Original Research Article

Utilization of multispectral remote sensing and K-Means algorithm to identify pruning intensity and productivity of tea in tropical plantation

ABSTRACT

Tea (*Camellia sinesis*) is an important commodity in the Indonesian economy, with production declining in the last two years. Because most tea plantations were inherited from the Dutch East Indies colonial government, monitoring of pruning is an important aspect of tea plantation management in Indonesia. Furthermore, manual monitoring methods are ineffective, so exploration of precision farming principles using satellite imagery and machine learning is required to overcome this problem. This study took place on a 231-hectare tea plantation south of the TangkubanPerahu Volcano in West Bandung Regency, Indonesia. Sentinel-2B imagery from June to October 2019-2023 is used to calculate Soil Adjusted Vegetation Index (SAVI) values and tea productivity. The K-Means algorithm was used to group productivity values and categorize pruning intensity into three classes, revealing the spatial dynamics that influence tea tree productivity. Here we show the different spatial patterns of pruning intensity across a 231-ha tea plantation, indicating three classes: less pruned, moderately intensive pruned, and intensively pruned. In particular, less pruned tea trees consistently demonstrated higher productivity, whereas the increase of productivity in intensively pruned occur after second pruning in 2022. Our findings suggest that satellite imagery and machine learning have the potential to improve precision monitoring in tea plantations, providing a practical method for long-term plantation management. This emphasizes the significance of pruning strategies for optimizing tea productivity in the face of environmental and management challenges.

Keywords: Remote sensing, machine learning, precision agriculture, plantation management

1. INTRODUCTION

Tea (Camellia sinesis) is a plantation commodity that contributes significantly to the Indonesian economy through exports. As previously stated, Indonesia is the world's seventh-largest tea exporter, trailing only China and India[1,2]. Indonesian tea production has decreased by 5.72% in the last two years, from 145,000 tons to 136,000 tons[3]. Climate change[4], selecting the wrong tea tree seeds[5], and ineffective plantation management can all contribute to this decline. Pruning is one of the tea tree management efforts to increase production. Pruning is a method of cutting the tea tree canopy to allow for the growth of new, healthier shoots while also suppressing pest and disease attacks [6].

Pruning techniques and intensities vary depending on the type, including skiff, cut-across, lung-prune, and clear prune[7]. Cut-across and lung pruning are effective methods for rejuvenating tea trees at low elevations, whereas skiff and clear pruning are more effective at higher elevations. The intensity of tea pruning can also influence subsequent productivity. Pruning is typically done every 2-4 years (Ramadanningrum et al., 2020). Tea plantations in

Indonesia are comprised of relatively old trees. Because most tea plantations in Indonesia, particularly West Java, were inherited from the Dutch East Indies colonial government in 1877 (Sriyadi et al., 2012), many tea trees have been poorly managed, particularly through plantation management such as pruning. As a result, knowing the locations of tea trees with rare pruning intensity and monitoring their productivity year after year is critical. Manually determining pruning intensity and monitoring tea plant productivity would be time-consuming, laborious, and expensive. Precision farming principles, which use satellite imagery and artificial intelligence, are one alternative that can reduce the efficiency of monitoring work.

Precision agriculture principles were applied through the use of satellite imagery and machine learning for monitoring plantation land, accelerating technological progress in the agricultural sector over the last decade. Satellite imagery has been widely used to monitor tea plantations. Most studies map changes in tea plantations using multispectral imagery such as WorldView-2[8], Landsat-8 OLI [9], and Sentinel 2 [10]. Furthermore, multispectral imagery (e.g., Landsat-8 and Sentinel-2) is capable of calculating tea productivity via spectral indices [2]. Several other studies have found that using machine learning techniques to analyze satellite images can help identify objects on the earth's surface such as tea plants. Wang*, et al.* [9], for example, discovered that the Random Forest Classifier supervised learning algorithm is capable of mapping tea plantation areas on Landsat-8 imagery. As a result, the use of multispectral imagery in conjunction with machine learning algorithms like K-Means is thought to be capable of mapping pruning intensity and calculating tea tree productivity.

In this study, we want to try the K-Means algorithm along with Sentinel-2 Level-2B spectral indices, focusing on the Soil-Adjusted Vegetation Index (SAVI). We want to figure out and map how many tea plants are pruned in different areas. By using this clustering method, we hope to show the details of pruning across tea plantations. The inclusion of SAVI was expected to connect pruning intensity with how much tea is being produced, giving us a fuller picture of how tea fields are managed. Through this mix of different approaches, we expect that our findings can improve how accurately we map pruning intensity and offer practical ideas for better tea farming and land use.

2. MATERIAL AND METHODS

2.1 Study Area

This study was conducted in a 231-ha tea plantation on southern part of TangkubanPerahu Volcano, West Bandung Regency, Indonesia (Figure 1a). Geographically, study area is located in the extent of longitude from 107.58009 to 107.59704 andlatitudefrom -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 [11], study area is classified into agroclimatic zone “A”. Annual rainfall is between 2213.43 to 3691.13 mm/year (Figure 1b), and the average temperature is 19-20°C. Monthly rainfall is around 100.67-619.00 mm/month (Figure 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 [11], wet months (≥ 200 mm/month) were observed in January-May and October-December, whereas no dry months (<100 mm/month) were observed.

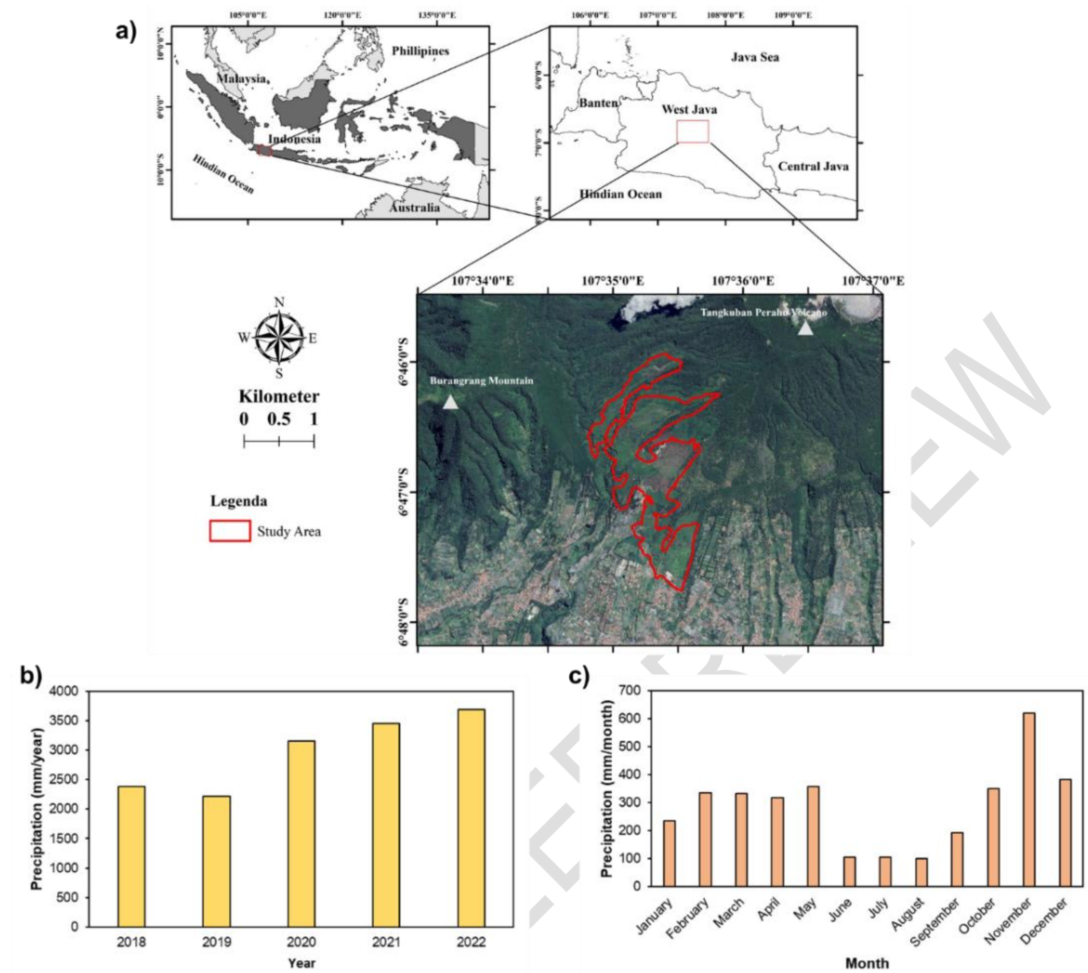

Fig.1.(a) Location map of study area, (b) mean annual rainfall from 2019 to 2022, and (c) mean monthly rainfall in the studied area.

2.2 Acquisition and Pre-Processing of Sentinel 2B Imagery

This study used Sentinel Multispectral Imagery (MSI) Level-2B which acquired on Juny-Oktober 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. 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 [12].

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

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). 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 byRamadanningrum, *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:

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

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

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

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. 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. 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 [13]:

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

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

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.

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

3.2 Classification of Pruning Intensity Using K-Means Algorithm

The pruning intensity map derived from the K-Means classification is shown in Figure 2a. 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 (Figure 2b). 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.

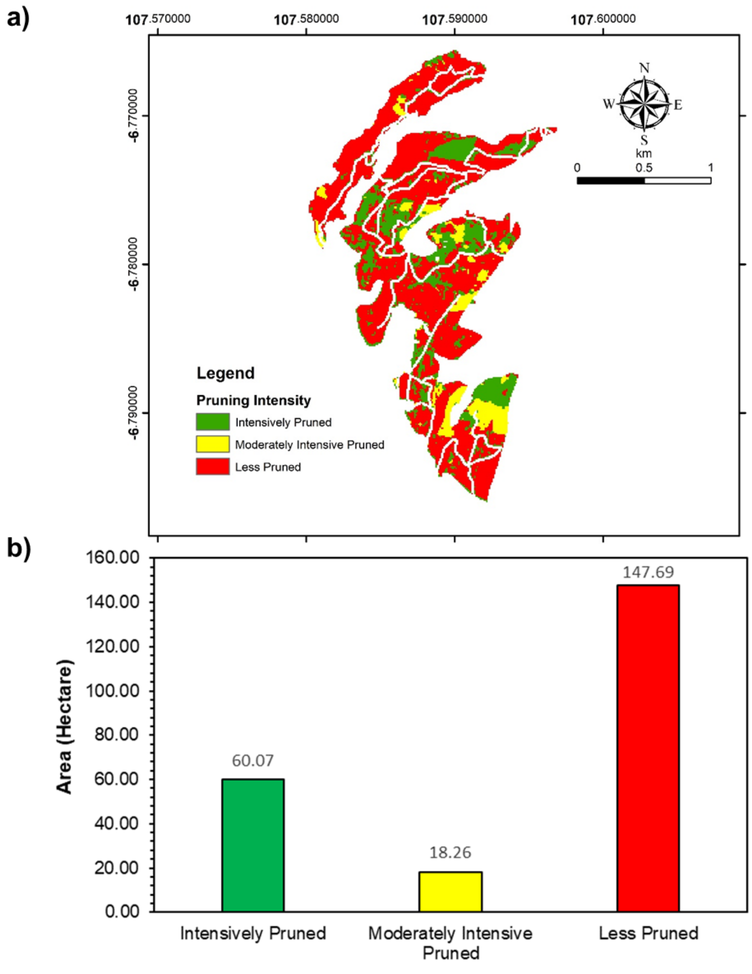

Fig.2.(a) Map which shows the spatial distribution of the three K-Means classified pruning intensity from SAVI and (b) the extent of each pruning intensity class.

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 Figure 3. 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.

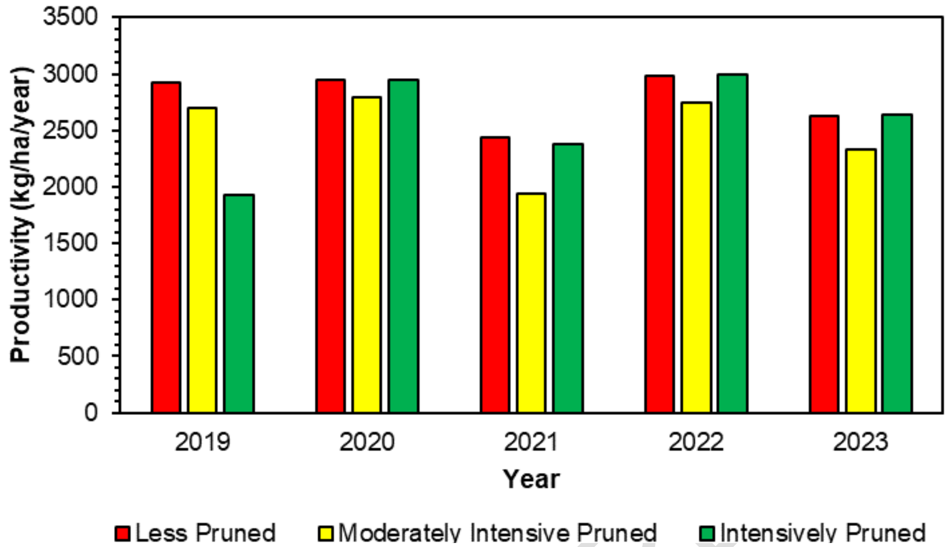

Fig.3.Productivity levels of tea trees in less pruned, moderately pruned and intensively pruned class from 2019 to 2023.

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.* [14] 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[14,15]. 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) (Figure 4). 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[16].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[14]. Pramanik*, et al.* [17], 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.4.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. 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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