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Assessing Pruning Intensity to Improve the Tea Productivity in Tropical Plantations by Multispectral Image Classification Model Using K-Means Algorithm

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Authors' contributions

This work was carried out in collaboration among all authors. Author IR designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Authors RD and MA supervised the study. All authors read and approved the final manuscript.

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ABSTRACT

Tea (*Camellia sinensis*) plays a crucial role in the Indonesian economy, but its production has witnessed a decline over the last two years. The majority of tea plantations in Indonesia have historical roots from the Dutch East Indies colonial government, underscoring the importance of monitoring pruning practices in tea plantation management. However, manual monitoring methods prove ineffective, prompting the exploration of precision farming principles using satellite imagery and machine learning to address this challenge. This study was conducted on a 231-hectare tea plantation south of the Tangkuban Perahu Volcano in West Bandung Regency, Indonesia. Sentinel-2B imagery from June to October 2019-2023 was utilized to calculate Soil Adjusted Vegetation Index (SAVI) values and assess tea productivity. Employing the K-Means algorithm, productivity

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values were grouped, and pruning intensity was categorized into three classes, revealing spatial dynamics influencing tea tree productivity. Our results illustrate distinct spatial patterns of pruning intensity across the 231-hectare tea plantation, identifying three classes: less pruned, moderately intensive pruned, and intensively pruned. We show that proposed model of pruning intensity from K-Means algorithm has overall accuracy of 0.57, with highest precision in less pruned class, while the lowest in moderately intensive pruned class. Notably, consistently higher productivity was observed in less pruned tea trees, while an increase in productivity in intensively pruned trees occurred after the second pruning in 2022. These findings highlight the potential of satellite imagery and machine learning for enhancing precision monitoring in tea plantations, offering a practical approach for long-term plantation management. Emphasizing the significance of pruning strategies, our study suggests that optimizing tea productivity amidst environmental and management challenges is achievable through informed monitoring and strategic pruning practices.

Keywords: Remote sensing; machine learning; precision agriculture; plantation management.

1. INTRODUCTION

Tea (*Camellia sinensis*) is a crucial plantation commodity that contributes significantly to the Indonesian economy through exports. Indonesia, as mentioned earlier, ranks as the world's seventh-largest tea exporter, following China and India [1,2]. Over the last two years, Indonesian tea production has witnessed a 5.72% decrease, dropping from 145,000 tons to 136,000 tons [3]. Factors such as climate change [4], improper selection of tea tree seeds [5], and ineffective plantation management can all contribute to this decline. Pruning emerges as a vital tea tree management practice to enhance production, involving cutting the tea tree canopy to encourage the growth of new, healthier shoots and curb pest and disease attacks [6].

Pruning techniques and intensities vary by type, including skiff, cut-across, lung-prune, and clear prune [7]. Cut-across and lung pruning prove effective for rejuvenating tea trees at lower elevations, while skiff and clear pruning excel at higher elevations. The intensity of tea pruning significantly influences subsequent productivity, typically performed every 2-4 years [2]. Indonesian tea plantations often consist of relatively old trees, particularly in West Java, inherited from the Dutch East Indies colonial government in 1877 [5]. Given the historical neglect in plantation management, precise knowledge of tea trees with rare pruning intensity locations and continuous productivity monitoring is crucial. However, manual determination of pruning intensity and monitoring tea plant productivity is time-consuming, laborious, and expensive. Precision farming principles, employing satellite imagery and artificial intelligence, emerge as a viable alternative to enhance monitoring efficiency.

Precision agriculture principles, utilizing satellite imagery and machine learning, have played a pivotal role in advancing technological applications in the agricultural sector over the past decade. Satellite imagery, including WorldView-2 [8], Landsat-8 OLI [9], and Sentinel-2 [10], has been extensively used to monitor changes in tea plantations. Multispectral imagery, such as Landsat-8 and Sentinel-2, can calculate tea productivity through spectral indices [2]. Machine learning techniques applied to satellite images have proven effective in identifying objects on Earth's surface, such as tea trees. For instance, Wang, et al. [9] demonstrated that the Random Forest Classifier supervised learning algorithm was able map tea plantation areas using Landsat-8 imagery. In particular, identifying the condition of tea plants through the application of machine learning is very rarely done. Some studies may have been executed to observe diseases in tea leaves using supervised classification e.g., Hossain, et al. [11], however, these studies have not been applied to map the condition of tea plants on a massive scale. Specifically, there is a lack of studies focusing on pruning management in tea plantation using supervised or unsupervised classification algorithm. Therefore, the combination of multispectral imagery and machine learning algorithms, such as K-Means, holds promise in mapping pruning intensity and determining tea tree productivity.

In this study, we aim to explore the K-Means algorithm in conjunction with Sentinel-2 Level-2B spectral indices, focusing on the Soil Adjusted Vegetation Index (SAVI). Our objective is to map and quantify pruned tea plants in different areas using this clustering method, providing detailed insights into pruning across tea plantations. The incorporation of SAVI is expected to establish a connection between pruning intensity and tea production, offering a comprehensive understanding of tea field management. By employing a combination of these approaches, we expect that our findings will enhance the accuracy of mapping pruning intensity and provide practical insights for improved tea farming and land use.

2. MATERIALS AND METHODS

2.1 Study Area

This study was conducted in a 231-ha tea plantation on southern part of Tangkuban Perahu Volcano, West Bandung Regency, Indonesia (Fig. 1a). Geographically, study area is located in the extent of longitude from 107.58009 to 107.59704 and latitude from -6.76557 to -6.79605. The study site consists of two different soil types, namely Typic Haplundands and Typic Udipsamments. According to climate classification from Oldeman [12], study area is classified into agroclimatic zone "A". Annual rainfall is between 2213.43 to 3691.13 mm/year (Fig. 1b), and the average temperature is 19-20°C. Monthly rainfall is around 100.67-619.00 mm/month (Fig. 1c). The highest rainfall is in November at 619.00 mm, and the lowest in August at 100.67 mm. In general, the average monthly rainfall in the study area is 285.58 mm. Based on classification Oldeman [12], wet months (≥ 200 mm/month) were observed in January-May and October-December, whereas no dry months (<100 mm/month) were observed.

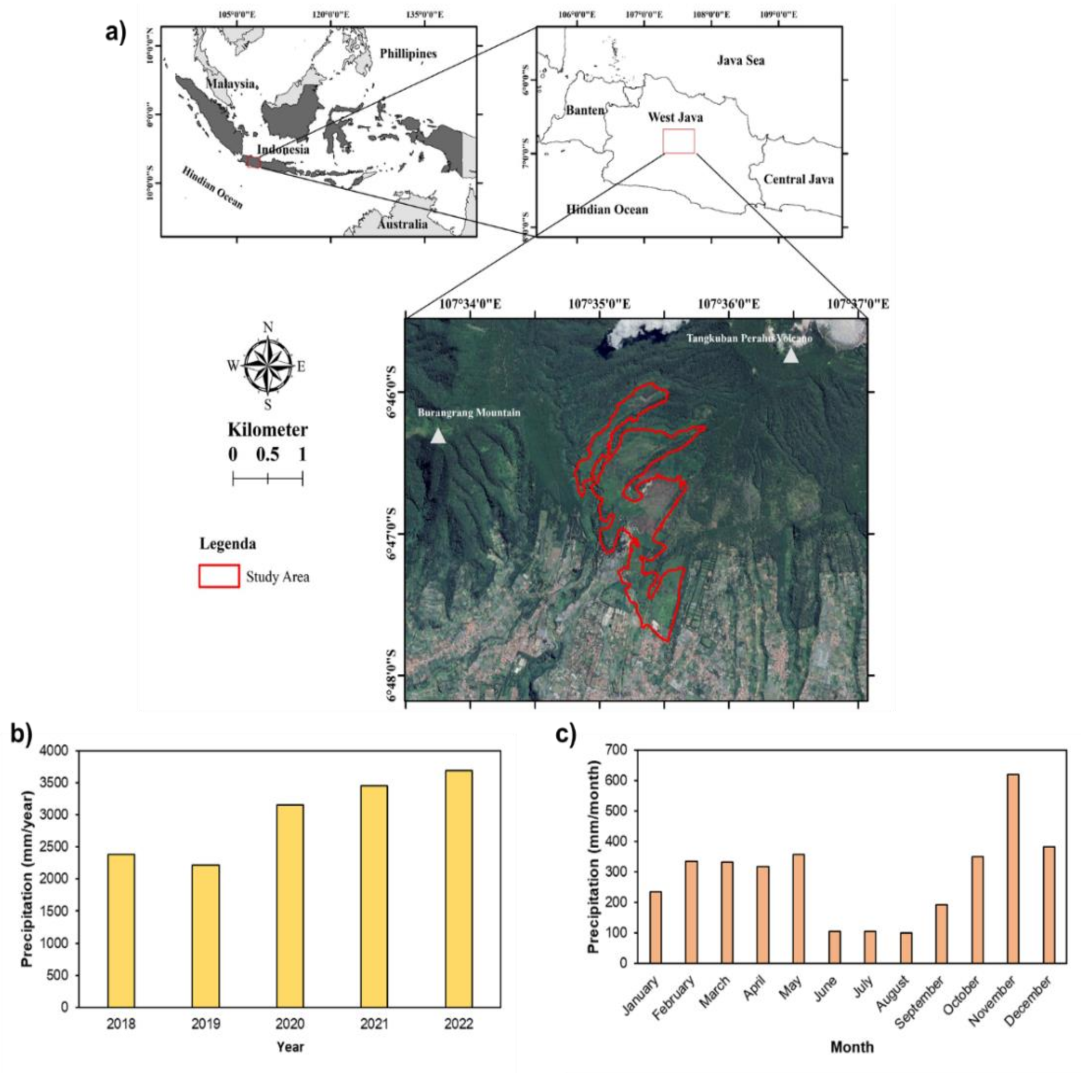

Fig. 1. (a) Location map of study area, (b) mean annual rainfall from 2019 to 2022, and (c) mean monthly rainfall in the studied area

2.2 Acquisition and Pre-Processing of Sentinel 2B Imagery

This study used Sentinel Multispectral Imagery (MSI) Level-2B which acquired on June-October 2019 to 2023. The Sentinel MSI Level-2B has five VNIR bands, two SWIR bands and four red edge bands (Table 1). Spatial resolution of VNIR bands is 10 m, while SWIR and red edge bands has 20 m spatial resolution. Before the imagery data is used for spectral index calculation, this satellite imagery was corrected through two steps of pre-processing includes radiometric and atmospheric correction (Fig. 2). Radiometric correction has done to convert digital number to radiance, while atmospheric correction was aimed to suppress aerosol influence resulting in surface reflectance in percentage unit. Radiometric and atmospheric correction was executed in ENVI 5.3 software (Harris Geospatial Solutions, Inc., Melbourne, Florida). Corrected multitemporal images of Sentinel MSI Level-2B was then stacked to produce mean composite data which represented each year of measurement using ".mean()" function in cloud-based geospatial data computing platform Google Earth Engine (GEE). This composite image synthesis has proven to be effective for land-use classification on large-scale area [13].

Table 1. Detailed specification of Sentinel MSI Level-2B spectral bands

Data	Spectral Band	Wavelength (nm)	Resolution
Sentinel 2 MSI Level-2B	B1 – Coastal Aerosol	443	60
	B2 – Blue	490	10
	B3 – Green	560	10
	B4 – Red	665	10
	B5 – Red Edge	705	20
	B6 – Red Edge	740	20
	B7 – Red Edge	783	20
	B8 – Near Infrared	842	10
	B8A – Red Edge	865	20
	B9 – Water Vapor	945	60
	B10 – Cirrus	1375	60
	B11 – Shortwave Infrared	1610	20
	B12 – Shortwave Infrared	2190	20

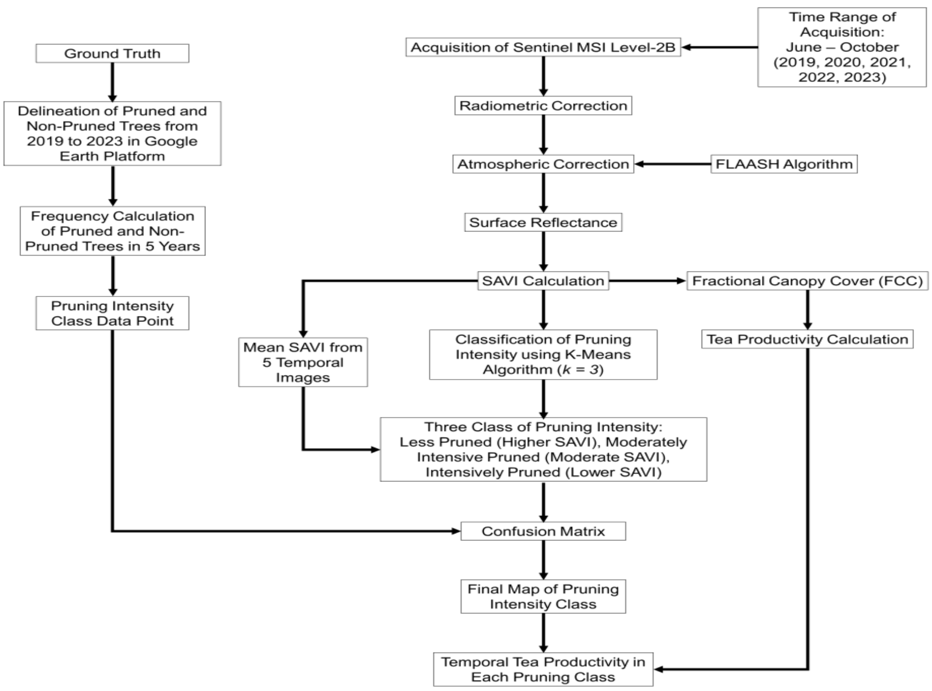

Fig. 2. Flow diagram of proposed model in this study

2.3 Calculation of Soil Adjusted Vegetation Index (SAVI), Fractional Canopy Cover and Productivity

Corrected imagery was then used for the calculation of the Soil Adjusted Vegetation Index (SAVI) (Fig. 2). SAVI is one of the vegetation indices that can suppress background noise from soil reflectance which utilizes the correction factor of soil brightness (Huete, 1988). In general, SAVI uses a similar spectral band with the Normalized Difference Vegetation Index (NDVI) for its calculation, namely NIR and red spectral bands, yet it also utilized the correction factor value of 0.5. SAVI is then used to calculate the fractional canopy cover (FCC) of tea trees utilizing a linear equation produced by Ramadanningrum, et al. [2]. Tea productivity is estimated using FCC value using a linear equation from the same study. SAVI, FCC, and productivity of tea trees were calculated using the following equation below:

$$\text{SAVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED} + \text{L}}(1 + \text{L})$$

$$\text{FCC} = (183.76 \times \text{SAVI}) + 52.652$$

$$\text{Productivity} = (0.173 \times \text{FCC}) - 2.4495$$

Where NIR is near infrared band, RED is red band, and L is correction factor of soil brightness with value of 0.5.

2.4 K-Means Clustering Implementation

K-Means unsupervised classification algorithm was used to classify the pruning intensity of tea trees (Fig. 2). This algorithm was applied to SAVI data which has been processed for each year of measurement (i.e., 2019 to 2023). The number of k was set into 3 which reflects three classes of pruning intensity: intensively pruned, moderately intensive pruned, and less pruned. Determination of pruning intensity class was done by comparing the calculated mean of SAVI value from 2019 to 2023 in produced pruning intensity classes. The mean of SAVI was expected to be high in less pruned class, moderate in moderately intensive pruned class, and low in intensively pruned class. K-Means classification, as an unsupervised machine learning technique, makes it possible to divide data into several different groups. The application of the K-Means algorithm was done through the use of the kmeans function in R 4.2.1. Specifically, the K-Means algorithm could be depicted by the equation below [14].

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left| x_i^{(j)} - C_j \right|$$

where $\left| x_i^{(j)} - C_j \right|$ is a distance between vector data $x_i^{(j)}$ and cluster center C_j.

2.5 Model Evaluation

The evaluation process actively assessed the K-Means model by calculating the confusion matrix, precision, and accuracy. Concurrently, we collected reference data on pruning intensity classes from 2019 to 2023 through visual assessment and delineation using Google Earth's satellite images, known for their higher spatial resolution (see Fig. 2). Subsequently, we categorized the assessment into two classes: pruned and non-pruned. Extracting reference data from delineation results involved utilizing each pixel location in the K-Means-derived maps. To determine the occurrences frequency of pruned and non-pruned classes over the 5-year assessment period, we calculated and classified them into three distinct groups: Less Pruned (0 year of pruning), Moderately Intensive Pruned (1-2 years of pruning), and Intensively Pruned (>3 years of pruning). By actively comparing this reference data, collected and categorized, with the predicted classes from the K-Means model, we gained insights into the model's performance. By comparing the collected and categorized reference data with the predicted classes from the K-Means model, we gained insights into the model's performance.

The confusion matrix is a representation of the truth matrix derived from machine learning prediction outputs. The number of positive and negative predictions for each class is displayed in this matrix. Calculating the confusion matrix could aid in determining the composition of the class that the model confuses as another class [15]. Each row of the matrix represents the actual class, while each column represents the predicted class, or vice versa. The actual and predicted classes are used to support the identification of system confusion in distinguishing class categories [16]. The correct prediction class is represented by True Positive (TP) and True Negative (TN), while the false prediction is represented by False Positive (FP) and False Negative (FN).

The confusion matrix values are used to determine the accuracy and precision. Precision evaluates the model's accuracy in terms of correct predictions. The ratio of True Positive to

Total Positive is used to calculate precision [15]. Precision calculations are ideal when we want to be more confident that the model is producing accurate predictions. The model's accuracy is calculated by dividing the number of correct predictions by the total number of predictions. The precision and accuracy are represented by following equations below:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$$

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP+FP+TN+FN}}$$

3. RESULTS AND DISCUSSION

3.1 SAVI Trends of Tea Plantation in The Past 5 Years (2019-2023)

This investigation of tea plant pruning dynamics using Sentinel-2 satellite data and the Soil-Adjusted Vegetation Index (SAVI) reveals subtle patterns spanning the years 2019 to 2023. Table 2 summarizes descriptive statistics for SAVI values during five years in detail. SAVI values varied moderately in 2019, extending from 0.54 to 1.35, with matching median and mean values of 1.18 and 1.17. Subtle but significant change were noticed in 2020, including a minor decrease in minimum SAVI to 0.49 and an increase in maximum SAVI to 1.40. The median and mean values were 1.30 and 1.29. In 2021, a wider range of SAVI values appeared, along with a decrease in the minimum value to 0.36. SAVI values at the median and mean were 1.12 and 1.09, respectively. In 2022, there had been a significant increase in variability, with SAVI values ranging from 0.62 to 1.41. 1.29 and 1.28 are the median and mean values, respectively. While SAVI values were steady within the range of 0.49 to 1.43 in 2023, a small decrease in both median (1.27) and mean (1.24) values.

3.2 Classification of Pruning Intensity Using K-Means Algorithm

The pruning intensity map derived from the K-Means classification is shown in Fig. 3a. According to the classification map, pruning intensity is divided into 3 different classes: less pruned, moderately intensive pruned, and intensively pruned. In general, tea trees in this plantation area were rarely pruned as represented by a large less pruned area. Pruning was intensive mainly in the central and southeast plantation areas. The less pruned tea trees nearly covered a whole tea plantation area with a proportion of about 147.69 ha or 65.34% of the total area (Fig. 3b). Moderately intensity of pruned tea trees has the smallest area covering about 18.26 ha or 8.08% of the total area. The different area extent of pruning intensity classes demonstrates that this plantation applies different treatments of pruning.

The model's precision in predicting "Intensively Pruned" and "Less Pruned" instances stand out in the confusion matrix, with values of 0.93 and 0.99, respectively (Table 3). These high precision scores indicate that the model is generally accurate when predicting these classes. A significant challenge emerges in predicting "Moderately Intensive Pruned" instances, where the precision is significantly lower at 0.17, indicating a significant number of false positives. Overall accuracy is reported to be 0.57, indicating a satisfactory level of performance, but there is potential for improvement. The model excels at predicting the majority of instances correctly, but addressing the challenges in predicting moderately intensive pruned class could significantly improve its overall accuracy. The findings suggest that the moderately intensive pruned class cannot be distinguished due to its SAVI characteristic, which is similar to less or intensively pruned classes. This was also observed in the study by Ramadanningrum, et al. [2], which demonstrates the tendency of SAVI values in tea plantation to split into two different groups in the regression plot.

3.3 Productivity of Tea Trees Under Different Pruning Intensity

The productivity level of tea from each pruning intensity class differs in 2019-2023 as shown by Fig. 4. The smallest productivity was observed in the intensively pruned class in 2019 with a value of 1934 kg/ha/year, while the highest is in 2022 in the same class with a productivity value of 2994.6 kg/ha/year. The less pruned tea trees were observed to be constantly productive (>2500 kg/ha/year) until they decreased in 2021 and 2023 to 2440.5 and 2627.7 kg/ha/year, respectively. A similar trend was shown by moderately intensive pruned tea trees which have productivity >2500 kg/ha/year, except in 2021 and 2023 with productivity levels at 1936.6 and 2328.4 kg/ha/year. According to the level of productivity, the pruning primarily took place in 2021 and 2019 which is represented by the low productivity level of all pruning intensity classes. In the 5 years, intensively pruned tea trees have been trimmed 3 times incrementally in 2019, 2021, and 2023. A significant increase in productivity was found after the second trim of intensively pruned tea trees in 2022. This second trim of intensively pruned tea trees caused the productivity level to rise to 2994.6 kg/ha/year, higher than those in less and moderately pruned tea trees. As we know this productivity was derived from fractional canopy cover calculation, the productivity of the less pruned class was found to be constantly higher than the other classes until the pruning time in 2021 and proved that tea trees in this class was rarely trimmed in the last 5 years.

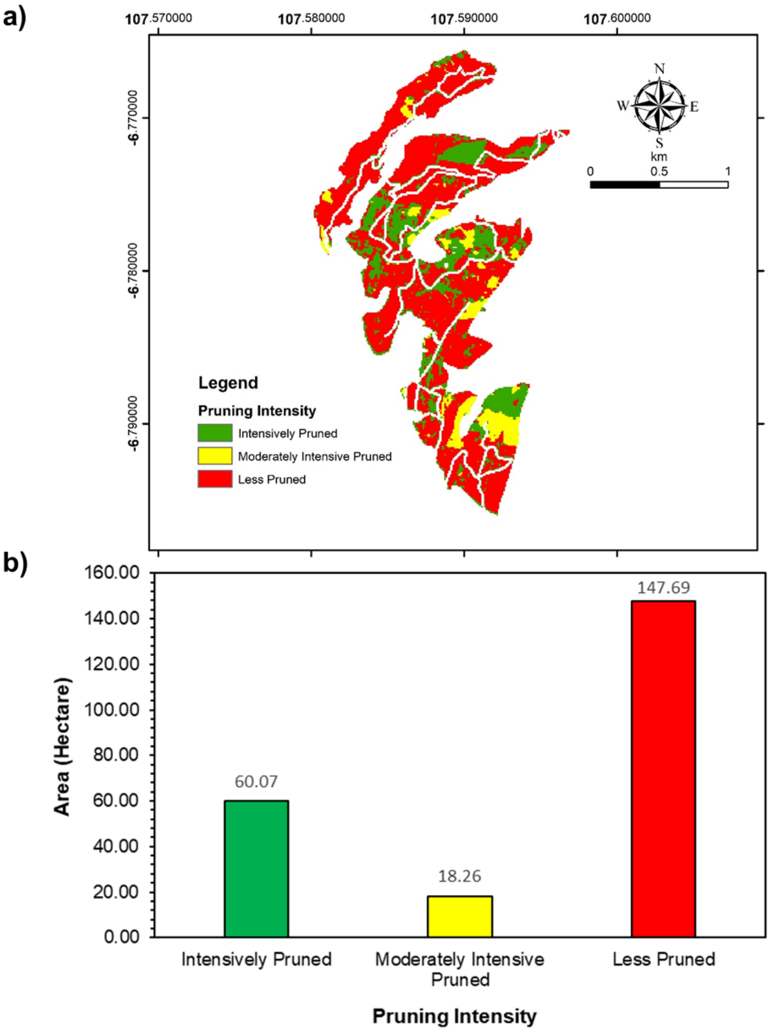

Fig. 3. (a) Map which shows the spatial distribution of the three K-Means classified pruning intensity from SAVI and (b) the extent of each pruning intensity class

Table 2. Descriptive statistics of SAVI trend from 2019 to 2023

Year	Min	Max	Median	Mean
2019	0.54	1.35	1.18	1.17
2020	0.49	1.40	1.30	1.29
2021	0.36	1.29	1.12	1.09
2022	0.62	1.41	1.29	1.28
2023	0.49	1.43	1.27	1.24

Table 3. Confusion matrix, precision, and overall accuracy of pruning intensity model from K-Means algorithm

Actual Predicted	Intensively Pruned	Moderately Intensive Pruned	Less Pruned	Precision
Intensively Pruned	871	61	1	0.93
Moderately Intensive Pruned	3565	1711	5006	0.17
Less Pruned	117	0	8853	0.99
Overall Accuracy = 0.57				

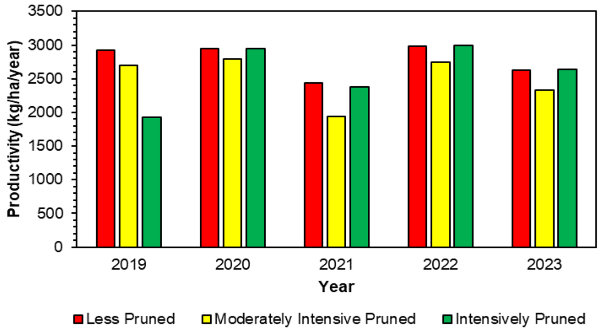

Fig. 4. Productivity levels of tea trees in less pruned, moderately pruned and intensively pruned class from 2019 to 2023

Generally speaking, pruning is the most important management of tea trees which could affect its productivity. Based on the results, light pruning of intensively pruned tea trees was carried out in 2021 and 2023. Pruning in 2021 was proven to increase productivity by 52.6 kg/ha/year compared to productivity in 2020. Several studies have recorded the advantages of the pruning method to the physiological characteristics of tea and its interaction with soil properties. For example, Zhang, et al. [17] reveal that pruning could increase the branches of tea trees, as well as their productivity. The branches of tea trees could significantly increase when pruning takes place in summer season [17,18]. In 2019, the productivity level of intensively pruned tea was observed to be lower than in 2021 and 2023. This indicates that the pruning method has been executed by trimming the entire shoot of tea trees (clear prune) while pruning in 2021 and 2023 the lung shoot part is excluded (rim lung prune) (Fig. 5). Rim lung pruning in 2021 will have a positive influence on productivity level in the next year. Excluded lung shoot in rim lung pruning acts as the center of auxin hormone synthesis for the new growth of buds [19]. Despite the advantages for physiological processes, pruning also has been proven could fix soil-plant interactions. Pruning could increase polyphenol oxidase activity in the soil, causing the shifting of soil pH to a near-neutral state [17]. Pramanik, et al. [20], reveals that pruning could decrease the number of nitrification bacteria, but increase other microorganisms in soil. Moreover, the remaining pruning litter that is starting to degrade can be a source of amino and carboxylic acids which are used by microorganisms. On the other hand, the high nitrogen requirements of tea plants after pruning need to be overcome by providing adequate amounts of nitrogen fertilizer.

Fig. 5. Field condition of intensively pruned class in 2023

4. CONCLUSION

In conclusion, our study demonstrated the capability of precision farming principles combining the K-Means algorithm and the Sentinel-2 Level-2B spectral index to monitor pruning intensity in tea plantations. Our model demonstrated high precision in predicting "Intensively Pruned" (0.93) and "Less Pruned" (0.99) instances, affirming its accuracy in identifying these classes. While achieving a satisfactory overall accuracy of 0.57, addressing challenges in predicting "Moderately Intensive Pruned" instances would further enhance the model's effectiveness in tea plantation management. The various spatial patterns revealed the importance of pruning strategies, with higher productivity consistently seen in less pruned trees. The increase in productivity of intensively pruned tea trees after the second pruning in 2022 indicates the potential for making appropriate management decisions in optimizing tea cultivation. These findings contribute valuable insights into sustainable tea farming practices in Indonesia, highlighting the importance of integrating technology to improve plantation management.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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