*Research Article*

# Identifying the Underlying Factors and Variables Governing Macronutrients in Cultivated Tropical Peatland Using Regression Tree Approach

## *Identifikasi Faktor dan Peubah Dasar yang Mengontrol Unsur Hara Makro pada Lahan Gambut Tropis Budidaya Menggunakan Pendekatan Pohon Regresi*

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***Abstract:*** The capability of machine learning/ML algorithms to analyze the effect of human and environmental factors and variables in controlling soil nutrients has been profoundly studied over the last decades. Unfortunately, ML utilization to estimate macronutrients and their governing factors in cultivated tropical peat soil are extremely scarce. In this study, we trained regression tree/RT, ML-based pedotransfer models to predict total N, P, and K in peat soils based on oil palm/OP and OP+bush datasets. Our results indicated that the dataset might contain outliers, non-linear relationships, and heteroscedasticity, allowing RT-based models to perform better compared to multiple linear regression/MLR models (as a benchmark) in estimating total N and P in both datasets, contrastingly, not in K. The difference of important variables in each RT-based model partially showed the vital role of land use in nutrient modeling in peat. The depth of sample collection, organic C, and ash content became the prominent factor and variables in regulating the entire predicted nutrients. Meanwhile, the distance from the oil palm tree and pH were the salient features of total P prediction models in OP and OP+bush sites, respectively. This study proposed employing ML-based pedotransfer models in analyzing and interpreting complex tropical peat data as an alternative to linear-based regression. Our initial study also shed more light on the development possibility of the pedotransfer models that agricultural practician, researchers, companies, and farmers can use to predict macronutrients, both in tabular and spatial terms, in cultivated tropical peatlands.

*Keywords:* artificial intelligence, GINI relative importance, machine learning, ICE-PDP

***Abstrak:*** Kemampuan algoritma pembelajaran mesin/ML untuk menganalisis pengaruh faktor dan variabel manusia dan lingkungan dalam mengontrol unsur hara dalam tanah telah dipelajari secara mendalam selama beberapa dekade terakhir. Sayangnya, studi mengenai penggunaan ML untuk memprediksi kandungan unsur hara makro dan berbagai faktor pengontrolnya dalam tanah gambut yang dibudidayakan sangatlah jarang. Dalam kajian ini, kami melatih model pedotransfer berbasis pohon regresi/RT ML untuk memprediksi total N, P, dan K menggunakan dataset kelapa sawit/OP dan OP+semak pada lahan gambut. Hasil analisis kami mengindikasikan bahwa dataset yang digunakan mengandung outlier, hubungan non-linier, dan heteroskedastisitas, yang memungkinkan model berbasis RT berkinerja lebih baik dibandingkan model regresi linier berganda/MLR (sebagai referensi) dalam mengestimasi total N dan P di kedua dataset. Tren yang berkebalikan terjadi pada prediksi K total. Perbedaan peubah penting pada setiap model berbasis RT secara parsial menunjukkan peran vital penggunaan lahan dalam pemodelan hara di gambut. Kedalaman pengambilan sampel, C organik dan kadar abu menjadi faktor dan peubah utama yang mengatur seluruh unsur hara yang diprediksi. Sementara itu, jarak dari pohon kelapa sawit dan pH merupakan peubah yang menonjol dari model prediksi P total secara berurutan pada lokasi OP dan OP+bush. Studi ini mengusulkan penggunaan model pedotransfer berbasis ML sebagai alternatif dari regresi berbasis linier dalam menganalisis dan menafsirkan data gambut tropika yang kompleks. Studi awal

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kami juga menjelaskan kemungkinan pengembangan model pedotransfer yang dapat digunakan oleh praktisi, peneliti, perusahaan pertanian, dan petani untuk memprediksi unsur hara makro, baik secara tabular maupun spasial, padahal lahan gambut tropis yang dibudidayakan.

*Kata kunci:* kecerdasan buatan, tingkat kepentingan relatif berbasis GINI, pembelajaran mesin, ICE-PDP

## INTRODUCTION

Tropical peatlands hold great importance in the agricultural sector of Southeast Asia/SEA. Due to the rising scarcity of mineral soil areas, farmers and plantation companies in the SEA lowland areas are currently utilizing peatlands as their second option for farming. In Indonesia, peatlands became the essential natural resource, particularly for the people who lived in the coastal lowland of Eastern Sumatera, as well as West and Central Kalimantan. In general, they are benefitted from OP smallholding or plantation companies (Jelsma et al., 2017; Pacheco et al., 2017; Bou Dib et al., 2018). Ditjen Perkebunan (2011) reported that about 20 percent of Indonesian OP plantations were located in peatland areas. Compared to other crops, a well-managed OP plantation could also support a complex ecosystem that harbors relatively high biodiversity (Koh, 2008; Hood et al., 2020; Pashkevich et al., 2022).

Determining the amounts of N, P, and K in peat are essential to OP plantation in obtaining and sustaining optimum yields. They are the major nutrients that OP plants essentially absorb at high levels (Wahid et al., 2005; Woittiez et al., 2017). The NPK-contained fertilizer demands are so high for the OP plantations since the natural concentration of the nutrients in peat soil does not meet the requirement of OP to produce an economically feasible yield (Ng et al., 1990; Pardon et al., 2016). The parent material of peats contained less P and K contents than mineral soils. Owing to a slower release of peat mineralization process, available N in peat is under the OP sufficiency levels for producing high yields, which requires an additional N fertilization (Mutert et al., 1999; Ariffin et al., 2019). Consequently, under-fertilized OP often undergoes a hidden hunger and yield below the average. At the same time, the soil nutrients were continuously mined, thus may leading to land degradation (Majumdar et al., 2016; Woittiez et al., 2018; Woittiez et al., 2019).

Conducting optimal fertilization in OP plantations requires soil and plant samplings, laboratory determination, data analysis, and reporting. These first and second procedures are considered arduous and tedious, especially for large-scale companies. Furthermore, laboratory determination resulted in a negative environmental impact since the destructive analyses require hazardous chemical extractants. Modeling techniques based on the pedotransfer function provide an alternative pathway to estimate soil nutrient contents using soil and environmental-related factors and variables (or predictors/covariates; Van Looy et al., 2017; Grunwald et al., 2021). Linear-based regression model employed with an ordinary least square/OLS algorithm was a common example. However, problems emerge while the models only rely on a linear approach in determining nutrients that possess complex and non-linear relationships with their predictors. The interactions among soil, microorganism, and plant roots were very complex with non-linear interrelationships and highly collinear (Vereecken et al., 2016; York et al., 2016; Gregory et al., 2022).

The complexity of the problems of the linear approach was also exacerbated by the variability of nutrient concentrations and characteristics in the spatial perspective, both laterally and vertically, as affected by management zonation at the block level (Nelson et al., 2015; Pulunggono et al., 2022a). Specific zone or microsite occurs on OP plantation following best management practices/BMP (RSPO, 2012). Moreover, the entire microsites had their specific ecosystem functioning, particularly in providing nutrients to the peat. For instance, amelioration and fertilization are carried out in the fertilization/weeded cycle, whereas pruned fronds are stacked in the row between the OP tree. Moreover, the interrows and stacked fronds are often left overgrown by the understory's fast-growing weeds or planted with leguminous land cover crops (Ariffin et al., 2019; Luke et al., 2019; Agus et al., 2019). Based on that, total N, P, and K at the surface peat near oil palm tree were likely higher than the farther distance or deeper layer due to fertilizer addition and peat mineralization in the fertilization circle. Total N might follow these trends to some length. However, the decomposition of understory detrital materials at the farthest distance from the oil palm tree might prohibit the decreasing pattern. The decreasing trends of K were obstructed by lateral and vertical leaching since K is considered highly mobile (Sparks, 2003). Meanwhile, P was an immobile nutrient in the soil (Sparks, 2003), which may follow these distance and depth trends. Hence, the complex site-specific micro-ecosystems and interrelationships explained above can not be simplified by performing linear-based regression.

During the last decades, machine learning/ML, a part of artificial intelligence/AI, was rapidly employed as the main algorithm for soil (Padarian et al., 2020; Grunwald et al., 2021), agriculture (Meshram et al., 2021), and environmental modeling (Zhong et al., 2021). ML algorithms have an exceptional ability to automatically learn the complex pattern from data, store the learned information, and use it to improve their performance when learning a new task. This capability is considered more powerful and flexible than commonly widespread modeling algorithms, such as OLS employed by linear-based regression, particularly for the model that consists of non-linear interrelationships between its variables (Jordan & Mithel, 2015; Grunwald et al., 2021). Several researchers reported promising performance of the ML-based regression (or pedotransfer) model in predicting or mapping soil properties in tropical mineral soil, such as cation exchange capacity (Teixeira et al., 2020), soil organic carbon (Gomes et al., 2019; Poppiel et al., 2019), soil macro- and micronutrients (Pulunggono et al., 2022b), and soil acidity (Teixeira et al., 2020; Pulunggono et al., 2022b). The regression tree (RT) algorithm is one of the firstly developed ML (Breiman et al., 1984; see review by Loh, 2014). RT was considered successful in modeling several chemical and physical characteristics of mineral soils compared to linear-based models and their derivatives (Vega et al., 2009; Pinheiro et al., 2018; Qiu et al., 2016; Rawal et al., 2019). Despite their widespread usage in other fields of study, RT-based pedotransfer models' capability to estimate soil nutrients using tropical peat data was understudied.

Based on the previous information, we hypothesized that the nutrient variability was less controlled by land use since there are differences in management both in OP and its surrounding bush environment, yet considering they might undergo similar hydrological regimes. Concerning the ability of RT to handle complex and non-linear interrelationships among soil variables, we believed that RT-based N, P, and K models are more convenient compared to MLR, regardless of the data types. Moreover, the depth of sample collection could be used as a general factor for the entire data and for each different land use due to the nutrient enrichment or concentration at the surface either from fertilizer addition (OP data) or peat mineralization (OP+bush data). Lastly, the effect of distance from the oil palm tree and the depth of the sample collection was constrained heavily in OP-based models. Therefore, this study intends to determine the underlying factors governing total N, P, and K in OP cultivated tropical peatlands and their surrounding environment using a common machine learning approach, namely the regression tree/RT method.

## MATERIALS AND METHODS

### Sampling Site and Laboratory Analyses

This study was conducted in oil palm cultivated peatland, Buatan Village, Koto Gasip District, Siak Regency, Riau Province, Indonesia, as shown in Figure 1. Field sampling and laboratory analysis were carried out from January 2020 to June 2021. This study used three factors with an unbalanced design. The first factor was land use, consisting of oil palm/OP and bush. The bush was located adjacent to the OP area, allowing the possible impact of OP management (*e.g.*, drainage, groundwater level/GWL) to influence the bush's soil system. The second factor was the depth of the sample collected, which consisted of 0-20, 20-40, and 40-60 cm depths. OP land use was furthermore divided based on three distances from the oil palm tree, namely 1.5, 3, and 4.5 meters. Approximately 2 kg of peat materials were compositely sampled using an eijelkamp hand auger of 50 cm in length. All samples were 120 in total, where 90 and 30 samples were taken from OP and bush sites, respectively.

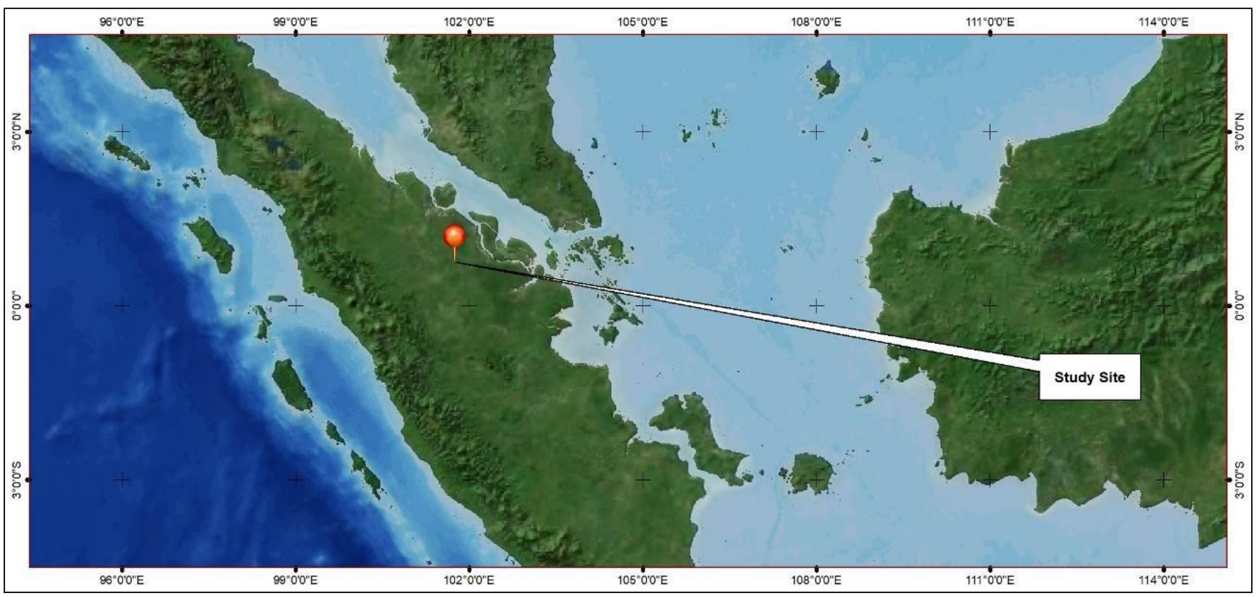



**Figure 1.** The study location

The laboratory analysis was carried out in Soil Chemistry and Fertility Laboratorium, Department of Soil Science and Land Resource, Faculty of Agriculture, IPB University. The analyzed peat chemical properties were pH, ash content, and organic C, as well as total N, P, and K. Peat pH was measured using $H_2O$ with a ratio of 1:5. Ash content and organic C were analyzed using the lost on ignition/LoI method. Total N was determined using the Kjeldahl method, whereas total P and K were determined using HCl25%.

## Statistical analyses

All graphical contents and analyses were conducted in the RStudio environment (R Core Team, 2022), except for correlation heatmaps. The packages employed in this study were tidyverse (Wickam, 2022), rpart (Therneau and Atkinson, 2022), caret (Kuhn et al., 2022), vip (Grenwell et al., 2020), rpart.plot (Milborrow, 2022), Metrics (Hamner et al., 2018), and ModelMetrics (Hunt, 2020) packages. Firstly, the tidyverse package was used to build boxplots. Then, the RT algorithm was executed utilizing the rpart and caret packages. Next, the vip package was used to extract and visualize the variable importance, partial dependence/PD, and individual conditional expectation/ICE plots. Lastly, to visualize the splitting procedure of RT after pruned, we used a rpart.plot package. Metrics and ModelMetrics packages were used to calculate model performance metrics. Furthermore, correlation heatmaps were visualized in Minitab software using the Pearson product-moment correlation method.

Before the analysis was run, the entire values (factors and variables) were qualitatively inspected, resulting in no extreme value. Therefore, we avoid the quantitative outlier detection since its consideration might be biased with respect to the high variability of tropical peat data. Moreover, we visually inspected each variable's maximum and minimum values to ensure they were inside the common ranges. Then, we run the analysis of variance and Tukey Honestly Significant Difference/HSD, as well as Pearson correlation tests to provide an initial indication of predictors' relationships with estimated nutrients and potential collinearity among the predictors. Furthermore, the datasets were randomly split into training (70%) and validation (30%) data (`seed 42`). The models were then assembled using the entire data (OP+bush) and OP data to predict the total N, P, and K in peat. This study did not consider bush data for the third model due to insufficient observation. OP+bush models involved the depth sample collection, pH, organic C, and ash content as their predictors. Moreover, OP models consisted of similar predictors to the previous models with the addition of distance from the oil palm tree. The entire predictors/covariates were chosen due to their widely known relationships with N, P, and K in soils.

This study performed the non-parametric statistical machine learning approach, namely regression tree/RT. RT was firstly formulated by Breiman, Friedman, Olshen, and Stone (Breiman et al., 1984). Thanks to its high interpretability, flexibility, and convenient usage, RT was widely used in practice and research (Ahn, 2014; Loh, 2014). Using the "divide and conquer" approach, RT partition the data recursively, diminishing the sum of squared error of model prediction/outcomes at each splits. The RT algorithm continuously undergoes the splitting process until a certain condition is achieved. The particular criterion was developed considering the trade-off between local accuracy and model complexity with the outcome's variances and model interpretability (Breiman et al., 1984). This study used the combination of cost complexity (`cp`), minimum observation in each node (`minsplit`), and maximum depth of the growing tree (`maxdepth`) parameters to penalize the tree from growing too deep (or 'pruning'), thereby preventing model overfitting. To select the best parameterization of each model, we used the grid search of a certain range of minsplit and maxdepth combined with the ten-fold cross-validation (`xval= 10`), as summarized in Table 1. This study also performed standard multiple linear regression (MLR) as a benchmark compared to RT's model performances, which selected RMSE, MAE, and Bias as the metrics. The relative variable importances were calculated using the Gini importance/GI or mean decrease in impurity/MDI approach for RT models and the absolute value of the t-statistic for MLR models (Grenwell et al., 2020). To gain more clearance on RT-based model interpretability, the marginal effects of each variable/predictor on the predicted nutrients were computed and visually plotted using partial dependence/PD and individual conditional expectation/ICE curves.

**Table 1.** Model parameterization of RT algorithm specified for each model employed in this study

| Model | Minsplit | Maxdepth | cp |
|---|---|---|---|
| *All (OP+Palm) Dataset* | | | |
| N | 5 | 6 | 0.02 |
| P | 21 | 17 | 0.01 |
| K | 24 | 21 | 0.01 |
| *OP Dataset* | | | |
| N | 7 | 7 | 0.03 |
| P | 11 | 4 | 0.01 |
| K | 18 | 16 | 0.01 |

## RESULTS

### Chemical Properties of the Studied Peat

The results of peat chemical analyses are summarized in Figure 2. The figures showed that the entire chemical variables were in the range of common values found on peat, as reported by other researchers (*e.g.*, Dhandapani et al., 2020). It could be observed that both land uses seemingly had similar ranges of soil chemical variables, overlapping one another. Other factors also exhibited similar trends, except for total P and K. Both variables were likely higher at the peat surface compared to the lowest sampling depth. However, the peat sampled at 20-40 cm had values in the range of other sampling depths.

The observed means of organic C were higher in the bush site compared to the OP site. However, contrasting patterns were observed in pH, ash content, and total P. Similar means at both sites were exhibited by total N and K. Based on the distance from the oil palm tree, ash content and total N showed relatively similar trends. Their means were increased along with the increasing distance up to three meters. Then, they dropped again at their farthest distances.

In contrast, the organic C content of the studied peat showed the pattern oppositely to the previously described pattern of other variables. They denoted the lowest mean at three meters from the oil palm tree, whereas the first and the last were relatively high. The resemblances also likely occurred for the ranges and means of ash content, total N and P sampled at the bush and the farthest distance from the oil palm tree. Obstructed effects of the distances from oil palm trees were exhibited by pH and total K, which showed relatively flat curves along the increase of the distance from the oil palm tree. Based on sampling depth, pH, ash content, and total P and K showed decreasing trends along with the increase in sampling depth. Opposite trends were exhibited by organic C and total N.

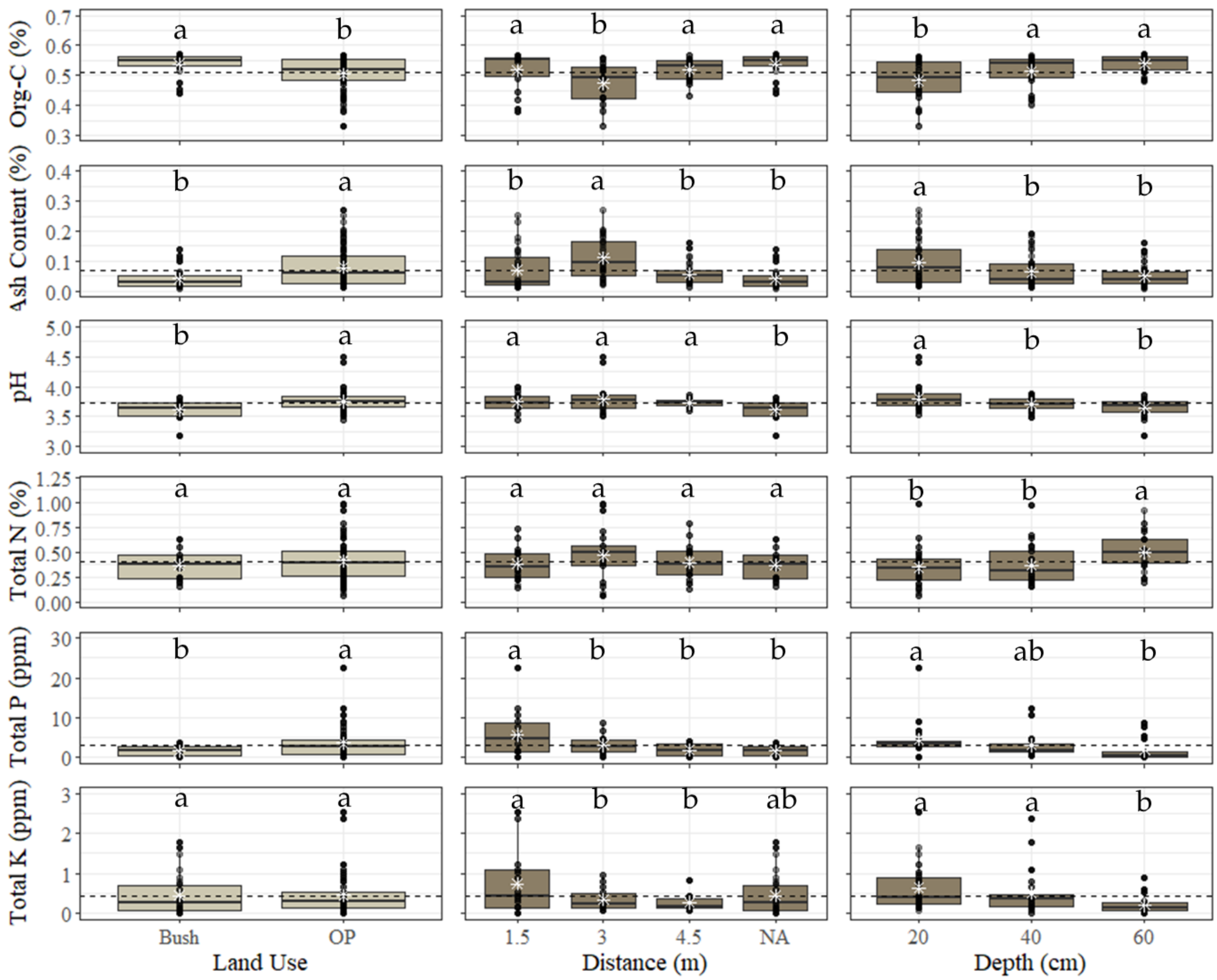



**Figure 2.** Chemical characteristics of studied peat based on land use, distance from the oil palm tree, and depth of sample collected. Note that NA's in distance graphs indicated the samples collected outside the OP area. The white asterisks and black horizontal lines inside the boxplot indicate mean and median values, respectively, whereas the black dotted lines indicate means from the entire data. Depth, Distance, and Org-C represent the depth of sample collection, distance from the oil palm tree, and organic C, respectively. The letter above the boxplots indicated differences concerning Tukey HSD test.

The correlation heatmaps are shown in Figure 3. All correlations were low to moderate on the entire variables, leaving only organic C and ash content with high correlations. OP data also showed similar relationship strengths. Total N generally exhibited a low correlation with other factors and variables, except for depth which had a moderately positive correlation in both OP+bush and OP data. Using OP+bush data, total P and K had moderate correlations with all factors and variables. Meanwhile, similar relationship strengths were denoted by the same variables using OP data, except for their insignificant strength with organic C and ash content (only for total P).

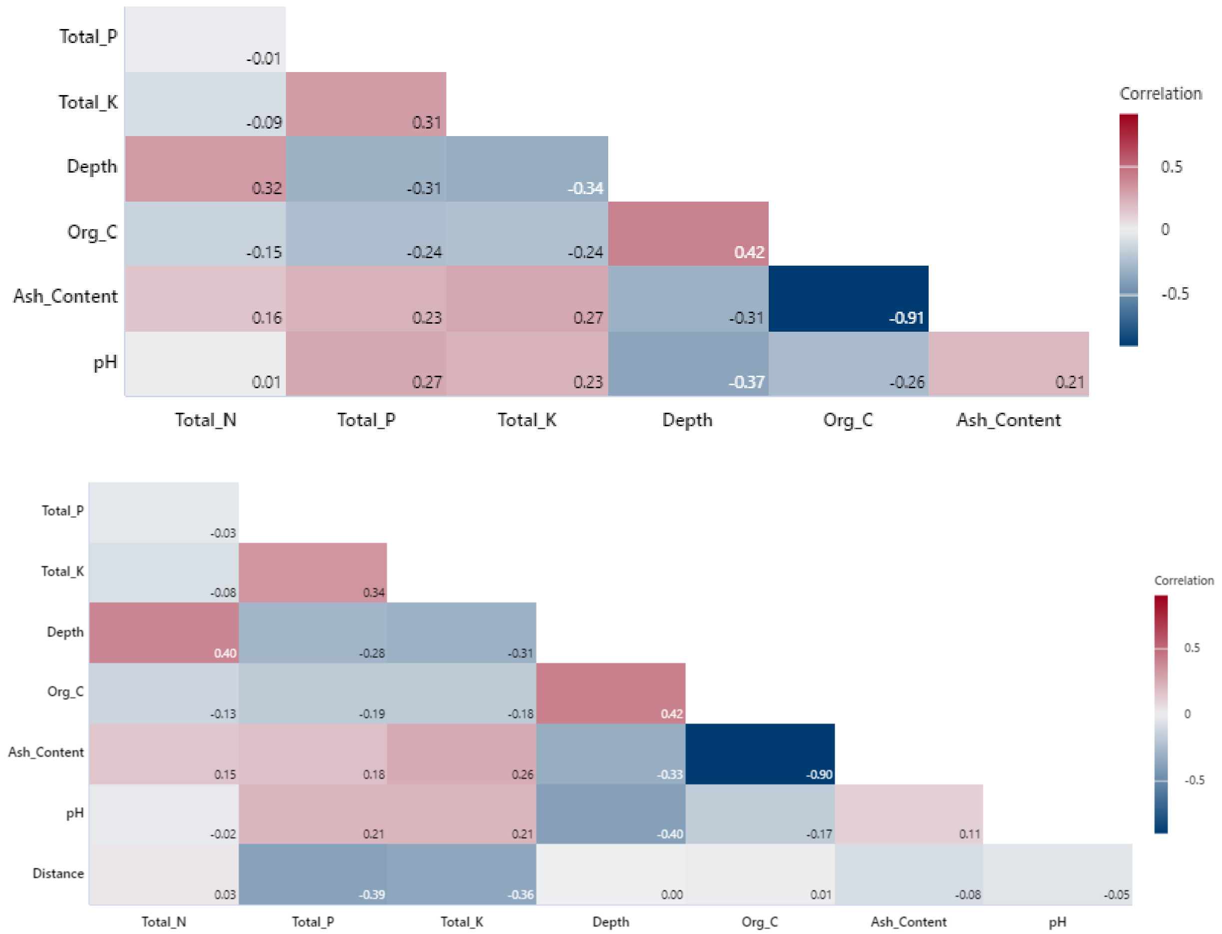



**Figure 3.** Correlation matrix supplied to heatmaps of all variables used in this study. The upper graph represents all data (OP+bush; N=120). The lower graph represents only OP data (N=90). Depth, Distance, and Org_C represent the depth of sample collection, distance from the oil palm tree, and organic C, respectively.

## RT-based Pedotransfer Model Evaluation

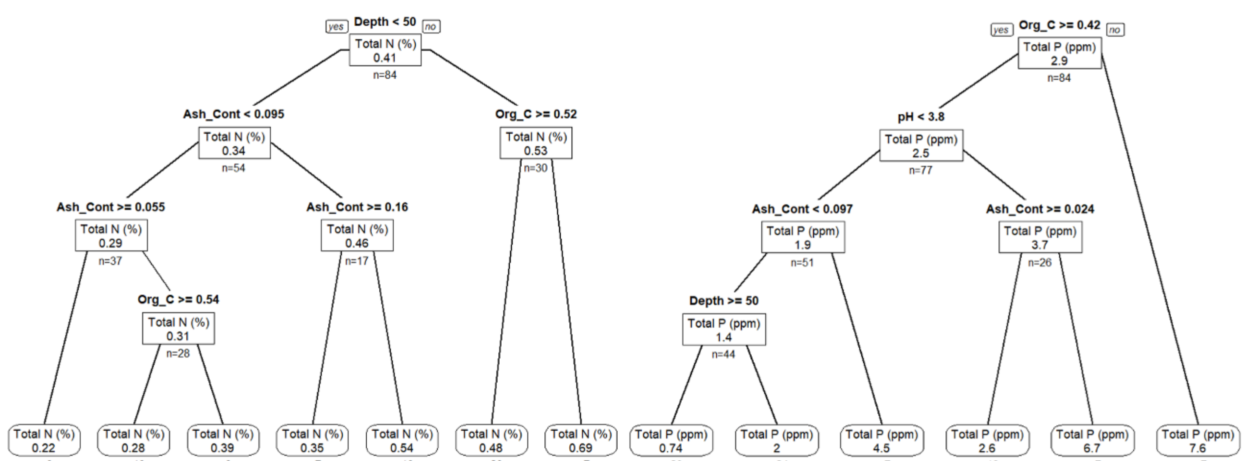
The model evaluation for the entire models employed in this study was presented in Table 2. In general, RT prediction of total N and P showed a slight improvement compared to MLR. However, the entire metrics of RT's models of total K exhibited poor performance than MLR. Generally, OP+bush models showed the predicted value of RT models overestimated the observed values. Oppositely, the contrasting patterns were denoted by OP-based models. Besides their huge algorithm differences, MLR and RT showed the same over-and underestimation patterns in bias regardless of the dataset types.

**Table 2.** Model evaluation from the entire RT models performed in this study in comparison with MLR models

| Dataset | Algorithm Type | Predicted Output | RMSE | MAE | Bias |
|---|---|---|---|---|---|
| OP+Bush | MLR | Total N | 0.18358 | 0.15554 | -0.01506 |
| | | Total P | 0.19548 | 0.12016 | 0.02820 |
| | | Total K | 0.64168 | 0.41581 | 0.11363 |
| | RT | Total N | 0.19149 | 0.14406 | -0.01017 |
| | | Total P | 0.19017 | 0.11210 | 0.02291 |
| | | Total K | 0.66864 | 0.44671 | 0.07962 |
| OP | MLR | Total N | 0.17566 | 0.14446 | -0.01823 |
| | | Total P | 4.37354 | 2.78739 | -0.11845 |
| | | Total K | 0.53507 | 0.36313 | 0.03928 |
| | RT | Total N | 0.17350 | 0.13196 | -0.03047 |
| | | Total P | 4.16727 | 2.75208 | -0.02595 |
| | | Total K | 0.61454 | 0.41430 | 0.03388 |

## RT-based Pedotransfer Model Interpretation

The RT approach in predicting total N, P, and K was shown in figures 4 (OP+bush data) and 5 (OP data), whereas the MLR model summary was presented in Table 3. The results showed that the entire OP+bush models contained the organic C, ash content, and depth of sample collection as their primary splitting rules. Meanwhile, ash content was a common variable in the entire OP-based models. Therefore, organic C and depth were considered variables that primarily influenced total N and P predictions in the OP area. Furthermore, the RT algorithm considered the distance from the oil palm tree as the factor that specifically influenced total P prediction. However, we did not observe similar effects on total N and K at the same site. When utilizing OP+bush data, both RT and MLR models agreed on depth as one of their building block variables, regardless of the predicted nutrients. In addition, pH and distance from the oil palm tree were involved in both RT and MLR model development.



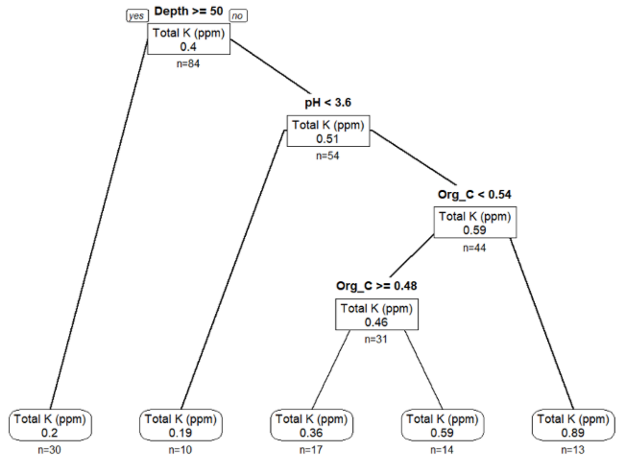



**Figure 4.** RT diagrams of the total N (upper-left), P (upper-right), and K (lower) using OP+bush data. Note that the values inside the boxes are means. The values outside the boxes represent the number of observations concerning the total amount of training data.

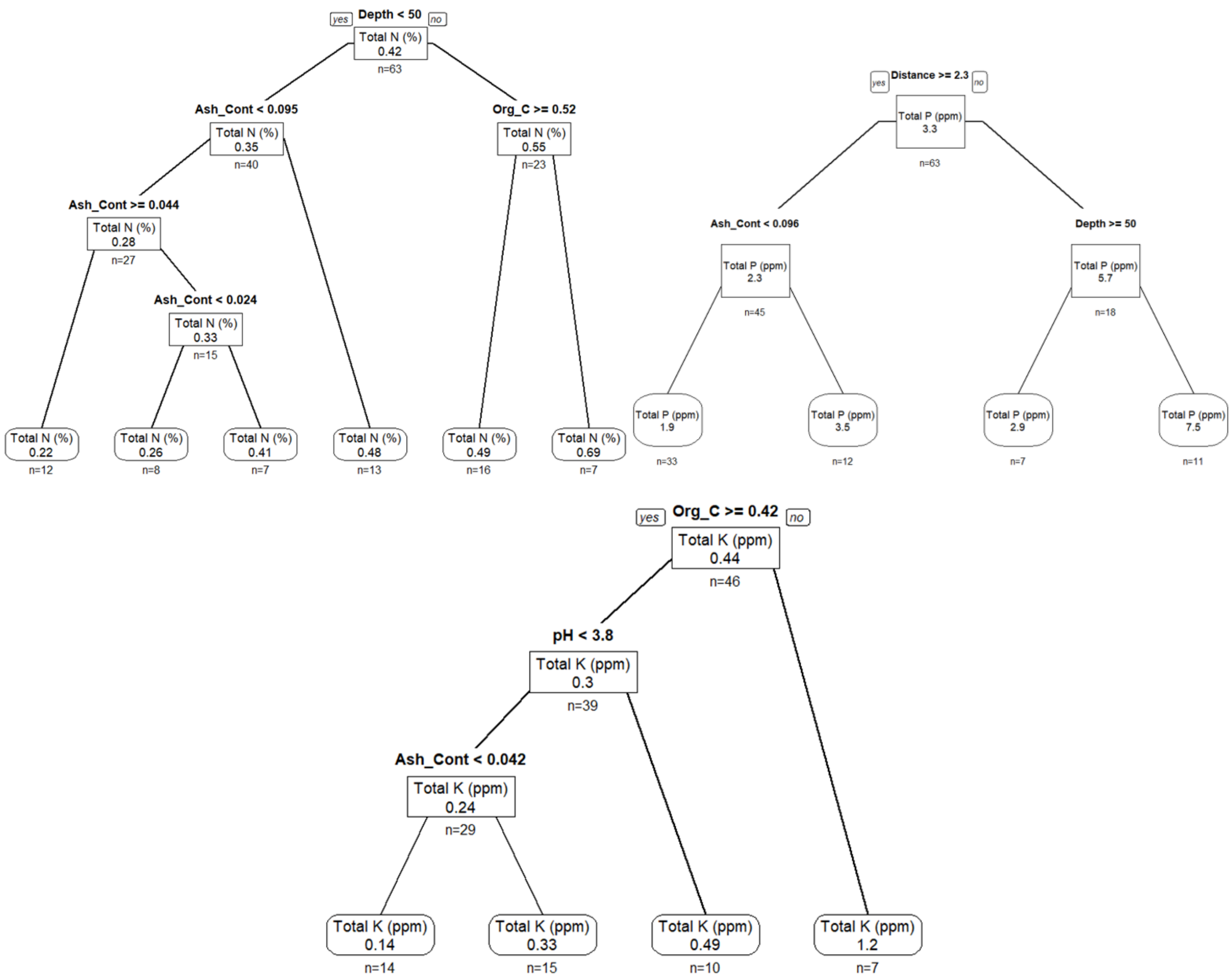



**Figure 5.** RT diagrams of the total N (upper-left), P (upper-right), and K (lower) using OP data. Note that the values inside the boxes are means. The values outside the boxes represent the number of observations concerning the total training data.

**Table 3.** Summary of the entire MLR models used in this study

| Factors | OP+Bush Dataset | | | OP Dataset | | |
|---|---|---|---|---|---|---|
| | Total N | Total P | Total K | Total N | Total P | Total K |
| Intercept | -0.043002 | -0.11077 | -1.703783 | 0.134981 | 5.91966 | -0.497520 |
| Distance | - | - | - | -0.005788 | **-1.32472** | **-0.128856** |
| Depth | **0.006764** | **-0.07056** | **-0.011289** | **0.320700** | -0.05087 | -0.004825 |
| Org_C | -0.429896 | 0.16669 | 2.292648 | -0.027073 | 2.55642 | -0.601756 |
| Ash Content | 0.716152 | 0.20206 | 1.138609 | 0.265964 | 14.75097 | 2.670156 |
| pH | 0.094643 | **0.23339** | 0.353830 | 0.146463 | 0.34123 | 0.426085 |

**Note:** Depth, Distance, and Org_C represent the depth of sample collection, distance from the oil palm tree, and organic C, respectively. Bold values indicated statistical significance using 90% confidence intervals.

Corroborating the previous results presented in Figures 4 and 5, the Gini/MDI-based relative variable importance of RT models in Figure 6 revealed that organic C was generally the most critical predictor in OP+bush or OP models. Moreover, ash content, depth, and pH were respectively the second, third, and fourth variables of RT models that were important to predict total N, P, and K using OP+bush and OP data. This study also found that the distance from the oil palm tree was the least important variable in predicting total N and K in the OP site. Particularly for total K prediction using OP data, we observed that both the distance from the oil palm tree and the depth of sample collection were considered unimportant, shown by their lowest relative importance compared to other variables. Unlike RT models, the organic C content showed less contribution to the MLR models developed on OP+bush or OP data.

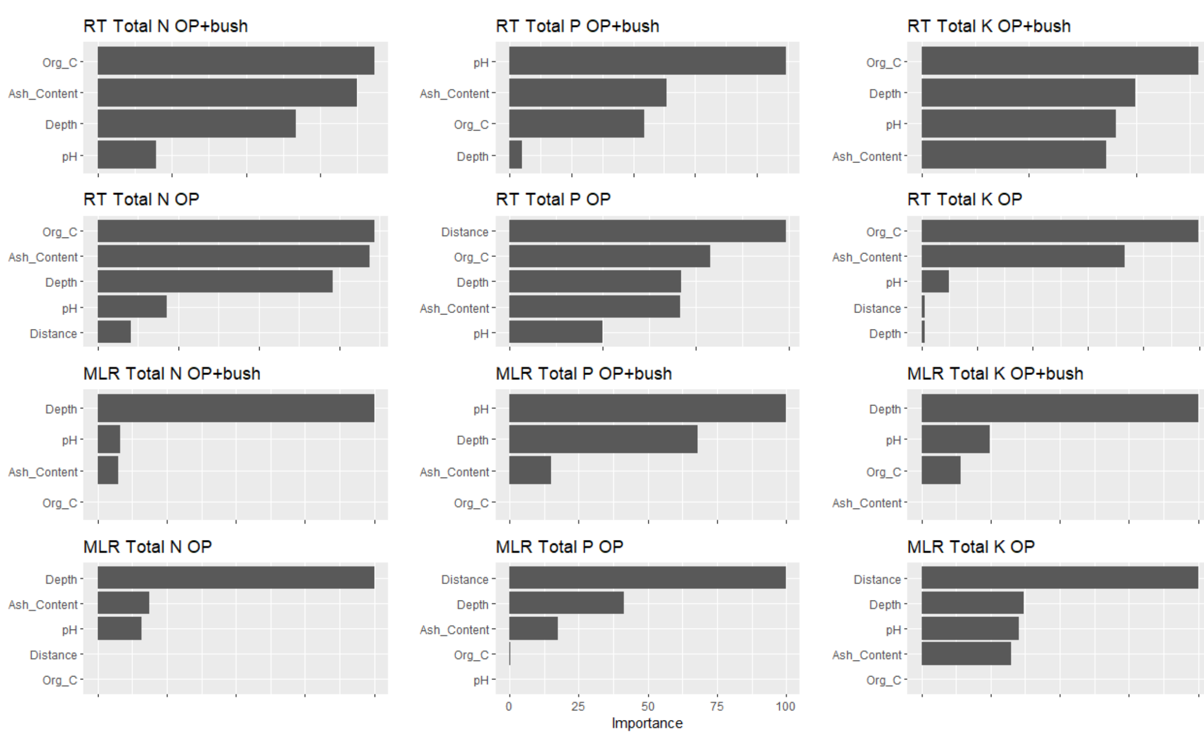



**Figure 6.** Relative variable importance from the entire models performed in this study.

The PD and ICE plots for the entire RT models employed in this study were presented in Figure 7. The figure showed that most variables exhibit non-linear relationships with the predicted nutrients (total N, P, and K; expressed as yhat). However, the marginal effect of PD and ICE curves denoted low or no relationships with the predicted nutrients, for example, pH for N prediction using OP+bush data and distance from the oil palm tree for N and K prediction using OP data.

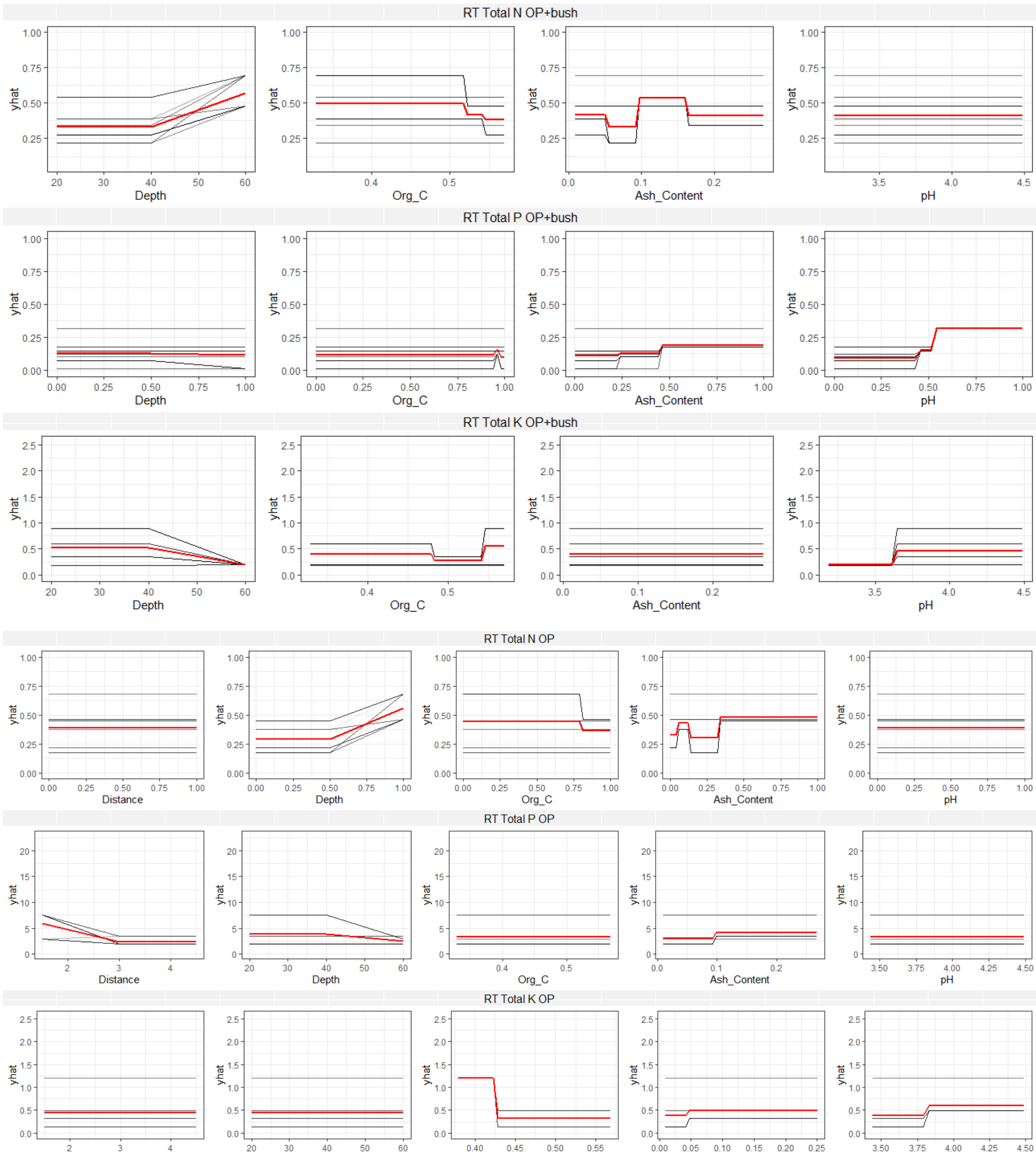



**Figure 7.** PD (red lines) and ICE (black lines) curves of the RT models in predicting total N, P, and K (expressed as yhat in the Y axis) using OP+bush and OP data.

## DISCUSSION

This study emphasized the importance of using a non-parametric ML approach, namely regression tree/RT, to analyze and interpret highly variable tropical peat data. This study also corroborates previous findings and results, reporting the promising performances of several RT-based models over their MLR counterparts.

Our RT approach showed that land use might be a primary factor in estimating total N, P, and K in cultivated tropical peatlands and their surrounding area. This was shown partially by the difference between the factors and variables controlling total N, P, and K in OP and OP+bush sites. Based on the RT approach (Figures 4, 5, and 6), organic C, ash content, and depth were the common variables and factors regulating total N, P, and K in OP+bush and OP sites. Notably, pH possessed high relative importance in developing an RT-based model for total P prediction at the OP+bush site (Figures 4 and 6). Furthermore, among other variables, distance from the oil palm tree became the salient feature that notably governed total P in the OP site (Figures 5 and 6).

The differences in variables controlling nutrients in the soil as affected by different land use can be explained by the difference in management and nutrients' chemical characteristics. The surface peat in the OP site was continuously fertilized and ameliorated along the fertilization circle following best management practices/BMP of the oil palm plantation in peatland (RSPO, 2012; Pauli et al., 2014; Corley & Tinker, 2015). This condition caused the distance from the oil palm tree, and the depth of sample collection becomes important for immobile nutrients such as P. Peat located closer to the oil palm tree might contain a higher P concentration compared to farther distance. Furthermore, a similar condition also undergoes between the surface and subsurface layers, respectively (Fairhurst, 1996; Woittiez et al., 2019). Meanwhile, the lessening effect of both variables on the total K model (Figure 6) was possibly caused by high K mobility. K had less tightened bonding with organic exchange sites than other ions (*i.e.,* Ca, Mg; Sparks, 2003; Tipping, 2004), provoking cation competition and vertical-lateral leachings.

Furthermore, our study's results also proved the "ecological fallacy" that could be made when comparing the difference between individual land use (OP) and the aggregate group (OP+bush) data. The relative strength of the variables in regulating more mobile nutrients, *i.e.,* total N and K prediction, exhibited slight differences between OP+bush and OP data, both in RT and MLR models (Figures 4, 5, and 6). This indicates the behavioral similarities of nutrients and their predictor between individual and aggregate data. These results were possibly due to relatively similar environmental conditions, particularly in hydrology or water management, since the sampling at the bush site was conducted adjacent to the OP site. Moreover, to avoid the fallacy, it can not be assumed that this similarity would also be undergone at the bush site with respect to our observation insufficiency. The difference was evident in immobile nutrients such as P (Figures 4, 5, and 6), suggesting the carefulness in interpreting individual and aggregate data and statistics. These contrasting conditions related to particular nutrients are an interesting subject. However, further study must be conducted using more observations that account for spatial and temporal variability to provide reliable models and gather sufficient evidence.

Similar marginal effects were shown by the distance from the oil palm tree on N prediction in the OP site (Figures 6 and 7). The BMP management allowed the fast-growing weeds (Ashton-Butt et al., 2018; Luke et al., 2019; Rahman et al., 2021) or leguminous plants (Arifin et al., 2015; Agus et al., 2019) to occupy the interrow and frond stack as understory cover crops/UCC. N mineralization derived from UCC's litter decomposition could enhance N in peat outside of the fertilization circle, hence, minimizing the effect of distance. However, the exact impact seemingly did not occur in K due to its low immobilization in the UCC plant (Joo et al., 1994) and poor K source of peat materials (Mohidin et al., 2019; Dhandapani et al., 2020). The obstructed effects of the distance from the oil palm to total N and K in the OP site could also arise while the OP management applies empty fruit bunches/EFB or EFB-based compost outside of the fertilization circle (*e.g.,* Rahman et al., 2021). Composted EFB contained relatively high N and K compared to other nutrients (Mardhiana et al., 2021), whereas EFB ash had K in a substantial amount (Anyaoha et al., 2018). Therefore, the EFB application could boost K in peat at the farthest distance from the oil palm tree, resulting in no distance relationships. Thus, incorporating bush data leads to more obfuscated effects on the sample collection depth since no additional nutrients were added to the peat (Figure 6).

As shown in Figure 2, the entire ranges of total N, P, and K overlap while divided by land use, distance from the oil palm tree, and depth of sampling collection. The obstructed effect would be detected by performing the classical parametric test (*e.g.,* F-test, T-test, MLR; Figure 2; Table 3). MLR capability was seemingly constrained (Table 3) since most of our predictors exhibited non-linear relationships with total N, P, and K, regardless of the dataset differences (Figure 7). Concerning common modeling considerations, all of our models might suffer low observation numbers, noisy variables (Figure 2), inadequate related predictors (Figures 3 and 7), and heteroscedasticity (Figure 3). Nevertheless, most of our RT models showed a relatively robust prediction against the confounding factors described above. In both datasets, RT-based total N and P models gained slight performance improvements compared to MLR (Table 2). The RT models reportedly outperformed MLR and its derivatives (*e.g.,* stepwise backward or forward eliminations, general linear model/GLM) in predicting sorption and retention of heavy metals (Vega et al., 2009), topsoil texture (Pinheiro et al., 2018), soil heavy metal content (Qiu et al., 2016), and base saturation percentages (Rawal et al., 2019). The higher capability of RT compared to MLR was also reported in other fields, such as airborne bacterial hazard assessment (Yoo et al., 2018) and landslide susceptibility (Pourgashemi & Rahmati, 2018).

Improved performances of our RT models' prediction would be achieved when the models are developed using outlier-removed and large quantities datasets. To build proper RT models, redesigning our sampling methodology could also be considered, concerning some gradual changes in total N, P, and K observed at several continuous factors (Figure 2). For example, the peat variables collected at 20-40 cm depth had intermediate values and ranges over their upper and lower depths. Similar patterns were also observed in the variables of peat collected at a 3 m distance from the oil palm tree, which exhibited the intermediate values and ranges of peat variables at near and farther distances. Since the RT algorithm works in partitioning terms, this approach is likely to prefer sharp or abrupt changes of their input variables and suffer from smooth and gradual variable changes (Trontelj ml. & Chambers, 2021). Without removing the intermediate-source classes in attributed factors, more flexible ML-based models (*i.e.,* random forest, gradient boosting regression, support vector regression) must be employed to obtain considerable prediction agreements.

## CONCLUSIONS

This study demonstrated the importance of the ML approach, namely regression tree/RT, in analyzing factors and variables controlling total N, P, and K in tropical cultivated peatlands and their surrounding environment. Our RT approach partially showed that land use might be vital in regulating N, P, and K in our study area. The depth of sample collection was found as an essential factor in predicting total N, P, and K in cultivated tropical peatlands and their surrounding area; meanwhile, a similar influence was exhibited by organic C and ash content. Notably, pH possessed high relative importance in developing an RT-based model for total P prediction at the OP+bush site; the same nutrient was importantly governed by the distance from the oil palm tree in the OP site. Despite the limitation of RT algorithm that prefers sharp or abrupt changes of the input variables values, this study's results indicated that integrating ML-based pedotransfer functions in the soil scientist statistical inventory is essential in analyzing and interpreting complex tropical peat data. Furthermore, our initial study also pinpointed the possibility of the tabular and spatial-based pedotransfer model development for agricultural practician, researchers, companies, and farmers to predict macronutrients in cultivated tropical peatlands.

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