanding of the FWB incidence in banana plantations. This article provides a perspective on the statistical applications to explore the possible interaction of FWB and soil environments. Thus, a statistical point of view can give insight into the development of early FWB diagnosis or FWB management controls based on the soil environmental variables. Therefore, this article aims to present statistical tools for direct and reflective information on the FWB occurrence by including the soil environmental factors. As a basis for the study, the researchers' sub-objectives are twofold: i) to identify the direct interaction of soil environmental factors towards FWB occurrence; ii) to identify the possibility of the reversed direction of soil environmental attributes that could be influenced by FWB occurrence. With the statistical application in this report, it will be possible to design appropriate scientific experiments to detect and control the FWB incidence at the early stage of the Foc infestation.

2. Materials and Methods

2.1. Study Area & Data Collection

Soil sampling was conducted in a small-scale banana plantation in Jeli, Kelantan, to ascertain the interactions between plant health status and soil conditions. The banana trees were planted on the slope and uphill. Healthy bananas were located in the upper section, while suspected FWB bananas were found in the lower section. With the owner's permission, clay soils were randomly collected according to the banana's health status. Determining healthy and diseased banana trees was entirely based on visible symptoms. Simple Foc culture and identification were performed to confirm the presence of Foc in the infected soil. A dummy variable was utilized for plant conditions, with 1 indicating infected banana plants and 0 indicating healthy banana trees. All data were analysed using SPSS Statistic 25.0 software (IBM, New York, USA) to reveal the unravelling of relationships between plant conditions and soil factors.

2.2. Statistical Analysis

In the present study, we analysed the direction of the plant disease triangle from different perspectives by utilizing statistical tools in plant pathology to explore the possible interaction of soil environmental factors and FWB occurrence. Thus, the analysis was conducted based on the modified plant disease direction. First, the investigation was done to identify the direct interaction of soil environmental factors towards FWB occurrence by utilizing a T-test and binary logistic regression. Second, to determine the possibility of the reversed direction of soil environmental attributes that could be influenced by FWB occurrence, including Pearson's correlation, MANOVA, and dummy linear regression. Figure 1 shows the details of variables included in the statistical analysis to explore the possible interaction of soil parameters and FWB occurrence. The analysis used plant conditions to represent FWB occurrence (the presence or absence of Foc).

2.2.1. T-test

T-test has been the fundamental method used by plant pathologists and other scientists for data analysis and statistical inference. T-test analysis can be grouped into one sample t-test, independent t-test, and paired sample t-test [7]. Regardless of its classification, t-test analysis aims to determine whether the two mean groups are statistically different. Theoretically, the formula for two independent sample T-tests is shown in Equation 1.

$$t = \frac{\bar{x}_1 - \bar{x}_2}{s\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \tag{1}$$

Where t is the t-value, x_1 and x_2 are the means of the two groups being compared, s is the pooled standard error of the two groups, and n_1 and n_1 are the number of observations in each of the groups.

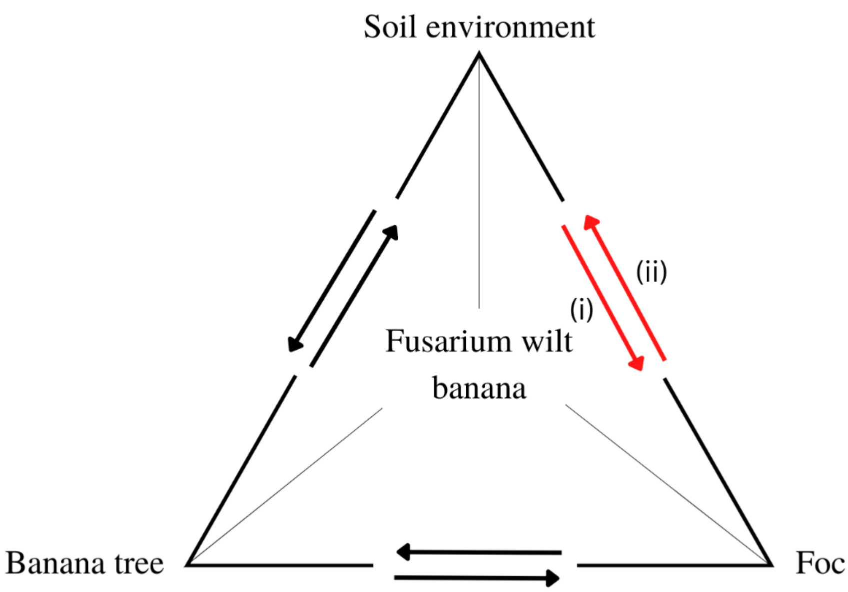

Figure 1. The modified FWB disease triangle used for statistical analysis. (i) Direct interaction of soil environmental factors toward FWB occurrence (X = soil environmental factors, Y = plant condition). (ii) The possibility of reversed direction of soil environmental attributes that could be influenced by FWB occurrence (X = plant condition, Y = soil environmental factors).

2.2.2. Pearson Correlation Coefficient

A correlation test is used to quantify the directionality of a linear relationship between two variables [8]. Pearson correlation coefficients (r) are intended for continuous or interval variables [8]. Additionally, if the scholar has one continuous variable and one dichotomous feature, Pearson r can be used [9]. Pearson r can take on only values between -1 and +1 that can be determined using the formula in Equation 2. The sign in front of the values indicates positively correlated (as one variable grows, the other increases) or negatively correlated (as one variable increases, the other decreases). The absolute value represents the relationship's strength.

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2(y_i-\bar{y})^2}} \quad (2)$$

Where r is the correlation coefficient, x_i are the values of the independent variable in a sample and $\bar{x}$ is its mean, y_i are the values of the dependent variable in a sample and $\bar{y}$ is its mean.

2.2.3. Multivariate Analysis of Variance (MANOVA)

MANOVA is a statistical tool to analyse the effects of independent variables (categorical data) on several of continuous dependent parameters [10-11]. This tool provides simultaneous analysis of several dependent attributes. There are various distinct statistics to pick from [12]. However, in this analysis, scholars only include Wilks' Lambda. The MANOVA model $y_i = B^T x_i + \epsilon_i$, for $i = 1, \ldots, n$ has $m \geq 2$ response variables $Y_1, \ldots, Y_m$ and d predictor variables $X_1, X_2, \ldots, X_d$. The i th case is $(x_i^T, y_i^T) = (x_{i1}, \ldots, x_{id}, Y_{i1}, \ldots, Y_{im})$. If a constant $x_{i1} = 1$ is in the model, then x_{i1} could be omitted from the case. In matrix form, the MANOVA model $Z = XB + E$ is summarised as presented in Equation 3 and Equation 4.

$$\begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,m} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ Y_{n,1} & Y_{n,2} & \cdots & Y_{n,m} \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d} \end{bmatrix} \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \cdots & \beta_{1,m} \\ \beta_{2,1} & \beta_{2,2} & \cdots & \beta_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{d,1} & \beta_{d,2} & \cdots & \beta_{d,m} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,1} & \epsilon_{1,2} & \cdots & \epsilon_{1,m} \\ \epsilon_{2,1} & \epsilon_{2,2} & \cdots & \epsilon_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon_{n,1} & \epsilon_{n,2} & \cdots & \epsilon_{n,m} \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} y_1^T \\ \vdots \\ y_n^T \end{bmatrix} = \begin{bmatrix} x_1^T \\ \vdots \\ x_n^T \end{bmatrix} [\beta_1 \quad \beta_2 \quad \cdots \quad \beta_m] + \begin{bmatrix} \in_1^T \\ \vdots \\ \in_n^T \end{bmatrix} \quad (4)$$

2.2.4. Regression Analysis

Generally, the linear regression equation can be denoted as $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$, where y is the dependent variable in the dataset, $x_1, x_2, \ldots, x_k$ are the independent variables in the dataset and $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients determined by chosen regression analysis. Several types of linear regression can be used based on the type of available dataset. This article used two types of regression analysis: logit regression and dummy regression. The logit regression analysis technique enables researchers to evaluate and forecast categorical variables with two or more categories [13]. Additionally, the predictor attributes could be categorical, continuous, or combined in a single model [14]. Although IBM SPSS includes a few logistic regression approaches, we chose the default process, the Forced Entry Method. By default, all predictors are analysed in a single block to determine their predictive power while considering the influence of other predictors in the model [15].

While dummy regression analysis enables researchers to analyse categorical variables through regression. A dummy variable is constructed to associate the numerical data with categorical variables. Each dummy variable corresponds to a single category of the explanatory variable and is coded as 1 if the event occurred and 0 if it did not. Scholars can analyse the link between factors by using a dummy variable and forecasting the event.

3. Result and Discussion

The descriptive statistics showed that soil pH and moisture are slightly higher in the infected banana trees compared to healthy banana trees. However, soil electrical conductivity (EC) is slightly high in healthy banana trees. According to the literature, there have been shortcomings in the current research and inconsistent empirical evidence to provide insight into agro-environmental factors that directly or indirectly affect the Fusarium wilt disease progression. For example, the relationship between pH and Fusarium wilt disease. The threshold values of this relationship are complex to be determined. Some studies reported low pH values associated with the Fusarium wilt incidence [16-17].

On the other hand, [18] revealed that high pH values increased the Fusarium wilt disease incidence. Soil pH and soil moisture is also a critical phytopathological factor for plant disease, including FWB [19]. Therefore, [20] concluded that soil moisture could be used as a soil property to diagnose the suspected FWB area early. In addition, [21] stated that soil moisture is significantly related to other soil factors such as pH, humidity, and temperature.

Despite the contradictory findings in the literature, all previous findings indicated a connection between soil environments and Fusarium wilt disease expression. However, the type of soil and banana cultivar used also could affect the result of this study because the interactions of banana cultivars, soil types, and Foc races may vary in Panama disease progression. Furthermore, a T-test analysis was used in this study to determine whether the mean difference of soil parameters in the diseased and healthy banana trees was significant at the 0.05 level. The analysis revealed that the soil moisture and pH in the healthy and infected banana trees were significant at the specified $p = 0.000$. At the same time, no significant difference was reported in EC ($p = 0.18$), as shown in Table 1.

Further analysis was done using binary logistic regression to examine soil factors influencing the FWB occurrence. Even though the overall model was statistically significant, $\chi^2(3) = 166.36$, $p < .05$, the results reported that soil moisture ($p = 0.980$), soil pH ($p = 0.990$), and soil EC (0.998) did not add significantly to the model, as shown in Table 2. Thus, the result indicated that the model could not distinguish between banana health status and soil moisture, EC, and pH.

Previous analysis using the T-test revealed a significant difference between the readings of soil pH and moisture in the healthy and infected banana trees. Following, there was no significant result in binary logistic regression. Then, we tried to reverse the data analysis according to the modified plant disease triangle. In the following analysis, we hypothesized that the presence or absence of Foc (plant conditions) may alter the condition of the soil parameters. Therefore, scholars used Pearson correlation, MANOVA, and simple linear regression to examine the possibility of soil attributes (y) explaining the FWB occurrence.

Pearson correlation was used in this analysis to determine how much soil variables tend to change with presence or absence of Foc as a causal agent for the FWB incidence. Among them, soil moisture (Pearson = 0.826, $p = 0.0$) and pH (Pearson = 0.343, $p = 0.0$) showed significantly positive correlation with plant condition or FWB occurrence, as presented in Table 3. While soil EC was not significantly correlated with Fusarium wilt disease (plant conditions). Multiple soil factors are responsible for Fusarium wilt infection as the soil parameters play an important part in most plant diseases, including FWB. In this study, we focused on the statistical application to explore the possible interaction of soil properties and FWB.

MANOVA was performed to identify possible interactions between three unrelated soil parameters as dependent variables and plant conditions as the independent variable. Generally, the data analysis using MANOVA revealed a statistically significant difference between diseased and healthy banana trees on the combined dependent soil variables, $F(3, 116) = 102.89$, $p = 0.00$, Wilks' Lambda = 0.273. The only no statistical difference was soil EC variable ($p = 0.184$), as presented in Table 4.

Table 1. Descriptive and T-test analysis

Soil properties	Plant condition	Min.	Max.	Mean ± S.E.[a]	*t* value[b]
Moisture content (%)	Healthy	7.47	25.40	22.26 ± 0.32	-15.90*
	Infected FWB	25.89	38.66	30.33 ± 0.40	
pH	Healthy	4.30	5.00	4.53 ± 0.02	-5.85*
	Infected FWB	4.30	6.70	5.03 ± 0.08	
Electrical conductivity (µs/cm)	Healthy	18.00	39.00	25.27 ± 0.63	1.34
	Infected FWB	15.00	35.00	24.25 ± 0.76	

[a] Data are means ± standard error.

[b] An asterisk (*) indicates significance at the $p < 0.05$ level.

Table 2. Binary logit regression analysis

	B	S.E.	Wald	df	p
Soil moisture	36.605	1462.422	0.001	1	0.980
pH	-19.035	1458.811	0.000	1	0.990
EC	-0.265	124.815	0.000	1	0.998
Constant	-841.693	33664.954	0.001	1	0.980
Model $\chi^2 = 166.36$*					

B = unstandardized regression weight, S.E. = standard error, df = degree of freedom, p = significant value; where $p < 0.05$

Table 3. Summary result for Pearson correlation coefficients (r)

		Soil factor[a]		
		Soil moisture	pH	Electrical conductivity
Plant condition (diseased or healthy)	Pearson	0.826	0.474	-0.122
	p-value[b]	0.000**	0.000**	0.184

[a] Soil factor as the dependent variable

[b]** indicates significance at the $p < .001$ level (2-tailed)

Table 4. Summary table for MANOVA analysis

Independent variable	Dependent variable	Type III sum of square	df	F	p value[a]
Plant conditions	Soil moisture	1951.488	1	253.092	0.000
	Soil pH	7.651	1	34.177	0.000
	Soil EC	52.008	1	1.782	0.184
Hypothesis df = 3					
Error df = 116					
Wilk's Lambda(Λ) = 0.273					

[a] p-value less than 0.05 indicates statistically significant.

Table 5. Simple linear regression analysis

Model 1: Linear regression taking the soil moisture as the dependent variable					
Variable entered	Unstandardized coefficient β	Standardized coefficient β	F	R^2	*p* value[a]
Plant condition	8.065	0.826	253.092	0.682	0.000
Model 2: Linear regression taking the soil pH as the dependent variable					
Variable entered	Unstandardized coefficient β	Standardized coefficient β	F	R^2	*p* value[a]
Plant condition	0.505	0.474	34.117	0.225	0.000
Model 3: Linear regression taking the soil EC as the dependent variable					
Variable entered	Unstandardized coefficient β	Standardized coefficient β	F	R^2	*p* value[a]
Plant condition	-1.317	-0.122	1.782	0.015	*0.184*

F = F-value, R^2 = R-squared.

[a] p-value less than 0.05 indicates statistically significant.

The linear regression was used to examine the possibility of using plant conditions or a dummy variable as a factor influencing the changes in soil parameters. Thus, a separate dummy linear regression was done for each soil parameter, as presented in Table 5. The first model of dummy linear regression taking the soil moisture as the dependent variable showed that R^2 was strongly and positively correlated with the plant conditions at the specified level p = 0.0. A second model dummy linear regression taking the soil pH as the dependent variable found that this model was the second largest R^2 and positively correlated with the plant conditions at the specified level p = 0.0. In contrast, the third model taking soil EC as a dependent variable was not statistically significant. Thus, this indicates an unclear relationship exists regarding the changes of soil EC with the presence of Foc in banana cultivated areas. In addition, there is a dearth of the previous study to identify the possible relationship between soil EC and FWB. [17] reported the soil EC values associated with the FWB in banana cv. Maçã is from 0.06 - 0.14 dSm^{-1}.

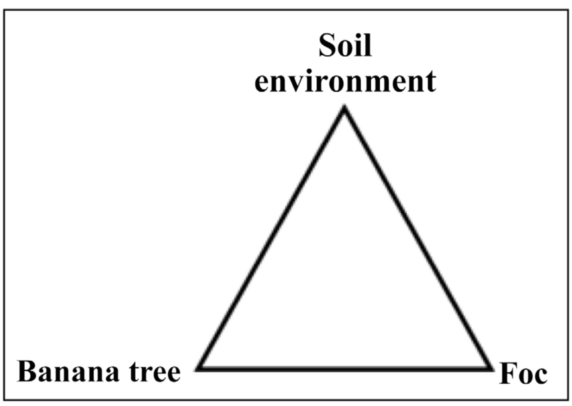

Figure 2. Classic FWB plant disease triangle

As outlined in the plant disease triangle, the soilborne infection in a plant community is determined by the presence of the host plant, pathogen, and environment [22]. Diverse soil microbiomes, including soilborne pathogens, can substantially affect plant disease in various natural environments. The classic disease triangle's concept is supported by the three critical elements required for a successful pathogen interaction and contact between pathogen and host [23], as presented in Figure 2. Nowadays, there are modified versions of the plant disease triangle [24-25]. Therefore, it is critical to identify the direction reflecting the interactions between the three elements in the plant disease triangle.

Theoretically, the environments can influence the susceptibility of Foc and banana trees, as well as the ability of the pathogen to affect banana trees and soil environments. The host and pathogen may affect the soil environment by influencing plant canopy microenvironments, a dead host's ground cover, and pathogen density. Using the field data on the soil of FWB infected and healthy banana trees, our findings could result from ineffective farm management. During the sampling, scholars observed that dead leaves and pseudostems of infected banana trees were not properly removed from the farm but remained near the banana trees. This ground cover may affect the microclimate of the soil ecosystems in that area. Thus, this ground cover resulted in high soil moisture in the diseased area. However, the interplay of environment-pathogen-host still remains unclear. If an additional deeper understanding on the effect of all direction among three elements can be obtained, a thorough finding could assist banana growers in effectively managing their farm, as well as early disease detection to reduce banana loss. The different experimental designs would be designed to understand the impact of soilborne pathogens. In addition, it will give insight to pathologists who sought to establish soil management strategies to maximize banana production.

Environmental parts have been proven more challenging to model due to climate changes and soilborne pathogens. Still, direct and reversed interaction knowledge can be beneficial in comprehending the effective plant disease study. The limitation is to signalling pathways grasp how changes in the host or pathogen composition translate into the effects on soil conditions throughout the progression of plant diseases. In addition, fundamental environmental variables, such as temperature, moisture, sunlight, etc., can significantly affect the host plant's pathophysiology and disease development and the interactions between the plant and pathogen [17].

Our findings established statistical relationships between components of risk variables involved in developing Fusarium wilt disease. The statistical linkage should provide a basis for disease management decisions and aid in developing early disease detection employing soil parameters. Additional research is required to establish injury thresholds and the direction of the typical illness triangle that contributes to disease development and banana loss.

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REFERENCES

[1] F. A. Garcia-Bastidas, A. J. T. Van der Veen, G. Nakasato-Tagami, H. J. G. Meijer, R. E. Arango-Isaza and G. H. J. Kema. An improved phenotyping protocol for Panama disease in banana, *Front. Plant Sci.*, Vol. 10, 1006, 2019.

[2] C. K. F. Wong, D. Zulperi, G. Vadamalai, N. B. Saidi and C. Y. The. Phylogenetic analysis of Fusarium oxysporum f. sp. cubense associated with Fusarium wilt of bananas from Peninsular Malaysia, *Sains Malays.*, Vol. 48, No.8, 1593-1600, 2019.

[3] S. Zhang, X. Li, Y. Ba, X. Lyu, M. Zhang and M. Li. Banana Fusarium wilt disease detection by supervised and unsupervised methods from UAV-based multispectral imagery, *Remote Sens.*, Vol. 14, No.5, 2022.

[4] G. Kannan, M. S. Saraswathi, R. Thangavelu, P. S. Kumar, M. Bathrinath, S. Uma, S. Backiyarani, A. Chandrasekar and T. R. Ganapathi. Development of fusarium wilt resistant mutants of Musa spp. cv.Rasthali (AAB, Silk subgroup) and comparative proteomic analysis along with its wild type, *Planta*, Vol.255, No.4, 80, 2022.

[5] C. Li, S. Chen, C. Zuo, Q. Sun, Q. Ye, G. Yi and B. Huang. The use of GFP-transformed isolates to study infection of banana with Fusarium oxysporum f. sp. cubense race 4, *Eur. J. Plant Pathol.*, Vol. 131, No.2, 2011.

[6] B. O. Olivares, J. C. Rey, D. Lobo, J. A. Navas-Cortés, J. A. Gómez and B. B. Landa. Fusarium Wilt of bananas: a review of agro-environmental factors in the Venezuelan production system affecting its development, *Agronomy*, Vol.11, No.5, 2021.

[7] B. Gerald. A brief review of independent, dependent and one sample t-test" *Int. J. Appl. Math. Theor. Phys.*, Vol.4, No.2, 50-54, 2018.

[8] P. Schober, C. Boer and L. A. Schwarte. Correlation coefficients: appropriate use and interpretation, *Anesth. Analg.*, Vol.126, No.5, 1763-1768, 2018.

[9] C. S. Lai, Y. Tao, F. Xu, W. W. Ng, Y. Jia, H. Yuan, C. Huang, L. L. Lai, Z. Xu and G. Locatelli. A robust correlation analysis framework for imbalanced and dichotomous data with uncertainty, *Inf. Sci.*, Vol.470, 58-77, 2019.

[10] P. Dattalo. *Analysis of multiple dependent variables*, Oxford University Press, United States of America, 2013.

[11] S. Sanogo and X. B. Yang. Overview of selected multivariate statistical methods and their use in phytopathological research, *Phytopathology*, Vol. 94, No.9, 1004-1006, 2004.

[12] C. Ateş, Ö. Kaymaz, H. E. Kale and M. A. Tekindal. Comparison of test statistics of nonnormal and unbalanced samples for multivariate analysis of variance in terms of type-I error rates, *Comput. Math. Methods Med.*, Vol. 2019, 2173638, 2019.

[13] R. D. Riley, K. I. Snell, J. Ensor, D. L. Burke, F. E. Harrell Jr, K. G. Moons and G. S. Collins. Minimum sample size for developing a multivariable prediction model: PART II-binary and time-to-event outcomes, *Stat. Med.*, Vol.38, No.7, 1276-1296, 2019.

[14] M. R. Abonazel and M. G. Ibrahim. On estimation methods for binary logistic regression model with missing values, *Int. J. Math. Comput. Sci.*, Vol. 4, No.3, 79-85, 2018.

[15] J. Pallant. SPSS survival manual: A step by step guide to data analysis using IBM SPSS, Routledge, New York, 2020.

[16] R. A. Segura, J. J. Stoorvogel, J. Z. Samuels and J. A. Sandoval. Managing the interactions between soil abiotic factors to alleviate the effect of Fusarium wilt in bananas, *Acta Hortic.*, Vol.1196, 163-168, 2018.

[17] P. Deltour, S. C. França, O. L. Pereira, I. Cardoso, S. De Neve, J. Debode and M. Höfte. Disease suppressiveness to Fusarium wilt of banana in an agroforestry system: influence of soil characteristics and plant community, *Agri. Ecosyst. Environ.*, Vol.239, 173-181, 2017.

[18] Y. Cao, J. Wang, H. Wu, S. Yan, D. Guo, G. Wang and Y. Ma. Soil chemical and microbial responses to biogas slurry amendment and its effect on Fusarium wilt suppression, *Appl. Soil Ecol.*, Vol.107, 116-123, 2016.

[19] S. Wahyuni and D. Nasution. Utilization of Trichoderma viride as organic fertilizer to induce the resistance of banana seeds on Fusarium oxysporum f. sp cubense (FOC), *IOP Conf. Ser.: Earth Environ. Sci.*, Vol.260, 012149, 2019.

[20] A. I. C. David and M. L. C. Guico. Presence or Absence of Fusarium oxysporum f. sp. cubense Tropical Race 4 (TR4)

Classification Using Machine Learning Methods on Soil Properties, *TENCON 2018 - 2018 IEEE Region 10 Conference*, (IEEE, 2018), pp. 0689-0694, 2018.

[21] G. Guo, B. Wang, W. Ma, X. Li, C. Zhu, J. Ming and H. Zeng. Biocontrol of Fusarium wilt of banana: Key influence factors and strategies, *Afr. J. Microbiol. Res.*, Vol.7, No.41, 4835-4843, 2013.

[22] S. Jayaraman, A. Naorem, R. Lal, R. C. Dalal, N. Sinha, A. Patra and S. Chaudhari. Disease-suppressive soils—beyond food production: a critical review, *J. Plant. Nutr. Soil Sci.*, Vol.21, No.2, 1437-1465, 2021.

[23] Y. Liu and F. He. Incorporating the disease triangle framework for testing the effect of soilborne pathogens on tree species diversity, *Funct. Ecol.*, Vol.33, No.7, 1211-1222, 2019.

[24] A. Chappelka and N. Grulke. Disruption of the disease triangle by chemical and physical environmental change, *Plant Biol.*, Vol.18, 5-12, 2016.

[25] Noman, M. Aqeel, M. Qasim, I. Haider and Y. Lou. Plant-insect-microbe interaction: a love triangle between enemies in ecosystem, *Sci. Total Environ.*, Vol.669, 134181, 2020.