

Quantitative Characterization of Marble Natural Aging through Pore Structure Image Analysis

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(Article begins on next page)

2 **Quantitative Characterization of Marble Natural Ageing through Pore**
3 **Structure Image Analysis**

4
5 Costanzo Peter¹, Eloisa Salina Borello², Oliviero Baietto³, Rossana Bellopede⁴, Filippo Panini⁵,
6 Alice Massimiani⁶, Paola Marini⁷, Dario Viberti⁸

7
8
9 1 Center for Sustainable Future Technologies, Fondazione Istituto Italiano di Tecnologia, Via
10 Livorno 60, 10144, Turin, Italy

11 (corresponding author): costanzo.peter@iit.it

12
13 2 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

14 eloisa.salinaborello@polito.it

15
16 3 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

17 oliviero.baietto@polito.it

18
19 4 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

20 rossana.bellopede@polito.it

21
22 5 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

23 filippo.panini@polito.it

24
25 6 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

26 Alice.massimiani@polito.it

27
28 7 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

29 paola.marini@polito.it

30
31 8 Politecnico di Torino, C.so Duca degli Abruzzi, 24, 10129, Turin, Italy

32 dario.viberti@polito.it

34 **Abstract**

35 The goal of this study is the quantitative characterization of the degree of natural alteration of marble samples by
36 using image analysis for the automatic characterization and comparison of the pore structure of rock samples
37 before and after weathering. The proposed methodology is based on a pore exploration path finding algorithm for
38 the identification of paths developing within the porous domain of marble samples in both natural conditions and
39 after weathering. Along each identified path the pore radius is measured providing a thorough description of the
40 pore space statistical distribution. The A* path finding approach was developed and applied to binarized images
41 obtained from 2D thin sections of marble samples in both natural conditions and after 10 years of natural decay.
42 The results are expressed in terms of 2D porosity and statistical distributions of the pore radius of the samples pre
43 and post weathering. A comparison with the information obtained from standardized laboratory tests used for the
44 physical and mechanical characterization of stone material is also provided. From a computational point of view,
45 the presented approach is highly parallelizable. The presented approach works wells in complex porous structures
46 characterized by high path tortuosity, pore size heterogeneity and pore surface roughness. Moreover, the
47 methodology is less affected by small-scale pore features and noise, produced during image binarization, compared
48 to other algorithms for pore structure morphological analysis such as skeleton-based and maximal ball approaches.
49

50 Keywords: marble weathering, pore network characterization, path finding, pore radius, image analysis

51

52 **1 Introduction**

53 The degradation of natural stone materials due to the interaction with the surrounding environment is strongly
54 affected by the chemical and mineralogical composition and the physical-structural properties of the material. The
55 active degradation processes are mainly governed by the microclimatic conditions of the environment (i.e.,
56 temperature, humidity, wind, rainfall), the conditions of installation and surface smoothing. One of the agents
57 responsible for the degradation of stone materials is water, which can act, either directly or indirectly, through
58 rainfall, condensation, humidity and/or rising humidity. Those alterations occur over a long period of time and
59 mainly affect the external surface of the stone (Franzen and Mirwald, 2004).

60 The quantity and structure of the voids inside the stone change with decay (Nicholson, 2001) and the measurement
61 of porosity provides the degree of this transformation (Da Fonseca et al., 2021; Çelik and Sert, 2021). The
62 deterioration of the stone slabs, used in construction as external cladding, affects stone mechanical resistance

63 because the increase in porosity deriving from decohesion produces a decrease in mechanical resistance (Ju et al.,
64 2022; Ferrero et al., 2014). The relation between stone porosity and decay has been investigated by studying the
65 petrographic features and bowing phenomenon for over 30 years (Winkler, 1985; Grelk et al., 2007; Schouenborg
66 et al., 2007; Marini and Bellopede, 2009; Sousa et al., 2021). Physical and mechanical stone characterization is
67 conventionally carried out through standardized laboratory tests. Porosity can be evaluated through the
68 measurement of Open Porosity (EN 11936), expressing the volume of the open pores present on the surfaces of
69 the specimen, and Water Absorption (EN 13755) indicating the mass of water that can enter through the open
70 pores (Winkler, 1985; Ozcelik and Ozguven, 2014; Aral et al., 2021). Other tests for porosity estimation are Hg
71 intrusion porosimetry (also named MIP), polarized light and fluorescent optical microscopy and micro computed
72 tomography (micro-CT) (Cnudde et al., 2009; Du Plessis. 2016; Murru et al., 2018; Scrivano et al., 2018).

73 The comparison of data obtained by means of the previously mentioned tests on specimens in natural and
74 weathered conditions provides reliable indications on the physical and mechanical behavior of rock allowing to
75 foresee the weathering resistance of the analyzed stone. However, Cnudde et al. (2009) found that the direct
76 correlation between micro-CT and MIP data with total porosity and pore-size distribution curves, is difficult.

77 Automated approaches for quantifying stone weathering from porosity through image analysis have been proposed
78 (Buckman et al., 2017; Datta et al., 2016; Pal et al., 2022 and reference therein). However, for a more thorough
79 description of stone alteration, porosity should be coupled with a more local evaluation of the change in the pre-
80 and post-weathered pore size pore distribution.

81 Several geometric methods based on pore structure extraction from 2D and 3D image analysis are proposed in the
82 literature. Among others, segmentation-based algorithms (Øren and Bakke, 2003; Sheppard et al., 2004; Rabbani
83 et al., 2014; Gotstick, 2017; Xu et al., 2020) allow the determination of the pore connectivity and calculation of
84 the pore radius on segmented pore portions. However, these algorithms are sensitive to pore surface roughness and
85 need supervision during image binarization (Wang et al., 2020). The fractal geometry approach (Xu and Yu., 2008;
86 Xiao et al., 2019; Cai et al., 2019), and percolation theory (Liu et al., 2014 and references therein) are mainly used
87 for total porosity and permeability estimation. Algorithms for pore skeleton extraction such as medial-axis
88 (Lindquist et al., 1996), medial surface (Al-Raoush and Madhoun, 2017), and thinning process can be coupled
89 with post-processing routines for pore radius estimation (Liang et al., 2019). However, these approaches can
90 underestimate the size of the pores especially when a second medial axis junction is present within the node radius
91 (Wang et al., 2020). Moreover, they are very sensitive to minor object boundary perturbations caused by image
92 discretization, binarization and noise (Shaked and Bruckstein, 1998). Pore structure can be characterized through
93 the Maximal Ball Method which consists in clustering balls into pore throats according to their sizes (Arand and

94 Hesser, 2017). However, this method can underestimate the pore space when it is tortuous (Wang et al., 2020).
95 Convolutional neural networks (CNN) can be used to estimate porosity, average pore size and specific surface of
96 the porous rocks (Alqahtani et al., 2020) as well as to estimate morphological, hydraulic, electrical, and mechanical
97 characteristics based on micro-tomography images of porous geo-materials (Rabbani et al. 2020). The CNN
98 approach is extremely fast but it needs to be trained on a large dataset of images. The availability of the images of
99 stone before and after natural weathering is very limited; the application of data augmentation techniques is not
100 recommended because of the lack in diversity of the available images (Shorten et al. 2019).

101 A promising approach is based on the A*path finding method to explore the porous domain using binarized images.
102 The A* algorithm allows the identification of paths developing within the porous domain in which fluid circulation
103 can occur. The identified paths can be exploited to estimate various geometrical parameters characterizing the
104 porous space such as tortuosity, effective porosity and permeability from 2D and 3D binary images of well-
105 connected rock samples (Viberti et al., 2020; Salina Borello et al., 2022).

106 In this study a revisited version of the approach presented by Viberti et al. (2020) is adopted to quantitatively
107 characterize the pore structure of 2D images of marble samples before and after 10 years of natural decay. The
108 advantage of using the A* is that the algorithm is less affected by complex pore structure, having high path
109 tortuosity, pore size heterogeneities and pore surface roughness, compared to skeleton-based and maximal ball
110 approaches. Results are compared with degradation information obtained by standard experimental procedures
111 (variations in ultrasound propagation speed, variation in flexural strength, and water absorption) in order to verify
112 if the variations of the physical parameters obtained with standard laboratory tests are in agreement with the
113 variations of the parameters evaluated with the use of the * A algorithm.

114 **2 Materials and Methods**

115 **2.1 Rock sample description**

116 The analyzed rock, named C1, is a white marble with light gray veins (Fig.1) obtained from the Tuscan extracting
117 basin. The composition of the marble is predominantly calcitic with some dolomitic rhombic crystals. Quartz is
118 instead present as an accessory mineral. The marble is made up of subhedral blasts sometimes interlobated with
119 dimensions ranging from 300 to 600 microns approximately with a slightly anisotropic microstructure.

120 One sample of the marble studied in this work (C1) was exposed to external degradation agents for about ten years
121 on the roof of the DIATI (Environmental, Land and Infrastructure Engineering Department) at the Politecnico di
122 Torino, while the other sample comes from a slab of the same marble in natural condition.

123 **2.2 *Physical and mechanical tests***

124 The physical and mechanical stone characterization is carried out through conventional and destructive tests such
125 as flexural strength coupled with non-destructive tests such as ultrasonic pulse velocity and water absorption
126 performed in the laboratory by means of standardized tests (EN 14579, UNI EN 12372, UNI 11432, EN 13755).
127 Two water absorption tests were carried out: water absorption (WA) by means of a contact sponge and water
128 absorption (Ab) at atmospheric pressure. They are simple and cheap standardized approaches used for testing
129 natural stones, widely used in stone laboratories as it is required for the CE marking.
130 All tests were performed both on weathered and non-weathered samples of C1 with dimensions according to
131 standards of each test described in the following sections

132 **2.2.1 *Variations in ultrasound propagation speed – UPV***

133 The UPV (Ultrasonic Pulse Velocity) test is a fast and efficient non-invasive approach for defining the mechanical
134 properties of a stone material. This method is based on the principle of the propagation of mechanical oscillations
135 in the ultrasound field: a transducer held in contact with the surface of the test material produces ultrasounds,
136 which after having crossed a path of known length within this material, are received from a second transducer and
137 converted into an electrical signal. It is possible to determine the characteristic speed of the material once the time
138 needed to cross this space is calculated. This speed is linked to the type of material and to its physical and
139 mechanical characteristics such as the crystalline structure, porosity and cohesion (Rasolofosaon et al., 2000). The
140 alteration of the properties of the material which underwent natural deterioration can be analyzed by comparing
141 the propagation speed of the weathered sample with the original one characterized by unaltered properties. The
142 degradation progress of the material is associated to a worsening of its mechanical characteristics and,
143 consequently, to a lowering of the ultrasound propagation speed compared to the one measured in the unaltered
144 sample. The test has been carried out on 10 specimens. The test results indicate that the measured propagation of
145 ultrasounds obtained from indirect method (EN 14579 (2005) standard) shows consistent variations in speed
146 between altered and unaltered specimens (Tab. 1).

147

148 **2.2.2 *Variation in flexural strength***

149 Flexural strength is defined as the resistance of a material to the forces that tend to bend it. This test is based on
150 the principle that a body undergoing a bending stress, due to the constraints to which it is subjected, reacts by

151 opposing a system of forces applied by means of a mechanical press, which would tend to make it rotate around
152 one of its points. The methods of carrying out the flexural strength test are described by the European Standard
153 UNI EN 12372 (2001). The test has been carried out on 10 specimens. Results are reported in Tab. 2.

154 2.2.3 *Variation of water absorption (WA) by means of a contact sponge*

155 Water absorption by contact sponge is a quick test which can be carried out directly in situ and is part of the Italian
156 Cultural Heritage standards. The contact sponge method is used to determine the amount of water absorbed by the
157 stone material per surface unit as a function of a pre-determined time interval equal to 60 seconds. The test is
158 carried out, both in the laboratory and in situ, on flat surfaces and the procedure is described in the Italian standard
159 UNI 11432 (2011). Through this test, it is possible to make qualitative considerations on the degree of absorption
160 of the material at its surface and to compare the variations of this parameter on altered and unaltered specimens.
161 The test has been carried out on 10 specimens. The results are reported in Tab. 3.

162 2.2.4 *Variation of water absorption (Ab) at atmospheric pressure.*

163 Water absorption capacity Ab is represented by the percentage ratio between the mass of water absorbed and the
164 dry weight of the specimen. This value is determined by following the procedure described in the European
165 Standard UNI EN 13755 (2001). The results allow a direct comparison between the characteristics of the non-
166 degraded and degraded material, both within it and on its surface. The test has been carried out on 10 specimens.
167 Results are reported in Tab. 4.

168 2.2.5 *Discussion*

169 All the physical tests carried out on the weathered and non-weathered specimens show how there is significant
170 increase in water absorption both at atmospheric pressure and by means of a contact sponge in the specimen that
171 underwent natural aging. The values of flexural strength and speed of propagation of ultrasonic waves confirm a
172 worsening of the mechanical characteristics of the specimen subjected to aging.

173

174

175 2.3 *Pore structure characterization from image analysis*

176 The characterization of the rock pore structure is obtained by analyzing a number of binarized microscope images
177 acquired from 2D thin sections obtained from impregnated specimens: a horizontal section on the non-weathered

178 specimen (initial), three horizontal sections taken at different depths (epar1, epar2 and epar3) from the weathered
179 specimen, and a vertical section (transv) taken from the weathered specimen (see fig. 4). The impregnation process
180 was carried out with epoxy resin and methylene blue, repeatedly, under vacuum in order to obtain a smooth surface,
181 when viewed under the microscope. Each image is processed for the identification and characterization of paths
182 developing within the porous domain through a revisited version of the approach presented by Viberti et al. (2020).
183 This technique was successfully used by the authors to estimate tortuosity, effective porosity and permeability
184 from 2D binary images of well-connected rock samples. Here the methodology has been revisited to allow a good
185 exploration of poorly connected samples/areas, focusing on pore size characterization.
186 The adopted workflow is qualitatively described in the flow chart in Fig. 2.

187 2.3.1 *Image acquisition and binarization*

188 Thin sections of marble samples described in paragraph 2.1, representative of pre- and post-weathering conditions,
189 were analyzed and compared. The images were acquired using a Leica MZ6 microscope (40X magnification) and
190 photographed by means of the Panasonic Lumix CMD-GF6 digital camera in *.tiff format at 12 Mpixels, with an
191 image resolution of 0.8 μm per pixel. Square subsections of 2.47 mm per side were extracted to avoid the peripheral
192 darkening (vignetting) reproducing the optical edge of the microscope's light path. Digital processing was then
193 applied to the images to highlight and extrapolate the impregnated paths according to the following steps:

194

- 195 1 Preliminary tuning of image parameters such as intensity, gamma, saturation, brightness and contrast is
196 applied to highlight the impregnated paths: originally blue on a gray background, impregnated paths
197 become light green on a purple background (see Fig. 5).
- 198 2 Gauss blur ($\mu=0$, $\sigma=3$) is applied to avoid artificial path fragmentation due to noise.
- 199 3 Image is binarized according to a color-based mask:

- 200 a. Being the impregnated paths green, a greenness index (i_g) is calculated for each pixel:

$$201 \quad i_g = \frac{g}{r+b} \quad (1)$$

202 Where r, g and b are the normalized RGB components of the images. The color index approach
203 is borrowed by image analysis of microfluidics (Mauk et al., 2013).

- 204 b. A greenness threshold (t) is fixed as the 80th percentiles of the greenness distribution within the
205 image.
- 206 c. All pixels with $i_g > t$ are assumed to be impregnated pixels and are assigned digital value 1

207 (depicted in white); all remaining pixels are assigned digital value 0 (depicted in black).
208 4 Bicubic interpolation with threshold 0.5 is applied to remove possible isolated pixels and to reduce the
209 computational cost of the subsequent analysis; the final resolution of the binarized images is 4 μm per
210 pixel.

211
212 Accuracy of image binarization was qualitatively evaluated by visual inspection. An example is shown in Fig. 6.
213 Further insights on image binarization are beyond the scope of this work.

214 A number of images representing well-spaced subsections were acquired from each thin section to guarantee a
215 statistical representativeness of the results. The number of images depends on the degree of heterogeneity of the
216 pore network observed within the thin section e.g., higher heterogeneity requires a higher number of images to
217 statistically represent the geometrical layout of the pore network.

218 High heterogeneity was observed, especially in the non-weathered and in the transversal sections. Five images
219 were acquired for the weathered horizontal sections (epar1, epar2 and epar3), while nine images were considered
220 for the non-weathered thin section (initial) and for the vertical (transv). The latter were divided in three groups: 3
221 subsections near the top (transv1), 3 in the middle (transv2) and 3 near the bottom (transv3) (see Fig. 3). This
222 subsection grouping allows the correlation between the horizontal and transversal subsections through the
223 association of epar1-transv1, epar2-transv2 and epar3-transv3 subsections as qualitatively shown in Fig. 4. For
224 example, some subsections are shown in Fig. 5 while the image binarization process is shown in Fig. 6 for one
225 subsection of transv2.

226 2.3.2 *Path identification in the porous domain*

227 The pore network is characterized by the identification of paths based on the approach presented by Viberti et al.
228 (2020) which relies on the A* pathfinding algorithm (Hart et al., 1968; Nilsson, 2014). A* is widely used to search
229 for the shortest path between a starting and an end point (Russel and Norvig, 2018). Each calculated path is
230 represented by a continuous graph developing from an initial to a final node which are connected through a set of
231 nodes and edges. Each node is identified by its coordinates. Only the continuous paths able to connect an initial
232 and final node are stored and used for pore network description (Viberti et al., 2020, Salina Borello et al., 2022).
233 However, when dealing with a marble pore structure characterized by truncated connectivity, the application of
234 A* to the binarized image is less effective due to the significant presence of dead-end paths (i.e., paths forming at
235 the initial node but not reaching the associated final node). Such paths would not be stored, thus blocking the
236 exploration of the inner part of the image. Therefore, a better characterization of the pore network of the poorly

237 connected areas of the image is achieved by adopting some modifications in the algorithm.
238 First of all, dead-end paths are recorded and accounted for. This is achieved by identifying the point at which a
239 dead end is reached during the path construction and store the path up to that point. Furthermore, each binarized
240 2D image is subdivided into sub-windows Fig. 7b) and inlet/outlet nodes are identified on the opposite sub-window
241 boundaries to investigate the path construction along the main directions (x,y). This allows the construction of
242 paths in the inner zones of the image even if connectivity is not preserved.
243 For the cases presented 36 sub-windows of 0.412 x 0.412 mm were adopted as a result of preliminary sensitivities.
244 For each of the 36 sub-windows, a set of nodes corresponding to the pore channel centers is located along the four
245 boundaries of the sub-image considering four main path development directions (N-S, S-N, E-W, W-E). The nodes
246 along the boundaries are then set as initial or final based on the considered direction (e.g., in the N-S scenario the
247 initial nodes are located on the top boundary while the final nodes on the bottom boundary). Along each direction
248 A* is run for each initial/final node pair combination giving a total number of $n_{initial} \times n_{final}$ output paths for
249 each main direction. Each path is resampled so that a path node is placed at each pixel crossed by a path (Viberti
250 et al., 2020). Eventually, the four sets of paths (N-S, S-N, E-W, W-E) are merged for each window (Fig. 7c-e).
251 The final output that accounts for all the 36 sub-windows is shown in Fig. 7d. The construction path process
252 described above can be highly optimized through parallelization.

253 2.3.3 Pore space characterization

254 The analysis of the weathering effect on marble slabs is carried out through the statistical characterization and
255 comparison of the pre- and post-weathered marble samples. Total porosity is calculated for each binarized image
256 by simply computing the ratio between void (e.g., pores) and total image area. Furthermore, the identified paths
257 are exploited for inner pore network characterization. The local pore radius is calculated at each path node location
258 along each path. This is achieved by identifying the local path direction (path slope) and by counting the number
259 of pore cells (e.g., white pixels) along the axis orthogonal to the local path direction as qualitatively shown in Fig.
260 8. It is possible to calculate the pore radius at a specific node location by knowing the pixel dimension. A more
261 thorough description of the pore radius calculation is provided by Viberti et al. (2020) and Salina Borello et al.
262 (2022). Eventually, the statistical outputs are extrapolated from porosity and pore size distributions.

263 3 Results and discussion

264 For all the analyzed images, a good pore space exploration was provided both in well-connected areas (Fig. 9c and
265 Fig. 9e) as well as in poorly connected areas (Fig. 9a-b and Fig. 9d). Results on the total porosity distribution for

266 the pre- (initial) and post- weathering (epar1, epar2, epar3, transv1, transv2, transv3) sections are compared and
267 summarized as percentiles (P10, P25, P50, P75 and P90) in Tab. 5, and as boxplots in Fig. 11a where the box
268 represents the P25-P75 range, the horizontal line the P10-P90 range and the vertical line the P50. Results on pore
269 radius distribution for the pre (initial) and post weathering (epar1, epar2, epar3, transv1, transv2, transv3) sections
270 are compared and summarized as distribution percentiles in Tab. 6, as histograms in Fig. 10 and as boxplots in
271 Fig. 11b.

272 The result comparison given in Fig. 10a and 10b shows a significant pore radius increase after weathering,
273 especially at the bottom section (epar3). The increase of the pore radius after weathering is comparable in the
274 median value (P50) between epar3 (20%) and epar1 (13%); the difference is more evident in the P90 where epar3
275 shows an increase of 30% vs. 9% for epar1. However, low percentile values are almost unchanged with respect to
276 the non-weathered sample indicating that small pores were less affected by degradation. Conversely, the
277 distribution on the internal section (epar2) is almost unchanged.

278 A coherent behavior is observed on the transversal sections (Fig. 10b), where the distribution of the bottom part
279 (transv3) is shifted to higher pore radius values while the distribution of the middle part (transv2) is concentrated
280 on lower pore radius values. However, as the sections were taken along the vertical direction, quantitative results
281 are not fully comparable with the initial horizontal sections. For instance, the middle part distribution of the
282 transversal section (transv2) shows lower percentiles with respect to the initial section for both total porosity and
283 pore radius.

284 The significant change in pore structure highlighted by the pore radius distribution is confirmed by a significant
285 increase in total porosity. By comparing total porosity calculated from the horizontal section of the non-weathered
286 marble (initial) with sections of naturally weathered specimens (epar1, epar2 and epar3) (Fig. 11a), the porosity
287 increase, in terms of P50, is about 90% for epar3 and 54% for epar1 and even doubled if considering P25 (about
288 170% for epar3 and 123% for epar1). A not negligible porosity increase is observed also in epar2, but way lower
289 than in the other two sections.

290 The same trend is observed at the transversal sections: bottom subsections (transv3) show a significantly higher
291 porosity value with respect to the other subsections (transv2 and transv1).

292 The detected degradation is in good agreement with the decreasing of mechanical resistance observed in
293 experimental measurements of flexural strength and Ultrasound Pulse Velocity (Tab. 1). In fact, the increase in
294 the average size of the pores is closely correlated both to the decrease in flexural strength and to the reduction in
295 the ultrasound propagation speed. Moreover, the experimentally measured increase of more than 200% in water
296 adsorption (Tab. 3 and Tab. 4) is coherent with the 170% increase of P25 of total porosity observed on epar3.

297
298 The analysis carried out when applying the A* algorithm on 2D thin section images from pre- and post- weathered
299 marble slabs, provide a quantitative characterization of the 2D pore structure alteration. Within each identified
300 group (top, mid, bottom in fig. 4) the corresponding epar and transversal sections show a coherent behavior. It
301 stands to reason that a 2D analysis can qualitatively mirror a similar alteration degree of the pore structure in the
302 three-dimensional space. However, in order to quantitatively describe the 3D pore network characteristics and the
303 propagation of the weathering effect within the porous domain of the rock sample, a more thorough analysis would
304 require further investigation using 3D micro-CT image as an input for A*, which could then be easily applied to
305 the 3D rock image (Salina Borello et al., 2022).

306 **4 Conclusions**

307 Stone degradation induces a change in the pore structure resulting in the reduction of mechanical resistance of the
308 material. Therefore, the evaluation of a change in porosity as well as in the pore structure can provide insights on
309 the degree of transformation of the physical characteristics of the stone.

310 In this study, several samples of a marble slab, both in natural conditions and after 10 years of natural weathering,
311 have been analyzed to study the relationship between the weathering effect and porosity and pore structure
312 variation.

313 An automatic approach has been used to quantitatively evaluate the pore radius distribution within the porous
314 domain. The method has been applied to 2D binarized images obtained from the digitalization of marble thin
315 sections pre- and post- weathering. The images were analyzed using the A* path finding algorithm. This algorithm
316 can efficiently work with complex pore structure being less affected by the geometry of the porous domain. It is
317 possible to calculate the local pore radius extension along each identified path. The pre- and post- weathering pore
318 radius distribution comparison allows a quantitative evaluation of the degree of variation of the pore structure.

319 The results highlight an increase in water absorption which occurred naturally in the specimen at 10-year exposure
320 compared to the non-weathered sections. The increase in the average size of the pores correlates well with the
321 results obtained from conventional laboratory tests, which highlight a decrease in flexural strength, a reduction in
322 the ultrasound propagation speed and an increase in water absorption.

323 Future work should be focused on the investigation of pore space connectivity distribution within the image. The
324 A* can be easily applied to extract this data. Connectivity could be then coupled with pore size variation to obtain
325 further insights on the effect of weathering to the pore structure.

326

327 **Data Availability Statement**

328 Some or all data, models, or code that support the findings of this study are available from the
329 corresponding author upon reasonable request, such as pore throat calculation script.

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475 **List of figure captions**

476 Fig. 1: Thin section in parallel light (left) and in polarized light (right) of the marble C1 (long side is of 1,37 mm).

477 Fig. 2: Workflow

478 Fig. 3: Qualitative representation of a thin section image subdivision into subsections. Example of the transversal
479 thin section in which three main groups are identified, each having 3 subsections, along the top row (transv1),
480 middle row (transv2) and bottom row (transv3).

481 Fig. 4: Qualitative representation of the weathered thin section position with respect to the marble slab and the
482 correspondence between epar sections and transv subsections.

483 Fig. 5: Images of some subsections from thin sections of impregnated marble, after preliminary image processing:
484 (a) non- weathered, (b) epar2, (c) epar3, (d) transv (middle), (e) transv (bottom - center).

485 Fig. 6: Binarization process: (a) image from thin section, after preliminary image processing; (b) superposition of
486 image and binary mask; (c) downsampled binary image.

487 Fig. 7: Schematic representation of the approach used to increase algorithm exploration in poorly connected areas:
488 (a) original binarized image; (b) image subdivision into 36 sub-windows; (c) example of path creation result within
489 an individual sub-window; (d) final output image that accounts for the contribution of all the 36 sub-windows; (e)
490 path creation along the main four directions (N-S, S-N, E-W, W-E) and path merging within a sub-window (right).

491 Fig. 8: Qualitative representation of pore throat description along a path. At each path node individuated by A*
492 the pore size is calculated perpendicularly to the local path direction. Only a few path nodes are shown as example.

493 Fig. 9: Examples of paths identified within the porous structure of the binarized images: (a) non- weathered, (b)
494 epar2, (c) epar3, (d) transv (middle), (e) transv (bottom - center).

495 Fig. 10: Comparison of pore radius distribution (a) in the horizontal sections before and post weathering, and (b)
496 in the three subdivisions (top, middle, bottom) of the transversal sections of the weathered sample.

497 Fig. 11: Statistical comparison between the horizontal and vertical subsections: (a) Pore radius distribution; (b)
498 porosity distribution. The vertical lines represent the mean values, the box limits are the P25 (left) and the P75
499 (right) values while the line limits represent the P10 (left) and the P90 (right).

500

501 Table. 1: Final results of UPV measurements: Velocities (v), standard deviation (St. dev.) and variations between
 502 non-weathered and weathered specimen (Δv) at different ultrasound oscillation frequencies (f).

Specimen	f = 33 kHz			f=250 kHz		
	v [m/s]	St. dev. [m/s]	Δv [%]	v [m/s]	St. dev. [m/s]	Δv [%]
non-weathered	2422	54	-16,43	3823	12	-42,32
weathered	2024	187		2205	193	

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Table. 2: Flexural strength (σ) test results.

Specimen	σ [MPa]	St.dev. [MPa]	$\Delta \sigma$ [%]
non-weathered	12,9	4,5	-28,48
weathered	9,2	1,9	

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Table. 3: Final values of the water absorption capacity (WA) obtained by means of contact sponge.

Specimen	WA $\left[\frac{g}{cm^2 \cdot min}\right]$	St. dev. $\left[\frac{g}{cm^2 \cdot min}\right]$	ΔWA [%]
non-weathered	3,37E-03	1,69E-03	293,75
weathered	1,33E-02	8,05E-03	

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Table. 4: Final values of the water absorption capacity (Ab) obtained at atmospheric pressure.

Specimen	Ab [%]	St.dev. [%]	Δ Ab [%]
non-weathered	0,186	0,072	203,49
weathered	0,564	0,065	

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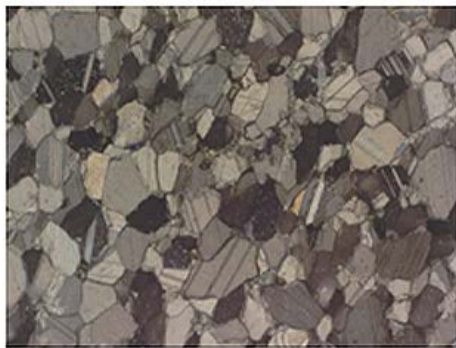
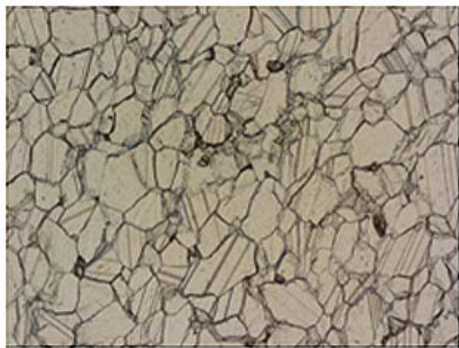
Table. 5: Percentile values of the porosity distribution.

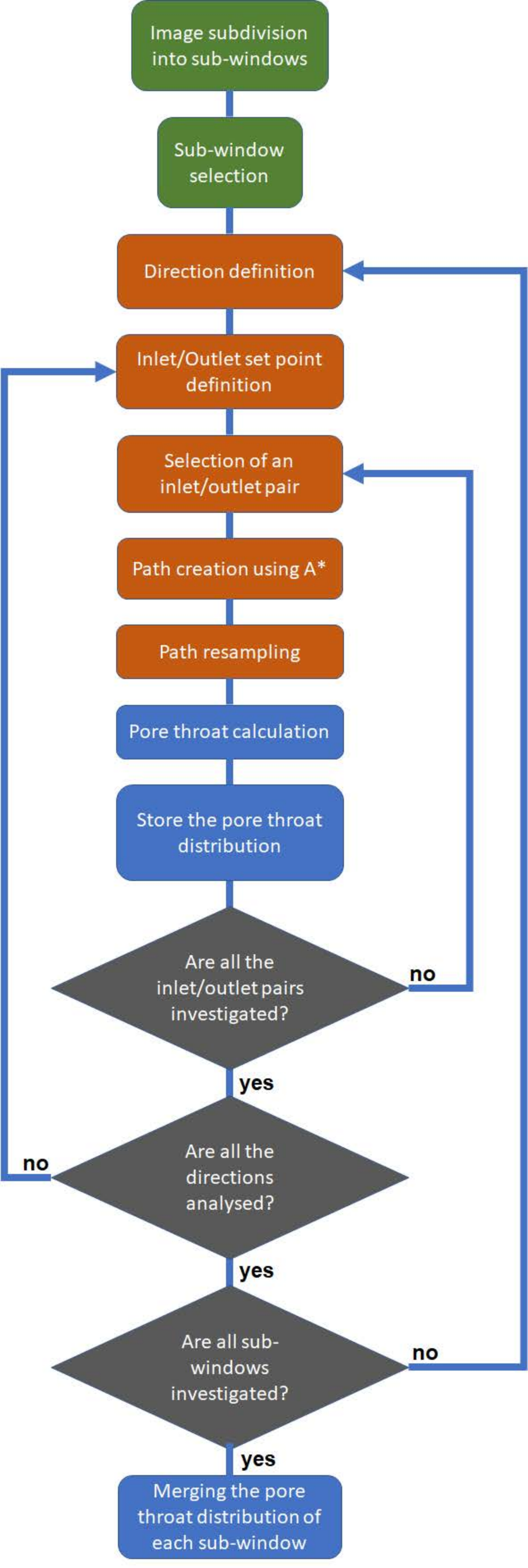
Section	Porosity (%)				
	P10	P25	P50	P75	P90
Initial	5.3467	8.1283	14.5186	21.8309	23.5754
Epar1	17.8861	18.1874	22.3606	26.8697	28.3669
Epar2	16.8431	17.9868	19.5253	23.8747	31.5994
Epar3	20.7917	22.0146	27.5460	28.5460	28.5814
Transv1	6.3058	7.8469	12.4700	20.2944	22.9025
Transv2	10.6411	10.7863	11.2219	18.0451	20.3194
Transv3	18.7181	20.0354	23.9875	26.2819	27.0467

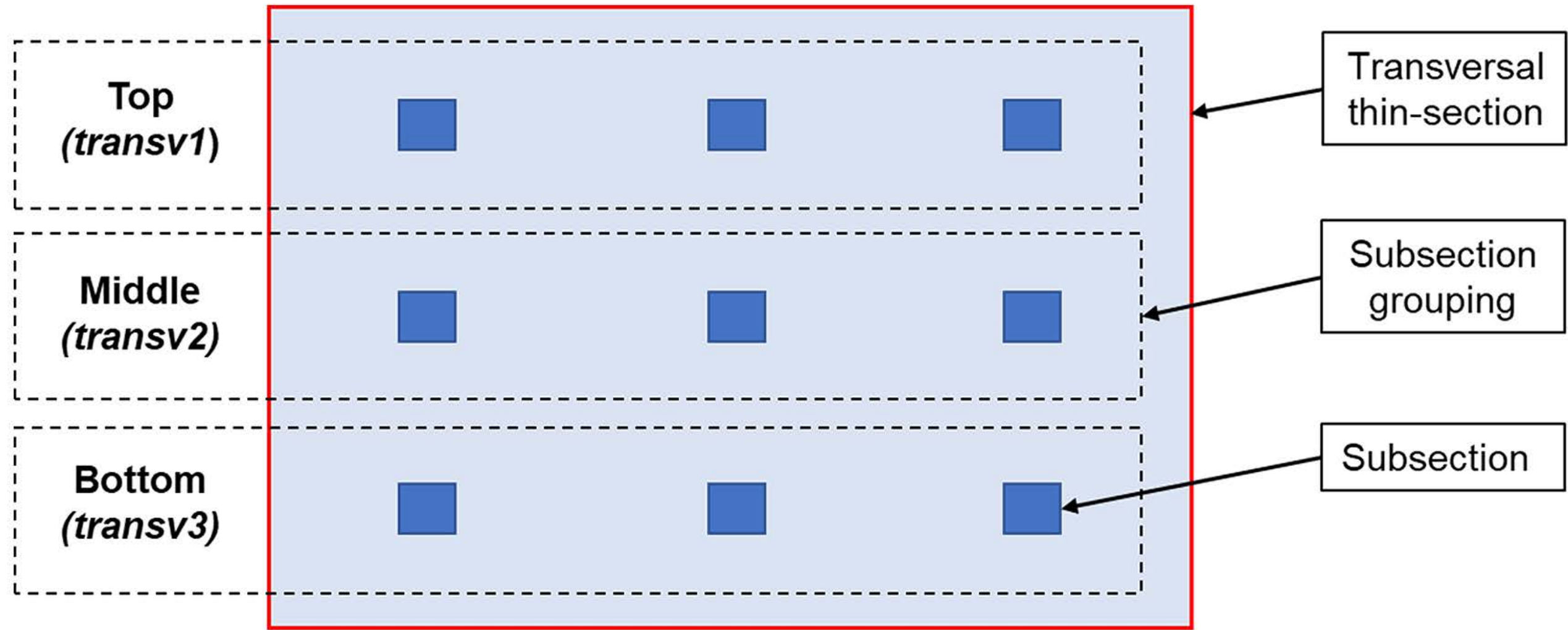
518

Table. 6: Percentile values of the pore radius distribution.

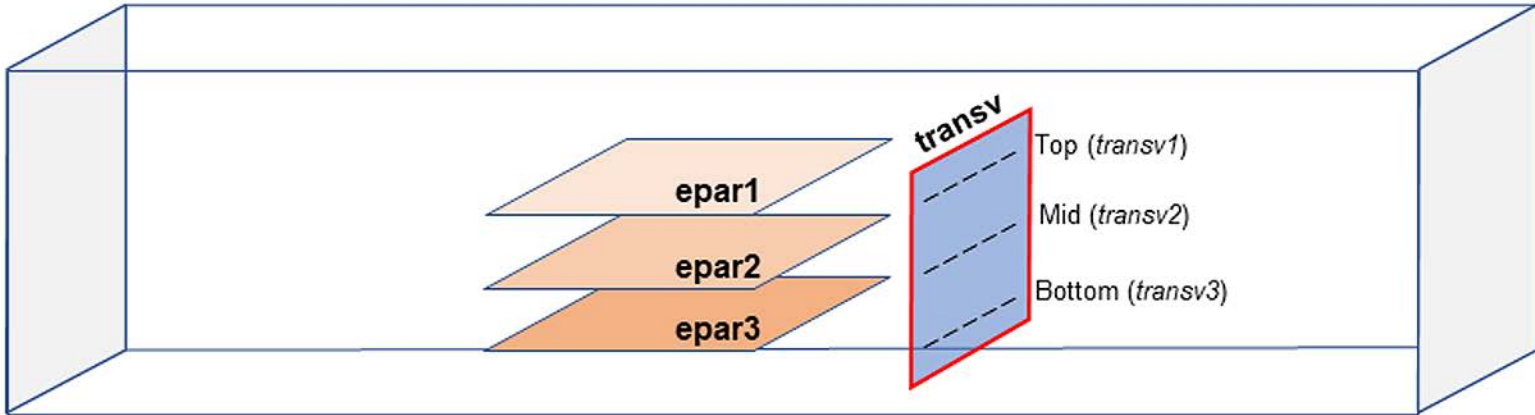
Section	Pore Radius Distribution (μm)				
	P10	P25	P50	P75	P90
Initial	4	5.6569	10	16.9706	26
Epar1	4	6	11.3137	16.9706	28.2843
Epar2	4	6	10	16.9706	28
Epar3	4	8	12	20	33.9411
Trasnv1	2.8284	5.6569	8.4853	16	26
Transv2	2.8284	5.6569	8.4853	14.1421	24
Transv3	4	6	10	16.9706	30

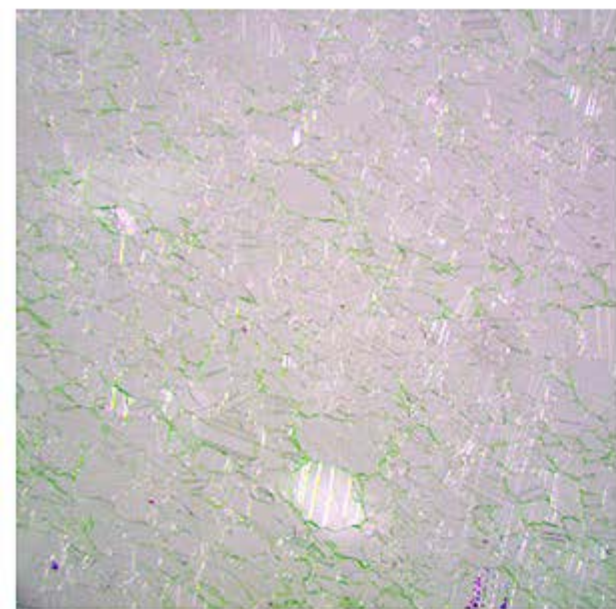






Marble slab

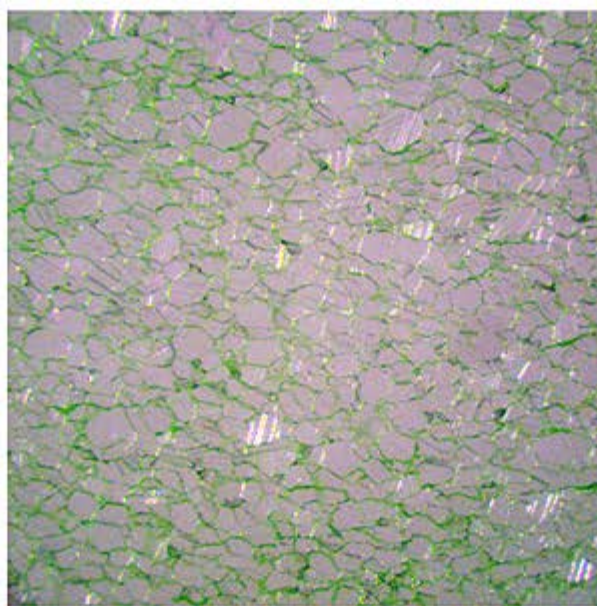




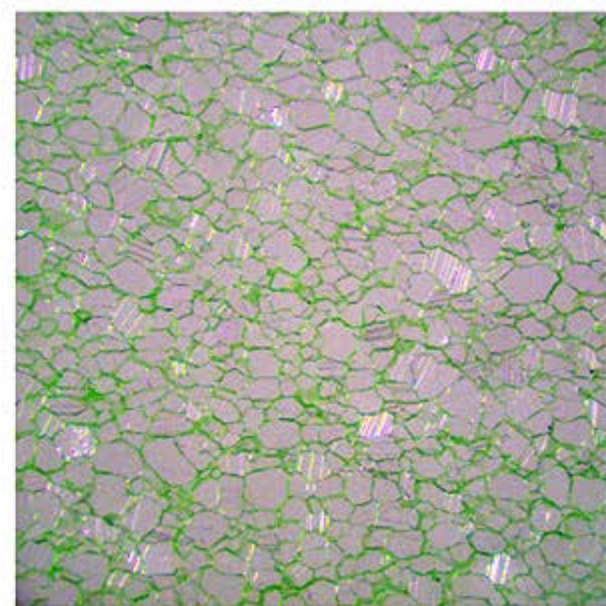
(a)

0.5 mm

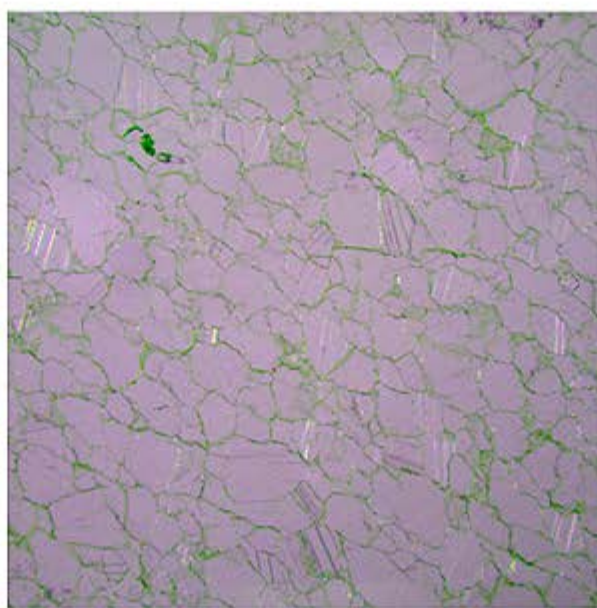
Grain
Impregnated pore



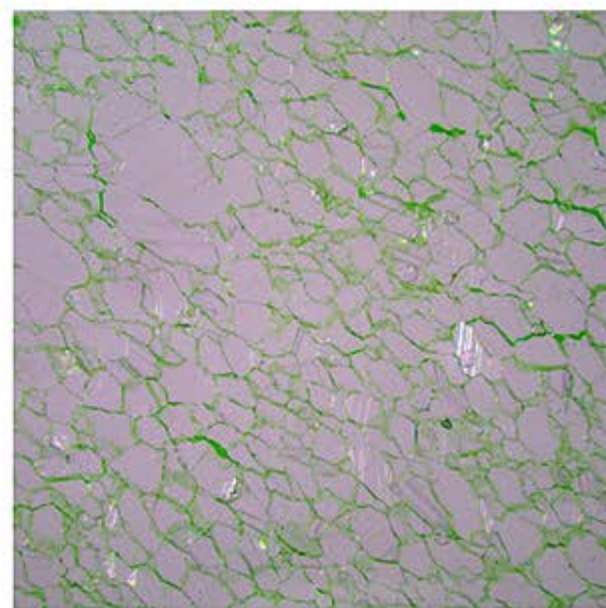
(b)



(c)

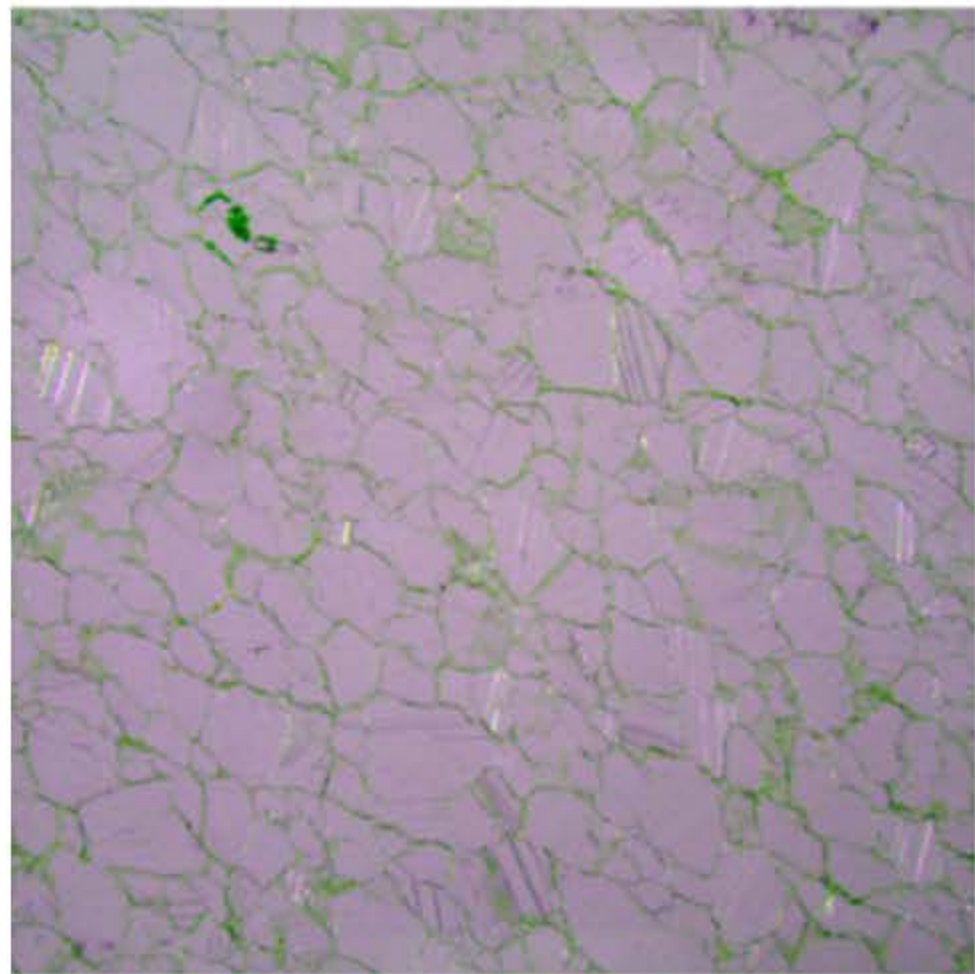


(d)



(e)

(a)



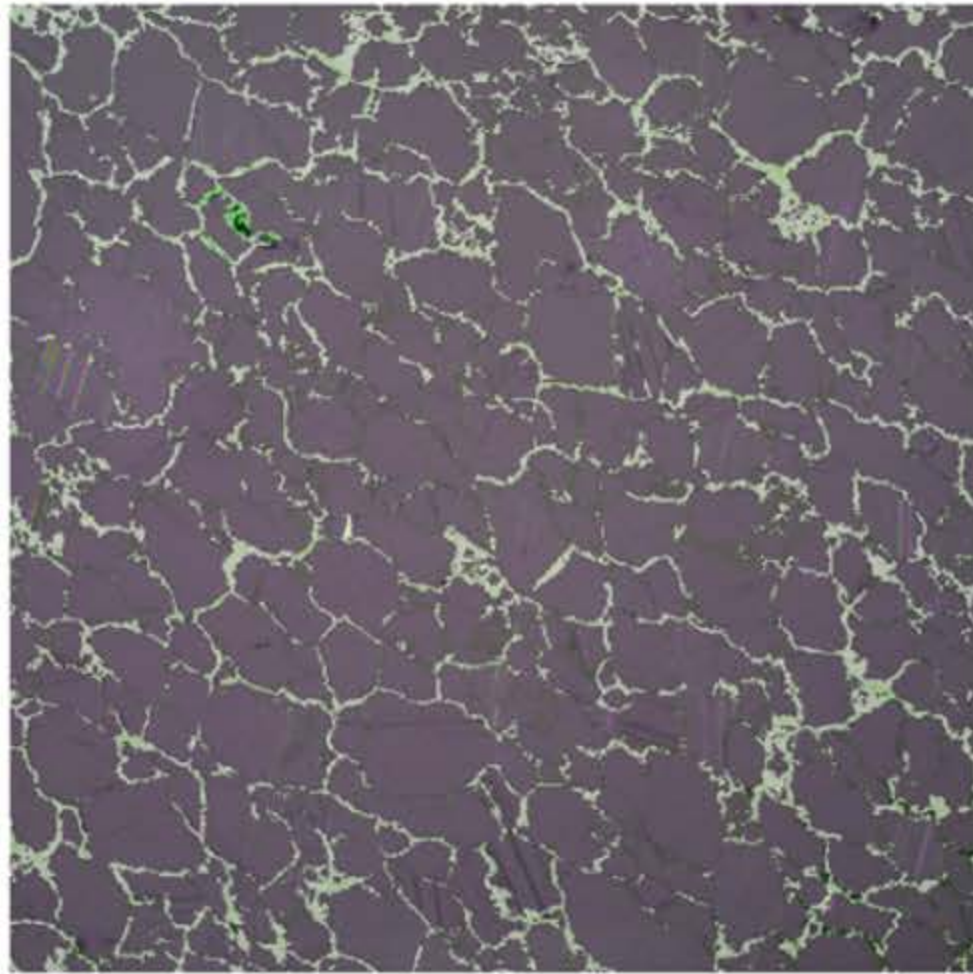
Grains



Impregnated path

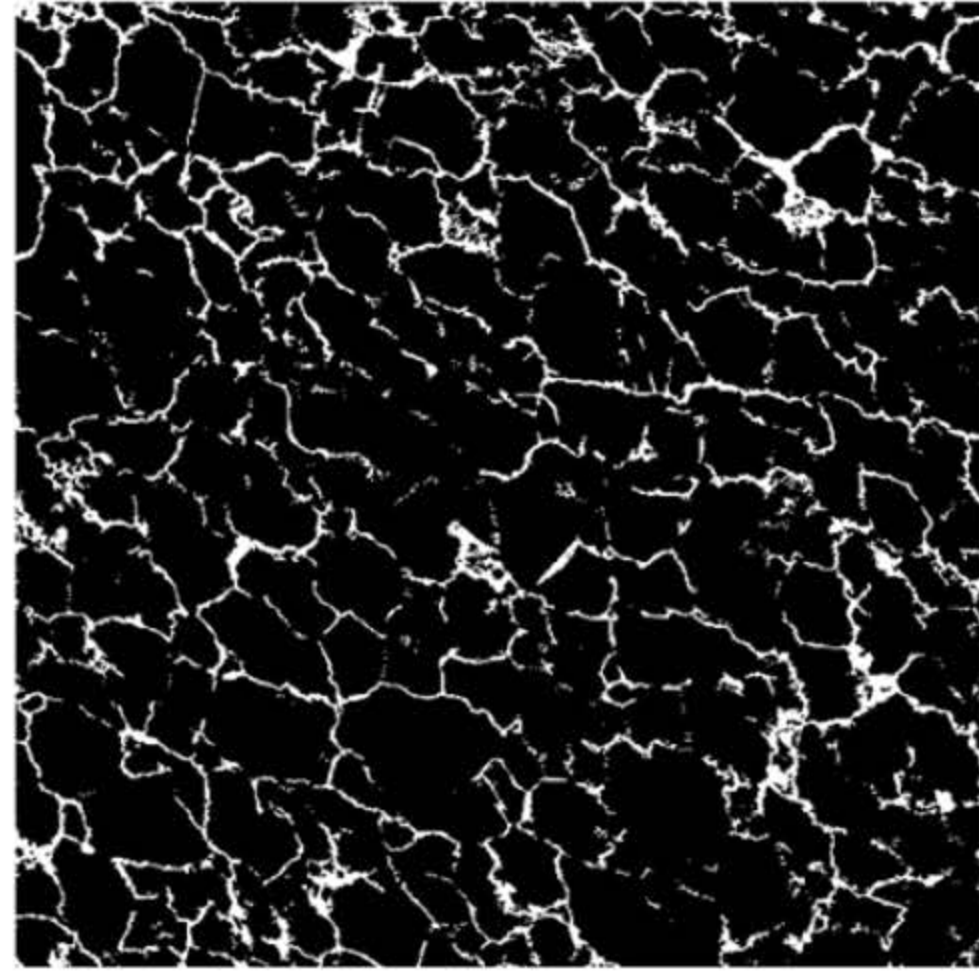
0.5 mm

(b)



Mask

(c)

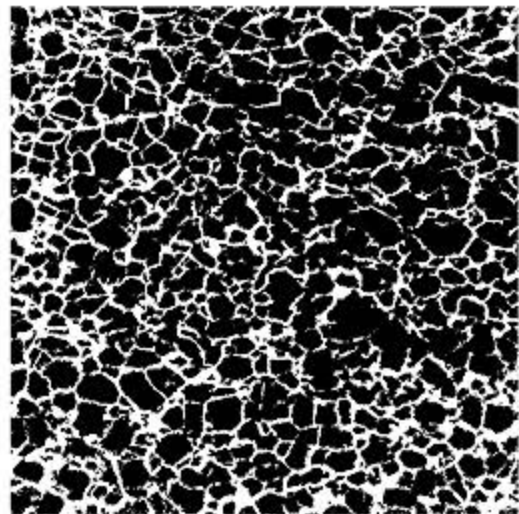


Grains

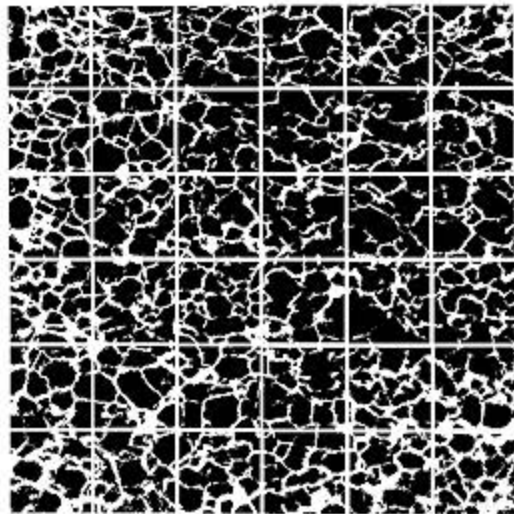


Pores

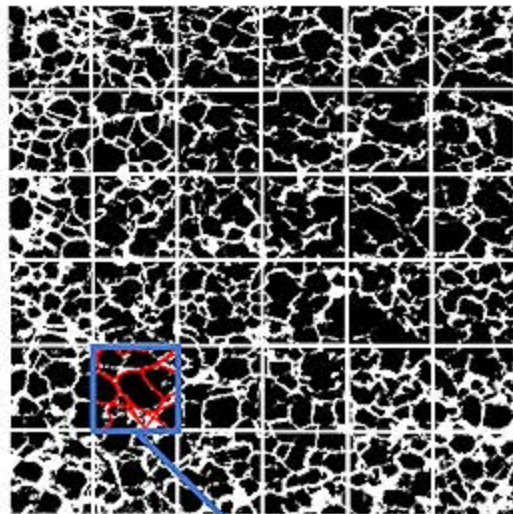
(a)



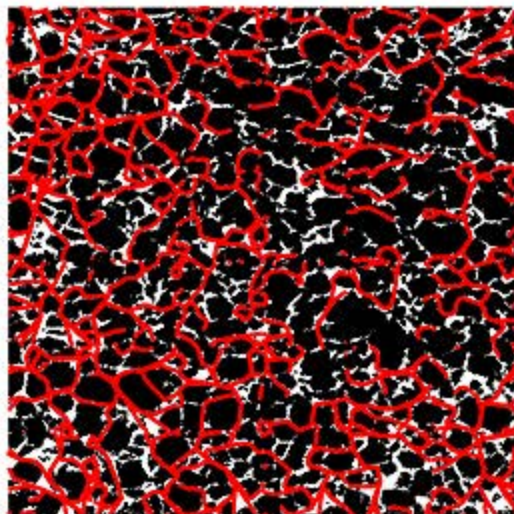
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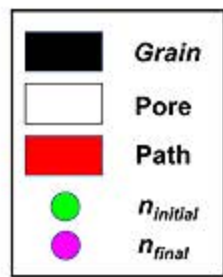
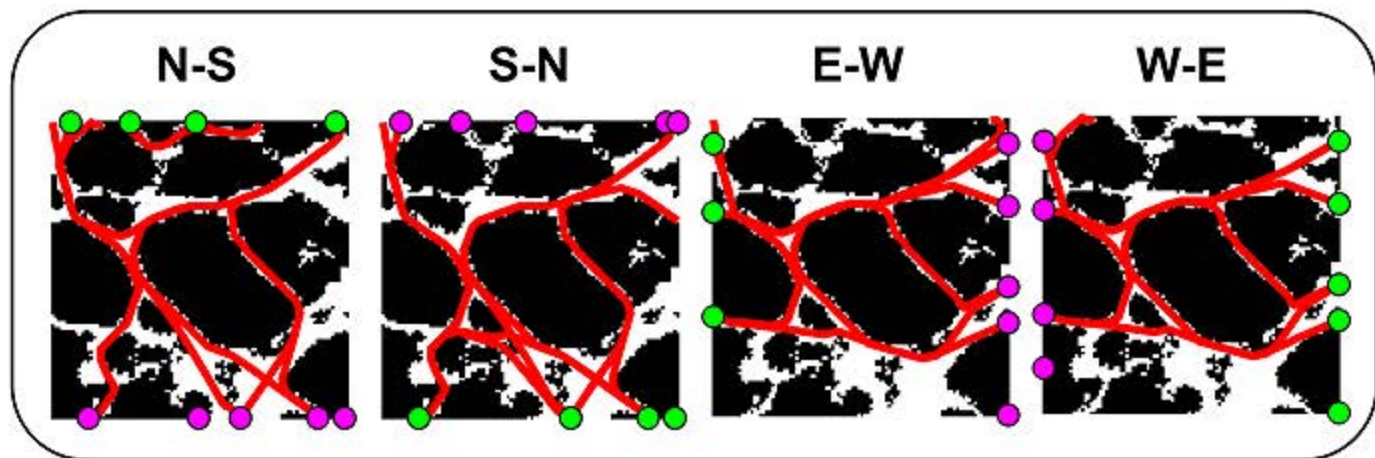
(c)



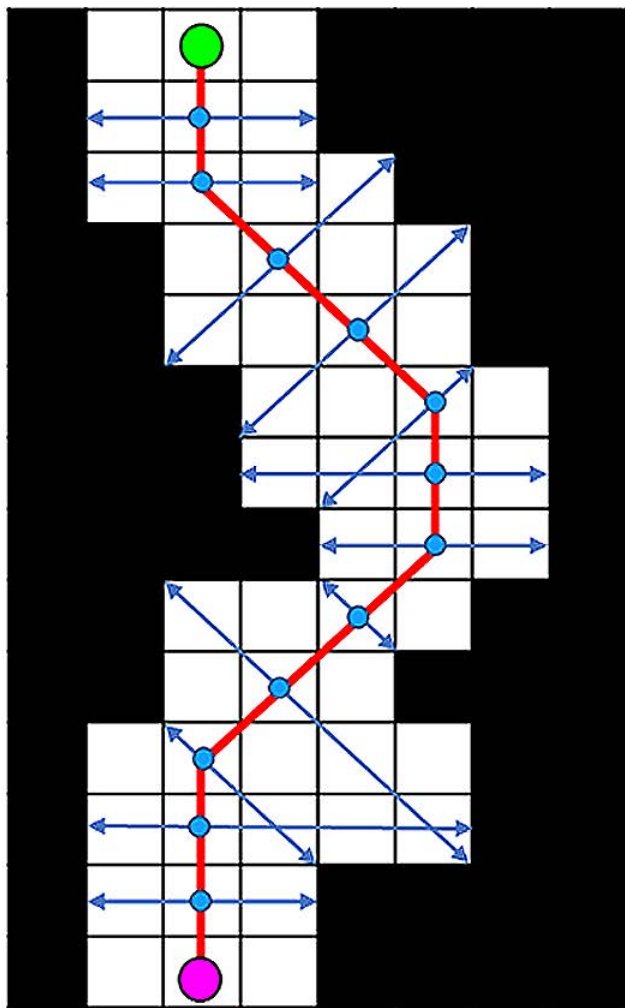
(d)



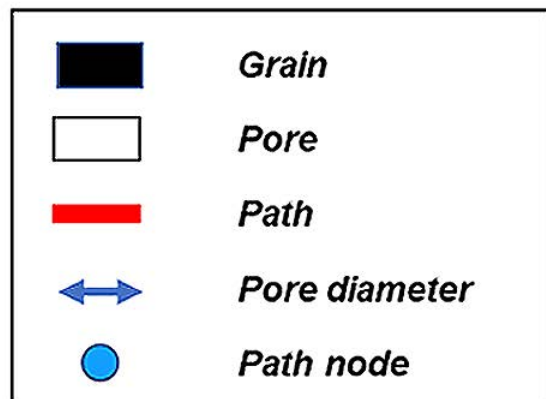
(e)

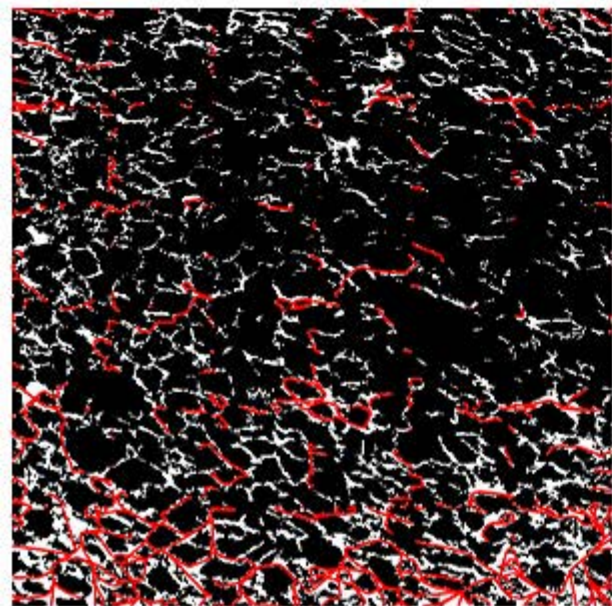
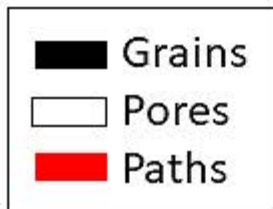


$n_{initial}$



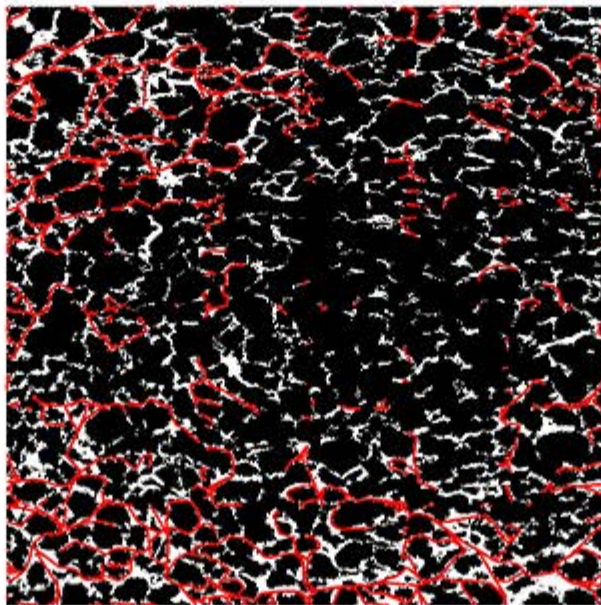
n_{final}



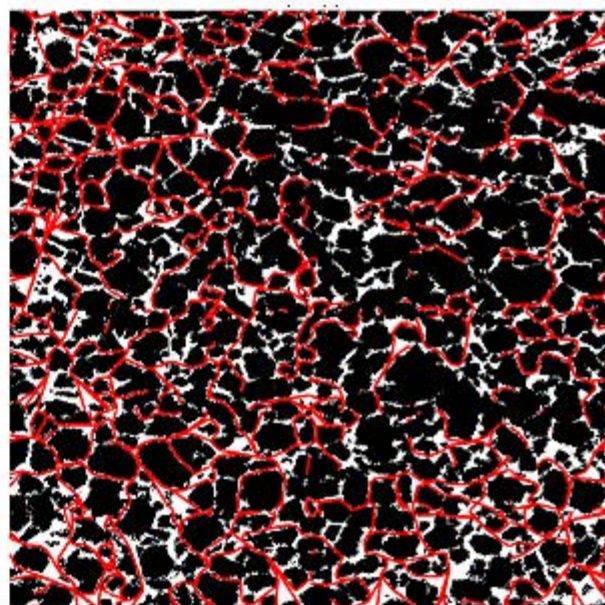


(a)

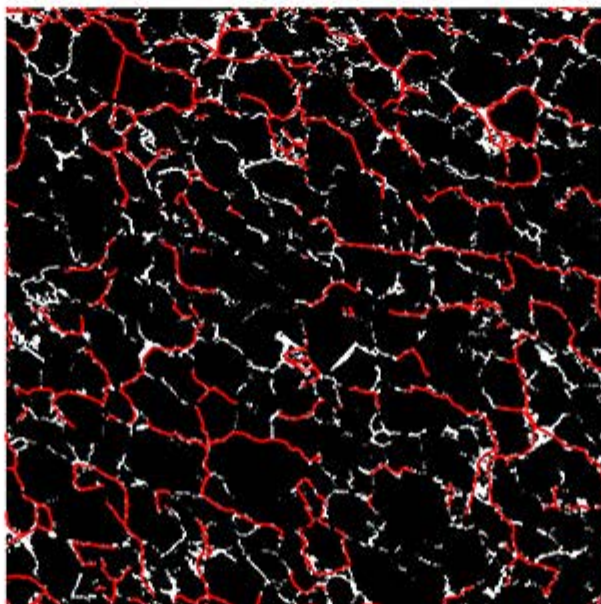
0.5 mm



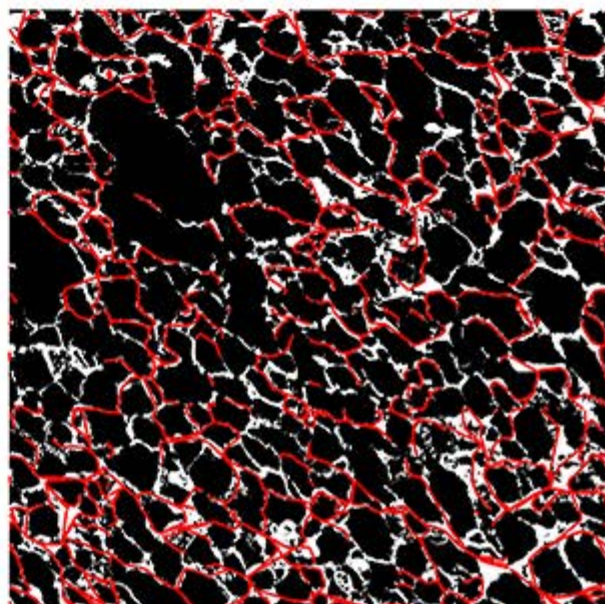
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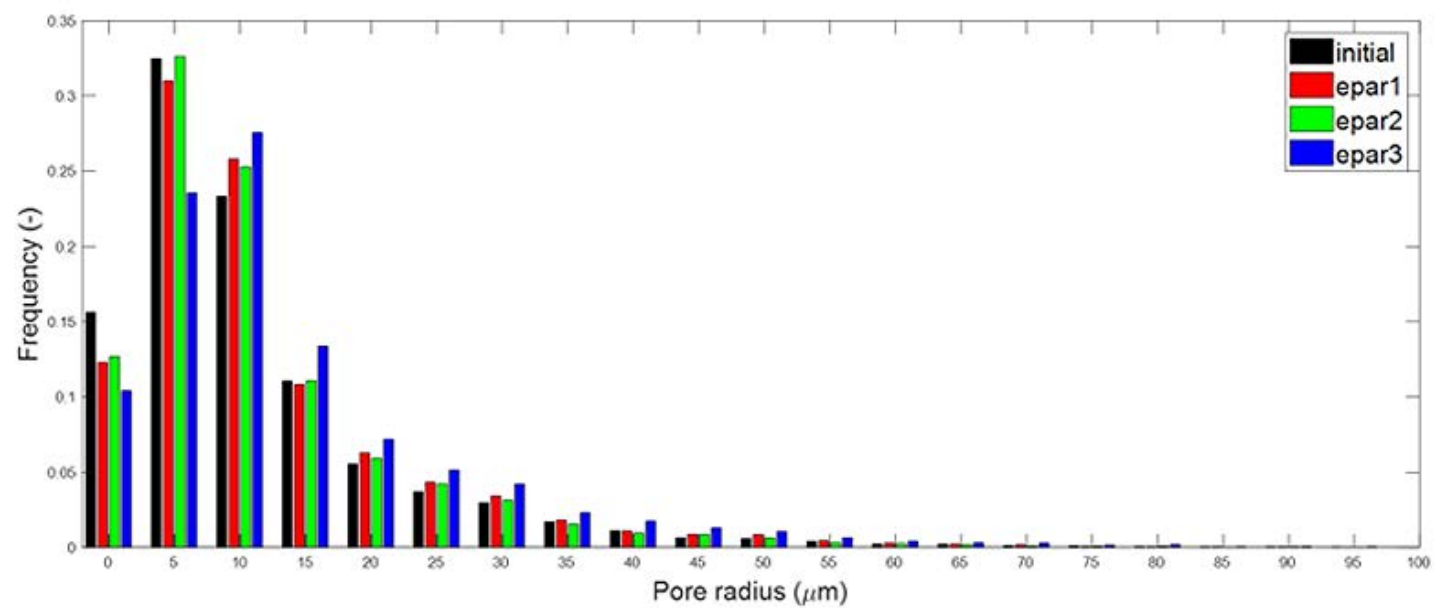
(c)



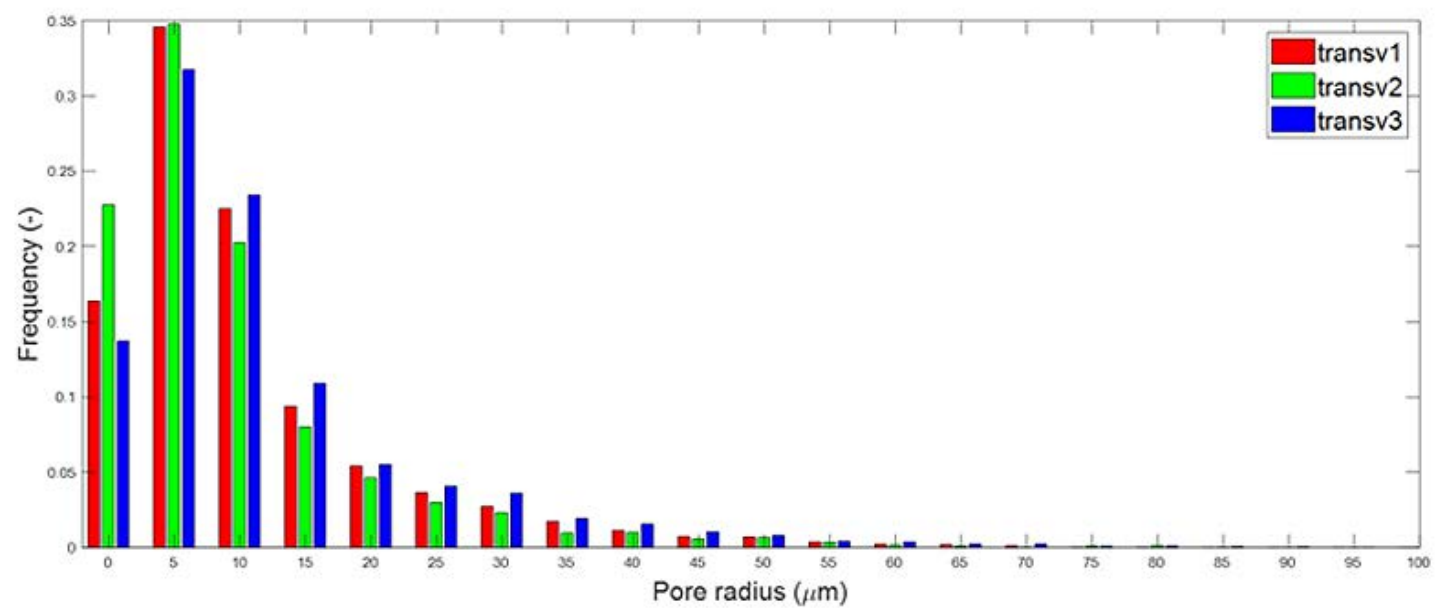
(d)



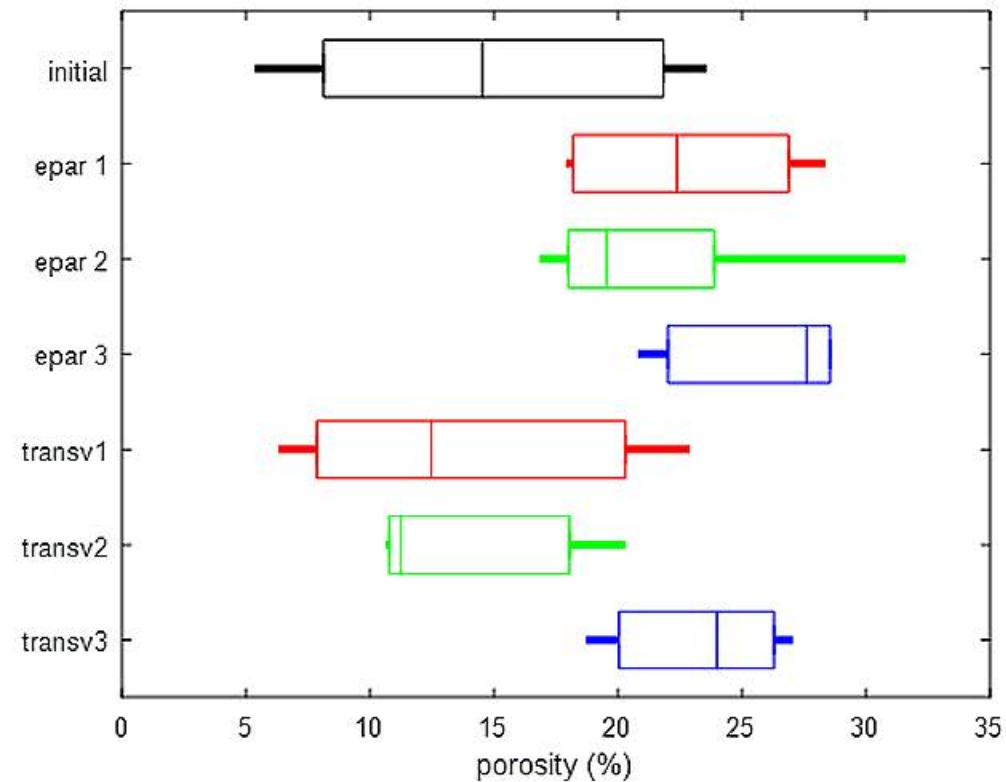
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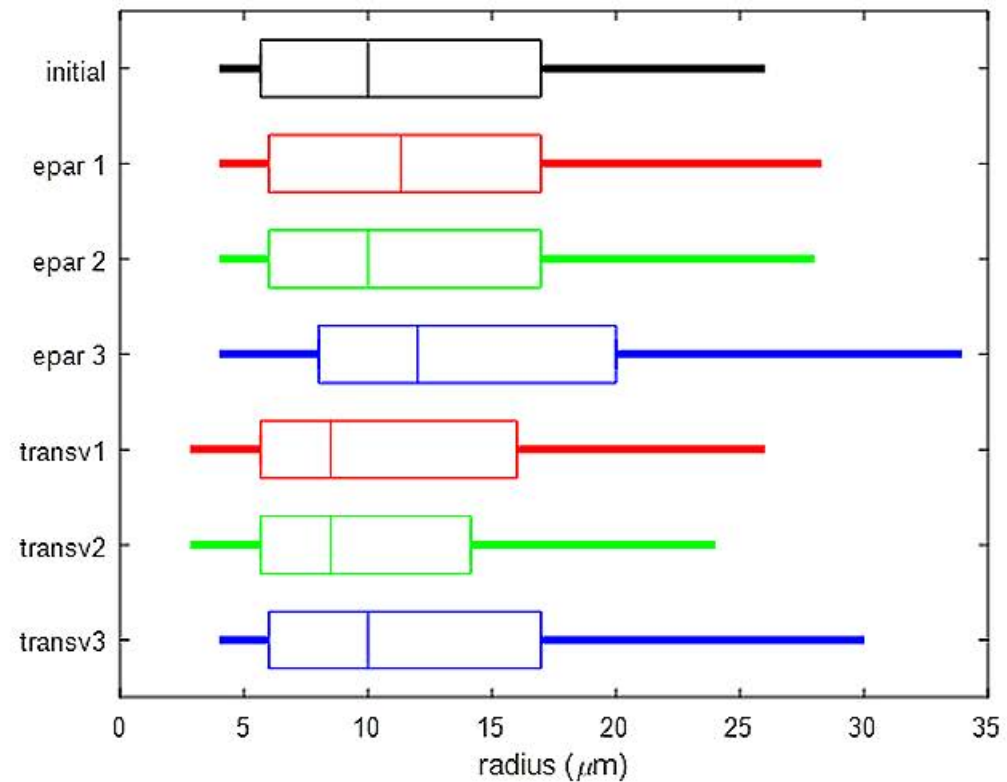
(a)



(b)



(a)



(b)