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Using visible-near-infrared spectroscopy to classify lichens at a Neotropical Dry Forest



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ARTICLE INFO ABSTRACT Keywords: The optical properties of lichens have been traditionally explored in the context of geological mapping where the Reflectance encrustation of lichens on rocks may influence the detection of minerals of interest. As of today, few studies have Lichen spectroscopy looked into the potential of using the optical properties of lichens to classify them; however, none has in-Species discrimination vestigated the classification of tropical lichens using spectroscopy. Here we explore the use of the visible-near Spectral classification infrared reflectance (VNIR; 450-1000 nm) to discriminate Neotropical corticolous lichens; the most abundant Wavelet analysis lichens in tropical forests. Reflectance measurements on lichens and their bark substrate were performed on 282 lichens samples of 32 species attached to their host's bark. Using these measurements, we first explored the degree of spectral mixing of bark and lichens by linear unmixing each lichen spectrum with the corresponding average species spectrum and bark spectrum. Overall, the results reveal that the lichen signatures tend to mask the spectral contributions from bark; however, there are some specific groups of species with high bark mixing probably due to their nature and the similarities between the lichen and bark spectra. Next, we classified the lichen spectra based on growth forms and taxonomic ranks (i.e., family, genus, species) using five machine

average species spectrum and bark spectrum. Overall, the results reveal that the lichen signatures tend to mask the spectral contributions from bark; however, there are some specific groups of species with high bark mixing probably due to their nature and the similarities between the lichen and bark spectra. Next, we classified the lichen spectra based on growth forms and taxonomic ranks (i.e., family, genus, species) using five machine learning classifiers. This analysis was conducted on raw reflectance spectra and wavelet-transformed spectra to enhance the absorption features prior to classification. As expected, the classification of lichen spectra is less accurate at species-specific levels, rather than higher taxonomic ranks. The wavelet transformation was found to enhance the general performance of classification; however, the accuracy of the classification depends on the classifier. Of the classifiers used in this study, linear discrimination applied to reflectance spectra presents the highest performance at the species level. Our results reveal the potential of using the VNIR reflectance as a method to discriminate Neotropical lichens. The introduced methodology may be conducted in the field, thus allowing the monitoring of lichen communities in forests; thereby furthering the current understanding of the role of lichens in ecosystem functioning.

1. Introduction

Classification using spectral data as input is a widely used technique to identify species, minerals and land cover types (Castro-Esau et al., 2006; van der Meer et al., 2012). This technique is founded on the fact that the interaction of electromagnetic radiation with a given object produces unique signatures that are associated with chemical and structural components; signatures that can be used to discriminate between different materials. In general, classification based on spectroscopic data has been applied to measurements obtained at varying scales from near-ground, to airborne, and satellite observations using different regions of the electromagnetic spectrum. In the tropics, this technique is revolutionizing the study of biodiversity through the mapping of forest species and processes associated with them (Sanchez-

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Azofeifa et al., 2017; Shiklomanov et al., 2019). Several studies have examined the discrimination of lichens based on their spectral features (e.g., Bechtel, Rivard & Sánchez-Azofeifa 2002; Rees, Tutubalina & Golubeva 2004; Morison, Cloutis & Mann 2014), but we know of no such studies for tropical lichens.

Lichens, an obligate symbiosis between a fungus (mycobiont) and an algae or cyanobacteria (photobiont) (Nash, 2008), are a highly diverse group with more than 17 500 species worldwide (Lumbsch et al., 2011). The optical properties of lichens have primarily been explored in high latitudes in a context of geological mapping, where rock-encrusting lichens can imped mineral exploration and lithological mapping activities (Ager and Milton, 1987; Bechtel et al., 2002; Feng et al., 2013: Satterwhite et al., 1985: Van Der Veen Cornelis and Csatho, 2005: Zhang et al., 2005). In this context it has been described that rock encrusting lichens are optically thick because they transmit less than 3% of light in the 350-2500 nm spectral range (Bechtel et al., 2002). This optical property implies that lichen signatures should not be affected by their substrate, allowing their accurate detection and discrimination. Three studies have addressed the classification of lichens based on their spectra: the first conducted in the Canadian Rockies (Bechtel et al., 2002), the second in subarctic Sweden (Rees et al., 2004) and the third in Manitoba, Alberta and Nunavut in Canada (Morison et al., 2014). These studies characterize the spectral properties of lichens based on a relatively few (5-10) rock-encrusting species (Bechtel et al., 2002, Rees et al., 2004) or attempt to discriminate lichens based on the colors of 16 species (Morison et al., 2014). To the knowledge of the authors, never before have tropical bark-encrusting (corticolous) lichens been investigated using spectroscopy.

Lichen signatures in the visible-near-infrared (VNIR) region of the spectrum (350-1100 nm) tend to be highly diverse (Rikkinen, 1995). However, most of the signatures exhibit a distinctive chlorophyll absorption feature close to 685 nm, attributed to the presence of this compound in the photobiont (Bechtel et al., 2002). Some lichen signatures tend to have a low reflectance in the ultraviolet region, and at the lower end of the visible spectrum due to the absorption feature of usnic acid located in the mycobiont (Ager and Milton, 1987). Other compounds such as beta-carotene, phycobiliproteins, phycoerythrin, phycocyanin, allophycocyanin, and pheophytin that present absorption bands similar to those of the chlorophyll have also been described in lichens and their photobiont (Goodwin and Mercer, 1988; Rao and LeBlanc, 1966; Wilhelmsen, 1959). This high diversity of compounds contributes to the spectral variation of different lichen species (Petzold and Goward, 1988; Shukla et al., 2010), a characteristic that may be used to discriminate them using hyperspectral data.

A good understanding of the optical properties of lichens and their use to discriminate among species could help in a wide variety of fields due to the functioning of lichens in the ecosystem (Asplund and Wardle, 2016). For example, since lichen reflectance depends on their chemical and structural compounds and those can be used as proxies of the overall health and adaptation to microenvironmental conditions (Asplund and Wardle, 2016; Garty et al., 2001), lichen signatures and the discrimination of lichen species may be used as reliable bioindicators of the health of a given environment. Also, spectral data can provide valuable knowledge associated with ecosystem dynamics because of the close relation between lichens and trees (Benítez et al., 2019; Wolseley et al., 1994), their sensitivity to drought (Nash, 2008), and forest fires (Lõhmus et al., 2017; Wolseley and Aguirre-Hudson, 2003).

In this study we evaluate the use of the VNIR reflectance as a method to classify neotropical corticolous lichens. We hypothesize that VNIR reflectance spectra can be used to discriminate lichens of different growth forms and taxonomic ranks, but the success of discrimination may depend on the taxonomic ranks of the groups, the preprocessing of the spectral data, and the type of classifier. To test the hypothesis, we evaluated the performance of five common classifiers to discriminate individuals of different growth forms and three different taxonomic ranks (families, genus, and species) applied to hyperspectral VNIR data. We further assessed the effect of the wavelet transformation preprocessing method on the accuracy of lichen discrimination. These analyses were conducted to provide a broad perspective for future research associated with spectral lichen discrimination.

2. Materials and methods

2.1. Study site and sample collection

This study was conducted at the Santa Rosa National Park Environmental Monitoring Super Site (SRNPEMSP, 10°48" N, 85°36" W), situated in a Tropical Dry Forest (TDF) located at the Guanacaste province in the northwestern Pacific coast of Costa Rica. This area has a mean air temperature of 26 °C during the wet season (May to November) and 29 °C during the dry season (December to April), and has a mean annual precipitation of 1720 mm (Kalacska et al., 2004). In general, the SRNPEMSP landscape is a mosaic of forest patches with different forest ages and land-use histories associated with anthropogenic fires, deforestation, and land clearing for pasture and agriculture (Arroyo-Mora et al., 2005; Calvo-Alvarado et al., 2009; Sánchez-Azofeifa et al., 2017). The SRNPEMSP hosts 96 species of trees of different life histories (Hilje et al., 2015) and may present about 160 lichen species, most of which are corticolous and represent crustose, foliose, squamulose and gelatinous growth forms.

Lichens adhering to tree trunks were collected together with a section of their underlying bark between June and July 2017 (wet season). A total of 282 samples were collected from the understory at a maximum height of 2 m following a haphazard sampling design based on morphospecies identification in the field. Samples were carefully extracted by slicing the bark beneath the thallus with a sharp knife. Then, samples were placed on a pH-free paper envelope and transported in a plastic bag to the laboratory for spectroscopic measurements within the following 24 h (See Section 2.2). After that, lichens were taxonomically classified using their morphological and chemical characters. The taxonomic classification was conducted using a stereoscope, a microscope (Leitz Laborlux 12), potassium hydroxide, iodine, sodium hypochlorite, and a UV flashlight (395 nm) following general and specific taxonomic keys (Brodo et al., 2001; Gumboski, 2014; Lücking et al., 2009; Moberg, 2018; Ramos, 2014; Sipman, 2005). In total, the lichens collected comprise four growth forms, 16 families, 25 genus, and 39 species (Table 1). Due to lack of distinctive features, it was not possible to taxonomically classify ten morpho-species to family and species. After classification, the samples were deposited in the Anastasio Alfaro Herbarium at the Escuela de Ciencias Biológicas, Universidad Nacional de Costa Rica for further reference.

2.2. Reflectance measurements

The acquisition of lichen and bark reflectance spectra were conducted using a UniSpec Spectral Analysis System (PP Systems, Amesbury, MA, USA) spectrometer. The data were acquired in 256 bands spanning a spectral range of 306-1138 nm, each with a spectral resolution (bandwidth) of 10 nm and a sampling of 3.3 nm. All the spectra were collected using a leaf clip sampling accessory that holds a foreoptic at 60° and provides illumination (7.0 W halogen bulb) to an area of 4.15 mm². Before the data acquisition, a white reference spectrum was acquired using the 99% reflectance target of the leaf clip accessory and a dark reference was acquired using the build-in shutter functionality of the spectrometer. The sample spectra were then acquired by carefully placing each sample in the leaf clip to ensure that only the desired component (lichen or bark) were in the field of view of the clip. Each spectral measurement was set to be an average of 40-60 scans. Lichen spectral measurements were conducted on the surface of the lichen attached to the bark below, while the bark spectral measurements were performed on a segment of the surface of bark exposed without lichens or other organisms. Following this protocol, ten lichen

Table 1

The lichen growth form, family, genus and species sampled at the Santa Rosa National Park Environmental Monitoring Super Site, Costa Rica. The number of samples and the minimum taxon used for classification (GF: growth form; F: family; G: genus; S: species) is given for each species.

Growth form		Family	Genus	Species	Number of samples	Minimum taxon used for classification
Crustose		Graphidaceae	Graphis	Graphis fournierii	6	GF, F, G, S
				Graphis furcata	15	GF, F, G, S
				Graphis librata	12	GF, F, G, S
				Graphis tenella	2	GF, F, G
		Lecanoraceae	Lecanora	Lecanora helva	16	GF, F, G, S
			Ramboldia	Ramboldia russula	10	GF, F, G, S
		Malmideaceae	Malmidea	Malmidea granifera	2	GF
				Malmidea leptoloma	4	GF
		Pertusariaceae	Pertusaria	Pertusaria cicatricosa	6	GF
		Physciaceae	Buellia	Buellia gerontoides	10	GF, F, G, S
				Buellia microsporella	26	GF, F, G, S
		Porinaceae	Porina	Porina tetracerae	16	GF, F, G, S
			Genus_01	Species_01	1	GF, F
		Pyrenulaceae	Pyrenula	Pyrenula pyrgillospora	27	GF, F, G, S
		Family_01	Genus_02	Species_02	2	GF
		Family_02	Genus_03	Species_03	2	GF
		Family_03	Genus_04	Species_04	4	GF
Foliose		Parmeliaceae	Parmotrema	Parmotrema aptrootii	1	GF, F, G
				Parmotrema conformatum	10	GF, F, G, S
				Parmotrema fasciculatum	3	GF, F, G
				Parmotrema mesogenes	4	GF, F, G
				Parmotrema peralbidum	5	GF, F, G
				Parmotrema praeisidiosum	14	GF, F, G, S
				Parmotrema tinctorum	7	GF, F, G
			Rimelia	Rimelia macrocarpa	3	GF, F
			Genus_05	Species_05	3	GF, F
			Genus_06	Species_06	2	GF, F
			Genus_07	Species_07	3	GF, F
		Physciaceae	Physcia	Physcia integrata	2	GF, F, G
				Physcia sorediosa	8	GF, F, G, S
			Pyxine	Pyxine cocoes	1	GF, F
				Pyxine convexior	4	GF, F
				Pyxine eschweileri	2	GF, F
		Family_04	Genus_08	Species_08	1	GF
Gelatinous		Collemataceae	Leptogium	Leptogium cyanescens	12	GF, F, G, S
		Lichinaceae	Lempholemma	Lempholemma sp.	11	GF, F, G, S
Squamulose		Ramaliaceae	Aciculopsora	Aciculopsora salmonea	21	GF, F, G, S
			Genus_09	Species_09	3	GF, F
		Family_05	Genus_10	Species_10	1	GF
Total	4	16	25	39	282	

and ten bark spectral measurements were acquired from each sample; enough to cover the surface of each lichen and their substrate.

2.3. Spectral quality control and preprocessing

First, the quality of the 5313 reflectance measurements of lichens and their host's bark was evaluated. As a result of this evaluation, 91 measurements were removed having relatively low signal-to-noise ratios. For each sample, the remaining measurements were averaged to create a single spectral representation of lichen and bark per sample. After the averaging, the final datasets comprise 282 lichen spectra and 277 bark spectra. Some spectra in the bark dataset are repeated due to some lichens sharing the same host's bark. These datasets are available at the Tropi-Dry Dataverse (https://doi.org/10.7910/DVN/Y1J0UQ).

The spectral dataset of lichens and bark were processed to extract the absorption features using a continuous wavelet transformation (CWT). From this transformation, each reflectance sample is described as a sum of wavelets, each representing spectral features of different scales (Rivard et al., 2008). The CWT was performed using a secondorder derivative of Gaussian with a variance of 1 and a range of scales between 1 and 9. From the wavelets extracted at these scales, wavelet spectra between scales of 2 and 5 were summed and these summed spectra, called summed-wavelet from herein, were used in the ensuing analysis. In general, the spectral features captured by these scales are best for the discrimination between different lichen species (Fig. S1). The CWT transformation was conducted using the '*wavCWT*' function in the *wmtsa* package (Constantine and Percival, 2016) of R (R Core Team, 2019).

The mean reflectance and its standard error were used for a visual representation of lichen spectra at the four levels of aggregation (growth form, families, genus, and species). Moreover, the bark spectra were visually represented by grouping all the bark spectra into six categories based on their reflectance characteristics. These categories were identified using the *k*-nearest neighbors because of a lack of taxonomic information of the host's bark. These analyses were performed to describe the diversity of the reflectance properties of the host's bark. After careful consideration, bands at the edges of the spectrometer range (the shortest and longest wavelengths) were omitted due to relatively low signal-to-noise ratios of these wavelength regions. As a result, the wavelength range of 450–1000 nm (171 bands) was retained for all the ensuing data analysis.

2.4. Endmember selection and linear spectral unmixing

We applied spectral mixture analysis (SMA) to test whether there is spectral mixing between lichens and the underlying bark. This analysis was conducted because spectral mixing could interfere with the ability to correctly classify tropical lichens using machine learning techniques. In practice, we conducted SMA using linear spectral unmixing, an established technique that uses a linear combination of endmembers to

J.A. Guzmán Q., et al.

Table 2

List of classifiers used with their respective tuning parameters.

Classifier	Abbreviation	Function	Library	Tuning parameters
Linear Discriminant Analysis	LDA	lda	MASS (Venables and Ripley, 2002)	_
k-Nearest Neighbors	KNN	knn	_	k = 4
Neural Networks	NN	nnet	nnet (Ripley and Venables, 2016)	Size = $1-6$; Decay = $0.1-0.5$
Random Forest	RF	rf	randomForest (Liaw and Wiener, 2002)	mtry = 1-5
Support Vector Machines with Radial Basis Function Kernel	SVMRK	svmRadial	kernlab (Karatzoglou et al., 2004)	Sigma = 0.01–1; Cost = 0.1–1

approximate their abundance in a mixed spectrum (Somers et al., 2011).

Lichen endmembers were determined by calculating an average reflectance of each lichen species. Here, each species was defined to be an endmember due to the inherent physicochemical variation that separates different species, and also due to the data acquisition setup that ensured that a given spectrum represented a single lichen. This analysis was conducted using all lichens samples (n = 284). The resulting lichen endmembers (i.e. lichen species; n = 34) represent 14 families and each endmember comprises 2 to 27 individual lichen spectra (mean = 8.11). Likewise, each bark reflectance per sample was defined to be an endmember, since each of these spectra were acquired from surfaces devoid of lichens or other vegetation. Lichen samples with no corresponding bark spectrum or those whose growth form was uncertain were left out from the SMA. Also, species that had only one sample were not deemed to be sufficiently representative for the SMA and hence such species were left out from the SMA. The resulting dataset comprises 262 lichen spectra (foliose, n = 57; crustose, n = 158; gelatinous, n = 23; squamulose, n = 24) and the corresponding bark spectra.

The SMA was conducted by unmixing each lichen spectrum with the corresponding bark spectrum (i.e. the bark endmember) and the average spectrum of the lichen species (i.e. the lichen endmember). The SMA was conducted using a partially constrained (unit-sum constraint = 1) linear spectral unmixing algorithm of the ENVI® (version 5, Harris Geospatial Solutions) software package. A boxplot showing the bark abundance per species was performed cutting the values between -0.3 and 0.6 to better exemplify the variation between species.

2.5. Spectral classification of lichens

The spectral classification of lichens was conducted at the growth form level (foliose, crustose, squamulose, and gelatinous) and taxonomic level, specifically i) family, ii) genus, and iii) species. The growth form and taxonomic levels are called "levels of evaluation" from herein. The number of classes used at each of these levels was based on the number of samples. As such, the analysis was conducted on classes that have more than 8 samples at each level of evaluation in order to have a good representation during the training and testing of the algorithm. From this, 4 classes of growth forms, 9 of families, 11 of genus, and 14 of species were used to evaluate the discrimination between lichens. The samples of a given species used as classes for classification is described in (Table 1). Moreover, lichen reflectance spectra and summedwavelet spectra of each class were analyzed separately. These datasets were randomly split 50:50 for training and testing purposes. This procedure was conducted to ensure an equal representation of each lichen species in the training and testing datasets. The procedure of splitting was performed using the 'createDataPartition' function of the caret package in R (Kuhn, 2008).

Using these datasets, five supervised classifiers were used to evaluate the discrimination of lichens: Linear Discriminant Analysis (LDA), *k*-Nearest Neighbors (KNN), Neural Networks (NN), Random Forest (RF), and Support Vector Machine with Radial Kernel (SVMRK). These classifiers were selected because they have been described as promising algorithms for the discrimination of species and life forms in studies that use reflectance data (e.g. Guzmán et al., 2018). Specifically, in the context of this study, the LDA is a parametric classifier that maximizes

the spectral differences between classes and minimizes these differences within classes, and then, finds a linear combination that best discriminates between them. KNN is a non-parametric algorithm that predicts classes of spectral samples based on the k-closest spectral sample from the training data determined by a distance matrix. The NN is a non-parametric classifier inspired by how the brain works. It uses a set of unobserved variables called hidden units, which are linear combinations of the original predictors, which in turn can be transformed into nonlinear function to represent classes. The RF classifier is also a non-parametric ensemble learning classifier that creates multiple decision trees during the model training and produces a class that represents the mode of classes of the individual trees for prediction. The SVMRK, in turn, is a non-parametric classifier that projects the reflectance of the different classes into a multidimensional space, and fits a hyperplane based on the radial kernel that best defines the separation boundaries of the classes.

The application of classifiers was computed using the *caret* package in R (Kuhn, 2008). The training of each classifier was tuned using 10fold cross-validation. The tuning parameters used for each classifier are described in Table 2. Finally, the classification results were evaluated using the accuracy and the mean F1 coefficient between classes following the '*confusionMatrix*' function of the *caret* package in R (Kuhn, 2008).

3. Results

3.1. Evaluation of datasets

The lichen spectra present a variability in reflectance between 0.02 and 0.94. In general, the higher values of reflectance tend to be between 720 and 1000 nm, while the lower values tend to be close to 450 and 500 nm (Fig. 1). At the growth form level, foliose lichens present the highest values of reflectance followed by crustose, squamulose, and gelatinous growth forms (Fig. 1a). Based on the summed-wavelets, the growth forms seem to present different feature positions in the range of 650 to 750 nm (Fig. 1b). The variability of features is also observed in the groups at the three taxonomic ranks (Fig. 1d, f, h). Likewise, the reflectance of squamulose and gelatinous lichens seems to be less variable than that of the other two growth forms based on their standard deviation across the VNIR spectrum; however, these are also the groups with less species and samples. At the family level, lichens of the Parmeliaceae family show the highest reflectance values, while lichens of the Collemataceae and Lichinaceae present the lowest values (Fig. 1b).

On the other hand, the bark spectra present variability in reflectance between 0.04 and 0.84. Similar to lichens, the higher values of bark reflectance tend to be between 720 and 1000 nm, while the lower values tend to be close to 450 and 500 nm (Fig. 2a). The grouping of bark spectra into six groups reveals that all of them have an absorption feature centered near 680 nm (Fig. 2b). This analysis also reveals that there are groups that tend to be relatively featureless and have low reflectance values (specifically groups E and F; Fig. 2a). In contrast, the spectral features of groups A-D resemble those of lichens (groups A and B; Fig. 2a).

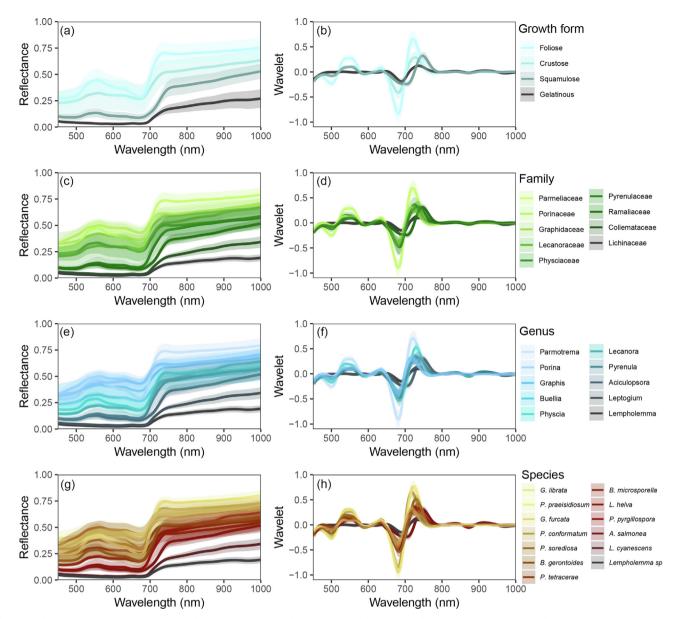


Fig. 1. Visible-near infrared spectra of corticolous lichens used for classification at different growth forms and taxonomic levels from Santa Rosa National Park Environmental Monitoring Super Site, Costa Rica. Growth forms (a, b), family (c, d), genus (e, f), and species (g, h). Unmodified reflectance spectra are shown in (a, c, e, g) and those processed using the continuous wavelet transformation are shown in b, d, f, h. Each line represents the average for each taxonomic group while the shade around each line represents the standard deviation.

3.2. Spectral mixture analysis

The results obtained through the SMA show that the bark abundance in the lichen spectra is generally low or negligible with an overall mean of 0.06 ± 0.28 (median = 0.01, RMSE = 0.02 ± 0.02) (Fig. 3, Table S1). The negative bark abundance bears no physical meaning, and in this context should be interpreted as minimal or no apparent spectral mixing between lichens and bark. Despite this, the SMA also reveals that the bark abundance may vary as a function of the growth forms and taxonomic ranks. For example, gelatinous and squamulose lichens show lower average values of estimated bark abundance and RMSE than foliose and crustose (Fig. 3, Table S1). In the crustose growth form there are species such as *G. librata and G. fournierri* (Graphidaceae family) with values of bark abundance much higher than the overall average. It should thus be noted that despite the generally low estimated bark abundance in the lichen spectra, individual lichen spectra can have relatively high abundance values (Table S1).

In terms of the sample size effect on the SMA, the results suggests

that there is a weak correlation between the number of samples that were used to create a lichen endmember and the estimated bark abundance ($R^2 = 0.01$) or the RMSE ($R^2 = 0.01$) (Fig. 4a and b).

3.3. Classification

The classification results show that the values of accuracy and the mean F_1 score are generally higher in classifications based on summedwavelet spectra than reflectance spectra in all taxonomic levels (Fig. 5). Regardless of the taxonomic rank or the classifier, accuracy values based on summed-wavelet datasets range from 0.71 to 0.97 (0.87 \pm 0.07), whereas the accuracy values based on reflectance datasets range from 0.53 to 0.95 (0.76 \pm 0.13). Overall, lower taxonomic ranks (e.g., growth form, family) tend to present higher accuracy and F_1 scores than higher taxonomic ranks (e.g., genus, species) (Fig. 5). More specifically, classification based on growth form shows mean accuracy values of 0.93 \pm 0.04 regardless of the classifier or the spectral processing, whereas based on family, genus, and species the accuracies

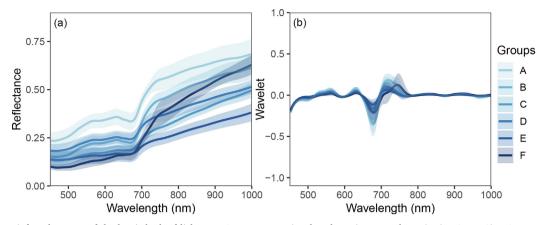


Fig. 2. Visible-near infrared spectra of the host's bark of lichens at Santa Rosa National Park Environmental Monitoring Super Site, Costa Rica. Unmodified reflectance spectra are shown in a, while the processed spectra using the continuous wavelet transformation are shown in b. Each line represents an average bark spectrum for each group. The shade around each line represents the standard deviation of the spectrum.

values are close to 0.81 \pm 0.09, 0.81 \pm 0.11, and 0.73 \pm 0.12, respectively.

Regarding the performance of each classifier, our results suggest that depending on the taxonomic ranks and spectral preprocessing, the overall discrimination of TDF lichens may be affected by selection of the classifier. For example, the RF and SVMRK classifiers tend to have higher values of discrimination on summed-wavelet datasets in comparison with other classifiers (Fig. 5). However, on the reflectance dataset, the LDA classifier tends to have higher values of classification than the other classifiers.

4. Discussion

This study reveals the potential of the VNIR spectroscopy to classify lichens at a Neotropical Dry Forests. Overall, our results suggest that the accuracy of lichen discrimination depends on the taxonomic ranks as well as the spectral preprocessing and the choice of classifiers.

4.1. Spectral features of lichens and their host's bark

In general, the spectral signatures of the neotropical lichens suggest the presence of absorption features of chlorophyll, photopigments based on green peaks, and absorption features of usnic acid due to the

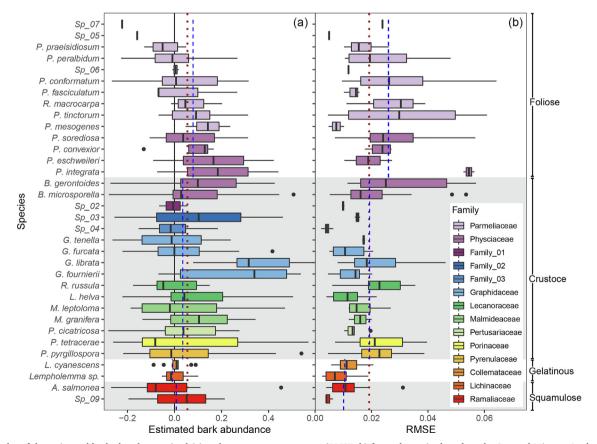


Fig. 3. Boxplot of the estimated bark abundance mixed (a) and root mean square error (RMSE, b) for each species based on the Spectral Mixture Analysis. Different colors represent the lichen families. The red vertical dotted lines represent the overall average, and the blue vertical dashed lines represent the average per growth form.

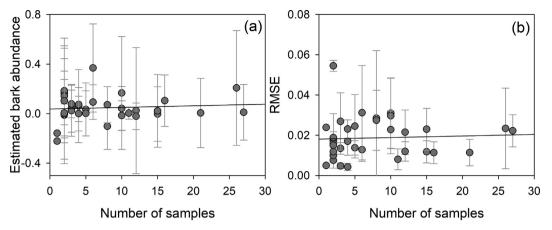


Fig. 4. Relationship between the estimated bark abundance (a) and the root mean square error (RMSE) (b) with the number of samples used to create an average representation of lichen species. Each point represents a lichen species, and the vertical bars represent the standard deviation within this species. The R^2 for both linear regressions is lower than 0.01.

low reflectance at the shortest end of the visible spectrum (Ager and Milton, 1987). These absorption features resemble those found in rockencrusting lichens observed at higher latitudes (Ager and Milton, 1987; Bechtel et al., 2002; Gates et al., 1965; Morison et al., 2014; Rees et al., 2004). The high diversity of lichens used in this study reveals a high variability of their spectra which could be attributed to the diversity of their compounds. Based on the results, the differences in the spectral features of different lichen species can potentially contribute to their discrimination. At the growth form level, for example, differences observed in the position of the absorption bands could be attributed to the presence and concentration of different photosynthetic pigments; which ultimately enhances the discrimination between growth forms. The presence of different types of photosynthetic pigments in growth forms tends to depend on the photobionts that integrate them. For example, lichen cyanobionts such as the Gelatinous species of this study tend to possess only chlorophyll a, while lichen phycobionts (e.g. Crustoce and

Foliose) tend to have both chlorophyll *a* and *b* (Rikkinen, 1995).

The lichen spectra also reveal that higher taxonomic ranks tend to have a higher variability in the amplitude of reflectance than lower taxonomic ranks. In general, differences in the reflectance amplitude can be attributed to the anatomical features or the water content of lichens (Gloser and Gloser, 2007; Rikkinen, 1995). It has been described, for example, that the physico-chemical properties of the epicortical layer of some lichens may affect the reflectance in the VNIR region (Rikkinen, 1995). This thin and continuous layer with air cavities may increase the backscattering of light and therefore increase the thallus reflectance (Rikkinen, 1995); favoring the spectral discrimination of lichen species that differ in this anatomical trait. Furthermore, the ability to store water varies among different lichen species (Gauslaa and Coxson, 2011), a variability that can potentially induce speciesspecific differences in the amplitude of reflectance. This may explain why gelatinous lichens, lichens that tend to have a higher water storage

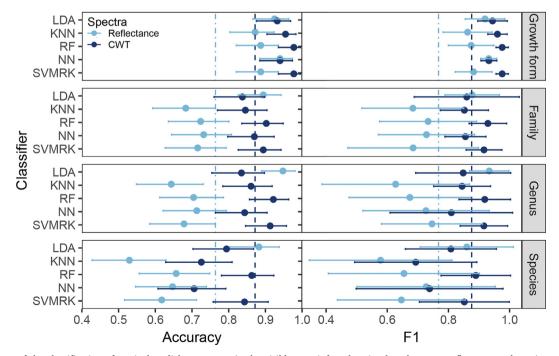


Fig. 5. Descriptors of the classification of corticolous lichens spectra in the visible-near infrared region based on raw reflectance and continuous wavelet transformation (CWT) data. Descriptors of classification include accuracy and the mean F1 values between classes. The error bars at the accuracy values describe the 95% interval coefficients, while at the F1 represent the standard deviation. Vertical light-blue dot-dash lines represent the average classification value across all classifiers and taxonomic level for raw reflectance, while dark-blue dashed lines do so for the CWT data. Refer to Table 2 for abbreviations for classifiers.

capability (Lange, 2000), present lower values of reflectance than other growth forms. It should be noted, however, that other factors than the physical and chemical characteristics of lichens can affect the amplitude of their spectrum (e.g. viewing and illumination angles). Therefore, caution should be exercised when using the amplitude, rather than the spectral features, to classify lichens.

On the other hand, the bark spectra of our study resemble those reported by Elvidge (1990). Specifically, bark signatures display a constant increase in reflectance without strong variation at any specific wavelength, resembling in some cases the reflectance spectra of green stems and dry vegetation. Despite some groups of bark reflectance appearing to be featureless, all of them present an absorption feature close to the chlorophyll band (680 nm) that is more evident for groups of higher reflectance than groups of low reflectance. The amount of green, photosynthetic tissue (chlorenchyma) in tree barks varies according to the species, age, and environmental conditions (Pfanz and Aschan, 2001). In some neotropical trees, for example, the chlorenchyma can be below to a thin cork layer (Pfanz and Aschan, 2001), a trait that may partially explain the prevalence of the chlorophyll band in the bark spectra. In general, the high variability of bark spectra, and the absorption features that can be found in these groups could be attributed to a high diversity of trees in the region (Hilje et al., 2015). Higher variability of bark spectra associated with a high diversity of trees has also been reported in other forest communities (Hadlich et al., 2018).

4.2. Spectral mixing between lichens and their host's bark

Despite the estimated bark abundance in the lichen spectra generally being low, some species or lichen groups reveal high spectral mixing between lichens and bark. Spectral mixing between lichens and their bark substrate could result from either of the form of growth of lichens, their optical properties, or the similarities between bark and lichen spectra. In this context, the form of growth of some lichens may influence the degree of spectral mixing induced by small gaps. For example, crustose lichens tend to present small thallus with branching cracks that could cause the passing of light through the samples leading to high bark mixing. The effect of the growth form on the degree of spectral mixing has not been systematically studied before, and hence it is difficult to draw conclusions on the significance of this finding.

In terms of the effect of the optical properties on the spectral mixing, it seems that some lichens species tend to be optically thick; resembling those findings in rock-incrusting lichens (Ager and Milton, 1987; Bechtel et al., 2002). However, some species may behave like those described by Solhaug et al. (1995), who suggested that crustose bark-incrusting lichens present a light transmittance of 20–30% through their thallus; thus, increasing the probability of spectral mixing. Similar to this result, Anthony et al. (2002) reveal that tropical foliicolous lichens present a light transmittance of 30–70%. Our results together with these studies may highlight the variability of the optical properties between lichens growing on different substrates; however, this variability may affect the lichen classification as discussed below.

The spectral similarity between lichens and their substrate makes the spectral mixing analysis more challenging, and combined with potential light transmittance to the lichen substrate, challenges the previous recommendations on the use of SMA. As suggested by Bechtel et al. (2002), linear unmixing methods are optimal for studying lichens that are optically thick. However, in the case of some groups with high bark mixing, it may be better to apply non-linear unmixing methods. To unequivocally determine the optical properties of the tropical lichen species, future research should aim to measure the transmittance of lichens following the protocols introduced by Bechtel et al. (2002) and measure the degree of transmittance of light through the lichen that is detached from its bark substrate. This approach was not deemed possible in our sample set as some of the lichens could not have been detached from their substrate without destroying the sample. Thus, a mixed approach of measuring transmittance either through the detached lichen or through the lichen attached to the phellem (cork tissue), as described in detail by Solhaug et al. (1995), could be considered.

Finally, as suggested by our results the number of samples per lichen endmember seems to have a minimal effect on the SMA. Thus, a lesser number of samples may provide results that are comparable to those composed by a larger number probably due to minimal intra-species variation of the lichen spectra.

4.3. Lichen discrimination using machine learning

Our results suggest that the success of using VNIR spectra to discriminate corticolous lichens depends on the taxonomic ranks, the spectral processing, and the type of classifiers used. The effect of the taxonomic rank lies in that some species with similar genus or families tend to behave more as spectral groups than biological groups; thus hindering the discrimination between genus or species. This effect is common between samples from groups of species or individuals that share similar phylogenies, use the same resources, and coexist together (Castro-Esau et al., 2006). In scenarios where it is not possible to discriminate lichens using the VNIR reflectance, the use of other spectral regions such as the short-, mid-, or long-wave infrared region (1.2–16 μ m) could be more promising due to lichen signatures being associated more with the structural compounds rather than the varying pigment content of different lichen species; the dominant source of spectral features of lichens in the VNIR wavelength region (Ager and Milton, 1987).

In terms of spectral processing, previous studies have shown that the use of summed-wavelet spectra is a promising approach to classify species or life forms (Guzmán et al., 2018; Harrison et al., 2018). This study also supports this conclusion. Despite this, the spectral transformation does not enhance the performance of all the classifiers. For example, the performance of LDA is better on the unprocessed rather than the summed-wavelet spectral data. This could be due to LDA being associated with techniques of data reduction that highlight the differences between groups (Kuhn and Johnson, 2013); favoring the discrimination of species that differ in their reflectance amplitude more than their spectral features. Unlike the LDA, other classifiers such as the KNN, RF, SVMRK or NN perform well using the transformed spectra. In addition to their good performance in this study, the SVMRK and NN have the benefit of limited requirements on the number of training samples (Kuhn and Johnson, 2013). This is particularly beneficial in studies that focus on rare species with a limited number of samples available in the field. However, the SVMRK and NN also have the disadvantage of being computationally intensive unlike the KNN and RF (Kuhn and Johnson, 2013).

It is important to highlight the importance of tuning parameters that may affect the reproducibility of the results. Because of this, no single classifier will always provide best solutions in all circumstances because the performance of each classifier always depends on factors such as optimization and the natural variability of the data (Wolpert, 1996; Wolpert and Macready, 1997).

4.4. Considerations and future directions for lichen classification

As a method, the success of the lichen classification using spectroscopy partially depends on the quality of the data acquired. The quality of data acquired lies on the lower variability of the lichen spectra needed to detect each group during the classification. The spectral variability could not only be affected by the methods of data collection, but also on the degree of bark spectra that is mixed in the lichen spectra. Potential spectral mixing between lichen and bark may increase the variability of the lichen spectra promoting changes in the detection rates during the classification and errors of discrimination. However, as the SMA suggest, the potential spectral mixing between lichens and bark is generally low and associated with certain taxonomic groups; therefore, it is expected that these groups could be more susceptible to classification errors.

Another factor that may affect the success of the lichen classification is their acclimation to the surrounding environmental conditions. These may play an essential role in the classification of lichen since the acclimation may lead to changes in the lichen spectra. For example, it has been described that some lichens species present higher spectral variability when exposed to different conditions (Gauslaa, 1984). This spectral variability could be due to the tendency of lichens to acclimate their traits (e.g., chlorophyll content, biomass per area) according to their surrounding environment such as light regimes (Gauslaa et al., 2005), temperature (Lange and Green, 2005), or water availability (Lange et al., 1997). Likewise, factors such as desiccation may also affect the variability of lichens signatures in the VNIR (Gloser and Gloser, 2007), especially in wavelengths regions of the water absorption bands.

Since the lichen diversity in TDF tend to be sensitive to anthropogenic disturbance, host tree traits, and tree species (Benítez et al., 2019), the classification of lichen species using spectroscopy and the monitoring the spectral diversity of lichens communities may help to quickly evaluate the ecosystem functioning in these environments.

5. Conclusions

This research shows the potential use of VNIR spectroscopy to classify corticolous lichens at a Neotropical Dry Forests. This work expands previous observations on the optical properties of lichens by Ager and Milton (1987) and Bechtel et al. (2002) by exploring the spectral mixing of lichens and their substrate using different growth forms. The spectral mixing analysis suggests that the lichen spectra tend to present low bark mixing. On the other hand, the spectral classification was explored using spectral transformations and five classifiers. The performance of lichen classification is partially improved using continuous wavelet transformation and it may depend on the type of the classifier. Linear discrimination analysis applied to reflectance spectra presents the highest performance of classification at the species level.

Future research should consider the natural variability of lichens by integrating detailed protocols of data acquisition and analysis. Likewise, future studies should explore the use of other spectral regions to improve the discrimination of lichens. In the presence of well established spectral libraries of different lichens species, the classification of lichens using reflectance could help the community of ecologists to conduct a quickly discrimination of lichens species in the field. This may allow more in-depth monitoring of lichen communities in the forests with the aim to further understand the role of lichens in ecosystem functioning.

CRediT authorship contribution statement

J. AntonioGuzmán Q.: Conceptualization, Data curation, Formal analysis, Software, Investigation, Methodology, Visualization, Validation, Project administration, Writing - original draft. Kati Laakso: Formal analysis, Methodology, Writing - original draft. José C. López-Rodríguez: Conceptualization, Data curation, Investigation, Methodology, Writing - original draft. Benoit Rivard: Validation, Supervision, Writing - review & editing. G. Arturo Sánchez-Azofeifa: Resources, Validation, Supervision, Funding acquisition, Project administration, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data accessibility

The spectral data used in this study is available at the Tropi-Dry Dataverse (https://doi.org/10.7910/DVN/Y1J0UQ).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.105999.

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J.A. Guzmán Q., et al.

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