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Advisor

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SAMUEL HERNÁN ARZAPALO HUANCAS

IMPACTO DA QUALIDADE DA SUPERFÍCIE DA MADEIRA NA IDENTIFICAÇÃO DE ESPÉCIES TROPICAIS USANDO ESPECTROMETROS NIR DE BANCADA E PORTÁTIL

IMPACT OF WOOD SURFACE QUALITY ON TROPICAL SPECIES IDENTIFICATION USING BENCHTOP AND PORTABLE NIR SPECTROMETERS

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I thank God for his infinite grace and for guiding me throughout this process. To my family, for being my refuge and unbreakable strength, and to my friends for their constant support and encouragement.

I dedicate

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RESUMO

A identificação de madeiras em florestas tropicais é um desafio devido à existência de muitas espécies com caraterísticas anatómicas semelhantes, o que dificulta a diferenciação visual. As técnicas tradicionais, como a caraterização anatómica e a análise das características organolépticas, são eficazes, mas lentas e dependentes dos conhecimentos dos anatomistas. A espetroscopia de infravermelho próximo (NIR), combinada com técnicas estatísticas multivariadas, tem mostrado resultados promissores na classificação exata da madeira. O objetivo deste estudo foi avaliar o impacto da qualidade da superfície da madeira no desempenho dos instrumentos NIR na identificação de espécies de madeira tropical. Dezesseis espécies de madeira tropical de interesse comercial foram selecionadas de campos e pátios de toras na microrregião de Lavras, em Minas de Gerais e sua identificação foi confirmada por comparação com amostras padrão da xiloteca do laboratório de anatomia da madeira. As amostras foram preparadas a partir de diferentes ferramentas. Os espectros NIR foram registrados com instrumentos NIR portátil e de bancada nas superfícies transversais das amostras de madeira em cinco situações: (1) condições de campo (sem tratamento), (2) motosserra, (3) serra circular, (4) serra fita e (5) lixa. A análise de componentes principais (PCA) e a análise discriminante de mínimos quadrados parciais (PLS-DA) foram utilizadas para avaliar as assinaturas NIR. Os modelos ajustados por PLS-DA com validação cruzada apresentaram taxas de sucesso elevadas, com classificações que variaram entre 95,3 % até 99,2 % para superfícies não tratadas, preparadas com serra circular, serra de fita e lixadas. As amostras cujas superfícies eram preparadas com motosserra resultaram em classificações menos exatas: 88,7% para sensores NIR de bancada e 92,8% para sensores NIR portáteis. Estes resultados destacam o potencial da espetroscopia NIR para a classificação de madeiras tropicais, mesmo quando há variações na superfície.

Palavras-chave: Inspeção florestal; processamento da madeira; textura da superfície; aprendizado de máquinas; identificação da madeira.

ABSTRACT

The identification of wood in tropical forests is a challenge due to the existence of many species with similar anatomical characteristics, which makes visual differentiation difficult. Traditional techniques, such as anatomical characterization and analysis of organoleptic characteristics, are effective, but slow and dependent on the knowledge of anatomists. Near-infrared spectroscopy (NIR), combined with multivariate statistical techniques, has shown promising results in the accurate classification of wood. The aim of this study was to evaluate the impact of wood surface quality on the performance of NIR instruments in identifying tropical wood species. Sixteen tropical timber species of commercial interest were selected from fields and log yards in the Lavras micro-region in Minas Gerais and their identification was confirmed by comparison with standard samples from the wood anatomy laboratory's xylotheque. The samples were prepared using different tools. NIR spectra were recorded with portable and bench NIR instruments on the cross-sectional surfaces of the wood samples in five situations: (1) field conditions (untreated), (2) chainsaw, (3) circular saw, (4) band saw and (5) sandpaper. Principal component analysis (PCA) and partial least squares discriminant analysis (PLS-DA) were used to evaluate the NIR signatures. The models fitted by PLS-DA with cross-validation showed high success rates, with classifications ranging from 95.3 % to 99.2 % for untreated, circular sawed, band sawed and sanded surfaces. Samples whose surfaces were prepared with a chainsaw resulted in less accurate classifications: 88.7% for benchtop NIR sensors and 92.8% for portable NIR sensors. These results highlight the potential of NIR spectroscopy for classifying tropical woods, even when there are variations in the surface.

Keywords: Forest inspection; wood processing; surface texture; machine learning; wood identification.

INDICADORES DE IMPACTO

O estudo teve o foco na identificação forense de espécies de madeireiras tropicais sob efeito da condição da superfície da madeira, utilizando a espetroscopia de infravermelho próximo (NIR) com instrumentos de bancada e portáteis. Os resultados obtidos evidenciaram o potencial da espetroscopia NIR para a classificação de madeiras tropicais em diferentes condições de superfície e tipos de dispositivos. Esta abordagem apresenta-se como valiosa ferramenta para fomentar o comércio legal, sustentável e rastreável de produtos madeireiros. A utilização da espectroscopia NIR neste contexto contribui aspectos sociais (facilita a proteção e a gestão sustentável das florestas tropicais), tecnológicos (progressos significativos em técnicas de identificação), econômicos (valor acrescentado nos mercados internacionais e potencial para melhorar as práticas comerciais) e culturais (contribui para o estabelecimento de regulamentos para garantir um comércio justo). Está igualmente alinhado com vários Objetivos de Desenvolvimento Sustentável (ODS) das Nações Unidas no domínio da inovação tecnológica, da produção sustentável e da conservação dos ecossistemas.

IMPACT INDICATORS

The study focused on the forensic identification of tropical timber species under the effect of wood surface condition, using near-infrared spectroscopy (NIR) with benchtop and portable instruments. The results show the potential of NIR spectroscopy for classifying tropical timber under different surface conditions and device types. This approach is a valuable tool for promoting legal, sustainable and traceable trade in timber products. The use of NIR spectroscopy in this context contributes to social (facilitates the protection and sustainable management of tropical forests), technological (significant progress in identification techniques), economic (added value in international markets and potential to improve trade practices) and cultural (contributes to the establishment of regulations to ensure fair trade) aspects. It is also aligned with several United Nations Sustainable Development Goals (SDGs) in the field of technological innovation, sustainable production and ecosystem conservation.

SUMMARY

FIRST PART

1 INTRODUCTION

Tropical wood has high demand and prominent value in national and international markets. Brazil is one of the main suppliers of tropical wood to the United States (30%) and the European Union (45%) of exports (FOREST NEWS, 2024). The most sought-after tropical species continue to be: Ipês (*Handroanthus serratifolius* (Vahl) S.O. Grose, *Handroanthus impetiginosus* (Mart. Ex DC.) Mattos), Jatobá (*Hymenaea courbaril* L), Masaranduba (*Manilkara huberi* (Ducke) A. Chev.), Muiracatiara (*Astronium lecointei* Ducke), and Angelim vermelho (*Dinizia excelsa* Ducke) (ITTO, 2024), especially for products such as flooring and decking (NORMAN and ZUNINO, 2022; ITTO, 2024).

However, many species have been exploited to such an extent that national and international policies and legislation have been created to regulate sustainable management or, in most cases, prohibit the extraction and trade of these resources, such as the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES), the US Lacey Act (2008), the European Union Timber Regulation (2013), and comparable legislation in Australia (in 2012), in China (in 2019) and in Japan (2017), since then, import markets have demanded specific efforts to guarantee the legality of wood supply chains (LEE et al., 2021; BRUSSELEN et al., 2023; RICHARDSON et al., 2023).

In the case of tropical timber, the great diversity of species makes their precise identification difficult. The identification and geographic origin of species is a prerequisite for forest law enforcement and the initiation of criminal proceedings (LOW et al., 2022). Although the Brazilian Government requires the Forest Origin Document (DOF), a permit used nationally and internationally to transport, store forest products and specify the species, quantity, commercial use, origin and destination of forest products (BRAZIL, 2006, 2012), criminals operating in the forest employ various methods to fraud the DOF system (SILVA et al., 2024).

Loads of timber with documentary inconsistencies are inspected by enforcement officers, usually lacking taxonomic knowledge necessary to verify consistency between physical material and documentation, or to decide whether additional forensic evidence is required (UNODC, 2016). The reliability of these decisions varies depending on the experience and training of the experts. While frequent checks and rapid field identifications are necessary, these often fail due to excessive effort and costs (OLSCHOFSKY and KÖHL, 2020).

In the case of tropical woods, the diversity of species makes definitive species identification difficult; The identification and geographic origin of species is a prerequisite for the application of forestry law and the initiation of criminal proceedings. Inspections of wood loads with inconsistencies in documentary information are carried out by agents from inspection bodies. They generally do not have sufficient taxonomic knowledge to check the consistency of physical material and documentation, and to decide whether further forensic testing is necessary. Depending on personal experience and training, the reliability of experts' decisions can vary substantially. From the point of view of effective classification, frequent checks and rapid identification in the field of the representative part of timber loads are necessary, but they often fail due to excessive effort and costs (UNODC, 2016; OLSCHOFSKY and KÖHL, 2020; LOW et al., 2022).

To date, field screening is carried out mainly by semi-skilled personnel, equipped with magnifying glasses and field instructions or illustrated species codes, producing results of variable and often questionable quality (ILIC, 1990; MILLER and WIEDENHOEFT, 2002). Insufficient controls and the lack of controls on logging create loopholes that encourage the trade of protected species (OLSCHOFSKY; KÖHL, 2020; NOVAES et al., 2023), while the challenging task of identifying wood species and the growing demand for wood make it urgent to develop new methods to assist in the identification of forest species.

Near infrared (NIR) spectroscopy has shown promising results in the classification of forest products (NOVAES et al., 2021; TSUCHIKAWA et al., 2023), distinguishing wood species from native forests (PAN et al., 2021; ROCHA et al., 2021). It is a forensic technique, valuable for technological characterization, provides fast and reliable results, and requires little preparation of the sampled materials (LIMA et al., 2022; LACERNA et al., 2024). In recent years, it has been widely explored to predict structural properties of wood on a laboratory scale, specifically moisture content. (SANTOS et al., 2021), density (AMARAL et al., 2021), chemical composition (TAORÉ and CORTIZAS, 2023), mechanical properties (SCHIMLECK et al., 2018; YU et al., 2020; NASIR et al., 2021) and defects on the surface (CAO et al., 2017; YU et al., 2019; GRAHN and YASSIN, 2022). Much research has shown that NIR spectroscopy and multivariate analysis work well in laboratories where conditions are controlled; however, there is still a gap between laboratory research and real-world situations regarding the performance of NIR models on wood. Studies demonstrating the success of NIR-based models in real situations would be useful, considering anatomical variations, moisture content, grain slope, surface quality, temperature and other sources of variation present in factory conditions (PIGOZZO, 2011; HEIN et al., 2017; MEDEIROS et al., 2024).

Some studies have reported the effects of wood surfaces on NIR spectral information (TSUCHIKAWA et al., 1992; GIERLINGER et al., 2004; NOVAES et al., 2023) and their influence on the performance of the predictive model (THUMM; MEDER, 2001; SCHIMLECK et al., 2003; JONES et al., 2006). However, there is little information available about the effect of sample preparation on model performance (HEIN et al., 2010). The appearance of products, which depends on the quality of the surface, has a considerable influence on their aesthetics. Therefore, the surface quality of wood directly affects the final use of the wood (MALKOCOGLU, 2007). However, determining surface quality is a complex process that depends on the heterogeneous structure of the wood, the kinematics of the cutting process and the machining conditions. Machining properties and surface roughness can be determined according to available standards (STANOJEVIC et al., 2017).

Several studies have demonstrated the potential of the NIR technique, using both portable and benchtop devices, to discriminate tropical woods with accuracies above 90% (PACE et al., 2019; KUNZE et al., 2021; SANTOS, 2021; VIEIRA et al., 2021; LIMA et al., 2022). However, most of these studies have been performed under laboratory conditions, where the surfaces of the samples were made uniform by sanding with different sandpaper grits. From this analysis, the following questions arise: *i*) Do different wood surface conditions affect the acquisition of spectra during the development of NIR models?; *ii*) Are portable and benchtop NIR devices efficient in discriminating between woods with different surface finishes?; *iii*) Are NIR devices efficient in discriminating between woods with different surface finishes?.

To date, no studies have been found using the NIR technique with portable and bench-top equipment to discriminate woods in different surface finishes. In addition, the contradictory results reported in the literature highlight the need to understand how variations in wood surface can affect the accuracy of species identification. This understanding is critical for the effective application of this technology in field conditions, especially during forest control actions.

2 OBJECTIVES

2.1 General objectives

Evaluate the influence of surface quality on the identification of tropical species of wood using a combination of near infrared spectroscopy and machine learning.

2.2 Specific objectives

- Classify wood surfaces processed by different machines based on spectral signature.
- Evaluate the predictive performance of models based on NIR spectra recorded with benchtop and portable equipment.
- Evaluate the influence of wood surface quality on the classification performance of models.

3 THEORETICAL REFERENCE

3.1 Overview of commercial wood identification

Traditional wood identification, which is based on the macroscopic and microscopic characteristics of wood, generally allows identification down to the genus level (DORMONTT et al., 2015; ZHANG et al., 2019), it is important to highlight that it is not always possible to identify at the species level, using an anatomical analysis. Furthermore, it is time-consuming and highly dependent on the experience of anatomists (YU et al., 2017; JIAO et al., 2018). However, there is currently a reduction in the number of wood anatomists specializing in determining the identity of wood.

Processed wood products seized by forestry authorities generally no longer possess the diagnostic characteristics necessary for identification (that is leaves, flowers, fruits), which makes identification of the species and geographic origin difficult (ESPINOZA et al., 2015; DORMONTT et al., 2015), only the wood is extracted to identify (PIGOZZO, 2011). In this way, identification is based only on the macroscopic or microscopic characteristics of the wood, as the elements that make up the secondary xylem of tree species have certain characteristics of taxonomic value, sometimes specific to certain families, genera or even species (ERGUN, 2024). Anatomical characteristics include aspects related to growth rings or layers, as well as the arrangement, shape, size or distribution of cellular elements, such as: type of porosity and arrangement of vessel elements, axial parenchyma and parenchyma rays (BOTOSSO, 2011; RUFFINATTO et al., 2015).

In the macroscopic process, observation of anatomy can generally be processed with the naked eye or through a ten-fold magnifying glass, while for the microscopic process there is the preparation of histological material such as slides, the use of chemicals, as well as the use of more sophisticated microscopy equipment, which is standardized according to the IAWA lists (WHEELER et al., 1989; RITCHER et al., 2004; BOTOSSO, 2011; PIGOZZO, 2011; KOCH et al., 2015). Observed differences in structure between various woods can be described, certain characters assigned (RUFFINATTO et al., 2015), and used for wood identification with the help of comprehensive reference material, for example, various wood atlases or benches. computerized data macroHolzdata, CITESwoodID and XyloTron, for example (RICHTER; TROCKENBRODT, 1995; KOCH et al., 2011; HERMANSON and WIEDENHOEFT, 2011), computerized databases such as: Commercial Timber (delta-intkey) or InsideWood (RICHTER; DALLWITZ, 2000; WHEELER, 2011), or comparisons with wood library samples (MOREIRA, 2021).

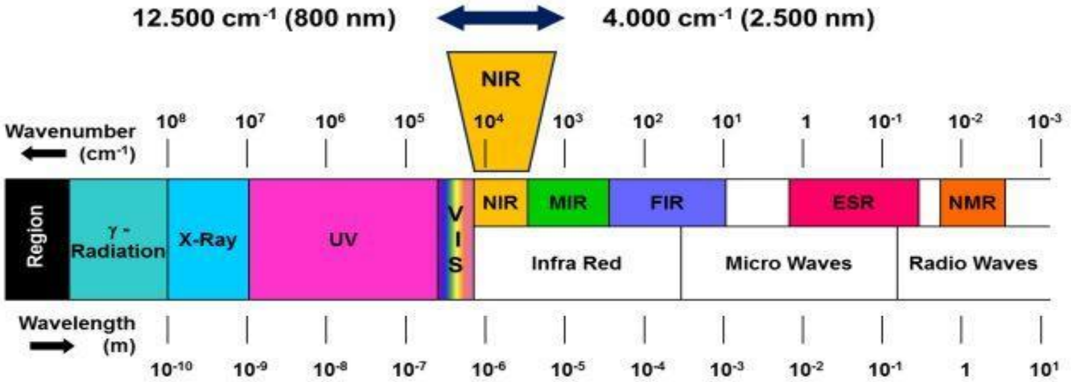
The species identity and harvest origin of a wood product can also be determined using various scientific methods. These techniques include anatomical analysis of wood using computer vision (FABIJAŃSKA et al., 2021), direct analysis in real time: time-of-flight mass spectrometry (DART-TOFMS) (DEKLERCK, 2023), DNA analysis using barcodes, fingerprints, etc. (BUT et al., 2023) and stable isotope analysis (BOESCHOTEN et al., 2023). However, each of these techniques is primarily comprised of laboratory systems that are currently expensive and not readily available, require reference data against which a product can be compared, and specific training is required to use and interpret the resulting data (SHUGAR et al., 2021; RICHARDSON et al., 2023). In addition to these studies, another proposed solution is the use of near-infrared spectroscopy (NIRS), which requires the collection of small samples for analysis, is fast, easy to use, can reduce errors in identification, and contribute significantly to inspection mechanisms and wood control.

3.2 Near infrared spectroscopy

Near infrared (NIR) spectroscopy is a vibrational technology based on the absorption of energy from infrared radiation, which causes changes in the vibrational and rotational states of molecules (SKOOG et al., 2009), analyzes the amount of energy irradiated on the surface of a material and the interaction with the organic molecular bonds of the sample's constitution (C-

H, O-H, N-H, C-C and C=O), generating visible absorption peaks in the NIR region (DINIZ et al., 2019; TOLVAJ, 2024). According to Yu et al. (2020), the spectrum of electromagnetic radiation lies between visible light and infrared light, with wavelengths ranging from 800 to 2,500 nm (Figure 1).

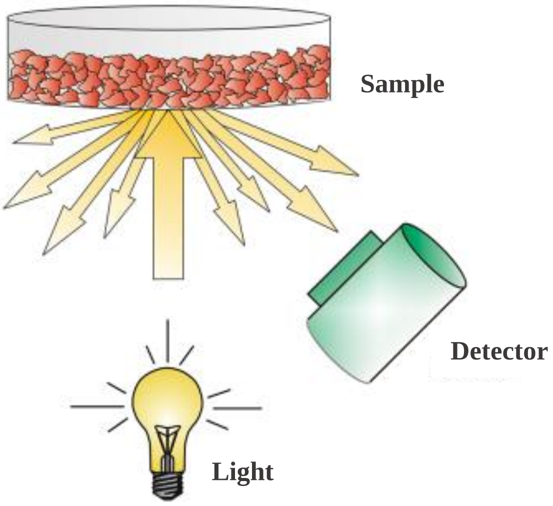
Figure 1 – Location of electromagnetic waves in the near-infrared.



Source: Bruker, 2023.

According to Taiz and Zeiger (2004), the acquisition of an absorption spectral profile occurs using spectrophotometer equipment. However, there are three types of measurement modes, namely: transmission, transflection, and diffuse reflection. The diffuse reflection mode is one of the most widely used because it requires little time and sample preparation, in which the light is reflected and directed by a wide beam parallel to the sample surface and is well distributed on the sphere by diffuse reflections, as illustrated in Figure 2 (WANG et al., 2022; BRUKER, 2023).

Figure 2 – Representation of a NIR spectrophotometer with diffuse reflection mode.



Source: Bruker, 2023.

The most used instrumentation for NIR are fourier transform near infrared spectrophotometers (FT-NIR, from the English Fourier Transform Near Infrared), as they guarantee a better signal/noise ratio and detection limit, high resolution and wavelength reproducibility, superior speed in obtaining the spectrum and greater use of radiant energy, which is not achieved with dispersive instruments (SILVERSTEIN et al., 2007; SKOOG et al., 2009; PAVIA et al., 2014; LOPES, 2015; SUGII et al., 2017; SHARMA et al., 2020).

The NIR technique has several advantages in its use, mainly because it involves rapid measurements, and is a non-destructive procedure used in the characterization of materials, obtaining information without carrying out previous treatments on the samples, and because has agility in data acquisition and manipulation of the equipment. Furthermore, it does not generate waste and does not require chemical reagents, which makes the technique economical, without causing environmental pollution (UDDIN et al., 2020; ZAHIR et al., 2022). However, the technique has disadvantages that involve low selectivity and sensitivity, difficulty in attributing the signal to specific connections, and the need for many samples to build the calibration model, depending on the application, which consequently involves costs, work, and time. (BLANCO and VILLARROYA, 2002; SOARES, 2018). O The use of NIRS depends on traditional chemical analyzes to interpret the data generated by the spectra, which requires the use of multivariate chemometric methods for calibration.

Chemometric methods are capable of translating an extensive database, reducing noise, subdimensionalizing variables, and evaluating their importance for the variance in the analysis space. This way, models with excellent predictive capabilities are built (ROSSO et al., 2013; BERGO et al., 2016; HEIN et al., 2017; RAMALHO et al., 2017; PACE et al., 2019).

3.3 Heterogeneity of the wood surface on the predictive performance of NIR

Wood is a porous, anisotropic, and heterogeneous material, whose surface characteristics of processed wood are influenced by the natural properties of wood (anatomical, physical, mechanical, and even chemicals), machining parameters (feed, spindle speed, pitch, and depth of cut), cutting tool parameters (tool angle, tool material, tool diameter, tip radius, tool shape) and cutting phenomena (vibrations and cutting force) (ZHANG et al., 2015; KOC et al., 2017, DEMIR et al., 2022). Surface roughness is difficult to control, as it is an important index that determines the surface quality of processed materials (RABIEI and YAGHOUBI, 2023).

Wood surface quality is important in developing NIR-based models to predict wood properties, as previously reported by (HOFFMEYER and PEDERSON, 1995; COSTA et al., 2018). However, the absorbance of the NIR spectral region is inversely proportional to the surface roughness of the wood (SCHIMLECK et al., 2005). Differences in surface roughness influence radiation scattering (SCHWANNINGER et al., 2011). This can lead to spectral changes such as baseline shift as well as slope and band shift (CIURCZAK et al., 1986; SHENK et al., 2001; SCHWANNINGER et al., 2011).

According to Tsuchikawa et al. (1996), the cross-section roughness is higher than the tangential and radial section roughness. The cross-section of wood is made up of numerous fibers and vessels from these hardwoods, whose longitudinal axes of the fiber cells and vessels are parallel to the direction of incident light in the NIR spectrum; therefore, NIR energy penetrates deeper into the wood, causing an increase in absorbance and, consequently, the acquisition of more spectral information (FUJIMOTO et al., 2008; PAN et al., 2021; XUE et al., 2022).

The radial section of the wood coincides with the longitudinal orientation of the radial parenchyma that forms the tissue that radiates between the medullary rays and the cortex. This results in a higher absorbance than for the tangential section (FUJIMOTO et al., 2008). Using simulations, Tsuchikawa et al. (1996) demonstrated that the effect of surface roughness on the absorbance of NIR radiation depends on the wavelength and orientation of tracheid in softwood. For a given wavelength and a given illumination angle for the normal direction, the absorbance of NIR radiation decreases with increasing surface roughness.

Previous studies have shown the influence of surface roughness on the NIR spectra of wood. The authors found that the predicted results of NIR-based models for smooth surfaces were better than those for rough surfaces (SCHIMLECK et al., 2005; LIU et al., 2006). Contrary results were reported in the literature (COSTA et al., 2018; SANTOS et al., 2020; AYANLEYE et al., 2021), in which rough surfaces outperformed smooth surfaces. Better predictions of higher roughness samples could be attributed to the capture of more information by electromagnetic radiation (EMR) during NIR spectral acquisition (COSTA et al., 2018).

These studies used several NIR instruments; however, approaches to spectral acquisition differ in two main aspects. The first is the spectroscopic method used to collect NIR spectra; some used a fiber optic probe, others an integrating sphere, or both acquisition systems on the surface of the wood sample (direct). The second is the surface of the wood used for analysis. Due to the structure of wood, the wood sample has three distinct surfaces (radial, tangential and cross section) available for testing. In addition to these differences, the size of the test sample varies, as does the size of the area analyzed by NIR. The area analyzed varies both in terms of the number of locations measured by a given piece of wood, and the NIR range, determined in the direct approach by opening the NIR instrument.

One hypothesis about the success of predictive models in wood samples with rough surfaces may be related to the different surface topographies obtained during the machining process, which creates surfaces with different smoothness, according to Schimleck et al. (2023) due to several factors (e.g., what constitutes a smooth or rough surface, variability of the dataset in terms of wood properties). This can affect the light scattering conditions recorded in the spectra. Therefore, for the classification of forest species, it is necessary to evaluate the effect of the type of processing on the quality of information recorded on wood surfaces in terms of classification performance on tropical wood species.

3.4 Chemometric models and multivariate calibration

NIR models employ machine learning algorithms to analyze and predict sample characteristics. Their development requires multivariate statistical techniques, so it is essential to consider the specific objectives of the analysis before selecting and applying them.

Principal component analysis (PCA) is one of the most used techniques, which works to: *i)* clarify results and demonstrate trends; *ii)* reduce the dimensions involved within the analysis space; *iii)* identify latent variables, which have explanatory power to visualize the trend, which are not easy to conclude in complex databases. With this clarification of variables, it is understood that the data may or may not present some tendency to differentiate. Thus, moving more consciously towards other analytical methods, with greater statistical robustness, to explain the differentiation of groups (PACE et al., 2019; HUANG et al., 2020; SANTOS, 2022).

Partial least squares regression (PLS-R) or multiple regression. It is used to model and investigate the relationship of n variables, capable of explaining the behavior of one variable by the behavior of other variables. Determining the linear relationships between a set of explanatory variables with a single response variable, and determines the best combination of the set of explanatory variables to predict this response variable (COSTA, 2017; PACE et al., 2019).

The technique used to predict wood quality classes is partial least squares discriminant analysis (PLS-DA), this analysis indicates which group a sample belongs to through the use of spectral information, so that it discriminates the explanatory variables that contribute most to the differentiation between groups of dependent variables, this technique is described in detail by Brereton and Lloyd (2014) and Ferreira (2018).

Another capability of PLS-DA is the creation of a classification matrix that contains the total number of cases correctly classified into a group and identifies classification errors. This matrix serves to understand the classificatory power of samples within groups (COSTA, 2016; FERREIRA, 2018; PACE, 2020), where samples are classified through cross-validation and external validation. From this approach, the studied variable is considered a categorical variable, as it does not have quantitative values, but, on the contrary, is defined by categories, that is, it represents the classification of the samples. Then, values 0 or 1 are assigned to all samples of each class, and when the sample belongs to that category, the value 1 was assigned and when the sample does not belong to that category, the value 0 was assigned. PLS-based regressions are carried out to estimate continuous values in each of the categories. The model whose estimate presents the highest value is considered as an indicator of the category to which the analyzed sample belonged (COSTA, 2021).

Chemometric models developed on portable NIR equipment show that linear discriminant analysis (LDA) models adjusted by means of cross-validation generated in the field cannot distinguish dry and wet tropical wood samples in the field 10 to 60 days after scanning (MOREIRA, 2021). However, they can trace Cedar (*Cedrela odorata*) with 76.2% compatibility on boards with sanded and brush-cleaned surfaces (KUNZE et al., 2024). Sorting errors have been reported on sanded samples of *D. nigra*, identified as *D. latifolia*, with efficiencies of 79.6% in PLS-DA models, suggesting chemical variations in this species (SNEL et al., 2018).

In benchtop equipment, classification errors were also observed in PLS-DA models, such as the incorrect identification of *Roupala* sp. as *Euplassa* sp. (SANTOS et al., 2021), as well as in the identification of *Hymenaea* sp. and *Dinizia excelsa*, with accuracies of 85.8% and 90.2%, respectively, attributed to anatomical similarities between species and possibly to the quality of the surface produced by the chainsaw (NOVAES et al., 2023). Therefore, it is critical to advance the development of NIR models under various surface conditions, not only to improve field discrimination but also to rigorously evaluate the reliability and effectiveness of NIR technology as a tool for accurate wood identification.

3.4.1 Spectral pretreatment

The reason for using pretreatment methods is that reflectance spectroscopy used on solid materials such as wood is easily affected by physical phenomena (such as light path changes, light scattering, baseline changes, etc.), and is prone to noise (WANG et al., 2021; TUNCER, 2023). To correct for these effects, the raw data in NIR spectra is pre-processed prior to the modeling phase in addition to the use of raw data sets. (NISGOSKI et al., 2018; LEANDRO et al., 2019; LI et al., 2019; PACE et al., 2019; VIEIRA et al., 2021; TUNCER, 2023).

The pre-processing methods commonly considered are: Multiplicative scatter correction (MSC), is based on the fact that the background signals due to light scattering, although they vary between samples, can be proportional or shifted by a fixed value in signal intensity, from smallest to largest. With this approach, MSC linearly adjusts the spectra to the average calibration spectrum by least squares and then subtracts the signal estimated by this adjustment from all the spectra (GELADI et al., 1985, GHOLIZADEH et al., 2015).

The standard normal variable (SNV), which corrects for the interaction between light scattering and particle size by aligning and scaling each spectrum. First, the average signal and standard deviation of each spectrum are estimated; then, the average signal is subtracted from each spectrum and the result is divided by the standard deviation. Thus, after scaling, the mean of each spectrum is zero and the standard deviation is 1, (BARNES et al., 1989; OLIVIERI, 2018).

In the Savitzky-Golay (SG) algorithm, the derivatives are used (1st and 2nd Derivatives), if only smoothing is applied, the degree of the derivative is considered to be 0. The data is fitted to a polynomial function within the moving window of a given width (odd number), and the parameters are estimated by averaging (SAVITZKY and GOLAY, 1964, OLIVIERI, 2018). It can also be used to correct the base (RINNAN et al., 2009). There are also other treatments such as excluding outliers (RAMALHO et al., 2017). These pre-treatments are used to improve model calibration by reducing variance within the explanatory variables (PACE, 2020).

3.4.2 Validation of the chemometric model

After generating and calibrating the models and discriminant functions, validation of the analyzed data begins. According to Rosso et al. (2013), Estopa et al. (2017), one way is to divide the database into two parts, one for calibrating the model and another part, always a minority, to validate the model. There are some types of model validation. The most used are validations with independent samples (*external validation*) and cross-validation (*cross-validation*). The function of validation is to evaluate whether the generated models and discriminant functions are reliable to the realities of the data (COSTA, 2017).

Cross-validation is an evaluation method that uses samples from the database itself to test the model, chosen randomly or in pre-established groups. Cross-validation can serve as an indicator of the robustness or fragility of the created model. Because the validation samples participate in the calibration (creation) of the model, it is expected that the validation coefficient (R^2) will be high, otherwise, it means fragility in the model, and it may not work for predicting independent samples, or the analysis space is still small (FERREIRA, 2018). The other type is validation with independent samples, which is the evaluation of models by predicting samples that did not participate in their calibration. It would be the application of the prediction model in the minority part of the previous division (PACE, 2020).

In both multivariate analyses, the indicators for validating the developed models are the number of latent variables (LV) discovered by the models, the square root of the mean calibration error (RMSE), the square root of the cross-validation error (RMSECV), the square root of the error in independent validation (RMSEP), and the coefficient of determination (R^2) (LAZZAROTO et al., 2016; ESTOPA et al., 2017; RAMALHO et al., 2017; SOARES et al., 2017, PACE et al., 2019). The development of NIR technology is strongly associated with the advancement of chemometric methods, one of the objectives is to try to find new pre-processing methods for the analysis of spectra, to improve prediction performance through the design of models capable of dealing with an NIR spectral dataset.

3.5 Challenges in identifying and classifying tropical woods using NIR

Illegal logging undermines legitimate logging operations through an unfair competitive advantage (DEARMORD et al., 2024), intensifying in situ forestry inspections could help determine the origin of the wood and reduce the scourge. One solution is the application of new technologies, such as near-infrared spectroscopy (NIR), which has demonstrated potential to combat the illegal timber trade. Recent studies (last five years), addressed its ability to identify various species of tropical wood, all of them reported promising results, however, most scientific studies were carried out in the laboratory, where the surface of the samples was homogenized, the temperature and the humidity was controlled.

Silva et al. (2018) differentiated the origin of Mahogany wood from Bolivia, Brazil, Guatemala, Mexico, and Peru, reporting efficiency rates ranging from 90 to 100% using the PLS-DA model. Snel et al. (2018) evaluated the potential of NIR in combination with PLS-DA to discriminate seven species of *Dalbergia*, found an efficiency rate of over 90% using the portable NIR technique in combination with PLS-DA. Kunze et al. (2021) evaluated the variation of humidity in native Brazilian species, to minimize the effects of moisture they applied the orthogonalization of external parameters (EPO), the PLS-DA models showed high-efficiency rates and a significant reduction from 87.8% to 18, 4% in the number of outliers. Santos et al. (2021) discriminated eight species commonly known as “Louros”, the models built with the PLS-DA algorithm had an accuracy and scores greater than 97%, being the most suitable for recognizing wood from this group.

Vieira et al. (2021) discriminated four native species of the Myrtaceae family, to avoid the influence of oxidation and sawdust, the PCA models with second derivative of the tangential section had adequate results with a rate index of 67%. Santos et al. (2022b) discriminated four species marketed as “Tauari”, the PCA analysis managed to explain 89.14% of the total variance in the original data. Reis et al. (2023) tested the efficiency of VIS spectroscopy in discriminating five wood samples from the genus *Manila*, in the PCA analysis with raw data in the tangential section they obtained an efficiency rate of 98%, radial 95%, and tangential 93% best grouped. Lima et al. (2022a, 2022b) classified residues from 12 tropical species, the PLS-DA model with the first derivative presented the highest correct classification rate of 97.9%.

NIR spectroscopy studies were also carried out on tropical woods, where the surface of the samples were not homogenized but were carried out under laboratory conditions. Ramalho et al. (2018) reported good classifications for differentiating wood specimens from natural or planted forests, reporting efficiency rates greater than 86% in radial cutting using the benchtop NIR technique in combination with PLS-DA. Ma et al. (2019) designed a NIR-SRS-based hyperspectral imaging (HSI) camera to identify fifteen wood species, the score of PCAs in five-fold cross-validation accuracy was 94.1%. Pace et al. (2019) identified and classified twelve native plantation species, the percentage of classifications generated by the PLS-DA model was 91.3%.

Adi et al. (2020) investigated the anatomical properties and absorbance characteristics of NIR spectra in wood samples of the genus *Shorea*, classification models *k*-nearest neighbor (*k*-NN) revealed 100% identification accuracy. Nascimento et al. (2021) determined the technological properties of three species of the genus *Eschweilera*, the PLS-DA models used showed a high coefficient of determination of 0.90 and low calibration and prediction errors.

Novaes et al. (2023) discriminated six species from the Amazon, the specimens were subjected to cuts in the transverse plane, and the PLS-DA models recorded on wooden surfaces processed with a circular saw obtained a higher percentage of correct classifications of 99.2%, while models based on signatures spectra taken from wooden surfaces processed with a chainsaw correctly classified 95.2%, favoring the use of the technique for the application, with spectra collected on different surfaces. Raobelina et al. (2023) identified four species of the genus *Dalbergia*, using a portable spectrometer to measure the transverse face of the wood using the PLS-DA models, an accuracy of 83.3% was obtained in wooden blocks and 81.8% in wooden cores, highlighting the usefulness of the technique for management and sustainable timber trade. The chemometric analyses and mathematical treatments used in studies involving NIR to identify and classify tropical species are summarized in Figure 3 and Table 1.

Figure 3 - Schematic drawing of the latest chemometric studies developed

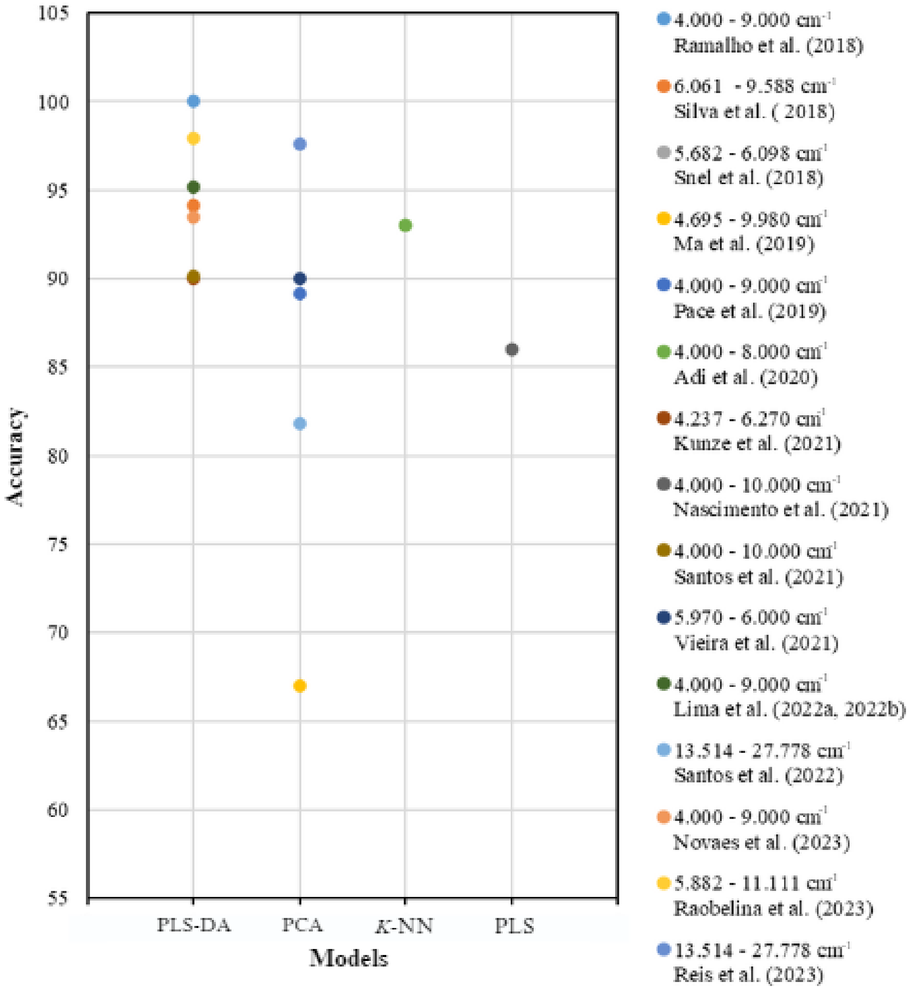


Table 1 - Summary of NIR spectroscopy studies with tropical wood

Wave number/authors	**Equipment**	**Models**	**Spectral pretreatment**	**Accuracy (%)**	**Spectral acquisition plan**	**Superficial treatment**
4.000 - 9.000 cm^{-1} Ramalho et al. (2018)	Benchtop	PLS-DA	1Dr, 2Dr, SG e SNV	86	Radial	
6.061 - 9.588 cm^{-1} Silva et al. (2018)	Portable	PLS-DA	1Dr, 2Dr, SG, SNV e MC	90.1		80 grit sandpaper
5.682 - 6.098 cm^{-1} Snel et al. (2018)	Portable	PLS-DA	1Dr, SNV, SG e MC	90		80 grit sandpaper
4.695 - 9.980 cm^{-1} Ma et al. (2019)	Benchtop	PCA		94.1	Transversal	
4.000 - 9.000 cm^{-1} Pace et al. (2019)	Benchtop	PLS-DA	1.Dr, 2Dr, SNV e SG	93.2	Transversal	circular saw
4.000 - 8.000 cm^{-1} Adi et al. (2020)	Benchtop	*k*-NN	2 Dr. SG	100	Radial	
4.237 - 6.270 cm^{-1} Kunze et al. (2021)	Portable	PLS-DA	1Dr, SNV, SG e MC	93.5	Tangential and radial	80 grit sandpaper
4.000 - 10.000 cm^{-1} Nascimento et al. (2021)	Benchtop	PLS	1Dr, 2Dr, NW e SG	90	Tangential and radial	
4.000 - 10.000 cm^{-1} Santos et al. (2021)	Benchtop	PLS-DA		97.61	Transverse, tangential and radial	80 grit sandpaper
5.970 - 6.000 cm^{-1} Vieira et al. (2021)	Benchtop	PCA	2 Dr. SG	67	Transverse, tangential and radial	100 grit sandpaper
4.000 - 9.000 cm^{-1} Lima et al. (2022a, 2022b)	Benchtop	PLS-DA	1Dr, 2Dr e SG	97.9	Transversal e radial	50, 80 and 100 grit sandpaper
13.514 - 27.778 cm^{-1} Santos et al. (2022)	Benchtop	PCA	2Dr	89.14	Transverse, tangential and radial	100 grit sandpaper
4.000 - 9.000 cm^{-1} Novaes et al. (2023)	Benchtop	PLS-DA	N, 1Dr, 2Dr, MSC, SNV	95.2	Transversal	Chainsaw and circular saw
5.882 - 11.111 cm^{-1} Raobelina et al. (2023)	Portable	PLS-DA	1Dr, 2Dr, SG e SNV	81.8	Transversal	
13.514 - 27.778 cm^{-1} Reis et al. (2023)	Benchtop	PCA	1Dr e SG	93	Transverse, tangential and radial	sandpaper

*PLS-DA: Partial Least Squares Discriminant Analysis, PCA: Principal Component Analysis, *k*-NN: *k*-Nearest neighbors and PLS: Partial least squares.

*N: Normalization, Dr: Derivative, MC: Mean Centering, MSC: Multiplicative Dispersion Correction, NW: Norris-Williams Algorithm, OSC: Orthogonal Signal Correction, SG: Savitzky-golay Algorithm, Sm: Smoothing, SNV: Normal Variable standard.

Several studies have been carried out using the NIRS technique to identify wood, it was observed that there is no established standard for pre-treatment of the wood surface. Therefore, there is a need to evaluate the influence of spectra on different surface conditions of the wood. This will help to better understand what is the best surface quality we could consider before spectral acquisition.

4 GENERAL CONSIDERATIONS

Comparing tropical wood species discrimination results obtained with portable and benchtop NIR spectrometers is crucial to understand their limitations and advantages. The literature indicates that inconsistencies in identification can arise due to variations in surface conditions and the quality of the equipment used. Therefore, the integration of both types of spectrometers, taking advantage of their specific strengths, is essential to obtain more accurate results, resolve discrepancies observed in previous studies and recommend their application in field conditions.

5 LIMITATIONS AND FUTURE PROSPECTS

To minimize distortion in the spectral information, it is essential to perform an accurate wavelength correction prior to analysis. It is essential that spectral analysis is carried out at the same wavelength on both portable and benchtop NIR equipment. Reducing the wavelength could contribute to lower analysis costs. However, however, further research is required to evaluate calibration performance within these shorter spectral ranges to ensure that the accuracy and reliability of the results are not compromised.

It is imperative to establish and maintain a spectral database that acts as a key reference, especially to ensure the robustness and accuracy of the models developed. From this database it will be possible to compare new spectral information on wood products from logged areas and even help determine the origin of the wood. This whole process improves monitoring and facilitates the accurate identification of wood species.

Future studies should investigate the influence of surface quality on wood identification, using broader spectral datasets with a greater diversity of spectral features, to evaluate performance in NIR models and machine learning.

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SECOND PART – ARTICLE

ARTICLE 1 – IMPACT OF SURFACE QUALITY ON THE IDENTIFICATION OF TROPICAL WOOD SPECIES USING BENCHTOP AND PORTABLE NIR INSTRUMENTS

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Impact of surface quality on the identification of tropical wood species using benchtop and portable NIR instruments

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Abstract

Near-infrared (NIR) spectroscopy combined with multivariate analysis has proven to be a fast and efficient method for identifying wood species. Despite significant technical advances in recent years, challenges remain that limit its application in field conditions, particularly the influence of sample surface preparation on the performance of classification models. This study aimed to evaluate the impact of wood surface quality on the performance of NIR instruments in identifying tropical wood species. Sixteen species of tropical wood were collected from fields and log yards and prepared using different tools. NIR spectra were recorded using portable and benchtop NIR instruments on the transverse surfaces of wood specimens subjected to five treatments: (1) field conditions (untreated), (2) chainsaw, (3) circular saw, (4) bandsaw, and (5) sandpaper. Principal Component Analysis (PCA) and Partial Least Squares Discriminant Analysis (PLS-DA) were performed using the NIR signatures. Spectra collected from surfaces prepared with a circular saw and sandpaper showed clearer groupings in the PCA score plot, facilitating the identification of distinct wood species. Cross-validated PLS-DA models showed high success rates, with classification accuracies ranging from 95.3% to 99.2% for untreated, circular saw, bandsaw, and sanded surfaces. Wood surfaces prepared with a chainsaw yielded lower classification accuracies: 88.7% for benchtop and 92.8% for portable NIR sensors. These results highlight the potential of NIR spectroscopy for classifying tropical woods, even when surface quality varies.

Keywords: forestry inspection, wood machining, surface quality, machine learning, wood identification.

Introduction

Addressing tropical forest loss presents enormous and diverse challenges (DeArmond et al. 2023). In the last 5 years, Brazil lost approximately 8.56 million hectares of native vegetation. Alarmingly, in 2023, the Cerrado biome surpassed the Amazon as the region with the largest deforested area, totaling around 1,110,326 hectares, while the Amazon came in second place, with 454,271 hectares, representing, together, more than 85% of the deforested area (MAPBIOMAS 2024). Furthermore, the increase in activities related to the transformation, use and commercialization of raw materials and tropical wood products has boosted the technological demand for rapid and non-destructive identification of wood species (Zhou et al. 2020; ForestNews 2024).

Traditional identification of wood species relies on experienced professionals evaluating samples for their macroscopic and microscopic characteristics (Low et al. 2022; Alves-Ferreira et al. 2023; Wang et al. 2024). This approach requires a considerable investment of time on the part of wood anatomists to prepare wood slides (Sun et al. 2021), and difficulties are often encountered in identifying wood samples to the species level (He et al. 2019). The increase in technology in computer-monitored identification techniques has led to the investigation of methods *on lines* non-destructive methods for rapid inspection of wood species, addressing the limitations of the traditional identification method (Pan et al. 2024). According to Tsuchikawa et al. (2023), the vast diversity of wood species in the modern timber trade necessitates a fast and non-destructive method of wood identification.

Near-infrared (NIR) spectroscopy technique has demonstrated great potential for use in wood identification and front-line (field or laboratory) detection analysis (Novaes et al. 2023; Raobelina et al. 2023), as well as in the procedures for determining geographic origin (Silva et al. 2018; Kunze et al. 2024). It is an accurate and reliable method, as it detects chemical components and their distribution in the internal structure of the wood. Furthermore, it is non-destructive, provides results in real time (<1 min), with commercially available portable equipment, low analysis cost and does not generate chemical waste (Pastore et al. 2022; Zahir et al. 2022). NIR technology is emerging as an essential auxiliary technology for the identification of Madeira species (Pan et al. 2024).

Compared to other wood species identification techniques, NIR spectroscopy is based on mathematical modeling methods and creating suitable models is an essential factor in the successful identification of wood species. Pasquini (2018) states that the most commonly used spectral data analysis methods are Partial Least Squares Discriminant Analysis (PLS-DA) and Principal Component Analysis (PCA). Several studies have used these analyzes to discriminate tropical species, achieving high success rates exceeding 90%. For example, Silva et al. (2018) differentiates mahogany wood from different origins. Pace et al. (2019) classified 12 wood samples from the Atlantic Forest. Snel et al. (2018) classified seven species of *Dalbergia*. Santos et al. (2021a) discriminated against 8 Amazonian species marketed as “Louros”. Lima et al. (2022a) classified wood residues from 12 Amazonian species and Novaes et al. (2023) identified six species in Amazonian tropical forests. These studies show that the NIR technique associated with multivariate analysis is highly effective in controlled laboratory conditions, where sample surfaces are uniform. However, variability in sample surface area can lead to variations in the performance of NIR models.

Surface quality is a complex process that depends on the heterogeneous structure of wood, the kinematics of the cutting process and machining conditions. Machining properties and surface roughness can be determined according to available standards (Stanojevic et al. 2017; Demir et al. 2022). Some studies have reported the effects of wooden surfaces on NIR spectrum information (Tsuchikawa et al. 1992; Gierlinger et al. 2004; Novaes et al. 2023), and their influence on predictive model performance (Thumm and Meder 2001; Schimleck et al. 2003; Jones et al. 2006). However, there is little information available on the effect of sample surface preparation on model performance (Hein et al. 2010; Xue et al. 2022).

The influence of surface quality on classifications based on NIR signatures is a topic that requires thorough analysis due to the contradictory results reported in the literature. Understanding how variations in the surface of wood affect the accuracy of species identification is fundamental for applying this technology in field conditions during forest monitoring actions. Therefore, this study aimed to understand the influence of the surface quality of raw wood, cut with a chainsaw, circular saw and band saw, and subsequently sanded, on the performance of the predictive models. Furthermore, it is expected to evaluate the potential of the portable and benchtop NIR device in identifying sixteen tropical species.

Materials and methods

Sample collection and preparation

Sixteen (16) tropical wood species (Table 1) were selected from fields and log yards located at southern Minas Gerais state (Latitude: 21°14′ 45″ S, Longitude: 44° 59′ 59″ West, Altitude: 920

m). Wood boards were acquired in the size of planks, that was stored and exposed to natural environmental conditions for a long (but unknown) period. From these boards, wood specimens were produced with nominal dimensions of approximately 100 cm (length) x 3 cm (width) x 3 cm (thickness), totaling 16 samples per species, which were previously identified with a pencil.

Table 1 List of tropical species selected for the study and their apparent (15%) and basic density (g/cm^3).

Code	**Scientific name**	**Family**	**Regional common name**	**ρ15** (g/cm^3)	**ρ** (g/cm^3)
CV	*Cedrela* sp.	Meliaceae	Cedro vermelho	0.45	0.39
CR	*Cedrela odorata* L.	Meliaceae	Cedro rosa	0.57	0.54
CM	*Roupala montana* Aubl.	Proteaceae	Carne de vaca	0.63	0.53
JÁ	*Dalbergia* sp.	Fabaceae	Jacarandá	0.71	0.61
UM	*Astronium lecointei* Ducke	Anacardiaceae	Muiracatiara	0.75	0.63
GU	*Calophyllum brasiliense* Cambess.	Calophyllaceae	Guanandi	0.78	0.66
TA	*Couratari* sp.	Lecythidaceae	Tauari	0.79	0.67
UC	*Goupia glabra* Aubl.	Goupiaceae	Cupiúba	0.83	0.70
AA	*Hymenolobium petraeum* Ducke	Fabaceae	Angelim-pedra-verdadeiro	0.84	0.74
JP	*Machaerium* sp.	Fabaceae	Jacarandá paulista	0.86	0.74
SU	*Diplotropis* sp.	Fabaceae	Sucupira	0.93	0.79
GA	*Apuleia leiocarpa* (Vogel) J.F.Macbr.	Fabaceae	Garapa	0.94	0.84
CA	*Dipteryx odorata* (Aubl) Willd.	Fabaceae	Cumaru-amarelo	1.05	0.87
PF	*Caesalpinia ferrea* Mart. ex Tul.	Fabaceae	Pau-ferro	1.05	0.84
JB	*Hymenaea oblongifolia Var. Palustris* (Ducke) Y.T. Lee & Langenh.	Fabaceae	Jatobá	1.08	0.91
CB	*Dipteryx* sp.	Fabaceae	Cumaru	1.10	0.97

Identification of wood in the laboratory

Samples measuring 2 cm x 2 cm x 2cm were prepared, oriented, coded and stored in the laboratory for natural drying, with a standardized temperature of 25°C. After drying, the samples were sanded with 80 to 1500 grit sandpaper. Macroscopic images were captured on a Nikon SMZ 1500 epi-fluorescence stereomicroscope (10x) coupled to a Nikon DS-Ri1 digital camera with 12.7 megapixels and the software NIS Elements D 3.2 (Fig. 1). Macroscopic identification of the woods was performed according to the methodologies described by Ruffinatto et al. (2015, 2023) and Barbosa et al. (2021). To validate and confirm the identification, standard samples from the wood anatomy laboratory's xylotheque were used, as well as literature with anatomical descriptions of wood (Mainieri et al. 1983; Mainieri and Chimelo 1989; Coradin and Muñiz 1992; Coradin et al. 2010; Brandes et al. 2021).

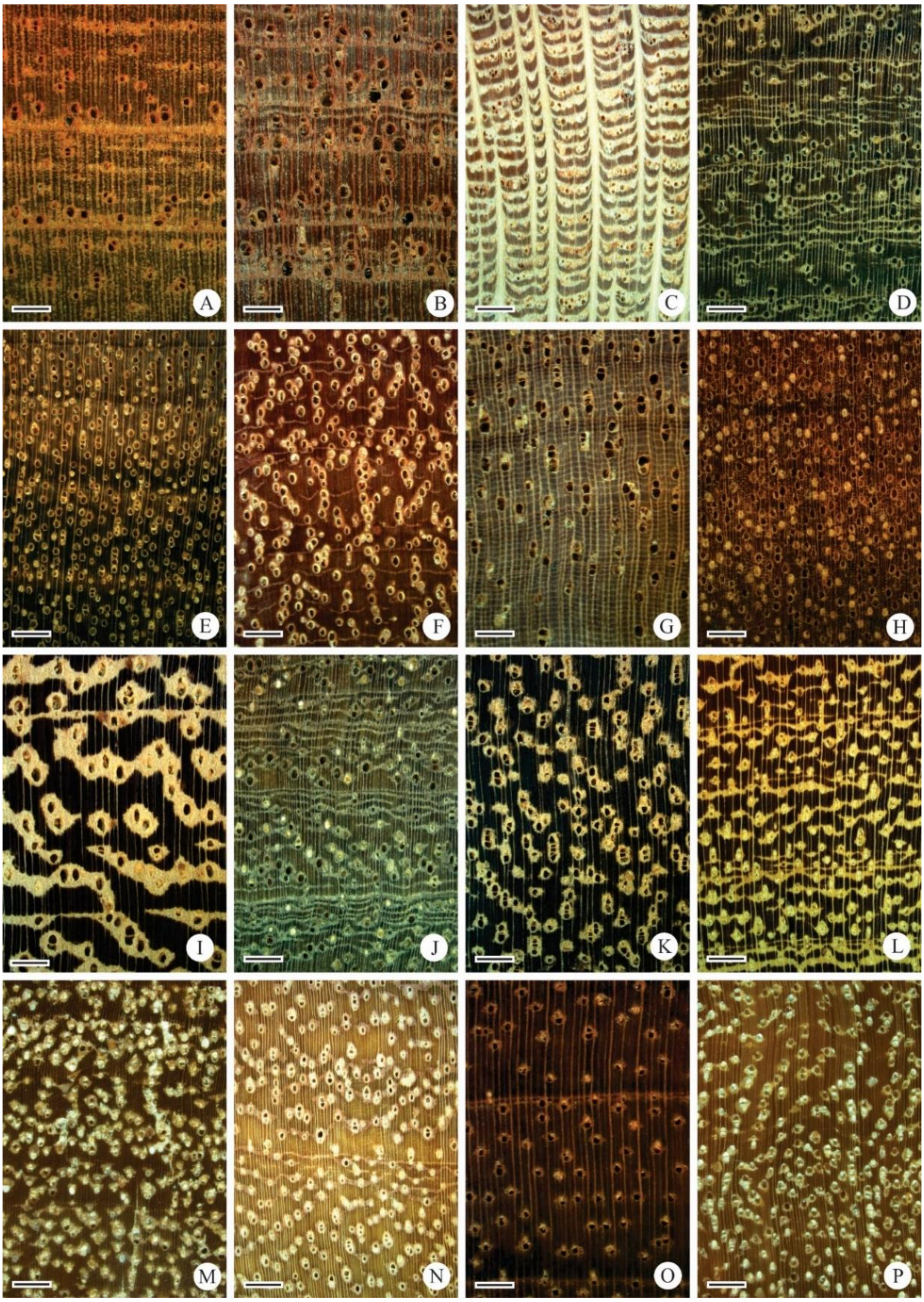

Fig. 1 Macroscopic images of the cross section of wooden blocks. *Cedrela* sp. (A), *Cedrela odorata* (B), *R. montana* (C), *Dalbergia* sp. (D), *A. lecointei* (E), *C. brasiliense* (F), *Couratari* sp. (G), *G. glabra* (H), *H. petraeum* (I), *Machaerium* sp. (J), *Diplotropis* sp. (K), *A. leiocarpa* (L), *D. odorata* (M), *C. férrea* (N), *H. oblongifolia* (O), and *Dipteryx* sp. (P); scale bar: 1000 μm.

Sample surface preparation

Five surface treatments were prepared to obtain the spectral signatures. The first treatment (**T1**) consisted of surfaces in real field conditions (without machining). From these wood samples, four additional surface conditions were generated. Each wood specimen had its transverse surface processed as follows: **T2**) with an electric chainsaw (Makita UC3041A), featuring a maximum chain speed of 14.5 m/s, toothed cutting type, and 1,710 W power; **T3**) with a circular table saw (Bosch GTS 10J), operating at 3700 RPM with an 1800 W motor; **T4**) with a band saw (Makita LB1200F), with a cutting speed between 6.7 and 13.3 m/s and 900 W engine power and **T5**) with an orbital sander (DEWALT DWE6411), equipped with a 230 W motor, 14,000 orbits per minute, vibration emission <4.0 m/s², and 80-grit sandpaper. The same wood specimens were used in each sanding process, reducing approximately 0.5 cm in the cross-sectional dimension of the samples with each cutting process. Subsequently, spectral signatures were collected using NIR equipment (Fig. 2). To observe surface irregularities, samples measuring 1 cm (width) x 1 cm (length) x 0.5 cm (thickness) were obtained and observed using scanning electron microscopy (SEM) (Fig. 3).

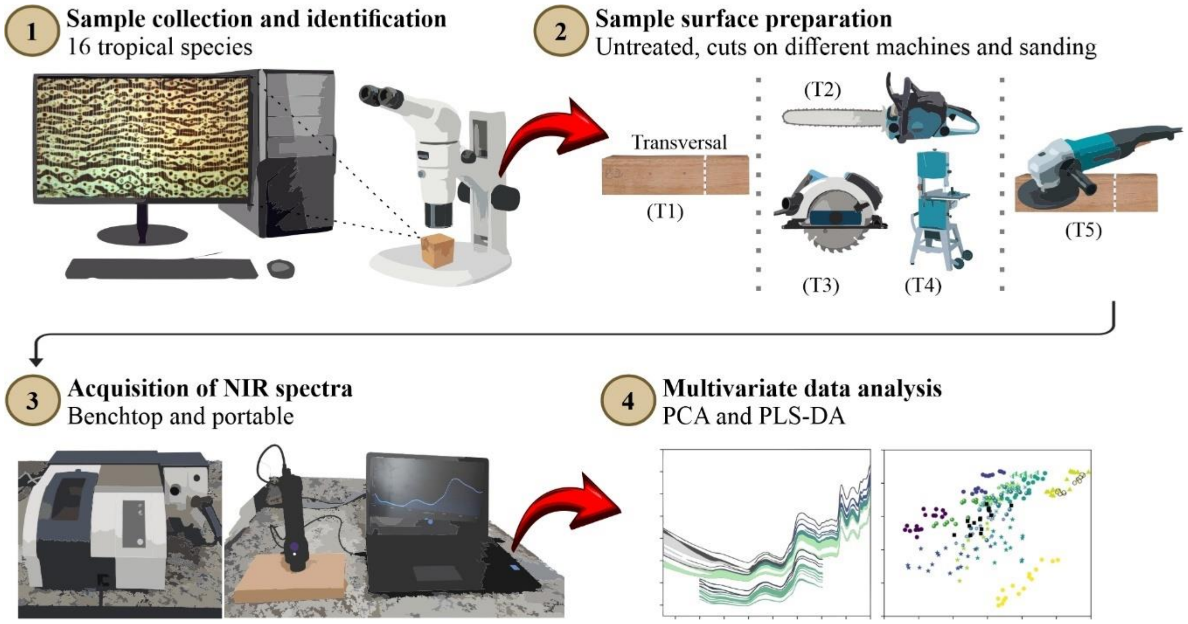

Fig. 2 General flowchart of the study stages.

NIR spectra equipment

The spectra were obtained with a benchtop and portable NIR spectrometer directly on the transverse surface of the wood, as previously describe by Medeiros et al. (2024), who used these two NIR equipment for comparing models for predicting wood density in *Eucalyptus* chips.

Benchtop: The stationary instrument used was a Fourier transform (FT) NIR spectrometer (MPA model, Bruker Optik GmbH, Germany) equipped with a diffuse reflection integrating sphere. The acquisition range was from 1112 to 2500 nm (9000 - 4000 cm^{-1}) with an 8 cm^{-1} resolution, resulting in 1,300 spectral variables. The equipment was connected to a computer running OPUS software (v.7.5). A sintered gold standard was used as a reference prior to obtaining the NIR spectra with the integrating sphere. NIR spectra were recorded in a climate-controlled room at approximately 20°C and 65% relative humidity.

Portable: the portable instrument was the MicroNIR On-site (Viavi Solutions Inc., CA, USA) configured in direct reflection mode on the wood surface. The acquisition range was from 908 to 1676 nm (11012 - 5966 cm^{-1}) with a resolution of 6,19 nm, generating 125 spectral variables. Using the point-and-shoot technique, a dark scan and a reference scan were performed approximately every 10 min, and the data was collected using the software SpectralSoft Solutions (Viavi Solutions Inc., CA, USA).

Sixteen spectra, corresponding to the number of wood samples per species, were recorded on each NIR instrument. Spectra were collected sequentially at different cross-sectional surface preparation, specifically in the central region of each wood specimen. In total, 256 spectra were obtained per surface treatment, adding up to a total of 1,280 spectra in the five surface conditions using benchtop and the portable NIR instrument.

Multivariate data analysis

The spectral data were analyzed by Chemoface v.1.63 software (Nunes et al. 2012) through principal component analysis (PCA) and partial least squares discriminant analysis (PLS-DA). PCA was applied to explore the data in a preliminary way, evaluate the dependence of the data by clustering and verify the spectral similarity between wood species, without losing the information obtained from the spectra. Subsequently, PLS-DA analysis was performed to verify the effect of surface quality on the classification of tropical species by cross-validation. Dummy binary codes were defined to indicate whether a sample belonged to one of 16 species classes. Samples belonging to a category received the value 1, while samples not belonging to that category received the value 0, this approach to the procedure is detailed in Lima et al. (2022a). From the organization of these values, the confusion matrix was obtained, which shows the percentages of errors and successes for each model generated in PLS-DA, in each surface treatment.

For each treatment, six adjusted models were evaluated for PCA and PLS-DA analysis. The first model was fitted with the original data, while the other five models were fitted with the following pre-treatments: normalization, first (1d) and second order (2d) derivatives, multiplicative dispersion correction (MSC) and standard normal variation (SNV). The first (13-point filter and second-order polynomial) and second derivative (25-point filter and second-order polynomial) were based on Savitzky-Golay (SG) algorithm, as suggested by Medeiros et al. (2023).

For the PLS-DA models, all fitted models in the experiment used 10 latent variables (LV) and no outliers were excluded. These pretreatments were selected due to their common use in processing spectral data in wood discrimination studies (Pace et al. 2019; Astete et al. 2023; Novaes et al. 2023; Raobelina et al. 2023).

Results and discussion

Scanning electron microscopy of wood

Figure 3 presents micrographs that highlight surface irregularities observed on a microscopic scale, including ripples, radii, and defects in the cross-sections of *Diplotropis* sp. samples.

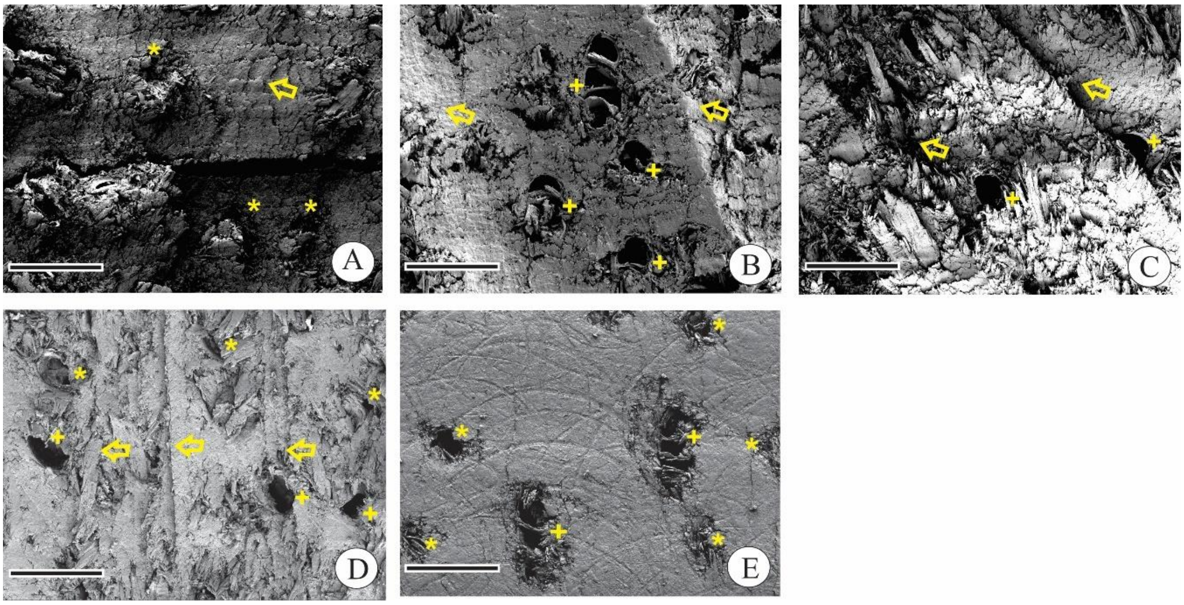

Fig. 3 Scanning electron microscopy (SEM) micrographs of the transverse surfaces of wood specimens prepared with different tools. A: Raw. – B: chainsaw. – C: circular saw. – D: bandsaw and E: sanded: 500 µm.

Figure 3A shows the raw surface, characterized by biodegradation and oxidation processes, with minimal visible porosity, likely due to dust or fungal colonization from environmental exposure. Figure 3B illustrates the surface processed with a chainsaw, featuring deeper cuts, diagonal scratches, and more visible pores. Figure 3C shows the surface processed with a circular saw, with shallower diagonal scratches and visible pores. Figure 3D presents the surface cut with a band saw, notable for its narrower grooves compared to the circular saw, an 'alfombra' pattern, a higher proportion of pores, and less clogging. Finally, Figure 3E depicts the sanded surface, which is more homogeneous; however, sanding can clog and mask pores, compress or deform the cell wall, and obstruct the cell lumen with dust (Santoni and Pizzo 2011; Sulaiman et al. 2009). All these surface conditions can interfere with the spectral signal during the development of NIR models by either affecting the absorbed radiation or causing information loss in the reflection.

According to Schimleck et al. (2023), the roughness of the wood surface is the result of the properties of the material itself and several variables associated with the tools used to prepare it. And increasing surface roughness has been shown to reduce the absorption of NIR radiation in wood samples, which can influence the performance of NIR calibration models (Schimleck et al. 2005; Zhang et al. 2015). This phenomenon causes light to scatter at different angles depending on the wavelength, affecting the resulting spectra (Sandak et al. 2016).

NIR spectra and absorption band assignments

The averaged spectral signatures with the original data from the 16 tropical species and the wood machining treatments are presented in Fig. 4A and Fig. 4B, respectively. In Fig. 4A, each spectrum represents the combination of several spectra collected from surface samples under field conditions, classified according to their bulk density. On the color scale, the darker lines in the upper region of the signatures represent the spectra of high-density species, and the lighter colored lines in the lower region of the spectral profile correspond to low-density species (Fig. 4A).

In absorbance values, overlap was observed in most species, with minimal variations in intensity, attributable to their densities, which are very close to each other. However, species such as *H. oblongifolia*, *Dalbergia* sp., *C. odorata* and *Cedrela* sp., present absorption peaks with more evident differences. The first two species may be related to a possible higher extractive content (dark-colored wood), while the last two species may be related to their lower density compared to the other species.

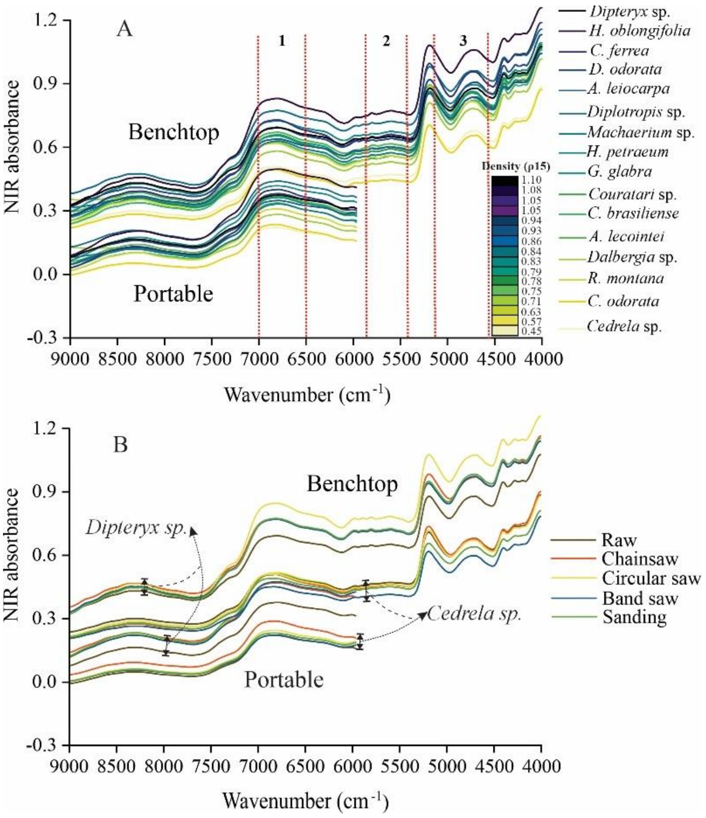

Fig. 4 Average of original spectra under field conditions of tropical species (A) and wood surface treatments with two tropical species (B).

The similarity between the different species can be attributed to the cellulose content in the wood evaluated. This chemical uniformity can make it difficult to distinguish accurately by visual inspection, making the use of advanced techniques, such as chemometrics, essential to obtain an accurate differentiation (Russ et al. 2009). Second Santos et al. (2021a) and Lima et al. (2022a), the main spectral regions for identifying tropical species are: 6500 - 7000 cm^{-1} (1), 5400 – 5900 cm^{-1} (2) and 4600 - 5200 cm^{-1} (3). Lima et al. (2022a) reported that these bands have the potential to distinguish species from various genera, such as *Dinizia*, *Licania*, *Manilkara*, *Pseudopiptadenia*, *Pouteria*, *Caryocar*, *Eschweilera*, *Brosimum*, *Simaba*, *Parkia* and *Tabirila*. Santos et al. (2021a) also found that regions 2 and 3 are effective in differentiating species from genera *Ocotea*, *Nectandra*, *Roupala*, *Euplassa*, *Mezilaurus* and *Aniba*. Vieira et al. (2021) emphasized the importance of the second region in distinguishing four native Brazilian species of the genus Myrtaceae.

The mentioned absorption bands correspond to specific functional groups present in wood (Brereton, 2003). In particular, bands in the range 6500 to 7000 cm^{-1} are related to the amorphous and crystalline regions of cellulose. The range from 5400 to 5900 cm^{-1} it is associated with all components of the cell wall, mainly cellulose, lignin and hemicellulose. In addition to these structural components of the cell wall, the ranges between 4600 and 5200 cm^{-1} are associated with extractive content (Schwanninger et al. 2011). It is important to note that many of the identified features are associated with well-known bond vibration bands. However, we cannot predict that these models are based directly on wood chemistry, as components such as cellulose, lignin and others contribute to these characteristics only to a certain extent. (Schimleck et al. 2023).

To facilitate the understanding of the NIR spectra by surface treatment, two species with different densities were selected (Fig 4B). In benchtop equipment, for species with low density (*Cedrela* sp.), the minimum absorbance was 0.2 on the surface processed with a band saw and the maximum absorbance was 0.9 in field conditions and processed with a chain saw. For the high-density species (*Dypteryx* sp.), a minimum absorbance of 0.3 was recorded under field conditions and a maximum of 1.3 on the surface processed with a circular saw. In portable equipment, for the type of *Cedrela* sp., the minimum absorbance was 0 under field conditions and on the surface processed with a band saw, while the maximum absorbance was 0.3 on the surface processed with a chain saw. The species *Dypteryx* sp. it showed a minimum absorption of 0.1 in field conditions and a maximum of 0.5 on the surface processed with a circular saw and finished with sandpaper (Fig. 4B).

Analyzing the intensity of NIR absorption bands in *Cedrela* sp., the highest absorbance was on the surface produced by chainsaws in both NIR equipment. Furthermore, in the bench equipment, greater absorbance was also observed on the surface produced by the circular saw. For the species *Dipteryx* sp., higher absorbance was observed on surfaces produced by circular sawdust in both equipment. However, the sandpaper-finished surface also showed significant absorbance peaks in portable NIR. Apparently, finer textures with lower roughness and higher gloss indexes favor greater absorbance, indicating a high influence of the surface on spectral acquisition. Novaes et al. (2023) found higher absorptions on surfaces produced with circular saws, suggesting that these surfaces have better potential to discriminate species. Although visual analysis showed differences, it is not sufficient to identify species.

Principal component analysis

The contributions of the main components by type of wood surface processing obtained a higher explanatory percentage of the data variation with the spectra pre-treated by normalization on the bench equipment and with the original spectra in the portable NIR (Table 2).

Table 2 Explanation of the variance of the main components, applied in other mathematical treatments, for the five surface qualities.

Equipment	Pretreatment	PCA- Wood processing Half hits (%)									
		Raw		Chainsaw		Circular saw		Band saw		Sanding	
		PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2	PC1	PC2
Benchtop	Untreated	99.24	0.68	99.32	0.61	99.02	0.92	99.3	0.65	99.1	0.84
	Normalize	**99.27**	**0.66**	**99.37**	**0.57**	**99.12**	**0.83**	**99.37**	**0.58**	**99.23**	**0.71**
	1d	98.33	0.45	98.2	0.38	98.15	0.59	97.88	0.58	97.92	0.54
	2d	80.06	2.38	72.8	3.79	78.95	2.68	75.84	3.19	73.96	3.35
	MSC	78.02	2.76	70.98	3.96	77.48	2.79	74.23	3.46	72.41	3.61
	SNV	79.21	2.44	72.88	3.6	78.77	2.62	75.56	3.12	73.81	3.21
Portable	Untreated	**98.43**	**1.37**	**99.3**	**0.61**	**99.08**	**0.82**	**98.97**	**0.91**	**98.79**	**1.08**
	Normalize	97.83	1.90	99.15	0.74	98.86	1.02	98.73	1.13	98.5	1.35
	1d	97.2	2.31	98.28	1.36	98.35	1.36	98.07	1.63	97.69	1.97
	2d	95.64	3.36	97.11	2.12	97.37	1.97	96.26	2.96	96.79	2.58
	MSC	94.22	4.81	96.45	2.82	96.57	2.77	95.85	3.39	95.23	4.13
	SNV	95.19	3.83	96.67	2.6	96.89	2.46	96.34	2.9	96.08	3.27

Where: 1d = first derivative, 2d= second derivative, MSC= Multiplicative scatter correction and SNV= Standard normal variate.

For the original data with surface under field conditions, recorded with the bench equipment, PC1 explained 99.24% and PC2 0.68%, while PC1 from the portable equipment explained 98.43% and PC2 1.37%. On the surface processed with a chainsaw, the sum of the main components in the bench equipment was 99.93%, while in the portable equipment it was 99.91%. When evaluating the total percentage of PCA in wood prepared with a circular saw, band saw and sandpaper, slightly higher values were found in the bench equipment, when compared to the results of the portable NIR: 99.95%, 99.95% and 99.94%, respectively.

Figure 5 illustrates the score plots from both benchtop and portable equipment, showing the grouping tendencies of tropical wood species. In raw, distinct groups were observed for *Cedrela* sp., *C. odorata*, *C. ferrea*, and *H. oblongifolia* (Fig. 5A). Using portable equipment under the same surface condition, the primary groups identified were *Dalbergia* sp., *C. ferrea*, and *H. oblongifolia*, with other species showing overlap, indicating spectral similarity (Fig. 5A and 5B). However, visual discrimination of the groups improved as the wood underwent machining processes, particularly with the circular saw and sander, in both benchtop and portable equipment.

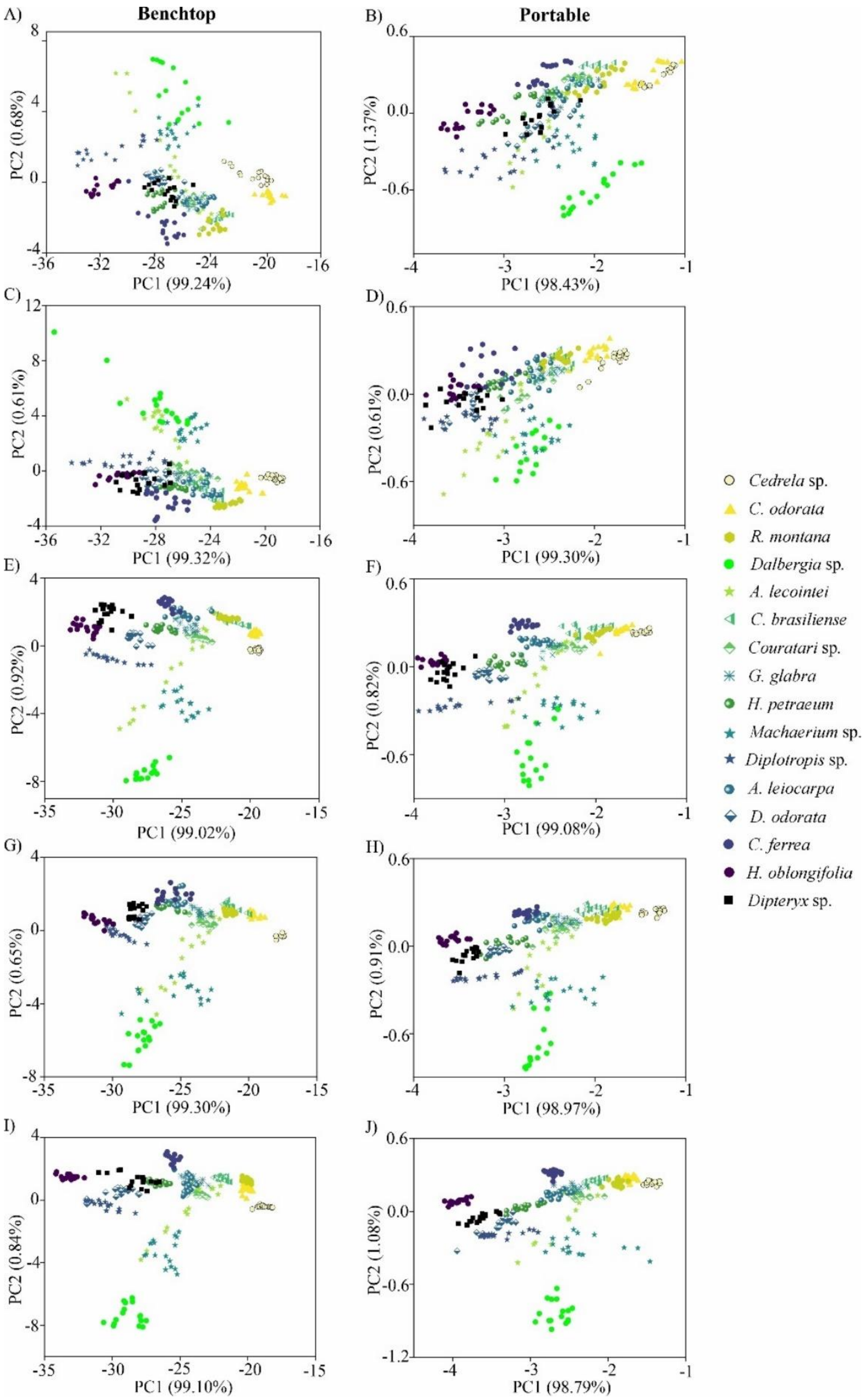

Fig. 5 PCA scores from original spectral data on benchtop and portable NIR equipment, obtained on surfaces under field conditions (A and B), chainsaw (C and D), circular saw (E and F), band saw (G and H) and sander (I and J).

The overlapping behavior of the species on raw surfaces can be explained by alterations in the appearance of the samples, due to their prolonged storage in yards. This implies changes in chemical composition, derived from wood biodegradation and photodegradation. According to Reis et al. (2023), oxidation also influences color change. All these conditions can cause variations in molecular composition and, consequently, in spectral signatures. Santos et al. (2022) classified different Tauari species without surface refreshing, achieving adequate identification percentages, which corroborates this study.

When machining with a chainsaw, visually the scores revealed a notable increase in overlapping areas for fourteen species, making their identification difficult, except for *Cedrela* sp and *C. odorata* (Fig. 5C and 5D). Novaes et al. (2023) performed PCA on spectra of wood processed with a chainsaw and treated by second derivative, which concluded that *M. elata* and *D. excelsa* presented partial similarities in their spectra, while *G. glabra, Himenea* sp., *M. melinoniana* and *Copaifera* sp. presented overlaps, which prevented their correct discrimination. In this study, chainsaw samples did not achieve satisfactory species identification, possibly due to the coarser texture and greater surface roughness of the wood.

On the surface produced with a circular saw, a reduction in overlapping areas between species was observed, in relation to previous graphs. The bench and portable equipment showed a slight separation of scores into distinct groups in *Cedrela* sp., *Dalbergia* sp., *C. odorata*., *H. petraeum*., *Machaerium* sp., *D. odorata*., *Diplotropis* sp., *H. oblongifolia* and *Dipteryx* sp. (Fig. 5E and 5F). Pace et al. (2019) identified the formation of four different groups in a set of twelve wood species cut with a circular saw, where the score plots explained 99% of the variance in PC1 of the original spectra. In contrast, Novaes et al. (2023) discriminated spectra collected on surfaces produced with circular saws for species such as *M. elata, D. excelsa, M. melinoniana, G. glabra* and *Himenea* sp., showing clustering trends with minimal overlap between spectra, which allowed better visual discrimination compared to the chainsaw results. Surfaces cut with the circular saw showed a higher level of uniformity, which facilitated species identification compared to other conditions. species identification compared to other surface conditions. The tabletop equipment produced denser clumps with no appreciable areas of overlap, while the portable equipment showed less defined clumps.

On the surface produced with a band saw, the benchtop equipment showed that PC1 explained 99.30% of the data variance and PC2 0.65%, while on the portable equipment PC1 explained 98.79% and PC2 0.91%. Visually, the bench equipment scores showed separation only for *Cedrela* sp. and *Dalbergia* sp. and, the portable equipment clearly discriminated the species *Cedrela* sp. and *H. oblongifolia* (Fig. 5G and 5H). Wood with a sanded surface of 80 grain presented PC1 of 99.10% and PC2 of 0.84% on the bench equipment. In portable equipment, PC1 explained 98.79% and PC2 1.08%. The scores on the bench NIR separated the groups *Cedrela* sp., *Dalbergia* sp., *C. odorata*, *C. brasiliense*, *R. montana*, *C. Ferrea* and *H. oblongifolia*. On the laptop, separation was observed for *Cedrela* sp., *Dalbergia sp*., C. *ferrea*, *H. oblongifolia* and *Dipteryx* sp. (Fig. 5I and 5J).

Reis et al. (2023) achieved 98% explanation of the variation in PC1 for wood with sanded surfaces and with original spectra collected on benchtop equipment. According to Costa et al. (2018), the greater dispersion of scores in the cross-sectional area of wood is due to the extensive volume of information from the cell wall. NIR radiation penetrates deeper into this surface, where the fibers function as light tubes, allowing a greater volume of wood to be evaluated. Although surface sanding slightly improved the identification of a greater number of species, it was not sufficient to identify all of them.

Partial Least Squares Discriminant Analysis

The PLS-DA models showed a high percentage of correct classification for tropical species (Table 3). The model implemented to analyze surfaces under field conditions, using original spectra, achieved accuracy levels of 96.5% and 93.4% for bench and portable instruments, respectively. After data processing, normalization maintained a success level of 96.5% for the bench instrument. In portable equipment, a slight improvement was observed (95.3%). To date, there are no reports in the literature of studies using NIR spectroscopy for this surface condition in the field. Although there is no research on the analysis of spectra on non-homogenized or untreated surfaces, it is known that such conditions affect the reliability of NIR spectroscopy and the performance of prediction models (Schwanninger et al. 2004; Sandak et al. 2016). Thus, this study indicates that NIR spectra obtained without prior treatment on the surface of materials, analyzed with multivariate statistics, can discriminate wood species with high efficiency.

Table 3 PLS-DA summary with percentage of cross-validation hits, considering acquisition equipment and mathematical pre-treatment used.

Equipment	Pretreatment (10LV)	NIR - Species classification				
		Average hits (%)				
		Raw	Chainsaw	Circular saw	Band saw	Sanding
Benchtop	Untreated	**96.5**	85.9	96.5	91	91.8
	Normalize	**96.5**	**88.7**	**96.9**	**96.9**	**92.2**
	1d	88.7	84	87.1	93.4	84
	2d	60.6	47.3	69.5	71.1	71.5
	MSC	46.9	37.1	56.3	61.3	64.8
	SNV	53.1	46.1	65.2	71.9	67.2
Portable	Untreated	93.4	84	92.6	94.9	92.6
	Normalize	**95.3**	78.5	95.7	95.3	97.3
	1d	93.8	87.5	90.2	93	98.4
	2d	94.9	88.7	93.8	96.1	98.4
	MSC	92.2	89.8	**99.2**	**97.3**	**99.2**
	SNV	94.5	**93.8**	96.5	95.3	**99.2**

Where: LV= latent variable, 1d= first derivative, 2d= second derivative, MSC= Multiplicative scatter correction and SNV= Standard normal variate.

In models on surfaces generated by chainsaws, the raw data reflected lower percentages of success, reaching 85.9% and 84%, in bench and portable instruments, respectively. By applying mathematical normalization pretreatment, improvement was observed in the benchtop device, while in the portable device the standard normal variation achieved better optimization. Novaes et al. (2023), obtained a better result when discriminating four Amazonian Forest species using PLS-DA models based on spectral signatures acquired on wooden surfaces produced with a chainsaw, achieving 90.09% success in classifying original data and 97.6% in original data. treated by second derivative.

The best classification performances were obtained on surfaces produced by circular saws, reaching 96% with the original data and 98.4% with data pre-treated with a second derivative. Possibly, this difference could be related to the increase in surface roughness due to machining with the cutting tool (Sandak et al. 2009), or variations in the density of the material, which can affect the dispersion of light recorded in the spectra, this being important aspect for wood classification (Ayanleye et al. 2021).

The surfaces produced with a circular saw showed a success rate of 96.5% for the bench instrument and 92.6% for the portable instrument, using original spectra. With the mathematical treatments were applied, there was a slight increase with normalization on the bench and a slight increase with multiplicative dispersion correction on the portable instrument. Novaes et al. (2023), analyzed cube-shaped samples of six Amazonian species, achieving 98.3% correct classification for original data and 99.2% for data pre-treated with second derivatives. Likewise, Pace et al. (2019) categorized samples of 12 native species from the Atlantic Forest of Brazil in recent conditions with circular saw and in equilibrium humidity state (12%), achieving a correct classification of 93.2% with PLS-DA models fitted by cross-validation for original spectral data. In both cases, the spectra were acquired with bench-top equipment. In this study, comparable results were obtained, with better success using the portable instrument, of which there are no previous reports of its use on surfaces processed with a circular saw.

Surface models produced with a band saw showed lower percentages of success with the original data, achieving 91% success with benchtop equipment and 94.9% with portable equipment. After data processing, a significant improvement was observed, reaching 96.9% through normalization for bench equipment and 97.3% with multiplicative correction for portable equipment. Therefore, the results show that after the mathematical treatment of the data, the difference in the percentages of successes between the finishes with circular saw and band saw was minimal, thus favoring the application of the NIR technique in the field for these types of surface finishes.

On sanded surfaces, the original and treated spectra showed higher results with the portable equipment, mainly with the application of multiplicative signal correlation pre-treatment, totaling 99.2% success. The discrimination of tropical Amazonian wood on sanded surfaces has been addressed in several studies. Santos et al. (2021a) achieved 97% accuracy using 80-grit sandpaper to distinguish eight wood species. Lima et al. (2022a, b) used 50, 80, and 100 grit sandpaper and found that spectra treated with the second derivative of the cross-sectional surface achieved a classification rate of 96.5% from residues of twelve wood species. Both studies used benchtop equipment to acquire the spectra. The use of portable equipment was also reported. Soares et al. (2017) classified six wood species and achieved efficiency greater than 90%, while Snel et al. (2018) identified seven species of the genus *Dalbergia* with a rating above 90%. Our results on both NIR devices were satisfactory and in line with the percentages reported in the aforementioned studies.

The PLS-DA confusion matrix, obtained from the bench instrument with the data treated by normalization to classify tropical species, shows that out of 256 samples analyzed, only 8 samples were incorrectly classified, corresponding to the species *A. lecointei* (7) and *D. odorata*. (1) (Table 4). On the other hand, the model provided classification with 100% accuracy for 14 species: *Cedrela* sp., *Dalbergia* sp., *C. odorata, Couratari* sp., *C. brasiliense, H.*

petraeum, R. montana, Machaerium sp., *G. glabra, A. leiocarpa, Diplotropis* sp., *C. ferrea, H. oblongifolia* and *Dipteryx* sp.

Table 4 PLS-DA confusion matrix obtained by cross-validation, for classification of tropical species with spectra treated by normalization and collected on bench equipment on wood processed by circular saws.

Species	Classification of wood predicted by Benchtop NIRS																Correct classification (10LVs)	
	CV	CR	CM	JA	MU	GU	TA	CU	AA	JP	SU	GA	CA	PF	JB	CB	n	(%)
CV	16																16	100
CR		16															16	100
CM			16														16	100
JA				16													16	100
MU			6		9						1						9	56
GU						16											16	100
TA							16										16	100
CU								16									16	100
AA									16								16	100
JP										16							16	100
SU											16						16	100
GA												16					16	100
CA													15			1	15	94
PF														16			16	100
JB															16		16	100
CB																16	16	100
Overall classification																	**248**	**96.9**

Where: CV = *Cedrela* sp., CR = *Cedrela odorata.*, CM = *R. montana*, JA = *Dalbergia* sp., MU = *A. lecointei*, GU = *C. brasiliense*, TA = *Couratari* sp., CU = *G. glabra*, AA = *H. petraeum*, JP = *Machaerium* sp., SU = *Diplotropis* sp., GA = *A. leiocarpa*, CA = *D. odorata*, PF = *C. ferrea*, JB = *H. oblongifolia*, and CB = *Dipteryx* sp.

The species *A. lecointei* (MU) was often classified as *R. montana* (CM) and, to a lesser extent, as *Diplotropis* sp. (SU), being the species that presented the lowest correct classification rate of 56%. This confusion can be attributed to the greater exposure of cellular elements obstructed by tylosis, resulting from the expansion of the radial and axial parenchyma cell walls through the pits towards the vascular elements. According to Melo et al. (2013) and Abreu et al. (2024), this phenomenon is common in the heartwood and in the transition zone between sapwood and heartwood in this species. Such a situation can cause a disordered refraction of light in multiple directions, leading to the loss or mixing of information in the sensor during the return of the spectrum, thus generating spectral noise.

D. odorata (CA) was incorrectly classified to a lesser extent than *Dipteryx* sp. (CB), it is possible that this slight confusion is influenced by cross-sectional anatomical similarities between these species of the same genus (Fig. 1M and 1P). This result is consistent with previous research; Santos et al. (2021a) reported confusion in samples of *Roupala* sp. and *Euplassa* sp., which share similar anatomical characteristics as they belong to the Proteaceae family. Furthermore, Novaes et al. (2023), presented erroneous classifications in *Hymenea* sp. and *Dinizia excelsa*, where these wood species had the worst accuracy performance (85.8% and 90.2%, respectively), due to the anatomical similarity of the two species.

In the PLS-DA matrix, for categorization of species with portable equipment, the models with spectra treated with multiplicative scatter correction correctly classified 254 of the 256 wood samples. Only 2 incorrectly classified species were recorded: *A. lecointei* (1) and *Machaerium* sp. (1) (Table 5).

Table 5 Confusion matrix of the classification of the model resulting from PLS-DA through cross-validation, of spectra collected on the surface produced with a circular saw with the portable equipment treated with multiplicative scatter correction.

Species	Classification of predicted wood by portable NIRS																Correct classification (10LVs)	
	CV	CR	CM	JA	MU	GU	TA	CU	AA	JP	SU	GA	CA	PF	JB	CB	n	(%)
CV	16																16	100
CR		16															16	100
CM			16														16	100
JA				16													16	100
MU			1		15												15	94
GU						16											16	100
TA							16										16	100
CU								16									16	100
AA									16								16	100
JP				1						15							15	94
SU											16						16	100
GA												16					16	100
CA													16				16	100
PF														16			16	100
JB															16		16	100
CB																16	16	100
Overall classification																	**254**	**99.2**

Where: CV = *Cedrela* sp., CR = *Cedrela odorata.*, CM = *R. montana*, JA = *Dalbergia* sp., MU = *A. lecointei*, GU = *C. brasiliense*, TA = *Couratari* sp., CU = *G. glabra*, AA = *H. petraeum*, JP = *Machaerium* sp., SU = *Diplotropis* sp., GA = *A. leiocarpa*, CA = *D. odorata*, PF = *C. ferrea*, JB = *H. oblongifolia*, and CB = *Dipteryx* sp.

In portable MicroNIR, only a sample of the species *A. lecointei* (MU) was confused with *R. montana* (CM). This confusion can be attributed to the surface quality generated by the circular saw, which makes the wood samples more similar. An erroneous classification was also recorded in a sample of *Machaerium* sp (JP) classified as *Dalbergia* sp (JA). These results are consistent with previous studies that discriminated species of the genus *Dalbergia*. Snel et al. (2018) achieve efficiencies above 90% in PLS-DA models, while Raobelina et al. (2023) report percentages of 82.3% and 81.8%. This confusion in the classification is justified by the similar transverse anatomical characters, mainly in the axial parenchyma, in both species (Fig. 1D and 1J).

These results corroborate previous studies identifying native species. The results revealed that the portable equipment presented better classification performance, compared to bench-top NIR. According to Santos et al. (2021b), the decrease in the predictive performance of benchtop NIR equipment models could be attributed to the spectral reading area. The integrating sphere used in the benchtop equipment was approximately 10 mm in diameter, while the portable optical system had a punctual area, resulting in a smaller representation of the wood surface. This disparity in spectral reading areas could explain the greater effectiveness of portable NIR in discriminating wood species. Despite this difference in classification performance, both instruments proved to be efficient for identifying and classifying timber species under different surface conditions.

Limitations

It is important to note that this study has some limitations. The number of species could have been greater, as there are thousands of tropical species. However, the authors chose these species due to their commercial importance in the State of Minas Gerais, where the research was conducted.

In treatment 1, there was heterogeneity in surface quality, as the samples were used as they were found. Thus, there was no type of control on surface quality in terms of processing time between samples (from months to years) and processing machine (some chainsaw, others circular saw or band saw. The fact that it is the first processing is completely unknown; it is not known how long ago it was carried out, nor which machine was used. From the second treatment onwards, the processing was fully controlled and standardized between the wood samples.

The initial idea of this study was to get an idea of the model's performance depending on the type of processing. The next steps in this line of research will be to produce a collection of wood samples in a real field or yard situation, to provide support for control and inspection actions.

Conclusion

This study highlights the importance of surface finish and the type of NIR equipment used in species discrimination. Although NIR spectral data contain information relevant for discrimination, they require appropriate treatment to maximize their explanatory potential. PCA proved to be effective in identifying wood, although some species overlapped in certain surface processes, with the circular saw being the most recommended in the machining process for spectral reading purposes.

The PLS-DA models adjusted through cross-validation were able to identify sixteen tropical wood species on surfaces under field conditions, produced by circular sawing, band sawing and sanding, with notable success percentages of 95.3% to 99%. Only slightly low accuracy percentages were observed on surfaces produced with chainsaws, 88.7% on benchtop equipment and 92.8% on portable equipment. These results highlight the high potential of the NIR technique to discriminate tropical wood species based on diverse surface qualities. This highlights the usefulness of the technique in identifying wood species during wood control and monitoring actions.

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Data availability Data will be available upon request.

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