

SPECTROSCOPY AND CHEMOMETRICS FOR RAPID CLASSIFICATION OF CONSTRUCTION AND DEMOLITION WASTE AS A POTENTIAL APPLICATION IN POST-EARTHQUAKE WASTE MANAGEMENT

Giuseppe Bonifazi ¹, Giuseppe Capobianco ¹, Riccardo Gasbarrone ², Roberta Palmieri ^{1,*} and Silvia Serranti ¹

¹ Department of Chemical Engineering, Materials & Environment (DICMA), Sapienza University of Rome, Via Eudossiana 18, 00184 Roma, Italy

² Research and Service Center for Sustainable Technological Innovation (Ce.R.S.I.Te.S.), Sapienza University of Rome, 04100 Latina, Italy

Article Info:

Received:
26 June 2026
Revised:
10 September 2026
Accepted:
16 September 2026
Available online:
30 September 2026

Keywords:

Construction and demolition waste (C&DW)
European Waste Catalogue (EWC)
Hazardous waste classification
Recycling quality control
Visible-short-wave infrared (Vis-SWIR) spectroscopy
Chemometrics

ABSTRACT

Construction and demolition waste (C&DW, chapter 17 of the European Waste Catalogue: EWC) is highly heterogeneous, and its rapid characterization is important for safe handling, sorting, recycling and appropriate waste management. These challenges become particularly critical in emergency and post-earthquake scenarios, where large quantities of mixed construction materials may be generated and rapidly require preliminary screening and routing. This study proposes a spectroscopy-chemometrics framework based on visible-short-wave infrared (Vis-SWIR, 350–2500 nm) reflectance measurements, acquired with an ASD FieldSpec 4 full-range spectroradiometer, to classify earthquake-generated C&DW according to EWC codes, main material categories and hazard status. Representative samples of major C&DW material groups, including concrete and mortar, bricks and ceramics, natural aggregates, insulation materials and potentially contaminated components, were characterized in reflectance mode and labelled according to their assigned EWC code, material macro-class, and hazardous/non-hazardous status. Partial Least Squares-Discriminant Analysis (PLS-DA) models were developed in hierarchical mode focusing on the binary distinction between pre-defined hazardous and non-hazardous classes and on the classification of EWC codes. The hierarchical PLS-DA approach achieved high prediction accuracy, demonstrating the potential of Vis-SWIR spectroscopy and multivariate analysis as a rapid screening and decision-support tool for C&DW classification and EWC-based sorting, with relevance to post-earthquake waste management.

1. INTRODUCTION

Construction and demolition waste (C&DW) represents one of the largest and most complex waste streams generated worldwide. In many regions, construction and demolition waste (CDW) accounts for a substantial proportion of municipal solid waste, ranging from 30% to 46% (Huang et al., 2018; Wan et al., 2026). Approximately 60% of this waste is generated by residential and commercial construction activities (Huang et al., 2018; Sirimewan et al., 2024).

A commonly cited definition distinguishes between demolition waste, consisting of materials generated from the dismantling of structures, and construction waste, which includes residues arising from construction, renovation, and repair activities in residential, commercial, and infrastructure projects (Chileshe et al., 2019; Tchobanoglous

et al., 1993). Due to the diversity of materials involved and the variability of construction practices, C&DW is inherently heterogeneous and often difficult to characterize accurately. Beyond its substantial volume, this waste stream carries considerable environmental consequences, including the depletion of natural resources, significant greenhouse gas emissions from material extraction and production processes, and the potential release of hazardous substances when materials are mismanaged or improperly disposed of (Sakthibala et al., 2025). Effective waste management could minimize landfill disposal and supports resource recovery, reducing the demand for virgin materials (Chien et al., 2023; Su, 2020). Consequently, improving the characterization and classification of C&DW is a key step toward enhancing recycling efficiency and supporting the transition to a circular economy in the construction sector.



* Corresponding author:
Roberta Palmieri
email: roberta.palmieri@uniroma1.it



To address these challenges, the European Union introduced the Waste Framework Directive 2008/98/EC (WFD), which provides a legislative framework for sustainable waste management (Directive, E.C., 2008) prioritizing prevention, reuse, and recycling ahead of disposal. It sets a target of recovering 70% of non-hazardous C&DW by 2020 and continues to encourage Member States to implement measures such as selective demolition. These practices support the safe removal of hazardous materials, enable higher-quality recycling, and help reduce overall waste generation. The WFD plays a central role in guiding construction and demolition waste management and in promoting more sustainable practices within the construction sector.

C&DW can generally be classified into three main categories (Bonifazi et al., 2025c). The first includes materials that may have value for construction applications, typically consisting of about 40-85% hardened concrete, 10-25% ceramics, and 20-25% bricks and tiles; these fractions can potentially be recycled and reused, for example, as cementitious precursors. The second category comprises easily recyclable materials, such as glass and metals, which usually represent less than 10% of the total waste stream. The third category includes hazardous waste, which may involve items such as lighting equipment, paints, and coatings, and in some cases, asbestos-containing materials (ACM) (Osmani, 2011); (Radica et al., 2024). Beyond conventional C&DW streams, increasing attention has recently been devoted to debris generated by earthquakes and other natural disasters. Post-seismic C&DW often consists of a highly heterogeneous mixture of structural materials, damaged building components, and potentially hazardous substances released during building collapse (Bonifazi et al., 2026). As a result, this waste stream poses significant challenges for rapid classification, safe handling, and efficient recycling, owing to both its compositional variability and the emergency conditions under which it is typically managed (Bonifazi et al., 2025a). Among the hazardous constituents that may be encountered, particular concern is associated with anthropogenic asbestos-containing materials, which, although banned in most countries, are still produced and used in some regions (Bonifazi et al., 2025b).

Proper assignment of European Waste Catalogue (EWC) codes is essential to enable high-quality recycling, distinguishing hazardous from non-hazardous waste, thus ensuring regulatory compliance. This task becomes particularly challenging in the case of “mirror entries”, where visually similar waste fractions may be classified as hazardous or non-hazardous depending on their chemical composition. In such cases, analytical evidence is required to support classification decisions. It should be noted that the regulatory determination of hazardousness cannot be based on Vis-SWIR spectroscopy alone. Spectral reflectance measurements do not directly provide the complete information required for regulatory assessment, such as the concentrations of specific hazardous substances, comparison with applicable concentration limits, or the determination of all relevant hazardous properties. Therefore, in the present work, the hazardous/non-hazardous labels

are considered as pre-established classes associated with the investigated materials and their EWC classification. The proposed spectroscopy-chemometrics approach is intended to provide rapid screening and decision-support information that can complement, rather than replace, conventional chemical characterization and regulatory assessment.

The EWC organizes waste types into six-digit codes grouped by industrial sector and origin. Within this system, some codes are defined as mirror entries, meaning that the same waste stream can receive two alternative codes depending on whether hazardous substances are present above regulatory thresholds. The correct attribution of these codes is therefore crucial not only for regulatory compliance but also for determining appropriate treatment, transport, and recycling pathways.

Traditional characterization approaches for C&DW rely on visual inspection, manual sorting and laboratory-based chemical analyses. While accurate, these methods are often time-consuming, costly, and poorly suited for rapid decision-making in operational environments such as recycling plants or demolition sites. Consequently, there is a growing interest in fast, non-destructive, and potentially automated techniques capable of supporting waste classification directly in the field. In this context, reflectance spectroscopy in the visible to short-wave infrared (Vis-SWIR) range has emerged as a promising tool for material identification. Spectral measurements in this range are sensitive to composition and surface characteristics of materials. When combined with advanced data analysis techniques, such as chemometrics, spectroscopy can represent a powerful tool for the classification of complex and heterogeneous materials. Previous studies have demonstrated the potential of spectroscopy-chemometrics frameworks for waste sorting and material discrimination (Bonifazi et al., 2015); however, their application to the hierarchical classification of C&DW according to hazard status and EWC codes remains relatively limited.

The present study aims to address this gap by proposing an integrated spectroscopy-chemometrics framework for rapid classification and screening of representative construction and demolition waste fractions. Samples spanning major material families, including concrete and mortar, bricks and ceramics, natural aggregates, insulation materials, and potentially contaminated components, were analyzed after appropriate spectral pre-processing and labelled according to their assigned EWC codes and pre-established hazardous/non-hazardous status under current EU legislation. Classification models were developed at two hierarchical levels: EWC code grouping and discrimination between hazardous and non-hazardous classes represented in the investigated dataset.

The overarching objective is to evaluate the capability of Vis-SWIR spectroscopy coupled with chemometrics to provide a reliable, rapid, and scalable decision-support information for C&DW sorting, preliminary screening and routing, while complementing the chemical and regulatory assessment required for definitive waste classification.

2. MATERIALS AND METHODS

2.1 Analyzed samples

Reflectance spectra in the Vis-SWIR range (350-2500 nm) were acquired from representative samples of major C&DW material families. In total, 167 independent physical items (i.e. the term “item” refers to a single physical sample: an individual debris fragment or material piece) were collected and analyzed from renovation, demolition, and post-earthquake sites across Italy.

These included mineral-based materials (e.g., concrete, cement, bricks, ceramics, and aggregates), soil and stone fractions, gypsum-based materials (gypsum and plasterboard), organic materials such as wood and plastics, metals, as well as potentially contaminated or hazardous materials, including bituminous mixtures containing coal tar and asbestos-containing materials. Overall, the dataset comprises multiple waste categories associated with specific European Waste Catalogue (EWC) codes and classified according to their hazardous or non-hazardous status.

For each material class, between 2 and 60 items were collected. For each item, at least 20 spectra were acquired to capture intra-sample variability.

The complete list of analyzed materials, together with the corresponding EWC codes, hazard classification, and the number of analyzed spectra (spectra considered excessively noisy or identified as outliers were excluded from the analyses), is reported in Table 1. Analyzed spectra were in total 3834, corresponding to measurements (except outliers) acquired on these 167 independent physical samples. Multiple spectra originating from the same item were always treated as measurements of the same

sample and were not considered independent observations.

2.2 Methods

2.2.1 Portable spectrophotoradiometer

Reflectance spectra were collected using a FieldSpec® 4 Standard-Res field-portable spectroradiometer (ASD Inc., Boulder, Colorado, United States). This instrument provides a spectral resolution of 3 nm at 700 nm and 10 nm at 1400/2100 nm and it can acquire spectra in the Vis-SWIR ranges (350 - 2500 nm) (Inc., 2015).

The spectroradiometer consists of a detector unit and a fiber-optic cable connected to a contact probe, controlled by a computer. The detector unit integrates three separate sensors equipped with different holographic diffraction gratings: a VNIR detector (512 element silicon array: 350-1000 nm), a SWIR 1 detector (Graded Index InGaAs. Photodiode, Two Stage TE Cooled; 1001-1800 nm), and a SWIR 2 detector (Graded Index InGaAs. Photodiode, Two Stage TE Cooled; 1801-2500 nm). A halogen lamp provides illumination with a colour temperature of 2901 +/- 10% °K. The contact probe spot is 10 mm in size. The ASD RS3 software was used for data collection and calibration procedures (ASD Inc., 2008). The spectroradiometer was calibrated by referencing the dark current calibration file and acquiring a standardized white Spectralon® ceramic material, spectrum is then acquired, and reflectance computed.

The ASD ViewSpec Pro (Ver. 6.2.0) was used to stack the spectroradiometer spectra “.asd” data files into an ASCII text file. An ad hoc written routine was used to import the converted data into the MATLAB environment (MATLAB R2019a; The Mathworks, Inc., Natick, Massachusetts,

TABLE 1: List of analyzed CDW materials, with the corresponding EWC codes and their classification according to waste hazard status.

Name	Code	Status	Number of analyzed spectra
Aggregates	17 01 07 - Mixtures of concrete, bricks, tiles and ceramics other than those mentioned in 17 01 06*	non-hazardous	60
Bituminous mixtures	17 03 01* - Bituminous mixtures containing coal tar (hazardous)	hazardous	60
Brick	17 01 02 - Bricks	non-hazardous	140
Ceramic and tile	17 01 03 - Tiles and ceramics	non-hazardous	120
Plastics	17 02 03 - Plastic	non-hazardous	312
Gypsum	17 08 02 - Gypsum-based construction materials other than those mentioned in 17 08 01	non-hazardous	60
Wood	17 02 01 - Wood	non-hazardous	160
Concrete	17 01 01 - Concrete	non-hazardous	60
Plasterboard	17 08 02 - Gypsum-based construction materials other than those mentioned in 17 08 01	non-hazardous	60
Asbestos Containing Material (AMC)	17 06 05* - Construction materials containing asbestos (hazardous)	hazardous	1161
Soil + ACM	17 06 03* - Soil and stones containing hazardous substances (hazardous)	hazardous	900
Soil + Cement	17 01 07 - Mixtures of concrete, bricks, tiles and ceramics other than those mentioned in 17 01 06*	non-hazardous	139
Cement	17 01 01 - Concrete	non-hazardous	19
Soil	17 05 04 - Soil and stones other than those mentioned in 17 05 03	non-hazardous	100
Marble (ornamental stone)	17 05 04 - Soil and stones other than those mentioned in 17 05 03	non-hazardous	340
Metals	17 04 05 - Iron and steel	non-hazardous	143

United States). Imported data files were analyzed in the MATLAB environment using PLS_toolbox (Ver. 8.2., Eigenvector Research, Inc., Manson, Washington, United States).

2.2.2 Spectral data acquisition and preprocessing

Spectra were cut to exclude the visible (VIS) region, retaining only the 1000-2500 nm interval for following analysis. The dataset was then pre-processed to minimize noise. Specifically, Multiplicative Scatter Correction (MSC), Generalized Least Square Weighting (GLS-W) and Mean Center (MC) algorithms were applied (Gasbarrone et al., 2018; Rinnan et al., 2009).

2.2.3 Hierarchical classification procedure

A hierarchical approach based on Partial Least Squares - Discriminant Analysis (PLS-DA) was implemented to achieve the classification. Classification techniques are designed to develop models that assign objects to specific classes using a set of descriptors. Among the classification algorithms, PLS-DA is a supervised classification method, combining the properties of partial least squares regression with the discriminating ability of a classification technique (Ballabio & Consonni, 2013).

The hierarchical model (Figure 1) is based on three main decision rules (model-based), each designed to discriminate between different levels of waste classification.

- **Rule 1:** Discrimination of pre-defined hazardous and non-hazardous classes. The first rule discriminates between samples belonging to the hazardous and non-hazardous classes represented in the investigated dataset. The corresponding labels were assigned a priori

according to the EWC classification adopted for the analyzed materials (this classification step serves as a spectral screening of pre-defined waste classes, rather than an independent regulatory determination of hazardousness).

- **Rule 2:** Classification of hazardous waste categories. Samples identified as hazardous are further classified according to the main hazardous EWC codes included in the dataset.
- **Rule 3:** Classification of non-hazardous waste categories. Samples identified as non-hazardous are assigned to the corresponding non-hazardous EWC groups, including concrete, bricks, tiles and ceramics, mixed mineral waste, wood, plastics, metals, soil and stones, and gypsum-based materials.

The hierarchical structure allows the model to first determine the hazard status of the waste and then refine the classification according to the corresponding EWC code groups. Samples not matching any of these classes are labelled as "NC". Models were calibrated by using the spectral information contained in the training sets and cross-validated by the Venetian Blinds (VBs) algorithm to assess the optimal complexity of the models. The VBs scheme was applied at the individual-spectrum level, i.e. spectra from the same physical sample could be distributed across different folds.

Classifier performance was assessed by computing Sensitivity, Specificity, Precision, and Accuracy from the confusion matrix (Ballabio et al., 2018; Fawcett, 2006) according to the following formulas:

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN}) \quad (1)$$

$$\text{Specificity} = \text{TN} / (\text{FP} + \text{TN}) \quad (2)$$

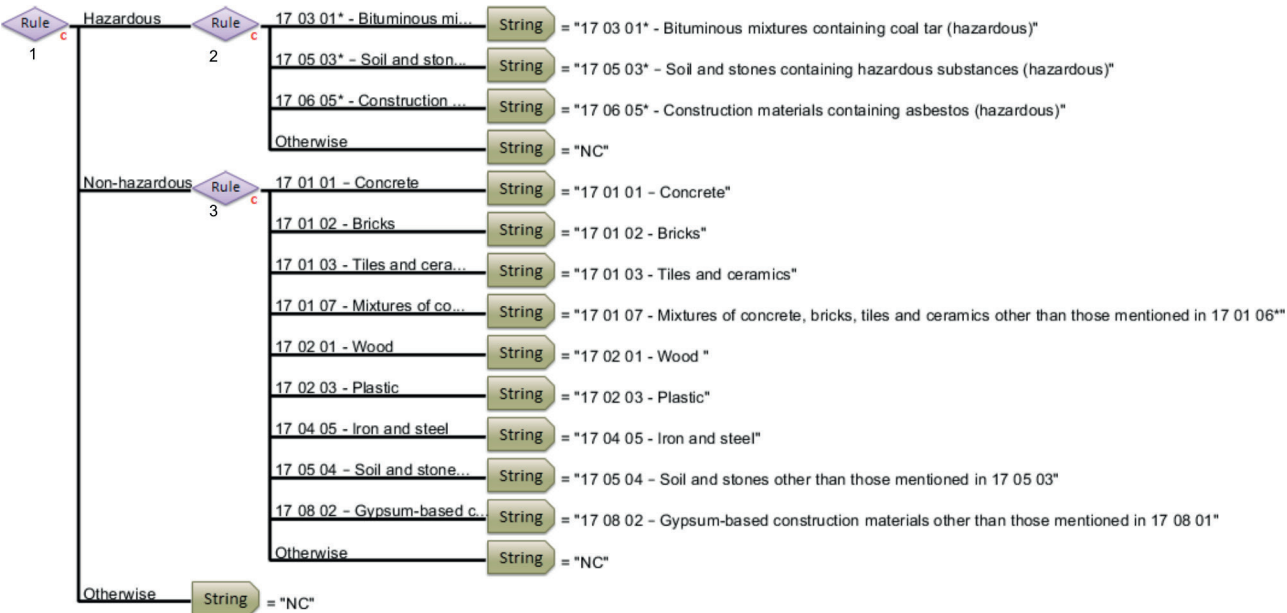


FIGURE 1: Hierarchical classification scheme for construction and demolition waste (C&DW) samples. The first decision rule separates hazardous from non-hazardous waste classes. Subsequent rules assign samples to the corresponding European Waste Catalogue (EWC) codes, including bituminous mixtures containing coal tar, soil and stones containing hazardous substances, asbestos-containing materials, concrete, bricks, tiles and ceramics, mixed mineral waste, wood, plastics, iron and steel, soil and stones, and gypsum-based construction materials. Samples not assigned to any of the predefined classes are labelled as NC (not classified).

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (3)$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (4)$$

In these equations, TP (True Positive) is a positive instance that is classified as positive; FN (False Negative) is a positive instance that is classified as negative; TN (True Negative) is a negative instance that is classified as negative, and FP (False Positive) is a negative instance that is classified as positive.

3. RESULTS AND DISCUSSION

Raw reflectance spectra used to calibrate the hierarchical classification model are shown in Figure 2. These spectra highlight the variability among the analyzed materials and provide the initial spectral information used to build the classification models. The observed differences in spectral patterns suggest that the SWIR spectral range contains relevant features for discriminating among the considered waste categories. Specific preprocessing techniques were then applied for each rule, as defined in the hierarchical model. The corresponding pre-processed spectra are shown in Figure 3. The preprocessing stage plays a key role in reducing noise, minimizing scattering effects, and enhancing the spectral features relevant for classification.

Sensitivity and Specificity in calibration, cross-validation and validation are shown in Table 2 for the Rule 1, Table 3 for Rule 2 and Table 4 for Rule 3. These performance indicators allow a comprehensive evaluation of the classifier reliability, highlighting its capability to correctly identify both positive and negative instances for each class.

Concerning Rule 1, which focuses on the discrimination between the pre-defined hazardous and non-hazardous waste represented in the dataset, the model achieved very high performance, with sensitivity, specificity, and accuracy

values equal or very close to 1 in both calibration and cross-validation. This result indicates that the spectral information captured by the model is highly discriminative for the investigated hazardous and non-hazardous material classes. However, this result should be interpreted as evidence of the potential of Vis-SWIR spectroscopy for rapid screening of the investigated classes rather than as a demonstration that spectroscopy alone can establish the regulatory hazardous status of an unknown waste stream. Moreover, the hazardous and non-hazardous groups comprise different material matrices and material types. Therefore, the observed discrimination may reflect differences in the overall spectral characteristics of the material matrices and cannot be attributed exclusively to the presence of hazardous constituents. For Rule 2, concerning the classification of hazardous waste categories, the obtained results also show excellent performance. Most classes present sensitivity and specificity values equal or very close to 1 during both calibration and cross-validation. This confirms that once the hazard status has been correctly identified, the model is able to further distinguish among hazardous EWC classes with a high level of reliability.

The built hierarchical model was then applied to the entire dataset of spectra, and the obtained results are in Table 5. The results confirm the overall effectiveness of the hierarchical approach, with high accuracy and very low error rates for most of the considered EWC classes. The lower sensitivity observed for some non-hazardous classes in the final hierarchical model can be related to the intrinsic spectral characteristics and variability of these materials.

The sensitivity for EWC 17 04 05 classes reached 0.755, despite the very high specificity (1.000), which may be associated with the relatively low and spectrally flat reflectance response of metallic materials in the spectral

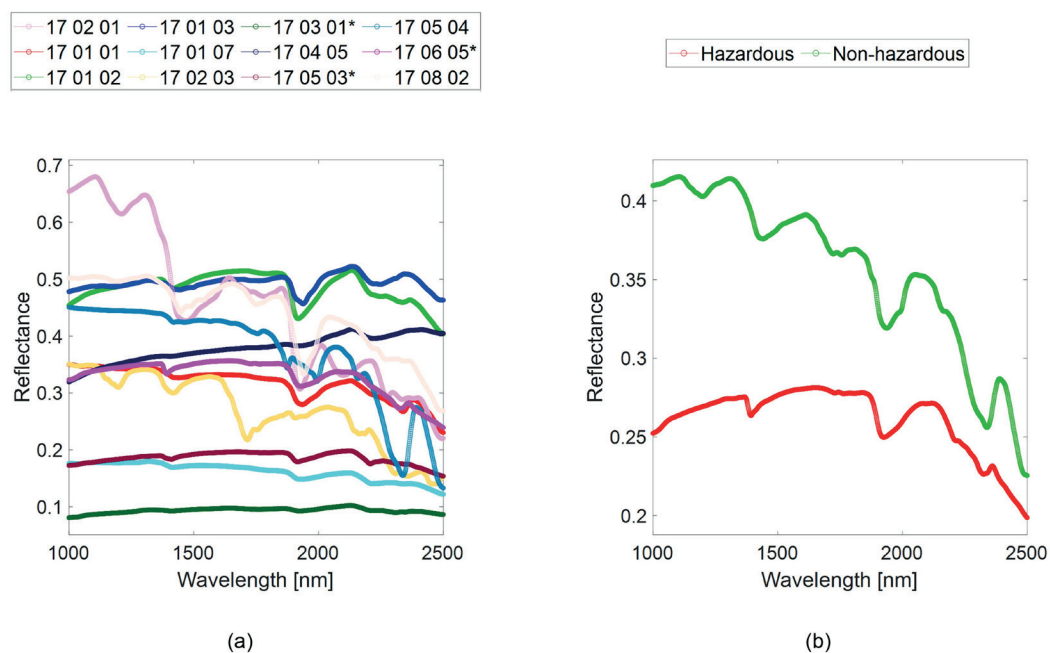


FIGURE 2: Raw reflectance spectra of samples classified according to the EWC code (a) and the hazard status (b).

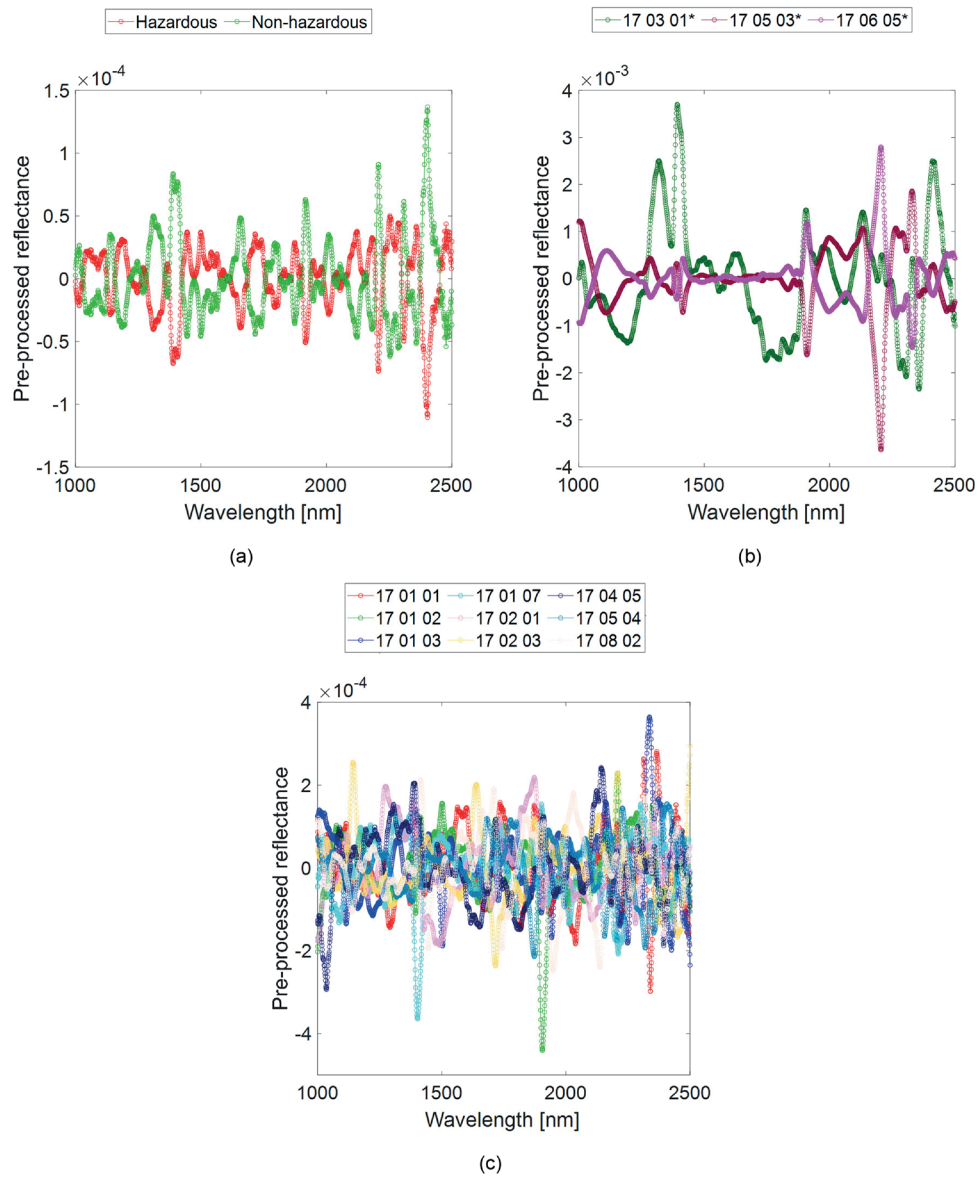


FIGURE 3: Preprocessed spectra corresponding to Rule 1 (a), Rule 2 (b), and Rule 3 (c) of the hierarchical classification model.

TABLE 2: Sensitivity and specificity in calibration and cross-validation for Rule 1.

Model phase	Class	Sensitivity	Specificity	Number of spectra	Precision	Accuracy
Calibration	Hazardous	1.000	1.000	2121	1.000	1.000
	Non hazardous	1.000	1.000	1713	1.000	1.000
Cross-validation	Hazardous	1.000	1.000	2121	1.000	1.000
	Non hazardous	1.000	1.000	1713	0.999	1.000

TABLE 3: Sensitivity and specificity in calibration and cross-validation for Rule 2.

Model phase	Class	Sensitivity	Specificity	Number of spectra	Precision	Accuracy
Calibration	17 03 01*	1.000	1.000	60	1.000	1.000
	17 05 03*	0.997	1.000	900	1.000	0.999
	17 06 05*	1.000	0.997	1161	0.997	0.999
Cross-validation	17 03 01*	1.000	1.000	60	1.000	1.000
	17 05 03*	1.000	1.000	900	1.000	1.000
	17 06 05*	1.000	1.000	1161	1.000	1.000

TABLE 4: Sensitivity and specificity in calibration and cross-validation for Rule 3.

Model phase	Class	Sensitivity	Specificity	Number of spectra	Precision	Accuracy
Calibration	17 01 01	1.000	0.999	79	0.975	0.999
	17 01 02	1.000	1.000	140	1.000	1.000
	17 01 03	0.983	1.000	120	1.000	0.999
	17 01 07	1.000	1.000	199	1.000	1.000
	17 02 01	1.000	1.000	160	1.000	1.000
	17 02 03	1.000	1.000	312	1.000	1.000
	17 04 05	1.000	1.000	143	1.000	1.000
	17 05 04	1.000	1.000	440	1.000	1.000
	17 08 02	1.000	1.000	120	1.000	1.000
Cross-validation	17 01 01	1.000	0.997	79	0.940	0.997
	17 01 02	1.000	1.000	140	1.000	1.000
	17 01 03	0.925	1.000	120	1.000	0.995
	17 01 07	1.000	1.000	199	1.000	1.000
	17 02 01	1.000	1.000	160	1.000	1.000
	17 02 03	1.000	0.999	312	0.994	0.999
	17 04 05	0.986	1.000	143	1.000	0.999
	17 05 04	1.000	1.000	440	1.000	1.000
	17 08 02	1.000	0.997	120	0.968	0.998

TABLE 5: Performance metrics of the hierarchical model approach.

Class	Sensitivity	Specificity	Number of spectra	Error rate	Precision	Accuracy
17 01 01	0.911	0.999	79	0.002	0.973	0.998
17 01 02	1.000	1.000	140	0.000	1.000	1.000
17 01 03	0.983	1.000	120	0.001	1.000	0.999
17 01 07	1.000	1.000	199	0.000	1.000	1.000
17 02 01	1.000	1.000	160	0.000	1.000	1.000
17 02 03	0.869	1.000	312	0.011	1.000	0.989
17 03 01*	1.000	1.000	60	0.000	1.000	1.000
17 04 05	0.755	1.000	143	0.009	1.000	0.991
17 05 03*	0.997	1.000	900	0.001	1.000	0.999
17 05 04	1.000	1.000	440	0.000	1.000	1.000
17 06 05*	0.947	0.999	1161	0.017	0.997	0.983
17 08 02	1.000	1.000	120	0.000	1.000	1.000

region used for the classification. A similar, although less pronounced, effect was observed for plastics (EWC 17 02 03) with a sensitivity of 0.869. This may be related to the variability of polymeric materials and to partial overlap of their spectral responses with those of other waste fractions. Concrete (EWC 17 01 01) also showed a low sensitivity (0.911), which can be reasonably associated with the compositional heterogeneity of this class.

It should be noted that the very high cross-validation metrics must be interpreted as indicators of internal consistency under a spectrum-level cross-validation scheme, rather than as definitive evidence of fully transferable performance. Because spectra from the same physical sample may occur in both calibration and validation folds, the reported figures are likely to overestimate the true generalization capability. Future work will therefore prioritize sam-

ple- or site-level cross-validation and external validation on independent datasets to obtain more realistic performance estimates.

4. CONCLUSIONS

This study demonstrates that a Vis-SWIR spectroscopy-chemometrics framework can effectively support the automated, hierarchical classification of construction and demolition waste (C&DW) according to European Waste Catalogue (EWC) codes and associated hazard status. By combining reflectance spectra with multivariate modelling, the proposed approach enables rapid and objective material identification, addressing key limitations of conventional, laboratory-based characterization and visual inspection in complex waste streams.

The hierarchical PLS-DA model achieved excellent classification performance for the pre-defined hazardous and non-hazardous classes represented in the investigated dataset. However, because these classes comprise different material matrices, the high performance of Rule 1 does not prove that the model specifically detects hazardous constituents independently of the underlying matrix. Controlled paired comparison using specific material matrix with and without specific contaminants are required to verify this capability, and further studies will be needed to validate the model true detection limits. On the other hand, hazardous EWC classes were correctly identified with similarly high figures of merit (Rule 2). For non-hazardous categories (Rule 3), the model maintained overall high accuracy across most classes, with slightly reduced sensitivity for the most heterogeneous or spectrally overlapping materials, such as certain plastic and metal fractions.

These results confirm Vis-SWIR reflectance spectroscopy can serve as a rapid, non-destructive and scalable screening technology to support EWC-oriented sorting and routing of the investigated C&DW classes. In particular, the proposed approach showed strong capability to discriminate between the pre-defined hazardous and non-hazardous classes represented in the dataset and to further classify these materials according to their associated EWC groups. However, Vis-SWIR spectroscopy should not be considered a stand-alone method for the definitive regulatory determination of hazardousness or for the resolution of mirror entries where chemical composition and concentration thresholds must be assessed. Rather, its potential lies in providing rapid preliminary information that can support operational decision-making and indicate materials or fractions requiring further analytical and regulatory assessment. Accordingly, the proposed methodology is best regarded as a complementary decision-support tool within a broader waste-characterization workflow, in which spectroscopic screening can be followed, where required, by targeted chemical analyses and regulatory assessment. This combined approach could be particularly valuable in post-earthquake scenarios, where a rapid screening of potentially hazardous fractions may help prioritize sampling, handling and subsequent analytical characterization.

Future work should prioritize external validation on larger and more diverse datasets, including additional construction typologies and contamination patterns, to further assess model robustness and transferability. Particular attention should also be given to reducing the imbalance among the investigated classes by increasing the number of spectra for the less represented materials, such as cement and some mineral-based fractions. This would provide a more balanced assessment of classification performance and further improve the robustness and transferability of the proposed hierarchical model. Moreover, integration with field-deployable systems (e.g. portable devices, conveyor-mounted sensors, or hyperspectral imaging units) and coupling with digital decision-support tools would enhance practical uptake, contributing to circular-economy strategies by maximising material recovery, limiting landfill disposal and improving the environmental sustainability of construction and demolition activities.

REFERENCES

- Directive, E.C. (2008). Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives. *Official Journal of the European Union L*, 312(3), 22.
- Ballabio, D., & Consonni, V. (2013). Classification tools in chemistry. Part 1: linear models. PLS-DA. *Analytical Methods*, 5(16), 3790-3798. doi:10.1039/C3AY40582F
- Ballabio, D., Grisoni, F., & Todeschini, R. (2018). Multivariate comparison of classification performance measures. *Chemometrics and Intelligent Laboratory Systems*, 174, 33-44. doi:10.1016/j.chemolab.2017.12.004
- Bonifazi, G., Capobianco, G., Serranti, S., Palmieri, R., & Trotta, O. (2025a). Support vector machine-discriminant analysis applied to post-earthquake building waste classification based on hyperspectral imaging. Paper presented at the Proc.SPIE.
- Bonifazi, G., Bellagamba, S., Capobianco, G., Gasbarrone, R., Lonigro, Iv., Malinconico, S., . . . Serranti, S. (2025b). Short-Wave Infrared Spectroscopy for On-Site Discrimination of Hazardous Mineral Fibers Using Machine Learning Techniques. *Sustainability*, 17(3), 972. doi:10.3390/su17030972
- Bonifazi, G., Gasbarrone, R., Gattabria, D., Palmieri, R., & Serranti, S. (2026). Earthquake-generated construction and demolition waste recovery using hyperspectral imaging aided by shallow neural networks technique. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 353, 127560. doi:10.1016/j.saa.2026.127560
- Bonifazi, G., Grosso, Chiara, P., Roberta, & Serranti, S. (2025c). Current trends and challenges in construction and demolition waste recycling. *Current Opinion in Green and Sustainable Chemistry*, 53, 101032. doi:10.1016/j.cogsc.2025.101032
- Bonifazi, G., Palmieri, R., & Serranti, S. (2015). Short wave infrared hyperspectral imaging for recovered post-consumer single and mixed polymers characterization. Paper presented at the Image Sensors and Imaging Systems 2015.
- Chien, C.-F., Aviso, K., Tseng, M.-L., Fujii, M., & Lim, M.K. (2023). Solid waste management in emerging economies: opportunities and challenges for reuse and recycling. *Resources, Conservation and Recycling*, 188, 106635. doi:10.1016/j.resconrec.2022.106635
- Chileshe, N., Jayasinghe, R.S., & Rameezdeen, R. (2019). Information flow-centric approach for reverse logistics supply chains. *Automation in Construction*, 106, 102858. doi:10.1016/j.autcon.2019.102858
- Fawcett, T. (2006). An introduction to ROC analysis. *Pattern recognition letters*, 27(8), 861-874.
- Gasbarrone, R., Currà, A., Cardillo, A., Bonifazi, G., & Serranti, S. (2018). Near infrared spectroscopy of human muscles (Vol. 10489): SPIE.
- Huang, B., Wang, X., Kua, Harnwei, G., Yong, B., Raimund, & Ren, J. (2018). Construction and demolition waste management in China through the 3R principle. *Resources, Conservation and Recycling*, 129, 36-44. doi:10.1016/j.resconrec.2017.09.029
- Inc., ASD. (2008). RS3™ User Manual, ASD Document 600545. In (Rev. E ed.): ASD Inc., Boulder, CO, United States.
- Inc., ASD. (2015). FieldSpec® 4 User Manual, ASD Document 600979. Retrieved from
- Osmani, M. (2011). Chapter 15 - Construction Waste. In Trevor M. Letcher & Daniel A. Vallero (Eds.), *Waste* (pp. 207-218). Boston: Academic Press.
- Radica, F., Iezzi, G., Trotta, O., Bonifazi, G., Serranti, S., & de Brito, J. (2024). Characterization of CDW types by NIR spectroscopy: Towards an automatic selection of recycled aggregates. *Journal of Building Engineering*, 88, 109005. doi:10.1016/j.job.2024.109005
- Rinnan, Åsmund, Berg, Frans Van Den, & Engelsen, Søren Balling. (2009). Review of the most common pre-processing techniques for near-infrared spectra. *TrAC Trends in Analytical Chemistry*, 28(10), 1201-1222. doi:10.1016/j.trac.2009.07.007
- Sakthibala, R.K., Vasanthi, P., Hariharasudhan, C., & Partheeban, P. (2025). A critical review on recycling and reuse of construction and demolition waste materials. *Cleaner Waste Systems*, 12, 100375. doi:10.1016/j.clwas.2025.100375
- Sirimewan, D., Harandi, M., Peiris, H., & Arashpour, M. (2024). Semi-supervised segmentation for construction and demolition waste recognition in-the-wild: Adversarial dual-view networks. *Resources, Conservation and Recycling*, 202, 107399. doi:10.1016/j.resconrec.2023.107399

- Su, Y. (2020). Multi-agent evolutionary game in the recycling utilization of construction waste. *Science of The Total Environment*, 738, 139826. doi:10.1016/j.scitotenv.2020.139826
- Tchobanoglous, G., Theisen, H., Vigilant, S. (1993). *Integrated solid waste management: engineering principles and management issues*: New York McGraw-Hill, Inc.
- Wan, T., Jiang, Yu, H., Xiaolong, Zheng, Y., & Ma, W. (2026). Intelligent construction and demolition waste detection in complex environments using an improved CLRD-YOLO model with knowledge distillation. *Case Studies in Construction Materials*, 25, e06230. doi:10.1016/j.cscm.2026.e06230