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Geographical origin differentiation of *Tectona grandis* wood using Near Infrared Spectroscopy and Support Vector Machine Classification

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ABSTRACT
The identification of the origin of a timber has always been seen to be a challenging process, and there are now no useful protocol/instruments available for this purpose. This study aimed to classify Tectona grandis wood (increment bores) taken from the trees of nearby regions and to recognize important variations in origin betweengroups of the same wood species using Fourier transform near-infraredspectroscopy (FT-NIR) and Support Vector Machine Classification (SVMC). The increment cores were taken from the Tectona grandis trees of two locations (28 km apart) in the Dehradun district of Uttarakhand State, India. Increment cores were taken out from the two locations: 23 from Kudkuwala and 31 from FRI. NIR spectra were recorded from the air dried and conditioned increment cores from two points: near periphery region and near core region. Support Vector Machine Classification (SVMC) was used to make three calibration models: SVMC model 1 with inner and outer spectra combined, SVMC model 2 with spectra only from inner side of the core, SVMC model 3 with spectra only from outer side of the core.Principal component analyses (PCA) was carried out to understand the variability in the data sets. Results suggest that SVMC models had classification success rate had 68.2% (combined inner and outer core) 75% each for rest of the two models. Taking specimens either from inner side or outer side performed well in classification as compared with that of combining the both.
Key words: *Wood Classification, SVMC, FT-NIRS*

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I. Introduction

In order to detect illegal trade of timbers and protecting rare and endangered species, detection of the geographical origin of the timbre becomes very important. There is no other feasible and rapid tool to identify illicit log harvests and to track the provenance of wood for various purposes. To confirm or deny claims about the provenance and species of traded forest products, scientific evidence is often required. It is hard to determine whether the woods in a product are sourced ethically, legally, or sustainably without knowing the identity and provenance of the woods. To monitor and support authentication and compliance with identification and geographical origin in the international trade of wood products, a program called WorldForestID is also being developed (Gasson et al., 2020).By enabling the identification of patterns in data sets and the creation of mathematical models for classification and traceability, NIR spectroscopy, when combined with multivariate analysis, can improve the information obtained from sample analysis.It has been reported that DART TOFMS mass spectra, NIRS spectra, or isotopic signatures can be used to determine the timber's provenance (Low et al., 2022). NIRS may prove rapid and cost effective solution.

Li et al. (2022) used NIR spectroscopy and support vector machine (SVM) in combination with grid search techniques and reported prediction accuracy rate 93.18% for tree species identification.According to Sierra et al. (2017), NIR technology has been found to be very useful in improving wood traceability and complying with European regulations on timber trade. Three commercial spectrometers were used to evaluate 16 commercial species in 25 localities in Spain, and percentages of correct identification were consistently over 80% using LDA, SIMCA and PLS-DA as supervised pattern recognition techniques. PLS-DA models had the greatest results, with over 90% of the classifications being correctly classified using the whole NIR spectral range. Silva et al. (2018) investigated the use of near-infrared spectroscopy (NIRS) to track the origin of mahogany wood from Bolivia, Brazil, Guatemala, Mexico, and Peru. They then employed partial least squares for discriminant analysis (PLS-DA) and soft independent modelling of class analogy (SIMCA) techniques for data evaluation. SIMCA's identification performance ranged from 70 to 98%, whereas the PLS-DA approach's performance ranged from 90% to 100%. Near infrared spectroscopy was employed by Sandak et al. (2009) to distinguish between distinct groups of timber specimens with closer origins. The impact of silvicultural factors, including soil, altitude, precipitation, slope, and others, on timber was emphasized. The chemical structures of the trees growing in different places vary, and the spectroscopic techniques are sensitive enough to pick up on these variations (Sandak et al., 2010).In addition to timber, NIRS has been used to study the geographical origin of other forest products. Apart from identification of geographical origin of timber, other forest produce has been classified using NIRS like Cork (Prades et al., 2012), walnut (Arndt et al., 2020), leaves and nuts (Nisgoski et al., 2023), seeds (Farhadi, 2017). Nisgoski et al. (2023) constructed classification models based on near infrared spectroscopy that had accuracy of 98.54% for leaves, 89%, and 90.91% for nuts with and without shell.

One effective supervised learning technique for regression and classification issues is Support Vector Machines (SVM). The SVM method finds the best hyperplane with the largest possible margin to divide the sample classes. The margin of the hyperplane, which is the separation between it and the samples nearest to it (support vector), determines how well it generalizes the differences across the classes.

Classification difficulties can be solved with SVM-based classifiers, often known as SVCs (Support Vector Classifiers). Two different built-in classifier types are available in the Unscrambler X[(R)]: The C-support vector classifier (C-SVC) and the nu-support vector classifier (Nu-SVC). The parameter utilized to regulate the quantity of support vectors is the primary distinction between the two. C in C-SVC, can have any value between 0 and infinity, whereas, Nu in Nu-SVC, can have any value between 0 and 1. Nu is the lower bound for the proportion of support vectors and the upper bound for the fraction of errors. When certain classes are partially overlapping and non-homogeneous, SVM performs well in this scenario. However, if all samples are used to generate local PCA models, one class may include more than one class, making this an unsuccessful attempt to develop a model. Compared to other nonlinear classification techniques, support vector machines (SVM) have the advantage of having a unique solution and less inclination toward overfitting than classification methods like neural networks. SVMs are comparatively insensitive to changes in parameters and are useful for modelling nonlinear data.Depending on the type of data, SVM can employ one of four kernel types: sigmoid, linear, polynomial, or radial basis function. The selection of the mapping kernel has an impact on the SVM. With both classifiers, comparable results can be achieved by optimizing these criteria.

The aim of this study is to classify *Tectona grandis* wood specimens obtained from two closely placed sites in the district of Dehradun (Uttarakhand, India), using Support Vector Machine Classification (SVMC).

II. Materials And Methods

The provenances of sample collection

The increment cores were taken from the trees of two locations Forest Research Institute, Dehradun, India (FRI) campus and a forest area, 28 km away (Kudkawala) in the Dehradun district of Uttarakhand State, India (Figure 1). The study site of FRI was developed in the 1920s to support forest management methods and the FRI campus was legally designated as a protected forest. Before 1970, forest practices were mostly centred on timber production, but after 1970, they shifted to a conservation-, owing in part to changes in India's forest policy. The FRI campus (N30º19'55" to N30º21'16" and E77º59'12" to E78º01'01") spreads over an area of 450-hectare (640 m above mean sea level). The entire New Forest campus is a small block of conserved forest located 5 kilometres north of Dehradun city. The FRI is a sprawling area featuring trees, gardens, and well-planned human settlements. New Forest campus receives an average annual rainfall of 2050 mm of rain per year on average. The average monthly temperature ranges between 32ºC and 33ºC. The hottest months are May and June, while the coldest months are December and January. The monsoon season normally begins in the middle of June and lasts until the middle of September.

The study site of Kudkawala is located in the north-western part of Dehradun district, Uttarakhand. Its coordinates are 30° 10'23.9412" N and 78° 6'19.026'' E, with an average elevation of 485m above mean sea level. The area falls within the Terai and Bhabhar region of the Doon Valley and is significant due to its central position within the triangle formed by three important metropolitan and cultural regions of Uttarakhand - Dehradun, Haridwar, and Rishikesh. The present study area of *Tectona grandis* (Teak) forest located near the Lachhiwala range, Kudkawala, receives an average annual rainfall of 2051.4 mm, with most of the rainfall occurring from June to September. The months of July and August are the wettest. The area experiences a temperate climate which changes from tropical conditions in summers to severe cold, depending on the season and the specific altitude. The temperature rarely drops below 0°C, with summer temperatures reaching highs of 43°C and winter temperatures dropping to as low as -0.5°C. The forest benefits from fertile alluvial soil, adequate drainage and plentiful rain, while the mountain areas are used for agriculture.

The tree species used in the experiment was *Tectona grandis* (Teak) which is a large deciduous tree species known for its high-quality timber and is native to the Indian subcontinent, Southeast Asia, and parts of Africa. Teak wood is renowned for its durability, strength, and resistance to decay. It contains natural oils that contribute to its weather-resistant properties, making it highly sought after for various applications, particularly in the construction of furniture, boats, and outdoor structures. The heartwood of teak is typically golden to medium brown, with a straight grain, although it can sometimes be irregular. Teak is often cultivated in managed plantations for its high economic value.

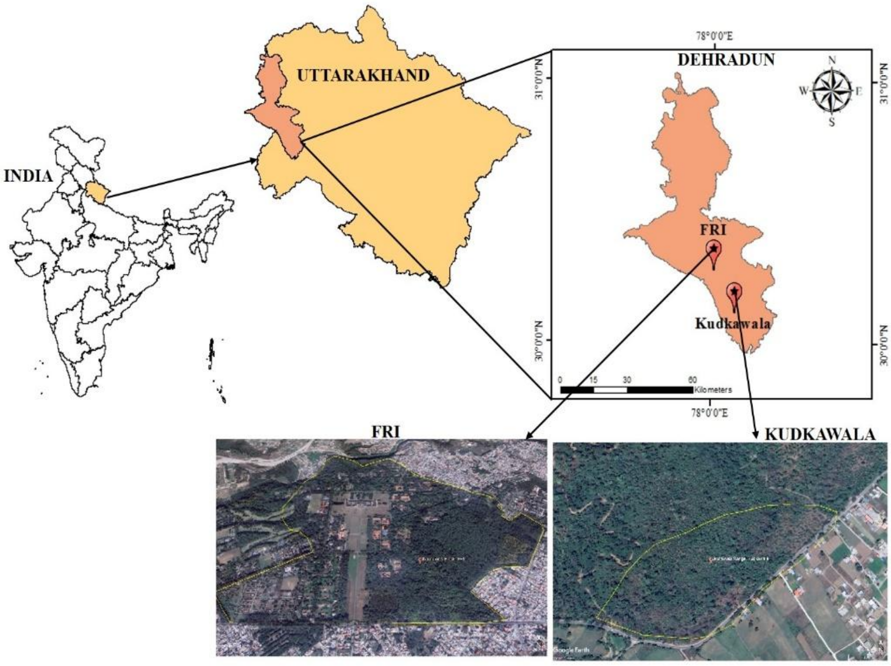

Figure: Location map of study area

Collection of wood samples from standing trees

The collection of wood samples from standing trees was conducted using an increment borer, a widely used tool for extracting cylindrical wood cores with minimal damage to the tree (Baker, 2010). The diameter at breast height (DBH) of the selected trees was measured at 1.3 meters above ground level, following standard forestry protocols (West, 2009). The mean DBH of the sampled trees was 35.45 cm (±16.2 cm) at FRI and 38.08 cm (±8.06 cm) at Kudkawala. Increment cores were extracted by drilling the borer into the tree trunk perpendicular to the growth rings to obtain a core sample extending from the outermost layers to the heartwood. The extracted cores, typically 5–6 mm in diameter, were carefully removed and stored in labelled tubes to prevent physical damage and contamination (Speer, 2010). Each core was marked with essential metadata, including tree species, site location, DBH, and core orientation for accurate reference.

The NIR spectrophotometer and the collection of spectra

Collected specimens were divided into two parts: calibration specimens (70%) and test specimens (30%). The spectra of the test and calibration specimens that had been air-dried were recorded using the FT-NIR spectrophotometer (Brucker, MPA). Cylindrical shape of the cores was flattened using a sharp knife on two points i.e. inner (near pith) and outer (near periphery) to facilitate the spectra recording. The spectra of the increment bores were obtained from the flattened surfaces using a fibre optic module. The spectra wavelength ranged from 780 to 2400 nm, or 4000 to 12820 cm^{-1}. The apparatus functions in the diffuse reflectance mode (resolution: 8 cm^{-1}, detector: Pbs). Four spectra from each point (core/ periphery) were obtained.Each spectra was made up of 32 scans, and the average of all the scans (04 number) was used to create a single average spectrum.

Data processing

The SVM classification model was developed and tested using Unscrambler 10.2 (CAMO Software AS, Oslo, Norway). The absorbance values from the raw data obtained from the NIR equipment were loaded into Unscrambler X software.The algorithm used within The Unscrambler® is based on code developed and released under a modified BSD license by the National Taiwan University (Hsu et al,2003). Three SVM classification models were developed: SVMC model I with inner and outer side of the core spectra combined, SVMC model II with only spectra from inner side of the core, SVMC model III with spectra from outer side of the core.Through grid search option, values of gamma and Nu was obtained for appropriate option of training and validation accuracy, number of support vectors.

SVMC model I with inner and outer spectra combined

Total number of the spectra was 76, out of which 54 (23 Kudkawala and 31 FRI) spectra were used for calibration of the model and remaining 22 (9 Kudkuwala and 13 FRI) used for testing the model. For decision on selection of calibration and test specimen's spectra, specimens 1 and 2 of each class was taken as calibration and specimen 3 as test specimen.

No pre-treatment/ transformation or wave range selection was opted. For the development of SVMC model I, SVM type nu-SVC classifier was used along with the kernel type Radial Basis Function (RBF) with the values 0.01 for Gamma, 0.5 for Nu, weight 1.0 for all specimens and 10 as number of cross validation segments for model development.

SVMC model II with spectra only from inner side of the core

For the development of SVMC model II, total 38 increment core specimens were used. Off these, 26 (15 from FRI and 11 from Pudkuwala) of the core specimens were used for calibration and validation of the model, whereas, 12 core specimens (5 from Kudkawala and 7 from FRI) spectra were used to test the model. Like in model I, no pre-treatment/ transformation was given. SVM type nu-SVC classifier was used along with the kernel type Radial Basis Function (RBF) with the values 0.01 for Gamma, 0.745 for Nu, weight 1.0 for all specimens and 10 as number of cross validation segments for model development.

SVMC model III with spectra from outer side of the core

As described in previous section (model II), the same number of calibration and test specimens were used to develop SVMC model 3 by taking spectra from outer side of the increment cores. Similarly, the spectra were used for the analyses without any pre-processing or transformation. The classifier type nu-SVC was used along with the kernel RDF. Values of gamma, nu and weights were 0.01, 0.255 and 1 respectively.

Testing of the models

All the test specimens of the respective models were imported into the software platform and prediction through model was carried out.

III. Results And Discussion

The NIR spectra

Figure 2 presents FT-NIR spectra taken from the increment cores samples of two locations.

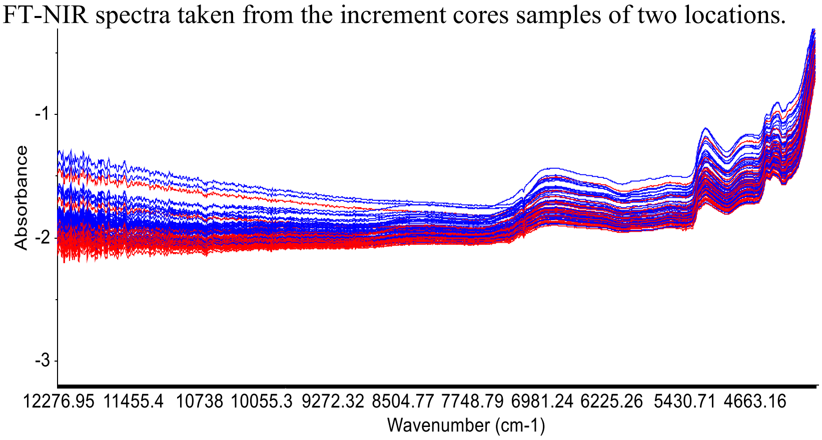

Fig. 2: Raw FT-NIR spectra of the increment borers (red for Kudkawala, and blue for FRI locations

X-axis represents wavenumber (cm⁻¹) ranging from 12,000 cm⁻¹ to 4,000 cm⁻¹. Lower wavenumbers (right side) correspond to longer wavelengths; higher wavenumbers (left) are shorter wavelengths. Y-axis represents absorbance i.e. the amount of NIR light absorbed by the sample. Multiple curves are shown in blue and red, which likely represent different sample groups i.e. red from Kudkawala, and blue from FRI locations. Wavenumbers ~6900–5200 cm⁻¹ are typically associated with first and second overtones of O–H, N–H, and C–H stretching vibrations, while ~5200 cm⁻¹ are a common region for combination bands, particularly involving water or hydroxyl groups. The rising absorbance at lower wavenumbers (right side) might indicate increasing contributions from organic compounds. The difference in red and blue curves suggests sample variation – perhaps due to differences in moisture content and chemical composition.

SVMC model I with inner and outer spectra combined

To obtain a clear picture of the data distribution, PCA was applied to the raw spectral data to show the samples in a well-reduced space (fig.2). According to PCA, the top two components (PC1: 88%, PC2: 10%) account for 98% of the dataset's overall variability. Figure 2 presents a general categorization of the samples based on their geographical origin. It also shows that the samples in each group exhibited comparable qualities related to NIR absorption.

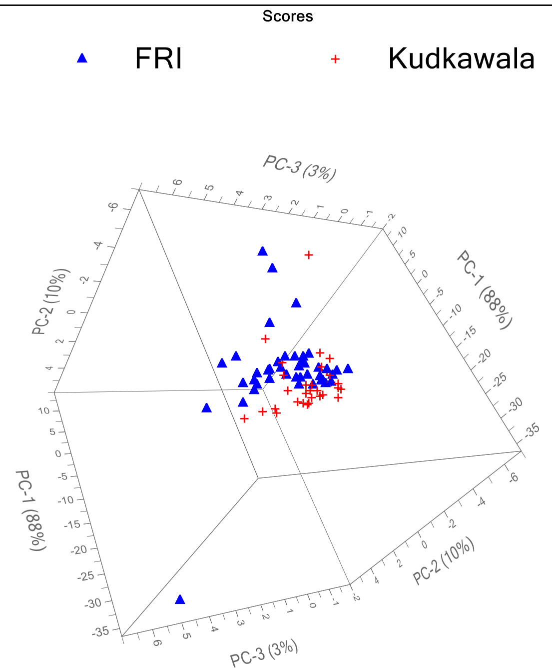

Fig. 2: PC for the two locations

On the other hand, the PCA map reveals that certain individual samples from the two locations showed significant overlap. To discern between Kudkawala and FRI, the first two PCs are adequate.

The training accuracy of the calibration of SVMC model 1 was found to be 87.04% whereas, that of cross validation of the calibration model was 81.48%. Total number of support vectors was 33 out of which 15 were from Kudkawala and 18 were from FRI.

Table 1 presents the prediction results of the cross validation of the calibration model (SVMC model I). Cross validation prediction results show that out of 33 FRI specimens, all 33 were correctly classified. Whereas, for the Kudkawala 22 specimens 15 were correctly classified and 7 were wrongly classified. Out of total 54 specimens, 48 were correctly classified and 7 were found to be classified incorrectly. Thus, 89% of the calibration specimens were correctly classified in cross validation of the model.

Table 1: Cross validation of the calibration model SVMC 1

	Number of specimens used in validation of training the model	Correctly classified	Wrong classified
FRI	33	33	0
Kudkawala	22	15	7
Total	54	48	7

Table 2 presents confusion matrix of SVMC model 1.

Table 2: Confusion matrix of SVMC model 1

	Kudkawala	FRI
Kudkawala	16	0
FRI	7	31

The confusion matrix results show that the model is able to place correctly 31 specimens from FRI, but there are 7 specimens which are placed in overlapping areas between Kudkawala and FRI.

Classification of the test samples using the model

Table 3 presents results of the classification of the test specimens using SVMC model I. The results suggest that out of 13 specimens from FRI, 11 were correctly classified, whereas, 2 specimens were placed in wrong class.

Table 3: Classification of test samples using SVCM model 1

	Number of specimens used in classification	Correctly classified	Wrong classified
FRI	13	11	2
Kudkawala	9	4	5
Total	**22**	**15**	**7**

Out of 9 Kudkawala specimens, only four specimens were classified correctly, while 5 were classified incorrectly. Thus, out of total 22 specimens, 15 were correctly classified and remaining 7 were wrongly classified. This makes correct classification rate to be 68.2%.

SVMC model II with spectra only from inner side of the core

Fig. 3 presents PCs and their score distribution when the spectra of only inner side of the increment cores were taken for the analyses.

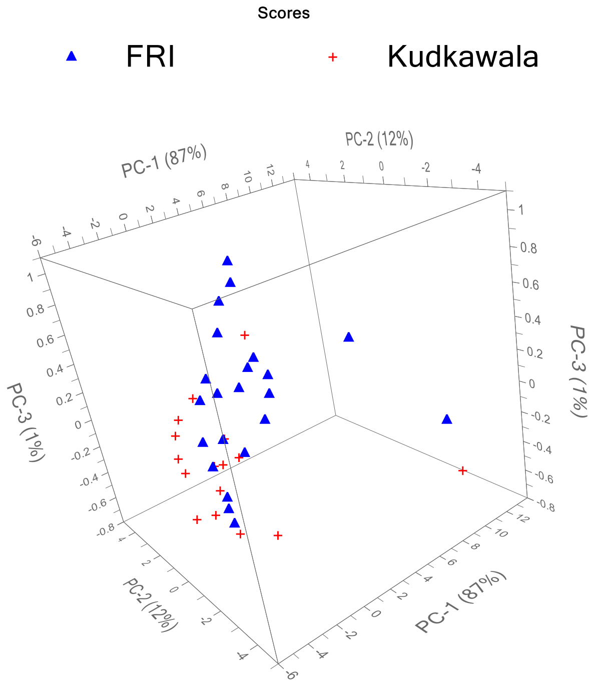

Fig. 3:PC for the two locations

From the Fig. 3, it is evident that the two classes (locations) are roughly separated in the score distribution. There are at least three specimens scores from Kudkawala which are stretched to be placed towards FRI specimens scores, indicating the overlapping. However, top two components i.e. PC1 (87%) and PC2 (12%) contribute towards 99% variability in the data set. Both the PCs appear to be sufficient for classification of the two origins.

However, when the specimen's spectra were used to develop SVM model for the classification, training accuracy and cross validation accuracy were found to be 57.69%. The number of support vectors was found to be 21, out of which 10 of them belonged to Kudkawala, and rest (11) were from FRI specimens.

Table 4 presents cross validation results using calibration specimen's spectra of SVMC II model. Out of total 26 specimens used in cross validation, 15 spectra belonged to FRI and these all (15) were classified correctly. However, as we see for the Kudkawala 11 specimens, all the 11 specimens have wrongly been classified leading to a poor SVM model of classification. Table 4 presents cross validation results of SVMC II model.

Table 4: Cross validation of the calibration model SVMC2

	Number of specimens used invalidation of training the model	Correctly classified	Wrong classified
FRI	15	15	0
Pudkuwala	11	0	11
Total	26	15	11

Overall correct classification % in cross validation was 57.7%. Since, few specimen's PC scores as seen in Fig.3, are sharing same space with FRI specimens scores, SVM model could not classify the specimens correctly.
Table 5 presents confusion matrix of SVMC model II.

Table 5: Confusion matrix of SVMC model 2

Confusion matrix		
	Kudkawala	**FRI**
Kudkawala	0	0
FRI	11	15

The confusion matrix of SVMC II model further strengthens the finding in cross validation of the model. As per the confusion matrix, all the 11 specimens of Kudkawala are put wrongly in class FRI. The SVMC2 model was used to classify 12 unknown test specimens as shown in table 6.

Classification of the test samples using the model
Table 6 presents the results of classification of test specimen using SVMC model II. Out of total 12 test specimens, 7 belonged to FRI, from which 6 specimens were correctly classified and 1 specimen was wrongly put in Pudkuwala class. Out of 5 test specimens from Pudkuwala, 3 specimens were correctly classified, whereas, remaining 2 were put in wrong class. Thus, 9 out of 12 specimens were correctly classified leading to success rate of 75%. This is a significant result as compared to poor cross validation result (57.7%). Even though, the training and cross validation accuracy were lower, the model gave better results in testing of unknown specimens.

Table 6: Classification of test samples using SVCM model 2

	Number of specimens used in classification	Correctly classified	Wrong classified
FRI	7	6	1
Pudkuwala	5	3	2
Total	**12**	**9**	**3**

SVMC model III with spectra from only outer side of the core
Fig. 4 presents scores of first three PCs after carrying out the PCA. PC1 accounted 90% variability in data set, whereas, PC2 and PC3 contributed smaller content (7% and 2%). Ocular observation of the PCs scores spatial distribution suggest that a comparable classification is possible with the data set. Except 2 specimens scores of Kudkawala, rest of the scores are congregated and appear to discern between the locations.

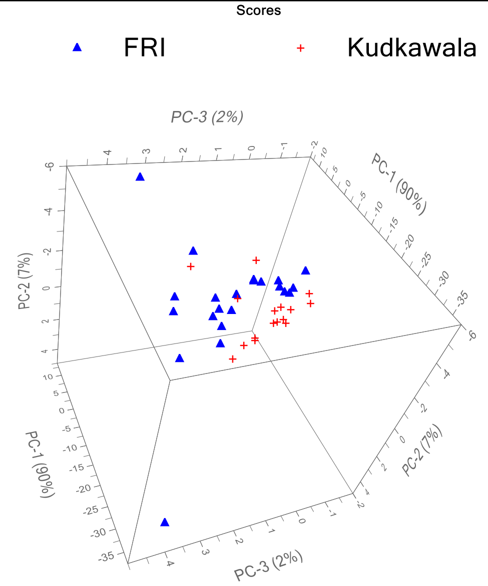

Fig. 4: PC for the two locations

The SVMC model III showed training accuracy of 100%, whereas, cross validation accuracy was 88.46%. As compared with both the previous two models, the results are quite better. Lower number of support vector count in SVMC III (12) as compared with SVMC I(33) and SVMC II (21) indicate that the separation of the classes was clearer.

Table 7 presents results of the cross validation of the model SVMC 3.

Table 7: Cross validation of the calibration model SVMC3

	Number of specimens used invalidation of training the model	Correctly classified	Wrong classified
FRI	15	15	0
Kudkawala	11	11	0
Total	26	26	0

During the cross validation of the calibration model, total 26 calibration specimens were tested, out of which, 15 were from FRI and 11 were from KUdkawala. The cross validation put 100% of the specimens into correct classes as shown in table 7. As compared with SVMC II (57.7%) and SVMC I (89%), the SVMC III model shows significantly higher success rate (100%) in cross validation, indication the superiority of using outer side of the increment core over inner sides for theclassificationof geographical origins. It will be interesting to see how well the model fares in classification of test samples.

Table 8 presents the confusion matrix of model III.

Table 8: Confusion matrix of SVMC model 3

Confusion matrix		
	Kudkawala	**FRI**
Kudkawala	11	0
FRI	0	15

The confusion matrix also supports the results of the cross validation as shown in table 7.

Classification of the test samples using the model

Table 8 presents the results of the classification of test specimens using SVMC III model. Total 12 numbers of the unknown specimens were tested, out of which, 7 were from FRI and 5 were from Kudkawala. As shown in the table 9, total 3 specimens were classified to the wrong classes of FRI (01) and Kudkawala. (02). Rest of the 9 specimens were placed in correct classes leading to a success rate of 75%.

Table 9: Classification of test samples using SVCM model 3

	Number of specimens used inclassification	Correctly classified	Wrong classified
FRI	7	6	1
Kudkawala	5	3	2
Total	**12**	**9**	**3**

As the results indicate, despite of having lower training and cross validation accuracy in SVMC II model (57.7%) as compared with that of SVMC III model (100%), the test results of unknown specimens were the same (75%). Smaller gamma value results in smoother and simple decision boundary. After the grid search, the identical gamma value (0.01) was applied to each model. However, the lower number of the support vectors in SVMC model III (12) as compared with that in SVMC model II (33) indicates that the SVMC model III data set is better in spatial distribution than SVMC model II. Using samples from close to the log's core was recommended by Sierra et al. (2017) for improved findings in these kinds of investigations. Good results of cross validation for SVMC model III (100%) also indicate that the outer side specimen's spectra of the increment core may give better results in classification for the geographical origin of the timbers. However, in order to undertake tests for detecting the geographic origin of a specimen, extensive sample collections that accurately depict the range of populations within a species are necessary for making generalizations about the origin of a timber (Dormontt et al., 2015).

IV. Conclusion

Principal Component Analysis (PCA) of the FT-NIR spectral data revealed that the first two principal components (PC1 and PC2) accounted for approximately 98–99% of the total variance, indicating a strong dimensionality reduction and high explanatory power of the selected components. Three Support Vector Machine Classification (SVMC) models were developed based on different combinations of spectra from the timber core. SVMC models using either inner or outer core spectra outperformed the combined model in classifying unknown timber samples. Model III (outer core) had the best training and validation performance. FT-NIR with SVMC proves effective for timber origin classification.

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