TEA PLANT HEALTH RESEARCH USING SPECTROMETER

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Abstract. The first symptom that confirms the leaves are sick is a change in color from green to some other color. Leaf color and chlorophyll have an important role in showing the growth and health of tea plants. Since chlorophyll is directly involved in photosynthesis and responds to a variety of stresses, it is frequently used as a general indicator of plant health. Sentinel 2 data were downloaded from the Google Earth Engine (GEE) to get the NDVI value and several samples of unhealthy tea plant leaves then measured for reflectance using a spectrometer to obtain NDVI values. The goal of this study was to find out how healthy tea plants are by comparing the NDVI values on Sentinel-2 imagery and a spectrometer. The results of spectrometer NDVI and Sentinel-2 imagery have differences. Spectrometer values for healthy plants have a range of 0.3 - 0.9 and NDVI values for diseased in the range of -0.5 - 0.2. The NDVI value of Sentinel 2 images is in the range of 0.6 - 0.8. There is a difference between the measurement results of the NDVI spectrometer and the sentinel image. This is because Sentinel 2 imagery is only capable of taking image pixels with the resolution, not the diseased part of the leaf such as using a spectrometer that directly extracts the value of the infected area from the normal part of the plant.

Keywords: *healthy tea, spectrometer, NDVI, Sentinel-2*

1. INTRODUCTION

Tea is one of Indonesia's export commodities, which is quite important as a foreign exchange earner besides oil and gas (Badan Pusat Statistik, 2022). Tea leaves are the most important part because they are used for consumption. Tea leaf diseases can make tea plants grow poorly, which means they won't produce as much or as good of tea leaves. Symptoms are seen on the leaves. The first symptom that confirms the leaves are sick is a change in color from green to some other color. (Mukhopadhyay et al., 2021) say that healthy leaves have a clear color, while unhealthy leaves have a color that is very different from the original.

Chlorophyll content is important for photosynthetic capacity (Croft et al. 2017) and stress detection (Raddi et al. 2022). Chlorophyll in leaves affects the reflection of infrared light, allowing healthy plants to reflect more infrared light than unhealthy plants. Leaf color and chlorophyll have an important role in showing the growth and health of tea plants. Since chlorophyll is directly involved in photosynthesis and responds to a variety of stresses, it is frequently used as a general indicator of plant health (Gitelson & Merzlyak, 1996)

In the last few decades, remote sensing has been used a lot to check on the health of plants. This helps predict changes in how crops grow and develop at just the right time. Remote sensing consists of collecting information about objects and features without contacting the equipment. Sensors are put on aircraft and spacecraft platforms to survey the Earth's natural resources (Pisharoty, P. 1983). The Vegetation Index (VI) converts the reflectance, including the green, red, and near-infrared (NIR) wavelength bands to which plants respond, into a dimensionless scalar variable for information extraction about plants and their state (Bannari 1995). The use of Vegetation Index to detect disease level in crops have been used in onions (Isip, Alberto, & Biagtan, 2019) and wheat (Liu et al., 2020). Saddik et al. developed spectral disease indices (SDIs) for grapevine disease identification. It was demonstrated that using vegetation indices was, in general, better than using complete spectral data.

The Normalized Difference Vegetation Index (NDVI) is now the most common way to measure plants. It was one of the first remote sensing analysis products used to make multispectral imaging easier to understand. This is because NDVI is easy to figure out with any multi-spectral sensor that has both visible and near-infrared bands. Rossi et al. (2019) found differences in NDVI between Spectral Reflectance Sensors (SRS), Phenocams, and Sentinel-2 MSI. These differences depend on the spatial and spectral resolutions and acquisition geometries of each sensor, as well as how the plants are managed and how much they grow throughout the year. To prevent tea yield loss and improve the quality of tea, tea leaf diseases need to be correctly identified and steps taken to stop them as soon as possible.

Often, different parts of the leaf have discolored spots due to health conditions or nutritional stress, so there are different spectral values on different parts of the leaf (Nansen et al. 2009). If different leaf health states cause the leaf spectrum to have different spatial characteristics, it makes sense to wonder if these spatial differences or image features can be used to calculate chlorophyll content. Only imaging spectroscopy systems can provide spatial detail. Most ground-based chlorophyll retrieval experiments use Analytical Spectral Devices (ASD; FieldSpecFR spectrometer; Analytical Spectral Devices Inc., USA) data from a single sensor spectrometer or images with a small number of wavelengths from multi-spectral systems (Liu et al., 2017).

Some previous research using spectrometer, Naidu et al. (2009) used leaf spectral reflectance to identify viral infections that cause grapevine leafroll disease in grapevines (*Vitis vinifera* L.) in the field. A plant-probe attachment device with a leaf clip was used to attach a portable spectrometer to each leaf of the plant and collect reflectance data from each leaf. Vegetative indices were used to determine whether spectral reflectance could be used to identify the disease in addition to the green, near-infrared, and mid-infrared regions of the spectra. Bagheri et al (2018), used a portable Vis-NIR spectrometer to identify between healthy pear trees and those with symptomatic and asymptomatic Fire Blight disease infection on their leaves. According to the research results, leaf sample pairwise classification was more sensitive to the structure-intensive pigment index. Sterling et al. (2020) used a portable Vis-NIR spectrometer to monitor the symptoms of the Hevea Leaf Blight infection. Young leaves from the two different resistant rubber trees were analyzed, and the result showed that the change in VIs was brought about by a spectral reflectance that increased differently in the visible bands and decreased in the near-infrared bands. The findings showed that the phenology and chlorophyll content of the lobules were related to the severity of disease infection.

Most ground-based chlorophyll retrieval experiments use data from a single sensor spectrometer or images with a small number of wavelengths from multi-spectral systems (Liu et al., 2017). The goal of this study was to find out how healthy tea plants are by comparing the NDVI values on Sentinel-2 imagery and a spectrometer.

2. MATERIALS AND METHODOLOGY

2.1 Location and Data

The research area, which is also a tea plantation, is in the Puncak area (Figure 1), with radiance, reflectance, or DN as input (Huang et al., 2021). This area is located in the administrative area of North Tugu Village and South Tugu Village, Cisarua District, Bogor Regency. The research area is located in block 6, 14 and 15 tea plantations of Gunung Mas.

Sentinel-2 data were downloaded from the Google Earth Engine (GEE). The Sentinel-2 data used was taken in July 2021, because the image data is cloud free. The spatial resolution of Sentinel-2/MSI is 10 m in the red and NIR bands.

Leaf spectra collected in the field were used to determine spectral regions (visible and NIR) and the vegetation indeces with which to detect diseases (Figure 2)

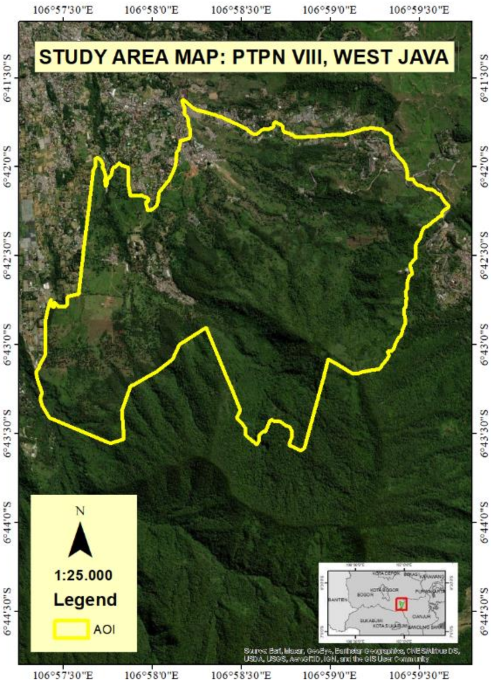

Figure 1. Study area map

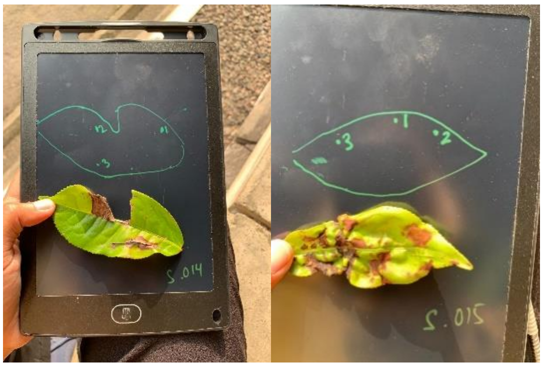

Figure 2. An example of unhealthy leaves

2.2 Sentinel-2

Two satellites are part of the Sentinel-2 mission to monitor the environment, vegetation, and land cover. ESA launched the Sentinel-2A satellite on June 23, 2015, and it operates in a sun-synchronous orbit with a 10-day repeat cycle. Sentinel-2B, a second identical satellite, was launched on March 7, 2017 (USGS EROS Archive, 2022; Drusch et al., 2012). Every five days, they collectively cover all of Earth's land, large islands, and inland and coastal waters. The Sentinel-2 Multi Spectral Instrument (MSI) collects data in 13 spectral bands over a 290-km orbital swath, from the visible and near-infrared (VNIR) to the shortwave infrared (SWIR).

Table 1. Characteristics of the Sentinel Band 2 (Satellite Imaging Corp, n.d.)

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

. 2.3 NDVI

NIR reflectance, which is related to internal leaf structure, decreased. Instead, reflectance went up with increasing severity in the green-to-red and red-edge regions, where the amount of chlorophyll in leaves and how well photosynthesis works have the most effect. The NDVI formula is as follows:

$$NDVI = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$

Description:
NDVI = Normalized Difference Vegetation Index
NIR = Band 8 in Sentinel 2
RED = Band 4 in Sentinel 2

The range of NDVI values is between 0 and 1, with a sensitive response to green vegetation even for low vegetation covered areas, due to the index being calculated through a normalization procedure. This index has been shown to be related to canopy photosynthesis as well as canopy structure and LAI, and it is frequently used in research on regional and global vegetation assessments (Gamon et al., 1995; Grace et al., 2007). But because NDVI is sensitive to factors like soil brightness, soil color, atmosphere, cloud cover and cloud shadow, and leaf canopy shadow, remote sensing calibration is needed.

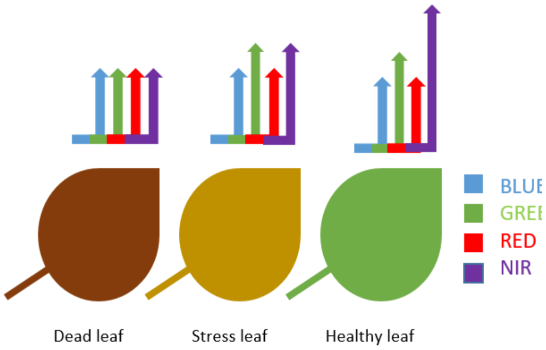

Figure 3. Relationship between NIR and visible reflectance values in dead, stressed and healthy leaf (Campbell et al., 2011; Ahmad et al., 2021).

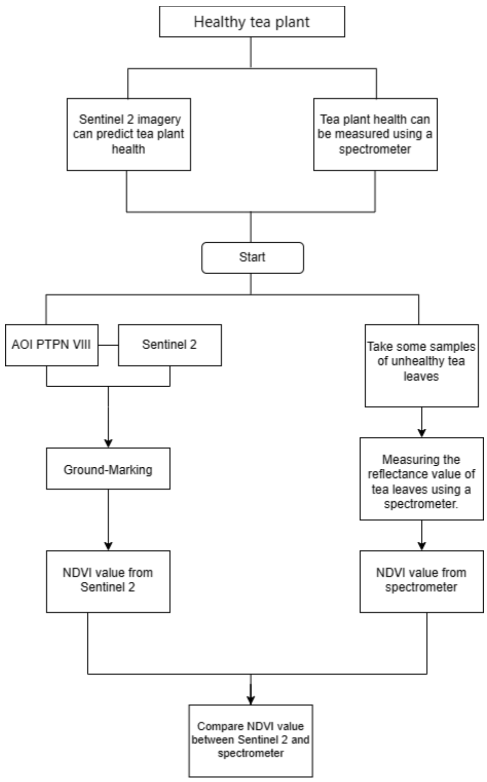

Figure 4. Flowchart

3. RESULTS AND DISCUSSION

3.1 The result of Spectrometer

The spectral analysis shows in **Figure 5**, there was a reliable difference in the slopes of the reflectance between the wavelength regions. Compare the variations in the tea leaves' spectral reflection properties between healthy and unhealthy tea leaves in the wavelength bands shown in the graph. First, the reflectance slope graph of the healthy tea leaves is steeper than that of the unhealthy tea leaves. These differences are in the range of about 510 to 550 nm. Second, there was a difference in wavelength at 750 nm. This range of wavelengths is the “red edge” wavelength, where the rate of reflection between the red and near-infrared wavelengths goes up quickly. It was found that the red edge wavelength is a good way to figure out how well tea leaves are growing. It is known to be helpful for assessing the status of chlorophyll, and leaf area index. At this point, it was found that there was a significant variation in the health status of tea leaves. The reflectance value at the NIR wavelength was higher than that of diseased tea plants. Healthy tea leaves have stronger light absorption in the NIR. The way the leaves are made may affect how much NIR radiation they reflect. How the leaves are made can affect how much NIR radiation they reflect. Furthermore, understanding the leaf structural elements that affect leaf reflectance is important for interpreting data from remote sensing, such as when identifying different plant functional types. Photosynthetic pigments dominate reflectance in the visible region (400-700 nm), and leaf structure has the greatest impact on reflectance in the near-infrared region (NIR; 750–1350 nm). Slaton et al. (2001) found that the "red edge" is a unique spectral feature that comes from the fact that the leaf reflectance goes up a lot as the wavelength goes from red to NIR. This edge's positioning has been related to plant stress, phenological stages, and chlorophyll content.

Damage to a leaf also damages the cells in the leaf's spongy tissue and makes the leaf hold less water. (Abdulridha et al., 2019) say that this damage can lower the near-infrared reflectance. The spectral recording of tea leaves requires an energy source for the waves to be reflected by objects. The measurements taken are outdoor measurements, and the energy source n addition, the problems experienced in using the spectrometer are the effects of leaf curvature and light source alignment, and these problems can cause distortion in the final result (Wei et al. 2019). Also, the effects of leaf curvature and the alignment of the light source can make it hard to use the spectrometer, which can cause the final result to be off (Wei et al., 2019). So, a good way to collect data with a spectrometer is to make sure the light source is aligned well.

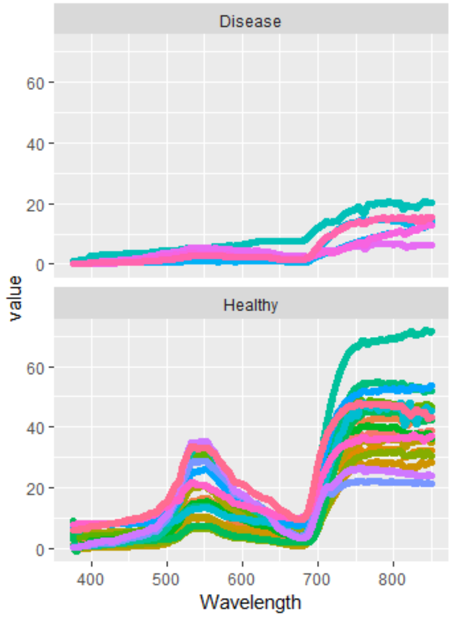

Figure 5. The graphical results of the spectrometer between healty and unhealthy tea

3.2 The result of Sentinel - 2

The bands used for NDVI analysis on Sentinel 2 are B4 for the red band and B8 for the NIR band. The image was obtained from GEE (Google Earth Engine) with a collection date of July 2021 because the research area in the image has a lot of clouds, so an image with few clouds has been chosen at a different distance from the time of the study. The results (**Figure 6**) showed that from the 3 research sample locations the NDVI values were obtained for each block 6 of 0.6, block 14 of 0.8, and block 15 of 0.8. According to the image results, the NDVI value is quite high, indicating the health level of the tea plant, and the vegetation density is dominated by green plants. The result of NDVI values of unhealthy tea plants range between 0.1 - 0.5 and healthy tea plants between 0.6-0.9 (**Figure 7**). Sentinel-2 has limitations when it comes to monitoring diseased tea plants because of its low pixel resolution, which makes it difficult to monitor pests and only detects damage when it is significant. It is difficult to distinguish between plant reflectance patterns caused by biotic stresses and determine the exact cause of the stress (Segarra et al., 2020).

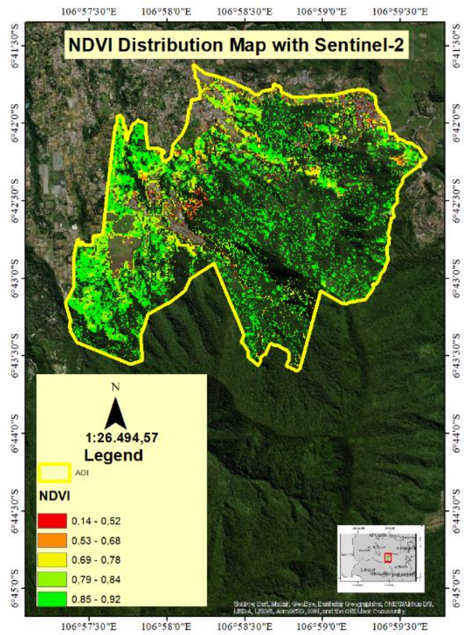

Figure 6. Map of NDVI distribution based on Sentinel 2

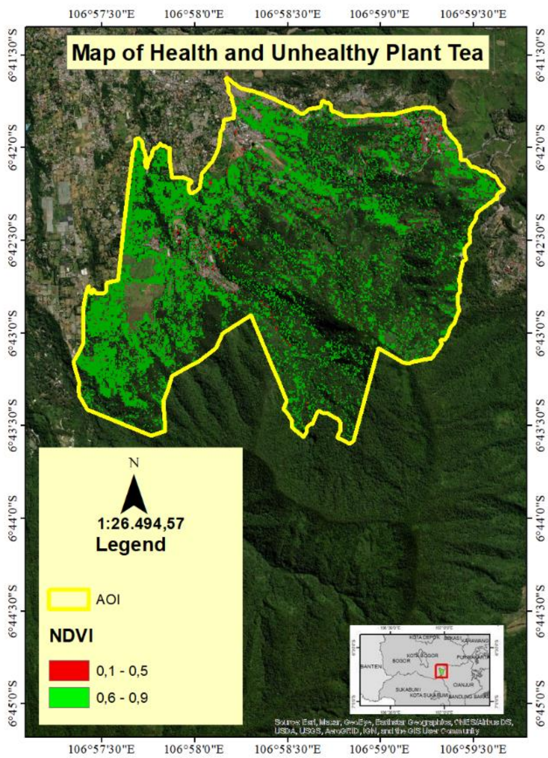

Figure 7. Map of health and unhealthy tea plant based on NDVI range.

3.3 Comparison of NDVI values between spectrometer and Sentinel-2

The results of spectrometer NDVI and Sentinel-2 imagery have differences. Spectrometer values for healthy plants have a range of 0.3-0.9 and NDVI values for diseased in the range of -0.5-0.2. The NDVI value of Sentinel 2 images is in the range of 0.6 -0.8. There is a difference between the measurement results of the NDVI spectrometer and the sentinel image. This is because Sentinel 2 imagery is only capable of taking image pixels with the resolution, not the diseased part of the leaf such as using a spectrometer that directly extracts the value of the infected area from the normal part of the plant. Obstacles in detecting plant diseases when the severity of the disease is less than 5%, due to small changes in the reflectance value (Ashourloo 2014). So the tea plants still appear green in the Sentinel 2 image. Although difficult to see, the differences in leaf structural characteristics allowed for spectroscopic detection (Fang et al., 2021).

4 CONCLUSION

One of the most important steps in the identification of unhealthy plant is to extract the infected area values from the normal parts of the plant. Infected leaves show that the green part of the leaf changes significantly compared to normal leaves. There is a difference in the NDVI value of the Sentinel 2 image with the spectrometer results. Obstacles in detecting plant diseases when the severity of the disease is less than 5%, due to small changes in the reflectance value. So the tea plants still appear green in the Sentinel 2 image.

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