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Particle-Scale Observation of Seepage Flow in Granular Soils Using PIV and CFD

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Abstract

Seepage-induced instabilities pose a challenge in many geotechnical applications. Particle-scale mechanisms govern the initiation of instability. However, current understanding is based on a macro-scale perspective that draws on continuum mechanics. Recent developments in imaging and numerical analysis can provide the particle-scale fundamental perspective needed to develop a comprehensive insight. This contribution demonstrates the value of combining particle-scale experimental and numerical studies. The experiments consider transparent soil samples created using refractive image matching and monitored by particle image velocimetry (PIV). Three-dimensional pore topology is extracted from a series of 2D images and imported into computational fluid dynamics (CFD) simulations. Permeability is estimated by three distinct approaches: using flow rate, PIV- and CFD-generated data. The flow fields obtained from PIV and CFD are in good agreement considering both flow rate contour plots and flow rate distributions; this demonstrates the successful reconstruction of three-dimensional pore structure and flow-field analysis. The comparison also reveals that the side boundary effects in CFD simulations are constrained within a limited region. The multi-plane results characterize the variance of flow

23 velocity with the three-dimensional pore topology. Finally, the fluid-particle interactions obtained
24 from CFD results show a larger variance in the angular particle packings.

25

26 **Keywords:** Particle-scale behaviour; permeability; seepage; laboratory tests; numerical modelling

27

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29

30 **1. Introduction**

31 A comprehensive understanding of seepage flow in cohesionless or granular soils is critical in
32 many geotechnical analyses associated with dewatering, dam and flood embankment design, slope
33 stability etc. Seepage analyses to inform engineering design typically adopt a continuum approach
34 with macro-scale parameters. However, the fundamental processes that lead to the internal erosion
35 in embankment dams (ICOLD, 2015) and settlement due to fines migration during dewatering
36 (Preene & Rosser, 2012) initiate at the particle scale. Understanding these processes is important
37 to inform robust approaches to design, e.g. considering whether to continue to use hydraulic
38 gradient rather than seepage velocity when assessing the risk of a seepage-induced instability
39 (Vogt et al., 2015). Incidents such as the failure of Gouhou Dam in 1993 (Zhang & Chen, 2006)
40 and the serious sinkhole incident at WAC Bennett dam in Canada in 1996 (Muir Wood, 2007)
41 remind us of the significant hazard that can be posed by seepage instabilities. Globally, seepage
42 instabilities have caused about 50% of recorded embankment dam failures (Foster et al., 2000).
43 This contribution adopts a combination of particle image velocimetry (PIV) and computational
44 fluid dynamics (CFD) to quantify seepage flow in the void space of a transparent granular soil and
45 to determine the fluid-particle interaction forces that can lead to particle migration and instability.

46 Saturated transparent soils can be created by refractive index (RI) matching between model
47 (analogue) sands formed of borosilicate glass and carefully selected pore fluids. Illumination by a
48 laser light sheet enables visualization of the particles along a plane within the material, and so the
49 internal mechanisms that underlie complex macro-scale behaviours can be studied (Hunter &
50 Bowman, 2018; Iskander et al., 2015). Hunter and Bowman (2018) developed a transparent soil
51 rigid-walled permeameter to study the particle-scale mechanisms that occur during internal erosion
52 in gap graded particulate systems. They considered a single plane within the sample and
53 successfully imaged particle migration. However, there was no local measurement of fluid flow,
54 and the data generated were two-dimensional. Saleh et al. (1992) and Northrup et al. (1993) applied
55 Particle Imaging Velocimetry (PIV) to tracer particles in the pore fluid to generate 2D images of
56 flow in transparent porous media created using RI matching. Peurrung et al. (1995) applied Particle
57 Tracking Velocimetry using a similar experimental set-up, again obtaining 2D data. Alternatively,
58 the flow fields in 2D transparent micromodels fabricated with soft lithography may be determined
59 with micro-PIV (Karadimitriou et al., 2013; Karadimitriou & Hassanizadeh, 2012; Meinhart et al.,
60 1999). However, it is the 3D geometry of the void space that controls flow in the pores; a complete
61 picture cannot be obtained from planar data. 3D flow data can be obtained using tomographic
62 technologies which can be used on opaque materials, e.g. Magnetic Resonance Imaging MRI and
63 Particle Emission Tomography PET (Khalili et al., 1998; Sederman et al., 1997). However, the
64 data generated are often of limited spatial or temporal resolution.

65 Computational fluid dynamics (CFD) has been applied to study flow in porous rocks
66 (Mostaghimi et al., 2013; Nunes et al., 2015; Piller et al., 2014) and in sands (Garcia et al., 2009;
67 Taylor et al., 2016, 2017). In these studies, the topology of the pore space was obtained from
68 micro-computed tomography scans. The volumes of soil/rock considered was relatively small, and

69 ideal flow boundary conditions were typically assumed along the sides of the sample. While the
70 resulting permeabilities appeared reasonable, the accuracy of the velocities within the pores could
71 not be verified, and the implications of the idealized boundary conditions could not be quantified.
72 Huang et al. (2008) and Thaker et al. (2019) determined the 3D topology of the void space in
73 transparent samples, and applied CFD to simulate flow and compared these data with flow field
74 data acquired using PIV. However, the comparisons considered only a single plane and spherical
75 particles.

76 Developing the work of Hunter & Bowman (2018), this study adopts refractive-index-matched
77 transparent materials and PIV to monitor the flow field in a transparent permeameter. A method
78 was developed to precisely control the laser sheet position in order to enable multiple images of
79 the pore topology and the fluid-flow field to be acquired so that, in contrast to earlier studies, quasi-
80 3D experimental data were recorded. Three-dimensional pore topologies reconstructed from slice-
81 by-slice scanning and image processing are incorporated in CFD simulations. This combination of
82 laboratory experiments and numerical modelling enables the following questions to be addressed:

- 83 i) Can PIV be used to develop a three-dimensional understanding of seepage flow in the void
84 space of granular soils?
- 85 ii) To what extent do the assumed flow boundary conditions compromise the accuracy of the
86 predictions of the local fluid velocities in CFD analyses of seepage flow in the void space
87 of soil?
- 88 iii) Particle migration induced by the fluid-particle interaction force initiates all of the
89 instabilities noted above. Can the combined PIV and CFD analyses enable quantification
90 of the fluid-particle interaction forces in real physical systems?

91 In a preliminary application of the approach proposed here, we considered two materials with very
92 different particle morphologies and show how this technique can be used to explore the influence
93 of morphology on flow fields and fluid-particle interaction forces.

94

95 **2. Experimental Setup**

96 *2.1. Transparent soil permeameter*

97 The experimental apparatus is a rigid-walled ‘transparent soil’ permeameter that has been
98 designed to visualize the mechanisms occurring during seepage-induced internal erosion in
99 susceptible granular media (Hunter & Bowman, 2018). Fig.1 is a sketch of the experimental device.
100 The permeameter is a rectangular cell (100 mm by 100 mm in plan area and 265 mm high). Five
101 vertical manometer ports are arranged at the back of the permeameter for local head measurements.
102 The flow is directed upward via a constant head applied at the base using an adjustable header tank.
103 Flow from the top of the cell is recirculated back into a reservoir and then pumped back into the
104 header tank. A constant head was applied, and the resulting local head values were measured using
105 the manometers located at the back of the permeameter cell. Consideration was restricted to
106 laminar, low Reynolds number flows, typically encountered in geotechnical applications. Particle
107 movement was not expected since the drag forces were relatively low compared with the particle
108 weights (i.e. gravitational force). Also, analysis of the images showed no visible particle movement
109 throughout testing.

110 *2.2. Laser and imaging systems*

111 A 1.5 mm thick laser sheet parallel to the direction of the flow was applied to the side of the
112 permeameter to illuminate a selected plane perpendicular to the z-axis in Figure 1. The light source
113 was a 1W Kvant continuous wave laser at 520 nm (green) wavelength with variable power control.
114 The laser beam was coupled from the laser head into an optical fibre, recollimated at the fibre
115 output, and then sent through a line generator lens mounted on a lens post and base plate to provide
116 height adjustment. This optical assembly was fixed on a linear micrometre stage with a 25 mm
117 travel range so that specific planes of interest could be imaged and returned to with precision over
118 long-running tests.

119 A high-speed camera, Phantom Miro 310, mounted on another linear micrometre stage with a
120 50 mm travel range was positioned in front of the permeameter cell to record images with a spatial
121 resolution of 1280×800 pixels at 200 frames/s. During each test, the position of the camera in the
122 z-direction was adjusted in accordance with the laser sheet position to retain a sharp image focus.
123 A Nikon AF Nikkor lens 85 mm was used with up to 34 mm of extension rings placed between
124 the lens and the camera sensor. All images were recorded using an aperture f -stop number of 4,
125 which was selected according to its influence on the tracer magnification, as discussed later.

126 *2.3. Tested materials*

127 Table 1 shows the physical and optical properties of the two model soils. The first sample
128 consisted of 7.5 ± 0.03 mm diameter spherical beads made of borosilicate glass purchased from
129 SiliBeads. The second sample consisted of angular particles made from Duran® glass with size
130 ranging from 6.7 to 9.5 mm (Sanvitale & Bowman, 2012).

131 The particle size was chosen based on a trade-off between different aspects related to the
132 optical technique, practical considerations and standard guidelines. As general rule, the size of the
133 particles must be large enough to ensure the tracers can flow easily through the pores without
134 blocking the channels. In addition, the procedure for Standard Test Method for Permeability of
135 Granular Soils (ASTM D 2434-68, 2000) requires the maximum particle size of the specimen to
136 be 8 to 12 times smaller than the diameter of the permeameter. Furthermore, in previous
137 experimental work (Sanvitale & Bowman, 2012) the same refractive index matched material was
138 used and it was observed that the presence of small particles produces a greater amount of scattered
139 light in the granular system owing to the slight differences in refractive indices at the grain–liquid
140 interfaces. It was found that better transparency even at the deepest illuminated sections, can be
141 obtained when large particles are used. Finally, the availability in the laboratory of a sample of
142 angular particles (that are not commercially available but hand-made, see Sanvitale & Bowman
143 2012) with gradations comparable to those of the beads was taken into account, in order to carry
144 out tests with grains of different shape but compatible drainage behaviour.

145 Each sample was prepared using a ‘slurry’ placement method to avoid entrapment of air
146 bubbles (Hunter & Bowman, 2018) to create a sample approximately 165 mm in height. In order
147 to develop a uniform pressure and velocity conditions entering the sample, a 45 mm layer of
148 ‘dispersing’ filter material, comprising a mixture of spherical borosilicate beads of 15 mm and 10
149 mm diameter, was placed at the bottom of the apparatus.

150 A hydrocarbon immersion fluid (Cargille Laboratories) was chosen to match the refractive
151 index of the glass particles (Sanvitale & Bowman, 2012; Wiederseiner et al., 2011). As well as a
152 close optical match, the fluid and solid mixture needed to behave similarly to soil and water in
153 terms of buoyancy. The effective specific gravity of the particles compared with the fluid was 2.64

154 – which is typical of soil in water. In order to achieve the best refractive index match during testing,
155 different room temperatures were used, 23 °C for the beads and 26 °C for the angular particles.
156 Figure 2(a) shows a typical outcome of refractive index matching under normal lighting conditions.
157 A small amount of Nile Red fluorescent dye, added to the fluid phase, enabled the application of
158 Planar Laser-Induced Fluorescence (PLIF) based imaging on identifying the solid particles with
159 respect to the fluid phase. To characterize the pore topology, the saturated sample was illuminated
160 by the laser sheet whose wavelength matched the absorption peak of the fluorescent dye within
161 the fluid. The resulting fluorescence (where the dye emits light at a wavelength greater than that
162 of the excitation wavelength) was recorded by the high-speed camera through a long-pass filter
163 placed over the lens to transmit only the fluorescence signal and discard the green laser light: the
164 particles show as dark on a bright fluid background.

165

166 **3. Particle Image Velocimetry (PIV) Analyses**

167 *3.1. Calibration for image size and distortion*

168 Before each test, the image size and distortion were calibrated with fixed grid dots at 1 mm ±
169 0.001 mm spacing inside the permeameter cell filled with the liquid phase at the locations of the
170 26 vertical planes imaged in the experiment. The distortion error due to the optical assembly was
171 corrected according to the procedure discussed in Gollin et al. (2017). The coordinates of the dots
172 were estimated with sub-pixel accuracy and associated with an undistorted grid and then
173 interpolated using a built-in MATLAB function Scattered-Interpolant (Brevis et al., 2011). This
174 approach adopts a linear interpolation based on Delaunay triangulation.

175 3.2. *Seed tracers*

176 The fluid flow field was imaged using reflective seed tracers dispersed in the liquid phase.
177 These seeding particles should be neutrally buoyant and small enough to follow the flow accurately.
178 Silver-coated hollow microspheres with a nominal size ranging between 5-30 μm were used at a
179 concentration of 35 mg/l. These had a density of 0.75 g/cm³, resulting in an effective specific
180 gravity of 1.13 compared to the fluid, i.e. close to unity. To ensure that the inertia effects due to
181 particle density were negligible so that the tracers would reliably follow the flow, the Stokes
182 number was calculated as follows:

$$Stk_s = \frac{\rho_s d_s^2 u_y}{18\nu\rho D} \ll 1 \quad (\text{Eq. 1})$$

183 where d_s and ρ_s are the seed diameter and density, respectively, D the bead diameter, ν and ρ the
184 fluid kinematic viscosity and density, respectively, and u_y is the axial (y-direction) fluid velocity
185 of the flow. For our set-up, the maximum Stokes number was calculated to be $Stk_s = 2.59 \times 10^{-6}$.
186 The movement of the tracers was recorded by removing the long-pass filter in front of the camera
187 lens to allow the light reflected from their surfaces to be captured. Figure 2(b) and (c) show how
188 laser illumination enables internal visualization of a plane within both spherical bead and angular
189 particle samples with the tracers. Two videos, V1 and V2 in the supplementary material, show the
190 movement of tracers in both spherical bead and angular particle samples. Figure 2(d) shows the
191 top view of the laser sheet illuminated plane with a finite thickness of around 1.5 mm.

192 3.3. *Image acquisition for 3D volumes*

193 The flow fields inside two 3D volumes were examined within each sample. The lower volumes
194 were located between manometer ports P2 and P3 and denoted as sub-volumes Beads-L and Ang-

195 L for the spherical sample and angular samples, respectively (Figure 1). The upper volumes were
196 located between manometer ports P3 and P4 and denoted as sub-volumes Beads-U and Ang-U,
197 respectively. The dimensions of sub-volumes varied slightly with the position of the high-speed
198 camera, as shown in Table 2. In each sub-volume, the flow fields on 26 planes parallel to the flow
199 directions were measured. These planes were evenly spaced at $1\text{ mm} \pm 0.001\text{ mm}$, centred in the
200 mid-section of the permeameter cell with at least 32 mm distance from the lateral sidewalls. The
201 choice of inter-plane spacing was made based on the laser sheet thickness of 1.5 mm. On each
202 plane, a series of images were taken over 2 seconds at 200 frames/s, i.e. 400 images were taken
203 per plane.

204 *3.4. PIV postprocessing*

205 An open-source software, PIVlab (Thielicke & Stamhuis, 2014), was used for image
206 processing to determine the flow velocities. PIVlab gives an Eulerian description of the
207 investigated velocity field, estimating the displacement for groups of tracers by determining the
208 peak of the cross-correlation of many small interrogation areas. This software uses a multi-pass
209 cross-correlation algorithm coupled with a window deformation technique to obtain the velocity
210 vectors (Thielicke, 2014). The 2-step correlation algorithm with decreasing window size (D_I) was
211 used to evaluate the recorded images with a final size of 32×32 pixels (approximately $1 \times 1\text{ mm}^2$
212 area), set to minimize the loss of in-plane particle pairs ensuring that the x and y displacements
213 were smaller than $D_I/4$. The loss of particle pairs between corresponding interrogation windows
214 due to out-of-plane motion was limited due to the fact that the z displacement of the tracer particles,
215 which can be assumed to be of the same magnitude as the tracer particle displacement in the x-

216 direction, was less than a quarter of the light sheet thickness (Atkins, 2016; Keane & Adrian, 1993).
217 The overlap of the interrogation windows was 50% for all steps.

218 The velocity fields for each plane position were calculated by averaging over 2 s of recorded
219 images, and the ‘instantaneous velocities’ were estimated on two successive frames separated by
220 a time steps Δt . The frame rate was 200 fps for all of the experiments. The influence of the time
221 step on the fluid velocities was studied by setting Δt equal to 5, 10, 20 and 40 ms, equivalent to 1,
222 2, 4 and 8 frames (Figure S1 is provided as supplemental material). Decreasing Δt from 40 to 10
223 ms caused an increase in the time-averaged u_y and u_x values. Further decreasing Δt from 10 to 5
224 ms led to little variation in either u_y or u_x , meaning the true maxima of velocity were captured at a
225 time step of around 10 ms. Therefore, a time step Δt of 10 ms was chosen for the PIV analyses to
226 avoid positional errors associated with reducing the time step to very low values (Gollin et al.,
227 2017).

228 The seeding density was approximately five tracers inside an interrogation window for both
229 tests (as shown in Figure S2 in the supplemental material) which is within the optimal range to
230 achieve a successful correlation and minimum random error (Thielicke, 2014). The seed image
231 size d_τ was estimated as the width of the autocorrelation peak of a typical set of interrogation
232 windows (Michaelis et al., 2016; Patil & Liburdy, 2013). The autocorrelation peak width was
233 calculated using the e^{-2} width. The resulting widths were 3.57 ± 0.72 pixels for the test with the
234 spherical beads and 3.27 ± 0.81 pixels for the test with angular particles (Figure S3). Both sizes lie
235 in the range of the tracer image diameter to achieve optimal measurements using the window
236 deformation algorithms in PIVlab (Thielicke, 2014).

237 3.5. *Boundary flow field on a single plane*

238 Figure 3 shows a typical flow field across the whole permeameter for a sample of beads,
239 considering three sub-volumes in the left, middle and right, respectively. The PIV analyses
240 performed here show how the rigid lateral boundaries of the permeameter can disrupt the particle
241 packing, leading to some areas of large flow velocity in comparison to the mean, for example with
242 the high flow at the left boundary of Figure 3(a) compared to (b) and (c). In this preliminary
243 examination of the flow, an image mask was manually applied to the particle positions to exclude
244 them from the fluid flow analysis. In contrast, for the following analyses focused on volumes at
245 the centre of the permeameter, the masks were automatically determined from image processing.

246

247 **4. Image Processing**

248 *4.1. Image segmentation*

249 Figure 4(a) shows a typical grey-scale image of a plane from sample Beads-U, illuminated by
250 the laser. As shown in the schematic diagram at the top of the image, the finite laser thickness
251 leads to non-uniform grey values because particles can partially fill the laser beam. This is similar
252 to the partial volume effect associated with microCT images and consequences for image quality
253 are related to the laser thickness. The histogram of grey values of the image as shown in Figure
254 4(b) indicates there is no clear separation between the grey values for the particles and the pore-
255 space. The distance between the scanning planes determines the image resolution in the z-direction,
256 i.e. the effective voxel length in the z-direction is 1 mm. Furthermore, the laser sheet creates linear
257 streaks or shadows in the direction of the laser, with grey values that can be similar to that of
258 particles. In previous studies, the 3D pore space was reconstructed by identifying the centre and

259 radius of each spherical particle from 2D slices (Huang et al., 2008; Thaker et al., 2019) rather
260 than considering the 3D dataset directly. This shape-matching approach cannot be used for samples
261 with irregular-shaped particles.

262 Image segmentation of granular materials classifies each pixel as being either within a particle
263 or within the pore-space. We explored three approaches to segment the images, and Figure 5
264 presents the results of each of these methods applied to three representative slices. The first
265 approach is threshold segmentation which classifies all pixels with a grey value lower than a
266 specified threshold as being in the particle phase and the remaining in the pore phase. The threshold
267 can be automatically determined by Otsu's algorithm based on the grey value histogram, as shown
268 in Figure 4(b) (Otsu, 1979). The Otsu-threshold segmentation method incorrectly classified some
269 linear shadows created by the laser as being in the particle phase.

270 The other two methods considered, namely the trainable Weka (Waikato Environment for
271 Knowledge Analysis, Arganda-Carreras et al., 2017) and the U-Net (Ronneberger et al., 2015), are
272 based on artificial intelligence. Artificial intelligence segmentation approaches learn from
273 manually segmented images to define a pixel-wise classifier which labels each pixel as being in
274 either the particle or pore phase. The trainable Weka algorithm was developed in the open-source
275 software platform Fiji (Schindelin et al., 2012). When compared with the Otsu threshold, this
276 method improved the segmentation quality to some extent, but it could not completely remove the
277 laser-induced linear shadows. Finally, the U-Net algorithm proved to be more robust in
278 segmentation, producing smooth particle-pore interfaces and no linear shadows, in contrast with
279 the other two methods. The segmented results from U-Net have smooth particle surfaces, no
280 internal voids in the particles and eliminate all linear artefacts induced by the laser, which is
281 important for constructing CFD models. U-Net performs segmentation based on both grey values

282 and morphological patterns, e.g., edges, curvatures, and spheres. The U-Net package was
283 implemented in Tensorflow and Keras following the U-Net architecture proposed by Ronneberger
284 et al. (2015).

285 The U-Net segmentation procedure can be divided into three major steps: (a) data preparation
286 for training; (b) U-Net training; and (c) new image segmentation (Figure 6). The U-Net
287 architecture requires an image dimension of 512×512. Therefore, the images were scaled from
288 1280×800 pixels to 512×512 pixels and scaled back after segmentation. Initially, eight images
289 were segmented by visual inspection. Data augmentation was performed to increase the diversity
290 of training data by shifting and rotating each annotated image to produce four images. Thus a total
291 of 32 images were obtained for training and validation. Then the U-Net algorithm was trained with
292 32 annotated images to define the classifier. The trained U-Net classification led to an accuracy of
293 about 93% for validation images and was used as a classifier to segment new images. The U-Net
294 classification generated a grey-scale image in which the grey value of a pixel reflected the
295 possibility of that pixel being in a particle. A target porosity was specified to generate an
296 appropriate threshold grey-level value to binarize the output of the U-Net algorithm. This porosity
297 was selected by considering the experimental whole-sample value. However, acknowledging the
298 sample heterogeneity, a parametric study was carried out considering a range of reasonable local
299 porosity values as discussed below.

300 *4.2. Three-dimensional pore structure reconstruction*

301 The slice-by-slice scanning method led to an in-plane pixel size of approximately 0.029 mm
302 along the x- and y-axes, and an out-of-plane distance of 1 mm along the z-axis. Therefore, we
303 applied a scaling to the output from U-Net to reconstruct a three-dimensional volume with an

304 identical voxel size of 0.1 mm along all directions. Figure 7 shows the effect of upscaling along
305 the z -direction with three different interpolation methods. The scaling without interpolation results
306 in a stepped particle surface, while both interpolation methods provide relatively smooth particle
307 surfaces. The bilinear interpolation is adopted in this study. Finally, we binarized the scaled three-
308 dimensional images with a threshold value to reach the porosity value determined experimentally.
309 The threshold value was determined from the linear relationship between the threshold value and
310 the resulting porosity. Three levels of porosity were used to reconstruct the pore topology to
311 investigate the influence of porosity on the CFD results.

312 We performed marker-based watershed labelling to identify individual particles from three-
313 dimensional binary images. The image processing steps involved in labelling particles are: (a)
314 construct a distance map representing the distance from a pixel to its closest particle surface; (b)
315 use marker identification based on the H-Maximum algorithm (Soille, 2013) on the distance map;
316 (c) implement marker-based watershed segmentation using the markers and distance map. A more
317 detailed description of this marker-based watershed segmentation approach can be found in Zhao
318 et al. (2015). Figure 8 illustrates the labelling results on typical 2D slices for beads and angular
319 particles. The particles are less regular on x - z planes than on x - y planes. This is mainly due to the
320 finite step distance during the slice-by-slice scanning along the z -axis.

321 A marching cubes algorithm was used to generate triangular surface meshes from the voxel
322 assembly representing individual particles (Lorenson & Cline, 1987). The surface meshes of
323 individual particles were cleaned, simplified and smoothed with GMSH, an open-source mesh
324 generator (Geuzaine & Remacle, 2009). Finally, the surface meshes of all particles were combined
325 into a single file with individual particles represented by a unique label. Figure 9(a) and (b) show

326 the three-dimensional views of the particle packings in the scanning region for the samples with
327 spherical beads and angular particles, respectively.

328

329 **5. Computed Fluid Dynamics (CFD) Simulation**

330 *5.1. Governing equation and numerical method*

331 For the fully saturated conditions assumed here, flow through the pore space is governed by
332 the incompressible Navier-Stokes equations formulated as:

$$\rho_f \left(\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} \right) = -\nabla p + \mu \nabla^2 \mathbf{u} \quad (\text{Eq. 1})$$

$$\nabla \cdot \mathbf{u} = 0 \quad (\text{Eq. 2})$$

333 where \mathbf{u} is the velocity vector, and p is the pressure. In the steady-state, $\partial \mathbf{u} / \partial t = 0$. Here the
334 Navier-Stokes equations were solved using the Semi-Implicit Method of Pressure Linked
335 Equations (SIMPLE) algorithm in the open-source CFD toolbox OpenFOAM (OpenFOAM
336 Foundation, 2019). The SIMPLE algorithm is a steady-state solver for incompressible flow. The
337 CFD analysis provides the velocity and pressure values at the centre of each CFD cell.

338 The simulation domain was discretized by the mesh generation algorithms available in
339 OpenFOAM, i.e., BlockMesh and SnappyHexMesh. BlockMesh decomposes the simulation
340 domain into blocks, while SnappyHexMesh takes the surface mesh defining the pore structure and
341 chisels it with the geometry defined by the combined surface mesh file. We applied localized
342 refinement at the particle surface, which increased the mesh densities close to the particle-particle
343 contacts in particular. This created CFD meshes with around 3.5 million cells. Figure 9(c) and (d)
344 show typical CFD meshes of pore space for spherical beads and angular particles, respectively.

345 In all simulations, a constant pressure boundary condition was applied at both the inlet (17 Pa)
 346 and outlet boundaries (0 Pa). A ‘slip’ condition was applied to the four lateral boundaries so that
 347 the velocity component normal to each of these boundaries was set to be zero while the tangential
 348 velocities remained unconstrained. A ‘no-slip’ boundary condition was applied to the particle
 349 surfaces so that the velocities normal and tangential to the surface were set to zero. These boundary
 350 conditions are similar to those applied in the CFD analyses by Taylor et al. (2016). They do not
 351 capture the heterogeneity of the pressure and velocity distributions that exist on the boundaries of
 352 sub-volumes in experiments. However, the flow velocity data available from the experiments are
 353 restricted to 2D and limited to 26 discrete vertical planes. A valid CFD analysis requires
 354 conservation of mass (adherence to continuity) in the model in all three dimensions. Consequently,
 355 it was not possible to use the experimental data to apply non-uniform velocity fields along the
 356 boundary to the simulation domain.

357 The normal and shear stresses on the particle surface were determined from the flow velocity
 358 and pressure fields. Each particle surface was discretized into surface elements. Then, the flow-
 359 induced force and moment on individual particles were calculated by integrating normal pressure
 360 and viscous shear stresses over all elements on the particle surface:

$$\mathbf{F}_p = \sum_{i=1}^{N_e} \rho p_i A_i \mathbf{n}_i \quad (\text{Eq. 3})$$

$$\mathbf{F}_v = \sum_{i=1}^{N_e} \mu \mathbf{R}_{dev} A_i \quad (\text{Eq. 4})$$

361 where N_e is the number of elements covering the particle surface, ρ is the fluid density, p_i is the
 362 kinematic normal pressure, A_i and \mathbf{n}_i are the patch area and normal vector, μ is the fluid dynamic

363 viscosity, and \mathbf{R}_{dev} is the deviatoric stress tensor. The integration was performed using the in-built
 364 function, ‘forces’, in OpenFOAM (OpenFOAM Foundation, 2019).

365 *5.2. Validation with regular packings*

366 The CFD simulation data are inherently dependant on the mesh density (cell size) (e.g. Knight
 367 et al. 2020). The sensitivity of the fluid-particle interaction forces obtained from the CFD
 368 modelling approach adopted here to the mesh density was examined by considering the data in
 369 Zick & Homsy (1982) for simple cubic (SC) and face-centred cubic (FCC) packings of uniformly
 370 sized spheres. Following Knight et al (2020), the models exploited geometric symmetry to reduce
 371 the calculation cost. As before, a specified pressure was applied at the inlet and outlet, while ‘cyclic’
 372 boundary conditions were applied to the four lateral boundaries. The sphere centroids were placed
 373 on a fixed lattice, and the particle sizes were changed to reach different packing densities; e.g. the
 374 particle diameter was increased from 4.4 mm to 4.9 mm in the FCC packings to achieve porosity
 375 between 0.495 and 0.303. The fluid-particle interaction coefficient, $\bar{F}_{f \rightarrow s}$, is the fluid-particle
 376 interaction force normalized by Stokes drag force $F_{f \rightarrow s}^S$:

$$F_{f \rightarrow s}^S = 3\pi\mu D|u| \tag{Eq. 5}$$

$$\bar{F}_{f \rightarrow s} = F_{f \rightarrow s} / F_{f \rightarrow s}^S \tag{Eq. 6}$$

377 where D is the particle diameter, u is the superficial flow velocity, and $F_{f \rightarrow s}$ is the fluid-particle
 378 interaction force, which includes both the pressure and viscous terms.

379 The fluid-particle interaction coefficient increases with reduced packing porosity, as shown in
 380 Figure 10(a). The results from CFD simulations are consistent with the Zick and Homsy solutions
 381 and the results from Immersed Boundary Method (IBM) obtained by Knight et al. (2020). The

382 CFD results are mesh dependent. As shown in Figure 10(b) and (c), the agreement between the
383 fluid-particle interactions obtained from these CFD simulations and the Zick and Homay data,
384 $|\bar{F}_{f \rightarrow s} - \bar{F}_{f \rightarrow s}^{ZH}| / \bar{F}_{f \rightarrow s}^{ZH}$, improves with increasing mesh density, D/d_m , where D is the particle
385 diameter, and d_m is a characteristic mesh element size. At the same D/d_m , the relative error
386 increases with sample density. The relative errors for most samples were smaller than 5% at a D/d_m
387 of 40. The results obtained from the unstructured mesh CFD analyses by Knight et al. (2020) show
388 a similar influence of mesh density on relative error for drag estimation. The average ratio between
389 particle diameter and mesh element size was chosen to be 40 for the permeameter simulations.

390

391 **6. Results**

392 The 2D-PIV measurements can only provide the components of flow velocities in the plane of
393 the laser, i.e. along the x- and y-directions. Within this plane, the distance between PIV data points
394 is around 0.5 mm, which is much larger than the CFD mesh size. Therefore, the CFD velocity
395 fields were interpolated to the centre of the PIV interrogation regions to allow a direct comparison
396 between the PIV and CFD results. The Reynolds number in this study is around one, which
397 indicates a laminar flow condition. We normalized the velocity values by the mean vertical
398 velocity either on each vertical slice (\bar{u}^s) or the mean value in each sub-volume (\bar{u}^v).

399 For each sub-volume, the PIV analysis was performed on 26 x-y planes at 1 mm intervals. The
400 x-y planes were referred with their z coordinates from 0 mm to 25 mm. The CFD domain is slightly
401 smaller than the PIV domain and has 24 x-y planes ($z = 1$ to 24 mm) to reduce the effects of
402 upscaling on boundary slices (Figure 7). The sub-volume has about six particles along the x-
403 direction and four particles along the y-direction, and there are about 20 particles completely inside
404 each sub-volume.

405 6.1. Permeability estimation

406 Table 3 shows the experimental measurements for each sub-volume. Each sub-volume is
407 named by the particle type, e.g. spherical (Beads) and angular (Ang), followed by the position, e.g.
408 upper (U) and lower (L). The overall packing porosity, n , permeameter cross-section area, A_{Exp} ,
409 and flow rate, Q_{Exp} , were measured during each permeameter test. Local manometer readings were
410 used to identify the hydraulic gradient for the experiments, and the two sub-volumes in the angular
411 particle sample had slightly different hydraulic gradients i_{exp} due to the inhomogeneous packing.
412 Seepage flow rates were determined from experimental measurements (u_{seep}^{Exp}), PIV analysis (u_{seep}^{PIV})
413 and CFD simulations (u_{seep}^{CFD}).

414 Figure 11 compares the permeability values estimated by the three types of seepage velocities.
415 In general, the permeability values estimated by PIV analysis (k^{PIV}) are smaller than the values
416 estimated from the experimental measurements (k^{Exp}). This is unsurprising as the PIV analysis
417 was performed over central sub-volumes, while the pump injection rate measures the cross-section
418 of the permeameter, including the larger voids commonly encountered at the side walls (Figure 3).
419 In addition, the sub-volumes for Ang show smaller permeabilities than the sub-volumes for Beads.
420 For k^{Exp} the sub-volume Ang-U has a higher permeability than for Ang-L due to the different
421 hydraulic gradient as measured using the manometers, while there was no evident difference in the
422 sub-volumes of the Beads sample. In Figure 11(a) the k^{CFD} data were obtained using the overall
423 experimental porosities, i.e. $n=0.38$ and 0.36 in the CFD simulations for Beads and Ang samples,
424 respectively. Perhaps surprisingly, the permeability values estimated by CFD simulations, k^{CFD}
425 (grey data points), are similar across the four sub-volumes, with only a slight decrease for the Ang
426 sample compared to the Beads. This means that, while the permeabilities estimated for CFD and

427 PIV in the Beads sub-volumes are quite close, for the angular sample, k^{CFD} measurements are
428 approximately twice that of k^{PIV} .

429 The differences between experimental and numerical permeabilities could be caused by (a)
430 local porosity variations, (b) CFD boundary effects, or (c) PIV velocity measurement errors. Figure
431 11(b) illustrates the sensitivity of the k^{CFD} results to porosity by considering three limiting
432 plausible porosity values. For Beads-U, k^{CFD} agrees with both k^{Exp} and k^{PIV} if local porosity is
433 changed from 0.38 to 0.40. For Ang-U, k^{CFD} agrees with k^{Exp} and k^{PIV} if the local porosity is
434 changed from 0.36 to 0.31 and 0.29, respectively. However, the segmented images seem to be
435 inconsistent with the grey-value images due to the large porosity change (Figure S4 in the
436 supplementary material). Furthermore, the variation in porosity had only a limited influence on the
437 flow field distributions. Potential PIV velocity measurement errors were also investigated by
438 changing the framerate. However, this did not lead to a noticeable change. A definitive, precise
439 explanation for the inconsistency in the permeability values could not be determined.

440 6.2. Flow fields – contour plots

441 The normalized flow fields obtained from PIV and CFD analysis within a typical x-y plane for
442 the Beads-U sub-volume are in good agreement, as shown by the normalized horizontal velocity
443 \bar{u}_x^s and vertical velocity \bar{u}_y^s in Figure 12. The heterogeneity in the packing leads to concentrated
444 flow paths for vertical flow at some large voids, e.g. close to the left bottom corner. The horizontal
445 velocity is determined by the local pore alignment relative to the macro-scale flow direction. The
446 lateral boundaries assumed in the CFD models prohibit horizontal flow, so the flow patterns at the
447 side boundaries differ. For example, the physical test data indicate a relatively large horizontal
448 flow close the left boundary in Figure 12(a) which is not captured in the CFD model in Figure

449 12(b). The difference in the boundary conditions also influences the vertical velocity values in this
450 region. The vector plots of flow fields on three x-y planes are shown in Figure 13 to further
451 demonstrate the similar patterns revealed by PIV and CFD estimations. Again, the lateral boundary
452 conditions inhibit horizontal flow in the CFD model.

453 The flow velocities on four x-y planes in the Beads-U sub-volume were analysed statistically,
454 as shown in Figure 14. The horizontal normalised velocity \bar{u}_x^S tends to form a Laplace distribution
455 with a mean velocity around zero (Figure 14(a)). While the distributions obtained from the PIV
456 analyses are similar for the four planes considered, the two CFD distributions with $z=1$ mm and
457 24 mm tend to have a higher proportion of data points with a velocity close to zero, due to the
458 lateral boundary effect experienced at the front ($z=1$ mm) and back ($z=24$ mm) of the studied
459 volume. The vertical normalised velocity \bar{u}_y^S tends to form a half Laplace distribution (Figure
460 14(b)). Similarly, the planes close to the front or back lateral boundary in the CFD simulation ($z=$
461 1 mm and 24 mm) have a higher proportion of velocity close to zero. The cumulative distributions
462 in Figure 14(c) and (d) show a good agreement between PIV and CFD results.

463 The pore topology is intrinsically correlated with particle morphology and granular material
464 packing/fabric. The flow fields on three x-y planes of the Ang-L sub-volume show the flow
465 patterns that are distinct from those developed in the Beads-U sub-volume (comparison between
466 Figure 15 and Figure 13). Some flow channels are straight rather than converging-diverging due
467 to the flat surfaces of angular particles, as indicated by arrows. The difference seems to be more
468 obvious for the angular particle sample than for the beads sample. However, the overall
469 distribution of flow velocity in the angular particles sample is very similar to that of the beads
470 sample, as shown in Figure 16. Previous studies have indicated that the flow velocity distribution

471 depends on packing density (Rong et al., 2013). Further tests are needed to investigate the influence
472 of particle shape on the flow velocity distribution.

473 The mapping of the CFD data onto the PIV grid allows spatial variation of the difference
474 between the two datasets to be examined, as shown in Figure 17(a) and (b). While the data in
475 Figure 12 showed the similarity of the flow patterns, there are large differences between the
476 normalized velocity intensities. Figure 17(c) and (d) show the cumulative distributions of the
477 velocity difference values for five x-y planes. The difference mainly lies between $\pm 50\%$ and
478 $\pm 100\%$ of the mean seepage velocity on each slice for horizontal and vertical velocity,
479 respectively. Perhaps unsurprisingly, the planes closest to the lateral boundaries ($z = 1$ or 24 mm)
480 have a higher velocity difference.

481 6.3. Mean flow rate on slices

482 Here, the mean velocity on each x-y plane is normalized by the seepage velocity in each sub-
483 volume. The normalized vertical velocity on each plane varies between 0.5 and 1.5, as shown by
484 Figure 18(a). The PIV and CFD data exhibit similar patterns of variation in $\langle \bar{u}_y^v \rangle$ along the z-axis.
485 In the CFD analyses, the lateral boundaries prohibit out-of-plane flow and lead to low velocity
486 values along z, as shown by the shaded area in Figure 18(b). However, $\langle \bar{u}_z^v \rangle$ increases to the
487 expected level after about 3 mm ($\sim D/2$) from the lateral boundary. The heterogeneity of the pore
488 structure and relatively small sub-volume leads to a large variance of the plane-based porosity
489 (Figure 18(c)). For example, the plane-based porosity for the Beads-U sub-volume ($n = 0.38$) varies
490 from 0.25 to 0.5.

491 The CFD analyses provide 3D data, enabling analysis of the velocity distribution in horizontal
492 x-z planes perpendicular to the flow direction. As expected, the variance of the mean vertical

493 velocity $\langle \bar{u}_y^v \rangle$ on x-z planes is inversely correlated to the plane porosity due to the fluid continuity
494 (Figure 19(a) and (b)). Where the porosity in the x-z plane is lower, $\langle \bar{u}_y^v \rangle$ is higher so that overall
495 flow rate is the same for each x-z plane in line with the principle of mass conservation. The pressure
496 dissipation is higher at the lower porosity plane, as shown in Figure 19(c).

497 6.4. Fluid-particle interactions

498 Each sub-volume contains around twenty particles that do not intersect the boundaries. Figure
499 20 shows the vector plots of the fluid-particle interaction coefficients $\bar{F}_{f \rightarrow s}$ (Equation 6) projected
500 onto x-y planes for four sub-volumes. The magnitudes of $\bar{F}_{f \rightarrow s}$ have a large variance, especially
501 for angular particles. The directions of $\bar{F}_{f \rightarrow s}$ slightly deviate from the flow direction – the mean
502 deviation angle equals 16° . The variance of $\bar{F}_{f \rightarrow s}$ arises mainly from the heterogeneous flow fields,
503 resulting from local packing and irregular particle morphologies.

504 Figure 21(a) shows the distribution of the fluid-particle interaction coefficient, which varies
505 approximately from 50 to 140 for beads and from 50 to 240 for angular particles. The mean value
506 of $\bar{F}_{f \rightarrow s}$ is influenced by the different packing densities, with the angular particle sample having a
507 slightly higher packing density than the beads sample. Figure 21(b) shows the fluid-particle
508 interaction coefficients normalized by their mean values. Clearly, the sample with angular particles
509 has a higher variance than the spherical beads sample. This variance may arise from packing
510 density or particle shape difference.

511 The fluid-particle interaction is contributed by two components, i.e. a viscous component due
512 to skin friction and a pressure component due to the pressure gradient. In dense packings, the
513 pressure component of fluid-particle interactions dominates the fluid-particle interaction, while the
514 viscous component accounts for about 20% on average, as shown in Figure 22(a). Spherical beads

515 tend to experience a slightly higher ratio of the viscous component to pressure component than
516 angular particles. Figure 22(b) shows the deviation angle of fluid-particle interactions from the
517 flow direction, i.e. $\theta_d = \arctan(\bar{F}_{f \rightarrow s, xz} / \bar{F}_{f \rightarrow s, y})$. Most particles have a deviation angle between 0°
518 and 30° .

519

520 7. Conclusions

521 This study investigated pore-scale seepage in granular packings with the combined
522 experimental and numerical methods. Permeameter tests were performed with transparent soils
523 consisting of spherical and angular particles. PIV analysis quantified 2D flow fields inside granular
524 packings on multiple planes. We adopted a series of image processing techniques to reconstruct
525 the 3D pore topologies from the slice-by-slice scanning images. Pore-scale CFD analysis was
526 performed on reconstructed volumes to obtain both flow fields and fluid-particle interactions. The
527 fluid-particle interactions obtained by CFD simulations were validated with existing results on
528 regular particle packings. The conclusions are summarised as follows.

529 PIV analysis can quantify the flow field for two-dimensional planes. The random packing of
530 particles leads to preferential flow paths at larger voids (e.g. close to boundary wall). Spherical
531 particles tend to form converging and diverging flow paths, while angular particles with flat
532 surfaces form straight channels. The interplays between local particle arrangement, particle shape
533 and pressure gradient determine the heterogeneous pore-scale flow fields.

534 The slice-by-slice images containing pore structure information were obtained by illuminating
535 the transparent soils at multiple locations with a sheet laser. An artificial intelligence algorithm
536 provided good image segmentation results for the images with poor contrast and artefacts. The
537 flow fields obtained from CFD analysis on the reconstructed pore structure show a good agreement

538 with PIV results. Similar patterns were obtained for the contour plots of flow fields, flow vector
539 plots and velocity magnitude histograms. This agreement demonstrates the successful
540 implementation of the three-dimensional pore structure reconstruction methods. However, while
541 there is good agreement between the average flow fields, the local differences in flow field data
542 are more significant.

543 This work supports the development of systems with thinner lasers (including the requisite
544 safety considerations) and exploiting recent advances in automated systems for macro photography
545 to reduce the observed partial volume effects and improve the resolution orthogonal to the
546 scanning planes (i.e. in the z-direction considered here).

547 The CFD results have a higher resolution in comparison with the PIV results and produce
548 three-dimensional velocity values. However, the analyses tend to have side boundary effects. The
549 comparison between CFD and PIV results indicate the side boundary effects are usually
550 constrained within a half particle diameter region. The point-by-point comparison of CFD and PIV
551 results was performed after downscaling the CFD results. The normalized velocity difference
552 remains large, even though the overall distribution of CFD and PIV flow fields are similar.

553 The fluid-particle interactions obtained from fully resolved CFD analysis are consistent with
554 previous numerical solutions. The fluid-particle interactions obtained the permeameter model tests
555 have a large variance, especially for angular particles. For relatively dense packings, viscous drag
556 contributes to a small fraction of the total fluid-particle interaction. The fluid-particle interaction
557 slightly deviates from the injection direction. However, for this study, the number of particles in
558 each CFD model was relatively small (around twenty), and the beads and angular particles samples
559 have slightly different packing density. Therefore, the fluid-particle interaction results should be
560 further investigated to elaborate on the particle shape effects.

561 **List of Figure and Table Captions**

562 Figure 1. Schematic of the experimental set up.

563 Figure 2. Images of experimental setup: (a) Permeameter cell partially filled with oil; (b) Beads
564 sample illuminated by laser sheet; (c) Angular particles sample illuminated by laser sheet; (d)
565 top view of the laser sheet.

566 Figure 3. Flow fields in the (a) left, (b) middle and (c) right for the permeameter with beads.

567 Figure 4. (a) Typical grey-scale image in Beads-U sub-volume, $z = 0$ mm. (b) Histogram of grey
568 values. Inset in (a) shows that the non-uniform intensity is a consequence of the finite laser
569 width.

570 Figure 5. Segmentation results for three typical slices in Beads-U sub-volume using three different
571 segmentation methods: threshold segmentation with Otsu's threshold, trainable Weka
572 segmentation, and U-Net segmentation. Note: red-dashed circles indicate the artifacts produced
573 by inaccurate segmentation.

574 Figure 6. U-Net segmentation procedure for Beads-U sub-volume: (a) Step-1: prepare training and
575 validating data sets; (b) Step-2: train U-Net algorithm; (c) Step-3: apply trained U-Net as a
576 classifier for segmenting new images.

577 Figure 7. Upscaling along z -direction on the U-Net classified image for Beads-U sub-volume: (a)
578 Unscaled image data; (b) Image obtained by scaling without interpolation; (c) Image obtained
579 by scaling with bilinear interpolation; (d) Image obtained by scaling with bicubic interpolation.

580 Figure 8. Labelled images with particles represented by different colours for Beads-U sub-volume
581 on (a) x - y plane and (b) x - z plane and Ang-U sub-volume on (c) x - y plane and (d) x - z plane.

582 Figure 9. Three-dimensional views of the combined surface meshes for (a) Beads-U sub-volume
583 and (b) Ang-U sub-volume. Note: colour is used to distinguish the surfaces of individual

584 particles. Hexahedron meshes which discretize pore structure for CFD simulation for (c)
585 Beads-U sub-volume and (d) Ang-U sub-volume.

586 Figure 10. Verification of CFD modelling approach: (a) Confirmation of ability to capture the
587 influence of porosity on the fluid-particle interaction coefficient $\bar{F}_{f \rightarrow s}$, dashed lines indicate a
588 curve fit to the Zick & Homsy (1982) data; (b) Mesh dependence of $\bar{F}_{f \rightarrow s}$ for SC packings; (c)
589 Mesh dependence of $\bar{F}_{f \rightarrow s}$ for FCC packings. The results predicted by the Immersed Boundary
590 Method (IBM) with a regular grid and from fully resolved CFD using an unstructured meshes
591 from Knight et al. (2020) are included in (a) and (c), respectively.

592 Figure 11. (a) Hydraulic permeability values predicted by experiments, PIV and CFD
593 measurements. (b) Influence of porosity on hydraulic permeability as estimated by CFD
594 modelling for Beads-U and Ang-U sub-volumes. The prediction results from Kozeny-Carman
595 Equation (KC Eq.) is included in (b).

596 Figure 12. Comparison of the PIV and CFD flow fields in Beads-U sub-volume on the vertical
597 slice with $z = 16$ mm.

598 Figure 13. Comparison of the PIV and CFD flow fields in Beads-U sub-volume on three slices
599 with $z = 1, 8$ and 16 mm. Velocity vector length is normalized by seepage velocity.

600 Figure 14. Cumulative distributions of flow velocity at four vertical planes in Beads-U sub-volume
601 obtained from PIV and CFD results.

602 Figure 15. Comparison of the PIV and CFD flow fields in Ang-L sub-volume on three slices with
603 $z = 1, 8$ and 16 mm. Velocity vector length is normalized by seepage velocity. Arrows indicate
604 narrow flow paths.

605 Figure 16. Cumulative distributions of flow velocity at four vertical planes in Ang-L sub-volume
606 obtained from PIV and CFD results.

607 Figure 17. Difference between PIV and CFD flow fields for the vertical slice with $z = 16$ mm in
608 Beads-U sub-volume: (a) horizontal velocity; (b) vertical velocity. The cumulative
609 distributions of PIV and CFD difference for (c) horizontal velocity and (d) vertical velocity on
610 five typical slices in Beads-U sub-volume.

611 Figure 18. Variation of the mean velocity values obtained from PIV and CFD results and the slice
612 porosity on x-y planes parallel to flow direction.

613 Figure 19. Variation of mean vertical velocity, porosity and hydraulic gradient on x-z planes
614 perpendicular to flow direction predicted by CFD simulations.

615 Figure 20. Projection views of drag force vectors for the particles that are not intersecting with
616 boundary walls.

617 Figure 21. Cumulative distributions of (a) fluid-particle interaction coefficients for beads and
618 angular particles and (b) the normalized fluid-particle interaction coefficients.

619 Figure 22. Distributions of (a) the ratio between pressure and viscous drag components, and (b)
620 the angle between fluid-particle interaction and flow direction.

621 Table 1. Particle and fluid properties

622 Table 2. Sub-volume dimensions

623 Table 3. Experimental and numerical measurements for each sub-volume

624 Figure S1. Example of the effect of time resolution of PIV analysis on the estimate of the time
625 averaged component (a) u_x and (b) u_y . The velocities are estimated along the yellow dashed
626 lined shown in the inset of (a).

627 Figure S2. Distribution of the number of tracers for a subsets of interrogation windows (32 x 32
628 pixels) for (a) beads and (b) angular particles.

629 Figure S3. Autocorrelation function for a subsets of interrogation windows (32 x 32 pixels) for (a)
630 beads and (b) angular particles. Histogram of autocorrelation peak width for (c) beads and (d)
631 angular particles.

632 V1. Video of an illuminated section in the bead sample showing the movement of tracers

633 V2. Video of an illuminated section in the angular sample showing the movement of tracers

634

Nomenclature

A_{Exp}	permeameter cross section area
A_i	area of CFD mesh element
d_m	characteristic mesh size
d_s	seed particle diameter
D	diameter of beads and angular particles
D_I	interrogation window size
$F_{f \rightarrow s}^S$	stokes drag force
$\bar{F}_{f \rightarrow s}$	fluid-particle interaction coefficient
$\bar{F}_{f \rightarrow s, xz}$	projection of fluid-particle interaction coefficient on x-z plane
$\bar{F}_{f \rightarrow s, y}$	projection of fluid-particle interaction coefficient on flow direction – y axis
$\bar{F}_{f \rightarrow s}^{ZH}$	fluid-particle interaction coefficient from Zick and Homsy solutions
F_p	pressure component of fluid-particle interaction force
F_v	viscous component of fluid-particle interaction force
k^{CFD}	hydraulic permeability determined through CFD analysis
k^{Exp}	hydraulic permeability determined through experimental measurements
k^{PIV}	hydraulic permeability determined through PIV analysis
n	packing porosity
n_i	normal vector of CFD mesh element
N_e	number of CFD mesh element on particle surface
p	fluid pressure
p_i	kinematic normal pressure on CFD mesh element

Q_{Exp}	permeameter flow rate
R_{dev}	deviatoric stress tensor
Stk_s	Stokes number for seed particles
Δt	time step used for PIV analysis
\mathbf{u}	fluid velocity vector
u_x	component of fluid velocity in the x -direction
u_y	component of fluid velocity in the y -direction
u_z	component of fluid velocity in the z -direction
u^s	velocity magnitude normalized by mean seepage velocity on each slice
u^v	velocity magnitude normalized by mean seepage velocity in each sub-volume
$\langle u^v \rangle$	mean velocity on slice normalized by mean seepage velocity in each sub-volume
u_{seep}^{Exp}	seepage velocity determined through experimental measurements
u_{seep}^{PIV}	seepage velocity determined through PIV analysis
u_{seep}^{CFD}	seepage velocity determined through CFD simulations
v_{seep}	seepage flow velocity
μ	fluid dynamic viscosity
ρ	fluid density
ρ_s	seed particle density
ν	fluid kinematic viscosity
θ_d	deviation angle of fluid-particle interaction from the fluid injection direction

635

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754
755

756 Table 1. Particle and fluid properties

	Particle diameter [mm]	Density [g/cm ³]	Refractive index	Viscosity	
				Kinematic [mm ² /s]	Dynamic [Pa·s]
SiLibeads Glass beads Type P Borosilicate	7.5 ± 0.03	2.23	1.46 (*)	-	
Duran® angular particles	6.7 – 9.5	2.23	1.47 (at 21°C)	-	
Cargille immersion fluid	-	0.846	1.47 (at 25°C)	16 (at 25 °C)	0.0135
Microsphere fluid seeding particles	0.005 – 0.030	0.750	-	-	

757 (*) The measurement temperature for the refractive index value was not given on the material certificate.
758 A sensitivity analysis to temperature was conducted to achieve the optimum optical transparency with the
759 immersion fluid.

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763 Table 2. Sub-volume dimensions

Sub-volume	Dimensions, x × y × z [mm ³]
Beads-U	37.4 × 23.4 × 25
Beads-L	40.4 × 25.3 × 25
Ang-U	38.5 × 24.0 × 25
Ang-L	38.5 × 24.0 × 25

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769 Table 3. Experimental and numerical measurements for each sub-volume

Sub-volume	n	i_{Exp}	A_{Exp} [cm ²]	Q_{Exp} [ml/s]	u_{seep}^{Exp} [mm/s]	u_{seep}^{PIV} [mm/s]	u_{seep}^{CFD} [mm/s]
Beads-U	0.38	0.086	100	30.3	8.0	7.1	6.8
Beads-L	0.38	0.086	100	30.3	8.0	5.7	6.2
Ang-U	0.36	0.143	100	28.5	7.9	4.5	6.0
Ang-L	0.36	0.114	100	28.5	7.9	4.5	5.9

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Figure 1. Schematic of the experimental set up.

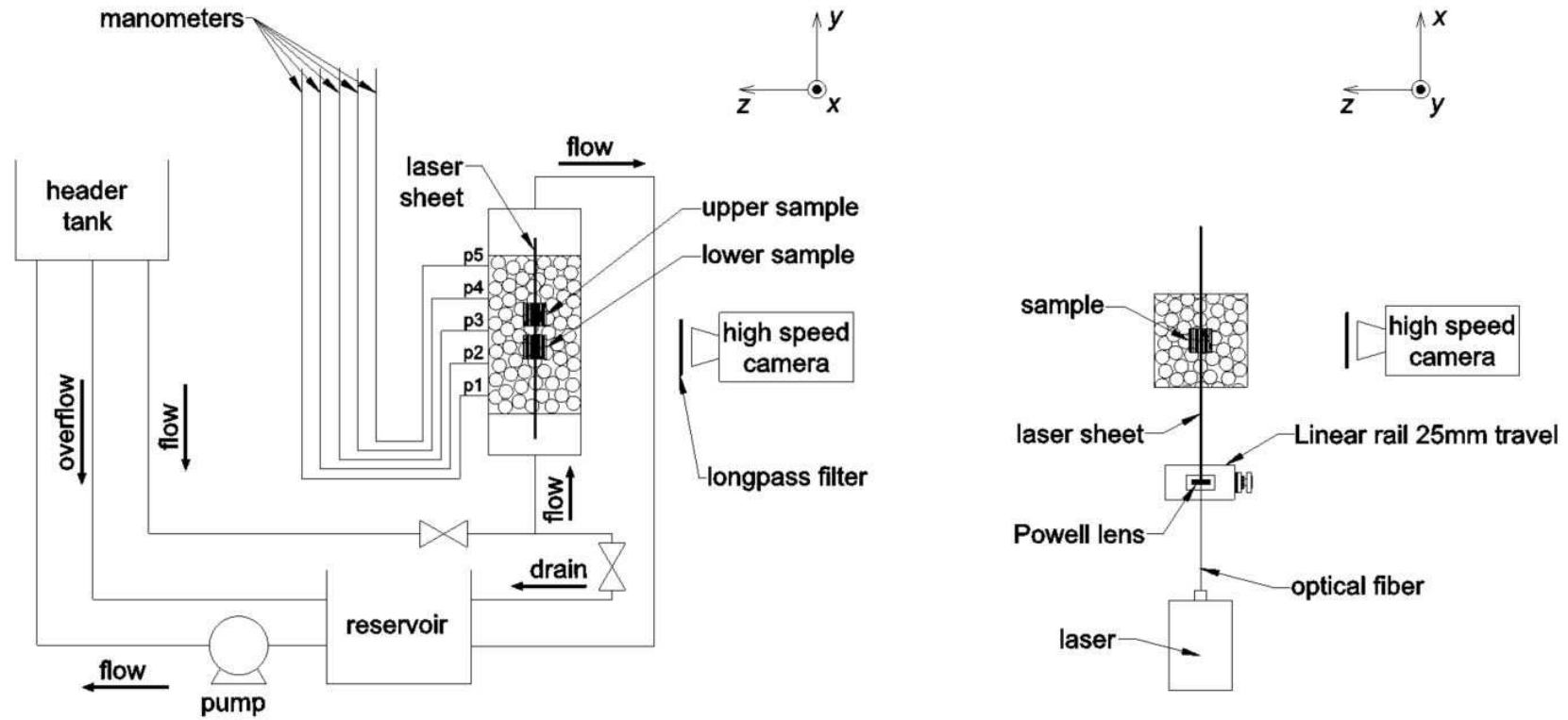


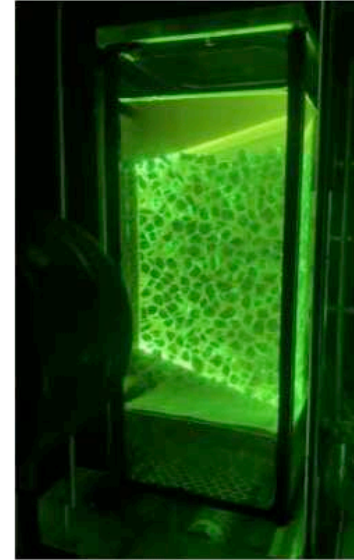
Figure 2. Images of experimental setup: (a) Permeameter cell partially filled with oil; (b) Beads sample illuminated by laser sheet; (c) Angular particles sample illuminated by laser sheet; (d) top view of the laser sheet.



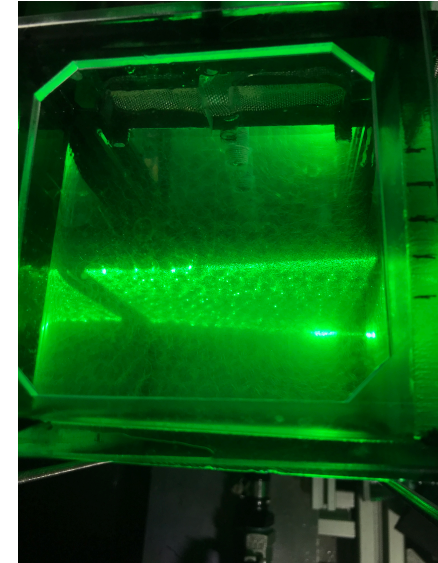
(a)



(b)



(c)



(d)

Figure 3. Flow fields in the (a) left, (b) middle and (c) right for the permeameter with beads.

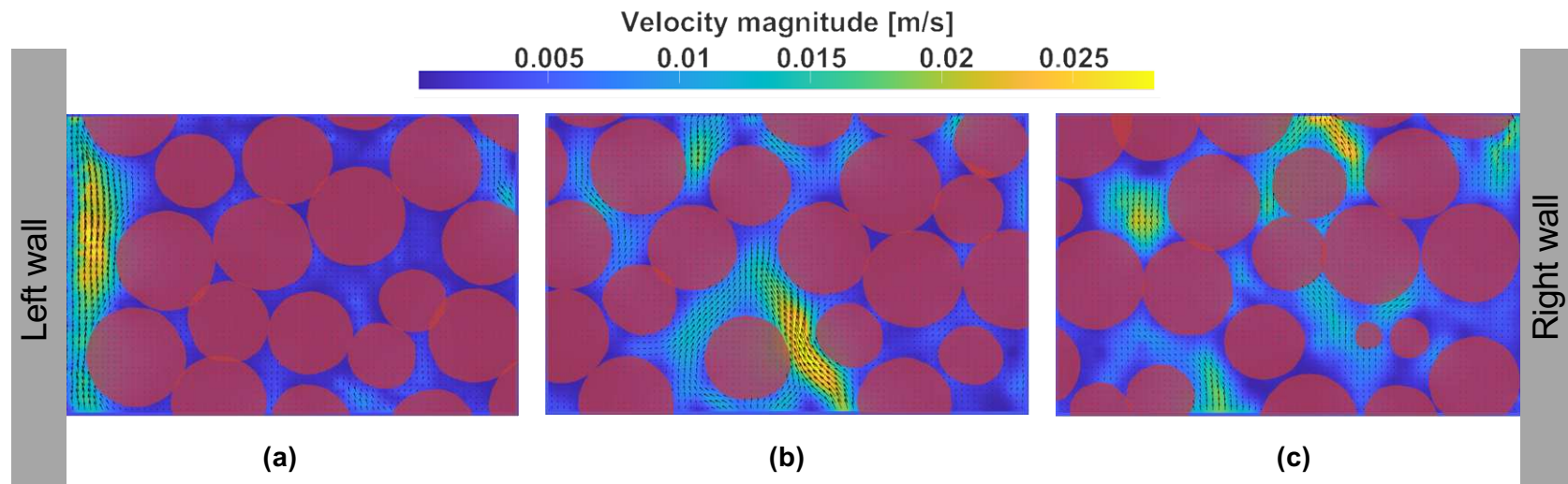


Figure 4. (a) Typical grey-scale image in Beads-U sub-volume, $z = 0$ mm. (b) Histogram of grey values. Inset in (a) shows that the non-uniform intensity is a consequence of the finite laser width.

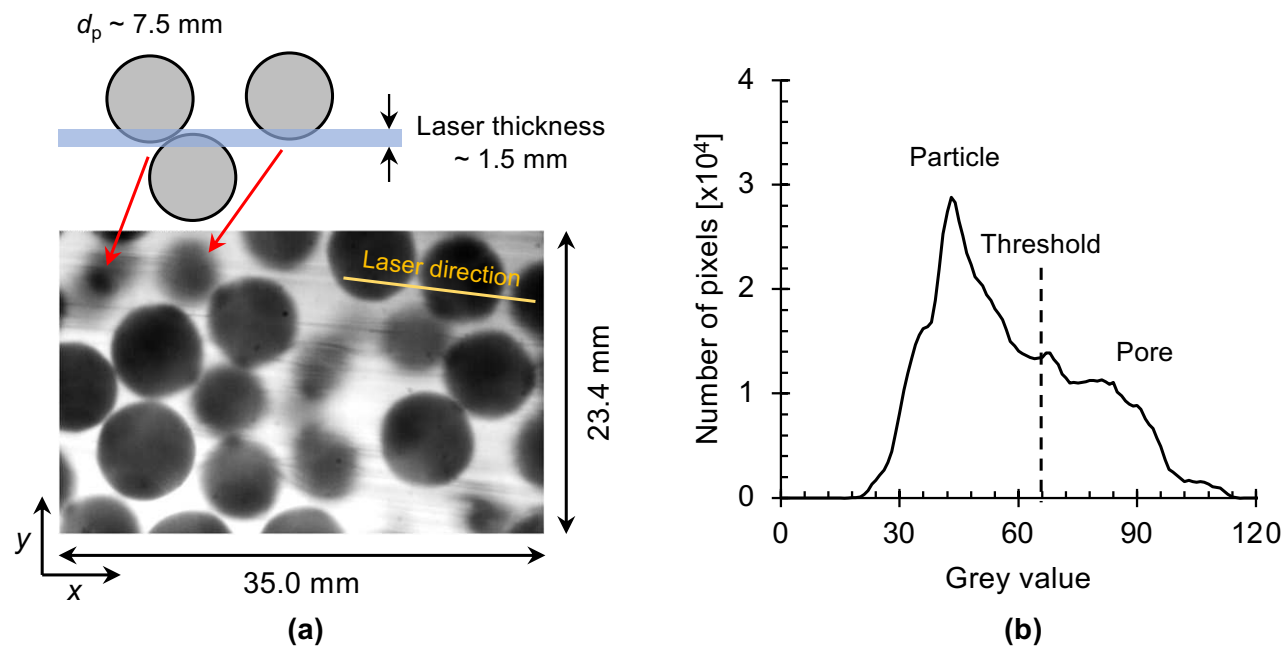


Figure 5. Segmentation results for three typical slices in Beads-U sub-volume using three different segmentation methods: threshold segmentation with Otsu's threshold, trainable Weka segmentation, and U-Net segmentation. Note: dashed circles indicate the artifacts produced by inaccurate segmentation.

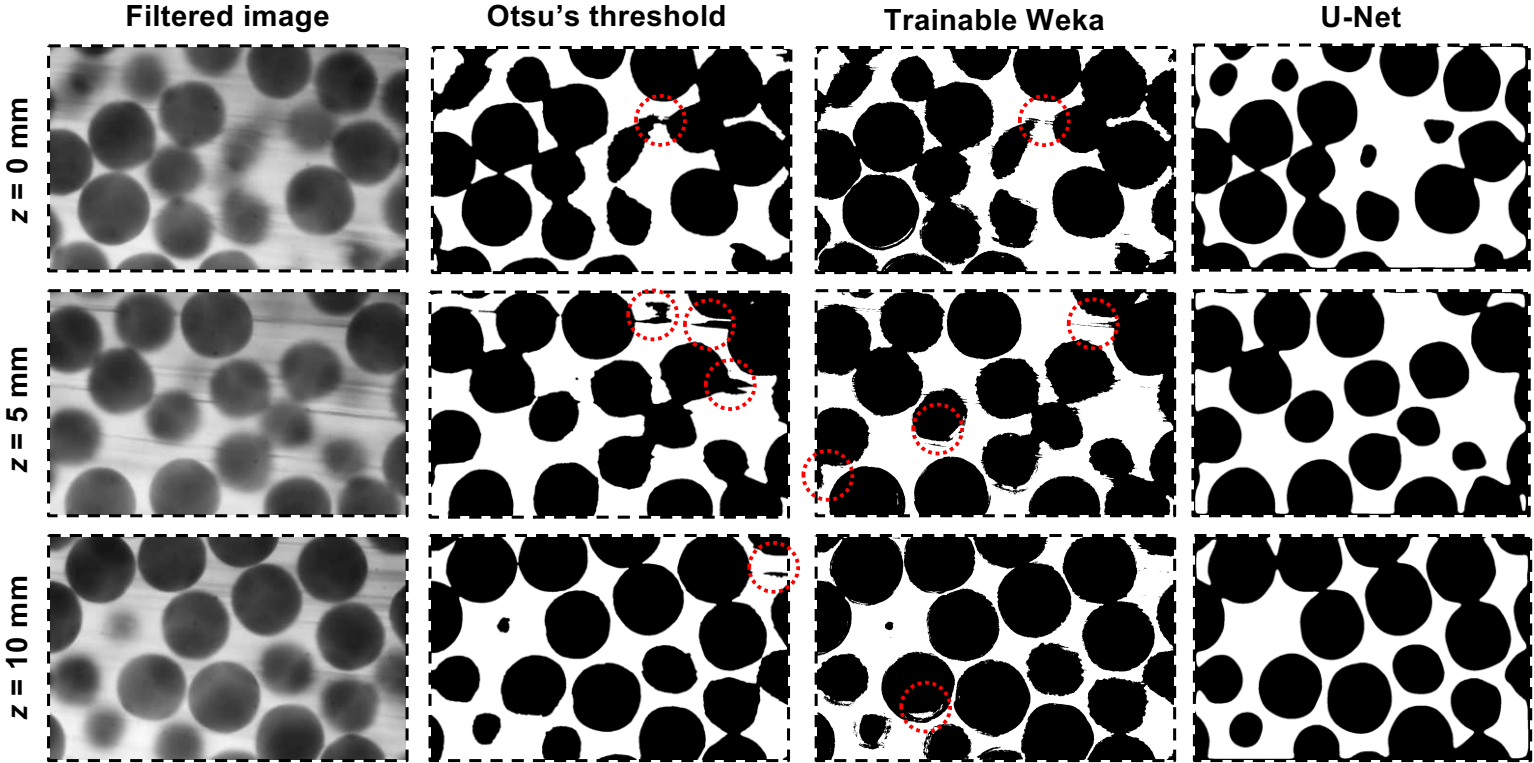


Figure 6. U-Net segmentation procedure for Beads-U sub-volume: (a) Step-1: prepare training and validating data sets; (b) Step-2: train U-Net algorithm; (c) Step-3: apply trained U-Net as a classifier for segmenting new images.

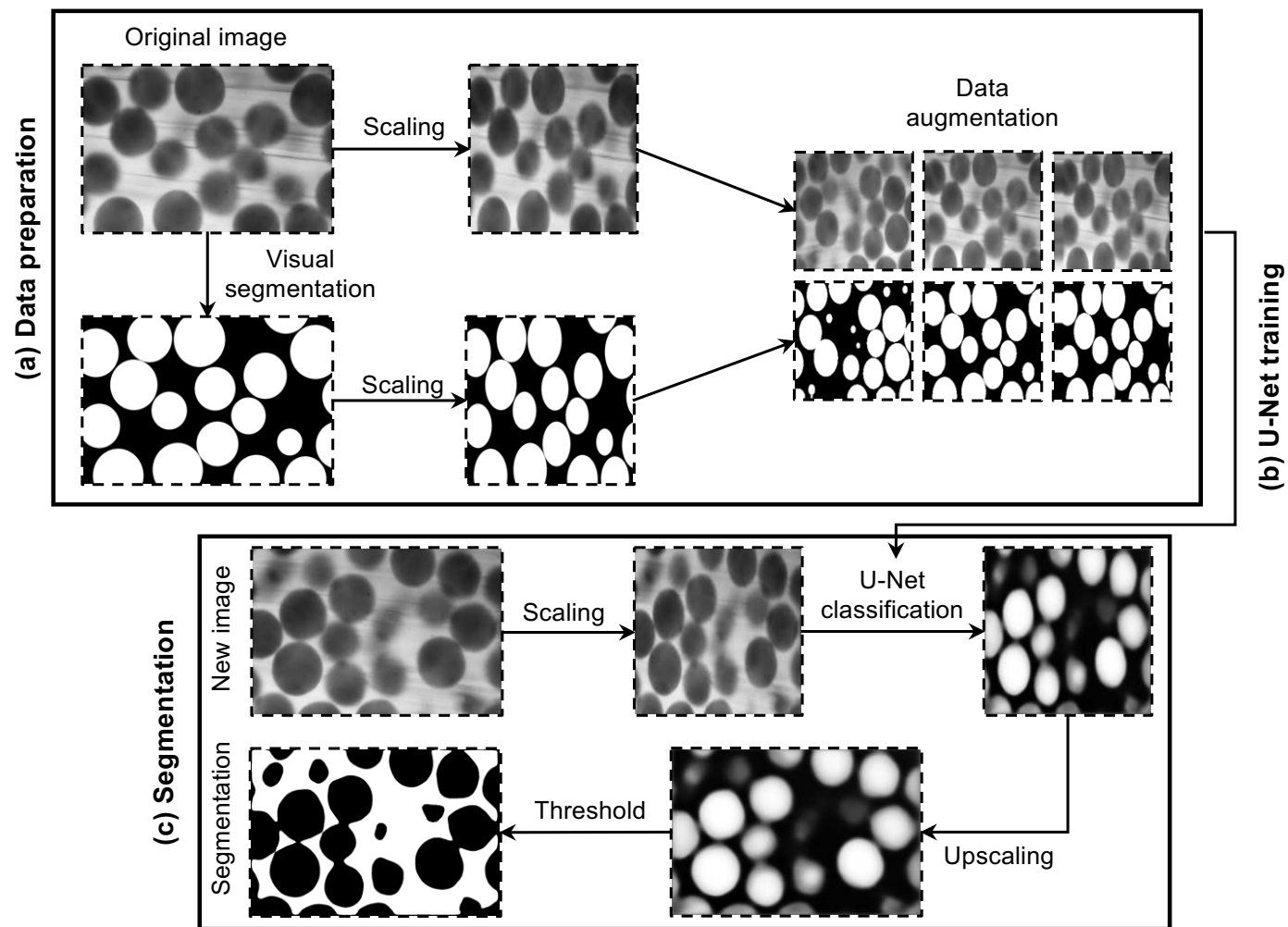


Figure 7. Upscaling along z-direction on the U-Net classified image for Beads-U sub-volume: (a) Unscaled image data; (b) Image obtained by scaling without interpolation; (c) Image obtained by scaling with bilinear interpolation; (d) Image obtained by scaling with bicubic interpolation.

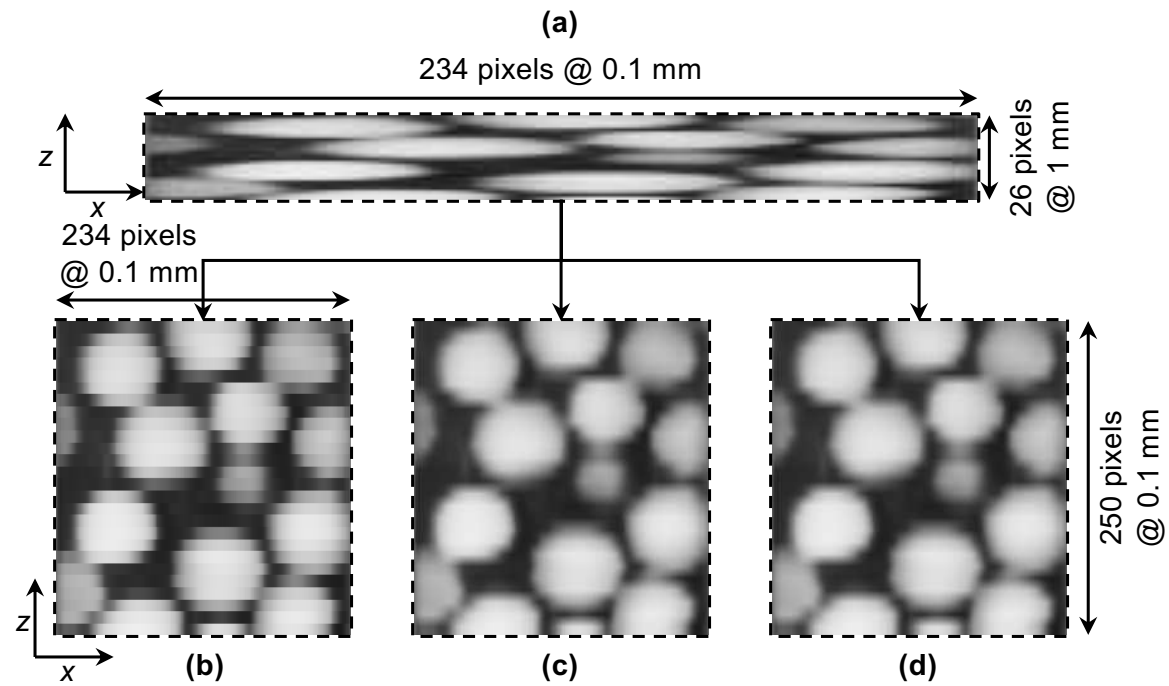


Figure 8. Labelled images with particles represented by different colours for Beads-U sub-volume on (a) x-y plane and (b) x-z plane and Ang-U sub-volume on (c) x-y plane and (d) x-z plane.

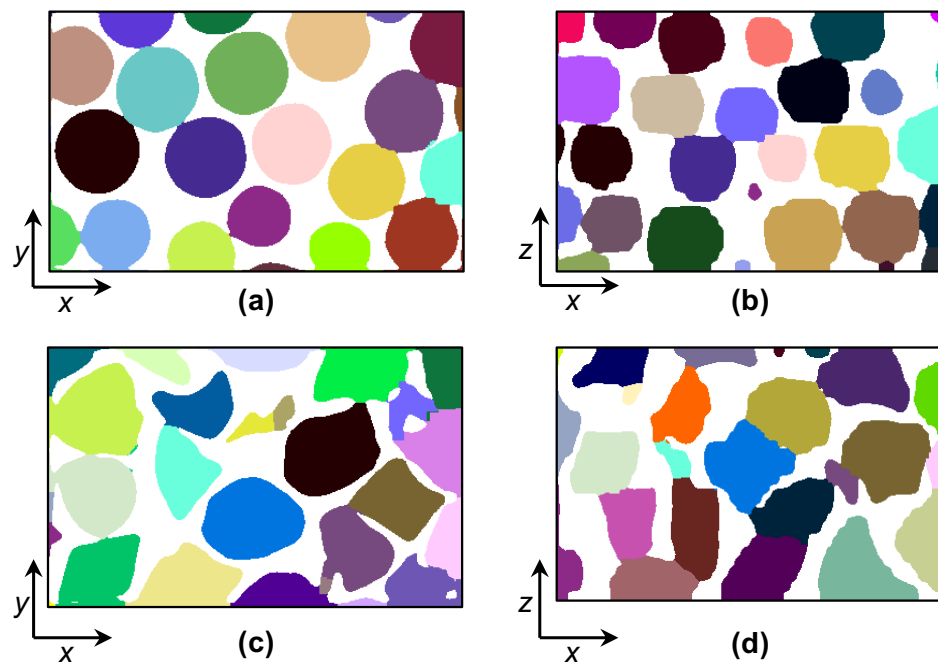


Figure 9. Three-dimensional views of the combined surface meshes for (a) Beads-U sub-volume and (b) Ang-U sub-volume. Note: colour is used to distinguish the surfaces of individual particles. Hexahedron meshes which discretize pore structure for CFD simulation for (c) Beads-U sub-volume and (d) Ang-U sub-volume.

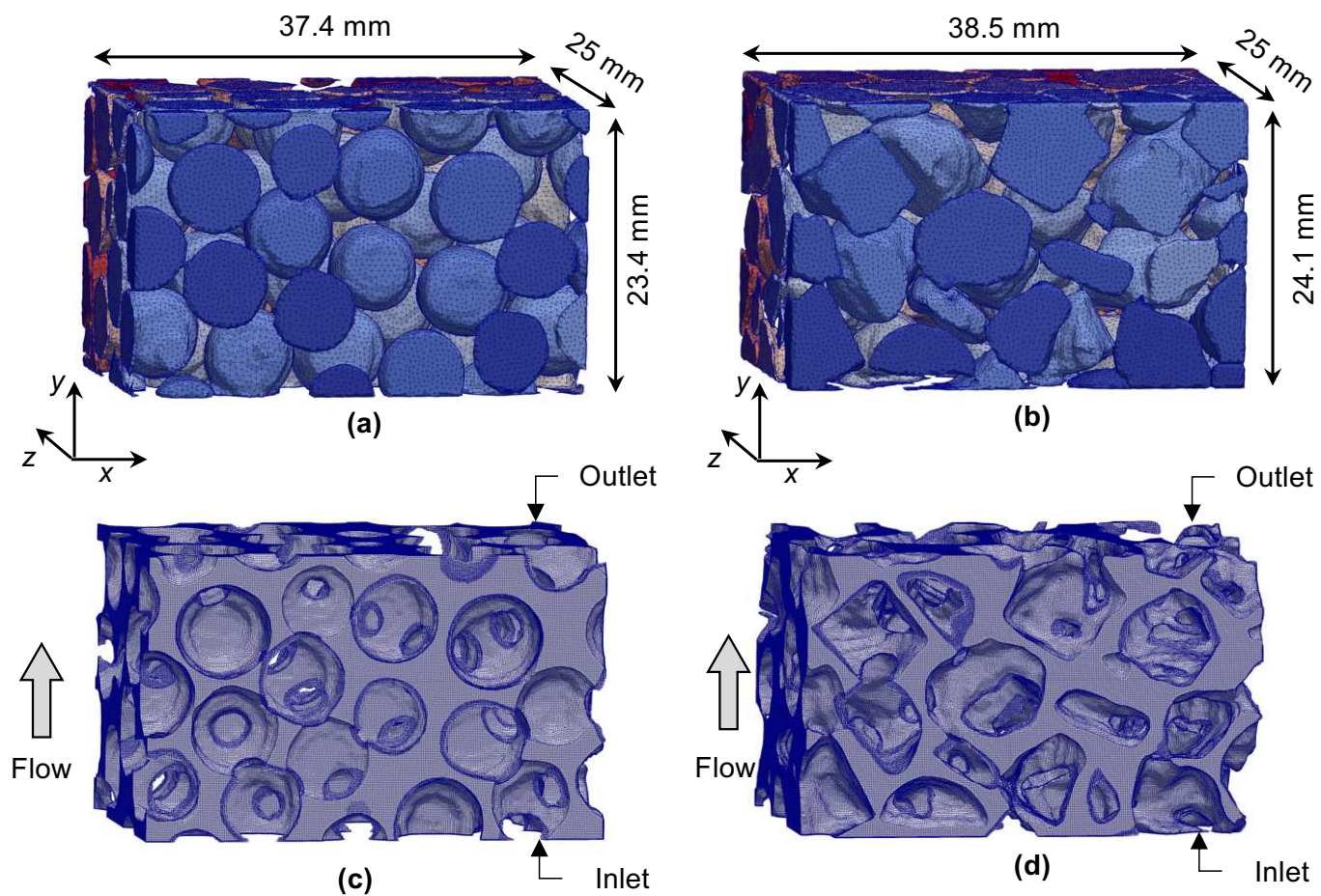


Figure 10. Verification of CFD modelling approach: (a) Confirmation of ability to capture the influence of porosity on the fluid-particle interaction coefficient $\bar{F}_{f \rightarrow s}$, dashed lines indicate a curve fit to the Zick & Homsy (1982) data; (b) Mesh dependence of $\bar{F}_{f \rightarrow s}$ for SC packings; (c) Mesh dependence of $\bar{F}_{f \rightarrow s}$ for FCC packings. The results predicted by the Immersed Boundary Method (IBM) with a regular grid and from fully resolved CFD using an unstructured meshes from Knight et al. (2020) are included in (a) and (c), respectively.

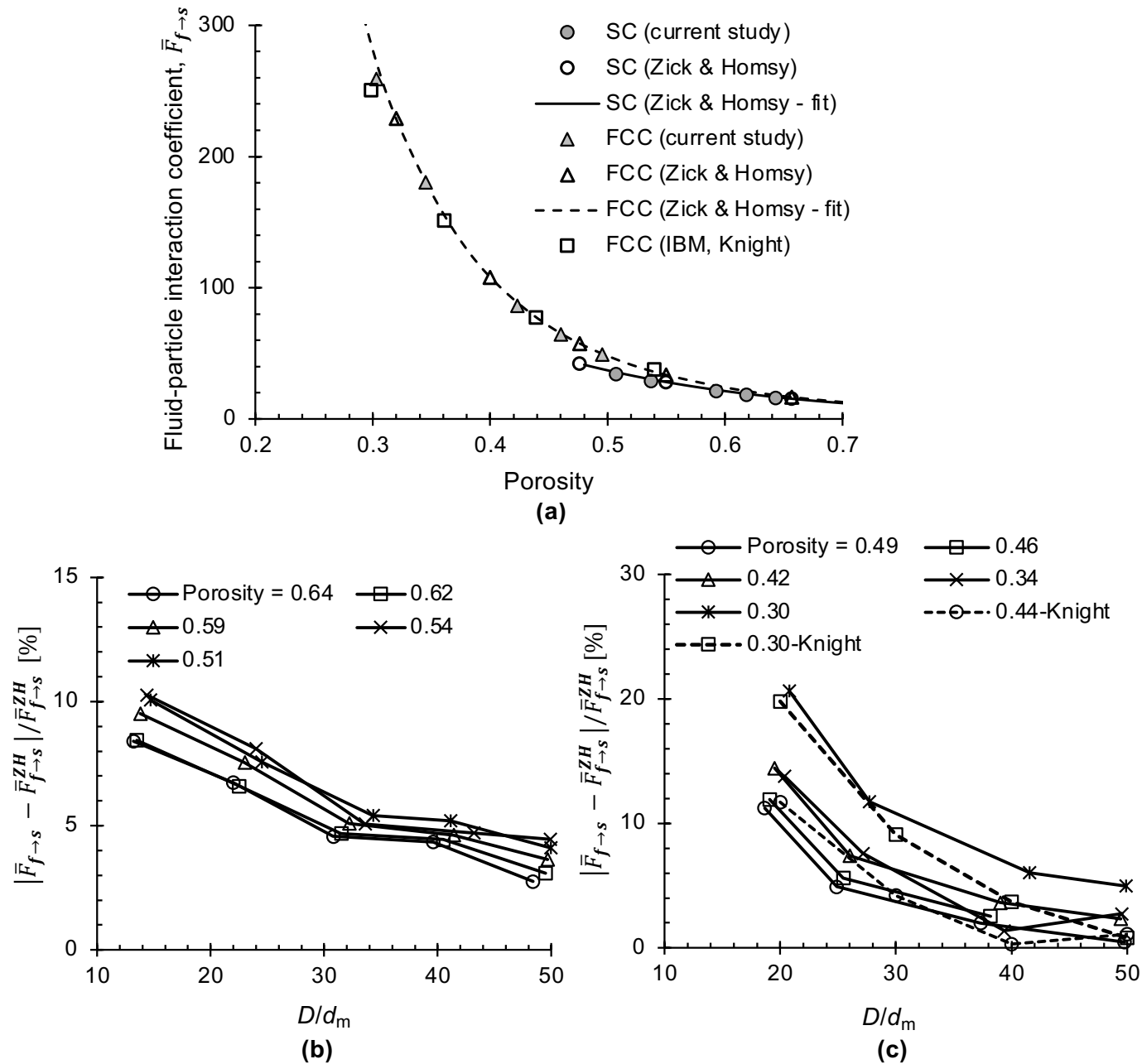
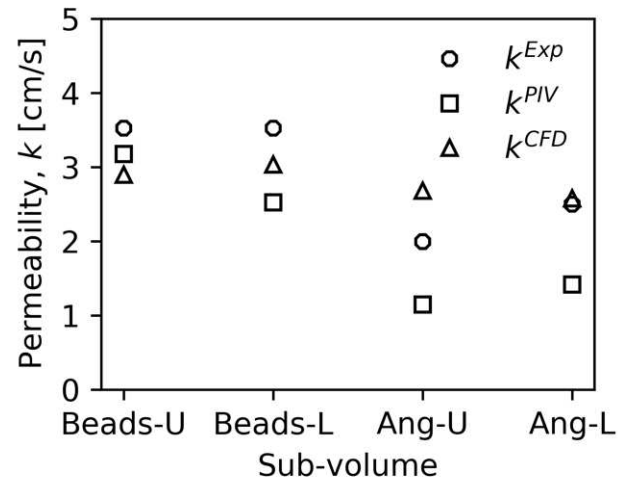
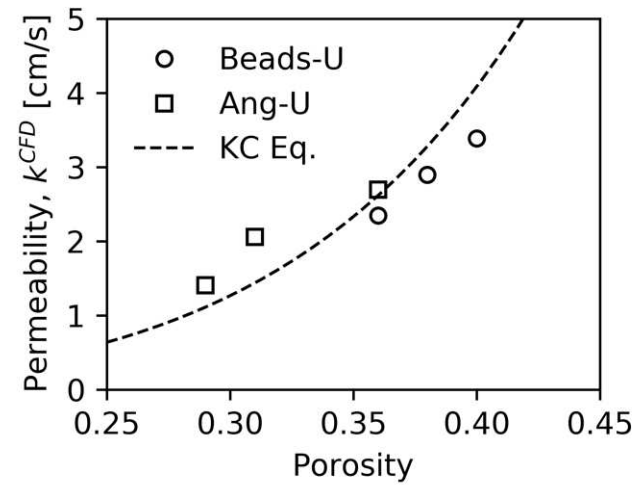


Figure 11. (a) Hydraulic permeability values predicted by experiments, PIV and CFD measurements. (b) Influence of porosity on hydraulic permeability as estimated by CFD modelling for Beads-U and Ang-U sub-volumes. The prediction results from Kozeny-Carman Equation (KC Eq.) is included in (b).



(a)



(b)

Figure 12. Comparison of the PIV and CFD flow fields in Beads-U sub-volume on the vertical slice with $z = 16$ mm.

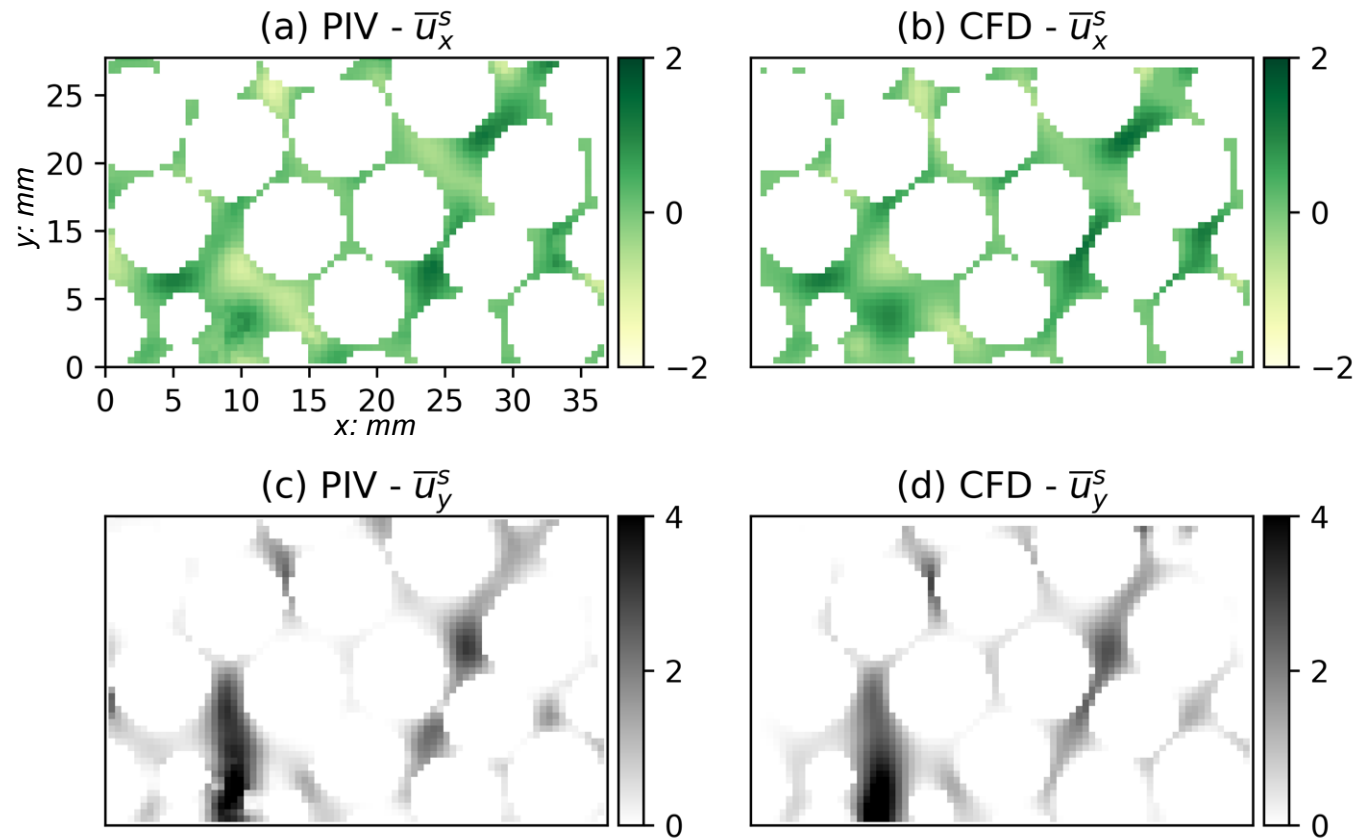


Figure 13. Comparison of the PIV and CFD flow fields in Beads-U sub-volume on three slices with $z = 1, 8$ and 16 mm. Velocity vector length is normalized by seepage velocity.

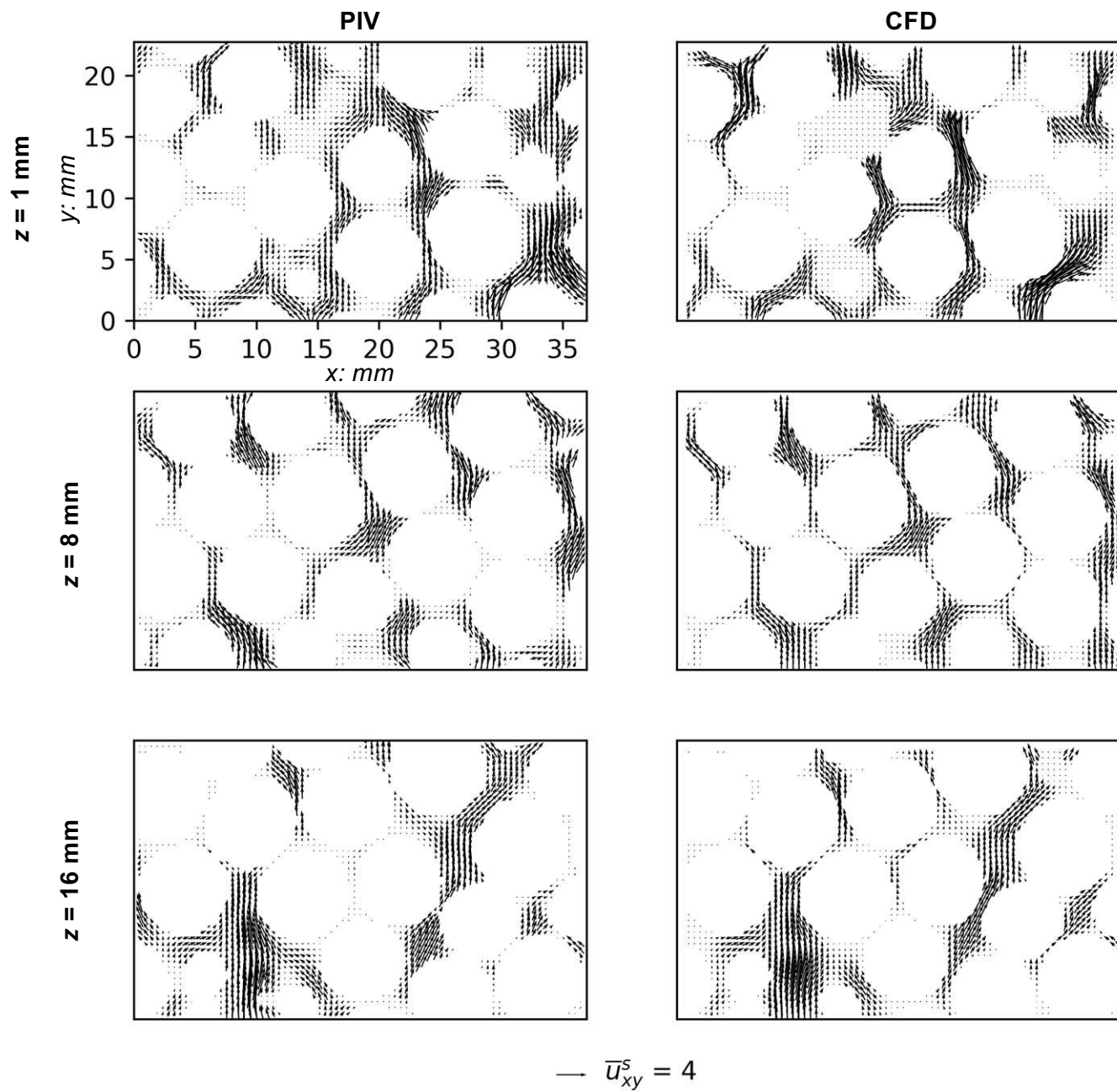


Figure 14. Cumulative distributions of flow velocity at four vertical planes in Beads-U sub-volume obtained from PIV and CFD results.

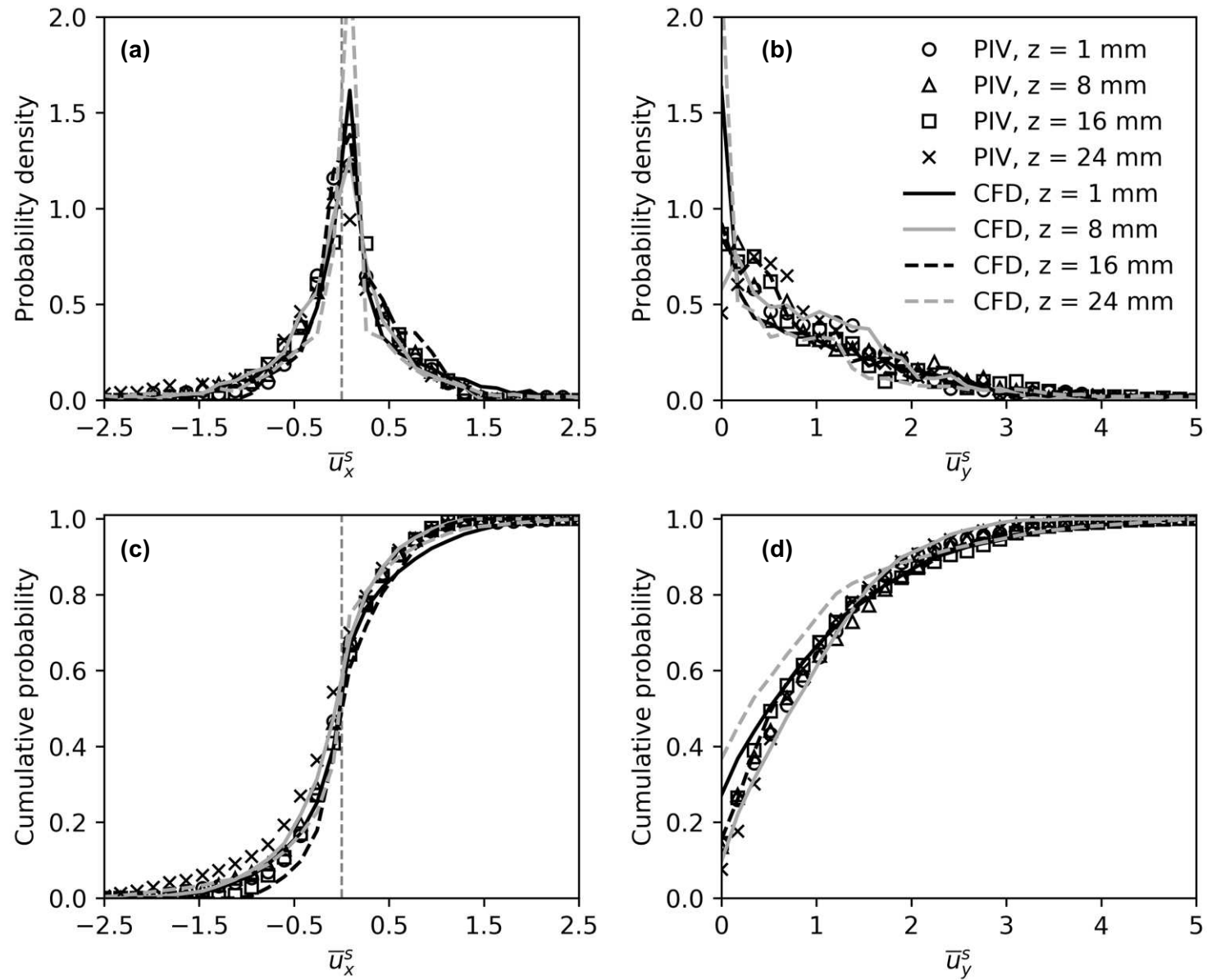


Figure 15. Comparison of the PIV and CFD flow fields in Ang-L sub-volume on three slices with $z = 1, 8$ and 16 mm. Velocity vector length is normalized by seepage velocity. Arrows indicate narrow flow paths.

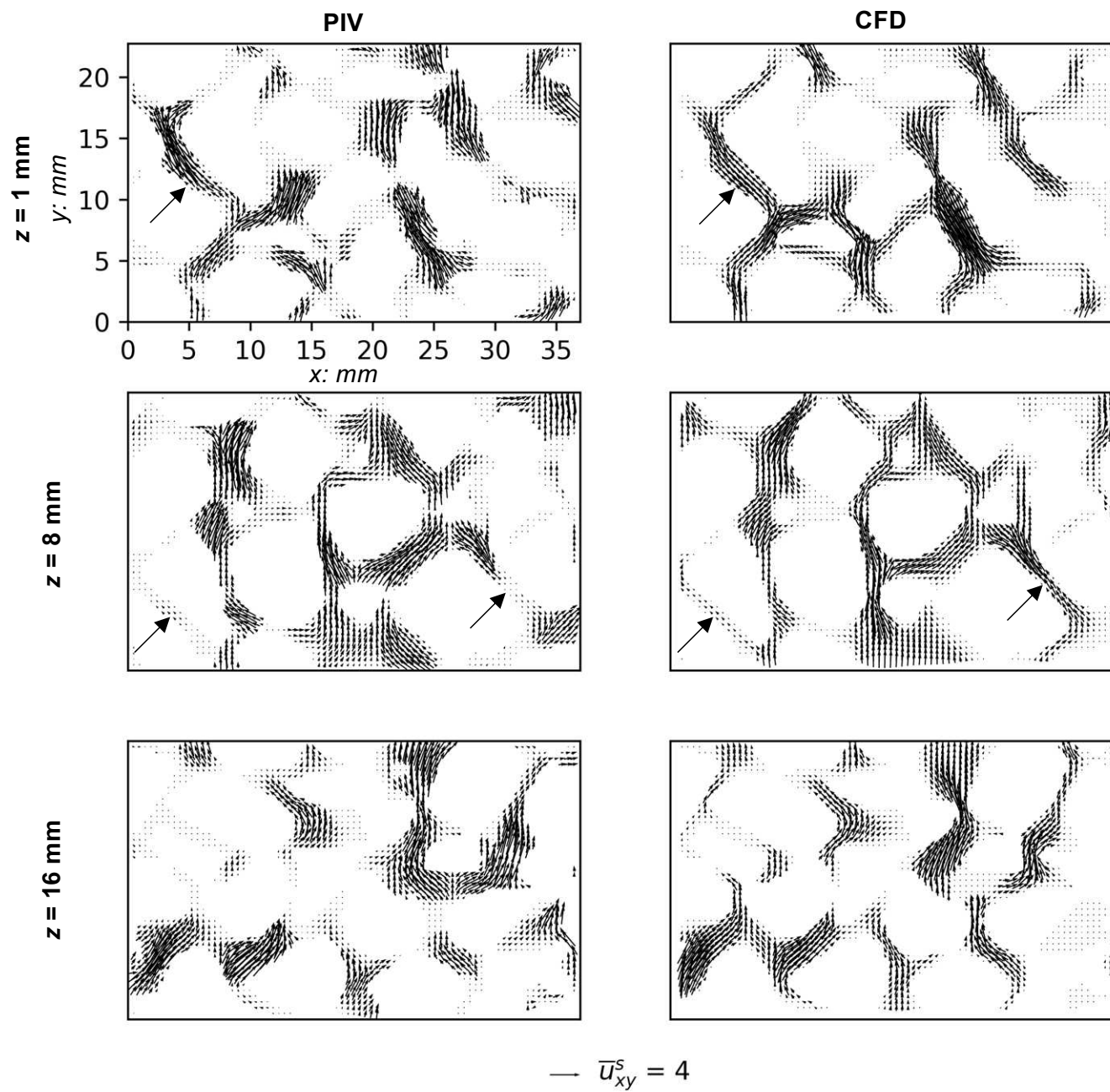


Figure 16. Cumulative distributions of flow velocity at four vertical planes in Ang-L sub-volume obtained from PIV and CFD results.

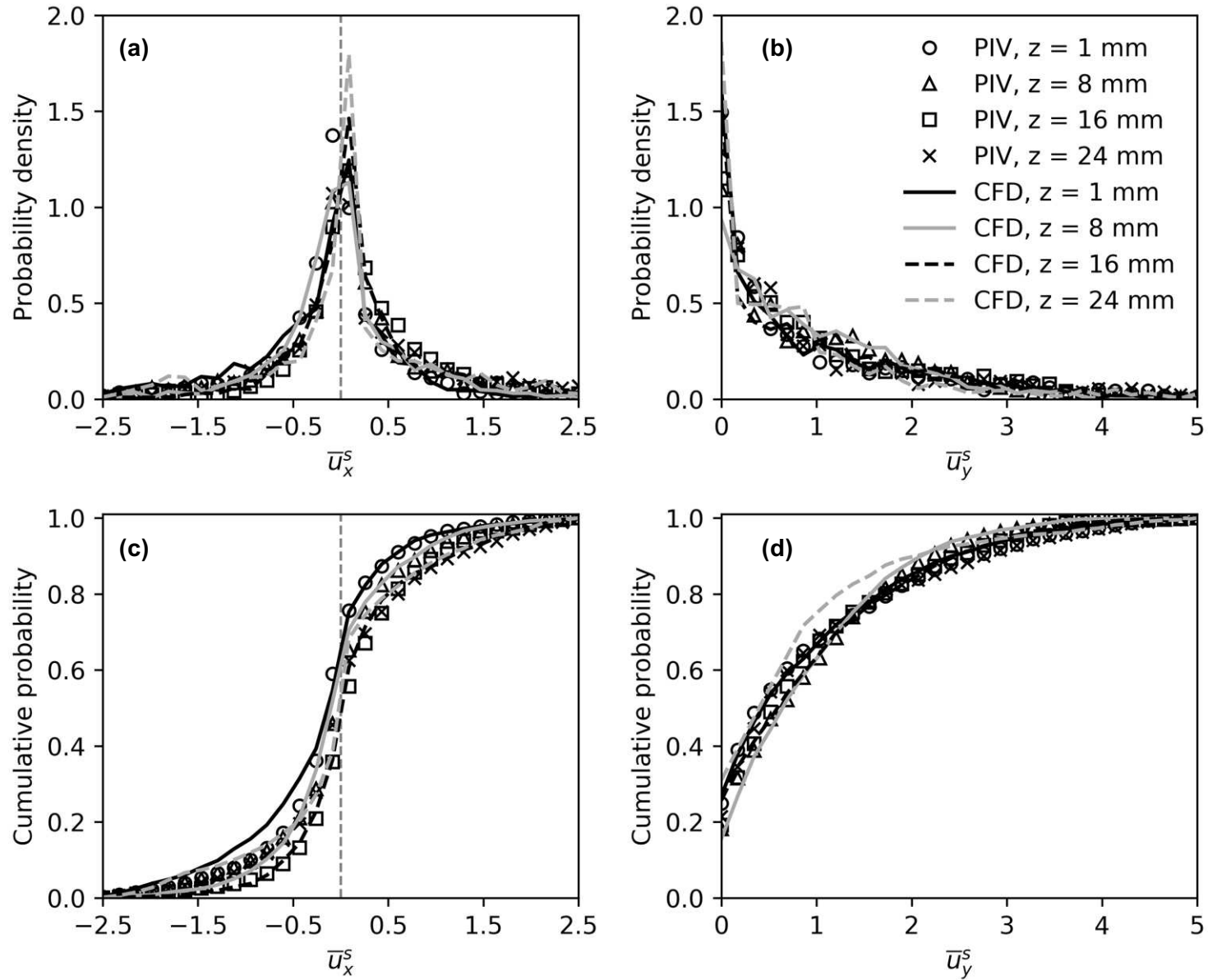


Figure 17. Difference between PIV and CFD flow fields for the vertical slice with $z = 16$ mm in Beads-U sub-volume: (a) horizontal velocity; (b) vertical velocity. The cumulative distributions of PIV and CFD difference for (c) horizontal velocity and (d) vertical velocity on five typical slices in Beads-U sub-volume.

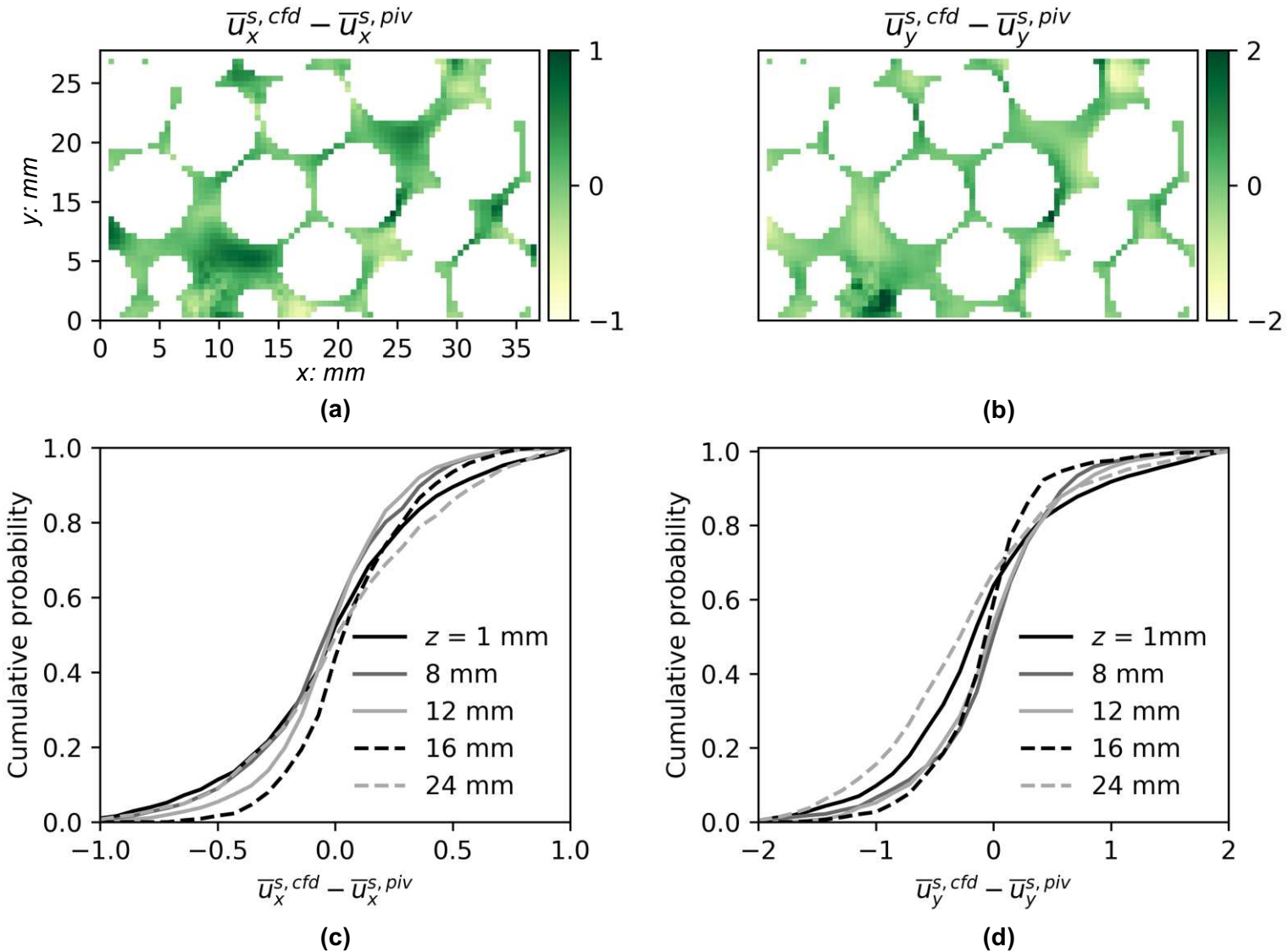


Figure 18. Variation of the mean velocity values obtained from PIV and CFD results and the slice porosity on x-y planes parallel to flow direction.

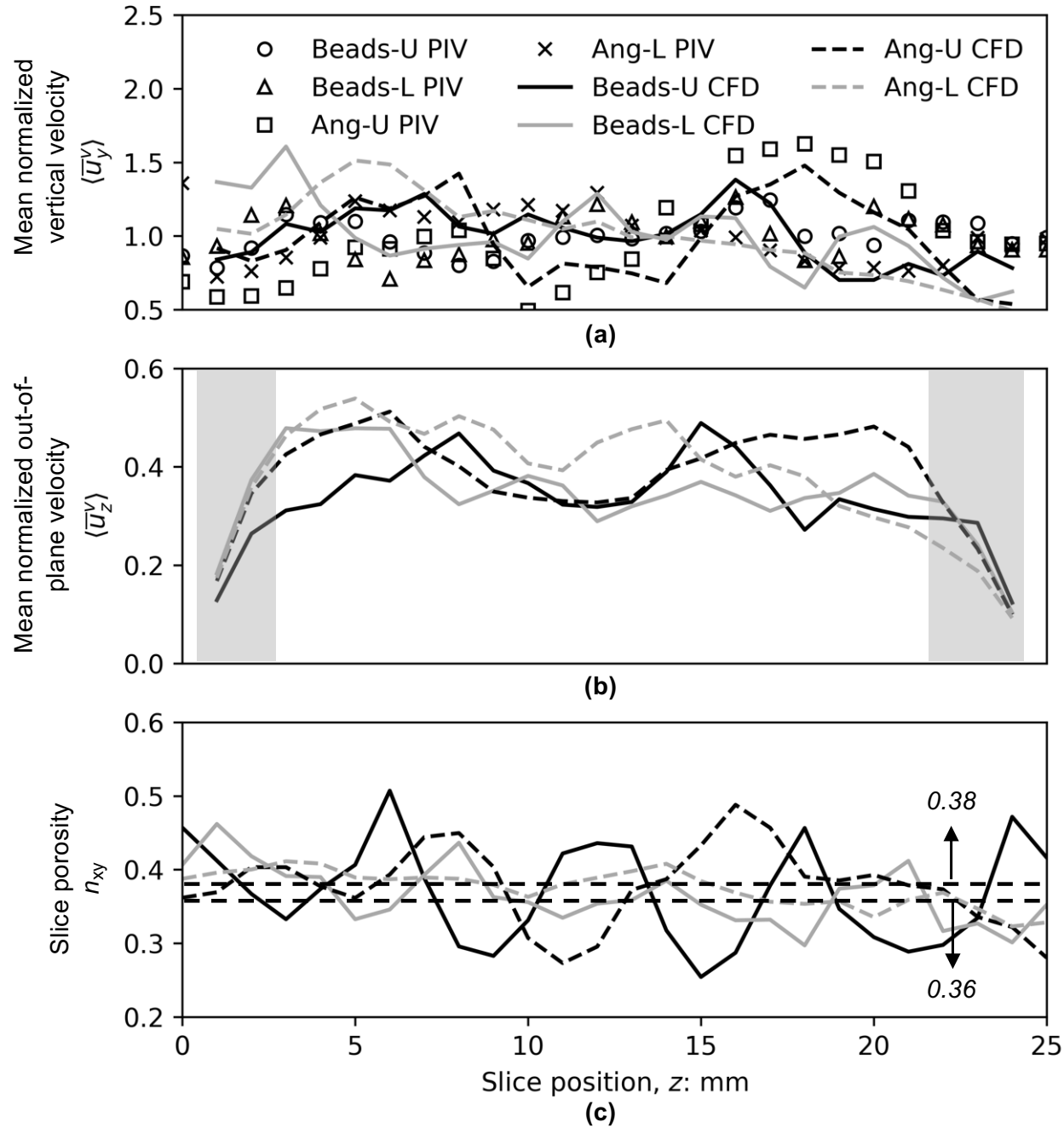


Figure 19. Variation of mean vertical velocity, porosity and hydraulic gradient on x-z planes perpendicular to flow direction predicted by CFD simulations.

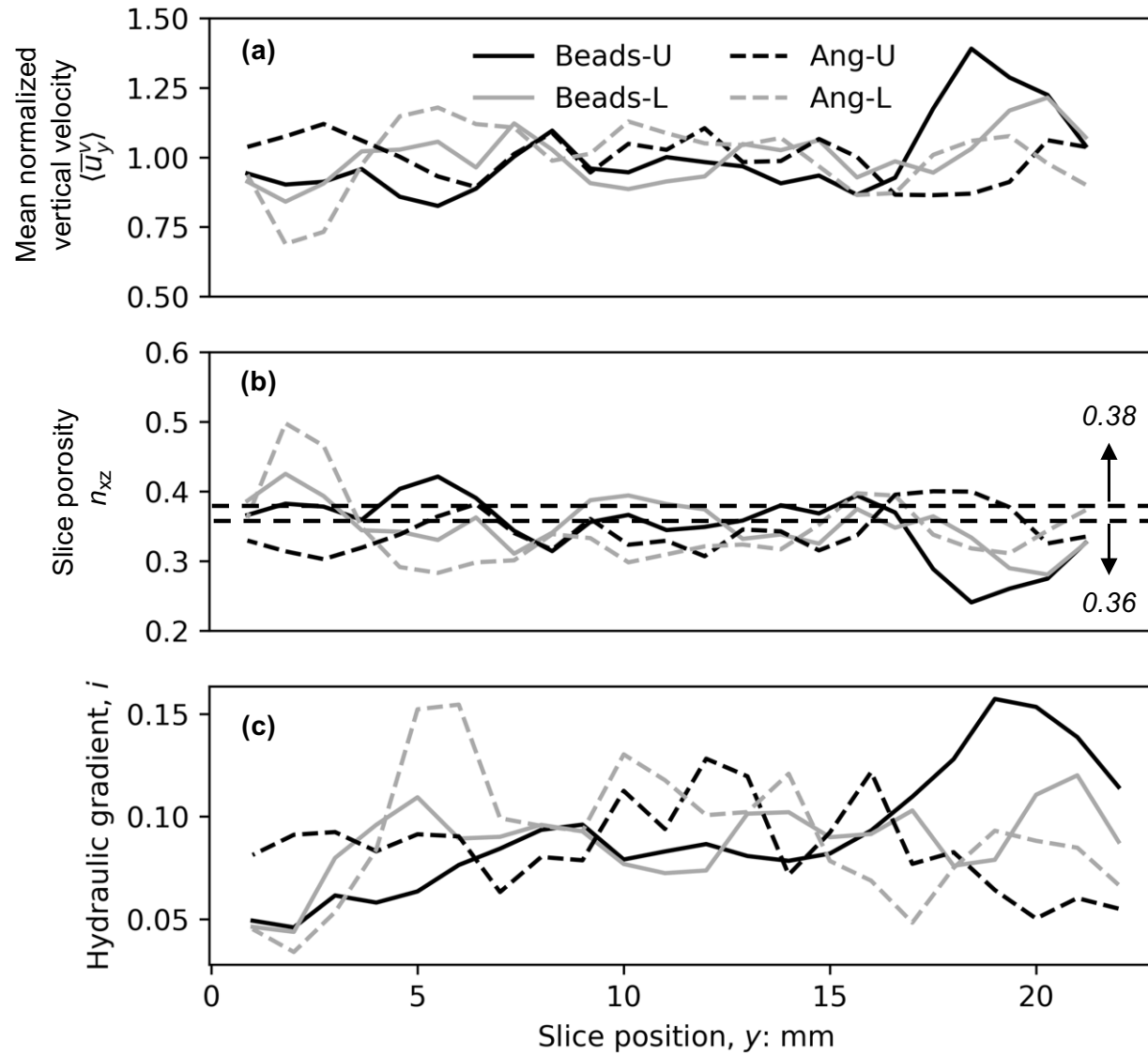


Figure 20. Projection views of drag force vectors for the particles that are not intersecting with boundary walls.

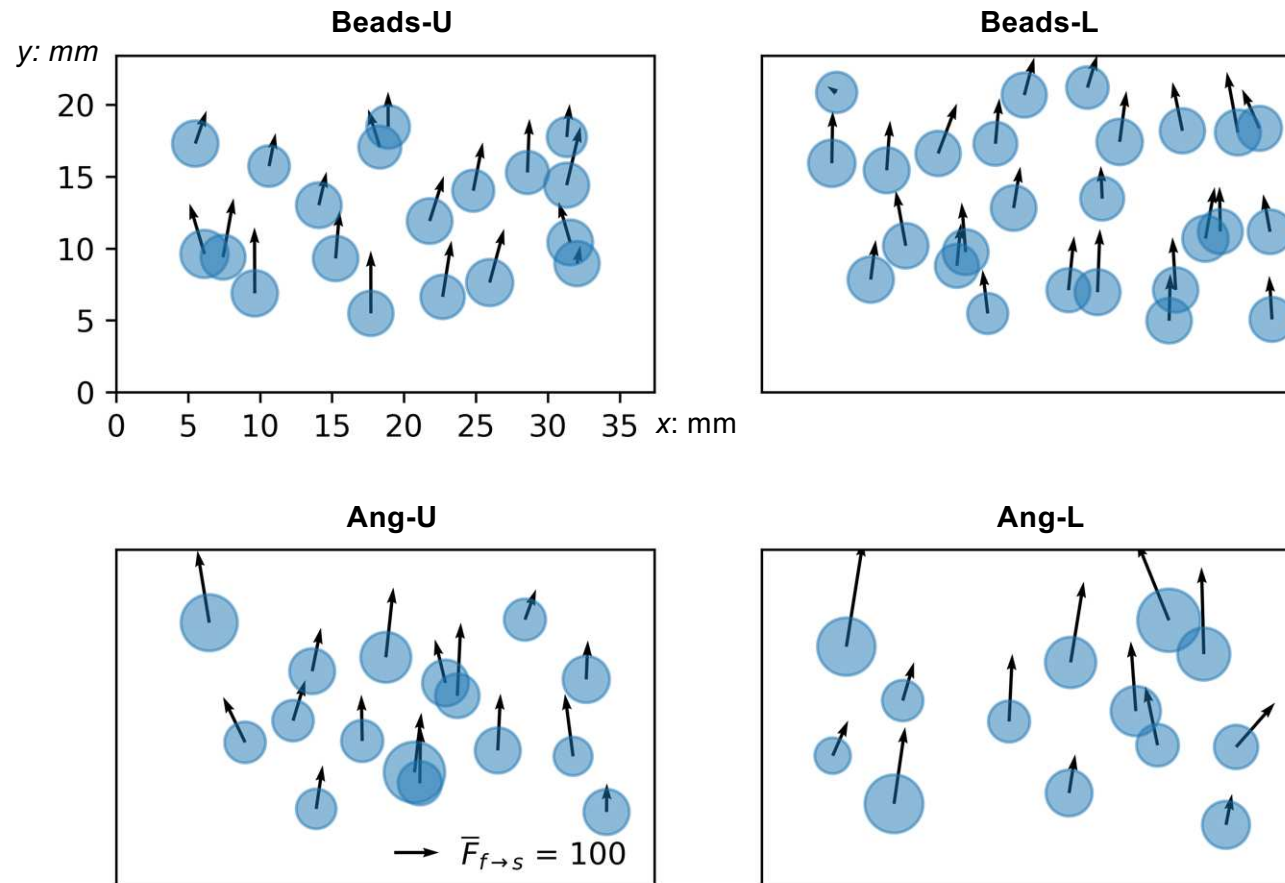


Figure 21. Cumulative distributions of (a) fluid-particle interaction coefficients for beads and angular particles and (b) the normalized fluid-particle interaction coefficients.

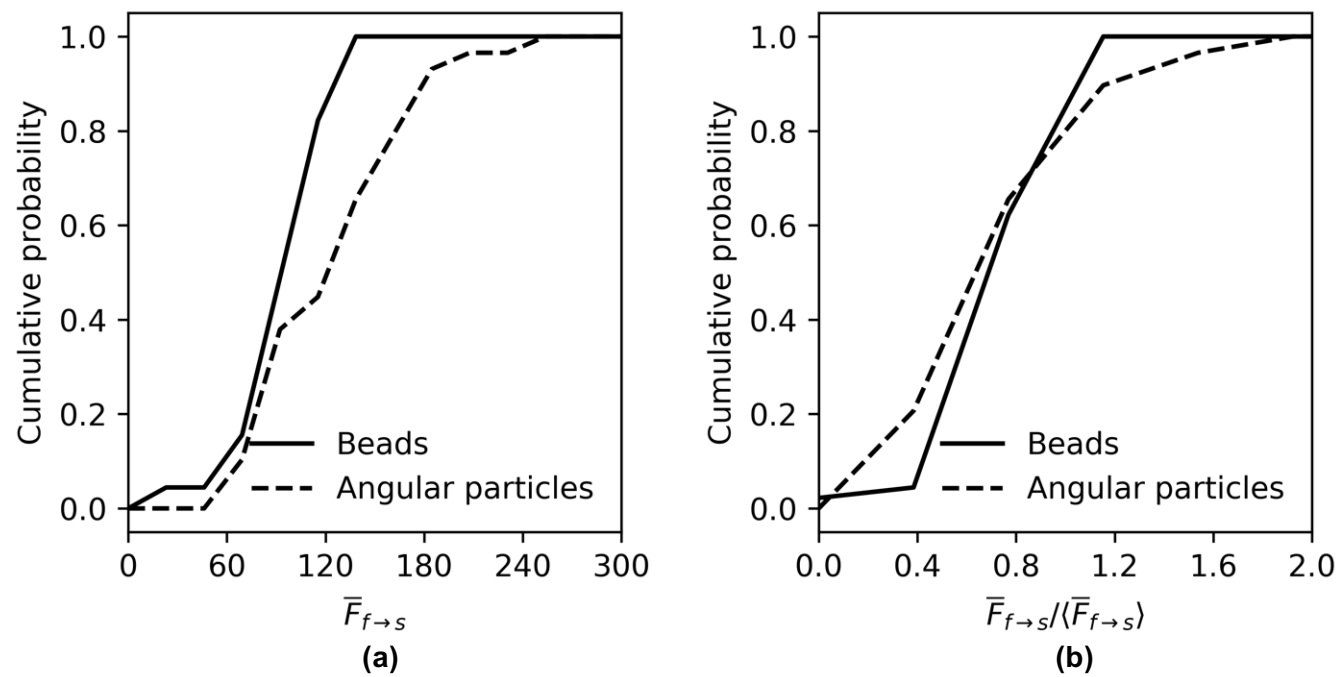


Figure 22. Distributions of (a) the ratio between pressure and viscous drag components, and (b) the angle between fluid-particle interaction and flow direction.

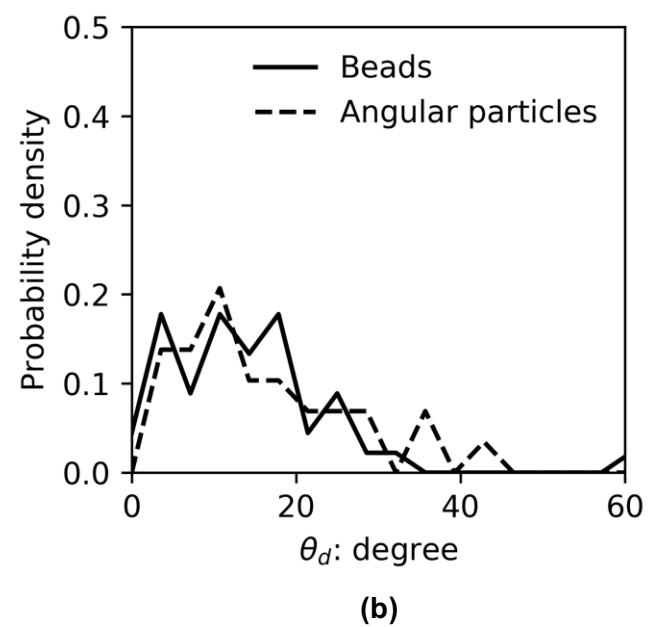
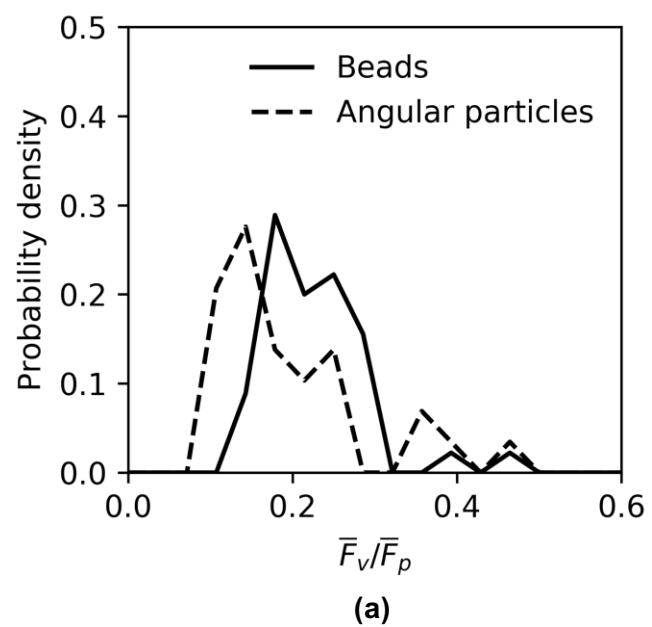
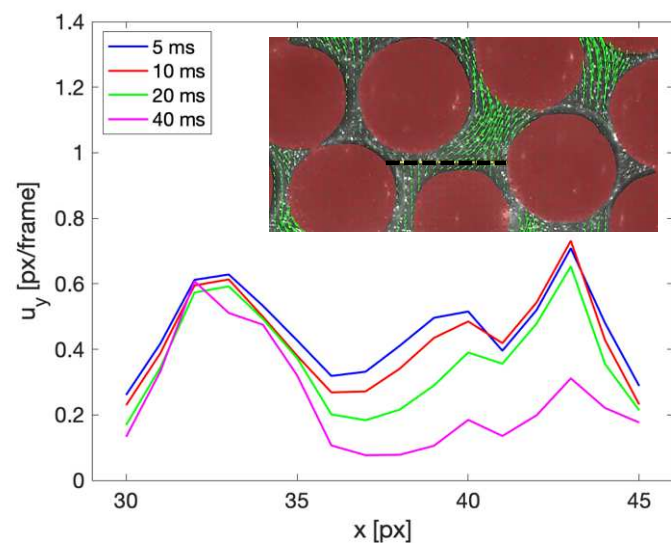
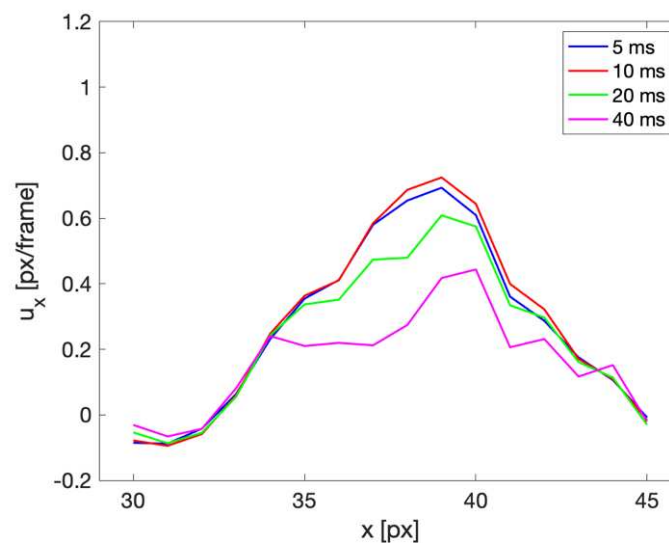


Figure S1. Example of the effect of time resolution of PIV analysis on the estimate of the time averaged component (a) u_x and (b) u_y . The velocities are estimated along the yellow dashed lined shown in the inset of (a).

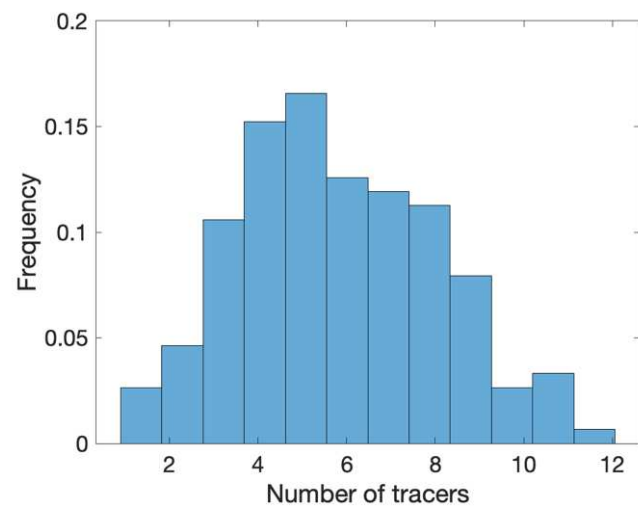


(a)

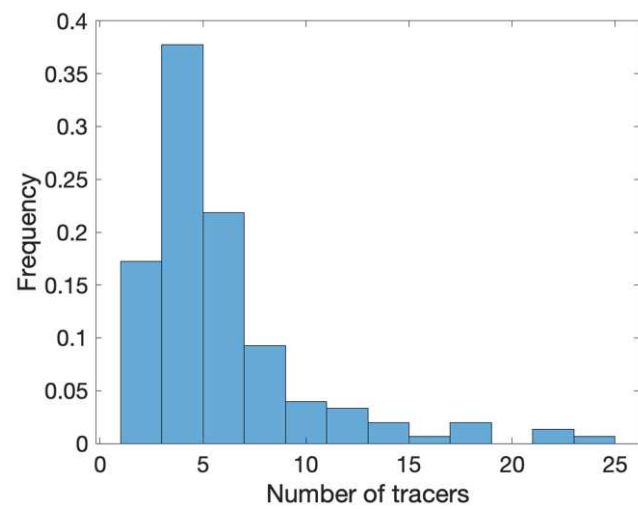


(b)

Figure S2. Distribution of the number of tracers for a subsets of interrogation windows (32 x 32 pixels) for (a) beads and (b) angular particles.



(a)



(b)

Figure S3. Autocorrelation function for a subsets of interrogation windows (32 x 32 pixels) for (a) beads and (b) angular particles. Histogram of autocorrelation peak width for (c) beads and (d) angular particles.

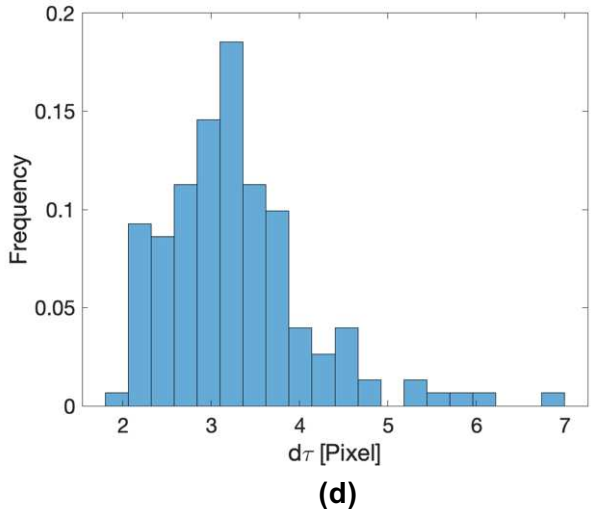
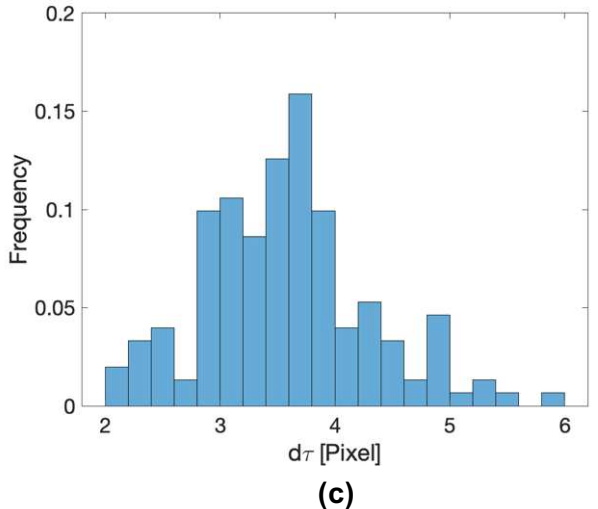
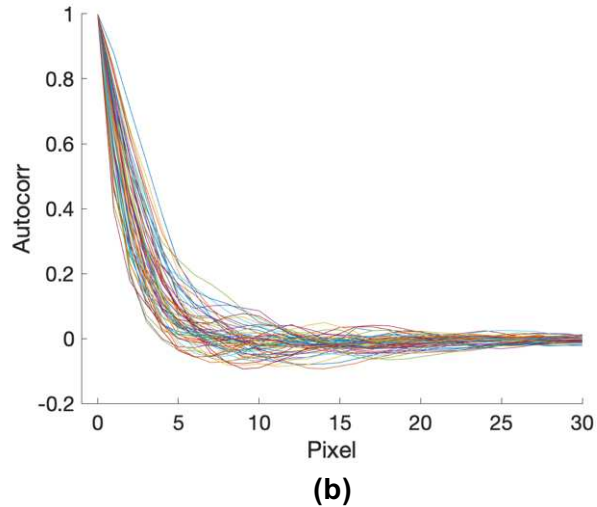
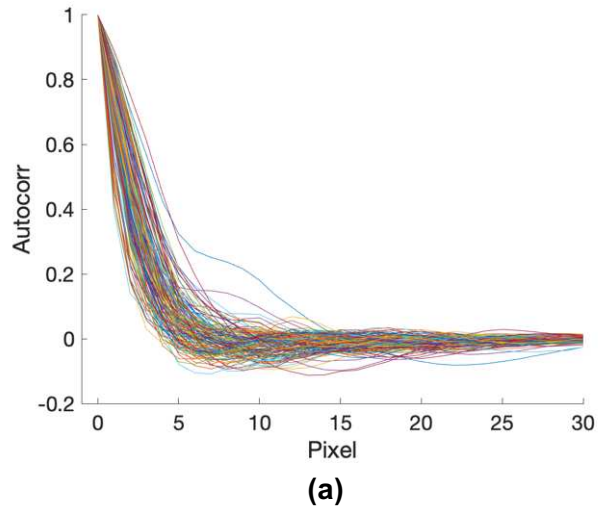
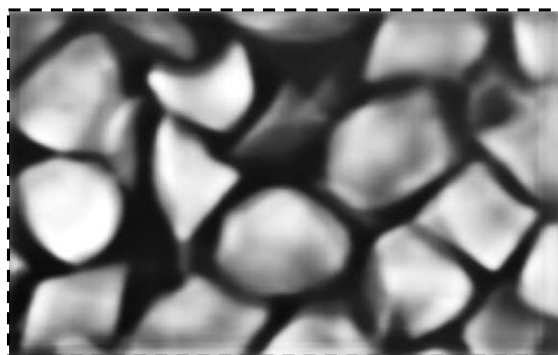
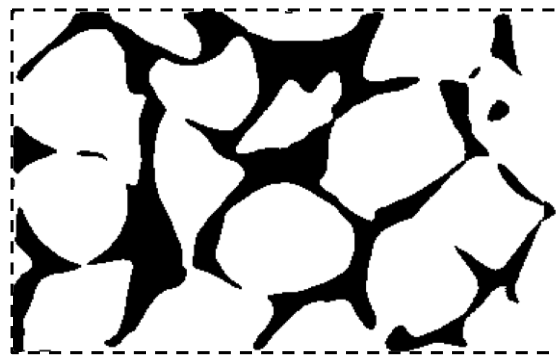


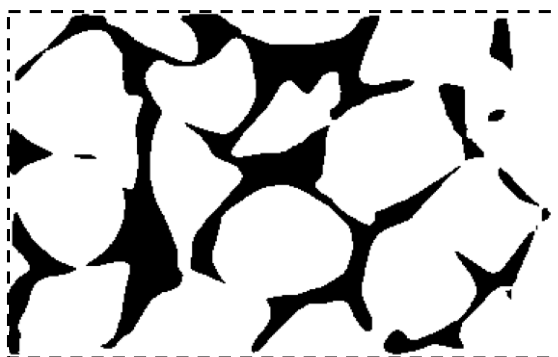
Figure S4. (a) Typical slice of Ang-U processed by U-Net, and the binarization results at different porosity values (b) 0.31, (c) 0.29, and (d) 0.27.



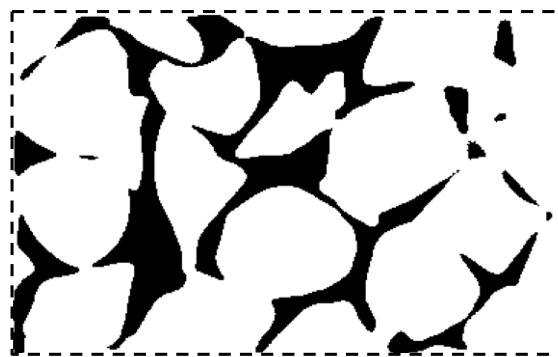
(a)



(b)



(c)



(d)