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# Enhancing image resolution of soils by stochastic multiscale image fusion

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ABSTRACT

Soil structure defines major physical properties and biophysical functions of soils. Imaging soil structure using different 2/3D techniques is a routine methodology used by soil scientists. Still, for structured soils their spatial variability and hierarchical structure imposes a significant challenge for all imaging methods in terms of field-of-view and resolution trade-off. While creating a truly multiscale 3D digital model of soil is without question of utmost importance, there is currently no single imaging method that could potentially encompass all necessary relevant soil scales within a single image. In this paper, we tested for the first time an image fusion technique to produce a multiscale soil image based on separate images obtained with different spatial resolutions. The method is based on universal soil structure descriptors, i.e. spatial correlation functions, which were shown to be very useful in soil applications. Using a relatively simple 2D test case based on X-ray tomography (XCT) images at three different scales, we show the applicability of image fusion for soil images and solve a long standing problem of imaging resolution. In total we fused seven images into a single image: one 114 µm resolution macroscale XCT image (porosity $< 0.01$), four 15 µm resolution microscale XCT images (with porosities 0.039–0.049), and two 3.3 µm resolution microscale XCT images (with porosities of 0.24 and 0.76). The resulting single, 15 µm resolution image represented $6 \times 6$ cm$^2$ of soil structure. Its porosity increased from $< 0.01$ to 0.073 due to representation of all pore sizes visible on the images prior to fusion. Current drawbacks of the approach are discussed and an outline is provided of its future usage to address important soil structure issues.

## 1. Introduction

Soil structure, i.e., the spatial distribution of solids, organics, fluids and pores within soils, defines physical (Karsanina et al., 2015) and numerous other important soil function properties (Kravchenko et al., 2015). Conventional imaging techniques to assess soil structure include thin-sectioning and SEM (Skvortsova, 2009; Vogel, 1997). Last decade has seen a rapid growth in the use of computed X-ray tomography (XCT) for soil imaging due to a significant development in this imaging technique, higher scanning resolution, and reduced scanner price. Previous applications of XCT to study soil structure typically focussed on a single scale, e.g. within the macro-aggregate scale (Kravchenko et al., 2015), matrix within soil samples of the conventional undisturbed core scale (Gerke et al., 2012a; Jassogne et al., 2007; Naveed et al., 2014), or macropore scale (Koestel and Larsbo, 2014; Luo et al., 2010). Such studies are without question very useful and provided valuable insights into particular soil processes, yet to fully describe a soil's integral structure a multiscale digital model is needed. For soils with complex hierarchical structure and numerous multiscale features such as macropores and intra-aggregate porosity embedded within different soil layers, obtaining a multiscale image with a single imaging method is currently not possible. This is due to the so-called field-of-view and imaging resolution trade-off characteristic of basically all imaging techniques. However, progress in different areas of soil science and hydrology requires detailed multiscale information (Pachepsky and Hill, 2017; Vogel and Roth, 2003). For example, description of water flow and solute transport properties, especially for Darcy-scale models (Flemisch et al., 2011; Šimůnek et al., 2008) informed by pore-scale simulations (Khan et al., 2012; Köhne et al., 2011), requires accurate spatial representation of all soil hierarchical domains, or their interfaces for estimation of mass transfer exchange coefficients (Gerke and van Genuchten, 1996; Gerke et al., 2015a).

A recent comparison between soil structural features measured on thin sections and simulated using so-called spatial correlation functions

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demonstrated the suitability of correlation functions as descriptors of soil structure (Gerke et al., 2012b; Karsanina et al., 2015). In addition to providing a rigorous description of the soil structure by means of mathematical functions, spatial correlation functions provide a way to solve stochastic reconstruction of soil structure by inverse modelling. Note that stochastic reconstructions based on multiple point statistics were attempted previously (Wu et al., 2004; Zhang et al., 2005). Based on the concept of rescaling correlation functions, stochastic reconstructions can be used as a tool to stochastically fuse multiscale images with different resolution (Gerke et al., 2015b). Soils represent one of the most complex porous media that can be found on Earth and their multiscale description by fusion of images of differing resolution into a single digital model has, to our best knowledge, never been attempted.

The objective of this paper is to demonstrate multiscale image fusion using 2D soil images with three different imaging resolutions, and outline what future research directions are needed to develop the method into a core toolkit of soil imaging.

## 2. Objects and methods

### 2.1. General soil description and sampling

An 80-cm-long and 10-cm-diameter undisturbed monolith was extracted from an agricultural soil at the experimental field of the V.V. Dokuchaev Soil Science Institute Experimental Station in Moscow region, Russia, Eldigino village. The soil was classified as Glossic Retisol (Aric, Loamic) (WRB, 2015). The current study focuses on the soil structure of the upper 10 cm from the Ap1 soil horizon.

### 2.2. Imaging, image processing and segmentation

After transferring the 80-cm-long monolith encased in a PVC cylinder to the laboratory, the full monolith was imaged using a petrophysical full-core scanner RKT-180 (Russia) with a resolution of 114 μm. Next, the PVC cylinder was carefully cut open and undisturbed, 1-cm and 3-cm-diameter cylindrical sub-samples were extracted at different depths along the major axis of the PVC core. This ensured that all scans were aligned along the same direction and all images lie in the same plane within the soil monolith. The sub-samples were scanned using a Bruker-Skyscan 1172 (Bruker, Belgium) desktop scanner with resolutions of 3.3 and 15 μm, respectively.

For the purpose of demonstrating the multiscale fusion approach we utilized preliminary soil structure information resulting from a single soil depth at 5 ± 2.5 cm. The following images were analysed: a single 2D macroscale image (114 μm resolution), four 2D coarse microscale images (15 μm resolution) and two 2D fine microscale images (3.3 μm resolution). All images were cropped to represent a square section and were chosen in such a way that the next finer scale images would represent additional structural information not available on the previous coarser scale due to the resolution limits (see Fig. 1). The macroscale image was rescaled using bicubic interpolation to magnify it 7.6 times up to a size of $4000^2$ pixels. This was necessary to allow image fusion into a single $4000 \times 4000$ pixel image.

Next, all images were subjected to a segmentation procedure which involved converting grey-scale XCT images into images representing a limited number of materials (or phases). In case of the microscale images, a binary segmentation was performed, i.e., all pixels were divided into either pores or solids. Microscale images with resolution of 15 μm were also filtered using a non-local means filter (Buades et al., 2015) to improve signal-to-noise ratio. The macroscale image was segmented into four phases: pores, soil solids (containing both solids and pores not visible at the 114 μm imaging resolution), loose and sponge-like solids. The choice of these four phases was logically dictated by the hierarchical soil structure observed at finer scales (Gerke et al., 2015b). More specifically, Fig. 1 shows how coarse microscale images provide additional structure about the solids on a macroscale image, while finer scale XCT resolves the filling of the large pores on the macroscale XCT image. The macroscale image contains some large pores, but comparison of its grey-scale histogram against a pure void signal clearly revealed macropores that were filled with different materials. Such materials were classified into the aforementioned loose and sponge-like solids. These fillings might represent decayed organic matter (e.g., roots), mixing of the soil material due to water flow or freeze/thaw cycles, or could result from the disturbance during PVC core extraction/transportation. In all cases, the indicator kriging segmentation method (Oh and Lindquist, 1999) was implemented within our in-house image processing code in a way similar to Houston et al. (2013). The only difference with the latter approach was the use of a kriging window with a fixed size of 10 voxels, modified to perform multiphase segmentation (as was used for the 2D macroscale image). This segmentation approach required two threshold confidence intervals (e.g., grey scale values that are pores or matrix with a high degree of certainty) for each two phases to be separated. All pixels with grey scale values in between those confidence intervals are kriged to decide their affiliation with the two phases under consideration. In this work, all threshold confidence intervals were chosen manually based on greyscale histogram and trial segmentation runs, as opposed to automatic thresholding (Schlüter et al., 2010) that showed significantly less robust results on our soil samples. For all microscale images binary segmentation was applied resulting in pores and solids. For macroscale image in addition to pores, three substructures were segmented out: solids, loose solids and sponge-like solids. Segmented images, as well as additional visual explanations about segmented phases, are shown in Fig. 2.

### 2.3. Stochastic multiscale image fusion

To perform stochastic multiscale image fusion (Gerke et al., 2015b), all available structural information from all scales needs to be merged into a single image of predefined resolution. The target resolution is generally optional and defined by the purpose of the fusion. As the fused image utilizes existing information, it should have the resolution of the finest scale image available. On the other hand, huge resulting images can be prohibitive for subsequent analysis or simulations (e.g., pore-scale modelling of flow and transport properties). Here, we show the usage of multiscale fusion that both super-resolves and coarsens input data by choosing a target resolution of 15 μm. This means the macroscale image will be improved using finer images, while information from coarse microscale images will be used as is, while fine microscale images will be coarsened. In what follows we describe all necessary procedures to perform fusion procedures and obtain the single fused image.

First, the 2D macroscale images have to be rescaled using a standard image processing procedure called bicubic interpolation. By doing so, the image was rescaled from 114 μm to 15 μm resolution (note that the ratio of resolutions $114 \div 15 = 7.6$ and thus the original 530-pixel image was rescaled to a 4000 pixel image yielding the same ratio of 7.6, i.e., $4000 \div 530 \approx 7.6$). This is a simplification of the original methodology proposed by Gerke et al. (2015b). As a result, the simplified procedure does not guarantee that the resulting image will be the exact rescaled representation. However, by rescaling grey-scale images and subsequent segmentation, we controlled the fraction of each segmented phase and by further adjusting segmentation thresholds the resulting ratios were the same as on the original segmented image. At least this guaranteed that rescaled porosities are similar and, according to Shah et al. (2016), adequate flow properties could be modelled from the rescaled image. This also highlights the drawback of the current methodology, which requires creating stochastic reconstructions for each rescaled structure (see SI Gerke et al. (2015b) for description and details). Yet, the approximation used here provides a good approach to avoid stochastic reconstruction at this step and utilizes the soil structure