Simulating and modeling CO$_2$ flux emitted from decomposed oil palm root cultivated at tropical peatland as affected by water content and residence time

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Abstract

Determining the oil palm dead roots contribution to total (R$_t$) and heterotrophic (R$_h$) respiration as a source of greenhouse gas/GHG emission in tropical peatland is urgently required, as well as predicting their magnitude to cope with difficulties of direct in-situ measurement. This study is designed to simulate the CO$_2$ flux emitted from oil palm dead roots/R$_{de}$ in tropical peatland as affected by water content/WC and residence time/RT. The dead oil palm roots were cleaned, treated with control/15, 100, 150, 300, and 450% WC, and then incubated for three months. CO$_2$ flux measurement, C, N, and CN ratio determination were conducted every month. This study demonstrated the importance R$_{de}$ among other CO$_2$ emission sources, ranging from 0.05-2.3 Mg CO$_2$ ha$^{-1}$ year$^{-1}$ with an average of 0.7 Mg CO$_2$ ha$^{-1}$ year$^{-1}$. R$_{de}$ contribution for literature R$_t$ and R$_h$ were around 0.3 to 1.3 and 0.9 to 3.5%, respectively. As a product of microbial respiration, R$_{de}$ was affected by WC and RT, supported by analysis of variance, linear mixed effect model/REML, and multivariate analysis. 100-150%WC resulting in significant and highest R$_{de}$, whereas the increase (300-450%WC) or decrease (15%WC) would generate lower emission. R$_{de}$ culminated in the first month after incubation; meanwhile, it declined in the following months. This study also emphasized non-linear relationships between CO$_2$ flux and other root properties, which can be modeled conveniently using non-linear approach, particularly using polynomial and artificial intelligence-based models. The simulation presented in this study served as an initial attempt to separate R$_{de}$ from R$_{de}$, as well as to predict CO$_2$ flux with reasonable accuracy and interpretable methods.

Keywords:
artificial intelligence
dead root
greenhouse gas
incubation time
respiration

Introduction

Oil palm (Elaeis guineensis Jack.) is a commodity that plays an essential role in the Indonesian economy, accounting for 11.58 percent of total export in 2020 (BPS-Statistics Indonesia, 2020; BPS-Statistics Indonesia, 2022). Capturing the high demands for global palm oil, the oil palm plantation spreads around 14.66 million hectares (BPS-Statistic Indonesia, 2022) across Indonesian islands. Due to the limited...
availability of permitted mineral soil areas, oil palm plantations expanded over peatlands (1.7 million hectares) and mainly occupied Sumatran peatlands (Dohong et al., 2018; Dadap et al., 2021). Managing cultivated peatlands in this area is considered necessary, owing to its ability to sequester vast amounts of carbon over a prolonged period, thus mitigating the detrimental impact of climate change.

The development of natural peatlands into oil palm plantations significantly impacts peatland ecosystems, particularly for generating high greenhouse gas (GHG) emissions (e.g., Hooijer et al., 2012; Leifeld et al., 2019); hence, changing peatlands from CO₂ sinks to sources (Miettinen et al., 2017). Widespread studies encompass CO₂ emissions from oil palm cultivated peatland, quantifying CO₂ fluxes from microsites (e.g., Manning et al., 2019; Dhandapani et al., 2022) to ecosystem scales (e.g., Deshmukh et al., 2021; McCalmont et al., 2021). Especially for Rₘ emission factor, many research works have been conducted involving the contribution of peat materials (Hergoualc'h et al., 2017; Pulunggono et al., 2022) as well as decomposed parts of oil palm pruned components (Wakhid and Hirano, 2021) and understory litters (Pulunggono et al., 2022). Autotrophic respiration (Rₐ) from living oil palm roots was also widely reported, contributing a significant portion to total CO₂ emission (Darrah et al., 2014; Sabiham et al., 2014). Unfortunately, searching for the reports concerning their decomposed dead parts’ contribution to Rₐ or Rₑ would return minimal information.

To the best of our knowledge, there are no studies investigating the potential of Rₑ tropical peatland. Differently from their living one, dead roots fragment is difficult to separate from the surrounding peat materials. Notably, insufficient available information could become the confounding factor in designing an appropriate method to insulate CO₂ that emanates from oil palm dead roots. However, their potential for CO₂ emission sources is urgent to be estimated since dead root contribution has been confirmed under different soil types and vegetations (Larionova et al., 2006; Zhou et al., 2021). Published reports in mineral soils revealed that the dry matter of living oil palm roots varied with age, ranging from 0.17±0.01 to 17±1.9 kg palm⁻¹ year⁻¹ (Khalid et al., 1999; Corley and Tinker, 2016; Siang et al., 2022). Oil palm roots have a higher density at the soil surface (Sabiham et al., 2014) and have undergone rapid normal dieback along with the increasing age, accounting for 82% of roots lost in the fourth year. Furthermore, root turnover was more intense on secondaries and fine roots (31% and 57%, respectively, for each year), annually incorporating 4.5 to 11.5 Mg ha⁻¹ of dry matter into the soil (Corley and Tinker, 2016). Although the previous information was based on different soil types, the magnitude of accumulated root dead material could be a plausible source of CO₂ with respect to the lower portion of solid fraction contained by peat soil (approximately 200 Mg ha⁻¹ at upper 20 cm; hemic-sapric peat with bulk density 0.1 g cm⁻³).

Extrapolating into the field level, this study expected a higher contribution of Rₑ to the Rₐ and Rₑ than oil palm fronds (Rₑ; Wakhid and Hirano, 2021). Meanwhile, Rₑ is assumed to contribute similarly or slightly lower compared to the understory litters (Rₑₘ; Pulunggono et al., 2022) since there is a trade-off between plant, soil, and climatic processes at the soil surface. Although both (roots and fronds) components possess high lignin content, as well as share comparable amounts of C, cellulose, and hemicellulose (Pulunggono et al., 2019; Shrivastava et al., 2020; Wakhid and Hirano, 2021), the most rapid turnover was undergone on the primary and secondary roots that have much lower CN ratio compared to the fronds (Violita et al., 2016; Pulunggono et al., 2019). Meanwhile, understory litters were contributed primarily by fern detrital materials, which also possibly possess a similar CN ratio with primary and secondary roots. Contrastingly, groundwater level (GWL) and peat water content/moisture (or water-filled pore space/WFPS) generally affect CO₂ emission in tropical peatlands (Melling et al., 2005; Ishikura et al., 2017; Manning et al., 2019). Carlson et al. (2015) find that the lower magnitudes of CO₂ emission from different plantation sites are attributed to the rise of GWL near the peat surface, therefore, increasing the peat water content/WFPS. Furthermore, Pulunggono et al. (2022) mentioned the importance of latency or residence time of precipitation that may affect GWL and peat water content/WFPS and restrict the peat aeration, thus halting the respiration process. However, under improper management or during the dry season/El-Nino, the deepening of GWL leads to decreasing peat water content/WFPS. It can significantly boost the microbial process in decomposing organic material near the peat surface, similar to microsites with the highest density of dead root fragments.

Measuring heterotrophic CO₂ flux directly in tropical peatland is challenging due to time-consuming, expensive instruments, and highly variable weather. Some particular skills and expertise are needed before, within, and after the measurement process, as well as while the main detectors/sensors go unstable, flawed, or damaged. Furthermore, advanced statistical modeling development provides an alternative solution to cope with the limitation and difficulties of traditional direct measurement. Artificial intelligence/AI-based models, for example, can "learn and recognize" patterns with reasonable accuracy, as well as less constrained from outliers, multicollinearity, heteroscedasticity, and non-linear relationships. Besides having the capability to manage either small or huge observation data, AI models also provide more flexibility than biochemical and process-based models due to their free-mechanism approach (Melling et al., 2005; Feng et al., 2019; Padarian et al.,
These abilities are considered very appropriate to overcome the interconnected and non-linear relationship problems demonstrated by peat chemical properties and CO$_2$ flux (e.g., Melling et al., 2005; Ishikura et al., 2017; Nurzakiah et al., 2021; Pulunggono et al., 2022). Current reports demonstrate promising performances of AI-based models in predicting CO$_2$ flux in subtropical peat and mineral soils at regional and global scales (Bond-Llamberty, 2018; Holl et al., 2020; Adjuik and Davis, 2022); unfortunately, their application in tropical peatland environment are limited, particularly for root-related respiration. This study hypothesized that the AI-based models could conveniently handle $R_{dr}$ prediction compared to the linear model.

Hence, this study is intended to simulate the effect GWL/WFPS and their residence times on $R_{dr}$ by conducting a simulation study with varied roots’ water content/WC and incubation time/IT. Furthermore, this study also develops several pedotransfer models and verifies their performance in predicting $R_{dr}$.

Materials and Methods

Research site

This study was conducted from January 2020 to June 2021. The research site was a 10-15 years old oil palm plantation in PT Kimia Tirta Utama plantation, Buatan Village, Koto Gasib District, Siak Regency, Riau Province (0°44'44" N; 101°46'22" E), as shown in Figure 1. Moreover, the incubation process was held in the Soil Chemistry and Fertility Laboratory, Department of Soil Science and Land Resources, Faculty of Agriculture, IPB University.

Research design, laboratory analysis, and CO$_2$ flux measurement

This study was carried out using a single factor, completely randomized design consisting of five treatments. Five treatments were applied, consisting of control (without water addition, water content (WC) = 15%), 100% water content, 150%, 300%, and 450%. Each treatment was repeated five times; hence, 25 experimental units were obtained. The incubation time lasted for four months.

The oil palm dead roots were purposively collected hemic peat, representing 0-60 cm depth. The samples were firstly air-dried. The soil particles were then removed through the flowing water (Figure 2). Moreover, the roots were sliced into 2 cm fragments and then incubated inside the container (averaged 100.09 g per container). N total was determined using the Kjeldahl method; meanwhile, organic C was determined using the loss on ignition/LoI method. The roots were also weighted at the first and last observations (months 0 and 3, respectively).

CO$_2$ flux measurement and analysis were carried out at the Soil Chemistry and Fertility Laboratory, Soil and Land Resources Department, Faculty of Agriculture, IPB University. The CO$_2$ flux of decomposition roots was measured every two weeks using calibrated IRGA (Infra Red Gas Analyzer) Li-COR 830 with the closed-chamber method. IRGA was flowed by gas from the chamber, and CO$_2$ flux concentration was read within ±2 minutes.

Figure 1. Map of the research site.
The CO\textsubscript{2} flux was measured concurrently with the temperature inside the chamber. Moreover, the height of the chamber lid to the surface of the root samples was also measured. The results are then calculated by the equation:

$$fc = \frac{Ph \, dC}{RT \, dt}$$

With the description, \(fc\) is the flux value (mg m\textsuperscript{-2} sec\textsuperscript{-1}), \(P\) is atmospheric pressure, \(h\) is the high cover of the surface, \(R\) is the gas constant (8.314 Pa m\textsuperscript{3} K\textsuperscript{-1} mol\textsuperscript{-1}), \(T\) is the temperature (°K), and \(\frac{dC}{dt}\) is the linear change in CO\textsubscript{2} concentration (Madsen et al., 2009).

The value calculated from the equation above is considered as CO\textsubscript{2} emitted from the surface that entirely consisted of dead roots. Concerning the lack of studies which quantified the percentage of peat surface occupied by dead root, this study developed an approach to solve the issues using the percentage of incorporated root dry mass to total solid masses in peat (root dry mass+peat) per meter cubic of soil column at 60 cm depth and 1.5 m distance from the oil palm tree. Incorporated root dry mass was calculated from root dry mass reported by Khalid et al. (1999) and the average of secondary and fine roots annual turnover (Corley and Tinker, 2016). Both root types were selected due to their high density and turnover compared to primary roots at the measured depth and distances (Sabiham et al., 2014; Corley and Tinker, 2016). Peat bulk density was set to 0.1 g cm\textsuperscript{-3}. The authors assumed that the roots were uniformly distributed along the depth and distance to simplify the equation, following the generalization of root density as described by previous reports (Khalid et al., 1999; Corley and Tinker, 2016) and the average depth of peat acrotelmic zone in the study area (Pulunggono et al., 2022).

**Statistical analyses and CO\textsubscript{2} flux modeling**

Data collation was performed using Microsoft Excel. Before the statistical analyses were conducted, the data was subjected to absolute value elimination, outlier removal, and normality inspection. Due to the measurement error, CO\textsubscript{2} fluxes exceeding 0.14 mg m\textsuperscript{-2} sec\textsuperscript{-1} were discarded. Then, log transformation was applied to attain normality. One-way analysis of variance/ANOVA was used to separately assess the difference of CO\textsubscript{2} flux as affected by the given factors, followed by Tukey honestly significant difference/HSD as the post hoc test. Moreover, a linear mixed-effect model with restricted maximum likelihood/REML was applied to obtain multiple effects with interaction, incorporating organic C, total N, and CN ratio as random factors. Incorporating random factors in REML maximized the model's capacity (with imbalance observation data) in explaining variance compared to two-way ANOVA type-III. Furthermore, principal component analysis/PCA was also employed to assess underlying factors that may control CO\textsubscript{2} emitted from decomposed oil palm roots. The entire analyses were executed in R environment using stat, multcompView (Graves et al., 2019), lme4 (Bates et al., 2021), factomineR (Husson et al., 2020), and factoExtra (Kassambara and Mundt, 2020) packages.

This study also developed several linear and non-linear-based pedotransfer models between CO\textsubscript{2} flux with the treatments and several root properties in the R environment. The model was divided by two conditions, as represented by the following formulas:

\[
\text{Model1} \leftarrow \text{CO}_2 \, \text{Flux} ~ \text{WC} + \text{IT} + \text{organic C} + \text{total N} + \text{CN ratio}
\]

\[
\text{Model2} \leftarrow \text{CO}_2 \, \text{Flux} ~ \text{WC} + \text{IT} + \text{organic C} + \text{total N} + \text{CN ratio} + \text{Weight loss}
\]

This study used nested division, which firstly divided the randomized dataset (seed = 42) into training (70%) and validation/testing (30%) datasets. Secondly, the best predictive models were acquired using grid search with tenfold repeated cross-validation on the training datasets.

Several polynomials and AI-based models, including machine learnings/ML's and deep learnings/DL's techniques, were assembled to fit the models. This study also performed standard multiple
Results and Discussion

*R* \(_h\) emission factor and its contribution to \(R_h\) and \(R_t\)

As shown in Table 1, CO\(_2\) emission studies in tropical peatland cultivated by oil palm plantations had been conducted over decades without any significant progress in separating heterotrophic respiration of oil palm dead roots from their surrounding peat materials. This study demonstrated the importance of \(R_h\) among other CO\(_2\) emission sources, which can be interpreted as an initial approach to confirm newly compartment of \(R_h\) in oil palm cultivated tropical peatland. The measured \(R_h\) emission was 0.05 to 2.3 Mg CO\(_2\) ha\(^{-1}\) year\(^{-1}\) with an average of 0.7 Mg CO\(_2\) ha\(^{-1}\) year\(^{-1}\). Assuming the \(R_t\) and \(R_h\) range from 13.8 to 178 Mg CO\(_2\) ha\(^{-1}\) year\(^{-1}\) and 5.2 to 66.3 Mg CO\(_2\) ha\(^{-1}\) year\(^{-1}\), respectively (Table 1); \(R_h\) contribution was low, both for \(R_t\) and \(R_h\). The contribution to \(R_t\) and \(R_h\) recorded around 0.3 to 1.3 and 0.9 to 3.5 percent, respectively. The average and upper range of \(R_h\) contribution to \(R_t\) and \(R_h\) are still considered low, owing to their contribution that is under 5 percent.

These estimations presented above seemingly contrasted with the second hypothesis, which is lower than the emission emanates from oil palm fronds decomposition (Manning et al., 2019; Wakhid and Hirano, 2021; Table 1). Furthermore, the contribution of \(R_h\) to \(R_t\) was outside the range of \(R_{Oph}\) contribution, which accounted for around 14.6 to 21.9 Mg CO\(_2\) ha\(^{-1}\) year\(^{-1}\) (Wakhid and Hirano, 2021; Pulunggono et al., 2022; Table 1), which was in contrast with the previous assumption.

Table 1. The review of surface emission measurements and their contributed fractions in tropical peatland cultivated by oil palm plantations.

<table>
<thead>
<tr>
<th>Component</th>
<th>CO(_2) Emission (Mg CO(_2) ha(^{-1}) year(^{-1}))</th>
<th>Method</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Respiration (Autotrophic+ Heterotrophic)</td>
<td>13.8 – 178</td>
<td>Static chamber, trenching collars, subsidence</td>
<td>Hooijer et al., 2012; Dariah et al., 2014; Hergoualc’h et al., 2017; Manning et al., 2019; Pulunggono et al., 2022</td>
</tr>
<tr>
<td>Autotrophic Respiration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Living root</td>
<td>30.7 - 137.7</td>
<td>Static chamber, trenching, distance differences</td>
<td>Meiling et al., 2013; Sabiham et al., 2014</td>
</tr>
<tr>
<td>Heterotrophic Respiration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peat materials (+OP dead roots)</td>
<td>5.2 – 66.3</td>
<td>Trenching, trenching collars, static chamber, distance differences</td>
<td>Dariah et al., 2014; Husnain et al., 2014; Marwanto and Agus, 2014; Comeau et al., 2016; Hergoualc’h et al., 2017; Manning et al., 2019; Pulunggono et al., 2022</td>
</tr>
<tr>
<td>Understory litters</td>
<td>14.6 – 21.9</td>
<td>Trenching collars</td>
<td>Pulunggono et al., 2022</td>
</tr>
<tr>
<td>OP fronds</td>
<td>4 – 6.6</td>
<td>litter bag decomposition/ gravimetric</td>
<td>Wakhid and Hirano, 2021</td>
</tr>
<tr>
<td>OP dead roots</td>
<td>0.05 – 2.3</td>
<td>Separation and incubation</td>
<td>This study</td>
</tr>
<tr>
<td>Drainage canals</td>
<td>1.4 – 1.6</td>
<td>Floating chamber</td>
<td>Manning et al., 2019</td>
</tr>
</tbody>
</table>
This study treated the dead root with various WC (Figure 3) to simulate the rise and deepening of GWL in the field. According to the figure, some of the treatments provide favorable conditions for microorganisms to thrive, resulting in maximum emissions as shown in Table 1 (2.3 Mg CO$_2$ ha$^{-1}$ year$^{-1}$). This value is lower than the lower level of $R_{fr}$ and $R_{uds}$. This study’s approach calculated root incorporation for only at a single year period, which is quite less flexible compared to their continuous process in nature. That limitation thereby restricts maximum heterotrophic respiration that feeds entirely from root dead materials (45.1 Mg CO$_2$ ha$^{-1}$ year$^{-1}$) to their corrected value at the field level (2.3 Mg CO$_2$ ha$^{-1}$ year$^{-1}$; Table 1). However, this study approach is still considered reasonable since there are large voids of available information, particularly in quantifying heterotrophic emission emanates from oil palm dead root fragments or basic knowledge regarding the percentage of specific oil palm root turnover near the peat surface during an extended monitoring period.

Compared to the living roots, their decomposed dead parts contribute to total CO$_2$ emissions about 97.03 percent lower (Meiling et al., 2013; Sabiham et al., 2014; Table 1). The amount and contribution of $R_{fr}$ are likely originated from a relatively quick turnover (primarily consisting of secondaries and fine roots), low CN ratio, and high magnitude of incorporated dry matter (Corley and Tinker, 2016). However, their maximum potential contribution was technically cannot be reached at the study site due to high precipitation and shallow GWL (Busman et al., 2021; Pulunggono et al., 2022), as well as lower and stabilized soil temperature under dense leaves shading of matured oil palm and pruned fronds coverage (Jauhainen et al., 2014; Manning et al., 2019).

Figure 3 shows the significant effect of WC in governing $R_{fr}$ as assessed by one-way analysis of variance and linear mixed-effects model with restricted maximum likelihood/REML. Statistically different and highest $R_{fr}$ emanated under the 100 and 150% of WC treatments. However, decreasing (control/15%) or increasing WC (300-450%) could generate lower $R_{fr}$. Furthermore, the treatment of 100 and 150%WC were also generating a relatively lower organic CN ratio and higher N compared to other treatments (Figure 4), whereas organic C seems to vary. Concerning CO$_2$ emission as a product of the microbial process, organic material with higher N and lower CN ratios would result in a higher respiration rate, hence, increasing CO$_2$ flux (Hutchings and Martin, 1934). These findings corroborate the general understanding that the dynamic of GWL in cultivated peatland must be maintained to sustain CO$_2$ emission at its lowest rate (Carlson et al., 2015; Manning et al., 2019). To obtain lower $R_{fr}$, in this study case, WC must be maintained at around 300 to 400%.

Furthermore, $R_{fr}$ culminated in the first month and was significantly different from the zero and last months. $R_{fr}$ inclined until the last observation, with both $R_{fr}$ were not significantly different from the early measurement. $R_{fr}$ at the first two months seemingly represents the variation of CN ratio possessed by diverse types of dead roots rather than the RT.

Figure 3. The effects of water content (WC; 3a) and incubation time (IT; 3b) to $R_{fr}$. The letters above the subfigures 3a and 3b were derived from multiple comparisons of REML. Subfigures 3c, 3d, and 3e represent the relationships among organic C, total N, and CN ratio to $R_{fr}$. The white asterisk and black horizontal line inside the boxplot represent mean and median values of of CO$_2$ flux in each class/factor, respectively; grayish dotted line represents the general averaging of CO$_2$ flux after outlier removal.

However, the authors supposed that high $R_{fr}$ in the first month represented fine roots decomposition which had a lower CN ratio (Violita et al., 2016), whereas roots with a high CN ratio would decompose slowly (Figure 3d; Figure 4c), referring to lower $R_{fr}$ at the following months. With regard to the high CN ratio used in this study, possibly longer period of measurements is needed to gain a general pattern of $R_{fr}$ and separation.
of roots based on its diameter, order, or function as other studies report (e.g., Moradi et al., 2013; Sabiham et al., 2014; Yang et al., 2019). Even though both fixed factors held strong effects on the dynamic $R_d$, they differently relate to $R_d$, as exhibited by the difference in $R_d$ pattern. By dropping control treatment, $R_d$ seemingly possessed a linear relationship with WC (Figure 3a). However, non-linear trends showed by $R_d$ along with the increase of IT (Figure 3b). The entire root properties (organic C, total N, and CN ratio; Figure 3c, 3d, and 3e, respectively) demonstrated a scattered pattern and possibly had non-linear relationships to $R_d$, albeit their trends (showed as a red line in Figure 3) were in agreement with the general consensus of decomposition rate. Higher C content and CN ratio, as well as lower N content in organic material, would result in slower rates of microbial decomposition and vice versa (Hutchings and Martin, 1934). REML analysis also showed that incorporating organic as a random factor affects $R_d$, whereas the other two covariates (N total and CN ratio) had no role in the REML model.

Descriptive multivariate analysis (PCA) used in this study revealed five principal components/PCs that accounted 100% of the total variance, as shown by screen plots in Figure 5a. This study utilized PC1, PC2 and PC3 since they had an eigenvalue of more than 1 and explained 87.5 of the total variance (Sharma, 1996; Figure 5a). CN ratio and N total significantly dominated PC1 (Figure 5b1). Meanwhile, organic C and weight loss were loaded solely by PC2 (Figure 5b2). Moreover, PC3 statistically correlated with $R_d$. The figure showed that PC1 and PC2 represented dead oil palm root chemical (organic C, N total and CN ratio) and physical (weight loss) properties, whereas PC3 was designated for its emission.

PCA results supported this study’s previous information generated from one-way ANOVA and REML, particularly in revealing underlying factors that affect dead oil palm root characteristics and their relationships with $R_d$. According to color grouping on the entire observation plot in Figures 5c1.1, 5c2.1, 5c3.1, the treatment (combined WC and IT) used in this study affected dead oil palm root characteristics, either its chemical and physical properties or emission, as shown by treatment group (blue points) separated from control (red points). However, changing oil palm dead root WC into several classes could not fully separate the dead root characteristics, as exhibited by several overlapping groups (Figures 5c1.2, 5c2.2, 5c3.2). Furthermore, visual grouping generally resulted in four groups, merging 100 and 150%WC. The gradual change was observed based on IT at all observation plots (Figures 5c1.3, 5c2.3, 5c3.3), indicating the entire dead oil palm root characteristics were affected by RT.
Figure 5. Statistic description of PCA analysis (a) scree plot percentage of explained variances of each PC; (b) contribution (expressed as percentages) of each variable in (b1) PC1, (b2) PC2, (b3) PC3; and biplot consisting of loading and observation plot of (c1) PC1:PC2, (c2) PC1:PC3, and PC2:PC3 (c3), grouped by (.1) status, (.2) water content, and (.3) incubation time. Note that 15%WC represented control treatment.
Modeling $R_\text{d}$ based on treatments and several root properties

This study highlighted the potential capability of polynomial and AI-based models as alternative pedotransfer models that can predict $R_\text{d}$ from cultivated tropical peatlands, as affected by WC and IT, with an acceptable agreement. Concerning the importance and significance of GHG emission in tropical peatland ecosystems, this study's results can be used as starting point to develop more complex models of CO$_2$ exchange representing $R_a$, $R_g$, $R_e$, and net ecosystem exchange/NEE in oil palm cultivated peatland.

In model 1, DL and ML-based models (particularly for ensemble learning: RF and GBM) outperformed linear and polynomial models. In general, both performed comparable RMSE, whereas SVR and GBM were considered more powerful at predicting CO$_2$ flux with the inclusion of weight loss parameters. The ensemble learning models achieved an $R^2$ value in the same magnitude with the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.” Many researchers, soil scientists, and practitioners relied mostly on the model itself: “the interpretability.”

With respect to higher $R^2$, ML-based models exhibit a higher agreement achieved by several models in this study considered reasonable since a nested separation strategy (single splitting and ten-fold cross-validation) was applied to avoid model overfitting.

Based on the model comparison, this study supposed that eliminating the weight loss variable significantly improved the model accuracy. According to Figures 6 and 7, Model1 generally exhibited good agreement at the entire metrics, particularly at ML and polynomial-based models. Meanwhile, Model2 had a lower agreement, both in RMSE and $R^2$, compared to Model1. Moreover, several best performance models (i.e., GAM, TR, RF, GBM) in Figure 9 also indicated some variables that gained less importance. Based on that, this study suggested that increasing variable importance and significance of GHG emission in tropical peatland ecosystems, this study's results can be used as starting point to develop more complex models of CO$_2$ exchange representing $R_a$, $R_g$, $R_e$, and net ecosystem exchange/NEE in oil palm cultivated peatland.

![Figure 6](image_url)
Figure 7. Model agreement as represented by the coefficient of determination ($R^2$) of predicted against observed $R_{dr}$.

Figure 8. Model regression tree of $R_{dr}$ modeled by its most important predictors (incubation time and organic C). The value inside and under the boxes are $R_{dr}$ means and observation number, respectively.
Figure 9. Feature importance computed using a permutation-based approach, utilizing mean square error/MSE as a loss function.
Conclusion

This study emphasized separating $R_d$ from $R_h$ in oil palm cultivated peatland by conducting a simulation study as an effort to mitigate greenhouse gas emissions. $R_d$ emissions were 0.05 to 2.3 Mg CO$_2$ ha$^{-1}$ year$^{-1}$ with an average of 0.7 Mg CO$_2$ ha$^{-1}$ year$^{-1}$. $R_h$ to $R_d$ and $R_h$ contribution were around 0.3 to 1.3% and 0.9 to 3.5%, respectively; based on the wide reports of $R_d$ and $R_h$ in oil palm cultivated peatlands (13.8 to 178 Mg CO$_2$ ha$^{-1}$ year$^{-1}$ and 5.2 to 66.3 Mg CO$_2$ ha$^{-1}$ year$^{-1}$, respectively). According to evidence supported by various statistical analyses (i.e., one-way ANOVA, REML, and PCA), WC and IC chiefly affected $R_h$, which favorable condition for heterotrophic respiration in dead root was achieved at 100-150%WC and the first month after incubation. Advanced pedotransfer models based on polynomial (MARS) and AI (RF and GBM) employed in this study provide new insight into predicting $R_h$ as a new compartment in $R_h$ research, as well as can be used as starting point to develop more complex models of CO$_2$ emission representing $R_h$, $R_d$, $R_h$, and net ecosystem exchange/NEE in oil palm cultivated peatland.

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