



School of GeoSciences

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Statement of originality

I declare that this dissertation represents my own work, and that where the work of others has been used it has been duly accredited. I further declare that the length of the components of this dissertation is 5320 words for the Research Paper and 7821 words for the Technical Report.

Signed:

A handwritten signature in blue ink, appearing to read 'D. S. S. S.', is written over a white rectangular box. The signature is stylized with a large initial 'D' and a long horizontal stroke.

Date:

2 August 2023

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UAV Remote Sensing for Disease Detection in Potato Leaf



Part I – Research Paper

Abstract

Disease detection is one of the most common applications of precision agriculture since early detection is vital to prevent the spread of diseases and minimize the potential damage to agricultural production. Drone-based remote sensing can monitor large agricultural areas and identify anomalies in crop health, such as changes in vegetation index or thermal patterns.

This study examines the use of UAV images (Mica Sense Red Edge-M sensor) to detect virus-affected (diseased) potato leaves at SASA Gogarbank Farm in Scotland using multispectral bands: Red, Green, Blue, Near-infrared, and Red-edge.

Although the resolution is high due to the low flight distance in the field where potato crops are located, it is almost impossible to visually distinguish between healthy and diseased ones. Therefore, vegetation indices (VIs), widely used in agronomic fields, were calculated using the plants' reflectivity profiles. As a result of these calculations, it has been observed that SAVI emphasizes soil pixels, and VARI emphasizes flower pixels. In this direction, these two indexes, SAVI and VARI, are used to delete non-leaf pixels in the data before classification. In addition, it has been determined that NDVI has the highest standard deviation, and the band stack has been made with this index, and NDVI has been added as the 6th band. ROIs were determined by selecting 6 different potato plant species in the study area since the number of viruses detected in each plant species and the type differences between varieties in the study area where there were different potato varieties.

According to the laboratory results provided by the SASA's guidance, it is known which plant is diseased and which is healthy. Accordingly, an object-based supervised, K-nearest neighbor (KNN) classification was performed. As it is supervised, the guideline provided by SASA is used for the training data process and the accuracy assessment.

As a result of the classification, an accuracy of over 85% was generally obtained for each ROI. The results show that the UAV remote sensing and computed vegetation indices can distinguish between diseased and healthy leaves. Also, since the difference in reflectance between the diseased and healthy leaf is observed the most in the Red-edge band, the Red-edge sensors tend to give better results in differentiating the leaves.

Keywords: Unmanned aerial vehicles; Remote sensing; Precision Agriculture; Multispectral imagery; Disease Detection; Machine Learning in Disease Detection

1. Introduction

A relatively new technique called precision farming provides advanced methods for raising agricultural output (Neelakantan, 2023). Crop yield monitoring, plant disease detection, weed identification, pest identification, and other uses of precision agriculture are among them. The drone would be used to regularly check on the health of the crops and identify issues as they arise (Neelakantan, 2023).

Food security, alleviating poverty, and promoting development are all impacted by agriculture. In addition, Scotland is also a significant exporter of high-quality potato seeds to the UK and other countries. Since Scottish seed potatoes are known for their high quality and reputation, protecting, and maintaining the production of potatoes has vital importance. The first critical step for protecting potato yields is detection and diagnosis of disease in early stages.

Plant illness and harm are caused by bacterial, fungal, and viral infections as well as insect infestations. A plant develops symptoms from infection that manifest on many areas of the plant and have a big agronomic impact (Sankaran, Mishra, Ehsani, & Davis, 2010). The most common practise now is the diagnosis of diseases based on their visually distinctive symptoms. However, this disease identification is complicated, time-consuming, and open to human error (Zhou, Zhang, & Liin, 2021). In addition, manually examining the crops by farmers or local experts to minimise the loss in production and optimise yields is impractical since it takes too long to complete, and there is a higher risk of human error. To overcome this predicament, an automated system that can precisely identify and categorise illnesses on plant leaves should be created (Mahum, et al., 2023). The spectroscopic and imaging techniques have been successfully applied for plant stress detection and tracking the quality of postharvest yields (Sankaran, Mishra, Ehsani, & Davis, 2010).

Regarding the importance of the subject, it is crucial to make advantage of the machine vision and image processing capabilities that are currently crucial to precision agriculture (Larijani, Asli-Ardeh, Kozegar, & Loni, 2019). Remote sensing techniques, such as drone imagery, can detect and monitor unhealthy plants' reflectance patterns (Chang J. , Clay, Clay, & Reese, 2013). These techniques can provide valuable information for farmers and researchers to identify and address plant health issues.

Agriculture has substantially used machine vision as a reliable and powerful tool. The main applications of machine vision and image processing in agriculture include

- precision agriculture (PA),
- managing and monitoring the quality of agricultural products during the post-harvest stage, and
- regulating and overseeing plants during the planting stage.

The primary reason for the continuously expanding use of machine vision and image processing science in various branches of agricultural science is that it can extract objects' numerical and quantitative characteristics and identify their shape, colour, size, and texture (Pydipati, Burks, & Lee, 2006) (Azarmdel, Mohtasebi, Jafari, & Munoz, 2019). Most plant diseases are caused by living organisms including insects, bacteria, viruses, and fungus, as well as non-living factors like temperature, humidity, soil pH, and nutrient deficiency. Based on the features of disease symptoms, UAV remote sensing provides remarkable spectral, spatial, and temporal resolution that might discriminate between healthy and diseased crop leaves (Zhou, Zhang, & Liin, 2021). Neelakantan (2023) studied supervised machine learning techniques like Random Forests (RF), K-nearest Neighbor (KNN), Support Vector Machine (SVM), The Naïve Bayes (NB), Decision Tree (DT), and Random Forests (RF) on a dataset of tomato disease in order to detect diseases in crop leaves such as leaf curl, Septoria leaf spot, bacterial spot, and early blight that are caused by insects, bacteria, viruses, or fungi.

Knipling(1970) claimed that spectral changes in crop leaves occurred by physiological stress, which can be found equally prominent in both the visible and the near-infrared electromagnetic regions. Experimental results supported this claim. Metabolic abnormalities impact the capacity of chlorophyll to absorb visible light, and as it deteriorates, the visible reflectance rises. Unhealthy plants can exhibit different electromagnetic reflectance patterns compared to healthy plants because the physical and chemical properties of the plant leaves change when the plant is unhealthy, affecting how it interacts with light. In general, unhealthy plants tend to have lower reflectance in the visible range of the electromagnetic spectrum (400-700nm) and higher reflectance in the near-infrared range (700-2500 nm) than healthy plants since unhealthy plants may have lower chlorophyll content or changes in leaf structure that affect how light is absorbed and reflected.

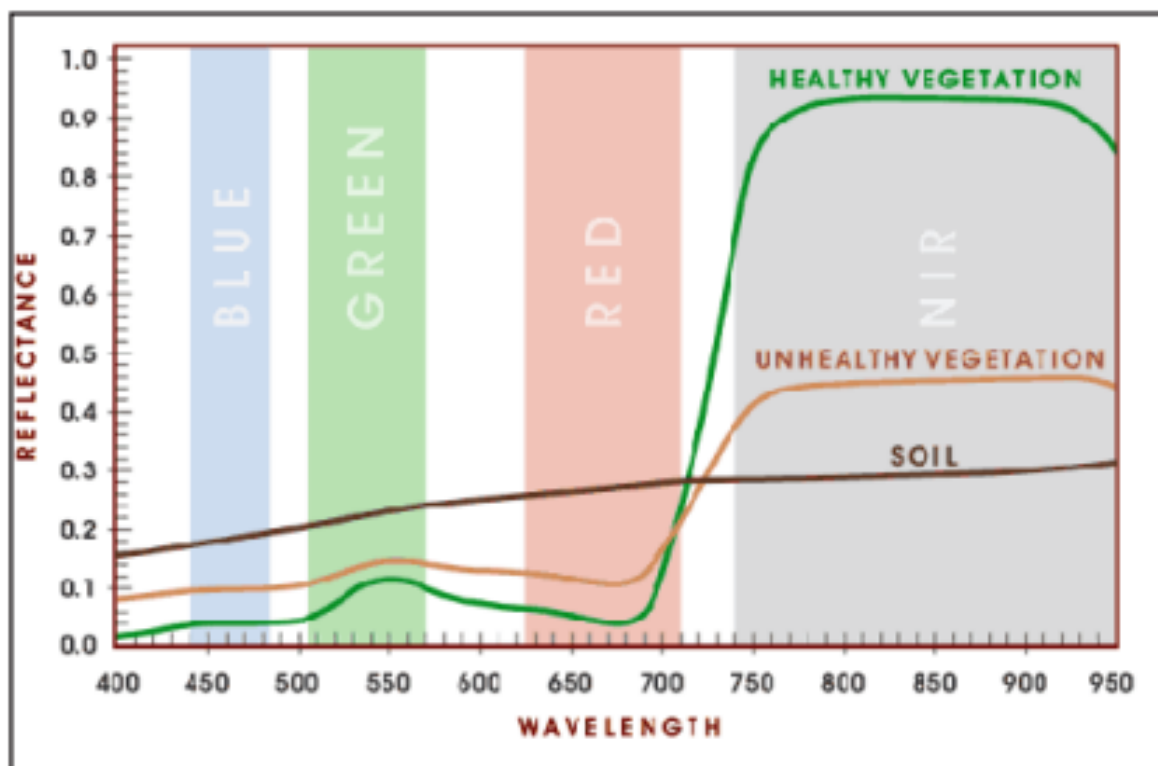


Figure 1 Spectral reflectance of healthy vegetation, unhealthy vegetation, and soil in visible and near-IR wavelength (Chang J. , Clay, Clay, & Reese, 2013).

Plant leaf characteristics, such as pigment and moisture content of tissue, leaf area index, ratio of living to senesced tissue biomass, and location of cells and structures, all affect the spectral characteristics of vegetation (Zhou, Zhang, & Liin, 2021). The spectral reflectance of the plant gives information about the chlorophyll level of the plant, which plays a crucial role in photosynthesis, the process by which plants convert light energy to chemical energy to fuel their growth. Chlorophyll absorbs light, particularly in the blue and red regions. It has higher reflectance in the NIR bands of the electromagnetic spectrum while reflecting or transmitting green light, giving plants their characteristic green colour. The level of chlorophyll in plants can affect their reflectance properties. The healthy plant, which has a high chlorophyll concentration, absorbs more light, resulting in lower reflectance in the visible spectrum. That means less green light is reflected, and the plant appears darker green. On the other hand, stressed or damaged plant absorbs less light, and more reflection, which leads to higher reflectance in the visible spectrum, particularly in the green region. As a result, plants with lower chlorophyll levels may appear lighter or yellowish as they reflect a higher proportion of green light (Chang et al., 2013).

The visible and NIR bands are combined in false colour images, combining green, red and NIR, and Normalised Difference Vegetation Index (NDVI). NDVI is a simple indicator that can be used to analyse remote sensing measurements and determine whether the observed target contains healthy crops (high index values) or unhealthy crops (low index values). The healthy crops appear in red in false images, whereas the unhealthy crops appear in light red.

In precision agriculture, low spatial resolution of satellite remote sensing makes it unsuitable for plot-level applications, which enable effective reduction of the effects of field variability to increase the genetic signal-to-noise ratio. Therefore, Unmanned Aerial Vehicles (UAVs) have increased in prominence due to their ability to meet the high spatial resolution real-time continuous monitoring requirements of precision agriculture. UAVs provide rapid and non-destructive phenotypic information of plants.

Although consumer-level digital camera-based visible light sensors are easy to operate, inexpensive, and can be utilized in agriculture, they are inadequate for more in-depth research and applications due to their lack of red-edge (RE) and near-IR (NIR) bands, which are highly sensitive bands used for vegetation monitoring. In contrast, multispectral sensors can easily be used to acquire high spatial resolution (centimetre-level) multiband (from the visible to the NIR) remote sensing data, thus achieving a balance between cost and useability.

Radiometric calibration is a further essential factor in evaluating spectral accuracy and reflectance-based components (like VIs). Radiometric calibration is a requirement and crucial step before employing multispectral imaging, allowing the camera's digital number (DN) value to be translated into spectral reflectance.

Diagnosing plant diseases quickly, automatically, affordably, and accurately is crucial in contemporary agriculture (Larijani, Asli-Ardeh, Kozegar, & Loni, 2019). Therefore, this research aims to create a system for image processing that can detect diseased crop leaves in potato crops.

1.1. Research aims and objectives

The specific aims of this study were:

- Using high spectral resolution UAV images to investigate changes in spectral reflectance associated with diseases that occur on leaves to discriminate between healthy and diseased leaves, identifying wavelengths that could be used as disease indicators for remote sensing, and determining VIs which can be used in disease detection studies. Moreover, emphasise the importance of remote sensing applications in Precision Agriculture studies.

1.2. Study Area

The data collection for the study occurred at Gogarbank Farm, a Scottish Agricultural Science Agency (SASA) research farm, including potato crops. SASA stands for providing scientific services and advice supporting Scotland's larger agricultural and environmental sectors and food safety and wildlife management. SASA seeks to protect agricultural and horticultural crops from dangerous diseases. In addition, potato crops are provided for inspectors to observe different types of single plants or crop conditions in large areas using a variety of plot sizes. Demonstration charts indicating widespread symptoms in several cultivars, a collection of cultivar genetic variations, and charts displaying black leg and herbicide damage symptoms are also accessible to them.

The study area was 176 potato plots grouped according to different variables and different symptoms of virus infection. The data about disease collection was provided by the Gogarbank guidance paper, which shows the variety and the virus test result of each plot.

2. Methodology

The general workflow consisted of the UAV imagery acquisition, image processing, and image classification applied to subset regions (ROIs), and the visualisation of results and computing accuracy assessment are all described, and the process is illustrated in Figure 2. These stages are described briefly below and in further detail in the Technical Report (Part II)



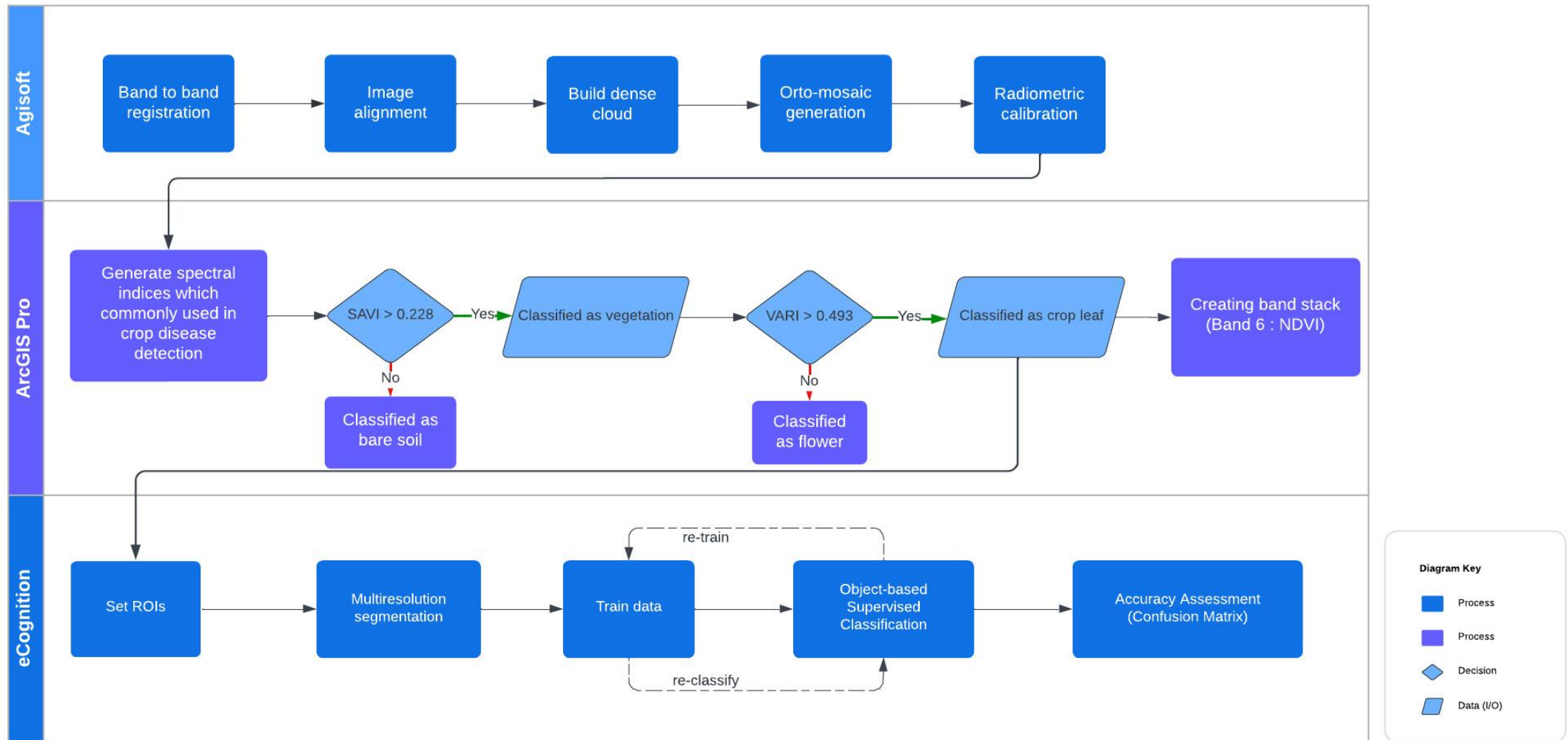


Figure 2 Flow chart of the disease detection

2.1. Aerial Imagery

Aerial images analysed in this study were taken in early July 2020 at Gogarbank Farm, allocated around 7 kilometres west of Edinburgh, near Ratho. The aerial images were taken on cloudless days with a 3DR Solo drone equipped with a calibrated Mica Sense Red Edge-M sensor. The average flight height was 15 meters above the field and a spatial resolution of 1.1 cm. The SASA independently identified diseased and healthy plots, which carried out a virus test of all varieties. In total, 58 potato varieties have one healthy plot and at least one virus symptom, such as Yⁿ, Yⁿ, A, V, M, Y^{NTN}, S, X. Moreover, the test results show that some plots have more than one virus or are likely to be virus-affected, labelled ‘likelihood ratio (LR)’.



Figure 3 The commercial ready-to-use 3DR Solo drone.

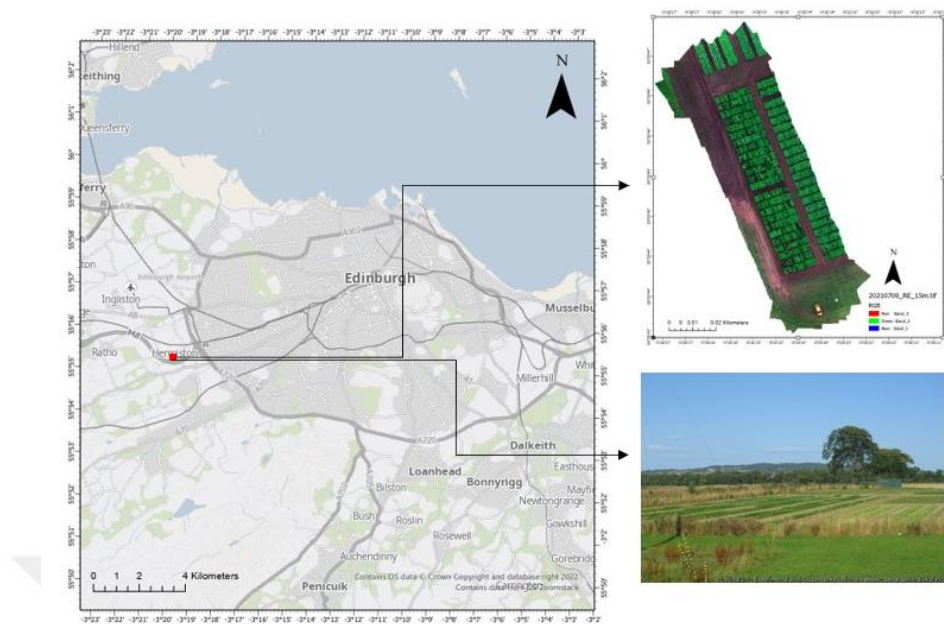


Figure 4 Location map of the study site at Gogarbank Farm in Edinburgh

The Mica Sense Red Edge-M sensor has custom narrow, non-overlapping bands in the visible and NIR range (from 400nm to 900nm) (Cao, et al., 2019), which are blue, green, red, red edge, and near-IR (Figure 5). The band locations were created to measure light in the visible range, where plants absorb light effectively to carry out photosynthesis, and light on the broader wavelength region, where plants significantly reflect light due to the structure of leaf cells (Table 1). Regarding the accuracy of the multispectral sensor, the band centre and its bandwidth play a key role. Large chunks of the light spectrum are measured using broadband sensors, such as modified cameras, by averaging the reflectance in that region to create a single result. In contrast, a narrow-band sensor records the reflectance of a relatively limited spectrum region. This results in more accurate and perceptive information about small changes that might occur at crucial periods. Moreover, Broge & Leblanc (2001) discovered that broadband VIs are considerably more accurate in predicting leaf area index (LAI) and canopy chlorophyll density (CCD) and less sensitive to external factors when compared to the narrow band VIs.

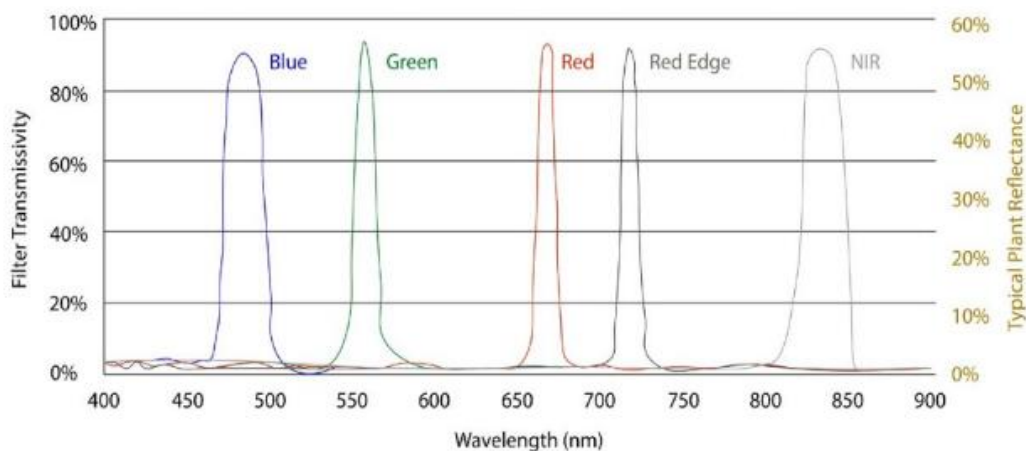


Figure 5 The reflectance and wavelength ranges of the different bands of narrow-band sensor which shows that a very narrow-band of the spectrum's reflectance is recorded by narrow-band sensor. More accurate and useful information is produced regarding any slight changes that might be taking place at important locations.

Band number	Band name	Centre wavelength (nm)	Bandwidth FWHM (nm)	Min	Max	Narrow
1	Blue	475	20	465	485	P450 P500
2	Green	560	20	550	570	P550 P570
3	Red	668	10	663	673	P670 P699
4	Near IR	840	40	820	860	P800 P800 wide P819 P857
5	Red-edge	717	10	712	722	P700 P715 wide P715 P720

Table 1 Band characteristics of the Mica Sense Red Edge-M. FWHM stands for full width at half maximum.

The Mica Sense RedEdge-M sensor also has a Red-edge band, which lies between the red and NIR bands, which is crucial for determining the chlorophyll content of plants. The red-edge band in Figure 6 illustrates where the variation will most likely be noticeable if a plant is under stress. It is most important to measure the Red-edge band since it exhibits the most significant amount of shift when compared to the red, red-edge, and NIR bands.

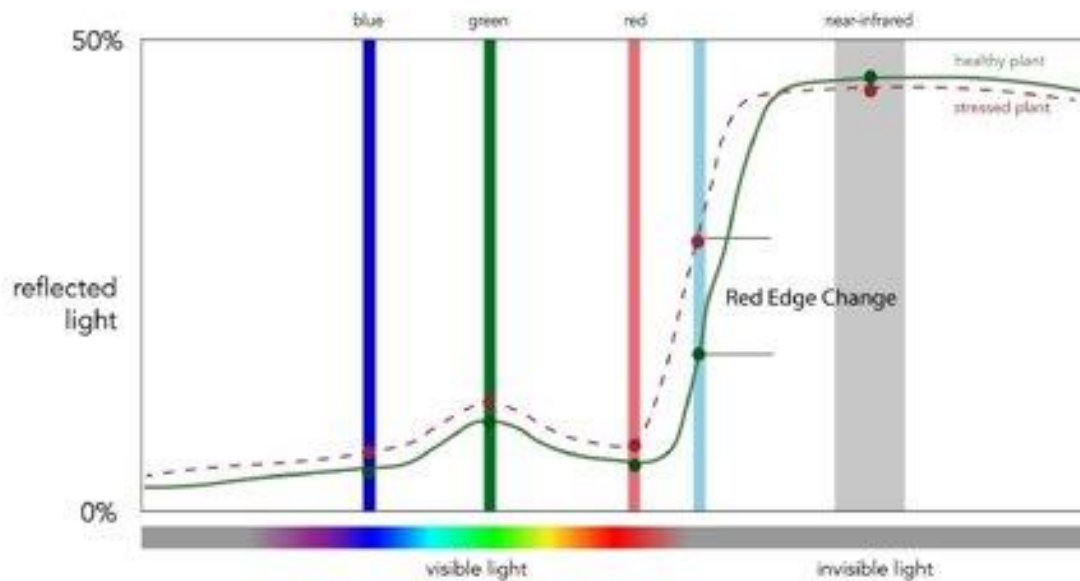


Figure 6 the red-edge band is crucial in determining the chlorophyll content of plants. The red-edge band is likely to show the most evident variance in a plant under stress.

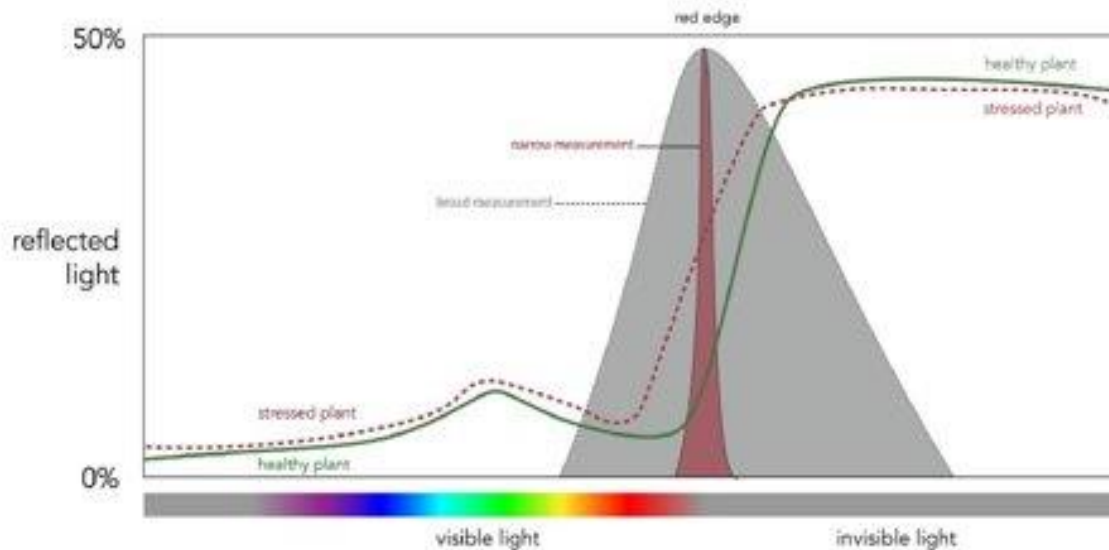


Figure 7 The red-edge band is crucial in determining the chlorophyll content of plants. The red-edge-band is likely to show the most evident variance in a plant under stress.

Additionally, the sensor includes Downwelling Light Sensors (DLS), which gauge and capture the amount of incoming light (irradiance) when every image is captured. When combining individual images to create a mosaic image, this data can be extracted from the image metadata to help adjust for the impacts of illumination variability (MicaSense, 2022).

2.2. UAS Image pre-processing

2.2.1. Mosaicking

UAVs capture images from lower altitudes than aircraft or satellites, so these images have a higher radiometric resolution. However, UAV images might have different spatial resolutions and geometric distortion because of less stable camera position (Lelong et al., 2008). In addition, lower flight altitude can also cause a more significant number of images per field. Therefore, one of the necessary pre-processing steps is the image mosaicking. Image mosaicking is a method that creates a continuous, high-resolution image by combining many images with overlapped portions (Kuswidiyanto, Noh, & Han, 2022). Mosaicking was accomplished using Agisoft PhotoScan Professional (v. 0.9.0; Agisoft et al., Russia) (Discover Intelligent Photogrammetry with Metashape, n.d.), a software application made for satellite imagery and aerial photography, and other forms of remote sensing, where large regions are captured in smaller segments due to limitations in sensor coverage or data acquisition. In order to choose and arrange couples, the software automatically chooses and compares an essential amount of the tie points in each image.

Additionally, the programme eliminates flight artefacts, such as camera angle and altitude changes. Low flying altitudes rendered radiometric distortions, often produced by atmospheric influences, insignificant (Knoth, Klein, Prinz, & Kleinebecker, 2013). Therefore, the radiometric calibration process comes next. The sensor's raw data, known as a digital number (DN), are arbitrary integers that must be transformed into radiation (Kuswidiyanto, Noh, & Han, 2022).

2.2.2. Reflectance calibration and correction

According to Mica Sense recommendations, reflectance calibration was performed. Therefore, the output band values would still be 16-bit integer values like input band values, but 100% reflectance for each band would correspond to the middle of the available range. Suppose it is necessary to export the reflectance normalized 0-1 range. In that case, it is required to create output bands in the raster calculator and divide the source value by the normalization factor for each of their formula.

2.2.3. Spectral reflectance and vegetation indices

Vegetation indices (VI), or spectral indices (SI), are numerical representations derived from images. These indices emphasise specific phenomena while minimising other elements that could lessen their impact. Image indices are calculated based on the spectral reflectance information captured by the sensor, which measures the amount of electromagnetic radiation (light) reflected or emitted by different surface materials. Coffee leaf rust disease was identified using 63 plant indices from multispectral images, and it found that model contribution from Modified Normalised Difference Red Edge (MNDRE) is most significant (Marin, et al., 2021). Similarly, (Abdulridha, et al. (2019) investigated 31 vegetation indices for citrus cancer disease identification. A comprehensive list of vegetation indices commonly used in agronomic and disease detection studies is shown in Table 2.

Vegetation/Soil Indices	Formulation	Explanation	Reference
MSAVI (Modified Soil Adjusted Vegetation Index)	$\frac{[2 p_{800}+1-[(2 p_{800}+1)^2-8(p_{800}-p_{670})]^{1/2}]}{2}$	The Modified Soil Adjusted Index approach reduces bare soil's impact on the SAVI.	(Qi, Chehbouni, Huete, Kerr, & Sorooshian, 1994)
EVI (Enhanced Vegetation Index)	$2.5 (p_{800}-p_{670})/(p_{800}+6 p_{670}-7.5 p_{450}+1)$	The EVI is an improved vegetation index that considers atmospheric factors and vegetation background signals. While comparable to NDVI, it is less sensitive to background noise.	(Huete, Liu, Batchily, & van Leeuwen, 1997)
NDVI (Normalized Difference Vegetation Index)	$(p_{800}-p_{670})/(p_{800}+p_{670})$	The red band chlorophyll pigment absorptions and the near-infrared (NIR) band's strong reflection of plant constituents are used to boost the Normalised Difference Vegetation Index, highlighting the image's greenness.	(Huang, Tang, Hupy, Wang, & Shao, 2021)
GNDVI (Green Normalized Difference Vegetation Index)	$(p_{800}-p_{550})/(p_{800}+p_{550})$	A standard vegetation index used to estimate water and nitrogen intake into the plant canopy is the GNDVI, which measures photosynthetic activity in the plants.	(Buschmann & Nagel, 1993)
Red-EdgeNDVI (Red-Edge Normalized Difference Vegetation Index)	$(p_{800}-p_{700})/(p_{800}+p_{700})$	Red-Edge NDVI, in contrast to normal NDVI, considers a smaller waveband near the edge of the chlorophyll absorption characteristic (for example, 705 nm) rather than at the centre.	(Evangelides & Nobajas, 2020)

PVI (Perpendicular Vegetation Index)	$(p_{800} - ap_{670} - b) / (1 + a^2)^{1/2}$ a = slope of the soil b = gradient of the soil line	The PVI technique is comparable to a differential vegetation index, although it is more susceptible to atmospheric changes. Only images adjusted for atmospheric distortion should be utilised when comparing images using this approach.	(Richardson & Wiegand, 1977)
SR (Simple Ratio)	p_{800}/p_{670}	SR is a widely used vegetation index for measuring the quantity of vegetation that mitigates the impacts of terrain and atmosphere.	(Birth & McVey, 1968)
CI-Green (Green Chlorophyll Index)	$(p_{800}/p_{550}) - 1$	By comparing the reflectance in the near-infrared (NIR) and green bands, CI-RedEdge calculates the chlorophyll concentration of leaves.	(Gitelson, Kaufman, & Merzlyak, Use of a green channel in remote sensing of global vegetation from EOS-MODIS, 1996)
CI- RedEdge(Red- edge Chlorophyll Index)	$(p_{800}/p_{700}) - 1$	Utilising the ratio of reflectivity in the near-infrared (NIR) and red-edge bands, this index was created to quantify the chlorophyll content of leaves.	(Gitelson & Merzlyak, Quantitative estimation of chlorophyll using reflectance spectra, 1994)
SAVI(Soil Adjusted Vegetation Index)	$((1+L) * (p_{833} - p_{664})) / (p_{833} + p_{664} + L)$ L=canopy background adjustment factor, ranging from 0-1	The Soil-Adjusted Vegetation Index (SAVI) uses a soil-brightness adjustment factor (L) to try and reduce the effects of soil brightness.	(Huete, A soil-adjusted vegetation index (SAVI), 1988)
TSAVI (Transformed Soil Adjusted Vegetation Index)	$(s * (p_{800} - s * p_{670} - a)) / (a * p_{800} + p_{670} - a * s + X * (1 + s^2))$ s: The slope of the soil line a: The soil line intercept. X: The adjustment factor that is set to minimize soil noise.	By assuming that the soil line has an arbitrary slope and intercept, the TSAVI approach, which measures vegetation, minimises the effects of soil brightness.	(Rondeaux, Steven, & Baret, 1996)
VARI (Visible Atmospherically Resistant Index)	$(p_{550} - p_{670}) / (p_{550} + p_{670} - p_{450})$	The VARI approach uses just the visible region of the spectrum to estimate the proportion of vegetation quantitatively.	(Anatoly, Yoram, Robert, & Don, 2002)
MCARI (Modified Chlorophyll Absorption Ratio Index)	$[(p_{700} - p_{670}) - 0.2(p_{700} - p_{550})] / (p_{700}/p_{670})$	The combined impacts of soil and non-photosynthetic surfaces are reduced by this index, which shows the relative quantity of chlorophyll.	(Daughtry, Walthall, Kim, Brown de Colstoun, & McMurtrey, 2000)
MCARI2 (Modified Chlorophyll Absorption Ratio Index)	$1.2[2.5(p_{800} - p_{670}) - 1.3(p_{800} - p_{550})]$	This index is similar to MCARI, but it is thought to be a better predictor of green leaf area index (LAI).	(Haboudane D. , Miller , Pattey, Zarco-Tejada, & Strachan, 2004)

MRENDVI (Modified Red Edge Normalized Difference Vegetation Index)	$p_{750}-p_{705}/p_{750}+p_{705}-2*p_{445}$	The index modifies the Red Edge NDI to account for specular reflection from leaves. It takes use of the red edge sensitivity of vegetation to slight variations in the canopy foliage content gap fraction and senescence	(Datt, 1999)
MTVI (Modified Triangular Vegetation Index)	$1.2[(1.2(p_{800} - p_{670}) - 2.5(p_{800} - p_{550}))]$	This index modifies TVI for LAI estimation.	(Haboudane D. , Miller , Pattey, Zarco-Tejada, & Strachan, 2004)
MTVI2 (Modified Triangular Vegetation Index – Improved)	$1.5[(1.2(p_{800} - p_{670}) - 2.5(p_{800} - p_{550}))(2p_{800} + 1)^2 - (6p_{800} - 5p_{670}) - 0.5]$	This index has similarities to the MTVI and is a better indicator of green LAI. While retaining sensitivity to LAI and resilience to chlorophyll's impact, it considers the soil background signature.	(Haboudane D. , Miller , Pattey, Zarco-Tejada, & Strachan, 2004)
REPI (Red- Edge Position Index)	$700+40[(p_{670} + p_{780})/2 - p_{700}]/(p_{740} - p_{700})$	It is sensitive to changes in chlorophyll concentration and assesses narrowband reflectance. More chlorophyll causes the red edge to move to longer wavelengths and widens the absorption characteristic.	(Guyot, Baret, & Major, 1988)
TCARI (Transformed Chlorophyll Absorption Ratio Index)	$3[(p_{700}-p_{670})-0.2(p_{700}-p_{550})(p_{700}/p_{670})]$	This index, which shows the relative quantity of chlorophyll, is one of numerous CARI indices. It is impacted by the reflectance of the underlying soil, especially in plants with a low LAI.	(Haboudane D. , Miller, Tremblay, Zarco-Tejada, & Dextraze, 2002)
TVI (Triangular Vegetation Index)	$0.5[120(p_{750}-p_{550})-200(p_{670}-p_{550})]$	This index is derived as the size of a fictitious triangle in spectral space connecting the NIR shoulder, the minimal chlorophyll absorption, and the green peak reflectance.	(Broge & Leblanc, 2001)

Table 2 Common vegetation indices for the assessment of plant health using multispectral images. p_{NIR} is the NIR reflectance; p_{red} is the red reflectance; p_{green} is the green reflectance; p_{blue} is the blue reflectance.

It is expected to have higher NDVI, GNDVI, SAVI, NIR-R, G/R and NIR/R values for healthy plants. In addition, Garcia-Ruiz and colleagues (2013) have shown that crops affected by stress will have higher R/NIR values than healthy plants. In addition, the differences between some indices are more significant than other indices. Greater differences between stress-affected and healthy plants could be observed in NIR-R and NIR/R indices. From the indices in Table 2 calculated from this point of view, the indices that best emphasize the targeted elements for this study area and their outputs are given in Figure 8.

2.2.4. Removing external pixels

Before classification, removing additional/nonrelevant features of the image is essential in terms of increasing the accuracy of the classification method. Removing soil from UAV images allows more accurate analysis and assessment of vegetation-related parameters. By eliminating soil pixels, the focus can be solely on the vegetation cover. Richardson and Wiegand (1977) were the ones who first proposed separating the vegetation from the soil background, and several more VIs were developed to emphasize the soil pixels. However, Huete (1988) established the Soil-Adjusted Vegetation Index (SAVI), which attempts to minimize soil brightness influences using a soil-brightness correction factor since other VIs cannot adequately describe the soil background's spectral behaviour. Therefore, SAVI was used to extract soil pixels from the overall image. The SAVI value of the image, soil and non-soil pixels were classified according to the classification value ranges ranging from -0.291 to 0.561. The threshold value was set for soil pixels, which was 0.228. Pixels less than or equal to 0.228 SAVI are assigned as soil pixels and removed from the image.

In addition to soil pixels, the floral pixels the study site includes might affect the classification's accuracy. Therefore, VARI was used to discriminate the floral pixels from the study area. VARI is a vegetation index that only uses the visible portion of the spectrum to estimate vegetation as a multiband raster. It determines if the green band has different values from the red band, which gives a reliable assessment of leafy foliage. The destruction of the blue band, which was created to reduce the impact of atmospheric factors on the index, is a prominent feature of VARI (Eng, Ismail, Hashim, & Baharum, 2019). According to the VARI value of the image, floral and leaf pixels were classified, and classification value intervals were from -0.828 to 1.166. The threshold value was set for flower pixels, which was 0.493. Pixels less than or equal to 0.493 VARI are assigned as flower pixels and removed from the image.

2.2.5. Band Stack (Band Combination)

Lee et al. (2018) carried out a study to show the effect of the layer stacking of Spectral Indices (SIs), and it showed that band stacking with SIs improves the overall accuracy. In deciding which indices will be used to increase accuracy, the standard deviation of all indices was calculated and shown that NDVI has the highest standard deviation value (0.206).

Before classifying the image, one of the indices was combined with multispectral data and obtained the 6th band image. Standard deviations are calculated while choosing the indices to combine with bands, and the index is the highest standard deviation. NDVI has the highest standard deviation, so band stack occurred with the NDVI index. A high standard deviation indicates a significant difference between the reflectance values. Therefore, combining existing bands with NDVI increases the reflection difference between diseased and healthy plant bands. Consequently, it is aimed to improve the classification algorithm's ability to distinguish diseased plant leaves caused by this difference.

2.3. Image Classification

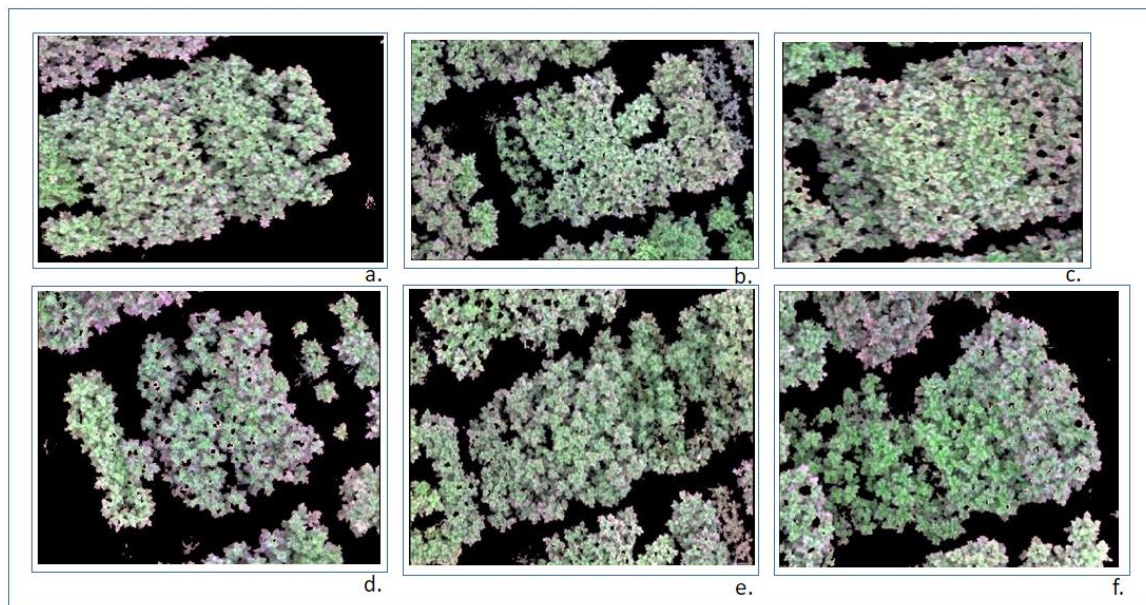


Figure 8 Selected ROIs. Cara(a), Desiree (b), Nicola (c), Maris Piper (d), King Edward (e), Marfona (f).

The process of classifying images involves putting them into a predetermined category (Elngar, et al., 2021; Elngar, et al., 2021). The collected data have a high spatial resolution of around 2 cm, allowing the determination of plant characteristics through unique pixel values at the branch level (Lehmann, Nieberding, Prinz, & Knoth, 2015). However, object-based classification provides several advantages over pixel-based classification, including capturing spatial patterns and contextual information, reducing the effects of mixed pixels, and enhancing classification accuracy.

The images' high spatial resolution made defining plant-related characteristics possible. These are required for object-based classification methods because they enable the distinction of various object classes in terms of different pixel values and texture patterns, geometry, segment dimensions, and topologies (Knoth, Klein, Prinz, & Kleinebecker, 2013). Multiresolution image segmentation, a pixel-level definition of an image, was performed as a subsequent image classification stage. Setting a threshold for scale, shape, and compactness allows for defining this criterion. In this study, the multiresolution segmentation was conducted with a scale parameter of 3, which is related to the resolution of the imagery (Benz, Hofmann, Willhauck, Lingerfelder, & Heynen, 2004), for each ROI. After evaluating several parameter levels iteratively, a ratio of 0.1 for shape was selected. If the shape level is low, the amount of compactness has relatively little impact on the produced items. Hence, a value of 0 was used for the compactness threshold. The areas are divided into segments with arbitrary forms and similar characteristics. The segments can be created to approximate the shape of each leaf or a portion of the leaf that shares attributes to identify plant diseases. Segments are transmitted to a classifier model and gathered to do the classification (Kuswidiyanto, Noh, & Han, 2022).

The following object-based classification (K-nearest neighbor/KNN algorithm) was performed by deciding on thresholds of class-specific image characteristics. Selecting class-specific samples manually using an on-screen interpretation allowed the thresholds of these attributes (Table 3) to be automatically registered.

K- Nearest Neighbor Algorithm Parameters

Layer Values	Mean Blue
	Mean Green
	Mean Red
	Mean NIR
	Mean Red-edge
	Mean NDVI
k value	1

Table 3 Object features used during KNN object-based classification with eCognition

An object-based image classification (OBIA) was conducted using eCognition (Trimble Geospatial, Munich, Germany). Due to the considerable spatial diversity among objects of interest, pixel-based classifications are less successful for high-resolution imaging, where OBIA is especially suitable (Laliberte et al., 2011). OBIA includes classifying image objects, but more often, a recursive approach is used, which involves image segmentation, classifying image objects, merging objects, re-segmentation and re-classification objects using a combination of fuzzy classification and the use of spectral, spatial, and contextual characteristics for the extraction of meaningful image objects.

In this study, it is used the nearest neighbor classification algorithm for object-based classification in each ROI. It is pointed out that when compared to a pixel-based approach, the image classification accuracy was significantly increased by segmenting the image into image objects and using the nearest neighbor classifier (Blaschke, 2010). Rule sets are stored as process trees, applied, and adapted to each ROI.

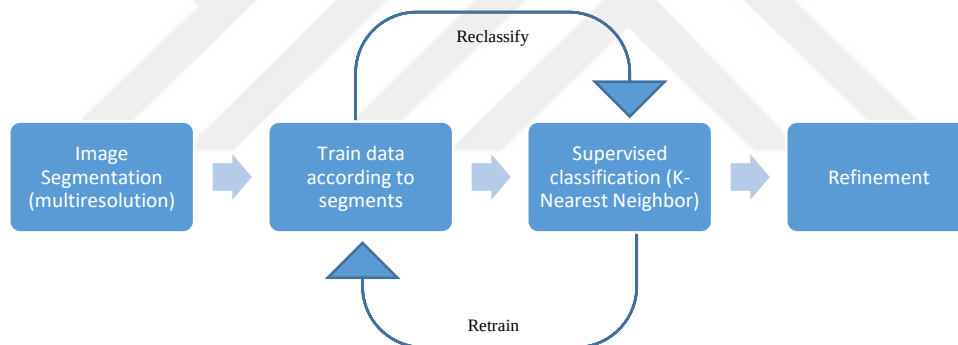


Figure 9 Rule set of the object-based classification used in study.

The accuracy of the final classification was then assessed using a confusion matrix, which includes four components:

1. The producer's accuracy is measured by the number of items allocated to a class's reference samples.
2. The user's accuracy, which is calculated as the percentage of correctly identified items among all the samples classified
3. The total accuracy, expressed as a percentage of all items that were adequately categorised
4. The Kappa, or the degree to which the classification findings and the matching reference data coincide (Foody, 1992).

Moreover, based on the categories Landis & Koch (1977) suggested, the Kappa results were interpreted (Table 4).

Kappa Value	Interpretation
0.00 – 0.20	Poor
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Good
0.80 – 1.00	Great

Table 4 Kappa value interpretation by category offered by Landis & Koch (1977).

3. Results

3.1. Vegetation Indices

From the indices in Table 2 calculated from this point of view, the indices that best emphasize the targeted elements for this study area and their outputs are given in Figure 8.

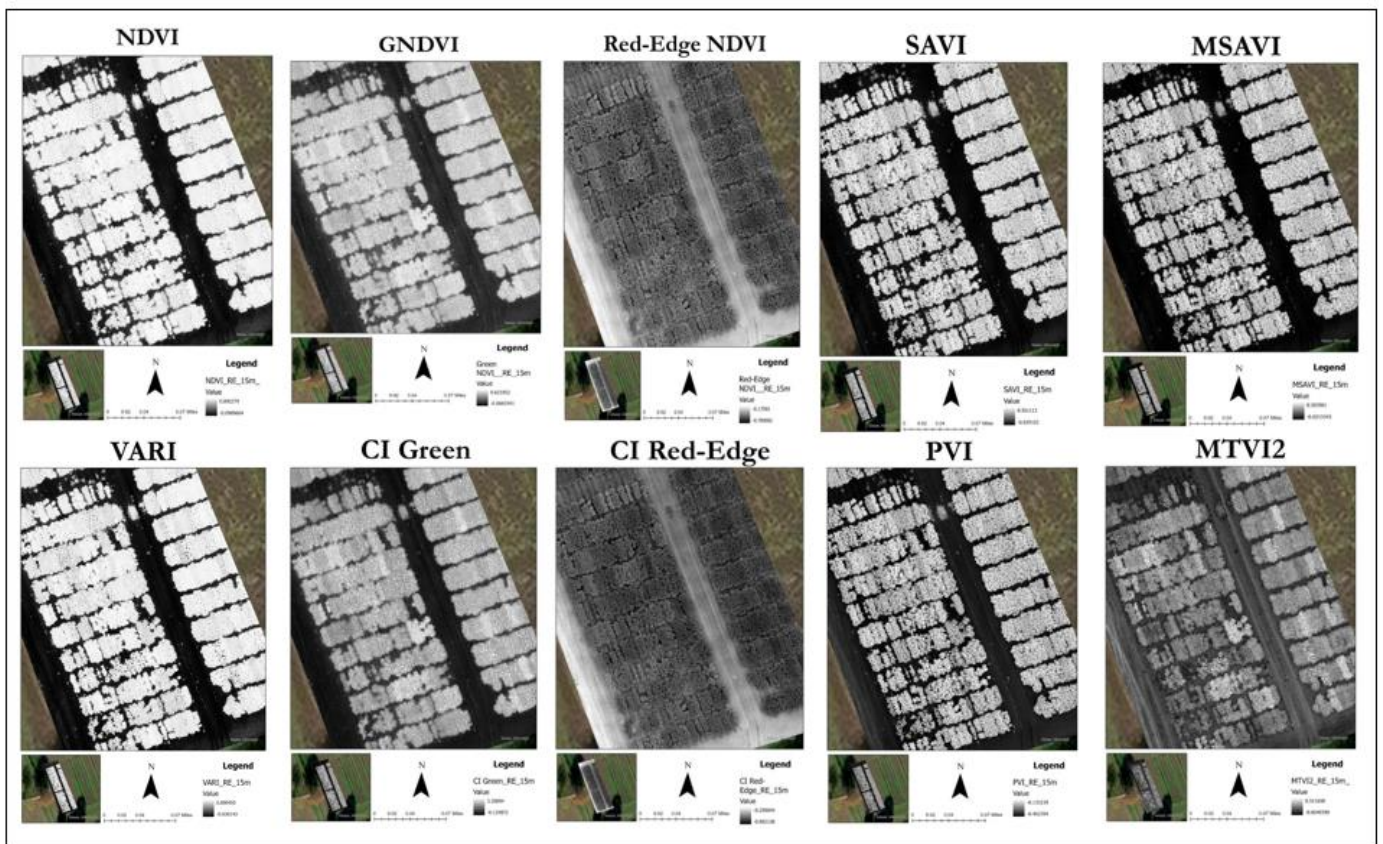


Figure 10 The output of the calculated VIs which mostly used agricultural studies.

3.2. Removing the external pixels

As shown in Figure 11.b, the SAVI value range is divided into five classes, and the values represented by the soil pixels were detected and set as the threshold value of 0.228. According to the threshold value, pixels equal to or smaller than the threshold value are removed from the study area. The illustration of SAVI calculation, the division into five classes, reclassifying the data as soil and vegetation, and the ground extracted data are shown in Figure 11. In addition, Figure 12 represents the RGB output of soil-extracted data.

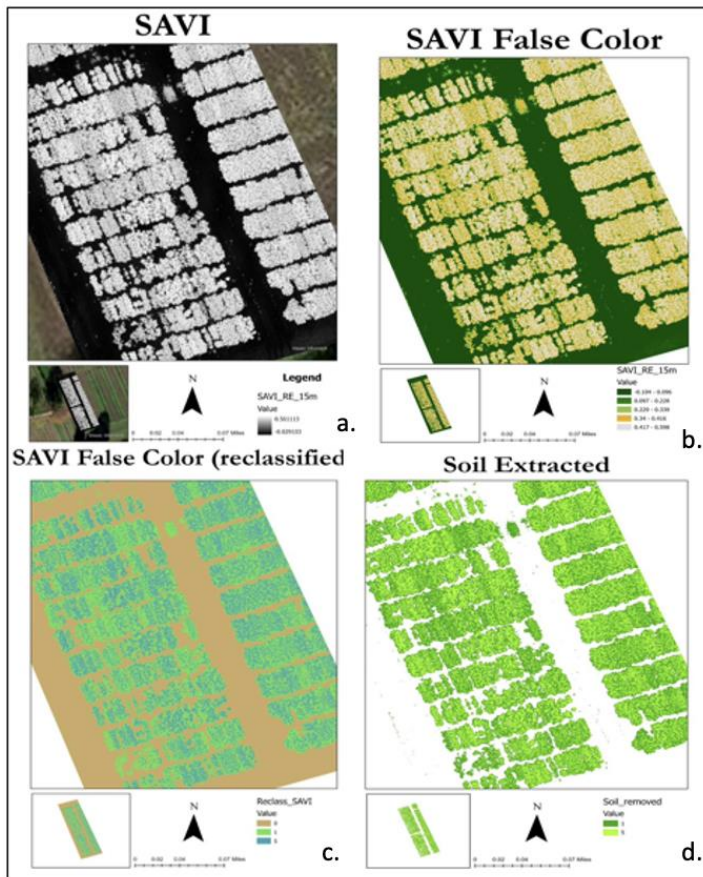


Figure 11 a. SAVI computed for study area; b. Classification of study area according to SAVI value; c. Soil pixels are put into one class using a threshold to distinguish vegetation and soil; d. The output of the soil extraction process for study site.



Figure 12 RGB output of soil extracted plots.

Figure 13 shows the VARI calculation for the study area from which the soil pixels are extracted and the classification by dividing it into five value ranges(a&b). According to the classified VARI values, it was determined that the VARI values of 0.493 and less represented the floral pixels, which were removed from the image.

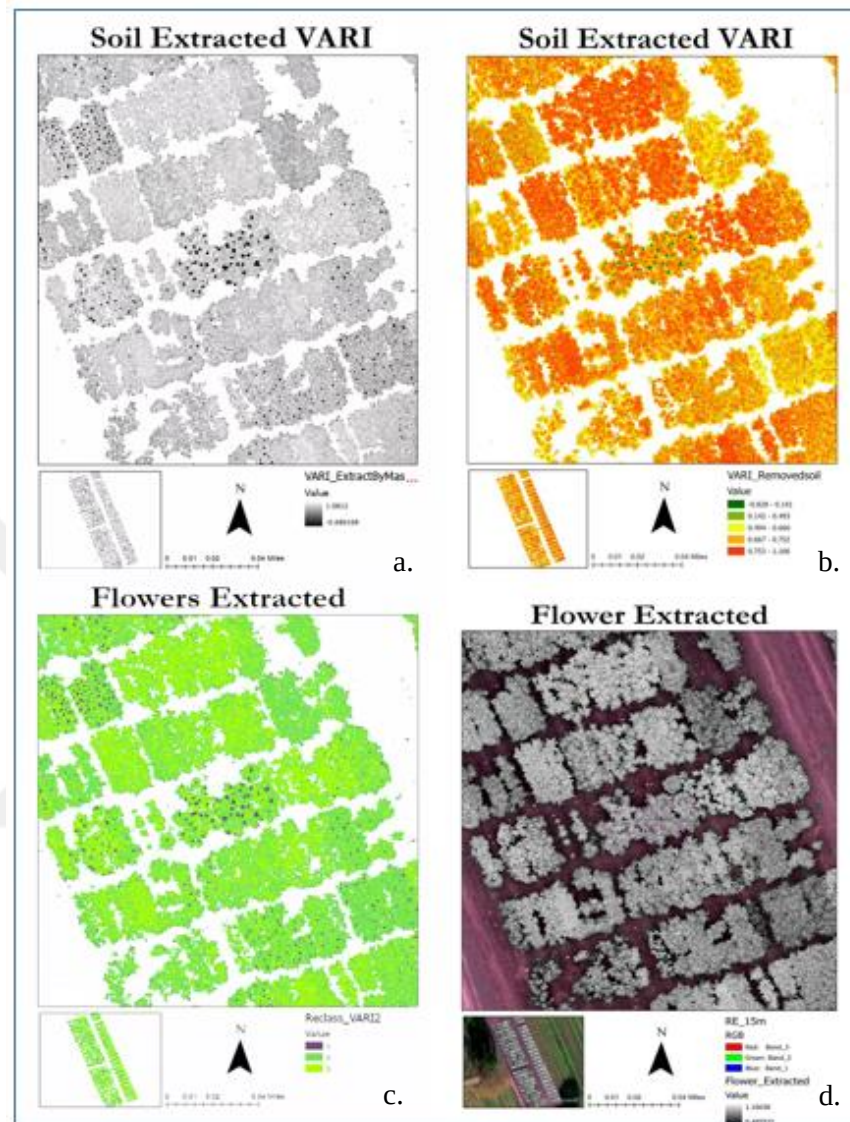


Figure 13 a. VARI computed for study area; b. Classification of study area according to VARI value; c. Floral pixels are put into one class using a threshold to distinguish flower and leaf pixels; d. The output of the floral pixel extraction process for the study site.

3.3. Composite Band (NDVI)

In terms of the increasing reflectance difference between healthy and diseased crops, NDVI was combined with the other bands. As a result of the addition of NDVI as an extra layer (Band 6), it was observed that the reflectance difference between healthy and diseased leaves increased, especially in Bands 4, 5 and 6, which stands for NIR, Red-edge and NDVI, respectively (Figure 14&15).

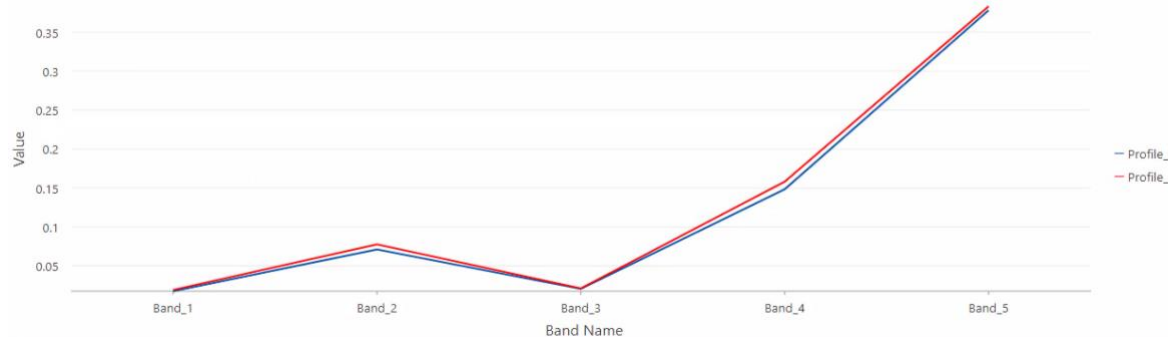


Figure 14 Spectral profile of healthy (blue) and Y^n virus effected (red) Arsenal potato crop

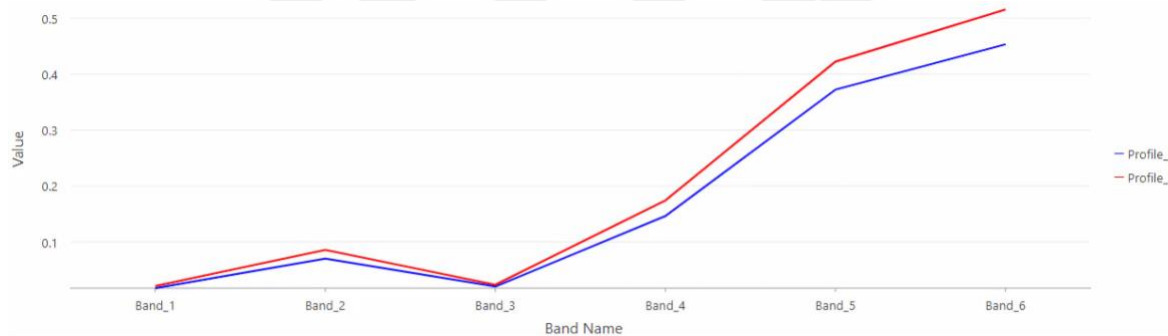


Figure 15 Spectral profile of healthy (blue) and Y^n virus effected (red) Arsenal potato crop after band layering.

3.4. Object-based supervised classification

A final classification of the ROIs is displayed in Figure 16. The resulting KNN classification maps of ROI are illustrated in Figure 13, and associated accuracy values are in Tables 5, 6, 7, 8, 9& 10. For each ROI, the semi-automatic object-based categorization discriminated between the various classes at an overall accuracy level of 96% for the Maris Pieper, 89% for King Edward, 90% for the Marfona, 96% for the Cara, 93% for the Desiree, and 94% for the Nicola respectively. Therefore, the overall accuracy of classification is rated as ‘Great’ for all plot (Table 4).

The result of the Kappa value of all ROIs showed that Cara is the most distinguishable crop with a coefficient of 0.94, followed by Maris Pieper (0.938). The class-specific producer’s accuracies for the Cara were 100% for background, 93% for healthy, 98% for Y^n , 93% for Y^o . For the Desiree 100% for background, 0.89% for A, 94% for A& Y^o , 85% for LR, 90% X& Y^n & Y^o , 100% for healthy. For the King Edward 100% for background, 88% for Y^n , 89% for Y^n & Y^o , 82% for Y^o and 100% for healthy. For Marfona 100% for background, 81% Y^n , 86% for Y^o , 97% for healthy. For Maris Piper 100% for background, 88% for LR, %100 for Y^n , 100% for healthy. For Nicola 100% for background, 94% for Y^n , 93% for healthy.

In addition, the graph which shows the overall accuracy and kappa value for each crop variety is given in Figure 17. It illustrates that King Edward and Marfona has the lowest Kappa and Overall Accuracy value.

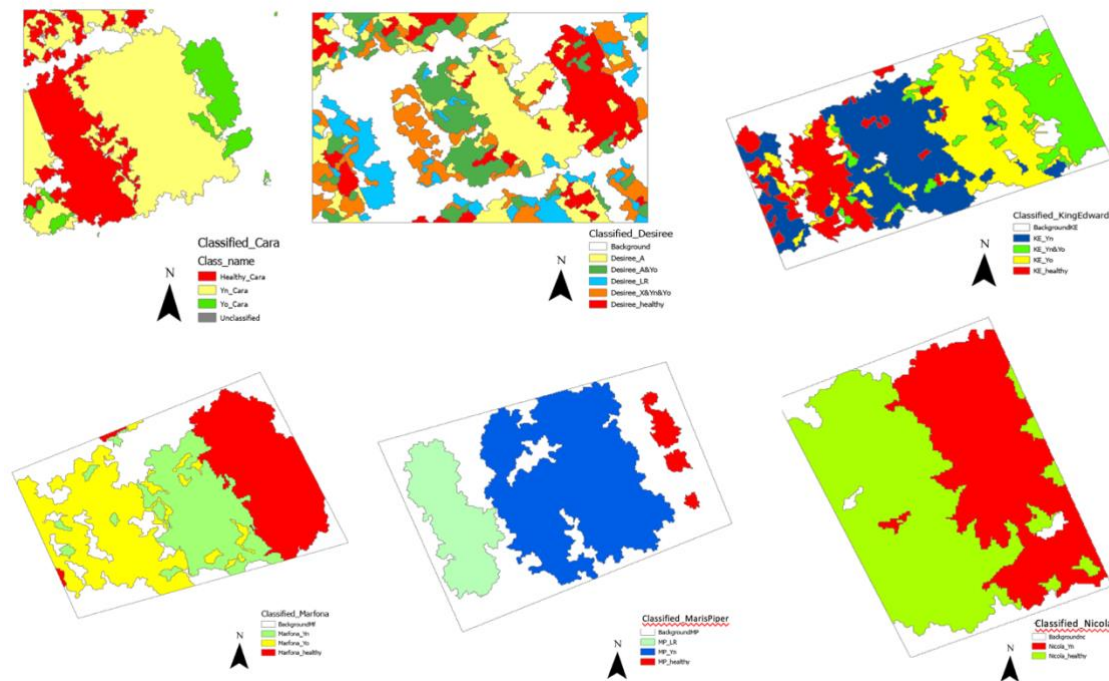


Figure 16 The KNN classification map of Cara, Desiree, King Edward, Marfona, Maris Piper, and Nicola crop acquired using object-based categorization after multi-resolution segmentation.

Nicola Plot	Nicola Background	Nicola Y ⁿ	Nicola healthy	Total	User's Accuracy	Kappa
Nicola Background	10	0	0	10	1	0
Nicola Y ⁿ	0	49	3	52	0.942308	0
Nicola healthy	0	3	41	44	0.931818	0
Total	10	52	44	106	0	0
Producer's Accuracy	1	0.942308	0.931818	0	0.943396	0
Kappa	0	0	0	0	0	0.902094

Table 5 Object-based image analysis (OBIA) confusion matrix and accuracy results for Nicola crop.

Marfona Crop	Marfona Background	Marfona Y ⁿ	Marfona Y ^o	Marfona healthy	Total	User's Accuracy	Kappa
Marfona Background	10	0	0	0	10	1	0
Marfona Y ⁿ	0	22	4	1	27	0.814815	0
Marfona Y ^o	0	5	24	0	29	0.827586	0
Marfona healthy	0	0	0	36	36	1	0
Total	10	27	28	37	102	0	0
Producer's Accuracy	1	0.814815	0.857143	0.972973	0	0.901961	0
Kappa	0	0	0	0	0	0	0.862737

Table 6 Object-based image analysis (OBIA) confusion matrix and accuracy results for Marfona crop

King Edward Crop	King Edward Background	King Edward Y ⁿ	King Edward Y ⁿ & Y ^o	King Edward Y ^o	King Edward healthy	Total	User's Accuracy	Kappa
King Edward Background	10	0	0	0	0	10	1	0
King Edward Y ⁿ	0	22	0	2	0	24	0.916667	0
King Edward Y ⁿ & Y ^o	0	0	17	4	0	21	0.809524	0
King Edward Y ^o	0	1	2	28	0	31	0.903226	0
King Edward healthy	0	2	0	0	16	18	0.888889	0
Total	10	25	19	34	16	104	0	0
Producer's Accuracy	1	0.88	0.894737	0.823529	1	0	0.894231	0
Kappa	0	0	0	0	0	0	0	0.863403

Table 7 Object-based image analysis (OBIA) confusion matrix and accuracy results for King Edward crop.

Maris Piper Crop	Maris Piper Background	Maris Piper LR	Maris Piper Y ⁿ	Maris Piper healthy	Total	User's Accuracy	Kappa
Maris Piper Background	12	0	0	0	12	1	0
Maris Piper LR	0	23	0	0	23	1	0
Maris Piper Y ⁿ	1	2	59	0	62	0.951613	0
Maris Piper healthy	0	1	0	9	10	0.9	0
Total	13	26	59	9	107	0	0
Producer's Accuracy	0.923077	0.884615	1	1	0	0.962617	0
Kappa	0	0	0	0	0	0	0.938391

Table 8 Object-based image analysis (OBIA) confusion matrix and accuracy results for Maris Piper crop.

Cara Crop	Cara Background	Cara healthy	Cara Y ⁿ	Cara Y ^o	Total	User's Accuracy	Kappa
Cara Background	10	0	0	0	10	1	0
Cara Healthy	0	26	1	0	27	0.962963	0
Cara Y ⁿ	0	2	48	1	51	0.941176	0
Cara Y ^o	0	0	0	14	14	1	0
Total	10	28	49	15	102	0	0
Producer's Accuracy	1	0.928571	0.979592	0.933333	0	0.960784	0
Kappa	0	0	0	0	0	0	0.940342

Table 9 Object-based image analysis (OBIA) confusion matrix and accuracy results for Cara crop.

Desiree Crop	Desiree Background	Desiree A	Desiree A&Y ^o	Desiree LR	Desiree X&Y ⁿ &Y ^o	Desiree Healthy	Total	User's Accuracy	Kappa
Desiree Background	10	0	0	0	0	0	10	1	0
Desiree A	0	25	0	0	0	0	25	1	0
Desiree A&Y ^o	0	0	16	0	0	0	16	1	0
Desiree LR	0	0	1	11	1	0	13	0.846154	0
Desiree X&Y ⁿ &Y ^o	0	1	0	2	9	0	12	0.75	0
Desiree Healthy	0	2	0	0	0	26	28	0.928571	0
Total	10	28	17	13	10	26	104	0	0
Producer's Accuracy	1	0.892857	0.941176	0.846154	0.9	1	0	0.932692	0
Kappa	0	0	0	0	0	0	0	0	0.916581

Table 10 Object-based image analysis (OBIA) confusion matrix and accuracy results for Desiree crop

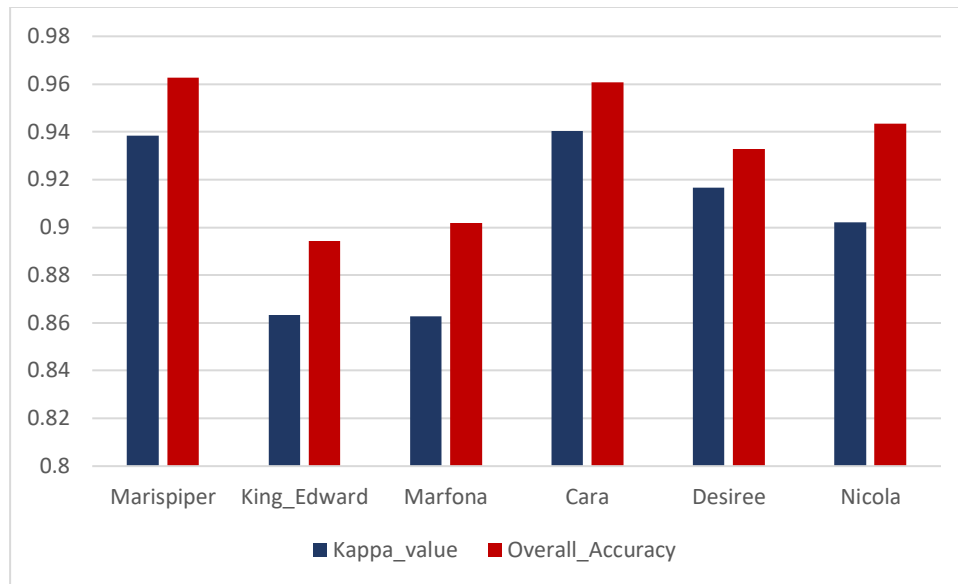


Figure 17 Kappa and overall accuracy values for each potato variety.

4. Discussion

This methodological study explored the capabilities of UAV-acquired high spatial resolution for detection of diseased crop caused by various virus with applying object-based supervised image classification technique. Infestation levels were determined based on certain object properties at branch level according to the high spatial resolution of the UAV-acquired images (1.1 cm) and resulted in a 'great' overall KIA statistic for all ROIs. However, the classification methods' accuracy could have been better for Desiree, Marfona and King Edward. The main problem that may encounter here is the variations of viruses. They have more variety as virus-affected crops, resulting in misclassifications between the classes. In addition, light effects (over or under-exposed areas) may have a negative impact on classification accuracies (Lehmann, Nieberding, Prinz, & Knoth, 2015). Even though removing external objects from data (soil and flower) and increasing differences between the reflectance of healthy and diseased data by combining NDVI increases classification accuracy, misclassification could not be reduced entirely.

Considering the classification results, a visible misclassification is observed in King Edward and Desiree. Nevertheless, when we look at the accuracy statistics, Desiree's accuracy comes in 3rd place when the accuracy of all ROIs is ranked from least to most. In this case, there could be multiple factors. It is seen that the classification needs to be revised for this variety of potato crops. However, the random sub-areas selected while performing the accuracy assessment and the distribution of the random accuracy assessment points produced in this direction may have been a factor in this situation.

Although there are certain standard practices for preparing images, no ideal image classification algorithms work in all cases. Designing efficient classifiers or creating new, efficient classifiers appropriate for applications is difficult. To get a better outcome or increase classification accuracy, auxiliary data such as site samples, topographic characteristics, environmental factors, and other digital data layers have shown to be very helpful. It is recommended to remember that technical advancements (creating more complex classifiers or getting images with higher resolutions, etc.) won't eliminate the issues with vegetation extraction from remote sensing data, but they will enhance outcomes (Xie, Sha, & Yu, 2008).

Therefore, additional data, such as elevation point clouds, might be an improved method for differentiating between the classes (Tiede, Lang, & Hoffmann, 2008). In addition, improved spectral resolution might help in the early identification of plant diseases (Lucieer, Malenovsky, Veness, & Wallace, 2014). A more accurate assessment of plants' biochemical and physical characteristics is made possible by high-spectral resolution sensors, leading to a more thorough detection of vegetative stress (Kokaly, Asner, Ollinger, Martin, & Wessman, 2009) (Hernández-Clemente, Navarro-Cerrillo, Suarez, Morales, & Zarco-Tejada, 2011). However, it is considered that appropriate hyperspectral sensors are expensive and correspondingly large, which dramatically reduces the flying durations of multirotor UAS aircraft (Lucieer, Malenovsky, Veness, & Wallace, 2014).

This study highlighted the apparent effect of applying the algorithm by dividing each potato plant into ROIs in achieving the 'great' result of the classification. Because when the same methodology is tried for the whole study area, the accuracy value obtained is incomplete since each healthy potato plant has its specific reflectance values and, in addition, the effect of each virus type on the spectral reflection of each potato plant leaf is different. In this direction, it is concluded that the higher the reflection diversity of the data given as input to the classification, the negative effect on the working accuracy of the algorithm. Moreover, it has been observed that performing the classification separately for each type significantly reduces the execution time of the algorithm, in addition to increasing the accuracy.

5. Conclusion

This study demonstrates the potential of UAS-based remote sensing techniques for disease detection in precision agriculture, particularly for potato crops. Object-based supervised classification (KNN) was used to detect the diseased affected potato leaves. As a pre-process, pixel values, which are not crop leaves, were filtered using appropriate VIs, and NDVI was combined with other bands as the 6th band to increase the differences between the reflection of disease and healthy crop leaf. Object-based classification (KNN) was used to classify the data. In order to increase the classification accuracy, to reduce the shadow effect caused by the height differences between the leaves, object segmentation is performed as a subprocess of the object-based classification. Although satisfactory overall accuracy values were obtained due to the classification, misclassified leaves were observed. In this case, it was noticed that factors such as the diversity of the viruses inserted into the algorithm, the density of the leaves, and the height difference between the crops (preventing reflection due to the shadow effect) were practical factors in the algorithm's accuracy.

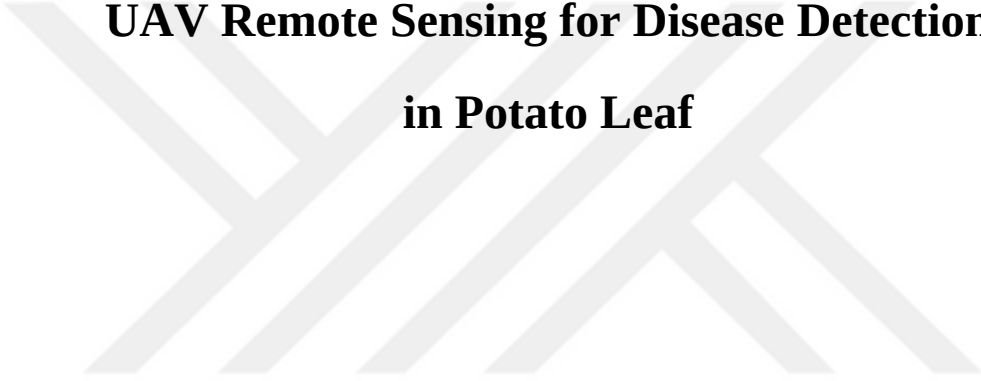
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UAV Remote Sensing for Disease Detection in Potato Leaf

Part II – Technical Report

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List of Acronyms

DN – Digital Number

KNN – K-Nearest Neighbor

NDVI – Normalised Difference Vegetation Index

NIR – Near Infrared

RGB - Red, Green, Blue (visible spectrum)

ROI – Region of Interest

SI – Spectral Index

UAV - Unmanned Aircraft Vehicles

UAV – Unmanned Aerial Vehicle

VI – Vegetation Index

Softwares used

ArcGIS Pro

eCognition

ENVI 5.5.3 + IDL 3.7

Introduction

One of the significant applications of agricultural remote sensing is the detection of diseased or stressed crops. Its importance comes from the ability to adjust estimates and allow for corrective action. The assumption behind the identification of stressed plants is that their reflectivity differs qualitatively and quantitatively from that of healthy, rapidly developing flora. Remote sensing data and experimental findings support this idea. There has been a propensity to assign individual leaf variations in the optical characteristics, especially in the nonvisible spectral ranges, for the differences in reflectance between stressed and non-stressed plants. (Knipling, 1970).

The following report is intended to supplement the study provided in Part I. Most of it consists of a thorough technical explanation of the methods used to acquire, understand, and analyse the data for this study. Additionally, other parts describe and debate findings that are unrelated to the arguments in Part I.

1. Data Sources

A list of the data sources used in this study is shown in Table 1.

Data	Format	Source
MicaSense-RedEdge UAV imagery	Raster (.tif)	-
Guide to Gogarbank Potato Plots 2021	PDF	Maureen McCreath (Potato Growing Crop Certification Manager)
Gogar Field Plan 2021	PDF	SASA

Table 1 Data sources used in this study.

2. Data Description

3.1. Study Area

The study occurred on Gogarbank Farm in Edinburgh. The farm is a research farm which depends on the Scottish Agricultural Science Agency (SASA).



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SASA (Science and Advice for Scottish Agriculture) is an organization based in Scotland that provides scientific and technical advice and regulatory and diagnostic services to support agriculture, horticulture, and the environment. SASA is part of the Scottish Government's Rural and Environment Science and Analytical Services (RESAS).

SASA has many responsibilities and expertise, including plant health, crop protection, seed testing, pesticide regulation, GMOs (Genetically Modified Organisms), variety testing, and certification. They also monitor and control plant and animal diseases to protect Scotland's agriculture and environment.



SASA operates several laboratories and research facilities, and they work closely with farmers, growers, researchers, and government bodies to ensure the safety, sustainability, and productivity of Scotland's agriculture sector. Their work contributes to developing Scottish agriculture policies, regulations, and best practices.

SASA has significant involvement in potato disease studies in Scotland. As part of their plant health responsibilities, they conduct research, monitoring, and diagnostic services related to potato diseases. Some of the key areas they focus on include:

Potato Virus Diseases: SASA conducts surveillance and testing for various potato viruses, such as Potato Virus Y (PVY), Potato Leafroll Virus (PLRV), Potato Virus X (PVX), and Potato Virus A (PVA). They provide diagnostic services to identify and confirm the presence of these viruses in potato plants.

The study plan is given in Appendix 1 that show plot's layout, classification of varieties according to their characteristics such as foliage colour, leaflet size, tuber colour, tuber shape. In order to train new and expert potato inspectors how to identify varieties, genetic variations, and diseases from leaf features, SASA's Gogarbank Farm provides potato plots. Inspectors can see the various types as single plants or in enormous blocks when grown in the field because of various plot sizes. Demonstration plots with various viral symptoms, a collection of genetic variations of types, and demonstration plots with blackleg and herbicide damage are also given (McCreath, 2021). Since the purpose of this study is disease detection, the virus disease collection, partly shown in the layout with the DV, has been dealt with.

3.2. Sensor Technique and Data Collection

This study used a 3DR Solo Quadcopter drone as a UAV (Unmanned Aerial Vehicle). The 3DR Solo drone is a quadcopter UAV (Unmanned Aerial Vehicle) manufactured by 3D Robotics. It was designed as a consumer-grade drone with advanced features and capabilities for aerial photography and videography.



Figure 1 The commercial 'ready-to-use' 3DR Solo drone.

Key features of the 3DR Solo drone include:

- It featured a camera gimbal that provided stabilized footage during flight, allowing for smooth aerial photography and video recording.
- The drone can carry payloads of up to 1.5 kg (3.3 lb) and can fly for 25-40 minutes with a range of up to 3.2 km (2 miles).
- The drone came equipped with various intelligent features, including Follow Me mode, Cable Cam, Orbit mode, and Selfie mode. These modes enabled the drone to autonomously track and capture footage based on the user's preferences.
- The 3DR Solo drone was controlled using a dedicated remote controller with a built-in holder for a smartphone or tablet. Users can access features, view live video feeds, and control flight parameters through the Solo app.
- One notable aspect of the 3DR Solo drone was its open-source nature, which meant that users and developers could customize and modify the drone's software and hardware, expanding its capabilities and integrating additional features.

The UAV was equipped with a calibrated MicaSense RedEdge-M sensor, a multispectral sensor designed to capture high-resolution data for agricultural and remote sensing applications. It is commonly used in Unmanned Aerial Vehicles (UAVs) or drones to gather data about crop health, vegetation analysis, and other environmental monitoring tasks (MicaSense, 2023).

The key features of the MicaSense RedEdge-M sensor:

- The RedEdge-M sensor captures data in five discrete spectral bands, including blue, green, red, red-edge and near-infrared, which allows for collecting detailed and precise information about the health and vigour of crops and vegetation.

Band number	Band name	Wavelength
Band 1	Blue	400-500nm
Band 2	Green	500-570nm
Band 3	Red	610-700nm
Band 4	NIR	780-2500nm
Band 5	Red-edge	670-780nm

Table 2 Band characteristics of the MicaSense RedEdge-M.

- The sensor provides a high resolution, resulting in a detailed imager for accurate analysis. The captured images have a spatial resolution of approximately 8 centimetres (about 3.15 in) per pixel when flown at a typical altitude of 120 meters (about 393.7 ft). This study collected data at 15m with 1.1cm (about 0.43 in) spatial resolution.
- The RedEdge-M sensor undergoes rigorous radiometric calibration to ensure accurate and consistent data acquisition. This calibration process allows precisely comparing images captured at different times or by different sensors.
- The sensor is designed to be lightweight and compact, making it suitable for integration with small UAVs or drones. Its small form factor minimizes the impact on flight characteristics and allows for efficient data collection over large areas.
- The sensor is designed to work seamlessly with various UAV platforms and mapping software. It can be easily integrated with popular drones, such as DJI Phantom and Mavic series, and the collected data can be processed using MicaSense's software or other industry-standard tools like Pix4D or Agisoft Metashape.

3.2.1. Narrow Band Sensor

Narrow band sensors play a crucial role in disease detection because they capture specific wavelengths or narrow spectral bands of light. Therefore, narrow-band sensors allow for the precise measurement of specific spectral features associated with disease-related changes. By comparing these spectral signatures with known patterns, it becomes possible to identify and differentiate between healthy and diseased states. In addition, narrow-band sensors often provide high-resolution spectral data, capturing fine-grained information about the reflectance properties of plants. It allows for extracting meaningful features and patterns, enhancing the accuracy and reliability of disease identification.

The MicaSense sensor has red edge waveband. It is located between red and near-IR and essential for determining the source of plant chlorophyll. The red edge illustrates where variation will most likely be visible if plant is under stress.

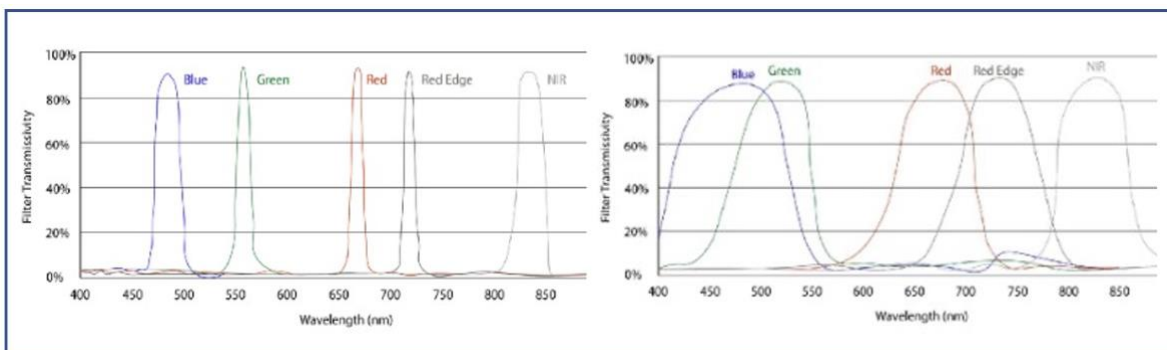


Figure 2 Narrow band and broadband sensors are compared (on the left and right, respectively). A wideband sensor has significant wavelength overlap across the various bands.

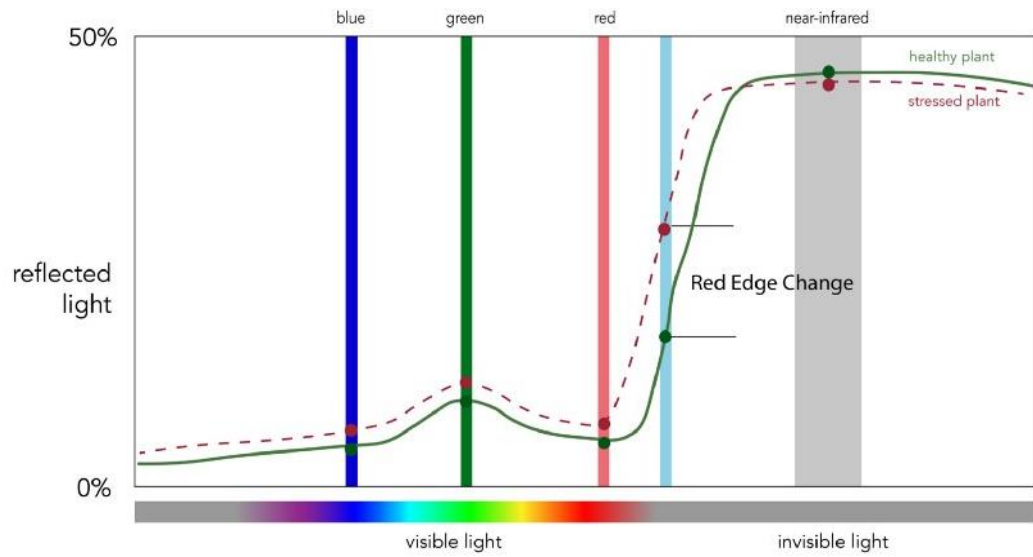


Figure 3

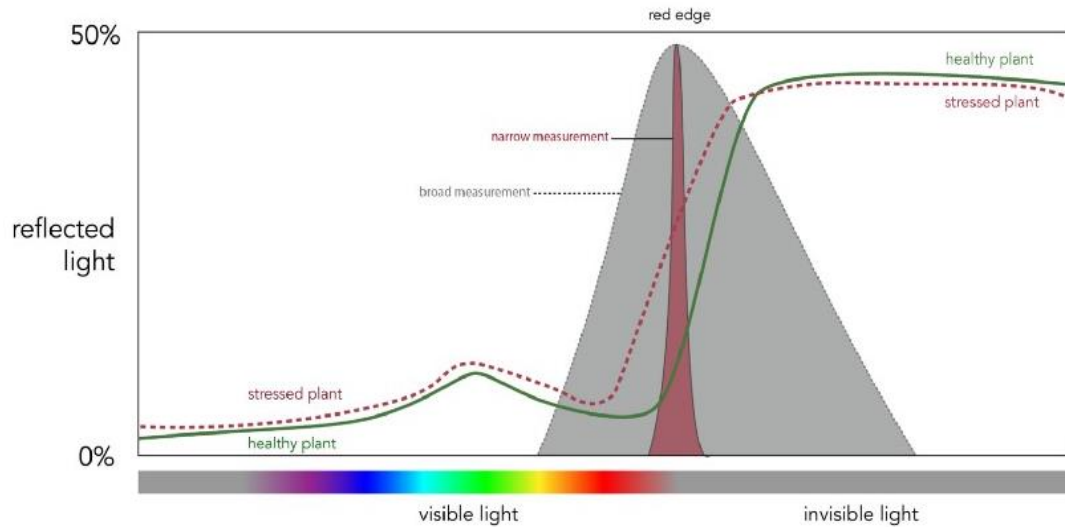


Figure 4

3.2.2. Downwelling Light sensor (DLS)

A Downwelling Light Sensor, often abbreviated as DLS, is a type of sensor used to measure the intensity of light coming from above or in the sky (known as downwelling light). DLS sensors are typically designed to measure the spectral distribution and intensity of incoming sunlight or natural light. They can provide valuable information about the amount of solar radiation reaching the Earth's surface, which is crucial for studying weather patterns, climate change, and environmental monitoring. A MicaSense RedEdge-M camera can be connected directly to the DLS, a 5-band incident light sensor. In order to correct global lighting changes in the middle of a light, such as those that can occur due to clouds blocking the sun, the DLS measures the ambient light during a flight for each of the five bands of the camera and records this information. Specialized processing tools, such as Pix4Dmapper, can then use this information.

3.2.3. Storing Data

The SDHC SD cards that RedEdge-M comes with and is made to work with have a storage capacity cap of 32 GB. RedEdge-M is incompatible with the SDXC format, which SD cards with larger storage capacities use.

3.2.4. Processing and Analysis

RedEdge-M can collect data in standard formats (TIFF) with standard metadata that various image viewing and editing programs may access. Photogrammetry software is necessary to align and register the bands and produce a georeferenced orthomosaic from the data because each capture creates five individual TIFF files that are not registered or aligned with one another.

3. Pre-processing

In order to get high-quality images for plant disease analysis, errors in aerial images captured from UAVs must be reduced during processing. Pre-processing is the term for this procedure, which also involves image mosaicking, georeferencing, radiometric calibration, and dividing the study area into ROI (Region of Interest) as input for the process (Kuswidiyanto, Noh, & Han, 2022). The process of producing an orthomosaic involves several phases to transform raw aerial or satellite imagery into a georeferenced, high-resolution, and geometrically accurate representation of the Earth's surface. Mosaicking is creating a single image from many overlapping field images. Using an orthomosaic image is essential since it corrects perspective distortion and offers accurate distance measurement. It mainly entails the following five phases:

1. Image preprocessing: The basic techniques include making templates for matching pictures, handling histograms, and denoising digital images.
2. Image matching: The image mosaic technique depends on image matching. This concept refers to finding tie points that reflect the precise positions in several photographs by identifying distinguishing characteristics (key points) in the overlapping image areas and matching related key points between overlapping images.
3. Develop a transformation model: By calculating the value of each model parameter based on the correlation between the template or image attributes, two pictures are transformed mathematically.
- 4- Consistent transformation of coordinates: The stitched picture is transformed into the reference image's coordinate system by the mathematical transformation model supplied, completing the unified transformation. (Zhang, Li, Yu , Kumar, & Mao, 2018).

Agisoft software was used for producing orthomosaic images. Leading software provider Agisoft specialises in photogrammetry and computer vision solutions for various industries. Agisoft Metashape is a powerful photogrammetry software that creates high-quality 3D models, digital elevation models (DEMs), orthomosaics, and dense point clouds from aerial or terrestrial imagery. Agisoft Metashape provides a robust set of tools for mesh editing, allowing users to clean up and refine 3D models quickly. Some users consider these editing capabilities more powerful and user-friendly than other software, such as Pix4D.

After mosaicking, reflectance of the leaves was explored, and most common Vegetation Indices (VIs) were calculated with using ArcGIS Pro to develop methodology. However, while the index calculation results should be between 0 and 1, it has been observed that this range is more extensive than the

expected range. Thereby, the normalization of the pixels of the image was performed. This process briefly was occurred by dividing each pixel by 32768 (16 bit), just did a raster calculation so that the whole raster is in units of reflection (0-1).

Before calculating VIs, data were explored, and differences between the reflectance of the healthy and diseased crops were observed and how the reflectance changed according to different viruses with using ENVI – Quick Stats Tool. According to the results obtained, it was determined that the Red-edge band (Band 5) had the highest max, min, mean and standard deviation values, confirming that the Red-edge band can best observe the changes in the leaf pixels (Figure 5).

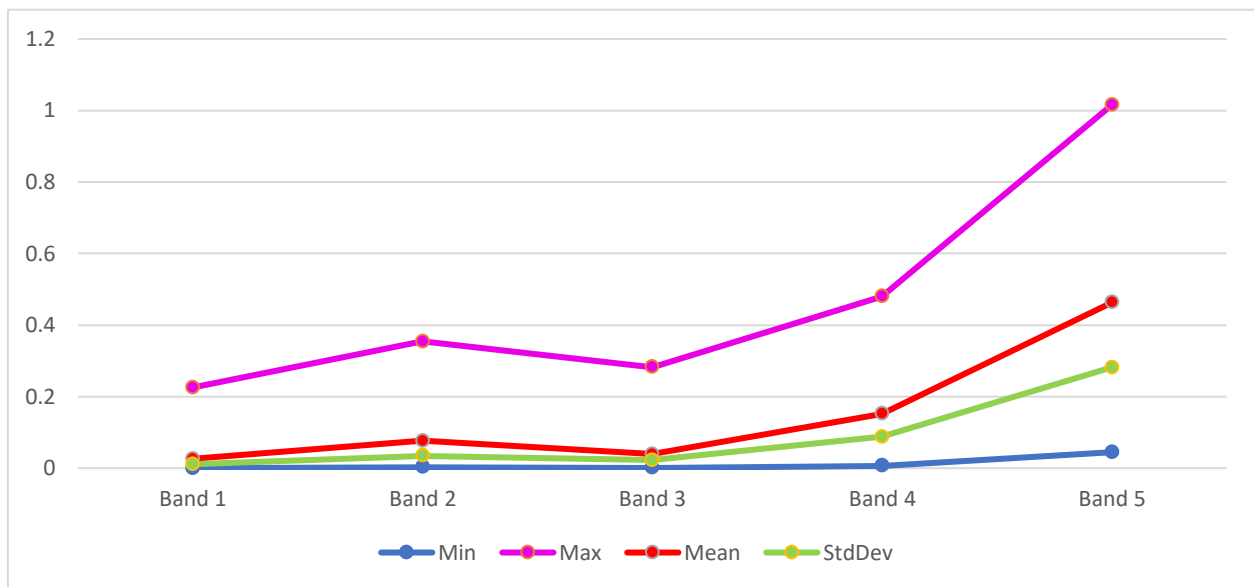


Figure 5 General statistic values for study site.

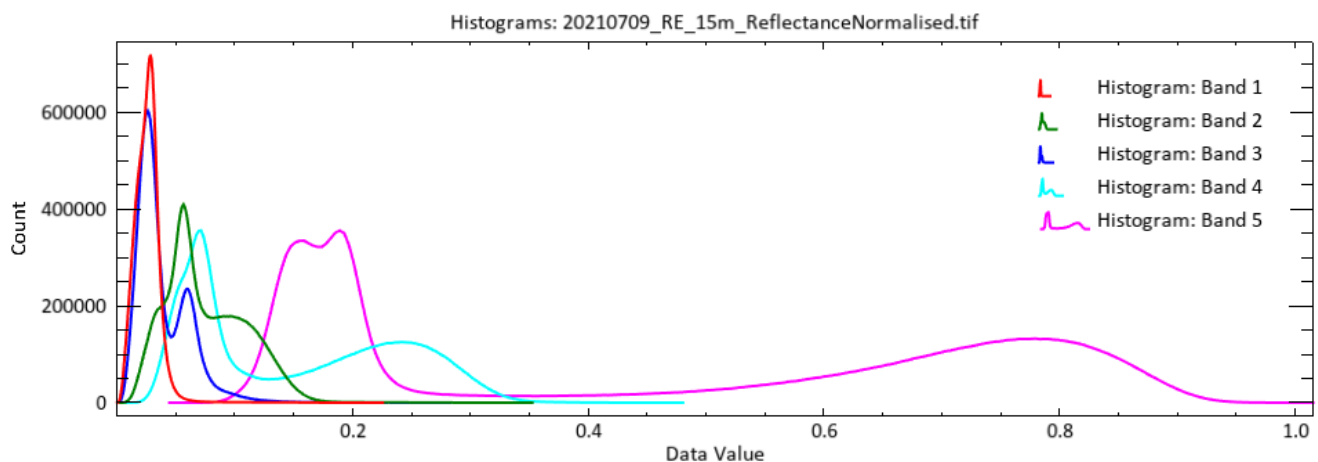


Figure 6 Histogram of band reflectances

3.1. Calculation of Vegetation Indices

Vegetation indices are mathematical formulas that combine the reflectance values of different spectral bands from remote sensing data to provide information from vegetation characteristics and health (Xue & Su, 2017). Different VIs obtained from image emphasize different features of the study area. Therefore, different VIs should be tried while deciding the robust indices for the specific study. In terms of agronomic studies, VIs play a vital role in studies such as disease detection, stress level measurement, biomass, chemical and water content assessment. Increasing study attempts in recent years have centred on figuring out the connections between plant optical characteristics and the concentrations of the photosynthetic pigments chlorophyll-a, chlorophyll-b, and carotenoids in the tissues of green leaves. These pigments exhibit distinct spectrum behaviour from an optical standpoint, with distinct absorption characteristics at various wavelengths, which enables remote sensing techniques to distinguish their individual effect on vegetation reflectance spectra (Chappelle, Kim, & McMurtrey, 1992) (Blackburn, 1998). Studies on the estimation of chlorophyll using optical indices have concentrated on analysing the reflectance in individual narrow bands, band reflectivity percentages and combinations, and the properties of derivative spectra. To reduce changes caused by outside variables and increase sensitivity to chlorophyll level, they used various combinations of spectral bands (Haboundane, Miller, Tremblay, Zarco-Tejada, & Dextraze, 2002)

In this study, different VIs were calculated to see which index emphasizes which features of plant. VIs were calculated using appropriate parameter values in ArcGIS Pro software. As a result, suitable VIs for filtering different pixels from plant leaves in the data were determined before classification. In this direction, VARI was decided to filter floral pixels, while SAVI was used for filtering soil pixels.

3.1.1. PVI (The Perpendicular Vegetation Index)

The Perpendicular Vegetation Index (PVI) is a vegetation index commonly used in remote sensing and agriculture to assess vegetation health and estimate vegetation properties. It is derived from the red and near-infrared bands of remote sensing data.

The PVI is calculated based on the perpendicular vegetation paradigm, which assumes that the near-infrared (NIR) reflectance is relatively constant for a given vegetation type, while the red reflectance varies with changes in vegetation cover, density, and health. The index takes advantage of this relationship to quantify vegetation characteristics.

The formula for the Perpendicular Vegetation Index is as follows:

$$PVI = (NIR - a * Red - b) / (\sqrt{1 + a^2})$$

Where:

NIR refers to the near-infrared band reflectance.

Red refers to the red band reflectance.

a refers to the slope of the soil line, set to 0.3 (default)

b refers to the gradient of the soil line' set to 0.5 (default)

The resulting PVI values range from -1 to 1. Higher PVI values typically indicate healthier and denser vegetation cover, while lower values may indicate sparse or stressed vegetation.

The Perpendicular Vegetation Index is often used in combination with other vegetation indices to monitor vegetation health, estimate biomass, detect vegetation stress, and assess vegetation dynamics over time. It can be applied in various applications, including agriculture, forestry, land management, and ecological studies.

As with any vegetation index, it's important to consider the limitations and specific conditions of the study area, such as soil type, atmospheric conditions, and sensor characteristics, to ensure appropriate interpretation and application of the PVI.

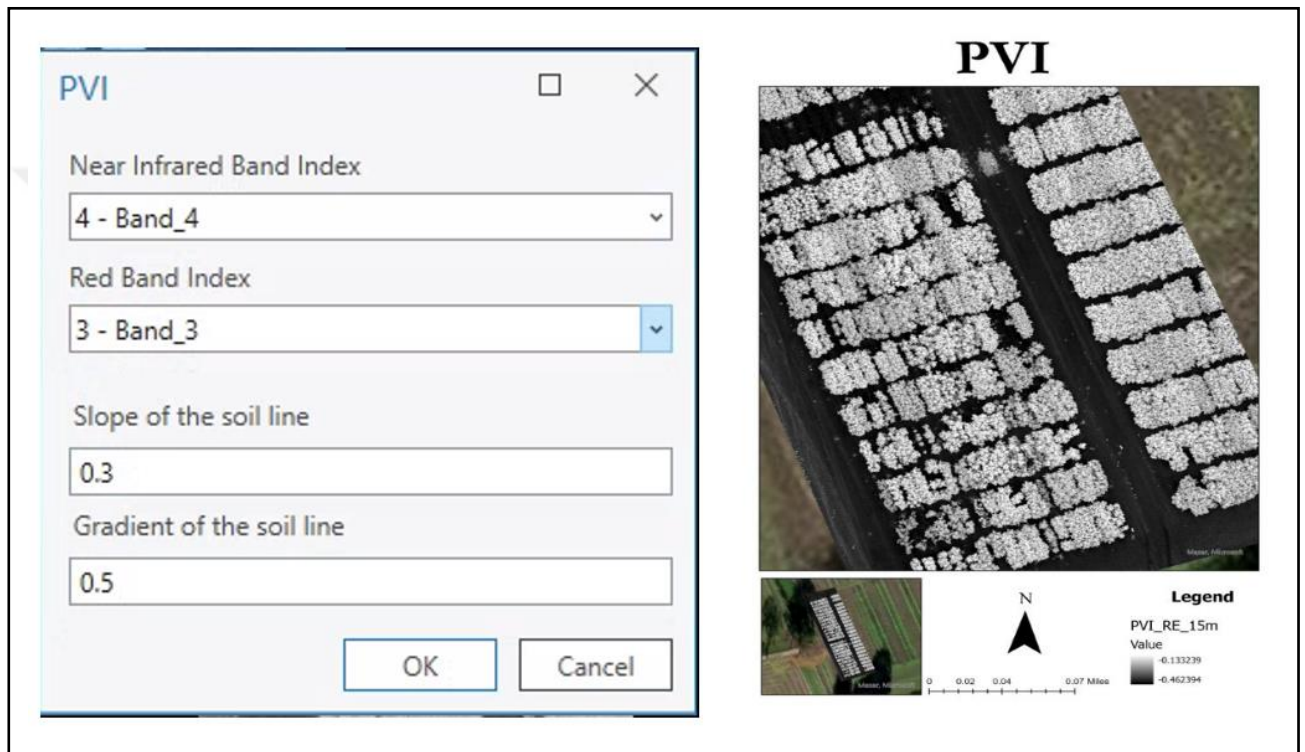


Figure 7 Used parameters for PVI calculation and output map for study site.

3.1.2. VARI (The Visible Atmospherically Resistant Index)

The Visible Atmospherically Resistant Index (VARI) derived from visible bands of remote sensing data and is designed to reduce the influence of atmospheric conditions on vegetation indices. By utilizing the green band, the VARI helps minimize the impact of atmospheric variations, such as aerosols and haze, on vegetation index calculations.

The formula for the Visible Atmospherically Resistant Index (VARI) is as follows:

$$\text{VARI} = (\text{Green} - \text{Red}) / (\text{Green} + \text{Red} - \text{Blue})$$

Where:

Green, Red, and Blue refer to the reflectance values in their respective bands.

In addition, higher VARI values indicate healthier and more vigorous vegetation, while lower values may indicate stressed or less vigorous vegetation.

In this study the VARI used to improve the accuracy and reliability of vegetation monitoring and analysis with using pre-processing step to reduce flower pixels from the image.

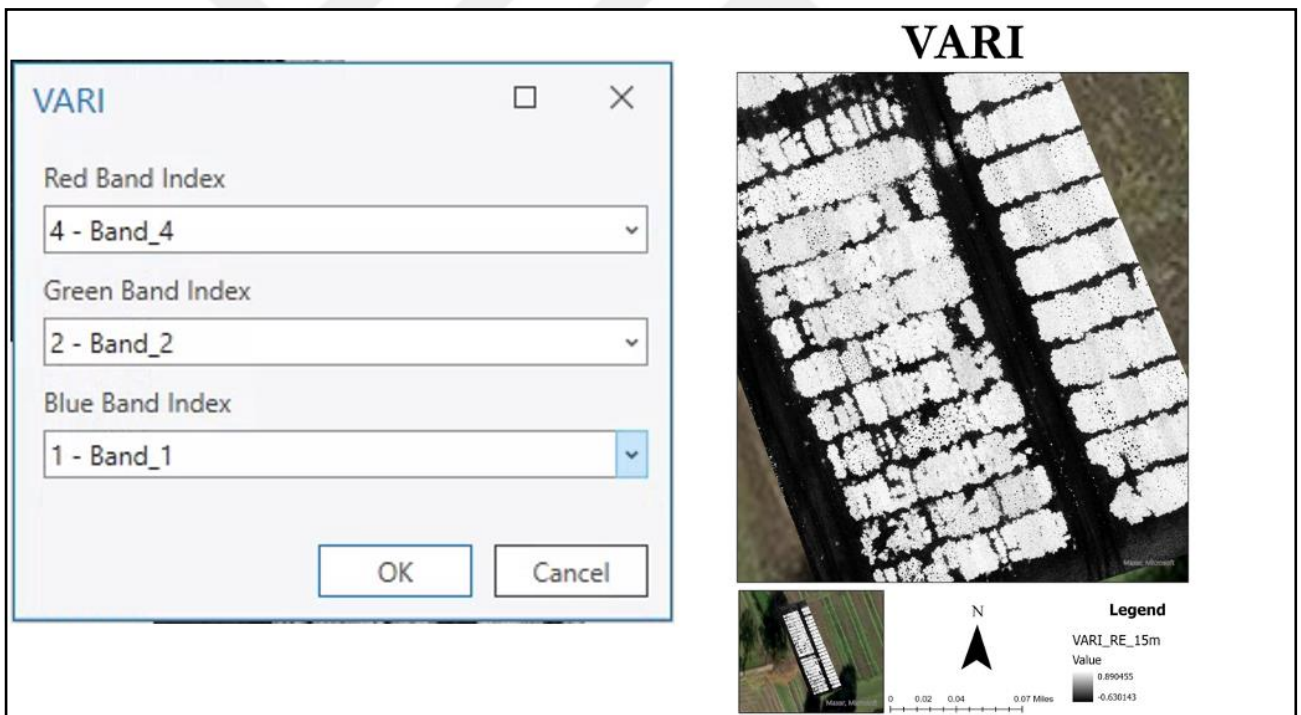


Figure 8 Used parameters for VARI calculation and output map for study site.

3.1.3. MTVI2

The Modified Triangular Vegetation Index 2 (MTVI2) enhances the sensitivity to vegetation changes and improves the detection of vegetation stress or damage with taking into account the sensitivity of the red and green band to chlorophyll content and the response of near-infrared band to vegetation health. It is an adaptation of the Triangular Vegetation Index 2 (TVI2) and is commonly used in remote sensing applications.

The MTVI2 is calculated using the red, green, and blue bands of remote sensing data.

The formula for calculating the MTVI2 is as follows:

$$\text{MTVI2} = 1.5 * (1.2 * (\text{NIR} - \text{Green}) - 2.5 * (\text{Red} - \text{Green})) / \sqrt{((2 * \text{NIR} + 1) ^ 2 - (6 * \text{NIR} - 5 * \sqrt{\text{Red}}) - 0.5)}$$

Where:

NIR refers to the near-infrared band reflectance.

Red refers to the red band reflectance.

Green refers to the green band reflectance.

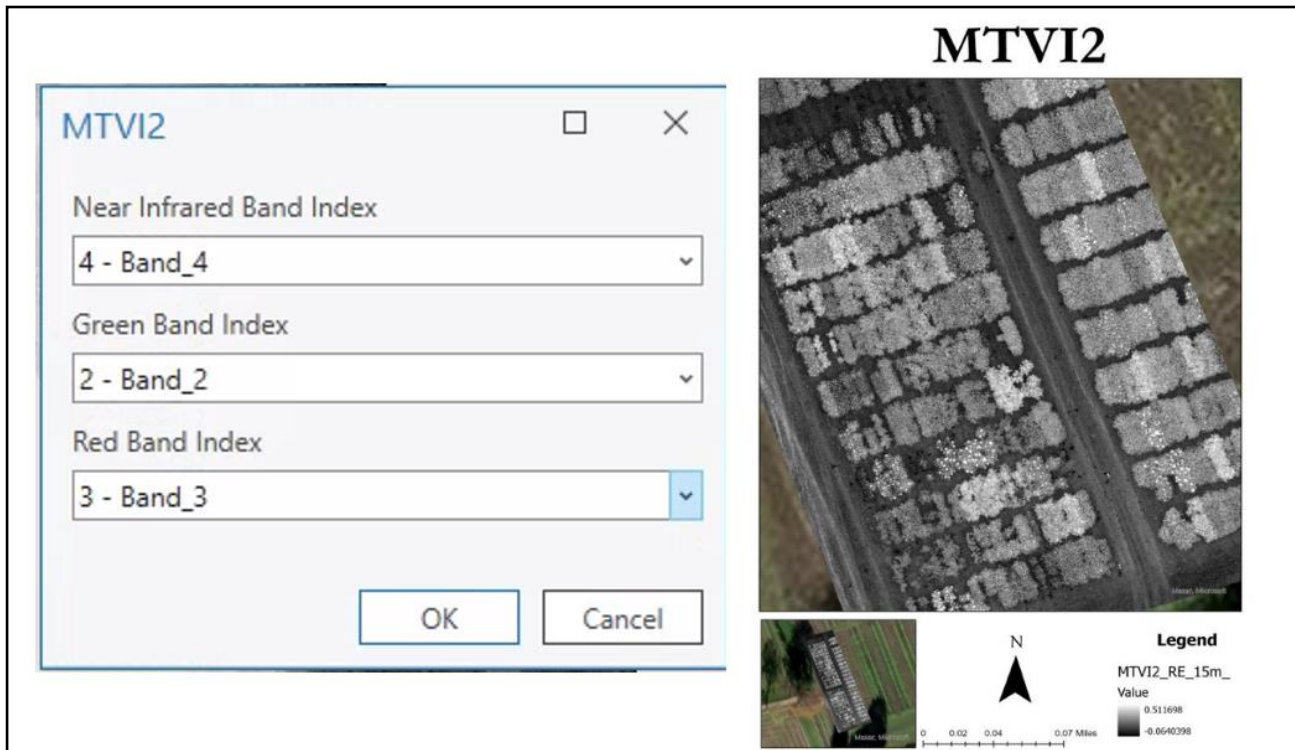


Figure 9 Used parameters for MTVI2 calculation and output map for study site.

3.1.4. CI-RedEdge

The Chlorophyll Index (CI) calculated using the reflectance values in the red and near-infrared (NIR) bands of the RedEdge sensor. The formula for the Chlorophyll Index is as follows:

$$CI = (NIR / Red) - 1$$

Where:

NIR refers to the near-infrared band reflectance

Red refers to the red band reflectance

The CI is designed to provide an estimate of chlorophyll content in vegetation and higher CI values generally correspond to healthier vegetation.

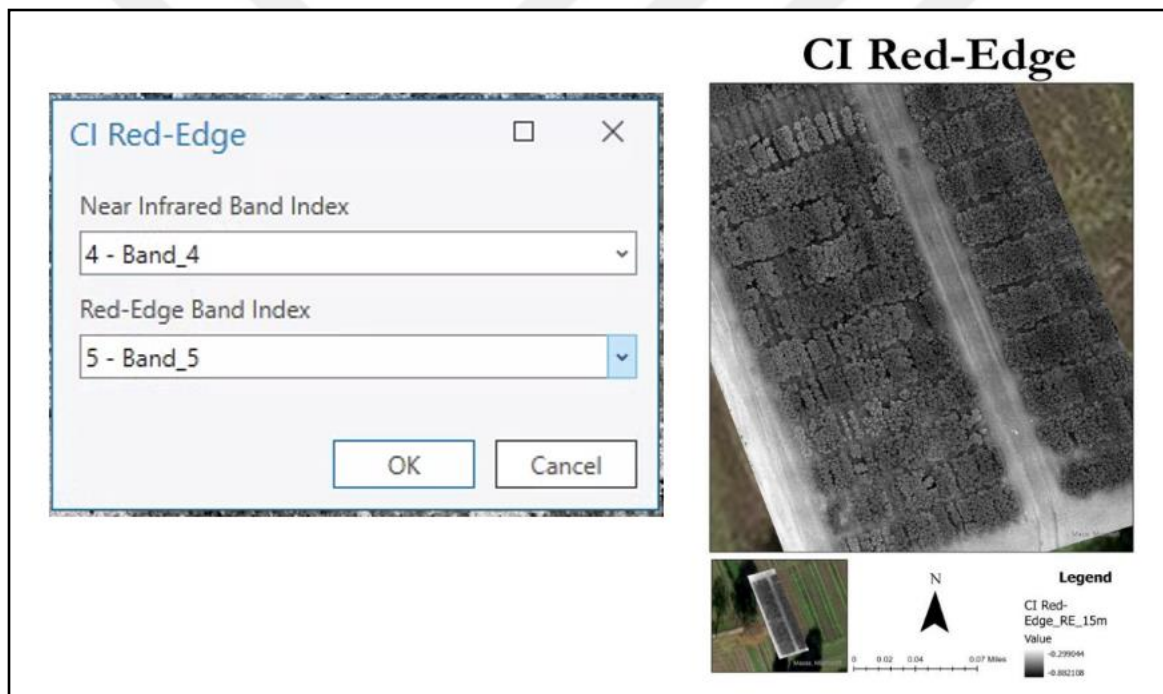


Figure 10 Used parameters for CI-RedEdge calculation and output map for study site.

3.1.5. NDVI

The Normalized Difference Vegetation Index (NDVI) is a widely used vegetation index in remote sensing and agriculture. It quantifies the density and health of vegetation based on the difference in reflectance between the near-infrared (NIR) and red bands of remote sensing data.

The formula for calculating the NDVI is as follows:

$$NDVI = (NIR - Red) / (NIR + Red)$$

Where:

NIR refers to the reflectance in the near-infrared band.

Red refers to the reflectance in the red band.

The resulting NDVI values range from -1 to 1. Higher NDVI values indicate denser and healthier vegetation, while lower values indicate sparse or stressed vegetation. Moreover, NDVI values close to 0 may correspond to non-vegetated surfaces, such as bare soil or water.

NDVI is particularly effective in capturing changes in photosynthetically active vegetation and is often used for monitoring crop health, assessing vegetation conditions, and detecting areas of vegetation stress or damage. It is an essential tool for precision agriculture, where it helps in optimizing resource allocation, monitoring crop growth, and identifying areas that require attention or intervention.

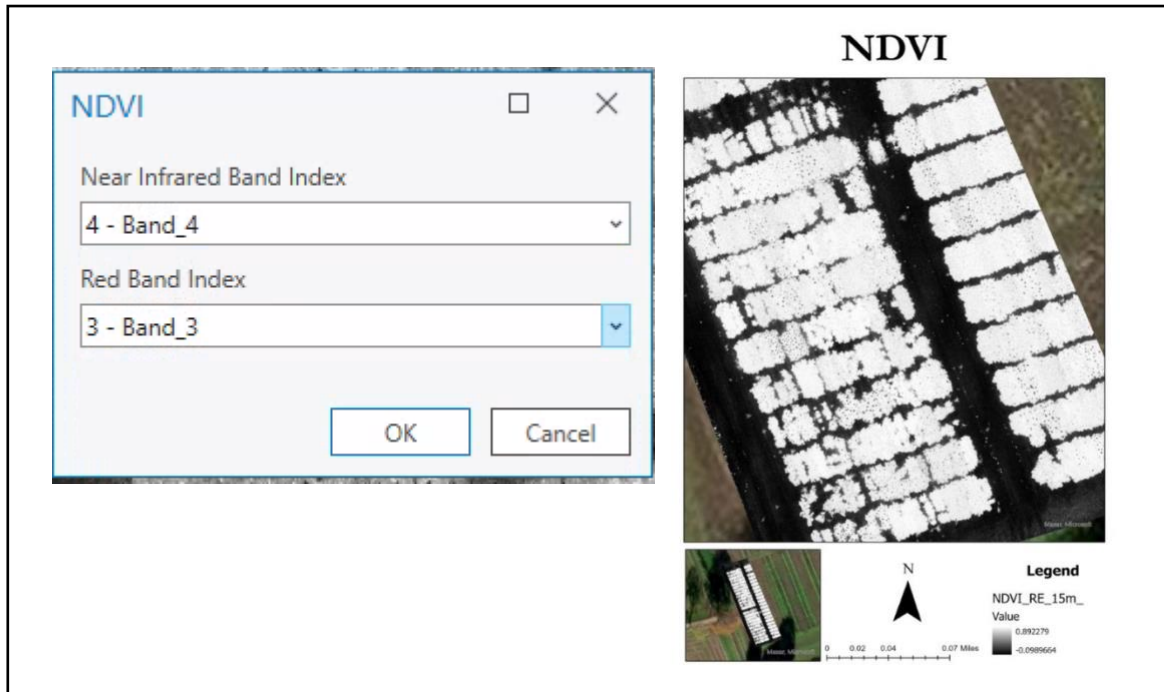


Figure 11 Used parameters for CI-RedEdge calculation and output map for study site.

3.1.6. Green NDVI

The term "Green NDVI" refers to a variation or modification of the Normalized Difference Vegetation Index (NDVI) that specifically utilizes the green band of remote sensing data. The traditional NDVI formula compares the near-infrared (NIR) and red bands to assess vegetation health and density.

The Green NDVI is calculated using the green and near-infrared bands and follows a similar formula to the traditional NDVI:

$$\text{Green NDVI} = (\text{NIR} - \text{Green}) / (\text{NIR} + \text{Green})$$

Where:

NIR refers to the reflectance in the near-infrared band.

Green refers to the reflectance in the green band.

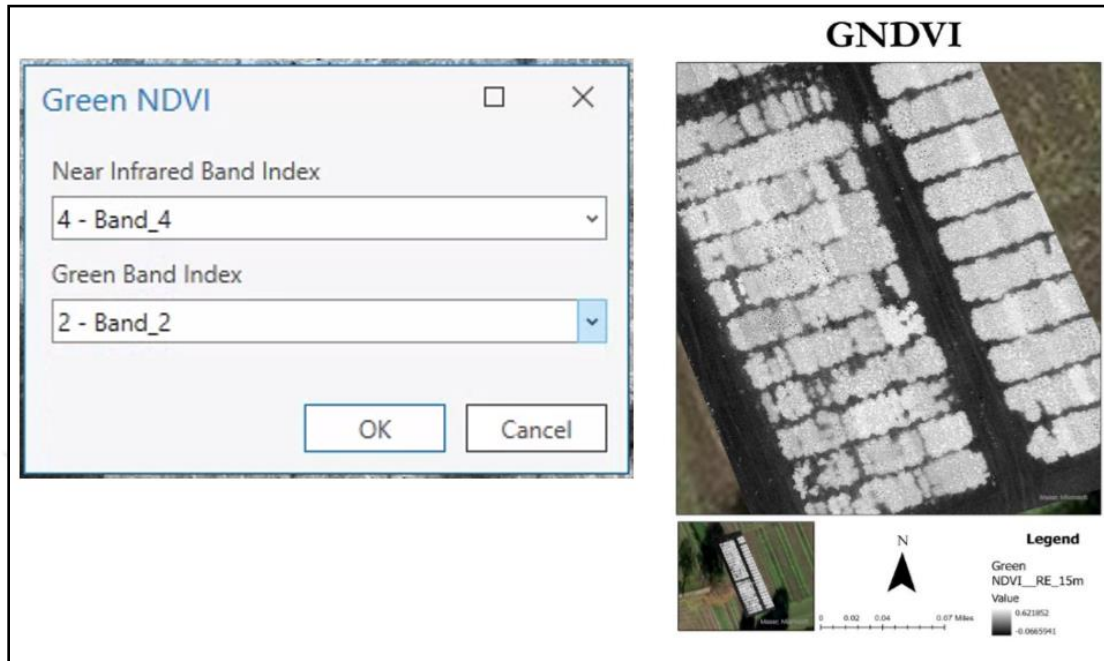


Figure 12 Used parameters for GNDVI calculation and output map for study site.

3.1.7. RedEdge NDVI

The RedEdge NDVI (Normalized Difference Vegetation Index) is a vegetation index specifically designed for use with the MicaSense RedEdge multispectral camera. The RedEdge camera captures images in five narrow spectral bands, including blue, green, red, red edge, and near-infrared. The RedEdge NDVI is calculated using the reflectance values in the red edge and near-infrared (NIR) bands of the RedEdge camera.

The formula for the RedEdge NDVI is as follows:

$$\text{RedEdge NDVI} = (\text{NIR} - \text{Red Edge}) / (\text{NIR} + \text{Red Edge})$$

Where:

NIR refers to the near-infrared band reflectance captured by the RedEdge camera.

Red Edge refers to the red edge band reflectance captured by the RedEdge camera.

The RedEdge NDVI provides an assessment of vegetation health and density based on the difference in reflectance between the near-infrared and red edge bands. Higher values of the RedEdge NDVI generally indicate healthier and more vigorous vegetation, while lower values may indicate stressed or less vigorous vegetation.

The RedEdge NDVI is specifically tailored for the RedEdge camera and takes advantage of its spectral bands to capture important vegetation information, particularly in the red edge region of the electromagnetic spectrum. By analyzing the reflectance in these specific bands, the RedEdge NDVI helps to assess vegetation conditions, detect stress, and monitor vegetation dynamics.

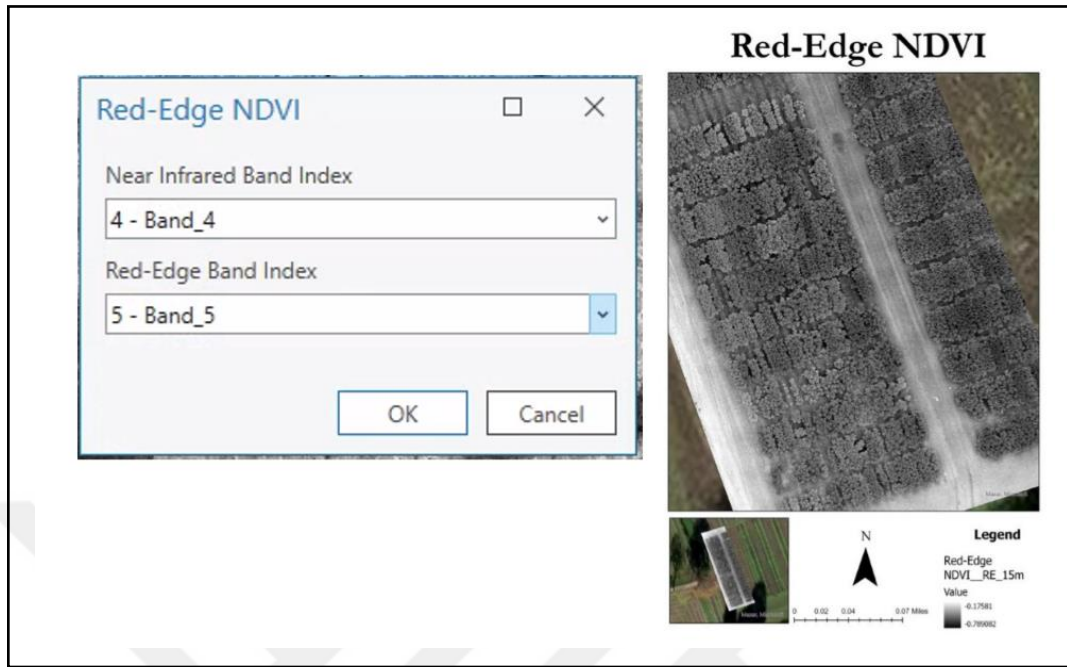


Figure 13 Used parameters for RedEdge NDVI calculation and output map for study site.

3.1.8. SAVI

SAVI stands for the Soil-Adjusted Vegetation Index. It is a vegetation index commonly used in remote sensing and agriculture to assess vegetation health and monitor vegetation vigour. The SAVI is an adaptation of the Normalized Difference Vegetation Index (NDVI) that considers variations in soil background reflectance.

The SAVI was developed to minimize the influence of soil reflectance on vegetation indices, particularly in areas with high soil reflectance. It provides a way to normalize the vegetation signal by considering the soil component. This is particularly useful in areas with exposed soil or when the soil reflects significant amounts of near-infrared radiation (Huete, 1988).

The formula for calculating the SAVI is as follows:

$$SAVI = ((NIR - Red) / (NIR + Red + L)) * (1 + L)$$

Where:

NIR refers to the near-infrared band reflectance.

Red refers to the red band reflectance.

L is the soil adjustment factor, set to 0.5 (recommended value for agricultural studies).

The SAVI values range from -1 to 1. Higher SAVI values generally indicate denser and healthier vegetation, while lower values may indicate stressed or less vigorous vegetation. The adjustment factor (L) helps balance the influence of soil reflectance and vegetation signal. By considering the soil background, the SAVI helps improve the accuracy and reliability of vegetation assessments in areas where soil variations can affect the interpretation of vegetation indices. Therefore, SAVI was used to remove soil pixels in this study, improving the image analysing accuracy.

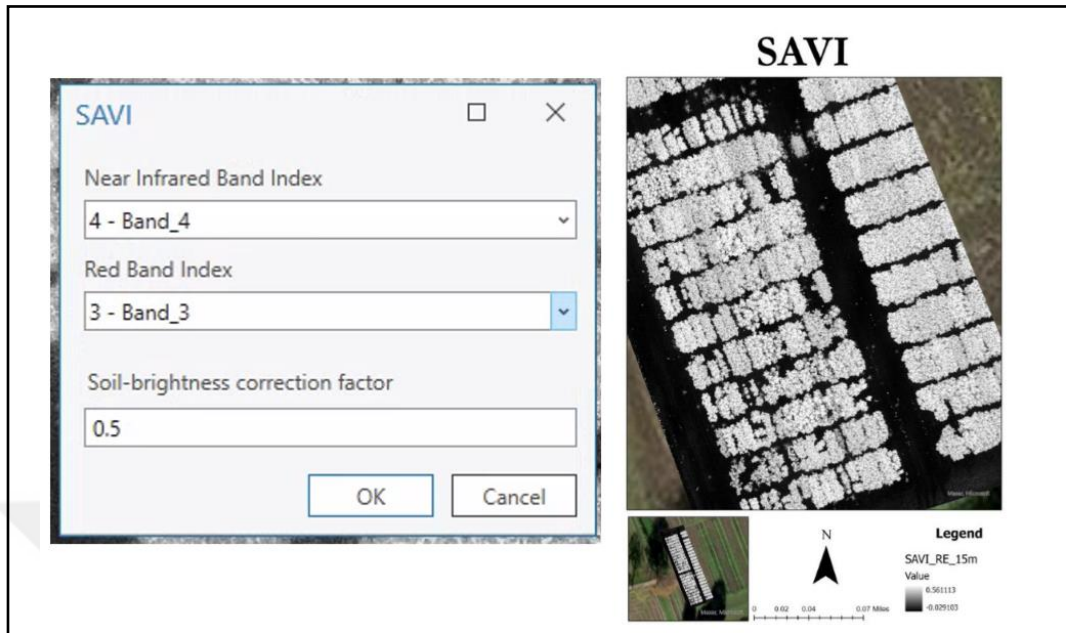


Figure 14 Used parameters for SAVI calculation and output map for study site.

3.1.9. MSAVI

MSAVI stands for the Modified Soil-Adjusted Vegetation Index is an adaptation of the Soil-Adjusted Vegetation Index (SAVI) and aims to improve the sensitivity of the index to changes in vegetation conditions.

The formula for calculating the MSAVI is as follows:

$$\text{MSAVI} = ((2 * \text{NIR} + 1) - \sqrt{(2 * \text{NIR} + 1)^2 - 8 * (\text{NIR} - \text{Red})}) / 2$$

Where:

NIR refers to the near-infrared band reflectance.

Red refers to the red band reflectance.

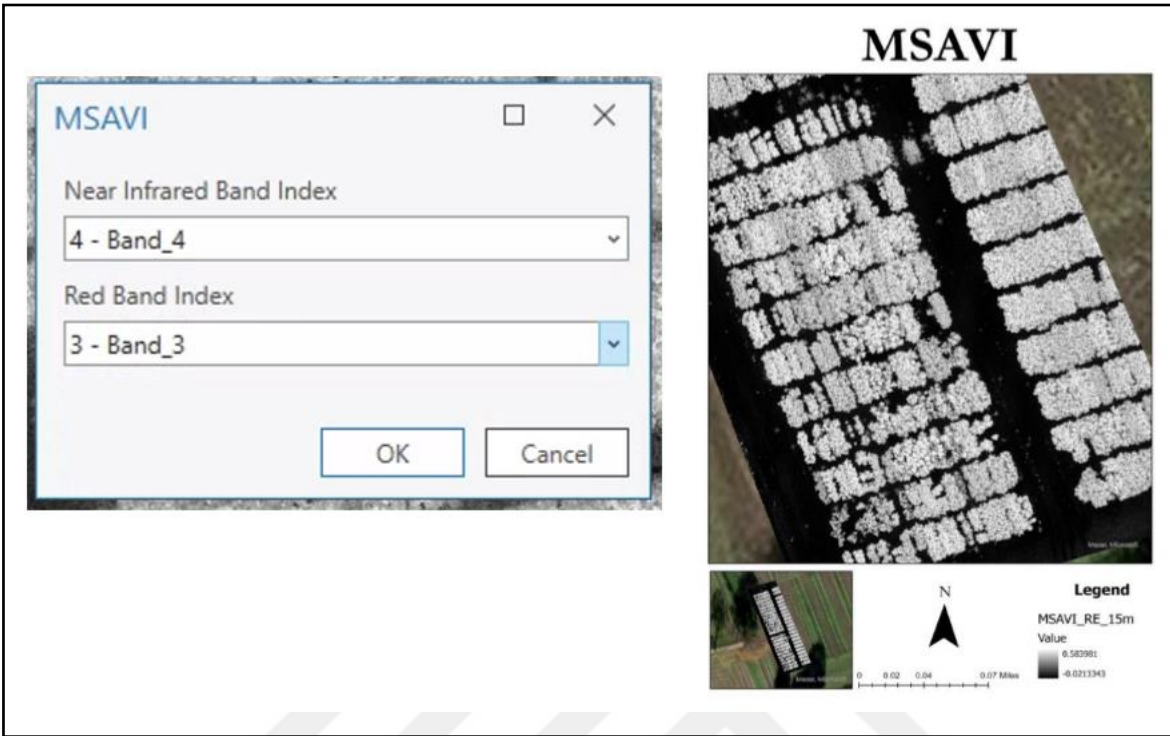


Figure 15 Used parameters for MSAVI calculation and output map for study site.

3.1.10. CI Green

The "Green Chlorophyll Index" (Green CI) designed to estimate the chlorophyll content in plant leaves, which is an essential indicator of plant health and photosynthetic activity. The Green CI is based on the principle that healthy vegetation absorbs more light in the red and blue wavelengths and reflects more light in the green wavelength due to the presence of chlorophyll.

The Green CI is calculated using the following formula:

$$\text{Green CI} = (\text{NIR} - \text{Green}) / (\text{NIR} + \text{Green})$$

Where:

NIR is the Near-Infrared reflectance value of the vegetation.

Green is the Green reflectance value of the vegetation.

In this index, the Near-Infrared (NIR) band measures reflectance in the wavelength region where healthy vegetation strongly reflects light, and the Green band measures reflectance in the wavelength region where healthy vegetation absorbs light. By taking the ratio of these two bands, the Green CI provides a relative measure of chlorophyll content, which is a good indicator of vegetation health. Therefore, higher values of Green CI indicate higher chlorophyll content and generally healthier vegetation. Conversely, lower values of Green CI are associated with lower chlorophyll content and may suggest stressed or less healthy vegetation. In addition, the Green CI is commonly used in conjunction with other vegetation indices like NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) to obtain a comprehensive understanding of vegetation health and dynamics.

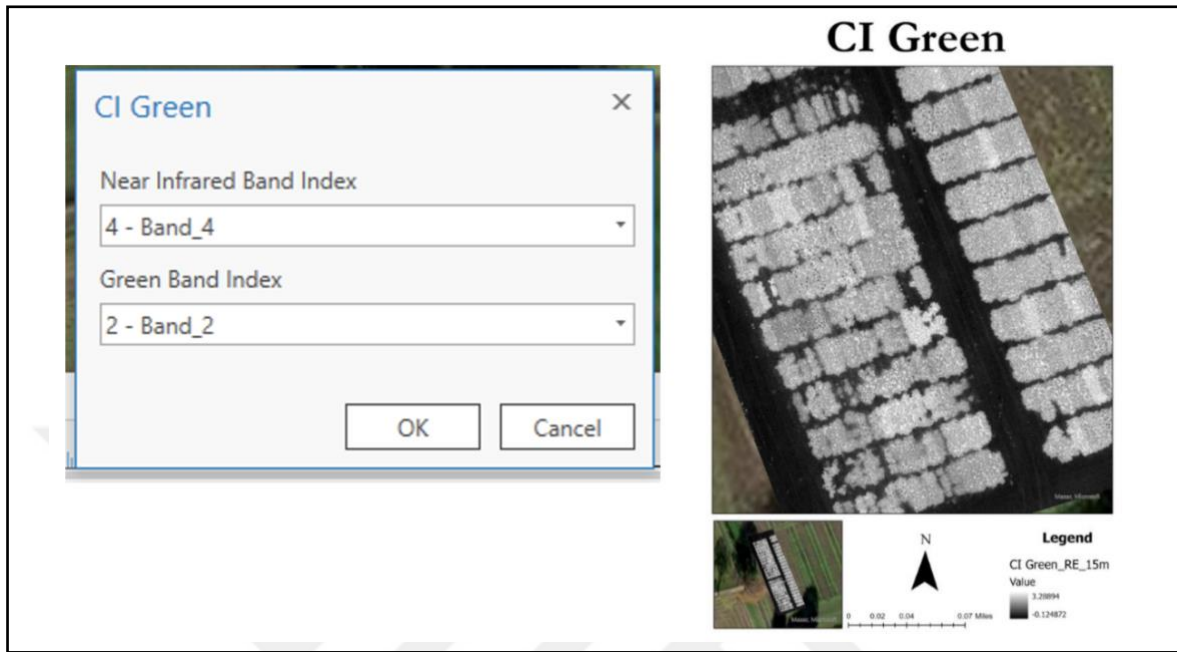


Figure 16 Used parameters for CI-Green calculation and output map for study site.

3.2. Removing Soil Pixels

After analysing different vegetation index outputs, indices were selected to use filter data to increase the accuracy of the classification. SAVI minimizes the influence of soil reflectance and normalizes the vegetation signal by considering the soil component. In addition, SAVI is particularly useful in areas with exposed soil or when the soil reflects significant amounts of near-infrared radiation. Therefore, SAVI was used to remove the soil pixels from the data. For this, SAVI values were classified into 5 classes to assess a threshold value for soil pixels. As shown in Figure 7, the value between -0.104 and 0.228 emphasizes the soil. The threshold value was set as 0.228, meaning the pixel values with less than 0.228 SAVI values will be removed from the data. This process includes re-classifying values lower than the threshold value (0.228) as soil and higher values as vegetation, assigning a value of 0 to soil pixels and removing them from the total image.

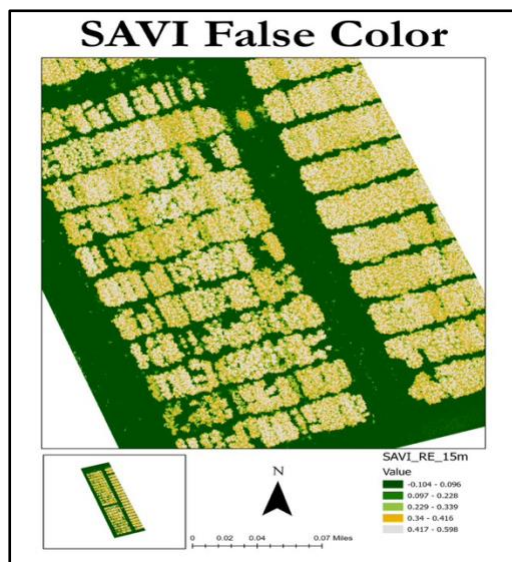


Figure 17 False colour SAVI that classified into 5 classes according to value.

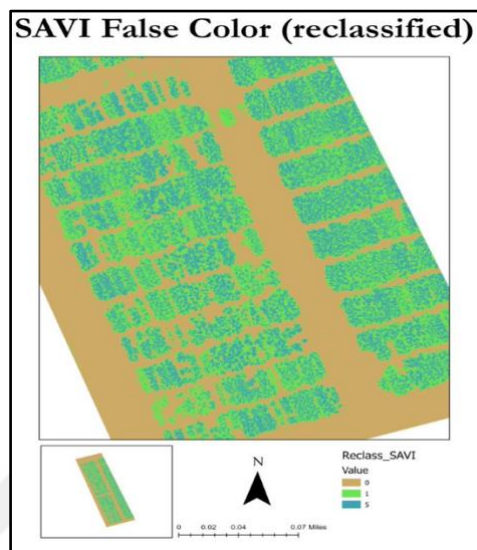


Figure 18 Reclassified SAVI output into two classes (vegetation and soil).



Figure 19 Study area without soil

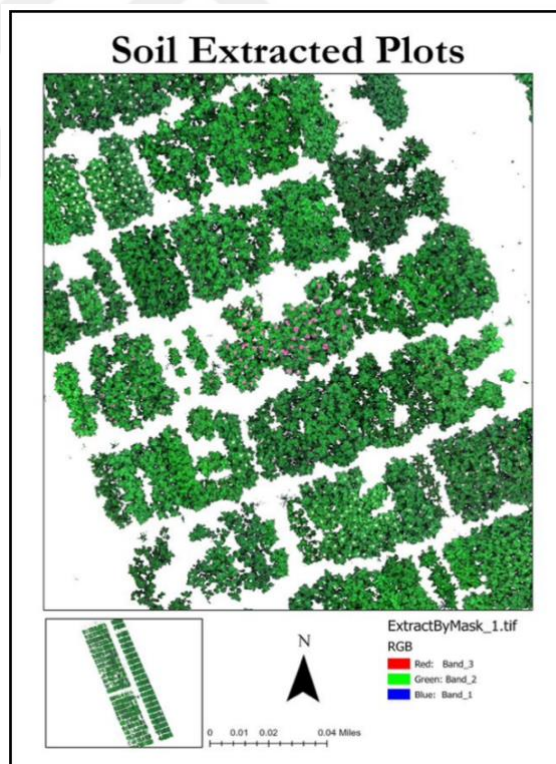


Figure 20 RGB image of study are without soil pixels.

3.3. Removing Floral Pixels

For the optimal solution, the flowers of some potato species were filtered because the reflection of the floral pixels can also affect the classification. VARI was used in the filtering process according to the calculated vegetation index outputs because it clearly indicates the floral pixels. This process was carried out by applying different threshold values in the same methodology as in the soil filtering process. When the VARI values were divided into 5 classes, the value 0.493 was assigned for the floral pixels, and the pixels below this threshold value were reclassified as flower pixels and the value above it as plant leaves. Two operations (removing soil and flower pixels from the image) were performed using the 'Reclassify' and 'ExtractByMask' tools in the ArcGIS Pro application.

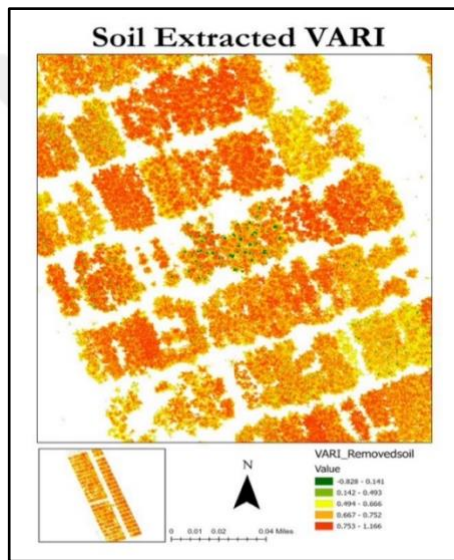


Figure 22 False colour VARI that classified into 5 clases

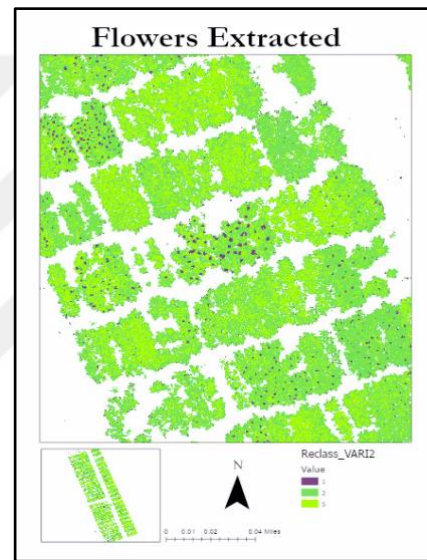


Figure 21 Reclassified VARI into three clases (floral and leaf)

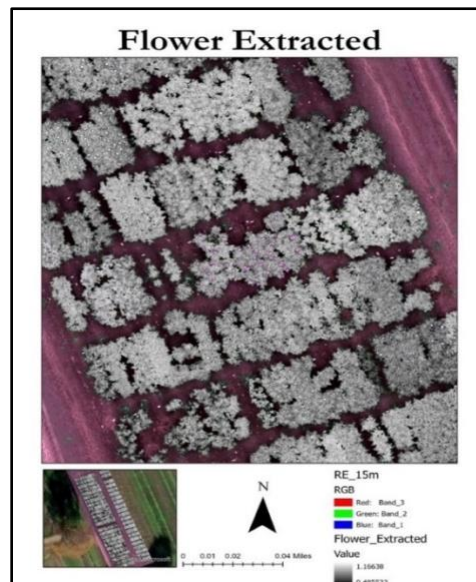


Figure 23 Study area with extracted soil and floral pixels. The output is shown with the RGB image layer to observe the deleted floral pixels better

3.4. Band Stack

In the classification process, layer stacking has been utilised extensively. Zhou et al. (2016) employed NDVI and enhanced vegetation index (EVI) for each image used to illustrate the possibility of the phenology-based rice paddy algorithm. To track the change in land cover, Rawat & Kumar (2015) also used the normalised difference water index (NDWI), normalised difference build-up index (NDBI), and NDVI.

Based on these studies, NDVI, one of the VIs, was added as the 6th band to increase the accuracy of the classification algorithm for detecting the diseased leaf pixel, using 'Composite Bands' tool in ArcGIS Pro. The factor in choosing NDVI is the standard deviation value. Compared with other VIs, the NDVI with the highest standard deviation value was observed, indicating that the difference between the largest and the smallest value is the largest compared to other vegetation indices. Accordingly, when this index and other bands are combined, it is aimed to increase the difference in diseased and healthy plant leaves reflectance values of the study area and thus to make the algorithm work more accurately by taking advantage of this difference while classifying.

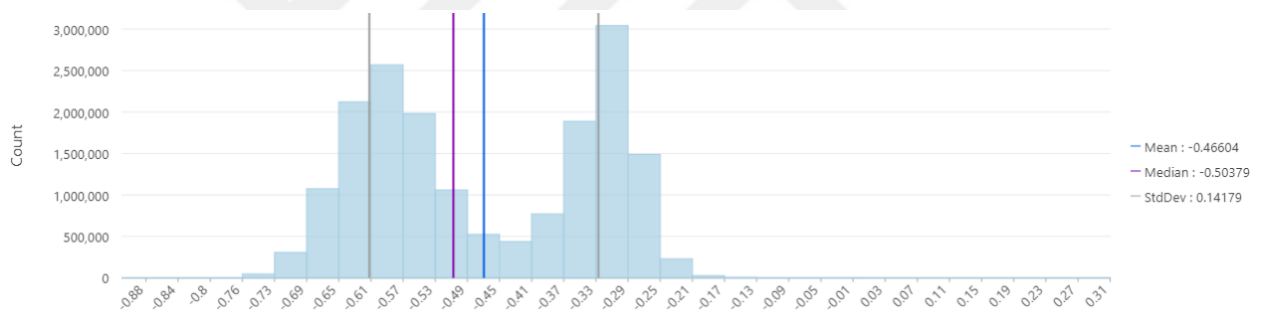


Figure 24 Mean, median and standard deviation value of the NDVI (in ArcGIS Pro).

To determine how much of a reflection difference was created with band stack processing, it was observed in Figures 25 and 26 how much the difference between the reflectance levels of the diseased and healthy plots of the same type (Asenal) potato plant changed (in ArcGIS Pro).

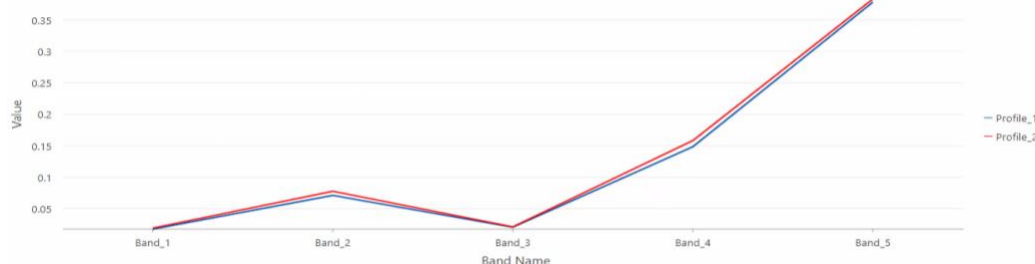


Figure 25 Spectral profile of healthy (blue) and Y^m virus effected (red) Arsenal potato crop

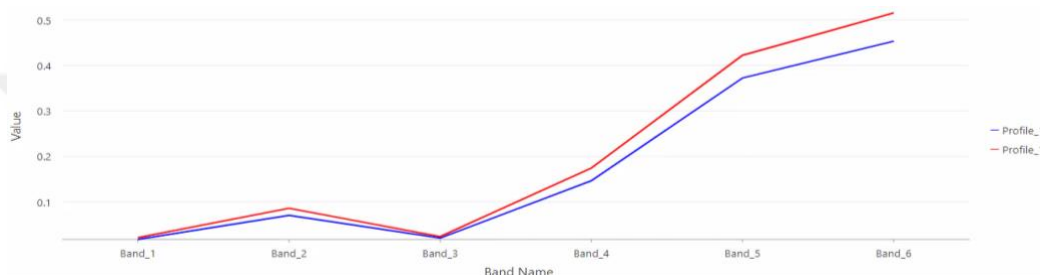


Figure 26 Spectral profile of healthy (blue) and Y^m virus effected (red) Arsenal potato crop after band layering.

4. Image Classification

Image classification involves assigning predefined labels or categories to pixels or regions within an image. Image classification aims to automatically distinguish and categorize objects, features, or land cover types present in the pre-processed image.

In general, applying the trained classification model to the entire image or regions of interest (ROIs) to classify each pixel or region into one of the predefined classes occurs in the classification. In this study, pixel-based supervised classification happened for the entire image. However, meaningful output and accuracy weren't achieved (Appendix 3). The algorithm could not accurately work for the whole field since the reflection levels differ according to the potato species and virus types. Therefore, the method was changed to object-based for ROIs (each ROI represents a different variable of potato crops)

Different potato varieties were chosen as ROIs from other countries to test the algorithm efficiently and according to the viruses affected. The table shows which variety (ROI) shows which signs of virus infections, and a detailed review of viral diseases is given in Appendix 1. For potato varieties, different species were selected based on other countries originally. Desiree(Netherlands), King Edward(England), Marfona (Netherlands), Maris Piper (England), Nicola(Germany) (De Jong, 2011), and Cara.

The basic workflow of classification is given in Figure 27, and the process sequence in eCognition is shown in Figure 28.

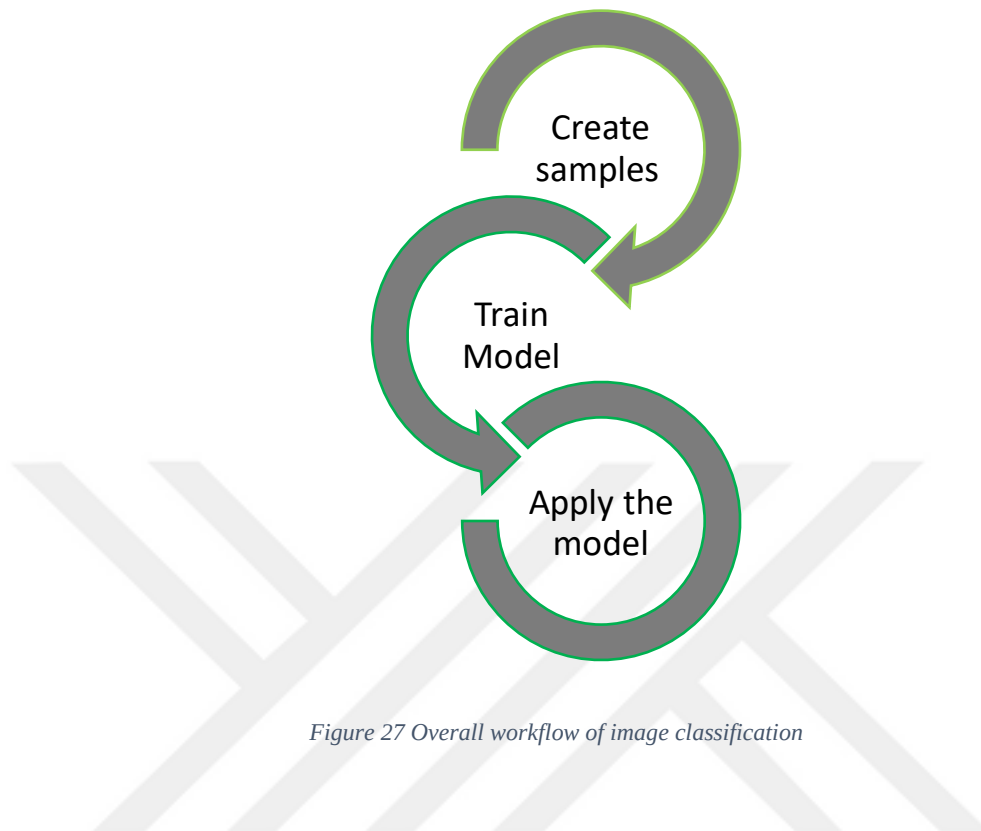


Figure 27 Overall workflow of image classification

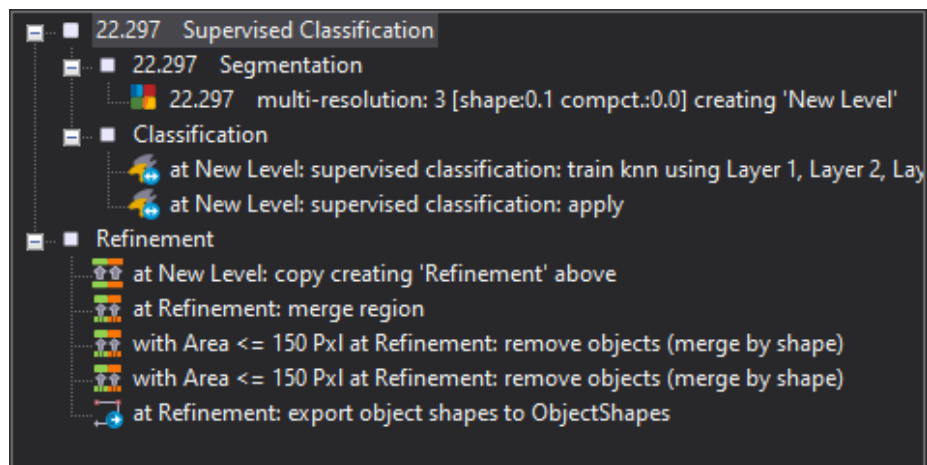


Figure 28 Overall steps of the Image Classification process (eCognition).

4.1. Image Segmentation

Image segmentation involves dividing an image into meaningful and semantically coherent regions or segments. The goal of image segmentation is partitioning an image into visually distinct and coherent regions based on their visual properties, such as colour, texture, or shape. It provides a more detailed representation of an image by identifying and delineating individual objects or regions of interest within the image.

A description of an image at the pixel level is known as object segmentation. It sets the border in accordance with the shape of the relevant object. It gives each group of pixels significance and is appropriate for interpreting complex situations (Kuswidiyanto, Noh, & Han, 2022). Since a high-performing deep-learning-based model requires an enormous amount of data, it is predicted that model performance would advance as data volume rises (Alzubaidi, et al., 2021). Additionally, the model must generalise the data, which entails learning from both training and unknown data (Grosse, 2018). To guarantee generalizability, large training datasets are often necessary.

In this study, multiresolution segmentation was occurred in eCognition for each ROI. Multiresolution segmentation is a specific approach to image segmentation that aims to capture objects and regions at multiple scales or levels of detail. It is particularly useful when dealing with complex scenes that contain objects of different sizes. Therefore, this segmentation method used in this study to segment different variables of potato crops.

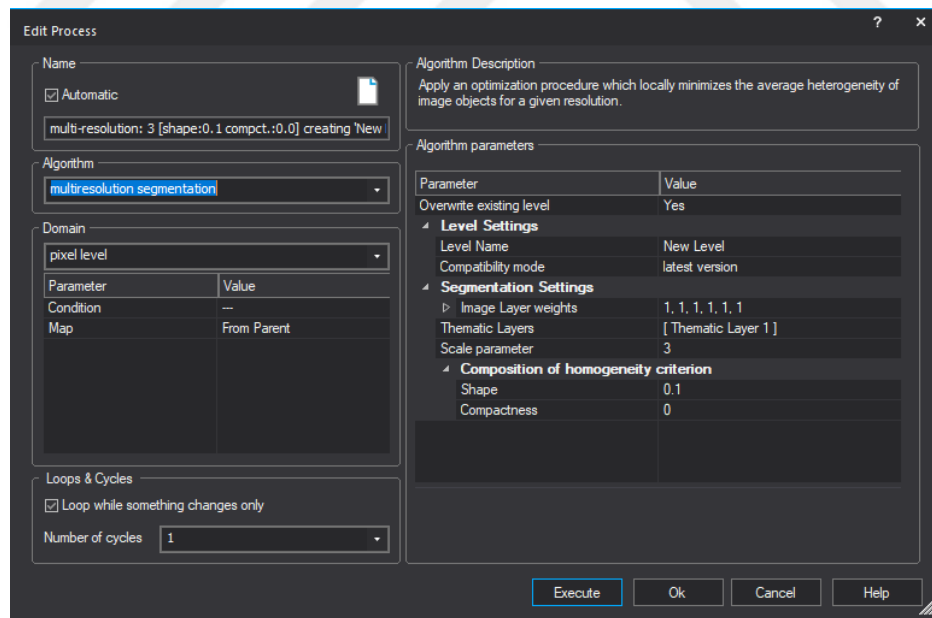


Figure 29 Image Segmentation method (multithreshold segmentation) parameters

Utilising the three segmentation factors of scale, shape, and compactness, which all contribute to the characterization of objects and object sizes (Laliberte, et al., 2004), multiresolution image segmentation was performed based on visual evaluations. Greater values of the scale parameter result in bigger objects since it is directly proportional to the resolution of the image (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). A value of 3 was eventually decided upon for this parameter. Additionally, a shape value of 0.1 was applied after repeated tests. The compactness value was set to 0 since it had little impact on the produced items. When the segmented items were visually evaluated, it was found that they closely resembled those that would have been defined manually by picture interpretation.

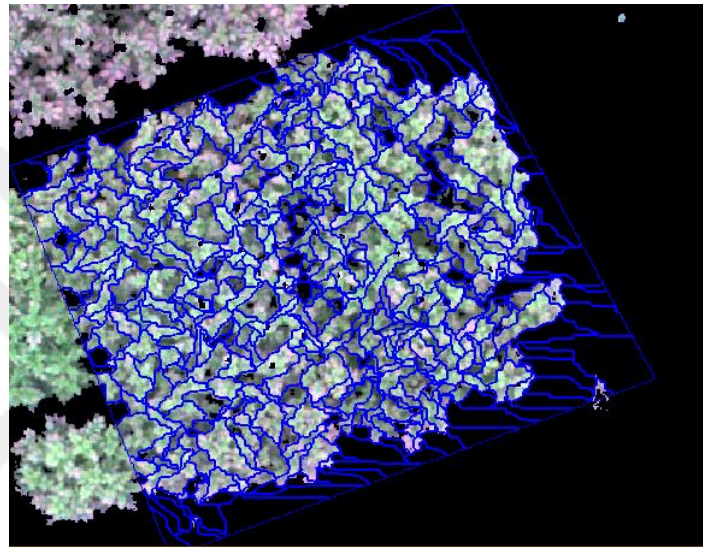


Figure 30 Image segmentation for Cara variation (which include healthy, Y^m virus and Y^o virus affected plots)

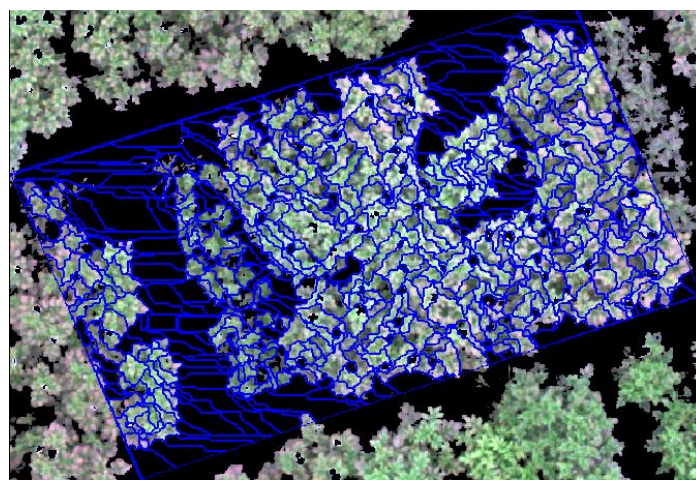


Figure 31 Image segmentation for Desiree variation (which include healthy, A virus, X virus, Y^m and Y^o virus affected plots)

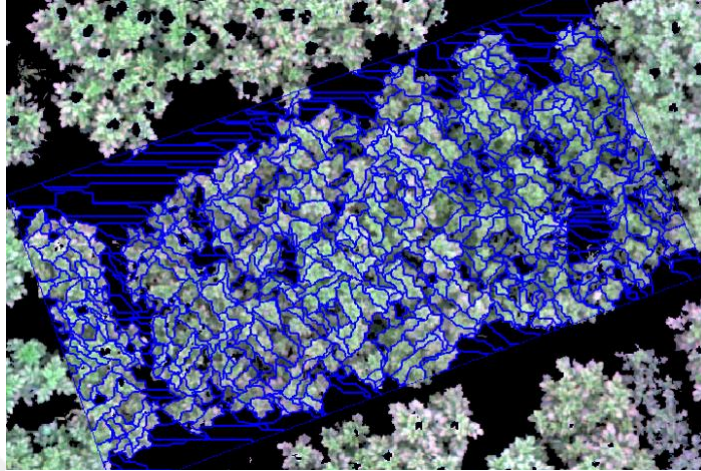


Figure 32 Image segmentation for King Edward variation (which include healthy, Y^n virus and Y^o virus affected plots)

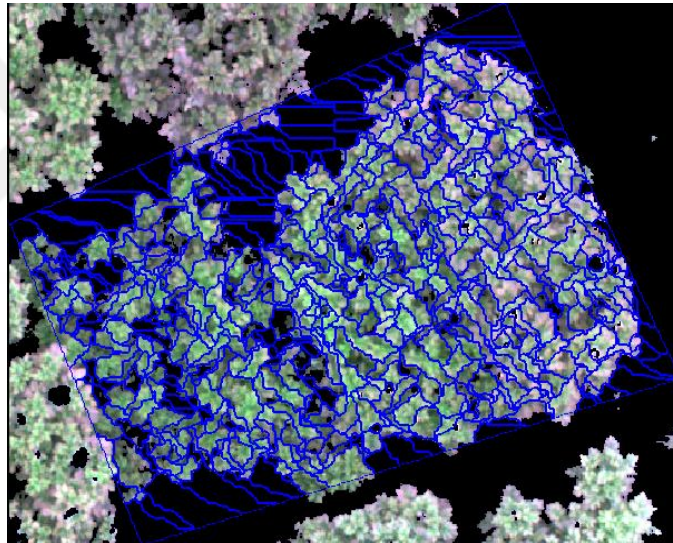


Figure 33 Image segmentation for Marfona variation (which include healthy, Y^n virus and Y^o virus affected plots)

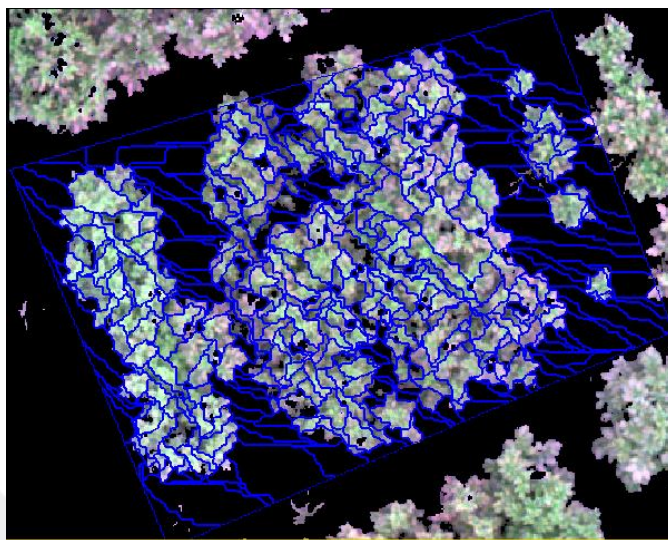


Figure 34 Image segmentation for Maris Piper variation (which include healthy, Y^n virus affected and Likelihood Ratio(LR)) plots

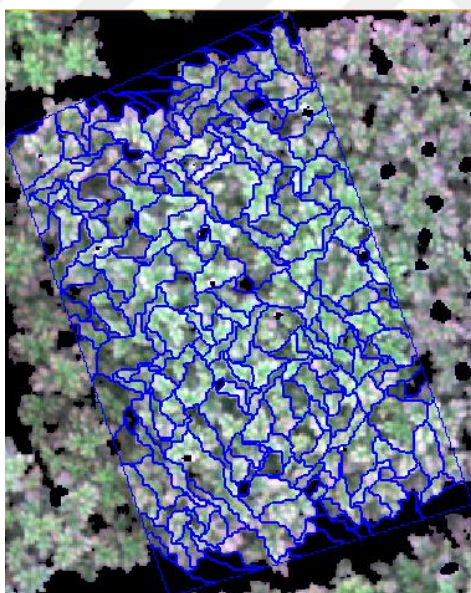


Figure 35 Image segmentation for Nicola variation (which include healthy and Y^n virus affected) plots

4.2. Train the Data

Training data is a process where the algorithm learns the relationship between the input image pixels and their corresponding class labels. It collected a representative set of training data. The important thing while training data is accurately reflection the variability of the classes in the image and covering different spectral characteristics.

This study used selected segments to train the data after segmentation. To train the data, you must know which plot is diseased. Therefore, the guide provided by SASA is used to label the training segments. eCognition offers an opportunity to use produced segments as training samples. In addition, you can do classification afterwards. If the classification result doesn't satisfy, you can change or add more training samples and re-classify until you get a satisfactory result.

As given the overall supervised classification framework in Figure 28, you don't need to do everything again for each ROI; however, since each variety has different features, such as other types of viruses, different leaf sizes, and different numbers of plots, the training process should be specific for each ROI.

The training segments used as samples for each type of potato crop are shown in Figures 36,37,38,39,40. And 41. The colour representation of classes was given in Figure 50.

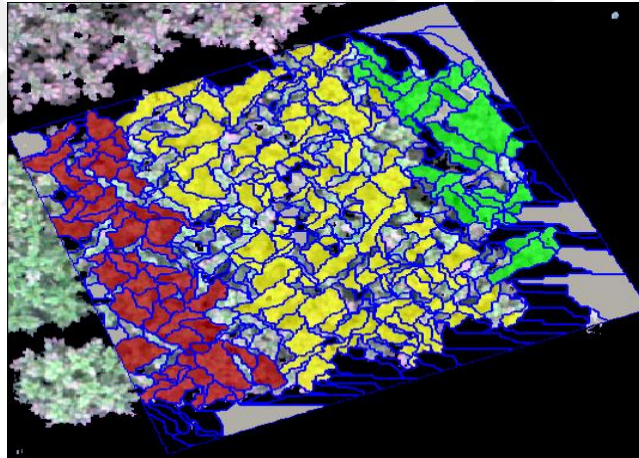


Figure 36 Training samples for Cara

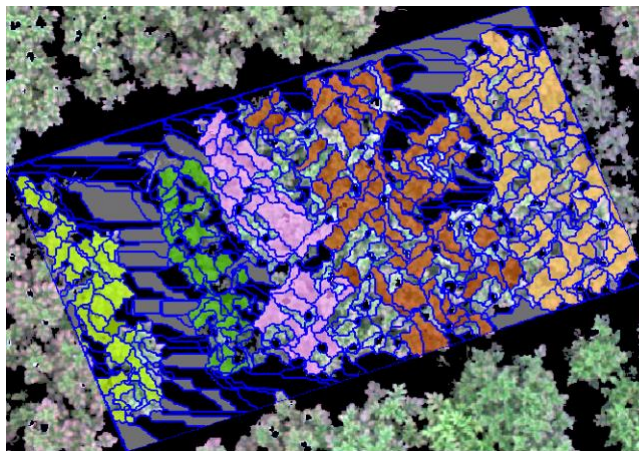


Figure 37 Training samples for Desiree

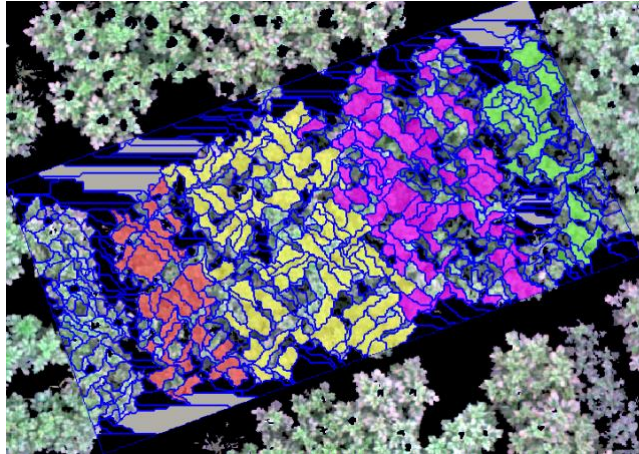


Figure 38 Training samples for King Edwards

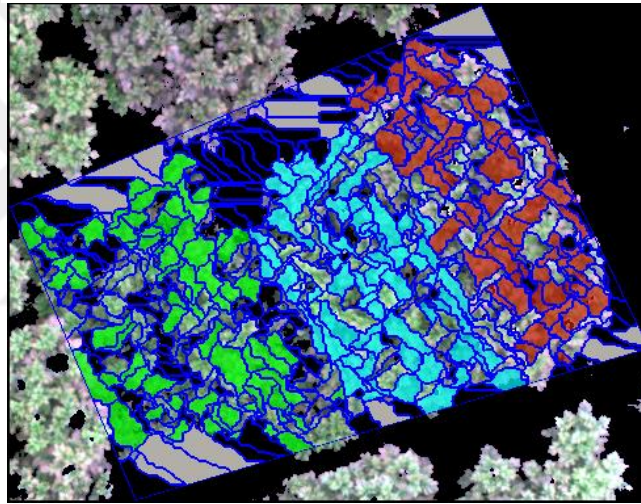


Figure 39 Training samples for Marfona

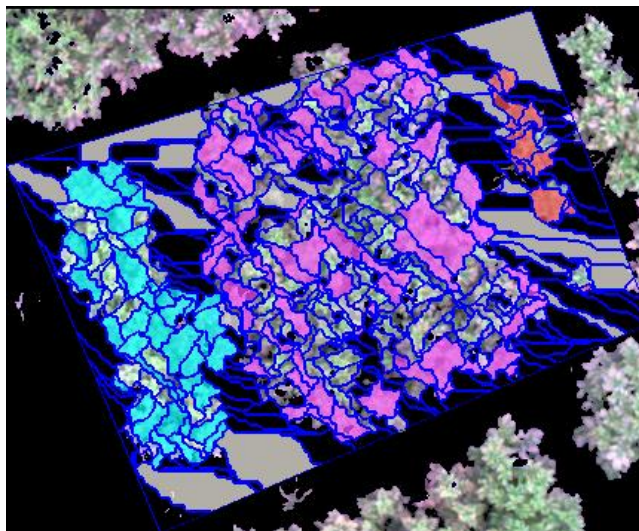


Figure 40 Training samples for Maris Piper

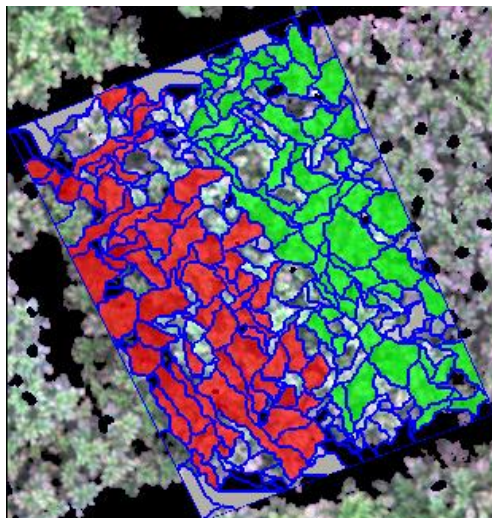


Figure 41 Training samples for Nicola

4.3. Supervised Image Classification and Classification Refinement

For disease classification, the K-Nearest Neighbor classification algorithm was used. KNN is a fundamental and standard machine-learning technique for pattern identification and classification problems. It is a non-parametric, instance-based approach that depends on directly comparing data points rather than making any assumptions about the distribution of the underlying data. The parameters used for classification was shown in Figure 42. The parameters used for classification are shown in Figure 42. The integer k determines how many samples should be considered around an unclassified item or pixel. The optimal value of k depends on the data; greater values minimise the impact of noise on classification, but the class boundaries are less defined.

Supervised classification involves using labelled training data that assessed the previous chapter and using image features while establishing the algorithm. For determining the proper characteristics for getting high accuracy in classification, the different combination was tried for the feature layer in classification (shown in Appendix 2), and it is observed that the mean value of blue, green, red, NIR, Red-edge and NDVI bands give the best result for K-Nearest Neighbor classification.

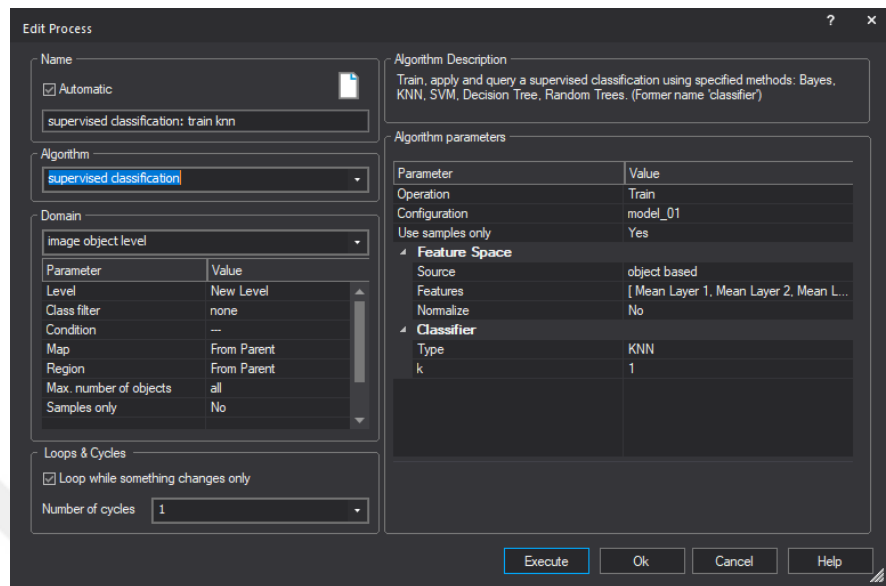


Figure 42 Used parameters for Supervised classification.

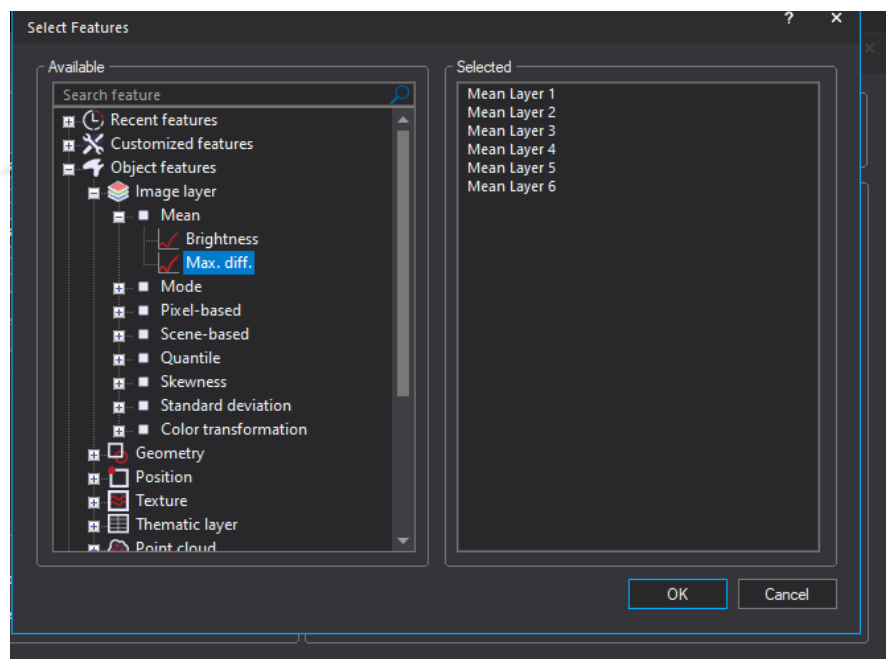


Figure 43 Used features of image for classification.

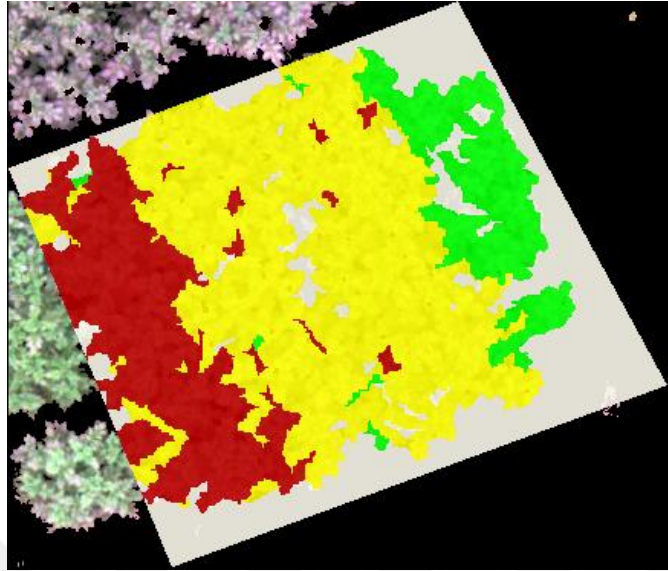


Figure 44 Classification Result for Cara

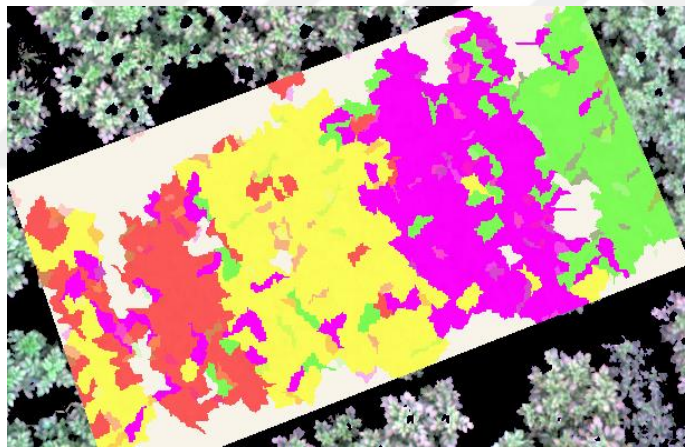


Figure 45 Classification Result for Desiree

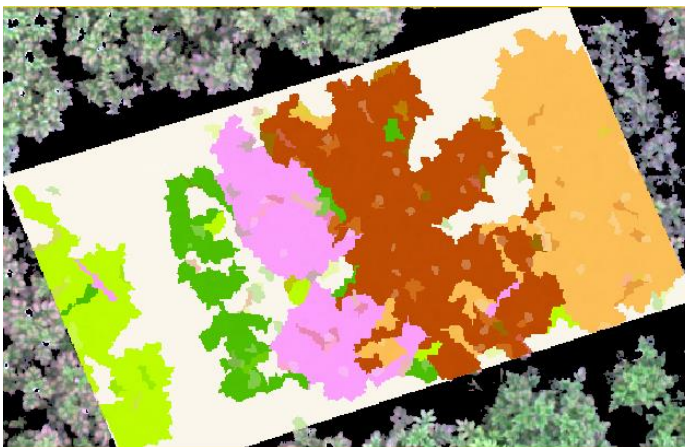


Figure 46 Classification Result for King Edward

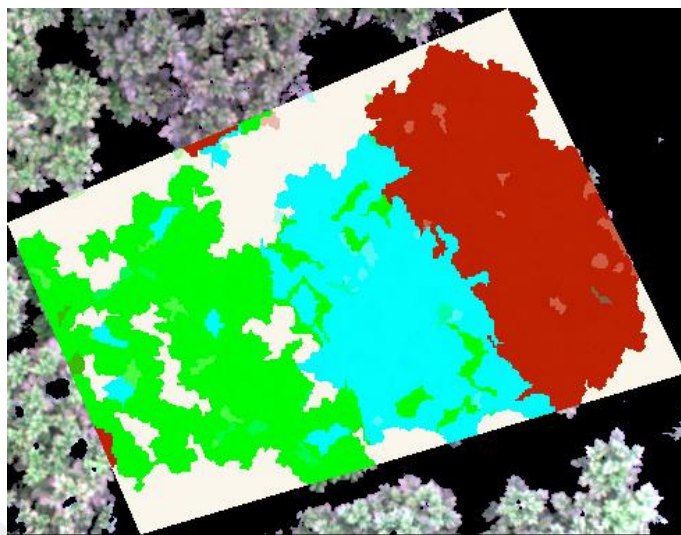


Figure 47 Classification Result for Marfona

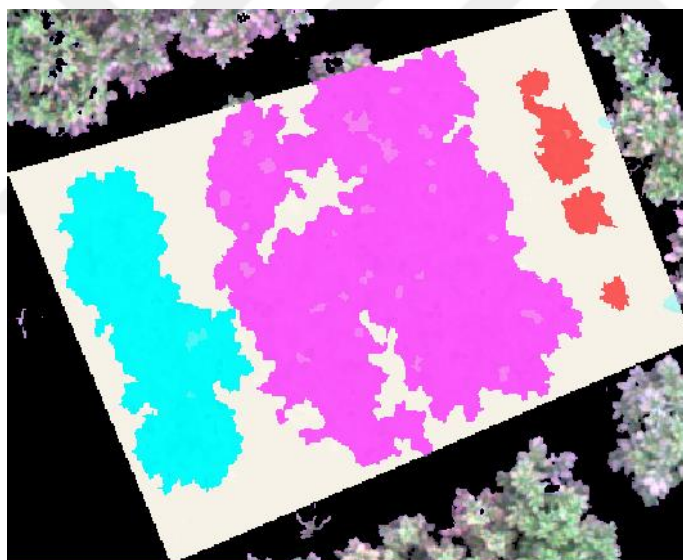


Figure 48 Classification Result for Maris Piper

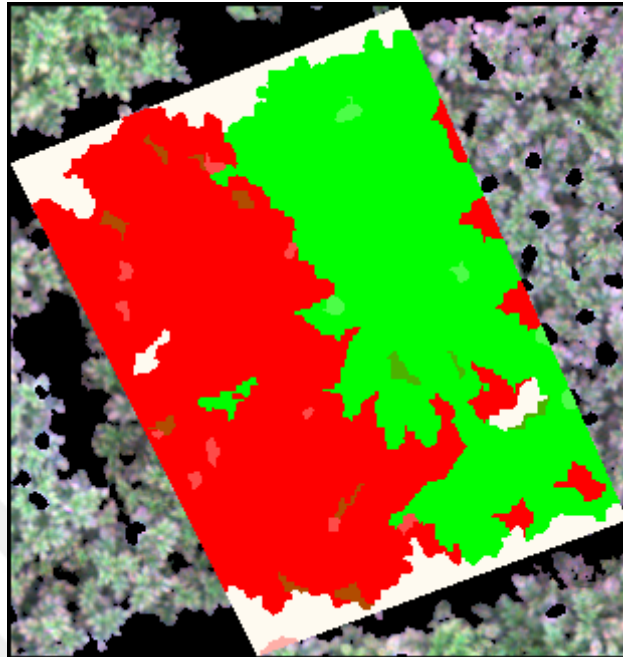


Figure 49 Classification Result for Nicola

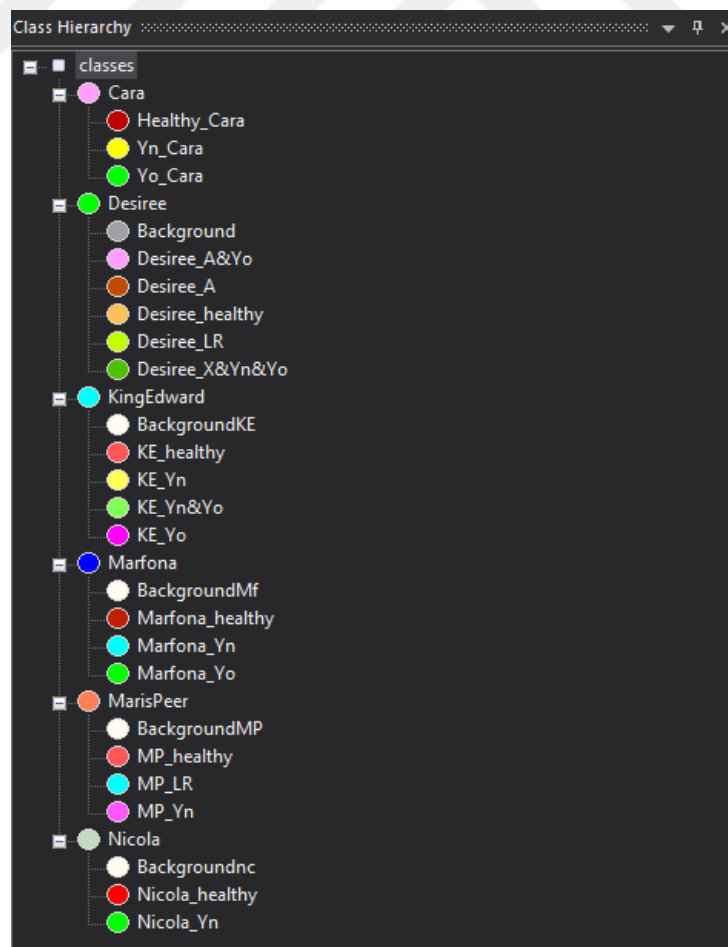


Figure 50 The all classes that used in Supervised classification for each ROI.

Some misclassified objects, which confused the algorithm, can be reduced at some level. Therefore, a structural process was created for refinement as the last step of the classification process (Figure 38). It contains the removal and merging of misclassified tiny pixels and smooths the boundaries between the classes. Then, I exported all classification results to compute the confusion matrix to assess the accuracy of the methodology. The classes were exported as a vector layer, and the export format was set as 'geojson', which adds the class names as an attribute in the attribute table.

4.4. Process Validation through Confusion Matrix

Evaluation the accuracy of classified image by comparing the result against reference data or ground truth information is occurred by confusion matrix. Accuracy assessment is a crucial topic and necessary for every classification. Accuracy assessment methods can produce statistical outputs to check the quality of the classification results. This is an important part of any classification. It compares classified objects with validation ground truth data. A confusion matrix is a table that is often used to assess the performance of a classification model. It summarizes the predictions of a model on a set of test data by comparing the predicted labels with the true labels. The confusion matrix has provided the producer's accuracy, the user's accuracy, kappa, and all sorts of statistics that help understand the accuracy of your classification.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive	False Negative
Actual Negative	False Positive	True Negative

Table 3 Accuracy from binary image classification for the producer, user, and overall.

In the matrix of confusion,

- True Positive (TP): Instances correctly predicted as positive.
- False Positive (FP): Instances incorrectly predicted as positive.
- True Negative (TN): Instances correctly predicted as negative.
- False Negative (FN): Instances incorrectly predicted as negative.

4.4.1. Producer's Accuracy

Producer's accuracy results in false negatives when pixels belonging to a recognised class are incorrectly identified as belonging to a different class. Errors of omission, or type 2 mistakes, are another name for producer accuracy.

4.4.2. User's Accuracy

User's accuracy demonstrates false positives when pixels are wrongly assigned to a recognised class when they need to be given to another. Errors of commission, or type 1 errors, are another name for the user's accuracy.

4.4.3. Kappa Coefficient

The degree of agreement between the expected and actual classifications in a classification task is measured statistically using the Kappa coefficient. In addition to providing a normalised measure of agreement above what may be predicted due to random chance, it also accounts for any agreement that could arise by chance.

The formula to calculate the Kappa coefficient is:

$$K = \frac{P_{\text{observed}} - P_{\text{chance}}}{1 - P_{\text{chance}}}$$

Where:

P_{observed} (Observed Proportion of Agreement) is the ratio of the number of instances that were correctly classified to the total number of instances.

P_{chance} (Expected Proportion of Agreement by Chance) is the ratio of the expected agreement by chance to the total number of instances.

4.4.4. Overall Accuracy

The percentage of correctly identified pixels in the classification—in this example, the percentage of sick and healthy pixels—relates to the overall accuracy. It is calculated by dividing the overall number of references by the number of pixels successfully referred to.

The accuracy assessment process was obtained on ArcGIS Pro. The polygons were assessed for each class and random ground truth points produces in the boundary of these polygons (100 points produced in total for each ROI). The confusion matrix outputs is given below:

Nicola Plot	Nicola Background	Nicola Y ⁿ	Nicola healthy	Total	User's Accuracy	Kappa
Nicola Background	10	0	0	10	1	0
Nicola Y ⁿ	0	49	3	52	0.942308	0
Nicola healthy	0	3	41	44	0.931818	0
Total	10	52	44	106	0	0
Producer's Accuracy	1	0.942308	0.931818	0	0.943396	0
Kappa	0	0	0	0	0	0.902094

Marfona Crop	Marfona Background	Marfona Y ⁿ	Marfona Y ^o	Marfona healthy	Total	User's Accuracy	Kappa
Marfona Background	10	0	0	0	10	1	0
Marfona Y ⁿ	0	22	4	1	27	0.814815	0
Marfona Y ^o	0	5	24	0	29	0.827586	0
Marfona healthy	0	0	0	36	36	1	0
Total	10	27	28	37	102	0	0
Producer's Accuracy	1	0.814815	0.857143	0.972973	0	0.901961	0
Kappa	0	0	0	0	0	0	0.862737

King Edward Crop	King Edward Background	King Edward Y ⁿ	King Edward Y ⁿ & Y ^o	King Edward Y ^o	King Edward healthy	Total	User's Accuracy	Kappa
King Edward Background	10	0	0	0	0	10	1	0
King Edward Y ⁿ	0	22	0	2	0	24	0.916667	0
King Edward Y ⁿ & Y ^o	0	0	17	4	0	21	0.809524	0
King Edward Y ^o	0	1	2	28	0	31	0.903226	0
King Edward healthy	0	2	0	0	16	18	0.888889	0
Total	10	25	19	34	16	104	0	0
Producer's Accuracy	1	0.88	0.894737	0.823529	1	0	0.894231	0
Kappa	0	0	0	0	0	0	0	0.863403

Maris Piper Crop	Maris Piper Background	Maris Piper LR	Maris Piper Y ⁿ	Maris Piper healthy	Total	User's Accuracy	Kappa
Maris Piper Background	12	0	0	0	12	1	0
Maris Piper LR	0	23	0	0	23	1	0
Maris Piper Y ⁿ	1	2	59	0	62	0.951613	0
Maris Piper healthy	0	1	0	9	10	0.9	0
Total	13	26	59	9	107	0	0
Producer's Accuracy	0.923077	0.884615	1	1	0	0.962617	0
Kappa	0	0	0	0	0	0	0.938391

Cara Crop	Cara Background	Cara healthy	Cara Y ⁿ	Cara Y ^o	Total	User's Accuracy	Kappa
Cara Background	10	0	0	0	10	1	0
Cara Healthy	0	26	1	0	27	0.962963	0
Cara Y ⁿ	0	2	48	1	51	0.941176	0
Cara Y ^o	0	0	0	14	14	1	0
Total	10	28	49	15	102	0	0
Producer's Accuracy	1	0.928571	0.979592	0.933333	0	0.960784	0
Kappa	0	0	0	0	0	0	0.940342

Desiree Crop	Desiree Background	Desiree A	Desiree A&Y ^o	Desiree LR	Desiree X&Y ⁿ &Y ^o	Desiree Healthy	Total	User's Accuracy	Kappa
Desiree Background	10	0	0	0	0	0	10	1	0
Desiree A	0	25	0	0	0	0	25	1	0
Desiree A&Y ^o	0	0	16	0	0	0	16	1	0
Desiree LR	0	0	1	11	1	0	13	0.846154	0
Desiree X&Y ⁿ &Y ^o	0	1	0	2	9	0	12	0.75	0
Desiree Healthy	0	2	0	0	0	26	28	0.928571	0
Total	10	28	17	13	10	26	104	0	0
Producer's Accuracy	1	0.892857	0.941176	0.846154	0.9	1	0	0.932692	0
Kappa	0	0	0	0	0	0	0	0	0.916581

Although confusion matrices are used for accuracy determination, they have some important limitations. First, they do not indicate how the error is distributed spatially. In addition, the error matrix obtained at the global scale could not adequately reflect the error for localised places where the error may be either bigger or lower than the global measure (McGwire & Fisher, 2001). This factor should be taken into account when making the classification evaluation.

5. Summary

In a field, remote sensing systems can find abnormal places that have been differently affected by weeds, diseases, or pests caused by arthropods. (Pinter, et al., 2003). It is an essential part of precision agriculture since it enables farmers to gather information about crops and soil remotely. Drones, also known as unmanned aerial vehicles (UAVs), are being utilised more often in agriculture since they are affordable and effective at gathering data. Additionally, high-resolution (cm-scale) crop health, growth, and yield monitoring may be done using UAVs fitted with cameras and sensors. This information may be utilised to spot disease or stress points, monitor the development of crops, and maximise inputs like fertiliser and water.

It was decided to focus on the potato plots at SASA's Gogarbank Farm for this project to teach new and experienced potato inspectors the identification of varieties, genetic variations, and diseases from leaf features. It is aimed to detect potato plants, which are determined to be healthy in the laboratory environment, using UAV-based remote sensing systems and calculating the accuracy of the developed methodology.

It was observed that the methodologies used were study-based variables, and it was determined that the object-based supervised classification (KNN) algorithm worked best for this study. In line with the results obtained, it was determined that the number of crops in the study area and the virus diversity were significant factors in the accuracy of the methodology.

In this direction, a hyperspectral sensor can be used to develop this classification methodology for future studies since it provides higher radiometric accuracy. In addition, since the software used to implement the process works according to the fixed operation method embedded in their systems, it gives a broader intervention to the algorithms implemented using one of the coding languages. Thus more specific algorithms can be developed.

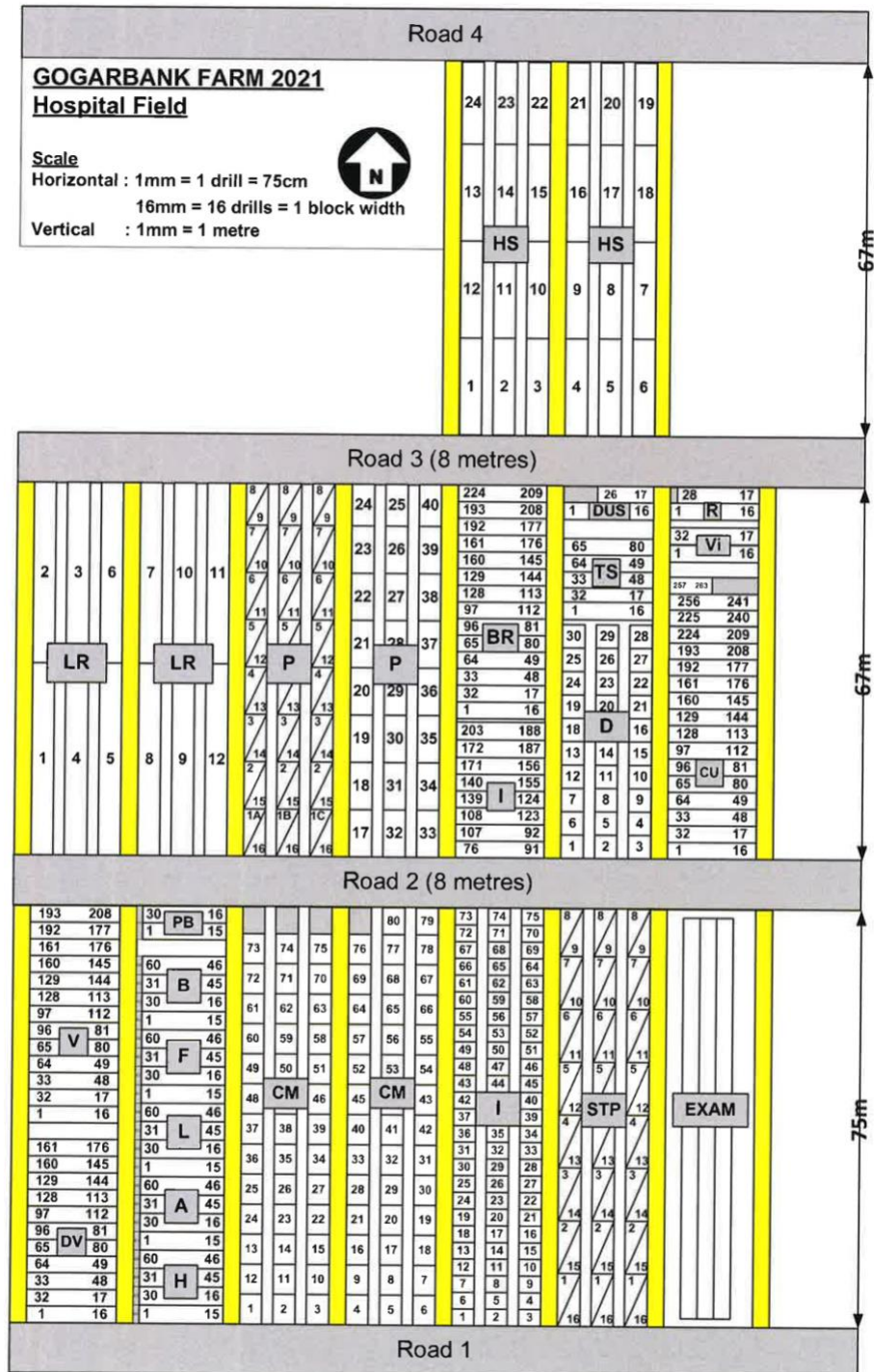
6. Bibliography

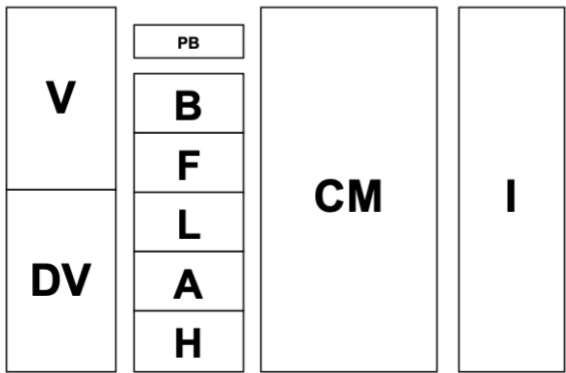
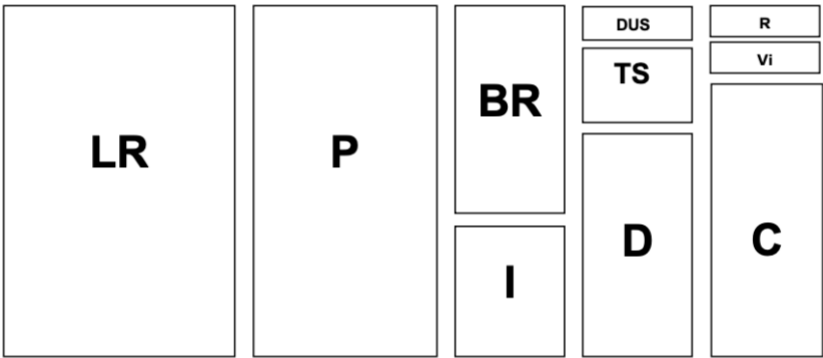
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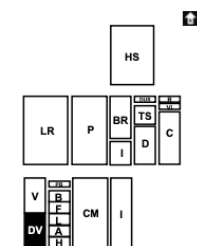


7.1. Appendix 1: Study field plan





Abbreviation	Name of Collection
H	Foliage Habit
A	Size of Area Entered for Classification in 2020 and Maturity
L	Foliage Colour and Leaflet Size
F	Flower and Tuber Colour
B	Tuber Shape and Sprout Colour
CM	Commercial Collection
I	Less Common Classified Varieties
DV	Virus Disease Collection
V	Variations Collection
TS	Inspectors' Tuber Samples
BR	Breeders' Plots
LR	Large Rogue Plots
D	Miscellaneous Demonstrations
P	Inspection Practice Plots
PB	PB Plots
DUS	Distinctness, Uniformity and Stability Reference Varieties
VI	Varietal Interest Plots
C	Variety Reference Collection
R	Virus Elimination Collection
HS	Healthy Stock Plots

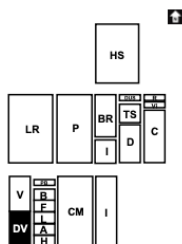


DV

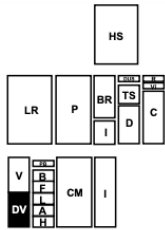
VIRUS DISEASE COLLECTION

6 tuber plots showing symptoms of virus infection in a range of varieties.

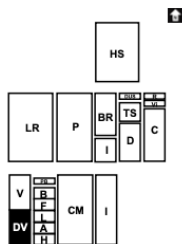
<u>Plot</u>	<u>Variety</u>	<u>Virus Test Result 2020</u>
1	Arsenal	Healthy
2	Arsenal	Y ^N
3	Atlantic	Healthy
4	Atlantic	Y ^N
5	Atlantic	Y ^N
6	Banba	Healthy
7	Banba	Y ^N
8	Brooke	Healthy
9	Brooke	LR
10	Burren	Healthy
11	Burren	Y ^N
12	Burren	LR
13	Cara	Healthy
14	Cara	Y ^N
15	Cara	Y ^N
16	Cara	Y ^O
17	Cara	Y ^N , Y ^O
18	Charlotte	Healthy
19	Charlotte	Y ^N
20	Charlotte	Y ^N
21	Charlotte	Y ^O
22	Desiree	Healthy
23	Desiree	A
24	Desiree	A
25	Desiree	A, Y ^O
26	Desiree	X, Y ^N , Y ^O
27	Desiree	LR
28	Estima	Healthy
29	Estima	A, V
30	Estima	A, V
31	Estima	A
32	Estima	A, Y ^N
33	Estima	LR
34	Gemson	Healthy
35	Gemson	Y ^N



<u>Plot</u>	<u>Variety</u>	<u>Virus Test Result 2020</u>
79	Rooster	X, Y ^N
80	Rooster	LR
81	Royal	Healthy
82	Royal	A
83	Royal	A, Y ^N
84	Russet Burbank	Healthy
85	Russet Burbank	A
86	Russet Burbank	A, Y ^N
87	Saxon	Healthy
88	Saxon	Y ^O
89	Saxon	Y ^O
90	Saxon	LR
91	Slaney	Healthy
92	Slaney	Y ^N
93	Slaney	Y ^N
94	VR 808	Healthy
95	VR 808	Y ^N
96	Argos	Healthy
97	Argos	Y ^N
98	Argos	M, V
99	Argos	M, Y ^N
100	Bambino	Healthy
101	Bambino	Y ^N
102	British Queen	Healthy
103	British Queen	Y ^N
104	Cabaret	Healthy
105	Cabaret	A
106	Casablanca	Healthy
107	Casablanca	A
108	Cultra	Healthy
109	Cultra	Y ^N
110	Eurostar	Healthy
111	Eurostar	Y ^N
112	Fontane	Healthy
113	Fontane	Y ^N
114	Galactica	Healthy
115	Galactica	Y ^N
116	Golden Wonder	Healthy
117	Golden Wonder	A
118	Harmony	Healthy
119	Harmony	Y ^N
120	Harmony	Y ^{NTN}
121	Harmonv	Y ^N , Y ^O



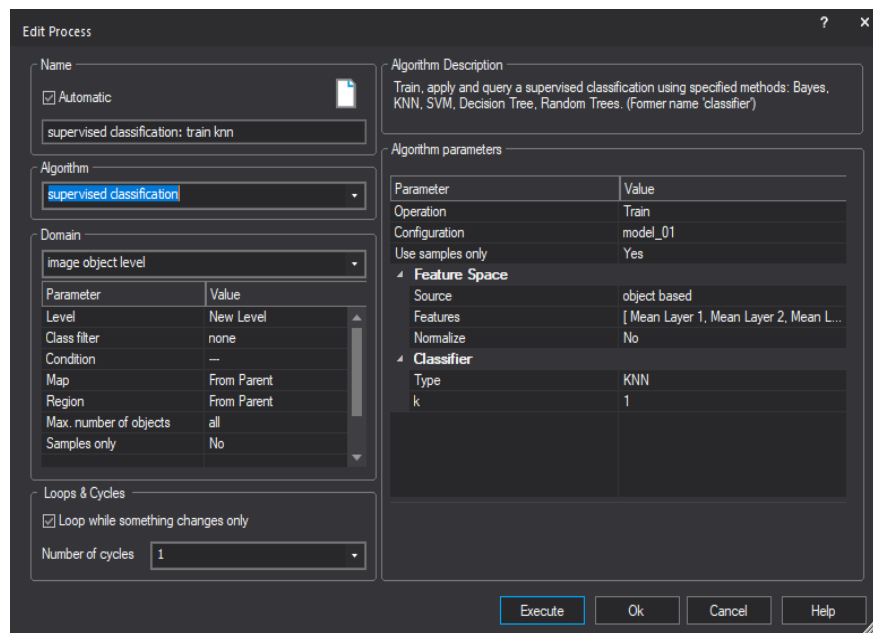
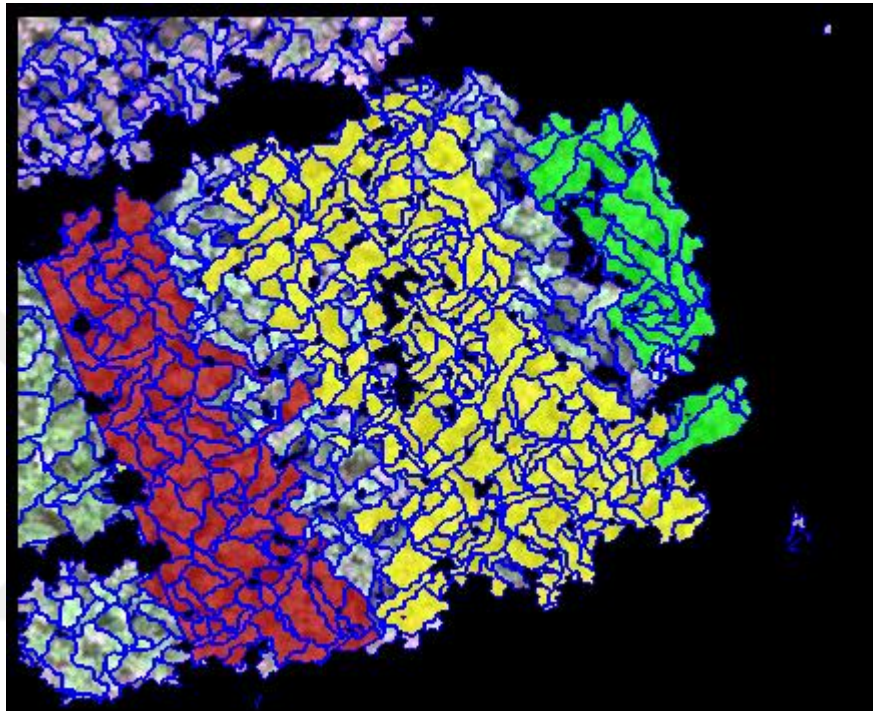
<u>Plot</u>	<u>Variety</u>	<u>Virus Test Result 2020</u>
122	Home Guard	Healthy
123	Home Guard	V
124	Kennebec	Healthy
125	Kennebec	A, X
126	Maris Bard	Healthy
127	Maris Bard	S, X
128	Morene	Healthy
129	Morene	Y ^O
130	Nadine	Healthy
131	Nadine	Y ^{NTN}
132	Nicola	Healthy
133	Nicola	Y ^N
134	Osprey	Healthy
135	Osprey	Y ^N
136	Ramos	Healthy
137	Ramos	Y ^N
138	Record	Healthy
139	Record	Y ^N
140	Record	Y ^O
141	Red Pontiac	Healthy
142	Red Pontiac	A
143	Red Pontiac	Y ^N
144	Rocket	Healthy
145	Rocket	Y ^N
146	Rudolph	Healthy
147	Rudolph	Y ^N
148	Saphire	Healthy
149	Saphire	Y ^N
150	Saturna	Healthy
151	Saturna	Y ^N
152	Shepody	Healthy
153	Shepody	Y ^N , Y ^O
154	Shepody	Y ^N , Y ^O
155	Shepody	Y ^O
156	Vales Sovereign	Healthy
157	Vales Sovereign	Y ^N
158	Valor	Healthy
159	Valor	Y ^O
160	Valor	Y ^O
161	Wilja	Healthy
162	Wilja	Y ^O
163	Wilja	X, Y ^O
164	Winston	Healthy
165	Winston	X



<u>Plot</u>	<u>Variety</u>	<u>Virus Test Result 2020</u>
166	Burren	LR
167	Cultra	LR
168	Desiree	LR
169	Estima	LR
170	Lady Rosetta	LR
171	Maris Peer	LR
172	Maris Piper	LR
173	Navan	LR
174	Pentland Dell	LR
175	Rooster	LR
176	Saxon	LR

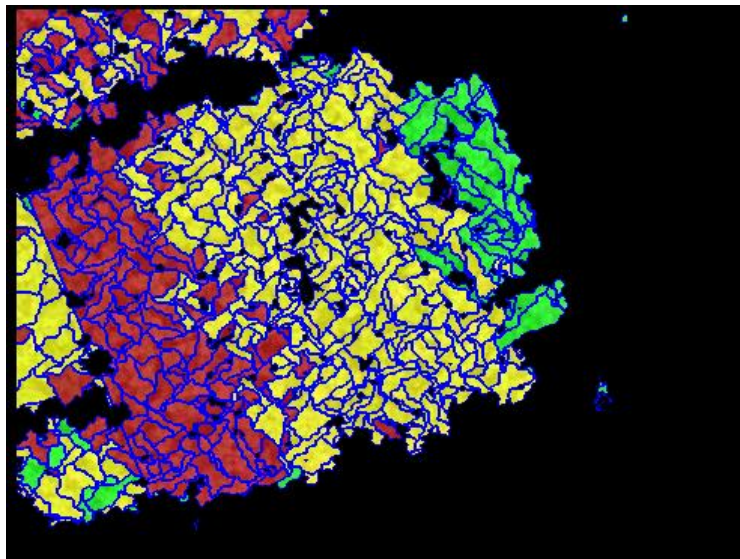
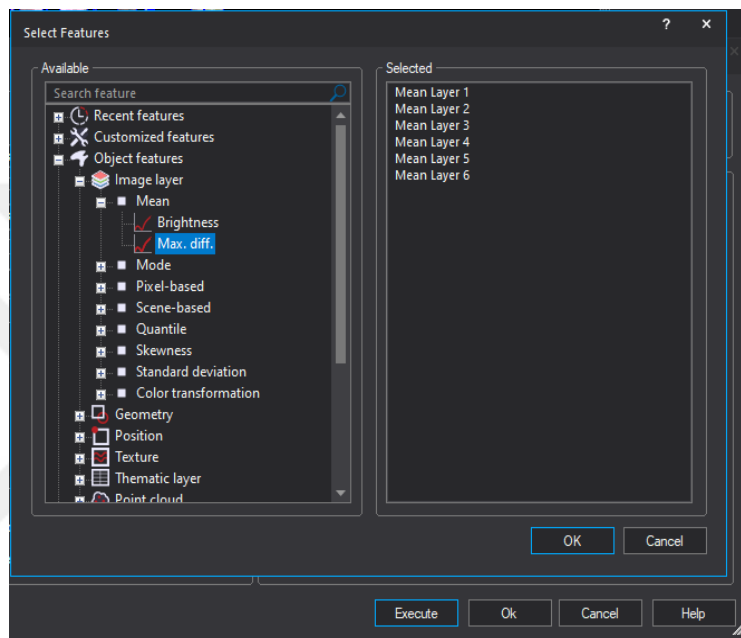
7.2. Appendix 2: Assessing the robust feature layers combination for classification

For the data with same training samples, 3 different layer features tried to find robust combination for classification.



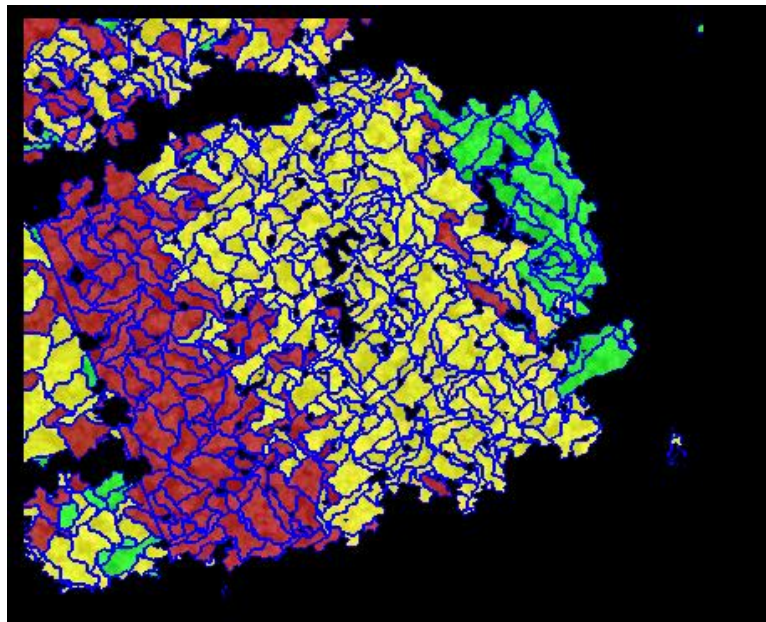
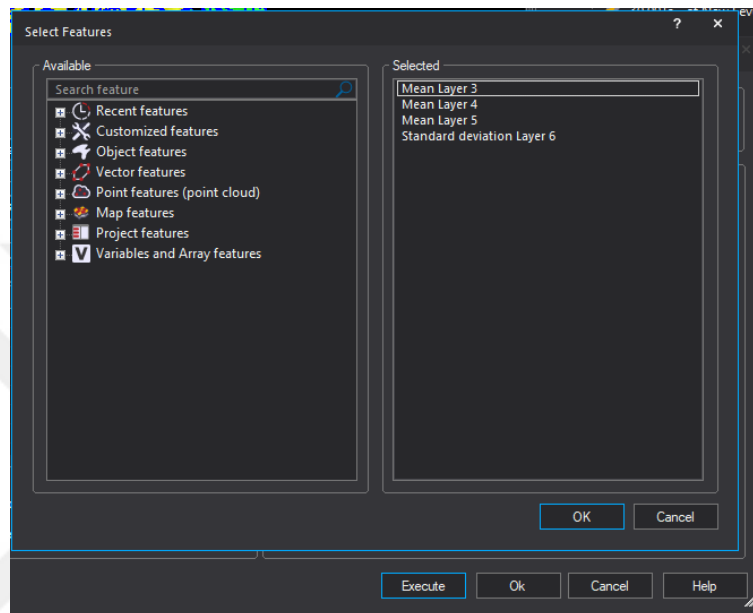
COMBINATION 1:

- Mean Layer 1 = Mean value of Blue band
- Mean Layer 2 = Mean value of Green band
- Mean Layer 3 = Mean value of Red band
- Mean Layer 4 = Mean value of NIR band
- Mean Layer 5 = Mean value of Red-edge band
- Mean Layer 6 = Mean value of NDVI



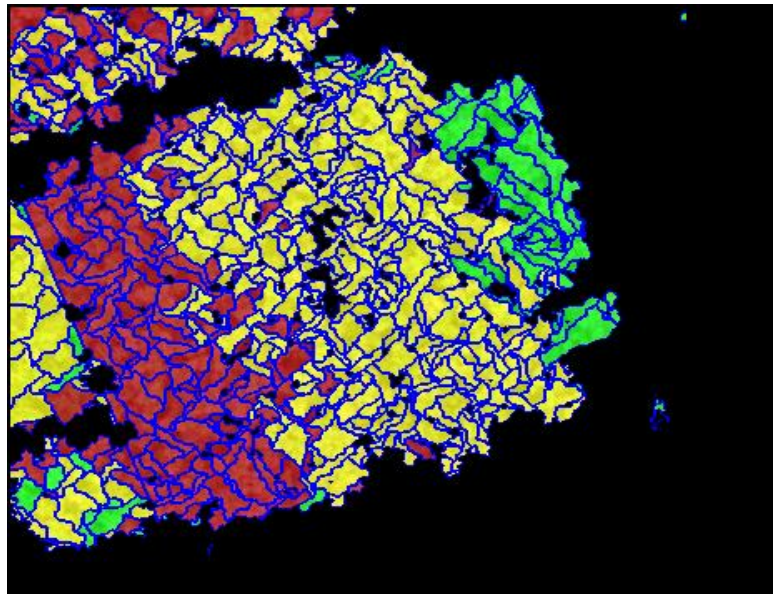
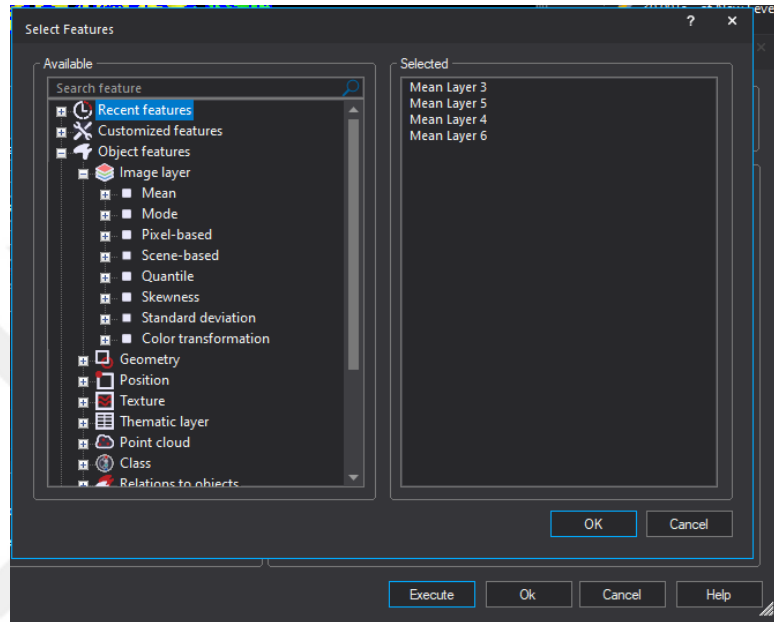
COMBINATION 2:

- Mean Layer 3 = Mean value of Red band
- Mean Layer 4 = Mean value of NIR band
- Mean Layer 5 = Mean value of Red-edge band
- Standard deviation Layer 6 = Standard deviation of NDVI



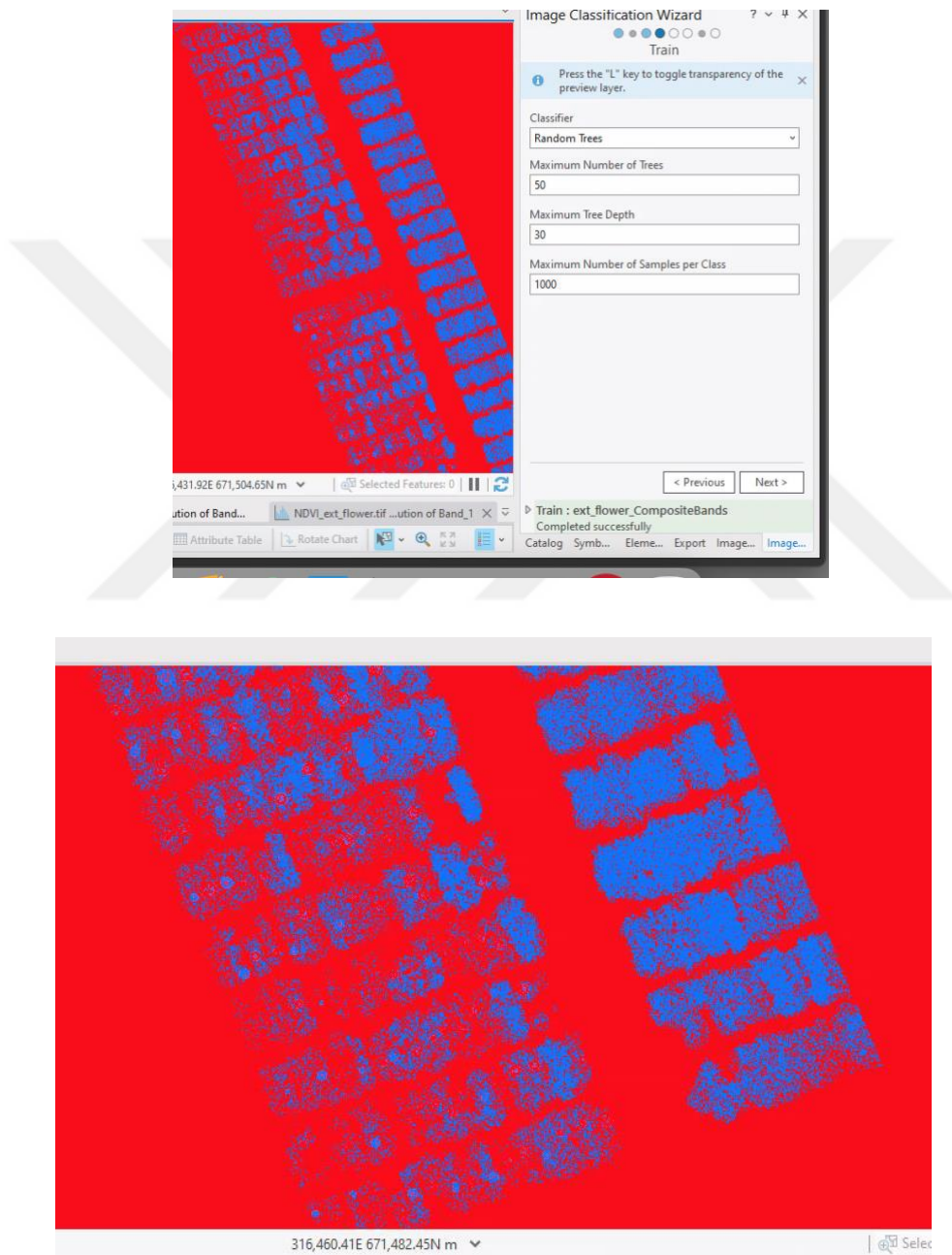
COMBINATION 3:

- Mean Layer 3 = Mean value of Red band
- Mean Layer 4 = Mean value of NIR band
- Mean Layer 5 = Mean value of Red-edge band
- Mean Layer 6 = Mean value of NDVI band



7.3. Appendix 3: Application of pixel-based classification to all study area

According to the algorithm, red areas should show diseased while blue indicates healthy vegetation.



7.4. Appendix 4: List of project files

Data file name	Description	Location
20210709_RE_15m_ReflectanceNormalised	Input Image/TIF File (520 MB)	M:\scratch\Dissertation\Input_data\Farm_img\PelinsuDemirci
VegetaionIndices	Vegetation index calculation/ArcGIS Pro project	M:\scratch\Dissertation\Vegetation Indices\VegetaionIndices
stddevcl	Comparison of standard dev. of indices and band combination with NDVI/ArcGIS Pro project	M:\scratch\Dissertation\BandCombination
MyProject2	Extraction of external pixels(soil and floral pixels)/ArcGIS Pro project	M:\scratch\Dissertation\Externalpixelextaction\MyProject2
Dissertation	Each ROI, trained data, and classification (classification project in eCognition)	M:\scratch\Dissertation\Classification_Imagery\Dissertation
confusionmatrix	Confusion Matrix/ArcGIS Pro prohect	M:\scratch\Dissertation\Confusion_Matrices