1	TITLE
2	Revisiting the statistical analysis of pyroclast density and porosity data
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12	Abstract
13	Explosive volcanic eruptions are commonly characterized based on a thorough analysis of the generated
14	deposits. Amongst other characteristics in physical volcanology, density and porosity of juvenile clasts are
15	some of the most frequently used characteristics to constrain eruptive dynamics. In this study, we evaluate the
16	sensitivity of density and porosity data to statistical methods and introduce a weighting parameter to correct
17	issues raised by the use of frequency analysis. Results of textural investigation can be biased by clast
18	selection. Using statistical tools as presented here, the meaningfulness of a conclusion can be checked for any
19	dataset easily. This is necessary to define whether or not a sample has met the requirements for statistical
20	relevance, i.e. whether a dataset is large enough to allow for reproducible results. Graphical statistics are used
21	to describe density and porosity distributions, similar to those used for grain-size analysis. This approach
22	helps with the interpretation of volcanic deposits. To illustrate this methodology we chose two large datasets:
23	1) directed blast deposits of the 3640-3510 BC eruption of Chachimbiro volcano (Ecuador) and 2) block-and-
24	ash-flow deposits of the 1990-1995 eruption of Unzen volcano (Japan). We propose add the use of this-
25	analysis for the incorporation of this analysis into future investigations to check the objectivity of results
26	achieved by different working groups and guarantee the meaningfulness of the interpretation.
27	Keywords: explosive eruptions, pyroclast textures, porosity, density, statistical analysis
28	1. Introduction
29	Pyroclast density and porosity are commonly used to reconstruct eruptive dynamics and feed numerical
30	models. The pyroclast density $\rho_{p}$ is defined as:

$$\rho = \frac{m}{V} \tag{1}$$

31

The mass of a pyroclast  $m_p$  is easily measured using a precision balance. The measurement of its volume  $V_p$  is a much greater task as pyroclasts have irregular shapes. According to the Archimedes' principle,  $V_p$  can be

34 calculated using the volume of water displaced by the pyroclast  $V_w$  that can be directly measured or calculated

35 <u>using the the</u> following equation:

$$V = V_{w} = \frac{m_{w}}{\rho_{w}}$$
(2)

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43

36

38 Wwhere the water density  $\rho_w$  depends on the ambient temperature and  $m_w$  corresponds to the mass of water 39 volume weight displaced by the pyroclast.

40 If the <u>density DRE</u> (Dense Rock Equivalent (DRE,  $\rho_{deDRE}$ ) is known, either assumed using the rock

41 composition or measured in laboratory (i.e. rock powder density using water or helium pycnometry), it can be

42 used along with the pyroclast density to calculate the pyroclast porosity  $(\varphi_{p})$ :

$$\varphi = 1 - \frac{\rho}{\rho_{DRE}} \tag{3}$$

44 It is important to note that measuring the density and the porosity of <u>irregularly shaped pyroclasts</u> is not-a

45 straightforward analysis. In particular, the parameter  $m_w$  is hard<u>difficult</u> to constrain preciselyaccurately as it

46 has to be achieved before or better without a significant portion of the pore space having been filled with-

47 water due to water infiltration in the pyroclast. The impact on the measurement increases for samples with

48 <u>high porosity and permeability.</u> In any case, the properties of the pore network, such as the permeability or

49 the pore tortuosity, have to be taken into account because they affect the  $m_w$ . Over the last decades several

50 methods have been developed to minimize the effect of intruding water (Houghton and Wilson, 1989;

51 Schiffman and Mayfield, 1998; Polacci et al., 2003; Kueppers et al., 2005). It is worth indicating that there are

52 many different techniques to obtain density and porosity other methods such as water saturation, pycnometry

53 (water or helium), photogrammetry, ealipercalliper techniques, and X-ray tomography-are also used to-

54 calculate density and porosity\_(Hanes, 1962; Manger, 1966; Giachetti et al., 2011). The increasing use of

55 regularly shaped core-samples (cores) with regular shape in the laboratory solves the problem of imbibition-

56 allows for an easy way to derive average density but provides partial information on the bulk density and

57 porosity of the starting pyroclasts due to 3D effects such as heterogeneous vesicle size and density

58 distribution. The purpose of this paper is not to compare the different methods used to obtain the

59 density/porosity data but to discuss how they should be treated statistically.

60 Another important aspect of density/porosity analysis is that pyroclastic deposits commonly present a large

- 61 range of density values, so sample sets must comprise a significant<u>large</u> number of clasts. Additionally, the
- 62 results must be checked for a low <u>amount of bias during sample selection</u>due to preferential sampling during
- 63 <u>field workfieldwork</u>. Then the density and porosity results are generally treated statistically using frequency
- 64 analysis including average and distribution histograms. These analyses are often <u>used to</u> interpreted as-
- 65 indicators of\_volcanic structures or explosivity (Kueppers et al., 2005; Belousov et al., 2007; Kueppers et al.,
- 66 2009; Shea et al., 2010; Mueller et al., 2011). The main issue in this approach is that density and porosity are
- 67 considered thermodynamically as intensive properties and that- are not additive unlike extensive properties
- 68 such as mass or volume (White, 2012). In consequence, if it cannot be added, it should not be possible to
- 69 average (sum divided by number of measurement) intensive properties. For homogeneous material such as
- 70 <u>native elements (diamond, gold) it is not a problem because the Pyroclast d density is will be the same</u>
- 71 <u>independently of the scalesize dependent even for samples with a homogeneous bubble distribution (increase</u>
- 72 <u>in density for particles smaller than the average bubble size, e.g., Eychenne <del>et aland Le Pennec.</del>, 201<del>32</del>). This</u>
- 73 <u>effect can be even stronger</u>. <u>Ffor heterogeneous matter such as pyroclastic material that commonly shows</u>
- 74 <u>bubble gradients.</u> Therefore, anthe average density  $\rho_a$  can be estimated as the total mass of the pyroclasts  $m_t$
- 75 <u>divided by their total volume  $V_t$ :</u>

$$\rho_a = \frac{m_t}{V_t} \approx \frac{\sum_{i=1}^n m_i}{\sum_{i=1}^n V_i}$$

(4)

76

- 77 The non-additive property of density and porosity also forbidlimits the use of frequency histograms. For
- 78 statistical analysis on the density/porosity distribution, the measurements must be weighted eannot be
- 79 summed or averaged. In fact intensive properties must be weighted in order to be treated-
- 80 statistically.adequately to be physically meaningful.
- 81 The purpose of this paper is to present a simple method to obtain weighted averages and histogramsstatistics
- 82 in order to analyszeanalyse density and porosity data. We also propose an *ipso facto* a stability analysis that
- 83 allows quantifying the quality of the sampling and the relevance of the results. Then we introduce graphical
- 84 statistical parameters similar to those used for the analysis of grain-size distribution (Inman, 1952; Folk and
- 85 Ward, 1957) that can help the interpretation of density and porosity datasets. In order to standardize the
- 86 description of grain-size distribution of sediments, Inman (1952) proposed a -set of graphical parameters
- 87 based on statistical analysis. The new parameters such as graphical standard deviation and graphical skewness
- 88 allowed to putputting numbers on descriptive terms. Few years later Folk and Ward (1957) proposed revised
- 89 parameters that better describe natural material in particular polymodal distributions. They also introduced the
- 90 kurtosis that allows to describe describing the shape of the mode. These parameters have been used ever since
- 91 to characterize and distinguish volcanic deposits (Walker, 1971). We propose to adapt those equations to
- 92 describe density and porosity distribution. This methodology is incorporated in an open source R script
- 93 (http://www.r-project.org/). R is a high-functioning freeware with excellent statistical capacities that provide

- an optimal platform for such analysis. In order to promote this analysis we also provide Those three steps are
- 95 incorporated in an open source R script (http://www.r project.org/) for easy usea similar MatLab numeric
- 96 code. An Excel spreadsheetspread sheet is also jointed but only with basic formulae as most of the
- 97 formulaeprotocol cannot be translate to a spreadsheetspread sheet format. -Finally we illustrate and discuss
- 98 this method using two large datasets from different pyroclastic deposits.

## 99 2. Methodology

# 100 2.1. Density and porosity datasets

- 101 We chose two large datasets from different pyroclastic deposits in order to assess the validity of our approach.
- 102 The Chachimbiro dataset (Bernard et al., 2014) is made of 32 sample sets from different outcrops of the 3640-
- 103 3510 BC directed blast from Chachimbiro volcano, Ecuador (Appendix 1). Each sample set contains between
- 104 15 and 103 clasts of the 16-32 mm fraction measured using the methodology of Houghton and Wilson (1989).
- 105 The Unzen dataset (Kueppers et al., 2005) is made of 31 sample sets from block-and-ash-flow deposits from
- 106 the 1990-1995 eruption of Unzen volcano, Japan (Appendix 2). Each sample set contains 24-33 large
- 107 pyroclasts (<del>100-5000 g>64 mm</del>) measured according to the methodology presented in Kueppers et al. (2005).

# 108 2.2. Weighting measurements

- 109 In order to perform a thorough statistical analysis of density and porosity data, each clast measurement in a
- 110 sample set with a number of "n" measurements *n* must be weighted. Based on the Eq. (1) the density/porosity
- 111 data can be weighted either by the volume or by the mass of the pyroclast as soon as the weighting parameter,
- 112 <u>here called the representativeness *R*, is defined as follows:</u>

$$\rho_a = \sum_{i=1}^n \left( R_i \times \rho_i \right) \tag{5}$$

- 114 Here we chose to present the weighting by volume but the same resolution can be used to weight by mass.
- 115 The Eq. (1) can be reformulate as follows:

$$m_i = \rho_i \times V_i$$
 (6)

117 Then the Eq. (6) can be inserted in the Eq. (4):

$$\rho_{a} = \frac{m_{t}}{V_{t}} \approx \frac{\sum_{i=1}^{n} m_{i}}{V_{t}} = \frac{\sum_{i=1}^{n} \left(V_{i} \times \rho_{i}\right)}{V_{t}} = \sum_{i=1}^{n} \left(\frac{V_{i} \times \rho_{i}}{V_{t}}\right)$$
(7)

118

113

116

119 <u>Using the Eq. (5) and (7):</u>

120 
$$\sum_{i=1}^{n} \left( \frac{V_i \times \rho_i}{V_t} \right) = \sum_{i=1}^{n} \left( R_i \times \rho_i \right)$$
(8)

121

On the basis of Eq. (1), it appears that the measurement must be weighted by the volume of the pyroclast . 122 Therefore the reprthe representativeness by volume of the any pyroclast  $R_{P}$ , which is the part of the 123 measurement in the whole sample setdefined as the volumetric portion of the pyroclast, is calculated as-124 follows in the whole sample: 125  $R_i = \frac{V_i}{V}.$  (9) 126 127  $R_i = \frac{V_i}{V}$ 128 Therefore if n = 1, R =129 dotRhoVp) and porosity (dotPhiVp) as follows: (5) 130 131 (6) In order to check if the weighting equation is correct, it is possible to solve the Eq. (5) using Eq. (1) and 132 133 (4): 134 (7) Therefore the weighted values do have a physical meaning whereas the frequency values don't. 135 136 2.3. Abundance histograms and cumulative plots Abundance histograms and cumulative plots are typical graphical representations of density and porosity data 137 138 (Fig. 1). The representativeness can be used to create weighted graphs. For the abundance histogram, in each 139 interval we sum the Rerepresentativeness of the measurements instead of counting the number of 140 measurements and dividing it by n. It is important to note that density and porosity histograms can have 141 different shapes due to the selected bin size [1] (Fig. 1A and C). Several studies have used mixed histograms, 142 with the main axis for density and a secondary axis for porosity (Houghton and Wilson, 1989; Formenti and 143 Druitt, 2003; Belousov et al., 2007; Shea et al., 2010; Komorowski et al., 2013). There is no consensus for the 144 histogram representation; nonetheless most studies used bin sizes between 50 to 100 kg m<sup>-3</sup> for the density (Cashman and McConnell, 2005; Kueppers et al., 2005; Bernard et al., 2014). In practice theory, the bin size 145 146 should be selected depending on the number of measurements and the density or porosity range, nevertheless for comparison purpose we chose a constant bin size (100 kg m<sup>-3</sup> and 5% porosity) that can be changed in the 147 148 numeric code. Cumulative plots (Fig. 1B and D) are easier to produce and have a unique representation as the 149 data are used directly to produce the plot. The data are sorted by increasing density or porosity and these 150 values are then plotted against the cumulative abundance that is the sum of  $R_{\rm e}$  the representativeness. The

151 density and porosity cumulative plots should have the same shape but rotated 180°[2].

### 152 2.4. Stability analysis

153 One of the main questions when performing a density and porosity analysis on pyroclastic deposits is: how 154 many measurements are required to have a statistically representative sample set? The sample set size, here 155 expressed as the number of measurements n, is primarily dependant on the dispersion of the data. Deposits with a large density range and a large standard deviation require a larger number of measurements. In order to 156 157 assess the quality of the sampling we propose a stability analysis based on the comparison between the final density average (including all the measurements) and intermediate density averages (including part of the 158 159 measurements). To avoid analytical skew, due to intentional or unintentional ordering of the samples during the measurements, the data must be ordered randomly several times. Then tThe density intermediate average. 160 161  $\rho_{ain}$  is calculated after each measurement and compared with the final average. the An absolute error (AE) is 162 calculated using as follows:

163

164

-with the final density average is determined. Each run with random ordering leads to a different AE after a 165 certain number of measurements. We chose to represent Tthe 95th quantile (2 sigma) of the absolute errorAE 166 167 is then plotted against the number of measurements (Fig. 2). We found that about 1,000 repetitive runs on one 168 sample set are required to achieve identical results. Finally, the slope of the curve is calculated below a 5% 169 threshold of the absolute error to avoid the large error associated to a very small number of measurements. 170 This slope is a direct indicator of the quality of the sampling with low slopes associated to high quality 171 sampling. The slope of the curve is also calculated below 1% of AE as an additional quality indicator but it 172 seemsappears not asless useful in practice.

## 173 **2.5. Graphical statistics**

- 174 As the frequency analysis is not suitable for density and porosity data, some interesting statistical parameters,
- 175 such as the standard deviation, are difficult to obtain. Based on the work achieved to characterize better
- 176 studies of grain-size distribution (Inman, 1952; Folk and Ward, 1957), we propose for the first time a similar
- 177 approach to calculate the graphical statistics of density and porosity using the cumulative plots (Fig. 1CB and
- 178 D). The main difference between graphical statistics for grain-size distribution or for density data is not the
- 179 equations but the data itself. Grain-size data obtained through sieving are partial data as the grain-size
- 180 distribution inside each size class (1 phi, ½ phi or ¼ phi) we cannot is unknown the grain size distribution.
- 181 The density data, on the other hand, are continuous through the whole sample set. An other difference is that
- 182 grain size data are weighted by mass whereas density data are weighted by volume. For informational
- 183 <u>purposeHere</u> we present the equations for the density, which are identical to the equations for the porosity.
- 184 2.5.1. Inman graphical statistics

187 • The dis Graphical Median Md is a proxy of the average:  

$$Md = \frac{P_{0}}{P_{0}} = \frac{P_{0}}{50} - \frac{P_{0}}{2}$$
187 • EMBED Microsoft Equation 3.08:  
188  $P_{Md} = \frac{P_{0}}{50} - \frac{P_{0}}{2}$ 
189 Where  $p_{0}$  corresponds to the value of  $p$  at 50% of cumulative abundance. Same notation is used for the  
190 following equations:  
191 • The dis Graphical Standard Deviation  $\sigma$  describe the dispersion of the dataset:  
192 • EMBED Microsoft Equation 3.08:  
193 • The dis Graphical Standard Deviation  $\sigma$  describe the dispersion of the dataset:  
194 • EMBED Microsoft Equation 3.08:  
195 • EMBED Microsoft Equation 3.08:  
196 • The disc Graphical Skewness SKG characterize the asymmetry of the data distribution:  
197 • EMBED Microsoft Equation 3.08:  
198  $SKG_{p} = \frac{P_{04} + P_{16} - 2P_{50}}{2(P_{04} - P_{16})}$  (10)  
199 • EMBED Microsoft Equation 3.08:  
199 • EMBED Microsoft Equation 3.08:  
199 • EMBED Microsoft Equation 3.08:  
199 • State describes that are considered by come authors (Folk,  
199 • Josh and Ward (1957) proposed different parameters that are considered by come authors (Folk,  
199 • Hold, and Ward (1957) proposed different parameters that are considered by come authors (Folk,  
199 • Hold, and Ward (1957) proposed different parameters is the inclusion of a L-signa parameter for the mean  
199 and a 2-signa parameter for standard deviation and skewness. In addition Folk and Ward (1957) included the  
200 • The distribution parameter for standard deviation and skewness. In addition Folk and Ward (1957) included the  
201 • EMBED Microsoft Equation 3.00:  
202 • The distribution parameter for the mean  
203 • The distribution for the main difference with the allows to characterize characterizing the shape of the distribution peak:  
204 • EMBED Microsoft Equation 3.00:  
205 • The distribution folk and M:  
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207 • EMBED Microsoft Equation 3.00:  
208 • The distribution folk and M:  
209 • The distribution folk and M:  
200 • The distribution fo

EMBED Microsoft Equation 3.09  $\sigma I_{\rho} = \frac{\rho_{84} - \rho_{16}}{4} + \frac{\rho_{95} - \rho_5}{6.6}$ 207  $\rho_{\sigma I} = \frac{\rho_{84} - \rho_{16}}{4} + \frac{\rho_{95} - \rho_5}{6.6}$ 208 209 The the Inclusive Skewness SkI:  $SkI_{\rho} = \frac{\rho_{84} + \rho_{16} - 2\rho_{50}}{2(\rho_{84} - \rho_{16})} + \frac{\rho_{95} + \rho_{5} - 2\rho_{50}}{2(\rho_{95} - \rho_{5})}$ **EMBED** Microsoft Equation 3.09 210  $\rho_{SkI} = \frac{\rho_{84} + \rho_{16} - 2\rho_{50}}{2(\rho_{84} - \rho_{16})} + \frac{\rho_{95} + \rho_{5} - 2\rho_{50}}{2(\rho_{95} - \rho_{5})}$ 211 212 The the Graphical Kurtosis KG:  $KG_{\rho} = \frac{\rho_{95} - \rho_5}{2.44(\rho_{75} - \rho_{25})}$ EMBED Microsoft Equation 3.08 213  $\rho_{K} = \frac{\rho_{95} - \rho_{5}}{2.44(\rho_{75} - \rho_{25})}$ 

(12)

(13)

The the Inclusive Standard Deviation  $\sigma$ I:

214

206

215 It is important to note that the values of Graphical Median and Mean should be relatively close to the

216 weighted average. Nevertheless, as the weighted average is physically the most accurate value, we propose to

(16)

use it for graphical representation. Standard deviation, skewness and kurtosis are important parameters that 217

218 have never been used yet to characterize density and porosity distributions but they are useful.

#### 219 2.6. R code

220 An open access R code has been created to simplifyautomate the calculations presented above. Additionally it

221 facilitates the automatic creation of abundance histograms, cumulative plots, and stability curves. The input

222 file must be in the format csv (field separated by comma) and structured as follows:

223 1) first column: pyroclast mass (in kg or g);

224 2) second column: pyroclast volume (in m<sup>3</sup> or cm<sup>3</sup>);

- 3) third column: pyroclast density (in kg m<sup>-3</sup> or g cm<sup>-3</sup>); 225
- 226 4) fourth column: pyroclast porosity (in decimal from 0 to 1).
- 227 The columns should have a header. All the values must have the decimal point separator for the R code to run

228	properly. The name of the file should correspond to the name of the sample set to avoid confusion when
229	compiling large datasets. The R code is provided in the supplementary material (Appendix 3) and to run the
230	code only twothree commands are required in R:
231	1) set the Working Directory where the R code and the input file are located: setwd("~/");
232	
233	<pre>42) load the code: source("stats.R");</pre>
234	
235	23) run the code: results<-stats("Input file name.csv").
236	For large datasets it is possible to create a list of csv files and treat them with a loop:
237	
238	34) create the list: <i>l</i> <- <i>list.files(path=".",pattern="csv")</i> ;
239	
240	45) run the code for the list: for (i in 1:length(l)) $\{a < -stats(l[i], plot=FALSE)\}$ .
241	The R code generates a text file with the statistical results and the figures in pdf format. Compiling the
242	Chachimbiro (33 sample sets, 1492 clasts) and Unzen (32 sample sets, 922 clasts) datasets with the R code
243	with 1000 runs for the stability analysis of each sample set take respectively 36 and 22 seconds on a 4 Gb ram
244	computer (~42 clasts/s in both cases). A translation of the R code in MatLab format is also provided in the
245	Appendix 3 as well as a basic spreadsheet including the formulae required to obtain weighted average
246	3. Contribution of the renewed methodology
247	3.1. Frequency versus weighted analysis
248	The absolute difference between frequency and weighted density/porosity averages for Chachimbiro and
249	Unzen datasets is up to 4% and 2% respectively (Fig. 3A, Appendix 4) that is close to the analytical error
250	(<5%)-(Fig. 3A, Appendix 4). This difference is not as important as the relative difference between individual
251	sample sets per volcano. To highlight this we chose two sample sets from the Chachimbiro, 021-B and 089-A.
252	These samples have almost the exact same frequency density average (1961 and 1960 kg m <sup>-3</sup> ) but a distinct
253	
	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro
254	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro (018-C and 095-A) show similar weighted density averages (2246 and 2242 kg m <sup>-3</sup> ) but distinct frequency
254 255	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro (018-C and 095-A) show similar weighted density averages (2246 and 2242 kg m <sup>-3</sup> ) but distinct frequency density averages (2284 and 2154 kg m <sup>-3</sup> ). Abundance histograms can also be biased by the use of frequency
254 255 256	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro (018-C and 095-A) show similar weighted density averages (2246 and 2242 kg m <sup>-3</sup> ) but distinct frequency density averages (2284 and 2154 kg m <sup>-3</sup> ). Abundance histograms can also be biased by the use of frequency analysis. We observed significant modification of the histogram shape such as fluctuation of the
254 255 256 257	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro (018-C and 095-A) show similar weighted density averages (2246 and 2242 kg m <sup>-3</sup> ) but distinct frequency density averages (2284 and 2154 kg m <sup>-3</sup> ). Abundance histograms can also be biased by the use of frequency analysis. We observed significant modification of the histogram shape such as fluctuation of the density/porosity modes (Fig. 3B), variation of the mode fraction, or change of the general density/porosity
254 255 256 257 258	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro (018-C and 095-A) show similar weighted density averages (2246 and 2242 kg m <sup>-3</sup> ) but distinct frequency density averages (2284 and 2154 kg m <sup>-3</sup> ). Abundance histograms can also be biased by the use of frequency analysis. We observed significant modification of the histogram shape such as fluctuation of the density/porosity modes (Fig. 3B), variation of the mode fraction, or change of the general density/porosity distribution (unimodal or plurimodal). For both of our study cases, the number of measurements and the
254 255 256 257 258 259	weighted density averages (2039 and 1892 kg m <sup>-3</sup> ). In contrast, two other sample sets from Chachimbiro (018-C and 095-A) show similar weighted density averages (2246 and 2242 kg m <sup>-3</sup> ) but distinct frequency density averages (2284 and 2154 kg m <sup>-3</sup> ). Abundance histograms can also be biased by the use of frequency analysis. We observed significant modification of the histogram shape such as fluctuation of the density/porosity modes (Fig. 3B), variation of the mode fraction, or change of the general density/porosity distribution (unimodal or plurimodal). For both of our study cases, the number of measurements and the number of samples per deposit is large enough for the effect of one method compared to the other to be

- 260 minimum (few percent of deviation). Even though, laboratory experiments have shown that porosity is one of
- 261 <u>the main parameters that controls fragmentation during decompression</u>explosive eruptions under the presence
- 262 of bubbles with gas overpressure (Alidibirov and Dingwell, 1996; Spieler et al., 2004), {Therefore a change of
- 263 only few percent of porosity might induce a large error on the calculation of pre-eruptive conditions such as
- 264 overpressure and fragmentation depth. Therefore, the use of frequency analysis alone can lead to-
- 265 misinterpretations. It is difficult to assess the effect of the statistical method based on literature as most of the
- 266 publications only provide the final density and porosity datasets and not the raw data (mass and volume).

# 267 3.2. Sample size

- 268 The stability analysis (c.f. 2.3) can be used to assess the quality of the sampling and also to estimate the
- 269 minimum number of measurements required to obtain meaningful results. When comparing the slope of the
- 270 stability curve below the 5% threshold and the number of measurements from the Chachimbiro dataset, it
- appears that sample sets with more than 40 clasts have a high stability (Fig. 4, Appendix 4). Below 40
- 272 measurements there is scattering in the results (from high to low stability) probably associated to the-
- 273 differences of in the standard deviation. The Unzen dataset exhibits a much smaller spread with a high
- 274 stability for most of the sample sets. This difference indicates that natural heterogeneity of pyroclasts and
- eruption, transport and deposition dynamics require a deposit-adapted sampling strategy. Houghton and
- 276 Wilson (1989) propose a minimum of 30 clasts per sample set. Our analysis shows that the minimum number
- 277 of measured clasts per sample set must be established according to the characteristics of the deposit itself and
- 278 therefore based on an *ipso facto* approach. When more raw data are available on different deposits,
- 279 thestability analysis results from this approach-could also-be useused to suggest a minimum number of
- 280 measurements for future investigations. Moreover, the stability analysis might be used to select only high
- 281 stability, ergo more representative; samples for further analyseis such as laboratory experimentation or
- 282 permeability measurements (Fig. 5).

## 283 **3.3. Distinguishing deposits**

- 284 Graphical statistics for grain-size analysis have been commonly used to identify the nature of volcanic
- 285 deposits (Walker, 1971). The same might be applied for density analysis. Figure 5 highlights the differences
- 286 between the Chachimbiro and Unzen datasets. For values of similar density/porosity averages the
- 287 Chachimbiro dataset shows almost systematically a higher standard deviation than the Unzen dataset
- 288 (Appendix 4). The two datasets also display a small degree of overlap when looking at skewness and kurtosis
- parameters. The Unzen deposits have principally a symmetric porosity distribution (SkG and SkI around 0)
- 290 while the Chachimbiro deposits have a clear asymmetric distribution (SkG and SkI mostly positive and up to
- 291 0.4). The porosity distribution for Unzen deposits is typically mesokurtic (KG ~ 1) while it is generally highly
- 292 leptokurtic (KG > 1) for Chachimbiro deposits, mostly associated to with a larger tail of data and wider
- 293 porosity modes. This might be interpreted as an expression of the outgassing processes in both contexts. The
- 294 dome collapses, associated to Unzen deposits, probably affected the outerupper part of the lava dome that has
- 295 been homogeneously fairly outgassed while the directed blast, associated to Chachimbiro deposit, removed

- 296 <u>most of the dome in one event, including the highly outgassed carapace</u>but also magma from the plumbing
- 297 system and the internal magma with still a higher volatile content. There is no major difference between the
- 298 <u>Inman (1952) and It appears that the Folk and Ward (1957) parameters for the Unzen dataset while the</u>
- 299 Chachimbiro dataset behave differently. In particular the Inclusive Skewness (Fig. 5D) allows for a better
- 300 distinction than the Inman parameters between the Unzen and Chachimbiro datasets. As indicated by Folk
- 301 (1966), the Folk and Ward parameters generally represent polymodal distribution better than do the Inman
- 302 parameters. Consequently, the bimodal distribution of most samples from the Chachimbiro deposit explains
- 303 why they are better described by the former the former better describes them than the latter. This is probably-
- 304 due to the bimodal distribution of most sample sets from the Chachimbiro dataset and agree with Folk (1966)-
- 305 conclusions made for grain size analysis. It is possible that the distinction made thanks to the graphical
- 306 parameters is related to the origin of the deposits (directed blast vs block-and-ash-flow) but more data from
- 307 different deposits are required to support this hypothesis.

## 308 4. Conclusion

- 309 This study presents a new methodology to treat density and porosity measurements from pyroclastic deposits.
- 310 It presents weighting equations that allow <u>a more robust proper</u>-statistical analysis. The evaluation of
- 311 Chachimbiro and Unzen density/porosity datasets indicate that frequency analysis alone can lead to
- 312 misinterpretations and that weighted analysis should be used to avoid analytical bias. The stability analysis
- 313 provides a tool to assess the quality of the sampling while the graphical parameters allow for a better
- 314 characterization of the deposits than the classical approach using only averages and histograms. The results
- 315 obtained show that for small numbers of measurements the Chachimbiro dataset sample sets is are less stable
- than the Unzen ones. This can be interpreted as being due to either the sampling method or due to the deposit
- 317 density/porosity distribution. Finally we propose tothe use of graphical statistics to represent the-
- 318 density/porosity data. The differences observed between the two datasets indicate that such representations
- 319 can be useful to distinguish pyroclastic deposits.

# 320 **5. Author contribution**

- 321 BB developed the methodology with contribution from all co-authors and prepared the Chachimbiro dataset.
- 322 UK prepared the Unzen dataset. HO developed the R code and its translation to MatLab format. BB processed
- 323 the data and prepared the manuscript with contributions from all co-authors.

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- 329 three research entities in France including the Laboratoire Magmas et Volcans (Blaise Pascal University,
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# **Figure captions**

- 335 Figure 1. Abundance histograms (A and C) and cumulative plots (B and D) for pyroclast density and porosity
- data. Sample CHA-201-A (n = 103) from Chachimbiro directed blast deposit.
- 337 Figure 2. Stability curves obtained after  $1_{2}000$  runs for two samples from Chachimbiro and Unzen datasets.
- 338 Note the constant slope below the 5% threshold.
- 339 Figure 3. Comparison between frequency and weighted analyses. A: weighted vs frequency density average
- 340 for Chachimbiro and Unzen datasets, note the large relative differences highlighted by the redblackred arrows
- 341 (see paragraph 3.1 for explanation); B: Porosity abundance histogram for one sample from the Chachimbiro
- 342 dataset, note the large fluctuation difference (10%) of the main porosity mode between the two statistical
- 343 methods represented by the redblackred arrow.
- 344 Figure 4. Results of the stability analysies for the Chachimbiro and Unzen datasets. Note that there is a large
- 345 scattering for Chachimbiro dataset below 40 measurements while the Unzen dataset has much less dispersed
- 346 values.
- 347 Figure 5. Graphical parameters for the Chachimbiro and Unzen datasets. Only high stability (slope < 0.5%)
- 348 sample sets are used in this figure. Note that the two datasets are better show lower superposition with the
- 349 Folk and Ward parameters than with the Inman parameters, in particular when using the Skewness (5D).