Evaluation of narrow-band vegetation indices for anomaly detection in grapevine leaves

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Abstract: Anomaly detection is a process of finding an element or a group of elements with anomalous behavior, which can be viewed from a different perspective (e.g. spatial, spectral or temporal aspects). In hyperspectral data, images' spectral information is robust and can bring additional information when compared to common RGB images. Each material has its own specific spectral reflectance within the electromagnetic spectrum - especially when dealing with vegetation - since spectral signatures can vary depending on their status. This will be explored in this study to detect anomalies in grapevine leaves. For this purpose, selected narrow-band vegetation indices were evaluated. These vegetation indices, when compared to common vegetation indices, use narrower portions of the electromagnetic spectrum, from the visible to the near-infrared parts. When the optimal combination of bands is used, specific grapevine leaves properties can be highlighted. Once an anomaly is detected, future research needs to be done to determine its type. After having an anomaly correctly categorized, proper actions can take place to stop a potential infection and thus maintain crops' health and yield.

1. Introduction

Wine production is an important part of Portuguese agriculture (Lains, 2017). Nevertheless, sustainable development challenges that were addressed by many scientists (Cusmano et al., 2010; Graci et al., 2013; Santini et al., 2013) emerged. To overcome those challenges is of great importance, especially for regions such as Douro Demarcated Region, which is best known for its wine production. Major economic losses in agriculture are caused by diseases (Martinelli et al., 2015) that are usually expressed by anomalous spots on leaves. In (Pinter et al., 2003; Sims & Gamon, 2002) is demonstrated that infections cause changes in pigments. However, when infections are detected at their early stages and before being widespread, their influence can be limited. To detect those anomalous spots on leaves, the plant's physiological condition needs to be known. Numerous vegetation indices (VIs) have been developed to assess this information. Their calculation consists in simple mathematical operations with available spectral bands. Common VIs use broad spectral bands because sensors providing those parameters are more common. But there are also VIs using more restricted bands, called narrow-band VIs (Agapiou et al., 2012). A comparative study about broad-band VIs and narrow-band VIs was conducted by Thorp et al., (2004) and Vincini & Frazzi (2011). Evaluation of both types of VIs for determining optimal hyperspectral wavebands for agricultural crop characterization was presented in (Thenkabail et al., 2002) and advantages of using narrow-band VIs in biomass estimation were highlighted in (Mutanga & Skidmore 2004).

Narrow-bands are obtainable from hyperspectral images. Hyperspectral data stores reflectance values over a wide range of the electromagnetic spectrum, encompassing hundreds of narrow-bands (some sensors can capture even thousands). This level of detail provides data that remains unseen for human eyes and thus potentially more relevant results when regarding the detection of anomalous parts representing potential risk to plants' development. Tucker (1979) demonstrated that VIs using near infra-red (NIR) bands contrast intense chlorophyll pigment absorption in red, against high reflectivity of plant materials.

Regarding the use of narrow-band VIs for disease detection, Naidu et al., (2009) studied the potential of spectral reflectance technique for the detection of grapevine leaves disease. Hou et al., (2016) researched grapevine leafroll disease detection and Mahlein et al., (2010) studied spectral signatures of sugar beet leaves for the detection and differentiation of diseases. However, common narrowband VIs are not directed to detect specific diseases. As such, an evaluation of available narrow-band VIs to detect anomalies in grapevines leaves - that may represent a disease - is done in this study. Section 2 presents the used material and methods in this study, followed by the results and a discussion in section 3. Section 4 contains some conclusions.

2. Material and methods

Hyperspectral images of five grapevine leaves were used (see Figure 1). The leaves contain visible anomalies, differently spread. Three main colors can be seen in the images: brown and light green - which were considered anomalies - and dark green, which represents leaves' healthy parts. Different colors in anomalous spots may indicate distinct stages of disease development, but this fact was not considered in this study. Leaves A, B and C) in Figure 1 have small anomalous spots, while leaves D and E have the anomaly spread.

Figure 1 – Grapevine leaves with visible anomalies

Images presented in Figure 1 were acquired in a controlled laboratory environment using Nano-Hyperspec (uVS-320) sensor with 15 ms frame period, 15 ms exposure, spectral range from 400 to 1000 nm (VNIR) and 270 bands. However, only 35 bands were used considering the bands needed to calculate the selected narrow band VIs (see Table 1). Thenkabail *et* al., (2002) pointed out that there is no best approach to select optimal number of narrow wavebands that are required for agricultural plant characteristics estimation. Images' size are ~1600 x 2153 pixels. In total, 24 narrow-band VIs were used, as presented in Table

1, where both the equations and references are provided. VIs results were thresholded to binary images by automatic image clustering Otsu´s method (Otsu, 1979). These were then compared with manually created anomaly masks and evaluated based on the proportion of correctly, over and under detected pixels.

VIs calculation is based on the fact that the reflectance from vegetation to the electromagnetic spectrum is determined by chemical and morphological characteristics of the surface of organs or leaves (Zhang & Kovacs, 2012). NDVI is probably the most used VI that calculates plants' greenness because of the high reflectance of chlorophyll in NIR (Zarco-Tejada, González-Dugo, & Berni, 2012). But during the last decades, numerous VIs were developed for many specific applications and thus, for a selection of optimal VI, advantages and limitations of existing VIs need to be considered.

3. Results and discussion

Results of VIs used in this study varied significantly (see Figure 2). Best results were achieved by NDVI modifications that use narrow bands of the red band both in the visible part and in the near infrared part. Overall, the best performance was of mNDVI2 (see Figure 3), with 96,17%, followed by a very similar result of NDVI2, with 96,16% of correctly detected pixels. Closely behind the four best VIs was PSND with 95,79%, which uses only about 5 nm different red band in the visible part than NDVI. The lowest performance VI were in those that use blue and green bands of the visible part. Overall, the worst performance was of PRI, with 29,41% and NPQI, with 30,70% of correctly detected pixels.

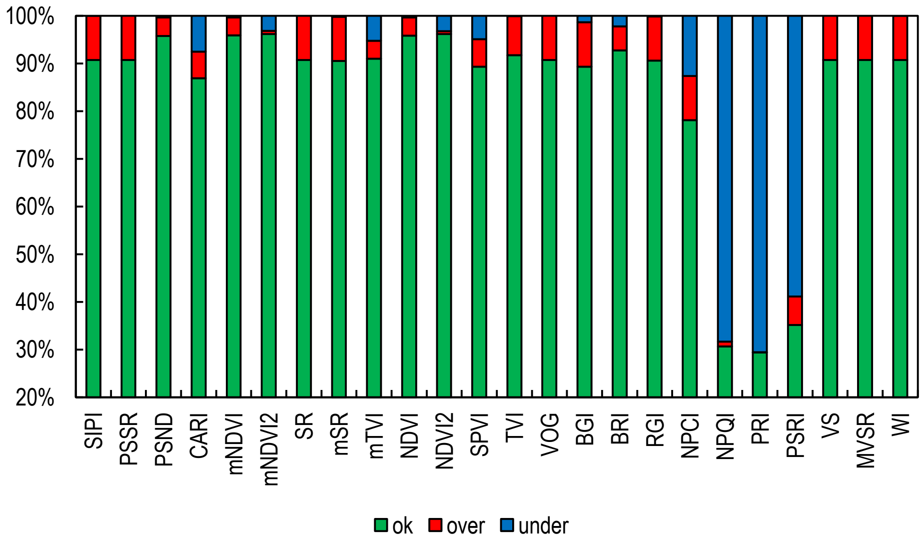


Figure 2 – Evaluation on narrow-band vegetation indices performance when detecting grapevines leaves anomalies

In Figure 3 are graphically highlighted results of the best and worst two VIs on leaf E, that has the anomaly more widespread. Green color represents correctly detected pixels, red color over detected and blue color under detected pixels.

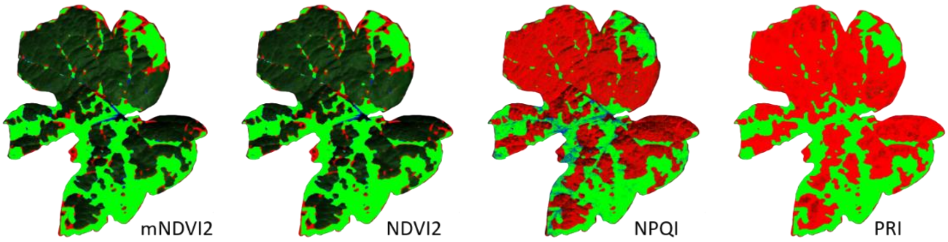
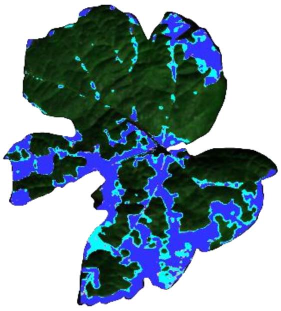


Figure 3 – Graphical depiction of two best and two worst VIs performances

Table 1 – Selected narrow band indices

Index	Equation	Reference
Structure Insensitive Pigment Index	SIPI = (R800-R445)/(R800-R680)	(Peñuelas et al., 1995)
Pigment-specific Simple Ratio	PSSR = (R800 / R675)	(Blackburn, 1998b)
Pigment-specific Normalized Difference	PSND = ((R800-R675))/(R800+R675))	(Blackburn, 1998a)
Chlorophyll Absorption Ratio Index	CARI = ((R700-R670)-0.2*(R700-R550))	(Kim, 1994)
Modified Normalized Difference Vegetation Index	mNDVI = (R800-R680)/(R800+R680-(2*R445))	(Sims & Gamon, 2002)
Modified Normalized Difference Vegetation Index	mNDVI2 = (R750-R705)/(R750+R705-(2*R445))	(Sims & Gamon, 2002)
Simple Ratio	SR = (R800/R680)	(Jordan, 1969)
Modified Simple Ratio	mSR = (R800-R445)/(R680-R445)	(Sims & Gamon, 2002)
Modified Triangular Vegetation Index	mTVI = 1.2*(1.2*(R800-R550)-2.5*(R670-R550)	(Haboudane et al., 2004)
Normalized Difference Vegetation Index	NDVI = (R800-R670)/(R800+R670)	(Rouse, 1974)
Normalized Difference Vegetation Index	NDVI2 = (R750-R705)/(R750+R705)	(Gitelson & Merzlyak, 1994)
Spectral Polygon Vegetation Index	SPVI = 0.4*(3.7*(R800-R670)-1.2*(R530-R670))	(Vincini et al., 2006)
Triangular Vegetation Index	TVI = 0.5*(120*(R750-R550)-200*(R670-R550))	(Broge & Leblanc, 2001)
Vogelmann Indices	VOG = (R740/R720)	(Vogelmann et al., 1993)
Blue Green Pigment Index	BGI = (R450/R550)	(Zarcotejada et al., 2005)
Blue Red Pigment Index	BRI = (R450/R690)	(Zarcotejada et al., 2005)
Red/Green Index	RGI = (R690/R550)	(Zarcotejada et al., 2005)
Normalized Pigment Chlorophyll index	NPCI = (R680-R430)/(R680+R430)	(Peñuelas et al., 1994)
Normalized Phaeophytinization Index	NPQI = (R415-R435)/(R415+R435)	(Barnes et al., 1992)
Photochemical Reflectance Index	PRI = (R531-R570)/(R531+R570)	(Gamon et al., 1997)
Plant Senescence Reflectance Index	PSRI = (R680-R500)/R750	(Merzlyak et al., 1999)
Vegetation Stress ratio	VS = (R725/R702)	(White et al., 2008)
Modified Vegetation Stress ratio	MVSR = (R723/R700)	(White et al., 2008)
Water Index	WI = (R900/R970)	(Peñuelas et al., 1993)

Performance differences between the five best VIs (mNDVI2, NDVI2, mNDVI, NDVI and PSND) are depicted in Figure 4, where the areas with corresponding similarity of the five best results can be seen. Maximum similarity is in areas where the results were computed by all VIs - in this case five -, while minimum similarity is in areas where the results are computed by only one VI (see corresponding Figure 4 caption with the associated percentage occurrence for all cases). Figure 4 caption points out that 68,57% of areas were computed by all the VIs, however, 27,43% of areas were detected only by two VIs (in this case, the two best VIs: mNDVI2, NDVI2).



	5	68.57 %
	4	1.69 %
	3	2.28 %
	2	27.43 %
	1	0.03 %

Figure 4 – Differences in the detection results obtained by the five best VIs: mNDVI2, NDVI2, mNDVI, NDVI and PSND

4. Conclusion

This study aimed to evaluate narrow-band VIs for anomaly detection in grapevine leaves. In total, 24 VIs were used and several of them achieved promising results. From the acquired results it can be stated that optimal selection of bands has a significant impact on a VIs performance for a specific application, because when not optimal bands were used, the performance dropped under 30%. The results of this study can help in selecting the best VIs for anomaly detection in grapevines leaves. Moreover, hyperspectral data has proved to be worth exploiting to select specific wavebands that fit for detecting the biophysical or biochemical properties and being able to detect specific anomalies.

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