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1 **Spectral signatures as evidence to test hypotheses in plant species complexes**

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17 **Short title: Spectral signatures in plant species complexes**

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## 23 **Abstract**

24 Traditional methods for species definition, based on macromorphological characteristics, face  
25 limitations due to the high phenotypic plasticity observed in plants, which makes it challenging  
26 to accurately identify species complexes. Fourier transform near-infrared spectroscopy emerges  
27 as a promising, non-destructive technique for analyzing plant material, enabling the distinction  
28 of species. This study focuses on the Scaly clade of the fern genus *Microgramma*, characterized  
29 by complex taxonomic boundaries and morphological variations. A total of 94 samples from  
30 eight species, including fertile and sterile leaves of dimorphic and monomorphic species, were  
31 evaluated to test the effectiveness of FT-NIR in distinguishing these lineages. The average  
32 identification accuracy ranged from 86% to 91%, depending on the models and validation  
33 employed. Species with better-defined morphological characteristics, such as *Microgramma*  
34 *percussa*, achieved an accuracy of 100%. Conversely, species with higher morphological  
35 overlap showed lower accuracy, which may be associated with hybridization, introgression, or  
36 cryptic variation. Dimorphic species, with morphologically distinct fertile and sterile fronds,  
37 exhibited higher intraspecific spectral variation compared to monomorphic species, which may  
38 explain their lower accuracy rates. Fertile fronds, in some cases, provided more informative  
39 data, possibly due to the presence of sori increasing the complexity of spectra. This study  
40 highlights the potential of FT-NIR as a complementary tool in plant systematics. However,  
41 further research is needed to understand the influence of processes such as hybridization and  
42 features such as the indumentum on spectral readings. Overall, FT-NIR presents itself as a  
43 promising method to elucidate species limits in ferns and improve knowledge about their  
44 diversity.

45 **Keywords:** ferns, FT-NIR spectroscopy, *Microgramma*, predictive models, species limits,  
46 systematics.

## 47 **1 Introduction**

48 The continuous evolution of lineages drives the necessity to develop new approaches to explore  
49 biodiversity and define taxonomic boundaries (Wiens, 2007; Hörandl, 2022). Traditional  
50 methods relying solely on macromorphological features constitute emerging challenges to our  
51 understanding of biodiversity (Dayrat, 2005). Species are often defined one-dimensionally,  
52 which presents significant challenges (De Queiroz, 2007). They are generally not constructed  
53 or considered testable hypotheses and are often described in ways that impede their validation  
54 (De Queiroz, 2007; Sites & Marshall, 2003; Wiens, 2007). Additionally, plants tend to exhibit  
55 greater phenotypic plasticity compared to animals (Huey et al., 2002; Borges, 2008; Palacio-  
56 López et al., 2015), making it even more challenging to understand the phenotypic complexity  
57 of this group.

58 An accurate and multidimensional definition of species boundaries is crucial for understanding  
59 the diversity of living organisms, allowing us to determine whether their definition correspond  
60 or not to a single lineage (Dayrat, 2005; Will et al., 2005). This is particularly important since  
61 species complexes represent a significant part of biodiversity (Pinheiro et al., 2018). Despite  
62 significant genetic divergences, these complexes are characterized by low levels of  
63 morphological disparity between lineages, making their identification more difficult (Struck et  
64 al., 2018). Integrating data from different sources can overcome the limitations of traditional  
65 methods (Yeates et al., 2011; Edwards & Knowles, 2014; Cheng et al., 2021) based mainly on  
66 macromorphological characters that are not always diagnostic and can sometimes be  
67 homoplastic (Quattrini et al., 2019). To address this, approaches incorporating data from  
68 different levels of biological organization (Dayrat, 2005) promote complementarity between  
69 fields of study and encourage collaboration among specialists. Emerging methods can help us  
70 understand taxonomically recalcitrant groups, advancing our knowledge of biological diversity  
71 and the evolutionary processes that shape it (Rouhan & Gaudeul, 2021; Sandall et al., 2023).

72 One method in evidence is Fourier-transform near-infrared spectroscopy (FT-NIR) (Pasquini,  
73 2018). This technique is promising due to its speed, accessibility, non-destructive nature, and  
74 lack of sample pre-treatment (Rodríguez-Fernández et al., 2011). The fundamental principle of  
75 the method involves exposing fragments of biological material (e.g., a dry leaf) to infrared  
76 radiation (Durgante et al., 2013; Paiva et al., 2021). The spectra generated by the material  
77 represent the energy absorbed by the C - H, C - N, and C - O bonds based on the amount of  
78 light absorbed (Pasquini, 2003, 2018). This process generates complex spectra that allow the  
79 sample's chemical and physical structure to be analyzed (Workman & Weyer, 2007; Durgante  
80 et al., 2013). Spectroscopy is the tool of choice in a wide range of studies, from those focused  
81 on understanding ontogeny (Fernandes et al., 2020) to plant stress (Zahir et al., 2022) and  
82 nutrient analysis of leaf tissues (Prananto et al., 2020), for example. It is also used to delimit  
83 and discriminate species, genera, and families (Xu et al., 2009; Prata et al., 2018), as well as for  
84 the recognition of new plant species (Vasconcelos et al., 2021; Gaem et al., 2020). In the context  
85 of spectral studies on ferns, only one study has been conducted specifically on this group,  
86 aiming to explore the method's efficiency (Paiva et al., 2021).

87 Ferns, the second most diverse group of vascular land plants (Nitta et al., 2022), are widely  
88 distributed around the world (Suissa et al., 2021). Their greatest diversity is found in tropical  
89 regions (Suissa et al., 2021). These plants, which lack flowers and fruits, have a life cycle  
90 characterized by alternating generations, including both sporophyte and gametophytic phases  
91 (Haufler et al., 2016). Since most lineages show uncommon cryptic variations (Kinosian et al.,  
92 2020; Ekrt et al., 2022; Wei et al., 2022; Yi et al., 2023), frequent hybridization events (Bloesch  
93 et al., 2022; Luo et al., 2024; Mendez-Reneau et al., 2024), and polyploidy (Fujiwara et al.,  
94 2023; Heslop-Harrison et al., 2023), it has proven challenging to delimit species based solely  
95 on morphological analyses. Although polyploidy is a crucial factor in speciation (Wood et al.,

96 2009; Alix et al., 2017), hybridization is equally significant, contributing to the emergence of  
97 new lineages and adding complexity to evolutionary processes (Sigel, 2016).

98 Our study focuses on the Scaly clade of the genus *Microgramma* C.Presl (Polypodiaceae),  
99 whose main synapomorphy is the presence of subulate and/or round scales on both sides of the  
100 leaf surfaces (sensu Almeida et al., 2021). The clade, with ca. 26 mya, was recovered in a recent  
101 study as the oldest lineage sister to all other clades within the genus (Almeida et al., 2021).

102 With a distribution that covers the entire neotropical region, it includes both species with  
103 distinct morphological traits and species with high morphological overlaps, which hinder  
104 taxonomic identification. Some species are widely distributed, such as *M. dictyophylla* (Kunze  
105 ex Mett.) de la Sota, *M. nana* (Liebm.) T.E.Almeida, *M. percussa* (Cav.) de la Sota, *M. reptans*  
106 (Cav.) A.R.Sm., and *M. tobagensis* (C.Chr.) C.D.Adams & Baksh.- Com., while others have  
107 restricted distributions, such as *M. piloselloides* (L.) Copel. (Central America and the  
108 Caribbean), or are microendemic, such as *M. latevagans* (Maxon & C.Chr.) Lellinger (Bolivia  
109 and Peru) and *M. tecta* (Kaulf.) Alston (Brazilian Atlantic Forest) (Almeida et al., 2021). The  
110 morphological disparity in the clade is also significant, with some species exhibiting leaf  
111 dimorphism (*M. nana*, *M. reptans*, *M. tecta*, and *M. tobagensis*) while others are monomorphic  
112 (*M. latevagans*, *M. piloselloides*, *M. dictyophylla*, and *M. percussa*) (Almeida, 2014; Almeida  
113 et al., 2021) (Fig. 1).

114 The phylogenetic inference by Almeida et al. (2021) revealed potential issues in the  
115 circumscription of species within the Scaly clade. For instance, *Microgramma tobagensis*,  
116 which has a disjunct distribution between the Andes+northern South America, and the  
117 easternmost part of Brazil, was recovered as polyphyletic. A sample from Peru clustered with  
118 *M. piloselloides*, while a specimen from eastern Brazil grouped with *M. reptans* (Almeida et  
119 al., 2021). Another example is *M. nana*, historically regarded as a variety of *M. tecta*. Despite  
120 their close morphological similarity and placement within the same subclade, they are not sister

121 lineages (Almeida et al., 2021). These findings highlight some of the challenges in defining  
122 species boundaries within the Scaly clade.

123 Using a spectral approach, this study aims to understand species boundaries by addressing the  
124 following questions: Is FT-NIR spectroscopy an effective tool for testing hypotheses in  
125 complex species of ferns, using the Scaly clade of the genus *Microgramma* as a case study?  
126 Are there differences in the spectral structure between fertile and sterile fronds, and if so, which  
127 is more informative for taxonomic purposes? To this end, we tested the following hypotheses:  
128 (I) the current circumscription of some species in the Scaly clade lacks clarity to define lineages  
129 because some species are poorly circumscribed; (II) there are significant differences between  
130 the spectra of fertile and sterile fronds in dimorphic ferns and less variation in monomorphic  
131 ferns.

## 132 **2 Material and methods**

### 133 2.1 Sampling

134 The study was based on vouchers deposited in the following collections: INPA, BHCB, MO,  
135 and NY (acronyms according to Thiers, 2024 continuously updated). We analyzed 94 samples  
136 from eight species within the Scaly clade (Fig. 1, Table S1), representing geographical and  
137 morphological variation within the clade. We followed a thorough protocol to select fronds for  
138 the spectral readings, avoiding fronds with damage, brittle, or the presence of fungi or other  
139 epiphyllous organisms (Oliveira et al., in prep). All the specimens analyzed in this study were  
140 identified and confirmed by the senior author. To test the difference in accuracy between fertile  
141 and sterile fronds in monomorphic and dimorphic species, we captured the spectra of three  
142 fertile fronds and three sterile fronds from each specimen, whenever available.

### 143 2.2 Spectral signature

144 We collected 1,882 spectral readings in absorbance values, two from each frond surface  
145 (abaxial and adaxial), using a Perkin Elmer Spectrum, Frontier MIR+SP10 STD infrared

146 spectrometer (FT-IR). Each measurement lasted 30 seconds, with 32 accumulation  
147 measurements to ensure the accuracy and quality of all spectra, at a resolution of 16 cm<sup>-1</sup>,  
148 totaling 2,001 absorbance values per measurement, in the spectral range from 4.000 cm<sup>-1</sup> to  
149 8.000 cm<sup>-1</sup> (wavenumber), equivalent to 1.000 to 2.000 nm (wavelength).

150 The equipment has an automatic performance verification (APV) system, which reduces the  
151 frequency of systematic calibrations by continually monitoring performance and alerting to the  
152 need for adjustments. Before reading each sample, we performed a background calibration  
153 using a white reference sphere made of Spectralon, a fluoropolymer with high reflectance and  
154 low absorption. To prevent light scattering, a metal body was placed over the fronds during the  
155 spectra capture. All raw data was collected in an environment with a constant and controlled  
156 temperature of 18 °C.

### 157 2.3 Data pre-processing

158 After collecting, we ran initial statistical tests to ensure the accuracy and consistency of the  
159 spectral data. Any discrepant values (outliers) were manually identified and removed from the  
160 dataset. Additionally, we applied standardization using the Standard Normal Variate (SNV)  
161 method. This method involves adjusting each spectrum by subtracting the mean and dividing  
162 by the standard deviation of each data point (Barnes et al., 1989). This process increases the  
163 comparability of the spectra by eliminating dispersion effects and variations in absolute  
164 intensity (Barnes et al., 1989). Normalization of spectra using the SNV method was performed  
165 using the base R functions 'mean' and 'sd' (Mailund, 2019; R Core Team, 2024).

### 166 2.4 Data analysis

167 We created three models for the spectral tests: Model (I) evaluated spectra from fertile fronds  
168 only; Model (II) investigated spectra from sterile fronds only; and Model (III) used a  
169 combination of data from fertile and sterile fronds. The data was prepared and manipulated  
170 using the *dplyr* package (Mailund, 2019). To explore the variation in raw spectral data in

171 multidimensional space, we performed Principal Component Analysis (PCA) (Kherif &  
172 Latypova, 2020) using the *stats* package (R Core Team, 2024).

173 Partial least squares discriminant analysis (PLS-DA) was performed for each model using the  
174 *pls* package (Mevik & Cederkvist, 2004), within the framework provided by the *caret* package  
175 (Kuhn, 2008). This analysis involves categorizing samples based on predefined categories,  
176 focusing on identifying components that effectively account for variations among the variables  
177 in different classes while disregarding noise and uncorrelated variations (Mevik & Cederkvist,  
178 2004). Despite the widespread use of linear discriminant analysis (LDA) in spectral studies  
179 (Durgante et al., 2013; Lang et al., 2017; Silva & Hopkins, 2024), its assumptions of normality  
180 and homogeneity of covariances (Hastie et al., 2009) are unlikely to apply to spectral data and  
181 biological samples.

182 Two cross-validation techniques were used to assess the performance of the models and their  
183 ability to discriminate between species. In the first, K-fold cross-validation, the dataset is  
184 divided into K sections or “folds”. In each iteration, the model is trained using K-1 of these  
185 folds and validated on the remaining fold. By repeating this process K times, with each fold  
186 serving as the validation set exactly once, and averaging the performance results across all  
187 iterations, a reliable assessment of the model's performance is obtained (Burman, 1989; Yadav  
188 & Shukla, 2016). The second validation was the Leave-One-Out Cross-Validation (LOOCV),  
189 which involves selecting a single sample for testing while using the remaining (N-1) samples  
190 to train the model. This procedure is repeated N times, so each sample is used once as a test set  
191 and (N-1) times as part of the training set (Kohavi, 1995). The final performance of the model  
192 is determined by averaging the results of the N iterations (Kohavi, 1995). All analyses were  
193 conducted in R version 4.2.3 (R Core Team, 2024).

### 194 **3 Results**

195 The average spectral signature of each species is distinct, with few overlaps (Fig. 2). The PCA  
196 including all species (Model III) captured 71.3% of the spectral variation in the first two axes  
197 (PCA1=47.7%, PCA2=23.7%), with considerable overlap between species (Fig. 3A). The same  
198 overlap was observed when exploring dimorphic and monomorphic species separately (Fig.  
199 3B). Despite overlapping, spectral variation appears to be higher in dimorphic than  
200 monomorphic species (3B). This divergence is better seen in the PCA of each species (Fig. 3C),  
201 where the dimorphic species (*M. nana*, *M. tecta*, *M. reptans*, and *M. tobagensis*) showed higher  
202 variation than the monomorphic species (*M. percussa*, *M. latevagans*, *M. dictyophylla*, and *M.*  
203 *piloselloides*).

204 In the PCA of model I, using data from fertile fronds only (Fig. 4A), 70.7% of the spectral  
205 variation was captured by the first two axes (PCA1=47.3%, PCA2=22.4%). In model II, using  
206 sterile fronds (Fig. 4B), the first two axes captured 77.3% of the variation (PCA1=60.8%,  
207 PCA2=16.5%). In both models I and II, the spectral overlap between species was quite evident  
208 (Fig. 4A-B). The occupation of spectral space by fertile (Model I) and sterile (Model II) leaves  
209 varied among species. For *M. dictyophylla*, *M. nana*, and *M. percussa*, fertile leaves (Model I)  
210 occupied a smaller spectral space than sterile leaves (Model II). In contrast, *M. reptans* showed  
211 the opposite pattern, with fertile leaves (Model I) occupying a broader spectral space than sterile  
212 leaves (Model II). The spectral space occupation in *M. latevagans*, *M. piloselloides*, and *M.*  
213 *tecta* did not differ between fertile and sterile leaves (Figs. 4A, 4B).

214 Based on a PCA of fertile and sterile fronds of all species (Fig. 5A), we found that fertile fronds  
215 vary significantly more in the occupation of spectral space than sterile fronds. When examining  
216 the variation for each species separately (Fig. 5B), dimorphic species (*M. nana*, *M. reptans*, *M.*  
217 *tecta*, and *M. tobagensis*) showed a higher spectral disparity between fertile and sterile fronds  
218 compared to monomorphic species (*M. dictyophylla*, *M. latevagans*, *M. percussa*, and *M.*  
219 *piloselloides*) (Fig. 5B).

220 In the discriminant analysis of the three tested models (Model I - fertile fronds only; Model II  
221 - sterile fronds only; and Model III - both fertile and sterile fronds), monomorphic species  
222 outperformed dimorphic ones (Table 1). Among the monomorphic species, *M. percussa* stood  
223 out with 100% prediction accuracy in all models for both validations (Fig. 6; Table 2).  
224 *Microgramma latevagans* and *M. dictyophylla* also performed well, each achieving a prediction  
225 accuracy higher than 90%. Among monomorphic species, *M. piloselloides* had the lowest  
226 accuracy rates, ranging from 82% to 88% (Fig. 6; Table 2). Despite this, it still outperformed  
227 many of the dimorphic species.

228 Among the dimorphic species, *M. reptans* performed best, with accuracy values ranging from  
229 83% to 95%. *Microgramma tecta* also displayed good results, ranging from 79% to 86% (Fig.  
230 6; Table 2). *Microgramma nana* showed a wide variation, between 74% and 91%, while *M.*  
231 *tobagensis* ranged between 72% and 90% accuracy (Fig. 6; Table 2). Although the dimorphic  
232 species showed varied performances, none reached the optimum accuracy achieved by *M.*  
233 *percussa*, which received 100% of the prediction.

234 The application of pre-processing, specifically removing outliers combined with Standard  
235 Normal Variate (SNV) correction (Table 1), demonstrated improved accuracy compared to  
236 datasets that only had outliers removed, particularly in Models II and III. Model I, which  
237 included fertile fronds only, showed a slight reduction in accuracy after the pre-processing,  
238 from 82% to 81% using K-fold cross-validation and from 81% to 77% using leave-one-out  
239 cross-validation (LOOCV). Despite this minor reduction, pre-processed data still outperformed  
240 raw data (Table 1). For the sterile fronds model (Model II), pre-processing the data resulted in  
241 a slight positive change in accuracy. In the K-fold cross-validation, accuracy increased from  
242 73% to 74%, representing a difference of 1.4%, and LOOCV showed an increase from 75% to  
243 76%, with a 1.3% improvement. The combined model (Model III) also improved considerably,

244 with K-fold accuracy increasing from 77% to 78%, a gain of 1.3%, while in the LOOCV,  
245 accuracy increased from 77% to 82%, representing a 6.5% improvement.

#### 246 **4 Discussion**

247 In the pioneering study by Paiva et al. (2021), the FT-NIR method was shown to have high  
248 accuracy in identifying fern species. However, this is the first study to assess the tool's  
249 efficiency on a clade of ferns with recognized species complexes (Almeida et al., 2021). Our  
250 results support the usefulness of FT-NIR even in groups with difficult taxonomic delimitation.  
251 The accuracy of species discrimination depends on the construction of robust spectral models  
252 (Vieira et al., 2021), which, in turn, reflect well-defined circumscriptions, as observed in some  
253 species in this study. In addition to species circumscription, variations in the spectral signature  
254 of a species can be affected by environmental conditions (e.g., temperature, humidity) (Xu et  
255 al., 2019), soil properties (Asner et al., 2014), and developmental stages, such as differences  
256 between young and adult fronds due to their chemical composition (Lang et al., 2015;  
257 Neuwirthová et al., 2021).

258 The species tested here are part of the Scaly clade of the genus *Microgramma*, in which  
259 morphological overlap and the occurrence of sympatric species make it difficult, in some cases,  
260 to precisely define and identify the individuals studied (Almeida, 2014). The average  
261 percentage of correct identifications for our three models (sterile fronds, fertile fronds, and  
262 both) ranged from 86% to 91% based on the validation methods we used, with an overall  
263 average of 88% correct identifications. Only three species (*M. tecta*, *M. nana*, and *M.*  
264 *tobagensis*) had accuracy percentages below 80%.

265 *Microgramma percussa* and *M. reptans* were two species that obtained high accuracy results,  
266 with 100% and 89% respectively (Table 2). This result was unexpected, given that these species  
267 occupy a variety of habitats ranging from open areas to forests, growing on rocks and as  
268 epiphytes from lower trunks to the canopy (Almeida, 2014). The fronds of *M. percussa* also

269 present a wide variation in width, length, and shape — a variation that, together with their wide  
270 distribution in the Neotropics, from Mexico to southern Brazil, is reflected in its ten heterotypic  
271 synonyms (Almeida, 2014). For *Microgramma reptans*, the results are unexpected because this  
272 species presents a wide variation in the shape of the sterile fronds, with sterile specimens being  
273 hard to distinguish from *M. tobagensis*, for example (Almeida 2014). *Microgramma*  
274 *dictyophylla* and *M. latevagans* also showed high identification accuracy rates, with 93% and  
275 94%, respectively. Although they are morphologically distinct, with variations in leaf shape  
276 and size, leaf surface indumentum, and spore type (Almeida, 2014), their distribution areas  
277 partially overlap (Almeida, 2014; Lima et al., in prep). *Microgramma latevagans* is endemic to  
278 Bolivia and Peru, while *M. dictyophylla* has a wider distribution, covering northern South  
279 America. However, they do not occur sympatrically, as *M. latevagans* is found at high  
280 elevations (above 2,000 m.a.s.l.), while *M. dictyophylla* grows in lowland forests. Furthermore,  
281 the high overall accuracy of their spectral models may reflect good circumscriptions, favored  
282 by the specific and striking morphological characteristics of each of them. The few errors in the  
283 discriminant analysis related to these two models did not occur between these two species (Fig.  
284 6).

285 Two morphologically similar species, *M. tobagensis* and *M. piloselloides*, obtained 83% and  
286 84% correct predictions in the PLS-DA (Table 2). The errors might have different explanations.  
287 First, the identifications might not be correct, as there is considerable overlap in some of the  
288 characteristics used to identify them (e.g., indument and shape of fertile and sterile fronds).  
289 Although they mostly do not occur sympatrically (Smith et al., 2018; Almeida et al., 2021),  
290 there are populations of *M. piloselloides*, *M. tobagensis*, and *M. reptans* co-occurring in  
291 Guatemala and Costa Rica (Almeida, 2014; Lima et al., in prep). Our results showed one  
292 incorrect prediction of *M. reptans* as *M. tobagensis* and five incorrect predictions of *M.*  
293 *tobagensis* as *M. reptans* (Fig. 6) — some sterile specimens of *M. tobagensis* make it difficult

294 to distinguish from *M. reptans*. On the other hand, phylogenetic data points to the polyphyly of  
295 *M. tobagensis* (Almeida et al., 2021), a conflicting circumscription that may be reflected in the  
296 observed spectral errors (Fig. 6). In our investigations, two specimens initially identified as *M.*  
297 *cf. tobagensis* were predicted as *M. piloselloides*. After reanalyzing these specimens, the  
298 identification was updated and confirmed as *M. piloselloides*, significantly improving the  
299 accuracy of the models. We believe that processes such as hybridization and introgression might  
300 be playing a role in the evolution of these populations. Adding to the phylogenetic evidence  
301 presented by Almeida et al. (2021), spectral data suggest that further studies should focus on a  
302 broad sampling of these species populations to test their circumscription.

303 *Microgramma tecta* and *M. nana*, which are morphologically similar (Almeida et al., 2021),  
304 also had lower predictive identification accuracy, *M. tecta* with an average accuracy of 83%  
305 and *M. nana* with 81%, considering all models and validation (Table 2). We believe that the  
306 small size of the fertile and sterile fronds, along with the high coverage of trichomes and scales,  
307 may have influenced the spectral accuracy. However, no tests have yet been conducted to  
308 determine the influence of indument on spectral readings. A fundamental aspect to be  
309 considered is the geographic overlap of *M. nana* with other species, such as *M. reptans*, *M.*  
310 *tobagensis*, and *M. dictyophylla*, which raises the possibility of hybridization and introgression  
311 between these lineages. Natural hybridization is well documented in vascular plants, especially  
312 between phylogenetically close species that co-occur (Liao et al., 2015; Wu et al., 2023). In  
313 these sympatry zones, where two or more species coexist under similar environmental  
314 conditions, the probability of interspecies crosses increases, generating viable hybrids with a  
315 combination of phenotypic traits from the parental species (Sawangproh et al., 2020).  
316 Furthermore, introgression – when hybrids backcross with their parental species – can promote  
317 the exchange of adaptive genes between populations, increasing genetic variability and  
318 potentially favoring local adaptation (Suarez-Gonzalez et al., 2018; Li et al., 2021). These

319 processes, by introducing new genetic traits, can impact the morphological and chemical  
320 responses of plants (López-Caamal & Tovar-Sánchez, 2014), creating additional variability  
321 between populations. This genetic and phenotypic complexity can theoretically influence the  
322 effectiveness of spectral predictive models, although further studies are needed to determine  
323 exactly how hybridization and introgression affect the results.

324 This study is the first to investigate the spectral behavior of functionally different  
325 photosynthetic organs, such as the dimorphic fronds of ferns. Heteroblasty and heterophylly are  
326 widespread among land plants and have ecological, evolutionary, and taxonomic importance  
327 (Zotz et al., 2011). The spectral data suggest that dimorphic species, which have fertile fronds  
328 morphologically differing in size and shape from sterile, photosynthetically-only ones, present  
329 significant spectral intraindividual variation. Our results also suggest that they have lower  
330 prediction percentages when compared to monomorphic species (Fig. 5, Table 1). This relates  
331 to the functional and morphological duality of the fronds of dimorphic species (Wagner &  
332 Wagner, 1977; Vasco et al., 2013; Watkins et al., 2016), which may introduce higher intrinsic  
333 variability into the spectral signature of these species. In contrast, monomorphic species have a  
334 single leaf morphotype that performs all functions (Vasco et al., 2013), resulting in less spectral  
335 variability within an individual and, therefore, better predictive accuracy.

336 In fertile fronds, the existence of sori on the abaxial side (Wagner & Wagner, 1977) may have  
337 contributed to a good overall accuracy of Model I, although Model III stood out with better  
338 accuracy values when considering the species together, without distinguishing between  
339 monomorphic or dimorphic ones (Table 1). However, when considering monomorphic and  
340 dimorphic species separately, our results indicate better performance for Models II and III  
341 (Table 1). Most FT-NIR studies suggest that models such as Model III that combine different  
342 data sets, in this case, fertile and sterile fronds, are the best predictive models due to their  
343 comprehensive assessment of spectral signatures. For example, Paiva et al. (2021) obtained

344 better results with the combination of abaxial and adaxial data. Similarly, Lang et al. (2015)  
345 obtained better prediction results by combining data from fronds of young and adult trees. Our  
346 results indicate a similar perspective concerning fertile and sterile fronds. The combination of  
347 data proved to be better; however, even if data combination can be beneficial, it is not  
348 necessarily essential to achieve high accuracy, as observed in our results (Table 1). It is  
349 important to consider that the robustness of the models may vary according to the specific  
350 context of each study and the characteristics of the species analyzed. Despite testing separate  
351 models for fertile and sterile fronds, the morphological variability between these fronds  
352 (Watkins et al., 2016) results in different spectral responses in dimorphic species compared to  
353 monomorphic ones. This variation occurs because fertile and sterile fronds are subject to  
354 additional variations arising from factors such as stage of development, light exposure, and  
355 environmental conditions (Moran, 1987; Dalgallo Rocha et al., 2013). This performance  
356 underscores the effectiveness and high quality of monomorphic species in the context of our  
357 analysis, as evidenced by their higher performance. However, the lower accuracy of dimorphic  
358 species does not necessarily diminish its relevance or usability in studies using spectral data. It  
359 reflects the complexity and variability associated with the morphofunctional frond duality of  
360 these species. We believe that when including dimorphic and monomorphic species in the same  
361 set of discriminant and validation data, controlling these variations separately can significantly  
362 improve the overall accuracy results of the models as observed in our results (Table 1). Given  
363 the diversity of heteroblasty found among ferns (Vasco et al., 2013), an expanded sampling to  
364 encompass other lineages is necessary to test whether the pattern we found here is relevant to  
365 other groups.

366 This study offers valuable insights into the use of FT-NIR in evidence-based testing of  
367 hypotheses in plant species, particularly ferns, which have fewer macromorphological  
368 characteristics compared to flowering plants. New methodological multidimensional

369 approaches must be sought, in addition to morphological data, especially when dealing with  
370 species complexes. The average overall accuracy of 88% in our validation models was elevated,  
371 reflecting good results considering the complexity of the clade. The prediction values are much  
372 more significant when applied individually, such as the 100% accuracy for *M. percussa*. Our  
373 results reflect in detail the complex relationships of phylogenetically close species, highlighting  
374 the usefulness of spectral data for species identification. Finally, we reinforce the importance  
375 of a well-planned experimental design for future studies using FT-NIR for other ferns or plant  
376 groups. Evaluating and designing effective strategies for utilizing this method will be crucial in  
377 employing new approaches and maximizing the potential of spectral data for species  
378 identification and analysis.

### 379 **Author Contributions**

380 NAM: Conceptualization; Data curation; Formal analysis; Investigation; Methodology;  
381 Resources; Validation; Visualization; Writing – original draft; Writing – review & editing.  
382 MHVO: Data curation; Formal analysis; Writing – original draft; Writing – review & editing.  
383 TEA: Conceptualization; Methodology; Project administration; Resources; Validation;  
384 Visualization; Writing – original draft; Writing – review & editing

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### 396 **Conflict of interest**

397 The authors declare no conflict of interest.

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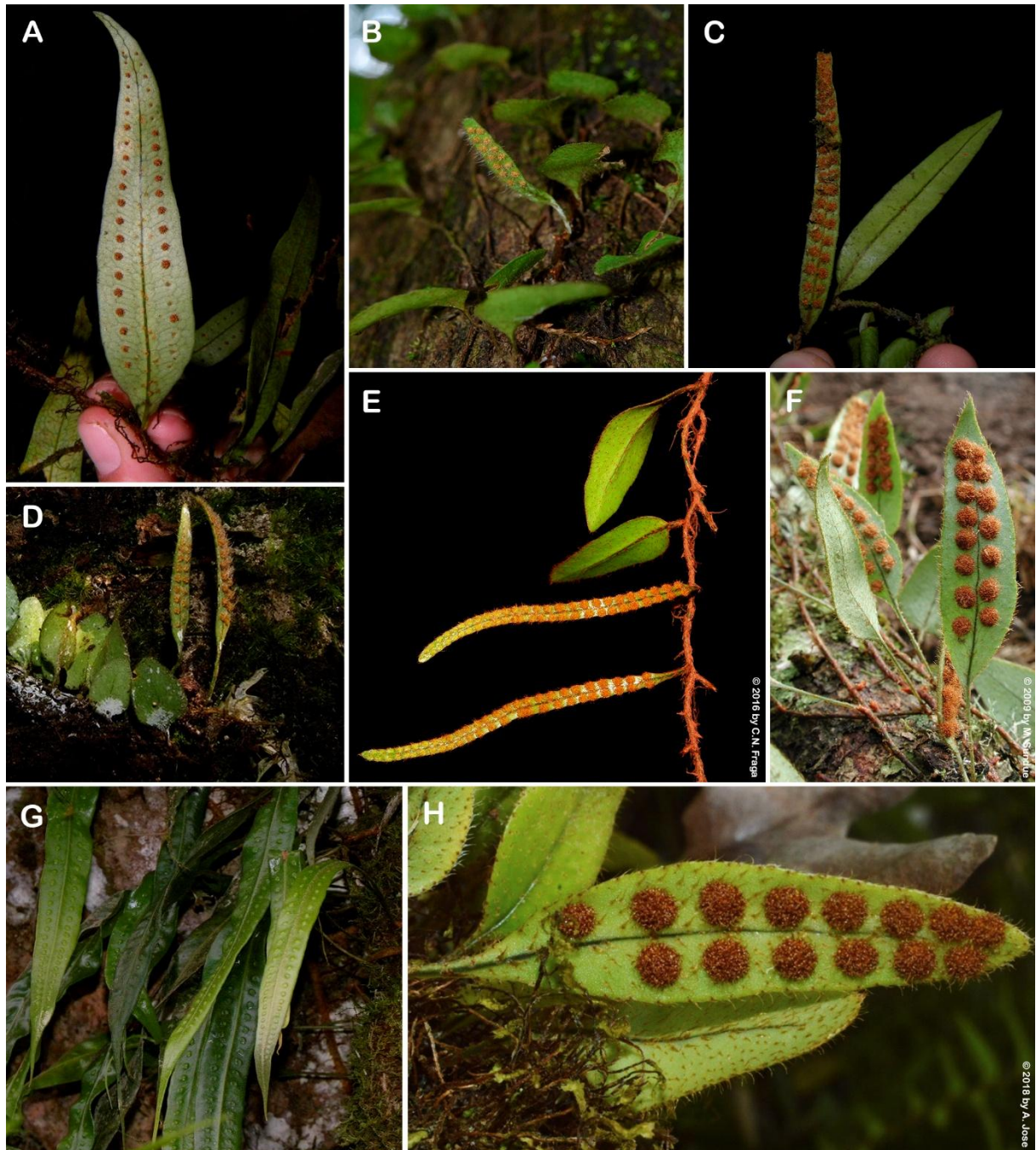
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**Tables****Table 1** Accuracy (%) of models tested in validations and Confidence Interval (CI%) before and after pre-processing.

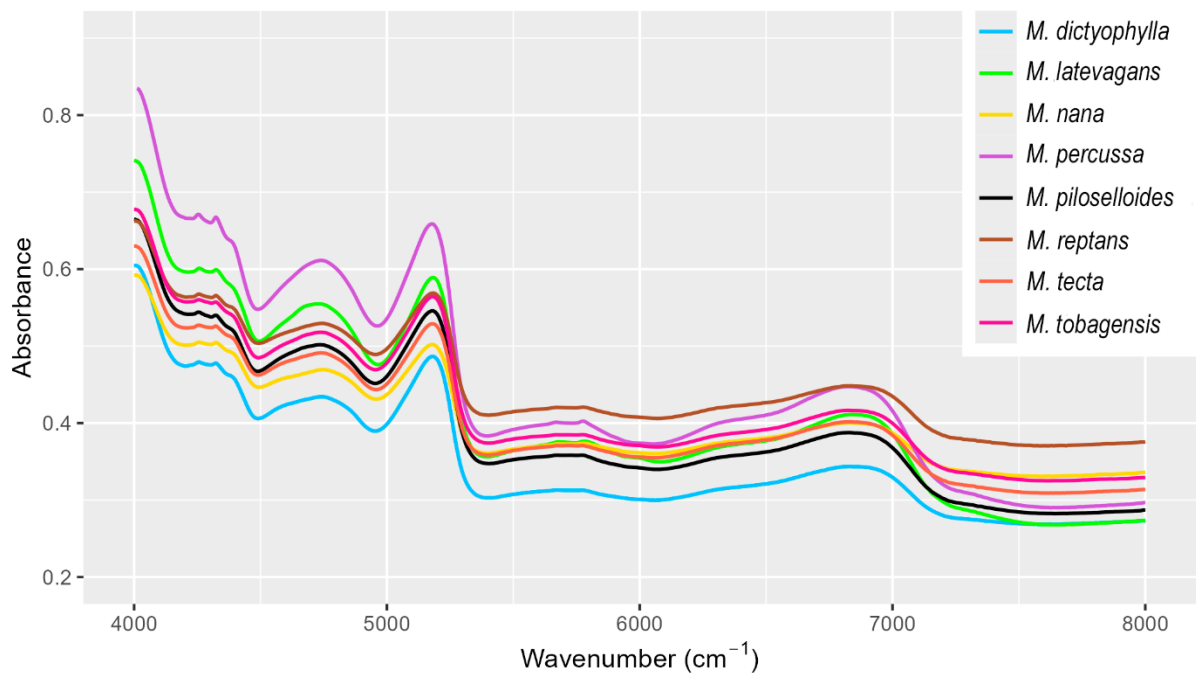
Data	Raw data		Outlier removal		Outlier removal + Standard Normal Variate (SNV)		Monomorphic species only		Dimorphic species only	
	K-fold	LOOCV	K-fold	LOOCV	K-fold	LOOCV	K-fold	LOOCV	K-fold	LOOCV
<b>Models</b>										
/Valida tion										
Fertile	77%	77%	82%	81%	81%	77%	95%	98%	76%	73%
	(69-85%)	(69-84%)	(73-89%)	(73-88%)	(71-88%)	(67-85%)	(84-99%)	(88-100%)	(61-87%)	(57-86%)
Sterile	75%	78%	73%	75%	74%	76%	100%	100%	76%	83%
	(66-84%)	(70-86%)	(65-82%)	(66-83%)	(64-83%)	(66-84%)	(90-100%)	(92-100%)	(60-88%)	(69-93%)
both	77%	76%	77%	77%	78%	82%	100%	100%	77%	83%
	(69-84%)	(68-84%)	(69-85%)	(68-85%)	(68-86)	(73-89%)	(92-100%)	(90-100%)	(61-89%)	(68-93%)

**Table 2** Number of species and hit rates (balanced accuracy%) for the tested models and functional types of fronds of the Scaly *Microgramma* clade (Polypodiaceae).

Species	Number of species	Model I - fertile		Model II - sterile		Model III - both		Average accuracy values
		K-fold	LOOCV	K-fold	LOOCV	K-fold	LOOCV	
Monomorphic	44	-	-	-	-	-	-	-
<i>M. dictyophylla</i>	08	93%	99%	90%	90%	90%	94%	93%
<i>M. latevagans</i>	07	99%	94%	93%	93%	94%	94%	94%
<i>M. percussa</i>	11	100%	100%	100%	100%	100%	100%	100%
<i>M. piloselloides</i>	19	88%	82%	84%	82%	83%	85%	84%
Dimorphic	50	-	-	-	-	-	-	-
<i>M. reptans</i>	14	87%	86%	94%	95%	83%	87%	89%
<i>M. nana</i>	11	80%	74%	77%	77%	90%	91%	81%
<i>M. tecta</i>	11	83%	84%	79%	86%	81%	86%	83%
<i>M. tobagensis</i>	13	88%	83%	72%	75%	88%	90%	83%

**Figures**

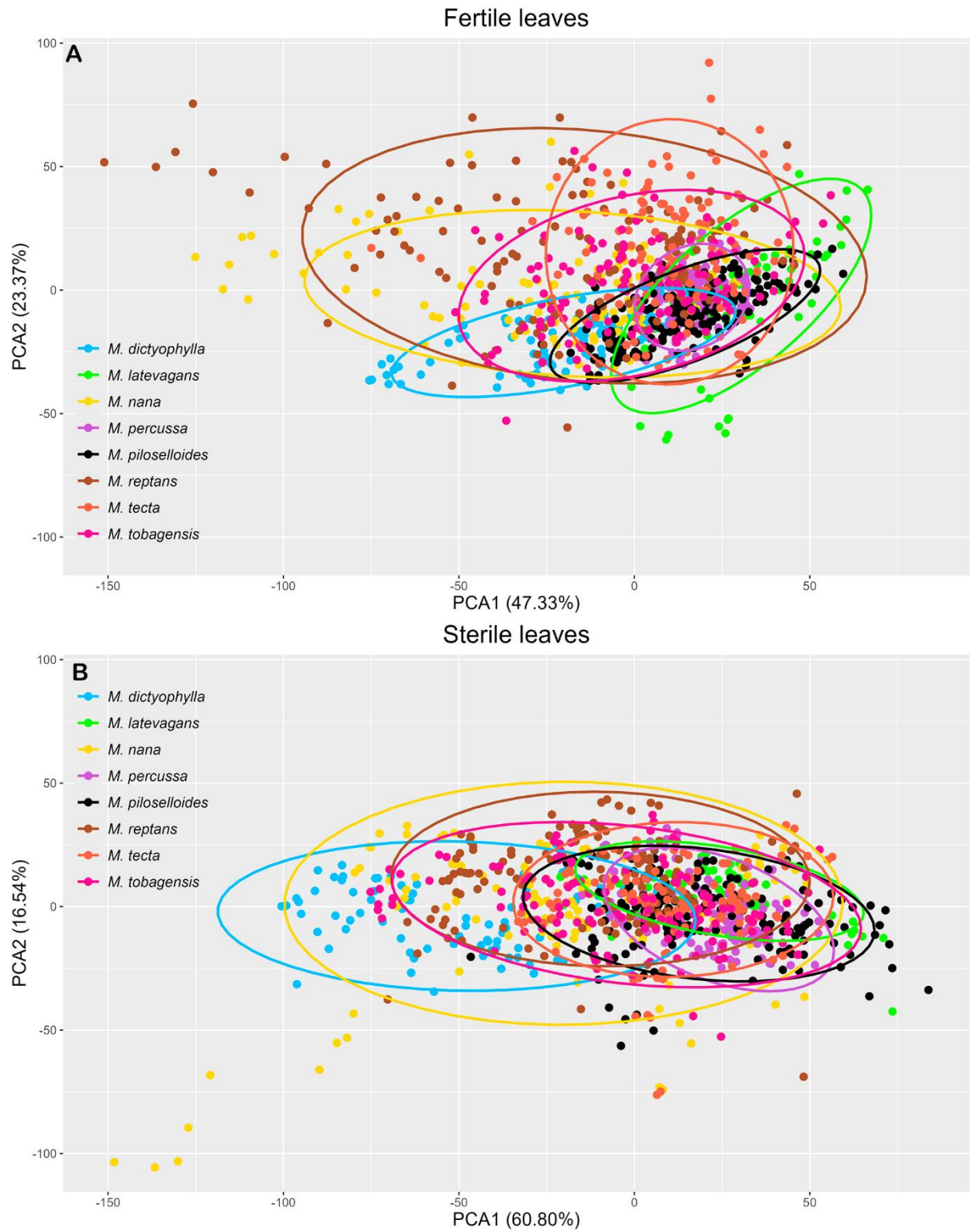
**Fig. 1.** *Microgramma* species from the Scaly clade (Polypodiaceae). **A**, *M. dictyophylla*. **B**, *M. nana*. **C**, *M. tobagensis*. **D**, *M. tecta*. **E**, *M. reptans* (© by 2016 C.N. Fraga). **F**, *M. latevagans* (© by 2009 M. Sundue). **G**, *M. percussa*. **H**, *M. piloselloides* (© by 2018 A. Jose).



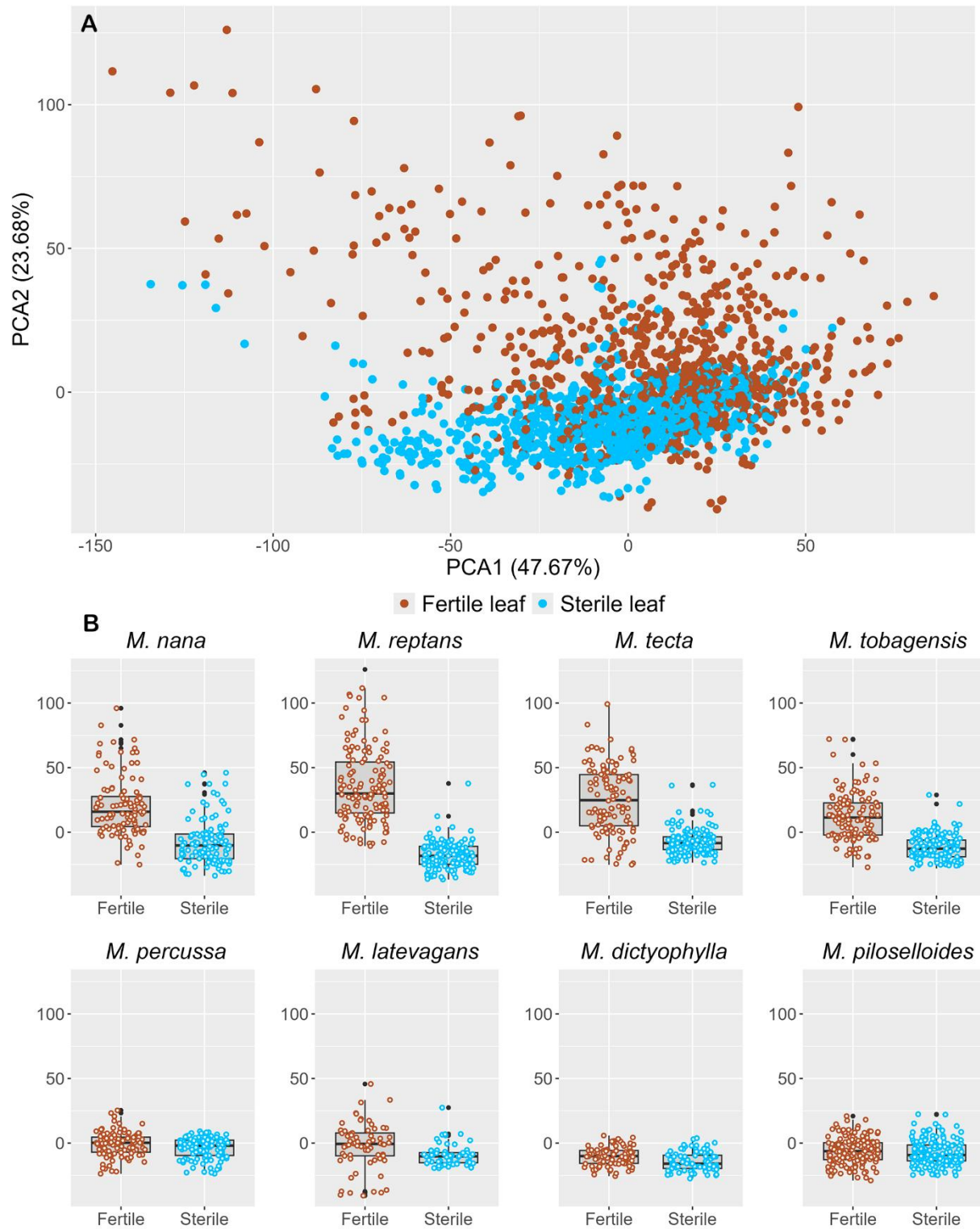
**Fig. 2.** Spectral signature (average data) for eight *Microgramma* species from the Scaly clade.



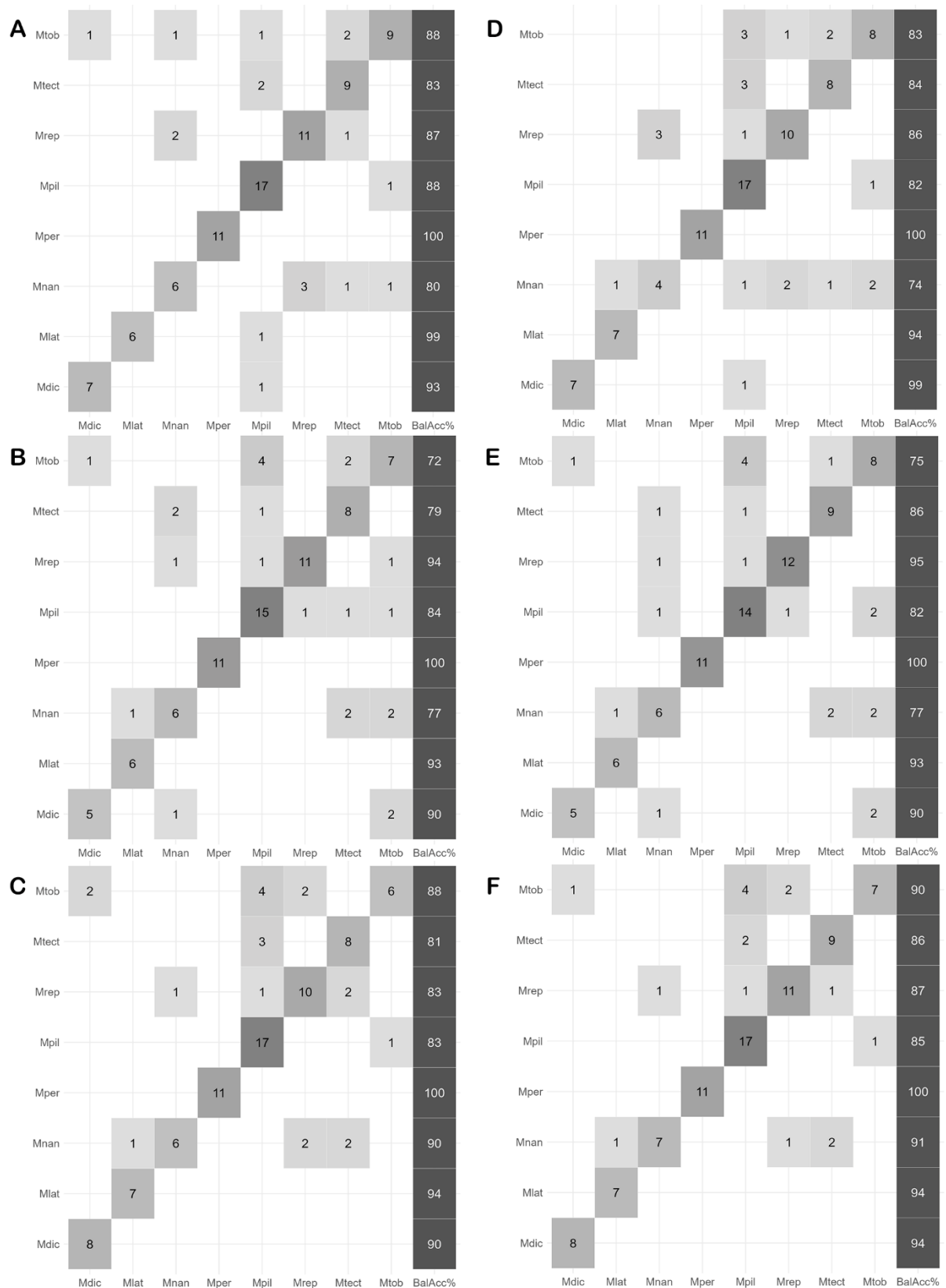
**Fig. 3.** Principal component analysis (PCA). **A**, Complete dataset showing the eight tested species: *Microgramma dictyophylla*, *M. latevagans*, *M. nana*, *M. percussa*, *M. piloselloides*, *M. reptans*, and *M. tobagensis*. **B**, PCA showing specimens categorized by the two functional types of fronds, dimorphic and monomorphic. **C**, Same PCA, showing the tested species separately.



**Fig. 4.** Principal component analysis (PCA). **A**, Dataset of the eight species plotted using the fertile leaf category. **B**, Dataset of the eight species plotted using the sterile leaf category.



**Fig. 5.** Principal component analysis (PCA) plot. **A**, Dataset of the eight species plotted, using the fertile and sterile leaf category. **B**, Fertile and sterile leaf category dataset by species.



**Fig. 6.** Confusion matrices resulting from partial least squares discriminant analysis (PLS-DA) for K-fold and LOOCV validations. **A**, K-fold validation for fertile fronds. **B**, K-fold validation for fertile fronds. **C**, K-fold validation for combined fronds. **D**, LOOCV validation for fertile fronds. **E**, LOOCV validation for fertile fronds. **F**, LOOCV validation for combined fronds.

## Supplementary electronic materials

Title: Spectral signatures as evidence to test hypotheses in plant species complexes

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Table S1 – Specimens used for spectral data capture. The acronym Herbaria follows Thiers (2024 continually updated: <https://sweetgum.nybg.org/science/ih/>).

**Table S1**

Species	Country	Voucher
<i>Microgramma dictyophylla</i>	Brazil	Vida 739 (BHCB145204)
<i>Microgramma dictyophylla</i>	Brazil	Almeida 2230 (BHCB136581)
<i>Microgramma dictyophylla</i>	Brazil	Almeida 2605 (BHCB144728)
<i>Microgramma dictyophylla</i>	Brazil	Cowan 38507 (NY00880074)
<i>Microgramma dictyophylla</i>	Ecuador	Gilmartin 320 (MO1799919)
<i>Microgramma dictyophylla</i>	Guyana	Maguire 40547 (NY03961499)

<i>Microgramma dictyophylla</i>	Peru	Foster 7419 (MO3232987)
<i>Microgramma dictyophylla</i>	Venezuela	Liesner 24298 (NY03961515)
<i>Microgramma latevagans</i>	Bolívia	Smith 13487 (MO4008613)
<i>Microgramma latevagans</i>	Bolívia	Rodriguez 1263 (MO6145673)
<i>Microgramma latevagans</i>	Bolívia	Antezana 1438 (MO04857892)
<i>Microgramma latevagans</i>	Bolívia	Lewis 881089 (MO4008174)
<i>Microgramma latevagans</i>	Peru	Sánchez Vega 5979 (MO3292118)
<i>Microgramma latevagans</i>	Peru	Dillon 6092 (NY03230430)
<i>Microgramma latevagans</i>	Peru	Bennett 2601 (NY03349971)
<i>Microgramma nana</i>	Brazil	Almeida 2732 (BHCB149816)
<i>Microgramma nana</i>	Brazil	Silva 168 (INPA113289)
<i>Microgramma nana</i>	Brazil	Carvalho UAT83 (INPA226341)
<i>Microgramma nana</i>	Brazil	Almeida 2632 (BHCB144755)
<i>Microgramma nana</i>	Costa Rica	Grayum 4884 (MO3324161)
<i>Microgramma nana</i>	Ecuador	Aulestia 128 (MO6016797)
<i>Microgramma nana</i>	Ecuador	Pérez 1185 (NY03962278)
<i>Microgramma nana</i>	México	Campos Villanueva 1011 (MO5069443)
<i>Microgramma nana</i>	Suriname	Maguire 24002 (MO1312664)
<i>Microgramma nana</i>	Suriname	Herrera 10088 (MO6069412)
<i>Microgramma nana</i>	Venezuela	Davidse 3042 (MO2982712)
<i>Microgramma percussa</i>	Brazil	Fraga 3104 (BHCB150254)
<i>Microgramma percussa</i>	Brazil	Dittrich 842 (BHCB64514)
<i>Microgramma percussa</i>	Brazil	Barreto 2595 (BHCB154070)
<i>Microgramma percussa</i>	Brazil	Almeida 372 (BHCB101385)
<i>Microgramma percussa</i>	Brazil	Salino 1988 (BHCB29357)

<i>Microgramma percussa</i>	Brazil	Madison 618 (INPA85192)
<i>Microgramma percussa</i>	Colombia	Croat 79621 (MO6027011)
<i>Microgramma percussa</i>	Colombia	Luteyn 10469 (NY03961982)
<i>Microgramma percussa</i>	México	Hernández 445 (NY03961228)
<i>Microgramma percussa</i>	Panama	McDaniel 8077 (MO6576856)
<i>Microgramma percussa</i>	Peru	Campos 3991 (MO5302244)
<i>Microgramma piloselloides</i>	Bonaire	Boom 11057 (NY02099903)
<i>Microgramma piloselloides</i>	Costa Rica	Rojas 2067 (MO5900546)
<i>Microgramma piloselloides</i>	Cuba	Underwood 831 (NY01842269)
<i>Microgramma piloselloides</i>	Cuba	Britton 5165 (NY01842276)
<i>Microgramma piloselloides</i>	Dominica	Chambers 2501 (NY01842425)
<i>Microgramma piloselloides</i>	Grenada	Broadway s.n. (MO5446677)
<i>Microgramma piloselloides</i>	Jamaica	s.c/s.n. (MO5462147)
<i>Microgramma piloselloides</i>	Jamaica	s.c/s.n. (MO5462145)
<i>Microgramma piloselloides</i>	Jamaica	Hitchcock s.n. (MO5446665)
<i>Microgramma piloselloides</i>	Jamaica	s.c/s.n. (MO5446680)
<i>Microgramma piloselloides</i>	Puerto Rico	Ahlquist 45 (BHCB173388)
<i>Microgramma piloselloides</i>	Puerto Rico	Britton 2062 (NY00989767)
<i>Microgramma piloselloides</i>	Puerto Rico	Underwood 11 (NY00989773)
<i>Microgramma piloselloides</i>	Puerto Rico	Shafer 3139 (NY00989780)
<i>Microgramma piloselloides</i>	Puerto Rico	Vincent 15355 (NY02150502)
<i>Microgramma piloselloides</i>	República do Haiti	Nash 217 (NY01842393)
<i>Microgramma piloselloides</i>	Republica Dominicana	Mejía 7508 (MO3859988)
<i>Microgramma piloselloides</i>	Republica Dominicana	Zanoni 28119 (NY01842360)

<i>Microgramma piloselloides</i>	St Vicent and The Grenadines	Badger s.n. (MO5484127)
<i>Microgramma reptans</i>	Brazil	Daly 1352 (INPA118203)
<i>Microgramma reptans</i>	Brazil	Matos 11468 (CEPEC15838)
<i>Microgramma reptans</i>	Brazil	Fraga 3090 (BHCB150244)
<i>Microgramma reptans</i>	Brazil	Fraga 2971 (BHCB143826)
<i>Microgramma reptans</i>	Colombia	Molina 18c716 (MO1626606)
<i>Microgramma reptans</i>	Costa Rica	Lesica 4136 (MO3416567)
<i>Microgramma reptans</i>	Ecuador	Aulestia 1560 (MO05055185)
<i>Microgramma reptans</i>	Guyana	MC Dowell 4809 (MO04621215)
<i>Microgramma reptans</i>	Nicaragua	Urbina 70 (MO6710204)
<i>Microgramma reptans</i>	Panama	Salino 15879 (BHCB173590)
<i>Microgramma reptans</i>	Panama	Stern 646 (MO1817771)
<i>Microgramma reptans</i>	Panama	Kennedy 3232 (MO3014609)
<i>Microgramma reptans</i>	Peru	Schunke-Vigo 3469 (INPA133051)
<i>Microgramma reptans</i>	Peru	King 451 (INPA123964)
<i>Microgramma tecta</i>	Brazil	Krieger 8862 (BHCB165025)
<i>Microgramma tecta</i>	Brazil	Salino s.n. (BHCB43418)
<i>Microgramma tecta</i>	Brazil	Salino 10145 (BHCB91558)
<i>Microgramma tecta</i>	Brazil	Salino 13779 (BHCB124333)
<i>Microgramma tecta</i>	Brazil	Mota 3160 (BHCB105182)
<i>Microgramma tecta</i>	Brazil	Schmitt 334 (BHCB142994)
<i>Microgramma tecta</i>	Brazil	Kollmann 4051 (BHCB108513)
<i>Microgramma tecta</i>	Brazil	Matos 415 (BHCB97283)
<i>Microgramma tecta</i>	Brazil	Salino 13595 (BHCB122753)

<i>Microgramma tecta</i>	Brazil	Salino 8637 (BHCB81163)
<i>Microgramma tecta</i>	Brazil	Cadorin 2121 (BHCB142972)
<i>Microgramma tobagensis</i>	Brazil	Thomas 9304 (MO04895073)
<i>Microgramma tobagensis</i>	Brazil	Mori 11468 (NY00674449)
<i>Microgramma tobagensis</i>	Brazil	Amorim 4205 (NY01241079)
<i>Microgramma tobagensis</i>	Brazil	Matos 1577 (NY02064119)
<i>Microgramma tobagensis</i>	Ecuador	Gudiño Jara 2256 (MO04911176)
<i>Microgramma tobagensis</i>	Ecuador	Clark 575 (MO5149584)
<i>Microgramma tobagensis</i>	Ecuador	Vargas López 5138 (MO6389474)
<i>Microgramma tobagensis</i>	Guatemala	Türkheim 125 (NY03961400)
<i>Microgramma tobagensis</i>	Peru	Klug 2539 (NY03966108)
<i>Microgramma tobagensis</i>	Trinidad and Tobago	Broadway 9959 (NY02027319)
<i>Microgramma tobagensis</i>	Trinidad and Tobago	Jermy 2870 (NY02027320)
<i>Microgramma tobagensis</i>	Trinidad and Tobago	Jermy 2680 (MO04642633)
<i>Microgramma tobagensis</i>	Venezuela	Steyermark 61888 (NY03966137)

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