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Innovative Digital Mapping of Soil Organic Matter Content in Oil Palm Using Image Analysis

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ABSTRACT

The goal of this study is to use image processing technology to map the organic matter content of soil in oil palm plantations. The data set comprises photos of oil palms and bare land, as well as field measurements of pH, humidity, temperature, total dissolved solids, and electrical conductivity. Correlation analysis revealed a strong link between picture spectral components (particularly in the blue channel, r = 0.3640) and soil organic matter content. The distribution of organic matter content ranges from 4.5 to 5.5%, with an average of around 5%. The image processing-based predictive model successfully mapped the spatial variation of organic matter content with high accuracy. The mapping results demonstrate spatial variability, which can be exploited to support precision agriculture in oil palm areas.

Keywords: soil organic matter, image processing, oil palm, mapping, precision agriculture

INTRODUCTION

Oil palm plantations are one of Indonesia's strategic commodities, and their long-term productivity is heavily dependent on soil fertility, namely soil organic matter (SOM) concentration (Akhtar *et al*. 2023). Soil organic matter contributes to soil structure, nutrient availability, water retention capacity, and microbial activity, all of which influence the growth and production of oil palms. Monitoring organic matter content at both the spatial and temporal levels is critical for sustainable oil palm plantation management (Chai & Draxler 2014).

Soil sampling and laboratory analysis are the most common procedures used to measure SOM. This strategy needs a significant amount of time, money, and energy, particularly over huge regions of land. These conditions need the use of more efficient, non-destructive technologies capable of producing quick results (Golicz *et al*. 2024). Image processing technology enables the use of soil spectral features that can be associated with organic matter content, allowing the construction of prediction models for spatial mapping (Haralick *et al*. 1973).

Previous research has shown that particular spectral parameters, such as vegetation indices or specific color channel ratios, can be used to determine soil properties, including organic matter concentration. However, most previous studies have used single variables or small spatial scopes, resulting in inferior accuracy and inadequate representation of the complexity of biophysical elements that drive SOM. This research gap stems from the requirement for a method that combines field data (pH, moisture, temperature, TDS, and EC) with digital picture parameters to increase SOM modeling accuracy on complicated oil palm land. Based on these settings, this study aimed to create a method for mapping soil organic matter content in oil palm farms by combining digital image analysis with field parameter measurements. This technique is projected to help plantation managers make precise and long-term soil fertility management decisions, as well as improve the use of precision agriculture in oil palm farms.

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METHODS

Location and Time of Research

Figure 1 shows a geographical map of Meurandeh Village in Langsa Lama. The bottom map shows a detailed view of Meurandeh Village, with red dots indicating sampling points distributed throughout the village.

Tools and Materials

Digital camera, pH meter, soil temperature, soil moisture sensor, EC meter, TDS meter, computer device running MATLAB software, GPS for locating sample points, and soil sampling instruments, digital photos of oil palm and fallow fields, as well as soil samples from them.

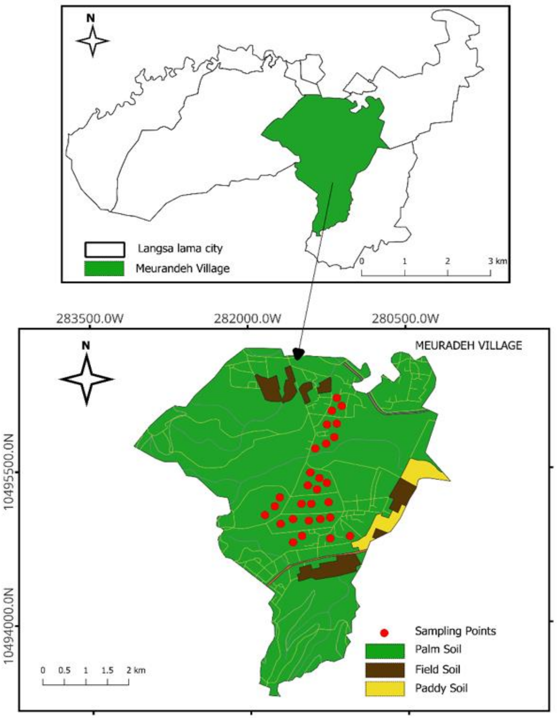

Figure 1 Geographical location of the study area.

Procedures

The purposive sampling method was used to establish the sample point, which was then followed by measurements of field parameters (pH, humidity, temperature, total dissolved solids/TDS, and electrical conductivity/EC). Digital camera was used to snap images of palm oil and fallow land (Figure 2).

Image analysis was performed using MATLAB with the following steps: RGB Channel Extraction is the process of separating an image into its red, green, and blue components. We calculated the G/R ratio as an indicator of vegetation. In filter application, we used a median filter to minimize noise, followed with texture feature extraction involving GLCM to acquire texture parameters like contrast, correlation, energy, and homogeneity. The following equations were used in the analysis of organic soil matter using image processing on palm oil land:

a) NDVI (Normalised Difference Vegetation Index) (Heil *et al.* 2022)

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$$

where:
NIR = Reflectance in the near infrared channel
Red = Reflectance in the red channel

b) Green–Red Canal Ratio

$$\frac{\mathrm{G}}{\mathrm{R}} = \frac{\mathrm{Green}}{\mathrm{Red}}$$

Texture Feature Extraction from GLCM (Grey Level Co–occurrence Matrix)
where:
Green = intensity of the green channel
Red = intensity of the channel

a) Contrast

$$\mathrm{Contrast} = \sum \mathrm{i,j}|\mathrm{i} - \mathrm{j}|^2 \mathrm{x}\ \mathrm{p(i,j)}$$

Measures the local contrast variations in the image.

p(i,j) = probability of occurrence of a pixel pair with gray level i and j

b) Correlation

$$\mathrm{Correlation} = \sum \mathrm{i,j}[(\mathrm{i} - \mu\mathrm{i})(\mathrm{j} - \mu\mathrm{j})\mathrm{p(i,j)}]/(\sigma\mathrm{i} \times \sigma\mathrm{j})$$

Measures the linear dependency between neighboring pixels

μ_i, μ_j = mean gray levels of rows/columns.
σ_i, σ_j = standard deviation of gray levels of rows/columns.

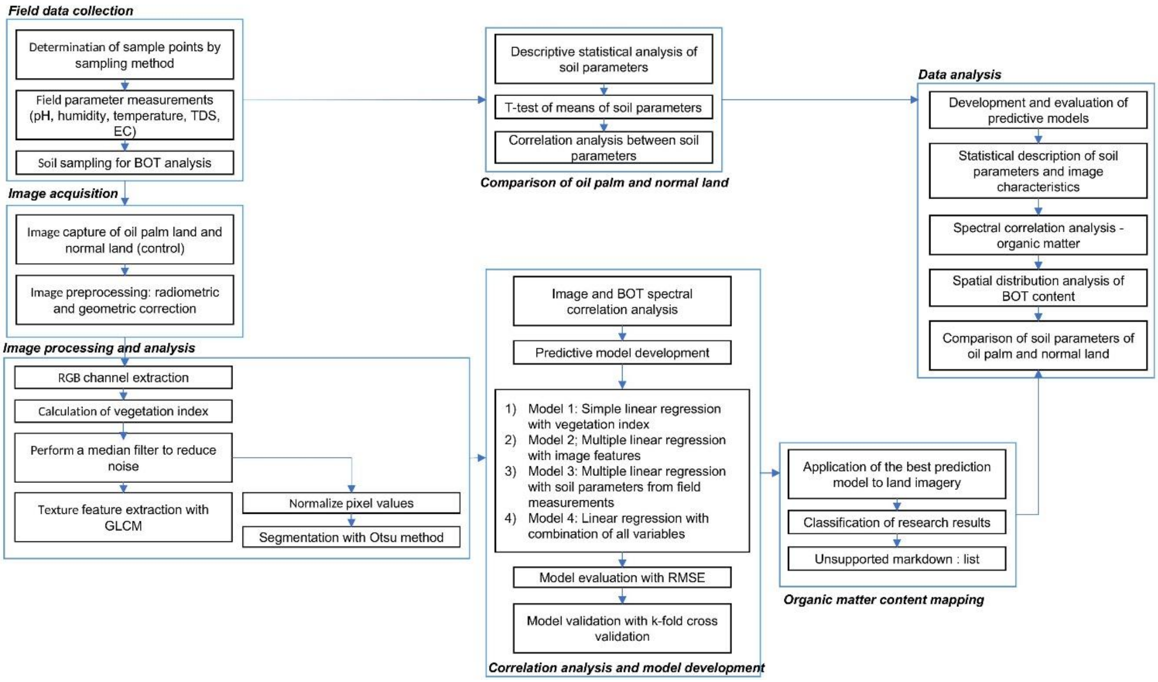

Figure 2 Flowchart of the Procedure of Research.

c) Energy

$$\text{Energy} = \sum i, j[p(i,j)]^2$$

p(i,j) = probability of occurrence of a pixel pair with gray level i and j

d) Homogeneity

$$\text{Homogeneity} = \sum i, j[p(i,j) \,/\, (1 + |i - j|)]$$

where:
p(i,j) = probability of occurrence of a pixel pair with gray level i and j

Four prediction models were developed to estimate soil organic matter content. The following equation was used: Prediction Model Based on Vegetation Index and Soil Parameters (Kačergius 2025, Luo *et al.* 2022)

$$BO = a_0 + a_1(\text{NDVI}) + a_2(\text{pH}) + a_3(\text{Kelembaban})$$

where:
BO = soil organic matter content (%)
a, a_1 … a_5 = regression coefficients
pH = soil acidity
Moisture = soil moisture
EC = soil electrical conductivity
TDS = total dissolved solids

Descriptive statistical analysis of soil parameters in oil palm and fallow land, using Pearson correlation coefficient (Kačergius 2025)

$$r = \left[n(\Sigma xy) - (\Sigma x)(\Sigma y)\right] / \sqrt{\left[n(\sum x^2) - (\sum x)^2\right]}\, x \sqrt{\left[n(\sum y^2) - (\sum y)^2\right]}$$

where:
r = Correlation coefficient
x = Independent variable value (e.g., pixel value)
y = Dependent variable value (e.g., organic matter content)
n = Number of samples

Root Mean Square Error (RMSE) (Luo *et al.* 2022)

$$\text{RMSE} = \sqrt{\left[\sum (y_i - \hat{y}_i)^2 / n\right]}$$

where:
y_i = Actual value
$\hat{y}_i$ = Predicted value
n = Number of samples
Coefficient of determination (R^2)

$$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2 \,/\, \Sigma(y_i - \bar{y})^2]$$

where:
$\bar{y}$ = Average value of y
Multiple linear regression (Nowkandeh *et al.* 2013)

$$BO = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

where:
$X_1, X_2, ..., X_n$ = Predictors (e.g., reflectance values of various channels or soil parameters)
$\beta_1, \beta_2, ..., \beta_n$ = Regression coefficient of each predictor

RESULTS AND DISCUSSION

Spectral Characteristics of Oil Palm and Normal Land Images

Figure 3 shows a boxplot study comparing the vegetation index (G/R ratio) of oil palm and normal land, which reveals considerable variances in characteristics. Oil palm land has a higher median vegetation index (0.967) than normal land (0.957), indicating more photosynthetic activity due to the higher biomass and chlorophyll content of oil palm plants. The range of vegetation index in oil palm (0.935-0.998) was greater than that on normal land (0.93-0.97), with higher maximum values. Oil palm also displayed greater variability (higher boxplots), indicating the diversity of complex vegetation conditions, whereas normal land had a more uniform distribution. Both data sets contained no outliers, indicating strong measurement consistency.

Although the numerical difference appears minor, in the context of vegetation study, it is rather important and consistent with research (Pearson 1901) that indicates typical spectral characteristics of oil palm farms. These findings demonstrate that image processing algorithms may efficiently detect changes in vegetation characteristics between oil palm and barren land and might possibly be used to map soil organic matter content using remote sensing technologies.

The GLCM texture analysis of the image reveals that the oil palm field is more uniform than the typical field (Figure 4). Palm oil fields have a smoother texture with less contrast (median 0.0035 vs 0.016), higher correlation (0.92 vs 0.90), more energy (0.95 vs 0.82), and higher homogeneity (0.998 vs 0.992). This is owing to the uniform vegetation cover of oil palm plantations, as opposed to typical land, which has a more variegated surface. This conclusion is consistent with previous studies (Rahman *et al*. 2021). The consistent differences in the four GLCM parameters prove that image processing technology can effectively detect differences in land types. The more homogeneous texture of oil palm land is related to the higher organic matter content. Therefore, the GLCM texture feature has the potential to be used as a prediction tool for soil organic matter content and can be applied in digital farmland condition mapping models.

Correlation between Image Spectral Characteristics and Soil Organic Matter Content

Figure 5 depicts a scatter plot of the intensity of color channels (red, green, and blue) vs organic matter content. The correlation study revealed a substantial link between the image's spectral components and soil organic matter content. RGB spectrum analysis of soil organic matter content reveals that the blue channel has the highest positive correlation (r = 0.3640), followed by the green channel (r = 0.2819) and the lowest red channel (r = 0.1341). The blue channel proved to be the greatest predictor, displaying a constant pattern of rising organic matter content as the intensity of the blue color increased (Figure 6). This study's interesting conclusion is that soils with high organic matter show higher reflectance in the blue and green channels, which contradicts the usual idea that soils with high organic content seem darker. This phenomenon occurs in plantations because vegetation, moisture, microbial activity, and root exudation all influence soil reflectance characteristics, resulting in a positive association between spectral intensity and organic matter concentration (Reyes *et al*. 2023a).

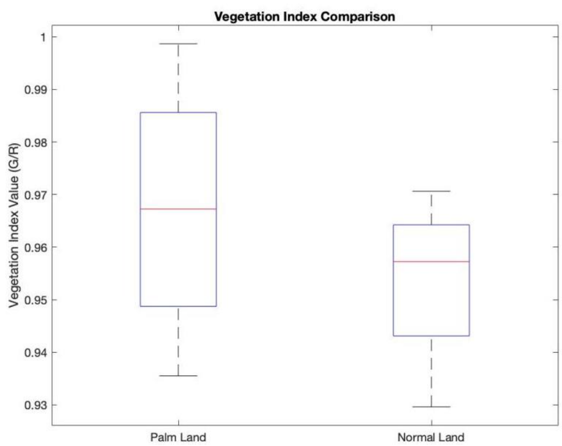

Figure 3 Boxplot comparison of the vegetation index of oil palm and normal land.

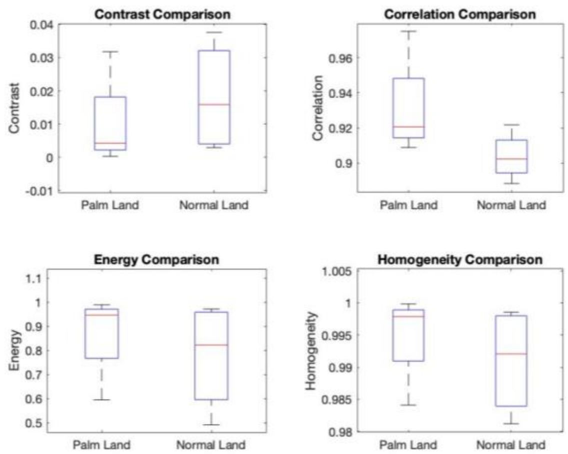

Figure 4 Visualisation results of GLCM texture extraction of oil palm and normal land.

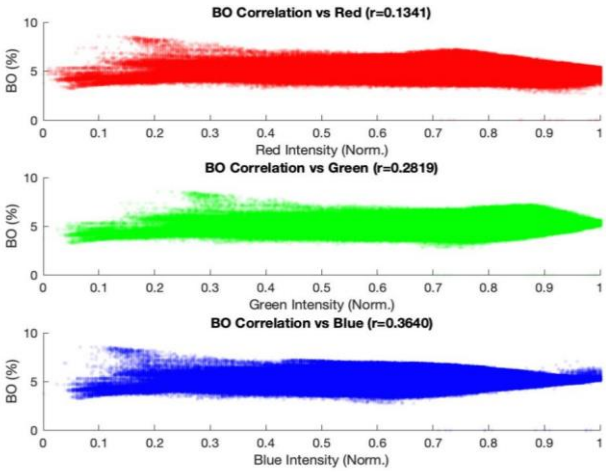

Figure 5 Results of correlation analysis between image spectral characteristics and soil organic matter content.

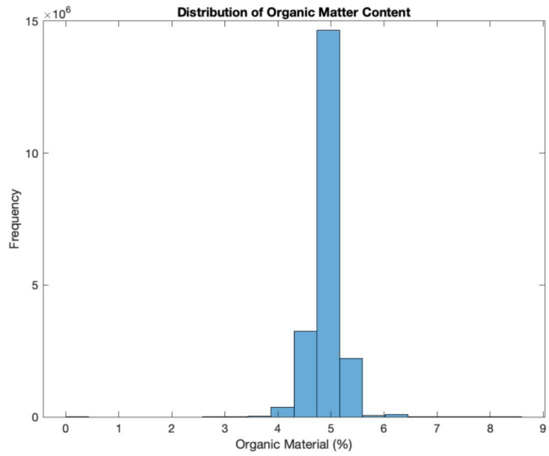

Figure 6 Histogram of soil organic matter content distribution.

Distribution of Soil Organic Matter Content in Oil Palm Fields

Figure 7 depicts the findings of the analysis of the distribution of organic matter content in oil palm farms as a distribution histogram of organic matter content, which reveals some essential characteristics. According to the distribution histograms, the organic matter content in the oil palm fields is relatively well dispersed. Most sites contain organic matter concentration ranging from 4.5 to 5.5%, with the maximum peak at 5%, indicating good soil quality for oil palm plantations. Although the range of readings ranged from 0 to 9%, only a few regions experienced severe low and high circumstances. Overall, organic matter level was very homogeneous, averaging 5%, with just a few locations requiring special treatment due to low or excessive organic matter content. These findings are consistent with previous study (Reyes *et al*. 2023b) on sustainable oil palm land management requirements, which typically contain 3−6% organic matter content depending on crop age and management strategies used.

Image Processing–based Predictive Model for Estimating Soil Organic Matter Content

This study examined four models for predicting soil organic matter concentration, yielding different findings. The first model, which relied solely on the vegetation index, had the lowest accuracy due to the limits of a single forecast in the face of soil and environmental complexity. This is similar with the findings of Ajeng *et al.* (2020). The second model, which incorporates visual properties like texture and color, is slightly better but still not ideal. In contrast, the third model, which incorporated field characteristics such as pH, moisture, temperature, TDS, and EC, achieved good accuracy (R^2 > 0.9) with low RMSE. The fourth model, which incorporated all variables, performed nearly identically to the third model, demonstrating that soil physicochemical factors were dominant, with picture attributes contributing just marginally. This finding is consistent with previous research (Romano *et al*. 2023), which found a substantial correlation between soil physicochemical parameters and soil organic matter concentration.

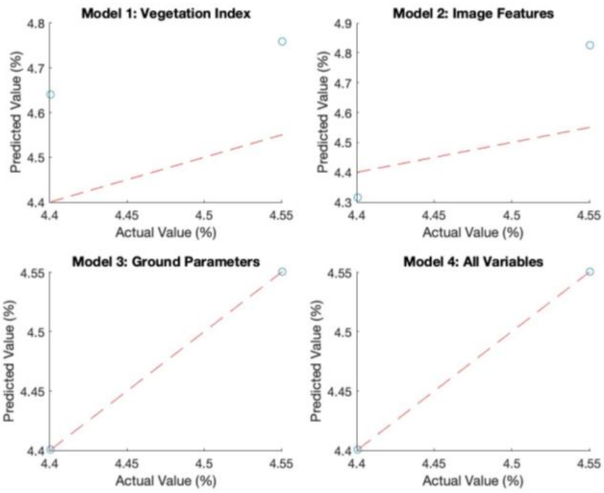

Figure 7 Comparative Analysis of Soil Organic Matter Content Prediction Models.

Although the soil parameter-based model is the most precise, the image-based model remains necessary for practical applications because it allows for wide-scale mapping without the constraints of significant field observations. Cross-validation revealed strong model consistency, implying that the development of image processing and machine learning technologies could bridge the gap between the demand for correct data and the field's practical limitations.

Spatial Mapping of Soil Organic Matter Content

According to the soil organic matter content map, the distribution of organic matter in the oil palm plantation area ranges from 0 to 8%, with most areas having a moderate amount of roughly 4−5%. Areas with high content (6−8%) are clustered at certain spots at the top of the map, which may be due to mature oil palm trees or changes in land management. These findings are consistent with prior studies (Rouse *et al*. 1973), that well-managed oil palm plantation soils typically had organic matter content in this range. The spatial distribution of soil organic matter content is visualized in Figure 8, which shows the map of soil organic matter content across the study area. The comparison of soil parameters between oil palm and normal land is presented in Figure 9.

The investigation revealed the strongest positive association (r = 0.3640) between organic matter content and the blue channel of the RGB picture, demonstrating that the blue channel is sensitive to humic chemicals found in soil organic matter. Although this association is moderate, it is consistent with other research (Segura *et al*. 2024), which indicate correlations ranging from r = 0.3 to 0.5. The highly homogenous distribution, with content about 5%, implies good organic soil matter conditions.

Zones with high content (6−8%) can be used as a guideline for appropriate management strategies, whereas those with low to medium content necessitate the addition of organic matter via mulching or organic fertilizer. This study confirms the use of image processing to map soil organic matter in oil palms. However, accuracy can be enhanced by combining spectral data with other environmental variables like topography and soil texture to aid in precision agriculture.

Comparison of Soil Parameters between Oil Palm Field and Normal Land

The comparison of soil properties between oil palm and normal land reveals considerable variances in a variety of categories. Oil palm land has a higher acidic pH (5.3−5.6) than normal land (5.5−6.7) due to plant absorption of base cations and fertilization. This soil acidity is consistent with prior studies (Taneja *et al*. 202), that oil palm plantations cause a progressive reduction in soil pH. Oil palm lands have lower soil moisture (68−77%), owing to broad root systems and high evapotranspiration, whereas customary lands have higher moisture (77−90%) (Zhang *et al*. 2019). Interestingly, soil temperature in oil palm is lower (26−28°C) than in conventional fields (30−32°C) due to the canopy's shading effect, which minimizes direct sun radiation.

TDS and EC parameters in oil palm soils were significantly higher (TDS: 800 ppm, EC: 0.4 µS/cm) compared to normal soils (TDS: 200−400 ppm, EC: 0.1−0.2 µS/cm), indicating high dissolved ion concentrations due to extensive fertilization, consistent with previous studies (Yu *et al*. 2024). A striking discovery was that the organic matter content of normal land (4.7−6.0%) was higher than that of oil palm land (4.0−4.6%), owing to poor litter control, and the majority of the carbon was deposited above ground. These

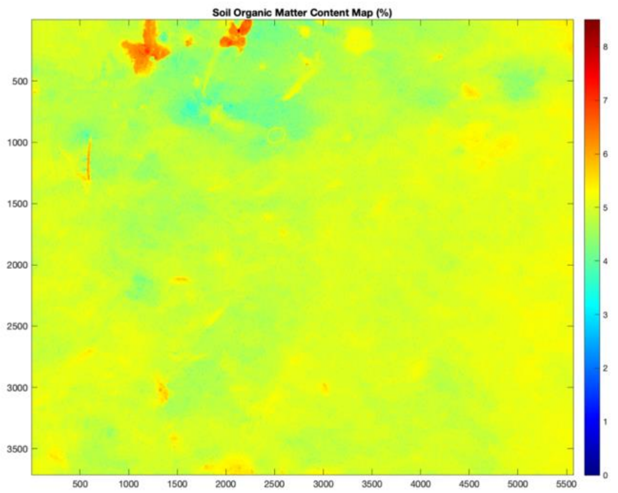

Figure 8 Map of soil organic matter content.

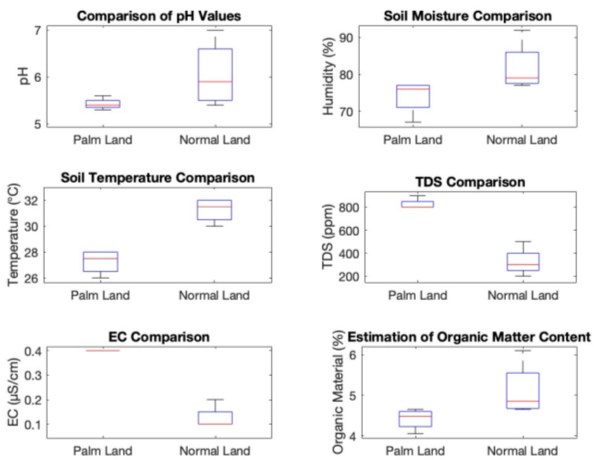

Figure 9 Results of soil parameter comparison between oil palm and normal land.

differences in characteristics provide a foundation for developing more accurate image processing technology using a multi-parameter approach, in which pH, temperature, TDS, and EC can be used as predictive variables in image-based prediction models for long-term soil monitoring and management in oil palm plantations.

CONCLUSION

Based on the results and discussion offered above, we can infer the following five conclusions: (1) Image processing technology is a promising non-destructive tool for mapping soil organic matter content in oil palm. The blue channel had the strongest positive correlation (r = 0.3640). (2) The distribution of soil organic matter content in oil palm lands is unimodal, centered at 4.5-5.5%, indicating favorable circumstances. (3) The prediction model using image processing and soil characteristics accurately mapped the geographical variation of organic matter content, with R^2 above 0.9 and low RMSE. (4) Oil palm farms had better soil parameters than bare fields, including higher and more consistent pH, more moisture, lower soil temperature, and 2−3 times more organic matter. (5) Soil organic matter content mapping enables precision agriculture in oil palm plantations by optimizing inputs and management strategies for different locations.

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