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1 **WAVELET-BASED CLOD SEGMENTATION ON DIGITAL**
2 **ELEVATION MODELS OF A SOIL SURFACE WITH OR**
3 **WITHOUT FURROWS**

4 E. Vannier^{1*}, R. Dusséaux¹, O. Taconet¹, F. Darboux²

5 ¹ LATMOS/IPSL, Université de Versailles St Quentin,
6 11 boulevard d'Alembert 78280 Guyancourt, France

7 ² Université de Lorraine, Inra, LSE, F-54000 Nancy, France

8 * Corresponding author: phone: + (33) 180285095, email: edwige.vannier@latmos.ipsl.fr

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10 **Abstract**

11

12 Soil surface roughness is a key factor for our understanding and modelling of
13 geomorphologic processes related to exchanges of soil, water and gas. It has an impact on
14 soil properties and tillage outcome. Soil surface roughness can be characterized both
15 globally and locally. The interest of clod segmentation is to allow for both characterizations.
16 Segmenting clods on a digital elevation model (DEM) of a soil surface is a complex problem
17 because soil surfaces are complex surfaces of several level of roughness and because
18 considering elevations results in smooth and poorly contrasted images. However, a DEM in 3
19 dimensions gathers more information than a profile of 1 dimension or an image of 2
20 dimensions.

21 Multiresolution analysis has shown interest for roughness analysis of complex surfaces. We
22 have used it to introduce a new approach for soil roughness analysis and to lay the
23 foundations for clod segmentation. In this paper, we propose a complete wavelet-based
24 approach for accurate clod contour delineation. It relies on several steps: detecting clods on
25 the surface approximations by a supervised detection of local maxima, validating and
26 merging the detections by shape and overlap tests, delineating the clod contours by
27 intersecting locally the soil surface elevations with the estimated plane of the clod base and
28 validating the contours by detecting and correcting the wrong patterns, with statistical pattern
29 recognition. This segmentation method was evaluated in several roughness conditions,
30 made in the laboratory, by comparison with other segmentation method. An indicator of
31 goodness of agreement was introduced for this purpose.

32 This wavelet-based segmentation method showed robustness to the presence of furrows and
33 to the smoothing by rainfall and showed ability to retrieve clod diameters.

34

35 **Key words: random roughness, 3D digital elevation model, multiresolution analysis,**
36 **statistical pattern recognition, clod size**

37 **1 Introduction**

38 The soil, being at the interface of the hydrosphere and the atmosphere, plays an important
39 role in exchanges of soil, water and gas and geomorphologic processes. The role of soil
40 surface roughness in the geomorphologic processes at small scale is commonly
41 acknowledged, (for example Garbout et al., 2013, Bretar et al., 2013, Thomsen et al., 2015,
42 Martinez-Agirre et al., 2016, Gilliot et al., 2017, Vannier et al., 2018 a, Zhao et al., 2018,
43 Schapel et al., 2019). In agricultural fields, the soil surface roughness is shaped by tillage
44 operations and is a result of soil and water mechanisms interaction and feedback. It is
45 related to soil moisture and fertility (Gilliot et al., 2017, Zhao et al., 2018, Schapel et al.,

46 2019). It is usually characterized by several indices, estimated on profiles or images of the
47 soil, characterizing the surface as a whole (Kamphorst et al., 2000, Taconet and Ciarletti,
48 2007, De Oro and Buschiazzo, 2011, Dusséaux et al., 2012, Smith, 2014). Roughness
49 parameterization is still in question (Martinez-Agirre et al. 2016 and Gilliot et al. 2017). A
50 second approach of the surface roughness considers the local irregularities such as
51 aggregates, clods and depressions (Sandri et al., 1998, Darboux et al., 2001, Kamphorst et
52 al., 2005, Arvidson and Bölenius, 2006, Bogrekci and Godwin, 2007, Vannier et al., 2009,
53 Wang et al., 2011, Garbout et al., 2013, Taconet et al., 2013, Chimi-Chiadjeu et al., 2014,
54 Jensen et al., 2016, Ajdadi et al., 2016, Vannier et al., 2018 a and b, Schapel et al., 2019).

55 The development of stereovision from photogrammetry or laser scanning allows for more and
56 more studies based on digital elevation models (DEMs). Analysing elevation changes from
57 DEMs can be interesting at different scales and in various contexts (Takken et al., 2001,
58 Darboux et al., 2001, Jester and Klick, 2005, Blaes and Defourny, 2008, Haubrock et al.,
59 2009, Ahmad Fadzil et al., 2012, Bretar et al., 2013, Jensen et al., 2016, Gilliot et al., 2017).
60 However, as some baseline roughness indices were defined from 1D profiles, the potential of
61 the three dimensions is not always exploited. In our recent studies, we showed that
62 millimetric DEMs allow for both local and global characterization of soil surface roughness
63 (Dusséaux et al., 2012, Taconet et al., 2013, Chimi-Chiadjeu et al., 2014, Vannier et al.,
64 2014, Vannier et al., 2018 a and b).

65 The soil cloddiness can be quantified with the size distribution of the aggregates and clods. It
66 serves to characterize soil quality produced by tillage and to control microrelief changes due
67 to rainfall impact (Sandri et al., 1998, Arvidson and Bölenius, 2006, Bogrekci and Godwin,
68 2007, Wang et al., 2011, Garbout et al., 2013, Jensen et al., 2016, Ajdadi et al., 2016,
69 Vannier et al., 2018 a and b) or control concentration of organic carbon (Schapel et al.,
70 2019). Segmenting the clods is a complex problem because they can be dimly demarcated
71 or embedded with each other or in another piece of relief. In (Vannier et al., 2009) we
72 showed that it is difficult to automatically detect clods of a large size range in natural soil

73 surfaces recorded in the field. In the present study, we address the problem of segmenting
74 clods in DEMs of laboratory made soil surfaces, with or without furrows, with different clod
75 sizes and spacing, at initial stage and after roughness evolution caused by rainfall events.
76 Let us underline that contrary to the 2D images usually processed for edge detection or
77 segmentation, a 3D DEM of a soil surface has a lower contrast. In the gradient-based
78 method of segmentation introduced in (Taconet et al., 2010), at least 90% of the gradient
79 values should be retained in order to detect the clods. In (Chimi-Chiadjeu et al., 2014), a
80 transformation of the image of the surface should be effected before the rough estimation of
81 the clod contours by watershed segmentation. In this paper, we have chosen a geometrical
82 approach, in order to take advantage of the three dimensions of the DEMs. Multiresolution
83 analysis has shown interest for roughness analysis of complex surfaces (Josso et al., 2001
84 and 2002, Vannier et al., 2006, Fernandez-Diaz et al. 2010, Ahmad Fadzil et al., 2012,
85 Labarre et al., 2017). This approach enabled us to detect the clods on soil surface DEMs
86 with satisfactory sensitivity (84%) and specificity (94%) and to localize clods by their summit
87 and extensions in two directions (Vannier et al., 2009). In this paper, we propose a complete
88 wavelet-based approach, relying also on statistical pattern recognition, in order to reach an
89 accurate delineation of the clod contours. The section materials and methods introduces the
90 data base used in this study, the segmentation method and its evaluation. Then
91 segmentation results are presented and compared with other segmentation methods in the
92 result and discussion section.

93 **2 Materials and methods**

94 **2.1 Soil preparation and measurement**

95 The database used in the present study is composed of laboratory made soil surfaces
96 prepared with two different soils and a various range of sieved clods, in order to evaluate the
97 segmentation method in various roughness conditions.

98 In order to do so, two trays of 50 x 50 cm² were prepared with loose silt loam soil for 10 cm
99 depth. One of them had a nearly planar surface (P) and the other one was shaped with
100 gentle furrows every 8 cm (F). Then air-dried clods collected in the field were set upon the
101 two soil surfaces, with various sizes and spacing to reproduce different roughness conditions
102 (Figure 1). These trays were subjected to controlled rainfalls with a laboratory rainfall
103 simulator similar in design to the one presented in (Foster et al., 1979) also described in
104 (Vannier et al., 2018 a and b). This simulator was equipped with oscillating nozzles
105 producing raindrops of 1.5 mm mean diameter at an adjustable number of sweeps per
106 minute to set the desired intensity. For each tray, we retained 3 stages of roughness: the
107 initial stage, the stage after 2 hours of rainfalls at 33 mm.h⁻¹ intensity, and the stage after 3
108 additional hours at 42 mm.h⁻¹ intensity. The DEM of each stage of surface roughness was
109 recorded with the laser scanner described in (Darboux & Huang, 2003, Vannier et al. 2018 a
110 and b). Summarily, the principle of recording relies on a laser producing a line on the soil
111 surface and a CCD camera set at an angle to measure the surface geometry along a profile
112 in the y-z planes. By moving the device along the x-axis, the whole surface elevations are
113 obtained. The accuracies were 0.5 mm in x and y axes, and 1 mm in z axis. In order to
114 introduce geometrical criteria for statistical pattern recognition used along with multiresolution
115 analysis in clod segmentation procedure (see section 2.2.2), the data were resampled at 1
116 mm resolution in x y z. We also referenced the elevations to be positive. Hereafter, the 6
117 DEMs are denoted P0, P1, P2 and F0, F1, F2 for the initial stage, the stage after one rainfall
118 event and the stage after two rainfall events for the planar soil surface and the furrowed soil
119 surface respectively (Fig. 2).

120 Then we added a third tray of 50 x 50 cm² prepared with Lavaur clay loam soil for 10 cm
121 depth, shaped with an oriented roughness of centimetric ridges and furrows. Air-dried 2-cm-
122 sieved aggregates were thrown upon and formed a thick cloddy structure. Figure 3 shows a
123 photo and the DEM of this one sieve range soil surface, called SR.

124 **2.2 Wavelet-based clod segmentation**

125 *2.2.1 Multiresolution analysis of the soil surfaces*

126 The detection and approximate localization of clods was performed according to the wavelet-
127 based detection method introduced in (Vannier et al. 2009). This method first processes to a
128 multiresolution decomposition of the soil surface by wavelet transform.

129 Let us now recall the basis of the multiresolution analysis theory, (Mallat, 1989, Daubechies,
130 1992, Choksi, 2018), and introduce the notations. It is possible to decompose the surface
131 elevations $z=S(x,y)$, into one approximation $A_N(x, y)$ and the sum of N details $D_1(x, y), \dots, D_N(x,$
132 $y)$, at different levels N :

$$133 \quad S(x, y) = A_N(x, y) + \sum_{n=1}^N D_n(x, y) \quad (1)$$

134 The approximations and details of the surface are computed by recurrence:

$$135 \quad S(x, y) = A_0(x, y) \quad (2)$$

$$136 \quad A_{n-1}(x, y) = A_n(x, y) + D_n(x, y) \quad (3)$$

137 Where $D_n(x, y)$ denotes the summation of the horizontal, vertical and diagonal detail surfaces:

$$138 \quad D_n(x, y) = D_{Hn}(x, y) + D_{Vn}(x, y) + D_{Dn}(x, y) \quad (4)$$

139 At each intermediate level n , $A_n(x, y)$ and $D_n(x, y)$ were computed with the decimated and
140 undecimated algorithms, which produce sub-images having the same size as the original
141 image. Indeed, the frequency plan is subdivided into two parts of low and high frequencies
142 along each dimension x and y . The approximation is the low-low frequency part, the
143 horizontal detail the high-low frequency part, the vertical detail is the low-high frequency part,
144 and the diagonal detail is the high-high frequency part. We used the orthogonal wavelet
145 family selected in (Vannier et al., 2009), with mother wavelet Daubechies of level 9
146 (Daubechies, 1992).

147 Then, a supervised local maxima extraction was performed on the retained surface
148 approximations and the results of all extractions were merged. As a result, the individual
149 clods of the soil surface were localized by their summit and extensions in the x y plane. The
150 whole procedure is detailed in (Vannier et al. 2009).

151 It was shown that the successive approximations of the soil surface contained most of the
152 surface energy. Selecting the proper levels of approximations, depending on the roughness
153 scale of the soil surface, allowed for the detection and localization of the range of clods
154 present on the soil surface. As an example, for the seedbed considered in (Vannier et al.
155 2009), containing clods of diameters less than 53 mm, the levels of approximations A3 and
156 A2 were relevant. Due to clod proximity, level A4 was not suitable. With the present silt loam
157 surfaces, containing spaced clods of diameters up to 76 mm, it was necessary to include the
158 levels A4 and A5, in order to detect also the larger clods. And with the Lavaur clay surface,
159 containing very small and nearby clods, the levels A1 to A3 were selected.

160 *2.2.2 Statistical pattern recognition of clods*

161 The accurate delineation of the clod contours was done by intersecting locally the soil
162 surface with the estimated plane of the clod base. This process relies on several steps of
163 validation, based on statistical pattern recognition of a good clod segmentation and improper
164 object segmentation. The algorithm is shown in Fig. 4. An introduction to statistical pattern
165 recognition can be found in (Webb, 2002). In the present study, linear discriminant analysis
166 was sufficient to detect the wrong patterns.

167 The first test of goodness of intersection of the local surface with its mean plane (Fig. 4, line
168 5) detected the cases where the contour does not suit the clod due to erroneous inclination
169 or level of the plane. It resulted in partially squared contour as illustrated in Fig. 5a. This
170 pattern could be detected using the quantiles of coordinates x_c and y_c of the data points of
171 clod contour at minimum, 12.5%, 87.5% and maximum. We had a wrong pattern if two
172 quantiles were equal for x_c or y_c . Then, the inclination and height of the mean plane were
173 refined when needed.

174 The second test of goodness of intersection (Fig. 4, line 6) checked for requirement of the
175 local surface to be extended in one or more than one direction. As illustrated in Fig. 5b, a too
176 small local surface due to inadequate extensions of detected clod, caused straight borders in
177 the clod contour. These lines were detected by thresholding the percentage of abscissa (or
178 ordinates) equal to their minimum or maximum value. The local surface was then extended a
179 little in the direction given by straight borders and the test repeated until no extension was
180 required.

181 The third test (Fig. 4, line 7) aimed at detecting blocks of clods (as in Fig. 5c) when the clods
182 were very close together. It could occur also due to furrow interference or presence of small
183 aggregates near a larger clod. At initial stage, we would like to distinguish the individual
184 clods. A block of clods was characterized by an elevated circularity and a gradient of clod
185 elevations with more than one mode or one enhanced mode. In that case, the clod contour
186 was searched as an iso-gradient or an iso-elevation contour.

187 The last test (Fig. 4, line 10) detected the squared like contours (as in Fig. 5d), where the
188 clod was partly squared. Again, the percentages of abscissa or ordinates equal to their
189 extremum value were computed. They were compensated for the clod perimeter and
190 diameter and thresholded. In that case, the level of the mean plane was elevated and the
191 clod contour re-evaluated. If a wrong pattern was obtained again, the contour was discarded
192 as it is the case in the example in Fig. 5d).

193 **2.3 Evaluation of segmentation method**

194 For the silt loam soil surfaces P0, P1, P2, F0, F1 and F2, we had a reference of contours
195 drawn by hand on a photo of the surface, with visual check looking at the surface in the
196 laboratory. This reference was scanned. In order to make a clod by clod survey, the studied
197 area was reduced to 30 x 30 cm² and the DEMs were shown in mm. The total number of
198 clods was near 300 for these silt loam soil surfaces.

199 We evaluated the wavelet-based segmentation by comparison with the hand-made
 200 segmentation and two other segmentation methods, the contour-based approach introduced
 201 in (Taconet et al. 2010) and the threshold method used in (Vannier et al. 2018 a and b). The
 202 hand-made segmentation is subjective and has a bias due to contours delineation on 2D
 203 photos of the soil surfaces. The threshold method detects objects having elevations above a
 204 fixed threshold. It therefore requires that the clod support is flat and horizontal, which is not
 205 the case of a furrowed surface. However, it is a solid objective reference for a planar
 206 horizontal surface. The contour-based method researches iso-elevation contours passing
 207 through high gradient data points. It has the advantage to be very close to the threshold
 208 method on a planar surface and to be still applicable on a clod support of variable heights. It
 209 nonetheless reaches its limits if the clod support is too much tilted [Chimi et al., 2013].

210 The reference index of segmented region similarity is Jaccard index also called Intersection
 211 over Union (IoU) (Shen and Zeng, 2019 and Zhang et al., 2019). It can be interpreted as an
 212 overlap rate between the two segmented regions. These indices were computed with one set
 213 of segmented contours serving as reference. The IoU of regions delimited by contours k and
 214 l was denoted $\tau_{k,l}$ and defined as in (Chimi et al. 2013):

$$215 \quad \tau_{k,l} = \frac{\mathcal{A}_k \cap \mathcal{A}_l}{\mathcal{A}_k \cup \mathcal{A}_l} \quad (5)$$

216 where \mathcal{A}_k is the area delimited by the contour k of the clod in the first set of segmented
 217 contours and \mathcal{A}_l is the area delimited by the corresponding contour l of the clod in the
 218 second set of segmented contours. The denominator $\mathcal{A}_k \cup \mathcal{A}_l$ makes the overlap rate
 219 stricter than taking just the area of the reference contour \mathcal{A}_k . However, it is necessary to
 220 prevent the case where \mathcal{A}_l would be very large including \mathcal{A}_k , giving an overlap rate of 100%
 221 whereas the contours would be of very different sizes. That is why the regions are
 222 considered similar if the IoU is above 50% and dissimilar otherwise (Wand et al., 2019). The
 223 average IoUs are usually reported. However, the average is limited to characterize the

224 segmentation results on a wide number of objects, therefore it is usually associated with
225 other indices of performance.

226 The IoU is sensitive to the discretization of the contours due to DEM accuracy and is stricter
227 for small clods than for large ones. As an example, figure 6 shows two contours of radius
228 respectively of 3 mm and 6 mm, and the same contours translated by 1 mm. The visual
229 agreement is quite satisfactory and yet the IoUs are respectively of 58% and 76%.

230 For the planar surfaces P0, P1 and P2, we used the hand-made segmentation and the
231 threshold segmentation as references. For the furrowed surfaces F0, F1 and F2, the
232 references were the hand-made segmentation and the contour-based segmentation applied
233 on a detrended surface, where the average of the rows has been removed. Let us specify
234 that both the hand-made and the wavelet-based segmentations were performed on the
235 original furrowed surfaces.

236 Then we also used other indices such as the clod coverage, which is the ratio between the
237 total area delimited by clod contours and the product of DEM horizontal dimensions, and the
238 mean weighted diameter (MWD) as defined in (Taconet et al. 2010):

$$239 \quad MWD = \sum_{i=1}^N \mathcal{D}_i \cdot s_i \quad (6)$$

240 Where N is the total number of clods, \mathcal{D}_i is the equivalent diameter of clod i (estimated here
241 from the area of clod, considered as a disk) and s_i is the fraction of the area covered by clod
242 i :

$$243 \quad s_i = \frac{\mathcal{A}_i}{\sum_{k=1}^N \mathcal{A}_k} \quad (7)$$

244 And, we introduce a fourth index based on the weighted cumulative distribution function
245 (WCDF) of the IoUs of the common segmented clods:

$$246 \quad F_w(\tau) = \sum_{i \text{ f } \tau_{k,i} < \tau} s_k \quad (8)$$

247 In (Chimi et al. 2013), we computed the cumulated distribution function (CDF) of the IoUs,
248 called overlap rates, which shows the probability that $\tau_{k,l} < \tau$, for $\tau \in [0 \ 1]$. In this paper, we

249 used rather weighted IoUs and we defined a quantitative index illustrating the low probability
250 to have a small IoU and the high probability to have a high IoU.

251 The difference between two segmentation methods is quantified with the help of the area
252 under curve (*AUC*) of $F_w(\tau)$. The smaller the *AUC*, the greater the agreement between the
253 segmentation methods. The goodness of the agreement can thus be defined as:

$$254 \quad G = 1 - \int_0^1 F_w(\tau) d\tau \quad (9)$$

255 The equality $G = 100\%$ would reflect the perfect accordance between all contours and $G = 0\%$
256 the total discrepancy. This index is very strict and reflects the overall distribution of the IoUs.
257 It can be considered satisfactory if greater than 0.5.

258 For the Lavaur clay loam soil surface SR, the clods are numerous, very small and very close
259 together, which hinders a clod by clod survey. A smaller area of 20 x 20 cm² was used to run
260 the wavelet-based segmentation and retrieve the clod equivalent diameters and an even
261 smaller part of the surface was segmented manually. We compared the MWD obtained by
262 segmentation to the one measured with a sample of this soil in the laboratory. The number of
263 clods was near 170 on the studied area.

264 **3 Results and discussion**

265 First of all, there is an overall good agreement between the segmentation methods for the
266 silt loam soil surfaces. The mean IoUs range from 54.7%, for F2 to 85.5%, for P0 (see Table
267 1). As the hand-made segmentation had its own bias, the IoUs were also estimated with an
268 automatic method serving as reference when possible. In average, for the wavelet-based
269 method, with all possible references, the mean IoU amounts 71.1%, which is in the order of
270 magnitude of encountered mean IoUs in the literature (Shen and Zeng, 2019 and Zhang et
271 al., 2019). The variations of mean IoUs from one surface to another will be explained with the
272 help of the other indices later on. Let us now look at segmentation results in more detail.

273 The segmentation results for the surface P0 can be seen in Figure 7. The three automatic
274 segmentation methods are quite close to the hand-made segmentation. We notice that the
275 contour-based approach (in blue) is very close to the threshold method (in green). Indeed,
276 the contour-based method captures contours defined as level lines passing through high
277 gradient points. If the clods are set upon a horizontal surface, the level lines are of very low
278 elevation. There is an exception for clod 31 ($x=175, y=225$), which is a two-summit clod that
279 have been captured by the contour-based approach instead of the clod base. Only the larger
280 summit contour was kept for the evaluation. The wavelet-based method (in magenta) is
281 closer to the hand-made segmentation than to the threshold one and tends to detect little
282 more clods.

283 For the surfaces F0, F1 and F2, the presence of furrows does not allow for thresholding at
284 constant elevation. The compared automatic method is the contour-based approach applied
285 on a detrended DEM, where the ridges and furrows were estimated as an average of the
286 DEM along the lines and removed. The effect of this detrending is strengthening the contour-
287 based approach (Fig. 8, in blue). We can see a few contours (in black) on the ridges between
288 the furrows that are not clod contours, for example numbers 7 ($x=240, y=60$) and 40 ($x=160,$
289 $y=160$), which are rather grapes of large aggregates melted with the ridge, or 2 ($x= 170, y=$
290 225) that exceeds true clod border. However, the true clod 44 ($x=45, y=150$) in a furrow, was
291 no more detected after detrending. Two clods (i.e. 19 ($x=45, y=230$) and 37 ($x=50, y=290$))
292 are difficult to segment by the contour-based approach, with or without detrending. We can
293 discuss the meaning of the large aggregates more or less captured or not. For a visual
294 survey, we can say that the minimum diameter of an aggregate should be at least 6 or 7 mm.
295 Figure 9 shows the contours obtained with the wavelet-based method on the raw DEM
296 (magenta) and with the contour-based approach on the detrended DEM (blue). The hand-
297 made segmentation is in yellow dotted line. We can see that most of the contours of large
298 clods are in good agreement. Some small clods or large aggregates were detected by one
299 automatic method and not the other. The contour-based method captured some large

300 aggregates located in the furrows, on the border of the ridges or on the ridges. The wavelet-
301 based method was able to capture the clod numbered 44 ($x=45$, $y=150$) in Figure 8, captured
302 some other large aggregates on the ridges, but captured also two mentioned grapes of
303 aggregates melt with the ridge ($x=160$, $y=160$, and $x=90$, $y=260$) numbered 40 and 47 on
304 Figure 8.

305 The clod coverages, estimated with the different segmentation methods, are shown in Table
306 2, and the MWDs in Table 3. We can see the overall agreement of the methods. The effect of
307 rainfall impact is first an increase of clod coverage and MWD (from P0 to P1 and F0 to F1)
308 and then a decrease of clod coverage due to disappearance or erosion of the smaller clods,
309 and a stabilization of MWD (from P1 to P2 and F1 to F2), which give more weight to the
310 larger clods. We can notice than the wavelet-based method tends to underestimate the MWD
311 due to difficulty to capture the borders of the very large clods (see Figure 6). The higher clod
312 coverage for P0 is due to the detection of more small clods. The lower MWD of contour-
313 based method for P0 can be explained by the mis-segmentation of a very large two-summit
314 clod. For P2, MWD is overestimated by threshold method because it captured three blocks of
315 nearby clods (8, 15, 18) while the other segmentation methods segmented them as single
316 clods by (see Fig. 10). For the different stages of furrowed surface F0, F1 and F2, we have
317 comparable MWDs for contour-based and wavelet-based segmentations but slightly higher
318 clod coverage by wavelet-based method. This can be explained by the fact that contour-
319 based method detects generally less clods than wavelet-based method. In particular, after
320 two rainfall events, the number of segmented clods decreased a lot due to erosion, resulting
321 in poorly shaped residual clods (see Fig. 11). Therefore, the MWD computed with contour-
322 based method for F2 is likely overestimated, due to deficit of middle-size clods.

323 Table 4 gathers the estimated goodness of agreements (eq. 9) between the segmentation
324 methods for the 6 roughness conditions. The three automatic segmentation overlap rates
325 rank at good level of goodness when compared to hand-made segmentation. The higher
326 score appears to be that of the threshold method, which is in agreement with the hand-made

327 method at 88.2% for planar surface at initial stage P0. When the threshold method is the
328 reference for the three stages of the planar surface, we can see the robustness of the
329 wavelet-based method, which has comparable or even better goodness of overlap rates. For
330 both references, we notice a low decrease of goodness with the roughness smoothing and
331 lowering due to rainfall. An explanation parameter is the size reduction of some clods. The
332 mean IoU is more sensitive to clod size than G, however if the larger clods are not suitably
333 segmented, the stabilizing property of G is lessened. It is the case, for P2, with the wavelet-
334 based segmentation, leading to lower values of G. When considering the furrowed surfaces
335 F0 to F2, G has less variations than mean IoU and the increase followed by a decrease of
336 these parameters can be explained by the proportion of small clods in the surface.

337 When the contour-based method is the reference for the three stages of both planar and
338 furrowed surfaces, a noticeable point is that the wavelet-based method performed well,
339 segmenting clods on the raw DEMs while the contour-based method needed a detrending of
340 the furrowed surfaces. Comparing the wavelet-based method to the contour-based method
341 leaded to globally better goodness of agreement than comparing the wavelet-based method
342 to the threshold method, because these two segmentation methods are sensitive to the slope
343 of the clod shape from the summit to the border. For P0, the agreement score is lower,
344 possibly due to the sensitivity of the segmentations to the small grains of the surface and to
345 the difference of contours on a large two-summit clod. For P1 and F1 the smoothing action of
346 rainfall enhanced the agreement score because the borders are less rough but still well
347 defined and because some small clods have disappeared. At final stage, there were less
348 common clods segmented because the residual clods are poorly shaped (see Fig. 11). The
349 clods segmented by the wavelet-based method on F2 were present at an earlier stage,
350 except one ($x=95$, $y=80$) forming a bump on a ridge. That means that the contours are
351 meaningful. The interest of the wavelet-based method relies in its ability to keep on
352 segmenting clods whatever the roughness conditions, with or without furrows, at initial stage
353 or after rainfall events. This method performs better for clods than for large aggregates. In

354 average, for the wavelet-based method, with all possible references, the mean value of G is
355 77.5 % whereas the mean IoU amounts 71.1%. This higher score suits well to the visual
356 agreement seen in the figures 7, 9, 10 and 11, and to the small root mean squared error
357 (RMSE) of MWDs of 4 mm when comparing the wavelet-based to the hand-made derived
358 diameters (see table 3). Therefore, it is a more robust performance indicator when changing
359 the roughness condition by adding furrows or subjecting the surfaces to rainfall (see tables 1
360 and 4). It reflects more the segmentation performance than the DEM resolution and the clod
361 size effect as the mean IoU.

362 Let us now focus on the ability of wavelet-based segmentation to derive suitably the clod
363 diameters. We already mentioned the low RMSE of 4 mm in estimating MWDs of the 6 silt
364 loam DEMs. As a comparison, in Bogrekcı and Godwin, 2007, the lowest RMSE between
365 sieve-derived and 2D image-derived MWDs was 14 mm. In our study, for the Lavour clay
366 loam surface, the sieve range was 2 cm. Unfortunately, the sieved-derived MWD was not
367 measured for this soil. With hand-made segmentation, the minimum diameter is 7.0 mm, the
368 maximum diameter 24.3 mm, and the MWD 15.9 mm. With the wavelet-based segmentation,
369 some clods were missed or were segmented as a block of clods instead of single clods (see
370 Figure 12). The minimum diameter is 7.2 mm and the maximum diameter 23.3 mm, which is
371 very good agreement with the hand-made segmentation. The overall estimated MWD is 14.2
372 mm, which is in good agreement with hand-made estimation with a relative deviation of 10.7
373 %. We assume that hand-made segmentation is difficult with such small and nearby clods so
374 that it was performed on a small area where the clods were well defined and likely larger
375 than in other areas. So, the hand-made derived MWD was likely slightly over-estimated. The
376 wavelet-based derived MWD was nevertheless a little under-estimated as it was already the
377 case for the silt loam surfaces in table 3.

378 The silt loam surfaces present a wider range of clod diameters. In order to compare our
379 results with other methods available in the literature, we considered the total of 113 clods
380 from surfaces P0 and F0 at initial stage. Figure 13 shows the equivalent diameters derived

381 from wavelet-based and hand-made segmentations. We can see that they are close to the
382 diagonal. The linear fit gave $y = 0.86x + 3.8$, with $R^2 = 96\%$. That is to say that the derived
383 diameters are highly correlated, with a slope quite close to 1 and an intercept quite close to
384 0. In Sandri et al. 1998, the linear regression of MWDs derived from 2D image segmentation
385 and from sieves gave $y = 1.02x + 3.9$, with $R^2 = 81\%$. The slope is closer to one but R^2 is
386 lower than in present study. In Bogrekci and Godwin, 2007, the linear regression of MWDs
387 derived from 2D image segmentation and from sieves gave $y = 1.21x$, with $R^2 = 96\%$. Here,
388 the intercept is exactly 0 but the slope is higher than in present study. On the whole, our
389 results are comparable to that of the literature, and the main advantage, is having the
390 individual clod diameters instead of MWDs. Let us notice that in the cited papers of the
391 literature, the linear regressions were estimated along fractions of clod size, which introduced
392 an average effect enhancing the accuracy of the fit. So, we also gathered the clods in ten
393 groups of clod size, with medians of fractions: 9.0, 12.5, 13.9, 15.7, 18.2, 20.0, 22.8, 26.3,
394 28.8, and 36.1 mm. The linear regression on these fractions of clods led to $y = 0.93x +$
395 1.9 , with $R^2 = 99\%$, which is globally better than the cited results.

396 Segmenting soil clods on a DEM is a complex problem because 1) soil surfaces are complex
397 surfaces of several levels of roughness and 2) considering elevations results in less contrast
398 than pixel brightness in a 2D image. However, a 2D image can have some bias due to the
399 projection of a 3D volume onto a plane with a given lighting and does not allow to estimate
400 clod volume. That is why different approaches taking benefit of the three dimensions of a
401 DEM have to be developed. In the present paper, we adopted a geometrical point of view
402 relying on multiresolution analysis and statistical pattern recognition. The segmentation was
403 based on geometrical properties of the objects to be detected. The evaluation of its
404 performance is linked to DEM accuracy and to clod size. When the size of clods decreases,
405 the proposed approach reaches its limits. Indeed, the properties of clods and aggregates are
406 quite different and the approaches performing well for small aggregates as in (Ajdadi et al.,
407 2016), reach their limits when considering larger aggregates or clods and conversely.

408 **4 Conclusion**

409 In this paper, we developed a wavelet-based method to segment the contours of clods on
410 DEMs of seedbed-like surfaces made in the laboratory with two different loams. The
411 presence or absence of furrows, different sizes and spacing of clods and the use of a rainfall
412 simulator allowed us to create different roughness conditions. We introduced a goodness of
413 agreement index in order to compare the proposed method with other segmentation methods
414 and computed also the mean IoU, clod coverage and mean weighted diameter. When the
415 size of clods decreases, the proposed approach reaches its limits. Nevertheless, the
416 wavelet-based method showed ability to keep on segmenting clods whatever the roughness
417 conditions, with or without furrows, at initial stage or after rainfall events. It also showed
418 ability to retrieve clod diameters with very good accuracy. It is therefore an efficient method
419 that allows in particular to detect the contours of clods deposited on furrows.

420 Soil roughness is a key factor for understanding and modelling soil water-interactions and
421 soil erosion. It can be estimated by several parameters, and characterized both locally and
422 globally. Estimating the soil cloddiness is one way of evaluating the soil surface roughness. It
423 is especially important for evaluating the soil quality after tillage operations, and for soil
424 conservation decisions. A reliable automatic clod segmentation on a DEM opens
425 perspectives for clod size distribution estimation and for numerical soil surface generation.

426

427

428

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431 **References**

- 432 Ahmad Fadzil, M.H., Sathyamoorthy, D., Asirvadam, V.S., 2012. Computing surface
433 roughness of individual cells of digital elevation models via multiscale analysis. *Computers*
434 *and Geosciences* 43, 137-146.
- 435 Ajdadi F.R., Abbaspour-Gilandeh Y., Mollazade K., Hasanzadeh R.P.R., 2016. “Application
436 of machine vision for classification of soil aggregate size”, *Soil and Tillage Research* 162, 8-
437 17.
- 438 Arvidsson, J., Bölenius, E., 2006. Effects of soil water content during primary tillage – laser
439 measurements of soil surface changes. *Soil and Tillage Research* 90, 222-229.
- 440 Blaes, X. and Defourny, P., 2008. Characterizing bidimensional roughness of agricultural soil
441 surfaces for SAR modelling: *IEEE Transactions on geoscience and remote sensing*, vol. 46,
442 pp. 4050-4061.
- 443 Bogrekci, I. and Godwin, R.J., 2007. Development of an image–processing technique for soil
444 tilth sensing. *Biosystems Engineering*. 97, 323-331.
- 445 Bretar, F., Arab-Sedze, M., Champion, J., Pierrot-Deseilligny, M., Heggy, E., Jacquemoud,
446 S., 2013. An advanced photogrammetric method to measure surface roughness: application
447 to volcanic terrains in the Piton de la Fournaise, Reunion Island. *Remote Sensing of*
448 *Environment* 135, 1-11.
- 449 Chimi-Chiadjeu, O., Vannier, E., Dusséaux, R., Le Hégarat-Masclé, S., Taconet, O., 2013.
450 Using simulated annealing algorithm to move clod boundaries on seedbed digital elevation
451 model. *Comput. Geosci.* 57, 68-76.
- 452 Chimi-Chiadjeu, O., Le Hégarat-Masclé, S., Vannier, E., Taconet, O., Dusséaux, R., 2014.
453 Automatic clod detection and boundary estimation from digital elevation model images using
454 different approaches. *Catena* 118, 73-83.

455 Choksi, P., 2018. Elementary theory of wavelets and filter bank. *International Journal of*
456 *Trend in Scientific Research and Development* 2, 571-576.

457 Darboux, F., Davy, P., Gascuel-Oudou, C., Huang, C., 2001. Evolution of soil surface
458 roughness and flowpath connectivity in overland flow experiments. *Catena* 46, 125-139.

459 Darboux, F., Huang, C. 2003. An instantaneous-profile laser scanner to measure soil surface
460 microtopography. *Soil Science Society of America Journal* 67, 92-99.

461 Daubechies, I., 1992. Ten lectures on wavelets, in: *CBMS Conf. Series in Appl. Math.*, Vol.
462 61, SIAM, Philadelphia.

463 De Oro, L.A., Buschiazzo, D.E., 2011. Degradation of the soil surface roughness by rainfall in
464 two loess soils. *Geoderma* 164, 46-53.

465 Dusséaux, R., Vannier, E., Taconet, O., Granet, G., 2012. Study of backscatter signature for
466 seedbed surface evolution under rainfall – Influence of radar precision. *Progress In*
467 *Electromagnetics Research* 125, 415-437.

468 Fernandez-Diaz, J.C., Judge, J., Slatton, K.C., Shrestha, R., Carter, W.E., Bloomquist, D.,
469 2010. Characterization of full surface roughness in agricultural soils using groundbased
470 LIDAR. *IGARSS July 25-30, 2010, Honolulu, Hawaiï, USA.*

471 Foster, G.R., Eppert, F.P. & Meyer, L. D. 1979. A programmable rainfall simulator for field
472 plots. In: *Proceedings of the Rainfall Simulator Workshop. Tucson, Arizona. March 7–9,*
473 *1979, pages 45–59, Sidney, Montana. Agricultural Reviews and Manuals, ARM-W-10. United*
474 *States Department of Agriculture - Science and Education Administration, Oakland, CA.*

475 Garbout, A., Munkholm, L.J., Hansen, S.B., 2013. Temporal dynamics for soil aggregates
476 determined using X-ray CT scanning. *Geoderma* 204-205, 15-22.

477 Gilliot, J.M., Vaudour, E., Michelin, J., 2017. Soil surface roughness measurement: a new
478 fully automatic photogrammetric approach applied to agricultural bare fields. *Computers and*
479 *Electronics in Agriculture* 134, 63-78.

480 Haubrock, S. N.; Kuhnert, M.; Chabrilat, S.; Güntner, A.; and Kaufmann, H., 2009.
481 Spatiotemporal variations of soil surface roughness from in-situ laser scanning: *Catena*, vol.
482 79, pp. 128-139.

483 Jensen, T., Green, O., Munkholm, L.J., Karstoft, H., 2016. Fourier and granulometry methods
484 on 3D images of soil surfaces for evaluating soil aggregate size distribution. *Applied*
485 *Engineering in Agriculture* 32, 609-615.

486 Jester, W., Klik, A., 2005. Soil surface roughness measurement—methods, applicability and
487 surface representation. *Catena* 64, 174-192.

488 Josso, B., Burton, D.R., Lalor, M.J., 2001. Wavelet strategy for surface roughness analysis
489 and characterisation. *Computer methods in applied mechanics and engineering* 191, 829-
490 842.

491 Josso, B., Burton, D.R., Lalor, M.J., 2002. Frequency normalised wavelet transform for
492 surface roughness analysis and characterisation. *Wear* 252, 491-500.

493 Kamphorst, E.C., Jetten, V., Guérif, J., Pitkänen, J., Iversen, B.V., Douglas, J.T., Paz, A.,
494 2000. Predicting depressional storage from soil surface roughness. *Soil Science Society*
495 *American Journal* 64, 1749-1758.

496 Kamphorst, E.C., Chadoeuf, J., Jetten, V., Guérif, J., 2005. Generating 3D soil surfaces from
497 2D height measurements to determine depression storage. *Catena*, 62, 189-205.

498 Labarre, S., Ferrari, C., Jacquemoud S., 2017. Surface roughness retrieval by inversion of
499 the Hapke model: A multiscale approach. *Icarus* 290, 63-80.

500 Mallat, S. G., 1989. A theory for multiresolution signal decomposition: the wavelet
501 representation, *IEEE transactions on pattern analysis and machine intelligence* 11, 674-693.

502 Martinez-Agirre, A., Alvarez-Mozos, J., Gimenez, R., 2016. Evaluation of surface roughness
503 parameters in agricultural soils with different tillage conditions using a laser profile meter. *Soil*
504 *and Tillage Research* 161, 19-30.

505 Sandri, R., Anken, T., Hilfiker, T., Sartori, L., Bollhalder, H., 1998. Comparison of methods for
506 determining cloddiness in seedbed preparation. *Soil and Tillage Research* 45, 75-
507 90. Schapel, A., Marschner, P., Churchman, J., 2019. Influence of clay clod size and number
508 for organic carbon distribution in sandy soil with clay addition. *Geoderma* 335: 123-132.

509 Shen, F., and Zeng, G., 2019. Semantic segmentation via guidance of image classification.
510 *Neurocomputing* 330: 259-266.

511 Smith, M.W., 2014. Roughness in the Earth sciences. *Earth Science Revue* 136, 202-225.

512 Taconet, O., and Ciarletti, V., 2007. Estimating soil roughness indices on a ridge-and-furrow
513 surface using stereo photogrammetry. *Soil and Tillage Research* 93: 64-76.

514 Taconet, O., Vannier, E., Le Hégarat-Masclé, S., 2010. A boundary-based approach for
515 clods identification and characterization on a soil surface. *Soil and Tillage Research* 109,
516 123-132.

517 Taconet, O., Dusséaux, R., Vannier, E., Chimi-Chiadjeu, O., 2013. Statistical description of
518 seedbed cloddiness by structuring objects using digital elevation models. *Computers &*
519 *Geosciences* 60, 117-125.

520 Takken, I., Jetten, V., Govers, G., Nachtergaele, J., Steegen, A., 2001, The effect of tillage-
521 induced roughness on runoff and erosion patterns: *Geomorphology*, vol. 37, pp. 1-14.

522 Thomsen, L.M., Baartman, J.E., Barneveld, R.J., Starkloff, T., Stolte, J., 2015. Soil surface
523 roughness: comparing old and new measuring methods and application in a soil erosion
524 model. *Soil* 1, 399-410.

525 Vannier, E., Gademer, A., Ciarletti, V., 2006. A new approach for roughness analysis of soil
526 surfaces. EUSIPCO, September 4-8, 2006, Florence, Italy.

527 Vannier, E., Ciarletti, V., Darboux, F., 2009. Wavelet-based detection of clods on a soil
528 surface. *Computers & Geosciences* 35, 2259-2267.

529 Vannier, E., Taconet, O., Dusséaux, R., Chimi-Chiadjeu, O., 2014. Statistical
530 characterization of bare soil surface microrelief. In: Marghany, M. (Ed.), *Advance geoscience*
531 *remote sensing*. Edition Intech. Rijeka, Croatia, pp. 207-228.

532 Vannier, E., Taconet, O., Dusséaux, R., Darboux, F., 2018 a. A study of clod evolution in
533 simulated rain on the basis of digital elevation models. *Catena* 160, 212-221.

534 Vannier, E., Taconet, O., Dusséaux, R., Darboux, F., 2018 b. Using digital elevation models
535 and image processing to follow clod evolution under rainfall. *Journal of Ecology and*
536 *Toxicology* 2: 113.

537 Wang, W., Kravchenko, A.N., Smucker, A.J.M., Rivers, M.L., 2011. Comparison of image
538 segmentation methods in simulated 2D and 3D microtomographic images of soil aggregates.
539 *Geoderma* 162: 231-241.

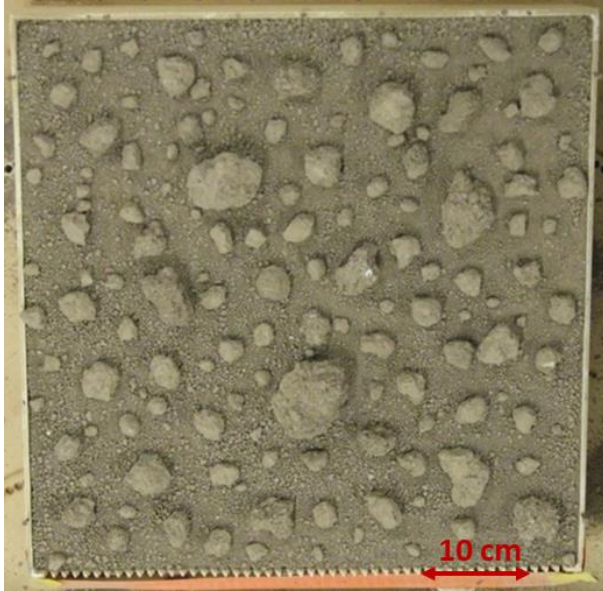
540 Wang, B., Tang, S., Xiao, J.B., Yan, Q.F., Zhang, Y.D. 2019. Detection and tracking based
541 tubelet generation for video object detection. *J. Vis. Commun. Image R.* 58: 102-111.

542 Webb, A. R., 2002. *Statistical pattern recognition*, second edition. John Wiley & Sons, Ltd.
543 QinetiQ Ltd., Malvern, UK.

544 Zhang, L., Lu, Y., Lu, L., Zhou, T., 2019. Refined video segmentation through global
545 appearance regression. *Neurocomputing* 334: 59-67.

546 Zhao, L., Hou, R., Wu, F., Keesstra, S., 2018. Effects of soil surface roughness on infiltration
547 water, ponding and runoff on tilled soils under rainfall simulation experiments. *Soil and*
548 *Tillage Research* 179, 47-53.

549



a)



b)

Figure 1: Laboratory made planar and furrowed surfaces with a wide range of clod size P0 and F0.

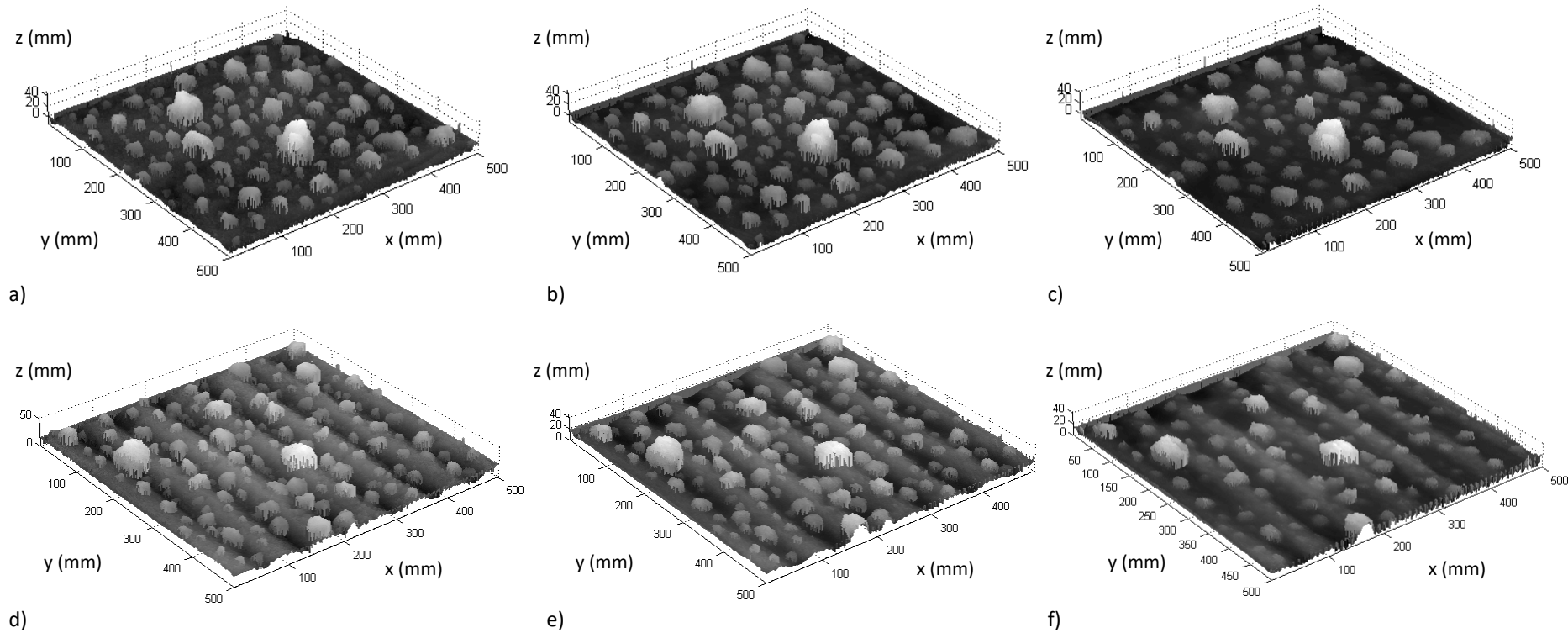
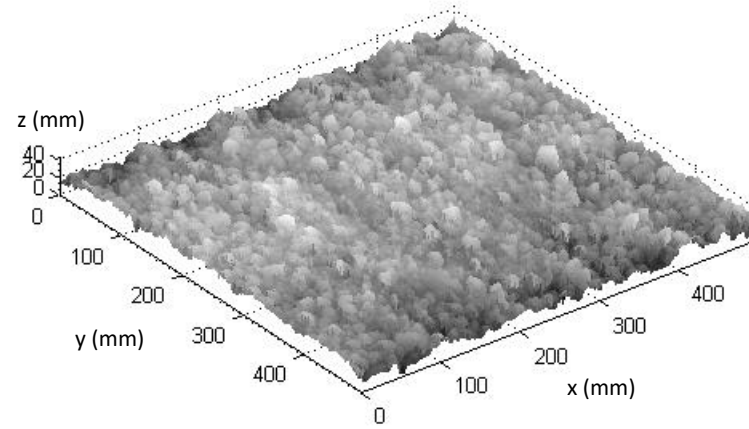


Figure 2: DEMs of planar and furrowed surfaces of wide range of clod size at initial and successive stages after rainfall; a) P0, b) P1, c) P2, d) F0, e) F1, f) F2.



a)

10 cm



b)

Figure 3: Laboratory made and DEM of surface composed of one sieve range of clods SR.

For each detected clod,

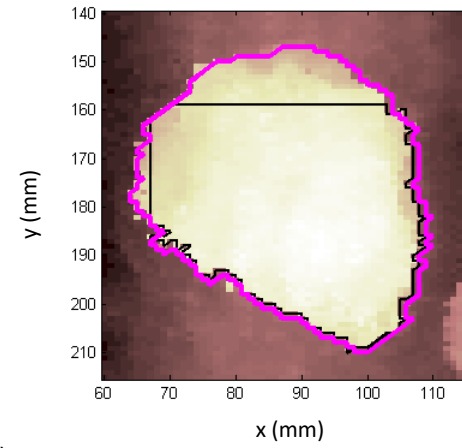
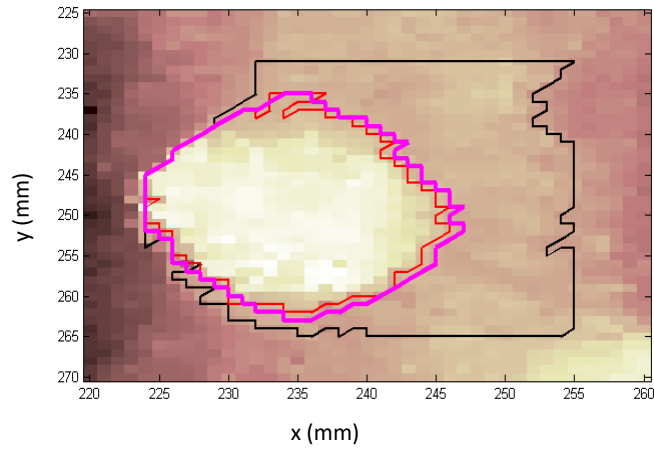
- 1) Extract local surface around clod from DEM
 $SC = S(bx:ex, by:ey)$
- 2) Remove mean plane of SC and get centered local surface SCf
- 3) Keep elevations above mean plane
 $MSC = SCf > 0$
- 4) Extract clod contour on clod mask MSC
- 5) Check goodness of intersection with mean plane and refine inclination and height of mean plane when needed
- 6) Check if local surface needs to be extended
- 7) Check for segmentation of a block of clods
- 8) Regularize clod contour by morphological opening (or closing for too small clods)
- 9) Rule out too flat clods
- 10) Correct or rule out squared clod contours.

Sort validated clod contours by decreasing size.

For each validated clod contour,

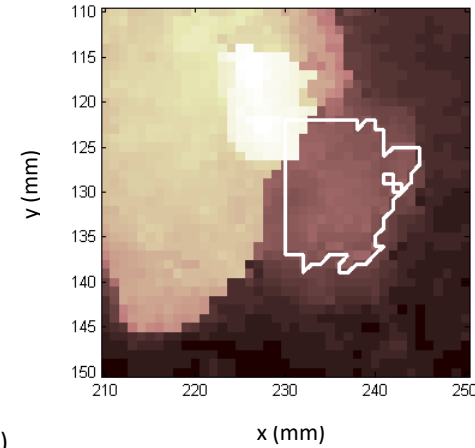
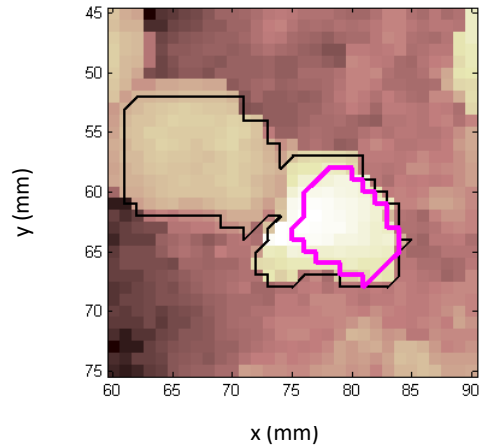
Check for inclusion or partial overlapping with other clod contours. Remove included clods and redelineate overlapping contours.

Figure 4: Algorithm of wavelet-based clod segmentation method. $[bx\ ex\ by\ ey]$ represent the extents of the local surface in the directions x and y .



a)

b)



c)

d)

Figure 5: Rectification of wrong patterns encountered during clod contours automatic delineation. Initial contour is in black (a, b, c) or white (d), final contour in red (a) and regularized contour in bold magenta (a, b, c, d).

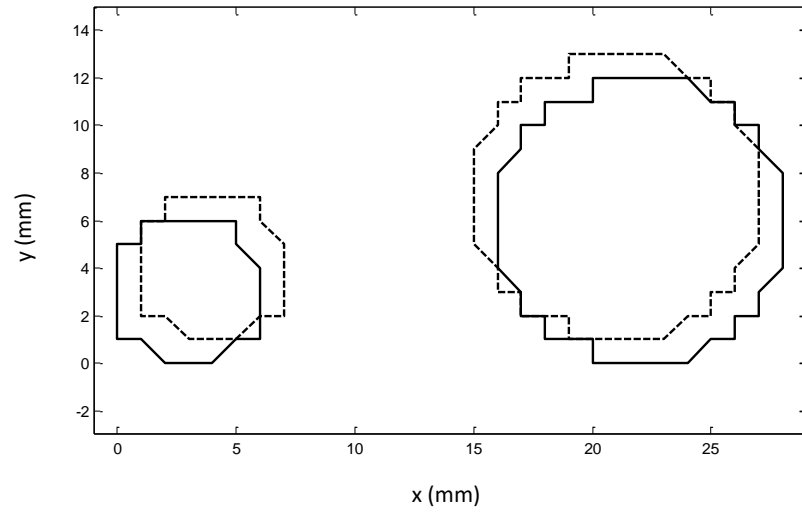


Figure 6: Dependence on clod size and DEM accuracy of goodness of agreement indicator. Discretized circles of 3 mm and 6 mm of radius (solid line) and translated circles by 1 mm (dotted line).

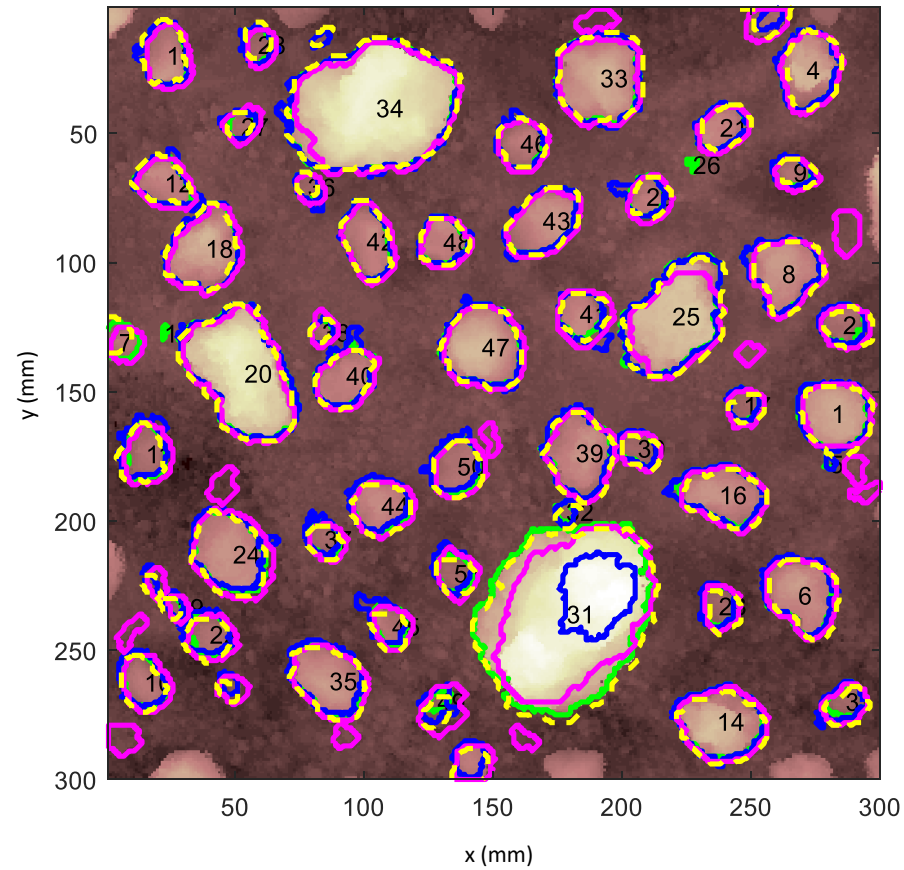


Figure 7: Clod contours obtained with hand-made segmentation (dotted yellow), thresholding (green), contour-based segmentation (blue) and wavelet-based segmentation (magenta) for planar surface at initial stage (P0).

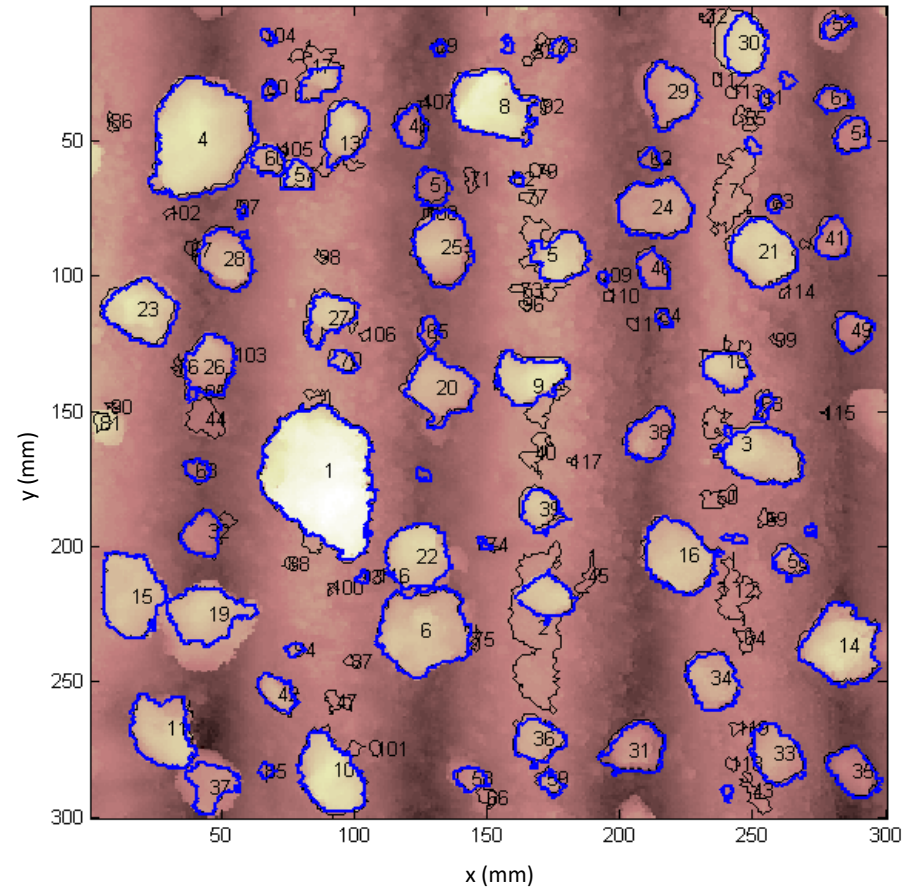


Figure 8: Clod contours obtained with contour-based segmentation without detrending (black) and after detrending (bold blue) for furrowed surface at initial stage (F0).

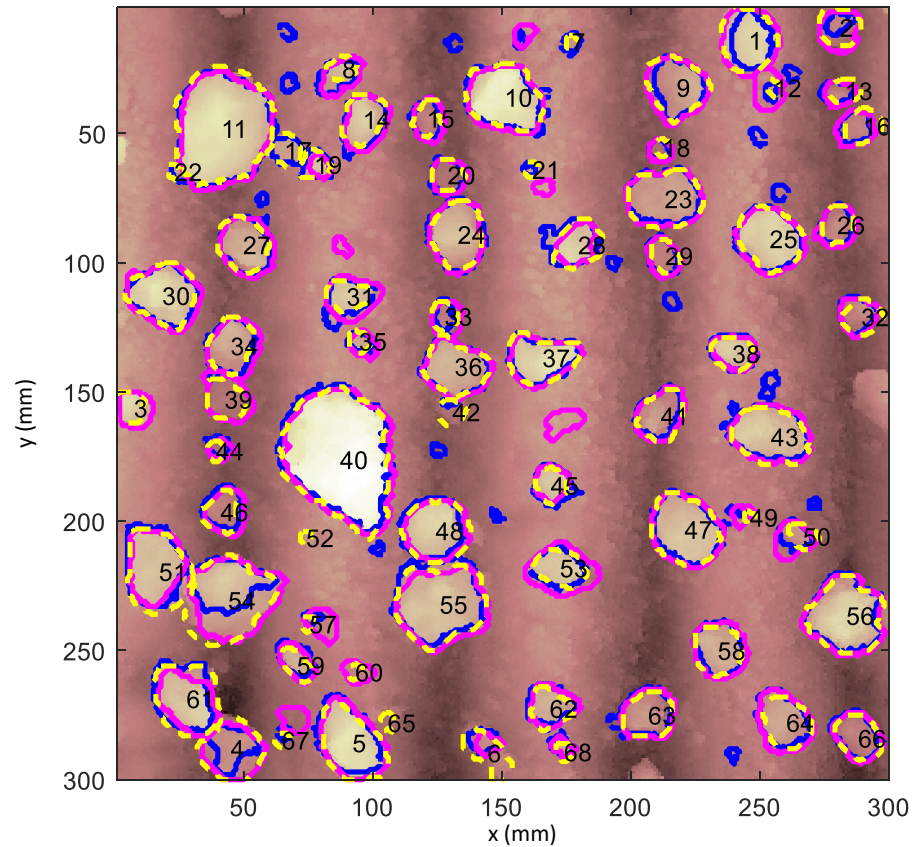


Figure 9: Clod contours obtained with hand-made segmentation (dotted yellow), contour-based segmentation after detrending (blue) and with wavelet-based segmentation (magenta) for furrowed surface at initial stage (F0).

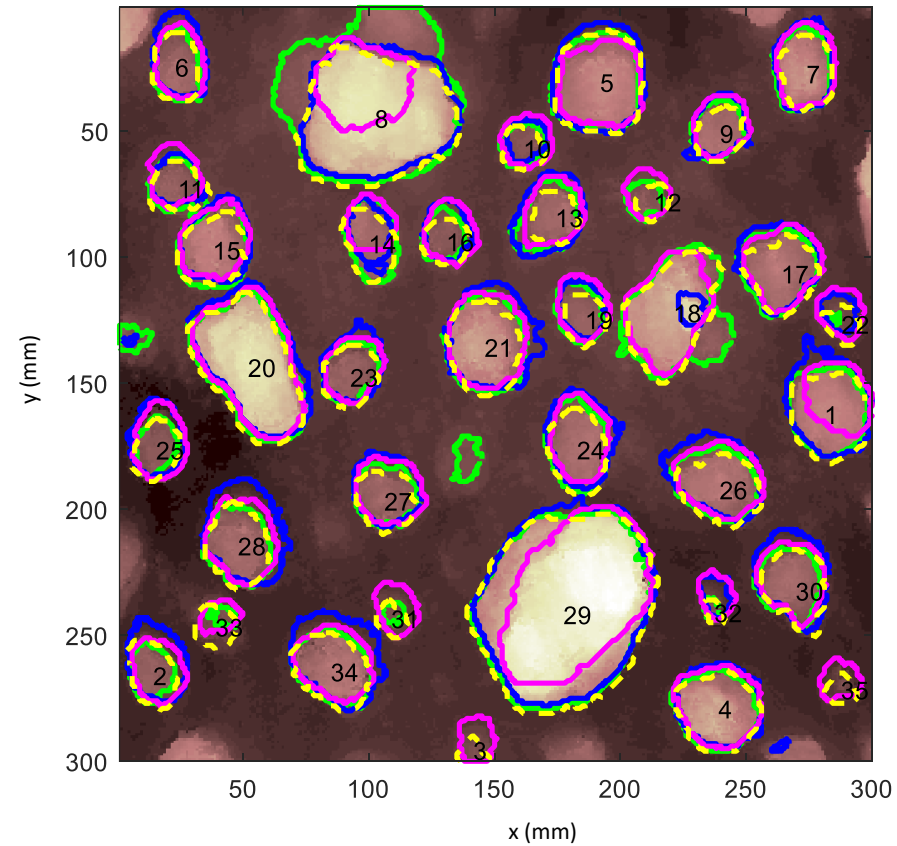


Figure 10: Clod contours obtained with hand-made segmentation (dotted yellow), thresholding (green), contour-based segmentation (blue) and wavelet-based segmentation (magenta) for planar surface after two rainfall events (P2).

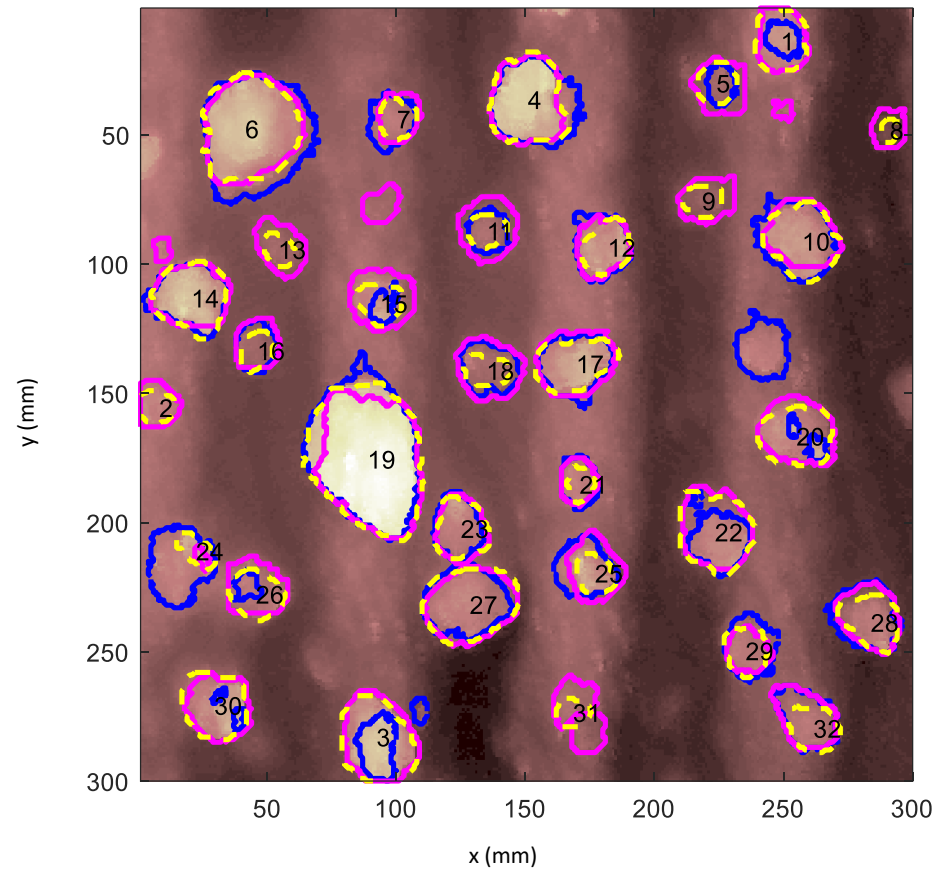


Figure 11: Clod contours obtained with hand-made segmentation (dotted yellow), contour-based segmentation after detrending (blue) and with wavelet-based segmentation (magenta) for furrowed surface after two rainfall events (F2).

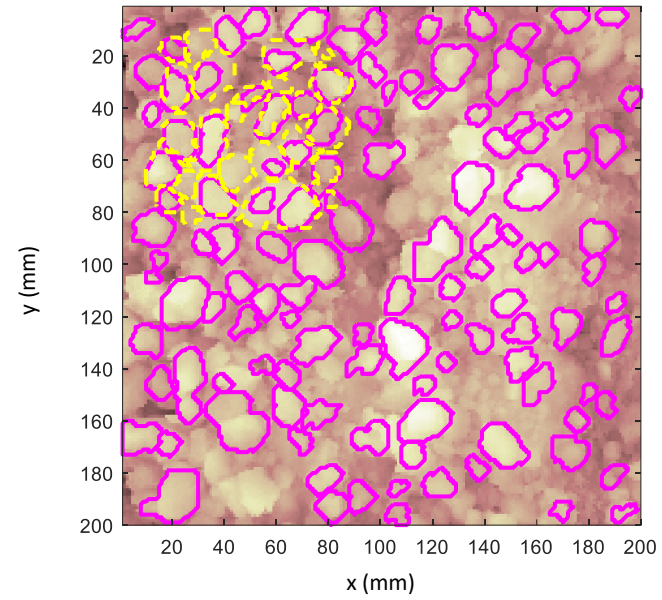


Figure 12: Results of wavelet-based segmentation (in magenta) on small size clod surface SR, with hand-made contours in dotted yellow.

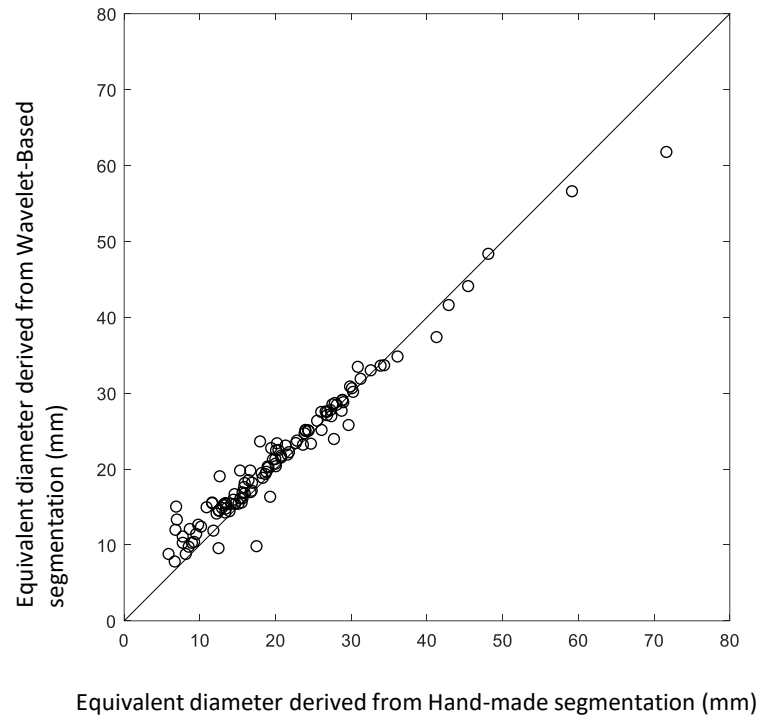


Figure 13: Clod diameters estimated from wavelet-based and hand-made segmentations on laboratory surfaces at initial stage P0 and F0.

Reference	Surface	Threshold	Compared method	
			Contour-Based	Wavelet-Based
Hand-made	P0	81.7	74.8	78.0
	P1	82.0	70.4	73.5
	P2	71.2	61.5	61.5
	F0		68.8*	70.2
	F1		74.6*	75.5
	F2		54.7*	66.1
Threshold	P0		85.5	74.5
	P1		73.4	74.6
	P2		64.4	65.8
Contour-Based*	P0			69.4
	P1			79.9
	P2			73.5
	F0			69.6
	F1			79.4
	F2			55.1

Table 1: Mean IoU in %, for three stages of planar surface P0 to P2 and furrowed surface F0 to F2. *from a detrended surface.

Surface	Segmentation method			
	Hand-made	Threshold	Contour-Based	Wavelet-Based
P0	29.5	27.9	26.4	30.5
P1	36.7	34.4	37.7	36.8
P2	28.4	30.7	30.9	26.7
F0	24.0		23.3*	25.6
F1	27.9		26.3*	28.2
F2	16.5		16.5*	19.7

Table 2: Clod coverage in %, for three stages of planar surface P0 to P2 and furrowed surface F0 to F2. *from a detrended surface.

Surface	Segmentation method			
	Hand-made	Threshold	Contour-Based	Wavelet-Based
P0	37.5	37.4	31.4	33.0
P1	39.9	41.4	41.6	36.9
P2	41.9	44.9	42.8	34.7
F0	26.6		25.9*	26.4
F1	30.8		30.1*	30.1
F2	30.5		31.8*	29.1

Table 3: Mean weighted diameter (MWD) in mm, for three stages of planar surface P0 to P2 and furrowed surface F0 to F2. *from a detrended surface.

Reference	Surface	Compared method		
		Threshold	Contour-Based	Wavelet-Based
Hand-made	P0	88.2	83.8	83.9
	P1	87.8	77.4	77.6
	P2	79.7	69.9	65.1
	F0		78.3*	81.6
	F1		81.1*	81.9
	F2		62.2*	78.2
Threshold	P0		91.7	80.7
	P1		78.9	78.3
	P2		72.0	66.7
Contour-Based*	P0			77.2
	P1			81.9
	P2			72.5
	F0			80.0
	F1			86.1
	F2			70.8

Table 4: Goodness of agreement (in %) between segmentation methods, for three stages of planar surface P0 to P2 and furrowed surface F0 to F2. *from a detrended surface.