# Uncertainty aware sample mass determination of coarse-grained soils for particle size analyses

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## Abstract

Determining particle size distributions (PSD) of soils is a basic first step in many geotechnical analyses and guidance is given in different national standards. For ambiguous reasons, the recommended minimum sample mass ($m_{min}$) for the PSD-analyses of soils with a main component of gravel or greater is based on equations including the soil's maximum grain diameter ($D_{max}$). We claim that the recommended $m_{min}$ is overestimated as $D_{max}$ does not represent the relevant large soil fraction but only the PSD's uppermost outlier. Furthermore, the recommended $m_{min}$ is not based on a specific sampling confidence (i.e. how closely does the sample's PSD need to approximate the soil's PSD?) and thus it is not clear why the $m_{min}$ should even be necessary. We conducted Monte-Carlo simulation-based sieve analyses of coarse-grained soils and developed a new, practically applicable framework to determine $m_{min}$ based on $D_{90}$ that also includes explicit consideration of sampling confidence. A survey was conducted that shows that there is no significant difference in how well operators are able to assess parameters like $D_{90}$ or $D_{max}$. Real sieve tests performed on three different sands and gravels corroborate the theoretical results and show that substantially lower sample masses yield PSDs with only marginal differences to PSDs from samples according to the standards. While the results are promising, they open up for new research questions about which geotechnical application requires which soil sampling confidence.

27 **List of notations**

28 $C_u$        coefficient of uniformity

29 $C_c$        coefficient of curvature

30 $D_{min}$        estimated minimum grain diameter of soil

31 $D_{max}$        estimated maximum grain diameter of soil

32 $D_{xx}$        grain diameter at xx percent of a sieve curve

33 $KS$        Kolmogorov-Smirnov statistic used as error metric between two sieve curves

34 $KS_{med}$        median of multiple $KS$ values

35 $KS_{p95}$        95th percentile of multiple $KS$ values

36 $m_{available}$        available soil sample mass

37 $m_{min}$        required minimum soil sample mass

38 $S_0$        sorting coefficient

39 $U$        Uniform distribution

40 $\varepsilon$        error exponent to control desired soil sampling confidence

41 $\rho$        grain density

42 **Definitions and conventions**

43 ▪ Soil: A volume of granular material in the ground that is too large to analyze as a whole. This

44      definition only applies in the herein given context of soil sampling for grain size distribution

45      determination. For other definitions of soil see e.g. EN ISO 14688-1.

46 ▪ Sample: a portion of a larger soil volume, taken to represent its characteristics (based on e.g.

47      O'Toole (2015)). The term "specimen" is not used herein due to ambiguous definitions where a

48      specimen may either be a subset of a sample or the other way round.

49 ▪ Grading and sorting are two equivalent terminologies to describe the shape of a sieve curve. In

50      this work, we consistently use "grading" where "well graded" ≈ "poorly sorted" and "poorly

51      graded" ≈ "well sorted".

52 ▪ Uncertainty communicating language is given in accordance with Erharter et al. (2024).

53 **Keywords**

54 Soil classification; Soil characterization; Grain Size Distribution; Uncertainty, Survey, Confidence

# 1. Introduction

55

56    A reliable particle size distribution (PSD) analysis is key in geotechnical front-end engineering

57    design and imperative for engineering geological soil characterization and classification. For

58    instance, preliminary design of offshore structures relies on PSDs as the percentages of fines

59    content, or $D_{10}$ are key to estimate soil behavior to loading, e.g. drainage conditions, cyclic

60    response, consolidation, etc. (see Andersen (2015); Andersen and Schjetne (2013)). In tailings

61    dams reliable PSDs are crucial for material characterization and modelling (Liu et al., 2024) and

62    to determine if the dam's composition complies with regulations in all depths. Extraterrestrial

63    geotechnics is a more exotic field where PSDs are required for preliminary ground investigations

64    for potential human settlements (Quinteros et al., 2024).

65    The first step to determine a PSD is to take a test sample from the soil. Several significant error

66    sources such as the sampling technique or the choice of the sample mass are entailed in this

67    process (Rawle, 2015). Readers are referred to works like Gerlach et al. (2002); Gerlach et al.

68    (2003) or Dubé et al. (2021) for information about sampling techniques such as riffle splitting or

69    fractional shoveling. With respect to the sample mass, the primary goal is to take a sample that is

70    sufficiently large to be representative for whichever characteristic of the soil that one is interested

71    in (Al-Rumaithi and Al-Sherrawi, 2020; Dubé et al., 2021; Pitard, 2019). It must be noted, however,

72    that it makes a difference for the practical sampling if, for example, an investigation's goal is a

73    soil's chemical composition that permits crushing of large grains, or an investigation's goal is the

74    actual soil PSD that does not allow that. The former case is relevant in the context of mining,

75    metallurgy and environmental studies (Gy, 2012). The latter case is relevant in engineering

76    geological investigations in the context of geotechnical engineering projects.

77    The present paper is exclusively concerned with the sample mass determination to assess a soil's

78    PSD for engineering geological soil characterization. In that context, achieving the best possible

79    representation of a soil is also the goal, but practical problems that come with too large samples

80    such as transport difficulties, storage capacity limitations or uneconomic testing efforts must

81    also be considered. In contrast to the above-mentioned applications, the literature on the sample

82    mass determination for engineering geological soil characterization is remarkably sparse and

83    Zhang et al. (2017) and the recent publication of Jia et al. (2024) are few exceptions.

84    Methods of engineering geological investigation such as soil sampling for PSD determination are

85    regulated and codified through different national and international standards. These methods are

86    related to sieving, sampling techniques, sampling of aggregates, reducing sample sizes,

87    alternative grain size determination through images, sample size estimates and sampling

88    probability: ISO 17892-4 (2017),  ASTM D6913/D6913M (2017), ASTM C136/C136M (2020), ASTM

89    C702 (2018), ASTM E1382 (2023), ASTM D75 (2019), ASTM D3665 (2024), ASTM E105 (2021), ASTM

90    E122 (2022), ASTM E141 (2023). Besides ISO and ASTM standards, other relevant ones are

91    AASHTO T2, Australian Standard AS 1141.11, DJS 112-4:2015. Standards from Ontario, Canada

92    recommend similar minimal masses, but lower than the European counterpart.

93    These standards recommend to determine the required minimum sample mass ($m_{min}$) as a

94    function of the soil's estimated maximum grain diameter ($D_{max}$). As also pointed out by Zhang et

95    al. (2017), the origin and scientific justification for this procedure is unknown, despite widespread

96    adoption. This is of particular relevance in coarse-grained soils (i.e. ≥ sand acc. to ISO 14688

97    (2019)) where the suggested sample masses easily exceed tens of kilograms if one follows the

98    recommendations. Equally unknown is the desired sampling confidence that the different

99    guidelines seek to achieve. Gale and Hoare (1992) also addressed the topic of soil sample mass

100   determination and give a recommendation based on $D_{max}$. But as others, i) they do not justify why

101   a $D_{max}$ based approach is adopted and ii) they aim for "reliable" grain size analyses but do not

102   specify what reliable means in terms of how close the soil is approximated.

103    From a statistical point of view, using $D_{max}$ as the decisive criterium to determine $m_{min}$ implies

104    that $m_{min}$ depends on the extreme large grain sizes of the PSD, resp. on the rightmost point of the

105    distribution. We hypothesize that today's standards overestimate the required sample mass in

106    many cases and that $D_{max}$ is a conservative criterium to determine $m_{min}$. This often forces

107    practitioners who deal with coarse-grained soils to act outside the standard framework without

108    being aware of what the consequences of smaller sample masses are. Furthermore, it is

109    problematic that the recommendations for $m_{min}$ are made without the indication of a desired

110    sampling confidence.

111    This paper investigates the issue of sample mass determination for coarse-grained soils and

112    proposes a new criterium to determine $m_{min}$ that is easily applicable in practice as it is just an

113    equation with estimated input values. We show through a dedicated survey that the inputs that

114    are required for our criterium can be as well estimated as those recommended by today's

115    standards. The new criterium is developed through Monte-Carlo simulation of virtual sieve tests

116    and allows one to explicitly set a desired level of confidence. The Monte-Carlo simulation

117    simulates real laboratory tests as closely as possible with only minor assumptions such as

118    spherical grain shapes. To provide a baseline, the sampling confidence of today's standards is

119    back calculated within the simulations. The approach i) allows one to take samples according to

120    a desired level of confidence that is to be achieved; ii) provides the possibility to assess the

121    uncertainty that needs to be expected if one has a sample mass that is $< m_{min}$; iii) reduces the

122    required $m_{min}$ for many soils and especially for those where $D_{max}$ comes from single large grains.

# 2. Background

124    In this section, extended information about the sample mass recommendations from ISO 17892-

125    4 and ASTM ASTM D6913/D6913M is given as they explicitly give recommendations for soil

126    characterization. The rest of this paper also directly refers to these two standards. Other

127    standards that were mentioned in the introduction are thematically connected to this work, but

128    are not directly relevant as they address other issues such as aggregates for concrete.

129    ISO 17892-4 (2017) defines that $m_{min}$ [kg] depends solely on $D_{max}$ [mm], for soils with a $D_{max}$ >

130    20 mm. $m_{min}$ according to this standard is to be derived from eq. 1.

$$m_{min} = \left(\frac{D_{max}}{10}\right)^2$$

<div align="right"><em>eq. 1</em></div>

131    The ASTM D6913/D6913M (2017) standard also defines $m_{min}$ in dependence of $D_{max}$, for a $D_{max}$

132    > 9.5 mm. $m_{min}$ is "based on the mass of an individual spherical shaped grains, at the given sieve,

133    multiplied by 100 then 1.2 (factor to account uncertainty) and finally rounded to a convenient

134    number." For soils with a $D_{max}$ > 76.2 mm, the same applies "except 1.2 factor is omitted". ASTM

135    D6913/D6913M only gives this instruction and no equation, so eq. 2 was reconstructed based on

136    that explanation. $\rho$ in eq. 2 denotes the grain density which is also not directly specified in the

137    standard but based on the therein given values for $m_{min}$, it can be back calculated that a $\rho$ of

138    3.016 g/cm$^3$ must have been applied.

$$m_{min} = \frac{4}{3} * \pi * \left(\frac{D_{max}}{2}\right)^3 * \rho * 100 * 1.2$$

<div align="right"><em>eq. 2</em></div>

139    Based on these equations, both standards require minimum sample masses in the range of

140    hundreds of kilograms for soils with a $D_{max}$ larger than 5-10 centimeters which is unpracticable

141    and often impossible to achieve in terms of practical sampling, availability and sievability in the

142    laboratory. Figure 1 shows the required $m_{min}$ for the mentioned standards for up to a maximum

143    grain size of 300 mm diameter where ISO 17892-4 would require a sample with a mass of 900 kg

144    and ASTM D6913/D6913M more than 1200 kg.
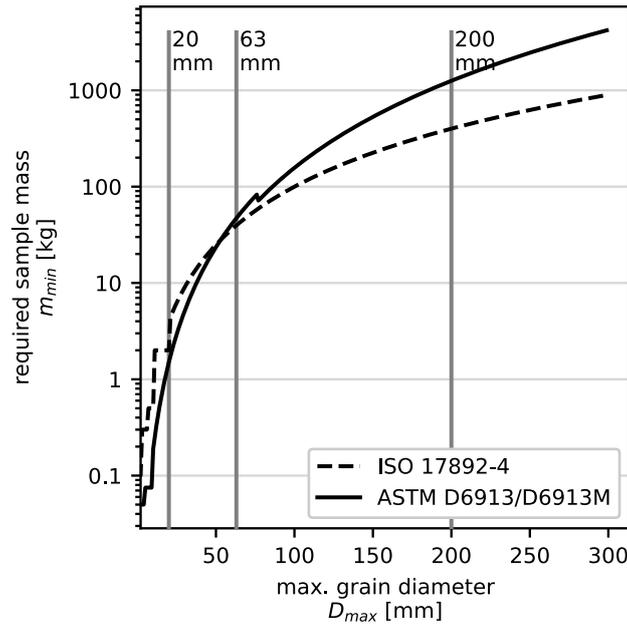
Figure 1: *Minimum required sample masses as defined in ISO 17892-4 and ASTM D6913/D6913M. Steps in the plot result from fixed sample masses and conditions in the standards.*

# 3. Development of new minimum sample mass criterium

In this study, we propose an alternative way of determining $m_{min}$. We first investigate the sample

mass determination problem theoretically with Monte-Carlo simulations using virtual sieve tests

and then underpin it with experimental results from real sieve tests. The Python source code, the

simulation- and experimental results are available in the Github repository in the supplementary

information of the paper.

## 3.1.    Monte-Carlo Simulations

To theoretically investigate this problem, virtual sieve tests were conducted on generated coarse-

grained soils. The basic idea is that first a "ground-truth" coarse-grained soil is generated and then

samples with different masses are taken from this soil to investigate how large the error between

the samples' PSDs and the soil's PSD is. The Monte-Carlo simulation was set up with the goal to

generate a wide variety of PSDs including poorly graded-, well graded- and gap graded coarse-

160    grained soils to reflect many possible geological scenarios. All grains are modelled as spherical

161    which slightly reduces its realism (Kaviani-Hamedani et al., 2024), (see also section 6).

162    The soils are generated by the following process:

163    ▪ Step 1: The simulation should include well- to poorly graded sediments. While poorly

164       graded sediments can be modelled with a single statistical distribution (e.g. normal as

165       done by Jia et al. (2024), lognormal or exponential) , well graded ones are compositions of

166       multiple distributions due to different depositional environments. To account for this in

167       the simulation, the first step is to randomly generate between 1 and 5 percentages of soil

168       distributions (e.g. a soil may consist 100% of one distribution, or, for example, 30% of

169       distribution A, 20% of distribution B and 50% of distribution C).

170    ▪ Step 2: For each distribution, randomly set the minimum- and maximum grain diameters

171       between 1 and 200 mm. The minimum diameter must be smaller than the maximum.

172       These diameters are sampled from a uniform distribution $U$ with $\ln(1)$ and $\ln(200)$ being

173       the lower and upper limits of the distribution. The logarithm is taken to avoid oversampling

174       of large diameters. The logarithmic values are then scaled back between 1 and 200 mm

175       by calculating their exponential. This gives: lower-/upper limit = $\exp\left(U\big(\ln(1),\ \ln(200)\big)\right)$.

176    ▪ Step 3: For each distribution, individual grain diameters are generated by sampling from a

177       beta distribution that gives numbers between 0 and 1 and then scaling the output to the

178       minimum and maximum grain diameters that were chosen in the previous step. The beta

179       distribution's parameters alpha and beta parameters are uniformly, randomly set between

180       1 and 4 for each sample.

181    This sample generation process is an attempt to mimic real soils that may consist of one or several

182    soil distributions dependent on the geological history. In Figure 2, 100 exemplary sieve curves are

183    shown to visualize the diversity of PSDs that were generated. The sieve curves are colored

184    according to the sorting coefficient ($S_0$, see eq. 5 in Table 1).

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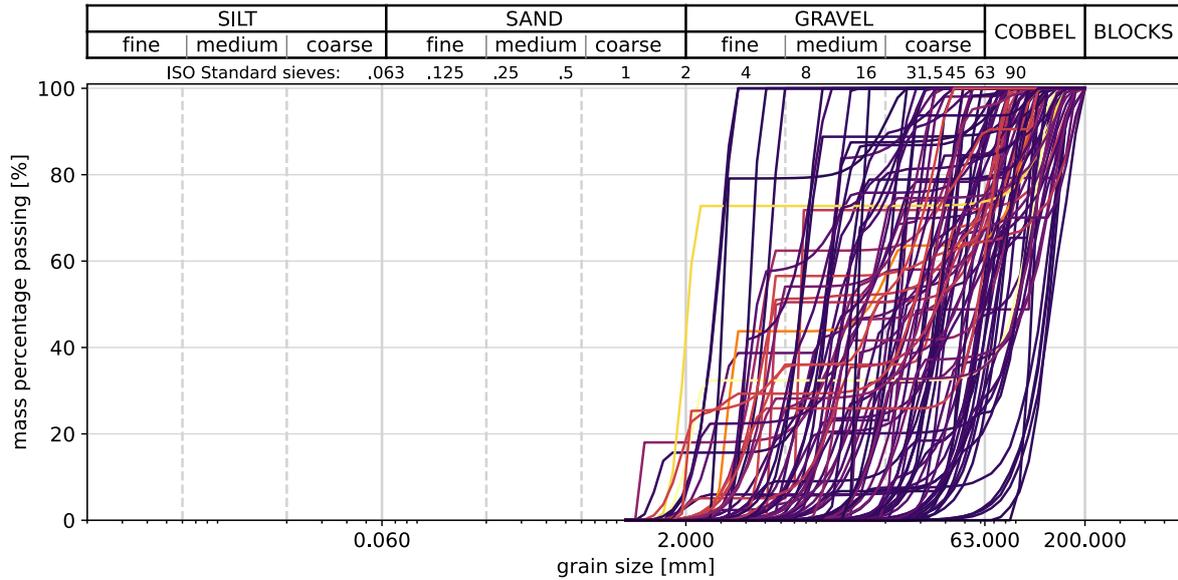
*Figure 2: 100 exemplary sieve curves of samples that were generated for the Monte-Carlo simulation. Sieve curves are colored according to the sorting coefficient ($S_0$): dark purple = 1, yellow = 7.*

To quantify the difference/error between the PSD of the soil and a sample's PSD, the Kolmogorov-Smirnov statistic ($KS$) was chosen. $KS$ denotes the maximum vertical distance between two cumulative density functions which in this case means the maximum mass percentage difference between two sieve curves. Thus, $KS$ – herein – has the unit of mass percent and the minimum and maximum of 0 or 100 would be reached if a sample's sieve curve either has a perfect fit or complete misfit with respect to the soil. For example, let $X = \{100, 95, 70, 20, 10, 5\}$ and $Y = \{100, 90, 50, 15, 7.5, 5\}$ be the mass percent passing sieves of mesh sizes 90-, 63-, 45-, 31.5-, 16- and 8 mm. $KS$ is then computed as $KS = \max(|X - Y|)$ and would be 20% in this example (Figure 3). $KS$ is seen as a well-suited error metric for this task as the goal for the soil sampling is to find a sample mass whose sieve curve fits as well as possible to the sieve curve of the soil.

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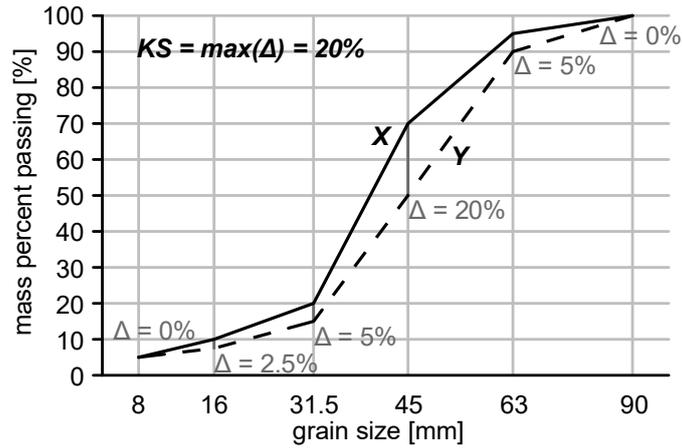
*Figure 3: Example of how the Kolmogorov-Smirnov statistic (KS) quantifies the difference between two sieve curves X (solid) and Y (dashed).*

Figure 4 shows an example where a soil was generated and multiple samples with decreasing masses were taken. The highest sample mass was determined according to eq. 1 (ISO 17892-4) and the subsequent samples are 75%, 50%, 25%, 10%, 5% and 1% fractions of the recommended sample mass. The lowest sample mass results in the highest $KS$ with respect to the soil (i.e. highest error). Note, however, that $KS$ is not consistently increasing with decreasing sample size which will be explained in the next section.



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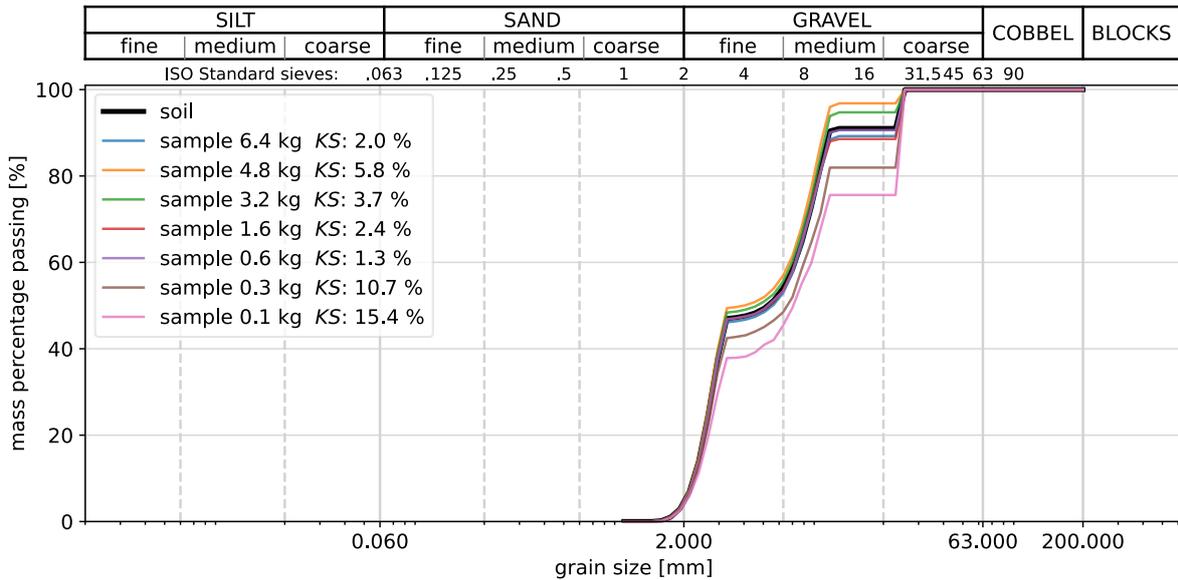
*Figure 4: One example of a generated soil, where multiple samples with decreasing sample masses were taken and the Kolmogorov-Smirnov statistic computed for each of them.*

210     For each simulation, the parameters given in Table 1 were recorded. A multitude of parameters

211     was recorded to facilitate comprehensive Monte-Carlo simulation analyses afterwards.

212     *Table 1: Parameters that are recorded for each simulated sample.*

| Parameter | Description | |
|---|---|---|
| ID | A unique id of the simulation for later identification. | |
| $C_u$ [-] | Coefficient of uniformity $C_u = \dfrac{D_{60}}{D_{10}}$ | eq. 3 |
| $C_c$ [-] | Coefficient of curvature $C_c = \dfrac{D_{30}{}^2}{D_{60} * D_{10}}$ | eq. 4 |
| $S_0$ [-] | Sorting coefficient $S_0 = \sqrt{\dfrac{D_{75}}{D_{25}}}$ | eq. 5 |
| USCS soil classes | Soil classification according to the unified soil classification system (ASTM D 2487 – 06, 2006). | |
| $D_{min}$ [mm] | Minimum grain diameter of soil. | |
| $D_{max}$ [mm] | Maximum grain diameter of soil. | |
| total masses [kg] | Total mass of generated underlying soil. | |
| req. mass ks_p95 <= 10 [kg] | Required mass to achieve a $KS_{p95}$ of ≤ 10% in a "bottom up" approach (see section 3.2). | |
| X.X mm sieve [m%] | Mass percent soil passing a sieve of mesh size X.X mm. Mesh sizes increase logarithmically from 1 to 200 mm in 50 steps. This large number of virtual mesh sizes was chosen to get higher resolution sieve curves than would be possible with standard mesh sizes. | |
| $D_{xx}$ [mm] | Grain diameters at 10, 12, 20, 25, 30, 40, 50, 60, 70, 75, 80 and 90 mass % of the soil from a cumulative density function. | |
| ISO req. mass [kg] | Required sample mass acc. to ISO 17892-4 (2017). | |
| ASTM req. mass [kg] | Required sample mass acc. to ASTM D6913/D6913M (2017). | |
| const req. mass [kg] | Constant sampling mass of 10kg as a reference. | |
| new X.X req. mass [kg] | Required sample mass acc. to eq. 6 with an $\varepsilon$ = X.X. X.X ranges from 1.0 to 2.5 in steps of 0.1 | |
| ISO ks [%] | $KS$ between a sample's sieve curve that was taken acc. to ISO 17892-4 and the underlying soil's sieve curve. | |
| ASTM ks [%] | $KS$ between a sample's sieve curve that was taken acc. to ASTM D6913/D6913M and the underlying soil's sieve curve. | |
| const ks [%] | $KS$ between the sieve curve of a sample with constant mass = 10 kg and the underlying soil's sieve curve. | |
| new X.X ks [%] | $KS$ between a sample's sieve curve that was taken acc. to eq. 6 and the sieve curve of the underlying soil with an $\varepsilon$ = X.X. X.X ranges from 1.0 to 2.5 in steps of 0.1. | |

213 ## 3.2.    Bottom-up determination of required sample mass

214 One of the goals of the simulation was to experimentally determine the required sample mass by

215 generating a soil and then taking samples with progressively increasing masses until a defined $KS$

216 threshold is reached. As individual samples with the same or only slightly differing masses may

217 show a significant variability of $KS$ (see Figure 4) each sampling was repeated 20 times as a trade-

218 off between computational efficiency and representative results. The large fluctuation in repeated

219 sampling with same masses originates from the chance whether or not individual large grains that

220 significantly influence the resulting PSD are being sampled. The $KS$ threshold was set so that the

221 sample mass is seen as sufficient if the p95 percentile (i.e. 95% of values are lower than this) of

222 the $KS$s of the 20 repeated samples is ≤ 10 mass %. In other words, if 19 of the 20 samples achieve

223 a $KS$ ≤ 10 mass %, the sample mass is sufficient. Note that this threshold has no general

224 geotechnical meaning and was only set to have a threshold to experimentally determine a

225 required sample mass to qualitatively investigate the relationship between sample mass,

226 sampling confidence and further parameters such as $D_{max}$ or $D_{90}$.

227 ## 3.3.    Insights from the Monte-Carlo Simulations

228 The Monte-Carlo simulations were used to i) investigate the sampling confidence / error that

229 results from determining $m_{min}$ according to ISO and ASTM and ii) to develop a new approach for

230 $m_{min}$ determination that reduces the required sample mass and explicitly considers the sampling

231 confidence. To this end, 1200 simulations were made and it was observed that the ISO

232 recommendation (eq. 1) achieves a median $KS$ ($KS_{med}$) of 3.5% and a p95 percentile of $KS$ ($KS_{p95}$)

233 of 8.0%. This means that 95% of samples taken according to ISO have a $KS$ < 8.0% to the soil. Due

234 to the higher required sample masses, the ASTM recommendation (eq. 2) achieves lower $KS$ error

235 of a $KS_{med}$ of 2.6% and a $KS_{p95}$ of 5.7%. A violin plot of the ISO- and ASTM- recommended sample

236 masses and the achieved $KS$ errors for all 1200 simulations is given in Figure 5.
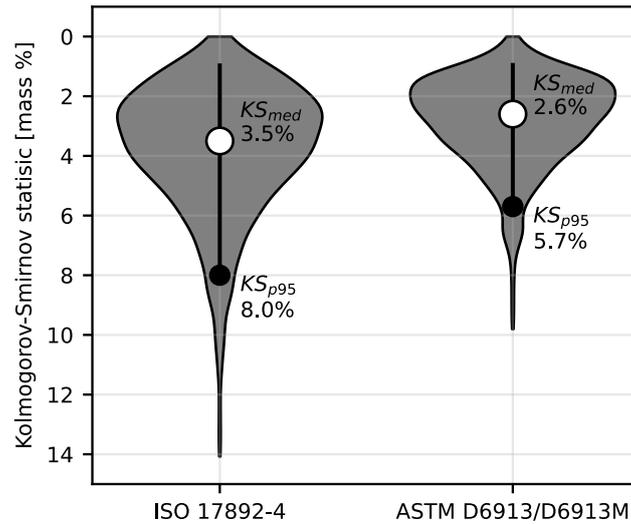
*Figure 5: Violin plots of the Kolmogorov Smirnov error for samples taken according to ISO and ASTM standards.*

The "bottom up" determination of required sample mass (see section 3.2) allows to investigate the relationship between the experimentally determined required sample mass to achieve a certain error and other parameters that describe the samples. This study's original hypothesis was that the required sample mass to achieve a certain error must be dependent on the grading of the soil rather than solely on $D_{max}$. Figure 6 was made to verify if grading can be used to complement the selection of $m_{min}$. The following insights are gathered from this:

- There is a relationship between grading and required sample mass as samples with a high $S_0$ (i.e. well graded) also require larger sample masses. However, the figure also shows that there are samples with a low $S_0$ that require a large sample mass and thus this hypothesis was rejected (high confidence).

- The recommendations from the standards (esp. ISO) do not always overestimate the required sample mass but rather describe the upper limit of the required sample mass. Thus, it can be qualitatively confirmed that there is a relationship between a soil's large grain sizes and the required sample mass to reach a certain sampling confidence (high confidence).

254     ▪   It is observed that there are samples that have a comparably large $D_{max}$ but require

255        sample masses several times smaller than suggested by the standards. It is thus shown

256        that the standards overestimate the required sample mass in several- but not in all cases

257        (high confidence).
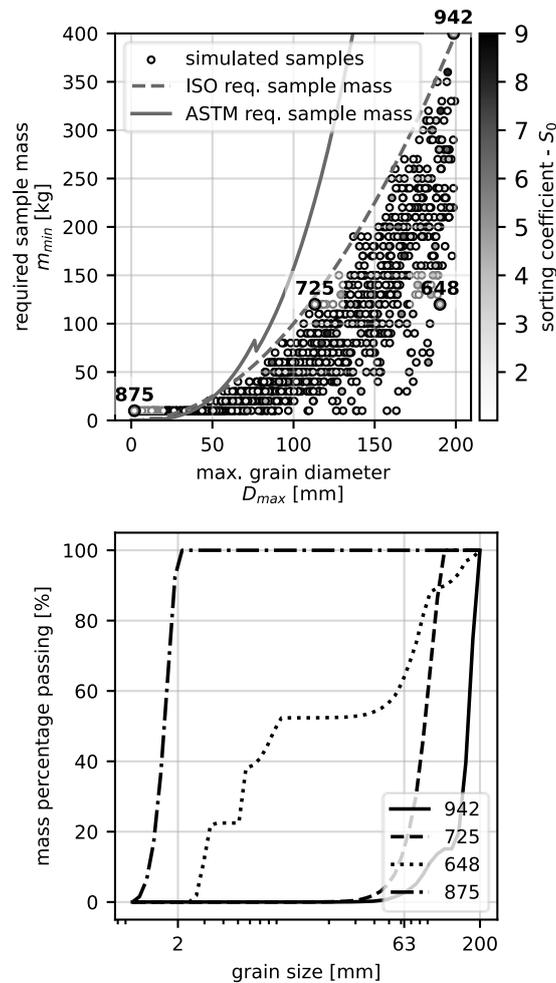


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259 *Figure 6: Top: Relationship between a soil's maximum grain diameter (x-axis) and the required sample mass (y-axis).*
260 *The datapoint color indicates the soil's sorting coefficient ($S_0$). Theoretically, required sample masses acc. to ISO and*
261 *ASTM are also shown for reference. Bottom: Exemplary sieve curves from the top figure, marked with sample "ID" (see*
262 *data in the supplementary information).*

263 Based on these insights, we investigated the correlation between different parameters that

264 describe a sieve curve's geometry and the required sample mass. We used Pearson's correlation

265 coefficient where values of 1 and -1 indicate very strong positive and very strong negative

266 correlations respectively and 0 indicates very weak correlation. The results are shown in Table 2.

267

268    *Table 2: Correlation analyses between parameters that describe a sieve curve's geometry and the required sample*
269    *mass that was determined in the Monte Carlo simulation.*

| Parameter | Correlation with required sample mass |
|:---:|:---:|
| $C_u$ [-] | 0.25 |
| $C_c$ [-] | 0.09 |
| $S_0$ [-] | 0.25 |
| $D_{min}$ [mm] | 0.12 |
| $D_{10}$ [mm] | 0.36 |
| $D_{20}$ [mm] | 0.42 |
| $D_{30}$ [mm] | 0.48 |
| $D_{40}$ [mm] | 0.56 |
| $D_{50}$ [mm] | 0.62 |
| $D_{60}$ [mm] | 0.72 |
| $D_{70}$ [mm] | 0.80 |
| $D_{80}$ [mm] | 0.87 |
| $D_{90}$ [mm] | 0.91 |
| $D_{max}$ [mm] | 0.84 |

270

271    This analysis showed that the currently used parameter to determine the required sample mass -

272    $D_{max}$ – only achieves a correlation of 0.84 with it. A slightly stronger correlation of 0.87 is achieved

273    by $d_{80}$ and the strongest correlation of 0.91 by $D_{90}$ (i.e. the grain size where 90% of a sample's

274    mass has a smaller diameter).

275    Visualizing the simulations as $D_{90}$ vs. required sample mass and coloring the data points

276    according to the maximum grain diameter (Figure 7) shows that soils with a large $D_{90}$ also require

277    large sample masses for representative sampling. The same exemplary PSDs as in Figure 6 are

278    marked in Figure 7. Note for example that samples 648 and 725 have very different $D_{max}$ but

279    similar $D_{90}$. In general, can it be seen that there are several soils with a low $D_{90}$ that still have a

280    large maximum grain diameter, but they do not require large sample masses for representative

281    sampling. We thus conclude with high confidence that the relationship between grain size and

282    required sample mass as implied by the standards is qualitatively correct, but $D_{max}$ is an ill-suited

283    criterium as it represents the rightmost point of a soil's PSD which is often an outlier in coarse-

284    grained soils. Consequently, $D_{max}$ does not represent a soil's significant large grain sizes and is

285    affected by outliers. $D_{90}$ – which is not a PSD's extreme value – on the other hand, is not sensitive

286    to outliers and shows a more robust relationship with the required sample mass.
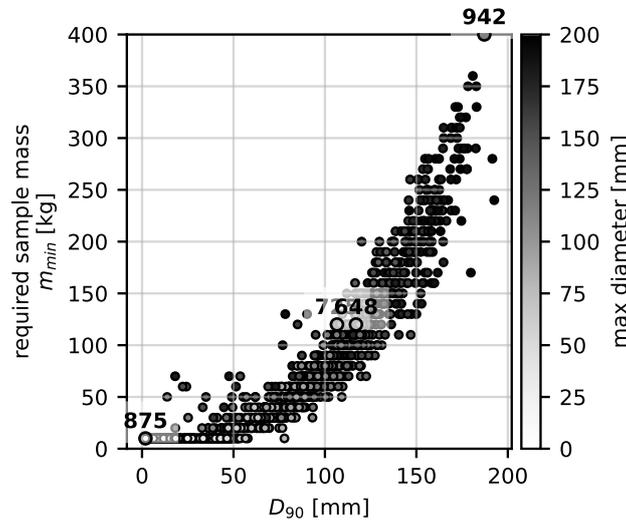


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288    *Figure 7: Relationship between a soil's $D_{90}$ (x-axis), the required sample mass (y-axis) and the maximum grain*
289    *diameter (datapoint color). The same PSDs as shown in Figure 6 (bottom) are marked.*

## 3.4.    Proposed criterium for minimum required mass

291    Based on the insights from the Monte-Carlo simulations, a new criterium to determine $m_{min}$ for

292    coarse-grained soils was developed. The theoretical framework is presented in this chapter and

293    an exemplary application is given in Appendix 1. Based on eq. 1, $D_{max}$ was replaced with $D_{90}$ and

294    a dedicated error-exponent $\varepsilon$ that gives control over the maximum error that one wants to achieve

295    with the taken sample mass was introduced (eq. 6).

$$m_{min} = \left(\frac{D_{90}}{10}\right)^{\varepsilon}$$

*eq. 6*

296    This new criterium was included in the Monte-Carlo simulation to determine the $KS$ errors that

297    are achievable with different $\varepsilon$ by repeated sampling from one soil with different masses (see

298    parameters "new X.X req. mass [kg]" and "new X.X ks [%]" in Table 1). As $KS_{med}$ and $KS_{p95}$ of the

299    current standards were determined in Figure 5 (section 3.3), we determined these errors for

300    different $\varepsilon$ on a range from 1 to incl. 2.5 (Figure 8, top). 2.5 was set as the upper limit as this yields

301    sample masses larger than the ASTM standard. Based on this, the relationships between the

302    achievable $KS_{p95}$ error and $\varepsilon$, respectively $KS_{med}$ error and $\varepsilon$ was assessed and is shown in Figure

303    8, bottom. These relationships can be described with the exponential functions of eq. 7 and eq.

304    8.

$$KS_{p95} = 118.11 * e^{-1.24*\varepsilon}$$

*eq. 7*

$$KS_{med} = 37.38 * e^{-1.09*\varepsilon}$$

*eq. 8*
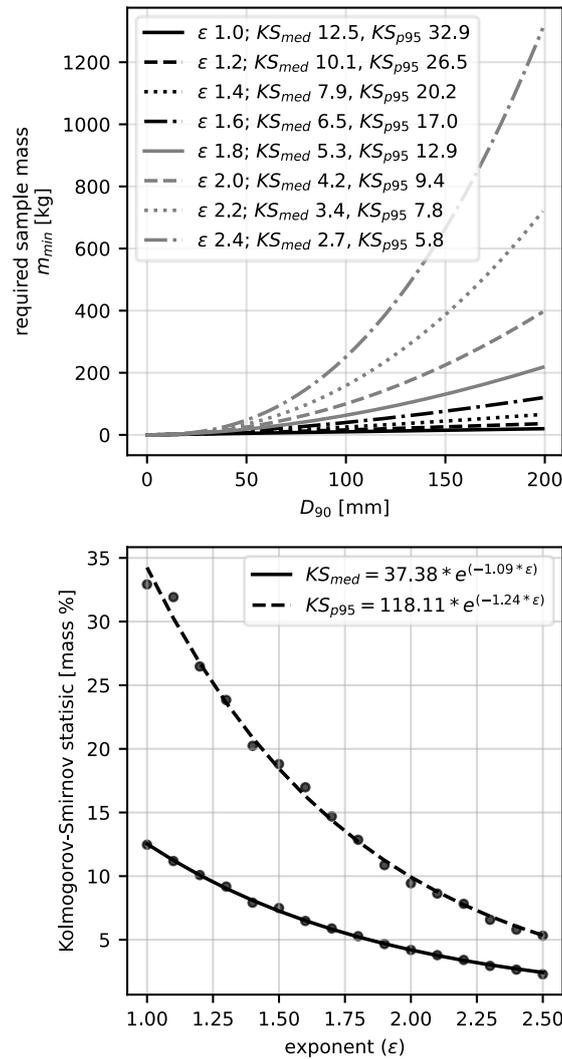


*Figure 8: Top: The new criterium to determine the minimum sample mass ($m_{min}$) with different error exponents ($\varepsilon$).*
*Bottom: The assessed $KS_{p95}$ and $KS_{med}$ vs. different error exponents $\varepsilon$.*

308    Solving eq. 7 for $\varepsilon$ and substituting for $\varepsilon$ in eq. 6, finally gives the new recommended equation to

309    determine $m_{min}$ in a sampling confidence-aware manner in eq. 9.

17

$$m_{\min} = \left(\frac{D_{90}}{10}\right)^{\frac{\ln(KS_{p95}) - \ln(118.11)}{-1.24}}$$

*eq. 9*

310    This equation allows one to determine the minimum required sample mass, given an estimated

311    $D_{90}$ of the soil and a desired sampling confidence in mass percent ($KS_{p95}$). The $m_{\min}$ will in 95%

312    of cases be a sample mass that is sufficient to satisfy the desired error threshold.

313    A decisive question that comes up in this context is how reliably an operator can come up with a

314    field estimate of a sample's $D_{90}$ vs. a field determination of a sample's $D_{max}$ as it is required in

315    today's standards. First, one must acknowledge that both parameters can only be estimated as

316    the full soil body under investigation is never observable. Secondly, a dedicated survey that

317    investigates whether operators achieve a higher performance in estimating one parameter over

318    the other showed that there is no significant reason to believe that. The capability to estimate

319    parameters is equally well / poor for all $D$-values. Gap graded soils may be the only exception here,

320    where it can be seen that the $D$-value closest to the gap has a significant variation but the

321    characterization of gap-graded soils constitutes a research problem on its own and cannot be

322    addressed herein.  The full survey results can be found in Appendix 2. We recommend estimating

323    $D_{90}$ in the field as *the maximum relevant grain size of the soil excluding obvious large outliers*.

324    Defining desirable PSD errors for different geotechnical applications is not in the scope of this

325    study and should be investigated with dedicated research (see discussion). As fine-grained soils

326    were not considered in the simulation and sands and fine-gravels only represent the lower

327    boundary of the Monte-Carlo simulation, the same criteria as specified in the ISO standard should

328    be applied for soils with a $D_{max}$ ≤ 20 mm. Furthermore, in cases where the estimated $D_{max}$ > 20

329    mm but the estimated $D_{90}$ < 10 mm, 1 kg of sample mass should be used. Otherwise, eq. 9 is to

330    be used.

331 ## 3.5.      Comparison to standards and further usage

332   Figure 5 shows that ISO and ASTM achieve $KS_{p95}$ of 8.0% and 5.7 % respectively. Using these

333   values in eq. 9 allows to directly compare the required sample masses from the new criterium to

334   the previous standards (Figure 9). On average, across all simulated samples, the new criterium

335   requires ca. 4 times lower sample masses than the ISO standard and ca. 9 times lower sample

336   masses than the ASTM to achieve similar sampling confidences. In extreme cases, however, the

337   required sample masses according to the new criterium are several thousand times lower than

338   the ISO or ASTM standards while reaching the same sampling confidence.

339   In Figure 9 top, it can be seen that for the majority of samples the new criterium to determine $m_{\mathrm{min}}$

340   yields a larger sample masses than the ISO standard. While this is only a theoretical result, it

341   indicates that the ISO standard is unconservative and inconsistent when it comes to

342   recommending required sample masses for very coarse-grained soils that contain a significant

343   amount of large grains (low confidence). Nevertheless, in both cases of ISO and ASTM, it can be

344   seen that there are samples that are far below the 1:1 line in Figure 9 thus suggesting with high

345   confidence that the newly proposed criterium is more precise for sample mass determination and

346   not sensitive to outliers.

347
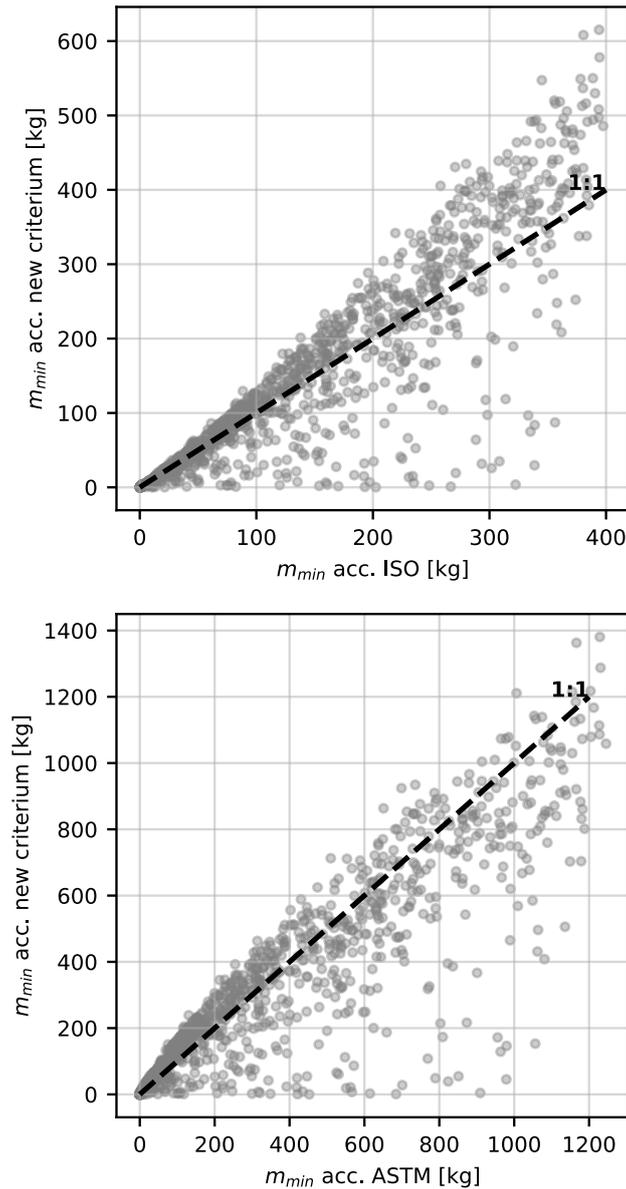
*Figure 9: Comparison between sample masses acc. to ISO (top) and ASTM (bottom) to the new criterium at equal confidence levels. Dashed lines indicate lines of 1:1 equal mass in the plots. Datapoints are 50% transparent.*

Lastly it must be acknowledged that there are cases where the available sample mass is smaller than the desired / required sample mass and acquiring more sample is unviable. Today, operators either avoid sampling all together in these cases or must do sampling outside the standards' framework. Thus they are not aware of the error that they may or may not introduce through this undersampling. We recommend also taking samples to determine a PSD in these cases, but the operator should be aware of the expectable error that the sampling is subjected to. In this case

356    $m_{min}$ in eq. 6 can be substituted with the available sample mass ($m_{available}$) and then the

357    equation solved for $\varepsilon$, thus giving eq. 10.

$$\varepsilon = \frac{ln(m_{available})}{\ln(D_{90}) - \ln(10)}$$

<div align="right">eq. 10</div>

358    By using the determined $\varepsilon$ in eq. 7 and eq. 8 or Figure 8 bottom, one can find which $KS_{med}$ and

359    $KS_{p95}$ is to be expected given the available sample mass. The consequence of knowing the error

360    that must be expected given the available sample mass is that the subsequent geotechnical

361    analysis can consider this uncertainty by setting a higher focus on probabilistic analyses,

362    adjusting how conservative approaches are or considering different plausible scenarios.

# 4. Experimental underpinning

## 4.1.    Experimental program and tested soils

365    Several sieve analyses were performed in the laboratory to practically test the hypotheses

366    presented in the previous chapter. The goal of the sieve analyses was to investigate if it is also

367    practically the case that significantly lower sample masses than recommended by the standards

368    yield sufficient PSDs. Three different soils were used, namely a (A) medium to fine sand, (B) a

369    medium to fine gravel and (C) a sandy, medium to coarse gravel. Different test programs were

370    conducted for each soil:

371    ▪  Soil A: A medium to fine sand from the Isle of Rum in Scotland (United Kingdom) was used

372        to investigate how far one can go with reducing the ISO recommended sample mass even

373        below the considered size of the Monte-Carlo analyses. With an estimated $D_{max}$ of 4 mm,

374        an ISO 17892-4 recommended (dry) sample mass of 200 g was taken from one large

375        sample. Further samples with 100 g, 75 g, 50 g, and 5 g were also taken and PSDs

376        determined for all of them.

377     ▪   Soil B: A medium to fine fluviatile gravel was collected from the river Akerselva in Nydalen,

378       Oslo (Norway). The $D_{max}$ is estimated to be 30 mm, thus the ISO required sample mass is

379       9 kg of soil (eq. 1) which was used for one sieve test. The estimated $D_{90}$, however, is around

380       8 mm and thus < 10 mm. Therefore, the new recommendation of 1 kg sample mass was

381       tested (see end of section 3.4). To also include an extreme case, one more sieve analysis

382       with 300 g of sample was done.

383     ▪   Soil C: An artificial, pre-sieved, sandy, medium to coarse gravel from Austria with a known

384       $D_{max}$ of 70 mm was used for soil C. One sieve test with a sample mass of 50 kg according

385       to ISO was done and one with a 2.5 times lower sample mass of 20 kg.

## 4.2.     Experimental results

387 Table 3 gives an overview of the experimental results and Figure 10 shows the sieve curves for the

388 different soils.

389 *Table 3: Overview of the experimental results.*

| Test | Sample mass [g] | $D_{10}$ [mm] | $D_{30}$ [mm] | $D_{60}$ [mm] | $C_c$ | $C_u$ | $KS$ to ISO [mass %] |
|---|---|---|---|---|---|---|---|
| Soil A (ISO) | 200 | 0.081 | 0.148 | 0.236 | 2.90 | 1.14 | - |
| Soil A1 | 100 | 0.085 | 0.145 | 0.227 | 2.66 | 1.08 | 3.32 |
| Soil A2 | 75 | 0.090 | 0.158 | 0.242 | 2.69 | 1.14 | 3.97 |
| Soil A3 | 50 | 0.082 | 0.140 | 0.227 | 2.74 | 1.05 | 3.18 |
| Soil A4 | 5 | 0.079 | 0.137 | 0.230 | 2.91 | 1.03 | 3.88 |
| Soil B (ISO) | 9000 | 0.599 | 1.557 | 3.615 | 1.12 | 6.04 | - |
| Soil B1 | 1000 | 0.608 | 1.536 | 3.527 | 1.10 | 5.80 | 1.34 |
| Soil B2 | 300 | 0.553 | 1.245 | 2.782 | 1.08 | 5.03 | 12.34 |
| Soil C (ISO) | 50000 | 0.369 | 3.694 | 14.167 | 2.610 | 38.387 | - |
| Soil C1 | 20000 | 0.563 | 5.152 | 18.451 | 2.557 | 32.802 | 7.8 |

390
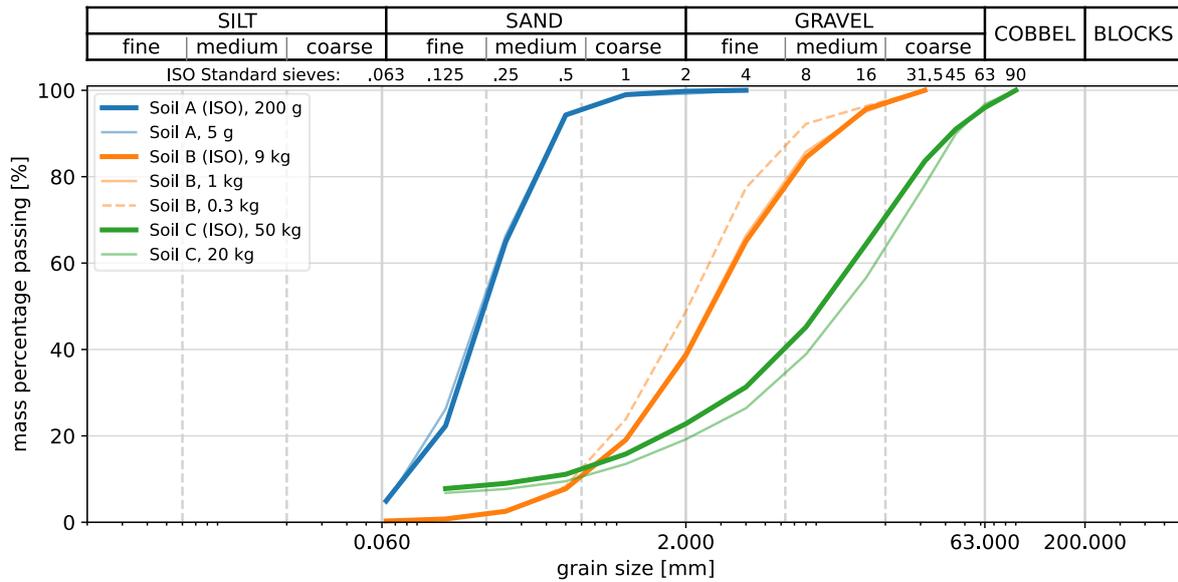
*Figure 10: Sieve curves of the conducted lab tests to investigate how different sample masses influence practical results. For each soil, the sieve curve with a sample mass acc. to ISO 17892-4 and the sieve curve based on the smallest sample mass is shown.*

For all soils, no remarkable discrepancy can be observed between the PSDs obtained using different amounts of sample mass. While this study aims at coarse-grained soils with the main grain size being gravel or larger, soil A demonstrates that lower sample masses can also give sufficient results for sands. In soil A, even a 40 times lower sample mass than what would be required by ISO 17892-4 only yields a $KS$ of 3.88%. For Soil B, a mass 9 times lower than the suggested by ISO (i.e. the mass as recommended herein) shows a $KS$ of 1.34% only. A test with a 30 times lower sample mass (300 g) was also conducted on Soil B and results in a $KS$ of 12.34% with respect to the ISO recommended of 9000 g. This more substantial deviation results from a low sample mass which is also not recommended, and the test was done for demonstration purposes only to show what happens in substantially lower sample masses in coarse-grained soils. In case of Soil C, the error between the PSD resulting from the ISO recommended sample mass of 50 kg and a test with a 2.5 times lower sample mass yielded a $KS$ of 7.8%. While the effort of doing a sieve test with 20 kg instead of 50 kg of sample mass is significantly lower, the resulting difference in the PSD is small and still leads to the same characterization of the soil as a sandy, medium to coarse gravel.

410    Table 3 shows that also the differences between the parameters that describe the sieve curves'

411    geometry are small and Figure 11 visualizes the difference in $C_c$ and $C_u$ between tests with a

412    sample mass according to ISO and tests with a lower sample mass. In all cases, the values

413    become slightly lower with decreasing sample masses. Nevertheless, the total differences are

414    small and would not change a soil's classification based on $C_c$ and $C_u$.
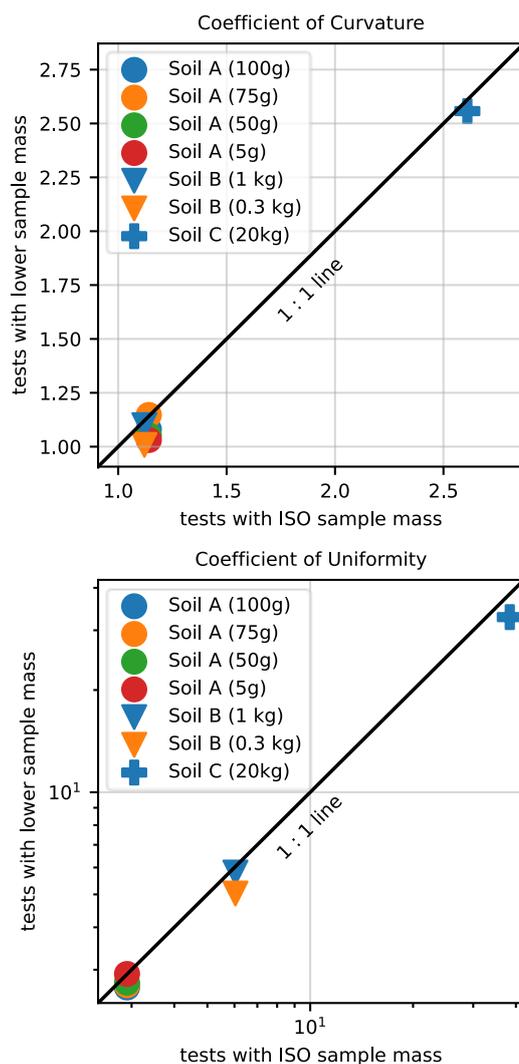


415

416    *Figure 11: $C_c$ and $C_u$ differences for tests with a sample mass acc. to ISO and tests with a lower sample mass.*

417

## 418  5. Discussion

419   The proposed new method for $m_{min}$ determination leads to more precise recommendations for

420   the required sample masses for coarse-grained soils including a significant reduction of the

421   required sample mass for few cases. It is easily applicable in practice and also permits to take

422   samples under explicit consideration of the sampling confidence. The practicality, outlier

423   awareness, explicit accounting for sampling confidence and consideration of a wide range of soil

424   types are improvements over previously proposed methods for sample mass determination (Gale

425   and Hoare, 1992; Jia et al., 2024; Zhang et al., 2017).

426   The proposed new methodology is based on simulations of laboratory sieve tests, but practical

427   laboratory sieve tests on real soils corroborate the theoretical results thus new recommendations

428   and conclusions are made with very high confidence. Nevertheless, the simulation includes some

429   simplifying assumptions such as perfectly spherical grains which might influence the result,

430   especially for very coarse grain sizes that seldomly are perfectly spherical. Studies such as

431   Kaviani-Hamedani et al. (2024) address this issue, but in large scale simulation of sieve tests,

432   explicitly including non-spherical grains heavily impacts the computational performance and

433   thus renders large scale Monte-Carlo simulations infeasible, today.

434   The simulation of individual and discrete grains and the subsequent explicit sampling from these

435   grains is on the one hand seen as a benefit of this study as it is the most realistic way of simulating

436   sieve tests, on the other hand it is computationally very demanding as especially memory limits

437   are reached fast the smaller the grain sizes become. Besides the main goal to investigate coarse

438   grain sizes, the lower grain size boundary of 1 mm in this study is related to computational

439   limitations of this approach. To conduct simulated PSD analyses starting from clay sizes, would

440   require a different simulation concept, that is rather based on statistical distributions than on

441   individual grains.

## 6. Conclusions and Outlook

442

443  A new method to determine the minimum required sample mass for PSD assessments was

444  proposed. The new method explicitly considers sampling confidence, which is an improvement

445  on the one hand but on the other opens up for a plethora of new research questions related to

446  "How much is enough for application X?". As given in the introduction, PSDs are not only

447  fundamental for general purpose soil characterization but also feed directly into different

448  geotechnical engineering applications. These may, however, tolerate different sampling errors

449  depending on the downstream usage of a PSD and derived parameters such as $D_{10}$, $D_{60}$, $C_u$, $C_c$,

450  etc. Speculating about required confidences of soil sampling for different geotechnical

451  applications is out of the scope of this study and future research related to this topic is highly

452  encouraged to provide a sound decision base for sampling confidences.

453  The conducted survey to investigate how reliable parameters like $D_{max}$ and $D_{90}$ can be estimated

454  by operators in the field showed that there is no significant difference for visual assessments

455  (medium confidence). More surveys like this and similar ones (Elmo and Stead, 2021; Skretting et

456  al., 2023) are required to get a quantitative understanding of the cognitive biases and human

457  uncertainty that is involved in engineering geological and geotechnical observations. Further

458  surveys like this are encouraged where the survey scope could be extended by the use of real soil

459  samples instead of generic visualizations. However, in the case of PSD determination of coarse-

460  grained soils the use of image processing technology for PSD-pre-assessment (Ferrer et al., 2021)

461  could be considered. Nevertheless, due to the required level of technological proficiency and

462  eventually also soft- and hardware cost, it is not expected that image processing techniques will

463  replace estimations of PSDs in practice in the near future and approaches like the one proposed

464  herein will remain relevant.

465 ## Supplementary information

466 The code for the Monte-Carlo Simulations and the results of the real laboratory tests can be found

467 in the following Github repository: https://github.com/norwegian-geotechnical-

468 institute/sieve_analyses/releases/tag/v2.0.0

469 # 7. References

470 Al-Rumaithi, A., Al-Sherrawi, M., 2020. Gravel Sampling for Testing. IOP Conf. Ser.: Mater. Sci. Eng.

471  739 1, 12034.

472 Andersen, K.H., 2015. Cyclic soil parameters for offshore foundation design. Frontiers in offshore

473  geotechnics III 5, 5–82.

474 Andersen, K.H., Schjetne, K., 2013. Database of Friction Angles of Sand and Consolidation

475  Characteristics of Sand, Silt, and Clay. J. Geotech. Geoenviron. Eng. 139 7, 1140–1155.

476 Dubé, J.-S., Ternisien, J., Boudreault, J.-P., Duhaime, F., Éthier, Y., 2021. Variability in Particle Size

477  Distribution Due to Sampling. Geotechnical Testing Journal 44 1, 148–173.

478 Elmo, D., Stead, D., 2021. The Role of Behavioural Factors and Cognitive Biases in Rock

479  Engineering. Rock Mech Rock Eng 54 5, 2109–2128.

480 Erharter, G.H., Lacasse, S., Tschuchnigg, F., Tentschert, E., Becker, D., Phoon, K.-K., 2024. A

481  consistent terminology to communicate ground-related uncertainty. Engineering Geology

482  342, 107744.

483 Ferrer, B., Nostas, C., Mas, D., 2021. Evaluation of a Simple and Affordable Image-Based

484  Procedure to Measure Particle Size Distribution. Geotech. Test. J. 44 3, 20190457.

485 Gale, S.J., Hoare, P.G., 1992. Bulk sampling of coarse clastic sediments for particle-size analysis.

486  Earth Surf Processes Landf 17 7, 729–733.

487 NS-EN ISO 17892-4:2016, 2017. Standard Norge. Geotechnical investigation and testing

488  Laboratory testing of soil: Part 4: Determination of particle size distribution 13.080.20; 93.020.

489    EN ISO 14688-1, 2019. Österreichisches Normungsinstitut. Geotechnische Erkundung und

490        Untersuchung - Benennung, Beschreibung und Klassifizierung von Boden: Teil 1: Benennung

491        und Beschreibung 13.080.05;93.020.

492    Gerlach, R.W., Dobb, D.E., Raab, G.A., Nocerino, J.M., 2002. Gy sampling theory in environmental

493        studies. 1. Assessing soil splitting protocols. Journal of Chemometrics 16 7, 321–328.

494    Gerlach, R.W., Nocerino, J.M., Ramsey, C.A., Venner, B.C., 2003. Gy sampling theory in

495        environmental studies. Analytica Chimica Acta 490 1-2, 159–168.

496    Gy, P., 2012. Sampling of Particulate Materials Theory and Practice, 1st Edition ed. Developments

497        in Geomathematics 4. Elsevier.

498    Jia, J., Tang, W., Zhu, Y., Zong, Y., Chen, Q., Cai, T., 2024. Grain size of gravel: recent progress on

499        sampling, analysis and calculation. Geo-Mar Lett 44 4.

500    Kaviani-Hamedani, F., Esmailzade, M., Adineh, K., Shafiei, M., Shirkavand, D., 2024. Quantifying

501        three-dimensional sphericity indices of irregular fine particles from 2D images through

502        sequential sieving tests. Granular Matter 26 1.

503    Liu, H., Nagula, S., Petter Jostad, H., Piciullo, L., Nadim, F., 2024. Considerations for using critical

504        state soil mechanics based constitutive models for capturing static liquefaction failure of

505        tailings dams. Computers and Geotechnics 167, 106089.

506    O'Toole, M.T. (Ed.), 2015. Mosby's medical dictionary. Elsevier/Mosby, St. Louis, (Missouri), 1

507        online resource.

508    Pitard, F.F. (Ed.), 2019. Theory of sampling and sampling practice, Third edition ed. CRC Press

509        Taylor & Francis Group, Boca Raton, London, New York, 693 pp.

510    ASTM E141-10, 2023. ASTM international. Practice for Acceptance of Evidence Based on the

511        Results of Probability Sampling, West Conshohocken, PA.

512    ASTM E122-17, 2022. ASTM international. Practice for Calculating Sample Size to Estimate, With

513        Specified Precision, the Average for a Characteristic of a Lot or Process, West Conshohocken,

514        PA.

515    ASTM E105-21, 2021. ASTM international. Practice for Probability Sampling of Materials, West

516        Conshohocken, PA.

517    ASTM D3665-24, 2024. ASTM international. Practice for Random Sampling of Construction

518        Materials, West Conshohocken, PA.

519    Quinteros, V.S., Mikesell, T.D., Griffiths, L., Jerves, A.X., 2024. Geotechnical laboratory testing of

520        lunar simulants and the importance of standardization. Icarus 408, 115812.

521    Rawle, A.F., 2015. Representative Sampling – Another Cinderella of Particle Size Analysis.

522        Procedia Engineering 102, 1707–1713.

523    Skretting, E., Erharter, G.H., Chiu, J.K.Y., 2023. Virtual reality based uncertainty assessment of

524        rock mass characterization of tunnel faces, in: Proceedings of the 15th ISRM Congress 2023

525        & 72nd Geomechanics Colloquium. CHALLENGES IN ROCK MECHANICS AND ROCK

526        ENGINEERING. 15th ISRM Congress 2023 & 72nd Geomechanics Colloquium, Salzburg /

527        Austria. 9.-14. October 203.

528    ASTM D 2487 – 06, 2006. ASTM international. Standard Practice for Classification of Soils for

529        Engineering Purposes (Unified Soil Classification System), West Conshohocken, PA.

530    ASTM C702/C702M-18, 2018. ASTM international. Standard Practice for Reducing Samples of

531        Aggregate to Testing Size., West Conshohocken, PA.

532    ASTM D75/D75M-19, 2019. ASTM international. Standard Practice for Sampling Aggregates, West

533        Conshohocken, PA.

534    ASTM C136/C136M-19, 2020. ASTM international. Standard Test Method for Sieve Analysis of Fine

535        and Coarse Aggregates, West Conshohocken, PA.

536    ASTM E1382-97, 2023. ASTM international. Standard Test Methods for Determining Average Grain

537        Size Using Semiautomatic and Automatic Image Analysis, West Conshohocken, PA.

538    ASTM D6913/D6913M-17, 2017. ASTM international. Test Methods for Particle-Size Distribution

539        (Gradation) of Soils Using Sieve Analysis, West Conshohocken, PA.

540    Zhang, S., Li, X., Teng, J., Ma, X., Sheng, D., 2017. A theoretical method for determining sample

541        mass in a sieving test. Computers and Geotechnics 91, 12–16.

542

# Appendix

## Appendix 1 – Application example

For example, one wants to determine the PSD of a coarse-grained fluviatile soil with an estimated $D_{max}$ of 150 mm (there are some cobbles) and an estimated $D_{90}$ of 80 mm. According to eq. 1 from ISO 17892-4 the required $m_{min}$ is 225 kg of soil (eq. 11) and it is not clear why so much soil would be required. In contrast to that, the new eq. 9 allows setting a desired maximum error / sampling confidence ($KS_{p95}$) of e.g. 10 %. Based on the estimated $D_{90}$ one can then estimate the required sample mass to be ~63 kg with explicit consideration of that desired sampling confidence (eq. 12). If the total available soil sample mass would, however, only be 20 kg, then eq. 10 can be used to determine the error exponent $\varepsilon$ (eq. 13) which is 1.44. Substituting this into eq. 7 reveals that in this particular soil, one needs to expect that the determined PSD has an error of up to ~20% with respect to the real soil's PSD if only 20 kg of soil sample are available (eq. 14).

$$m_{min}[kg] = 225 = \left(\frac{150}{10}\right)^2 \qquad\qquad eq.\ 11$$

$$m_{\min}[kg] = 63 = \left(\frac{80}{10}\right)^{\frac{\ln(10)-\ln(118.11)}{-1.24}} \qquad\qquad eq.\ 12$$

$$\varepsilon = 1.44 = \frac{\ln(20)}{\ln(80) - \ln(10)} \qquad\qquad eq.\ 13$$

$$KS_{p95}[m\%] = 19.8 = 118.11 * e^{-1.24*1.44} \qquad\qquad eq.\ 14$$

555

## Appendix 2 - Grain size distribution characterization survey

A survey was conducted to investigate how well operators can visually estimate different parameters that describe the geometry of a sieve curve. The survey was done using Microsoft Forms and responses that were submitted between the start of the survey on 25th of November 2024 until its end on the 9th of December 2024 were included in this analysis.

The following metadata was collected from each participant:

- Name

- Email Address

- Main area of expertise, where participants could choose one of the following answers: Geotechnical engineering, Engineering Geology, Sedimentology, Hydrogeology, Quaternary geology, other (to be specified).

- Current main field of work, where participants could choose one of the following answers: Academia, Industry (consulting, contractors, technology development,…), Other

- Years of experience post master, where participants could choose one of the following answers: 0-5, 5-10, 10-20, 20-30, >30, None (still student or not from this field).

After collecting this information, the participants were presented with a series of four synthetic sediment samples that were generated with the code framework of this project that is provided in the Supplementary information of the paper. Each sample shows spherical black grains in a 500 by 500 mm large field on white ground. A measuring scale is given on the border of the field with 50 mm spaced ticks and some reference grains are given below the sample with sizes between Ø=100 to Ø=2mm. The samples are shown in Figure A 1 to Figure A 4.
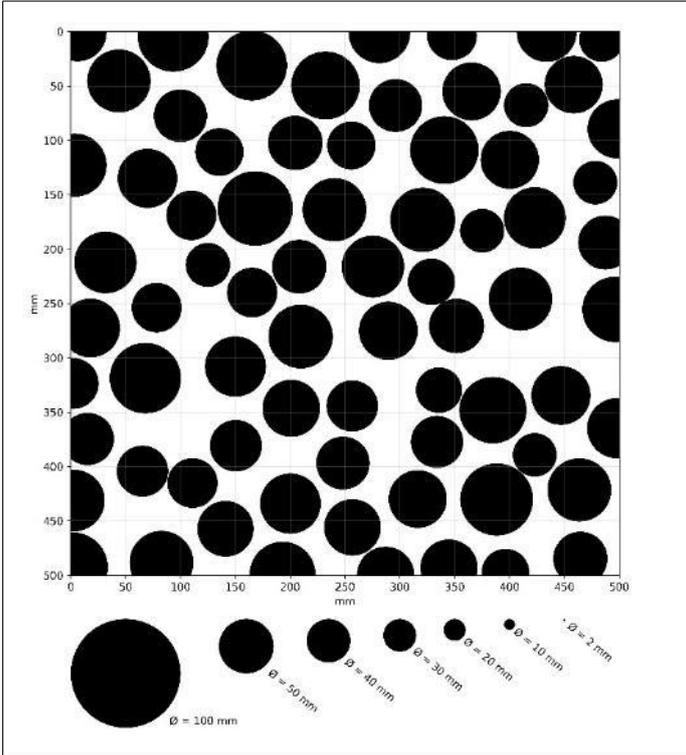
577

578                                  *Figure A 1: Sample 1.*
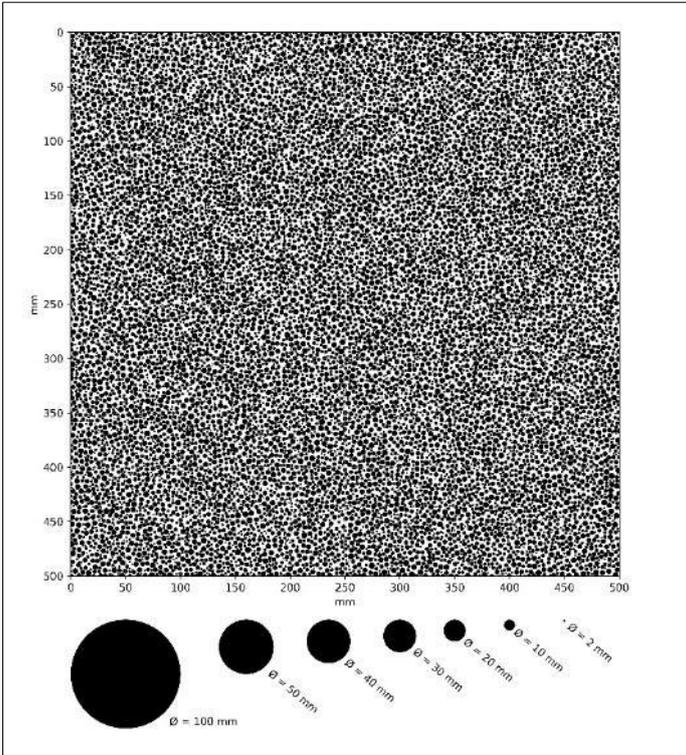


579

580                                  *Figure A 2: Sample 2.*
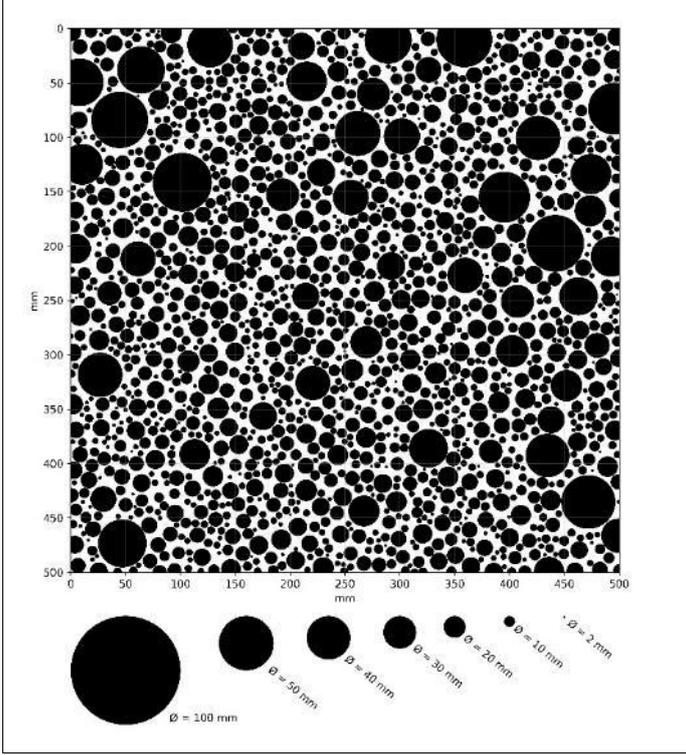
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582

*Figure A 3: Sample 3.*
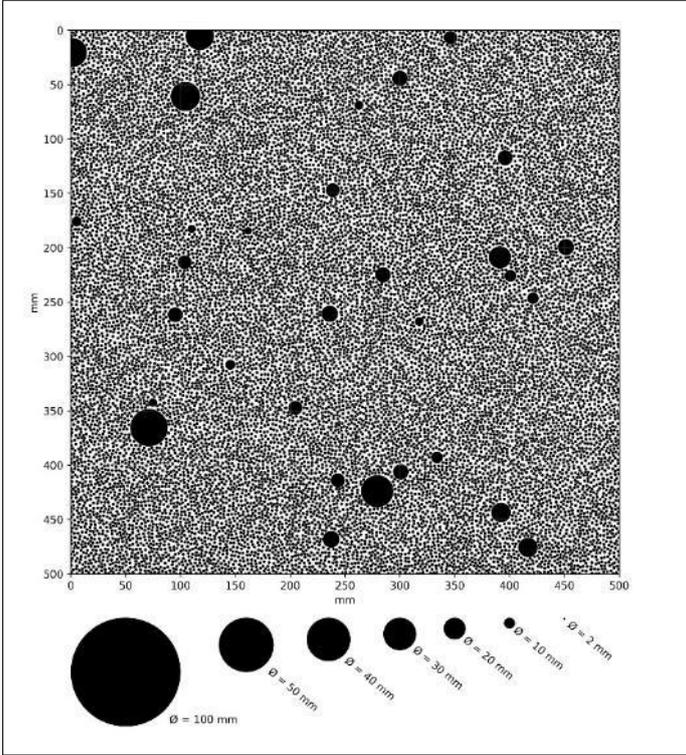
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584

*Figure A 4: Sample 4.*

585   For each sample, the participants were asked to estimate the $D_{min}$, $D_{10}$, $D_{30}$, $D_{50}$, $D_{60}$, $D_{90}$ and

586   $D_{max}$. The participants were told not to be too precise and to take not more than 3 minutes per

587   sample. A total number of 95 responses were collected. From these 95 responses, 14 had to be

588   completely removed because the participants gave consistently not credible responses that

589   indicated a misunderstanding of the survey (e.g. always the same number, decreasing grain sizes

590   from $D_{min}$ to $D_{max}$, etc.). Furthermore, single results for samples had to be removed for similar

591   reasons but it can be observed that there are more erroneous submissions for sample 1 than for

592   the others, thus indicating that some participants needed the first sample to get used to the task.

593   After response cleaning, a total of 71, 81, 80 and 80 responses were left for the samples 1-4

594   respectively. A visualization of the collected participant metainformation is shown in Figure A 5.

## Main area of expertise



## Main field of work



## Years of experience post master



595
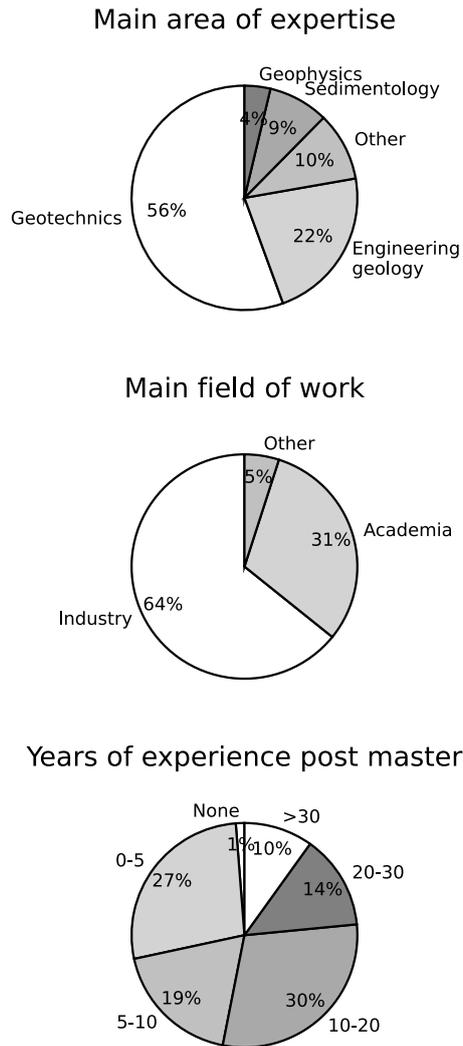
*Figure A 5: Statistics of the metainformation that was collected from the participants in the survey.*

597 A visualization of the participants' responses in relation to the true values (assessed based on the

598 simulated grain distribution) for every sample is given in figure Figure A 6. While the average

599 estimated parameters are close to the true values, it can be seen that all parameters show

600 substantial variability. There are no generally observable trends, and it is not observable that the

601 $D_{max}$ is, for example, significantly easier to assess than other $D$-values. The only exception is

602 sample 4 which has a pronounced gap graded distribution, and it is visible that participants

603 alternate between assigning the $D_{90}$ to the small or the large grain sizes. Analyzing these results

604 also must consider the logarithmic scale of the problem where e.g. overestimating the size of a 4

605 mm grain by 100% is less severe than overestimating the size of a 40 mm grain by 50%.
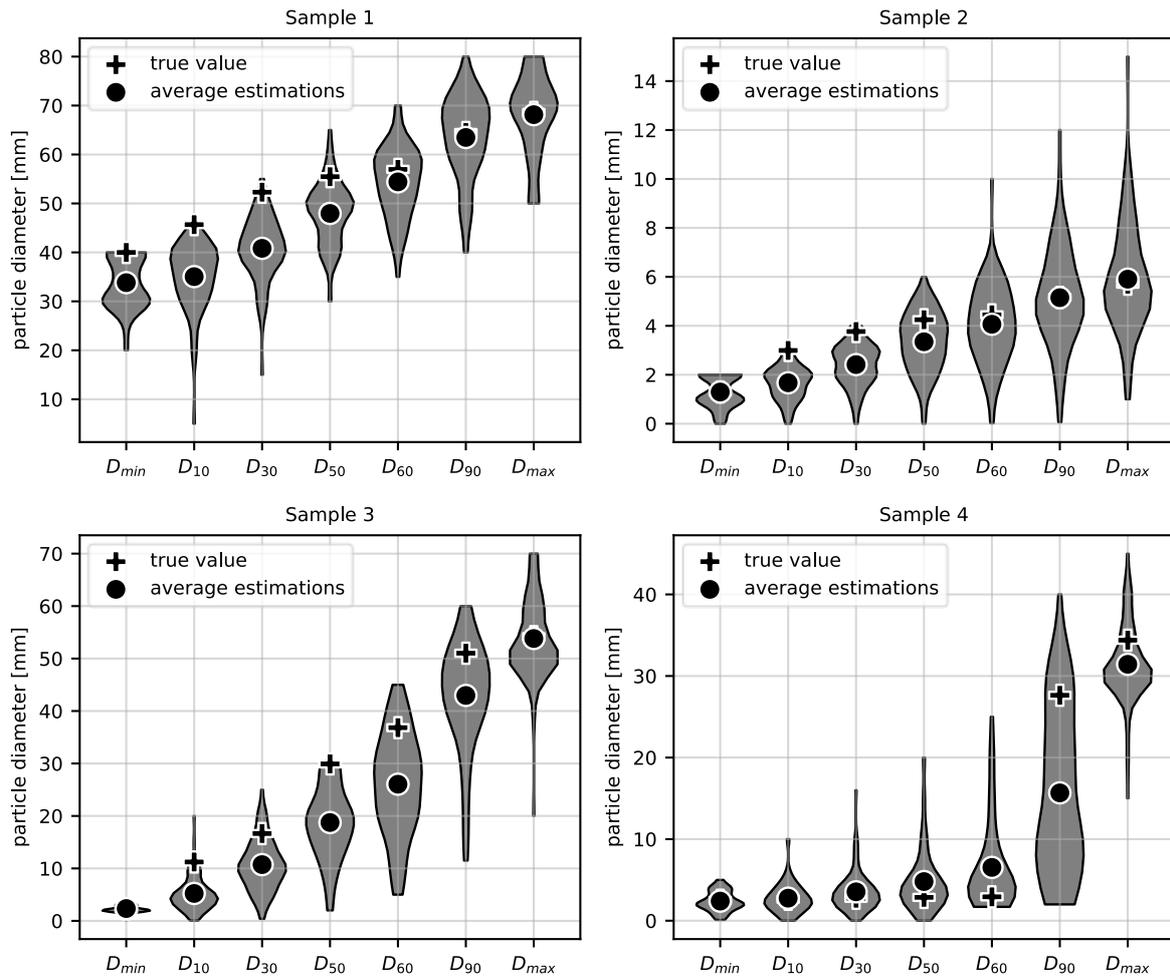
*Figure A 6: Results of the survey. The distribution and bandwidth of participants' responses is shown with grey violin plots.*

Lastly, the participant assessed values were used to compute $C_u$ and $C_c$ for the samples and their respective distribution based on the participants feedback variability (Figure A 7). It can be seen that the variability for these computed values is substantial but it also must be considered that these are calculated values and not directly estimated values. The ground truth values for the parameters under investigation of the survey are given in Table A 1.
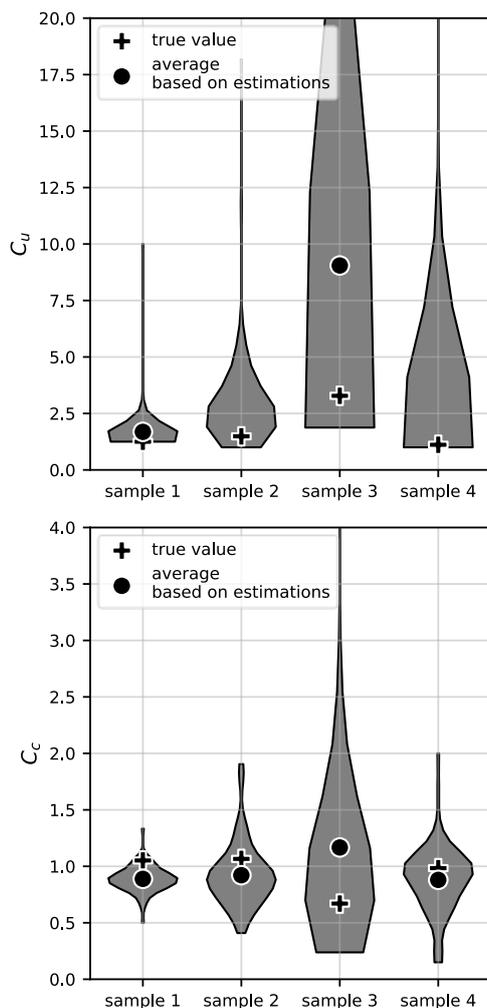
*Figure A 7: Variability of $C_u$ and $C_c$ computed from the participants responses.*

*Table A 1: Ground truth values for the parameters of the survey.*

| Sample | $D_{min}$ [mm] | $D_{10}$ [mm] | $D_{30}$ [mm] | $D_{50}$ [mm] | $D_{60}$ [mm] | $D_{90}$ [mm] | $D_{max}$ [mm] | $C_u$ | $C_c$ |
|--------|------|------|------|------|------|------|------|------|------|
| 1 | 40.0 | 45.7 | 52.3 | 55.5 | 57.0 | 64.5 | 68.6 | 1.2 | 1.1 |
| 2 | 1.3 | 3.0 | 3.8 | 4.2 | 4.4 | 5.2 | 5.7 | 1.5 | 1.1 |
| 3 | 2.3 | 11.2 | 16.6 | 29.9 | 36.8 | 51.0 | 54.2 | 3.3 | 0.7 |
| 4 | 2.5 | 2.6 | 2.8 | 2.9 | 2.9 | 27.6 | 34.4 | 1.1 | 1.0 |