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Enhancing Kiwi Bacterial Canker Leaf Assessment: Integrating Hyperspectral-based Vegetation Indexes in Predictive Modeling

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Abstract: The potential of hyperspectral UV–VIS–NIR reflectance for in-field, non-destructive discrimination of bacterial canker on kiwi leaves caused by *Pseudomonas syringae* pv. *actinidiae* (Psa) was analyzed. Spectral data (325–1075 nm) of twenty kiwi plants were obtained in-vivo, in-situ, with a handheld spectroradiometer in two commercial kiwi orchards in northern Portugal, for 15 weeks, resulting in 504 spectral measurements. The suitability of different vegetation indexes (VIs) and applied predictive models (based on supervised machine learning algorithms) for classifying non-symptomatic and symptomatic kiwi leaves was evaluated. Eight distinct types of VIs were identified as relevant for disease diagnosis, highlighting the relevance of the Green, Red, Red-Edge, and NIR spectral features. The class prediction was achieved with good model metrics, achieving an accuracy of 0.71, kappa of 0.42, sensitivity of 0.67, specificity of 0.75, and F1 of 0.67. Thus, the present findings demonstrated the potential of hyperspectral UV–VIS–NIR reflectance for non-destructive discrimination of bacterial canker on kiwi leaves.

Keywords: Kiwi; Bacterial canker; Pseudomonas syringae; plant pathology; Optical sensing; In-field diagnosis; vegetation index

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1. Introduction

Bacterial Canker of Kiwi (BCK) disease, caused by *Pseudomonas syringae* pv. *actinidiae* (Psa), is accountable for numerous epidemics in Kiwi orchards annually [1, 2]. Scouting and laboratory-based techniques (e.g., Polymerase Chain Reaction – PCR –, and Enzyme-linked Immunosorbent assay – ELISA) are currently applied as diagnostic procedures. While insightful, these methods are hindered by labor intensiveness, time requirements, complex sampling, and unsuitability for rapid real-time field decisions, thus limiting their use in disease monitoring and field mapping [3, 4].

Early diagnosis, especially before symptoms' visible appearance, is of paramount importance in plant disease diagnosis. This proactive approach allows for timely and targeted intervention, reducing the spread of the disease and minimizing crop damage. It also enables more efficient resource allocation and cost-effective management strategies, safeguarding agricultural productivity and food security.

Hyperspectral Spectroscopy (HS) techniques have alternatively been recently applied as an innovative indirect plant disease diagnostic tool capable of retrieving relevant

information about host-pathogen interactions related to the host's biochemical and biophysical modifications. Briefly, changes promoted by pathogens related to plants' pigment concentration and physiological processes (e.g., photosynthesis) produce changes in the quantitative and qualitative patterns of plants' spectral behavior, namely in the visible region of the electromagnetic spectrum (VIS, 400–700 nm). In turn, modifications in leaf water levels, chemical composition (i.e., lignin and protein content), structure, and internal scattering processes impact the spectral signatures in infrared wavelengths (IR, 800–2500 nm) [5, 6]. Hence, HS could be successfully applied in the detection of pests [7, 8] and fungi [9, 10], bacteria [11], and viruses [12] affecting different crops, even at non-symptomatic stages [13].

Nevertheless, data collected from HS frequently presents redundant information from proximal bands. Hence, only a few spectral wavelengths might help assess plant disease [14, 15]. Approaches including statistical signal processing, mathematical combinations of different bands, and applied predictive models may be computed to extract meaningful information, reduce data dimensionality, and/or select relevant features [16, 17]. Vegetation Indices (VIs) exemplify these techniques, as they are numerical measures derived from the parametric formulations of different spectral bands or wavelengths associated with essential plant biophysical parameters like photosynthetic pigments, structural molecules, and water content. These indices are widely employed because of their simplicity and comprehensiveness, users' limited knowledge requirement, fast processing, and computationally inexpensiveness [18]. VIs formalizations can be combinations of two-bands (most frequent case), three-bands, and four or more bands (combination of two VIs) [18]. Among the most frequently computed VIs are the Normalized Difference Vegetation Index (NDVI) [19, 20], and the Enhanced Vegetation Index (EVI) [21, 22], which are effective in assessing parameters related to the plant's status and structure. VIs developed specifically for parameter estimation (e.g., leaf's photosynthetic pigment and water levels) are frequently employed. Some examples include the Anthocyanin reflectance index (ARI) [23], Browing Reflectance Index (BRI) [24], Chlorophyll Green (Chlgreen) [25], and Coloration Index (CI) [26], among others. Furthermore, Vegetation Indices (VIs) can undergo band optimization procedures, enhancing their spectral sensitivity to the target parameters and enabling a more comprehensive analysis of the variable under consideration [27].

The present research aims to compare the suitability of VIs and classification modeling for discriminating non-symptomatic and BCK symptomatic kiwi leaves in-field, using ground-level UV–VIS hyperspectral reflectance assessments.

2. Methods

2.1. Experimental site

Two commercial orchards cultivated with kiwi plants (*Actinidia deliciosa*) were monitored in 2020, both located at Guimarães, Portugal: one situated in Caldas das Taipas (CT; 41°29′09.8″ N 8°21′54.3″ W), and the other in Briteiros (BT; 41°30′53.3″ N 8°19′20.5′ 'W). Twelve feminine kiwi plants of the variety Bo.Erika® in CT, and eight in BT were chosen, identified with tape, and classified according to the absence or presence of typical BCK visual symptoms (i.e., minor greasy dark lesions which turn brown to black overtime, and are usually randomly spread on leaves surface). Visual phenotyping was performed on both the adaxial and abaxial sides of the leaves.

2.2. Ground-based hyperspectral reflectance acquisition

A portable spectroradiometer (ASD FieldSpec® HandHeld 2, ASD Instruments, Boulder, CO, USA) was used for leaf spectra capturing between May and August 2020 (9 visits), ending when the full development of Psa symptoms was reported in the plants' growing season. More details of the spectra measurement procedure can be found in [28].

A total of 504 spectral averaged signatures were collected in both test sites, and the dataset was balanced regarding class distribution (Table 1).

Table 1. Number of test sites, visits, plants, and leaves assessed per location of experimental sites [28].

Experimental site	*Sites*	*Visits*	*Plants*	*Non-symptomatic leaves*	*Symptomatic leaves*	*Total measurements*
Briteiros (BT)	1	9	8	89	127	216
Caldas das Taipas (CT)	1	8	12	192	96	288
Total	2	17	20	281	223	504

2.3. Data modeling

Spectral pre-processing was performed by computation of a multiplicative scatter correction (MSC) [29]. A total of 751 wavelength predictors were considered (325–1075 nm). Due to overlapping nature of hyperspectral data and multi-scale interference, auto-correlated signals may arise across various scales [30]. Thus, techniques capable of identifying the most relevant wavelengths or bands for discrimination and not considering redundant information are essential.

In this regard, reflectance data were processed into 32 spectral VIs, resulting in 41 distinct band combinations (Table A1). To calculate them, the wavelengths considered were: i) the ones enumerated in their original formula (as indicated in Table A1) or ii) default values chosen by the authors, namely 450 nm (representing the Blue region of the electromagnetic spectrum), 550 nm (Green), 680 (Red), Red Edge (700 nm), and 800 nm (NIR).

Applied predictive modeling was then performed using a model with a built-in Feature Selection (FS) method called Flexible Discriminant Analysis (FDA) (Figure 1). Leaf symptomatology was used as a binary variable in the models tested taking the values 'No' (asymptomatic) and 'Yes' (symptomatic). The dataset was split into training (70% of random observations) and validation data (the remaining 30% of the observations), following a holdout method. A resampling approach was performed followed by a repeated cross-validation strategy using a repeated 10-fold cross-validation to estimate model evaluation criteria. The confusion matrix (CM), accuracy score, kappa coefficient, and F1-score were considered to determine model performance. A detailed description of these metrics applied, and about the R packages used can be found in [28].

3. Results

Model results showed the capacity of classifying the kiwi leaf measurements into 'Non-symptomatic' and 'Symptomatic' with 0.71 accuracy (proportion of correctly classified instances), 0.42 of Cohen's kappa (agreement between predicted and actual classes beyond random occurrence), 0.67 of sensitivity (ability to identify diseased measurements), 0.75 of specificity (ability to identify healthy assessments), and 0.67 of F1 score (harmonized measure of precision and recall) for the test set (Table 2). Confusion matrix (CM) results (Table 3) demonstrate that 63 samples were correctly classified as non-symptomatic (True Negatives), and 44 as symptomatic (True Positives). Nevertheless, 21 measurements were wrongly classified as symptomatic (False Positives), and 22 as non-symptomatic (False Negatives). Thus, the model performs better at predicting non-symptomatic assessments than symptomatic measurements. These findings indicate a reasonably effective model performance, with an overall ability to distinguish between classes and make accurate predictions.

The built-in Feature Selection tool highlighted eight distinct VIs for sample discrimination, namely the Chlorophyll Green (Chlgreen), modified Simple Ratio (mSR), Coloration Index (CI), Simple Ratio Greenness Index (GI), Browning Reflectance Index (BRI), Ashburn Vegetation Index (AVI), Hyperspectral perpendicular VI (PVIhyp), and

Reflectance at the inflexion point (Rre). These VIs are mostly based in the NIR, Red and Green regions of the electromagnetic spectrum (Table 2).

Table 2. Classification results of the Flexible Discriminant Analysis (FDA) model computed for the train and test datasets. Legend: Acc. – Accuracy, Kap. – Kappa coefficient, Sen. – Sensitivity, Spe. – Specificity, Pre. – Precision, Rec. Recall, F1 – F1 score.

Modeling Approach		*Acc.*	*Kap.*	*Sen.*	*Spe.*	*Pre.*	*Rec.*	*F1*
FDA	Train	0.76	0.48	0.68	0.80	0.73	0.68	0.70
	Test	0.71	0.42	0.67	0.75	0.68	0.67	0.67

Table 3. Vegetation Index (VI) importance for class discrimination and Confusion Matrix (CM) results according to Flexible Discriminant Analysis. Legend: Pred – Predicted, 'No' – Non-symptomatic, 'Yes' – Symptomatic.

VI	*Wavelength (nm)*	*Importance (a.u.)*	*CM Train*		
Chlgreen	**553, 800**	100	Pred	'No'	'Yes'
mSR	705, 750	67.15	'No'	157	50
CI	450, 700	52.94	'Yes'	40	107
GI	554, 677	44.45			
BRI	450, 690	40.55	*CM Test*		
AVI	400, 994	33.71	Pred	'No'	'Yes'
PVIhyp	800, 1000	24.46	'No'	63	22
Chlgreen	530, 730	19.65	'Yes'	21	44
Rre	670, 780	16.46			

Chlgreen– Chlorophyll Green, mSR – Modified Simple Ratio, CI – Coloration Index, GI – Simple Ratio Greenness Index, BRI – Browning Reflectance Index, AVI – Ashburn Vegetation Index, PVIhyp – Hyperspectral perpendicular VI, Rre – Reflectance at the inflexion point

4. Discussion

Eight distinct VIs (nine wavelength combinations) were identified as highly relevant for disease discrimination. They mostly consider the NIR, Green, and Red spectral regions. These findings present biological significance since they are coherent with the impact of *Pseudomonas syringae* pv. *actinidiae* (Psa) in kiwi leaves. Briefly, these pathogens cause modifications in pigment concentration and physiological processes (e.g., photosynthesis), resulting in changes in plants' spectral behavior in the VIS wavelengths (Blue, Green, Red). Furthermore, they cause changes in the leaf water levels, chemical composition (namely lignin and protein content), structure, and internal scattering processes which impact the NIR features [6, 31]. Similar spectral regions were also identified as relevant for late blight, target and bacterial spots detection in tomato leaves [32], and for the assessment of Cercospora leaf spot, sugar beet rust and powdery mildew in sugar beet plants [33]. Model evaluation metrics also supported the model ability in discriminating non-symptomatic from symptomatic samples. Model performance may be enhanced by further fine-tuning, particularly in addressing models' sensitivity and minimizing the occurrence of false negatives.

Hyperspectral data may have redundant information in adjacent bands, and only a few wavelength features might be interesting in classifying a diseased plant [15]. For that reason, in crop remote sensing (both, ground, aerial and satellite-based solutions) spectral VIs are still the most common approaches studied to identify and manage biotic stresses in different crops [34]. Despite its substantial inherent potential, the discernment of the responsiveness of this extensive array of VIs to the target variable remains occasionally ambiguous. Furthermore, concerns related to the susceptibility to disturbances from confounding elements can arise, mostly encompassing fluctuations in leaf or canopy properties, background soil reflectance, solar illumination, and atmospheric composition. Such

a confluence of factors can generate instabilities in the spectral attributes of surfaces [35]. Furthermore, VIs were developed when the first applications of broadband sensor occurred, when only a small set of spectral bands were available and the computational power was limited. With the development of narrowband devices (i.e., with a few hundred spectrally narrow bands), this VIs may use the available information within the spectral observation range inefficiently, often relying on only a partial spectral subset. Algorithms for extracting optimized band information were thus created, utilizing well-established index formulations such as simple ratios and normalized differences. These algorithms involved the correlation of all potential band combinations to generate 2D correlation matrices, allowing for the visual identification of the most effective band combinations. Nevertheless, this approach can conduct to optimize indices which are strongly case specific, successfully optimized for local applications but not to generic cases [18]. FS nonparametric methods which evaluate all the spectral wavelengths provided by hyperspectral sensors constitute an interesting option for disease assessment, providing more robust and customized information for modeling data class characteristics, and greater model performance [28, 36]. Thus, future research is needed to better explore different information extraction (e.g., modeling) approaches suitable to comprehend plant–pathogen interactions and their effect on host spectral behavior.

5. Conclusions

The present work aimed to apply hyperspectral reflectance in-field measurements for the diagnosis of bacterial canker of kiwi (BCK) disease, which is caused by the bacteria *Pseudomonas syringae* pv. *actinidiae* (Psa). Different vegetation indices were computed, and later used to classify symptomless and symptomatic kiwi leaves signatures. Chlgreen, mSR, CI, GI, BRI, AVI, PVIhyp, and Rre were signed as the most relevant for disease discrimination, highlighting the Green, Red, Red Edge, and NIR regions of the electromagnetic spectrum. These findings are in line with the metabolic and structural changes promoted by the pathogen in the host tissues. Classification modeling allowed disease discrimination with fair model metrics, showing the suitability of this approach for disease assessment. Nevertheless, further research exploring different Feature Selection methods considering a broader range of wavelengths is advised.

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Appendix A

Table A1. Spectral Vegetation Indices (VIs) computed in this study.

Vegetation Indices	*Formula*	*Ref.*
Ashburn Vegetation Index (AVI)	$2.0 \times \mathrm{NIR} - \mathrm{RED}$	[37, 38]
Anthocyanin reflectance index (ARI)	$\frac{1}{GREEN} - \frac{1}{RED}$	[23]
Blue Green Pigment Index (BGI)	$\frac{BLUE}{GREEN}$	-
Browning Reflectance Index (BRI)	$\frac{\frac{1}{GREEN} - \frac{1}{RED}}{NIR}$	[24]
Chlorophyll Green (Chlgreen)	$\left(\frac{NIR}{GREEN}\right)^{(-1)}$	[25]
Coloration Index (CI)	$\frac{RED - BLUE}{RED}$	[26]
Chlorophyll Index Green (CIgreen)	$\frac{NIR}{GREEN} - 1$	[39-41]
Chlorophyll Index Red Edge (CIrededge)	$\frac{NIR}{RED\ EDGE} - 1$	[39-41]
Chlorophyll vegetation index (CVI)	$NIR * \frac{RED}{GREEN^2}$	[42]
Double Difference Index (DD)	$(749nm - 720nm) - (701nm - 672nm)$	[43, 44]
Enhanced Vegetation Index (EVI)	$2.5 \times \frac{NIR - RED}{(NIR + 6RED - 7.5BLUE) + 1}$	[21, 22]
Green atmospherically resistant vegetation index (GARI)	$\frac{NIR - (GREEN - (BLUE - RED)}{NIR - (GREEN + (BLUE - RED)}$	[45, 46]
Green-Blue NDVI (GBNDVI)	$\frac{NIR - (GREEN + BLUE)}{NIR + (GREEN + BLUE)}$	[47]
Global Environment Monitoring Index (GEMI)	$\left(n \times (1 - 0.25n) - \frac{RED - 0.125}{1 - RED}\right)$ $n = \frac{2 \times (NIR^2 - RED^2) + 1.5 \times NIR + 0.5 \times RED}{NIR + RED + 0.5}$	[48]
Simple Ratio Greenness Index (GI)	$\frac{GREEN}{RED}$	[49, 50]
Green Normalized Difference Vegetation Index (GNDVI)	$\frac{NIR - GREEN}{NIR + GREEN}$	[22, 51]
Tasselled Cap – vegetation (GVI)	$-0.2848 \times Blue - 0.2435 \times Green - 0.5436 \times Red + 0.7243 \times NIR + 0.0840 \times SWIR - 0.1800 \times SWIR$	[52, 53]
Infrared percentage vegetation index (IPVI)	$\frac{\frac{NIR}{NIR + RED}}{2} \times (NDVI + 1)$	[54, 55]
Log Ratio (LogR)	$log\left(\frac{NIR}{RED}\right)$	-
Misra Green Vegetation Index (MGVI)	$-0.386 \times GREEN - 0.530 \times RED + 0.535 \times REDEDGE + 0.532 \times NIR$	[56, 57]
Modified NDVI (mNDVI)	$\frac{NIR - RED}{NIR + RED - 2 \times BLUE}$	[49, 58]
Modified Simple Ratio (mSR)	$\frac{NIR - BLUE}{RED - BLUE}$	[49, 55]
Modified Simple Ratio 2 (mSR2)	$\left(\frac{NIR}{RED}\right) - \frac{1}{\sqrt{\left(\frac{NIR}{RED}\right) + 1}}$	[59]
Normalized Difference NIR / Red Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - RED}{NIR + RED}$	[19, 20]
Normalized Green (NG)	$\frac{GREEN}{NIR + RED + GREEN}$	[60]

Normalized Near Infrared (NNIR)	$\frac{NIR}{NIR + RED + GREEN}$	[60]
Hyperspectral perpendicular VI (PVIhyp)	$\frac{NIR - a \times 807 - b}{(1 + a^2)^{0.5}}$ $a = 1.17, b = 3.37$	[61]
Plant Senescence Reflectance Index (PSRI)	$\frac{RED - BLUE}{NIR}$	[62, 63]
Reflectance at the inflexion point (Rre)	$\frac{RED + NIR}{2}$	[64]
Red-Edge Stress Vegetation Index (RVSI)	$\frac{718 + 748}{2} - 733$	-
Structure Intensive Pigment Index (SIPI)	$\frac{NIR - BLUE}{NIR - RED}$	[50, 65]
Simple Ratio (SR)	$\frac{NIR}{RED}$	-

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