

Article

Fire Blight Monitoring in Pear Orchards by Unmanned Airborne Vehicles (UAV) Systems Carrying Spectral Sensors

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Abstract: Controlling fire blight in pear production areas depends strongly on regular visual inspections of pome fruit orchards, nurseries and other hosts of *Erwinia amylovora*. In addition, these inspections play an essential role in delineating fire blight free production areas, which has important implications for fruit export. However, visual monitoring is labor intensive and time consuming. As a potential alternative, the performance of spectral sensors on unmanned airborne vehicles (UAV) or drones was evaluated, since this allows the monitoring of larger areas compared to the current field inspections. Unlike more traditional remote sensing platforms such as manned aircrafts and satellites, UAVs offer a higher flexibility and an extremely high level of detail. In this project, a UAV platform carrying a hyperspectral COSI-cam camera was used to map a heavily infected pear orchard. The hyperspectral data were used to assess which wavebands contain information on fire blight infections. In this study, wavelengths 611 nm and 784 nm were found appropriate to detect symptoms associated with fire blight. Vegetation indices that allow to discriminate between healthy and infected trees were identified, too. This manuscript highlights the potential use of the UAV methodology in fire blight detection and remaining difficulties that still need to be overcome for the technique to become fully operational in practice.

Keywords: fire blight; UAV; spectral sensors; precision agriculture

1. Introduction

Fire blight caused by the Gram-negative bacterium *Erwinia amylovora* (Burr.) Winslow et al., represents an important threat to pome fruit cultivation worldwide. *E. amylovora* can affect rosaceous plants, such as apples and pears as well as ornamental shrubs such as *Cotoneaster*, *Crataegus* and *Pyracantha* [1,2]. The pathogen enters the host plants via natural openings such as the stigmas and nectaries of flowers, stomata, hydathodes or via wounds, and spreads systemically within the plants. Common symptoms of fire blight are initially a water-soaked appearance of infected plant parts, followed by wilting, and eventually necrosis of flowers, leaves, fruits, and terminal shoots. In addition, cankers can develop on branches, trunks, and rootstocks [3–6]. Trees with fire blight infection often exhibit yellow to burgundy foliage about a month before normal onset of autumn coloration [7]. The severity of the disease is favored by specific weather conditions such as high humidity and high temperature especially during the vegetative growth [8,9]. Fire blight is difficult to control as the pathogen can infect all host tissues at different times during the season [8,9]. *E. amylovora* is capable of rapid systemic movement in trees and can spread from the site of infection throughout the tree within one season [10]. Ooze droplets containing a mixture of bacterial cells and exopolysaccharides

can emerge from infected tissues and can spread the disease between plants [3,10,11]. Rain, wind, insects, birds, and orchard workers are important vectors in spreading the fire blight disease within and between orchards and their surroundings [1,3,12–14].

Regular inspections of pome fruit orchards, nurseries and other hosts of *E. amylovora* remain an important measure in a fire blight control strategy. As visual inspections are labor intensive, time consuming, and limited by the ability of the human eye to discriminate between healthy plants and plants suffering from stress, more rapid and reliable fire blight detection techniques are needed.

The development of aerial and ground-based hyperspectral and multispectral imaging technology has been a major breakthrough in precision agriculture techniques including in targeted stress management. The spectral reflectance of plants in the visible (VIS) and near infrared (NIR) region of the electromagnetic spectrum is primarily affected by plant pigments and cellular structure of the leaves. Since stress factors alter these plant parameters, they will result in a change in the reflectance signal [15,16]. Furthermore, it is well-known that the Red Edge (RE) spectral region (i.e., transition between VIS and NIR spectral region) is closely linked to the plant's health status [17,18]. Hence, spectral characteristics can be used as indicators of plant health and the remote detection, mapping and monitoring of such plant health linked parameters provides essential information for making timely and effective management decisions. Because VIS and NIR spectrometry is an accurate tool for plant status monitoring, it has been implemented in a wide variety of decision support systems in agriculture and various researchers have used these techniques for disease detection in plants [19,20]. For example, Delalieux et al., 2007 [20] concluded that the visible wavelengths around 650–700 nm and the spectral domains between 1350–1750 nm and 2200–2500 nm were the most important regions for separating stressed apple leaves from healthy leaves immediately after infection of *Venturia inaequalis*.

Recent developments in unmanned airborne vehicles (UAV) allow faster and more cost-efficient collection of aerial imagery on a local scale than visual inspections. UAVs allow to monitor crop health status on a regular basis, estimate plant water needs, and even detect diseases [21–23]. They represent a low-cost method for the collection of high-resolution images and are increasingly used for agricultural applications especially in arable crops. Specifically for plant disease monitoring, Zhang et al., [24] recently published a review paper highlighting the need for hyperspectral data to detect subtle changes in pigments. In addition, the necessity for identifying different spectral features at different development stages of the disease was underlined. Similar results were found specifically for fire blight using hyperspectral images of detached leaves [19,25]. Although highly promising, these results need further validation at tree and orchard levels to allow their practical application. So far, UAV based multispectral data yielded only a low to moderate fire blight detection accuracy as demonstrated by the same authors [25].

The high spatial resolution that can be obtained by spectral sensors introduces an unexplored complexity. Differences in natural leaf colors, shadows, twigs, unwanted objects such as poles, wires, stones can be detected and add complexity to the image analysis. Although high detail can be obtained, local fire blight symptoms can be hidden by healthy leaves and twigs or shadows causing them hard to detect.

In this study, we discuss the potential use of UAV systems carrying a hyperspectral sensor for identifying fire blight infection in pear under orchard conditions. A spectral wavelength selection was performed to detect fire blight. Vegetation indices enabling the discrimination between healthy and infected trees were determined.

2. Materials and Methods

2.1. Study Area

The research was conducted in a commercial pear orchard cv. “Durondeau” that had a long history of fire blight infections. The orchard was located in the district Leuven (Flanders, Belgium). At the time of the study, the trees were twenty years old. The trees were grafted on Quince C rootstocks

and trained in a free spindle system with a tree height of 3.5 m. The trees were planted at 3.5 m between the rows and with variable distance within the row. The planting distance between the trees in the rows was measured to locate the trees correctly in the UAV images afterwards. Despite the disease pressure present in this orchard and favorable weather conditions to further spread of the fire blight infections, no spray applications to control the fire blight were performed by the grower.

2.2. Ground Data Collection by Visual Inspections

In 2015, 440 trees in the trial orchard were scored for visible fire blight symptoms and their severity (no to severe symptoms). The presence of *E. amylovora* was confirmed by diagnostic research according to EPPO guideline PM7/20 (2) [26] including crushing of the samples in phosphate buffered saline at 10 mM followed by isolation of the bacteria on King's B medium [27] and indirect immunofluorescence techniques (serological test). In addition, it was noted if symptoms resembling fire blight but originating from other causes were present as they can interfere with fire blight detection by RGB and hyperspectral sensors (e.g., pear blast caused by *Pseudomonas syringae* pv. *syringae*, herbicide damage, canker caused by *Neovectria ditissima*, problems of incompatibility between cultivar and rootstock). Based on the above mentioned symptoms a fire blight infection score (0–2) was assigned to each tree at each visual inspection date, ranging from no over moderate to severe fire blight symptoms. Asymptomatic trees were only scored as “class 0” (non-infected) when no fire blight symptoms were observed by trained and experienced researchers over all inspections throughout the whole season (classification by expert decision).

From the 440 trees under study 24 reference “infected” trees were selected because they showed visible disease symptoms throughout the whole season and 23 trees of class 0 were selected as reference “healthy” trees. These 47 trees constitute the training set for subsequent tree based modelling (paragraph 2.4.2).

2.3. Image Collection by UAV

On 7 July 2015, a UAV flight with an Altura X8 octocopter, carrying a hyperspectral camera (COSI-cam) with a spectral range of 600–900 nm was performed. The COSI-cam has a 2048×1088 pixels sensor (pixel pitch of 5.5 μm) with a Linear Variable Filter (LVF) deposited directly on the sensor surface [28], with a total of 72 narrow (Full Width Half Max—FWHM 5 nm to 10 nm) spectral bands [28] ranging from 600 to 900 nm. Images were taken in rapid succession (340 frames/s in 8 bit mode) so that every location on the ground was imaged by all spectral bands creating two dimensional hyperspectral images [29]. The imager captures very high spatial resolution data, i.e., images captured with a 9 mm lens at 40 m altitude cover the swath of ~ 40 m with a ~ 1.5 cm ground sampling distance (GSD). Geometrically correct (orthorectified) hyperspectral data can be reconstructed with a GSD of ~ 4 cm.

On the same day, also an RGB image acquisition was performed with a fixed wing SenseFly eBee platform carrying the S.O.D.A. camera (Sensefly.com, Lausanne, Switzerland). Flights were performed at 65 m above ground level, resulting in a spatial resolution of 2 cm resolution.

2.4. Hyperspectral Data Analysis

2.4.1. Preprocessing of Hyperspectral Images

Raw images that were captured with the fixed-wing SenseFly eBee platform (SenseFly.com, Lausanne, Switzerland) were processed with Agisoft Photoscan software (www.agisoft.com) to generate high resolution georeferenced orthomosaic and detailed Digital Surface Models (DSM). Hyperspectral images captured with the Altura X8 octocopter on 7 July 2015, were processed with a processing solution developed at VITO. The raw image data of the camera were transformed into a hyperspectral reflectance image product containing orthomosaics for all 72 spectral bands [29].

A Digital Terrain Model (DTM) was extracted from the obtained DSM by interpolating between the lowest height values of the DSM in a window of approximately 3×3 m. More specifically, background and grasses were masked for further analysis by removing all pixels below a 20 cm threshold. In this image the fruit trees under study were identified based on the distance between the trees as measured in the field. For the obtained UAV images, the spectral information of the trees could as such be extracted. A difficulty was introduced by the within-canopy shadow. To deal with this challenge, the assumption was made that all trees had a similar structure with an equal amount of about 10% shaded pixels.

2.4.2. Selection of Spectral Reflectance Bands

In remote sensing, vegetation indices are an established method to relate hyperspectral space- and airborne observations to plant physiological parameters. Many different vegetation indices exist and each uses a different set of wavelength measurements for describing physiological attributes of vegetation, looking at either general properties of the plant or at specific parameters of its growth [18]. Vegetation indices result in data dimensionality reduction, which is valuable in terms of data processing and analysis. Furthermore, they are able to surpass the limitations of single bands by minimizing external factors, resulting in improved sensitivity for the detection of vegetative biochemical constituents [30–33]. One of the most used and implemented index calculated from multispectral information as normalized ratio between the red and near infrared bands is the Normalized Difference Vegetation Index (NDVI) [31,34,35]. This index is mainly used as a proxy for LAI and leaf chlorophyll concentration. However, this index saturates at a moderate level of LAI content, which causes serious limitations in its use. Notwithstanding this drawback, such a normalized or standardized index has the potential of estimating biophysical parameters in a manner more meaningful than simple ratio indices due to their inherent characteristic of reducing undesired spectral effects caused by, e.g., differences in illumination [20].

In this study, a standardized difference vegetation index (SDVI) of the measured reflectance values R was calculated for each possible combination of two different wavelengths λ_1 and λ_2 as shown in Equation (1).

$$SDVI = \frac{R(\lambda_2) - R(\lambda_1)}{R(\lambda_2) + R(\lambda_1)} \quad (1)$$

The calculated SDVI was then used as an independent variable in a logistic regression analysis to evaluate which wavelength combinations were important in differentiating between binary responses (i.e., infected “1” vs. healthy “0”). The ability of the indices to discriminate between infected and healthy trees was tested using ROC (“Receiver-Operator Characteristic”) analysis [36]. ROC plots are created by plotting the “1-sensitivity” values, the true positive fraction (i.e., infected trees correctly classified as infected) against “1-specificity”, the false-positive fraction (i.e., non-infected trees classified as infected). A curve that maximizes the sensitivity for low values of the false-positive fraction is considered a good model and is quantified by the area under the curve (c-index). The c-index is an easily interpretable and objective statistical measure to evaluate and compare the discriminatory performance of the different wavelengths or their linear combinations, and has values usually ranging from 0.5 (random) to 1.0 (perfect discrimination). Lower values indicate a model that is worse than just random values selection [37]. Values above 0.8 are generally accepted to represent significant discriminative models [38].

Next, the signals of the 47 selected trees (23 healthy trees vs. 24 trees with fire blight symptoms) were used as input for a tree based model (TBM) [39]. Tree based learning algorithms are non-parametric supervised classification or regression methods that do not require the assumption of probability distributions and empower predictive models with high accuracy, stability and ease of interpretation. Unlike linear models, they map non-linear relationships quite well. Other advantages are that specific interactions can be detected without previous inclusion in the model, non-homogeneity can be taken into account, mixed data types can be used and dimension reduction of high dimensional datasets

is facilitated. To avoid overfitting, obtained trees were pruned to lower levels [40]. A ten-fold cross-validation approach was used to determine the classification accuracy and the optimal size of the tree.

Cohen's kappa coefficient (κ) was calculated as it is generally a more robust measure than simple percent agreement calculation, because κ takes into account the possibility of the agreement occurring by chance.

Finally, the most discriminative model to detect healthy and infected trees was subsequently applied to the other trees in the orchard to decide if they were infected or not. The performance of the model is shown by a confusion matrix, including sensitivity and specificity rate. This analysis was done on a per-pixel basis (around 650 pixels per tree, 440 trees) where the number of infected pixels was counted per tree. This number of infected pixels was subsequently divided by the total number of pixels in that tree, obtaining a degree of infection.

3. Results

3.1. Ground Data Selection by Visual Inspection

Six intensive field inspections were carried out by experienced researchers in the period from June 12 till September 10, 2015. This resulted in an orchard map indicating the location of the healthy, the moderately fire blight-infected, and the severely fire blight-infected trees. Table 1 summarizes the fire blight disease incidence and severity as determined by the visual inspections for the 440 trees under investigation. These data clearly demonstrate that the number as well as the severity of infections increased during the season. On the one hand, this was partly due to insufficient removal by the fruit grower of infections, which then progressed and became more apparent. On the other hand, the infection pressure was very high in this orchard causing new infections throughout the season and finally, leading to the loss of this orchard at the end of 2015.

Table 1. Disease incidence and severity scores for 440 trees in a pear orchard cv “Durondeau” at the field inspection dates June 12, June 19, June 29, July 7, August 11, and September 10, 2015. At each observation date the number of healthy trees (class 0), moderately fire blight infected trees (class 1) and severely fire blight infected trees (class 2) were counted.

Visual FB * Infection Status	No. of Trees Scored Per Orchard Inspection In 2015						
	June 12	June 19	June 29	July 7	August 12	September 10	Entire Season
Class 0 (Healthy)	338	323	209	236	161	76	39
Class 1 (Moderately FB infected)	72	86	203	155	240	242	263
Class 2 (Severely FB infected)	28	28	20	19	14	57	78
No. fire blight infected trees	100	114	223	174	254	299	341

* FB = fire blight.

3.2. Hyperspectral Data Analyses for Fire Blight Detection

The spectral information of the selected 24 infected and 23 healthy trees was extracted from the orthomosaic to be further used as input data in the search for SDVIs and TBMs that could detect fire blight infections.

The combinations of spectral bands between 42–45 (784–798 nm) with spectral bands between 1 to 5 (604–620 nm), as well as spectral bands 25 to 30 (708.5–732 nm) combined with spectral bands 42 to 45 (784–798 nm) had the highest discriminatory performance as shown by their high (>0.8) c-values (Figure 1).

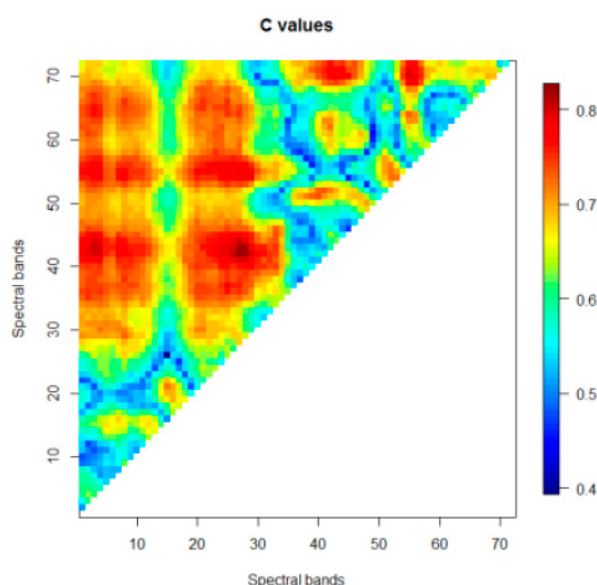


Figure 1. Results of the logistic regression on all possible two-band combinations (standardized difference vegetation index (SDVI)) for the 47 selected reference trees.

Tree based model analysis on the training dataset of 47 trees resulted in a tree model with the first decision node selecting wavelength 611 nm, which subdivides all records into two mutually exclusive subsets. All pixels with reflectance values at 611 nm above 0.08 were considered as infected (1). The remaining pixels were categorized as healthy (0) if reflectance at 784 nm was equal or higher than 0.62. A training accuracy of 85% (kappa = 70%) was obtained by using this TBM model for dividing the dataset in infected and healthy trees (Figure 2). Twenty-two trees were successfully classified by the model as infected (true positive), while 18 trees as healthy (true negative). Five trees that were visually scored as healthy were classified as infected (false positive), while two visually infected trees were classified as healthy (false negative).

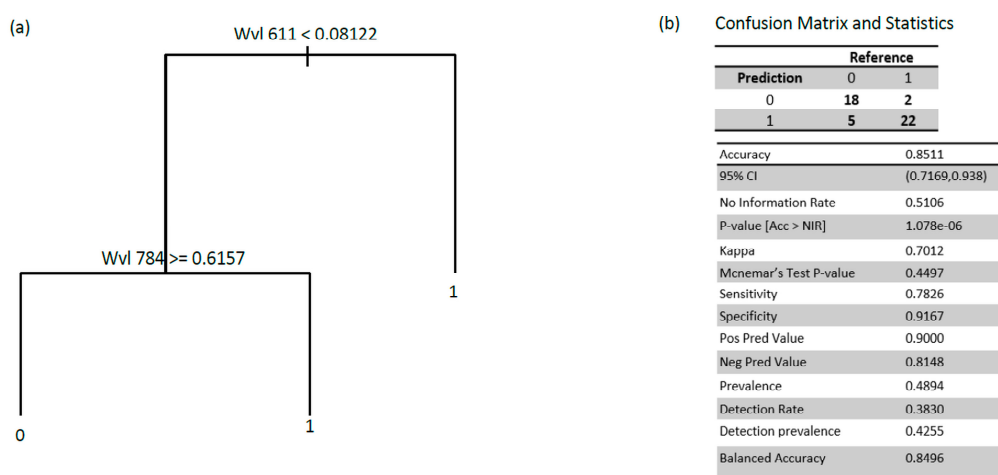


Figure 2. (a) Resulting tree-based model (TBM) using the 47 selected trees as input variables for infected (1) and healthy (0) trees. (b) Confusion matrix and statistics of the pruned training model.

In both methods (vegetation indices and TBM), wavelengths 611 nm (RED) and 784 nm (NIR) were most appropriate to detect symptoms associated with fire blight with c-values above 0.8 and a training classification accuracy of 85%.

3.3. Application of Selected Wavelengths on the Entire Data Set

In a next step, the SDVI combining the two selected spectral bands (611 and 784 nm) was calculated for all pixels of the trees under investigation (around 650 pixels per tree, 440 trees). The ratio of infected vs. healthy pixels was then used to represent the probability of infection of each tree in the orchard (Figure 3).

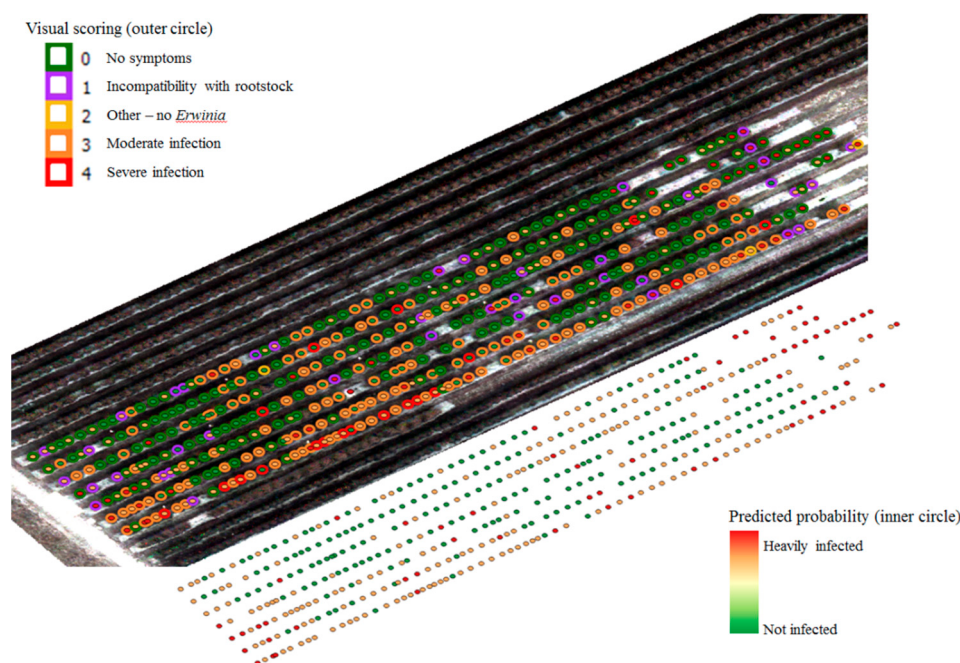


Figure 3. Probability of infection for each tree in the pear orchard calculated from the COSI-cam imagery acquired on 7 July 2015 (inner circle) overlaid on the visual scoring (outer circle). Red indicates high probability, while green corresponds to low probability of infection.

Subsequently, infection probabilities calculated from the COSI-cam imagery were compared to the infection status obtained by the visual field inspection carried out on the same day. The visual inspection data shown in Table 1 indicate that on 7 July, 2015 about 236 trees were classified as healthy, while 174 of the observed trees were classified as fire blight infected. Table 2 summarizes the relation between these visual field data and the hyperspectral COSI-cam data.

Table 2. Relation between visual field data of fire blight detection with the infection probability calculated based on the hyperspectral COSI-cam data of 7 July, 2015 and expressed as the number of trees classified as true positive, true negative, false positive and false negative.

FB* Infection Status	Visual Scoring on 7 July 2015	Relation with Hyperspectral Data			
		True Negative	True Positive	False Negative	False Positive
Healthy	236	126	/	/	110
Fire blight infected	174	/	108	66	/

* FB = fire blight.

This comparison indicated that 62% (108/174 infected trees) of the trees with symptoms associated with fire blight were correctly detected (true positive) by the hyperspectral data analysis, whereas 47% of the visually healthy trees (110 trees/236 healthy trees) were classified as ‘infected’ (false positive). Almost 40% of the infected trees were classified incorrectly as healthy (false negatives; 66 trees/174 infected trees). Consequently, an overall accuracy of only 52% (kappa = 0.13) was obtained for the detection of healthy vs. infected trees on 7 July 2015.

Since visual assessments were repeated until 10 September 2015, it was possible to further monitor the infection status of the trees classified as true/false positive or negative based on the relation between visual and hyperspectral data of 7 July 2015. These data are summarized in Table 3 and revealed that 82 out of 110 false positive classified trees (based on July 7 visual and hyperspectral data), were classified as fire blight infected by the visual scoring over the entire season until 10 September 2015. In addition, 17 of the false positive classified trees showed other symptoms like incompatibility with the rootstock or other fire-blight resembling symptoms at the end of the season. The trees that were incorrectly classified on July 7 as healthy (false negative, 66 trees) were all scored as fire blight infected at the end of the season. In contrast, 86 trees out of 126 trees classified as true negative on July 7, developed fire blight symptoms throughout the season.

Table 3. Comparison of the true/false positive and negative classification based on the 7 July 2015 visual and hyperspectral COSI-cam data (Table 2) and the visual scoring over the entire season till September 10, 2015 as fire blight infected (FB), healthy or other symptoms (i.e., incompatibility with the rootstock or symptoms resembling fire blight).

Classification Based on the Relation Between Visual Scoring and Hyperspectral COSI-Cam Data of 7 July 2015		No. of Trees Visually Scored (Entire Season, Until 10 September 2015)		
Class	No. of trees	FB* infected	Healthy	Other
True positive	108	107	1	0
True negative	126	86	27	13
False positive	110	82	11	17
False negative	66	66	0	0

* FB = fire blight.

4. Discussion and Conclusions

Fruit growers need to frequently inspect their orchards and remove infected plant parts to combat the spread of fire blight. In this study, a heavily infected pear orchard was monitored with a UAV carrying a hyperspectral COSI-cam with a spectral range between 600 and 900 nm. This hyperspectral camera was chosen as it was already concluded from previous spectral studies on fire blight detection that simple RGB cameras do not provide the spectral detail needed for an accurate detection of fire blight symptoms [19,21]. In contrast, RGB imagery was found useful for the application in plant senescence studies [41,42] generating a good general view on the coloration pattern within the orchard. In addition, early autumn coloration is an indicator of the overall low plant vigor and, as such, can be induced by fire blight infections. And thus, in this way RGB data could partly contribute to the detection of fire blight infected trees.

In this study, wavelengths 611 nm (RED) and 784 nm (NIR) were found appropriate to detect symptoms associated with fire blight based on a set of 47 selected trees and with a high accuracy of 85% to distinguish healthy trees from the infected trees that visually show consistent fire blight symptoms throughout the season (Figure 2). These selected bands correspond to the results obtained by Jarolmasjed et al. 2019 [25] on fire blight detection in apple trees. Moreover, most studies have identified the green, red and NIR spectral regions as being sensitive to a variety of plant diseases and pests as summarized by Zhang et al., 2019 [24]. In addition, research studies on multispectral or hyperspectral fungal disease detection like *Botrytis cinerea* in tomato [43] and leaf rust *Naohidemycos vaccinii* in blueberry [44] confirmed that wavelengths located in the VIS and NIR regions are useful to detect diseases. From the studies of Jarolmasjed and co-workers [25] as well as Ahlawat and co-workers [44], it became evident that even better information can be obtained using SWIR (short wavelength infrared) sensors, which were, however, not available in this study.

The combination of these two selected spectral bands (611 nm and 784 nm) was then used to check how many pixels (around 650 per tree) of each tree (440 trees) in the infected test orchard were classified as “healthy” and “infected”. The ratio of infected over total pixels per tree represents the probability of

infection of each tree in the study orchard. With this approach, however, tree infections based on the image dataset of 7 July 2015 were predicted correctly for only 62% of the infected trees (true positive), whereas 47% of the healthy trees were incorrectly indicated as infected (false positive). Moreover, nearly 40% of infected trees were classified incorrectly as healthy (false negatives) (Table 2). Infection probability was thus less accurately predicted for trees that showed no clear symptom expression or trees that scored visually healthy because infections might have been removed by the fruit grower in between the field inspections as part of the disease management strategy or because infections are still latent at the time of the hyperspectral UAV flight (Table 3). These above-mentioned results indicate that the current set-up needs fine-tuning of the model to lower the percentages of false negative and false positive results. The reference trees that were used as input for the TBM and index analyses, were only selected when consistent scoring was observed throughout the season, which explains the high training accuracy of 85%. Most orchard trees, however, showed less clear symptoms or were only slightly infected. Including these trees in the training set, might give better prediction results, and should be tested in future research. A more detailed ground truth collection is needed for this, too.

On the one hand, in the case of false positive classification of healthy trees, the following factors may play a role: (1) As indicated in Table 3, 82 out of 110 false positive classified trees (based on July 7 visual and hyperspectral data), were scored as fire blight infected at the end of the season. This may be due to infections removed early in the season by the grower but reappeared later in the season on adjacent branches and fruits. Moreover, infections that were still asymptomatic during the inspections of July 7, could become symptomatic later in the season. (2) Within-canopy shadow introduced difficulties as dark (shaded) pixels can result in false positive identification as well as spectral analysis at different phenological stages of the trees can be different. We therefore assumed that all trees had a similar structure with an equal amount of about 10% shaded pixels in healthy trees. A shadow removal algorithm should be applied to check this hypothesis. However, existing shadow removal algorithms were developed for spaceborne and airborne remote sensing studies [45] and, to our knowledge, have never proven to be applicable on highly detailed UAV imagery of vegetation. (3) In addition to shade, also fire blight-like symptoms like broken shoots and branches, pear blast caused by *Pseudomonas syringae* pv. *syringae* infections and canker caused by *Neonectria ditissima*, all of which were noted by the visual field inspections, could be mistaken for fire blight by spectral analysis causing false positives. Jarolmasjed and co-workers [25] also encountered these issues in their study on fire blight detection in apple trees. They mention the need for an automated phenotyping system to cover the canopy with controlled lighting and imaging conditions in addition to accurate estimation of distances with 3D cameras. (4) Furthermore, an imperfect delineation of the trees due to the asymmetric shape of many trees and geometric artefacts in the orthomosaic resulted for some trees in only a limited number of pixels and biased infection probability. For example, at the end of the fifth row, only a few, mainly shaded pixels were used for analysis due to an incorrect delineation of the trees as the trees were not perfectly aligned at the end of that row. Very accurate GPS coordinates of each tree could overcome this problem. In the near future, it is expected that all fruit growers will plant more using GPS systems as it increases planting efficiency and will be the basic tool to optimize production and harvest in a precision farming context.

On the other hand, the high percentage of false negative classification of infected trees can be linked to the presence of limited fire blight symptom expression and infections hidden in the tree. These types of infections were observed during the field inspections, but they can easily be overlooked by the spectral imagers. Therefore, we believe that a combination of side viewing and top viewing imagery will improve the detection capacity of this proposed RS method. And with the coming of robotics and autonomous drones, a detailed image database can be obtained. Training artificial intelligence systems in recognizing the (spectral) symptoms of the fire blight disease, would help fruit growers to monitor and map the disease incidence.

A multitemporal approach might be useful to improve the infection detection probability, and to lower the number of trees for which the disease status was misclassified. Symptom scoring at one

moment in time is not always representative for the health status of the trees. Trees can show infected plant parts, which are removed afterwards by the fruit grower, and reappear after some days on adjacent twigs, fruits. Furthermore, a multitemporal approach may be preferred for a better indication of fire blight incidence and severity as *E. amylovora* can be present in the tree without showing any symptoms [46]. Moreover, multitemporal detection helps to overcome problems with interference of shadow on and within the trees, detection of small infections and to distinguish between fire blight-like symptoms caused by other factors than *E. amylovora*.

As is concluded from this work, further optimizations and improvements are needed to enable an operational monitoring of fire blight with spectral sensors carried by an UAV. Nevertheless, this study revealed a high potential in the detection of clearly diseased and asymptomatic healthy trees.

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