Modelling soil physical properties based on XCT scans processed using state-of-the-art local and machine learning based segmentation approaches

Konstantin Romanenko[1,2], Efim Lavrukhin[2,3], Roman Vasilyev[2,3], and Kirill Gerke[3]

- [1]Lomonosov Moscow State University
- [2]Dokuchaev Soil Science Institute
- [3]Schmidt's Institute of Physics of the Earth of Russian Academy of Science

EGU2020

Samples

Samples:

- Grey-Luvic Phaeozems (Sample 1,2) and Chernozems (samples 3-7)

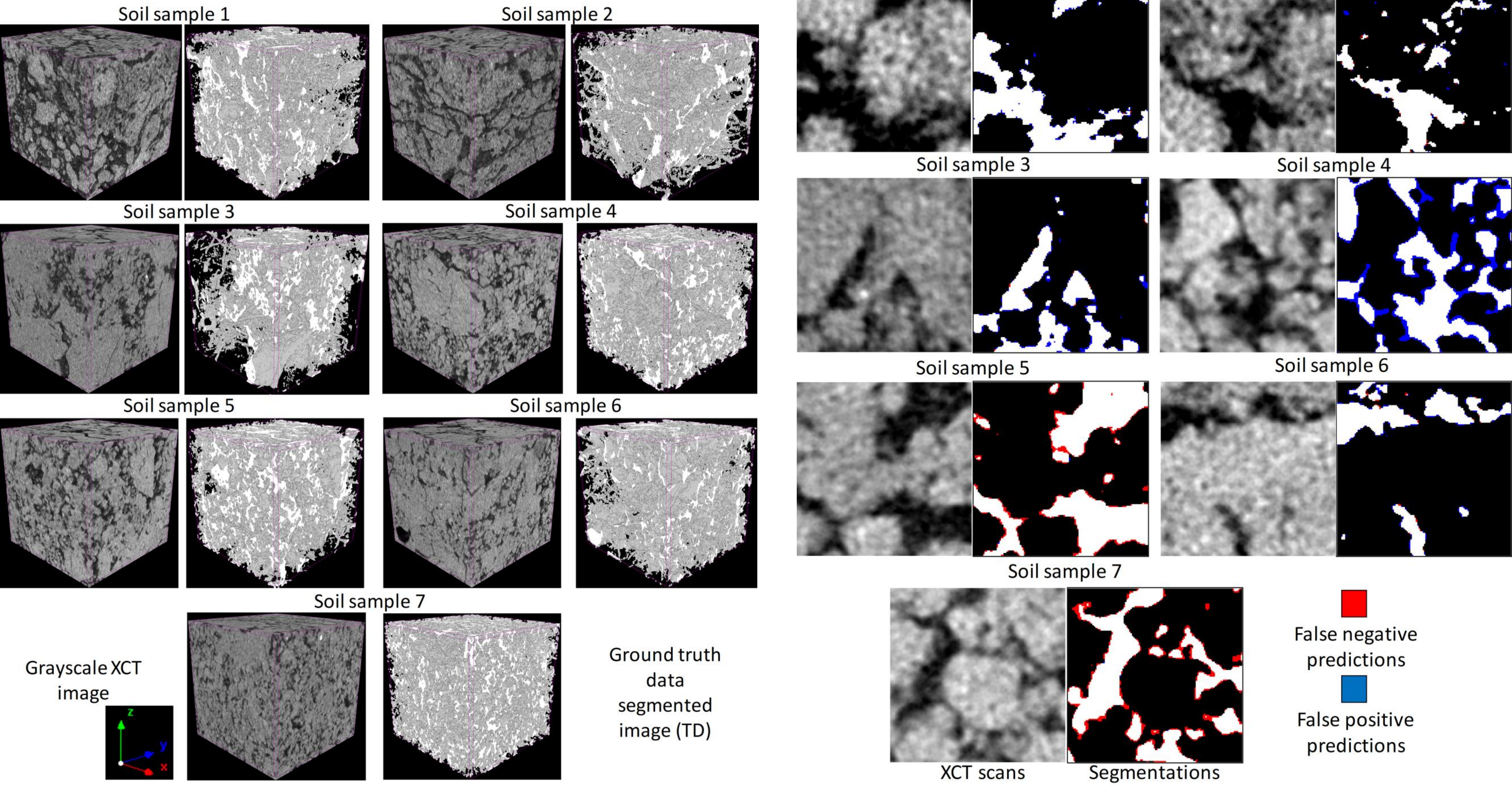
Segmentation to obtain True data:

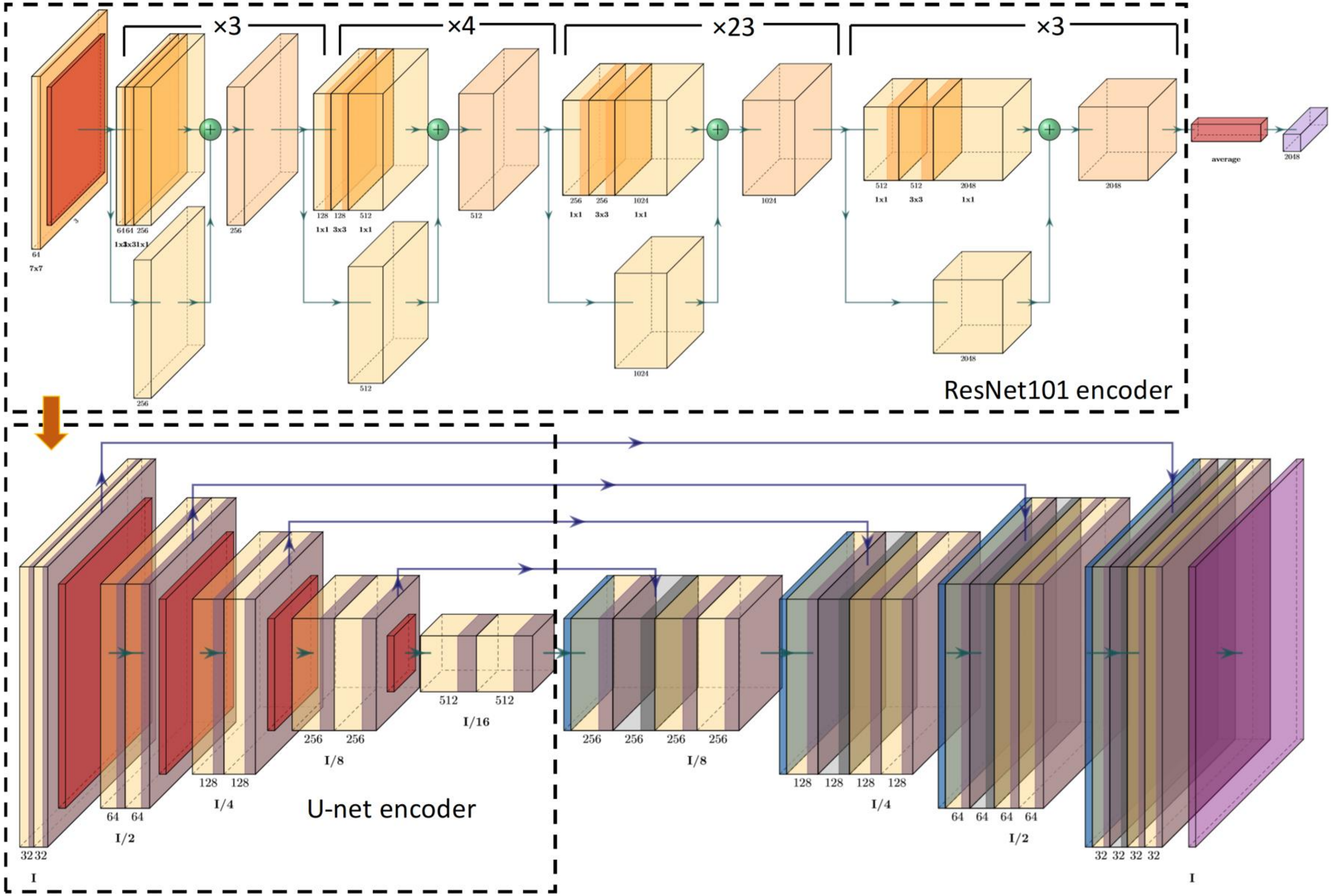
- converging active contours (Sheppard et al., 2004) and region growing (Mehnert and Jackway, 1997) algorithms

Neural network architecture:

- U-net architecture. the U-net encoder replaced with ResNet101 encoder

Soil samples and segmentation differences





The general architecture of neural network used in this study. The lower part represents vanilla U-net architecture. The upper part shows ResNet101 architecture. In our neural network we replaced the U-net encoder with ResNet101 encoder (these parts are highlighted with dotted line areas).

General segmentation results

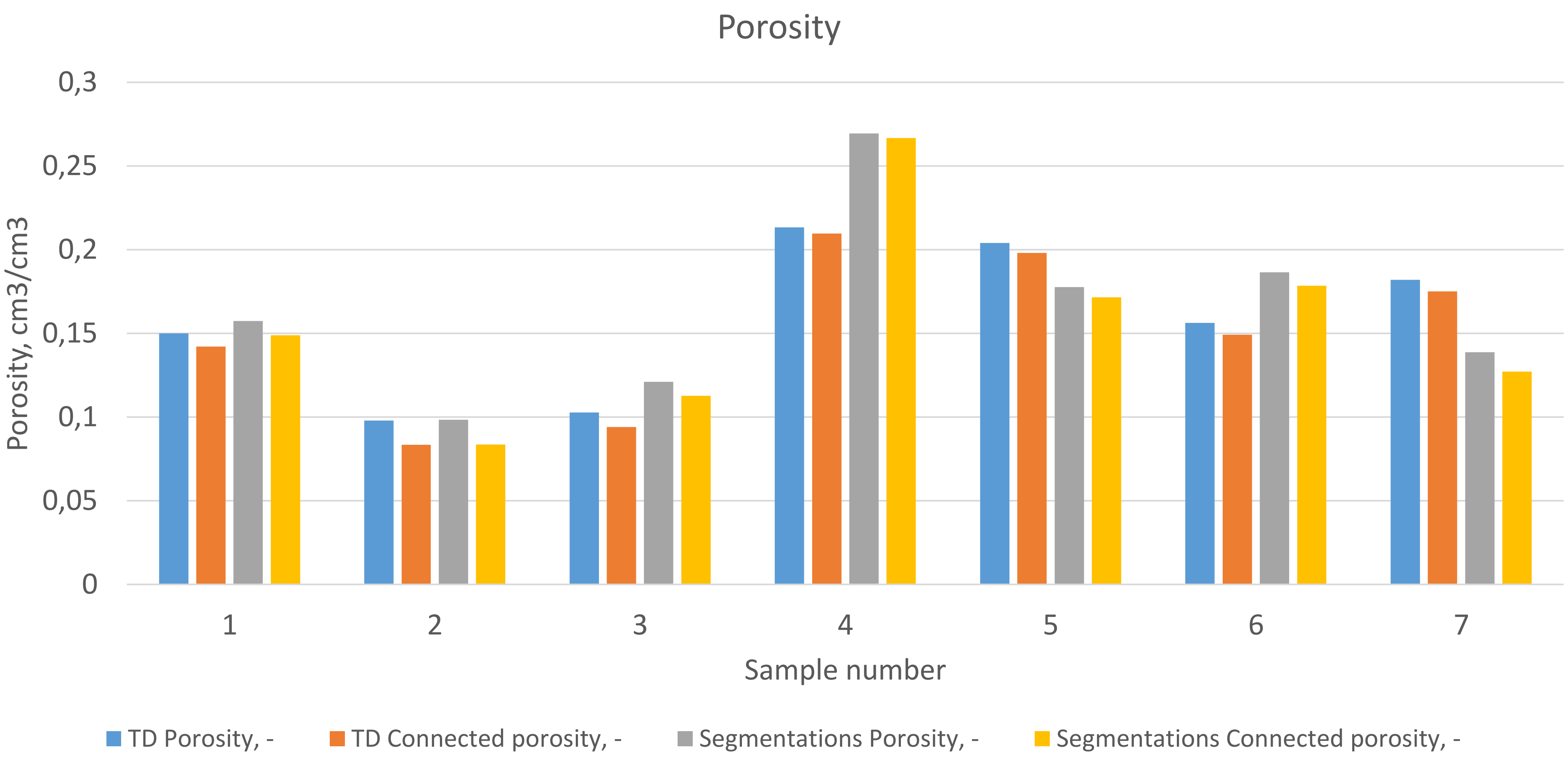
Computer vision metrics for neural network-based binarizations

Sample	Accuracy	Precision	Recall	F1	PR_AUC	IOU
1	0.990278	0.943769	0.996358	0.969351	0.998623	0.940524
2	0.996335	0.968988	0.993439	0.981061	0.998841	0.962826
3	0.973652	0.820249	0.995574	0.899447	0.990357	**0.817269**
4	0.939552	**0.792140**	0.999917	0.883983	0.996171	**0.792088**
5	0.969022	0.998757	0.865202	0.927195	0.996564	**0.864272**
6	0.975915	**0.863557**	0.994796	0.924542	0.993793	**0.859673**
7	0.958027	**0.998234**	**0.760084**	**0.863031**	0.989519	**0.759064**

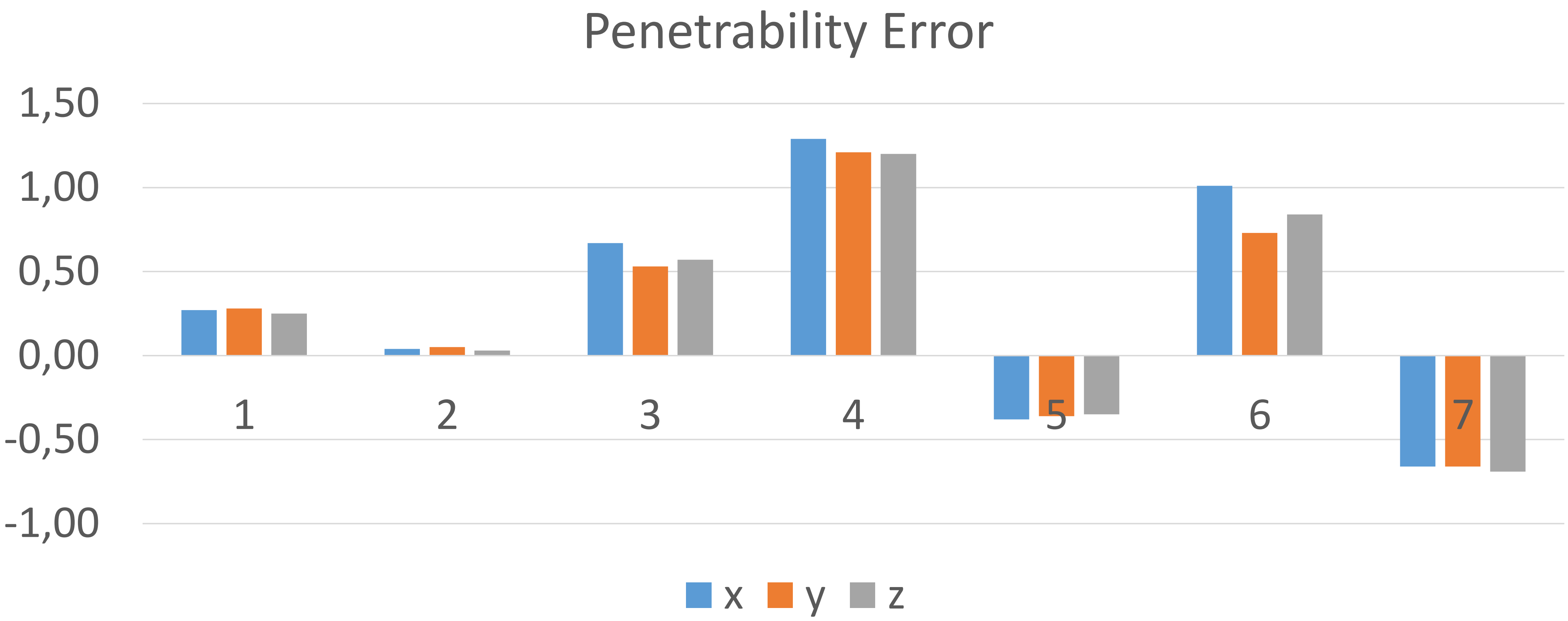
Computer vision metrics for neural network-based binarizations with training on all 3D images.

Sample	Accuracy	Precision	Recall	F1	Pr_auc	iou
1	0.993453	0.954353	0.997504	0.975451	0.999157	0.952079
2	0.993797	0.951161	0.995484	0.972818	0.998651	0.947074
3	0.983351	0.884995	0.991901	0.935403	0.992297	**0.878646**
4	0.966813	**0.873061**	0.997794	0.931269	0.994909	**0.871378**
5	0.983910	0.964919	0.956062	0.960470	0.995234	**0.923946**
6	0.985962	**0.926988**	0.992029	0.958406	0.997118	**0.920134**
7	0.978669	**0.908644**	**0.985702**	**0.945606**	0.994329	**0.896824**

General segmentation results

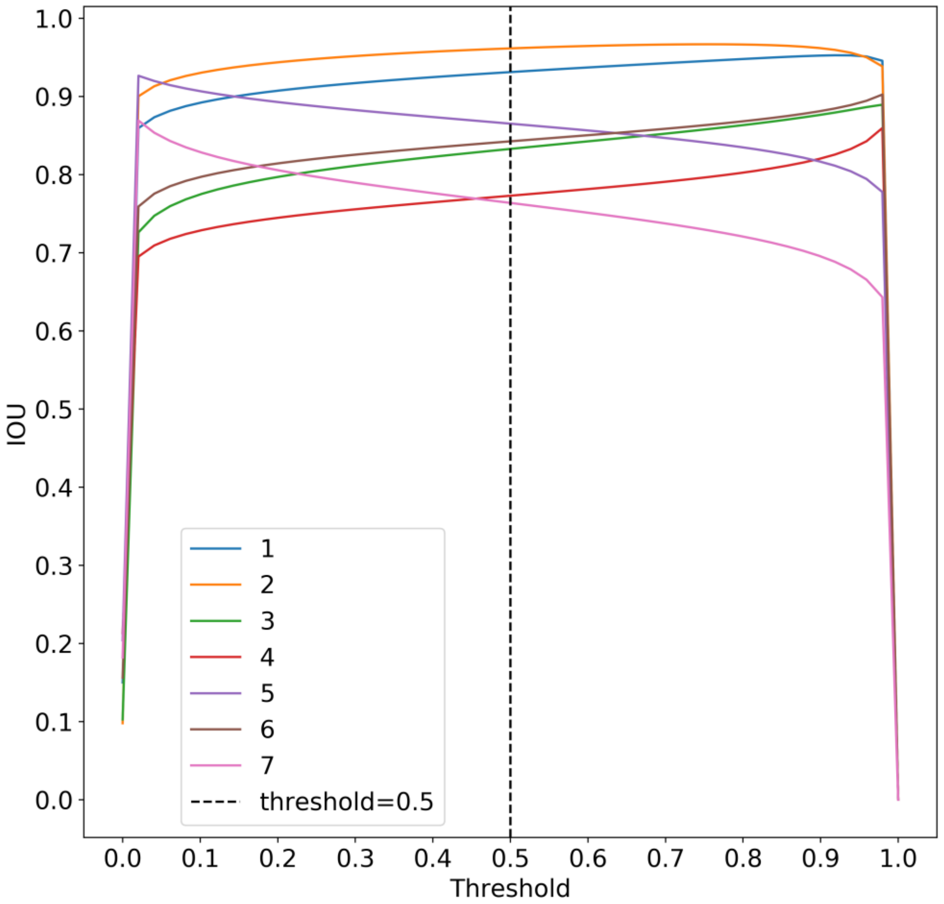


Single phase flow simulation results

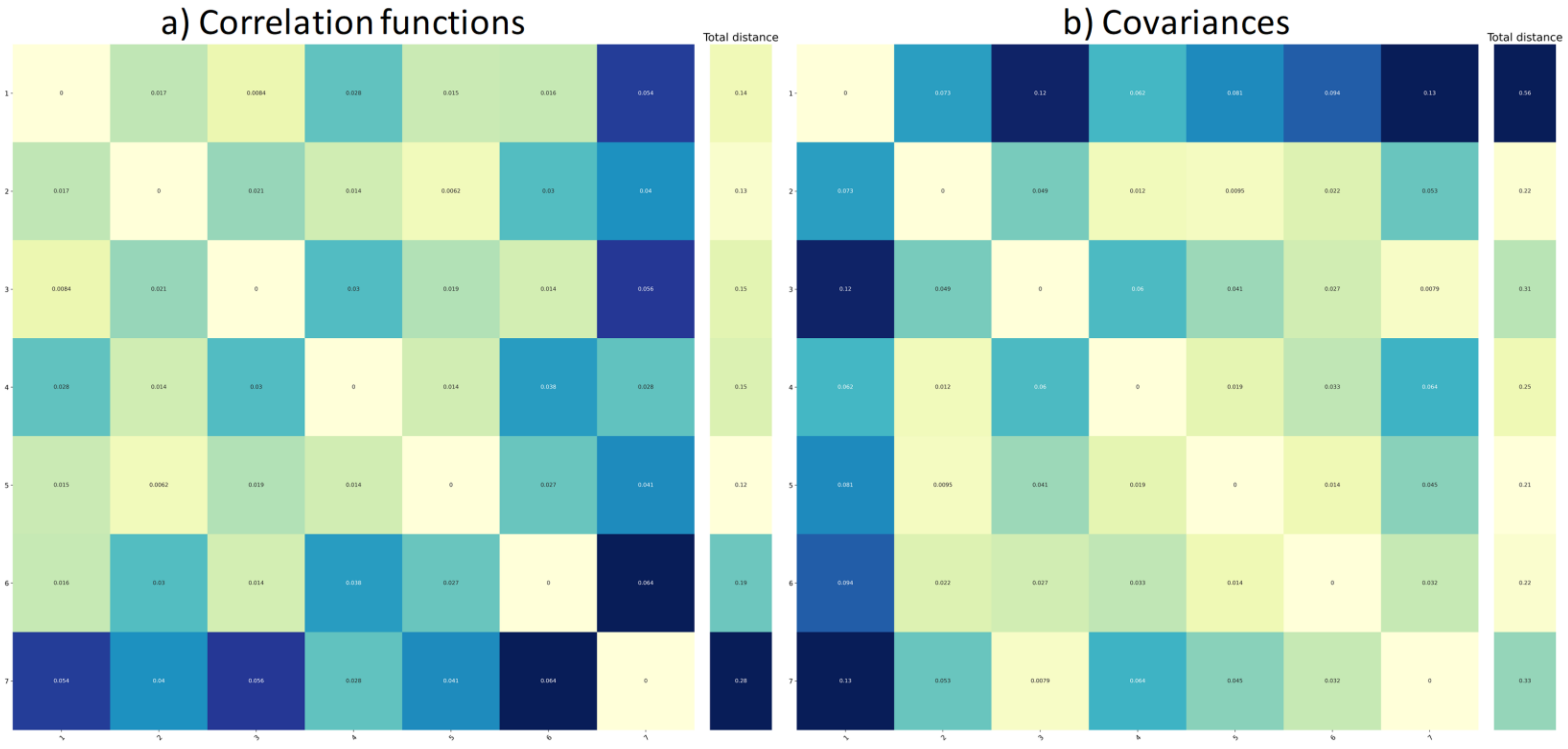


$$Error = \frac{K_{seg}}{K_{TD}} - 1$$

Samples 4,6,7 have quiet different structure



The influence of the threshold value on the quality of the segmentations.



The pairwise and total distances between samples in terms of: a) correlation functions for TD images, and b) covariances for original XCT greyscale images.

Highlights:

- We present the first results for soil XCT image segmentation using neural networks.
- Depending on the sample the accuracy in terms of permeability reached 5% error.
- To segment soil images we utilized hybrid U-net+Resnet101 architecture.
- Low accuracy cases can be explained by low representativity of XCT images.
- Larger image libraries, better true data and network architecture were proposed as ways forward.

Acknowledgements

- This work was supported by Russian Science Foundation grant 19-74-10070.

The paper with detailed description of all results is currently submitted to Soil and Tillage Research journal.