

1 Convex Hull Approach for Determining Rock Representative Elementary Volume for
2 Multiple Petrophysical Parameters using Pore-scale Imaging and Lattice-Boltzmann
3 modelling.

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11 **Highlights**

- 12 • Qualitative and quantitative method to capture heterogeneity at pore-scale
 - 13 • Multiple petrophysical parameters to determine Representative Element Volume
 - 14 • Enhancing computational efficiency to calculate petrophysical properties
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28 **Abstract**

29 In the last decade, the study of fluid flow in porous media has developed considerably due to
30 the combination of X-ray Micro Computed Tomography (micro-CT) and advances in
31 computational methods for solving complex fluid flow equations directly or indirectly on
32 reconstructed three-dimensional pore space images. In this study, we calculate porosity and
33 single phase permeability using micro-CT imaging and Lattice Boltzmann (LB) simulations
34 for 8 different porous media: beadpacks (with bead sizes 50 μm and 350 μm), sandpacks
35 (LV60 and HST95), sandstones (Berea, Clashach and Doddington) and a carbonate (Ketton).
36 Combining the observed porosity and calculated single phase permeability, we shed new light
37 on the existence and size of the Representative Element of Volume (REV) capturing the
38 different scales of heterogeneity from the pore-scale imaging. Our study applies the concept
39 of the ‘Convex Hull’ to calculate the REV by considering the two main macroscopic
40 petrophysical parameters, porosity and single phase permeability, simultaneously. The shape
41 of the hull can be used to identify strong correlation between the parameters or greatly
42 differing convergence rates. To further enhance computational efficiency we note that the
43 area of the convex hull (for well-chosen parameters such as the log of the permeability and
44 the porosity) decays exponentially with sub-sample size so that only a few small simulations
45 are needed to determine the system size needed to calculate the parameters to high accuracy
46 (small convex hull area). Finally we propose using a characteristic length such as the pore
47 size to choose an efficient absolute voxel size for the numerical rock.

48 **Keywords**

49 Representative Element Volume, porosity, single phase permeability, pore-scale, convex hull

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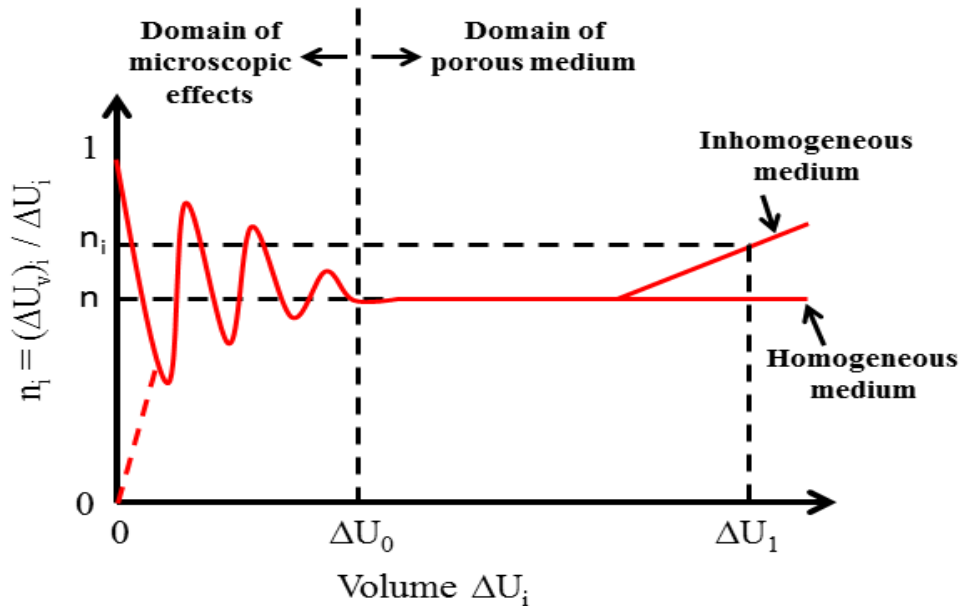
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57 1. Introduction

58 The physics of fluid flow through complex porous media has important applications in
59 petroleum and reservoir engineering, including the displacement of oil, gas and water in
60 hydrocarbon reservoirs and is of particular interest to understand the trapping of CO₂ for
61 carbon storage applications (Fredrich, 1999; Andrew, Bijeljic, & Blunt, 2013; Shah, Yang,
62 Crawshaw, Gharbi, & Boek, 2013). In the past, many researchers have attempted to relate
63 fluid transport properties such as permeability to the bulk porosity and specific surface area,
64 but complexity arises in predicting permeability accurately (Bear, 1972; Walsh & Brace,
65 1984; Mostaghimi, Blunt, & Branko, 2013). Fluid transport properties depend critically on
66 the size, shape and connectivity of the pore space and geometry of the porous medium.
67 However, there is no accurate formula which can correlate permeability with bulk porosity
68 without ambiguity. This motivated research in pore-scale imaging and modelling to obtain
69 detailed information about the geometry of complex porous media and modelling the fluid
70 flow at the pore-scale using different numerical simulation methods to predict the
71 permeability accurately (Blunt, Jackson, Piri, & Valvatne, 2002; Valvatne & Blunt, 2004;
72 Dong & Blunt, 2009; Boek & Venturoli, 2010; Yang, Crawshaw, & Boek, 2013; Shah,
73 Crawshaw, & Boek, 2016). Pore-scale imaging and modelling is developing quickly and has
74 now become a routine service in the petroleum industry, principally to understand
75 displacement processes and to predict single phase and relative permeability (Blunt, et al.,
76 2013). The fundamental problem in pore-scale imaging and modelling is how to represent
77 and model the different range of scales encountered in porous media, starting from the
78 unresolved sub-resolution micro-porosity. Bear [1972] has explained the concept of
79 Representative Element of Volume (REV), qualitatively taking into consideration a
80 macroscopic property, such as porosity. The REV is the minimum volume that can represent
81 a particular macroscopic property of the sample. Figure (1) shows a graph to define the REV,
82 where ΔU_i is defined as a volume in a porous medium, and is considered to be much larger
83 than a single pore or grain. ΔU_v is the volume of void space, and the fractional porosity is
84 defined by n_i , as the ratio of void space to volume. As shown in Figure (1), there are minimal
85 fluctuations of porosity as a function of volume at large values of ΔU_i . As the volume
86 decreases, fluctuations in the porosity increase, specifically as ΔU_i approaches the size of a
87 single pore, which has a fractional porosity of 1. Therefore the REV is defined by the term
88 ΔU_0 , above which fluctuations of porosity are minimal, and below which fluctuations of

89 porosity are significant. The determination of the volume ΔU_i is related to the different length
 90 scales varying from pore-scale to core scale to continuum scale (Crawshaw & Boek, 2013).

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93 Figure 1 Schematic diagram showing the measured property varies with the sample volume and the domain of
 94 the Representative Element Volume (REV) (Crawshaw & Boek, 2013).

95 Pore-scale techniques have to answer questions such as: “What is the actual size of an REV?
 96 Does the size of the REV vary for different rock types? Are the REV’s similar or significantly
 97 different for different quantities at a given location? How do the transport and structural
 98 properties such as permeability and porosity vary with scale?” (Zhang, Zhang, Chen, & Soll,
 99 2000). The above listed questions were partly answered by Bear [1972], Bosl et al. [1998],
 100 Pan et al. [2001], Zhang et al. [2000], Keehm [2003], Peng et al. [2012], Peng et al. [2014]
 101 and Mostaghimi et al. [2013].

102 Two types of numerical method for assessing the size of an REV are commonly used. The
 103 first is the “deterministic REV”, in this scheme, a sub-sample centred within a larger domain
 104 is gradually expanded. When the variation of petrophysical properties with sample size
 105 becomes small enough, REV size is considered to have been reached. Zhang et al. (2000)
 106 used this approach to compare results obtained from crushed glass beads and sandstone, and
 107 found that the size of an REV varies spatially and depends on the quantity being represented.
 108 Keehm [2003] found that to predict the absolute and relative permeability of porous media, a
 109 minimum REV of size $L = 20a$ is needed, where a is the mean pore size of the porous

110 medium using analysis of 2D thin sections. Mostaghimi et al. [2013] demonstrated that the
111 REV for permeability is larger than for static properties, such as porosity and specific surface
112 area. They also found that the REV for carbonate rocks appears to be larger than the image
113 size considered. The alternative approach is the “statistical REV” in which a number of sub-
114 volumes at a given size are sampled over a larger domain. The width of the distribution of a
115 given property decreases with increasing sub-sample sizes and can be used to define an REV
116 below a certain threshold (Al-Raoush & Papadopoulos, 2010). However these previous
117 studies only partly address issues regarding the concept of REV for pore-scale imaging and
118 modelling and show its limitations. In this study we will address the correlation of REV with
119 pore size and introduce a method by which the REV can be established for multiple
120 parameters, considering porosity and permeability as an example.

121 We will now discuss the concepts of homogeneity and heterogeneity related to porous media
122 studies. Homogeneity is defined qualitatively as the characteristic that a physical property has
123 the same value in different elemental volumes regardless of their location (Olea, 1991).
124 Therefore, the terms heterogeneity and homogeneity are dependent on the model or sample
125 volume of the measured physical property (Nordahl & Ringrose, 2008). In this study, we
126 systematically investigate the relation between two important macroscopic properties,
127 porosity and absolute permeability, using pore-scale imaging and modelling techniques, to
128 predict the representative element volume (REV). We use the mathematical concept of the
129 Convex Hull, C_H to investigate the relation between porosity and permeability and examine
130 the effects of rock sample heterogeneity and increasing sample size. The main aim is to
131 explore this relation for 8 different types of porous materials, ranging from beadpacks to
132 sandpacks to sandstones to carbonate rocks in terms of increasing heterogeneity and
133 quantitatively determine the size of the REV for each. The approach could be extended to
134 more complex flow calculations in porous media such as two-phase relative permeability and
135 capillary pressure prediction.

136 **2. Pore-scale Imaging and Modelling**

137 The problem of REV determination in porous media can be quantitatively addressed using X-
138 ray micro computed tomography (micro-CT), which is a widely used 3D imaging technique
139 to obtain 3D images of porous media (Zhang, Zhang, Chen, & Soll, 2000). In addition, we
140 use recent advances in computational methods for solving flow equations in complex
141 geometries (Blunt, Jackson, Piri, & Valvatne, 2002; Blunt, et al., 2013; Boek & Venturoli,

142 2010; Yang & Boek, 2013). Pore-scale images of the rocks can be obtained using micro-CT
143 equipment using laboratory and synchrotron sources. Spanne et al. [1994] and Auzeais et al.
144 [1996] used micro-CT to obtain 3D voxel data of sandstone at a voxel resolution of around
145 7.5 μm . Blunt et al. (2013) have obtained data for carbonate samples at different voxel
146 resolutions ranging from 2.68 μm to 13.7 μm . The reconstructed pore geometries from micro-
147 CT have been used for the prediction of petrophysical properties including permeability,
148 porosity and formation factor (Arns, Knackstedt, Pinczewski, & Martys, 2004; Knackstedt, et
149 al., 2006; Shah, Crawshaw, & Boek, Micro-Computed Tomography Pore-scale Study of Flow
150 in Porous Media:Effect of Voxel Resolution, 2016).

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152 In this study, we compute absolute permeability using the Lattice Boltzmann (LB) method.
153 This model is particularly suited to direct numerical simulation on pore-space images because
154 of its ability to handle complex boundaries accurately. Moreover, the LB method does not
155 require extracting a simplified network of flow paths, as in network modelling (Zhang,
156 Zhang, Chen, & Soll, 2000), and so is able to give accurate permeability results in highly
157 heterogeneous media. The LB model describes the fluid as a velocity distribution of particle
158 distribution function at each node. These undergo streaming and collision steps according to a
159 discrete form of the Boltzmann equation, and can be shown to recover the incompressible
160 Navier-Stokes equations (Chen, Wang, Shan, & Doolen, 1992). The single-phase D3Q19
161 lattice Boltzmann (LB) model with a multiple-relaxation-time (MRT) operator is used in our
162 code (Yang, Crawshaw, & Boek, 2013).

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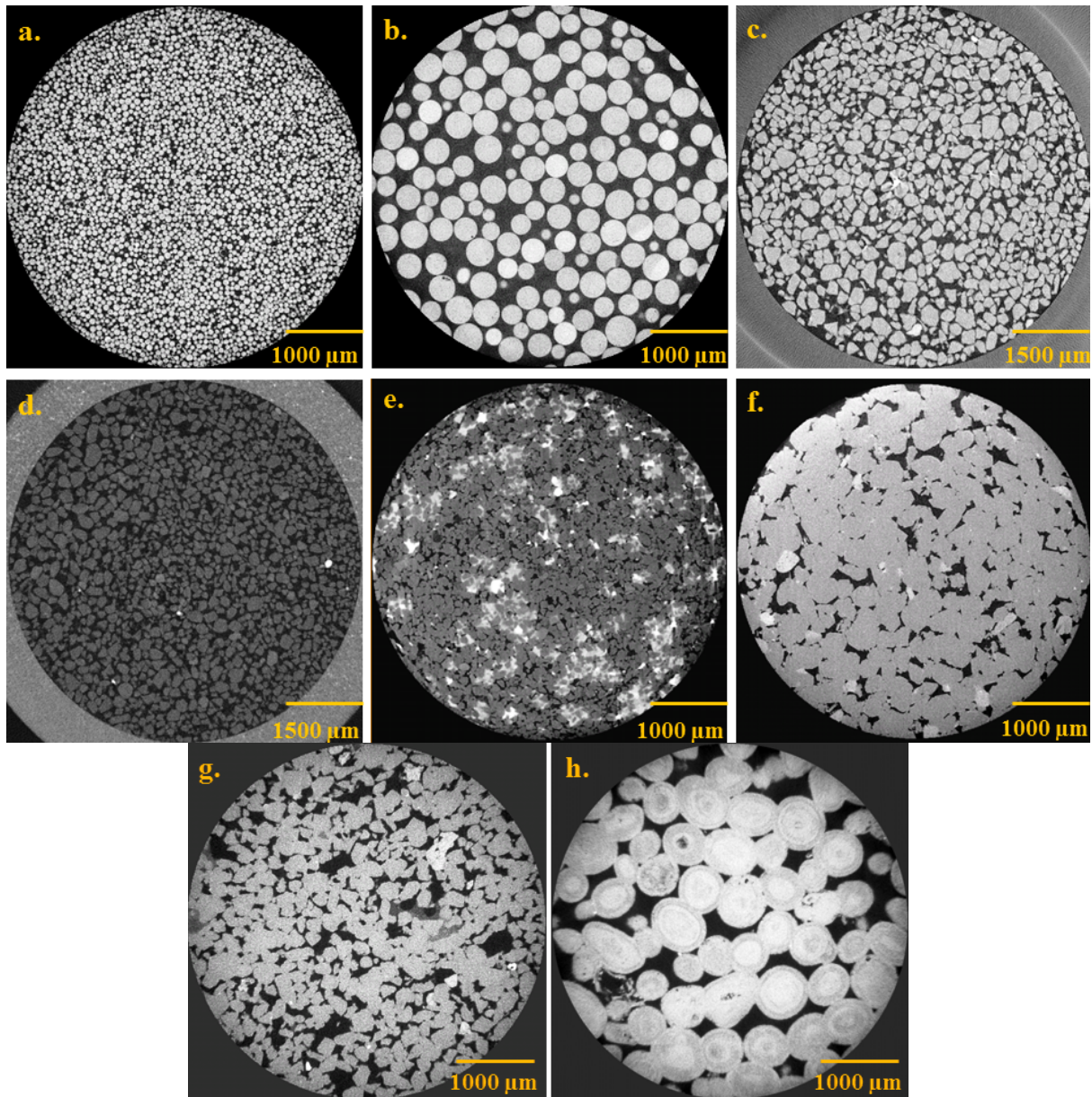
164 **3. Methods and Techniques**

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166 The detailed 3D micro-CT image acquisition procedure is presented by Shah et al. [2015].
167 Figure 2 shows 2D cross sections of 3D voxel data for 8 different porous materials, including
168 beadpacks of two different bead sizes, two sandpacks, three sandstones and one carbonate.
169 The 3D images for all the samples were subsequently segmented into binary images based on
170 a 2D histogram segmentation analysis by using marker seeded watershed algorithm within
171 the program Avizo Fire 8.0 (Visual Sciences Group, Burlington, MA, USA) (Shah,
172 Crawshaw, & Boek, Micro-Computed Tomography Pore-scale Study of Flow in Porous
173 Media:Effect of Voxel Resolution, 2016). 3D images of beadpacks, sandpacks, sandstones

174 and carbonate samples were first cropped into 3D cubic images. The exact image dimensions,
175 properties and details are summarized in Table 1.

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180 Figure 2 Two-dimensional cross sections of three dimensional micro-CT images of different samples. (a)
181 Beadpack with grain size 50 μm . (b) Beadpack with grain size 350 μm . (c) LV60 sandpack (d) HST95 sandpack
182 (e) Berea sandstone (f) Clashach sandstone (g) Doddington sandstone (h) Ketton carbonate. In all figures, the
183 pore space is shown in dark.

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188 Table 1: Summary of the rocks and images studied in this paper. Porosity and single phase permeability
 189 obtained from computation.

Sample	Source/ Scanner	Image Size, Voxels	Voxel Size (μm)	Porosity [†] (%)	Single Phase Permeability [†] (mD)
Beadpack -50 μm	Micro-CT	700 ³	4.21	28.5	1474
Beadpack- 350 μm ^a	Synchrotron	700 ³	5.35	36.40	95400
LV60 sandpack ^b	Micro-CT	400 ³	7.24	30.55	11860
HST95 sandpack ^b	Micro-CT	400 ³	7.89	30.27	5235
Berea sandstone	Micro-CT	700 ³	4.52	9.52	58
Clashach sandstone	Micro-CT	700 ³	4.52	10.78	448
Doddington sandstone	Micro-CT	700 ³	4.52	16.35	2442
Ketton carbonate	Micro-CT	700 ³	4.52	13.04	5648

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191 [†] Computed from the destined voxels using Lattice Boltzmann code192 ^a Data obtained from Kamaljit Singh through personal communication193 ^b (Dong & Blunt, 2009)

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195 The properties predicted from the images depend on the segmented pore space adequately
 196 representing the voids in the rock sample. This becomes problematic when a significant
 197 fraction of the porosity contributing to flow is below the resolution of the micro-CT image, as
 198 can be the case for many carbonate rocks (Grey, Cen, Shah, Crawshaw and Boek 2016). In
 199 the Ketton carbonate used here, the segmented pore space image was well connected and
 200 micro-porous regions were assigned to the solid phase without compromising the subsequent
 201 flow simulations.

202

203 The experimental (total) porosity and single-phase permeability were measured on each of
 204 the cylindrical core samples except beadpacks and sandpacks. The total porosity was
 205 measured using bulk volume measurements and single phase permeability was measured
 206 using the Darcy flow equation. Brine was injected at constant flow rate and the pressure drop
 207 across the length of the sample was monitored using a high precision pressure transducer. A
 208 flow cell was designed to accurately measure the single phase permeability of the core
 209 samples at three different flow rates (Gharbi & Blunt, 2012). Note that these measurements
 210 are for the whole sample volume and not only the scanned region. The experimental porosity
 211 and single phase permeability of each sample are presented in Table 2.

Samples	Length [mm]	Diameter [mm]	Experimental Porosity [%]	Experimental Permeability [mD]
LV60 sandpack**	-	-	37.00 ±0.2	32000 ±300
HST95 sandpack**	-	-	33.4	7900
Berea sandstone	15.2	5	11.17 ±0.4	17.5 ±0.7
Clashach sandstone	11.6	5	11.02 ±0.2	365 ±116
Doddington sandstone	17.8	6	18.41 ±0.5	2362 ±221
Ketton carbonate	15.1	5	19.02 ±0.1	4271 ±300

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215 Table 2: Experimental petrophysical properties of the rocks considered in the present study

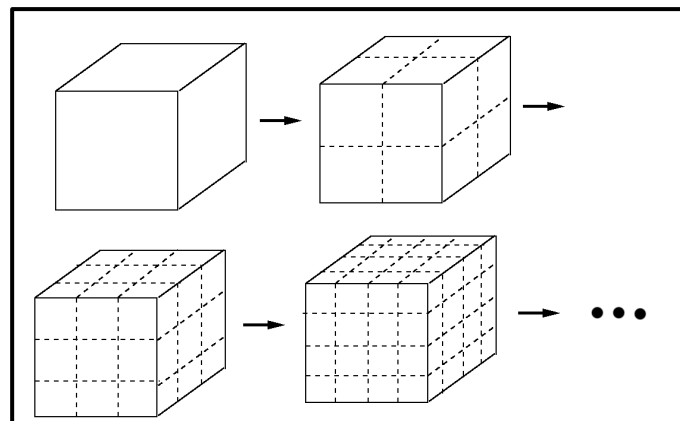
216 **Experimental porosity was measured on a packed column using bulk volume measurement and experimental
217 brine permeability was measured on a packed column by injecting brine at a constant flowrate (Pentland, 2010).

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220 The pore geometries of the porous samples are partitioned into several sub-domains which
 221 are of the same size (Figure 3). For example, we consider 3D micro-CT data of a Doddington
 222 sandstone sample consisting of 700^3 voxels with $4.5\mu\text{m}$ voxel resolution representing a
 223 physical area of 3.15 mm. We then perform this subsampling procedure with each of the 6
 224 sub-domain sizes given in Table 3. The division of the geometry into different voxels or
 225 image sizes is done in x-, y- and z- directions. The statistical distribution of parameters
 226 obtained from individual subsamples allows for the characterisation of the sample REV.

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229 Figure 3 An example of domain partition. The scanned sample was divided into n^3 sub-domains which have the
 230 same size.

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For the LB flow simulation, we impose a body-force throughout the domain or sub-domain and periodic boundary conditions at the inlet and outlet faces, iterating the flow-field until it reaches steady-state. Then, the single phase permeability is obtained from Darcy’s law. For smaller sub-domains, there is no guarantee of convergence of the velocity field to steady-state. This is either because there is no flow path percolating between flow faces, or because there is too little solid phase. In these cases, the simulation continues for up to 50,000 LB time-steps. The sub-volume is discounted if the velocity field does not converge by this limit. The calculation was run on a Tesla K20 GPU with a 5GB memory but in cases where the sub-volume calculation required more memory than this, the calculation was deferred to CPUs. The calculated LB single phase permeability varies significantly for sub-domains therefore we normalise the permeability independently for each porous sample by $k' = \frac{k_{\text{sub-domain}}}{k_{\text{total}}}$ where $k_{\text{sub-domain}}$ is the calculated LB permeability of the particular single sub-domain size [mD], k_{total} is the calculated LB permeability of the whole domain (700^3 voxel) [mD] and k' is the normalised dimensionless permeability.

Table 3 Division of sub-domain voxel size from the whole domain of 700^3 with calculated linear dimensions from the voxel resolution for Doddington sandstone sample.

Doddington sandstone Resolution – $4.5\mu\text{m}$	Sub-domain 700^3 voxels	Linear dimension [μm]
1	50 x 50 x 50	225
2	100 x 100 x 100	450
3	150 x 150 x 150	650
4	200 x 200 x 200	900
5	250 x 250 x 250	1125
6	300 x 300 x 300	1350
7	350 x 350 x 350	1575

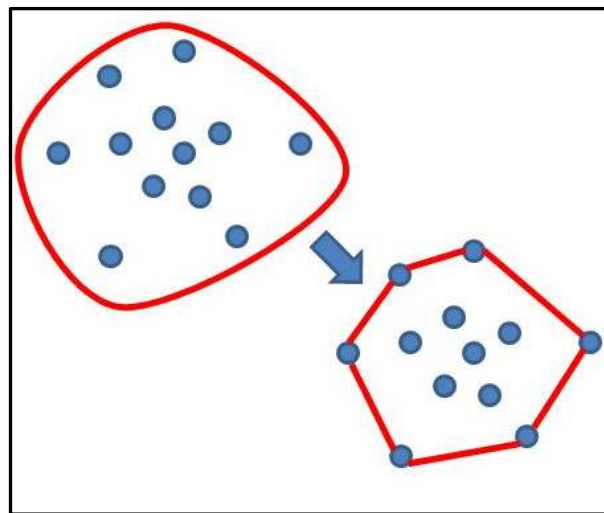
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255 4. Results and Discussion

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257 The porosity and single phase permeability for each sub-domain is calculated and used to
258 obtain the 'Convex Hull' for that domain size. The concept of the convex hull was explained
259 by Andrew (1979). Let us imagine the points S as being pegs; the convex hull of S is the
260 shape of a rubber band stretched around the pegs. The formal way to define the convex hull
261 of S is the smallest convex polygon that contains all the points of S as shown in figure 4.

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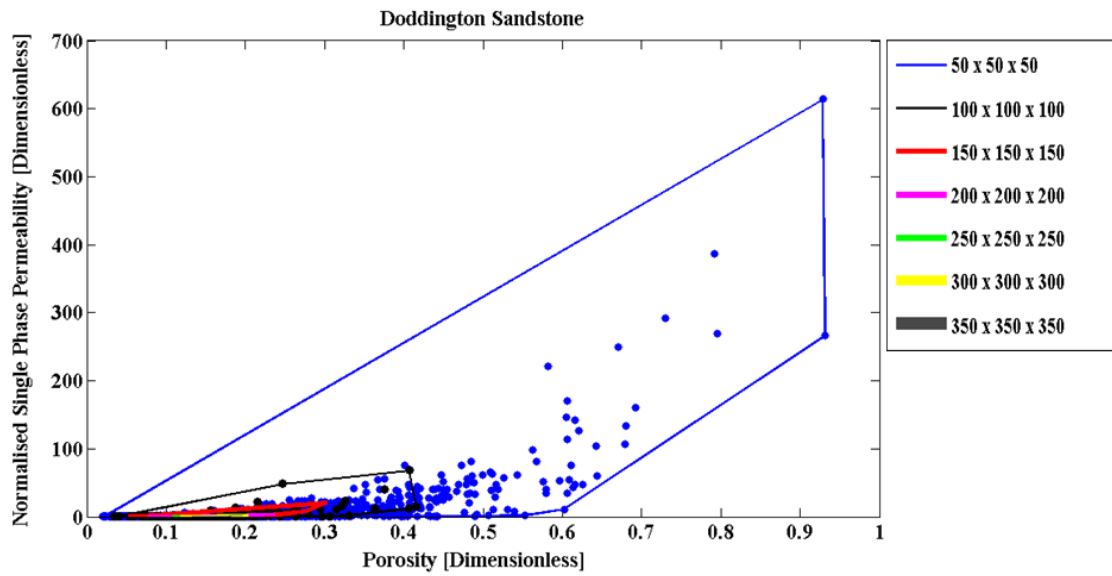


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264 Figure 4. Example explaining the definition of convex hull of set of points S.

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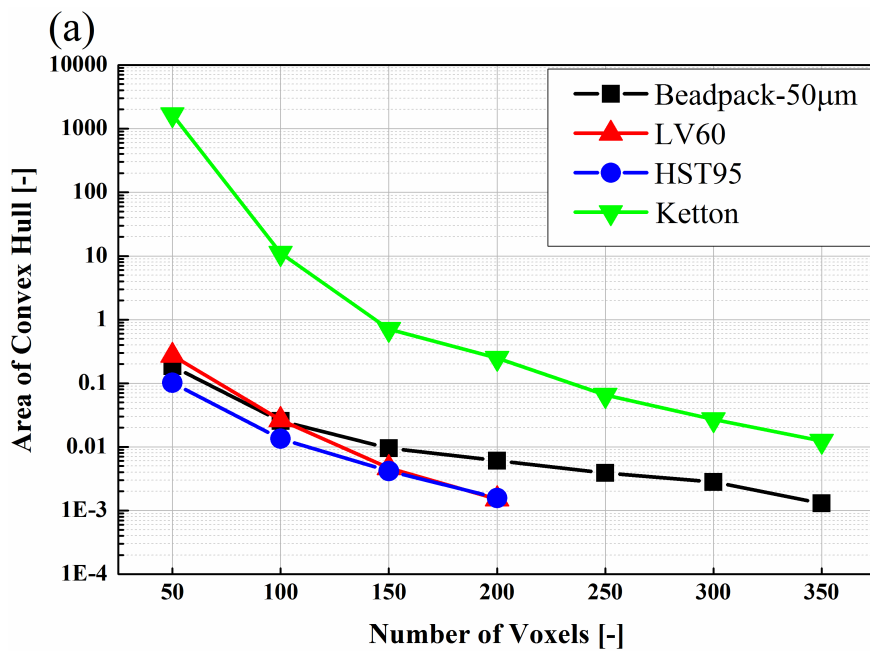
266 The process of obtaining a convex hull for each sub-domain was repeated for each of the 7
267 samples. Figure (5) shows the calculated porosity and single-phase permeability together with
268 the corresponding convex hulls for Doddington sandstone, for different sub-domains varying
269 from 50^3 to 350^3 voxels. Next we calculate the area of the resulting convex hulls and plot
270 these against the domain size in voxels, shown in Figure 6 for all the samples.



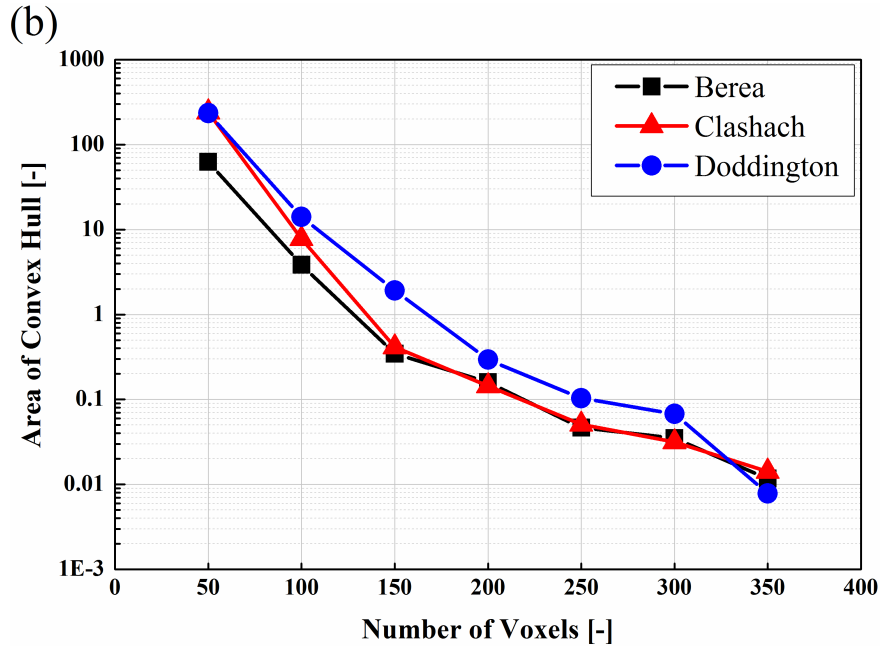
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Figure 5. The concept of convex hull applied to the plotted values of porosity and single-phase permeability calculated using LB method for different divided sub-domains varying from 50^3 to 350^3 voxels. The data is shown for a Doddington sandstone sample.

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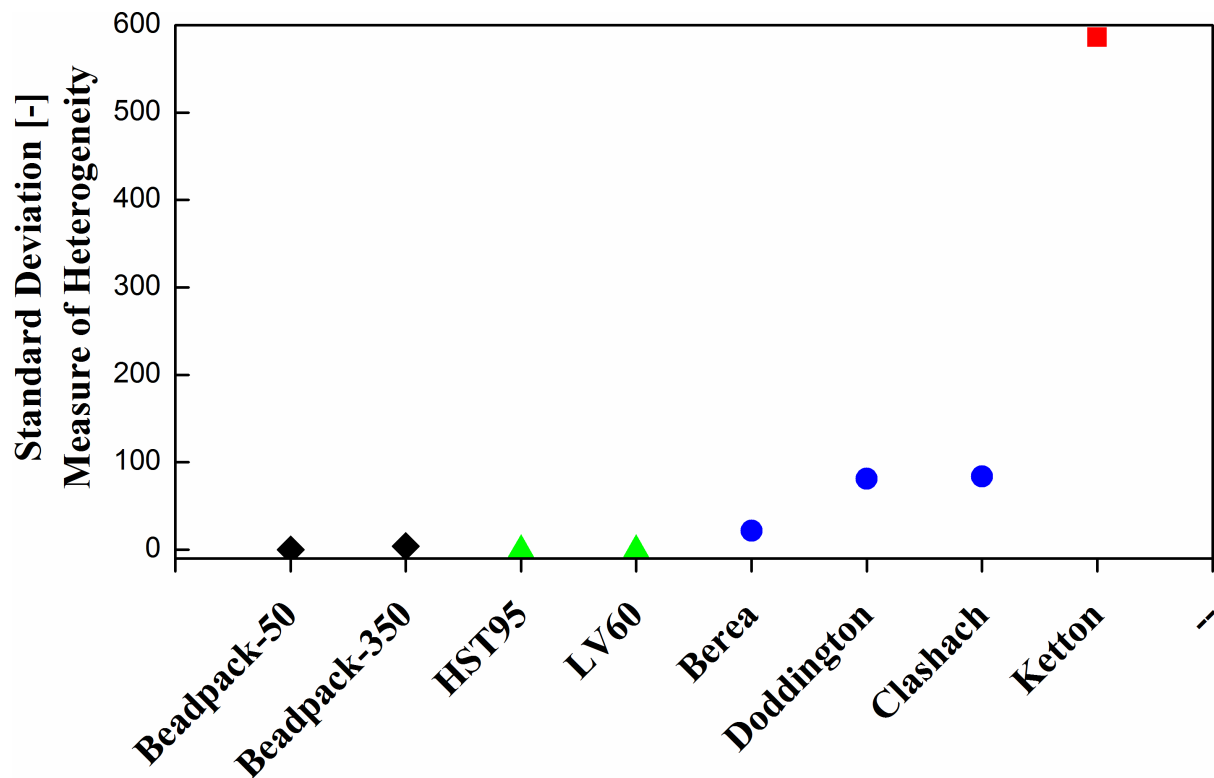


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281 Figure 6. The calculated area of convex hull for domain sizes ranging from 50^3 to 350^3 voxels is shown for
282 beadpack, sandpacks and carbonate in figure (a), for sandstones in figure (b). The REV size for each sample can
283 be determined by choosing an acceptable area for the convex hull, for example 0.5 will be used here, and
284 reading the corresponding system size.

285 From Figures 5 and 6, we observe that the area of the convex hull systematically decreases as
286 the size of the sub-domain increases from 50^3 to 350^3 voxels for each of the rock types. The
287 REV is then estimated by choosing a value of the area of the convex hull area below which
288 the variations of both parameters are acceptable, for example 0.5. We note that one limitation
289 of this approach is that the hull area cannot be simply related to statistical measures such as
290 the variance of the individual parameters, so the choice of threshold is somewhat arbitrary.
291 From figures 6 (a) and (b) we can then determine the REV size for beadpacks, sandpacks,
292 sandstones and carbonate rock types. The beadpacks and the two sandpacks samples, LV60
293 and HST95, converge faster than sandstones and carbonate needs only a sub-domain greater
294 than 50^3 voxels (or $250\ \mu\text{m}$ in linear dimensions). Using the same hull area threshold of 0.5,
295 the REV size for Berea and Clashach sandstone comes to 150^3 voxels ($750\ \mu\text{m}$), while for
296 Doddington it is somewhat larger, around 200^3 voxels ($904\ \mu\text{m}$). The REV size for Ketton is
297 greater than 150^3 voxels ($750\ \mu\text{m}$).

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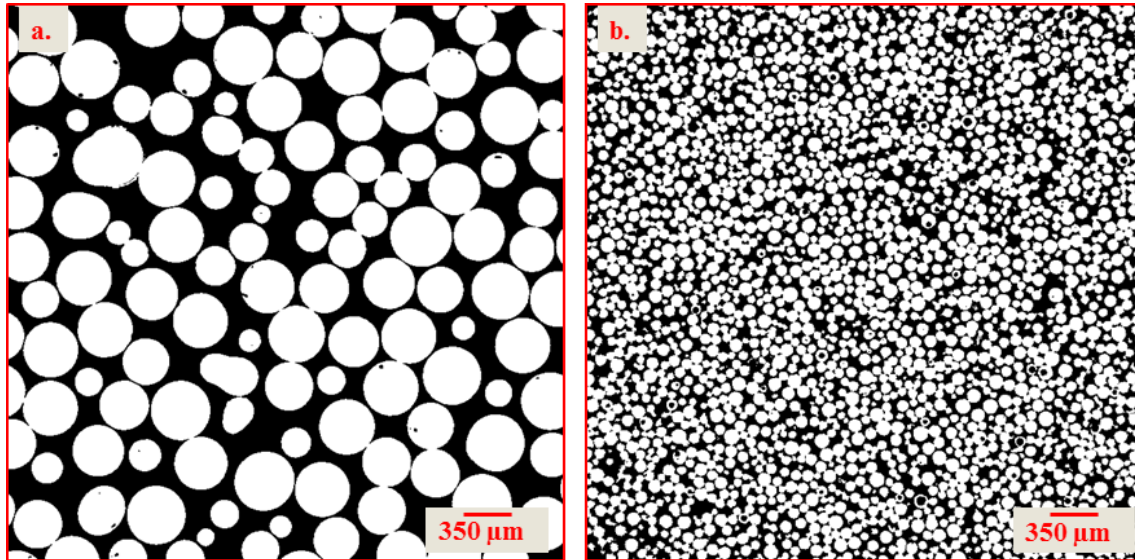
301 Figure 7. Standard deviation values for the calculated convex hull area for each rock sample as a function of
302 measure of heterogeneity. Black indicates beadpacks, green indicates sandpacks, blue indicates sandstones and
303 red indicate carbonate samples.

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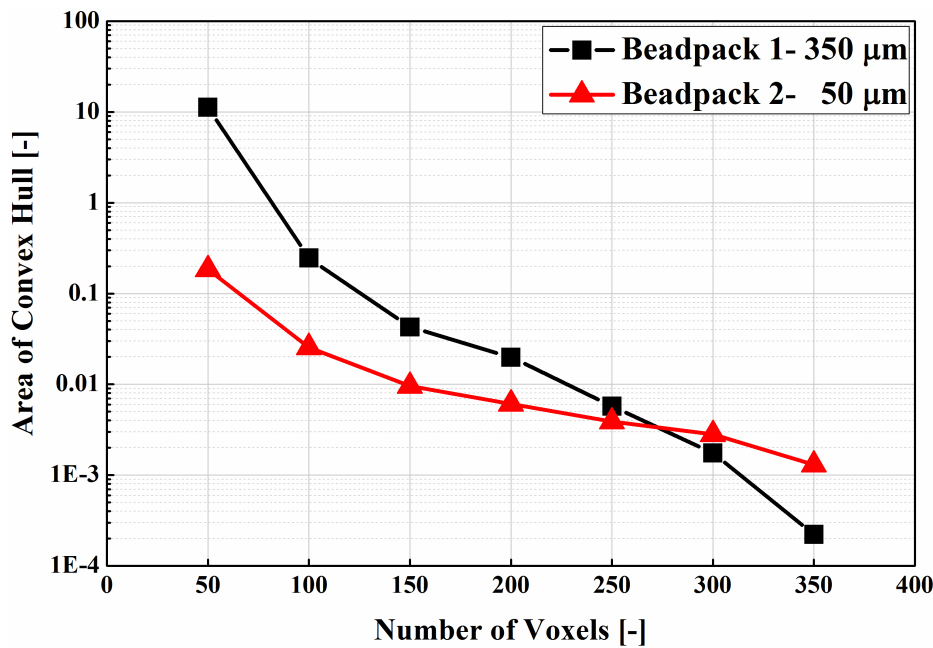
305 Another quantitative measure of heterogeneity is defined here as the standard deviation of the
306 calculated area of the convex polygon for the entire sub-divided domain varying from 50^3 to
307 350^3 voxels. Figure 7 shows this measure of heterogeneity for the entire library of rocks used
308 in this study. Comparing the standard deviations, to understand the heterogeneity of the rock
309 across the whole domain of 700^3 voxels, we observe that the calculated values of the standard
310 deviation are very small and constant for beadpacks and two sandpacks, LV60 and HST 95.
311 For beadpacks and sandpacks, the calculated standard deviations vary within a small range,
312 whereas sandstone and carbonate rocks show a significant variation in the calculated standard
313 deviation for different rock samples indicating the heterogeneity across the whole domain of
314 700^3 voxels.

315 The REV sizes determined above suggest that we can capture a typical length scale of
316 heterogeneity. However, this estimated REV size, although useful to estimate the size of
317 simulation required for parameter estimation, does not allow a satisfactory ranking of sample
318 heterogeneity. To illustrate this issue, consider two bead packs, of different grain size that are

319 otherwise identical, as shown in Figure 8. The permeability/porosity convex hull areas of the
 320 two bead packs, shown in Figure 9, are very different, but intuitively both are equally
 321 homogeneous. Hence, there is a need to introduce a new scaling factor for sub-domain or
 322 voxel size to optimize the convex hull process to obtain a more satisfying description of the
 323 heterogeneity.



324
 325 Figure 8. Binarized two-dimensional cross-sections of the three dimensional data set of Bead packs with (a)
 326 Grain size = 350μm and (b) Grain size = 50μm respectively. White colour represents the grain space and black
 327 colour indicates the pore space



328
 329 Figure 9. Calculated area of convex hull for voxel sizes ranging from 50³ to 350³ is shown for two bead packs
 330 with grain sizes 350μm and 50μm.

331 The origin of the characteristic length is open to choice and the grain size is commonly used
 332 in the literature (Kameda & Dvorkin, 2004). However, while this may be appropriate for
 333 estimation of mechanical properties, the average pore diameter is a more natural choice for
 334 fluid flow parameters. The average pore diameter for all the samples was estimated using the
 335 maximum ball algorithm approach where spheres are grown in the pore space of segmented
 336 3D micro-CT data, centred on each pore voxel (Dong & Blunt, 2009). Table 4 shows the
 337 calculated mean pore size for the library of rock images used in this study.

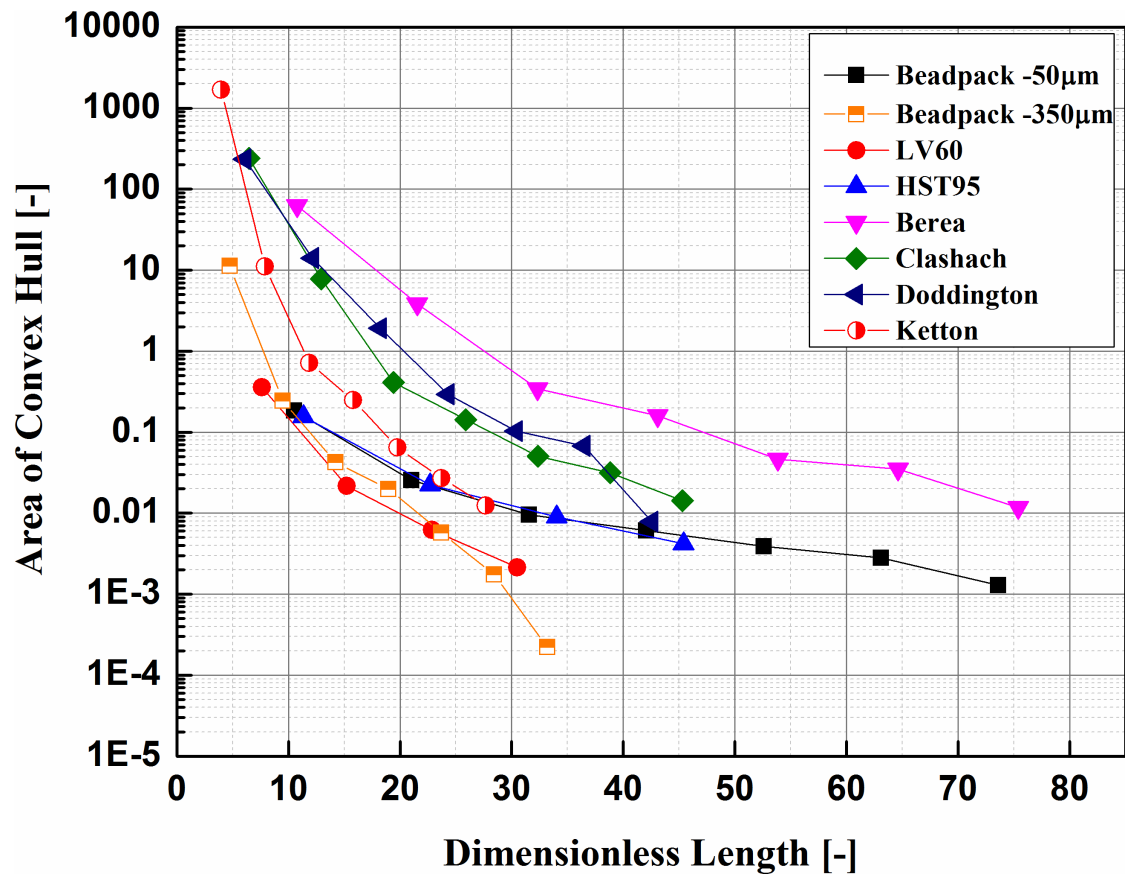
338 Table 4 Mean pore size for all samples estimated by the maximum ball algorithm.

Sample	Mean Pore Size (μm)
Beadpack – 50 μm	20.02
Beadpack – 350 μm	56.44
LV60 sandpack	47.5
HST95 sandpack	34.76
Berea sandstone	20.98
Clashach sandstone	34.92
Doddington sandstone	37.18
Ketton carbonate	57.18

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 340 We have scaled the sub-domain sizes for all the samples by the corresponding mean pore size
 341 and Figure 10 shows the convex hull areas plotted against the resulting dimensionless length.
 342 The scaling resolves several issues in the comparison of relative heterogeneity. In the earlier
 343 analysis Ketton, a well-sorted oolitic limestone with almost spherical grains, appeared more
 344 heterogeneous than the sandstones, whereas Figure 10 shows that this was mostly due to the
 345 large pore size of Ketton which now falls close to the group of sandpacks.

346
 347 Figure 10 also shows that simply relating the REV to pore size is insufficient as the data do
 348 not collapse onto a master curve now system size is scaled by pore size. Keeping our choice
 349 of acceptable hull area at 0.5, only Clashach and Doddington fall close to the $L = 20a$
 350 relationship proposed by Keehm (Keehm, 2003). The beadpacks and sandpacks, on the other
 351 hand, reach the threshold around $10a$ and Ketton carbonate around $12a$. The more complex
 352 Berea sandstone requires around $35a$.

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356 Figure 10. Porosity/permeability convex area against dimensionless for the entire rock library.

357 In the examples above, the permeability ranges over several orders of magnitude.

358 Consequently the variance to small permeability has little impact on the area of the convex

359 hull, as can be seen in Figure 5 where the shape of the hull becomes rather linear as the

360 system size is increased. A more evenly weighted convex hull can be made when the log of

361 the permeability is taken first for each of the sub-sampled system sizes and then normalised

362 with respect to the log of the permeability calculated from the largest system size. This is

363 shown, again for the Doddington sandstone, in Figure 11 where the hull retains its two-

364 dimensional shape at intermediate system sizes.

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366 Note that there is evidence for a correlation between permeability and porosity in figure 11,

367 as the hull for the 50µm bead pack in particular tends towards a line with a finite slope at

368 large system size. The use of such correlations, for example the Carman-Kozeny equation, for

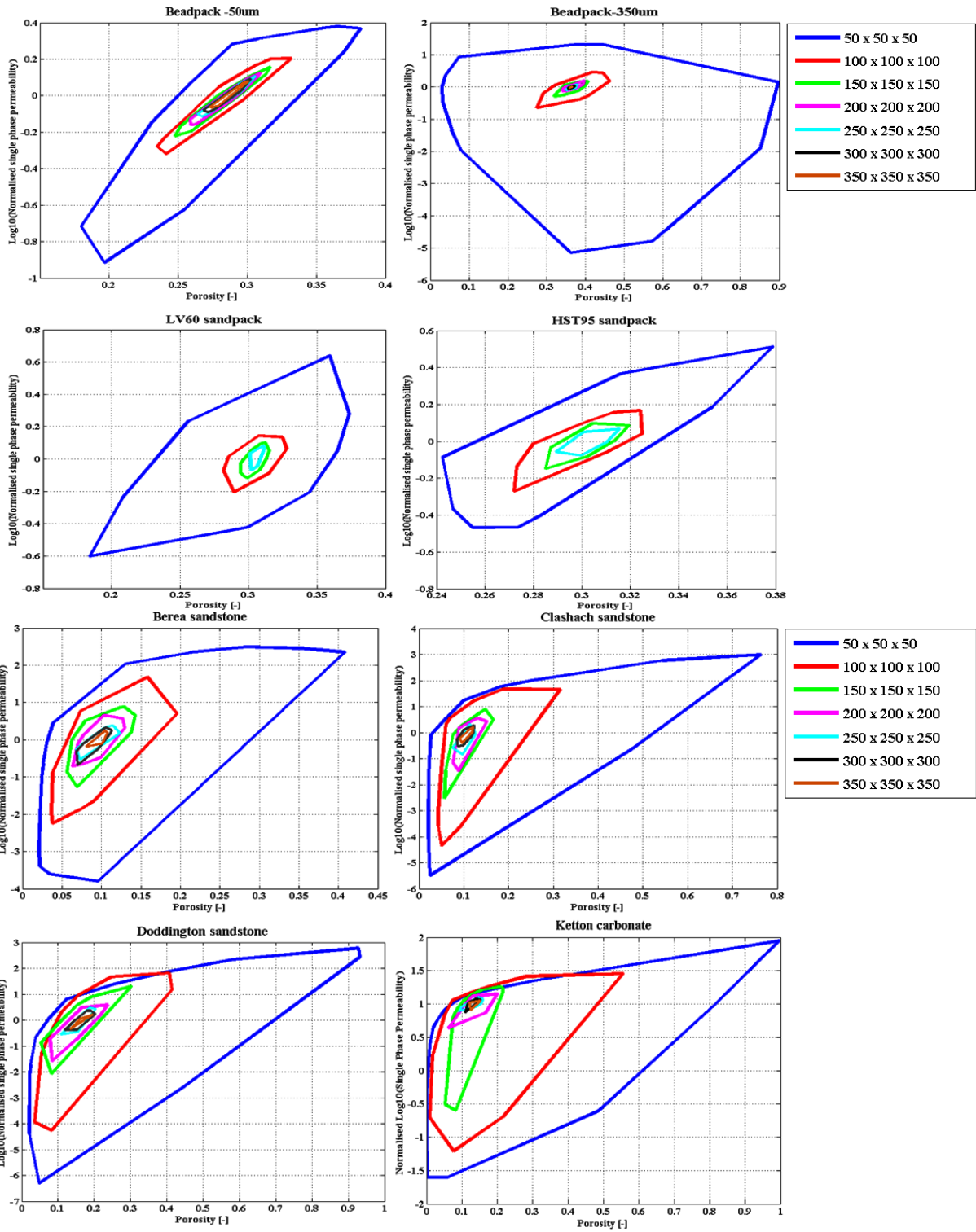
369 estimating the permeability of complex rocks from the correlation between permeability and

370 porosity has been discussed in the literature, see for example Mostaghimi et al. (2013). The

371 main issue being that the Kozeny constant can take a wide range of values depending on the

372 rock structure. Here the main emphasis is on estimating the REV rather than comparing
373 methods for estimating the permeability. In this case the porosity and permeability converge
374 at a similar rate, as the hull would tend towards either a vertical or horizontal line if one
375 variable reached a stationary value before the other as the system size was increased. This
376 implies that the REV for permeability and porosity are similar in the Beadpack-50 μ m sample
377 and there is strong correlation between porosity and permeability. However this behaviour
378 was not universal and a non-linear hull is persistent, particularly for the sandpacks

379 The convex hull approach would not be appropriate for rocks in which the parameters
380 converged to their REV values at very different rates. In this case one parameter would come
381 to dominate the variation and the hull would appear as a horizontal or vertical line, however
382 this was not the case for any of the examples shown here.



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386 Figure 11. Convex hull of $\text{Log}_{10}(K)$ against porosity. (a) Beadpack 50 μm . (b) Beadpack 350 μm . (c) HST95
 387 sandpack (d) LV60 sandpack (e) Berea sandstone (f) Clashach sandstone (g) Doddington sandstone (h) Ketton
 388 carbonate.

389

390 Interestingly, plotting the convex hull area of the $\log(k)$, porosity space against the
 391 dimensionless length, improves the exponential decay fit as is shown in Figure 12 (a) for

392 beadpacks, sandpacks, carbonate and Figure 12 (b) for sandstones rocks respectively. They
 393 are all linear on a log (area of convex hull) – linear (length) graph. This suggest a further gain
 394 in computational efficiency to be made by only computing the parameters for small system
 395 sizes and using the resulting exponential to extrapolate REV. Table 5 shows the predicted
 396 exponential decay constant and the pre-factor predicted from the exponential decay fit to
 397 obtain quantitative data for all the rocks studied using

398

$$399 \quad A = ae^{kl}, (k < 0) \quad (1)$$

400 where,

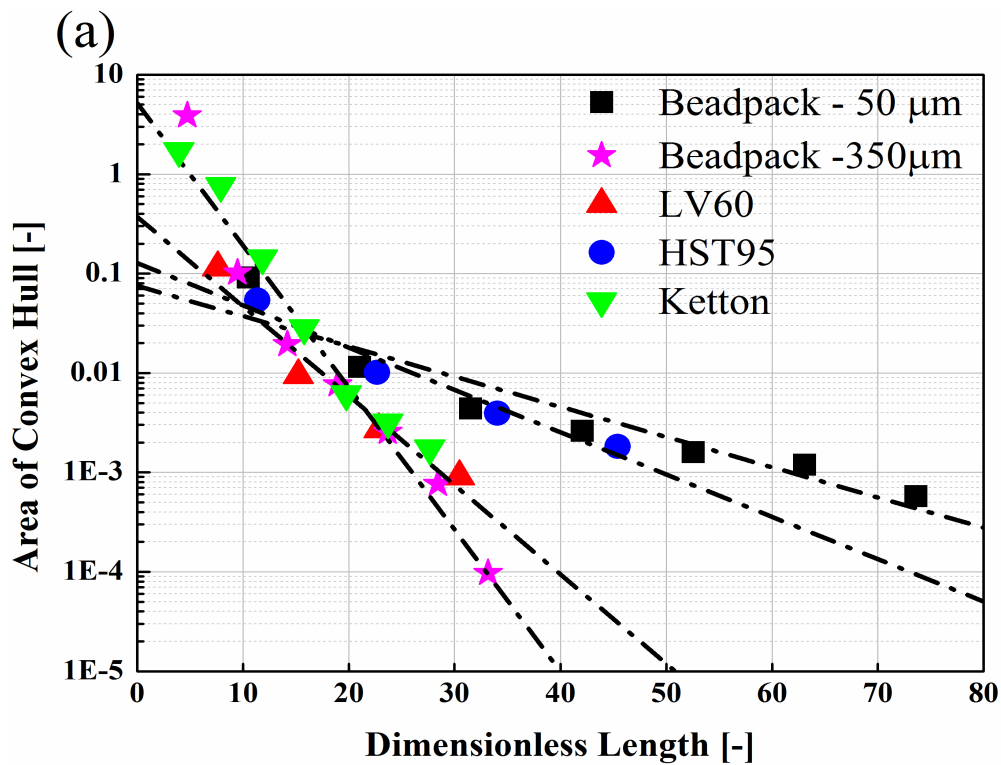
401 A = Convex hull area

402 a = Exponential pre-factor constant

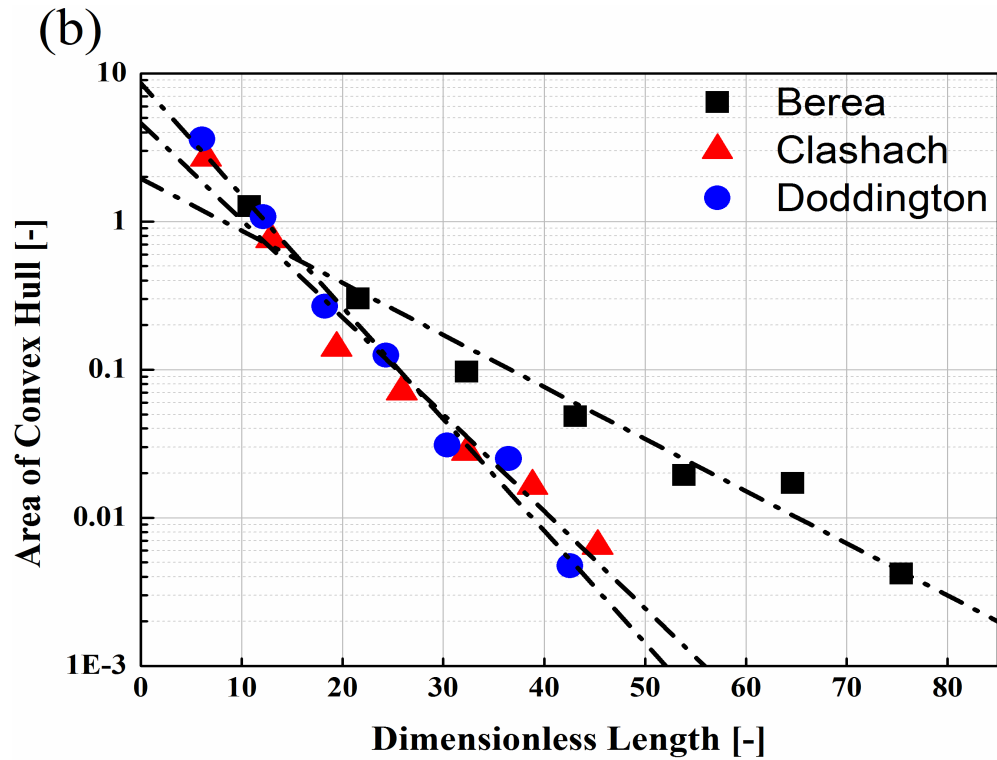
403 k = Exponential decay constant

404 l = dimensionless length

405



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407

408 Figure 12. Logarithmic area of convex hull showing exponential decay (dash line, black colour) when plotted
 409 against dimensionless length. (a) Beadpacks, sandpacks and carbonate samples. (b) Sandstone samples.

410

411 Table 5 Predicted exponential pre-factor and decay constant for the different rocks studied.

Sample	Exponential pre-factor constant	Exponential decay constant	R ²
Beadpack-50µm	0.0752	-0.07	0.8966
Beadpack-350µm	5.164	-0.329	0.9512
LV60 sandpack	0.3725	-0.207	0.9575
HST95 sandpack	0.128	-0.098	0.9656
Berea sandstone	1.95	-0.081	0.968
Clashach sandstone	4.6473	-0.151	0.9721
Doddington sandstone	8.5826	-0.174	0.984
Ketton carbonate	5.8244	-0.314	0.9754

412

413 The values of the exponential pre-factor and decay constant in Table 4 show a systematic
 414 trend for the different rocks studied. The decay constant for Berea is -0.08 and about -0.17 for
 415 Doddington sandstone. This means that the decay is slower for a heterogenous rock (Berea)

416 than for a relatively homogenous rock (Doddington and Clashach). This in turn suggests that
417 a critical value of the REV is reached more quickly (at smaller dimensionless length) for
418 homogenous than for more heterogenous sandstones. This is what we expect qualitatively
419 (see Figure 10), but now we can quantify this for different rocks by providing the value of the
420 decay exponent and the pre-factor from the exponential fit.

421 5. Conclusions

422 We quantified the degree of heterogeneity for different rock images by sampling the porosity
423 and permeability at different sub-volume sizes and using the convex hull concept. In the past,
424 the REV size was determined from individual macroscopic properties such as porosity,
425 permeability and specific surface area, but here we are computing an REV size based on two
426 parameters combined. By scaling the volume dimension with an average pore-diameter, a
427 quantitative measure of REV size was obtained from the convergence behaviour of the
428 convex hull area as the volume considered increased. It was found that this convergence
429 behaviour can be extrapolated from a few data points from small sub-volume sizes on a
430 logarithmic scale, potentially reducing the computational workload required in REV
431 determination with this method. The convex hull technique can in principle be extended to
432 include further macroscopic properties, and this will be investigated in future studies.

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