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Research Article

Elemental profiling as a tool for geographical origin classification of Vietnamese wines

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Abstract The objective of this research was to distinguish Vietnamese wines based on their geographical origin using chemistry and chemometric methods. Forty wine samples from Vietnam, France and Italy were collected and analyzed. The multi-element determination ability of Inductively Coupled Plasma Mass Spectrometry (ICP-MS) was used to analyze 20 elements in wine samples. Principal Component Analysis (PCA) was used for exploratory analysis and Linear Discriminant Analysis (LDA) was used for geographical classification of wine samples. The result of PCA explained 85.86% of the total variance contribution. LDA achieved 100% accuracy in correctly classifying all wine samples in both the training and cross-validation sets according to their geographical origin using nine elements (As, Li, Be, Ti, V, Cr, Mo, Cd, and Tl). The outcomes emphasize that the combination of ICP-MS with PCA and LDA offers a reliable technique to validate the geographical origin of wine samples, particularly for distinguish Vietnamese wines form French and Italian wines.

Keywords geographical origin, wine, ICP-MS, PCA, LDA

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1. Introduction

Wine is an alcoholic beverage that is widely consumed and plays an important social and economic role all over the world (Azcarate et al., 2015; Huang et al., 2017; Shen et al., 2013). Wine authenticity and traceability have become critical concerns in the food and beverage industry, particularly due to rising consumer demand for product quality and safety (Azcarate et al., 2015; Kruzlicova et al., 2013; Tian et al., 2017). Among various indicators of wine authenticity, geographical origin plays an important role in its commercial value (Rodrigues et al., 2020; Tian et al., 2017). Therefore, robust methods to classify geographical origin and prevent adulteration and mislabeling are highly required (Hopfer et al., 2015; Taylor et al., 2003).

Elemental profiling has emerged as a powerful tool for verifying the geographical origin of food and beverages, including wine (Geana et al., 2013). The elemental composition of wine is influenced by several factors, such as soil, climate, grape variety, agricultural practices (pesticides, fungicides, fertilizers) and various stages of the winemaking process (machinery, barrels, additives like bentonite) (Kruzlicova et al., 2013; Woldemariam and Chandravanshi, 2011). Among the analytical techniques available, inductively coupled plasma mass spectrometry (ICP-MS) offers exceptional sensitivity, accuracy, and the ability to simultaneously quantify a wide range of elements. As such, ICP-MS has been widely applied in wine authentication studies across Europe, South America, and other wine-producing regions (Coetzee et al., 2005; Mazarakioti et al., 2022; Popîrdă et al., 2021; Taylor et al., 2003; Versari et al., 2014).

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The elemental profile generated from ICP-MS analysis, utilized for the authentication and meticulous characterization of wine products, inherently yields a multivariate dataset. This chemical information, referred to as first-order data, consists of an array of quantified elemental concentrations. To get meaningful scientific conclusions from this complex information, specialized data treatment methodologies known as chemometrics are routinely applied. These chemometric approaches are generally segregated into two fundamental categories: unsupervised methods and supervised methods. Unsupervised methods employed for exploratory analysis to reveal underlying data structure and natural sample groupings without prior knowledge of class membership, such as principal component analysis (PCA) (Rodrigues et al., 2011; Serapinas et al., 2008; Šperková and Suchánek, 2005; Villagra et al., 2012) and cluster analysis (CA) (Pasvanka et al., 2021). Supervised methods are applied when the classes or categories (such as geographical origin or grape variety) are known in advance, with the objective of developing a robust classification model, such as linear discriminant analysis (LDA) (Martin et al., 2012; Rodrigues et al., 2011; Villagra et al., 2012), partial least square discriminant analysis (PLS-DA) (Bronzi et al., 2020; Shen et al., 2013).

Vietnam, while a relatively young player in the global wine industry, has seen rapid development in wine production, especially in Ninh Thuan, Lam Dong and Son La Provinces. However, limited research has been conducted to characterize the elemental profile of Vietnamese wines or to explore the potential for using elemental fingerprints to verify their geographical origin. This lack of scientific data hinders the development of effective traceability and quality assurance systems for domestic wines, which are essential for promoting consumer confidence and protecting local producers against fraud.

In this study, we employed ICP-MS to determine the elemental composition of Vietnamese wines collected from major wine-producing regions. Multivariate statistical analyses were then applied to evaluate the potential of elemental fingerprints in distinguishing wines based on their geographical origin. The findings provide a scientific basis for origin authentication and contribute to the broader efforts of improving traceability and quality control in the Vietnamese wine industry.

2. Materials and methods

2.1. Wine samples

Forty commercial red wines were purchased from local supermarkets. Samples were selected based on a clear designation of geographical origin, resulting in a set from Vietnam (number of samples n=11), France (n=16), and Italy (n=13) (See Table S1 in the Supplementary materials for more information). All wines were stored at 3-4°C until analysis to maintain chemical stability.

2.2. ICP-MS analysis

The wine samples were taken from freshly opened bottles and prepared by using nitric acid digestion, where 4 mL of wine was weighed into a vessel and digested with 4 mL of concentrated nitric acid. The digestion was carried out in 1,000 W microwave with a 30 min ramp, and 20 min hold at 180°C, followed by 20 min cooling. The digest was then transferred to a 25 mL volumetric flask and diluted to volume with ultrapure water, ready for elemental analysis. Multi-element determinations were carried out using an ICP-MS (NexION 2000, Perkin-Elmer Co., Shelton, CT, USA) employing the Kinetic Energy Discrimination technique with oxygen gas. The optimization of sample preparation, and operating conditions for elemental analysis are reported in Supplementary material (see Tables S2 and S3).

2.3. Chemometrics

Multivariate analysis, consisting of principal PCA as unsupervised chemometric methods and LDA as supervised chemometric methods, was employed for wine classification according to geographical origin. The classification results were validated through a full cross-validation procedure. One-way ANOVA was employed to assess significant differences in elemental concentrations among wine samples. All statistical analyses were performed by means of the statistical software OriginPro 2024 (OriginLab Corp., Northampton, MA, USA).

3. Results and discussion

3.1. Element content in wine samples

Average concentration with standard deviations, and range for the three wine countries Vietnam, France, and Italy along with method limits of detection of each element are depicted in Table 1. The major elements in wine samples among 20 elements evaluated are B, Mn, Fe, Zn, and Sr. The analysis revealed the highest mean boron concentration in Italian wines (7,210.89 μg/L), followed by French wines (5,279.14 μg/L) and Vietnamese wines (3,487.97 μg/L). The elevated B levels in wine primarily reflect the geochemistry and physicochemical properties of vineyard soils (Coetzee et al., 2005; Kruzlicova et al., 2013; Rodrigues et al., 2020). In contrast to elements such as K, Na, and Cu, which can be introduced or modified through fertilizers, fining agents, or winemaking equipment, B concentrations appear less influenced by anthropogenic inputs during vinification. Therefore, B can serve as a distinctive "fingerprint" of a wine's terroir. Besides, Boron uptake by grapevines increases in alkaline soils (Di Paola-Naranjo et al., 2011; Padbhushan and Kumar, 2017), which may explain the lower boron content of Vietnamese wines produced from grapes grown in Lam Dong's basaltic red soils of low pH (Lam et al., 2023; Thi and The Anh, 2017).

The concentration of Iron (Fe) in Vietnamese, French and Italian wines are 2,617.11 μg/L, 2,199.94 μg/L, and 3,017.31 μg/L, respectively. Manganese (Mn) concentrations in Vietnamese, French and Italian wines are 1,460.58 μg/L, 1,140.27 μg/L, and 1,482.23 μg/L, respectively. Zn concentrations in Vietnamese, French and Italian wines are 470.33 μg/L, 1,236.43 μg/L, and 1,233.36 μg/L, respectively. The elements of Fe, Mn and Zn concentrations in wine arise from both natural and anthropogenic inputs, with contamination during vinification often exerting the greatest influence. Endogenously, vineyard

Table 1. **Inorganic element content in wine samples (μg/L)**

Element	LOD (μg/L)[1]	Vietnam (n=11)[3]				France (n=16)				Italy (n=13)				p-value
		Mean	SD[2]	Minimum	Maximum	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum	
As	0.05	13.39	8.14	3.93	31.44	3.11	2.97	0.59	12.66	1.80	0.68	0.67	3.32	***[4]
Li	0.06	24.43	6.65	11.87	35.98	7.60	5.24	0.03	18.59	31.68	20.87	5.30	77.01	***
Be	0.05	0.66	0.39	0.08	1.21	0.16	0.10	0.03	0.36	0.77	0.49	0.08	1.65	***
B	3.45	3487.97	1703.36	675.56	5625.97	5279.14	1058.59	3398.26	6997.83	7210.89	3180.81	2199.70	13174.11	***
Ti	0.18	43.82	11.61	23.69	62.00	57.92	59.25	16.94	254.63	47.98	38.47	20.75	168.24	NS
V	0.03	53.77	32.86	14.05	129.04	32.63	47.77	0.79	165.37	6.13	8.38	1.65	33.23	**
Cr	0.03	26.55	8.55	16.18	43.96	24.97	11.29	11.31	48.69	31.92	26.04	12.25	106.20	NS
Mn	0.37	1460.58	499.47	879.25	2625.22	1140.27	347.04	561.82	1845.08	1482.23	459.38	630.72	2112.13	**
Fe	3.42	2617.11	1238.50	428.12	4489.57	2199.94	1878.97	343.08	7569.89	3017.31	1634.80	1031.72	7910.40	NS
Co	0.02	4.03	0.85	2.77	5.26	4.19	2.53	1.60	11.51	3.42	1.00	1.68	5.70	NS
Ni	0.11	15.96	5.57	4.74	23.82	92.55	275.12	12.63	1123.94	29.59	9.64	16.27	44.26	NS
Cu	0.40	106.78	106.07	18.66	345.60	194.61	210.91	26.00	832.66	163.42	174.55	16.86	529.95	NS
Zn	3.93	470.33	196.10	210.67	803.44	1236.43	1520.41	381.68	6555.49	1233.36	959.89	403.98	2921.42	NS
Sr	0.44	1184.58	598.13	411.02	2110.21	382.33	107.70	260.14	696.74	987.41	331.77	466.78	1496.12	***
Mo	0.11	6.38	2.73	2.50	11.81	3.76	6.79	0.05	27.28	1.94	1.73	0.05	5.03	**
Cd	0.05	1.21	0.56	0.37	1.98	0.30	0.21	0.02	0.69	0.55	0.42	0.02	1.14	***
Sn	0.60	7.16	3.53	4.65	14.46	7.53	4.50	3.44	17.68	9.14	4.31	4.91	20.06	NS
Ba	0.40	166.42	28.41	115.13	205.58	148.86	53.17	58.30	215.71	171.28	90.73	107.25	440.00	NS
Tl	0.02	0.44	0.22	0.14	0.84	0.14	0.08	0.01	0.35	0.41	0.14	0.22	0.61	***
Pb	0.13	10.66	5.43	5.85	24.47	22.40	19.28	7.01	69.90	17.28	7.46	5.18	31.09	**

[1] LOD, limit of detection.
[2] SD, standard deviation.
[3] n, number of samples.
[4] **$p<0.01$, ***$p<0.001$; NS, not significant.

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soil and underlying geology determine a baseline elemental profile; as a geogenic element, Fe, Mn, and Zn reflects the mineral composition of the terroir. Grape variety, ripening stage, and prevailing climatic conditions further modulate elemental uptake. Exogenous sources, however, frequently account for higher Fe, Mn, and Zn concentrations. Contact between wine and metallic surfaces including pipes, pumps, casks, barrels, and especially stainless-steel vats can leach Fe, Mn, and Zn indicating a shared anthropogenic origin. Agricultural inputs such as fertilizers, fungicides, and pesticides may also introduce Fe, Mn and Zn while oenological practices, including the use of clarifying agents like bentonite, can alter mineral composition during processing (Azcarate et al., 2015; Fermo et al., 2021; Gajek et al., 2021). Collectively, these data suggest that although vineyard geology sets the natural baseline, anthropogenic factors particularly metal contact during winemaking are the predominant drivers of elevated Fe, Mn and Zn in finished wines.

The Strontium (Sr) concentrations in Vietnamese, French and Italian wines are 1,184.58 μg/L, 382.33 μg/L and 987.41 μg/L, respectively. Sr ratios in wine reflect the ratios of the soil. Sr has high geochemical mobility and is easily absorbed by all parts of the vine, including grapes, and it is then transferred into wine without being altered during the winemaking process (Geana et al., 2013; Hao et al., 2021). Therefore, Sr in wine directly originates from the soil, and it could be an excellent marker for determining the geographical origin and authenticity of wine.

On the other hand, toxic elements such as As, Cd, Cr, and Pb are generally low in concentration, falling into the category of trace or ultra-trace elements. The data show that As, Cd, Cr, and Pb concentration in all samples comply with the permissible limits set by international health standards (OIV, 2025) (See Table S4 in the Supplementary materials for more information).

3.2. PCA of wine samples

Basic unsupervised chemometric technique for wine samples is conducted by using PCA. The PCA is widely utilized to identify the direction that retains the most information in the multidimensional space of variables to reduce the dimensionality of the system. PCA works by reducing a large number of original, often correlated, variables, in this study they are concentrations of various elements obtained by ICP-MS, into a smaller set of principal components (PC). These PCs are uncorrelated linear combinations of the original variables, optimized to explain the maximum amount of total data variance.

In order to verify a potential correlation between the geographical origin and the element content, PCA at first considers the original data of all 20 elements as input variables. Fig. 1A is the scatter plots obtained considering the

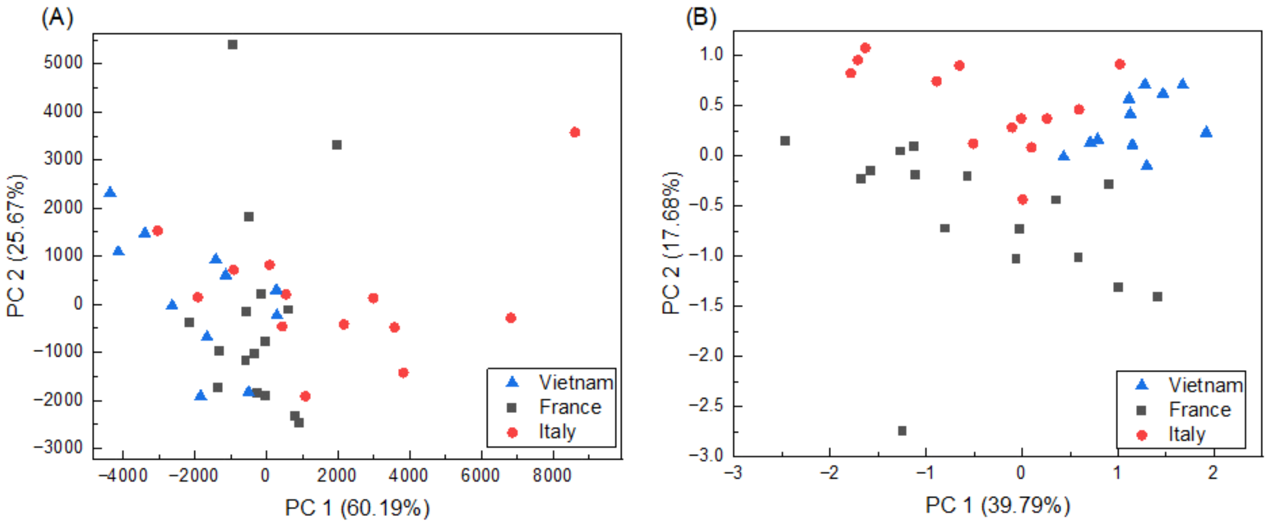

Fig. 1. PCA score plots of the first two principal components for 40 wine samples (Vietnam, France, and Italy); (A), original data; (B), log-transformed data. PC1 and PC2 are first and second principal components. Percentage number next to each PC is their variance contribution.

first two components of 40 wine samples using the original data of 20 elements. The first two principal components (PC1 60.19%, PC2 25.67%) accounted for 85.86% of the total variance contribution. Major elements including B, Fe, Sr, Mn and Zn were the dominant variables in the first PC (Table S5). However, the results show that there are no obvious groupings observed based on geographical origin. Instead, wine samples were grouped based on the concentrations of some elements, as the PCA on untreated concentration reflects which metals dominate the elemental composition and where high concentrations occur.

Considering that some elements are 4-5 orders of magnitude larger than the others (10^{-3}-10^{-2} μg/L), PCA again was applied on the log transformed elements concentrations allowing all major and trace elements to contribute comparably and reveals relative geochemical patterns rather than mere concentration magnitude. The results of PCA from log transformed data show informative geographical distinction between wine samples from Vietnam, France, and Italy (Fig. 1B).

3.3. LDA of wine samples

Too many characteristic elements obtained from PCA increase the cost and reduce the efficiency of origin traceability. Therefore, the correlation analysis combined with LDA was employed to obtain fewer elements for origin recognition, which is also convenient for practical application.

Predictors for LDA were selected based on PCA loadings of log-transformed data. The LDA was subsequently performed by using the log transformed data from 9 elements with the highest loading values on the first principal component (Table S5), including As, Li, Be, Ti, V, Cr, Mo, Cd, and Tl. Elements such as B, Sr, and Mn, which are major elements in wine samples, and exhibit high loading values on the PCA of raw concentrations, were not selected because variable selection for LDA was based on multivariate statistical criteria rather than univariate differences alone. When PCA is performed on raw concentrations, elements with large absolute concentrations dominate the principal components, potentially masking patterns associated with trace-level discriminating elements. In contrast, PCA on log-transformed data emphasizes relative (multiplicative) differences rather than absolute magnitudes, allowing the model to better capture subtle but meaningful compositional differences among wines of different geographical origins. Discriminant functions (DF) were obtained from the training set using all 40 samples:

$$\begin{aligned}DF1 &= -5.91 - 4.85As - 0.23Li + 1.01Be + 3.47Ti - 1.49V \\ &\quad + 3.26Cr + 1.16Mo - 1.77Cd + 0.70Tl\\ DF2 &= 1.55 + 0.66As + 1.47Li + 1.98Be - 1.60Ti - 1.78V \\ &\quad + 1.95Cr + 0.91Mo + 0.19Cd + 1.19Tl\end{aligned}$$

Table 2 shows that LDA achieved 100% of all samples correctly classified in the training and cross-validation sets. In Fig. 2 it could be clearly seen the separation among wine from Vietnam, France and Italy.

The fundamental assumption of elemental fingerprinting is that geographical origin exerts the strongest influence on the elemental profile, as it reflects the persistent natural signature of the soil (Versari et al., 2014). It is acknowledged, however, that not all elements are determined solely by geography; some are also affected by grape variety, wine style of production, and production year. Nevertheless, even when this heterogeneity is explicitly documented, the use of chemometric techniques and the strategic selection of geogenic elements enable the isolation of the geographical signal and ensure that the resulting classification accuracy is robust rather than misleading. In this study, the LDA model still achieved clear separation among countries, indicating that geographical origin imparts a measurable and discriminative elemental signature.

Robust LDA classification requires appropriate variable reduction, adherence to key statistical assumptions, balanced and well-characterized samples, and strong cross-validated performance to ensure model stability and generalizability (Brereton, 2007). Although wine classification studies, including this study, often face the challenge of relatively small sample sizes (Versari et al., 2014), a reduced dataset can still yield a reliable LDA model when dimensionality is minimized and rigorous validation is performed. In this study, log transformation and PCA-based variable selection helped stabilize variance and isolate the most discriminating elements. The consistently high classification accuracy observed across cross-validation suggests that the underlying geographical elemental differences are sufficiently strong to support a robust predictive model despite the limited number of samples. However, the limited number of wine samples per country may still restrict the generalizability of the discriminant functions. Future work with larger and more balanced

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Table 2. Classification performance of the LDA model for wines by geographical origin

Group	Vietnam	France	Italy	Total	Classification accuracy (%)
Classification					
Vietnam	11	0	0	11	100
France	0	16	0	16	100
Italy	0	0	13	13	100
Total	11	16	13	40	100
Prediction by cross-validation					
Vietnam	11	0	0	11	100
France	0	16	0	16	100
Italy	0	0	13	13	100
Total	11	16	13	40	100

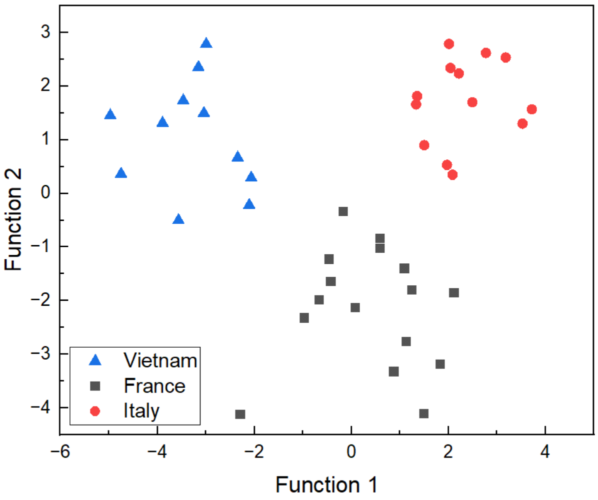

Fig. 2. LDA score plot of 40 wine samples (Vietnam, France, and Italy) based on log-transformed data of nine elements (As, Li, Be, Ti, V, Cr, Mo, Cd, and Tl). Function 1 and function 2 are first and second discriminant functions.

datasets will be essential.

4. Conclusions

This study suggests that combining ICP-MS elemental analysis with PCA and LDA provides a reliable approach for classifying the geographical origin of wines. Using nine key elements (As, Li, Be, Ti, V, Cr, Mo, Cd, and Tl), the method achieved complete discrimination among Vietnamese, French, and Italian wines with 100% classification accuracy. These results confirm the potential of multi-elemental and chemometric analysis as an effective tool for authenticating and protecting the identity of Vietnamese wines.

Supplementary materials

Supplementary materials are only available online from: https://doi.org/10.11002/fsp.2026.33.2.214.

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Conflict of interests

The authors declare no potential conflicts of interest.

Author contributions

Conceptualization: Hoang TTH. Methodology: Khuat HN, Mai TTP, Nguyen VT, Nguyen ATQ. Formal analysis: Khuat HN, Mai TTP, Hoang TTH. Writing - original draft: Khuat HN, Hoang TTH. Writing - review & editing: Khuat HN, Mai TTP, Nguyen VT, Nguyen ATQ, Hoang TTH.

Ethics approval

This article does not require IRB/IACUC approval because there are no human and animal participants.

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Supplementary Materials

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1. *Wine sample information*

Table S1. Wine sample information

No.	Sample	Country	Grape variety	Wine style	Production year
1	V1	Vietnam	Syrah	Still wine	2023
2	V2	Vietnam	Cardinal	Still wine	2022
3	V3	Vietnam	Cardinal, Syrah	Still wine	2022
4	V4	Vietnam	Carbenet Sauvignon, Merlot	Still wine	2021
5	V5	Vietnam	Cardinal, Syrah	Still wine	2018
6	V6	Vietnam	Cardinal, Syrah	Still wine	2021
7	V7	Vietnam	Cardinal	Still wine	2021
8	V8	Vietnam	Carbenet Sauvignon, Cardinal	Still wine	2021
9	V9	Vietnam	Cardinal, Syrah and red grape varieties	Still wine	2021
10	V10	Vietnam	Carbenet Sauvignon, Merlot	Still wine	2018
11	V11	Vietnam	Cardinal	Still wine	2022
12	P1	France	Carbenet Sauvignon, Merlot	Still wine	2020
13	P2	France	Carbenet Sauvignon, Merlot	Still wine	2020
14	P3	France	Merlot, Cabernet Sauvignon	Still wine	2011
15	P4	France	Merlot, Sauvignon, Cabernet Franc, Petit Verdot	Still wine	2020
16	P5	France	Carbenet Sauvignon, Merlot	Still wine	2020
17	P6	France	Merlot, Cabernet Franc, Cabernet Sauvignon	Still wine	2020
18	P7	France	Merlot, Cabernet Franc, Cabernet Sauvignon	Still wine	2021
19	P8	France	Merlot, Sauvignon, Cabernet Franc, Petit Verdot	Still wine	2016
20	P9	France	Carbenet Sauvignon, Merlot	Still wine	2020
21	P10	France	Syrah, Grenache, Mourvèdre	Still wine	2021
22	P11	France	Merlot, Cabernet Sauvignon, Cabernet Franc, Blend	Still wine	2021
23	P12	France	Grenache, Syrah	Still wine	2017
24	P13	France	Merlot, Cabernet Sauvignon	Still wine	2020
25	P14	France	Cabernet Sauvignon, Merlot	Still wine	2022
26	P15	France	Merlot	Still wine	2020
27	P16	France	Merlot, Cabernet Sauvignon, Cabernet Franc	Still wine	2016
28	Y1	Italy	Cabernet Sauvignon	Still wine	2021
29	Y2	Italy	Negroamaro	Still wine	2015

30	Y3	Italy	Primitivo, Negroamaro	Still wine	2020
31	Y4	Italy	Primitivo, Negroamaro	Still wine	2021
32	Y5	Italy	Lambrusco	Still wine	2023
33	Y6	Italy	Primitivo	Still wine	2021
34	Y7	Italy	Montepulciano	Still wine	2021
35	Y8	Italy	Primitivo	Still wine	2020
36	Y9	Italy	Primitivo	Still wine	2021
37	Y10	Italy	Sangiovese, Montepulciano	Still wine	2016
38	Y11	Italy	Primitivo, Negroamaro	Still wine	2017
39	Y12	Italy	Merlot	Still wine	2016
40	Y13	Italy	Negroamaro, Sangiovese	Still wine	2021

2. *ICP-MS analysis*

Multi-element determinations were carried out using an ICP-MS (NexION 2000, Perkin Elmer Co., USA) employing the Kinetic Energy Discrimination (KED) technique with oxygen gas. The 5 µg/L In solution was used as an internal standard and was added online via a T-connector installed after the peristaltic pump to mix with the sample stream during sample introduction into the instrument. The operating conditions for analysis of the wine samples are listed in Table S1.

Table S2. Operating conditions for the ICP-MS NexION 2000 instrument used for the analysis of wine samples.

Parameter	**Condition**
Radio-frequency power (W)	1600
Plasma gas flow rate (L/min)	15
Auxiliary gas flow rate (L/min)	1.2
Nebulizer gas flow rate (L/min)	1.00
Nebulizer	Glass concentric
Spray chamber	Glass cyclonic
Sampler voltage (V)	-7
Skimmer voltage (V)	-7
Sample uptake time (s)	75
Measurement mode	Kinetic Energy Discrimination (KED) mode with helium gas at 4.5 mL/min for As and Se, and 5.5 mL/min for other metals
Measuring mode	Peak hopping

3. *Optimization of sample preparation*

In this study, an optimization of the sample preparation method was conducted to mitigate potential matrix interferences from the complex composition of wine, which includes ethanol, sugars, and other inorganic and organic compounds. The direct analysis of wine by ICP-MS can be challenging, as the organic matrix can affect plasma stability and lead to a loss of detection power. To address this, three common pretreatment methods were evaluated: simple dilution with water, microwave-assisted digestion with a single acid (HNO_3) (Avram et al., 2014; Gajek et al., 2021; Geana et al., 2013; Pasvanka et al., 2021; Pérez-Álvarez et al., 2019; Shimizu et al., 2018), and microwave-assisted digestion with multiple reagents ($HNO_3 + H_2O_2$) (Bronzi et al., 2020; Cerutti et al., 2019).

The methods employed were: (1) a nitric acid digestion, where 4 ml of wine was weighed into a vessel and digested with 4 ml of concentrated nitric acid; (2) a nitric acid-hydrogen peroxide digestion, where 4 ml of wine was digested with a mixture of 4 ml concentrated nitric acid and 1 ml hydrogen peroxide (H_2O_2); and (3) a dilution method, wine was subjected to 5-fold dilution with ultrapure water. Based on the recovery rates, the nitric acid digestion method was selected for the final sample preparation protocol. The digestion was performed with a ramp of 30 min and a hold time of 20 min under microwave conditions at 1000 W, reaching a maximum temperature of 180 °C, followed by 20 min cooling. After cooling to ambient temperature, the reactors were opened, and the content was quantitatively transferred into a 25 ml volumetric flask and brought to the volume with ultra-pure water. All the elements were measured from these extraction solutions by ICP-MS.

In this study, the analytical performance of these three methods was conducted and validated through recovery studies of wine sample. For all 20 elements evaluated, the recoveries were consistently within the acceptable range of 80% to 120% (Table S2), indicating that all three methods are suitable for the accurate analysis of wine samples. However, despite the comparable accuracy, microwave-assisted digestion with a single acid (HNO_3) was selected as the optimal method. This choice is justified by several factors related to efficiency, contamination risk, and methodological robustness. While simple dilution is often praised for its speed and reduced contamination risk, however, dilution method could leave residual sugar and organic components, which is highly possibly condense on the cones, producing instability of the plasma, leading to a rapid loss of detection power. When comparing the two digestion protocols, the use of a single, high-purity acid (HNO_3) is preferable to a combination of reagents ($HNO_3 + H_2O_2$), because a single-reagent protocol is simpler, faster to prepare, and less prone to volumetric errors than a multi-reagent one.

Table S3. Recovery of 20 elements in a wine sample with different sample preparation methods.

Element	**Recovery of HNO_3 Digestion (%)**	**Recovery of HNO_3 + H_2O_2 Digestion (%)**	**Recovery of Dilution (%)**
As	111.21	112.65	108.50
Li	100.58	100.79	108.05
Be	84.42	83.39	108.75
B	91.83	83.63	115.16
Ti	113.32	109.14	117.31
V	120.39	120.09	108.11
Cr	110.97	113.99	101.73
Mn	101.35	105.29	114.08
Fe	96.86	99.47	100.54
Co	114.55	114.86	86.27
Ni	111.63	113.59	88.00
Cu	109.19	110.71	95.58
Zn	87.25	88.13	120.85
Sr	111.66	108.90	108.15
Mo	114.27	113.84	83.69
Cd	92.80	94.68	78.57

Sn	106.54	108.72	60.71
Ba	106.03	108.25	92.99
Tl	103.68	105.40	95.31
Pb	96.98	97.92	93.89

4. *Regulatory limits (OIV) and measured concentrations of toxic elements*

Table S4. Regulatory limits (OIV) and measured concentrations of toxic elements in wines from Vietnam, France, and Italy.

	Concentration of Metals				
	As	Cd	Cu	Pb	Zn
OIV (µg/L)	200	10	1000	150	5000
Vietnamese (µg/L) (this paper)	13.39	1.21	106.78	10.66	470.33
France (µg/L) (this paper)	3.11	0.30	194.61	22.40	1236.43
Italia (µg/L) (this paper)	1.80	0.55	163.42	17.28	1233.36

5. *Principal component analysis (PCA)*

Table S5. Factor loadings obtained from PCA for original and log-transformed element concentrations in wines using the first two components (PC1 and PC2)

Elements	**Original data**		**Log transformed data**	
	PC1	**PC2**	**PC1**	**PC2**
As	-0.00117	0.00050	0.327260	0.038500
Li	0.00367	0.00119	0.076490	0.713940
Be	0.00004	0.00010	0.140420	0.394220
B	0.98016	-0.17439	-0.088220	-0.000935
Ti	0.00258	0.00559	0.104740	-0.004470
V	-0.00448	0.00480	0.496720	-0.022820
Cr	-0.00002	0.00403	0.088270	-0.034000
Mn	0.05606	0.04893	0.015780	0.073410
Fe	0.17203	0.91877	0.059300	0.213050
Co	0.00009	0.00042	0.062160	-0.001430
Ni	0.00956	0.03431	-0.013930	-0.073250
Cu	0.01575	-0.02143	0.037480	-0.186110
Zn	0.02826	0.34817	-0.004220	-0.122330
Sr	0.07285	0.00311	0.064910	0.185820
Mo	-0.00044	0.00069	0.656390	-0.225090
Cd	-0.00005	0.00006	0.362780	-0.072470
Sn	0.00055	-0.00021	0.001270	0.035300
Ba	0.00745	0.01026	0.038210	0.014190
Tl	-0.00001	0.00005	0.114590	0.359750
Pb	0.00100	-0.00012	-0.059550	-0.068160

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