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Handheld Laser-Induced Breakdown Spectroscopy (LIBS) as a fast and easy method to trace gold

Anthony Pochon^{*} (pochon.anthony@gmail.com), Anne-Marie Desaulty (am.desaulty@brgm.fr), Laurent Bailly (I.bailly@brgm.fr)

BRGM, F-45060, Orléans, France

* Corresponding author

Abstract

Gold is traded in virtually every country around the world. Consequently, tracing gold provenance is a difficult but necessary task to ensure a responsible supply chain from deposit to consumer. Measuring the silver content is often the first step in characterizing gold to retrace its origin. In this study, laser-induced breakdown spectroscopy (LIBS) using a handheld instrument was evaluated as a fast and easy method to analyse the silver content in natural gold. Six commercial gold alloys and natural gold from French Guiana were used. Our results demonstrate that a handheld LIBS is relevant to gold traceability and is simple to use in the field. The micron-scale focused laser beam allows in-situ analyses of small gold grains with acceptable reproducibility. Univariate and multivariate regression modelling was performed to assess the best calibration model for quantification of the Ag content. The quadratic univariate model was selected for its good predictive ability, with a coefficient of determination R² of 0.99 and a mean average error of 0.36 wt.% Ag for prediction. The LIBS analyses of natural gold were compared to the EPMA data using a statistical test that allow distinct gold populations to be discriminated (or matched) and the results indicate it would be suitable for identifying unknown samples. We were able to successfully trace the origin of our "unknown" samples, a promising first step in the goal of delivering a low-cost fieldbased tool for responsible supply chain management.

Keywords: Laser induced breakdown spectroscopy, quantitative analysis, traceability, gold, silver content

48 **1. Introduction**

Gold is one of the most ancient and important metals worldwide. Considering its high 49 50 economic importance, the ability to identify the provenance of gold is fundamental in the minerals industry. Traceability is particularly important for ensuring a responsible supply chain, especially in 51 the European Union given the recent emphasis on due diligence for minerals from conflict-affected 52 and high-risk areas (i.e. tin, tantalum, tungsten and gold)^[1]. The best indicator mineral to trace 53 gold sources is gold itself^[2] because it is a dense mineral, chemically stable and easily found in 54 the erosional products of gold systems (*i.e.* alluvial gold from placers). Indeed, drainage sediment 55 56 sampling, often the first step in a gold exploration strategy, is used to characterise alluvial gold 57 through its intrinsic features, such as its silver (Ag) content or its mineral inclusions, in order to establish a link between a secondary (placer) deposit and its potential primary deposit [3-10]. 58 59 Currently, the Ag content of a gold population is analysed with an electron probe micro analyser (EPMA) and is generally displayed in cumulative percentile plots. This way of presenting the data 60 61 provides an easy and visually graphic comparison of the statistical distribution of the Ag content of distinct gold populations and is helpful in understanding and constraining their origin ^[6, 9]. Whereas 62 the EPMA-based method is highly accurate and a proven method to characterize gold, the 63 approach is limited by both the cost of analyses and the time needed for laboratory preprocessing 64 (e.g. instrument calibration). 65

Hence, this study focusses on a fast and simple way to analyse the Ag content in natural 66 gold in a field laboratory with direct application for exploration and traceability. Laser-induced 67 breakdown spectroscopy (LIBS) was selected as the technology instead of X-Ray fluorescence 68 spectroscopy (XRF) principally because the newer handheld devices generally have a focused 69 laser beam less than 100 µm, whereas the analysed surface area (*i.e.* several mm) of a classical 70 handheld XRF system is much larger than most natural gold grains, except rare gold nuggets. The 71 LIBS method has already been applied to the accurate quantitative analysis of commercial gold 72 alloys and jewelry in order to determine their fineness ^[11-16]. Recently, Harmon et al. ^[17] 73 successfully used a handheld LIBS unit on natural gold nuggets from a museum collection to 74 75 classify and distinguish distinct populations of gold grains, most of which came from the USA, but

their analyses was not quantitative. Finally, the LIBS method has also been used in the field on conflict-affected minerals (*e.g.* "coltan" ore ^[18]) and for the geochemical fingerprinting of geomaterials ^[19-20].

79 To assess the performance of handheld LIBS instrumentation in determining Ag content in gold grains, we analysed gold grains from five French Guiana gold populations. French Guiana 80 was chosen for a case study because it is currently explored for gold and constitutes a high-risk 81 82 area due to the presence of numerous illegal small-scale gold mines that represent a loss of revenue for the government and cause widespread mercury pollution. In such a region, developing 83 an analytical method to determine the origin of gold to ensure its traceability has major health, 84 environmental and economic issues. A pilot study on gold from French Guiana led by BRGM and 85 WWF (World Wildlife Fund), has already developed a set of techniques for physicochemical 86 traceability of gold ^[21]. However, these techniques require extensive and time-consuming 87 laboratory preparation and analysis (e.g. EPMA, identification of mineral micro-inclusions, Pb-Aq-88 Cu isotopic analyses). In this study, we propose that a handheld LIBS device can be used for rapid 89 90 in situ analysis of gold, thereby serving as a field-based decision-making tool for protecting human health and the environment. 91

92

93 2. Materials and methods

94 2.1 Standards and samples

95 Six commercial gold alloys (18K5N, 18K4N, 18K3N, 18K2N, 18KPd13, 24K) from Cookson-96 clal refinery (*i.e.* an affiliate of Heimerle + Meule GmbH) were used as standards for LIBS 97 calibration. The Ag content of these six commercial standards (*i.e.* according to the refiner) range 98 between 0.01 and 16 wt.%, comparable to the range of natural samples in French Guiana.

99 Natural gold grains used for this study consist of 13 samples coming from five alluvial gold 100 populations. The first one, Marc creek, were first studied by Augé *et al.* ^[21] as part of a project 101 funded by the WWF to test the analytical traceability of gold from French Guiana. Three samples of 102 gold grains were collected from this placer: the "B2", "X2" and "A7" samples. Gold grains from the 103 others populations were provided by the official French Guiana refiner (SAAMP): the "33", "39",

"43" samples from the "Petit Inini" river; the "30", "46", "47" samples from the "Serpent" creek; the 104 "23", "26", "29" samples from the "Dimanche" creek and the "37" sample from the "Awa" creek. 105 Each sample of gold grains consists of about 20-40 individual grains between 0.05 and 3 mm in 106 size that were embedded in epoxy resin blocks and polished to expose grain cores. The dataset of 107 13 samples were divided in training and testing samples, following a classical ratio of about 3:1. 108 Among these 13 samples, four samples ("X2", "43", "46" and "29") were randomly selected as 109 testing samples and considered as "unknown" samples and the nine remaining samples were used 110 for the characterisation of the five populations of gold grains. The analytical feasibility and 111 effectiveness of the LIBS method was thus tested by comparing the results obtained on the training 112 dataset to the four "unknown" samples. In addition, 10 individual gold grains from the "B2" sample 113 were selected and analysed without any preparation ("raw" gold grains) for comparison with the 114 polished gold grains. Standards and natural gold grains were analysed using Cameca SX-Five 115 electron probe micro-analyser (EPMA) at the ISTO-BRGM facilities (Orléans, France) (see details 116 in Table 1S, ESI). Five analyses for each standards and up to two analyses in the core of gold 117 grains were performed for Ag using a 20 kV accelerating voltage, a beam current of 40 nA and a 118 119 counting time of 30 s on peak. Whereas only the Ag content is of interest for our purpose, Au, Cu, Hg and Pd were also analysed to obtain a full suite of elements concentrations in the standards. 120

121

122 **2.2 Instrumentation and measurement parameters**

The commercial SciAps © Z-200 C+ handheld LIBS analyser was used for this study. Its 123 portability and broad spectral range (i.e. 190-625 nm) make it a suitable tool to perform real-time 124 analyses in the field or measurements in a field laboratory^[17, 22]. The LIBS unit uses a 1064 nm 125 Nd:YAG pulsed laser with a 50 µm focused beam size to produce a plasma. This laser can deliver 126 energy pulses of 5-6 mJ per pulse with a 1-2 ns pulse duration and a repetition rate of 50 Hz. The 127 Z-200 C+ LIBS analyser displays multiple CCD based spectrometers covering a spectral range of 128 129 190-625 nm. The handheld unit can be operated in ambient atmosphere, but is also capable of argon (Ar) purging that flows Ar directly to the focusing area on the sample surface at the location 130 of laser-induced plasma for signal enhancement (i.e. 10-fold increase in emission intensity ^[23]). 131

Each analysis was performed under constant argon flow with a pressure of around 10 psi. 132 Spectrometers are calibrated daily by ablating a piece of stainless steel inside the LIBS system in 133 134 order to correct possible spectral shifts. Because the LIBS system requires that the sample to be 135 held flush to the sampling window during acquisition and to prevent analytical bias, the LIBS unit was anchored on a support with a xyz linear stage. For each standard, data acquisition consists of 136 11 single-shots for the calibration and 5-7 single-shots for the prediction. Each single-shot consists 137 of 8 cleaning (laser) pulses in order to ensure tape breakthrough, followed by the collection of 32 138 averaged spectra at the same location (Fig. 1a) in order to minimise the size of the affected 139 surface on the gold grains (because of their small size) and to avoid striking mineral inclusions. 140 Table 1 shows a summary of the acquisition parameters for the measure of the Ag content. 141

142

143 **2.3 Post-processing and statistical analysis of LIBS spectra**

SciAps Profile Builder software was used to initially process all data prior to exporting. 144 Microsoft Excel and its XLSTAT add-in were then used for additional data processing and for 145 statistical analysis. The three single-shot spectra for each standard were collected (*i.e.* 15 spectra) 146 by the LIBS units for the calibration of the Ag content. Before normalising the spectra, a polynomial 147 fitting of the baseline is applied followed by a baseline subtraction (Fig. 1b), which increases the 148 analytical performance ^[24]. For the calibration, the emission line at 546.58 nm was selected for Ag 149 amongst the others possibilities (328.06, 338.31 and 520.92 nm) because it is the most intense 150 line. Following recommendations from others studies ^[24-26] about the extraction method of raw LIBS 151 spectra, normalisation modes and calibration model validation, the following approach was used to 152 153 select the best calibration model:

155

156

154

 All the raw LIBS data were divided by the signal intensity of the Au emission line at 479.24 nm, representing the matrix-dominant element and the maximum signal intensity. The 11 single-shots of the six standards were averaged later (Fig. 1b);

157 (2) Calibration models (Fig. 1c) were performed. The peak area of the emission line at 158 546.58 nm is extracted for univariate regressions (linear and quadratic) and multivariate 159 regressions (principal component (PCR) and partial least squares (PLSR) regressions)

were performed using a small portion of spectra comprised between 520 and 548 nm to
 overcome the overfitting;

162 (3) The validity and predictive ability of calibration models were assessed through an 163 internal cross-validation test—the "classic" leave-one-out (LOO)—as well as an external 164 prediction dataset. The external dataset consisting of 35 spectra thus corresponds to 165 five LIBS single-shot spectra of the 24K and 18K5N standards, six LIBS single-shot 166 spectra of the 18K4N, 18K3N and 18KPd13 standards and seven LIBS single-shot 167 spectra of the 18K2N standard.

Table 1Summaryofacquisitionmeasurement using LIBS on	parameters during Ag gold grains				
Number of locations	Standards: 11 single- shots for calibration and 5 or 6 for prediction Unknown samples: up to 3 single-shots				
Cleaning shots per location	8				
Data shots per location	32				
Integration period	0				
Integration delay	30				
Argon flush (ms)	300				
Test rate (Hz)	50				
Clean rate (Hz)	50				
Number of shots to average	32				
Averaging method	Linear				

168

- 169 For the goodness of fit and the predictive model assessment, the R², LOO q^2 , root mean squared
- 170 error (RMSE), and mean absolute error (MAE) were used and are respectively defined in Eqs. (1),
- 171 (2), (3), and (4):

172
$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (\gamma_{i} - \widehat{\gamma}_{i})}{\sum_{i=1}^{n} (\gamma_{i} - \overline{\gamma})} = 1 - \frac{\text{sum of squared residuals (SSR)}}{\text{total of sum of squares (TSS)}}$$
(1)

173

 $LOO q^2 =$ leave-one-out cross-validated R^2 (2)

174
$$RMSE = \sqrt{\frac{1}{n}} \sum_{i=1}^{n} (\gamma_i - \hat{\gamma}_i)^2$$
(3)

175 where RMSECV and RMSEP relate to the RMSE of cross-validation and prediction, respectively.

176
$$MAE = \frac{\sum_{i=1}^{n} |\hat{\gamma}_i - \gamma_i|}{n}$$
(4)

177 where MAECV and MAEP relate to the MAE of cross-validation and prediction, respectively.



Fig. 1 Schema illustrating the LIBS analysis approach used in this study. (a) Experimental setup used for Ag calibration on commercial gold alloys with the handheld LIBS tool. (b) Post-processing approach of LIBS spectra for calibration with the description of each step.
 (c) Regression modelling method for the Ag calibration.

3. LIBS approach for quantifying silver in alluvial gold

3.1 Regression modelling: univariate versus multivariate models

The analytical reproducibility of all measurements on the standards, given by the relative 184 standard error of the mean (SE) and the relative standard deviation (RSD), is largely satisfactory 185 with values of 2.5 % and 8.2 %, respectively (see details in Table 2S, ESI). For the conventional 186 187 univariate calibration (linear and quadratic), a simple ordinary least squares (OLS) regression method was applied to calibration standards. Indeed, LIBS intensity is supposed to be a linear 188 function of the concentration of the chemical element of interest, even if curvatures can be 189 observed because of the self-absorption effects ^[27-28]. In our experiment, the relationship between 190 191 the Ag content and the intensity of the Ag emission line could be linear (Fig. 2) because of the good superposition of the linear and quadratic curves. However, a comparison of the figures of 192 193 merit (Fig. 3a and Table 2) between the two univariate models displays difference of predictive ability between them. A cross-validation test is rarely applied to an OLS regression, but the cross-194 195 validation test were also performed on the univariate models for comparison with multivariate models and to assess the best modelling. 196



197

Fig. 2 Linear and quadratic calibration curves using a classical OLS regression. The green line represents the quadratic regression while the dashed line represents the linear one.

201 The guadratic model yields better results to the linear model with extremely low RMSE and MAE values of 0.05713 and 0.04453 wt.% Ag, respectively (0.20124 and 0.17110 wt.% Ag for the 202 203 linear model). The coefficient of determination R² is also better for the quadratic regression with a 204 value of 0.99991 compared to the value of 0.99888 for the linear regression (Fig. 3a and Table 2). The LOO q^2 is higher in the quadratic model than the linear one (0.99969 and 0.99693) 205 respectively), which indicates that the predictive power is more efficient for the quadratic 206 regression. RMSECV and MAECV also show clearly that the quadratic model improve Ag 207 calibration (Fig. 3a and Table 2). Finally, the quadratic model with the best RMSE and MAE of 208 prediction (0.53320 and 0.36049 wt.% Ag, respectively) relative to linear model (i.e. 0.59573 wt.% 209 Ag and 0.42835 wt.% Ag) is the best compromise to use as a univariate calibration model for 210 quantifying Ag content in gold. 211



Fig. 3 Figure of merit used to assess univariate (a) and multivariate (b) quantitative models. Coefficient of determination of the training calibration dataset (R2) and of the prediction dataset (R2 prediction) and the leave-one-out cross-validated (LOO) q2 are displayed on the left. Root mean square error of calibration (RMSE), cross-validation (RMSECV) and prediction (RMSEP) and the mean absolute error of calibration (MAE), cross validation (MAECV) and prediction (MAEP) obtained for models displayed on the right.

For the multivariate calibration, the principal component regression (PCR) and the partial 218 least square regression (PLSR) chemometric methods were used to quantify silver in gold. These 219 220 methods are frequently used in LIBS quantification to overcome potential matrix effects in 221 geological samples or to take into consideration the spectral interdependence between the lines of the considered elements and others elements ^[29]. Indeed, each line reflects varying degrees of 222 information about the concentration of an element and potential correlations with others lines, 223 increasing the number of independent variables and the complexity of the calibration. The PCR 224 225 and the PLSR can extract relevant and hidden information in the LIBS spectra and then predict the concentration of the element of interest. PLSR is more complex than PCR because it takes into 226 account all the variables (independent and dependent) and the signal noise. PLSR generally gives 227 better results, although it has a general tendency of overfitting the training dataset. 228

		Univariate models		Multivariate	models	
		Linear	Quadratic	PSLR	PCR	
Calibration						
(n = 66 spectra)	R²	0.99888	0.99991	0.99979	0.99952	
	RMSE	0.20124	0.05713	0.08627	0.13114	
	MAE (wt %)	0.17110	0.04453	0.06039	0.09968	
LOO cross validation						
(repeated 6 times)	LOO <i>q</i> ²	0.99693	0.99969	-0.38727	0.99693	
	RMSECV	0.33335	0.10538	7.08045	0.33332	
	MAECV (wt %)	0.27631	0.08767	4.87009	0.30601	
Prediction						
(n = 35 spectra)	R²	0.99055	0.99243	0.98442	0.99280	
	RMSEP	0.59573	0.53320	0.76487	0.51996	
	MAEP (wt %)	0.42835	0.36049	0.61748	0.35509	

Table 2	2
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Results of the figures of merit obtained for univariate (linear and quadratic) and multivariate (PLSR and PCR) regression modelling

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The coefficient of determination R^2 is high and associated with low RMSE and MAE for the PLSR (0.99979, 0.08627 wt.% Ag and 0.06039 wt.% Ag respectively) and the PCR (*i.e.* 0.99952, 0.13114 wt.% Ag and 0.09968 wt.% Ag). However, the negative value of LOO q^2 and the large RMSECV and RMSEP (7.08045 wt.% Ag and 0.76487 wt.% Ag respectively) for the PLSR model compared to univariate models illustrate very well its poor predictive modelling ability (Fig. 3b and Table 2). At the opposite, the similar results of cross-validation and prediction for the PCR model compared to the univariate regressions, with a value of RMSECV of 0.33332 wt.% Ag and a value of RMSEP of 0.51996 wt.% Ag, show that the PCR model has a good predictive power. However, the PCR model appears more sensitive to missing data compared to quadratic regression as highlighted by the slightly poorer cross-validation result (Fig. 3b and Table 2). In this study, multivariate models appear not more powerful in prediction than a simple univariate model, which is why we selected the quadratic univariate regression as the best calibration curve for quantifying the Ag content in alluvial gold.

Table 3

Summary of descriptive statistics of the Ag content of the French Guiana gold samples

ЕРМА						LIBS					
	Descriptive statistics				Descriptive statistics						
	Min	Max	Median	Mean	Std		Min	Max	Median	Mean	Std
"Marc" creek ^[21]											
B2 (n=16)	3.60	11.85	5.08	6.09	2.72	(n=56)	1.08	13.09	4.57	4.82	3.69
B2 "raw" (n=12)							0.27	3.90	1.39	1.62	1.08
X2 ¹ (n=18)	2.57	11.14	4.41	5.21	2.56	(n=32)	2.14	12.78	5.17	5.83	2.92
A7 (n=15)	1.96	22.60	5.89	7.46	5.74	(n=15)	1.45	12.72	4.76	5.32	2.46
"Petit Inini" river											
SP33 (n=20)	6.27	19.05	8.17	8.88	2.81	(n=22)	2.46	13.33	7.43	7.51	2.26
SP39 (n=20)	2.58	12.55	7.24	7.51	2.25	(n=20)	2.25	12.12	7.07	7.24	2.17
SP43 ¹ (n=19)	6.08	12.37	7.55	7.92	1.76	(n=24)	6.06	13.91	7.77	7.98	1.61
"Serpent" creek											
SP30 (n=18)	1.10	2.37	1.66	1.71	0.35	(n=26)	0.34	3.16	1.55	1.60	0.65
SP46 ¹ (n=21)	1.22	6.92	1.84	2.33	1.55	(n=21)	1.01	2.87	1.40	1.61	0.54
SP47 (n=21)	1.23	2.67	1.69	1.80	0.39	(n=27)	1.10	2.79	1.63	1.71	0.46
"Dimanche" creek											
SP23 (n=26)	1.88	8.51	2.83	3.50	1.66	(n=24)	1.41	6.36	2.51	3.02	1.33
SP26 (n=22)	0.95	7.64	3.23	3.24	1.56	(n=25)	0.87	7.24	3.34	3.25	1.73
SP29 ¹ (n=29)	1.02	7.58	3.53	3.58	1.32	(n=22)	0.87	7.22	3.21	3.04	1.44
"Awa" creek											
SP37 (n=21)	5.17	16.77	6.76	7.76	2.84	(n=21)	4.78	8.09	6.61	6.64	0.86

¹ testing samples considered as "unknown" samples during this study in order to validate the methodology of traceability

243

244 **3.2 Quantifying silver in alluvial gold**

The LIBS analysis on alluvial gold grains was conducted in the same operating conditions as the gold alloy standards used in the calibration step (Table 1). The single-shot was performed on the core of each gold grain and the number of single-shots by grain depended on the grain size (*e.g.* only one single-shot for a small grain and up to three single-shots for larger grains). The depth of the laser ablation hole is about 4 μ m, leading to a mass loss of about ~ 150 ng of gold and making the LIBS technique barely destructive. The previously selected quadratic univariate regression was then applied to quantify the Ag content in alluvial gold grains (see previous section). Analyses of the Ag content obtained by the EPMA and LIBS methods are summarized in Table 3 (complete analyses in Tables 3S and 4S, ESI, respectively). Note that gold grains analysed with EPMA method are not necessarily the same as those analysed by the LIBS method.

The distribution of the Ag content of the different samples of gold grains, obtained by LIBS, 255 256 was compared to EPMA values using the non-parametric statistical test of Kolmogorov-Smirnov (Table 4). This test, also called the K-S two samples test, compares the cumulative distribution 257 functions (CDFs) of two known samples ^[30-32]. It assesses the likelihood that two samples have the 258 same distribution (*i.e.* the "null" hypothesis). The K-S test calculates the maximum distance D 259 between two empirical CDFs. The more D increases, the more the distribution is different, meaning 260 that they are two distinct populations. If the distance D is lower than the critical distance D_{critical} and 261 the *p*-value (*i.e.* value of probability) is higher than the level of significance α , then the "null" 262 hypothesis cannot be rejected and the two subpopulations are considered as originating from the 263 264 same population. The level of significance α of the statistical test used in this study is 0.05. This commonly used value gives a confidence degree of $1 - \alpha$ (95 %). The critical distance is 265 dependent on sample size and the level of significance ^[31]. In addition to K-S results, the CDFs of 266 267 the Ag content (LIBS and EPMA) of each training sample (*i.e.* the nine samples used for the characterisation of the five populations of gold grains) are displayed in the Figure 4. Only the 268 269 training samples are mentioned in the following subsections.

"Marc" creek population: the Ag contents of the gold grains from "B2" and "A7" samples 270 share first-order similarities with those obtained by EPMA (Table 3 and Fig. 4a). Except 271 for the maximum values of "A7" sample, which largely differ, the descriptive statistics 272 273 are similar, as illustrated by the limited gap of the median Ag values (about 0.8 wt.% Ag for EPMA and for LIBS). When the EPMA and LIBS analyses of the gold grains from 274 "B2" are compared (Fig. 4a), the K-S test shows that the two distributions are similar 275 276 with a distance D of 0.286 lower than the critical distance (0.386) and a *p*-value of 0.262 higher than the level of significance α (Table 4). The K-S test shows a similar result 277 between the EPMA and LIBS analyses of the "A7" sample with a distance D of 0.333 278

279 lower than the critical distance (0.497) and a *p*-value of 0.375 higher than the level of 280 significance α . The strong similarities between the two analytical methods (see the 281 close proximity between the CDFs displayed in the Fig. 4a) provide a validation of the 282 accuracy of Ag analysis in gold by handheld LIBS and a comparison between EPMA 283 and LIBS datasets.

Table 4

Kolmogorov-Smirnov tests for the Ag content between the EPMA and the LIBS values from the studied French Guiana gold samples

	D	D critical	p-value ¹
"Marc" creek			
B2 (LIBS) / B2 (EPMA)	0.286	0.386	0.262
A7 (LIBS) / A7 (EPMA)	0.333	0.497	0.375
B2 (LIBS) / A7 (LIBS)	0.315	0.395	0.190
B2 (LIBS) / B2 "raw" (LIBS)	0.798	0.433	< 0.0001
"Petit Inini" river			
33 (LIBS) / 33 (EPMA)	0.232	0.420	0.627
39 (LIBS) / 39 (EPMA)	0.100	0.430	1.000
33 (LIBS) / 39 (LIBS)	0.186	0.420	0.860
"Serpent" creek			
30 (LIBS) / 30 (EPMA)	0.252	0.417	0.508
47 (LIBS) / 47 (EPMA)	0.258	0.415	0.474
30 (LIBS) / 47 (LIBS)	0.234	0.394	0.530
"Dimanche" creek			
23 (LIBS) / 23 (EPMA)	0.199	0.385	0.708
26 (LIBS) / 26 (EPMA)	0.190	0.408	0.817
23 (LIBS) / 26 (LIBS)	0.268	0.389	0.341
"Awa" creek			
37 (LIBS) / 37 (EPMA)	0.238	0.420	0.591

¹ the level of significance is $\alpha = 0.05$.

284

<u>"Petit Inini" river population:</u> the Ag contents of the gold grains from "33" and "39" samples appear very similar to that obtained by EPMA and between them (Table 3 and Fig. 4b). Except for EPMA extremum values of "33" sample, the descriptive statistics are extremely close, as illustrated by the slight difference between the median Ag values and the mean values (0.19 wt.% Ag and 0.27 wt.% Ag, respectively). The CDFs and the K-S tests between the two samples (LIBS and EPMA analyses) clearly shows that their

distributions are almost identical. The best example is illustrated by the comparison between EPMA and LIBS values of "39" sample with a distance D of 0.100 lower than the critical distance (0.430) and a maximum p-value of 1 (Table 4), and by the superposition of the two CDFs (Fig. 4b).

<u>"Serpent" creek population:</u> such as the preceding gold populations, the Ag contents of 295 the gold grains from "30" and "47" samples share several similarities between them and 296 297 with those obtained by EPMA (Table 3 and Fig. 4c). The median and the mean values are very close and relatively low (~ 1.6 wt. % Ag and ~ 1.7 wt. % Ag, respectively). The 298 Ag content of the "Serpent creek" population varies very little only with a standard 299 deviation of 0.46, that is also well illustrated by the tight CDFs (Fig. 4c). The K-S tests 300 also show that the distributions between LIBS and EPMA data are very similar with a p-301 value of 0.508 for the "30" sample and 0.474 for the "47" sample (Table 4). Result is 302 identical when comparing "30" and "47" samples with a distance D of 0.234 lower than 303 the critical distance (0.394) and a *p*-value of 0.530 higher than the level of significance 304 305 α.

- <u>"Dimanche" creek population:</u> as shown in Table 3 and Figure 4d, the Ag content of the
 gold grains from the "Dimanche creek" population (*i.e.* "23" and "26" samples) appears
 comparable with those obtained by EPMA. The median and the mean values are close.
 For example, the mean values of the "26" sample are 3.24 wt. % Ag for EPMA and 3.25
 wt. % Ag for LIBS, giving a difference of only 0.01. Unsurprisingly, the K-S tests gave a
 result showing the close similarity between the CDFs (*e.g.* the *p*-value is 0.817 for the
 "26" sample).
- <u>"Awa" creek population:</u> the Ag content of the gold grains from the "37" sample appears
 very similar to that obtained by EPMA (Table 3 and Fig. 4e). Except for maximum
 values, which largely differ, the descriptive statistics are relatively similar, as illustrated
 by the limited gap of the median Ag values (only 0.15 wt.% Ag). Furthermore, the major
 part of the CDFs is strictly superposed. The comparison between the EPMA and LIBS
 analyses of the gold grains by the K-S statistics shows that the two distributions are



322 323 Fig. 4 Plots of cumulative distribution functions (CDFs) of the Ag content in alluvial gold grains. (a) Comparison between the EPMA21 and LIBS analyses of the "B2" and "A7" samples from the "Marc" creek population. (b) Comparison between the EPMA and LIBS analyses of the "33" and "39" samples from the "Petit Inini" river population. (c) Comparison between 324 the EPMA and LIBS analyses of the "30" and "47" samples from the "Serpent" creek population. (d) Comparison between 325 the EPMA and LIBS analyses of the "23" and "26" samples from the "Dimanche" creek population. (e) Comparison 326 327 between the EPMA and LIBS analyses of the "37" sample from the "Awa" creek population.

Concerning the "raw" gold grains from "B2" sample ("Marc" creek population), the Ag 328 contents obtained by ablating the unpolished surface by LIBS are different when compared to the 329 330 polished gold grains (Table 3), and appear very low with a mean and median value about 3.2 times 331 lower than expected (Table 3). Furthermore, the K-S test indicate that the "raw" population is totally different from the "polished" population (Table 4). The main causes of this difference could be 332 explained either by a poor laser-matrix interaction due to the surface roughness of a "raw" gold 333 grain and/or because the Ag content of the rim of an alluvial gold grain is typically depleted 334 compared to its core ^[21, 34-36]. This result implies that a minimum amount of sample preparation is 335 needed to expose the core of the grain in order to perform LIBS analysis on alluvial gold. 336

337

4. Application to gold traceability

339 **4.1 Discriminating distinct populations of gold**

A handheld LIBS could be used for analysing the silver content of gold during mineral 340 exploration in order to trace the primary sources of alluvial gold or for certifying the origin of gold 341 for traceability purposes (e.g. comparing the data to a database of French Guiana gold). In the 342 following subsections, the Ag content obtained by LIBS analyses are used to exhibit how an 343 handheld LIBS device might be useful to help discriminating distinct populations of gold grains and 344 tracing the golds grains origin. The nine training samples studied in the previous section have been 345 compiled into the five populations of gold from French Guiana with "B2" and "A7" samples forming 346 347 the "Marc" creek population, "33" and "39" samples forming the "Petit Inini" river population, "30" and "47" samples forming the "Serpent" creek population, "23" and "26" samples forming the 348 "Dimanche" creek population and the "Awa" creek population which only consists of the "37" 349 sample (see the CDFs on the Fig. 5). These five populations of gold grains were compared 350 351 between them using the K-S test in order to check if we can discriminate distinct populations. Results are displayed in the Table 5. The K-S tests clearly highlighted that the five populations are 352 statistically well distinct because the major part of results show a *p*-value lower than 0.0001, which 353 indicates that distributions are different with a confidence of 95 % (i.e. $1 - \alpha$). Consequently, in this 354

- study, the distribution of the Ag content of these five populations of gold grains is significantly
- discriminant to be a key feature of a given population of gold.

Table 5

Comparison of the Ag content between the five French Guiana gold populations using the Kolmogorov-Smirnov test

	D	D critical	p-value ¹
"Marc" creek / "Petit Inini" river	0.523	0.265	< 0.0001
"Marc" creek / "Serpent" creek	0.798	0.254	< 0.0001
"Marc" creek / "Dimanche" creek	0.475	0.253	< 0.0001
"Marc" creek / "Awa" creek	0.539	0.338	0.0002
"Petit Inini" river / "Serpent" creek	0.929	0.287	< 0.0001
"Petit Inini" river / "Dimanche" creek	0.847	0.286	< 0.0001
"Petit Inini" river / "Awa" creek	0.452	0.363	0.006
"Serpent" creek / "Dimanche" creek	0.609	0.276	< 0.0001
"Serpent" creek / "Awa" creek	1.000	0.356	< 0.0001
"Dimanche" creek / "Awa" creek	0.878	0.355	< 0.0001

 1 the level of significance is α = 0.05. "Marc" creek correspond to "B2" and "A7" samples, "Petit Inini" river correspond to "33" and "39" samples, "Serpent" creek correspond to "30" and "47" samples,"Dimanche" creek correspond to "23" and "26" samples, "Awa" creek only correspond to "37" sample

357

358 **4.2 Tracing gold provenance**

Because the previous subsection has demonstrated that the five population of gold studied 359 were significantly distinct, this major feature can be used to match (or not) a potential "unknown" 360 sample to a known populations of gold from a database (*i.e.* the nine samples in our study), a 361 362 useful tool which could strongly help to retrace the provenance of gold. The CDFs of the Ag content obtained by LIBS for the five populations of gold and the four "unknown" samples set aside 363 at the beginning of this study (*i.e.* the "X2", the "43", the "46" and the "29" samples) are displayed in 364 the Figure 5. The CDF of the "X2" sample fits well with the CDF of the "Marc" creek population 365 366 (Fig. 5a), suggesting that differences are not significant. Furthermore, the *p*-value (0.181), obtained from the K-S test on the LIBS analyses, indicates that the Ag contents follow a similar distribution 367 function. The K-S tests between "X2" sample and others populations are displayed in the ESI 368 (Table 5S) and show that "X2" only comes from the "Marc" creek population. Thereby, it can be 369 370 statistically considered, with 95% confidence, as only one population of gold grains coming from 371 the same location. The same reasoning can be applied to the three others "unknown" samples. The CDFs and results of the K-S tests (Table 5S, ESI) clearly demonstrate that the "43" sample fits 372

well with the "Petit Inini" river population (Fig. 5b), the "46" sample fits well with the "Serpent" creek population (Fig. 5c) and the "29" sample fits well with the "Dimanche" creek population (Fig. 5d). Thus, only with the distribution of the Ag content of gold grains, we are able to retrace the provenance of the four "unknown" samples among five populations of gold, making the handheld LIBS has a very useful tool for traceability purposes.



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Fig. 5 Plots of cumulative distribution functions (CDFs) of the Ag content of the five gold grains populations from French
Guiana and the four "unknown" samples split at the beginning of this study: the "X2" sample (a), the "43" sample (b), the
"46" sample (c) and the "29" sample (d).

382

383 4.3 Technical discussion

384 It should be noted, however, that a handheld LIBS is not a "magic" tool and has its limits.
385 Our calibration has been only tested up to a content of 16 wt.% Ag, and further tests are needed

for gold grains with higher silver content. Furthermore, a large population database complicates 386 discrimination (or a matching) and should be coupled with other key elements (e.g. mineral micro-387 inclusions, trace elements composition or isotopic analyses) as proposed by Chapman et al. [6] and 388 Augé et al. [21], which require more expensive and time-consuming techniques (e.g. EPMA, SEM) 389 relative to handheld LIBS. A critical point to take into consideration is the need of sample 390 preparation. Indeed, as for EPMA, the LIBS method requires a first step of polishing (see § 3.2). 391 However, whereas EPMA analyses require a fine polishing and a finishing with a very small 392 393 abrasive, which is achieved using diamond pastes of grades 1 µm and 0.25 µm, a coarse polishing with silicon carbide disks is enough for analyses by handheld LIBS. Indeed, the only key point to 394 consider is to expose the grain core to the surface, a simple manual polishing of "raw" gold grain 395 could be enough to expose the core. Consequently, the time of sample preparation is considerably 396 reduced for LIBS relative to EPMA analyses. Furthermore, a handheld LIBS is easily transportable 397 and allows field investigations which is not the case of the EPMA. Thus, our results using a 398 handheld LIBS and the CDFs of the Ag content are very promising. This method could be a first 399 step in establishing gold traceability and opens a new realm of possibilities for supply chain 400 401 management.

402

403 5. Concluding remarks

The main motivation of this preliminary study was to investigate a technique that can rapidly 404 detect the Ag content in natural gold grains for tracing applications, thus reducing or avoiding more 405 406 costly sample preparation and processing requirements. A handheld LIBS unit was selected to perform this test because it is compact and lightweight, making analysis an easy adaptation for a 407 field laboratory. The methodology developed in this study demonstrated the relevance and 408 409 usefulness of the LIBS technique. Univariate and multivariate models were developed from commercial gold alloys for the calibration of the Ag content. The best calibration model is the 410 quadratic univariate model, providing an R² of 0.99991 and a good predictive power with RMSEP 411 of 0.53320 wt.% Ag and MAEP of 0.36049 wt.% Ag. This quadratic model is easy to use and 412 largely reduces the need for the classic but time-consuming multivariate model. The statistical 413

comparisons between the LIBS analyses of the five populations of gold (*i.e.* the nine training 414 samples) and the four "unknown" sample from French Guiana have shown that it is possible to 415 match two gold populations coming from the same location. Results have also shown that it is 416 417 possible to discriminate distinct populations, which would constitute a major advance in gold traceability. The use of a handheld LIBS to trace the origin of gold from French Guiana gold 418 districts appears to have been successful and could be applied to other French Guiana gold 419 districts and other conflict-affected and high-risk areas afflicted by illegal mining, for example in 420 421 Democratic Republic of Congo within the Great Lakes region.

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