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A study on spatio-temporal trend of rubber leaf fall phenomenon using planetscope multi-index vegetation imagery in relations to climatological conditions

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ABSTRACT

Background: Rubber plants are one of the most important plantation commodities in Indonesia. However, rubber production has declined due to leaf fall disease caused by the pathogen *Pestalotiopsis sp*. This study aims to analyze the spatial and temporal distribution of rubber plant leaf fall disease using multi-vegetation indices from PlanetScope imagery, as well as to analyze the influence of climatological conditions on the disease. **Methods:** The research was conducted at the Sembawa Rubber Research Center Garden, South Sumatra, using PlanetScope imagery data and climatological data in 2017 (before leaf fall) and 2023 (after leaf fall). **Findings:** Spatially, the 2023 leaf fall occurred in almost the entire garden area with poor to moderate levels. Blocks 2013D, 2012F, and 2009F experienced the most severe levels, with a total defoliated area reaching 396.76 ha. Analysis of monthly variations in vegetation index values revealed a decrease in values during leaf fall due to *Pestalotiopsis sp.*, specifically in February, May, and September 2023. Statistical test results showed significant differences in vegetation index values between 2017 and 2023. Furthermore, based on Spearman's correlation analysis, there was a positive correlation between vegetation index values and humidity, but no significant correlation with rainfall and temperature. **Conclusion:** This research provides insights into mapping and monitoring rubber leaf fall disease using remote sensing data and climatological factors, which can be used for more effective rubber plantation management. However, the study has some limitations: monthly Planet data for 2017 is not fully available, several Planet image scenes from 2017 still have more than 50% cloud cover, and there may be biases as plants falling into the low health class are included in the high range of vegetation index values. **Novelty/Originality of this Study:** By integrating spatial and temporal analyses with climatological data, the research provides a precise and comprehensive method for monitoring LFD and understanding its environmental determinants, thereby enhancing traditional rubber plantation management practices.

KEYWORDS: rubber plant; leaf fall disease; vegetation index; remote sensing; climatological conditions.

1. Introduction

The rubber plant (*Hevea brasiliensis*) is one the most crucial plantation commodities for the Indonesian economy (Kementerian Pertanian, 2022). In addition to creating new

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fields of employment and driving regional development, rubber has also supported various sectors of agribusiness, agroindustry, and environmental conservation. South Sumatra has become the province with the largest smallholder owned rubber plantation area in Indonesia (Badan Statistik Pusat, 2022).

The rubber plantations in the Regency of Banyuasin have become one of the largest economic contributors in the province of South Sumatra. Banyuasin Regency itself has a rubber research institute known as the Sembawa Rubber Research Center under the management of PT Riset Perkebunan Nusantara with an area encompassing 3,379 hectares for conducting research and development on rubber commodities.

Though the area of rubber plantations continues to increase, rubber production has actually decreased in the year 2021, which indicates a discrepancy between the increase in area against the production results (Febbiyanti and Fairuzah, 2019). This decline in productivity could be attributed to the rubber leaf fall disease (LFD) caused by the pathogen *Pestalotiopsis sp.* (Sahuri and Cahyo, 2018; Saputra, 2019). LFD disease could cause plant canopy loss of >50% and latex production loss of >25% (Sahuri and Cahyo, 2018); Saputra, 2019). The massive attack that has taken place at Sembawa Rubber Research Center has caused necrosis, yellowing, leaf fall, and the loss of latex production of more than 25% (Febbiyanti, 2020). Physical factors such as rainfall, humidity, and temperature have also contributed towards the spread of this disease (Febbiyanti, 2020).

In response to the problems occurring in the rubber plants, continuous monitoring needs to be carried out, to increase rubber commodity production. According to (Azizan et al. 2021), traditional monitoring of rubber plantations is time and labor-consuming. Therefore, monitoring plantations using a remote sensing approach will be more effective to observe the extent and distribution of leaf fall disease due to the high availability of complete spatial and temporal data. PlanetScope imagery is a type of remote sensing data in the form of satellite imagery that provides high spatial and temporal resolution. This satellite carries optics and pushbroom scanning sensors capable of recording the surface area of the earth 350 km x 350 km in a single shot with a spatial resolution between 3-5 meters (Team, 2017). In addition, PlanetScope imagery has 5 spectral bands that are good for identification and monitoring of vegetation (Mesas-Carrascosa et al., 2015).

In this specific research, a multi-vegetation index approach is used, which combines several vegetation indices to improve the accuracy of LFD disease detection and assessment (Mu et al., 2018). The vegetation indices used are the Green Normalized Difference Vegetation Index (GNDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Modified Soil-Adjusted Vegetation Index (MSAVI) to see the vegetation indices on rubber plants that are correlated with their health. The aim of this research is to analyze the spatial and temporal distribution of GDK disease using multi-vegetation indices from PlanetScope imagery, as well as to analyze the impact of climatological conditions (rainfall, humidity, and temperature) on GDK disease at Sembawa Rubber Research Center.

2. Methods

2.1 Study area

This research was conducted at the Sembawa Rubber Research Center plantation, which is administratively located in Banyuasin Regency, South Sumatra Province. Administratively, the Sembawa Rubber Research Center is located in three sub-districts, namely Banyuasin III Sub-District, Sembawa Sub-District, and Rantau Bayur Sub-District. The Sembawa Rubber Research Center is part of PT Riset Perkebunan Nusantara (PT RPN), which owns rubber plantations among smallholder rubber plantations (Figure 1).

The plantation area owned by the Sembawa Rubber Research Center is approximately 1036 hectares and consists of 2 afdelings (divisions), namely Afdeling 1 planted with rubber plants and Afdeling 2 planted with rubber plants and some blocks planted with oil palm. Afdeling 1 is located in Sembawa Sub-District, and Afdeling 2 is partially located in Sembawa Sub-District, while the other part is located in Rantau Bayur Sub-District. The table below shows the size of each afdeling (Table 1).

Table 1. The area of the Sembawa Rubber Research Center division

Area	Area (Ha)	Percentage
Afdeling 1	457,27	44%
Afdeling 2	407,92	39%
Non rubber	170,00	16%

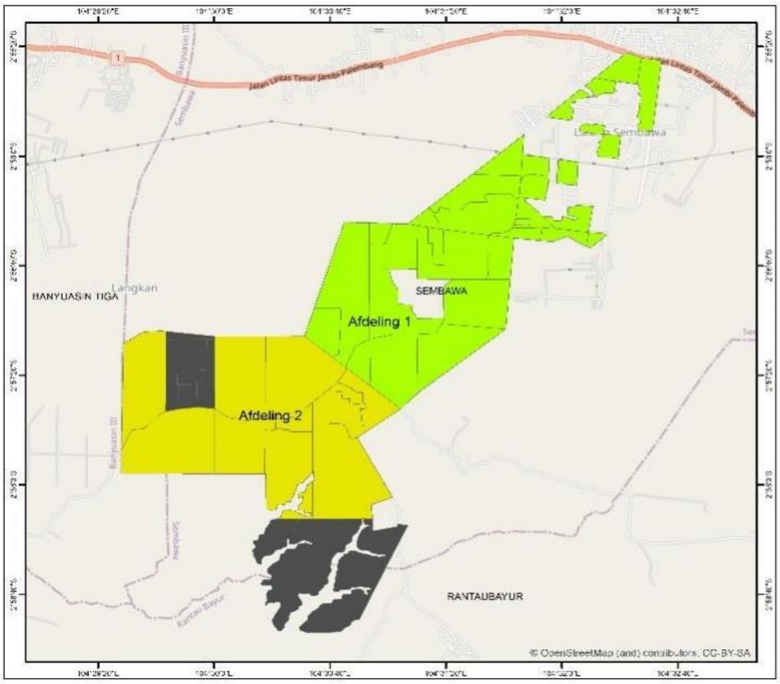

Fig. 1. Research location

2.2 Data collection and data processing

For this study, two types of data were used: secondary and primary data. The secondary data includes satellite imagery, while the primary data consisted of Point of Interest (POI) for plant health classes. The satellite imagery used in this research was the PlanetScope Ortho Scene Product Level 3B, which in its processing has included scene classification and atmospheric correction.

In an effort to collect field data, a sampling approach was used to ensure efficient data collection while representing the entire population. The method applied in this research was stratified purposive sampling. Stratified purposive sampling is a method of taking samples that involves dividing the population into subgroups or strata based on certain characteristics, and then selecting samples from each sub-group based on certain purposes or criteria (Neyman, 1992). Tree sampling was carried out at 623 points on 3 blocks of rubber plants with different clones. The aspect used as a consideration for stratification in this approach was the level of rubber leaf fall. This approach was used to ensure that the samples represented various strata in the population, in this case, the level of rubber leaf fall.

2.3 Data processing

Data processing was carried out after primary and secondary data were successfully obtained. Primary data obtained were the plot data of rubber plants experiencing rubber leaf fall, which would later be recapitulated into a distribution model of leaf fall on rubber plants. As for secondary data, it began with creating a base administrative map in the study area. Followed by processing PlanetScope image data, which would produce vegetation index algorithms such as GNDVI, EVI, SAVI, and MSAVI, as well as spectral values from the bands. In general, the data processing steps were divided into several stages, including preprocessing and PlanetScope Image processing, vegetation index value extraction, and classification. Calculation data and models were presented in graphical form, while the distribution of rubber leaf fall was presented in map form.

2.3.1 Preprocessing and planetscope image processing

Data preprocessing was carried out by ordering PlanetScope images through Google Collabs software. The process of ordering PlanetScope satellite images with Google Collabs begins with importing the Planet library and authenticating our planet account by entering the authentication code and API key. After that, we could determine the desired image scene search parameters including location, time range, and desired image product type. These search parameters were then used to search the available PlanetScope image data. The search results need to be filtered based on desired criteria, such as ordering the latest image per month. After obtaining a list of suitable images, we could place an order and download the images to our Google Drive. Once all the required image scenes were downloaded, PlanetScope image processing could continue using Google Earth Engine software.

The PlanetScope images used in this study were PlanetScope Ortho Scene Product Level 3B data, which in processing included scene classifications and atmospheric corrections. The next stage was adding an image collection, which means selecting the latest pixel, the last pixel in the image stack. By using the median to reduce clouds (which have high reflectance values) and reduce shadows (which have low reflectance values). By using the median value, the middle value of each band would be selected over the required period, which was throughout 2017 and 2023. After that, the image clipping process was carried out according to the boundaries of the rubber plantation at the Sembawa Rubber Research Center. The final step in this process was to process the PlanetScope image data to obtain the vegetation indices required in this study, namely the Green Normalized Difference Vegetation Index (GNDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Modified Soil-Adjusted Vegetation Index (MSAVI).

2.3.2 Vegetation index value extraction

The vegetation index value extraction stage was a process to obtain vegetation index values from satellite images after going through geometric and radiometric correction stages, before finally being extracted and interpreted. The vegetation indices used in this study included.

GNDVI has a wider dynamic range and is more sensitive to chlorophyll concentration than NDVI (Dubbini et al. 2022). Therefore, GNDVI is suitable for detecting wilted or aging plants. The GNDVI value range is between -1 and +1. The GNDVI value can be calculated using the following Equation 1 (Gittelson et al., 1996):

$$GNDVI = \frac{(NIR - Green)}{(NIR + Green)} \quad \text{(Eq. 1)}$$

where, NIR = reflectance in the near-infrared band.

The Enhanced Vegetation Index (EVI) is a vegetation index developed to optimize NDVI results with improved sensitivity in better vegetation areas, through canopy background decoupling and atmospheric effect reduction. The EVI value range is between -1 and +1. The EVI value can be calculated using the following Equation 2 (Liu and Huete, 1995):

$$EVI = G\ x\ \frac{(NIR - Red)}{(NIR + (C1\ x\ Red\ ) - (C2\ x\ Blue) + L} \quad \text{(Eq. 2)}$$

where, NIR = reflectance in the near-infrared band; G = gain factor (G = 2.5); C1, C2 = aerosol coefficient (C1 = 6, C2 = 7.5); L = canopy calibration factor and soil effect (L = 1).

SAVI aims to improve NDVI values in dry areas with sparse vegetation and open soil surfaces (Dubbini et al., 2022). By incorporating calculations that consider the effect of soil background, SAVI provides more accurate information about vegetation distribution and land conditions in the observed area in remote sensing images. The SAVI value range is between -1 and +1. The SAVI value can be calculated using Equation 3 (Huette, 1998):

$$SAVI = (1 + L)\ x\ \frac{(NIR - Red)}{(NIR + Red + L)} \quad \text{(Eq. 3)}$$

where, NIR = reflectance in the near-infrared band; L = adjustment factor to reduce the brightness of the soil (L = 0.5).

MSAVI was developed to overcome some limitations in using NDVI and SAVI, especially when there is a soil background that has a significant impact on satellite or aerial imagery. MSAVI uses the ratio between near-infrared reflectance (NIR) and red reflectance (RED) from the plant surface. The MSAVI formula is as follows in Equation 4 (Qi et al., 1994):

$$MSAVI = (2\ x\ NIR + 1)\ X \sqrt{\frac{(2\ x\ NIR + 1)^2 - 8\ x\ (NIR - RED))}{2}} \quad \text{(Eq. 4)}$$

2.3.3 Classification and accuracy stage

Classification was performed using multi-vegetation index data, including GNDVI, EVI, SAVI, and MSAVI, along with rubber leaf fall sample class data as training data. The Random Forest approach was employed for classification in this study. Based on the sample data of leaf fall levels, the classes were divided into low, medium, and high categories. The classification was based on the relationship between the GNDVI, EVI, SAVI, and MSAVI vegetation indices and the level of leaf fall. The classified rubber leaf fall levels were then applied to the entire area of the Sembawa Rubber Research Center plantation.

After the classification stage, an accuracy test was conducted to assess the accuracy of the classification results compared to the field conditions. The confusion matrix method was utilized in this accuracy test stage, involving calculations such as Producer Accuracy (PA), User Accuracy (UA), Overall Accuracy (OA), and the Kappa HAT value (Kunz, A., 2017). Producer Accuracy (PA) measures the model's ability to accurately predict new data, while User Accuracy (UA) evaluates the model's accuracy against existing data. Overall Accuracy (OA) quantifies the overall accuracy of the model, and the Kappa HAT value measures the degree of agreement between two raters in classifying objects (Congalton and Green, 2019). This accuracy test was performed to determine the accuracy level of the rubber plant health classification, thereby assessing the reliability of the rubber health mapping.

$$\textit{Overall Accuracy}\ \text{(OA)} = \frac{\sum_{i=1}^{k} n_{ii}}{n}$$

$$\textit{Producer Accuracy}\ \text{(PA)} = \frac{n_{ii}}{n_{+j}}$$

$$\textit{User Accuracy}\ \text{(UA)} = \frac{n_{ii}}{n_{+i}}$$

$$\text{Kappa} = \frac{(N\ x\ D) - Q}{N^2 - Q} \quad \text{(Eq.5)}$$

2.4 Climatological data and data analysis

Climatological data including monthly rainfall, soil moisture, and temperature were obtained from the Automatic Weather Station (AWS) at the Sembawa Rubber Research Center over the period of 2017 to 2023. The rainfall data was classified based on Oldeman's climate classification into wet months (>200 mm), humid months (100-200 mm), and dry months (<100 mm). The collection of these environmental data aims to provide further insights into how physical factors influenced the levels of leaf fall observed in the rubber plants. Understanding the relationships between vegetation index values and variables like precipitation, soil moisture content, and ambient temperature was crucial for comprehensively analyzing the phenomenon of defoliation in the rubber plantation.

The data analysis was divided into two parts based on the proposed objectives and research questions, encompassing both spatial and temporal analyses. For the spatial-temporal analysis of rubber leaf fall distribution, we examined the changes in vegetation index values from previously collected sample data over the specified time periods. The spatial analysis focused on the distribution patterns of rubber leaf fall, while the temporal analysis investigated the severity of leaf fall caused by Pestalotiopsis sp. across different phases. Leaf fall severity was determined using monthly vegetation index values from the Rubber Research Center plantation and analyzed based on the phenology of rubber leaf fall, considering phases before and after the onset of leaf fall. This analysis employed statistical methods, specifically the Paired T-Test, to compare the means of two related sample groups.

To strengthen the temporal analysis of rubber leaf fall due to Pestalotiopsis sp., we conducted a correlation analysis between leaf fall severity and physical condition data (rainfall, humidity, and temperature) obtained from the Automatic Weather Station (AWS) at the Sembawa Rubber Research Center. This statistical analysis was based on Spearman's correlation test to determine the relationship between rubber leaf fall severity and physical variables at the research site. In this analysis, rubber leaf fall severity and physical variables such as rainfall, humidity, and temperature were examined using Spearman's correlation test to determine the strength and direction of relationships between these variables. The results of this statistical analysis based on Spearman's correlation test provided crucial information about the influence of environmental factors such as rainfall, humidity, and temperature on the severity of rubber leaf fall caused by *Pestalotiopsis sp.*

3. Results and Discussion

3.1 Tree cover classification

The classification process was carried out in two periods, namely in 2017 (before leaf fall occurred) and 2023 (after leaf fall occurred). The classification process was divided into 3 stages, the first stage was the classification of vegetation and non-vegetation land. The result of the classification stage 1 was the vegetation area used for the classification process stage 2. The classification process stage 2 was carried out to divide the land class into rubber plant land and non-rubber plants. The result of stage 2 was the rubber plant area which would be used in the classification process stage 3, namely canopy cover classification. The result of the canopy cover classification was carried out with a confusion matrix accuracy test which would produce user accuracy, producer accuracy, overall accuracy, and Kappa values.

For the pre-defoliation year of 2017, the low canopy density class was classified with 80% overall accuracy and a 0.61 Kappa for training data (61% sample agreement). Validation data had 41% overall accuracy with a 0.38 Kappa. Medium density had an 82% overall accuracy with a 0.56 Kappa for training (56% sample agreement). Validation showed 43% overall accuracy and 0.37 Kappa. The high canopy density class was 82% overall accurate with a 0.61 Kappa for training data (61% agreement). Validation results were 42% overall accuracy with a 0.35 Kappa (Figure 2).

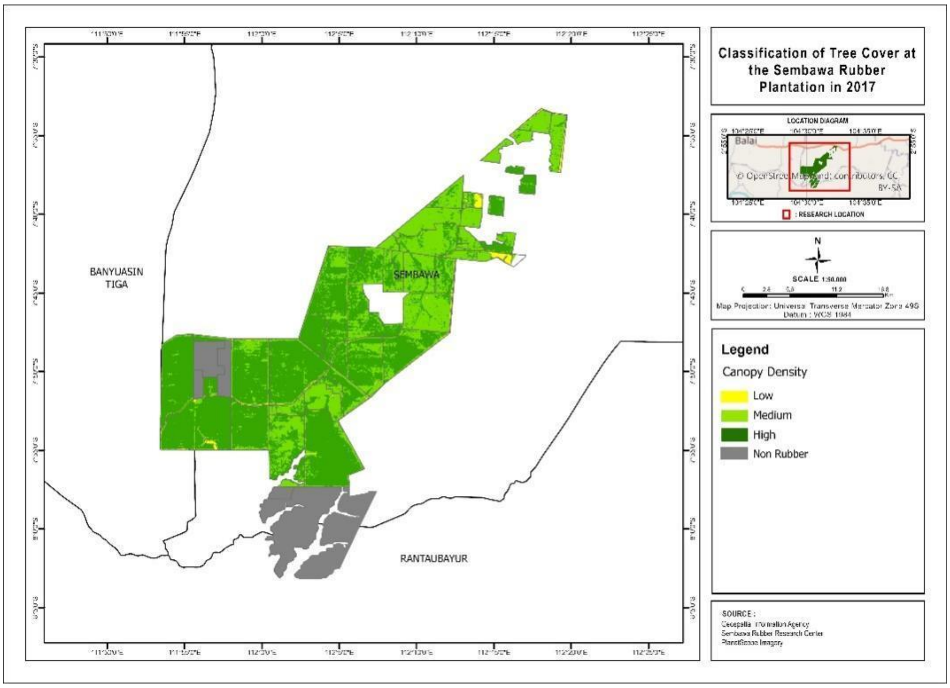

Fig. 2. Classification of tree cover at Sembawa Rubber Plantation in 2017

In 2017, low density covered 31.42 ha, medium density was 388.14 ha, and high density was 581.64 ha. A multi-stage classification process was carried out on PlanetScope imagery from 2023 after the rubber tree defoliation event. For the low canopy density class in 2023, the overall accuracy was 81% with a Kappa coefficient of 0.62 for the training data set, indicating 62% of sample points were correctly classified. Validation accuracy was lower at 44% overall with a Kappa of 0.41.

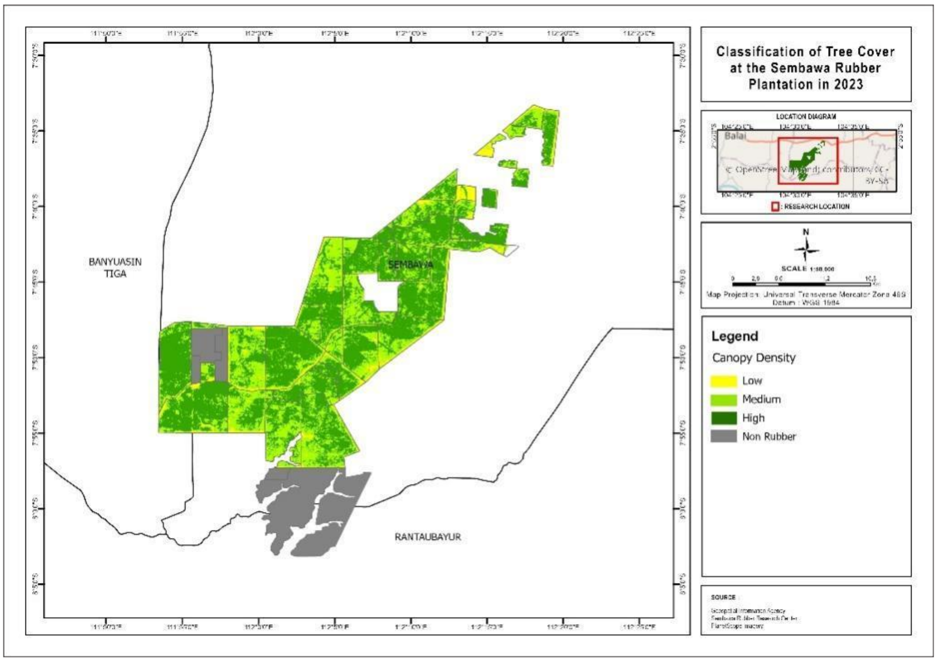

Fig. 3. Classification of tree cover at Sembawa Rubber Plantation in 2023

The medium canopy density class had an overall accuracy of 83% and Kappa of 0.58 for training data (58% sample agreement). Validation showed 42% overall accuracy and a Kappa of 0.38. High canopy density was classified with 84% overall accuracy and a Kappa of 0.62 for training data (62% sample agreement). Validation accuracy was 51% overall with a 0.43 Kappa (Figure 3). The area extent for each defoliation level based on canopy density was: 115.21 ha low density (severe defoliation), 397.76 ha medium density, and 514.22 ha high density (minimal defoliation).

3.2 Monthly variation of vegetation index values for plant health in 2017 and 2023

The monthly multi-vegetation index values for 2017 remained relatively constant as the Pestalotiopsis pathogen had not yet affected the rubber plantation. Starting from 0.7167 in January, the index gradually decreased until March, then dropped dramatically to its lowest point in May (0.5490), likely due to natural annual defoliation. This was followed by a significant increase to the highest value in July (0.7265). Subsequently, the index fluctuated within a narrower range, showing a gradual increase from August to October, a slight decrease in November, before rising again in December (0.729). Despite these significant fluctuations, especially mid-year, the trend line (indicated by the red line) showed a gradual improvement throughout the year. This suggests that although there were monthly variations, overall vegetation conditions tended to improve from the beginning to the end of 2017. It is worth noting that there were some data limitations, with no PlanetScope imagery available for February, April, and June of that year (Figure 4).

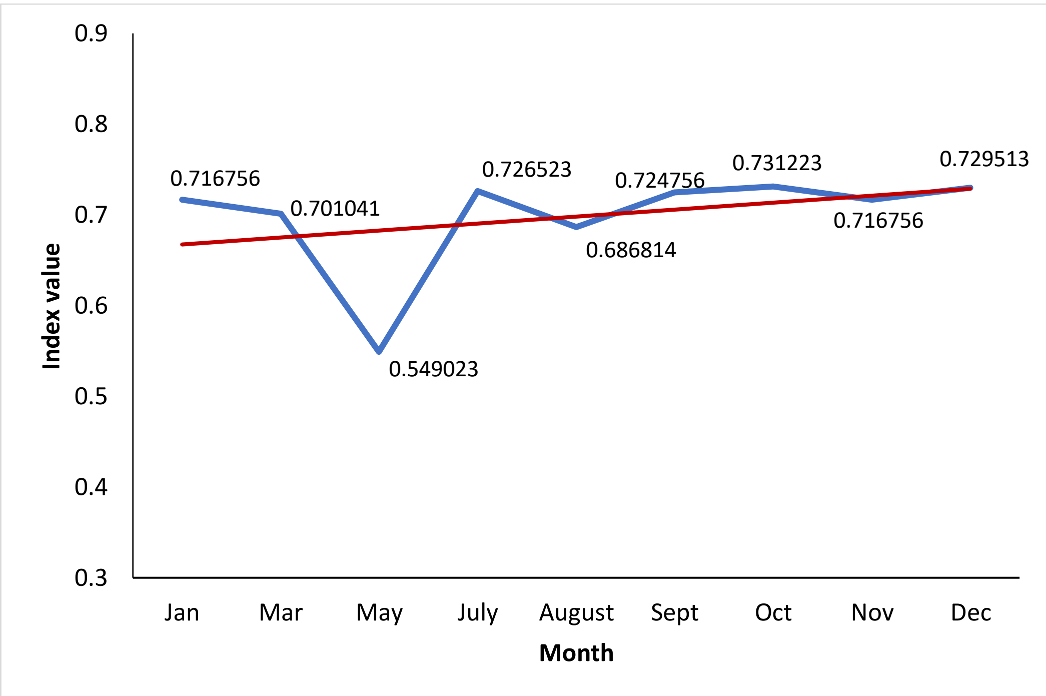

Fig. 4. Trends of monthly multi-vegetation index values in 2017

The monthly multi-vegetation index values for 2023 experienced dynamic fluctuations throughout the year. Starting with the highest value in January (0.7767), the index sharply decreased in February before increasing again until April. Subsequently, there was a gradual decline, reaching the lowest point in mid-year. Entering August, the index surged sharply, but this was immediately followed by a dramatic drop in September, recording the year's lowest value (0.4995). The year-end was marked by a strong recovery, reaching the second peak in November (0.7665) before slightly decreasing in December. Despite significant fluctuations, the overall trend line showed relative stability throughout the year. Within this pattern, three key phases were identified in the 2023

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monthly vegetation index data related to rubber defoliation: The first phase in February, May, and September 2023 showed defoliation events caused by the Pestalotiopsis sp. pathogen, evident as drops in vegetation indices (Figure 5). The second phase from March to April 2023 exhibited increasing vegetation index values, indicating regrowth of new rubber tree leaves. This coincided with a rise in rainfall in the study area during these months. The third phase in June and July 2023 showed declining vegetation indices again due to natural annual defoliation of rubber trees during the dry season (Figure 5).

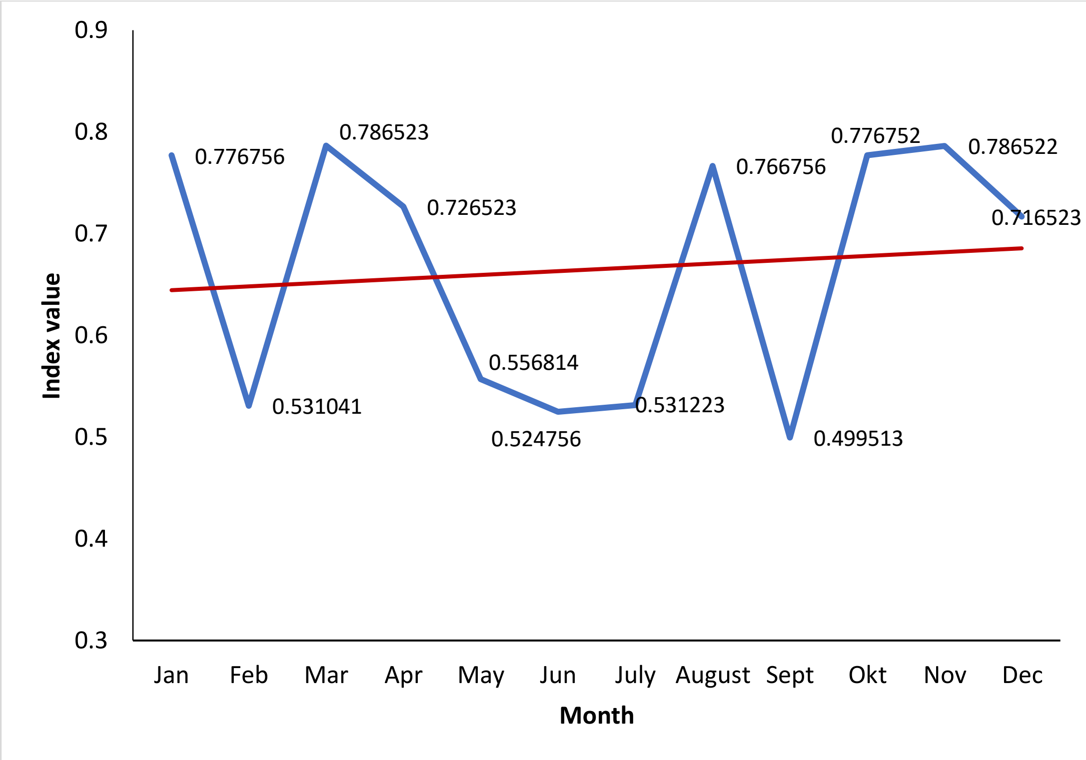

Fig. 5. Trends of monthly multi-vegetation index values in 2017

3.3 Spatial distribution of defoliation classes in 2017 and 2023

For the multi-index vegetation values of PlanetScope imagery in 2017, they tended to have a range of values from 0.3677 to 0.8280 (Table 2). The following is the result of classifying the multi-vegetation index values based on leaf fall severity & canopy density in 2017. In contrast, the pre-defoliation year of 2017 was dominated by good plant health conditions, with 973.84 ha not experiencing any significant defoliation. Moderate defoliation occurred over 387.74 ha. Severe defoliation was minimal, only detected in May over 96.41 ha likely due to natural annual leaf shedding. (Figure 6). However, it should be noted that PlanetScope data availability was limited in 2017, with many scenes having >60% cloud cover.

Table 2. Classification of multi-vegetation index values based on leaf fall severity & canopy density in 2017

Vegetation index value	Canopy density	Leaf fall severity
0,3677 - 0,5173	Low	Bad
0,5173 - 0,6679	Medium	Average
0,6680 - 0,8280	High	Good

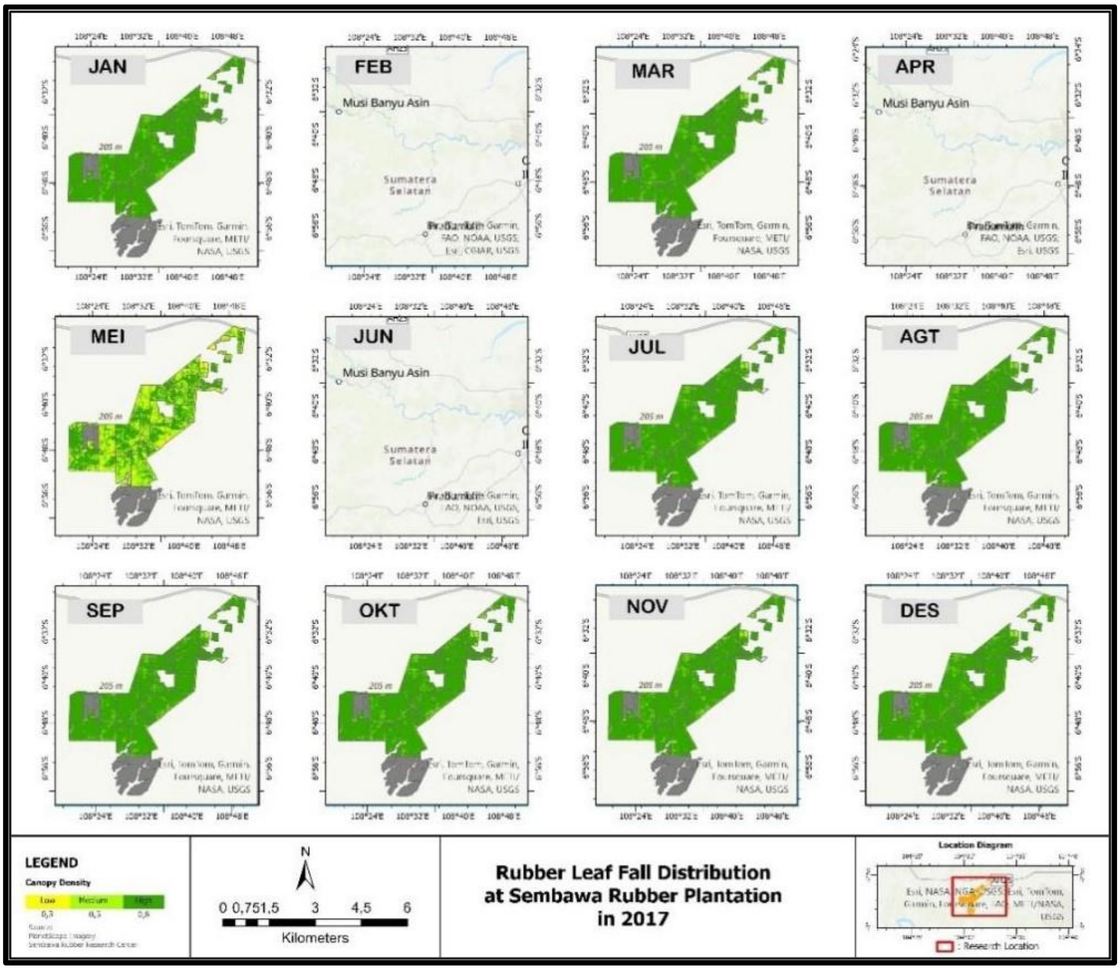

Fig. 6. Rubber leaf fall distribution at Sembawa Rubber Plantation in 2017

This resulted in some areas being misclassified as moderately defoliated when vegetation was likely healthy. Furthermore, for the multi-index vegetation values of PlanetScope imagery in 2023, they had a range of values from 0.3775 to 0.8180. The following is the result of classifying the multi-vegetation index values based on leaf fall severity & canopy density in 2023 (Table 3).

Table 3. Classification of multi-vegetation index values based on leaf fall severity & canopy density in 2023

Vegetation index value	Canopy density	Leaf fall severity
0,3775 - 0,5167	Low	Bad
0,5168 - 0,7366	Medium	Average
0,7367 - 0,8180	High	Good

Spatial analysis revealed that severe defoliation levels in 2023 were concentrated in Blocks 2013D, 2012F, and 2009F, totaling 172.34 ha in the peak month of September. Overall, for 2023, 396.76 ha experienced severe defoliation conditions, while 281.32 ha had moderate defoliation levels (Figure 7). From October to December 2023, rubber plant health improved as indicated by increasing vegetation index values. The area affected by severe defoliation dropped to 52.37 ha, and moderate defoliation covered 97.46 ha during this recovery period. Most of the plantation (843.22 ha) transitioned to good or minimal defoliation conditions.

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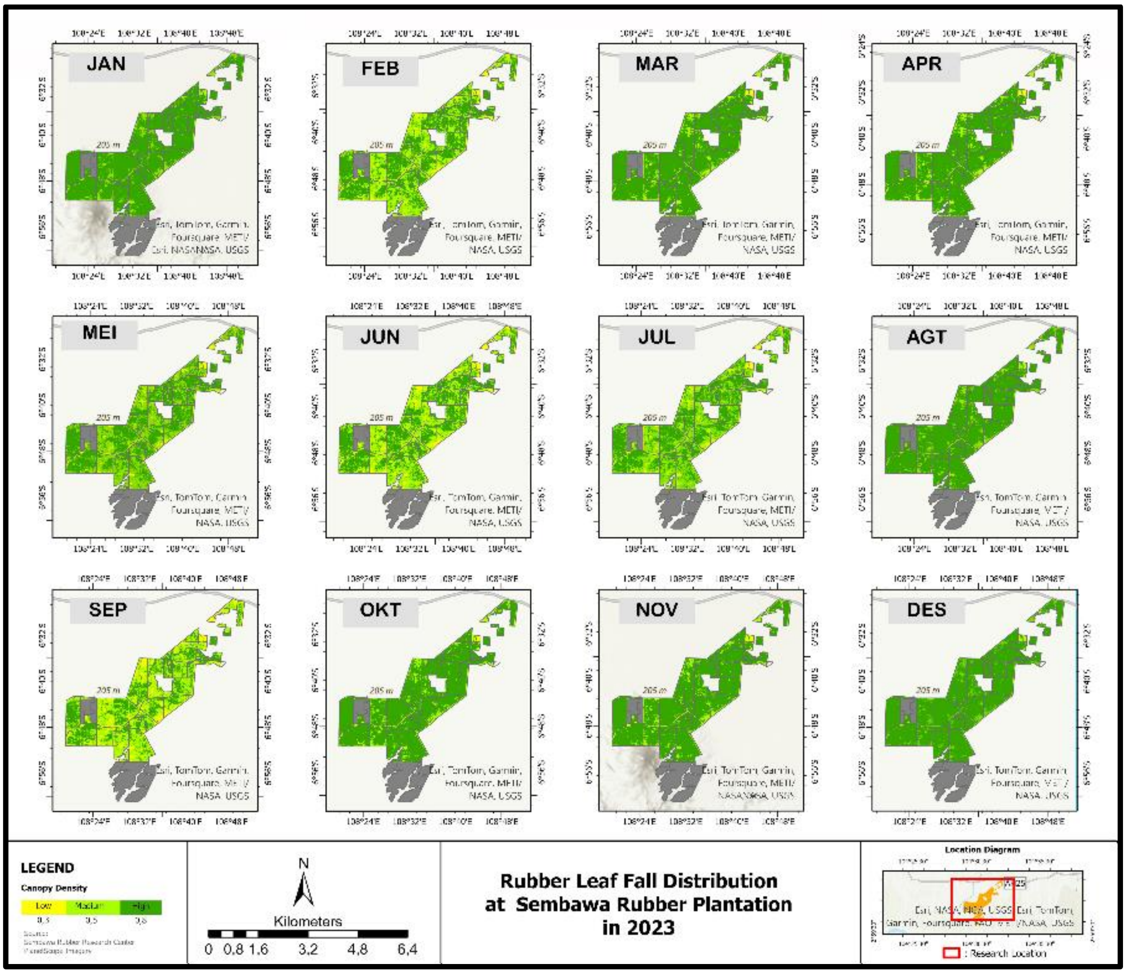

Fig. 7. Rubber leaf fall distribution at Sembawa Rubber Plantation in 2023

3.4 Statistical test of VI values for plant health in 2017 and 2023

A paired t-test was used to examine the difference in mean multi-vegetation index values at the same locations between 2017 (pre-defoliation) and 2023 (post-defoliation). The null hypothesis of no difference in means was rejected ($t=19.660$, $p<0.05$, $df=622$). This indicates there was a statistically significant change in vegetation index values before and after the rubber tree defoliation event.

3.5 Relationship between vegetation index values and climatological conditions

The vegetation index is used to assess vegetation condition, with high values indicating healthy, green vegetation and low values indicating damage or deterioration. This index has a significant relationship with climatological factors like rainfall, humidity, and temperature in terms of rubber tree defoliation.

Rainfall plays a key role, as low rainfall or drought leads to water stress, triggering defoliation to reduce transpiration water loss. Low humidity also accelerates evaporation from plants, while high humidity helps maintain water availability. High temperatures increase transpiration rate, causing faster water loss and defoliation. Monitoring the vegetation index provides valuable information about rubber tree conditions related to these climatological factors.

Correlations

			Nilai_VI_Bulanan	CH_Bulanan	Suhu	Kelembaban
Spearman's rho	Nilai_VI_Bulanan	Correlation Coefficient	1.000	-.056	-.190	.592*
		Sig. (2-tailed)	.	.863	.554	.043
		N	12	12	12	12
	CH_Bulanan	Correlation Coefficient	-.056	1.000	-.451	.317
		Sig. (2-tailed)	.863	.	.141	.315
		N	12	12	12	12
	Suhu	Correlation Coefficient	-.190	-.451	1.000	-.417
		Sig. (2-tailed)	.554	.141	.	.178
		N	12	12	12	12
	Kelembaban	Correlation Coefficient	.592*	.317	-.417	1.000
		Sig. (2-tailed)	.043	.315	.178	.
		N	12	12	12	12

*. Correlation is significant at the 0.05 level (2-tailed).

Fig. 8. Spearman correlations

Analysis using Spearman's correlation of data Automatic Weather Station (AWS) from the Sembawa Rubber Research Center in 2023 showed the vegetation index had a weak negative correlation (0.056) with monthly rainfall, indicating little relationship between the two variables. However, it had a moderately strong positive correlation (0.592) with humidity, where higher vegetation index values corresponded to higher humidity. The correlation with average monthly temperature was negligible (-0.190), suggesting little relationship between vegetation index and temperature. In summary, humidity was the key climatological factor linked to changes in the vegetation index and rubber tree condition based on Spearman's analysis (Figure 8).

4. Conclusions

Based on the research results, the spatial and temporal distribution patterns of rubber tree defoliation were obtained at the Sembawa Rubber Research Center. Spatially, the distribution of defoliation generally occurred almost across the entire area of the Sembawa Rubber Research Center plantation, with severe to moderate levels of defoliation. The rubber plant blocks that experienced the most severe defoliation levels were Blocks 2013D, 2012F, and 2009F, with a total area of 396.76 ha. Temporarily, natural rubber tree defoliation in 2017 occurred in May, indicated by a decrease in the vegetation index value, with a total defoliated area of 96.41 ha. Meanwhile, rubber tree defoliation in 2023 occurred during certain months: in February, May, and September, it was caused by an attack of the Pestalotiopsis sp. pathogen, while in June and July, natural defoliation occurred, indicated by a decrease in the vegetation index value.

To prove the change in vegetation condition due to rubber tree defoliation, a paired t-test was conducted by comparing the average vegetation index values in 2017 (before defoliation) and 2023 (after defoliation). The test results showed a calculated t-value of 19.660, which is greater than the t-table value (1.964). Thus, the null hypothesis (Ho) was rejected, and it can be concluded that there is a significant difference between the average vegetation index values before and after rubber tree defoliation. Furthermore, based on the results of Spearman's correlation analysis, the physical condition variable that most influenced defoliation was humidity, with a correlation coefficient of 0.592, which is close to 1. This indicates a fairly strong correlation or relationship between the multi-vegetation index values and humidity.

However, this study has several limitations that should be considered. Monthly Planet data for 2017 was not fully available, and several Planet image scenes from 2017 still had more than 50% cloud cover, which may have affected the analysis. Additionally, there may be biases in the results as plants falling into the low health class were included in the high range of vegetation index values.

For future research, it is recommended to: (1) Use a longer time series of satellite imagery to better understand the long-term trends of rubber tree defoliation. (2) Incorporate more advanced remote sensing techniques, such as hyperspectral imaging or LiDAR, to improve the accuracy of vegetation health assessment. (3) Conduct ground-truthing surveys to validate the remote sensing results and better understand the relationship between vegetation indices and actual plant health. (4) Investigate the potential use of machine learning algorithms for early detection of leaf fall disease in rubber plantations. (5) Expand the study to include other rubber-growing regions to assess the broader applicability of the findings. These future directions could help to overcome the current limitations and provide more comprehensive insights into rubber tree defoliation patterns and their relationship with climatological conditions.

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Author Contribution

Conceptualization, M.D.M.M., S., R.N., I.P.A., M.H., and N.A.M.S.; Data Curation, M.D.M.M. N.A.M.S.; Formal Analysis, N.A.M.S.; Investigation, N.A.M.S.; Methodology, M.D.M.M and N.A.M.S.; Software, N.A.M.S.; Visualization, N.A.M.S; Supervision, S. and M.D.M.M.; Writing – Original Draft Preparation, N.A.M.S.

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Not applicable.

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Data Availability Statement

The data is available upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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