



Laser-induced breakdown spectroscopy (LIBS) for the characterization of demolition waste: an exploratory study

J. Ghani^{a,*}, A. Bisciotti^a, G. Bianchini^a, R. Tassinari^a, G. Iezzi^b, F. Radica^b, G. Cruciani^a

^a Department of Physics and Earth Science, University of Ferrara, Via Saragat 1, 44122 Ferrara, Italy

^b Department of Engineering and Geology, University of Chieti-Pescara 'G. d'Annunzio', 66100 Chieti, Italy

ARTICLE INFO

Keywords:

Construction and demolition waste (CDW)
Laser-induced breakdown spectroscopy (LIBS)
Matrix-matched calibration
Geochem calibration
National Institute of Standards and Technology

ABSTRACT

Laser-induced breakdown spectroscopy (LIBS) is a fast, and non-destructive technique for real-time elemental analysis, ideal for in-line characterization of construction and demolition waste (CDW). This study evaluates and improves the accuracy of portable LIBS for elemental quantification in pressed pellets from CDW. Pressed powder pellets of different CDW categories (i.e., cements, concrete, masonry), previously analysed by X-ray fluorescence (XRF), were measured using the SciAps Z900 handheld LIBS spectrometer. Total of 71 selected samples were used to build a new library dataset based on a matrix-matching calibration (MMC) approach. The resulting MMC library was then compared with the built-in SciAps "Geochem" library, which is designed for inorganic-mineral rock matrices. MMC method shows higher Si and Ca levels with similar concentrations, as main components of mixed CDW materials. Results show that MMC reduces matrix effects and analyte signal interference, enabling accurate elemental quantification, particularly for CDW samples dominated by high Si (20–70 wt%), and Ca contents (10–75 wt%). The accuracy and measurements of Ca contents are better for both MMC and Geochem calibration (GC) models, although the average relative difference decreases from 10.9% (GC) to 4.55% (MMC). Comparable accuracy improvements are found for other major elements (Si, Al, Ti, Fe, Mn, Mg, Na, K). To further validate MMC-library performance, certified reference materials from the National Institute of Standards and Technology (NIST) for building materials were also analysed. Our findings suggest that the MMC approach improves both the accuracy and precision of LIBS measurements on pressed pellets from CDW.

1. Introduction

The extraction of sand and gravel for the construction sector represents the most significant fraction of mineral resource use worldwide, with annual volumes ranging from 32 to 50 Gt [1]. Over 90% of these materials are sourced from riverbeds, causing significant disruption and degradation to natural ecosystems [2]. Sand and gravel make up over 70% of concrete's volume, which is currently the second most consumed material worldwide, only after drinking water [3]. At the end of their service life, building materials become construction and demolition waste (CDW), which contributes to 37.5% of the solid waste landfilled globally [4]. CDW generation exceeds 800 Mt. annually in the European Union [5]. CDW typically contain crushed concrete, bricks, tiles, gypsum boards, natural stones, timber, metals and plastic compounds [6]. The types, abundance and recycling performance of CDW, markedly depend on geographical and geological peculiarities [7].

Thereby, recycling CDW can produce secondary raw materials and

reduce the demand for primary resources [8], and landfill volumes [9]. However, current CDW management suffers from inadequate on-site sorting, resulting in low-grade recycled materials [10]. Traditional CDW recycling involves mechanical crushing of large debris, followed by screening and separation of unwanted fraction like metals, plastic and timber. This process often relies also on manual sorting to improve the homogeneity of the waste stream [11], resulting as expensive, labour-intensive, and scarcely safe for the health of the workers [12]. Existing CDW industrial sorting technologies accounts for advanced automated methods, like magnetic and gravity concentration [13], and RGB color recognition [14]. The other technologies like near-infrared (NIR) detection [15], and hyperspectral imaging [16] have primarily been tested and validated at the laboratory scale, whereas portable NIR for field detection and in situ analysis is well developed. These technologies have limitations such as high cost, complexity, and limited material discrimination, especially for mixed CDW. In order to increase performance, a significant contribution comes from machine learning,

* Corresponding author.

E-mail address: ghnjnd@unife.it (J. Ghani).

<https://doi.org/10.1016/j.sab.2026.107458>

Received 20 October 2025; Received in revised form 29 December 2025; Accepted 19 January 2026

Available online 19 January 2026

0584-8547/© 2026 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

enabling automatic classification [17,18]. However, more rapid, efficient, economical and effective methods are constantly introduced and tested. In this realm, laser-induced breakdown spectroscopy (LIBS) has recently gained interest in the field of waste recycling for in-line quality inspection [19]. LIBS is a rapid, in situ technique for elemental analysis across matrices, requiring minimal sample preparation [20]. LIBS characteristics, such as high efficiency and accuracy make it ideal for fast, precise, and on-site elemental determination and classification of CDW, toward the developing of efficient sorting technologies [21].

Rapid developments and applications of LIBS analysis during the last 20 years have increased in various fields [22–26]. Previous studies have shown the application of LIBS with univariate calibration methods for elemental analysis on pressed pellets to characterize various materials, such as cement and concrete [27–29], coal deposits [30,31], CDW by combining LIBS and NIR spectroscopy [32,33], soil samples (pellets) [34], and molten metals [35]. LIBS have also shown potential in recycling and sorting of wastes, such as classification of post-consumer aluminium metal scrap [36,37], recycled concrete aggregates [19], refractory residues [38], landfill leachates [39], residual wastes [40], and for other specific industrial applications [41,42]. To the best of our knowledge, characterization of complex and mixed heterogeneous CDW by portable LIBS has not been yet reported for elemental analysis in previous studies, while primarily focus was given on more homogeneous materials or simple waste streams.

Numerous studies have combined the used of LIBS with various algorithms for direct material identification, like linear discriminant analysis (LDA) [43], partial least squares discriminant analysis (PLS-DA) [44], and factorial discriminant analysis (FDA) [45]. Despite these developments, enhancing the precision of LIBS remains imperative. Quantitative analysis by LIBS is often challenged by differences in complex environmental matrices (e.g., wastes and soil) and matrix effects that can affect and alter signal intensity and accuracy. For this reason, LIBS requires specific calibration methods and data processing to improve measurements accuracy, which depends on the materials under analysis [24]. In the elemental determination process, the standard univariate calibration methods used in LIBS are matrix-matching calibration (MMC), internal standardization, and standard addition [46,47]. The MMC can minimize discrepancies using reference standards previously analysed having a composition similar to those of the unknown sample. In previous studies, MMC curves by LIBS were used to quantitatively measure the elements in certified reference materials (CRMs) of cements from the National Institute of Standards and Technology (NIST) [27], and 20 CRMs of iron oxide powder samples [48]. Previous LIBS calibration studies focused on relatively uniform matrices with significant deficiencies and limitations in the development of universally applicable calibration protocols. In the present research an MMC approach is specifically developed for CDW accounting for heterogeneous materials, tackling the matrix effects while improving calibration accuracy and robustness.

In a previous study, Junwei et al. [49] adopted a univariate calibration for LIBS measurements achieving good accuracy for Ca, Si, Fe, Al, Mg, Na, K and Ti in homogeneous cement raw materials (pellets). However, univariate calibration struggles to provide accurate and robust quantitative analysis for complex, and heterogeneous materials where matrix variations impact plasma conditions and emission signals. Thus, challenges remain in achieving accurate elemental quantification of complex mixed materials like CDW due to calibration limitations, and matrix effects. Current built-in LIBS calibrations like SciAps “Geochem” for rocks and ores do not adequately address the heterogeneous and variable composition of CDW. The present study addresses this gap by presenting a LIBS library developed for heterogeneous CDW samples to improve the accuracy of elemental quantification. In this study, an MMC method is performed using only the elemental bulk composition obtained via XRF analysis of selected CDW products, representative of the most common types found in landfills. The accuracy of the MMC is then compared with the built-in SciAps Geochem calibration (GC), obtained

from CRMs of rocks and ore deposits with similar compositions. The main objectives of the present study are (i); to assess elemental composition in characterization of recycling CDW materials, (ii) to assess MMC method to improve the accuracy of portable LIBS analytical performance, and (iii) eventually, comparing the analytical measurements of major elements by MMC calibration and the built-in GC in CDW materials. Developing calibrations like MMC and other analytical protocols tailored for chemical characterization of CDW are critically needed to unlock the potential of handheld LIBS in enhancing elemental quantification and recycling efficiency.

2. Materials and methods

2.1. Materials

The LIBS calibration investigated here is conducted on 71 variable samples of CDW collected from stockpiles of landfilled materials from three different recycling facilities in Italy, located in Ferrara (Emilia Romagna region), Pescara (Abruzzo region) and Macerata (Marche region). To encompass the most common products found in the CDW, the sample set in this study includes: 35 mixed CDW products, 16 ceramics among bricks, tiles, stoneware and porcelain and 20 samples of different concrete. For each material, at least 20 kg was collected, following the standard UNE-EN 932-1 (1998). The samples were then homogenized (90 μm) and reduced using the quartering methods (UNE-EN 932-2, 2000).

2.2. Methods

2.2.1. X-ray fluorescence

Bulk major oxides concentrations (CaO, SiO₂, Al₂O₃, Fe₂O₃, MgO, Na₂O, MnO, K₂O, TiO₂) were determined by X-ray fluorescence wavelength-dispersive spectrometry (XRF-WDS) on pressed powder pellets using an ARL Advent-XP+ spectrometer. All the samples were crushed, grinded and homogenized into powder form. Pressed powder pellets were prepared with wax glue binder (Polyvinyl alcohol called “Mowiol”) by hydraulic press machine. Each sample preparation procedure involved the pressing of powder for 12 s and repeated three times to achieve compact pressed pellets. The wax glue as a binder in pellets provided bond strength by holding the powder particles together during pressing in sample holder, resulting in compact and mechanically stable pellets. The matrix correction method proposed by Traill and Lachance [50] was applied. Precision in terms of repeatability (% RSD) is better than 4–5% on average (for most abundant elements better than 2–3%). The XRF results of Si, Ca and Al (high compositions) demonstrate good accuracy relative to the certified values of similar cementitious NIST samples, showing low average errors. Relative percentage error in CRMs (NIST samples) measurements was <15% for Si, and < 10% for Ca and Al. Volatile contents were determined as loss on ignition (LOI) at 1000 °C. The XRF laboratory of the Department of Physics and Earth Sciences at the University of Ferrara has extensive experience in the analysis of CDW matrices, as documented in recent studies [7,18,51].

2.2.2. LIBS calibrations (MMC vs GC)

The elemental compositions of Ca, Si, Al, Fe, Mg, Na, Mn, K, Ti in the CDW and standards are determined by the LIBS (SciAps Z-900 handheld spectrometer, Inc., Woburn, MA, USA). The handheld-LIBS consisted of a spectrometer with a spectral range (180–950 nm), a 1064 nm laser (pulse energy (5 mJ) and pulse width (1–2 ns)), and an optical assembly in a handpiece enclosure [52]. The nominal spectral resolution (FWHM) of the SciAps Z-900 optical system is <0.15 nm. Elemental analysis of LIBS was quantified by using MMC and GC following the experimental procedure (Fig. 1), respectively. For GC, the built-in database consisting of geological CRMs such as NISTs, ores, soil, and clay materials (Fig. S1a and S1b). For MMC, the previously analysed XRF dataset of elemental composition of mixed CDW samples are added to create a new database.

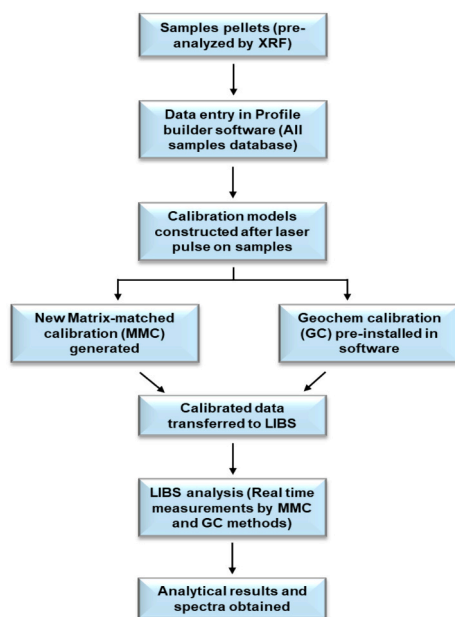


Fig. 1. Flow chart shows experimental procedure for calibration and LIBS analysis.

The database of XRF composition of 71 CDW samples was used to construct the LIBS MMC calibration model in Profile Builder Software. All reference XRF values of major elements (in ppm) were entered into the software. The laser pulse was then used on each sample to create a calibration curves model for each element (Fig. S2a, S2b). In addition, 31 independent samples containing similar matrix of NIST (Portland cements) and geological materials standards were used as unknown samples for validation testing of LIBS MMC model. These unknown samples are independent from our calibration dataset of CDW samples and considered as a practical validation set to assess the predictive performance of MMC model's on real-world similar and different matrices. The calibration curves are generated for each major element and scattered sampling points are excluded to improve calibration and minimize the matrix effects (Fig. S2a and S2b). All calibration curves are created with low root mean square (RMS) error to improve the quality of a calibration curve between the predicted values (from the LIBS analyzer) and the actual reference values (from XRF analytical measurements). The MMC was then transferred and installed into the LIBS application.

The pulsed laser used in the handheld SciAps LIBS analyzers usually delivers 5–6 mJ per pulse at a repetition rate of 50 Hz. To decrease discrepancies and matrix effects, each sample pellet was measured by LIBS in triplicate by directing the laser pulse at three distinct spots. The laser pulse results in ablation of a small spot of material (roughly a diameter of 25 μm) of total depth. Ablation typically removed a microscale depth which is sufficient for elemental detection by LIBS without extensive damage of the sample. The number of laser pulses per measuring spot was around 20–30 pulses and measurement time of one spot by laser pulse was typically around 3 s. The spectra collected and systematically averaged for analysis precision, and then the average of triplicate measurements for each sample was used for spectral analysis. The results of all major elements are obtained in weight percentage (wt %) and converted into parts per million (ppm) and used for further analysis.

2.3. Evaluation indices

The average relative difference (ABS-D) is an evaluation tool used to determine the magnitude of absolute differences in elemental compo-

sition of measured value vs true reference values among samples. This tool serves as a foundation concept for highlighting statistical differences and for quality use assessments. The ABS-D is calculated by the given eq. (1);

$$ABS - D = |MV - TV| \quad (1)$$

Where ABS-D in wt% is the absolute difference between the measured values MV and the true value TV (i.e. the XRF value).

Where TV represents true values, and MV represents measured values, respectively. An empirical correction method was also used for adjusting the results of models (MMC and GC methods) for LIBS measurements. The empirical correction typically involves the multiplication of actual values by the observed linear regression model ($Y = mX \pm b$) to minimize error, where Y is the response (dependent) variable, m is the estimated slope, X is the predictor (independent) variable as actual elemental concentration, and b is the estimated intercept. The actual values of Si were corrected by applying this equation ($Y = 0.8787 \times X + 3.0056$) for MMC, and ($Y = 1.8309 \times X - 48.664$) for GC. While for Al, the actual values of Si were corrected by applying an equation ($Y = 1.3072 \times X - 3.4308$) for MMC, and ($Y = 1.0563 \times X - 1.6311$) for GC. Where Y represents “empirical corrected” and “X” indicates actual concentration in these equations.

3. Results and discussion

3.1. XRF composition

Samples were labelled and categorized into three main groups: (i) ceramic (CER), (ii) concrete (CON), and (iii) mixed construction and demolition waste (CDW). The bulk chemical compositions of the collected CDW samples are provided in Supplementary Table S1. XRF analysis revealed a considerable variability in the major elements' composition, particularly among the three primary constituents: CaO, SiO₂, and Al₂O₃ (Fig. 2). CER samples are predominantly silica- to silicate-based, with SiO₂ contents ranging from 55 to 80 wt%, typically derived from high temperature firing of quartz- and feldspar-rich sands. In contrast, CON samples exhibit a calcium-rich composition (CaO: 50–80 wt%), primarily due to the presence of Portland cement binders, limestone aggregates, and gypsum additives [53]. By referencing the known chemical compositions of key minerals—such as cristobalite (Cris.), mullite (Mul.), anorthite (An.), wollastonite (Woll.), tricalcium silicate (C₃S), dicalcium silicate (C₂S), and aluminate (C₃A)—distinct

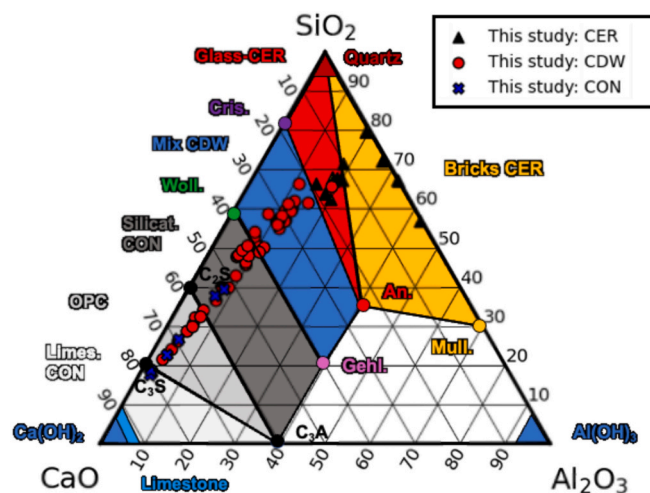


Fig. 2. Ternary plot of the most abundant major oxides (CaO, SiO₂ and Al₂O₃ measured by XRF) in CER, CON and CDW materials. Where Gehl. stands for gehlenite ($\text{Ca}_2\text{Al}_2(\text{AlSi})\text{O}_7$ or $\text{Ca}_2\text{Al}_2\text{SiO}_7$), An. for anorthite ($\text{CaAl}_2\text{Si}_2\text{O}_8$) and Mull. for mullite ($3\text{Al}_2\text{O}_3 \cdot 2\text{SiO}_2$).

compositional regions were delineated to aid in characterizing the materials under investigation. Given the composite nature of CON, samples were further distinguished into high-Ca due to limestone aggregates (Limes. CON), Ordinary Portland Cement (OPC), and high-Si from silicate aggregates (Silicat. CON) in Fig. 2. Many mixed CDW samples were distributed across these regions, reflecting the widespread presence and variable fraction of OPC in mixed waste environments. The characteristic mixed CDW region represents materials composed of varying proportions of CER and CON. Lastly, CER products were distributed between the Glass-ceramic regions, reflecting their primary composition and sintering temperature.

To better illustrate the compositional differences and similarities among the 71 studied samples, their bulk chemical compositions were compared with those of 135 additional CDW samples from XRF analyses reported in the literature [7,18,51]. As previously introduced, most samples analysed here are distributed along the SiO_2 – CaO trend (Fig. 3a) along a relatively narrow compositional range (SiO_2 40–70 wt% and CaO 5–25 wt%). Threshold values indicative of pure CER materials can be inferred from enrichments in Al_2O_3 (typically >15 wt%) and/or SiO_2 contents (> 50 wt%), as shown in Fig. 3b. Conversely, pure CON materials are generally characterised by low Al_2O_3 concentrations (<10 wt%). Plotting Fe_2O_3 against MgO offers further discrimination among CER products, enabling the identification of brick fragments—distinguished by relatively elevated Fe_2O_3 and MgO contents—from other market-available CER materials such as stoneware, porcelain, and tiles commonly encountered in CDW (Fig. 3c). Lastly, alkali oxides, particularly K_2O versus Na_2O (Fig. 3d), are of practical importance in recycling processes, especially in the production of recycled aggregates, where high concentrations of alkali may adversely affect durability. A more detailed discussion of the bulk chemical composition, including trace element data, is provided in the Supplementary Information.

3.2. LIBS spectral wavelengths analysis

Fig. 4a and b show average LIBS spectra of all CDW samples with the elements labelled, by MMC and GC method, covering the wavelength range of 180–950 nm. MMC provides stronger, better-resolved peaks for abundant elements likely due to improved optimal calibration. The elemental makeup of heterogeneous CDW samples in both spectra, confirming the applicability of calibration models relevance. The favourable atomic emission properties and transition probabilities of elements like Ca and Al, generate high spectral lines under the plasma excitation conditions of LIBS by MMC and GC models.

In addition, LIBS spectra of the target elements with the corresponding characteristic spectral lines are identified and labelled (Fig. 4). Calcium peaks are strong in CDW because calcite, calcium silicate hydrates, and portlandite are common in concrete and mortar. Aluminium is identified at wavelength (308.2 nm, and 309.3 nm), and a strong resonance line of Al peak at 309 nm is helpful for detection in complex matrices. Aluminosilicate minerals, including feldspars, ceramics, and clays are the primary source of strong emission lines for Al in CDW. Alumina is also largely contributed and derived by bricks, clays, and tiles particularly in fine material fractions. These materials are highly presented in CDW, especially in fine fractions (<4 mm), leading to higher elemental concentration with strong LIBS emission. LIBS spectra reveal emission line for Si (251.6 nm and 288.2 nm), reflecting the quartz, glass, and silicate minerals that are common in bricks and cement in CDW [54].

The other elements are quantified with specific emission lines like Na (818.3 nm and 819.6 nm), Fe (259.9 nm), Mg (880.7 nm), K (766.4 nm and 770 nm), Mn (403.3 nm), and Ti (336.1 nm) in Fig. 4, are commonly occurring from minor constituent oxides, and easily detected correspond to their varied concentrations. Moderate level of Mg can be found in

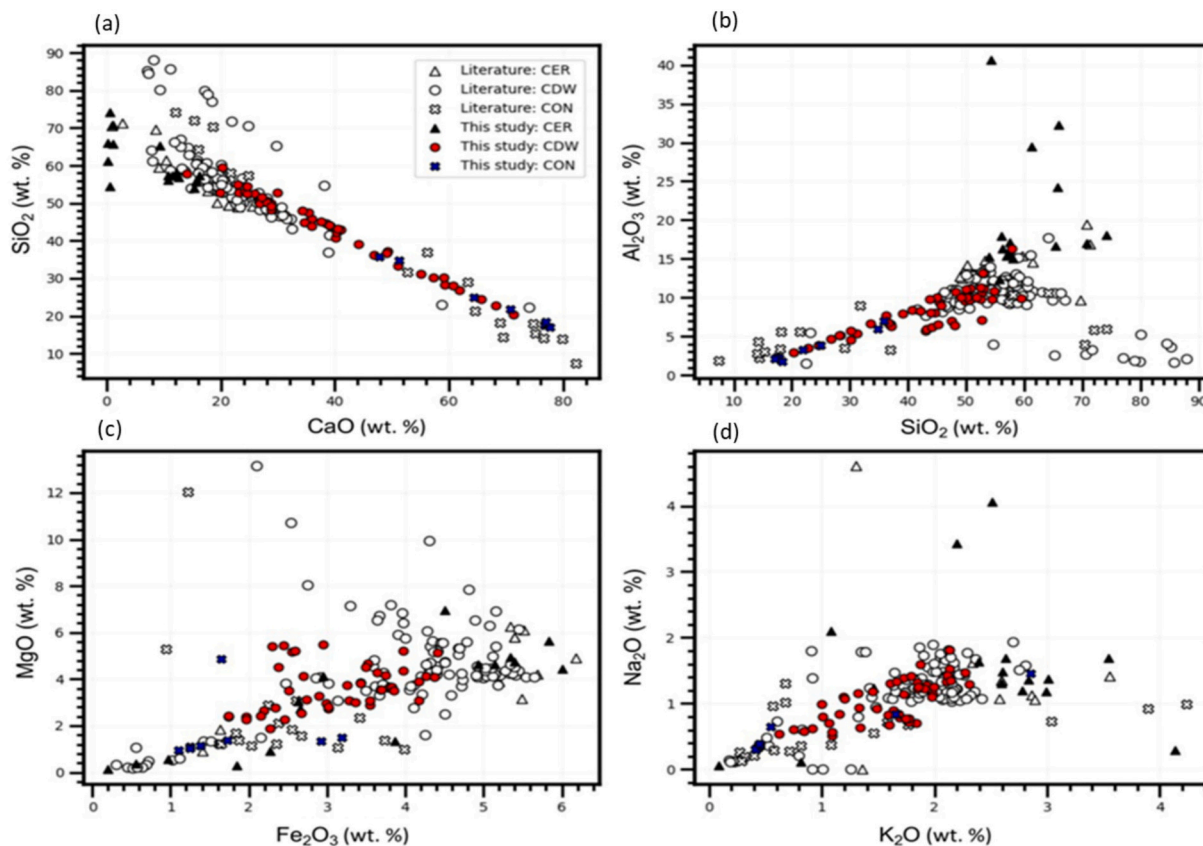


Fig. 3. Scatter plots of major oxides (XRF) compositions (a) SiO_2 vs CaO , (b) Al_2O_3 vs SiO_2 , (c) MgO vs Fe_2O_3 , and (d) Na_2O vs K_2O for CER, CON, and CDW materials and previous studies of literature [7,18,51].

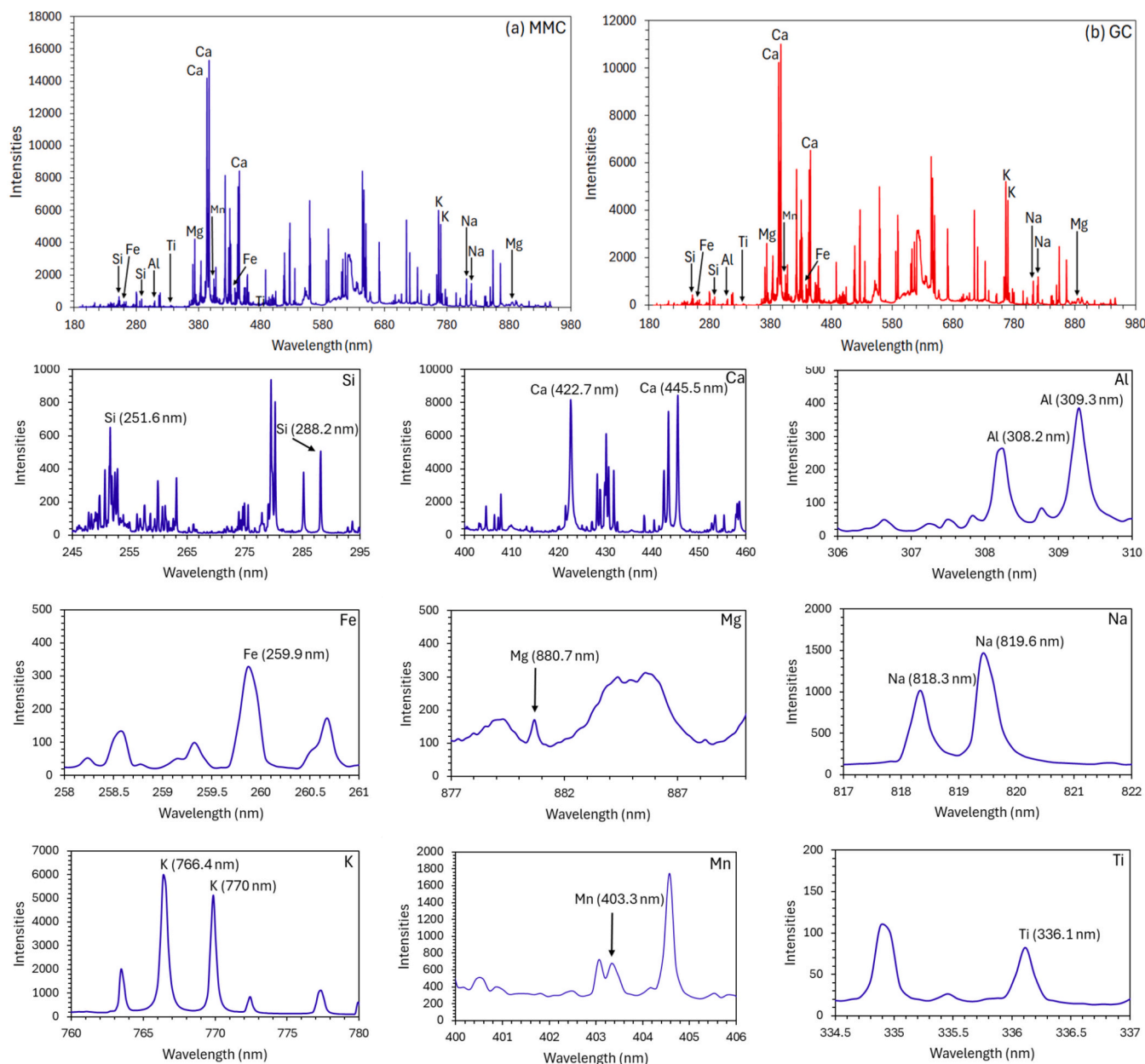


Fig. 4. Average spectra of (a) MMC method and (b) GC method for all the samples. High resolution of average LIBS spectra of each major element labelled for CDW samples with specific wavelengths.

dolomite ($\text{CaMg}(\text{CO}_3)_2$), ceramics, and cement additives. Iron, Mn, and Ti are present in trace levels or in small mineral phases within the waste matrix, with weaker emission lines. Manganese has distinct and low spectral lines and is found in steel, bricks, and colours with low quantity. Potassium is found in mineral phases in CDW samples, including feldspars, muscovite, biotite, and clay minerals bounded in concrete, bricks, and tiles which is identified by its strong emission lines. White pigments (TiO_2), ceramics, and tiles all contain Ti, which is identified by its effective emission. Low to moderate peaks of Fe are associated to mineral phases, brick colorants, and reinforcement steel. Sodium with high emission intensity by LIBS, is frequently associated to glass, mortars, and bricks in CDW. Fine particle size in CDW samples also increases characteristic emissions and enhances detection for all elements, by improving plasma homogeneity and laser ablation efficiency.

3.3. Elemental composition analysis by LIBS

The concentrations of major elements measured by LIBS for all investigated samples (CER, CON, and CDW) are compared, highlighting the differences in the values obtained by MMC and GC methods, as shown in Fig. 5 and Table S1. From the comparison between the two models, the MMC method showed significant results achieving higher accuracy in elemental quantifications than the GC model, with lower matrix effects and minimal interference of the analyte's signals from the sample matrix. The CDW materials used for MMC have enlarged Si contents (from 20% to 70 wt%) than the certified standards used for the GC calibration (Fig. 5). Overall, about 40% to 60% of Si is quantified well for all mixed CDW samples in MMC, while 60% to 80% of Si is well distributed for MPC samples (Fig. 5 and Table S1). These samples exhibit exceptionally high aluminosilicate levels, resulting in uncertainty in calibration curves by MMC method. The calibration curves for high Si-rich samples (i.e., ceramics MPC series samples; Table S1) could be

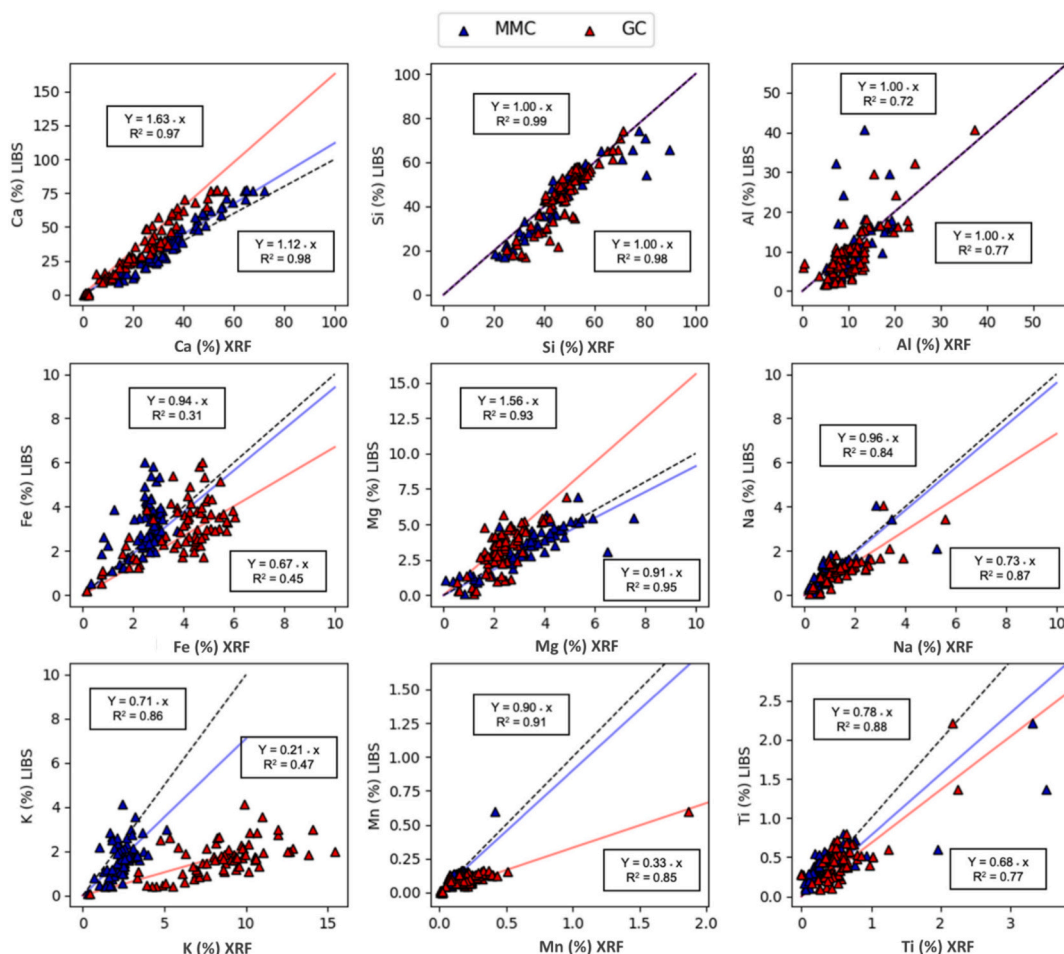


Fig. 5. Comparative analysis of major elements by LIBS measurements for MMC and GC methods.

affected by self-absorption and matrix effects, resulting in uncertainty in analytical results [53,55]. All the mixed CDW materials have much higher Ca measured contents (up to 75 wt%) for both calibrations. The accuracy and measurements of Ca contents are better for both MMC and GC models (Fig. 5), indicating that Ca (LIBS) vs Ca (XRF) trend lies more along the 1:1 trend, with linear regression value (R^2 : 0.98) for MMC and (R^2 : 0.97) for GC. Univariate calibration methods like MMC are suitable for elements like Si- and Ca-rich samples at higher concentrations due to consistent peak intensities and stable plasma conditions [56]. Our results align with Zhang et al. [57], who reported comparable results for major elements (Ca: 65%, and Si: 42% on average) in 58% cement samples (pressed pellets), by MMC method.

For Al, most (85%) of the samples are well distributed with 5% to 15% compositions showing high accuracy for both calibrations. In comparison, a small percentage (15%) of samples exhibit varying compositions (15% to 40%) for both MMC and GC. Our findings are consistent with LIBS results of NIST cement pressed pellets samples (Ca: 40–68%; Al: 3–40%) by LIBS [27]. Similar results of high Si and Al are documented in the previous study of heterogeneous refractory waste materials by LIBS [36]. Dong et al. [30] also reported high Si and Al in LIBS measurements of coal pressed pellets samples, and calibration improvement enhanced the accuracy of quantitative analysis and by partial least square regression method.

Results for the other elements (Fe, Mg, Na, Ti, Mn) except K, showing similar accuracy for the MMC and GC. For Fe, the MMC method is relatively better for all CDW samples from 1% to 3% composition, compared with the GC. By contrast, the samples (3% to 6% of total composition) are highly distributed for Fe for both calibrations. The

accuracy of Fe measurements in samples in ceramic, concrete and mixed CDW materials is primarily affected by matrix effects, inherent variations in physical properties and elemental interference [58]. Physical matrix effects of high Si- and Al-rich mineral phases altered signal intensity of Fe at the same wavelength. Zhang et al. [57] also stated that the accuracy of quantitative analysis is compromised by distortion of ideal linear relationship between signal intensity and analyte concentration. However, MMC analysis of mixed CDW materials by LIBS has improved analytical measurements, with minimal matrix interference of analyte concentrations.

The analysis of Mg yielded optimum results in mixed CDW samples, particularly for MMC, exhibiting a substantial overlap with the XRF values (Fig. 5). In contrast, the K analysis revealed that both models overestimated its content. In detail, the GC results are exceptionally scattered with modelled compositions ranging from 1% to 16%; in comparison, the results from the MMC model are much more accurate (with a range from 1% to 5%) and compliant with the measured XRF values. MMC being able to normalize K emission lines' intensity variations in LIBS and minimized signal distortions from matrix effects, unlikely GC uses unrelated standards with compositional variability, leading to high interferences. The results of Mn, and Na are relatively similar with low compositions, showing similar accuracy with both MMC and GC methods. Titanium also shows relatively similar accuracy for both MMC and GC with less improvement. The lower Ti concentration in CDW led to weaker emission lines with higher noise levels, restricting the effectiveness of both MMC and GC methods that depends on stable signal patterns. Our findings are consistent with low Ti, Mg, and Mn composition by LIBS in NIST cement samples (pressed pellets)

[27]. Likewise, LIBS technology has shown optimum results in soil samples (pellets) with high accuracy measurements for Si, Al, Fe, Mg, Ca, Na, and K [34]. Similarly, Junwei et al. [49] also reported that analysis of MMC method improved measurements accuracy of Ca, Si, Fe, Al, Mg, Na, K and Ti within wider range in cement raw materials (pellets) by LIBS and thereby reduced matrix effects.

3.4. Linear regression and empirical correction

Linear regression model showed that the model fits well the calibration data of MMC with accurate quantification by LIBS, as compared to the GC method (Fig. 5). Si, and Ca showed high linearity ($R^2 > 90\%$), while Al, Na, Ti, and Mn showed moderate linearity ($R^2 > 70\%$), confirming that the regression model is statistically meaningful (Fig. 5). K shows strong linearity ($R^2 = 86\%$) for MMC, while poor for GC ($R^2 = 47\%$), respectively. The accuracy of Mg is improved for MMC ($R^2 = 91\%$), compared with the GC ($R^2 = 85\%$), respectively. Fe showed lowest linear regression ($R^2 = 31\%$) for MMC, and for GC ($R^2 = 45\%$), respectively, indicating high data scattering, and linear models of Fe, and K inadequately capture data variance.

The slope for Si, Ca and Mg in Fig. 5, is close to 1 and intercepts near 0 with narrow confidence intervals indicate robust MMC calibration without major systematic errors. The slope deviates from 1 (intercepts near 0) for Al, Na, Mn, and Ti in both GC and MMC, indicating elemental intensities of these elements do not scale linearly due to instrumental biases. The confidence intervals for slope are wider for Fe, and K with low R^2 values and intercepts near 0, indicating poor linear correlation, potential systematic errors. In addition, MMC data points align better with the bisecting line than GC for Ca, Si, Fe, Na, Mg, K, and Mn except Ti, highlighting MMC's superior quantification.

An empirical correction was adopted based on the linear regression model in section 2.3, to fit well Si and Al sampling points well in regression plots (Fig. 5; Table S2), to decrease discrepancies between predicted and actual values observed in MMC and GC samples. The improved dataset results in accurate and reliable Si and Al measurements with enhanced linearity. The other major elements were well-

fitted for both calibrations without empirical corrections, as shown in Fig. 5. Similar method has been employed in the previous studies, such as Li et al. [59] that reported partial least square method used for uncertainty reduction in LIBS measurements and accurately reproduce well-fitted data points between the nominal and calculated concentrations of elements.

3.5. LIBS analysis of NIST standards and geological samples

The quantitative analysis of major elements by LIBS was extended to assess the accuracy of MMC and GC on NIST standards and test samples (Fig. 6 and Table S3). Silicon, Ca, Mg, and Ti show comparable results between both calibrations, however; MMC performed well for quantification of Si, Ca, Al, Fe, Na, and Mg, in standards closely matching true certified values, as compared to the GC method. Silicon shows similar compositional range (MMC: 8 to 91%, and GC: 6 to 91%) for all standards. Calcium also showed most significant compositional range (MMC: 0.55 to 79%, and GC: 0.44 to 69%). In contrast, Al has high compositional discrepancy by GC (ranged from 0.33 to 93.3%), while MMC showed optimal results for Al (from 0.71 to 55.5%), compared to the reference values (Table S3). Iron, Mg, Na, Mn, and Ti showed bit of similar compositions by both calibrations except K (MMC: 0.02 to 4.20% and GC: 0.1 to 16.5%), showing discrepancy for GC.

Our findings show that calibration methods enable substantial quantification of major elements, however; MMC revealed superior results, reflecting consistent spectral responses and plasma conditions that minimize systematic errors in standards and test samples. Certain elements exhibit uncertainty due to exceptionally high Al concentration in some samples (GXR-2, MPC-15, and BR; Table S3) due to high alumina. The matrix effects arise from these sample's physical properties and chemical composition, affecting the emission phenomenon during LIBS analysis [60].

3.6. Absolute difference (MMC vs GC)

The results of ABS-D showed significant differences between the two

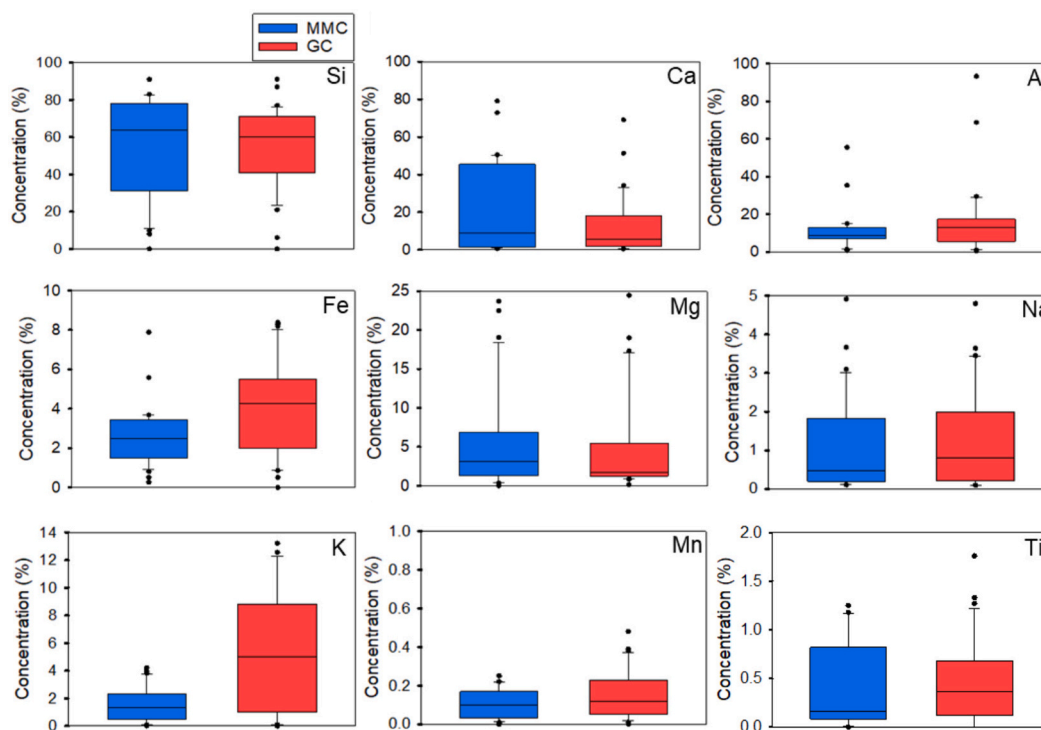


Fig. 6. Abundance of major elements (%) in NIST standards and geological test samples, measured by MMC and GC methods.

calibration methods, as shown in Table 1 and Fig. S3. Ca accuracy is substantially improved (average ABS-D from 10.9% GC to 4.55% MMC), while Si also improved modestly (5.08% to 4.34%). High Si quantification and its low ABS-D is attributed to strong plasma emission signals enabling accurate calibration and improve measurements accuracy [56]. The ABS-D of Al remains similar (3.36% MMC vs. 3.16% GC), while Ti also showed negligible difference (0.19% vs. 0.18%). The quantifications of Fe, Mg, Na, K, and Mn are also significantly improved by MMC with low to moderate ABS-D, as shown in Table 1. These results showed that MMC method enhances accuracy of LIBS measurements for high- and low-concentration elements in complex matrices.

For standard samples, Si exhibit comparable results of ABS-D (12.9% MMC vs. 13.1% GC). MMC outperformed GC in accuracy with lower average ABS-D for Ca (6.11% vs. 12.2%), Al (7.37% vs. 9.18%), Mg (4.16% vs. 4.78%), K (0.76% vs. 4.08%), and Mn (0.04% vs. 0.08%), with values closely matching reference concentrations (Table 1, and Fig. S4). Na and Ti also showed similar results (0.76% vs. 0.78%) and Ti (0.31% vs. 0.35%) for GC and MMC, respectively, while GC was slightly better for Fe (2.68% vs. 3.62% MMC). These results also confirm that MMC method enhanced LIBS performance for standards as unknown samples due to optimized calibration, plasma conditions noise reduction, and effectively minimized the matrix effects.

4. Conclusion

In the present study, two calibration strategies for LIBS-MMC and built-in SciAps GC calibration were tested for mixed CDW materials and on reference NIST specimens. The newly developed MMC library demonstrated clear advantages, exhibiting reduced matrix effects and minimal analyte signal interference. The elemental makeup of CDW in spectral analysis confirm the applicability of calibration models relevance, which is associated to diverse minerals phases in CDW. MMC method shows higher Si and Ca levels with similar concentrations as main components of mixed CDW materials, than the built-in SciAps GC method, making the GC calibration insufficiently accurate for mixed CDW. MMC provided substantially more accurate quantification of major elements (Si, Ca, Fe, Mg, Na, K, and Mn) in mixed CDW materials, and significantly lowering the average absolute differences, compared to the built-in GC calibration. MMC also improved the quantification of Ca, Al, Mg, K and Mn in NIST standards, compared to the GC, confirming its robustness. Despite these benefits, MMC remains constrained to specific CDW types, as LIBS accuracy depends on calibrations tailored to matrices closely matching the sample composition. Future work should expand MMC datasets to capture diverse CDW types such as gypsum-based materials like plasters waste, mixed aggregates (mortar and masonry waste), concrete with admixtures, as well as inorganic wastes like mine tailings and metallurgical slags and municipal solid waste incineration waste.

It is imperative to explore novel methods to enhance calibration robustness and transferability by integrating MMC with machine learning algorithms like cluster-based classification, support vector machines algorithm, convolutional neural networks, and t-distributed stochastic neighbor embedding present promising advantages for LIBS analysis of complex matrices. These approaches enable automated classification, adaptive calibration, exploratory data analysis, handling nonlinear plasma-matrix interactions and elemental overlaps, matrix variability, and spectral interferences. Pilot-scale sorting trials combining LIBS with MMC should also be explored to assess real-world applicability for CDW recycling and sorting operations. Calibration-free LIBS methods like local thermodynamic equilibrium-independent, and random sample consensus, or hybrid strategies of combining MMC and non-matrix-matched like internal standardization, and multi-element ratio models may increase applicability with minimum calibration requirements. Overall, portable LIBS technology with accurate calibration methods has potential to replace conventional analytical techniques, offering rapid, reliable, real-time chemical analysis in laboratory and

Table 1

ABS-D (%) of major elements for all mixed CDW materials and standards by MMC and GC methods.

Elements	CDW		Standards	
	MMC	GC	MMC	GC
Si	4.34	5.08	12.9	13.1
Ti	0.19	0.18	0.35	0.31
Al	3.36	3.16	7.37	9.18
Fe	0.84	1.23	3.62	2.68
Mn	0.03	0.15	0.04	0.08
Mg	0.49	1.20	4.16	4.78
Ca	4.55	10.9	6.11	12.2
Na	0.34	0.42	0.76	0.78
K	0.90	6.83	0.76	4.08

field applications.

CRediT authorship contribution statement

J. Ghani: Writing – original draft, Software, Methodology. **A. Bis-ciotti:** Writing – review & editing, Software, Methodology. **G. Bianchini:** Writing – review & editing, Supervision, Conceptualization. **R. Tassinari:** Writing – review & editing. **G. Iezzi:** Writing – review & editing, Methodology. **F. Radica:** Writing – review & editing, Methodology. **G. Cruciani:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The project was financially supported by the National Recovery and Resilience Plan, Mission 4, Component 2, Investment 1.1, Call for Tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union–NextGenerationEU–Project titled “Rubble-to-Resource (RUB2RES): Earth science knowledge for sorting and recycling Construction and Demolition Waste” (CUP F53D23002140006), with Grant Assignment Decree No. 965, issued on 30.06.2023 by the MUR. The authors gratefully acknowledge Gian Marco's assistance in sampling, size-sorting, sample powdering, and XRF pellet preparation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.sab.2026.107458>.

Data availability

Data will be made available on request.

References

- [1] A. Torres, J. Brandt, K. Lear, J. Liu, A looming tragedy of the sand commons, in: Science 357, American Association for the Advancement of Science, 2017, pp. 970–971, <https://doi.org/10.1126/science.aao0503>.
- [2] L. Koehnken, M.S. Rintoul, M. Goichot, D. Tickner, A.-C. Loftus, M.C. Acreman, Impacts of riverine sand mining on freshwater ecosystems: a review of the scientific evidence and guidance for future research, River Res. Appl. 36 (2020) 362–370, <https://doi.org/10.1002/rra.3586>.
- [3] C.R. Gagg, Cement and concrete as an engineering material: an historic appraisal and case study analysis, Eng. Fail. Anal. 40 (2014) 114–140, <https://doi.org/10.1016/j.engfailanal.2014.02.004>.

- [4] J. Sagan, A. Mach, Construction waste management: impact on society and strategies for reduction, *J. Clean. Prod.* 486 (2025) 144363, <https://doi.org/10.1016/j.jclepro.2024.144363>.
- [5] P.S. Villoria, M. Osmani, A diagnosis of construction and demolition waste generation and recovery practice in the European Union, *J. Clean. Prod.* 241 (2019), <https://doi.org/10.1016/j.jclepro.2019.118400>.
- [6] R.V. Silva, J. De Brito, R.K. Dhir, Properties and composition of recycled aggregates from construction and demolition waste suitable for concrete production, *Constr. Build. Mater.* 65 (2014) 201–217, <https://doi.org/10.1016/j.conbuildmat.2014.04.117>.
- [7] A. Galderisi, G. Iezzi, G. Bianchini, E. Paris, J. de Brito, Petrography of construction and demolition waste (CDW) from Abruzzo region (Central Italy), *Waste Manag.* 137 (2022) 61–71, <https://doi.org/10.1016/j.wasman.2021.10.028>.
- [8] D. Caro, C. Lodato, A. Damgaard, J. Crist'obal, G. Foster, F. Flachenecker, D. Tonini, Environmental and socio-economic effects of construction and demolition waste recycling in the European Union, *Sci. Total Environ.* (2024), <https://doi.org/10.1016/j.scitotenv.2023.168295>, 908.
- [9] A.D. Maria, J. Eyckmans, K. Van Acker, Downcycling versus recycling of construction and demolition waste: combining LCA and LCC to support sustainable policy making, *Waste Manag.* 75 (2018) 3–21, <https://doi.org/10.1016/j.wasman.2018.01.028>.
- [10] A. Mahpour, Prioritizing barriers to adopt circular economy in construction and demolition waste management, *Resour. Conserv. Recycl.* 134 (2018) 216–227, <https://doi.org/10.1016/j.resconrec.2018.01.026>.
- [11] D. Demetriou, P. Mavromatidis, P.M. Robert, H. Papadopoulos, M.F. Petrou, D. Nicolaides, Real-time construction demolition waste detection using state-of-the-art deep learning methods; single – stage vs two-stage detectors, *Waste Manag.* 167 (2023) 194–203, <https://doi.org/10.1016/j.wasman.2023.05.039>.
- [12] M.O. Erkinay, Z. Ali, B. Subeshan, E. Asmatulu, Applying machine learning approach in recycling, *J. Mater. Cycle. Waste Manag.* 23 (2021) 855–871, <https://doi.org/10.1007/s10163-021-01182-y>.
- [13] A.T. Gebremariam, F.M. Di, A. Vahidi, P. Rem, Innovative technologies for recycling end-of-life concrete waste in the built environment, *Resour. Conserv. Recycl.* 163 (2020), <https://doi.org/10.1016/j.resconrec.2020.104911>.
- [14] V. Nežerka, T. Zbíral, J. Trejbal, Machine-learning-assisted classification of construction and demolition waste fragments using computer vision: convolution versus extraction of selected features[formula presented], *Expert Syst. Appl.* (2024) 238, <https://doi.org/10.1016/j.eswa.2023.121568>.
- [15] F. Radica, G. Iezzi, O. Trotta, G. Bonifazi, S. Serranti, J. de Brito, Characterization of CDW types by NIR spectroscopy: towards an automatic selection of recycled aggregates, *J. Build. Eng.* 88 (2024) 109005, <https://doi.org/10.1016/j.jobe.2024.109005>.
- [16] S. Serranti, R. Palmieri, G. Bonifazi, R. Gasbarrone, G. Hermant, H. Bréquel, An automated classification of recycled aggregates for the evaluation of product standard compliance, *Sustainability* 15 (2023) 15009, <https://doi.org/10.3390/su152015009>.
- [17] A. Bisciotti, D. Jiang, Y. Song, G. Cruciani, Estimating attached mortar paste on the surface of recycled aggregates based on deep learning and mineralogical models, *Cleaner Mater.* 11 (2024) 100215, <https://doi.org/10.1016/j.clema.2023.100215>.
- [18] A. Bisciotti, V. Brombin, Y. Song, G. Bianchini, G. Cruciani, Classification and predictive leaching risk assessment of construction and demolition waste using multivariate statistical and machine learning analyses, *Waste Manag.* 196 (2025) 60–70, <https://doi.org/10.1016/j.wasman.2025.02.033>.
- [19] C. Chang, F. Maio, P.D. Rem, A.T. Gebremariam, F. Mehari, H. Xia, Cluster-based identification algorithm for in-line recycled concrete aggregates characterization using laser-induced breakdown spectroscopy (LIBS), *Resour. Conserv. Recycl.* 185 (2022), <https://doi.org/10.1016/j.resconrec.2022.106507>.
- [20] F.J. Fortes, J. Moros, P. Lucena, L.M. Cabalín, J.J. Laserna, Laser-induced breakdown spectroscopy, *Anal. Chem.* 85 (2013) 640–669, <https://doi.org/10.1021/ac303220r>.
- [21] E. Nanou, N. Pliatsika, D. Stefanis, D. Polygenis, S. Couris, Laser induced breakdown spectroscopy as an emerging technique for olive oil, milk and honey authentication and traceability, *J. Food Compos. Anal.* 107650 (2025), <https://doi.org/10.1016/j.jfca.2025.107650>.
- [22] A. De Giacomo, M. Dell'Aglío, O. De Pascale, R. Gaudioso, A. Santagata, R. Teghil, Laser induced breakdown spectroscopy methodology for the analysis of copper-based-alloys used in ancient artworks, *Spectrochim. Acta Part B* 63 (2008) 585–590, <https://doi.org/10.1016/j.sab.2008.03.006>.
- [23] De Giacomo, M. Dell'Aglío, O. De Pascale, S. Longo, M. Capitelli, Laser induced breakdown spectroscopy on meteorites, *Spectrochim. Acta Part B* 62 (2007) 1606–1611, <https://doi.org/10.1016/j.sab.2007.10.004>.
- [24] R. Gaudioso, M. Dell'Aglío, O. De Pascale, G.S. Senesi, A. De Giacomo, Laser induced breakdown spectroscopy for elemental analysis in environmental, cultural heritage and space applications: a review of methods and results, *Sensors* 10 (2010) 7434–7468, <https://doi.org/10.3390/s100807434>.
- [25] G.S. Senesi, M. Dell'Aglío, R. Gaudioso, A. De Giacomo, C. Zaccone, O. De Pascale, T.M. Miano, M. Capitelli, Heavy metal concentrations in soils as determined by laser-induced breakdown spectroscopy (LIBS), with special emphasis on chromium, *Environ. Res.* 109 (2009) 413–420, <https://doi.org/10.1016/j.envres.2009.02.005>.
- [26] S.C. Jantzi, V. Motto-Ros, F. Trichard, Y. Markushin, N. Melikechi, A. De Giacomo, Sample treatment and preparation for laser-induced breakdown spectroscopy, *Spectrochim. Acta Part B* 115 (2016) 52–63, <https://doi.org/10.1016/j.sab.2015.11.002>.
- [27] A. Mansoori, B. Roshanzadeh, M. Khalaji, S.H. Tavassoli, Quantitative analysis of cement powder by laser induced breakdown spectroscopy, *Opt. Lasers Eng.* 49 (2011) 318–323, <https://doi.org/10.1016/j.optlaseng.2010.10.005>.
- [28] H. Yin, Z. Hou, L. Zhang, X. Zhang, Z. Wang, Z. Li, Cement raw material quality analysis using laser-induced breakdown spectroscopy, *J. Anal. At. Spectrom.* 31 (2016) 2384–2390, <https://doi.org/10.1039/C6JA00323K>.
- [29] L. Zhang, W. Yin, L. Dong, W. Ma, L. Xiao, S. Jia, Stability enhanced online powdery cement raw materials quality monitoring using laser-induced breakdown spectroscopy, *IEEE Photonics J.* 9 (2017) 1–10, <https://doi.org/10.1109/JPHOT.2017.2741066>.
- [30] M. Dong, D. Oropeza, J. Chirinos, J.J. González, J. Lu, X. Mao, R.E. Russo, Elemental analysis of coal by tandem laser induced breakdown spectroscopy and laser ablation inductively coupled plasma time of flight mass spectrometry, *Spectrochim. Acta Part B* 109 (2015) 44–50, <https://doi.org/10.1016/j.sab.2015.04.008>.
- [31] K. Liu, C. He, C. Zhu, J. Chen, K. Zhan, X. Li, A review of laser-induced breakdown spectroscopy for coal analysis, *Trends Anal. Chem.* 143 (2021) 116357, <https://doi.org/10.1016/j.trac.2021.116357>.
- [32] T. Klewe, T. Völker, J. Götz, M. Landmann, G. Wilsch, S. Kruschwitz, Sorting of construction and demolition waste by combining LIBS with NIR spectroscopy, in: *International Symposium Non-Destructive Testing in Civil Engineering*, 2022, pp. 1–9, <https://doi.org/10.58286/27220>.
- [33] T. Klewe, T. Völker, M. Landmann, S. Kruschwitz, LIBS-ConSort: Development of a sensor-based sorting method for construction and demolition waste, *ce/papers* 6, 2023, pp. 973–976, <https://doi.org/10.1002/cepa.2866>.
- [34] K.Q. Yu, Y.R. Zhao, F. Liu, Y. He, Laser-induced breakdown spectroscopy coupled with multivariate chemometrics for variety discrimination of soil, *Sci. Rep.* 6 (2016) 27574.
- [35] S.W. Hudson, J. Craparo, R. De Saro, D. Apelian, Applications of laser-induced breakdown spectroscopy (LIBS) in molten metal processing, *Metall. Mater. Trans. B Process Metall. Mater. Process. Sci.* 48 (2017) 2731–2742, <https://doi.org/10.1007/s11663-017-1032-7>.
- [36] D.J. Díaz-Romero, S. Van den Eynde, W. Sterkens, A. Eckert, I. Zaplana, T. Goedemé, J. Peeters, Real-time classification of aluminum metal scrap with laser-induced breakdown spectroscopy using deep and other machine learning approaches, *Spectrochim. Acta Part B* 196 (2022) 106519, <https://doi.org/10.1016/j.sab.2022.106519>.
- [37] S. Van den Eynde, D.J. Díaz-Romero, B. Engelen, I. Zaplana, J.R. Peeters, Assessing the efficiency of laser-induced breakdown spectroscopy (LIBS) based sorting of post-consumer aluminium scrap, *Proc. CIRP* 105 (2022) 278–283, <https://doi.org/10.1016/j.procir.2022.02.046>.
- [38] J. Moros, L.M. Cabalín, J.J. Laserna, Refractory residues classification strategy using emission spectroscopy of laser-induced plasmas in tandem with a decision tree-based algorithm, *Anal. Chim. Acta* 1191 (2022) 339294, <https://doi.org/10.1016/j.aca.2021.339294>.
- [39] B.S. Marangoni, G. Nicolodelli, G.S. Senesi, N. Fonseca, H.J. Izario Filho, A. A. Xavier, P.R. Villas-Boas, D.M. Milori, C.R. Menegatti, Multi-elemental analysis of landfill leachates by single and double pulse laser-induced breakdown spectroscopy, *Microchem. J.* 165 (2021) 106125, <https://doi.org/10.1016/j.microc.2021.106125>.
- [40] B. Yan, R. Liang, B. Li, J. Tao, G. Chen, Z. Cheng, Z. Zhu, X. Li, Fast identification and characterization of residual wastes via laser-induced breakdown spectroscopy and machine learning, *Resour. Conserv. Recycl.* 174 (2021) 105851, <https://doi.org/10.1016/j.resconrec.2021.105851>.
- [41] G. Jeon, H. Keum, H. Lee, K. Oh, J. Choi, Effects of feature engineering on the robustness of laser-induced breakdown spectroscopy for industrial steel classification, *Spectrochim. Acta Part B* 212 (2024) 106857, <https://doi.org/10.1016/j.sab.2024.106857>.
- [42] F.A. Casian-Plaza, O. Urbán, Á. Bélteki, M. Aladi, M. Kedves, A. Bonyár, J. Kopniczyk, M. Veres, G. Galbács, Quantitative characterization of the lateral distribution of gold nanoparticles in polystyrene nanocomposite thin films by laser-induced breakdown spectroscopy elemental mapping, *Appl. Surf. Sci.* 700 (2025) 163276, <https://doi.org/10.1016/j.apsusc.2025.163276>.
- [43] R. Gaudioso, E. Ewusi-Annan, N. Melikechi, X. Sun, B. Liu, L.F. Campesato, T. Merghoub, Using LIBS to diagnose melanoma in biomedical fluids deposited on solid substrates: limits of direct spectral analysis and capability of machine learning, *Spectrochim. Acta Part B* 146 (2018), <https://doi.org/10.1016/j.sab.2018.05.010>.
- [44] H. Xia, M.C.M. Bakker, Reliable classification of moving waste materials with LIBS in concrete recycling, *Talanta* 120 (2014) 239–247, <https://doi.org/10.1016/j.talanta.2013.11.082>.
- [45] N. Baskali-Bouregaa, M.L. Milliand, S. Mauffrey, E. Chabert, M. Forrester, N. Gilon, Tea geographical origin explained by LIBS elemental profile combined to isotopic information, *Talanta* (2020) 211, <https://doi.org/10.1016/j.talanta.2019.120674>.
- [46] G. Gupta, B. Suri, A. Verma, M. Sundararaman, V. Unnikrishnan, K. Alti, V. Kartha, C. Santhosh, Quantitative elemental analysis of nickel alloys using calibration-based laser-induced breakdown spectroscopy, *J. Alloys Compd.* 509 (2011) 3740–3745, <https://doi.org/10.1016/j.jallcom.2010.12.189>.
- [47] V. Unnikrishnan, R. Nayak, P. Devangad, M. Tamboli, C. Santhosh, G. Kumar, D. Sardar, Calibration based laser-induced breakdown spectroscopy (LIBS) for quantitative analysis of doped rare earth elements in phosphors, *Mater. Lett.* 107 (2013) 322–324, <https://doi.org/10.1016/j.matlet.2013.06.036>.
- [48] T. Stehrer, B. Praher, R. Viskup, J. Jasik, H. Wolfmeir, E. Arenholz, J. Heitz, J. Pedarnig, Laser-induced breakdown spectroscopy of iron oxide powder, *J. Anal. At. Spectrom.* 24 (2009) 973–978, <https://doi.org/10.1039/B817279J>.

- [49] J. Junwei, F. Hongbo, H. Zongyu, W. Huadong, N. Zhibo, D. Fengzhong, Calibration curve and support vector regression methods applied for quantification of cement raw meal using laser-induced breakdown spectroscopy, *Plasma Sci. Technol.* 21 (2018) 034003, <https://doi.org/10.1088/2058-6272/aae3e1>.
- [50] R.J. Traill, G.R. Lachance, A practical solution to the matrix problem in X-ray analysis. II. Application to a multi-component alloy system, *Can. J. Spectrosc.* 11 (1966) 63–71.
- [51] G. Bianchini, I. Ristovski, I. Milcov, A. Zupac, C. Natali, G.M. Salani, C. Marchina, V. Brombin, A. Ferraboschi, Chemical characterisation of construction and demolition waste in Skopje City and its surroundings (Republic of Macedonia), *Sustainability* 12 (2020) 2055, <https://doi.org/10.3390/su12052055>.
- [52] A.P. Rao, P.R. Jenkins, J.D. Auxier II, M.B. Shattan, Comparison of machine learning techniques to optimize the analysis of plutonium surrogate material via a portable LIBS device, *J. Anal. At. Spectrom.* 36 (2021) 399–406, <https://doi.org/10.1039/D0JA00435A>.
- [53] E. Moreno-Pérez, J. Hernández-Ávila, Y. Rangel-Martínez, E. Cerecedo-Sáenz, A. Arenas-Flores, M.I. Reyes-Valderrama, E. Salinas-Rodríguez, Chemical and mineralogical characterization of recycled aggregates from construction and demolition waste from Mexico City, *Minerals* 8 (2018) 237, <https://doi.org/10.3390/min8060237>.
- [54] C. Zanelli, E. Marrocchino, G. Guarini, A. Toffano, C. Vaccaro, M. Dondi, Recycling construction and demolition residues in clay bricks, *Appl. Sci.* 11 (2021) 8918, <https://doi.org/10.3390/app11198918>.
- [55] J.M. Andrade, G. Cristoforetti, S. Legnaioli, G. Lorenzetti, V. Palleschi, A. A. Shaltout, Classical univariate calibration and partial least squares for quantitative analysis of brass samples by laser-induced breakdown spectroscopy, *Spectrochim. Acta B* 65 (2010) 658–663, <https://doi.org/10.1016/j.sab.2010.04.008>.
- [56] W. Skrzeczanowski, M. Długaszek, Al and Si quantitative analysis in aqueous solutions by LIBS method, *Talanta* 225 (2021) 121916, <https://doi.org/10.1016/j.talanta.2020.121916>.
- [57] C. Zhang, W. Song, Z. Hou, Z. Wang, Improving quantitative analysis of cement elements in laser-induced breakdown spectroscopy through combining matrix matching with regression, *J. Anal. At. Spectrom.* 38 (2023) 2554–2561, <https://doi.org/10.1039/D3JA00306J>.
- [58] Z. Wang, T.B. Yuan, Z.Y. Hou, W.D. Zhou, J.D. Lu, H.B. Ding, X.Y. Zeng, Laser-induced breakdown spectroscopy in China, *Front. Phys.* 9 (2014) 419–438, <https://doi.org/10.1007/s11467-013-0410-0>.
- [59] X. Li, Z. Wang, S.L. Lui, Y. Fu, Z. Li, J. Liu, W. Ni, A partial least squares based spectrum normalization method for uncertainty reduction for laser-induced breakdown spectroscopy measurements, *Spectrochim. Acta B* 88 (2013) 180–185, <https://doi.org/10.1016/j.sab.2013.07.005>.
- [60] T. Takahashi, B. Thornton, Quantitative methods for compensation of matrix effects and self-absorption in laser induced breakdown spectroscopy signals of solids, *Spectrochim. Acta B* 138 (2017) 31–42, <https://doi.org/10.1016/j.sab.2017.09.010>.