

1 **Synchrotron Microtomographic Quantification of Geometrical Soil Pore**
2 **Characteristics Affected by Compaction**

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5 Ranjith P. Udawatta*^{1,2}, Clark J. Gantzer¹ Stephen H. Anderson¹, and
6 Shmuel Assouline³

7 Dept. of Soil, Environmental and Atmospheric Sciences¹, The Center for Agroforestry²
8 School of Natural Resources, University of Missouri,
9 Columbia, MO 65211, USA and
10 Dept. of Environmental Physics and Irrigation, Agricultural Research Organization,
11 Volcani Center, Bet-Dagan, Israel³.

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18 *Corresponding author's

19 Telephone number: 573-882-4347

20 Fax number: 573-882-1977

21 E-mail address: UdawattaR@Missouri.edu

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**Synchrotron Microtomographic Quantification of Geometrical Soil Pore
Characteristics Affected by Compaction**

Ranjith P. Udawatta*, Dept. of Soil, Environmental and Atmospheric Sciences¹, The
Center for Agroforestry², School of Natural Resources, University of Missouri,
Columbia, MO 65211, USA

Clark J. Gantzer, Dept. of Soil, Environmental and Atmospheric Sciences, School of
Natural Resources, University of Missouri, Columbia, MO 65211, USA

Stephen H. Anderson, Dept. of Soil, Environmental and Atmospheric Sciences, School of
Natural Resources, University of Missouri, Columbia, MO 65211, USA

and

Shmuel Assouline, Dept. of Environmental Physics and Irrigation, Agricultural Research
Organization, Volcani Center, Bet-Dagan, Israel.

*Corresponding author's

Telephone number: 573-882-4347
Fax number: 573-882-1977
E-mail address: UdawattaR@Missouri.edu

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50 **ABSTRACT**

51 Soil compaction degrades soil structure and affects water, heat, and gas exchange
52 as well as root penetration and crop production. The objective of this study was to use X-
53 ray computed microtomography (CMT) techniques to compare differences in geometrical
54 soil pore parameters as influenced by compaction of two different aggregate size classes.
55 Sieved (diam. < 2mm and < 0.5mm) and repacked (1.51 and 1.72 Mg m⁻³) Hamra soil
56 cores of 5- by 5-mm (average porosities were 0.44 and 0.35) were imaged at 9.6-
57 micrometer resolution at the Argonne Advanced Photon Source (synchrotron facility)
58 using X-ray computed microtomography. Images of 58.9 mm³ volume were analyzed
59 using 3-Dimensional Medial Axis (3DMA) software. Geometrical characteristics of the
60 spatial distributions of pore structures (pore radii, volume, connectivity, path length, and
61 tortuosity) were numerically investigated. Results show that the coordination number
62 (CN) distribution and path length (PL) measured from the medial axis were reasonably fit
63 by exponential relationships $P(\text{CN})=10^{-\text{CN}/\text{Co}}$ and $P(\text{PL})=10^{-\text{PL}/\text{PLo}}$, respectively, where Co
64 and PLo are the corresponding characteristic constants. Compaction reduced porosity,
65 average pore size, number of pores, and characteristic constants. The average pore radii
66 (63.7 and 61 μm ; $p<0.04$), largest pore volume (1.58 and 0.58 mm³; $p=0.06$), number of
67 pores (55 and 50; $p=0.09$), characteristic coordination number (6.32 and 5.94; $p=0.09$),
68 and characteristic path length number (116 and 105; $p=0.001$) were significantly greater
69 in the low density than the high density treatment. Aggregate size also influenced
70 measured geometrical pore parameters. This analytical technique provides a tool for

71 assessing changes in soil pores that affect hydraulic properties and thereby provides
72 information to assist in assessment of soil management systems.

73

74 **Abbreviations:** 3-DMA, 3-Dimensional Medial Axis software; 3-D, three dimensional;
75 CN, coordination number; Co, characteristic coordination number constant; CMT,
76 computed microtomography; diam., diameter; PL, path length; PLo, characteristic
77 path length constant.

78

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INTRODUCTION

80 Degradation of soil structure is a serious worldwide problem (Schrader et al.,
81 2007). Soil structure is important for crop production because it partly determines
82 rooting depth, the amount of water that can be stored, and movement of air, water,
83 nutrients, and soil microfauna (Brussaard and van Faassen, 1994; Whalley et al., 1995).
84 During soil compaction, soil structure is degraded and soil aggregates are consolidated
85 decreasing soil porosity; and subsequently these changes alter water, heat, and gas
86 transport as well as root penetration and soil productivity (Kim et al., 2010). Assessment
87 of soil compaction is a fundamental way to evaluate environmental impacts of
88 agricultural operations on soils.

89 Researchers have been evaluating soil compaction due to natural and
90 anthropogenic activities (Soane and van Ouwerkerk, 1995; Assouline et al., 1997; Marsili
91 et al., 1998; Green et al., 2003). Differences in porosity among dissimilar soils and
92 treatments are often quantified using bulk density estimated with soil cores, changes in
93 soil thickness, and changes in penetrometer resistance. Porosity determined by

94 traditional methods often lacks detailed information on spatial variability in geometrical
95 pore characteristics. In addition, porosity is often estimated by indirect procedures which
96 do not contain information on the spatial distribution of pores and most measurements are
97 based on observations in two-dimensions (Beven and Germann, 1982; Gantzer and
98 Anderson, 2002; Mooney, 2002).

99 Soil scientists are working to examine microstructure of the soil system to better
100 predict water and gas movement, to assess the effects of management on soil pore
101 parameters and microbial habitats, as well as to evaluate treatment effects on root
102 development. Microstructure governs the flow of resources through the pore space of the
103 soil media and creates spatial and temporal differences in the media (Young and
104 Crawford, 2004; Zhang et al., 2005). Research suggests that understanding of
105 geometrical pore parameters is critically important to issues related to movement of
106 microfauna, water, solute, and gases as well as root development. These pore parameters
107 include: pore dimension, pore size distribution, connectivity, shape factor, and tortuosity
108 as well as distributions or probabilities of these parameters (Ioannidis and Chatzis, 1993;
109 Tollner et al., 1995; Ioannidis and Chatzis, 2000; Lindquist et al., 2000).

110 Computed microtomography can be viewed as a technique in soil studies that
111 enables examination of local variation (micrometer scale), whereas conventional
112 tomography enables examination at a millimeter scale (Macedo et al., 1998). CMT has
113 been used in examination of pores in sealing materials for nuclear waste and in rock and
114 soil media as well as evaluation of fluid transport; in addition pore dynamics, and
115 bacterial and root studies have been reported (Coles et al., 1998; Kozaki et al., 2001;
116 Lindquist, 2002; Gregory et al., 2003; Thieme et al., 2003; Udawatta et al., 2008; Peth et

117 al., 2010). However, these procedures require images at μm resolution to accurately
118 describe changes within the media. Better resolution in tomography requires a smaller
119 sample size. Advantages of CMT procedures include repeated examination of interior
120 structural features of samples at micrometer-scale resolution within three dimensions,
121 measurement of connectivity and tortuosity, nondestructive evaluation of sample interiors
122 retaining connectivity and spatial variation in pores, as well as enabling examination of
123 dynamic soil processes and quantification of pore geometry (Asseng et al., 2000; Al-
124 Raoush, 2002; Mooney, 2002; Pierret et al., 2002; Carlson et al., 2003; Udawatta et al.,
125 2008).

126 Quantitative information of soil structure is required to improve understanding of
127 infiltration, contaminant movement through porous media, and quantification of model
128 parameters associated with fluid and gas movement (Pachepsky et al., 1996; Perret et al.,
129 1999; Ioannidis and Chatzis, 2000; Wildenschild et al., 2002; Fox et al., 2004; Assouline,
130 2004). However, CMT, volume rendering and three-dimensional (3-D) image analysis
131 studies focusing on soil compaction are rare. The objective of this study was to use
132 synchrotron X-ray computed microtomography to quantify the influence of mechanical
133 compaction on geometrical soil pore characteristics of two soil aggregate classes.

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135

MATERIALS AND METHODS

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Soil and Sample Preparation

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The soil used for this study was a loamy sand (Typic Rhodoxeralf) collected from
the 0-100 mm depth of an experimental field at Bet-Dagan, Central Israel ($32^{\circ} 12' \text{N}$ and
 $35^{\circ} 25' \text{E}$). The soil contains 87% sand, 2% silt, and 11% clay (mainly smectite). Air-dry

140 soil was sieved through 2.0 and 0.5 mm mesh sieves to separate into two aggregate size
141 classes: < 2 mm and < 0.5 mm. Soil was packed in 5 mm long by 5 mm diameter
142 aluminum cores with 1.0 mm wall thickness, in three replicates for each treatment. Soil
143 cores from each aggregate class were compacted with a small press to obtain pre-
144 determined bulk density values of 1.51 and 1.72 Mg m⁻³. The selected two values
145 represent the range in bulk densities commonly found with these soils and site conditions.
146 The open ends of the soil core were covered with aluminum plates and sealed with tape to
147 secure soil materials inside the core. Samples were stored at room temperature before
148 scanning.

149

150 **Image Acquisition and Tomographic Reconstruction**

151 Air-dry soil cores were transported to the GeoSoilEnviroCARS (GSECARS)
152 sector at the Argonne Advanced Photon Source for image acquisition at the X-ray
153 computed microtomography facility (<https://gsecars.uchicago.edu/>). Soil cores were
154 imaged at a 9.6 μm resolution using the bending magnet beam line 13-BM-D, which
155 provides a parallel beam of high-brilliance radiation with a vertical beam size of about 5
156 mm. Specific synchrotron tomographic procedures and additional details can be found in
157 Kinney and Nichols (1992).

158 The data processing consisted of three main steps: preprocessing, sinogram
159 creation, and reconstruction. Since there is a constant digitization offset (~ 50 counts)
160 this value was subtracted from each pixel. The second step was to remove "zingers",
161 these are bright pixels caused by scattered X-rays striking the CCD chip. The third step

162 of the preprocessing was completed to normalize each data frame to the field image and
163 to correct for drift.

164 The first step of sinogram creation was to take the logarithm of the data relative to
165 air. Centering the rotation axis of the projection was completed by fitting a sinusoid to
166 the center-of-gravity of each row in the sinogram. Ring artifacts were removed by
167 detecting and correcting anomalous columns in the sinogram. Tomographic
168 reconstruction was completed using filtered back projection with the IDL programming
169 language (Rivers, 1998). The raw data used for tomographic reconstruction were 12-bit
170 images with a total of 360 images collected as the sample was rotated twice from 0 to
171 180° in 0.5° steps. The data were piped to massive parallel SGI computers to view real
172 time data before image acquisition was completed.

173

174 **Image Analysis**

175 The 3-Dimensional Medial Axis (3-DMA) computer software was used to
176 examine differences in geometrical pore characteristics among the treatments (Lindquist
177 and Venkatarangan, 1999) using a 1.7 GHz Linux computer with 2 GB of memory. Pore
178 characteristics were analyzed at $9.2 \times 10^2 \mu\text{m}^3$ voxel size (1 pixel=9.61 μm and 1 slice=10
179 μm ; voxel size=9.61x9.61x10). Images were cropped into a 3.7 by 3.7 by 4.3 mm
180 rectangular array block to remove artifacts. Spatial distributions for nodal pore volume,
181 coordination numbers, pore path length, and tortuosity, were obtained for 58.9 mm³
182 volumes. The six main analysis steps in 3-DMA were completed by a number of
183 imbedded algorithms: segmentation of image, extraction and modification of the medial
184 axis of pore paths, throat construction using the medial axis, pore surface construction,

185 assembly of pore throat network, and geometrical characterization of pore throat network
186 (http://www.ams.sunysb.edu/~lindquis/3dma/3dma_rock/3dma_rock.html accessed June
187 2012).

188 The grey-scale intensity of each CT-image voxel is an integer value from 0-255
189 (2^8 bit scale). Simple thresholding and indicator kriging (IK; Oh and Lindquist, 1999)
190 separated the voxels into two populations using intensity values and voxels having
191 intermediate intensities by using the maximum likelihood estimate of the population set,
192 respectively (Fig. 1). Indicator kriging requires sub-populations of voxels for each phase
193 (pore and solid) to be positively identified. The remaining voxels were assigned by the
194 IK algorithm according to neighborhood statistics. This was satisfied by using grey-scale
195 intensity values for air and aluminum as threshold cutoff values. These two thresholds
196 were set manually on histograms to separate populations.

197 The *Medial Axis* of a digitized sample is a 26-connected centrally-located
198 skeleton of voids which preserves the topology and geometry of the object (Sirjani and
199 Cross, 1991). An erosion-based algorithm is used to extract and modify the medial axis
200 of the pore space (Lee et al., 1994). Spurious paths, which are not significant descriptors
201 of the object, and all dead-end paths were removed (trimmed) from the volume. A filter
202 was used to minimize misidentification of segmentation artifacts such as small isolated
203 pores/clusters. The process resulted in the medial axis, ‘backbone’.

204 3DMA uses throat finding algorithms (Venkatarangan, 2000; Shin, 2002) to
205 determine the location of minimal area cross-sectional surfaces where one or more void
206 paths pass, called pore-throats (Kwiecien et al., 1990). The throat region is defined by

207 the voxel sets through which each triangulated throat surface pass, and throat surface
208 areas are determined as triangulated interfaces.

209 The next step is to determine the network of pore paths (a connected curve of
210 voxels) and vertices (a cluster of one or more voxels where three or more paths intersect).
211 Throat surfaces separate pore spaces and determine network of pores. Pores are cross-
212 indexed with their connecting throats and adjoining pores while throats are cross-indexed
213 with the pores they connect. The algorithm also computes a center of mass, principal
214 directions for each pore, and the diameter passing through the center of mass in each
215 principal direction. An effective pore radius can be computed using the sphere of
216 equivalent volume. The analysis generated distributions of the principal diameters and
217 the effective radius values for the pores and throats.

218 Path length (the distance between the centers of any two adjacent nodal pores
219 along the mid line of the connecting path) is determined by the distance measure
220 algorithm (Lindquist, 2002). Dijkstra's algorithm (Cormen et al., 1990) embedded as
221 part of the 3DMA software determined path tortuosity. The algorithm uses a gamma
222 distribution for tortuosity probability distribution (Lindquist et al., 1996) and generated
223 tortuosity of each pore and, and average and cumulative tortuosity values for each
224 sample. The software generated an assembly of pore networks and geometrical
225 characteristics of pore networks. The following information generated by the 3DMA was
226 analyzed as outlined in Lindquist et al. (2005): effective radius, pore volume,
227 coordination number, path length, and path tortuosity along with their corresponding
228 probability density relationships.

229 The coordination number (CN) is measured by directly counting the distribution
230 of medial axis vertex sets. Coordination numbers between 3 and 20 were used to develop
231 exponential distribution relationships [$P(\text{CN}) = 10^{-\text{CN}/\text{Co}}$] between coordination numbers
232 and probability density values to determine characteristic coordination number constants
233 (Co) for each sample. A similar approach was used to determine characteristic path
234 length constants (PLo), fitting an exponential distribution [$P(\text{PL}) = 10^{-\text{PL}/\text{PLo}}$] of path
235 length (PL) and probability density. Pore radii (μm), pore volume (mm^3), coordination
236 number, path length, and tortuosity differences were compared among treatments. A
237 selected replicate for each treatment was used to show the distributions of above
238 properties in figures.

239

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Statistical Analysis

241 Geometrically determined pore parameters were analyzed to examine differences
242 and similarities among treatments for: pore radius, volume, porosity, mean pore volume,
243 number of pores, coordination number, path length, and tortuosity as described by
244 Lindquist et al. (2000). Bulk averaged variables have become the “historical operational
245 descriptors” in theoretical description of porous media microstructure. Therefore, the
246 averaged values are given in Table 1 with respective standard deviations. Four
247 treatments in factorial design (two factors of density and aggregate size; two levels) were
248 compared: two aggregate size classes (<2.0 and <0.5 mm diam. referred to as H2 and H5,
249 respectively) and two compaction levels identified as low (L) and high (H) representing
250 two bulk density values (1.51 and 1.72 Mg m^{-3} , respectively) with three replicates.
251 Analysis of variance was conducted with SAS using the GLM procedure to test
252 differences between treatments (SAS Institute, 1999). Least square means were

253 calculated to find significant differences between treatments for each measured
254 parameter. Statistical tests included normality of data distribution and significant
255 differences among treatments.

256

257 **RESULTS AND DISCUSSION**

258 **Effective Pore Radii and Volume**

259 Since effective pore radii were not normally-distributed, log-transformed effective
260 pore radii values were used in the statistical analysis. Effective pore radii were 63.75 and
261 61.18 μm for 1.51 and 1.72 Mg m^{-3} treatments (averaged for both aggregate sizes),
262 respectively (Table 1, Fig. 2) and the compaction was significant ($p=0.04$). As expected,
263 pore radius decreased with increasing density. However, aggregate particle size had no
264 significant effect on measured pore radii. Mean pore radii were 62.64 and 62.29 μm for
265 0.5 and 2.0 mm aggregate sizes (averaged for both densities), respectively.

266 Similar to effective pore-radii, log-transformed pore volumes were used for
267 analysis. Table 1 shows that total pore volume, largest pore size, mean pore volume, and
268 number of pores decreased with increasing compaction for the high density samples
269 compared to low density. The largest pore volume and number of pores were different
270 ($p<0.10$, Fig. 3). However, the largest pore size was 2.7 times larger in the less
271 compacted treatment as compared to the high-density treatment. The average pore
272 volumes were 7.1×10^5 and $6.6 \times 10^5 \mu\text{m}^3$ for 1.51 and 1.72 Mg m^{-3} bulk density treatments
273 (averaged for both aggregate sizes), respectively. CMT-measured porosity values were
274 10.9% and 4.9% for the high and low-density treatments, respectively. Note that the
275 CMT-measured porosity is lower than the core-estimated porosity due to the limited

276 resolution of the scanner. Total core porosity was 1.2 times smaller and CMT-measured
277 pore volume was 2.2 times smaller in the high-density treatment as compared to the low-
278 density treatment. This result is consistent with the fact that the soil porosity should
279 decrease when moving from low to high bulk density; although the range in values will
280 be smaller for the bulk core properties. The aggregate size-class containing finer
281 aggregates (H5) had 1.7 times more pore volume, 2.1 times greater largest pore volume,
282 and more pores than the aggregate class including larger aggregates (H2). In terms of the
283 effect of compaction on pore size distribution, Figures 1 and 2 show that compaction
284 preferentially affected the larger pores, reducing them in size (radius and volume) in both
285 aggregate categories. This is in agreement with the estimated effect of compaction on the
286 pore size distribution derived from changes in the water retention curve (Assouline,
287 2006a).

288 The results observed in this study agree with findings between soil porosity and
289 pore size distribution relationships in previously published data (Lindquist et al., 2000;
290 Seright et al., 2001; Udawatta et al., 2008). Although differences in pore volume and
291 radii may exist among treatments, the effects may be somewhat less dominant due to
292 fewer aggregates (due to sandy texture) and/or few inter-aggregate spaces (due to sandy
293 texture).

294

295

Coordination Number

296 Higher pore coordination numbers (CN) imply greater connectivity developing
297 between nodal pore sites that are well connected and extended; a good pore network.

298 Coordination numbers varied between 3 and 40 and ≤ 20 were used to develop

299 relationships (Fig. 4). Coefficients of determination for the CN and probability
300 relationships were > 0.99 for all treatments. The coordination number constant (Co)
301 values varied between 5.70 and 6.62 with a mean of 6.13 ± 0.32 for all samples.
302 Coordination number constants were greater for low-density (6.32) than high-density
303 (5.94) treatment (Table 1; $p < 0.10$). The low-density treatment had 6% greater probability
304 for pore connectivity than the high-density treatment. The same trend was observed for
305 both aggregate categories of low-density treatments as compared to the high-density
306 (Table 1). The mean Co values were 6.01 and 6.25 for 0.5 and 2.0 mm diameter
307 aggregate treatments, respectively (not significantly different). The results of the study
308 show that compaction reduced the Co of larger aggregate samples by $\sim 4\%$ more as
309 compared to the smaller aggregates.

310 The range of Co values observed in this study were greater compared to values
311 observed for heterogeneous soil material (Udawatta et al., 2008). In Udawatta et al.
312 (2008), larger soil cores were analyzed at $84 \mu\text{m}$ resolution and Co values ranged
313 between 3.30 and 5.14. The selected 3 to 20 coordination number range for the current
314 study resulted in a straight line as compared to the ranges used by Lindquist et al. (2000)
315 and Udawatta et al. (2008) in their relationships. Lindquist et al. (2000) imaged rock
316 material at $6\text{-}\mu\text{m}$ resolution, as compared to $9.6\text{-}\mu\text{m}$ resolution in this study. Both
317 Lindquist et al. (2000) and Udawatta et al. (2008) reported significant differences in Co
318 values among treatments. We speculate that soil material with more uniform size
319 particles and lack of aggregates may have caused small differences among treatments. In
320 addition, treatments examined in this study further segregated soil particles by creating
321 aggregate size classes as a treatment and thereby forming more homogeneous samples.

322 This also suggests that these soils with more uniform larger grain size lose more pore
323 connectivity than small particles during compaction. Results may indicate that the rate of
324 air and liquid flow may be reduced by compaction due to a lower number of connected
325 pores. Another reason for the observed C_o values could be that compaction preferentially
326 affected larger pores reducing them in size while smaller pores maintained the same
327 connectivity (Fig. 1, 2, and 3). This pattern has been observed by soil water retention
328 studies as influenced by compaction (Or et al., 2000; Assouline, 2006a; Kumar et al.,
329 2008).

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331

Path Length

332 Path lengths (PL) measured in this study ranged from 3 to 597 μm (Fig. 5). Path
333 lengths between 100 and 400 μm were selected for the development of exponential
334 relationships [$P(\text{PL}) \sim 10^{-\text{PL}/\text{PL}_o}$] between path length and probability density. The selected
335 range exhibited a linear relationship with coefficients of determination ranging from 0.96
336 to 0.98 with a mean of 0.97. Characteristic path length constants (PL_o) ranged from
337 102.3 to 122.3 with a mean of 110.5 ± 6.5 . Mean PL_o values for the low density and high-
338 density treatments were 116.0 and 105.0, respectively, and the difference was significant
339 (Table 1). The greater PL_o of low density implies a greater probability of occurrence of a
340 given path length than in the high-density treatment. Between the two aggregate size
341 classes, 0.5 mm aggregates had a significantly larger PL_o (112.8) as compared to the
342 larger aggregates (108.1). This high PL_o of small aggregates is an indication of greater
343 probability of paths in a soil with small aggregates.

344 Researchers have used differences in path lengths imaged by varying resolutions
345 to compare porosity in sandstone and conservation management effects on path lengths.
346 Lindquist et al. (2000) observed differences in PLo values in sandstone with porosities
347 varying from 7 to 22%. Udawatta et al. (2008) showed that PLo was significantly higher
348 for buffer treatments as compared to row-crop management. Similar to other studies, the
349 differences in PLo values as influenced by compaction and aggregate size were
350 significant between treatments in the current study. According to Wu et al. (2006), path
351 length was higher for smaller particles. The greater path lengths in smaller particle media
352 have been attributed to larger pore spaces among larger particles that reduced the distance
353 due to relatively easier corners in the media. They also noticed that relative path lengths
354 were higher through pores as compared to over the grains in their scanning electron
355 microscope study with cubic sodium chloride.

356

357 **Path Tortuosity**

358 Figure 6 shows that probability decreased with increasing path tortuosity and
359 tortuosity values ranged from 1 to 3.7. The highest probability occurred at a path
360 tortuosity of 1.12. In general, the probability was less than 0.05% for path tortuosity
361 values greater than two and the distribution of data points were more scattered for
362 tortuosity values > 2.5 , greater deviation from a linear distribution with probability.

363 Although tortuosity of the pore network depends on the grains in the media
364 (Friedman and Robinson, 2002), the aggregate treatment was not significant in the
365 current study ($p=0.13$; Table 1). Slightly greater tortuosity for smaller particles could be
366 due to image analysis techniques as larger particles create larger spaces between particles

367 thus reducing the tortuosity of paths. In contrast, tortuosity increased linearly with
368 increasing particle size and the gas diffusion coefficient decreased in a plant growth
369 media study with 1 to 16 mm size bark materials (Knongolo and Caron 2006). Higher
370 tortuosity values due to compaction, aggregate size, or management affect water, solute,
371 and gas movement through the media and higher tortuosity imposes greater resistance.

372 Mean tortuosity values were 1.20 and 1.21 for 1.51 and 1.72 Mg m⁻³ bulk density
373 treatments, respectively (Table 1). Pore paths were 0.8% more tortuous for the higher
374 compaction as compared to the lower compaction (not significantly different). In
375 addition, the probability was slightly higher for tortuosity > 2.5 for more compacted soils
376 than the 1.51 g cm⁻³ bulk density soil.

377 Average tortuosity values between 1.46 and 1.74 were observed among crop and
378 buffer soils (Udawatta et al., 2008). The mean tortuosity value was 2.7 with a 1.5 to 4.5
379 range in a fluid transport study, using synchrotron CMT (Coles et al., 1998). Path
380 tortuosity values observed in this study and the Udawatta et al. (2008) were less than 1.75
381 while Perret et al. (1999) observed values as high as 2.4. The difference can be attributed
382 to image resolution and image analysis software.

383 Imaging techniques are capable of estimating tortuosity in X, Y, and Z directions
384 (Wu et al., 2006). Such measurements are important for materials with anisotropic pore
385 structure that have preferential pore directions. For example, clay soils with restrictive
386 horizons may promote lateral flow above the restrictive horizons. In contrast,
387 compaction may occur in three dimensions and pore structure may not always form a
388 continuous network; could be an isolated entity. At this time, it is not clear whether
389 tortuosity data measured in all cardinal directions and locations will be useful in

390 predicting transport. Future studies are needed to examine how water, solute, and gas
391 movement are affected by anisotropic tortuosity among porous media with heterogeneous
392 particles.

393

394 **Pore characteristics of (Co) and (PLo) as influenced by aggregate-size and**
395 **compaction.**

396 Conventional methods for determination of porosity document that aggregate size and
397 compaction significantly decrease pore-size. Our results show that these changes are
398 relatively small making it difficult to discriminate among soils of differing aggregate-size
399 and compaction.

400 Using CMT methods, determination of the network of pore paths (Co) and the path
401 length of pores (PLo) is possible. Results show much greater change in these
402 characteristics compared to pore-size. Change in Co from 2- to 0.5-mm aggregates
403 averaged over density reduced the connections 4%, while change in Co from 1.51- to
404 1.72 - Mg m⁻³ reduced the pores connections 6.4%, a much greater reduction than the
405 reduction in pore radius. Values for PLo reflecting the tortuous nature of path lengths
406 show the greatest discrimination among the aggregate-size and compaction treatments.
407 Not surprisingly, change in PLo from 2- to 0.5-mm aggregates averaged over density
408 increased path tortuosity by 4.3% as smaller aggregates reduced the probability of direct
409 pore paths. In contrast, change in PLo from 1.51- to 1.72 - Mg m⁻³ decreasing PLo by
410 10.5%, demonstrated the greatest ability to discriminate among treatments.

411 Our results suggest that inclusion of CMT pore characteristics allow a better
412 description of soil structure that can discriminate differences in pore characteristics of
413 soil.

414

415 **CONCLUSIONS**

416 This study provides insight into the effects of compaction of two aggregate-size
417 classes on soil structure parameters through the application of computed
418 microtomography technology at a 9 μ m scale using a nondestructive and 3-dimensional
419 rendering microtomography of a loamy sand soil. Two compaction levels on pore radius,
420 largest average pore volume, number of pores, characteristic coordination number, and
421 path length were investigated. The results provide a picture of how the pore space
422 changes as the porosity decreased with compaction. These results can improve
423 quantification and the ability to model soil structure. This method should aid with the
424 development of tools to better assess soil structure and the measure the benefits of soil
425 management to improve soil quality.

426 The study approach detected significant differences in certain measured
427 parameters. The study results also show that differences in tortuosity were not clearly
428 detected by the microtomography method used in this study. This could possibly be
429 because of the imaging resolution and image analysis procedures used in the study.

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597 Table 1. Geometrical pore parameters (pore radius, pore volume, number of pores,
 598 characteristic coordination number, characteristic path length, and tortuosity) as
 599 influenced by aggregate size and compaction treatments and the ANOVA. Soil
 600 cores were scanned at the GeoSoilEnviroCARS (GSECARS) sector at the
 601 Argonne Advanced Photon Source X-ray computed microtomography facility.
 602 Values in parenthesis indicate standard deviations).
 603
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Treatment	Mean Pore radius μm	Total Pore volume mm^3	Largest Pore volume mm^3	Mean pore volume μm^3
Aggregate Treatment means				
0.5 mm	62.64(2.41)	5.87(5.36)	1.47(1.02)	$6.8 \times 10^5(6 \times 10^5)$
2.0 mm	62.29(1.99)	3.45(3.52)	0.69(0.76)	$6.9 \times 10^5(7 \times 10^5)$
Compaction Treatment means				
1.51 Mg m^{-3}	63.75(1.26)	6.45(4.81)	1.58(0.86)	$7.1 \times 10^5(6 \times 10^5)$
1.72 Mg m^{-3}	61.18(2.08)	2.87(3.71)	0.58(0.82)	$6.6 \times 10^5(6 \times 10^5)$
Analysis of variance				
Treatment	0.183	0.478	0.129	0.640
Aggregate (0.5 vs. 2.0 mm)	0.753	0.384	0.127	0.790
Compaction (1.51 vs 1.72 Mg m^{-3})	0.044	0.212	0.063	0.286
Aggregate * compaction	0.533	0.852	0.773	0.556
Analysis of variance				
Treatment	Number of pores	Characteristic coordination number (Co)	Characteristic path length number (PLo)	Tortuosity
Aggregate Treatment means				
0.5 mm	54(6)	6.01(0.28)	112.77(10.54)	1.21(0.01)
2.0 mm	50(4)	6.25(0.29)	108.14(6.13)	1.20(0.01)
Compaction Treatment means				
1.51 Mg m^{-3}	55(5)	6.32(0.31)	115.96(8.40)	1.20(0.01)
1.72 Mg m^{-3}	50(4)	5.94(0.27)	104.95(11.30)	1.21(0.01)
Analysis of variance				
Treatment	0.184	0.192	0.005	0.341
Aggregate (0.5 vs. 2.0 mm)	0.193	0.217	0.047	0.134
Compaction (1.51 vs 1.72 Mg m^{-3})	0.089	0.092	0.001	0.346
Aggregate * compaction	0.537	0.461	0.291	0.747

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List of Figures:

Figure 1. Cross sectional and three dimensional images of soil core samples for bulk density 1.51 Mg m^{-3} (left) and 1.72 Mg m^{-3} (right).

Figure 2. Probability density distributions versus pore radii for Hamra 2.0 and 0.5 mm aggregate treatments (H2 and H5) and Low and High compaction treatments (L and H). Selected replicates are shown in the figure (last number in treatment name is replicate). The number within parentheses is the sample mean pore radius in μm . The circle represents the average pore radii and the horizontal line indicates the standard deviation of the mean.

Figure 3. Probability density distributions versus pore volume for Hamra 2.0 and 0.5 mm aggregate treatments (H2 and H5) and Low and High compaction treatments (L and H). Selected replicates are shown in the figure (last number in treatment name is replicate). The number within parentheses is the sample mean pore volume in μm^3 . The circle represents the average pore volume and the horizontal line indicates the standard deviation of the mean.

Figure 4. Probability density distributions versus coordination number for Hamra 2.0 and 0.5 mm aggregate treatments (H2 and H5) and Low and High compaction treatments (L and H). Selected replicates are shown in the figure (last number in treatment name is replicate). Coordination number (CN) is number of curve segments meeting at the vertex and C_0 is the characteristic coordination number constant which is the value in each equation.

Figure 5. Probability density distributions versus pore path length for Hamra 2.0 and 0.5 mm aggregate treatments (H2 and H5) and Low and High compaction treatments (L and H). Selected replicates are shown in the figure (last number in treatment name is replicate). Path

length (PL) is the length of the path between adjacent connected nodal pores and PLo is the characteristic path length constant which is the value in each equation.

Figure 6. Probability density (solid points) versus path tortuosity and cumulative probability density (solid line) versus path tortuosity for Hamra 0.5 and 2.0 mm aggregate treatments (H0.5 and H2.0) and Low and High compaction treatments (L and H). Selected replicates are shown in the figure (last number in treatment name is replicate). The vertical line and the number within parenthesis is the sample mean tortuosity.