Article

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A Study on the Distribution Pattern of Banana Blood Diseases (BDB) and Fusarium Wilt Using Multispectral Aerial Photo and Handheld Spectrometer in Subang-Indonesia

Ketut Wikantika [1], Mochamad Firman Ghazali [2]*, Fenny M. Dwivany [3], Tri Muji Susantoro [4], Lissa Nur Fajri [5], Diah Sunarwati [6] and Agus Sutanto [7]

[1] Department of Geodesy and Geomatics Engineering, Faculty of Earth Sciences and Technology, Bandung Institute of Technology, Indonesia; ketut.wikantika.@itb.ac.id
[2] Faculty of Engineering, Lampung University, Indonesia; firman.ghazali@eng.unila.ac.id
[3] School of Life and Sciences and Technology, Bandung Institute of Technology, Indonesia Faculty of Engineering, Lampung University, Indonesia; fenny@sith.itb.ac.id
[4] Research Center for Remote Sensing, Aeronautics and Space Research Organization, National Research and Innovation Agency, Jakarta, Indonesia; tri.muji.susantoro@brin.go.id
[5] Department of Geodesy and Geomatics Engineering, Faculty of Earth Sciences and Technology, Bandung Institute of Technology, Indonesia; lissafajri@gmail.com
[6] Badan Standardisasi Instrumen Pertanian, Kementerian Pertanian-Indonesia; sunarwati.diah@yahoo.com
[7] Pusat Riset Hortikultura and Perkebunan, National Research and Innovation Agency, Bogor, Indonesia Balai Penelitian Tanaman Buah, Kementerian Pertanian-Indonesia; bagussutanto@gmail.com
* Correspondence: firman.ghazali@eng.unila.ac.id

Abstract: Knowledge on the health of banana trees is critical for farmers to profit from banana cultivation. Fusarium wilt and banana blood diseases (BDB), two significant diseases infecting banana trees, are caused by *Fusarium oxysporum* and *Ralstonia syzygii*, respectively. They have successfully caused a decline in crop yield as they destroy the trees, starting sequentially from the pseudostem to the fruits. The entire distribution of BDB and Fusarium on a plantation can be understood using advanced geospatial information obtained from multispectral aerial photographs taken using an unmanned aerial vehicle (UAV), combined with the reliable data field of infected trees. Vegetation and soil indices derived from a multispectral aerial photograph, such as normalized difference vegetation index, modified chlorophyll absorption ratio index, normalized difference water index (NDWI) and soil pH, may have to be relied on to explain the precise location of these two diseases. In this study, a random forest algorithm was used to handle a large dataset consisting of two models: the banana diseases multispectral model and the banana diseases spectral model. The results show that the soil indices, soil pH and NDWI are the most important variables for predicting the spatial distribution of these two diseases. Simultaneously, the plantation area affected by BDB is more extensive than that affected by Fusarium, if the variation of planted banana cultivars is not considered.

Keywords: banana diseases; blood diseases banana (BDB); Fusarium wilt; random forest; spatial pattern; multispectral images; spectral analysis

1. Introduction

The initial use of spatial data to observe plant diseases has been well documented in studies, indicating its importance in analysis and the role of plants in the support of human life. In 1996, Real & McElhany (1996) began studying plant diseases caused by *Microbotryum violaceum* in *Silene latifolia* based on its spatial distribution. Of course, they considered using the location attribute of a healthy and unhealthy plant as the main parameters. Plant location describes each plant's connectedness to its neighbouring systems, giving an overview on how diseases diffuse over time, increasing the number of affected plants. Plant neighbouring systems, also known as plant communities, are believed to be one of the anthropogenic factors introduced by farmers that may have increased the number of plants affected by disease [2]; this factor is strengthened by other ecological and environmental factors, including air temperature, soil, elevation, insect and fungus [2,3].

In banana cultivation, these factors are explained in many ways by many studies. Géoffroy Dato et al.[4] tried to elaborate on the relative risks of banana disease that vary between geographical areas and landscapes. Considering the Banana Bunchy Top Disease (BBTD) which is caused by the Banana Bunchy Top Virus (BBTV), this study found that there is a spatial cluster of significant high-risk areas of BBTD distribution in banana fields in open and backyard gardens. Growing banana in a monoculture system in both areas showed the most significant risk for BBTV infection, while implementing the multi-crop system showed a lower risk, and similar to the increasing day of planting (DAP). Older banana crops with a higher density of stems were associated with the highest risk for BBTD. In contrast, securing clean seeds, implementing field isolation, intercropping and border vegetation of different species and keeping a distance between an infected and an infected field were also significantly associated with a lower risk for BBTD, as these parameters correspond to the number of clusters that exist in highland banana gardens compared to lowland areas, for both open and backyard gardens.

Regarding banana blood disease (BDB), we found that practicing field isolation, intercropping and border vegetation of different species methods was useless since the causative factors of BDB are more uncontrollable and sophisticated than those of BBTV. BDB is caused by *Ralstonia syzygii* subsp. *celebesensis*, a bacterial wilt causing significant crop losses in Indonesia and Malaysia, which can spread locally or short-distance through insects and possibly contaminated tools, water and soil. It also likely spreads utilizing both cultural and natural factors. This rapid expansion means it can be found in any geographical area; it was recently found in many places in Indonesia and many countries in Southeast Asia [5]. Moreover, two natural substances—water and soil—are easily used by *Ralstonia syzygii* subsp. *celebesensis* for spread; however, the exact way this occurs is yet to be fully understood.

In the spatial context, banana's biodiversity and biogeography in Indonesia have been discussed [6]. In Indonesia, studies on the spread of many banana diseases like BBTV, BDB and Fusarium (which is caused by the fungus *Fusarium oxysporum* f. sp. *cubense*) [7] seem more interested in elaborating on banana diseases in the tropics. These studies have already described the infection process as occurring on the surface, that is, from the soil to the plant [8–10]; therefore, obtaining spatial data on soil characteristics is mandatory. However, many studies that use spatial data, like satellite imagery from satellite observation, have explained that various environments (e.g. climate, soil and plant) have often use for vegetation observation. The soil index known as the normalized difference water index (NDWI) is capable of estimating the water content of the soil, and this information is related to drought and soil moisture [11]. This index does not directly explain how healthy or unhealthy a vegetation is [12]. However, Chen et al. [13] used NDWI to assess the potential of water content for corn *(Zea may)* and soybeans *(Glycine max)*, which they found to be 6 to 1.2 Kg/m^2 of water. How about for Banana? Does the water content in the soil and banana plants correlate with the existence of BDB and Fusarium? The relationship between Fusarium and soil moisture has been explained in many studies. The survival of the fungus decreases with increased soil moisture [14–16] and Segura-Mena et al. [17] has suggested a correlation between the fungus survival and soil pH.

Since the soil is related to vegetation, the actual condition of the soil may influence vegetation growth. *Ralstonia syzygii* subsp. *celebesensis and Fusarium oxysporum* f. sp. *cubense* are both too small to be investigated using satellite imagery, especially using moderate resolution (Landsat and Sentinel 2). Similar to the soil, the normalized difference vegetation index (NDVI) can be used to understand the quality of banana plants [18]. Studies have found that the information derived from NDVI allows one to distinguish between healthy and unhealthy plants [19]. An unhealthy vegetation is indicated

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by lower NDVI values; expectedly, plants affected by BDB and Fusarium will have a lower NDVI value. Therefore, it is reasonable to use both NDVI values to explain the physical relationship between the NDVI values of group banana plantations (plant communities). Banana plants will have lower capabilities for conducting photosynthesis and lower chlorophyll in unhealthy vegetation.

The most recent studies on banana diseases using remote sensing data have shown progress in studying banana. A study by Ye et al. [20] utilized eight vegetation indices (VIs) related to pigment absorption, namely NDVI, normalized difference red edge index [21], green chlorophyll index [22], red-edge chlorophyll index [23], structural independent pigment index (SIPI) [24], red-edge SIPI [25], carotenoid index (CARI) [26] and anthocyanin reflectance index (ARI) [27] along with plant growth changes to determine the biophysical and biochemical characteristics of plants. All these VIs were integrated using multivariate analysis methods for calculating banana regions infected or not infected with Fusarium wilt disease by Binary Logistic Regression.

Compared to the study by Ye et al. [20], the study conducted by Zhang et al. [28] involved ten additional VIs and one soil index. Three visible-band and five multispectral-band images were processed, using four supervised (support vector machine, random forest (RF), back propagation neural networks and logistic regression) and two unsupervised (hotspot analysis and iterative self-organizing data analysis technique algorithm) methods to detect the Fusarium in banana canopies trees. Here, a renormalized difference vegetation index (RDVI) and wide dynamic range vegetation index (WDRVI) were used to monitor vegetation coverage and water stress due to their sensitivity to healthy vegetation and insensitivity to soil and solar geometry. Both RDVI and WDRVI can quantify the biophysical characteristics of crops and enable dynamic monitoring of crop growth status [29,30]. Moreover, a transformed difference vegetation index is commonly used to monitor vegetation cover since it has a linear relationship with vegetation cover [31], and a modified simple ratio index (SRI) has also been considered since it has increased sensitivity to vegetation biophysical parameters. Furthermore, when SR is incorporated into the RDVI formula, it can be used to estimate leaf area indices [32].

Besides the abovementioned VIs, a non-linear index (NLI) and modified NLI have been used to estimate biophysical information and incorporate soil adjusted vegetation index (SAVI) to account for soil background [33], and green difference vegetation index (GDVI) [34] has an ability, that similar to NDVI's to strengthen the SAVI so as to minimize the effects of soil pixels [35]. These two studies mentioned above likely highlighted the need to optimize the capability of VIs to interpret a tree's biophysical properties (e.g. canopy). However, the use of soil-related index has not been considered. As mentioned above, BDB and Fusarium have increased their infectivity and spread, both of which are controlled by the soil condition. This soil bacteria and fungus reach their optimal cycle life when the soil condition is suitable. Therefore, the novel approaches in this study make it different from any previous similar research.

2. Materials and Methods

2.1. Study location

The Materials and Methods should be described with sufficient details to allow others to replicate and build on the published results. Please note that the publication of your manuscript implicates that you must make all materials, data, computer code, and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited. For this study, the local plantation called Tropical Fruit Research Institute, Agricultural Technology Research and Assessment Installation (IP2TP), managed by the Ministry of Agriculture of the Republic of Indonesia, was explored. This institute is located in the Subang Regency in the northern part of West Java Province. Mainly focusing on fruits research, at least four banana cultivars, including Pisang Kepok *(Musa paradisiaca* L*)*, Pisang Ambon *(Musa)*, Pisang Kapas *(Musa)* and Pisang Raja *(Musa),* are

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planted at this small plantation which covers 40 hectares of land. As much as 5 hectares of this plantation are used specifically for bananas (Figure 1).

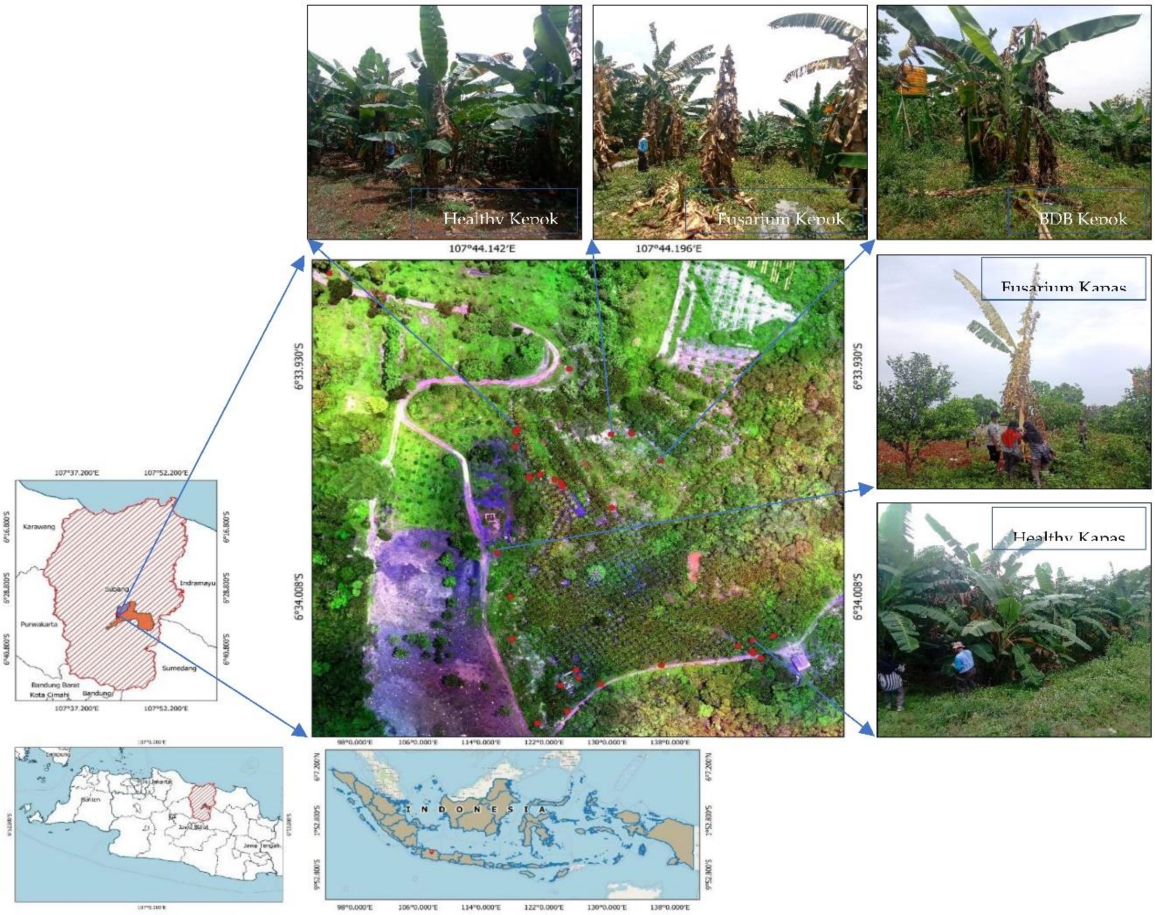

Figure 1. The location for the study on the distribution pattern of banana blood diseases (BDB) and Fusarium wilt using a multispectral aerial photograph in Subang-Indonesia. Red dots represent the location of individual banana trees infected by BDB or Fusarium.

The Subang Regency spreads from the highland to the lowland, from south to north. It ranges from approximately 2.084 meters above sea level (asl) to 0 meters (asl) near the coastline of the Java Sea. The Indonesia Meteorological Agency (BMKG) documented that the annual precipitation in the entire area of Subang ranged from 5,167 millimetres (mm) in January to 4,044 mm in December 2022 [36], with decadal variability. There has been a change in the distribution of rainfall in each period compared to the previous one, including changes in the rainfall pattern in the dry and rainy seasons; this change occurred from 1987 to 1996 and from 1995 to 2004 [37].

2.2. Data

2.2.1. Multispectral aerial photo taken via a UAV

Obtaining a multispectral aerial photograph of individual banana trees infected by BDB and Fusarium is mandatory to understand the spatial distribution patterns of BDB and fusarium wilt in a plantation. For this study, a Dji Matrice equipped with a Micasense camera was used to take 250 aerial photos that capture the entire area, using six different bands including blue, green, red, near-infrared (NIR), red edge and thermal bands (Table 1), from 150 meters above the surface (Figure 2). It produced approximately 1500 photos which cover the whole area in which banana trees had been planted. The orthophoto comes with un-calibrated pixel values and need to be processed to obtain

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the reflectance values using other satellite imagery. The process of generating an orthophoto and the calibration process run concurrently [38,39].

Source: https://enterprise.dji.com/matrice-300, https://aeromao.com/product/micasense-altum/, and [40]

Figure 2. A Dji Matrice (left) equipped with a Micasense camera (right) used for obtaining the aerial photos and an ASD Fieldspec II Handheld spectrometer (below) for acquiring the spectral reflectance of banana trees affected by banana blood diseases (BDB) and Fusarium wilt in Subang-Indonesia.

Table 1. The specification of spectral bands owned by the Micasense camera used for taking aerial photos of banana trees affected by banana blood diseases (BDB) and Fusarium wilt in Subang-Indonesia.

No	Band Name	Centre Wavelength	Bandwidth
1	Blue	465 nm	32 nm
2	Green	560 nm	27 nm
3	Red	668 nm	16 nm
4	Red edge	717 nm	12 nm
5	Near-infrared	842 nm	57 nm
6	Thermal	11µm	6 µm

2.2.2. Banana leaves' spectral reflectance

The banana leaves' spectral reflectance was obtained using the ASD Handheld spectrometer which is a portable hyperspectral measurement tool that captures leaf reflectance in a portion of wavelength. It can record spectra ranging from 350 to 2429 nm and operate from 10.00 to 02.00 pm (Figure 2).

2.3. Methods

The entire workflow implemented in this study consisted of two parts: the retrieval of the UAV-derived spectral indices (Soil pH, NDVI, NDWI and MCARI) and banana leaves spectral indices (implementing the RF algorithm for visualizing the distribution of banana trees affected by the BDB and Fusarium) and comparing the RF result against the banana leaves spectral indices. Details of this research workflow are displayed in the diagram below (Figure 3).

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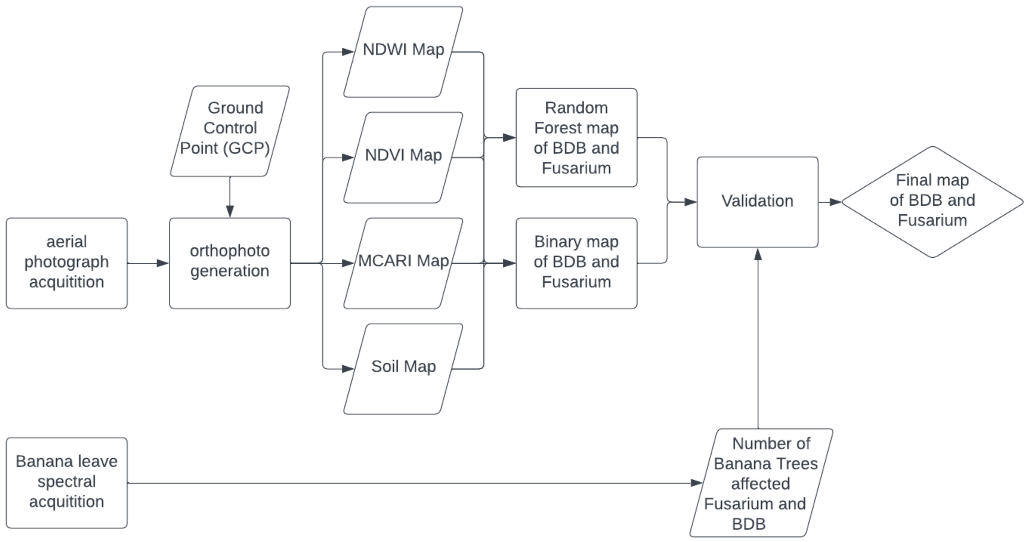

Figure 3. Study workflow on banana blood diseases (BDB) and Fusarium wilt distribution pattern using a multispectral aerial photograph and spectral reflectance in Subang-Indonesia.

Based on the spectral bands available on the Micasense camera, several vegetation and soil indices derived from the multispectral aerial photograph, such as NDVI, MCARI, NDWI and soil pH, were produced. NDVI is expected to distinguish the health level of banana trees. Stamford et al. [41] explained that it is one of the spectral indices most frequently used in research and agriculture to rapidly and easily detect vegetation and assess overall plant health. It was previously introduced by Rouse et al. [18] and recently used in many studies in the agricultural field as the main parameter to understand the biophysical characteristics of vegetation, such as chlorophyll [42], leaf area index [43] and nitrogen [44]. NDVI is calculated from the visible and NIR light reflected by vegetation. A healthy vegetation (left) absorbs most of the visible light that hits it and reflects a large portion of the NIR light. An unhealthy or sparse vegetation (right) reflects more visible and less NIR light. The formula used to estimate the banana trees' health includes NDVI and is shown in Equation (1).

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \tag{1}$$

Like NDVI, MCARI can also be used to assess BDB's and Fusarium's existence in banana trees. These indices and their derivatives have also been used by Ghazali et al. [45] to determine the chlorophyll content in a paddy field, especially MCARI. Both BDB and Fusarium can make banana leaves dry—the leaves change from green to yellow and finally brown; indirectly, this decreased the ability of the remaining leaves to perform photosynthesis. To obtain the chlorophyll content of a leaf using MCARI, at least three spectral bands are required: red edge, red and green. The formula used for estimating the chlorophyll content of the banana trees is shown in Equation (2).

$$MCARI = ((Red\ edge - Red) - 0.2 * (Red\ edge - Green)) * \frac{(Red\ edge)}{(Red)} \tag{2}$$

NDWI was selected as the third spectral index for measuring the water content of banana leaves. Similar to NDVI, the NDWI values derived were unitless and ranged from -1 to 1, which represent the drought and wetness levels, respectively. NDWI was calculated from the green and NIR light reflected by vegetation. Leaves on healthy vegetation can absorb adequate water as part of photosynthesis, while unhealthy leaves are less able or unable to absorb enough water. To calculate the NDWI, visible light (green) and NIR light are required. The formula used for estimating the banana trees' health includes NDWI and is shown in Equation (3).

$$NDWI = \frac{(Green-NIR)}{(Green+Red)} \tag{3}$$

A study on soil pH estimation and its relationship to the agricultural field has been conducted using a modified formula of the Soil pH Index (SpHI) proposed by Ghazali et al. [46]. This study used a combination of blue, green, red and shortwave infrared (SWIR) spectral bands of Landsat as a multiple regression equation. Because the Micasense camera has no SWIR bands available, the new formula for calculating SpHI only comprises three visible bands: blue, green and red, (Equation 4).

$$pH = 6.871 * Blue - 1.068 * Green + 1.195 * Blue \quad (4)$$

The spectral reflectance obtained corresponded to healthy Kepok banana trees as well as those infected by BDB and Fusarium. This data also NDVI, MCARI, and NDWI as proposed by Gao [12] instead of the formula proposed by McFeeters [47]. The results were similar to multispectral aerial photos, but the formula used were different and used the same band number with the wavelength centre of the bands in the aerial photo (Equations 5 and 6).

$$NDVI = \frac{(\rho840-\rho668)}{(\rho840+\rho668)} \quad (5)$$

$$MCARI = (\rho717 - \rho668) - 0.2 * (\rho717 - \rho560)) * \frac{(\rho717)}{(\rho668)} \quad (6)$$

$$NDWI = \frac{(\rho840-\rho1450)}{(\rho840+\rho1450)} \quad (7)$$

3. Results

3.1. Status of the banana trees based on the aerial photos-derived spectral indices

The NDVI map showed values ranging from -0.17 to 0.80. Although these values are unitless, the negative values indicate that water bodies exist around the plantation. In contrast, values ranging from 0 to 0.75 indicate bare soil and sparse and dense vegetation (Figure 3). NDVI values for Ambon, Kapas and Kepok ranged from 0.21 to 0.80, 0.42 to 0.73 and 0.05 to 0.74, respectively (Table 2). Additionally, the NDVI values seemed to be able to distinguish the type of disease that infected the bananas. The range of NDVI values for Fusarium were lower than those for BDB in Kepok and Ambon bananas. However, the highest (maximum) NDVI values did not always correspond to healthy bananas. All cultivars also had a good maximum NDVI value, whether they were infected by Fusarium or by BDB (Table 2). Therefore, we concluded that NDVI has limitations when it comes to determining the type of disease affecting a banana tree.

Table 2. A summary of the status of banana trees infected by banana blood diseases (BDB) and fusarium wilt based on the NDVI, NDWI, MCARI and Soil pH values derived.

No	Cultivars	Diseases	NDVI		NDWI		MCARI		Soil pH	
			Min	Max	Min	Max	Min	Max	Min	Max
1	Ambon	Fusarium	0.35	0.80	-0.24	-0.02	-33029.25	16547.45	6.06	6.41
		BDB	0.63	0.63	-0.15	-0.15	21073.20	21073.20	5.95	5.95
		Healthy	0.21	0.61	-0.27	-0.04	6773.85	12734.36	5.79	6.31
2	Kapas	Fusarium	0.49	0.57	-0.13	-0.04	16608.73	25183.98	5.56	6.05
		Healthy	0.42	0.73	-0.26	-0.03	-35623.27	12617.84	6.16	6.59
3	Kepok	Fusarium	0.05	0.61	-0.17	-0.07	-1463.12	21841.52	5.71	6.34
		BDB	0.24	0.74	-0.32	-0.08	-27543.98	5746.49	6.11	6.53
		Healthy	0.17	0.71	-0.23	-0.06	-8423.26	10640.53	5.92	6.65

Unlike the NDVI map, the NDWI map showed that the level of soil moisture or available water content in the soil ranged from -0.32 to 0.02. This range explains the near real-time condition of soil below the canopy, and bare soil areas are driest (Figure 4). In an ideal situation, NDWI will show values ranging from -1 (driest) to 1 (wettest). Fusarium and BDB affecting Ambon and Kapas bananas had higher NDWI values than those affecting Kepok. BDB was also found in the driest soil (Table 2). Similar to those of NDVI, MCARI values are also unitless, and their uncertainty in investigating banana diseases becomes the principal issue. However, the lowest MCARI value indicates the lowest capability for photosynthesis. The MCARI values ranged from -33.352 to 26.083 and describe the variation in photosynthesis for all plants that appear in the aerial photos (Figure 4). This is likely only suitable for studying Fusarium and BDB in Ambon and Kepok bananas with the lowest MCARI values (Table 2). A better interpretation was obtained using soil pH for all infected bananas. Fusarium and BDB are primarily found in soil with a pH lower than 6.00 (Table 2).

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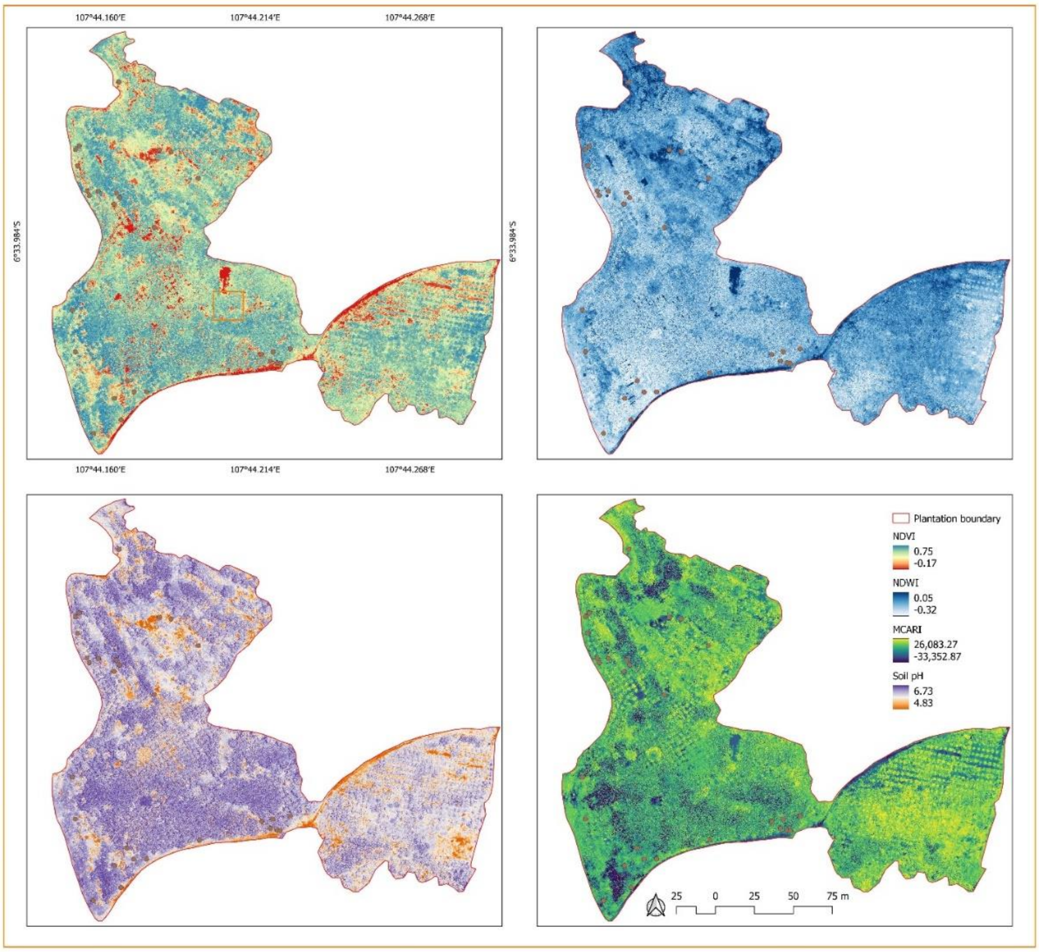

Figure 4. Distribution of healthy and infected banana trees corresponds to the aerial photos-derived vegetation and soil indices: NDVI, NDWI, MCARI, and Soil pH.

All derived vegetation indices maps and their estimated values created uncertainties. However, we thought a different perspective might have the potential to give new insight. Each banana cultivar observed in the field was supported by a longitude and latitude, which also correspond to the vegetation-soil indices values shown in Table 2. Therefore, once we sorted it from the lowest to the highest, we understood how the relative spatial distribution of Fusarium and BDB can be related to the environmental condition based on vegetation- and soil-derived indices (Figure 5a-d).

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Diseases	Fsm	Hth	Hth	Bdb	Fsm	Fsm	Hth	Fsm	Fsm	Hth	Hth	Fsm	Fsm	Fsm	Hth	Hth	Bdb	Hth	Fsm	Hth	Hth	Bdb	Fsm	Bdb	Hth	Hth	Hth	Bdb	Fsm
Cultivars	Kp	Kp	Am	Kp	Am	Am	Ks	Kp	Ks	Ks	Am	Kp	Ks	Ks	Am	Kp	Kp	Am	Kp	Kp	Kp	Am	Am	Kp	Kp	Ks	Ks	Kp	Am
NDVI values	0.05	0.17	0.21	0.24	0.35	0.38	0.42	0.46	0.49	0.51	0.51	0.53	0.57	0.57	0.58	0.58	0.59	0.61	0.61	0.61	0.61	0.63	0.64	0.66	0.71	0.72	0.73	0.74	0.80
	Less Healthiest																												Healthiest

(a)

Diseases	Bdb	Bdb	Hth	Hth	Fsm	Hth	Hth	Hth	Bdb	Hth	Hth	Hth	Fsm	Fsm	Fsm	Bdb	Hth	Fsm	Fsm	Bdb	Fsm	Hth	Hth	Fsm	Fsm	Hth	Hth	Fsm	Fsm
Cultivars	Kp	Kp	Am	Ka	Am	Kp	Am	Kp	Kp	Ka	Kp	Ka	Kp	Am	Kp	Am	Kp	Ka	Kp	Kp	Kp	Am	Kp	Ka	Ka	Am	Ka	Am	Am
NDWI values	-0.32	-0.31	-0.27	-0.26	-0.24	-0.23	-0.22	-0.21	-0.20	-0.20	-0.18	-0.17	-0.17	-0.17	-0.16	-0.15	-0.13	-0.13	-0.09	-0.08	-0.07	-0.06	-0.06	-0.06	-0.04	-0.04	-0.03	-0.03	-0.02
	Driest																												

(b)

Diseases	Hth	Fsm	Bdb	Bdb	Hth	Hth	Bdb	Fsm	Hth	Hth	Fsm	Bdb	Hth	Hth	Fsm	Hth	Hth	Hth	Hth	Hth	Hth	Fsm	Fsm	Fsm	Fsm	Fsm	Bdb	Fsm	Fsm
Cultivars	Ks	Am	Kp	Kp	Ks	Kp	Kp	Kp	Kp	Kp	Kp	Kp	Am	Kp	Kp	Am	Am	Kp	Ks	Ks	Am	Am	Am	Am	Ks	Ks	Am	Kp	Ks
MCARI Values*	-35.6	-33.0	-27.5	-23.5	-22.0	-8.4	-5.6	-1.4	-0.053	4.4	5.1	5.7	6.7	8.8	9.5	10.3	10.6	10.6	12.4	12.6	12.7	13.7	13.9	16.5	16.6	18.7	21.0	21.8	25.1
	Less Healthiest and Lowest photosynthesis																												Healthiest and Highest photosynthesis capability

(c)

Diseases	Fsm	Fsm	Fsm	Hth	Hth	Bdb	Fsm	Fsm	Fsm	Fsm	Bdb	Hth	Hth	Hth	Fsm	Hth	Fsm	Hth	Hth	Fsm	Bdb	Hth	Bdb	Fsm	Hth	Hth	Bdb	Hth	Hth
Cultivars	Ks	Ks	Kp	Am	Kp	Am	Ks	Am	Kp	Kp	Kp	Ks	Kp	Ks	Am	Am	Am	Am	Am	Kp	Kp	Kp	Kp	Am	Kp	Ks	Kp	Ks	Kp
pH values	5.56	5.57	5.71	5.79	5.92	5.95	6.05	6.06	6.08	6.10	6.11	6.16	6.17	6.18	6.19	6.25	6.26	6.28	6.31	6.34	6.35	6.38	6.41	6.41	6.43	6.46	6.53	6.59	6.65
	Acid soil																												Healthy soil with pH values close to neutral

(d)

Figure 5. Distribution of healthy and infected banana trees corresponds to the following aerial photos-derived vegetation and soil indices: NDVI, NDWI, MCARI and Soil pH. Where, Fsm = Fusarium, BDB = Blood Disease Banana, Kp = Kepok, Ks = Kapas, Am = Ambon, and Hth = Health.

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This explanation is regarding the dynamic range of NDVI values rather than the sample size. Next, we considered using the extracted NDVI values to determine the number of banana trees infected by BDB and Fusarium, as well as the healthy bananas. Once the median value of NDVI values was set at 0.50, the number of healthy bananas increased along with the NDVI values. In contrast, when the NDVI values decreased, the number of infected trees increased. However, the affected banana trees were still found to have high NDVI values. This is better than many affected banana trees which had decreased NDVI values (Figure 5a)

Unfortunately, the same procedure failed when applied to the NDWI values. Since the soil condition during the time of this study was the driest although it was not drought season, we found that when the NDWI values decreased, the number of affected trees exceeded that of healthy trees. On the other hand, soil moisture is not our focus. We assumed that the banana trees were already affected by BDB and Fusarium a day or more before our observation. However, Clayton, Oritsejafor, and Yan & Nelson were confident in explaining that the survival of the fungus may decrease with increased soil moisture [14–16]. According to the present study's findings, banana trees affected by BDB and Fusarium increased when soil moisture (expressed by NDWI) decreased (Figure 5b). Moreover, NDWI explains how remote sensing can measure the actual water content absorbed by the soil in any condition [12,48].

Similar to NDVI, MCARI values ranged from -35 to 26, and we divided them into two groups: positive and negative. This is helpful for explaining why more healthy banana trees had positive (highest) values compared to negative (lowest) values. Once NDVI rises, it is likely to be followed by increasing MCARI values. Besides, lower NDVI values mean banana trees may become unhealthy and thus have decreased photosynthetic capabilities (Figure 5c). For instance, a banana tree may have dried leaves due to drought. A study found that when a plant absorbs limited water, its leaves will slowly get decoloured and dry [49]. At this stage, hopefully, there is a possibility of making a connection between NDVI, MCARI, NDWI and soil pH, as well as the critical values used to identify the banana trees affected by BDB and Fusarium.

The soil pH map showed pH values ranging from 4.83 to 6.73. The soil in the study area was situated in the acidic-to-almost-neutral range. The optimum soil pH for banana growth ranges from 5.8 to 6.5 [50,51]. Within this range, banana trees can grow well without worries that they may not be receiving adequate minerals from the soil. In a low soil pH (< 5) there is often associated low concentrations of base cations and nutrients such as Ca^{2+} and Mg^{2+} or high contents of aluminium and manganese [52–54]. In this study, some areas of the banana plantation had a lower soil pH (<5), which means the soil there has increased the amounts of aluminium and manganese. However, the samples of the soil where infected and healthy banana trees grew had pH ranging from 5.56 to 6.65. According to Orr & Nelson [55], Fusarium generally has an inversely proportional relationship with soil pH and will only grow well when the soil pH is lower. This explains the situation we observed on the banana plantation (Figure 5d). The number of healthy banana trees were more in places where the soil pH was high. This is similar to what Segura et al. [56] found, taking the Gros Michel bananas (Musa AAA) as samples. Their study found that with an increase in soil pH, a reduction in the incidence of Fusarium wilt occurred in almost all cases. This is why the number of healthy bananas increased and that of affected bananas reduced with a high soil pH. Unfortunately, Fusarium can still be found whether the soil pH is high or close to neutral [17].

The effort of UAV's derived soil information represented by the NDWI and soil pH and vegetation information represented by MCARI and NDWI linked together as the main parameters to explain the existence of BDB and Fusarium in plantation scale (Figure 6). It is surprising that all parameters mostly had a moderate relationship. First was the lowest to the highest coefficient of determination (R^2), 0.47, -0.65 and -0.68 for soil pH against NDVI, NDWI and MCARI, respectively. The soil pH can explain the condition of banana trees at 47% accuracy. A moderate positive correlation was observed and describes the number of healthiest bananas increasing while the NDVI values move highest (Figure 4a). The soil pH showed a moderate negative relationship (65%) with NDWI in terms of describing the banana diseases. This relationship is consistent with the finding that a decrease in NDWI values will be followed by an increase in the number of affected trees. A slightly

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higher negative correlation was observed between soil pH and MCARI. It reached 68% to use the relationship of soil pH and MCARI while explaining the BDB and Fusarium. For more detail on all the possible relationships between the indices, please see the pairwise correlation matrice in Figure 5.

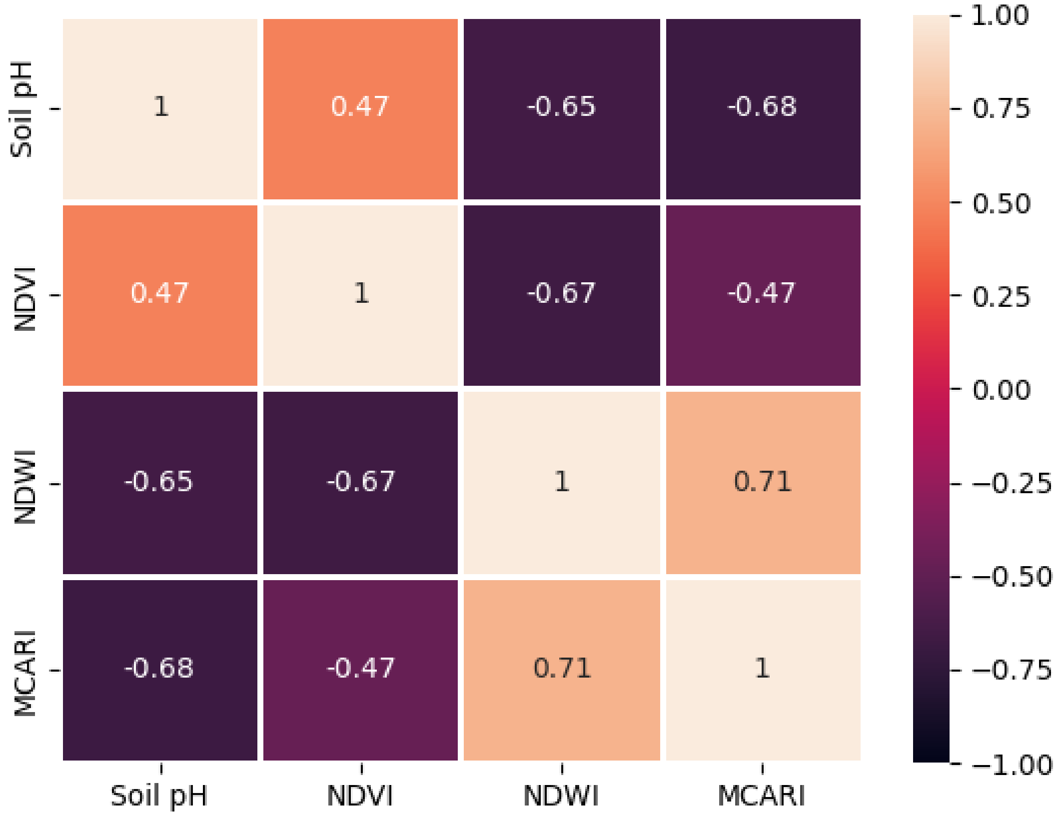

Figure 6. Coefficient of determination (R^2) for the UAV-derived NDVI, NDWI, MCARI and Soil pH in the banana plantation.

All the results were satisfactory since the UAV-derived spectral indices (Soil pH, NDVI, NDWI and MCARI) all showed a moderate relationship (Figure 5) and the relationship between these spectral indices and the number of banana trees affected by BDB and Fusarium was qualitative (Figures 4a-d). Regardless of this result, more attention needs to be paid to the unknown characteristics of the number of unhealthy and healthy banana trees in any condition explained by all derived spectral indices (Soil pH, NDVI, NDWI and MCARI). This might create an overlap and lead to difficulties determining where the clustered area of healthy banana trees and those affected by BDB and Fusarium is simultaneous. The overlapping situation shown in the paired scatterplot adequately explains how these difficulties arise.

The scatterplot in Figure 7 shows the pairing of soil pH with MCARI, NDWI and NDVI in the first column. Here, the scatterplot of soil pH values and NDVI corresponding to disease types of the group of banana trees affected by Fusarium has a probability in the soil pH values below 6.0, while BDB below 6.50 is the same as with the healthy groups of bananas. These values correspond to NDVI values lower than 0.6 and have a probability to yield unhealthy banana trees due to infection by BDB and Fusarium. The area of intersection between these three groups of bananas is slightly challenging to classify. Unfortunately, other scatterplots of soil pH against MCARI and NDWI showed a similar pattern (Figure 7). This situation needed to be handled in a sophisticated manner. Therefore, the distribution of BDB-infected, Fusarium-infected, and healthy banana trees was appropriately mapped. Similar to the first column, the scatterplot in the second to fourth columns had random patterns, while that between NDWI and MCARI did not and showed that healthy banana trees are likely separated from unhealthy banana trees.

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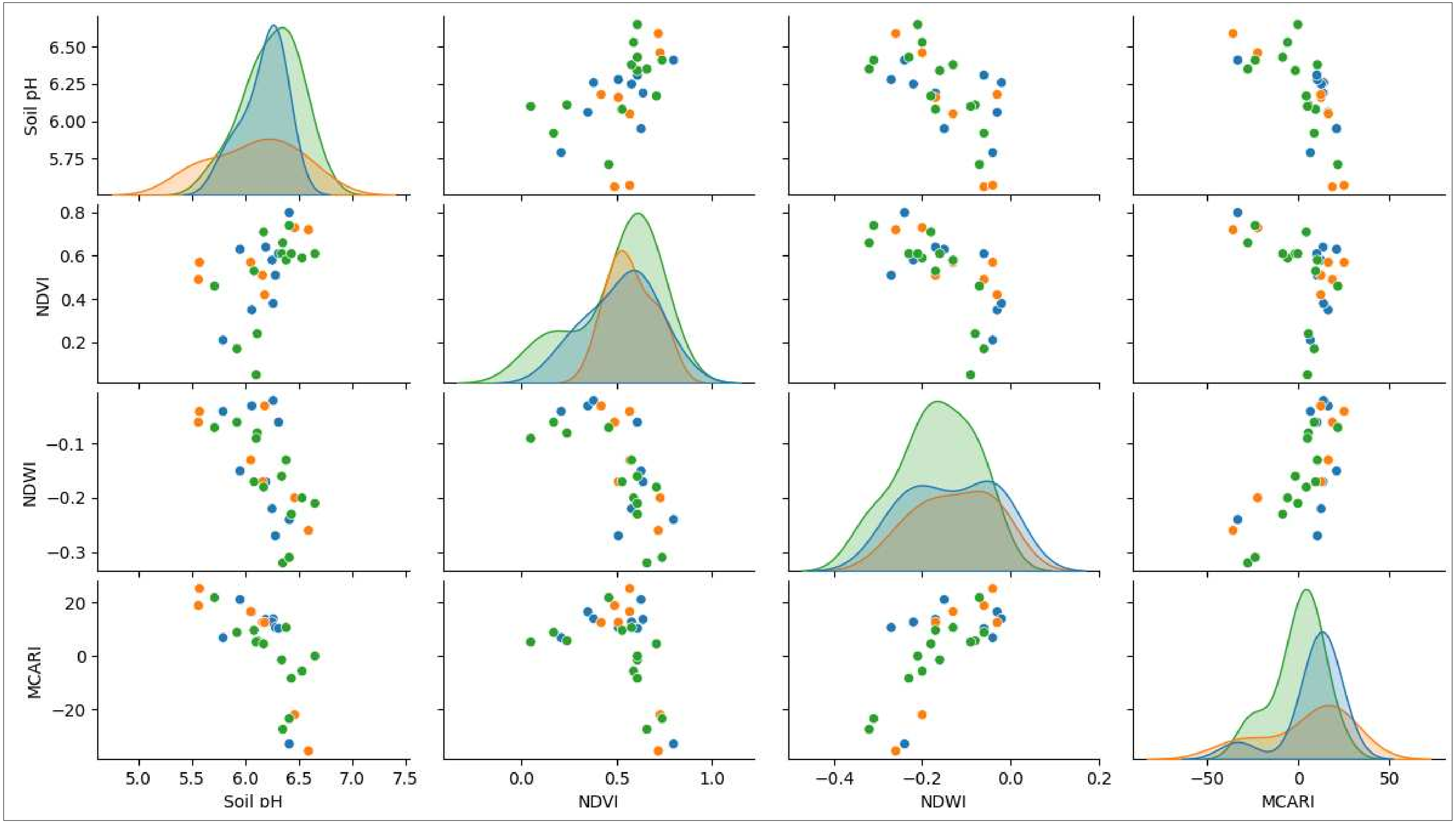

Figure 7. Relationship between NDVI, NDWI, MCARI and Soil pH and its potential for distinguishing the type of diseases affecting a banana trees.

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3.2. The distribution of BDB and Fusarium wilt based on aerial photos-derived spectral indices

A distribution map of affected and healthy banana trees derived using the RF algorithm showed a dominance of Fusarium followed by BDB; healthy banana trees were the least dominant (Figure 8). From this map, it is hard to say whether the entire banana plantation is already affected. However, since banana trees do not entirely planted in this area, and these two diseases are significant factors causing a decline in banana production, mitigating and limiting BDB and Fusarium distribution must be a priority. As suggested by Thi et al. [58], Fusarium wilt not only impacts the overall yield during the time of infection but also affects the land used for banana cultivation for the next 20 years. In addition, all affected banana trees may have to be removed to solve the problem [59,60]. However, Fusarium spores will remain in the soil, and as a result, reinfection of new banana accessions in the same area is very likely in the absence of complete soil disinfection [61].

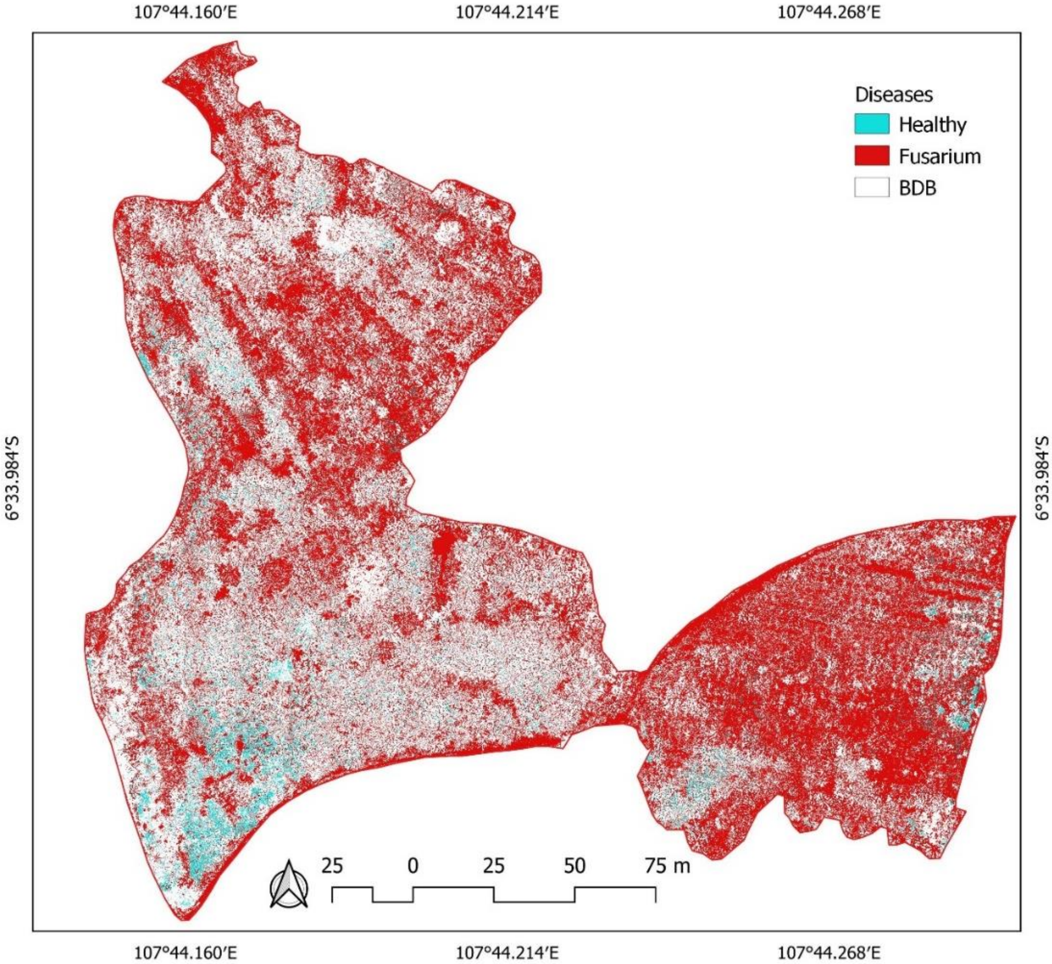

Figure 8. Distribution of healthy banana trees and those affected by BDB and Fusarium based on UAV-derived NDVI, NDWI, MCARI, and Soil pH in the banana plantation, generated using a random forest algorithm.

Unfortunately, this study's RF and available dataset can neither predict when BDB and Fusarium first attacked the banana trees nor can it detect the level of affectation by BDB and Fusarium. These two diseases already affected all the mature banana trees. Using UAV-derived spectral indices—NDVI, MCRI, NDWI and soil pH—we satisfactorily determined the distribution of BDB and Fusarium. As the study by Zhang et al. [28] stated, using derived red edge band spectral indices can also yield similar information. Here, MCARI has a critical role in determining whether the banana trees are healthy or affected. The Gini index values had the highest score at about 0.35 (35%), while NDWI, NDVI and soil pH were 0.28, 0.22 and 0.15, respectively (Table 3). Along with this result, the

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overall accuracy for distribution classification reached 100% based on the RF and spectral indices used for 5 hectares (Table 4).

Table 3. A summary of the importance of UAV-derived NDVI, NDWI, MCARI and Soil pH for the classification of the distribution of healthy banana trees and those affected by BDB and Fusarium.

UAV-derived Spectral Indices	NDVI	NDWI	MCARI	Soil pH
Gini Index	0.22	0.28	0.35	0.15

Table 4. A comparison matrices of classification result of healthy and affected banana trees based on the random forest algorithm.

		Predicted			Total
		BDB	Fusarium	Healthy	
True	BDB	5	0	0	5
	Fusarium	0	11	0	11
	Healthy	0	0	13	13
Total		5	11	13	29

4. Discussion

In the real world, Pisang Kepok, Pisang Ambon and Pisang Kapas have different genome configurations, but they are classified as plantains (Kepok and Kapas) and bananas (Ambon). However, this comparison does not explain how to identify the banana has potential to be affected by the BDB and Fusarium. We started with the sensing technology using the range of spectral wavelength from a handheld spectroradiometer. Through a collection of spectral reflectance from 350 to 2425 nm, the observer was able to determine what occurred during the BDB and Fusarium infection process. Physically, the leaves on the affected banana trees turned from green to yellow and finally to dark brown.

BDB and Fusarium do not only cause leaf decolorization, they also cause a decrease in a tree's ability to absorb water from the air and soil. An increase in the reflectance values from 1000 to 2500 nm indicates decreasing water absorption by the plant. Since the amount of water absorbed by the leaves and soils corresponds to the leaf and soil moisture, the reflectance values will be lower. This is similar to the change that occurs when the reflectance values range between in 350 to 1000 nm. This spectral range corresponds to chlorophyll, xanthophyll and other leaf pigments that play a role in biophysical and chemical processes, including the rate of photosynthesis. As the reflectance value increases, the plant's photosynthetic capability decreases and the rate of regeneration of leaf pigments also decreases. Once this happens, the banana trees, whatever their name or genome configuration, might die.

At least, the spectral pattern in Figure 9 above explains how the spectral reflectance of healthy, mature banana leaves and that of those affected by BDB and Fusarium can be to distinguish the type of disease affecting a tree. First, the Fusarium-infected trees' spectral pattern had a lower reflectance of 1000 to 2500 nm compared to that of the healthy banana tree. This implies that the banana trees infected by Fusarium have much water in their soil and leaves. In contrast, the BDB-infected trees had less water in their soil and leaves. Since it is impossible to observe the presence of BDB in banana Kapas and Ambon due to unavailable spectral data for both cultivars, this explanation is only relevant for banana Kepok (Figure 9b-c).

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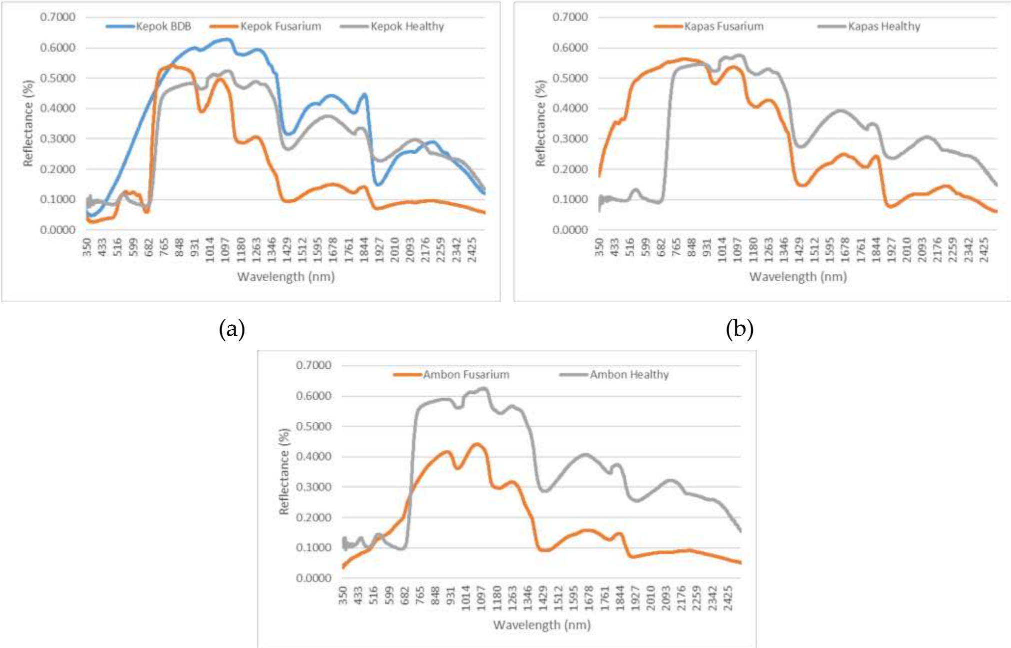

(a) (b)

(c)

Figure 9. Spectral pattern comparison for three cultivars of banana trees affected by BDB and Fusarium, observed based on spectral measurement.

With a spectral reflectance ranging between 350 and 1000 nm, it is safe to say that the bananas Kepok and Kapas have the highest reflectance values for BDB and Fusarium in this region compared to healthy banana trees of the same cultivars. Both cultivars experience abnormalities in the function of chlorophyll, xanthophyll and other leaf pigments related to their biophysical and chemical processes (Figure 9a and b). However, a different pattern is shown by Ambon cultivars. In the red region at 600 to 700 nm, Ambon banana trees affected by Fusarium have the highest reflectance compared to the healthy banana trees. However, the spectral reflectance value between 350 and 599 nm likely shows a standard pattern (Figure 9c). At the same time, while observing the Kapas by affected Fusarium and their healthy counterparts, we found a significant difference in their spectral reflectance. An in depth investigation should be conducted in the future.

The R^2 is another parameter that is critical to ensuring that BDB and Fusarium might be detected and a promising result can be produced using spectral reflectance. It successfully enhanced the capability of UAV and its multispectral sensors to map disease distribution and that of the spectroradiometer to deeply explore the leaves' and trees' biophysical and chemical processes.

Since the soil spectral reflectance is absent, utilizing data from the spectroradiometer can only characterize the relationship between NDVI, MCARI and NDWI. In this study, we obtained three types of correlation among these spectral indices: a moderately positive relationship between NDVI and MCARI, with an R^2 of 0.66; a low negative correlation between NDWI and MCARI, with an R^2 of -0.37; and a highly negative correlation between NDVI and NDWI, with an R^2 of -0.85. Compared to the similar spectral indices derived using UAVs, the correlation between NDVI and MCARI was negative with an R^2 of -0.47, that between NDWI and MCARI was moderately positive with an R^2 of 0.71, and that between NDVI and NDWI was negative with an R^2 of -0.67 (Figure 10).

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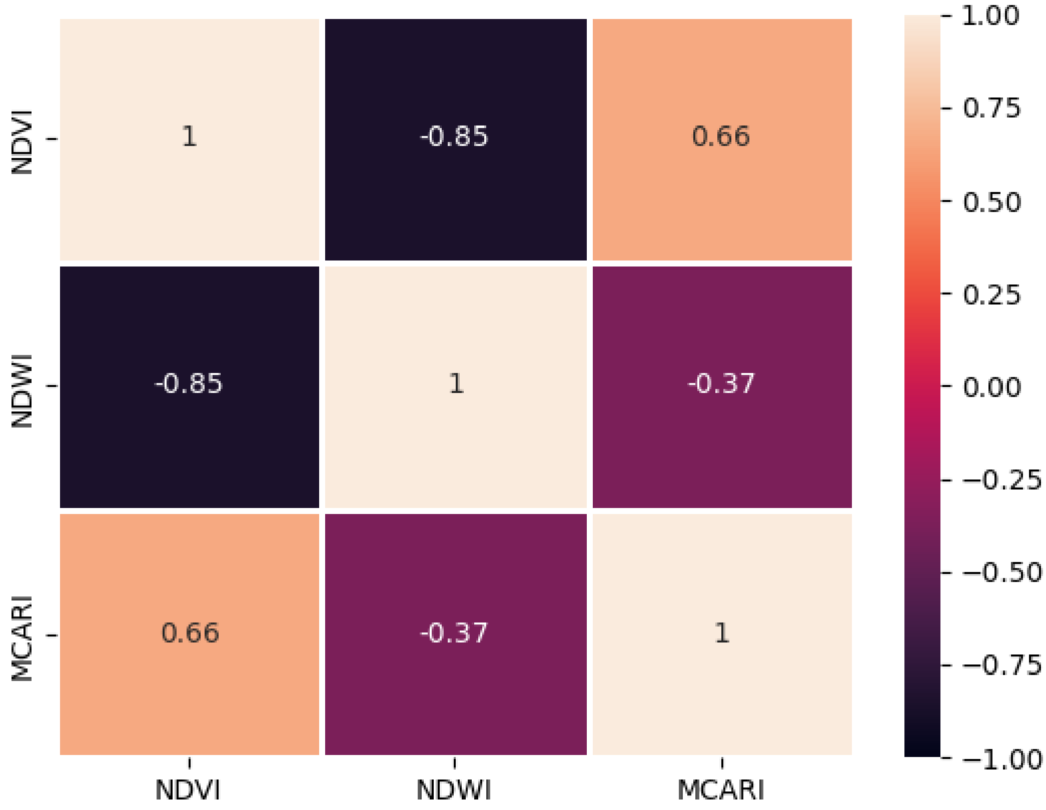

Figure 10. Coefficient of determination (R^2) for spectroradiometer-derived NDVI, NDWI and MCARI in the banana plantation.

The correlations of UAV and spectroradiometer-derived NDWI with MCARI showed a decrease in R^2 values from 0.71 to 0.66 (Figure 10). Although both values indicate the a moderate correlation strength, it does not explain the different performance of the two different sensors. This situation occurred because the band combination used for the UAV-derived NDWI was different from that used for the spectroradiometer-derived NDWI. Since the UAVs derived NDWI using green and NIR bands, it can detect the water content in the soil but not in the leaves. As the soil moisture decreases, both reflectance band values increase. This pattern means that the reflectance fluctuates once the amount of soil-water absorbed changes. The same NIR band, in a spectroradiometer, always shows a higher reflectance for healthy leaves and corresponds with the number of chlorophyll and the photosynthetic and water absorbance capabilities.

At this point, the NIR bands have similar behaviour. The green bands of the healthy leaves have lower reflectance values (about three or six times lesser) than the NIR bands. This reflectance value will be lowest once the level of healthy leaves increases; however, the reflectance cannot penetrate past the leaves and reach the soil surface. This is why the correlation values for NDWI in UAVs decrease when monitored using a spectroradiometer (Table 5). However, similar changes with increasing R^2 also occurred for NDVI-NDWI and NDVI-MCARI. At this point, these two comparisons indicate two different analyses, along with spectral and spatial resolution differences. Even if UAV's aerial photographs can observe objects in centimetres (cm), the spectroradiometers can observe smaller objects. Even though both measurements (using UAVs and spectroradiometers) were conducted using the same spectral wavelength range, in general, both R^2 values obtained from UAVs- and spectroradiometer-derived spectral indices enhanced each other. For details, see Table 5.

Table 5. Comparison of the correlation strength indicated by the coefficient of determination (R^2) change for UAVs- and spectroradiometer-derived spectral indices.

No	Pairs of spectral indices	Coefficient of Determination (R^2)	
		UAV	Spectro

1	NDVI-MCARI	-0.47	0.66
2	NDVI-NDWI	-0.67	-0.87
3	NDWI-MCARI	0.71	0.66

5. Conclusions

The banana trees affected by BDB and Fusarium were successfully detected on a small plantation scale. The methods used have the potential to be applied on a large plantation. They are advantageous for sustainable banana cultivation and for bridging the gap between remote sensing technologies-based photogrammetry observation and biological and plant disease observation. Based on the spectral reflectance measurement, the biophysical and chemical characteristics of banana leaves provided a new insight into how BDB and Fusarium can be explained by fluctuating reflectance values in a specific wavelength range. Both observations have different standards of procedure but still strengthen each other. Therefore, the findings of this study are promising and already interconnected. For future investigations, both methods could be considered for use in an integrated mode. This will not only help with mapping out the disease distribution but will also reveal the level of affectation of the banana trees by BDB and Fusarium, as well as the time- taken for infection to occur. Furthermore, the process of infection rate till the exact calculation of how much banana fruits production can be estimated during the spread of banana diseases occurs in the plantation. Allowing the stakeholder is possible to develop future policies.

Author Contributions: This research article is arranged according to the individual contributions of the authors. The "Conceptualization, KW. and FMD.; methodology, KW. and MFG.; software and validation, MFG. and TMS.; formal analysis and investigation, MFG., LNF., DS., TMS., and AS; resources and data curation, TMS.; writing—original draft preparation, KW., FMD., and MFG.; writing—review and editing, LNF.; visualization, MFG.; supervision, KW. and FMD.; project administration, LNF.; funding acquisition, KW.

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