Geophysics-based subsurface conceptualization for improved prediction of plant productivity beyond field scale

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Transregional Collaborative
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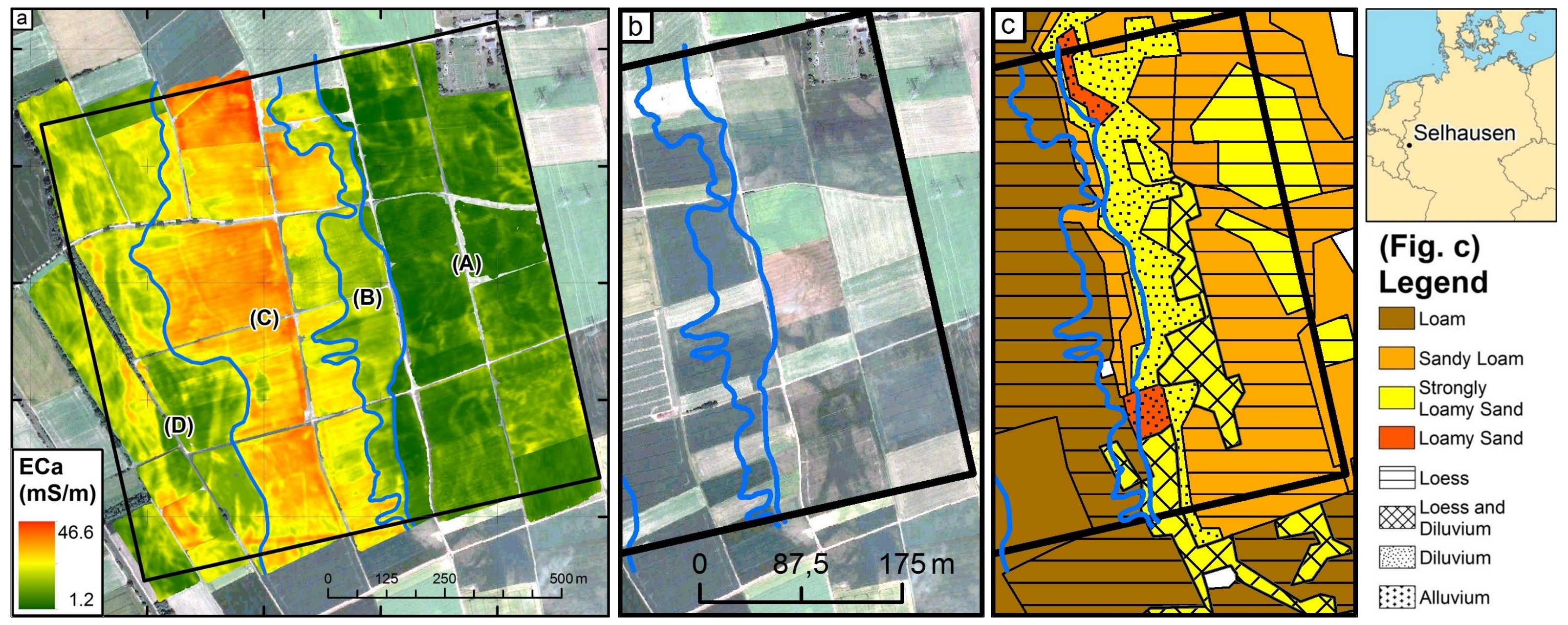
Introduction and motivation

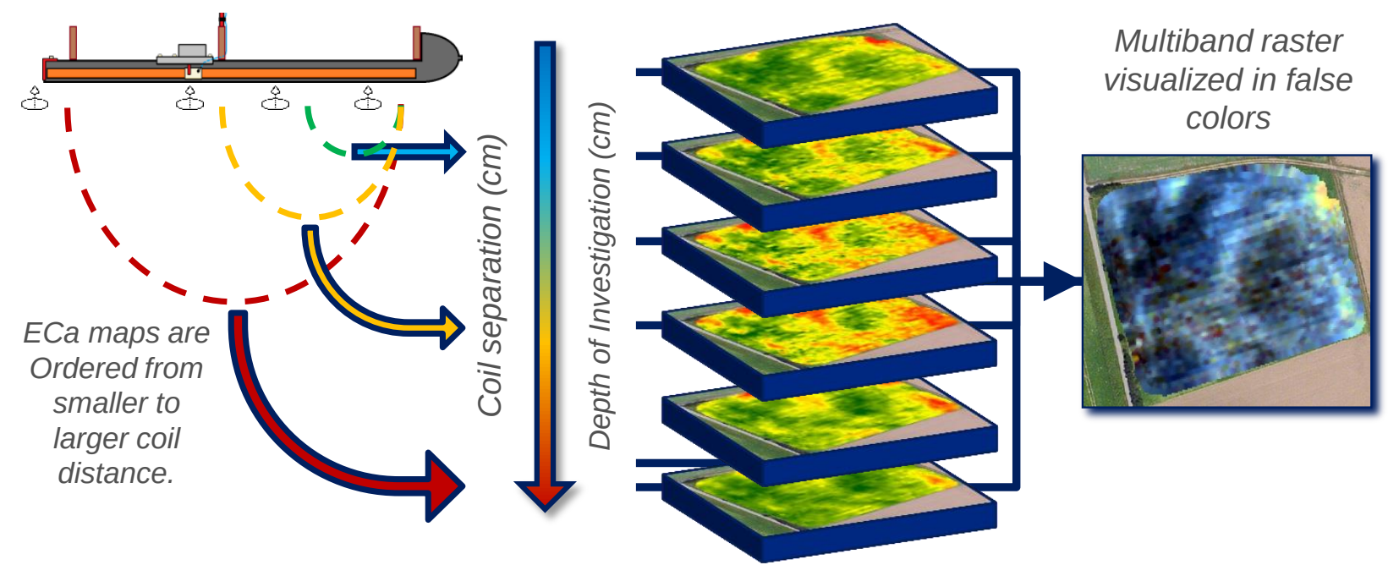


The study area is located in Selhausen (Germany), a) ECa map of the HCP 97 cm configuration, b) satellite image with patterns in plant productivity caused by water stress, c) detailed soil map of the study area used for farming taxation.

Characterizing the shallow subsurface is vital for environmental modelling. The exploration of large farm-scale (~100 ha) still presents challenges. In this study, we applied image classification to multi-configuration EMI data and used a limited amount of samples to create an high resolution soil map of a 1 km^2 study area composed of 51 agricultural fields. With this soil map and using an agroecosystem model, we simulated patterns in plant productivity during water stress and we compared them with satellite data.

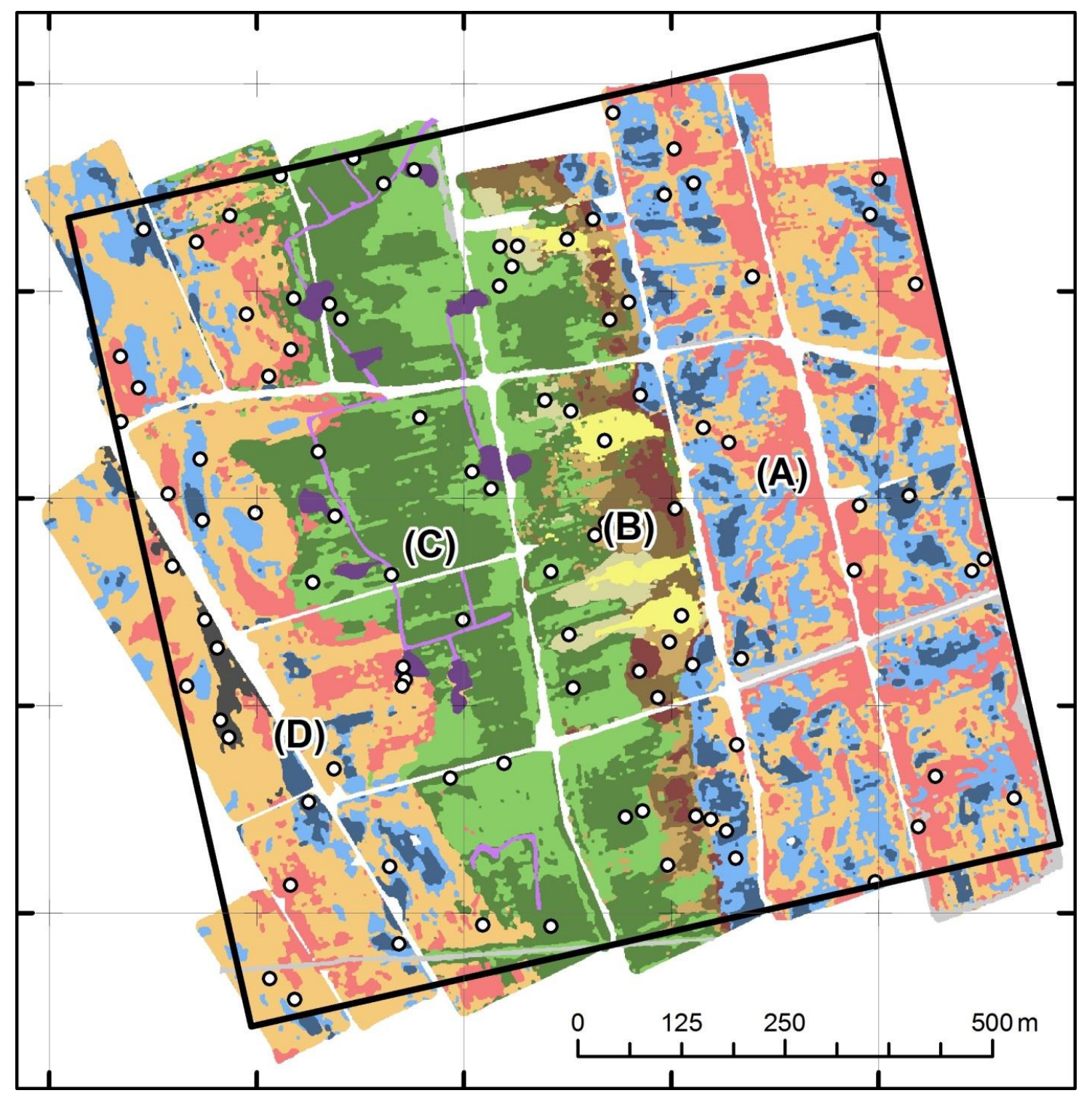
Geophysics-based high-resolution soil map

Image classification of ECa maps can generalize a large study area into homogeneous subsurface structures with typical characteristics (e.g. layering and texture).

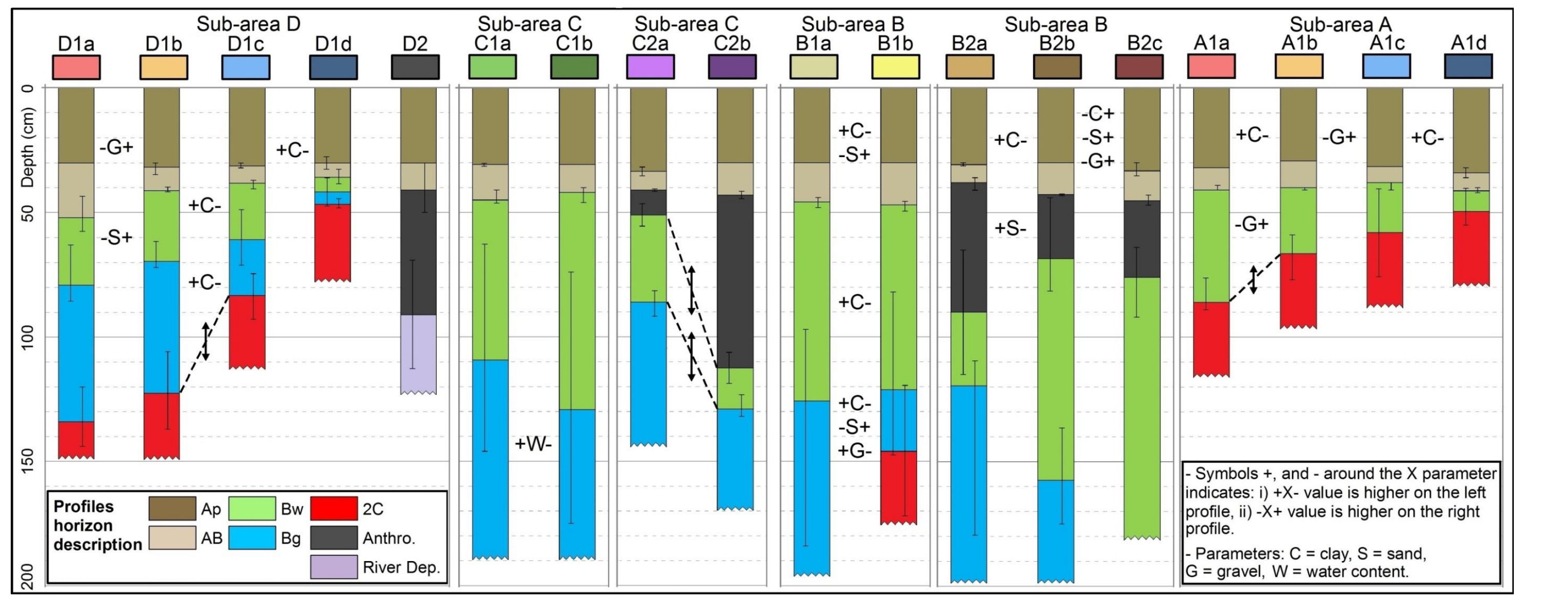


Creation of a multiband raster image from the ECa interpolated maps on one field.

For each field, a multiband raster was created using ECa maps with increasing coil separation and a supervised classification was performed. Hundred locations were sampled to assign a typical soil profile to each soil unit. The texture was obtained using a combined sieving and pipette method.



Classified map of the study area with 18 soil units and location of the ground truth points.



Averaged soil profile of the 18 classes with horizon type and depth. For profiles located in the same sub-area, the characteristics that are statistically different (t-test, p = 2.5 % in each tail) are shown in between the profiles.

Agroecosystem modelling

In this study, we focus on the growth of sugar beet over structures A1a, A1b, A1c, and A1d of Sub-area A. This area is characterized by coarse sediments buried in variable thickness fine loess. The loess thickness is known to drive the plant productivity during water stress periods (Rudolph et al 2015). Hydraulic parameters were calculated using the Rosetta pedotransfer function (Zhang and Schaap, 2016).

Class

A1a 🟥

Horizon	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	Gravel (%)	BD (g/cm3)	θs	θr	α	n	Ks (cm/h)
Ap	32.0	**17.1**	63.0	19.8	10.8	1.4	0.0682	0.3736	0.0040	1.5339	0.7061
Ah	40.7	17.1	63.0	19.8	10.8	1.5	0.0667	0.3542	0.0044	1.5108	0.4614
Bg	**86.0**	21.3	58.0	20.6	**14.0**	1.6	0.0666	0.3170	0.0050	1.4450	0.1877
2C	ND	20.3	41.7	38.0	54.4	2.0	0.0347	0.1682	0.0103	0.1572	0.0238

A1b 🟧

Horizon	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	Gravel (%)	BD (g/cm3)	θs	θr	α	N	Ks (cm/h)
Ap	29.0	**13.0**	66.6	20.4	**16.7**	1.4	0.0555	0.3550	0.0040	1.5630	0.9268
Ah	39.9	13.0	66.6	20.4	**16.7**	1.5	0.0540	0.3374	0.0044	1.5392	0.6251
Bg	**66.6**	18.2	57.9	23.9	**27.6**	1.6	0.0498	0.2775	0.0053	1.4588	0.2028
2C	ND	20.3	41.7	38.0	54.4	2.0	0.0347	0.1682	0.0103	0.1572	0.0238

A1c 🟦

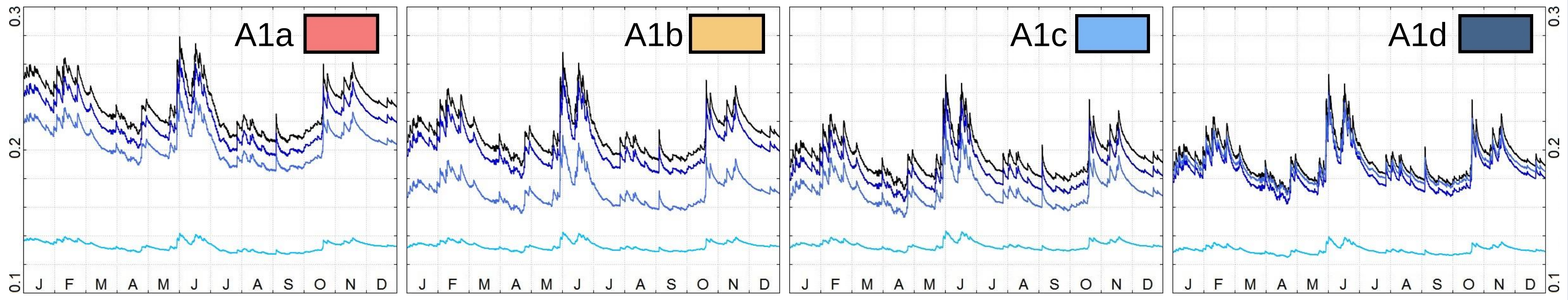
Horizon	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	Gravel (%)	BD (g/cm3)	θs	θr	α	n	Ks (cm/h)
Ap	31.7	**14.4**	66.8	18.8	**29.8**	1.4	0.0486	0.3216	0.0039	1.5555	0.7161
Ah	37.6	**14.4**	66.8	18.8	**29.8**	1.5	0.0474	0.3055	0.0043	1.5323	0.4787
Bg	58.1	16.8	62.7	20.5	29.1	1.6	0.0467	0.2763	0.0049	1.4790	0.2337
2C	ND	20.3	41.7	38.0	54.4	2.0	0.0347	0.1682	0.0103	0.1572	0.0238

A1d 🟦

Horizon	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	Gravel (%)	BD (g/cm3)	θs	θr	α	n	Ks (cm/h)
Ap	33.5	**12.9**	66.0	21.1	18.6	1.4	0.0538	0.3492	0.0041	1.5626	0.9123
Ah	41.0	**12.9**	66.0	21.1	18.6	1.5	0.0215	0.1831	0.0045	1.5386	0.2874
Bg	49.6	17.3	69.7	13.0	18.2	1.6	0.0568	0.3144	0.0044	1.4885	0.2693
2C	ND	20.3	41.7	38.0	54.4	2.0	0.0347	0.1682	0.0103	0.1572	0.0238

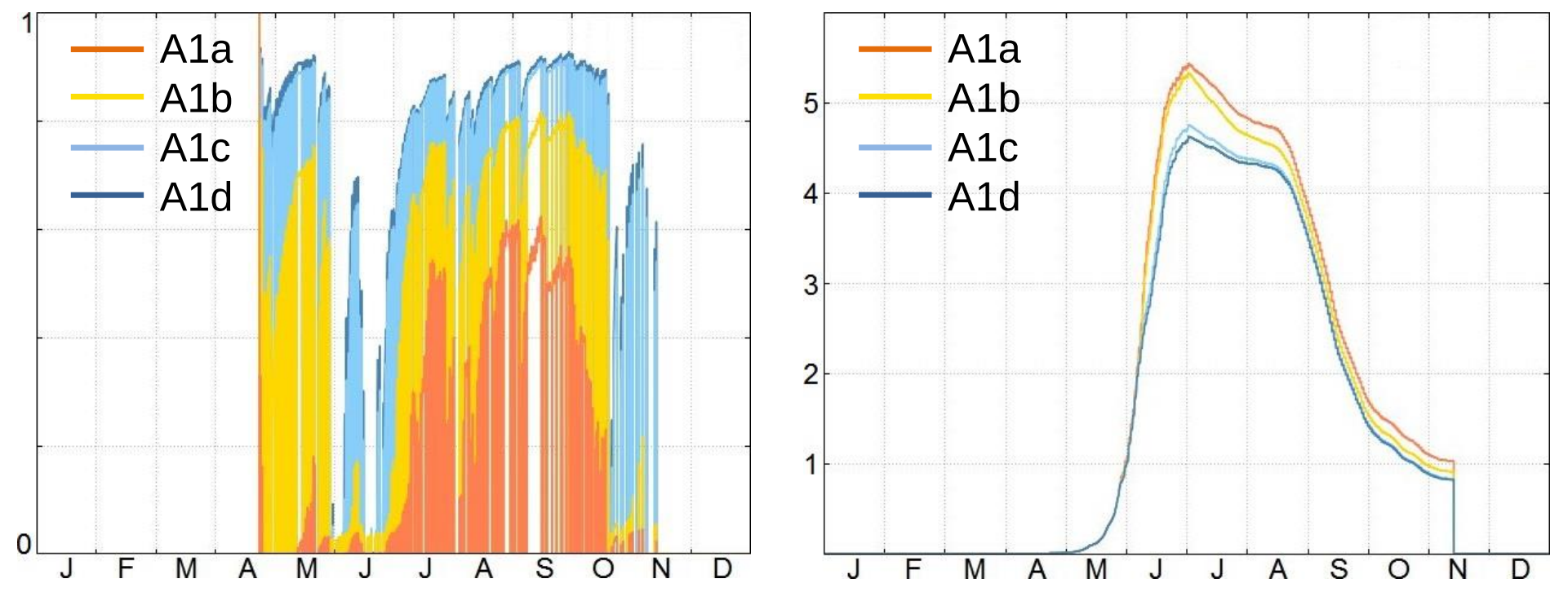
Horizon description and depth, textural information, and hydraulic parameters. The statistically different characteristics between profiles are connected with a blue bar (t-test, p= 2.5% in each tail) .

AgroC couples a one-dimensional soil water, heat, and CO2 flux model (SOILCO2), a pool concept of soil carbon turnover (RothC), and a crop growth module (SUCROS). We used AgroC to simulate the LAI of sugar beet, water stress, and water content for the four soil profiles of sub-area A in 2016.



Water content in the four soil units of sub-area A at the depth of 10 cm (black), 25 cm (dark blue), 45 cm (blue), and 90 cm (light blue).

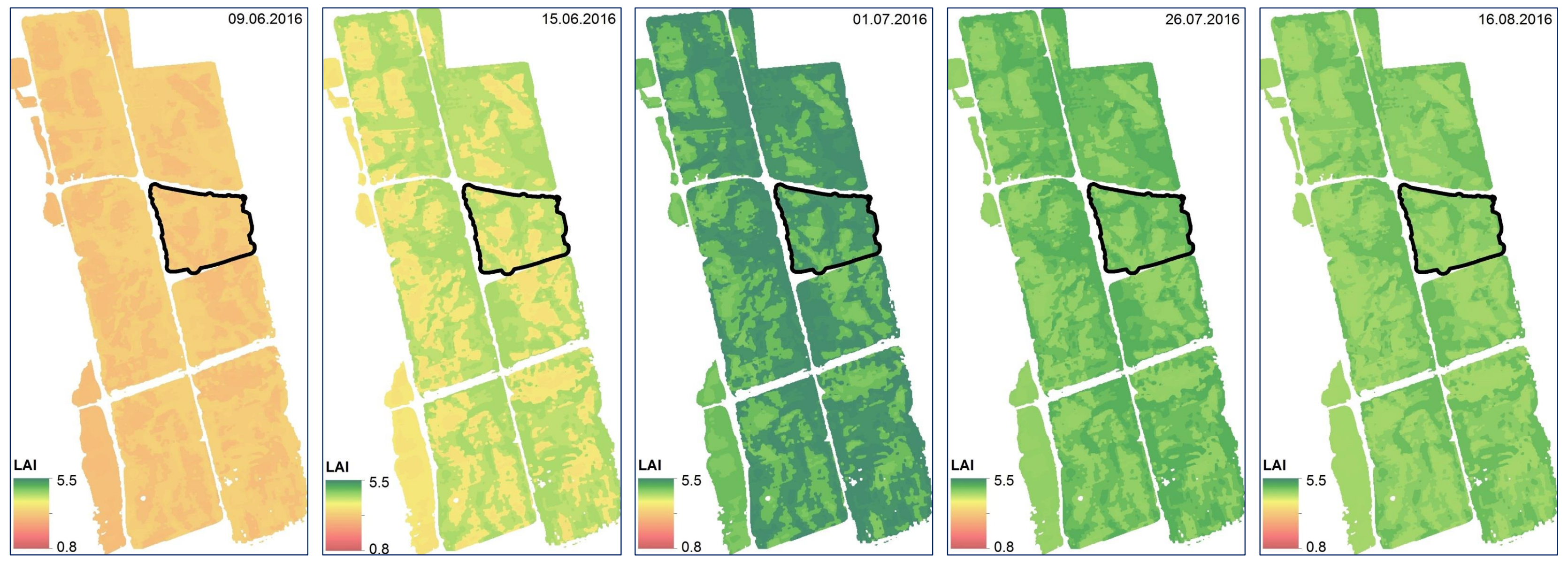
The four profiles are showing typical water content dynamics over the year, resulting in different water stress and LAI of the sugar beet plant. This difference is caused by the depth and characteristics of the loess sediments.



Simulated water stress (left) and LAI (right) on sugar beet in the four structures of sub-area A.

Spatio-temporal development of LAI and comparison with satellite data

The results of the AgroC simulation are used to analyze spatio-temporal variability of LAI for 2016. In particular, a lower LAI is associated with higher water stress and reduced productivity.

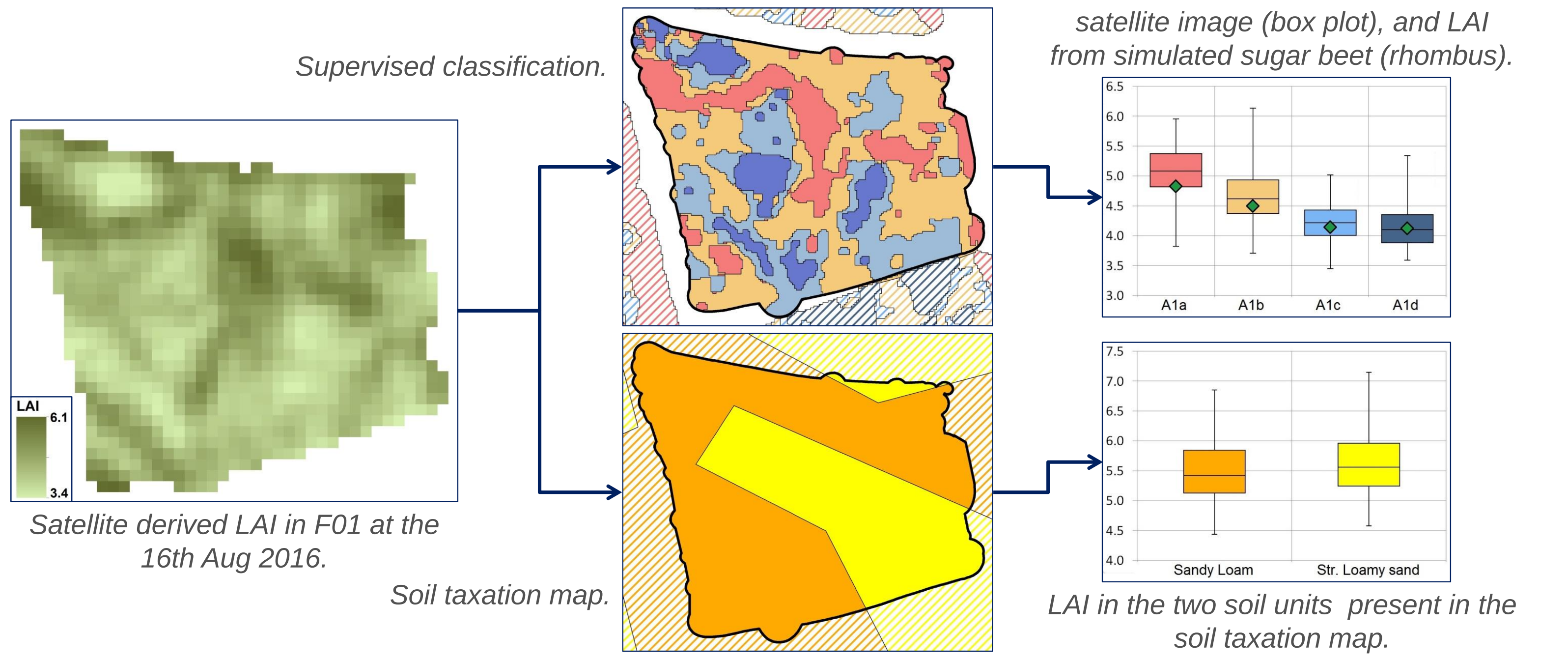


Patterns in LAI of simulated sugar beet plants. Simulation of the typical soil profile of the four classes of sub-area A at the a) 9th June 2016, b) 15th June 2016, c) 1st July 2016, d) 26th July 2016, e) 16th August 2016.

This dataset can be compared with other data such as field measurements or satellite images. In this study, we compared simulated LAI patterns with RapidEye multispectral images.

To test the effectiveness of the simulated LAI patterns we calculated satellite-derived LAI over field F01 following the method of Ali et al (2015).

In this 2.8 ha field located in sub-area A, the geophysics-based soil map proved its effectiveness in reconstructing the trend of actual LAI patterns.



Supervised classification.

LAI in the four soil units from the satellite image (box plot), and LAI from simulated sugar beet (rhombus).

Satellite derived LAI in F01 at the 16th Aug 2016.

Soil taxation map.

LAI in the two soil units present in the soil taxation map.

At the same time, the soil taxation map, the most detailed available subsurface conceptualization, could not reproduce meaningful patterns in LAI when compared to satellite data.

Conclusions

- ❖ Successful production of a geophysics-based high-resolution soil map composed of 18 soil unit with typical soil profile geometry and texture.
- ❖ Successful representation of the patterns in plant productivity that are visible in satellite multispectral data.
- ❖ Reliable and cost-effective methodology to produce high resolution soil maps and simulate a large agricultural environment.

References and acknowledgments

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