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## Nondestructive measurement of microfibril angle of wood by using near-infrared spectroscopy

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1 Nondestructive measurement of microfibril angle of wood by using near-infrared  
2 spectroscopy

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**ABSTRACT**

17 Fast-growing tree species, such as Eucalyptus, are used extensively in plantations  
18 for timber, but their mechanical properties are not well understood, especially the  
19 microfibril angle (MFA), which affects wood stiffness. MFA measurement is complex  
20 and expensive, but near-infrared spectroscopy (NIRS) offers a non-destructive  
21 alternative. This study aims to evaluate the effectiveness of NIRS in predicting MFA  
22 across different regions and environments. The results showed that NIRS could predict  
23 MFA, but the accuracy varied. In Brazil, higher prediction accuracy was observed when  
24 data from multiple regions were combined. In Laos, the presence of juvenile wood  
25 significantly decreased prediction accuracy. Combining data from multiple sites  
26 improved prediction accuracy, but decreased accuracy when juvenile wood was  
27 included. The study concludes that effective MFA prediction models must consider  
28 regional and environmental differences. Creating region-specific models is necessary  
29 for reliable wood quality assessment using NIRS. This research underscores the  
30 potential of NIRS as a practical tool for wood quality evaluation, highlighting the  
31 importance of accounting for factors such as wood maturity and environmental  
32 conditions in developing robust predictive models.

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35 **Keywords:** Near Infrared Spectroscopy; eucalyptus; microfibril angle; non-destructive  
36 measurement; reflectance; wood property

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## INTRODUCTION

40 Fast-growing tree species are cultivated in plantations. As timber use shifts from  
41 natural forests to plantations, there are high expectations for utilization of wood due to  
42 increased growth and biomass production. These fast-growing species, such as  
43 *Eucalyptus* spp., have primarily been bred to supply pulp and fuelwood, making them  
44 less valuable as commercial frame timber for building materials. Consequently, there  
45 is currently limited information available on the mechanical properties of fast-growing  
46 species. It is necessary to measure wood physical properties such as stiffness, modulus  
47 of rupture, microfibril angle (MFA) and so on as using frame timber. In particular,  
48 MFA, which significantly affects physical properties, has rarely been investigated due  
49 to the difficulty of the measurement procedure and its time-consuming nature. Even if  
50 there were easy ways to measure parameters of wood quality, such as the Silvi  
51 Scan, the device is expensive and the number of devices and the countries that  
52 own them are limited.

53 MFA is related stiffness and physical properties of wood, such as elongation and  
54 contraction. Therefore, understanding MFA variation in wood is important for  
55 utilization of the wood; however, it can only be measured with expensive equipments  
56 or with time- consuming and laborious ways (Isik et al. 2011). That is why the data has  
57 not been collected for a variety of wood species, especially fast-growing hard wood.

58 To achieve rapid measurement of MFA in numerous wood samples, we focused  
59 on utilizing Near-infrared spectroscopy (NIRS). NIRS is a non-destructive  
60 measurement technique widely used in fields such as food science, agriculture,  
61 pharmaceuticals, and forestry (Tsuchikawa et al. 2022, Pasquini et al. 2018, Bec et al.

62 2021). In the field of wood science, NIRS has been used to estimate cellulose and lignin  
63 content, as well as wood density and Young's modulus (Kelley et al. 2004, Ma et al.  
64 2018). Hence, we hypothesized that simplifying and expediting the evaluation of wood  
65 quality using NIRS, we could accumulate a substantial amount of the data, and analyze  
66 the differences among wood species, growth regions, and patterns of wood quality  
67 distribution.

68 Several studies have attempted to predict MFA using NIRS (Schimleck et al.,  
69 2001, 2002, 2003, 2005; Jones et al., 2005). Previous NIR spectroscopic studies utilized  
70 MFA data provided by SilviScan analysis for calibration purposes. The MFA was  
71 determined by SilviScan using scanning X-ray diffraction with the X-ray beam  
72 approximately parallel to the growth ring. Schimleck (2007), determined MFA for each  
73 sample by measuring the relative width of 002 diffracted X-ray arcs from an X-ray  
74 beam on a tangential cross-section and utilizing a predictive model for the NIR. In this  
75 study, the MFA was determined using the modified Cave's method with X-ray  
76 diffractometry, where the X-ray beam was irradiated on the tangential section.

77 Previous research has demonstrated a strong correlation between the values of  
78 MFA measured by SilviScan and estimated by NIR in *Eucalyptus delegatensis* and  
79 *Pinus radiata* (Schimleck et al., 2001; Schimleck et al., 2002). While it is clear that  
80 MFA can be predicted using NIRS, adaptability of a model created for a specific site  
81 or tree species has not been investigated.

82 In a calibration model using NIRS, Wang et al. (1991) stated that calibrations  
83 created for certain products may not be useful to predict other products. In the field of  
84 fruit research, modelling errors can easily double when calibration models are applied  
85 to spectral datasets from different seasons or orchards (Nicolăi et al., 2007). These

86 problems are less pronounced for products whose quality is stable, such as  
87 manufactured goods, but can be significant for plants and living organisms.

88         Similar to fruit, it is generally recognized that properties of wood vary based on  
89 factors such as the planting site and soil (Zobel et al. 1998, Kojima et al. 2009a).  
90 Therefore, a predictive model for the estimation of the properties of wood derived from  
91 a certain plantation may not be applicable as a general predictive model for other  
92 plantations. In other words, it is important to evaluate whether models that use near-  
93 infrared to predict the properties of wood grown in a particular region can be adapted  
94 to predict wood properties in different regions.

95         In a previous study, estimation of wood density, MFA, and stiffness of *Pinus*  
96 *taeda* (loblolly pine) using NIRS have been successfully applied to cores taken from  
97 various sites, with samples representative of a variety of sites and geomorphological  
98 regions in Georgia (USA) (Jones et al. 2005). These results suggest that general models  
99 for the estimation of wood properties of different species or site can be developed in  
100 the field of wood science. The above results suggest that wood qualities can be  
101 predicted using NIRS in the same way, regardless of sites where the samples are  
102 collected. However, it is necessary to examine whether the same predictions can be  
103 made in environments with significantly different growth habitats.

104         Based on the aforementioned context, our research focused on examining  
105 whether consistent predictions of MFA could be yield regardless of the planted location.  
106 In this study, we tested whether different prediction models can be adapted between  
107 regions with a different climatic division within an extensive area or regions with  
108 extremely variable planting environments within a narrow area. We conducted the  
109 following experiments using the MFA, which is related to the physical properties of  
110 wood such as stiffness and shrinkage.

111 1(Brazil): Eucalyptus trees planted in Brazil were used to examine the  
112 adaptability of the predictive model in regions with extensive climatic divisions. Brazil  
113 spans a vast north-south range, and the same tree species are planted across various  
114 latitudes and climatic zones, allowing us to investigate differences in planting locations  
115 over a wide range.

116 2(Laos): The adaptability of the prediction model was also examined using  
117 eucalyptus trees planted in Laos, where the planting environment changes significantly  
118 within small areas. In Laos, despite being in the tropics, there are many areas with poor  
119 river management, leading to some regions being flooded during the rainy season while  
120 others remain dry. This variability in the soil moisture environment enabled us to study  
121 planting areas with extremely different conditions.

122 3(Unified Model): Finally, we explored the possibility of developing a predictive  
123 model that could cover all the planting environment described in points (1) and (2)  
124 above.

## 125 MATERIALS AND METHODS

### 126 Sampling area and sample preparation

127 Wood sampling was conducted in Brazil and Laos to investigate the effects of  
128 different latitudes and climates in Brazil and the influence of habitat environments in  
129 Laos on NIR results. Detailed locations of the sampled sites are shown in Table 1.

130 At each site the test trees were selected to represent a wide range of diameters at  
131 breast height (DBH). For sample collection with a wide range of diameters, we utilized  
132 the existing diameter data of the plantation trees. We selected the trees with the largest  
133 and smallest diameters, and then chose the remaining samples to ensure an even  
134 distribution of diameters. This method ensured a balanced representation of trees with

135 varying diameters. A rectangular specimen was collected at three-four cardinal points  
136 at breast height on each tree with a hand saw and chisel. This three-four cardinal  
137 sampling points method was used in order to account for the presence of reaction wood  
138 and variations in wood properties depending on the sampling points.

139 We cut off the sample as L:10mm R: 1mm T: 10mm to measure the microfibril  
140 angle (MFA) in the S<sub>2</sub> layer of the secondary wall.

141

#### 142 **Samples from the different latitudes in Brazil**

143 We studied *Eucalyptus grandis* W. Hill ex Maiden planted in three plantations  
144 in different latitudinal divisions, including tropical and subtropical climates in Brazil.

145 Sixty-nine wood samples were tested from an 18-year-old plantation in  
146 Açailândia in Brazil (B1). Eighty-five wood samples were collected from a 17-year-old  
147 plantation in Posto da Mata, Brazil (B2). Ninety-one wood samples were tested in a 16-  
148 year-old plantation in Porto Alegre, Brazil (B3). Detailed plantation information can be  
149 found in a previous paper (Kojima et al. 2009a).

150

#### 151 **Samples from the different habitat environment in Laos**

152 The locations of our study areas are in central Laos. We studied *E. camaldulensis*  
153 × *E. deglupta* clones from three plantations; a non-flooded plantation, a slightly flooded  
154 plantation, and a flooded plantation, all planted in 2007. The slightly flooded plantation  
155 is not flooded above ankle height, but the flooded plantation is flooded to chest height  
156 in the rainy season. The three study plantations are located at almost the same latitude  
157 and climate zone; only their water condition differs.

158 Sixty-four wood samples were tested from a 3-year-old plantation in a non-  
159 flooded plantation (L1-NF), Paksuun, and in a flooded plantation (L2-F), Nong boua



160 PK in Laos. Fifty-two wood samples were tested from a 3-year-old plantation in a  
161 slightly flooded plantation (L3-SF), Nong boua PK in Laos. The plantation being in its  
162 third year of growth suggests that there is a high probability of it containing a significant  
163 proportion of juvenile wood.

164

#### 165 ***Measurement of the microfibril angle in the middle layer of the secondary wall***

166 Microfibril angle (MFA) in the S<sub>2</sub> layer of the secondary wall was determined  
167 for all test specimens. MFA in a thin tangential section (1mm thick) was determined  
168 with the modified Cave's method using X-ray diffractometry (CuK $\alpha$  line) (XD-D1w;  
169 Shimadzu Company Kyoto, Japan)(Cave 1966, Meylan 1967). The distribution of the  
170 diffraction intensity along the cellulose (200) arc was recorded by means of X-ray  
171 diffractometry and the "angle *T*" was determined according to Cave (1966), which is  
172 the basis for MFA determination by equation "MFA = 0.6 $\times$ angle*T*". In the present study,  
173 we used raw MFA data obtained from our previous paper (Kojima et al. 2009a),  
174 collected in Brazil.

175

#### 176 ***NIR device and spectra acquisition***

177 For NIR measurement, we used the same samples used for the MFA  
178 measurements using X-ray diffractometry. The diffuse reflectance spectra of a spot (3  
179 mm diameter) were collected at 8 cm<sup>-1</sup> intervals over a range of 12000-4000 cm<sup>-1</sup> (830-  
180 2500 nm) and the resolution was 8 cm<sup>-1</sup> using a MATRIX-F spectrometer (Bruker  
181 Optics) equipped with an NIR fiber optic probe. The X-ray beam was irradiated on the  
182 tangential section, similarly to the NIR measurement. 32 scans were performed for each  
183 sample; these scans were averaged to give a single spectrum per sample. All the spectra  
184 were acquired at 20  $\pm$  2°C and 65  $\pm$  5% relative humidity.

185

186

187 ***Multivariable Analysis of the NIR Data Set***

188 Statistical analysis of MFA for the training set and test set is presented in Table  
189 2. The training set encompassed both high and low values for each parameter. Raw NIR  
190 spectra often exhibited baseline shifts or drifts due to variations in NIR measurements.  
191 Additional factors, such as instrument stability, temperature, humidity, or surface  
192 conditions of the sample, could also influence the spectra (Candolfi et al., 1999).  
193 Therefore, data pretreatment played a vital role in the analysis to eliminate such  
194 variations. For NIR measurement, pretreatment techniques were employed to mitigate  
195 these variations. In this study moving average smoothing (21points), baseline  
196 correction and second derivative calculation (Norris gap) were applied as the spectra  
197 pretreatment. Pretreated NIR spectra were utilized for subsequent analysis.

198 Partial least squares regression (PLSR) was employed for regression analysis.  
199 PLSR aimed to minimize the discrepancy between the target variable (MFA value) and  
200 the explanatory variable (NIR spectral data). The optimal number of factors used for  
201 each calibration was determined based on recommendations from the Unscrambler X  
202 software (version 10.1; Camo Software, Oslo, Norway). The data were assessed by  
203 examining the determinant coefficient ( $R^2$  for the training set and  $R_{\text{test}}^2$  for the test set)  
204 between the predicted and measured values. Additionally, the root mean square error  
205 of cross-validation (RMSECV) and the root mean square error of prediction for the test  
206 set (RMSEP) were statistically evaluated and compared for calibration and prediction  
207 models.

208

**RESULTS AND DISCUSSION****209 Prediction accuracy**

210 Calibration tests were performed to predict values for samples unrelated to the  
211 sample used to develop the calibration. Table 3 presents a comprehensive overview of  
212 the outcomes obtained from predictions made on the distinct test set. To gauge the  
213 quality of the predictions, determinant coefficient of the prediction ( $R^2_p$ ) was computed,  
214 reflecting the extent to which the variation in the independent set was estimated by the  
215 calibration.

216 When training samples were employed from each specific plantation site to  
217 construct prediction models, the prediction accuracy for each plantation site was (B1)  
218  $R^2 = 0.46$ , (B2)  $R^2 = 0.44$ , (L1-NF)  $R^2 = 0.28$  and (L3-SF)  $R^2 = 0.34$ . However, it was  
219 not feasible to predict the MFA for B3 and L2-F. Conversely, when training samples  
220 from all countries were used to create prediction models for each country, the prediction  
221 accuracy for each plantation site was (B1)  $R^2 = 0.49$ , (B2)  $R^2 = 0.49$  and (L1-NF)  $R^2 =$   
222  $0.17$ . However, it was not feasible to predict the MFA for B3, L2-F and L3-SF.

223 Figure 1 shows the average of (a) all raw spectra, (b) all pretreated NIR spectra  
224 after smoothing, baseline correction, and second derivative calculations, and (c)  
225 regression coefficients from PLS model used for prediction. The regression coefficients  
226 of the PLS model used for the prediction were derived from the training set. Although  
227 the average results are shown, the results for Brazil and Laos exhibit a similar trend.  
228 Regression coefficients can be used to determine important spectral regions that are  
229 responsible for the correlation with MFA. It is obvious in the absorbance spectrum that  
230 at least three peaks exist at wavelengths of 1916, 2092 and 2361 nm. A highly negative  
231 impact and positive impact on the calibration model were found at these wavelengths,  
232 indicating that their absorbance was highly correlated with MFA. The absorption

233 bands at these wavelengths can be attributed to chemical components such as cellulose  
234 and water (Table 4) (Schwanninger et al., 2011). As reported in a previous study  
235 (Okuyama et al., 1994), MFA is strongly dependent on cellulose content. Therefore,  
236 cellulose composition has a relatively high influence on the calibration model, as  
237 indicated by the regression coefficients at wavelengths of 2092 and 2361 nm.

238

239

#### 240 **The different latitudes**

241 Utilizing samples gathered from different latitude regions in Brazil, the  
242 predictive precision exhibited a lower accuracy in the B3 plantation, while  
243 demonstrating higher accuracy in other locations. In Porto Alegre (B3), we observed  
244 an NIR to predict the MFA (Table 3). The MFA values displayed minimal variation  
245 across the three plantations in Brazil.

246

#### 247 **Impact of data variability on estimation**

248 To ascertain the underlying cause, we conducted an examination of data  
249 variability within each plantation site (Table 2). The outcomes revealed that the B3  
250 plantation exhibited less data variability in comparison to the other plantations,  
251 potentially influencing the diminished accuracy in predictions. Previous research has  
252 indicated that wood quality tends to remain relatively stable within a specific plantation,  
253 independent of the growth rate (Kojima et al. 2009a, 2009b, 2009c). In essence, if the  
254 prediction model were exclusively created for a single plantation, the data variability  
255 would be minimal, consequently leading to poorer accuracy. To achieve highly accurate  
256 MFA predictions, it is deemed necessary to develop a prediction model incorporating

257 data samples collected from diverse plantations, thereby enhancing the variability  
258 within the dataset.

259

### 260 **The different habitat environment**

261 Utilizing samples collected from different environments in Laos, the  
262 predictive accuracy proved to be significantly low for each plantation site, particularly  
263 in L1-NF and L3-SF (Table 3). Similar to the findings in Brazil, the MFA values  
264 displayed minimal variation across the three plantations in Laos. While the Brazilian  
265 plantation, aged over 16 years, had reached the commercial harvest stage, the Laos 3-  
266 years-old plantation was still below the harvest age and predominantly consisted of  
267 juvenile wood. It is postulated that the inferior accuracy of the data collected in Laos  
268 can be attributed to the higher prevalence of a substantial amount of juvenile wood,  
269 compared to Brazil. The data was scattered due to the presence of juvenile wood, but  
270 the accuracy of the MFA forecast did not improve.

271

### 272 **Samples from all sites**

273 The relationships between measured values and NIR-estimated values are  
274 shown in Figure 2. A prediction model for MFA was employed, incorporating data  
275 from both Brazil and Laos, to compute the NIR-estimated MFA values for Brazil and  
276 Laos (Figure 2 A). In the case of Brazil, the MFA estimation was performed using the  
277 entire Brazilian dataset (Figure 2 B), while for Laos, the estimation was conducted  
278 utilizing the complete Laos dataset (Figure 2 C). The correlations between measured  
279 values and NIR-estimated values are  $R^2 = 0.53$ ,  $R^2 = 0.62$ , and  $R^2 = 0.48$ , figure 2, A, B,  
280 and C, respectively. The prediction model for MFA, incorporating data from both  
281 Brazil and Laos, was employed to derive the NIR-estimated MFA values for Brazil and

282 Laos. The correlations between the measured values and NIR-estimated values were  $R^2$   
283 = 0.50 for Brazil and  $R^2 = 0.45$  for Laos (Table 3).

284 In this study, we collected wood samples from numerous sites across various  
285 locations in Brazil, enabling the comprehensive MFA prediction model that  
286 encompassed the entire dataset from Brazil. Remarkably, this consolidated model  
287 demonstrated higher accuracy compared to the individual plantation-specific prediction  
288 models within Brazil. This result can be attributed to the increased variability present  
289 in the comprehensive dataset from Brazil. Likewise, when all samples from Laos were  
290 analyzed, the prediction model yielded superior accuracy compared to the individual  
291 plantation-specific models (Table 3).

292 Schimleck et al, (2002, 2005) reported a strong correlation in samples  
293 containing juvenile wood with an MFA exceeding 20 degrees. However, in this study,  
294 the observed correlation was not as strong as reported by Schimleck et al, (2002, 2005)  
295 in any case. Schimleck et al, (2002, 2005) estimated the measured MFA using SilviScan  
296 and conducted X-ray irradiation on the radial surface. In contrast, in this study, MFA  
297 was measured using X-ray diffraction and performed X-ray irradiation on the tangential  
298 surface. Furthermore, in addition to these differences, the plantation environment in  
299 this study consisted of a mixture of distinct individuals, which could potentially impact  
300 the detected correlations.

301

## 302 CONCLUSIONS

303

304 The results of this study highlight the feasibility of utilizing near-infrared  
305 spectroscopy (NIRS) as a reliable method for predicting wood quality, particularly the  
306 microfibril angle (MFA). The predictive potential of NIRS was demonstrated by  
307 developing a robust MFA prediction model using wood samples collected from various

308 regions in Brazil and Laos. In the different latitude regions of Brazil, the variability of  
309 the data had a noticeable impact on the accuracy of the predictions. As a result, the  
310 prediction model that incorporated data from multiple regions exhibited higher  
311 accuracy compared to models based solely on individual plantations. On the other hand,  
312 in different habitats in Laos, the presence of juvenile wood emerged as a significant  
313 factor contributing to decreased prediction accuracy.

314         When combining data from both Laos and Brazil, the prediction accuracy of  
315 the model decreased. This decline is primarily attributed to the issue of prevalent  
316 juvenile wood in the Laotian samples. Consequently, it became evident that, in order to  
317 develop an effective prediction model, it is imperative not to rely solely on a single site  
318 but rather create separate models accounting for the immaturity of the timber, while  
319 acknowledging the necessity of incorporating variation within the dataset.

320         Hence, it is evident that in order to develop an effective prediction model, it is  
321 imperative to account for the variability of the data and avoid relying solely on a single  
322 region. Furthermore, the presence of juvenile wood necessitates the creation of distinct  
323 prediction models. These findings highlight the importance of considering data  
324 variability, in addition to factors such as age or diameter, when evaluating wood quality  
325 using NIRS. To enhance and broaden the scope of the prediction models, it will be  
326 essential to gather data from a broader range of wood species and growth regions.

327         It can be suggested that when predicting the properties of biological samples  
328 such as wood, increasing the number of sample locations may enhance the accuracy of  
329 the prediction. However, it is crucial to ensure that conditions, such as the number of  
330 years of growth, are consistent.

331

332

333

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339

340

**Data availability**

341 Data generated or analyzed during this study are provided in full within the published  
342 article.

343

344

**Competing interests statement**

345 The authors declare there are no competing interests.

346

347

**References**

- 348 Bec K.B., Grabska J., Huck C.W., 2021. Principles and Applications of Miniaturized  
349 Near-Infrared (NIR) Spectrometers. *Chemistry*. 27(5): 1514–1532.
- 350 Cave, I.D., 1966. Theory of X-ray measurement of microfibril angle. *Forest Prod. J.* 16,  
351 37–42.
- 352 Candolfi, A., De Maesschalck, R., Massart, D.L., Hailey, P.A., Harrington, A. 1999.  
353 Identification of pharmaceutical excipients using NIR spectroscopy and SIMCA. *J.*  
354 *Pharm. Biomed. Anal.* 19: 923–935.



- 355 Isik, F., Mora, C.R., Schimleck, L.R. 2011. Genetic variation in *Pinus taeda* wood  
356 properties predicted using non-destructive techniques. *Annals of Forest Science*. 68:  
357 283–293.
- 358 Jones, P.D., Schimleck, L.R., Peter, G.F., Daniels, R.F., Clark, A. 2005. Nondestructive  
359 estimation of *Pinus taeda* L. wood properties for samples from a wide range of sites  
360 in Georgia. *Can. J. For. Res.* 35: 85–92.
- 361 Kelley, S.S., Rials, T.G., Snell, R., Groom, L.H., Sluiter, A. 2004. Use of near infrared  
362 spectroscopy to measure the chemical and mechanical properties of solid wood.  
363 *Wood Sci Technol.* 38:257–276.
- 364 Kojima, M., Yamaji, F.M., Yamamoto, H., Yoshida, M., Nakai, T. 2009a. Effects of  
365 the lateral growth rate on wood quality parameters of *Eucalyptus grandis* from  
366 different latitudes in Brazil and Argentina. *For. Ecol. Manage.* 257(10): 2175–2181.
- 367 Kojima, M., Yamamoto, H., Marsoem, S.N., Okuyama, T., Yoshida, M., Nakai, T.,  
368 Yamashita, S., Saegusa, K., Matsune, K., Nakamura, K., Inoue, Y., Arizono, T.  
369 2009b. Effects of the lateral growth rate on wood quality of *Gmelina arborea* from  
370 3.5, 7, and 12-years-old plantations. *Annals of Forest Science* 66, Article Number  
371 507.
- 372 Kojima, M., Yamamoto, H., Okumura, K., Ojio, Y., Yoshida, M., Okuyama, T., Ona,  
373 T., Matsune, K., Nakamura, K., Ide, Y., Marsoem, S.N., Sahri, M.H., Hadi, Y.S.  
374 2009c. Effect of the lateral growth rate on wood properties in fast-growing hardwood  
375 species. *J. Wood Sci.* 55:417–424.
- 376 Ma T., Inagaki T., Tsuchikawa S. 2018. Non-destructive evaluation of wood stiffness  
377 and fiber coarseness, derived from SilviScan data, via near infrared hyperspectral  
378 imaging. *Journal of Near Infrared Spectroscopy.* 26(6) 398–405

- 379 Meylan, B.A., 1967. Measurement of microfibril angle by X-ray diffraction. Forest  
380 Prod. J. 17, 51–58.
- 381
- 382 Nicolaï B.M., Beullens K., Bobelyn E., Peirs A., Saeys W., Theron K.I., Lammertyn  
383 J. 2007. Nondestructive measurement of fruit and vegetable quality by means of NIR  
384 spectroscopy: A review. Postharvest Biology and Technology. 46 : 99–118
- 385 Okuyama T., Yamamoto H., Yoshida M., Hattori Y., Archer RR. 1994. Growth stresses  
386 in tension wood: role of microfibrils and lignification. Annals of Forest Science. 51  
387 (1994) 291-300.
- 388 Pasquini C., 2018. Near infrared spectroscopy: A mature analytical technique with new  
389 perspectives – A review. Analytica Chimica Acta. 1026:8-36.
- 390 Schimleck, L.R., Evans, R., Ilic, J. 2001. Estimation of *Eucalyptus delegatensis* wood  
391 properties by near infrared spectroscopy. Can. J. For. Res. 31(10):1671-1675.
- 392 Schimleck, L.R., Evans, R., Matheson, A.C. 2002. Estimation of *Pinus radiata* D. Don  
393 clear wood properties by near-infrared spectroscopy. J. Wood Sci. 48:132-137.
- 394 Schimleck, L.R., Evans, R., Ilic, J. Application of near infrared spectroscopy to the  
395 extracted wood of a diverse range of species. 2003. IAWA Journal. Vol. 24 (4),  
396 2003: 429 – 438.
- 397 Schimleck, L.R., Evans, R., Jones, P.D., Daniels, R.F., Peter, G.F., Clark, A. 2005.  
398 Estimation of microfibril angle and stiffness by near infrared spectroscopy using  
399 sample sets having limited wood density variation. IAWA Journal, Vol. 26 (2): 175–  
400 187.
- 401 Schimleck L.R., Sussenbach E., Leaf G., Jones P.D., Huang C.L. 2007. Microfibril  
402 angle prediction of *Pinus Taeda* wood samples based on tangential Face Nir spectra.  
403 IAWA journal. 28 (1) : 1-12

- 404 Schwanninger M., Rodrigues J.C., Fackler K. 2011. A review of band assignments in  
405 near infrared spectra of wood and wood components. *Journal of Near Infrared*  
406 *Spectroscopy*. 19(5):287-308
- 407 Tsuchikawa S., Ma T., Inagaki T., 2022. Application of near-infrared spectroscopy to  
408 agriculture and forestry. *Analytical Sciences*. 38: 635–642.
- 409 Wang Y., Veltkamp D.J., Kowalski B.R. 1991. Multivariate Instrument Standardization.  
410 *Analytical Chemistry*. 63(23) : 2750-2756
- 411 Zobel, B.J., Sprague, J.R., 1998. *Juvenile Wood in Forest Trees*. Springer-Verlag,  
412 Berlin, Germany, pp. 300.
- 413

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**414 Tables**

415 Table 1. Detailed geographical coordinates of the sampled sites, along with the  
416 corresponding tree ages and the total number of trees sampled.

417

418 Table 2. Range of wood properties for training set and test set for each plantation.

419

420 Table 3. Statistical analysis of MFA values for both the training set and the test set,  
421 categorized by each wood district. The prediction coefficient of determination ( $R^2$ ) was  
422 calculated based on the predictions made specifically for the distinct test set.

423

424 Table 4. Assignment of absorption bands in the NIR region. Peak number corresponds  
425 to those in Figure 1.

426

427 **Figure caption**

428 Figure 1 (a) Average of all raw spectra, (b) Average of all pretreated NIR spectra by  
429 smoothing, baseline correction, and second derivative calculations. (c) regression  
430 coefficients from the PLS model used for prediction.

431

432 Figure 2 Relationships between measured MFA and NIR-estimated MFA. MFA  
433 prediction model, integrating data from both Laos and Brazil, was employed to  
434 determine the estimated MFA using near-infrared spectroscopy (NIRS) for (A) Brazil  
435 and Laos. For (B) Brazil, the MFA estimation utilizing the complete Brazilian dataset  
436 was conducted, while for (C) Laos, the estimation was carried out using the entirety of  
437 the Laos dataset.

438

sample No.	Country	city	latitude and longitude	climate	tree age	number of sample trees	number of samples
B1		Acailandia	5°5'S, 47°39'W	tropical	18	18	69
B2	Brazil	Posto da Mata	18°05'S, 39°33'W	tropical	17	21	85
B3		Porto Alegre	30°05'S, 51°10'W	subtropical	16	22	91
L1-NF		Paksuun (non-flooded )	18°19'N, 104°02'E	tropical	3	16	64
L2-F	Laos	Nong boua PK (flooded )	18°19'N, 104°02'E	tropical	3	16	64
L3-SF		Nong boua PK (slightly flooded)	18°19'N, 104°02'E	tropical	3	13	52

Table 1

780x118mm (144 x 144 DPI)

	MFA(°) for training set					MFA(°) for test set				
	Average	Min	Max	STDEV	sample number	Average	Min	Max	STDEV	sample number
B1	14.3	9.6	24.6	3.1	56	13.9	10.2	18.0	2.5	13
B2	12.4	7.8	22.2	2.7	69	11.8	8.4	16.2	2.5	16
B3	9.3	7.2	13.8	1.3	73	9.5	7.8	13.2	1.4	18
Brazil all	11.8	7.2	24.6	3.2	198	11.5	7.8	18.0	2.8	47
L1-NF	11.0	8.4	17.2	1.9	52	11.5	8.4	14.8	2.1	12
L2-F	16.9	10.9	25.6	3.8	52	17.0	11.6	24.8	3.8	12
L3-SF	11.7	8.0	17.6	2.0	42	12.4	9.2	16.0	2.0	10
Laos all	13.3	8.0	25.6	3.9	146	13.7	8.4	24.8	3.7	34
ALL	12.4	7.2	25.6	3.6	344	12.4	7.8	24.8	3.4	81

Table 2

184x49mm (300 x 300 DPI)

		Training set			Test set		
		Number of factors	R2	RMSE			RMSEP
					R2		
Brazil	B1	1	0.94	3.45	B1	0.46	1.78
	B2	2	0.95	2.69	B2	0.44	1.78
	B3	2	0.99	1.14	B3	NA	1.53
Laos	L1-NF	1	0.97	1.93	L1-NF	NA	2.13
	L2-F	2	0.98	2.94	L2-F	NA	3.1
	L3-SF	1	0.97	1.94	L3-SF	0.34	1.57
Brazil	Brazil all	2	0.95	2.64	B1	0.49	1.73
					B2	0.49	1.70
					B3	NA	1.64
					Brazil all	0.62	1.68
					Los all	0.19	3.27
Laos	Laos all	2	0.96	2.69	L1-NF	NA	2.12
					L2-F	0.17	3.32
					L3-SF	NA	2.24
					Laos all	0.48	2.63
					Brazil all	NA	2.80
ALL	ALL	2	0.95	2.84	Brazil all	0.50	1.91
					Laos all	0.45	2.69
					ALL	0.53	2.28

Table 3

178x129mm (300 x 300 DPI)



peak number	wavelength(nm)	component	Bond vibration
1	1916	Water	O-H antisymmetric, stretching vibration, +O-H deformation vibration of H <sub>2</sub> O
2	2092	Cellulose	O-H and C-H deformation vibration, +O-H stretching vibration
3	2361	Cellulose	O-H deformation vibration or C-H deformation vibration,+C-H stretching vibration or C-H <sub>2</sub> stretching vibration

Table 4

608x177mm (144 x 144 DPI)

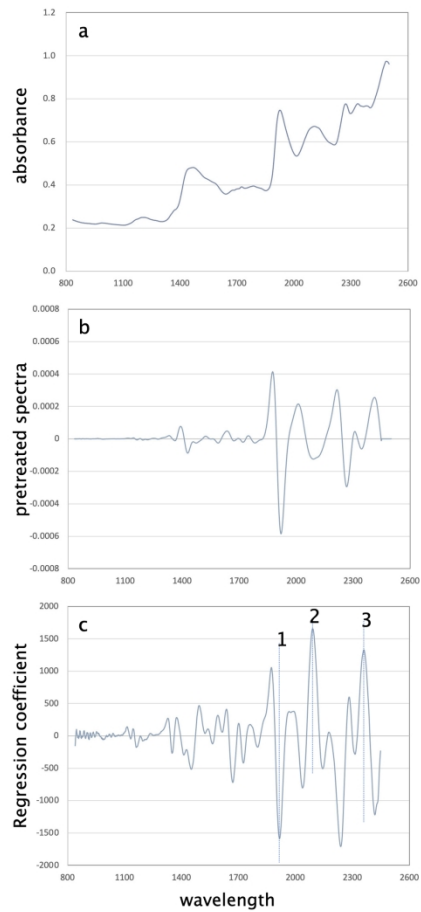


Figure 1. (a) Average of all raw spectra, (b) Average of all pretreated NIR spectra by smoothing, baseline correction, and second derivative calculations. (c) regression coefficients from the PLS model used for prediction.

175x268mm (300 x 300 DPI)

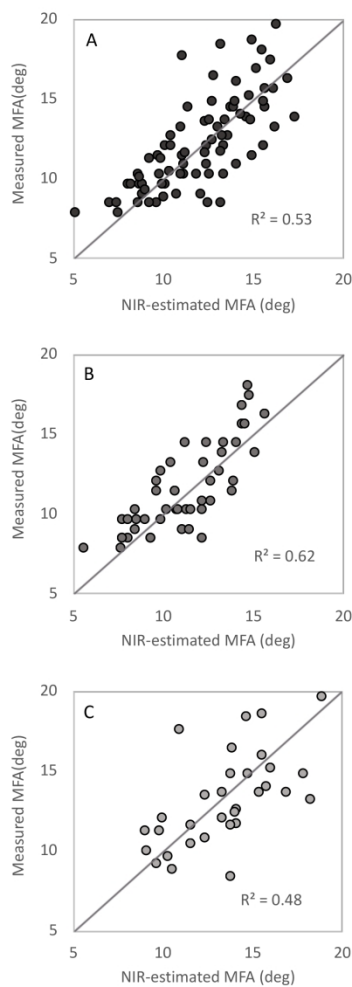


Figure 2. Relationships between measured MFA and NIR-estimated MFA. MFA prediction model, integrating data from both Laos and Brazil, was employed to determine the estimated MFA using near-infrared spectroscopy (NIRS) for (A) Brazil and Laos. For (B) Brazil, the MFA estimation utilizing the complete Brazilian dataset was conducted, while for (C) Laos, the estimation was carried out using the entirety of the Laos dataset.

209x297mm (300 x 300 DPI)