SPATIAL ANALYSIS OF LAND USE AND LAND COVER VARIATIONS AFFECTING TEA PRODUCTION IN GUNUNGMAS PLANTATION THROUGH REMOTE SENSING TECHNIQUES

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Abstract. Tea is a popular manufactured beverage consumed worldwide. In value chain analysis to increase efficiency, remote sensing technology can used to monitor Land use/cover change (LUCC) and vegetation health conditions. This study aims to identify LUCC in tea plantations, determine the health condition of tea plantations, and subsequently analyze spatial trends of changes in tea productivity in Gunungmas Afdeling-1 due to changes in tea area or tea vegetation health condition. The identification of LUCC in tea plantations can be carried out through remote sensing technology and machine learning. The Land Use/Land Cover (LULC) classification was obtained using a supervised classification with Random Forest (RF) algorithm on Google Earth Engine (GEE). LULC classification in 2019 results has an overall accuracy of 56.1%, 64.86% for 2020, and 56% for 2021. Tea productivity decreased from 2019 to 2020 but increased from 2020 to 2021. The data presented indicates a declining trend in areas of tea plantation classifications. Based on the findings derived from the Normalized Difference Vegetation Index (NDVI), most of the decreased tea plantation areas are within healthy vegetation. Changes in tea productivity are not in line with alterations in the LUCC of tea plantation classification class and tea vegetation health condition.

Keywords: *LUCC, spatial analysis, random forest, google earth engine, NDVI*

1 INTRODUCTION

Tea (Camellia sinensis) is the world's most consumed and produced beverage (Chang, 2015). The tea segment is expected to bring in $232,381.2 million worldwide in 2021, and the market is expected to grow yearly (Rahimi-Ajdadi & Khani, 2021). Total tea consumption climbed by over 5% in 2013 to 4.84 million metric tons, with Indonesia consuming 64.9 thousand metric tons (Chang, 2015). PT Perkebunan Nusantara VIII is a state-owned company that manufactures, processes, and sells plantation goods like tea.

A value chain analysis is an approach employed to examine and evaluate how various activities contribute to value enhancement (Porter, 1985; Tippayawong et al., 2017). Tippayawong et al. (2017) say that value chain analysis is used to understand the production chain's social, economic, and power relationships, from raw materials to finished goods. Value chain analysis can be used in the food sector to develop and improve efficiency in benefits for a wide range of producers and consumers, as well as better demand management (Bloom & Hinrichs, 2011; Taylor & Fearne, 2009; Tippayawong et al., 2017). In value chain analysis to increase efficiency, remote sensing technology enables monitoring Land use/cover change (LUCC) and assessing vegetation health.

Dihkan et al. (2013) used remote sensing to map and study the effects of tea plantations on Land Use and Land Cover (LULC). A remote-sensing approach is a convenient tool for observing the LULC process, including the tea plantation area, in both spatial and temporal observation (Dihkan et al., 2013). Identifying and analyzing LULC changes within tea plantations can be conducted using remote sensing technology and machine learning. Rahimi-Ajdadi & Kahni (2021) identified and analyzed changes in tea plantations with artificial neural networks and multi-temporal satellite images using Geographic Information Systems (GIS) and Remote Sensing (RS) technology; they employed Landsat satellite imagery and applied a multilayer percep-tron (MLP) artificial neural network (ANN) for classification. Dihkan et al. (2013) employed a modified vegetation index with a Support Vector Machine (SVM) method to classify LULC by extracting spectral and textural information from high-resolution digital aerial pictures. Zhu et al. (2019) identified and classified tea plantations using multi-temporal Sentinel-2 remote sensing and the RF classification feature importance algorithm for feature selection. Parida et al. (2023) used Landsat-5 and Sentinel-2 satellite data to identify and map tea patches using a Random Forest (RF) classifier to monitor tea plants at decadal time scales to evaluate their expansion.

Kumar et al. (2013) say that the main things that affect tea plantation productivity and quality are the type of plant, its age, its stage of growth, how it is pruned, how much light it gets, and how often it gets sick. The utilization of remote sensing technologies for monitoring vegetation status has been extensively employed during the past few decades, allowing rapid estimation of crop growth and development changes (Doraiswamy et al., 2003; Huang et al., 2014; Phan et al., 2020). Many previous studies have demonstrated that NDVI is a widely used spectral transformation method and a helpful crop monitoring tool (Phan et al., 2020). Phan et al. (2020) used multi-temporal MODIS NDVI data to monitor tea health and predict yield using support vector machine (SVM), random forest (RF), and traditional linear re-gression model (TLRM).

The development of remote sensing cloud platforms has presented an updated technologi-cal approach for retrieving and processing extensive remote sensing data, leveraging the swift advancements in cloud storage and cloud computing technology (Cui et al., 2022). Google Earth Engine offers high-performance computing resources for processing large geographical datasets in the cloud, and they are designed to seamlessly share research findings with researchers, policymakers, non-governmental organizations (NGOs), field workers, and the wider public (Gorelick et al., 2017). Many machine learning classifiers and models are accessible on GEE, which runs on Javascript, Python, or GEE standard Machine Learning models (Pande, 2022). Parida et al. (2023) use A Random Forest (RF) supervised classifier deployed on the Google Earth Engine (GEE) platform to classify tea plantations. The RF classifier performs with higher accuracy than CART and SVM regarding overall accuracy and coefficient kappa in LULC Classification (Aldiansyah & Saputra, 2023).

Spatial analysis in the context of tea productivity encompasses the analysis of various phenomena associated with tea plantations. These phenomena include changes in health and land use land cover, specifically in tea cropland. The application of remote sensing technology facilitates identifying changes in LULC and vegetation health conditions. This study examines the spatial analysis of land use/cover change (LUCC) in the tea plantation area on tea productivity using remote sensing, which begin by identify changes in LULC in tea plantations using supervised classification with a random forest algorithm on the Google Earth Engine (GEE) platform using Sentinel-2. Then, using remote sensing data, determine the health of the tea vegetation in the tea plantation. Then, conduct a spatial analysis of trends in changes in tea productivity in Gunungmas Afdeling-1 to changes in the LULC of the tea plantation classification class area or the health of the tea vegetation.

2 MATERIALS AND METHODOLOGY

2.1 Location

This research was conducted at the Gunungmas Afdeling-1 tea plantation PT Perkebunan Nusantara (PTPN) VIII. PT Perkebunan Nusantara VIII is a state-owned business that takes care of, processes, and sells products from plantations. The location of tea plantation, which is the research area, is in the Puncak area, located in Tugu Selatan Village, Cisarua District, Bogor Regency, West Java Province. The study area shows in Figure 2-1.

2.2 Data

The three factors in the phenomenon to be observed are Land use/cover change (LUCC), tea plant health, and tea crop productivity. Sentinel-2A satellite images, field survey data, section (Afdeling) boundary data, and data on how well tea grows at PTPN VIII Gunungmas are all used to make the model. The Afdeling boundary data and tea productivity data from PTPN VIII Gunungmas are secondary data. The primary data for processing Land Use/Land Cover (LULC) and vegetation health conditions are satellite imagery data which in this case is Sentinel-2A satellite imagery. Field survey data is the result of marking LULC in the field as a reference in making sample points. The survey was carried out using a systematic sampling approach, which predetermined sampling points before surveys. The data collection for the field survey was conducted using the purposive sampling technique. A sample of points was selected from the entire population of LULC in the study area to ensure representativeness. The selection of sampling points for field surveys in the Gunungmas Afdeling-1 tea plantation of PT Perkebunan Nusantara (PTPN) VIII used a random distribution method. The field surveys were conducted via the Avenza Maps application. The data used in this study can be seen in Table 2-1.

Table 2-1 Data Source.

Data	Source
Sentinel 2A (Data Date 18/08/2019, 27/08/2020, 12/08/2021)	European Union/ESA/Copernicus
Field Survey Data Marking	Field Survey
Section (*Afdeling*) boundary	PT. Perkebunan Nusantara (PTPN) VIII Gunungmas
Tea productivity	PT. Perkebunan Nusantara (PTPN) VIII Gunungmas

The Afdeling boundary data used in this study is limited to Gunungmas Afdeling-1. This Afdeling boundary data is used as a reference for Area of Interest (AOI) as a work area boundary. A yearly trend of changes in tea productivity can be generated using PTPN VIII Gunungmas tea productivity data. This data will be used as a reference for the spatial analysis of data related to LULC and the condition of the tea vegetation. In this spatial analysis, LULC data is needed to make a trend of LUCC for the tea plantation classification class. Meanwhile, data on the health condition of tea plantation vegetation is required to produce a trend of changing the area of the tea crop's health condition.

The data used to obtain LULC data and NDVI are Sentinel 2A satellite imagery data. Data processing of LULC and condition of tea plantation vegetation is carried out using Google Earth Engine. Google Earth Engine offers high-performance computing resources for processing large geographical datasets in the cloud, making it simple to do so without having to deal with the IT issues currently associated with either (Gorelick et al., 2017).

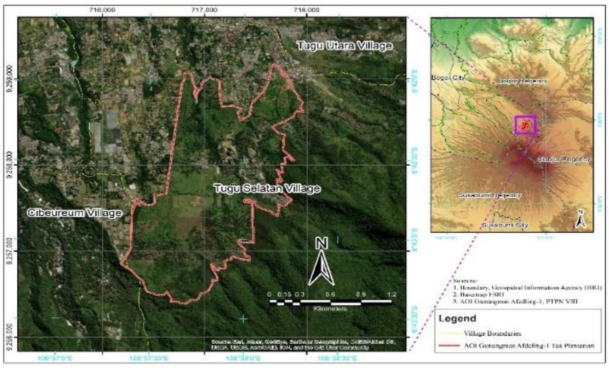

Figure 2-1: Study Area Map.

GEE has datasets that were collected by the Sentinel satellites of the European Space Agency (Amani et al., 2020). (Sentinel-1 Synthetic Aperture Radar (SAR) (2014–present), Sentinel-2 multispectral (2015–present), Sentinel-3 Ocean and Land Color (2016–present), and Sentinel-5P Tropospheric Monitoring (2018–present) all have data sets from the Sentinel collection (Amani et al., 2020). The Sentinel-2 satellite offers multispectral data, and the dataset consists of four bands with a spatial resolution of 10 m, six bands with a spatial resolution of 20 m, three bands with a spatial resolution of 60 m, and three quality assessment (QA) bands, one of the QA bands is a bitmask frequency band that contains cloud mask information (Ji et al., 2020). Sentinel-2 data can potentially be used for global land use and land cover monitoring and crop health monitoring (Phiri et al., 2020).

Sentinel-2A satellite imagery was selected as the primary data using the GEE platform. This study chose images from 2019, 2020, and 2021 to see how the trend changed from year to year. In this study, we looked for images that had at least 5% cloud cover. After obtaining the dates when the images were taken with 5% cloud cover, the images were selected in the same month in each of the three years.

2.3 Methods

In order to limit the processing area, a Bound AOI filter uses when selecting image data. The bands used are Blue, Green, Red, and NIR bands. From the Sentinel-2 data, apart from looking at images related to LULC, they also want to see NDVI values. The NDVI value is also used as a point of reference when putting together sample data to show the vegetation density. Sample data for the classification process refers to data from field surveys, satellite imagery conditions that year, and NDVI. To generate LULC using supervised classifi-cation with the Random Forest (RF) algorithm. Random Forest (RF) is made up of several trees (Zhu et al., 2019), each of which is made up of a certain number of random samples and trained on random features. The advantages of RF are no overfitting, high accuracy, and estimating missing data. Using multiple decision trees reduces the risk of overfitting. RF runs efficient databases. For big data, RF produces accurate predictions. RF data can maintain accuracy when most of the data is lost. Trisasongko et al., (2022) found that both RF and SVM achieved comparable levels of accuracy; however, the accuracy of RF models exceeded that of SVM in land cover classification.

In the results of the LULC class classification, the identification of changes every year in the LULC classification class of tea gardens is carried out. The results will be analyzed to see trends in LUCC in tea plantations. Concerning the condition of tea plantation vegetation, the NDVI value is processed on the GEE platform to identify areas of the tea plantation vegetation's health condition. Also, the results will be examined to see how the health of the plants in the tea plantation has changed over time. The research block diagram is depicted in Figure 2-2.

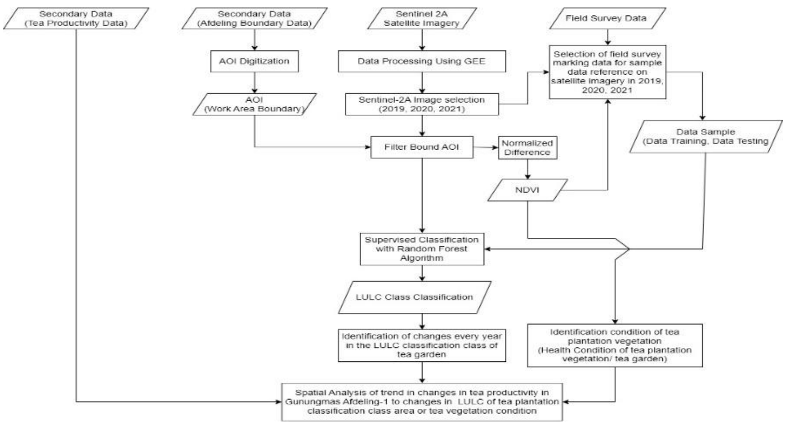

Figure 2-2: Research Block Diagram.

2.4 Data Processing

LULC processes its data with the GEE and RF algorithm, a supervised classification method. After the LULC results have been classified, LUCC in the plantation classification class are found each year. The LULC classification was carried out in 2019, 2020, and 2021. The 2019 LULC classification uses 132 sample points, 2020 uses 140 sample points, and 2021 uses 151 sample points. At these sample points, of 70% training and 30% testing were randomly selected.

The classification was made into 11 classes. The classification class used partially refers to the 2021 RBI Element

Code (Kode Unsur RBI). In the 2021 Kode Unsur RBI, there is only one plantation class, but the field survey results found that several types of plantations need to be distinguished. There are several forest classes in the 2021 Kode Unsur RBI, but this study only used one forest class. The class classified as forest in this study is land covered with tall and dense vegetation. This research area has been excluded from protected forest area. A description of the LULC sourced from the 2021 Kode Unsur RBI and the field survey results are shown in Table 2-2. LULC Classification Classes used in this study are listed in Table 2-3.

Table 2-2: Land Cover Reference Derived from Kode Unsur RBI 2021 (BIG, 2021).

No	Classification Class	Description
1	Perkebunan/ Kebun (Plantation/ Gardens)	Individuals manage the land cultivated for gardens and plantation crops, the private sector, and BUMN.
2	Tanaman Campuran (Mixed plantation)	Land that is overgrown/planted with natural/semi-natural vegetation, both annual and seasonal crops, is managed or controlled by the people, and the products are not explicitly utilized.
3	Rumput (grass)	Land overgrown with grass species with a not-too-vast ex-panse, either cultivated or grows naturally (the appearance of grass on a soccer field).
4	Semak Belukar (Shrubs)	Dryland has been overgrown with various heterogeneous and homogeneous natural vegetation, the density of which is rarely too dense and dominated by low vegetation.
5	Hutan Rimba (Forest)	Land covered with tall forest plants.
6	Kosong/ Gundul (Vacant/ barren land)	Land that is not cultivated, including vacant or barren land.

Regarding tea plantation vegetation conditions, on the GEE platform, processing NDVI values are carried out to identify areas of tea plantation vegetation health conditions. The health of the vegetation was estimated using NDVI, a qualitative and quantitative measure of vegetation cover based on the reflected light of the vegetation at specific frequencies (Phan et al., 2020). Chlorophyll (a health indicator) absorbs visible light strongly, while the leaf's cellular structure strongly reflects near-infrared light. In comparison to stressed vegetation, healthy vegetation will reflect more near-infrared (Phan et al., 2020). Phan et al. (2020) proposed the class names "moderate" and "healthy" for monitoring tea NDVI status, where a value between 0.4 and 0.59 is considered moderate and ≥0.6 is considered healthy.

Table 2-3: LULC Classification Class used.

No	Classification Class
1	Perkebunan Teh (*Tea Plantation*)
2	Perkebunan Bunga (*Flower Plantation*)
3	Perkebunan Alpukat (*Avocado Plantation*)
4	Perkebunan Kayu Manis (*Cinnamon Plantation*)
5	Tanaman Campuran (*Mixed plantation*)
6	Lahan Terbangun (*Built-up area*)
7	Semak Belukar (*Shrubs*)
8	Rumput/Lahan Terbuka (*grass/Open Field*)
9	Tanah Kosong (*Vacant land*)
10	Badan Air (*Waterbody*)
11	Hutan (*Forest*)

3 RESULTS AND DISCUSSION

3.1 Land Use Land Cover (LULC) Classification

The Land Use Land Cover (LULC) Classification results in 2019, 2020, and 2021 are shown in Figure 3-1. LULC classification in 2019 results has an overall accuracy of 56.1%, 64.86% for 2020, and 56% for 2021. This research used a confusion matrix to validate the classification results of the features inside the study area and describe the classification results accuracy by calculating the overall accuracy using the GEE platform. Classification accuracy can be assessed using the ee.confusionMatrix function in the context of GEE. A confusion matrix was generated using train and test data.

The most extensive LULC for 2019, 2020, and 2021 classification results in are tea plantations class area. Data for the LULC area for each classification in 2019, 2020, and 2021 are shown in Table 3-1. Tea plantation class from 2019 to 2020 reduced from 162.17 ha to 143.68 ha, where the reduction in tea plantations class was 18.49 ha. The reduction area of the tea plantation class from the classification results shows LULC conversion. LULC conversion can be from reducing the area tea plantation class to another LULC or adding an area tea plantation class from another LULC. Changes in the Tea plantation class area converted into another LULC yearly are shown in Table 3-2. Class changes of tea plantations where there are additional areas from another LULC yearly are shown in Table 3-3.

Based on the LULC classification in 2019 and 2020, the reduction of the tea plantation class to other LULC classes was 48.57 ha, and the addition of the tea plantation class from other LULC classes was 30.08 ha. The largest land reduction from 2019 to 2020 was the LULC change from tea plantation class to avocado plantation class of 14.64 ha, and the second largest change was the LULC change from mixed plantation class of 12.29 ha. The largest addition of the tea plantation class in 2019 to 2020 was the change of area into tea plantation class from forest class of 8.67 ha, and the second largest was the change of area into tea plantation class from grass/open field of 5.66 ha.

Table 3-1: LULC for each Classification in 2019, 2020 and 2021.

No	Classification Class	Area in 2019 (Ha)	Area in 2020 (Ha)	Area in 2021 (Ha)
1	Perkebunan Teh (*Tea Plantation*)	162.17	143.68	115.61
2	Perkebunan Bunga (*Flower Plantation*)	9.21	0.75	1.78
3	Perkebunan Alpukat (*Avocado Plantation*)	7.17	25.09	44.97
4	Perkebunan Kayu Manis (*Cinnamon Plantation*)	3.79	2.73	11.36
5	Tanaman Campuran (*Mixed plantation*)	7.22	30.59	12.65
6	Lahan Terbangun (*Built-up area*)	23.74	24.12	32.69
7	Semak Belukar (*Shrubs*)	3.45	5.96	0.19
8	Rumput/Lahan Terbuka (*grass/Open Field*)	14.65	8.02	15.79
9	Tanah Kosong (*Vacant land*)	6.38	1.11	3.25
10	Badan Air (*Waterbody*)	0.20	0.19	0.17
11	Hutan (*Forest*)	20.88	16.60	20.39

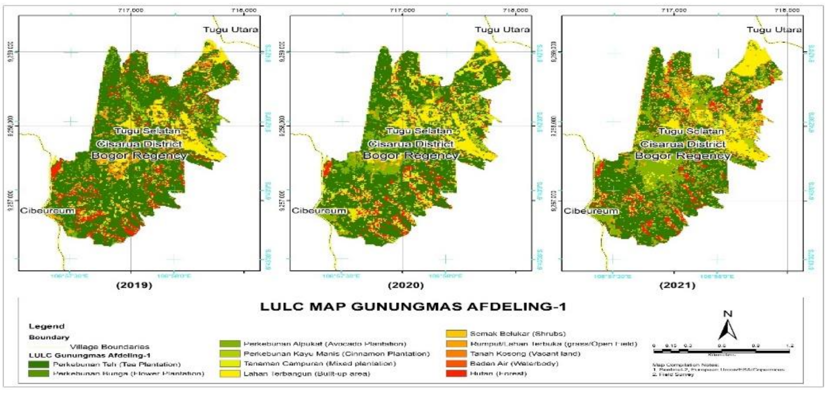

Figure 3-1: Map of Gunungmas Afdeling-1 LULC Classification Results in 2019, 2020 and 2021.

Tea plantation class from 2020 to 2021 reduced area from 143.68 ha to 115.61 ha, whereas the reduction in tea plantation class is 28.07 ha. Based on LULC classification in 2020 and 2021, the reduction of tea plantation class area to other LULC is 56.14 ha, and the addition of tea plantation class from other LULC is 28.19 ha. The largest area reduction in 2020 to 2021 is the change of the area from tea plantation class to avocado plantation class of 17.28 ha, and the second largest is the change of the area from tea plantations class to built-up area class of 9.95 ha. The largest addition of the tea plantation class in 2020 to 2021 was the change of area into tea plantation class from mixed plantation class of 10.41 ha, and the second largest was the change of area into tea plantation class from forest class of 6.12 ha. The class classified as forest in this study is land covered with tall and dense vegetation. This research area has been excluded from protected forest area.

Table 3-2: Changes in the Tea plantation class area converted into another LULC yearly.

No	Classification Class	From 2019 to 2020 (Ha)	From 2020 to 2021 (Ha)
1	(*Flower Plantation*)	0.37	0.58
2	(*Avocado Plantation*)	14.64	17.28
3	(*Cinnamon Plantation*)	0.95	3.93
4	(*Mixed plantation*)	12.29	6.55
5	(*Built-up area*)	4.07	9.95
6	(*Shrubs*)	4.13	0.13
7	(*grass/Open Field*)	3.76	9.78
8	(*Vacant land*)	0.43	1.81
9	(*Waterbody*)	0.04	0.04
10	(*Forest*)	7.89	6.09

Table 3-3: Class changes of tea plantations where there are additional areas from another LULC yearly.

No	Classification Class	From 2019 to 2020 (Ha)	From 2020 to 2021 (Ha)
1	(*Flower Plantation*)	1.79	0.24
2	(*Avocado Plantation*)	4.41	5.13
3	(*Cinnamon Plantation*)	0.78	0.17
4	(*Mixed plantation*)	2.34	10.41
5	(*Built-up area*)	3.5	1.28
6	(*Shrubs*)	0.91	3.17
7	(*grass/Open Field*)	5.66	1.51
8	(*Vacant land*)	1.97	0.15
9	(*Waterbody*)	0.05	6.12
10	(*Forest*)	8.67	0.24

Table 3-4: Area of the three classifications of the NDVI range in 2019, 2020, and 2021.

No	Classification Class	Area in 2019 (Ha)	Area in 2020 (Ha)	Area in 2021 (Ha)
1	Unhealthy < 0.4	0.020	0	0
2	Moderate 0.4-0.59	2.138	0.145	0.067
3	Healthy ≥ 0.6	156.919	141.274	112.223

3.2 Identification of Tea Plantation Vegetation Health

Regarding the condition of vegetation of the tea plantation class, on the GEE platform, the NDVI value is processed to identify the vegetation health of the plantation class. Identification of vegetation health is carried out only in tea plantation class areas. The value used as a reference for classifying the range of NDVI values refers to (Phan et al., 2020). In monitoring the health condition of tea plantation, NDVI value between 0.4 and 0.59 is considered moderate, and ≥0.6 is considered healthy. Then the NDVI value < 0.4 is classified as unhealthy.

The results of the NDVI value are only used to see the value for identifying the health of tea plantation vegetation. No validation of the accuracy of the NDVI value results was carried out. The result of the identification of tea plantation vegetation health in 2019, 2020, and 2021 are shown in Figure 3-2. The area of the three classifications of the NDVI range in 2019, 2020, and 2021 are shown in Table 3-4. In addition to obtaining NDVI values in the tea plantation class area, NDVI values are also observed in areas that have changed from the previous tea plantation class to other LULC classes yearly, which are shown in Table 3-5.

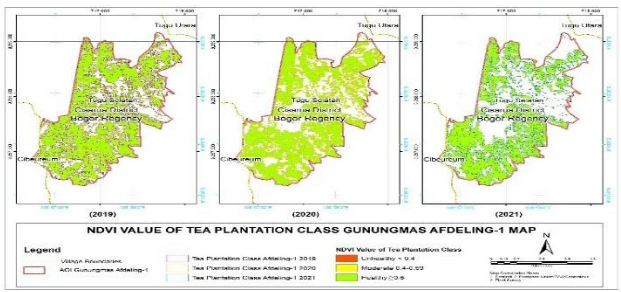

Figure 3- 2: NDVI value of Tea Plantation Class GUNUNGMAS Afdeling-1 Map in 2019, 2020, and 2021

Table 3-5: NDVI value in areas that have changed from the previous tea plantation class to other LULC classes yearly

No	Classification Class	From 2019 to 2020 (Ha)	From 2020 to 2021 (Ha)

1	Unhealthy < 0.4	0.020	0
2	Moderate 0.4-0.59	1.137	0.138
3	Healthy ≥ 0.6	41.471	51.370

3.3 Trends in changes in tea productivity in Gunungmas Afdeling-1 to changes in LULC of tea plantation classification class area or tea vegetation health condition.

The trend of tea productivity in Gunungmas Afdeling-1 has increased from 2019 to 2021, where each year, tea productivity has decreased from 2019 to 2020 and increased from 2020 to 2021, as shown in Table 3-6 and Figure 3-3. The trend of changes in the area of the tea plantation class in Gunungmas Afdeling-1 is decreasing, as shown in Table 3-1 and Figure 3-3. Based on the results of the NDVI value in the tea plantation class area, the NDVI value was also observed in areas that changed from the previous tea plantation class to another LULC class which is shown in Table 3-5. This observation demonstrates that the majority of areas reduced from the tea plantation class have healthy vegetation, and the reduced area of healthy vegetation grows yearly.

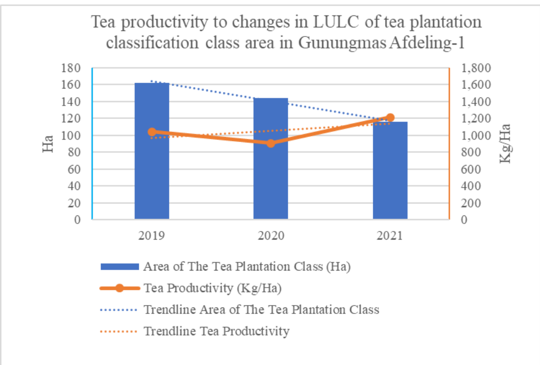

Figure 3-3: Tea productivity to changes in LULC of tea plantation classification class area in Gunungmas Afdeling-1.

Table 3- 6: Tea Productivity in Gunungmas Afdeling-1 in 2019, 2020 and 2021.

2019 (Kg/Ha)	2020 (Kg/Ha)	2021 (Kg/Ha)
1,040	905	1,212

4 CONCLUSION

The identification of LUCC in tea plantations can be carried out through remote sensing technology and machine learning. According to the classification results, the area in the tea plantation class decreased by 28.07 ha between 2020 and 2021 due to LULC conversion. This decreasing area can mean that the tea plantation area class is being changed to another LULC or that another LULC is being added to the tea plantation area class. The largest reduction area from 2019 to 2020 was the LULC change from a tea plantation class to an avocado plantation class of 14.64 ha. The largest area addition from 2019 to 2020 was the LULC conversion to tea plantations of 8.67 ha from forest classes. The largest reduction area from 2020 to 2021 is the change of LULC from tea plantations to avocado plantations, which is 17.28 ha. The largest addition from 2020 to 2021 is the conversion of a mixed plantation class into a tea plantation class of 10.41 ha.

Identification of the health condition of tea plantation vegetation can be generated using remote sensing technology and machine learning, as in this study using GEE with Sentinel-2 with NIR and Red Band. From the NDVI results for the health of tea plantation vegetation, only a small part was included in the unhealthy and moderate classes. The majority were in the healthy class. The trend of tea productivity in Gunungmas Afdeling-1 has increased from 2019 to 2021, where each year, tea productivity has decreased from 2019 to 2020 and increased from 2020 to 2021. The trend of change in Gunungmas Afdeling-1's tea plantation class area is decreasing. From 2019, all unhealthy vegetation converted from the tea plantations class to another LULC. However, the majority of the area lost from the tea plantation class was in areas with healthy vegetation, and the area lost in healthy vegetation increased yearly. These results show that the trends in tea productivity changes are different from changes in the LULC area of tea plantation classification class and tea vegetation health condition.

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AUTHOR CONTRIBUTIONS

Conceptualization: Elok Lestari Paramita, Masita Dwi Mandini Manessa, Mangapul Parlindungan Tambunan, Rudy Parluhutan Tambunan; methodology: Elok Lestari Paramita, Masita Dwi Mandini Manessa; investigation: Elok Lestari Paramita; writing—original draft preparation: Elok Lestari Paramita; writing—review and editing: Masita Dwi Mandini Manessa; visualization: Elok Lestari Paramita. All authors have read and agreed to the published version of the manuscript.

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