

Article

Field Assessment Strategies: Assessing and Classifying Blight Disease in Wild Blueberry Populations Using Multispectral and Hyperspectral Sensors

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Abstract

(1) Background: Monilinia and Botrytis blight are significant diseases affecting wild blueberry fields, leading to substantial yield losses. Traditional methods for disease assessment rely on destructive sampling, which is labor-intensive and subjective. This study explored the use of multispectral and hyperspectral sensors through simple and machine learning approaches to detect and assess Monilinia and Botrytis blight diseases. (2) Methods: In this study, we adopted two experimental approaches: plot and patch assessment trials. These were conducted using a randomized complete block design at three locations in Nova Scotia. Disease detection was performed using vegetative indices (VIs) and spectral reflectance analysis, with destructive samples also assessed. Analysis of variance, correlations and classification approaches were used in the analysis. (3) Results: Significant spectral differences were observed between healthy and diseased plants, particularly in the near-infrared region (715–1050 nm). Nine significant wavelength bands were identified for blight disease detection. Classifier analysis revealed that support vector machines (SVM) and random forests (RF) outperformed k-nearest neighbors (KNN), achieving an overall accuracy of 96.6% and 76.8% in the broad and severity disease level classifications. (4) Conclusions: Despite some limitations, these findings underscore the potential of remote sensing tools for efficient, non-destructive disease management in wild blueberry fields.

Keywords: remote sensing; vegetation indices; hyperspectral imaging; Monilinia blight; Botrytis blight; disease classification



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1. Introduction

Wild blueberries are a significant economic crop that is native to Northeastern America [1]. In Canada, the crop covers a large production area, accounting for 48.9% of the land area for fruit crop cultivation [2]. Wild blueberries consist of several species, including *Vaccinium angustifolium*, *Vaccinium angustifolium* f. *nigrum*, and *Vaccinium myrtilloides*, with *Vaccinium angustifolium* being the dominant species (80%) [3]. The plant grows naturally, but is managed using several practices, including biennial pruning, fertilization, pest and disease control, and pollination support, among other field practices. Despite efforts to control diseases, it remains a major challenge in the production of wild blueberries.

Wild blueberry crops face multiple disease challenges, with Monilinia blight and Botrytis blossom blight being the most economically significant threats [4–6]. Monilinia blight caused by *Monilinia vaccinii-corymbosi* (Reade) Honey (M.vc) affects mainly plant

foliage by forming a water-soaked or dark brown colouration along the midrib and veins of leaves during the F2–F5 phenological stage [6]. Similarly, Botrytis blossom blight, caused by *Botrytis cinerea* Pers.: Fr., also affects the aerial parts of the plant, especially the flowers, by turning infected inflorescences brown and shriveled up, usually covered with greyish mycelia and *Botrytis cinerea* spores during the F6–F7 phenological stage, affecting both wild and cultivated blueberries [6,7]. In Nova Scotia, Botrytis blight has caused yield losses of approximately 30 to 35%, with the extent of the impact varying by the area affected by the disease [8]. The severity of these diseases varies annually depending on field conditions, inoculum levels, field history, duration of wetness, phenotype susceptibility, and temperature [9,10]. Studies have indicated potential disease-tolerant or avoidance phenotypes, with *Vaccinium angustifolium* f. *nigrum* being the most susceptible, and *Vaccinium myrtilloides* exhibiting the tolerant or avoiding traits [7]. Over the years, traditional methods for assessing diseases have relied on extensive field sampling using physical observation and line and transect surveys, which, despite their effectiveness, are time-consuming, labor-intensive, and often destructive [11].

Recent developments and advancements in remote sensing technologies and precision agriculture have shifted the focus toward non-destructive disease assessment methods [12–14]. These remote sensing techniques detect spectral reflectance variations influenced by the plant's physiological changes, such as leaf pigment composition and structural properties [15]. Therefore, disease-affected plants exhibit distinct reflectance patterns in the visible (VIS) and near-infrared (NIR) regions, with a noticeable reduction in reflectance at NIR wavelengths [16]. Several studies conducted in different crops have demonstrated the potential of the hyperspectral and multispectral sensors in detecting plant stress, classifying diseases, and differentiating between healthy and infected crops using spectral signatures and vegetative indices (VIs) [17–19].

Following the developments of remote sensing techniques, machine learning (ML) techniques have further enhanced disease classification and prediction by learning patterns from large spectral datasets [20]. Several ML models, including Support Vector Machines (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNNs), have been successfully applied in remote sensing-based disease detection [3,18]. These classifiers leverage their different capabilities of handling small datasets, improving performance, and avoiding data overfitting in managing different data types to achieve significant accuracies. CNNs have been utilized to extract deep spectral features from multispectral and hyperspectral images, improving classification accuracy. Furthermore, reflectance and vegetative indices (VIs) like the normalized difference vegetative index (NDVI) and green leaf index (GLI) have also been used in this approach [19]. For instance, Mahlein et al. [17] developed a spectral disease index (SDI) to classify *Cercospora* leaf spot, sugar beet rust, and powdery mildew, while Calderón et al. [21], used high-resolution hyperspectral and thermal imagery to detect *Verticillium* wilt in olive trees. Other studies have explored both VIs and spectral-based ML classification for wheat yellow rust [22], rice leaf folder damage [23], and myrtle rust detection in lemon myrtle plantations [24].

Despite the success of these methods in various crops [18], there is a limited adoption of ML-based remote disease detection, particularly using UAV and hyperspectral sensing in wild blueberry production. Current wild blueberry disease assessments are primarily based on physical leaf and floral bud inspections, with limited use of sensor-based technologies [11]. While Botrytis blight detection has been explored in other crops, including strawberry [18], eggplant [25], and lettuce [26]. There is a knowledge gap regarding the lack of comparative studies evaluating UAV-based multispectral versus handheld hyperspectral sensors for remote disease detection in wild blueberries.

Given these diseases' significance and impact on crop productivity, there is a growing need to explore ML-driven, remote sensing approaches for early detection and precision management. Rather than relying on field and laboratory-based destructive methods, field assessments can be enhanced using multispectral and hyperspectral sensors coupled with ML classification models to automate disease detection. Therefore, this study aimed to evaluate the potential of remote sensing and vegetative indices (e.g., NDVI, GLI, GRVI, VARI) to assess *Monilinia* and *Botrytis* blight in wild blueberry fields, integrate ML models (SVM, RF, and KNN) to classify and differentiate between diseased and healthy plants, and compare the effectiveness of multispectral and hyperspectral sensors in disease determination assessments.

2. Materials and Methods

2.1. Study Area

In the 2019/2020 growing season, trials were established in two commercial fields for this study. These sites consisted of Farmington (FT), Lemmon Hill (LH), and Kemptown (KT). These sites are considered among some of the main blueberry production sites located in Colchester County, Nova Scotia, Canada, with the geographic coordinates: 45.573652°N, 63.894130°W for Farmington, 45.188587°N, 62.874343°W for Lemmon Hill, and 45.498936°N, 63.100716°W for Kemptown (Figure 1). The fields are old commercial fields that have been managed for several years; thus, they exhibit good plant coverage and a minimal occurrence of bare patches or weeds, making them suitable for these trials.

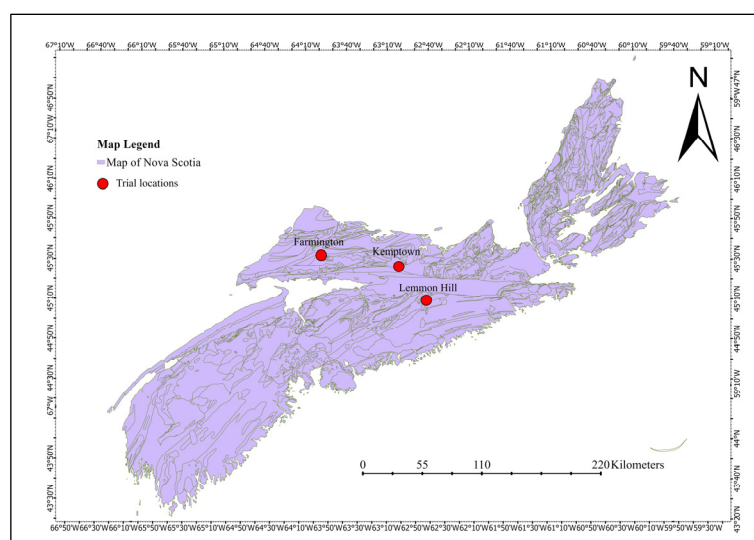


Figure 1. The map of Nova Scotia showing the three study locations, Farmington, Lemmon Hill, and Kemptown.

These areas can be prone to wet conditions that can be encountered for extended periods. This increases the devastating effect of diseases on the field, which affects plant yield; therefore, disease-controlling fungicides are used to mitigate the effect of *Monilinia* and *Botrytis* blight diseases on the field (Figure 2B,C) [11]. Furthermore, the fields are relatively flat and enjoy favorable climatic conditions, with annual rainfall ranging from 1550 mm to 2000 mm. Temperatures typically range from 16 °C to 22 °C between May and August for agricultural activities. The fields were at the same cropping stage of production, exhibiting significant variability among vegetation, uniform plant coverage, and identical plant stages [3].

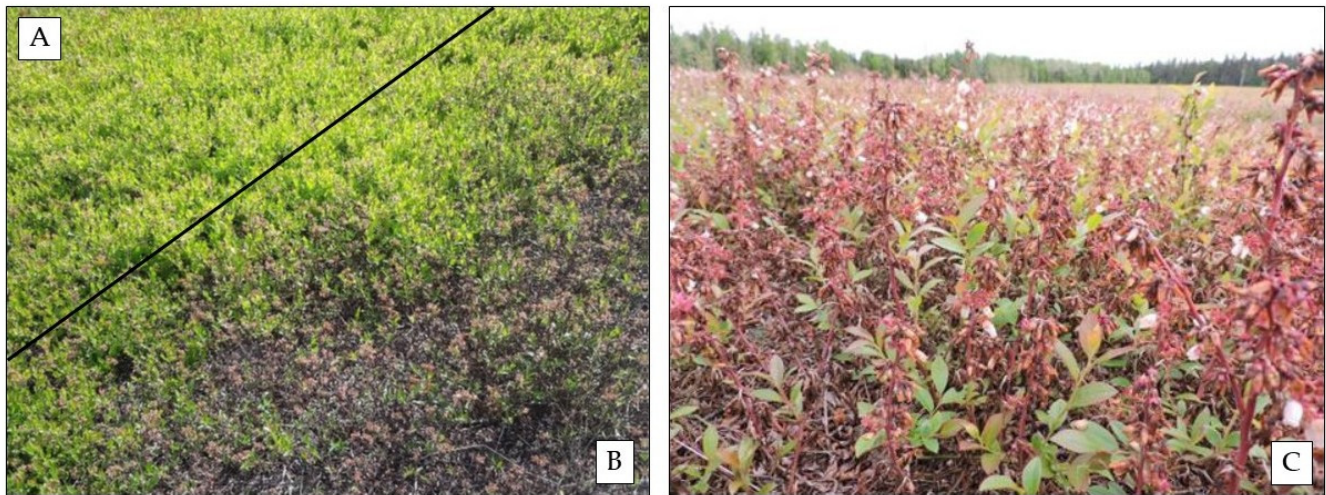


Figure 2. Disease spread in the wild blueberry field: (A) a healthy blueberry patch, (B) a *Monilinia* blight disease-infested patch, and (C) a *Botrytis* blight disease-infested field.

2.2. Experimental Design and Treatment Application

Two field experimental approaches were adopted in this study: (i) a plot assessment trial using the multispectral sensor and (ii) a patch assessment trial using the hyperspectral sensor. In the plot assessment trial, the experimental design was a randomized complete block design (RCBD) with six replications, 4 treatments, and a plot size of 6×8 m with 2 m buffers between plots. A 1×1 m white marker card was placed outside the stake at each corner and georeferenced with an SX Blue Platinum GPS device. Treatments consisted of (i) untreated control (i.e., no *Monilinia* or *Botrytis* blight prevention treatments), (ii) MB but no BB control, (iii) no MB control but BB control, and (iv) MB control and BB control. Fungicide applications followed the description by Anku et al. [27].

In the patch assessment trial, clusters of lowbush plants were identified (0.2×0.2 m), and their phenological growth and development stages were carefully monitored. The patch assessment was conducted using 3 replicates and 3 treatments. The treatments consisted of: (i) Healthy patch (H) -control, (ii) *Monilinia* blight (MB) patch, and (iii) *Botrytis* blight (BB) patch, with 3 levels (i) low, (ii) moderate, and (iii) severe of each treatment were used in this trial (Figure 2).

2.3. UAV Data Collection Using the Micasense Camera

The DJI Matrice Pro 600 UAV (a product of SZ DJI Technological Co., Ltd., Shenzhen, China) was equipped with a 3-band Zenmuse X5, 16-Megapixel (MP) digital camera, and a 5-band MicaSense RedEdge™ 3 multispectral camera (AgEagle, Wichita, KS, USA) (Figure 3c) to collect reflected lights at these wavelengths. The Zenmuse camera was used to collect reflected light at these wavelengths: blue (448), green (548), and red (650), and the Micasense camera was used to collect blue (475), green (560), red (668), red edge (717), and near-infrared (840) banded imagery. The UAV system was flown at a height of 30 m with a frontal image overlap of 75% and a side image overlap of 70%, resulting in a spatial resolution of 2.2 cm/pixel. This height was adopted to avoid the tall vegetation, particularly coniferous and deciduous trees in the field.

The imagery was acquired within an interval of 7 to 11 days, depending on weather conditions, for a total of 4 flights (Table S1). The image collection was conducted under clear conditions (between 10 am and 2 pm) to minimize the effects of clouds, wind, and rain. Calibration and adjustments were carried out using the calibration panel before and after aerial surveys, and ground control points were used to minimize the effects of distortion on the quality of imagery obtained.



Figure 3. Remote sensing tools. (a) Ground control point, (b) Calibration panel, (c) DJI M600 fitted with an MX multispectral sensor, and (d) SX Blue Platinum GPS device.

2.4. Measurement of Spectral Data Using the Hyperspectral Device

A hand-held FieldSpec[®]3 hyperspectral radiometer (Analytical Spectral Devices, ASD, Inc., Boulder, CO, USA) was used to collect accurate and high-resolution spectral signatures of blueberry tissue. The device measures between 350 and 2500 nm in a 1 nm interval, producing 2151 individual wavebands. The instrument was calibrated by taking both dark and white measurements from the spectralon. The final reflectance obtained was determined by a ratio of the data sample compared to the standard data from the white measurements. Therefore, the data represent an average of 50 reflectance spectra. The 10° field-of-view optical lens was held at nadir, at a height of 65 cm above the plant canopy. This reflectance measurement produced a diameter of 11.4 cm circular field of view, large enough to cover a cluster of plants and reduce the effect of background (soil). All measurements were conducted at the same time as aerial imagery was collected.

2.5. Disease Assessment Using the Hyperspectral Sensor

Field assessments of the diseased patch were calculated as a percentage area of plant tissue infected with the disease, as adopted by Percival & Beaton [11]. Therefore, spectral readings were collected once at the 3 disease severities: low (1–30%), moderate (30–70%), and high (70–100%) disease damage (Figure 4 and Figure S1). At every hyperspectral reading, 10 spectral measurements were captured for each severity level.

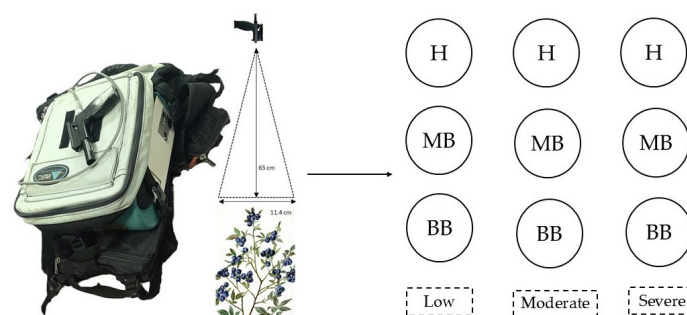


Figure 4. Treatment layout for data collection using the handheld hyperspectral radiometer. H—Healthy patch, MB—Monilinia blight patch, and BB—Botrytis blight patch. Low, moderate, and severe represent disease severity levels.

2.6. Assessment of Disease Incidence and Severity

Fifteen (15) stems per patch were randomly assessed by an experienced pathologist, who helped with the disease assessment process. Disease identification was determined by the usual visual morphological symptoms diagnosis. Therefore, MB was identified by observing a water-soaked or dark brown colouration along the midrib and veins of leaves during the F2–F5 phenological stage [6]. Similarly, BB was identified by the inflorescences turning brown and shriveled up, covered with greyish mycelia and spores during the F6–F7 phenological stage [6,7]. Disease incidence and severity were determined by adopting the method of Percival & Beaton [11]. The disease incidence was determined as the proportion of floral buds or leaf buds with visual symptoms of disease within a stem (A). Severity was estimated by the proportion of tissue area of each flower with visual symptoms of Monilinia and Botrytis blight on a stem. Disease severity was assessed as the percentage of floral tissue area or leaf tissue area infected with visual symptoms of the disease on the stem (B).

A. Disease incidence% (e.g., Floral/Leaf basis):

$$= \frac{\text{Number of floral or vegetative nodes with at least one lesion}}{\text{Total number of floral/vegetative nodes}} \times 100\%$$

B. Disease Severity (e.g., Surface Area Basis) 0 to 100% rating scale where 0 = no disease and 100% = entire surface of each blossom/leaf tissue area affected (average of the overall percentage of blossom/leaf surface area affected)

2.7. Vegetative Indices (VIs)

Vegetative indices (VIs) computed using light bands have been used to perform several functions, including monitoring phenology, disease, and nutrient assessments, which formed a significant aspect of the process workflow (Figure 5). Of the several vegetative indices (VIs) that could have been utilized, these selected indices (VIs) were adopted in this study using the Solvi online platform (Table 1 and Figure 6). These indices were selected based on their ability to determine changes in plant health, greenness of leaf or leaf chlorophyll, and plant density.

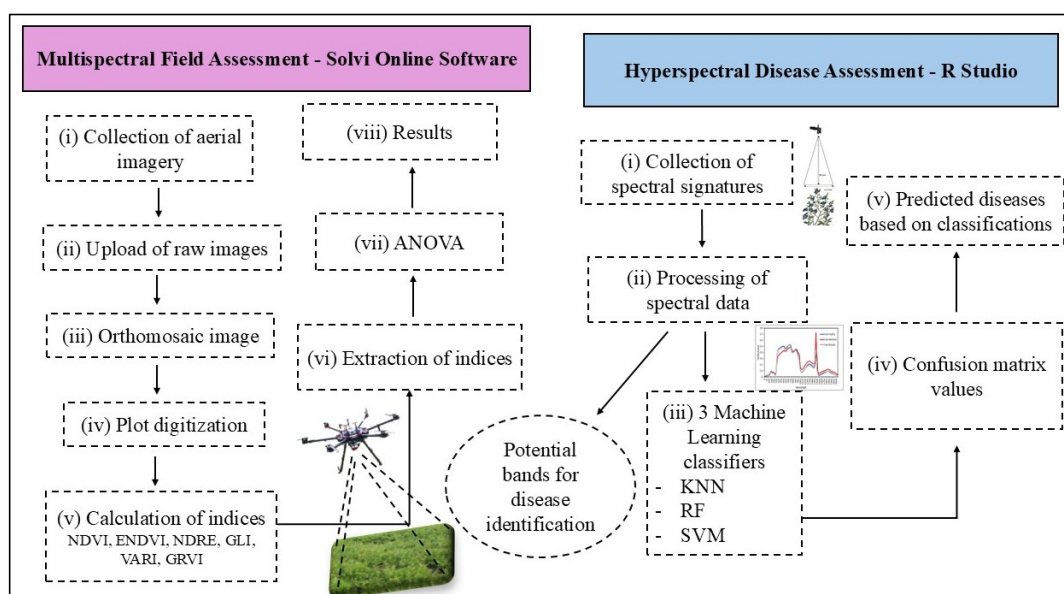


Figure 5. Workflow of the various processes and activities conducted in the disease assessment process.

Table 1. Some vegetative indices computed from the hyperspectral sensor.

Vegetation Indices	Equation ^a
Green Leaf Index (GLI)	$GLI = (2 \cdot R560 - R668 - R475) / (2 \cdot R560 + R668 + R475)$
Green, Red Vegetation Index (GRVI)	$GRVI = (R560 - R668) / (R560 + R668)$
Normalized Difference Vegetation Index (NDVI)	$NDVI = (R840 - R668) / (R840 + R668)$
Enhanced Normalized Difference Vegetation Index (ENDVI)	$ENDVI = (R840 + R560) - (2 \times R475) / (R840 + R560) + (2 \times R475)$
Normalized Difference Red Edge (NDRE)	$NDRE = (R840 - R717) / (R840 + R717)$
Visible atmospheric red index (VARI)	$VARI = (R560 - R668) / (R560 + R668 - R475)$
Soil Atmospheric Vegetative Index (SAVI)	$SAVI = (1 + 0.5) (R840 - R668) / (R840 + R668 + 0.5)$

^a Indices are grouped based on the major wavelengths of the micasense sensor: NIR (n, 840 nm), red edge of chlorophyll absorption (RE, 717 nm), red (R, 668 nm), green (G, 560 nm), blue (B, 475 nm).

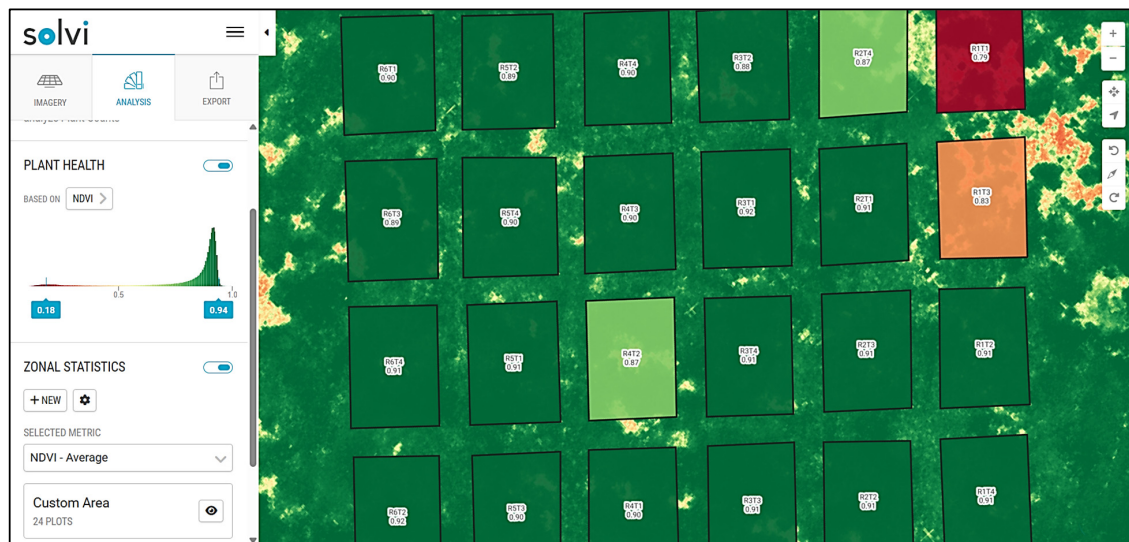


Figure 6. Zonal statistics from the field treatment trial showing raw VI values obtained through the Online Solvi platform. The image was accessed on 17 June 2020 from Lemmon Hill after fungicide application, for which assessments were conducted.

2.8. Statistical Analysis

2.8.1. Analysis of Variance (ANOVA)

As adopted by Devadas et al. [28], an ANOVA was performed to determine which treatments, healthy, MB, and BB disease, were significantly different under the two assessment processes. Healthy, MB, and BB treatments were compared at 3 severity levels (low, moderate, and severe) for all vegetative indices as adopted by Zheng et al. [22] and Calderón et al. [21], under the patch assessment. Similarly, field data from the multispectral trial were also analyzed using ANOVA to assess the treatment effects on disease incidence and severity and their corresponding effects on VIs. Therefore, where differences are observed, the least significant difference (LSD) was used for multiple means comparison at $\alpha = 0.05$. Furthermore, a correlation analysis was conducted to establish a relationship between VIs and disease incidence and severity; thus, the correlation measured the strength of the relationship between the variables. For statistical testing, the error terms fulfill all model assumptions; thus, the assumptions of normality (Anderson–Darling test at $\alpha = 0.1$), constant variance, and independence of the error terms were fulfilled. The ANOVA was conducted using the Statistical Analysis System (SAS) (version 9.4, SAS Institute, Inc., Cary, NC, USA).

Spectral data was explored to distinguish between diseased and healthy plant treatments at different stages using two parameters: (i) spectral difference value (Equation (1)), and (ii) sensitivity values (Equation (2)).

$$\text{Spectral difference value} = x - y \quad (1)$$

$$\text{Sensitivity Value} = \frac{y}{x} \text{ (for each wavelength)} \quad (2)$$

where x = mean reflectance value of healthy plants, and y = mean reflectance of diseased plants.

2.8.2. Classification Algorithms

This study employed three widely used machine learning (ML) classifiers, Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbour (KNN) for the classification task. Each classifier was chosen for its ability to handle small datasets, high-dimensional data, missing values, and outliers, ensuring robust and accurate predictions [20,29]. The SVM classifier functions as a linear binary classifier, identifying an optimal hyperplane to separate different classes. With kernel functions, it efficiently handles both linear and non-linear classifications, making it effective for high-dimensional datasets and small sample sizes [20,30]. The RF classifier, a powerful ensemble learning method, constructs multiple decision trees and aggregates their outputs to enhance classification performance. It reduces variance, mitigates overfitting, and ranks feature importance, making it useful for feature selection and high-dimensional data analysis [20]. The KNN algorithm is a non-parametric, instance-based learning method that classifies data based on its k -nearest neighbors in the feature space. It is particularly effective for non-linear decision boundaries and datasets with unknown input–output relationships [31]. Additionally, these classifiers were selected due to their robustness, adaptability, and effectiveness in various real-world applications, including agriculture, remote sensing, and environmental monitoring.

Classification analysis was performed on the hyperspectral data using these 3 classifiers, as has been conducted in other studies [3,32]. A dataset of 270 spectral readings was computed into 90 VIs, which were subjected to classification with 0.75 and 0.25 of the datasets used as test and training samples, respectively. For the SVM classifier, a radial basis function kernel was used. In the RF model, the number of trees was set to 500, with no maximum depth to allow the trees to grow fully until a default stopping criterion was met. For the KNN classifier, the optimal k -value was determined using a grid search and set to $k = 5$, based on the best performance from cross-validation. This approach was subjected to a 10-fold cross-validation, and the process was repeated 20 times.

The variable importance plot was utilized as adopted by Anku et al. [3] and indicated the contribution of specific VIs. Therefore, predictors were represented as vegetative indices, allowing a VI value to determine which group a treatment belonged to. To address multicollinearity in this machine learning analysis, a Variance Inflation Factor (VIF) analysis was conducted to assess the degree of correlation among the independent variables. Based on the VIF results, the number of variables was reduced from seven to three, ENDVI, NDRE, and VARI, which were retained for the classification process due to their lower multicollinearity. This reduction ensured that the model output could more accurately reflect the individual contributions of each variable.

The selected vegetation indices (VIs) were then evaluated using variable importance plots and Accumulated Local Effect (ALE) plots across different classifiers. These tools helped identify the predictors that significantly influenced classification performance. Previous findings supported the decision to reduce the number of independent variables [33], where strong correlations among predictors in a multiple regression context were shown to distort interpretability. The refined subset of variables was subsequently used in supervised classification to enhance model clarity and reliability.

In addition, the probability histogram function, which defines the likelihood of a series of random variable outcomes predicting a discrete variable or a continuous variable, was assessed. This plot was a statistical measure used to determine the ability of a VI

to discriminate between diseases [19]. These classification analyses were conducted in R software version 4.2.3.

3. Results

3.1. UAV Plot Assessment Using the Multispectral Sensor

On the plot assessment aspects, the general field assessment and statistical analysis revealed that there were no significant differences between treatments. Thus, VIs did not perform as expected in determining blight diseases from an aerial perspective (Figure 6 and Tables 2–5 and S2–S5). Though there were largely no significant differences between the treatments on disease incidence and severity (Tables 2 and 4), the corresponding analysis using VIs (Tables 3 and 5) also revealed similar results.

Table 2. Incidence and severity of Monilinia and Botrytis blight disease from the plot assessment trial at Lemmon Hill after the 2nd fungicide application. Plant samples for this observation were collected on 4 June 2020.

Treatment	Monilinia Incidence of Floral Nodes (%) ¹	Monilinia Incidence of Vegetative Nodes (%) ²	Monilinia Severity of Floral Node ³	Monilinia Severity of Vegetative Node ⁴	Botrytis incidence of Floral Nodes (%) ⁵	Botrytis Incidence of Vegetative Nodes (%) ⁶	Botrytis Severity of Floral Node ⁷	Botrytis Severity of Vegetative Node ⁸
Untreated Control	0	1.58 a	0	9.78 a	0	0	0	0
Monilinia Control	0	0.62 b	0	4.91 b	0	0	0	0
Botrytis Control	0	0.76 b	0	3.72 b	0	0	0	0
Monilinia & Botrytis Control	0.02	0.02 c	0.11	0.09 c	0	0	0	0
ANOVA Results ⁹	NS	Sig. ($p < 0.0001$)	NS	Sig. ($p < 0.0001$)	NS	NS	NS	NS

^{1,2,5,6} % Incidence = 0 to 100%, where 0 = no blossoms/leaves affected and 100 = all blossoms/leaves are affected with at least one lesion. ^{3,4,7,8} Severity = 0 to 9 rating scale, where 0 = no disease and 9 $\geq$ 90% of each blossom/leaf tissue is affected. ⁹ Analysis of variance (ANOVA) results refer to treatment effects that were either not significant (NS) or significant at $p < 0.05$, where the letters (a–c) indicate significant differences between treatments. Mean separation was completed using Fisher’s multiple means comparison test procedure ($\alpha = 0.05$).

Table 3. Mean vegetative indices (VIs) from the plot assessment trial at Lemmon Hill after the 2nd fungicide application [4 June 2020].

Treatment	GLI	GRVI	VARI	NDVI	NDRE	ENDVI	SAVI
Untreated Control	0.112	0.133	0.115	0.545	0.170	0.500	0.458
Monilinia Control	0.146	0.129	0.111	0.523	0.162	0.490	0.475
Botrytis Control	0.110	0.145	0.132	0.525	0.154	0.515	0.620
Monilinia & Botrytis Control	0.100	0.162	0.185	0.540	0.155	0.485	0.470
ANOVA Results ¹	NS	NS	NS	NS	NS	NS	NS

¹ Analysis of variance (ANOVA) results refer to treatment effects that were either not significant (NS) or significant at $p < 0.05$. Mean separation was completed using Fisher’s multiple means comparison test procedure ($\alpha = 0.05$).

Table 4. Incidence and severity of Monilinia and Botrytis blight disease from the plot assessment trial at Kempton after the 2nd fungicide application. Plant samples for this observation were collected on 2 June 2020.

Treatment	Monilinia Incidence of Floral Nodes (%) ¹	Monilinia Incidence of Vegetative Nodes (%) ²	Monilinia Severity of Floral Node ³	Monilinia Severity of Vegetative Node ⁴	Botrytis Incidence of Floral Nodes (%) ⁵	Botrytis Incidence of Vegetative Nodes (%) ⁶	Botrytis Severity of Floral Node ⁷	Botrytis Severity of Vegetative Node ⁸
Untreated Control	0	0.01	0	0.06	0	0	0	0
Monilinia Control	0	0	0	0	0	0	0	0
Botrytis Control	0	0	0	0	0	0	0	0
Monilinia & Botrytis Control	0	0	0	0	0	0	0	0
ANOVA Results ⁹	NS	NS	NS	NS	NS	NS	NS	NS

^{1,2,5,6} % Incidence = 0 to 100%, where 0 = no blossoms/leaves affected and 100 = all blossoms/leaves are affected with at least one lesion. ^{3,4,7,8} Severity = 0 to 9 rating scale, where 0 = no disease and 9 $\geq$ 90% of each blossom/leaf tissue is affected. ⁹ Analysis of variance (ANOVA) results refer to treatment effects that were either not significant (NS) or significant at $p < 0.05$. Mean separation was completed using Fisher’s multiple means comparison test procedure ($\alpha = 0.05$).

Table 5. Mean vegetative indices (VIs) from the plot assessment trial at Kemptown after the 2nd fungicide application [2 June 2020].

Treatment	GLI	GRVI	VARI	NDVI	NDRE	ENDVI	SAVI
Untreated Control	0.044	−0.109	−0.147	0.559	0.281	0.645	0.810
Monilinia Control	0.070	−0.084	−0.113	0.601	0.291	0.678	0.844
Botrytis Control	0.080	−0.067	−0.093	0.556	0.275	0.640	0.768
Monilinia & Botrytis Control	0.082	−0.070	−0.095	0.605	0.289	0.680	0.847
ANOVA Results ¹	NS	NS	NS	NS	NS	NS	NS

¹ Analysis of variance (ANOVA) results refer to treatment effects that were either not significant (NS) or significant at $p < 0.05$. Mean separation was completed using Fisher's multiple means comparison test procedure ($\alpha = 0.05$).

Despite that no significant differences between treatments were observed, some patterns did emerge (Tables 3 and 5). The control treatments had low mean values for the light VIs on all sampled days, except for the Near-Infrared (NIR) indices, where the Botrytis control had the lowest values, and the combined treatments showed higher values (Tables 3 and 5). Although the differences were not statistically significant, some variations in mean values suggest some levels of treatment differences. The combined treatments (MB + BB control) had the highest values across different VIs. Overall, we observed minimal differences in VI values.

Correlation analysis between VIs and disease incidence and severity varied between the two variables (Tables 6 and 7). Generally, the correlation between these variables was low, with a blend of both positive and negative correlation strengths across the different locational trials. Moderate correlation values occurred between VIs (NDVI, ENDVI, VARI, & SAVI) and MB leaf incidence.

Table 6. Correlation of different VIs with Monilinia blight (MB) incidence and severity on floral buds (Fb) and leaves (L) obtained from trial plots at Lemmon Hill on the 4 June 2020.

Vegetative Indices	4 June 2020			
	MB/Fb Incidence	MB/Fb Severity	MB/L Incidence	MB/L Severity
GLI	−0.33	−0.33	−0.11	−0.12
GRVI	−0.34	−0.34	−0.078	−0.12
VARI	−0.31	−0.31	−0.01	−0.05
NDVI	−0.10	−0.10	−0.41 *	−0.34
ENDVI	−0.04	−0.04	−0.39 *	−0.30
NDRE	−0.01	−0.01	−0.35	−0.29
SAVI	0.12	0.12	0.09	0.11

* Significant at $p < 0.05$.

Table 7. Correlation of different VIs with Monilinia blight (MB) and Botrytis blight (BB) incidence and severity on floral buds (Fb) and leaves (L) obtained from trial plots at Kemptown on 17 June 2020.

Vegetative Indices	17 June 2020					
	MB/Fb Incidence	MB/Fb Severity	MB/L Incidence	MB/L Severity	BB/Fb Incidence	BB/Fb Severity
GLI	0.26	0.31	0.37	0.31	−0.24	−0.26
GRVI	0.27	0.32	0.38	0.31	−0.24	−0.26
VARI	0.27	0.31	0.39 *	0.32	−0.25	−0.27
NDVI	0.21	0.29	0.32	0.25	−0.25	−0.23
ENDVI	0.21	0.29	0.29	0.23	−0.24	−0.24
NDRE	0.08	0.15	0.04	0.02	−0.19	−0.14
SAVI	0.20	0.28	0.40 *	0.33	−0.25	−0.24

* Significant at $p < 0.05$.

3.2. Patch Assessment and Disease Classification Using the Hyperspectral Sensor

It was observed that disease treatments exhibited significant spectral differences compared to healthy patches, especially as the severity of the disease increased. These differences were evident in the visible and near-infrared light regions (Figure 7). The spectrum of diseased plants showed a low absorption of light in the blue and red regions, along with low reflectance in the green and near-infrared regions. In contrast, healthy patches displayed strong absorption of blue and red light and high reflectance of green and near-infrared light. These variations were linked to changes in leaf pigments, primarily evident in the visible light region (455–770 nm) (Figure 7). For each treatment category, the spectral signatures were averaged into a single representation. The progression of disease severity had a notable impact on the different treatment signatures. At low severity stages, the spectral curves for all treatments were nearly identical, except for the MB treatment (Figure 7). As the severity increased, distinct differences emerged between the various severity levels.

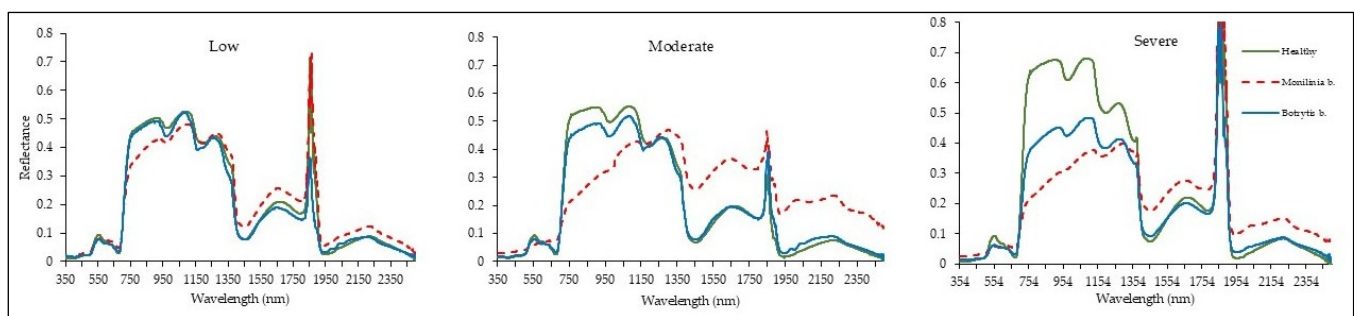


Figure 7. Spectral signature of the three treatments at the three severity levels (low, moderate, and severe).

The spectral signature of healthy plants corresponded to high photosynthetic activity in the visible (VIS) region, showing a pronounced reflectance peak of photosynthetic pigments in the green region, along with high reflectance in the near-infrared (NIR) region (Figure 8a). For this reason, the signatures of healthy plants were used as standards to compare against the spectral signatures of diseased tissues. The reflectance graph displays an average of the spectral signatures for healthy plants and those with MB and BB diseases across different severity levels. Notable differences were detected between the signatures of healthy and diseased treatments in both the visible (350–700 nm) and near-infrared (701–1050 nm) regions.

Spectral differences between the healthy patch and those exhibiting various severities of MB revealed several important findings. All three severities (high, moderate, and low) revealed similar patterns, identifying 555, 681, and 761 nm as the most significant points of interest (Figure 8b). Notably, low severity exhibited the lowest spectral difference, while high and moderate severities observed a much greater spectral deviation. Sensitivity values slightly differed but were largely similar across the three severities. In all three severities, these wavelengths, 745, 680, 554, 484, and 415 nm, were the highest sensitivity points and consistently reflected the same results across all conditions (Figure 8c).

Spectral reflectance for the healthy and diseased signatures was consistent with established principles, thus, similar to the observation under *Monilinia* blight (Figure 9). Spectral differences between the different treatments were observed at the visible (350–700 nm) and near-infrared (701–1050 nm) portions of the light spectrum. However, similar spectral patterns were observed for the diseased signatures except for the high severity, which observed a low reflectance in the VIS regions.

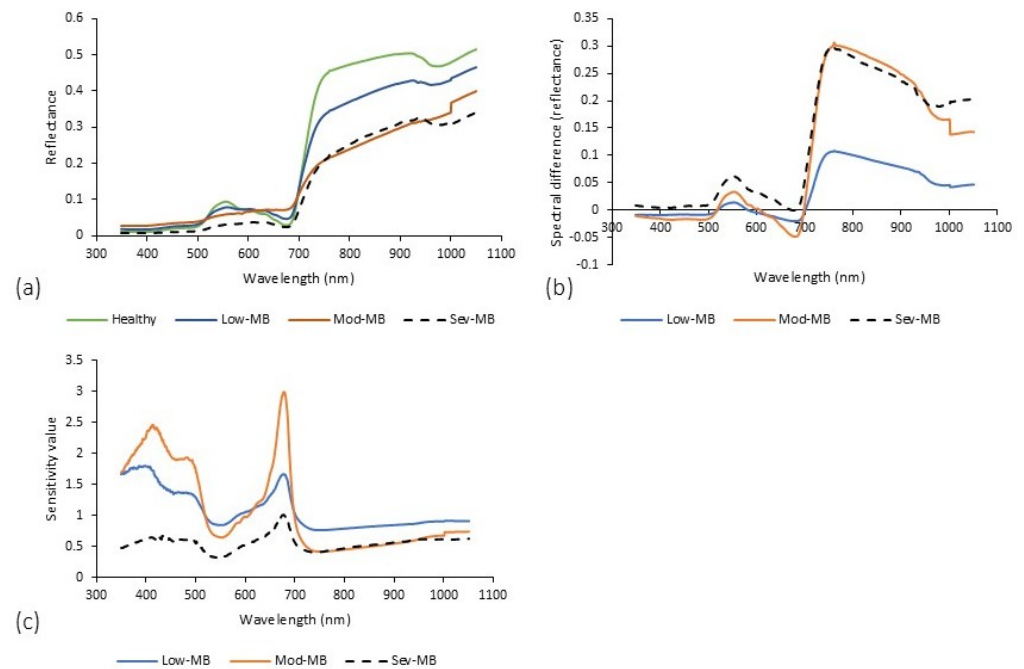


Figure 8. Reflectance data on Monilinia blight (MB) disease: (a) Mean reflectance values, (b) Spectral difference, and (c) Sensitivity values.

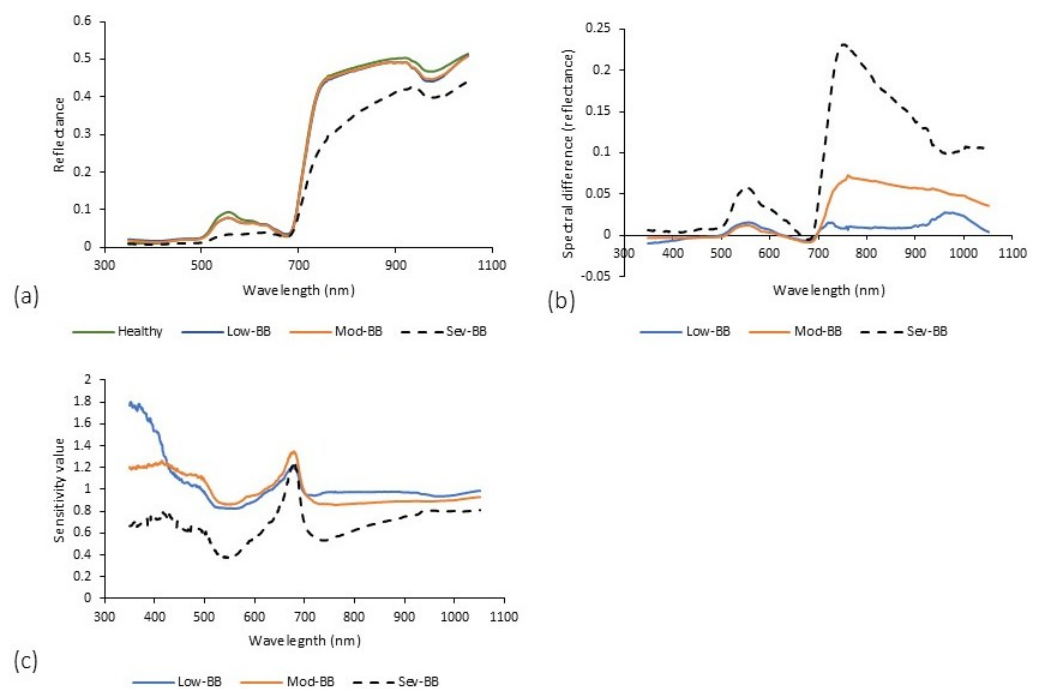


Figure 9. Reflectance data on Botrytis blight (BB) disease: (a) Mean reflectance values, (b) Spectral difference, and (c) Sensitivity values.

The reflectance values varied with disease severity under Botrytis blight, showing significant changes in high severity compared to moderate and low levels (Figure 9b). Differences were found between high, moderate, and low severities in the 500 to 680 nm wavelength ranges, but no distinction was made between low and moderate. In the 710 to 1000 nm range, variations were significant across severity levels. Sensitivity differences appeared in both the VIS and NIR regions, similar to those of Monilinia blight (Figure 9c). High severity exhibited clear differences in both regions, while low and moderate severity showed similar responses, with high severity having a notable difference in sensitivity.

3.2.1. Analysis of Variance on Spectral Signatures Using Vegetative Indices

An analysis of variance on vegetative indices showed that there were significant differences between treatments (Table 8). At the 3 severity levels, significant differences were established across all treatments. Consistently, MB was significantly different from the healthy treatment, with some significant differences from the BB treatment. The BB treatment was not consistent under both moderate and severe disease levels; however, low BB showed levels of consistency across all 6 VIs. Therefore, it indicates that there is a clear potential in identifying or classifying these broad treatment groups.

Table 8. Analysis of disease assessment on healthy patch, Monilinia diseased patch, and Botrytis disease patch at the different severities using vegetative indices (VIs).

Treatments	NDVI ^L	NDVI ^M	NDVI ^S	ENDVI ^L	ENDVI ^M	ENDVI ^S
Healthy	0.879 a	0.903 a	0.903 a	0.548 a	0.610 a	0.610 a
MB	0.771 b	0.571 c	0.621 b	0.412 b	0.170 c	0.019 c
BB	0.830 ab	0.652 b	0.652 b	0.590 ab	0.219 b	0.219 b
ANOVA	$p < 0.004$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
	GLI ^L	GLI ^M	GLI ^S	GRVI ^L	GRVI ^M	GRVI ^S
Healthy	0.565 a	0.590 a	0.590 a	0.501 a	0.538 a	0.538 a
MB	0.345 b	0.056 c	0.105 c	0.229 b	−0.08 c	−0.004 b
BB	0.428 b	0.199 b	0.194 b	0.327 b	0.028 b	0.028 b
ANOVA	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
	NDRE ^L	NDRE ^M	NDRE ^S	SAVI ^L	SAVI ^M	SAVI ^S
Healthy	0.288 a	0.299 b	0.299 a	0.670 a	0.720 a	0.720 a
MB	0.269 c	0.245 c	0.241 b	0.545 b	0.345 b	0.281 c
BB	0.302 b	0.315 a	0.315 a	0.621 a	0.377 b	0.377 b
ANOVA	$p < 0.001$	$p < 0.008$	$p < 0.001$	$p < 0.007$	$p < 0.001$	$p < 0.001$
	VARI ^L	VARI ^M	VARI ^S			
Healthy	0.600 a	0.645 a	0.645 a			
MB	0.292 b	−0.112 b	−0.007 b			
BB	0.404 b	0.035 b	0.035 b			
ANOVA	$p < 0.001$	$p < 0.001$	$p < 0.001$			

Analysis of variance (ANOVA) with significance at $p < 0.05$. Mean separation was completed using Fisher's multiple means comparison test procedure ($\alpha = 0.05$), where the letters (a–c) indicate significant differences between treatments. Means with the same letters mean they are not significantly different from each other. L, M, and S represent low, moderate, and severe disease damage.

3.2.2. Classification of Treatments Using KNN, RF, and SVM Classifiers

Classification using vegetative indices under the different classifiers revealed similarities and differences between some of these classifiers. Results have shown that discrimination or classification into the three broad groups achieved significant results with the highest OA value of 96.6% (Table 9). Across the entire table, between the producer and user accuracy, the highest accuracy achieved was 100%, and this occurred under Botrytis blight disease using the RF classifier. Classification of Botrytis blight received high percentages under both user and producer accuracies of RF and SVM classifiers. However, comparing the 3 classifiers and their disease treatments, results have shown that the SVM classifier generated the best outcome among the three classifiers. Conversely, some relatively low accuracy values obtained for Monilinia indicate levels of misclassifications (Table 9).

The classification of MB under both RF and SVM classifiers of the user's and producer's accuracy observed the lowest values under both SVM and RF classifiers. Generally, these results have shown that broadly identifying these major classes is possible using VIs, with the highest possibility of identifying Botrytis blight conditions (Table 9).

Table 9. Confusion matrix on the 3 broad conditions using KNN, RF, and SVM classifiers.

Classifier		Botrytis	Healthy	Monilinia	U. Accuracy
K-Nearest Neighbour	Botrytis	31.8	1.2	1.9	91.1%
	Healthy	1.1	32.2	0.9	94.2%
	Monilinia	0.4	0.0	30.5	98.7%
	P. accuracy	95.5%	96.5%	91.5%	94.7%
Random Forest	Botrytis	33.3	0.0	0.1	99.8%
	Healthy	0.0	31.1	1.3	96.1%
	Monilinia	0.0	2.2	32.0	93.5%
	P. accuracy	100%	93.3%	96.0%	96.5%
Support Vector Machine (SVM)	Botrytis	32.2	0.0	0.1	99.8%
	Healthy	0.0	32.2	1.2	96.5%
	Monilinia	1.1	1.1	32.1	93.5%
	P. accuracy	96.7%	96.7%	96.3%	96.6%

Conversely, classification of the three disease severities highlighted levels of misclassification both under user and producer accuracies (Table 10). However, results using the overall accuracy (OA) showed that the SVM classifier among the three classifiers was the best, with a value of 76.83%, followed by KNN (70.8%) and then the RF (70.67%) classifier. Furthermore, results from all three classifiers have shown that determination of BB at low severity was consistently high under both users' and producers' accuracy, with the highest value of 95.27%. Determination of both moderate and severe BB conditions was very poor under all 3 classifiers. Conversely, MB low, moderate, and severe conditions were highly classified under all 3 classifiers.

Table 10. Confusion matrix of the different disease severities using KNN, RF, and SVM classifiers.

Classifier		Low-BB	Mod.-BB	Sev.-BB	Healthy	Low -MB	Mod. -MB	Sev.-MB	U. Accuracy
K-Nearest Neighbour (KNN)	Low-BB	7.89	1.00	1.00	1.11	0	0.50	0	68.6%
	Mod.-BB	1.06	0.44	9.67	0	0	0.33	0	3.9%
	Sev.-BB	1.17	9.50	0.28	0	0	0.28	0	2.5%
	Healthy	1.00	0	0	32.11	1.11	0	0	93.8%
	Low-MB	0	0.17	0.17	0.11	10.00	0	0	95.8%
	Mod.-MB	0	0	0	0	0	10.00	1.00	90.9%
	Sev.-MB	0	0	0	0	0	0	10.11	100%
	P. accuracy	71%	4%	2.5%	96.3%	90%	90%	91%	70.8%
Random Forest (RF)	Low-BB	8.72	1.56	1.83	0	0	0	0	72.02%
	Mod.-BB	1.94	0.78	9.22	0	0	0	0	6.51%
	Sev.-BB	0.28	8.78	0.06	0	0	0	0	0.61%
	Healthy	0.17	0	0	31.11	1.11	0	0	96.05%
	Low-MB	0	0	0	2.22	10	0	0	81.82%
	Mod.-MB	0	0	0	0	0	10	1.11	90%
	Sev.-MB	0	0	0	0	0	1.11	10	90%
	P. accuracy	78.5%	7%	0.5%	93.33%	90%	90%	90%	70.67%
Support Vector Machine (SVM)	Low-BB	7.83	0.17	0.22	0	0	0	0	95.27%
	Mod.-BB	1.11	2.28	8.56	0	0	0	0	19.07%
	Sev.-BB	1.11	8.67	2.33	0	0	0.06	0	19.18%
	Healthy	0.00	0	0	32.22	1.11	0	0	96.67%
	Low-MB	1.06	0	0	1.11	10.00	0	0	82.19%
	Mod.-MB	0.00	0	0	0	0	11.06	0	100%
	Sev.-MB	0.00	0	0	0	0	0	11.11	100%
	P. accuracy	70.5%	20.5%	21%	96.6%	90%	99.5%	100%	76.83%

The healthy plants were highly classified under all classifiers with SVM and RF generating the two highest classification values of 96.67% and 96.05%, respectively (Table 10). Generally, SVM performed best compared to KNN and RF classifiers, with a consistent outcome across the 3 disease levels of both MB and BB. Therefore, it can be stated that all 3 severity levels of MB disease can be determined; however, only the low severity of Botrytis blight disease was determined. Moderate and low severity conditions of BB have shown difficulty in their classification; thus, identifying them accurately may pose some significant challenges (Table 10).

3.2.3. Variable Importance Plot

Comparing all 3 classifiers, the contribution of VARI in classifying BB, Healthy, and MB was significant under KNN and RF (Figure 10 and Figure S2), but was second under SVM. NDRE was significant under only SVM, but second under RF in classifying BB, Healthy, and MB treatments. The contribution of ENDVI was low as it was represented second under only KNN, but last in both SVM and RF classifiers, which is further explained by the ALE plots (Figure S3). The same output was observed under the disease severity levels, except that VARI was significantly high in all 3 classifiers.

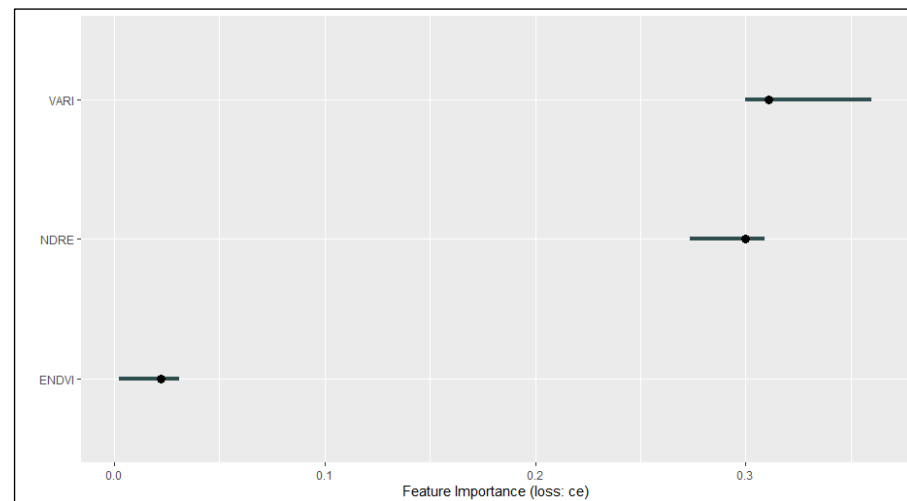


Figure 10. A variable importance plot on the 3 VIs using the RF classifier to determine the 3 conditions, BB, Healthy, and MB treatments.

The broad classification under disease severity also followed similar patterns of contribution from VARI, NDRE, and ENDVI; thus, the ALE plot demonstrates the individual contributions in achieving the established classifications from the different classifiers (Figures S4–S6).

In addition, the Probability density function (PDF) establishes the likelihood of these variables predicting or classifying any of these treatments. Results have shown that the visible light vegetative indices (VIs) contributed significantly (Figure 11 and S7).

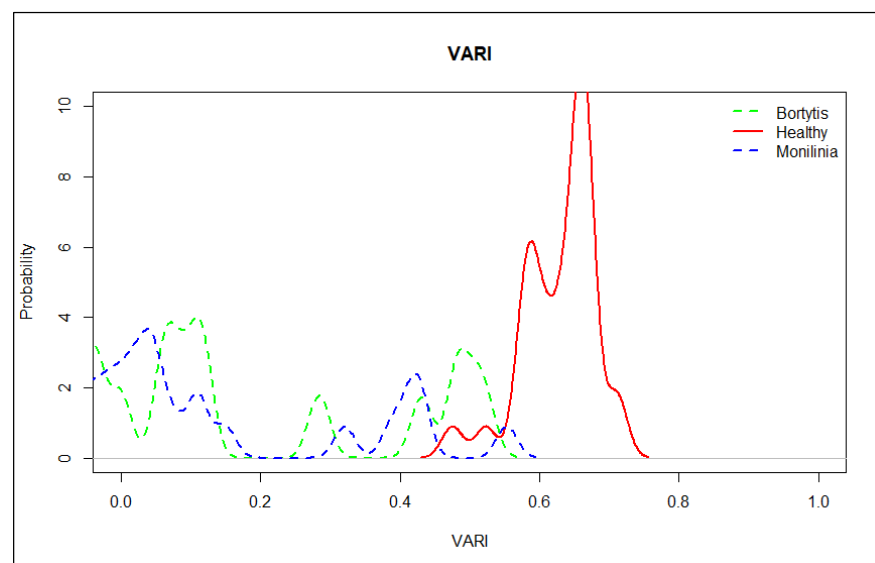


Figure 11. Probability density function of VARI conducted on the 3 treatment conditions.

4. Discussion

4.1. Plot Assessments of Monilinia and Botrytis Blight Diseases Using the Multispectral Sensor

Field conditions are critical determinants of disease incidence and severity [34]. In this study, the incidence and severity of Monilinia blight (MB) and Botrytis blight (BB) were either absent or sparsely observed in several plots (Tables 2 and 4). Despite the isolated cases of infection, the overall disease spread and severity remained substantially low. This can be attributed to unfavorable weather conditions (Figure S8) during the observation period and differences in the phenotypic resistance of the wild blueberry plants [7,34].

Effective aerial detection of MB and BB using remote sensing remains challenging in wild blueberries unless widespread symptoms are present across large plant patches. This is largely because symptoms of these diseases, such as the dark brown lesions or dense grey discoloration, affect the plant's physiology in subtle ways that are not easily detected from above [7,34]. As indicated, the spectral analysis showed that infected areas demonstrated increased reflectance in the visible (VIS) region, coupled with reduced reflectance in the red-edge and near-infrared (NIR) regions, relative to healthy plants (Figures 7–9). These spectral patterns were consistent with previous studies [17,22]. Such variations in VIS and NIR reflectance are linked to a decrease in chlorophyll pigmentation and structural alterations in the leaves, including water content loss [17]. Additionally, shifts within the shortwave infrared (SWIR) reflectance are also attributed to changes in lignin and protein composition [22]. As noted by Yue et al. [35], the VIS and NIR regions are especially relevant because of their role in activating plant biochemical and physiological processes.

Although overall differences in vegetation indices (VIs) were not statistically significant across treatments, mean differences were observable. In contrast, some significant differences were established using the destructive ground-truth method, such as the line transect assessment (Table 4). This outcome supports findings by Devadas et al. [28], who observed that canopy-level VI assessments can be ineffective in disease quantification and identification. In their earlier controlled lab studies [36], significant VI differences were identified at the individual leaf level; however, translating these results to field conditions proved less reliable, showing a contrast between the two findings. This discrepancy may be due to the physical structure and growth habit of the wild blueberry plant, which is low-growing, deciduous, and possesses a dense, compact canopy. Such morphology limits aerial visibility, making it difficult to detect internal canopy disease infections. Furthermore, disease-related reductions in leaf area and shrinkage of other affected structures minimize the spatial footprint of diseased tissues relative to the total plot area, affecting their detection and visibility. When disease assessments are averaged across entire plots, the impact of disease may be masked by the surrounding healthy plant population.

At the individual plant or patch level, however, significant spectral differences can be observed (Table 8). Yet at the canopy or whole-plot level, several confounding factors, such as mixed healthy plant conditions and structural heterogeneity, reduced sensitivity to disease symptoms (Tables 3 and 5). These findings are consistent with the work of Di Gennaro et al. [37], who used VIs to monitor esca complex disease in grapevines. While their methods enabled treatment differentiation, they also highlighted similar limitations of VI-based assessments at larger spatial scales. Our results also align with Huang et al. [23], who used hyperspectral imaging to monitor rice at the canopy level, confirming the reduced effectiveness of VIs at broader scales. Conversely, Vélez et al. [38] demonstrated significant differences between BB-infected and healthy grapevines using Wilcoxon tests. However, their variable importance plot revealed NDVI as the least useful index for disease differentiation, an outcome that supports our findings regarding the limitations of NDVI at the plot scale.

The correlation (r) analysis between the VIs and the incidence and severity of *Monilinia* and *Botrytis* blights revealed some promising, though inconsistent results (Tables 6 and 7). VIs such as NDVI, VARI, ENDVI, and SAVI showed moderate correlations with disease presence, aligning with findings by Devadas et al. [28,36] and Di Gennaro et al. [37], who reported similar relationships between aerial multispectral data and ground-based disease assessments. While these results suggest potential for remote disease detection, variability across growing seasons points to the complex nature of field conditions. Factors such as leaf pigmentation, stress tolerance, canopy structure, and interference from weeds or other vegetation [39] likely influence the accuracy of VI-based assessments. In dense wild blueberry canopies, it becomes particularly challenging to detect disease severity when symptoms are obscured within the foliage. Often, disease detection occurs only after visible symptoms like necrosis appear, by which point plant damage is already significant. This delay reduces the effectiveness of early intervention strategies. Moreover, flush growth [40], a natural recovery response, may mask disease effects, further complicating disease differentiation. Thus, while aerial tools offer potential for monitoring disease presence, their effectiveness is limited until disease symptoms are pronounced at the canopy-surface level. Therefore, enhancing early detection will require better strategies to distinguish subtle disease signals in complex plant environments.

4.2. Patch Assessment of *Monilinia* and *Botrytis* Blight Disease Using the Hyperspectral Radiometer

This study revealed that there was a significant treatment difference between healthy, MB, and BB patches of wild blueberry plants at different severity levels (Figure 7). This result was similar and agrees with the findings of Vaštakaitė-Kairienė et al. [26], who established significant differences between *Botrytis cinerea* and healthy plant tissues at different time/sampling points. This study also agreed with the work of Devadas et al. [28] and Di Gennaro et al. [37] as discussed previously. Furthermore, this study's findings also agree with the work of Abdulridha et al. [16], who discriminated between disease severities using VIs and identified target spots in tomatoes using the hyperspectral technique. The established differences between healthy and diseased plants may seem general in most situations but can differ in some circumstances. Focusing on the spectral reflectance diagrams (Figure 7), indications showed that similar trends or patterns were observed between healthy and BB-infested plants with slight differences at the NIR regions [26]. BB disease affects mainly flowers [7], which are a fraction of the total plant area; thus, the effect of the disease is overshadowed by the canopy effect. However, the other consideration was to focus on the related biochemical and biophysical portions of the spectrum. Despite these developments, the reflectance from these plants compared to a healthy plant looked similar, with very slight differences. This is because the gross effect of the affected floral tissue compared to foliage may be insignificant, thus accounting for the similarity between spectral readings of healthy and BB disease. Unlike MB, which affects plant foliage, this should command a significant spectral difference when compared to the healthy treatment. These results have indicated that the VIS and NIR regions contribute significantly to the identification of disease severity. In this study, 8 wavelength bands, 415, 484, 554, 555, 680, 681, 745, and 761 nm, have been shown to be sensitive in the determination of MB disease, whereas 3 bands, 457, 665, and 694 nm, were sensitive to BB disease. The identification and detection of *Botrytis cinerea* disease in this study has shown great similarity to several studies despite the differences in the crop types [25,26,38,41]. Findings from this study strongly agree with the work of Polder et al. [42] and Wu et al. [25], who identified selected bands of interest in the identification of BB disease. The 3 sensitive bands identified in this study closely relate to the work of Polder et al. [42], despite some slight variations. Conversely, apart from pathological determinations of the MB disease, there are little to

no studies on specific remote sensing work conducted in other crops or wild blueberries. Therefore, this study provides a basis and grounds for further research in remote sensing of MB disease.

Despite the success in using other VIs, results highlighted the ability of VARI, GLI, and GRVI in discriminating healthy plants from diseased plants with minimal overlap. Therefore, the probability graph has shown the discriminating abilities of the different VIs (Figure 11 and Figure S6), with VARI performing best among all VIs. This result partially agrees with the work of Su et al. [19], who identified the abilities of NDVI, SAVI, GLI, and NDRE, in their order of importance, as being able to discriminate between diseases. Although both studies highlight some of these VIs, the order of importance was different. Thus, this study suggests the light vegetative indices (VARI, GLI) ahead of the other near-infrared VIs (ENDVI, NDVI), confirming the work of Anku et al. [3]. Further confirmation is derived from the variable importance plots, which also put VARI ahead of the near-infrared VIs. Since high correlation exists between VARI, GLI, and GRVI, it can therefore be assumed that these VIs have a great impact in discriminating diseases.

Clearly, results have shown that healthy tissues can be discriminated against diseased tissues, but with significant challenges in discriminating against BB severity levels. This result agrees with the findings of Mirandilla et al. [32], who detected three major diseases in rice using spectral reflectance. Aside from establishing good classification at a more progressed disease severity level, their work highlighted the significance of RF and SVM classifiers. In another related study, Abdulridha et al. [16] detected the laurel wilt disease and discriminated between healthy and non-healthy plants in avocado using KNN and the neural network multi-layer perceptron (MLP). Despite the low performance of the KNN classifier, this study has shown levels of accuracy of the KNN classifier that is promising to use in estimating diseases. Estimations of the low, moderate, and severe BB severity were consistent between the different classifiers. Consistently, all three classifiers generated very good producer and user accuracies on low BB, from low to severe MB, and healthy plants. Generally, moderate and severe BB were poorly determined across the 3 classifiers. This may imply a systemic difficulty in identifying BB at moderate and severe levels. Again, it can be observed that SVM performed better than RF and KNN classifiers with an overall accuracy of 76.83% as against 70.8% and 70.67% for KNN and RF, respectively.

The machine learning (ML) classifiers adopted in this study proved robust as the overall accuracy of the 3 classifiers was 94.7%, 96.5%, and 96.6% for KNN, RF, and SVM, respectively. Despite the success of using any of these classifiers, generally, most research points to the use of SVM and RF, as they are considered best in most classification work. This result agreed with the works of Mirandilla et al. [32] and Huang et al. [23], who established RF and SVM as the best among several classifiers adopted in their study. Similarly, the RF classifier also proved better compared to KNN and thus has been adopted in several other studies [32]. The levels of accuracy displayed in this study have shown the potential of using these classifiers in estimating diseases. The significance of the two techniques cannot be underplayed, but results point to the use of the hyperspectral spectroradiometer as a superior sensor over the micasense. Therefore, whereas a spectrum list of VIs can be generated using the hyperspectral device, the multispectral sensor limits the number of VIs [43]. Therefore, Huang et al. [23] concludes that the hyperspectral reflectance device can achieve great results over the multispectral sensor.

Effective pest and disease management in wild blueberry fields is essential for improving disease control and maximizing yield. Therefore, the ability to detect blight disease early and accurately will enable effective and timely mitigation strategies. The broader implication of this study lies in its potential to inform the development of

sensor-based technologies capable of discriminating between healthy and diseased plants in wild blueberry fields. This advancement would enhance decision-making and minimize environmental impact through the use of disease control products. Ultimately, this approach will improve productivity, profitability, and the long-term sustainability of production.

The scalability of UAV and handheld hyperspectral sensing for disease detection in wild blueberry production is limited by several factors. UAV operations face constraints related to flight altitude over tall vegetation, short battery life requiring multiple flights, weather dependency, regulatory restrictions, and the high computational demands of processing large hyperspectral datasets [27]. Handheld hyperspectral devices, while precise, are labour-intensive, time-consuming, and cover only small areas per scan due to fixed measurement heights, making them impractical for large-scale monitoring [3]. Both approaches also present cost barriers, require specialized skills for operation and data analysis, and face challenges in integrating datasets across platforms, which collectively hinder their widespread adoption for large-area disease surveillance.

Notwithstanding the successes observed, the study presents an initial assessment of the UAV multispectral and handheld hyperspectral sensing for disease detection in wild blueberry fields. These significant challenges affect its broader applicability, including scalability of technology, limited disease pressure and sampling diversity, restricted data contamination control, and phenological timing, which affects real-world scenarios. Furthermore, limited use of multispectral data and algorithm complexity, and lack of time-series analysis to allow for monitoring and predictability, affected the overall success of the study. While these limitations constrain immediate large-scale adoption, the findings demonstrate the potential of remote sensing for disease monitoring and highlight areas for future research, particularly regarding automation, advanced analytics, and scalable workflows. To address these challenges, future research should focus on automation, advanced analytics, and scalable workflows. Thus, more practical approaches can be adopted, like integrating hyperspectral sensors on UAVs or ground-based platforms to achieve high throughput or using high-capacity UAVs for extended coverage.

5. Conclusions

Vegetative indices have played a significant role in disease determination, and this study has established that potential. However, determining *Monilinia* and *Botrytis* blight severity was achieved using the hyperspectral sensor. Results were narrowed down by identifying 415, 484, 554, 555, 680, 681, 745, 761 nm and 457, 665, 694 nm as significant wavelength bands for the determination of MB and BB diseases. Interestingly, direction points to the use of the visible light vegetation (VIS) indices like VARI, as they have proven capable in the disease determination process. Despite the success achieved using the hyperspectral sensor, VIs at the plot level could not establish clear treatment differences. Despite the confounding effect from healthy plants within the plots, which affected the overall disease effect and reduced the significance of the disease, other limitations, like complex data exploration, sampling diversity, and limited disease pressures, caused the VIs' inability at the plot level to differentiate diseases.

The general assessment between the two techniques showed that the classifications using the hyperspectral sensor generated significant results compared to those from the micasense. Despite the similarities observed in using different classifiers, RF and SVM proved superior in their classification process with an overall accuracy of 96.6%. Notwithstanding the success observed in this study, we recommend that further work be conducted to determine early blight disease detection in wild blueberries. There is a need for future

studies to explore advanced ML techniques like CNN and stacking to explore the significant details from these sensory data.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs17173074/s1>, Figure S1: Monilinia and Botrytis blight severity level determinations in the wild blueberry field. (a) Advanced MB development (70–100% MB severity), (b) Moderate development of MB (30–70% MB severity), and (c) Early development of MB (1–30% MB severity level), (d) Early development of BB (1–30% BB severity level), (e) Moderate BB development (30–70% BB severity), and (f) Advanced BB development (70–100% BB severity); Figure S2: Variable importance plot for the selected VIs under the combined condition (BB, Healthy, and MB) using (a) KNN and (b) SVM classifiers; Figure S3: ALE plot on the broad treatment classifications of the contributions from the 3 variables under the (a) KNN, (b) RF, and (c) SVM classifiers; Figure S4: ALE plot of ENVI, NDRE, and VARI under the different levels of disease severity using the KNN classifier; Figure S5: ALE plots of ENVI, NDRE, and VARI under the different levels of disease severity using the RF classifier; Figure S6: ALE plot of ENVI, NDRE, and VARI under the different levels of disease severity using the SVM classifier; Figure S7: Probability density function (PDF) plot on all six VIs under the three (3) conditions; Figure S8: Environmental conditions (Leaf wetness, temperature, and rainfall) observed in Lemmon Hill, NS, in 2020 represent the Monilinia and Botrytis blight infection periods. X: High risk blight infection period and +: Moderate risk blight infection period; Table S1: Flight details conducted at Lemmon Hill and Kemptown locations at the different Phenological stages; Table S2: Aerial vegetative indices (VI's) observed from Kemptown after 3rd fungicide application. Image samples for this observation were collected on [10 June 2020]; Table S3: Aerial vegetative indices (VIs) observed from Kemptown after the 4th fungicide application. Image samples for this observation were collected on [18 June 2020]; Table S4: Aerial vegetative indices (VI's) observed from Lemmon Hill after the 3rd fungicide application. Image samples for this observation were collected on [9 June 2020]; Table S5: Aerial vegetative indices (VIs) observed from Lemmon Hill after the 4th fungicide application. Image samples for this observation were collected on [17 June 2020]; Table S6: Infection periods for Monilinia and Botrytis blight observed at Lemmon Hill in June 2020.

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Abbreviations

The following abbreviations are used in this manuscript:

MB	Monilinia blight
BB	Botrytis blossom blight
Vis	Vegetative indices
GLI	Green Light Index
GRVI	Green Red Vegetative Index
VARI	Visible Atmosphere Red Index
NDVI	Normalized Difference Vegetative Index
ENDVI	Enhanced Normalized Difference Vegetative Index
NDRE	Normalized Difference Red-Edge
SAVI	Soil Atmospheric Vegetative Index
VIS	Visible light region
NIR	Near-infrared
ANOVA	Analysis of Variance
SVM	Support Vector Model
RF	Random Forest
KNN	K-Nearest Neighbour
ALE	Accumulated Local Effect
VIF	Variable Inflation Factor
OA	Overall accuracy
SWIR	Shortwave Infrared
PDF	Probability density function
Mod.	Moderate disease condition
Sev.	Severe disease condition

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