



Application of near-infrared spectroscopy to agriculture and forestry

Satoru Tsuchikawa¹ · Te Ma¹ · Tetsuya Inagaki¹

Received: 29 November 2021 / Accepted: 3 March 2022 / Published online: 26 March 2022
© The Author(s), under exclusive licence to The Japan Society for Analytical Chemistry 2022

Abstract

Depending on the uniformity of the quality attribute within agricultural products, there is often a need to develop non-destructive and efficient evaluation methods to assure their qualities. Near-infrared spectroscopy (NIRS) is a well-suited method to characterize organic compounds, particularly when coupled with multivariate analysis methods. This review article introduces scientific and technical reports using the NIRS to evaluate food, agriculture, and forest products. Overall, basic spectroscopic research is continuously progressing; indeed, in combination with big-data information technology and spectral imaging techniques, material analysis is improving to maximize performance. Portable and low-cost devices have also been designed and produced, enabling remote analysis. Future advancements are expected to result in its applications in even more fields for online or at-line quality monitoring.

Keywords Near-infrared spectroscopy · Food agriculture and forest products · Non-destructive quality evaluation · Quality mapping · Portable design

Introduction

Near-infrared spectroscopy (NIRS), in terms of reflected or transmitted absorbance of electromagnetic energy in the range 800–2500 nm, has been studied for the non-destructive measurement of organic materials such as foods, agricultural products, and forest products.

Figure 1 shows the NIR spectra of apple, chocolate, kiwifruit, spinach, and wood. The NIR absorption is attributed mainly to overtones and combinations of vibrational bands involving C–H, O–H, and N–H in the infrared (IR) region. The weaker absorption of NIR energy, compared to the IR region, leads to the measurement of high density and concentration organic materials non-destructively. Since the molar absorptivity of water in the NIR range is 1/1000–1/10000 compared to that in the IR region, it is also useful for high water content samples, such as fruits. However, as the overtones or combinations of fundamental vibrations multiply and are, therefore, overlapped in the NIR range, measured spectra are “opaque information”.

Chemometrics is a term applied to the generic discipline involving computational mathematics to derive meaningful information from the measured spectra. It utilizes multivariate techniques to calibrate the NIR spectra with reference data that obtained through traditional standard methods. The commonly used chemometric methods for the analysis of NIR spectra include, mathematical pretreatments, classification methods (e.g., soft independent modelling by class analogy) [1], and regression methods (e.g., partial least squares (PLS) regression analysis) [2]. Review papers concerning chemometrics have been written by Lavine [3], and Roggo et al. [4].

Karl Norris, who was an agro-industrial researcher at the United States Department of Agriculture, discovered the usefulness of the NIRS in the 1960s. [5] In 1975, Phil Williams utilized NIRS to determine protein in wheat instead of conventional Kjeldahl testing method [6], which was the first-ever industrial application. Since then, NIRS has rapidly extended to cover a broad scope of agriculture products as a rapid and non-destructive quality control tool [7, 8]. In the case of forest products, Brikett and Gambino investigated NIRS to evaluate Kappa number over 30 years ago [9]. This method has demonstrated a marked improvement, as it is also suitable for high moisture samples. Although only overtones and combination tones in relation to the stretching of C–H, O–H, and N–H bonds absorb are mainly observed in

✉ Satoru Tsuchikawa
st3842@agr.nagoya-u.ac.jp

¹ Graduate School of Bioagricultural Sciences, Nagoya University, Furo-Cho, Chikusa, Nagoya 464-8601, Japan

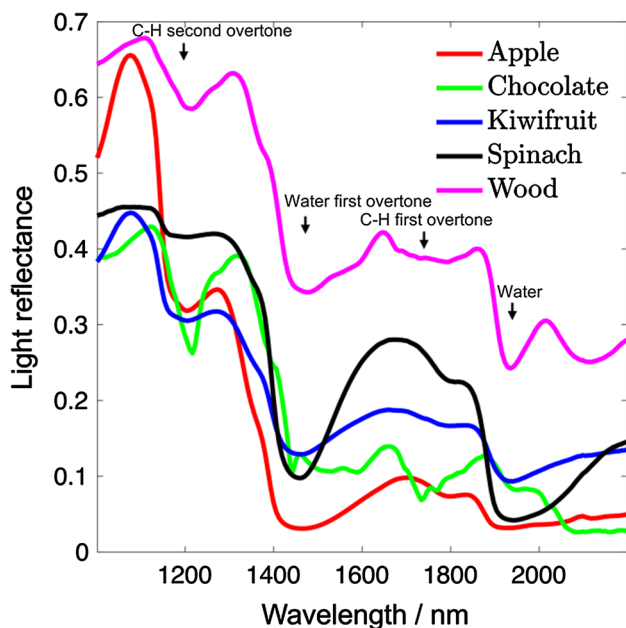


Fig. 1 NIR spectra of different agricultural products

the NIR region, calibration models could also be developed to predict the physical, mechanical, and anatomical properties of wood materials [10–12]. With the development of powerful computers and data analysis tools, the application of quality monitoring and quality control, as much as is practical, is desired as the next step. This review will briefly discuss quantitative and qualitative NIRS to food, agriculture, and forest products.

Food and agriculture products

Cereals and cereal products

Cereals are the most important agricultural crops worldwide and provide more than half of the dietary calorific intake [13]. The approach of NIRS has successfully been developed to predict protein and water content in wheat decades ago [14, 15]. Since then, it has been characterized by rapid development from the prediction of major constituents to the prediction of functional properties, such as fiber added to semolina [16], talc content [17], and texture properties of cooked cereals [19]. It can help to meet the requirements of the intended purposes, such as the production of pasta, bread, and cookies. Thanks to the development of NIRS approaches, cereal quality control can be rendered more efficient compared to traditional chemistry methods [18, 20]. However, the conventional NIR approach has the difficulty on the quantity evaluation of small cereals all individually. Additionally, the calibration

accuracy is affected by the non-uniform quality attributes within cereal products. In contrast, NIR hyperspectral imaging (HSI) provides an NIR spectral image at each wavelength and enables quality evaluation across an entire surface. Recently, Mahesh et al. utilized the NIR–HSI for the prediction of protein and hardness of Canadian wheat [23]. Sun et al. evaluated the HSI for rapid identification of rice origin [25]. It is expected that the HSI method will be increasingly adopted in this field.

Meat and meat products

The first NIRS models were developed to determine the intramuscular fat and MC in meat [18]. Nowadays, NIRS instruments are well designed for various meat products taking into prediction of their various physico-chemical properties [21]. The sensory characteristics have also been considered, both intramuscular fat and water content seem to be useful in calibration model construction [22]. One of the recent new areas for investigation has been the assessment of minced beef adulteration [24, 26]. More recently, a new NIR-based classification method of turkey meat products was also reported [27]. For the traditional “point” spectral measurement, it is important to provide a homogeneous sample, as well as to be consistent between spectral data collections. In contrast, ElMasry et al. utilized HSI method to successfully assess the quality of cooked turkey hams [28], and the major constituents (water, fat, and protein) in beef [29]. Ropodi et al. used multispectral imaging coupled with a two-step support vector machines for the detection of beef adulteration with horsemeat, approximately 95% classification accuracy was achieved for independent validation [30]. Such spectral imaging approaches are more powerful to evaluate the heterogeneous characteristics of meat products.

Fish and fish products

Fish freshness and microbial spoilage are essential quality characteristics due to their highly perishable nature. Researchers have presented evidence that NIRS can quantify moisture, fat, and free fatty acids in fish [31]. It is of particular importance to sell frozen and thawed fish with a guarantee of freshness. Reis et al. demonstrated the ability of NIRS in the quality control of frozen-then-thawed tuna samples [32]. Cascant et al. reported the NIRS coupled with PLS regression analysis can be used to predict triglycerides, free fatty acids, and diglycerides in salmon oil [33]. O'Brien et al. demonstrated a miniature handheld NIR device in fish authenticity studies, proving the added advantage of its onsite analysis [35].

Milk and milk products

Milk is a highly scattering medium that contains casein micelles and fat globules [36]. Thus, NIRS had initially only been used on milk powders, typically the detection of melamine [37, 38]. Melamine gives a false indication of increased protein content. Since it is harmful to health [39], sensitive method is essential to detect the presence of melamine. However, with the development of powerful hardware and chemometrics, NIRS is more widely evaluated for the quality control of various dairy products, such as cheese, liquid milk, and ice cream. Generally, it has been used to estimate the contents of moisture, fat, and protein. [16, 40, 41].

Tea, coffee, and alcoholic beverages

NIRS is also has application in functional food and bioactive ingredients, such as quantifying bioactive compounds within tea [42], and rapid geographical origin classification of roast green tea [43]. Correia et al. (2018) used a handheld device to grade Arabica coffee and detect the presence of sticks, maize, and Robusta coffee [44]. The quality analysis of wine is another hot topic in the NIR field, and many previous studies have been reported on the successful prediction of total acid, total sugar, and alcohol [45–47]. NIRS also has been developed for process control in beer production, with the main application is being selection of the best barley varieties to produce high-quality malt [48].

Soil

Soil is a fundamental natural resource for food and energy production [47]. NIRS also has been well evaluated for soil analysis [46]. Hutengs et al. compared the performance of a portable NIR device to that of mid-infrared device in assessing organic carbon in soils [51]. Another application is to use the NIRS to detect microplastics (i.e., persistent contaminants) in soil. The microplastics come mainly from mulching film, sludge, wastewater irrigation, and atmospheric deposition that influence soil physio-chemistry and biota [52]. Soil components which were estimated by a NIR sensor built into a tractor [54]. Such application can easily visualize the soil quality characteristics from hundreds of areas in farmlands [55]. Such cooperation will be more effective for fertilization management and understanding farmland characteristics. With the visible-NIR HSI techniques, global soil quality mapping and monitoring is undergoing a rapid development, supporting for a more sustainable use of soil resources [56].

Fruit and vegetables

Since the beginning of the twentieth century, NIRS has been comprehensively evaluated as non-destructive technique to rapidly and cost-effectively assess the quality of fruit and vegetables. [57, 58] Some authors have reported using NIRS to determine soluble solids content (SSC), polyphenols, vitamin C, acidity, and firmness in apple with sufficient reliability [59–61]. Marques et al. measured SSC and dry matter in mango fruits during ripening using a handheld device (950–1650 nm), results show that approximately 7.4 mm into the fruit tissue could be evaluated [62]. Yang et al. calibrated the NIR-HSI to evaluate the nitrate contents (NC) in spinach effectively (*Spinacia oleracea* L.) leaves. The mapping results display their distribution in the petiole, vein, and blade. Finally, the mapping results could also visualize the dynamic changes of the NC under different storage conditions [63]. Ma et al. successfully mapped the SSC in apple at a high spatial resolution using the same NIR-HSI approach. The key wavelengths were selected to improve the stability of the prediction model and reduce the time required for data analysis [64]. The same team also mapped the SSC and pH in kiwifruit by an object rotation approach. The mapping results showed a distinct spatial distribution of their values in each sample (Fig. 2) [65]. Several of the existing models in the field conditions have been restricted in applicability due to the large instrument size and low robustness. The development of NIR spectrometers and data acquisition strategies have significantly reduced the size and cost of these instruments. Recently, a novel multifiber-based spectra measurement system was designed and evaluated for the firmness prediction of apples. The experimental results showed remarkably accurate predictions without using complex and time-consuming data analysis algorithms [66].

Information and communication technology (ICT) in agriculture

Information and communication technology (ICT) has a significant effect on equipment management and data transfer, dramatically expanding the applications of NIRS. There is a notable advantage in connecting the NIR network to the internet [67]. Taira et al. utilized a NIR network system to assist sugarcane quality evaluation [68]. The data analysis result was used for fertilization. NIRS has also received significant attention in the application of unmanned aerial vehicle (UAV). The utilization of a UAV is a potential approach to explore desired crop parameters. A sugarcane monitoring platform was established in Thailand, including the applications of UAV and multispectral cameras. It is operated with a customizable flight planner and analysis software for visualizing the quantity and quality of sugarcane in fields. It enables monitoring of yield,

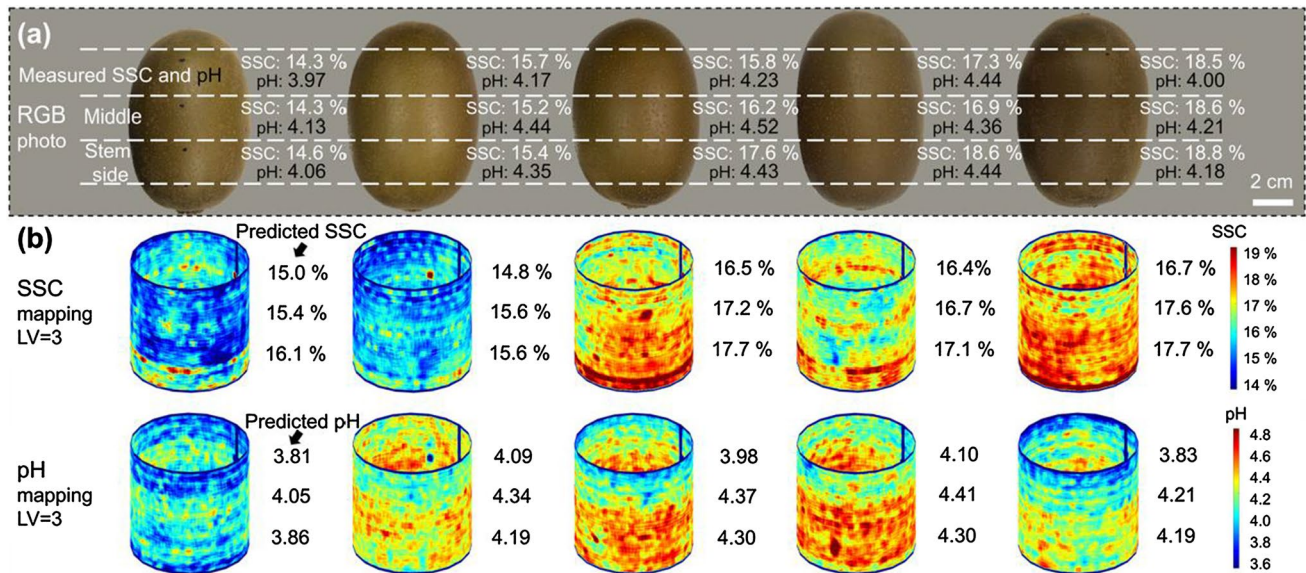


Fig. 2 Kiwifruit (a) RGB photos (b) SSC and pH mapping results

Brix, fertilizer requirement, and white leaf disease spots. The yield of cane was predicted using a density-adjusted digital surface volume with coefficient of determination (R^2) of 0.75. The Brix was predicted by an optimum vegetation index involving pre-processing, resulting a calibration with an R^2 of 0.91 [69, 70]. NIRS coupled with the ICT is promising for optimizing limited natural resources and positively supporting smart farming.

Forest products

Chemical composition

Wood is a heterogeneous matrix that suffers from poor dimensional stability and suffers from swelling, shrinking, and twisting. Non-destructive evaluation methods are needed to reduce the uncertainties in quality. Many researchers have proposed and developed various NIR-based approaches. Except for the main chemical components: cellulose, hemicellulose, and lignin, wood also contains extractives that play an essential role in protecting the living tree and wood products [71]. Da Silva et al. showed that NIRS is useful to evaluate the total phenolic compounds and the extractive contents of mahogany wood [72]. Lepoittevin et al. reported that the extractives should be previously removed to construct more robust prediction model of wood chemistry traits [73]. Üner et al. calibrated the NIR spectra to the extractive content and lignin content of Turkish pine trees [74], where the standard error of calibration and validation ranged between 0.35 and 2.40%.

Moisture content

Since the NIR spectra include rich absorption information of moisture, a number of studies have been carried out using NIRS to predict moisture content (MC) in wood samples. Watanabe et al. evaluated NIRS to sort green timbers based on MC [75]. They pointed out that NIRS can estimate the average MC of green timber, although it only measures the sub-surface area. Due to the limitation of penetration depth, Tham et al. tested the approach using NIRS coupled with a capacitance sensor to predict MC in wood samples with various thicknesses and wood species. The accuracy was $R^2 = 0.80$, root mean square error of cross-validation (RMSECV) 25.70%, and performance to deviation (RPD) 2.22 from greenwood to totally dried conditions. It suggests that NIRS can be assisted by other techniques with higher transmission abilities when measuring timber and lumber woods [76].

Density and wooden anatomical features

Density measurement is important to estimate wood properties, such as strength and stiffness. Previous studies indicated NIRS is useful to predict wood density indirectly via the relationship between density and the light absorption caused by the wood chemical components. Alves et al. successfully calibrated wood density reference values measured by X-ray to NIR spectra for the species of Hybrid larch and Maritime pine. [77] Fujimoto et al. indicated the prediction of wood density with few effects from MC. From PLS regression coefficients, the absorption bands of 7000 cm^{-1} , 7160 cm^{-1} , and 7320 cm^{-1} contributed a lot in predicting wood density

[78]. Hans et al. evaluated time-of-flight NIRS for the density prediction based on the light scattering information in sample [79]. Ma et al. used a NIR imaging camera to catch the light scattering patterns on the wood surface illuminated by a spot light, namely spatially resolved spectroscopy (SRS). Wood density could be predicted using the estimated light absorption and scattering coefficients by a steady-state diffusion theory [80]. Ma et al. further constructed density calibration models using NIR-HSI imaging using density from the SilviScan analysis system [81]. Wood density was successfully mapped at a spatial resolution of 156 $\mu\text{m}/\text{pixel}$ (Fig. 3) [10]. Isik et al. have built the prediction models for air-dry density, MFA, modulus of elasticity (MOE), cell wall thickness, and coarseness of Loblolly pine [82].

Mechanical properties

The mechanical properties could also be predicted well using the NIRS combined with chemometrics. Horvath et al. evaluated NIRS to predict the green mechanical properties of transgenic and wild-type aspen [83]. A good prediction accuracy ($R^2=0.78$) was achieved in the prediction of green MOE. Additionally, there was a strong correlation ($R^2=0.91$) between green ultimate compression strength and NIR spectra. Kothiyal et al. investigated the estimation of specific gravity and mechanical properties for Eucalyptus by NIRS under a wide MC range [84]. Scimleck et al. constructed the calibration models of MOE, modulus of rupture (MOR), and density together using NIR spectra collected from the transverse surface of Pernambuco blocks [85]. Kobori et al. and Sofianto et al. tested acquisition of NIR spectra from Hinoki [86] and Sugi [87] lumbers at a feed rate of 120 m min^{-1} to assess their effectiveness. Sufficient prediction accuracy was achieved with PLS analysis, although the Sugi lumber

samples had more knots, which affected the robustness of spectra collection.

Wood modification and degradation

Wood modification and degradation have been well studied by NIRS. Green et al. used NIRS to monitor the wood degradation in pine sapwood wafers [88]. They illustrated that the early stages of wood decay could be predicted well, as well as the levels of white-rot degradation in Cottonwood [89]. Jones et al. evaluated NIRS to predict the natural durability of the heartwood of coast Redwood [90]. Inagaki et al. collected NIR reflectance spectra from wood samples thermally treated at 90, 120, 150, and 180 $^{\circ}\text{C}$ in an air-circulating oven for periods ranging from 5 min to approximately 1.4 years. Principal component scores coupled with kinetic analysis could be utilized to understand the chemical changes in thermally treated wood samples [91].

Pulp and paper

NIRS research on pulp and paper has a long tradition. Downes et al. evaluated NIRS to predict radial variation in Kraft pulp yield and cellulose content in Eucalyptus wood [92]. Meder et al. performed a non-destructive prediction of Kraft pulp yield from increment cores using NIRS [93]. Tyson et al. constructed NIR calibration models for evaluating the eucalyptus pulp properties of mill-line origin [94]. Yonenobu et al. utilized NIRS to investigate the chemical conditions of literally “Japanese paper”, the obtained results were consistent well with conventional sugar analysis [95].

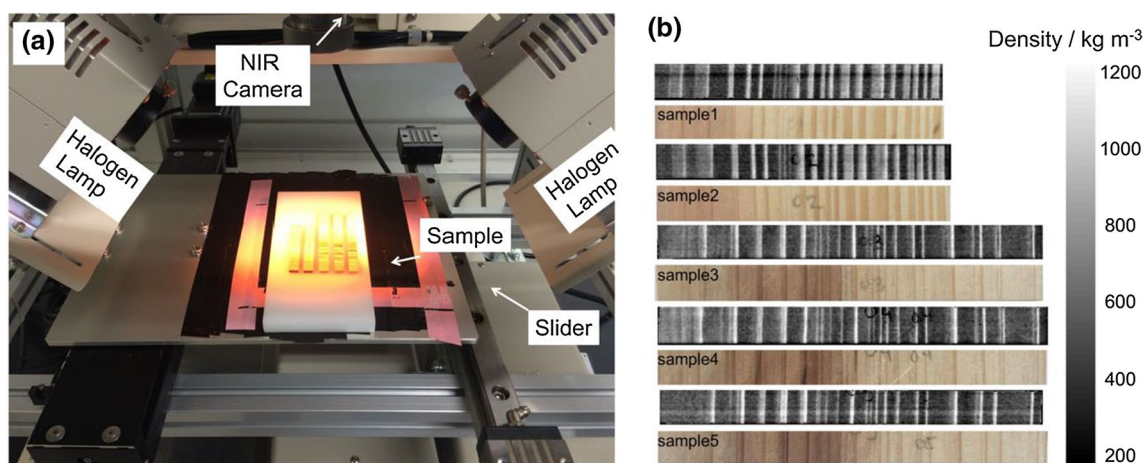


Fig. 3 a NIR-HSI system, b Wood density mapping results

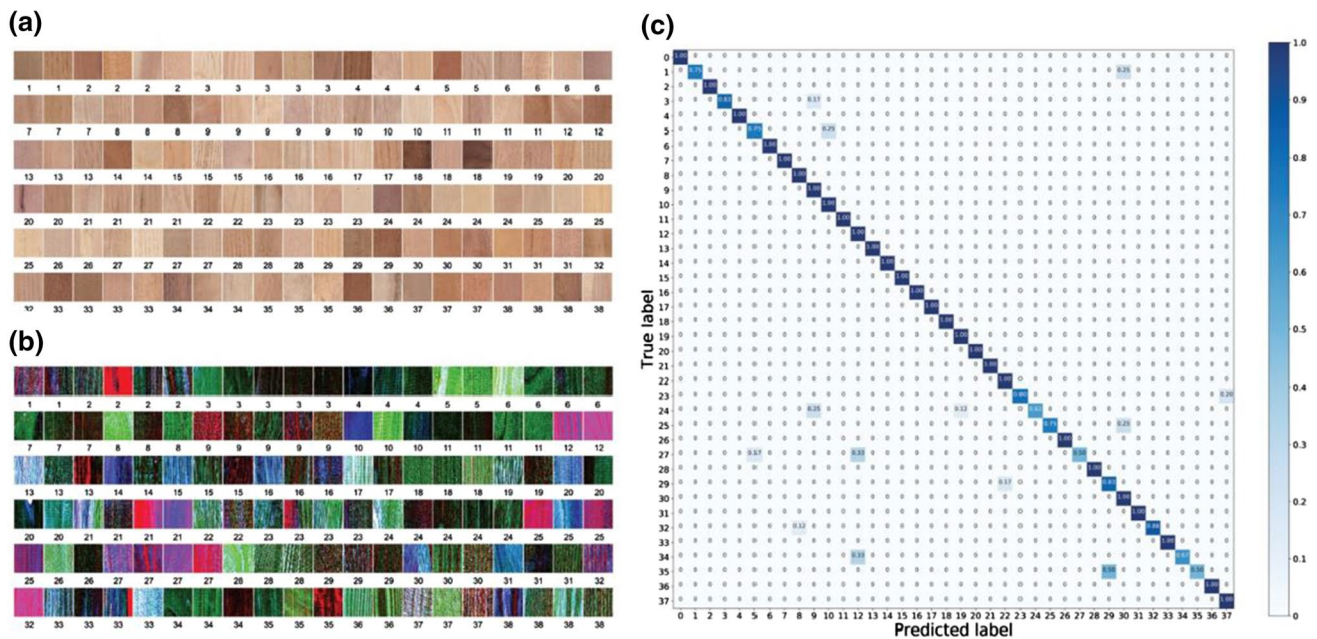


Fig. 4 Wood images generated by (a) digital and (b) NIR-HSI camera, respectively. **c** The classification result of 38 hardwood species

Classification

Conventional wood classification methods based on macroscopic characteristics are time-consuming and require in-depth training in wood histology and anatomy systematics [96]. Due to the high diversity of species, rapid and non-destructive method for wood identification is needed in the modern timber trade. Some investigators have investigated whether NIRS is useful for classification purposes. Batista et al. tested the wood classification using NIRS [97]. The discriminant models showed high accuracy for each species. Abe et al. compared the spectral data between softwood species and indicated that light-transmitting properties inside wood might be used for wood species classification with advanced measurement systems [98]. Recently, Ma et al. evaluated the light scattering characteristics in 15 wood species by Visible-NIR SRS and utilized the light scattering patterns for wood species classification [99]. Kanayama et al. (2019) tested a deep convolutional neural network approach to study the NIR-HSI data of 38 hardwood species. The classification accuracy was 90.5% using 6 PC scores, which was much higher than that of 56.0% obtained with RGB images (Fig. 4) [100].

Conclusion

Due to its distinctive simplicity, speed, and accuracy, NIRS is preferred over the food and beverage industries as a prominent analytical tool, especially for quality control purposes.

With the development of spectral imaging techniques, the capabilities of NIR instrumentation are continually improving to maximize its performance. Additionally, small handheld instruments are getting more affordable. Future advancements are expected to result in applications in more fields for online or at-line quality monitoring.

References

1. S. Wold, *Pattern Recognit.* **8**, 127 (1976)
2. H. Martens, T. Naes, *Multivariate calibration* (John Wiley & Sons, Hoboken, 1992)
3. B.K. Lavine, *Anal. Chem.* **72**, 91 (2000)
4. Y. Roggo, P. Chalus, L. Maurer, C. Lema-Martinez, A. Edmond, N. Jent, *J. Pharm. Biomed. Anal.* **44**, 683 (2007)
5. K.H. Norris, W.L. Butler, *Ire Trans. Biomed. Electron.* **8**, 153 (1961)
6. P. Williams, M. Manley, J. Antoniszyn, *Near infrared technology: getting the best out of light* (African Sun Media, Stellenbosch, 2019)
7. T. Woodcock, G. Downey, C.P. O'Donnell, *J. Near Infrared Spectrosc.* **16**, 1 (2008)
8. M. Manley, *Chem. Soc. Rev.* **43**, 8200 (2014)
9. M.D. Birkett, M.J.T. Gambino, *Tappi J.* **72**, 193 (1989)
10. T. Ma, T. Inagaki, S. Tsuchikawa, *Holzforchung* **71**, 341 (2017)
11. A. Alves, A. Hevia, R. Simões, J. Majada, R. Alia, J. Rodrigues, *Wood Sci. Technol.* **54**, 1151 (2020)
12. I.A.D. Sofianto, T. Inagaki, T. Ma, S. Tsuchikawa, *Holzforchung* **73**, 259 (2019)
13. J.M. Awika, *Advances in cereal science: implications to food processing and health promotion* (ACS Publications, Washington, 2011)
14. G. Downey, S. Byrne, *Irish J. Food Sci. Technol.* **7**, 135 (1983)

15. P.C. Williams, S.G. Stevenson, P.M. Starkey, G.C. Hawtin, J. Sci. Food Agric. **29**, 285 (1978)
16. F.A. Silaghi, A. Giunchi, A. Fabbri, L. Ragni, Bull. Univ. Agric. Sci. Vet. Med. Cluj-Napoca. Agric. **66**, 1843 (2009)
17. Y.I. Liu, L. Sun, Z. Ran, X. Pan, S. Zhou, S. Liu, J. Food Prot. **82**, 1655 (2019)
18. M. Pojić, J. Mastilović, and N. Majcen, *Infrared Spectrosc. Biomed. Sci. Theophanides, T.(ed.), Rijeka, Croat. Intech Publ., 2012, 167.*
19. J. Hu, Z. Wang, Y. Wu, Y. Liu, J. Ouyang, Infrared Phys. Technol. **94**, 165 (2018)
20. Y. Ozaki, A.A. Christy, W.F. McClure, *Near-infrared spectroscopy in food science and technology* (John Wiley & Sons, Hoboken, 2006)
21. Y. Dixit, M.P. Casado-Gavaldà, R. Cama-Moncunill, X. Cama-Moncunill, M. Markiewicz-Keszycka, P.J. Cullen, C. Sullivan, Compr. Rev. Food Sci. Food Saf. **16**, 1172 (2017)
22. S. Andrés, I. Murray, E.A. Navajas, A.V. Fisher, N.R. Lambé, L. Bünger, Meat Sci. **76**, 509 (2007)
23. S. Mahesh, D.S. Jayas, J. Paliwal, N.D.G. White, Food Bio-process Technol. **8**, 31 (2015)
24. C. Alamprese, M. Casale, N. Sinelli, S. Lanteri, E. Casiraghi, LWT-food. Sci. Technol. **53**, 225 (2013)
25. J. Sun, X. Lu, H. Mao, X. Jin, X. Wu, J. Food Process Eng. **40**, e12297 (2017)
26. A. Rady, A. Adedeji, Meat Sci. **136**, 59 (2018)
27. D.F. Barbin, A.T. Badaro, D.C.B. Honorato, E.Y. Ida, M. Shimokomaki, Food Control **107**, 106816 (2020)
28. G. Elmasry, A. Iqbal, D.W. Sun, P. Allen, P. Ward, J. Food Eng. **103**, 333 (2011)
29. G. ElMasry, D.W. Sun, P. Allen, J. Food Eng. **117**, 235 (2013)
30. A.I. Ropodi, E.Z. Panagou, G.J.E. Nychas, Food Control **73**, 57 (2017)
31. D. Liu, X.-A. Zeng, D.-W. Sun, Appl. Spectrosc. Rev. **48**, 609 (2013)
32. M.M. Reis, E. Martínez, E. Saitua, R. Rodríguez, I. Pérez, I. Olabarrieta, LWT **78**, 129 (2017)
33. M.M. Cascant, C. Breil, A.S. Fabiano-Tixier, F. Chemat, S. Garrigues, M. de la Guardia, Food Chem. **239**, 865 (2018)
34. N. O'Brien, C.A. Hulse, F. Pfeifer, H.W. Siesler, J. Near Infrared Spectrosc. **21**, 299 (2013)
35. S. Grassi, E. Casiraghi, C. Alamprese, Food Chem. **243**, 382 (2018)
36. D.J. Dahm, J. Near Infrared Spectrosc. **21**, 323 (2013)
37. O. Abbas, B. Lecler, P. Dardenne, V. Baeten, J. Near Infrared Spectrosc. **21**, 183 (2013)
38. E. Domingo, A.A. Tirelli, C.A. Nunes, M.C. Guerreiro, S.M. Pinto, Food Res. Int. **60**, 131 (2014)
39. D. Schoder, *Case studies in food safety and authenticity* (Elsevier, Amsterdam, 2012), p. 309
40. S.E. Holroyd, J. Near Infrared Spectrosc. **21**, 311 (2013)
41. S. Grassi, L. Strani, E. Casiraghi, C. Alamprese, Foods **8**, 405 (2019)
42. C.M. McGoverin, J. Weeranantanaphan, G. Downey, M. Manley, J. Near Infrared Spectrosc. **18**, 87 (2010)
43. Q. Chen, J. Zhao, H. Lin, Spectrochim. Acta Part A Mol. Biomol. Spectrosc. **72**, 845 (2009)
44. R.M. Correia, F. Tosato, E. Domingos, R.R.T. Rodrigues, L.F.M. Aquino, P.R. Filgueiras, V. Lacerda Jr., W. Romão, Talanta **176**, 59 (2018). <https://doi.org/10.1016/j.talanta.2017.08.009>
45. L. Hu, C. Yin, S. Ma, Z. Liu, Spectrochim. Acta Part A Mol. Biomol. Spectrosc. **205**, 574 (2018)
46. J. Véstia, J.M. Barroso, H. Ferreira, L. Gaspar, A.E. Rato, Food Chem. **276**, 71 (2019)
47. M.J. Martelo-Vidal, M. Vázquez, Food Chem. **158**, 28 (2014)
48. V. Sileoni, O. Marconi, G. Perretti, Crit. Rev. Food Sci. Nutr. **55**, 1771 (2015)
49. V. Bellon-Maurel, E. Fernandez-Ahumada, B. Palagos, J.-M. Roger, A. McBratney, TrAC. Trends Anal. Chem. **29**, 1073 (2010)
50. B. Stenberg, R.A. Viscarra Rossel, A.M. Mouazen, J. Wetterlind, *Visible and near infrared spectroscopy in soil science*, 1st edn. (Elsevier Inc., Amsterdam, 2010)
51. C. Hutengs, M. Seidel, F. Oertel, B. Ludwig, M. Vohland, Geoderma **355**, 113900 (2019)
52. S. Piehl, A. Leibner, M.G.J. Löder, R. Dris, C. Bogner, C. Läforsch, Sci. Rep. **8**, 1 (2018)
53. F. Corradini, H. Bartholomeus, E.H. Lwanga, H. Gertsen, V. Geissen, Sci. Total Environ. **650**, 922 (2019)
54. S. Shibusawa, *Handbook of precision agriculture* (CRC Press, Boca Raton, 2006), p. 87
55. M. Kodaira, S. Shibusawa, Geoderma **199**, 64 (2013)
56. S. Chabrilat, E. Ben-Dor, J. Cierniewski, C. Gomez, T. Schmid, B. van Wesemael, Surv. Geophys. **40**, 361 (2019)
57. E. Arendse, O.A. Fawole, L.S. Magwaza, U.L. Opara, J. Food Eng. **217**, 11 (2018)
58. B. Zhang, B. Gu, G. Tian, J. Zhou, J. Huang, Y. Xiong, Trends food Sci. Technol. **81**, 213 (2018)
59. B.M. Nicolaï, K. Beullens, E. Bobelyn, A. Peirs, W. Saeys, K.I. Theron, J. Lammertyn, Postharvest Biol. Technol. **46**, 99 (2007)
60. E. Bobelyn, A.-S. Serban, M. Nicu, J. Lammertyn, B.M. Nicolai, W. Saeys, Postharvest Biol. Technol. **55**, 133 (2010)
61. A. Pissard, J.A. Fernández Pierna, V. Baeten, G. Sinnaeve, G. Lognay, A. Mouteau, P. Dupont, A. Rondia, M. Lateur, J. Sci. Food Agric **93**, 238 (2013)
62. E.J.N. Marques, S.T. de Freitas, M.F. Pimentel, C. Pasquini, Food Chem. **197**, 1207 (2016)
63. H.Y. Yang, T. Inagaki, T. Ma, S. Tsuchikawa, Front. Plant Sci. **8**, 1 (2017)
64. T. Ma, X. Li, T. Inagaki, H. Yang, S. Tsuchikawa, J. Food Eng. **224**, 53 (2018)
65. T. Ma, Y. Xia, T. Inagaki, S. Tsuchikawa, Postharvest Biol. Technol. **174**, 111440 (2021)
66. T. Ma, Y. Xia, T. Inagaki, S. Tsuchikawa, Postharvest Biol. Technol. **173**, 111447 (2021)
67. P. Tillmann, T.-C. Reinhardt, C. Paul, J. Near Infrared Spectrosc. **8**, 101 (2000)
68. E. Taira, M. Ueno, N. Furukawa, A. Tasaki, Y. Komaki, J.-I. Nagai, K. Saengprachatanarug, J. near infrared Spectrosc. **21**, 477 (2013)
69. L. M. Kumar, B. Pavan, P. V Kalyan, N. S. Paul, R. S. Prakruth, and T. Chinnu, in 2014 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), **2014**, IEEE, 1–6.
70. K. Bougot-Robin, J. Paget, S.C. Atkins, J.B. Edel, J. Chem. Educ. **93**, 1232 (2016)
71. A.M.M. Alves, R.F.S. Simões, C.A. Santos, B.M. Potts, J. Rodrigues, M. Schwanninger, J. Near Infrared Spectrosc. **20**, 275 (2012)
72. A.R. Da Silva, T.C.M. Pastore, J.W.B. Braga, F. Davrieux, E.Y.A. Okino, V.T.R. Coradin, J.A.A. Camargos, A.G.S. Do Prado, Holzforchung **67**, 1 (2013)
73. C. Lepoittevin, J.P. Rousseau, A. Guillemain, C. Gauvrit, F. Beson, F. Hubert, D. Da Silva Perez, L. Harvengt, C. Plomion, Ann. For. Sci. **68**, 873 (2011)
74. B. Üner, İ Karaman, H. Tanrıverdi, D. Özdemir, Wood Sci. Technol. **45**, 121 (2011)
75. K. Watanabe, S.D. Mansfield, S. Avramidis, J. Wood Sci. **57**, 288 (2011)
76. V.T.H. Tham, T. Inagaki, S. Tsuchikawa, Wood Sci. Technol. **52**, 115 (2018)

77. A. Alves, A. Santos, P. Rozenberg, L.E. Pâques, J.P. Charpentier, M. Schwanninger, J. Rodrigues, *Wood Sci. Technol.* **46**, 157 (2012)
78. T. Fujimoto, H. Kobori, S. Tsuchikawa, *J. Near Infrared Spectrosc.* **20**, 353 (2012)
79. G. Hans, R. Kitamura, T. Inagaki, B. Leblon, S. Tsuchikawa, *Wood. Mater. Sci. Eng.* **10**, 57 (2015)
80. T. Ma, G. Schajer, T. Inagaki, Z. Pirouz, S. Tsuchikawa, *Holzforchung* **72**, 789 (2018)
81. R. Evans, *Holzforchung* **48**, 168 (1994)
82. F. Isik, C.R. Mora, L.R. Schimleck, *Ann. For. Sci.* **68**, 283 (2011)
83. L. Horvath, I. Peszlen, P. Peralta, S. Kelley, *Wood Sci. Technol.* **45**, 303 (2011)
84. V. Kothiyal, A. Raturi, *Holzforchung* **65**, 757 (2011)
85. L.R. Schimleck, J.L.M. De Matos, O.J.T. Da Silva, G.I.B. Muniz, *J. Near Infrared Spectrosc.* **19**, 411 (2011)
86. H. Kobori, T. Inagaki, T. Fujimoto, T. Okura, S. Tsuchikawa, *Holzforchung* **69**, 329 (2015)
87. I.A. Sofianto, T. Inagaki, K. Kato, M. Itoh, S. Tsuchikawa, *Int. Wood Prod. J.* **8**, 193 (2017)
88. B. Green, P.D. Jones, D.D. Nicholas, L.R. Schimleck, R. Shmulsky, *Wood Sci. Technol.* **45**, 583 (2011)
89. B. Green, P.D. Jones, D.D. Nicholas, L.R. Schimleck, R. Shmulsky, J. Dahlen, *Holzforchung* **66**, 515 (2012)
90. T. Jones, R. Meder, C. Low, D. O'Callahan, C. Chittenden, N. Ebdon, A. Thumm, M. Riddell, *J. Near Infrared Spectrosc.* **19**, 381 (2011)
91. T. Inagaki, Y. Asanuma, S. Tsuchikawa, *J. Wood Sci.* **64**, 6 (2018)
92. G.M. Downes, C.E. Harwood, J. Wiedemann, N. Ebdon, H. Bond, R. Meder, *Can. J. For. Res.* **42**, 1577 (2012)
93. R. Meder, J.T. Brawner, G.M. Downes, N. Ebdon, *J. Near Infrared Spectrosc.* **19**, 421 (2011)
94. J. A. Tyson, L. R. Schimleck, A. M. Aguiar, J. I. Muro Abad, G. D. S. P. Rezende, and O. M. Filho, *J. Near Infrared Spectrosc.*, **2012**, 20, 287
95. H. Yonenobu, S. Tsuchikawa, H. Oda, *J. Near Infrared Spectrosc.* **11**, 407 (2003)
96. C. Lang, F.R.C. Costa, J.L.C. Camargo, F.M. Durgante, A. Vicentini, *PLoS One* **10**, 1 (2015)
97. J.W.B. Braga, T.C.M. Pastore, V.T.R. Coradin, J.A.A. Camargos, A.R. da Silva, *Iawa J.* **32**, 285 (2011)
98. H. Abe, K. Watanabe, A. Ishikawa, S. Noshiro, T. Fujii, M. Iwasa, H. Kaneko, H. Wada, *J. Wood Sci.* **62**, 210 (2016)
99. T. Ma, T. Inagaki, M. Ban, S. Tsuchikawa, *Holzforchung* **73**, 323 (2019)
100. H. Kanayama, T. Ma, S. Tsuchikawa, T. Inagaki, *Analyst* **144**, 6438 (2019)