Nondestructive Classification Analysis of Wood Soaked in Seawater by Using Near-Infrared Spectroscopy

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Abstract

Large amounts of construction wood were generated as disaster waste during the 2011 Tōhoku, Japan, earthquake and tsunami. The construction wood waste had been immersed in seawater and thus contained salts. When the saltwater-immersed wood was incinerated during restoration efforts, dioxins harmful to human health were likely produced. Thus, it is necessary to determine if wood waste had been exposed to saltwater before combustion. Furthermore, online recycling of coastal wood debris containing saltwater could be applied to the disposal of industrial wastes. Near-infrared (NIR) spectroscopy was used to distinguish saltwater-immersed wood. Three wood species, *Cryptomeria japonica, Chamaecyparis obtuse,* and *Larix kaempferi,* which are commonly used in the construction of Japanese houses, were prepared. Immersion time was changed from 24 to 72 hours to investigate the time-dependent change. NIR spectra were obtained from wood samples before and after immersion in seawater and were used in classification analysis by soft independent modeling of class analogy (SIMCA). For SIMCA at immersion time of 24 hours, the percentage of correct classification was for 94 percent for *Cryptomeria japonica,* 96 percent for *Chamaecyparis obtuse,* and 92 percent for *Larix kaempferi*. There is no difference in the classification accuracy by the wood species and immersion time. Moreover, another classification analysis (partial least-squares discriminant analysis [PLS-DA]) was performed to raise the classification precision. The result of PLS-DA was superior to SIMCA. NIR was a powerful tool in identifying saltwater-immersed wood samples and indicated the possibility of using it at the wood-recycling factory.

The 2011 Tōhoku earthquake and resulting tsunami off the Pacific Coast of Japan was a large-scale disaster that destroyed numerous public buildings and houses. The total waste generated from the disaster reached 23 million tons in the three hardest-hit prefectures. The waste generated was about 10 times that disposed annually in the respective prefectures, and approximately 50 percent of the disaster waste consisted of construction wood (Japan Ministry of Agriculture, Forestry and Fisheries 2011). In Japan, waste such as construction wood is typically used to fuel incinerators at thermal power plants. However, after the 2011 earthquake and tsunami, a general disposal process was not developed because of the large amount of waste involved. Instead, temporary incinerators were used to facilitate rapid waste disposal. However, the burning capacities of the temporary incinerators were insufficient compared with the incinerators situated at the thermal power plants (Japan Ministry of Agriculture, Forestry and Fisheries 2012).

Construction wood, which constituted most of the disaster waste, was exposed to seawater as a result of the tsunami. The seawater had a salt content of 3 percent, and the salt content (including chloride) was concentrated in the wood during drying (Yamada et al. 2014). Salt permeation and desalination of wood has been investigated in detail in the context of recycling of coastal wood debris (Saito et al. 2011).

The production of dioxins during the burning of seawater-impregnated wood under conditions of low combustion temperatures (400°C to 500°C) or inadequate air availability is cause for concern. Dioxin is a general term for a group of chemical compounds that has strong toxic and mutagenic effects and has been linked to immune suppression in humans (Tame et al. 2007). Detailed discussions of the harmful effects of dioxins can be found in Lavric et al. 2004. Because of the potential for dioxin production, it is vital to determine whether wood has been exposed to saltwater before burning. Near-infrared (NIR) spectroscopy has been the subject of focus as a classification tool. NIR spectroscopy is an increasingly popular technique used in the

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nondestructive evaluation of organic materials and has found widespread use in a variety of industries, including the food, agricultural, pharmaceutical, and forestry sectors. In this report, NIR spectroscopy was applied to differentiate wood that had been immersed in seawater. Three wood species commonly used in Japanese residential and commercial construction were prepared by immersion in seawater at various exposure times (24 to 72 h), and temporal changes were investigated.

Materials and Methods

Wood sample preparation

Three wood species (*Cryptomeria japonica, Chamaecyparis obtusa,* and *Larix kaempferi*) commonly used in the construction of Japanese buildings and that constitute 70 percent of domestic logging were used in this study. The basic constituents of the Japanese softwood samples are summarized at Table 1 (Shimizu 1990) and values are presented as percent total. All wood samples were obtained from the commercial Japanese lumber mill, and a total of 200 wood samples were subjected to measurement. Breakage occurred in several samples as a result of wood expansion during seawater immersion, the effect of knots, or subsequent drying, and these samples were discarded. Thus, the final number of wood samples per measurement condition was less than 200 (Table 2). The measurement data sets were divided into two groups (training set and test set). The training set was used to establish the model for water content prediction and the test set was used for validation. Each wood sample was approximately 150 mm in length, 90 mm in width, and 10 mm in thickness.

NIR measurement

A schematic diagram of the measurement system is presented in Figure 1. To control for the influence of stray light, a blackout curtain was used during the measurement.

Table 1.—Basic constituents of Japanese softwood samples.

Wood species	Ash (%)	Extract with water (%)	Hemicellulose and noncrystalline cellulose (%)	α-Cellulose (%)	Lignin (%)
Cryptomeria japonica	0.81	4.2	21.2	41.1	32.6
Chamaecyparis obtuse	0.48	4.2	20.8	44.8	29.6
Larix kaempferi	0.34	9.5	18.8	43.3	28.0

Table 2.—Outline of wood sample numbers in the training and test sets for each measurement condition.

Wood species	Immersion time in saltwater (h)	Measurement sample (divided into two groups)	
		No. in training set	No. in test set
Cryptomeria japonica	24	140	50
	48	146	50
	72	142	50
Chamaecyparis obtusa	24	117	50
	48	138	50
	72	132	50
Larix kaempferi	24	136	50
	48	138	50
	72	128	50

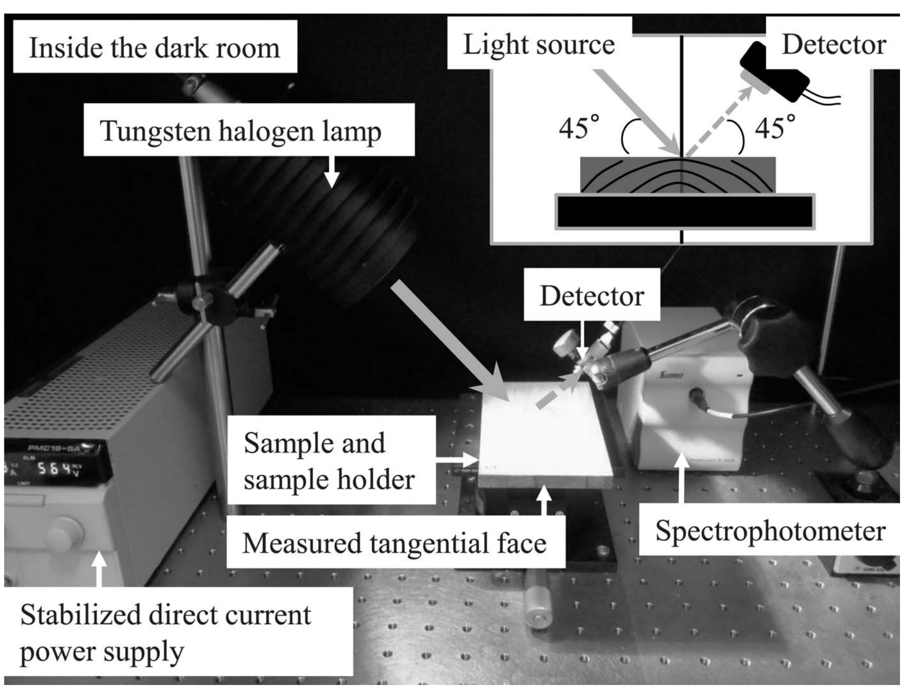

Figure 1.—Schematic diagram of the near-infrared measurement system.

The system consisted of a light-source unit (tungsten halogen lamp and stabilized direct-current power supply), a sample stage, and a spectrophotometer (Fastevert Usb S-2930, Soma Optics Ltd., Tokyo, Japan). The NIR spectra were obtained at 1-nm resolution over the wavelength range from 700 to 1,050 nm.

First, the wood sample was maintained in an air-dried state, and NIR spectra were obtained from the tangential face of the wood sample. Next, the wood sample was immersed in seawater for the specified time. After immersion, the wood sample was oven-dried (105°C, 3 h) and then maintained in an air-dried state (10 days). Seawater was obtained directly from the nearby sea (Sagami Bay, Japan). Finally, NIR spectra were obtained at the same locations on the wood as before immersion. Wood is a highly heterogeneous material with anisotropic properties, and measurement error could have been introduced by varying the measurement position (Fujimoto et al. 2008). Thus, three positions per sample were measured and the spectral results were averaged to decrease the measurement error.

Data processing

Raw NIR spectra often exhibit a baseline shift or drift owing to variations in measurement compared with ideal NIR spectra. Moreover, different factors can affect the spectra, such as instrument stability, temperature, humidity, or the surface condition of the sample (Candolfi et al. 1999). Therefore, data pretreatment is an important step to control for these factors in data analysis. In general, pretreated data results are superior to raw data results because of noise reduction. In this study, the raw data analyses were omitted. Basic pretreatments such as moving average smoothing, multiplicative scatter correction (MSC), and the second derivative are often used to pretreat NIR data. Moving average smoothing eliminates the random noise of NIR spectra. The MSC was used to compensate for both multiplicative and additive effects in the spectra. The second derivative also reduced the multiplicative and additive effects in the spectral data and increased peak amplification in the spectra. Pretreated NIR spectra (moving average smoothing with segment size 13, MSC, and the second derivative) were used for this analysis (Fujimoto et al. 2010). The second derivative spectra were processed using the Norris Gap algorithm with a gap size of 13 (Meza-Marquez et al. 2010).

Classification analysis

Soft independent modeling of class analogy (SIMCA) was used by focusing on similarities within classes. The theory behind SIMCA has been extensively discussed by several authors (Dunn and Wold 1980, Maesschalck et al. 1999, Tominaga 1999). SIMCA is a classification method based on principal component analysis (PCA). PCA involved several calculations utilizing orthogonalization procedures, such as singular-value decomposition, eigenvector calculation with the use of a covariant matrix, nonlinear iterative partial least squares, and successive average orthogonalization (Donahue and Brown 1991, Malinowski 1991, Hasegawa 1999). The estimated spectral data were obtained by PCA with a certain number of optimal principal components (PCs). The estimated data captured only the NIR spectral changes within the measurements. In this work, the appropriate number of PCs was determined by cross-validation (Candolfi et al. 1999). Moreover, two important values (loading and score) were obtained by PCA. The loading identified meaningful variations in the spectral data and suppressed spectra changes due to measurement variation. The scores showed the locations of samples along each model component and detected patterns in the samples (Esbensen et al. 2010). In this article, the percentage of correct classification is shown for the SIMCA result.

Furthermore, another classification analysis (partial least-squares discriminant analysis [PLS-DA]) was performed (Ruth et al. 2010). PLS-DA is a classification method that is based on partial least squares (PLS). PLS for relating response variables and predictors with the smallest optimal latent variables might produce better results compared with the SIMCA method (Galtier et al. 2011). Unscrambler software (version 9.6, Camo Software, Oslo, Norway) was used for spectra pretreatment and quantitative analysis with PCA, SIMCA, and PLS-DA.

Results and Discussion

Figure 2 shows the raw NIR spectra and pretreated spectra of the tangential face of *L. kaempferi* samples before

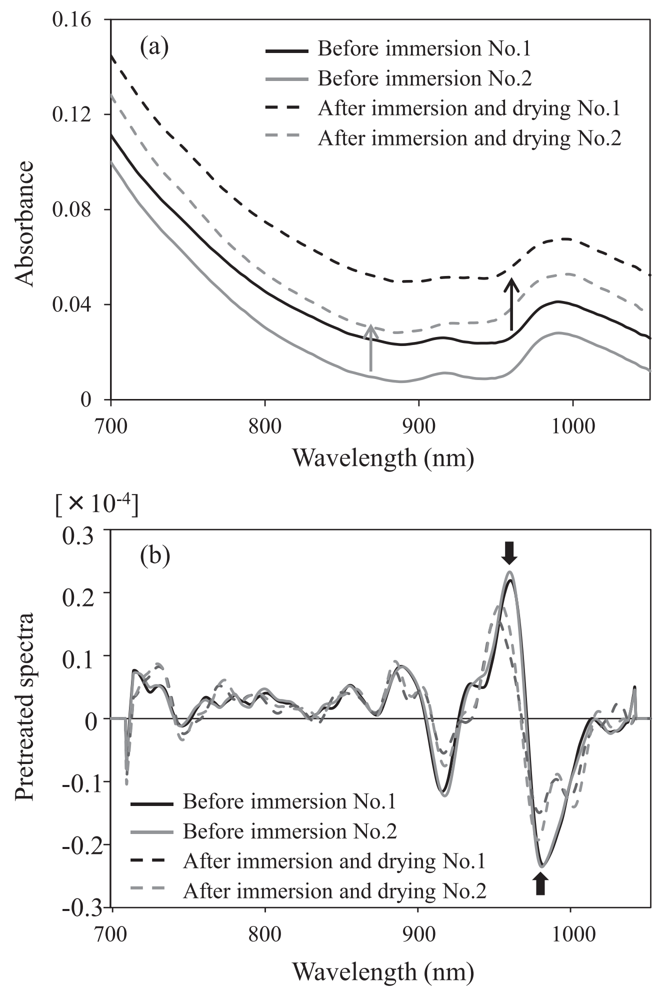

Figure 2.—Near-infrared spectra of Larix kaempferi *from the tangential face in two representative samples: (a) raw spectra, (b) pretreated spectra. Solid line indicates before seawater immersion, and broken line indicates after immersion and subsequent drying.*

and after immersion in seawater. The baseline spectrum after immersion was greater than that of the sample before immersion (Fig. 2a). In Figure 2b, some spectral peaks in the NIR region were observed in the pretreated spectra. It is important to detect water salinity in the NIR region in comparison with the visible region (Pegau et al. 1997). The pretreated data were used in the following analysis.

The PC1 versus PC2 score plot from PCA of training set before and after 24-hour immersion in seawater is shown in Figure 3. The before and after classes were separated along PC2 in all wood species. Figure 4 shows the loading plots of PC1 from PCA before and after immersion of the wood samples in seawater for 24 hours as a representative treatment time. Some peaks were detected around 900 to 1,000 nm. In this region, there is a water absorption band, and the modality of the water hydrogen band has been extensively discussed (Abe et al. 1995).

Table 3 shows the SIMCA classification results for the three wood species at several immersion times. The significance level for SIMCA was 0.05. For SIMCA at the 24-hour immersion time, the percent correct classification was 94 percent for *Cryptomeria japonica,* 96 percent for *Chamaecyparis obtusa,* and 92 percent for *L. kaempferi*. Moreover, Figure 5 indicates the model distance for the before and after immersion classes at 24 hours. The before immersion model with each wood sample was defined as 1. A model distance of greater than 3 indicated models that were significantly different from another model. In the result for *L. kaempferi,* the model distance value after immersion was slightly greater than 3. Thus, a less robust classification was obtained for *L. kaempferi*. Various immersion times (24

Table 3.—Soft independent modeling of class analogy classification results for wood samples at various immersion times.

Wood species	Immersion time in saltwater (h)	No. of principal components	Correct classification (%)
Cryptomeria japonica	24	6	94
	48	6	94
	72	6	92
Chamaecyparis obtusa	24	5	96
	48	5	98
	72	5	96
Larix kaempferi	24	5	92
	48	5	98
	72	5	90

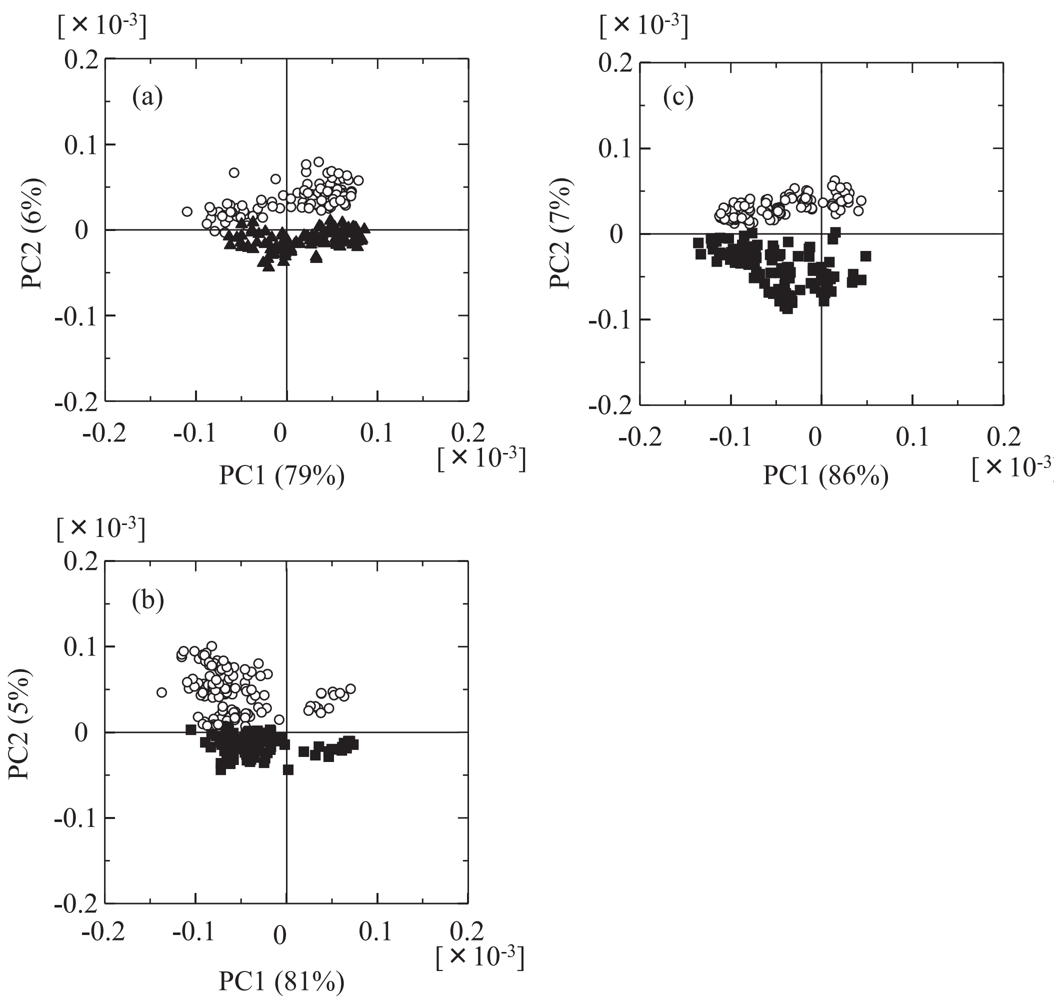

Figure 3.—Principal component 1 (PC1) versus PC2 score plot for before and after 24-hour seawater immersion with (a) Cryptomeria japonica, *(b)* Chamaecyparis obtusa, *and (c)* Larix kaempferi. *Open circle indicates before seawater immersion, and solid square indicates after immersion.*

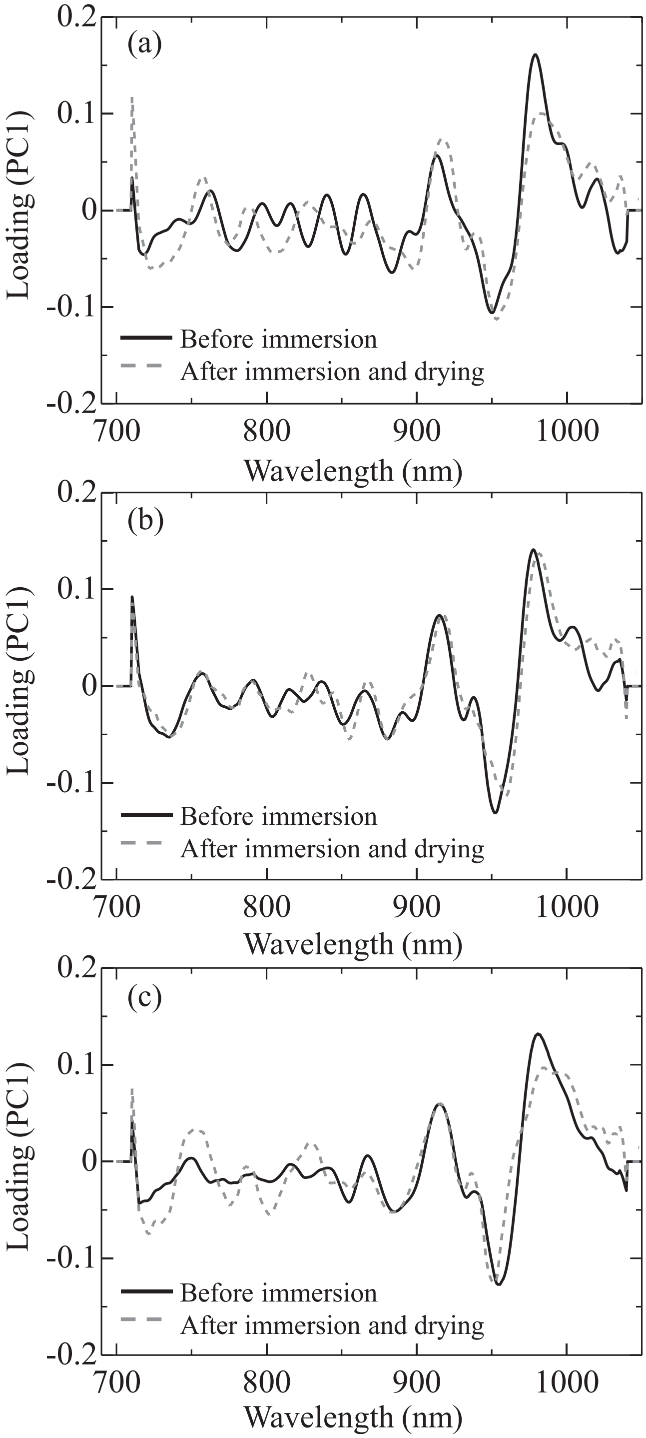

Figure 4.—Loading plot with principal component 1 (PC1) before and after 24-hour immersion: (a) Cryptomeria japonica, *(b)* Chamaecyparis obtusa, *and (c)* Larix kaempferi. *Solid line indicates before seawater immersion, and broken line indicates after immersion.*

to 72 h) were investigated, and it was revealed that immersion time did not affect the classification results. Also, there were no large differences in classification accuracy according to wood species.

The results of PLS-DA are summarized in Table 4. The results were superior to those of SIMCA for all measurement conditions. Although the number of latent variables for the PLS-DA model was greater than the PCs of SIMCA, a more informative PLS-DA model with less error might be obtained. It should be valuable to compare the basic data derived from PLS-DA and SIMCA. In this experiment, some water-soluble components were dissolved into the seawater, which showed a slightly brown coloration. However, as shown in Figure 4, the loading plot of the visible light regions did not change. Some peaks around 900 to 1,000 nm were detected and are depicted in Figure 4. The inorganic salt in the seawater could not be directly measured in the NIR region. The modality of the water hydrogen band might change because of salt formation on the wood surface. Such modality changes in water absorption may be directly detected in the NIR region. Thus, NIR spectroscopy could be used to detect and identify wood immersed in seawater.

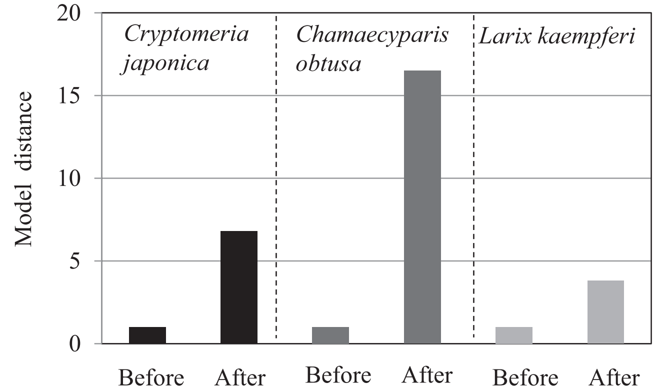

Figure 5.—Model distances of before and after immersion classes.

Table 4.—Partial least-squares discriminant analysis classification results for wood samples at various immersion times.

Wood species	Immersion time in saltwater (h)	No. of latent variables	Correct classification (%)
Cryptomeria japonica	24	7	98
	48	7	98
	72	6	96
Chamaecyparis obtuse	24	6	100
	48	6	100
	72	5	100
Larix kaempferi	24	6	98
	48	6	100
	72	4	98

Conclusions

This study demonstrated that NIR spectroscopy could be used to classify whether wood has been immersed in seawater. Various seawater immersion times were used and the results for three wood species that are commonly used in Japanese construction were compared. Both SIMCA and PLS-DA were performed as classification analyses, and good classification results were obtained. The PLS-DA results were superior to those of SIMCA in all wood species. However, neither the wood species nor the immersion time affected the classification results. Thus, detection results could be obtained after immersion times of less than 24 hours. NIR spectroscopy represents a powerful, nondestructive technique for the identification of wood exposed to seawater (e.g., disaster waste and driftwood) during line sorting at waste disposal sites.

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