

Improved spatial modelling of crop productivity using geophysics-based soil mapping: a case study beyond the field scale



Cosimo Brogi



Sander Huisman



Michael Herbst



Lutz Weihermüller



Transregional Collaborative
Research Centre 32 (TR32)



Swedish University of
Agricultural Sciences



Anne Klosterhalfen



Carsten Montzka



Heye Bogena

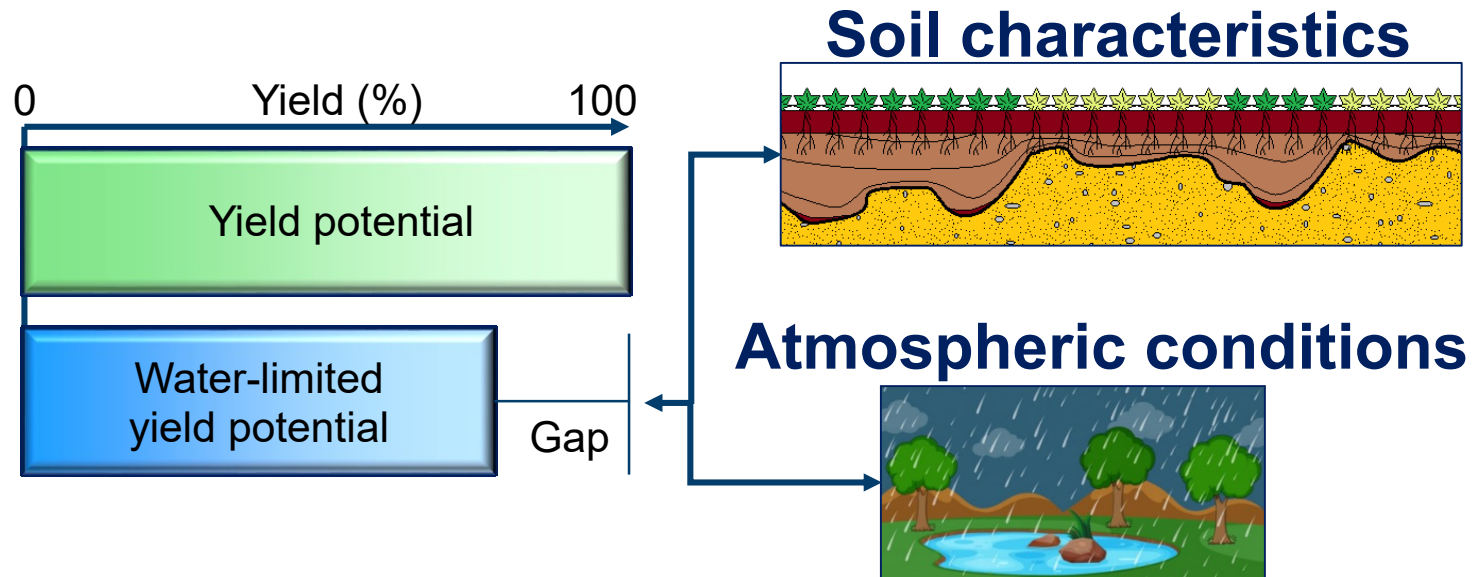


Harry Vereecken

Yield gap is a constant threat in agriculture


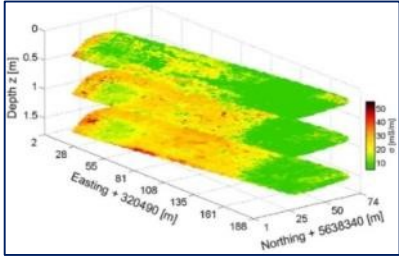

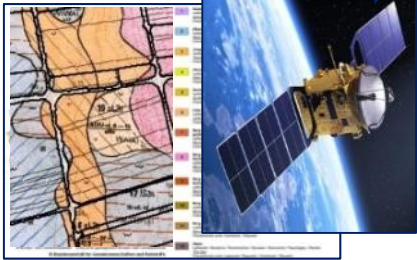
Reduces farmer's income and can undermine the sustainability of agricultural practices.

- **Water scarcity in soil** is one key causes for reduced crop performance
- Other causes such as nutrients availability, pests, disease and weeds contribute to further yield gaps



An accurate soil description is key to simulate and predict the effects of water scarcity

Accurate soil description

Small-scale	Field-scale	Intermediate	Large-scale
(few m ²)	(~1 to 5 ha)	(~1 km ²)	(~10 km ² or more)
 <ul style="list-style-type: none">- Soil sampling- Lab analysis	 <ul style="list-style-type: none">- Geophysics- EMI inversion	 <p>Still challenging!</p>	 <ul style="list-style-type: none">- Remote sensing- Soil map

General-purpose maps are often not detailed enough

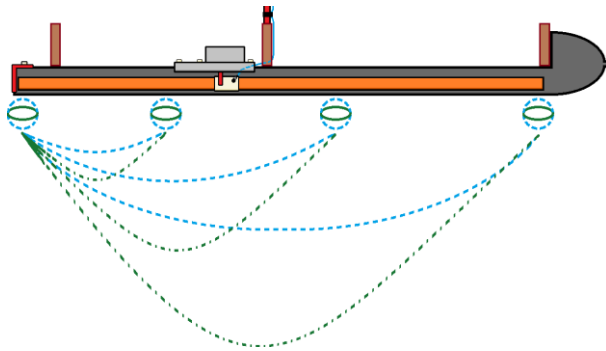
→ **Can geophysics-based soil mapping fill this gap?**

And what is the added value? For example in:

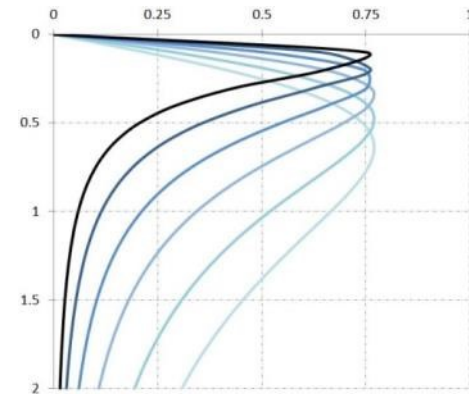
- Hydrological and agro-ecosystem modelling
- Precision agriculture (management zones)
- Yield simulation and prediction

Electromagnetic Induction EMI

Measures the apparent electrical conductivity (ECa) of the ground. ECa is related to texture, layering, water content, temperature, and other characteristics of the soil.



Increased distance between transmitter and receiver results in an increased depth of investigation



Different sensitivity of EMI instrument for six different coil distances

Modern multi-configuration instruments can measure multiple depths of investigation simultaneously.

High Resolution:

- In line resolution = ~30 cm
- Measurement lines every 2.5 m

Fast Methodology:

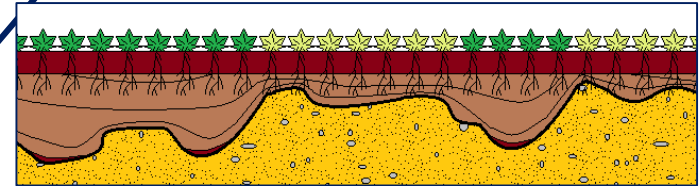
- Measure 1 ha in ~1 hour

1x1 km study area

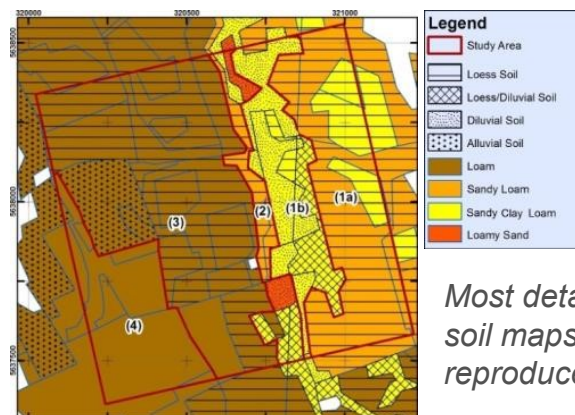
Soil heterogeneity affects crop development during water scarcity.



*Water stress in silage maize and sugar beet
Courtesy of F. Jonard*



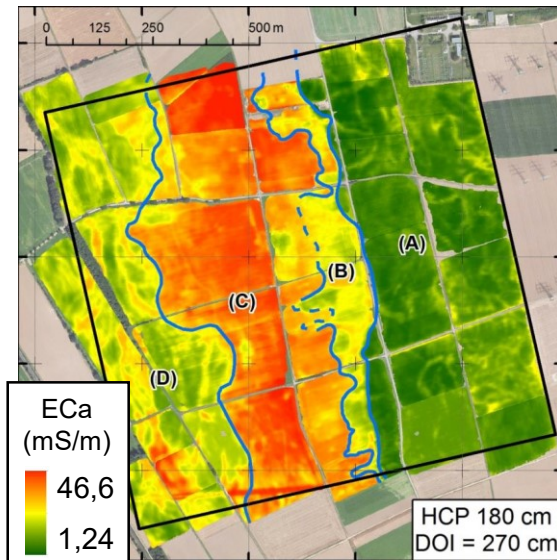
The thickness of loess top soil overlying coarse layers and the characteristics of these soils is key to understand and simulate the occurrence of water stress.



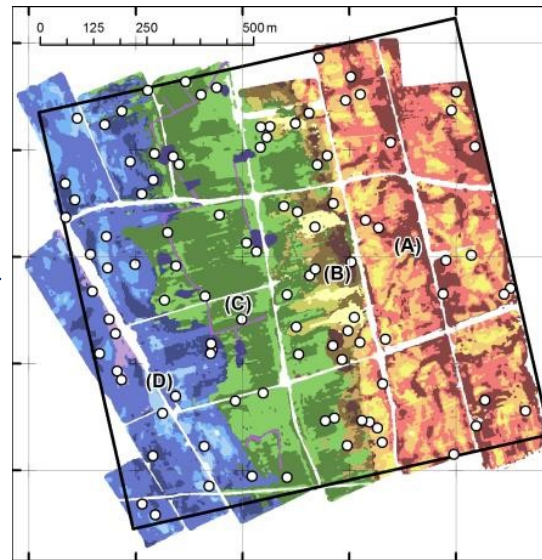
Most detailed available soil maps probably cannot reproduce these patterns



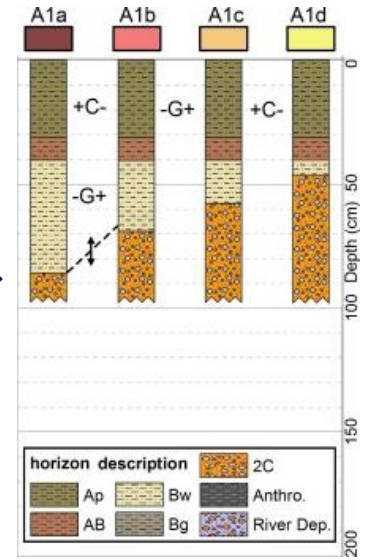
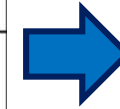
From EMI measurements to an EMI-based soil map



Six ECa maps were available after measuring the study area



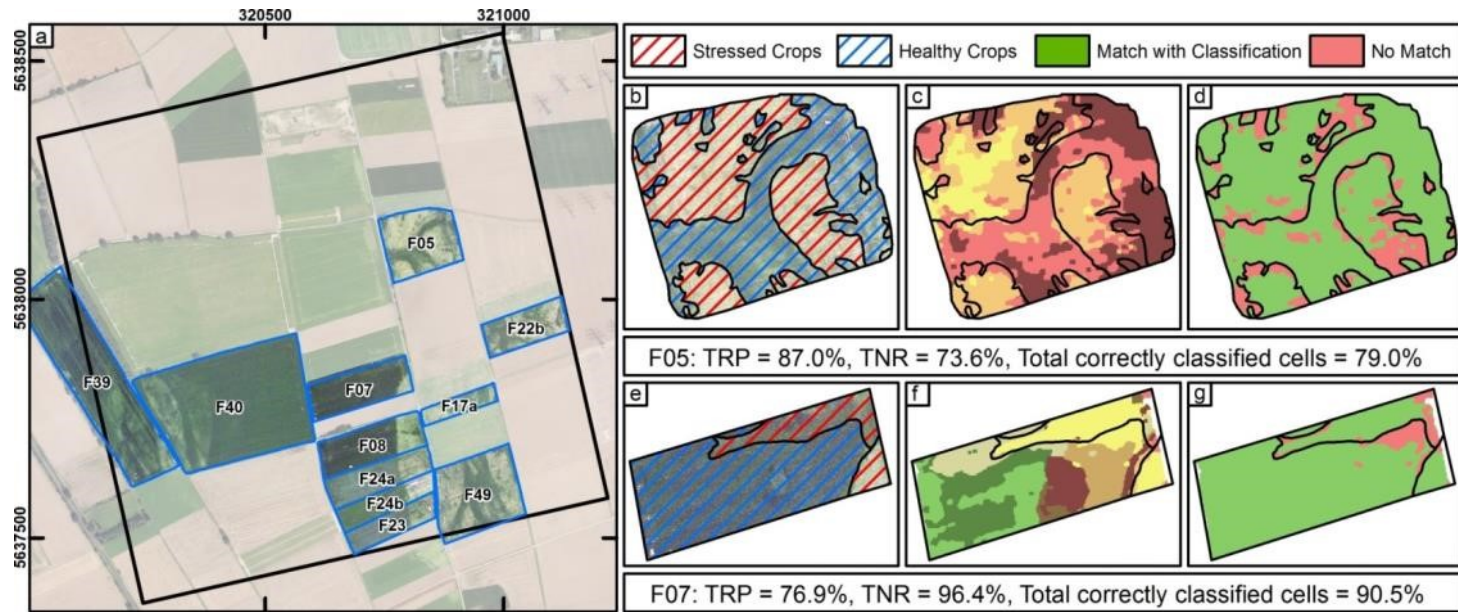
Clustering of ECa-maps with 18 soil units and 100 sampling locations



Quantitative soil profiles available in each soil unit

- 1) EMI measurements resulted in six ECa maps with depth of investigation between 0.5-2.7 m. These maps were combined in a multiband image.
- 2) The resulting multiband image that was analyzed with a supervised image classification technique (cluster soils with similar signatures).
- 3) Direct soil sampling at 100 locations and laboratory analysis provided quantitative soil description up to 2 m depth (texture and horization)

Comparison with patterns in crop stress



Ability of the high resolution soil map to reproduce water stress patterns on sugar beet

Correctly classified cells:

- Upper Terrace = 76.6%
- Lower Terrace = 91.1%



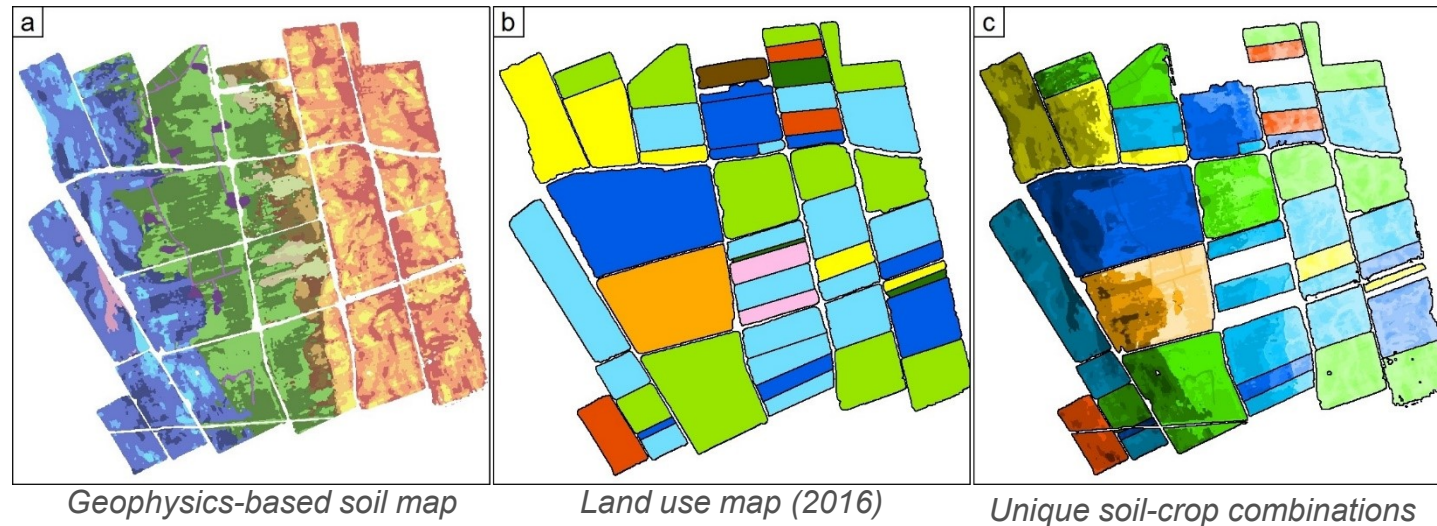
Large-scale soil mapping using multi-configuration EMI and supervised image classification

C. Brogi^{a,*}, J.A. Huisman^a, S. Pätzold^b, C. von Hebel^a, L. Weihermüller^a, M.S. Kaufmann^a, J. van der Kruk^a, H. Vereecken^a

How to valorize and exploit these quantitative information?

Agro-ecosystem modelling using EMI-based data

The agro-ecosystem model AgroC was used to simulate soil-crop interaction and crop growth on the 1km² study area.



One AgroC model was set-up in each unique soil-crop combination:

- 80 different model set-ups (each with one soil unit and one crop)

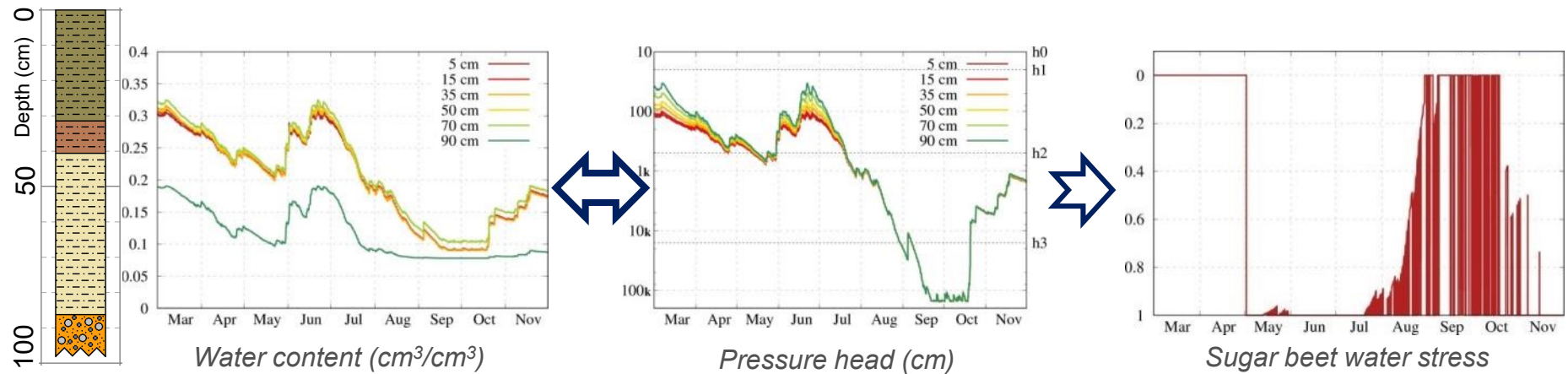
Meteorological information for 2016 were used:

- (e.g. rain, temperature, humidity, solar radiation).

Agro-ecosystem model AgroC

AgroC is a 1-D numerical model that couples three modules:

- SOILCO2: vertical water, heat, and CO₂ fluxes
- RothC: turnover of organic carbon
- SUCROS: crop growth and organic matter accumulation rates

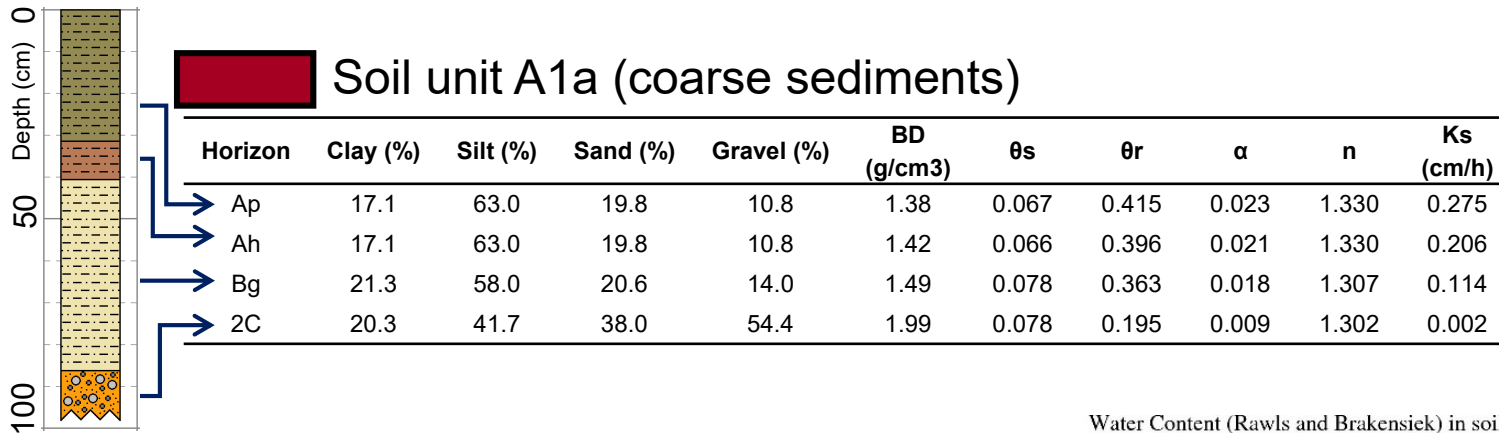


Pressure head influences crop stress (Feddes 1982) and reduces:

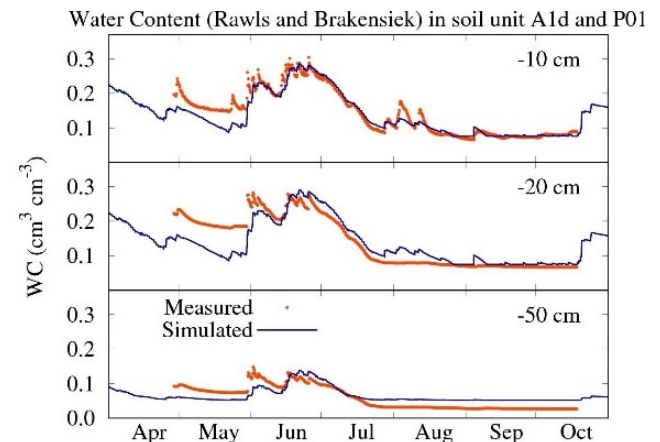
- Root water uptake
- Carbon assimilation and increase of biomass

Soil hydraulic parameters to feed AgroC model

Soil hydraulic parameters calculated using pedotransfer function (Rawls & Brakensiek 1985) for each horizon.

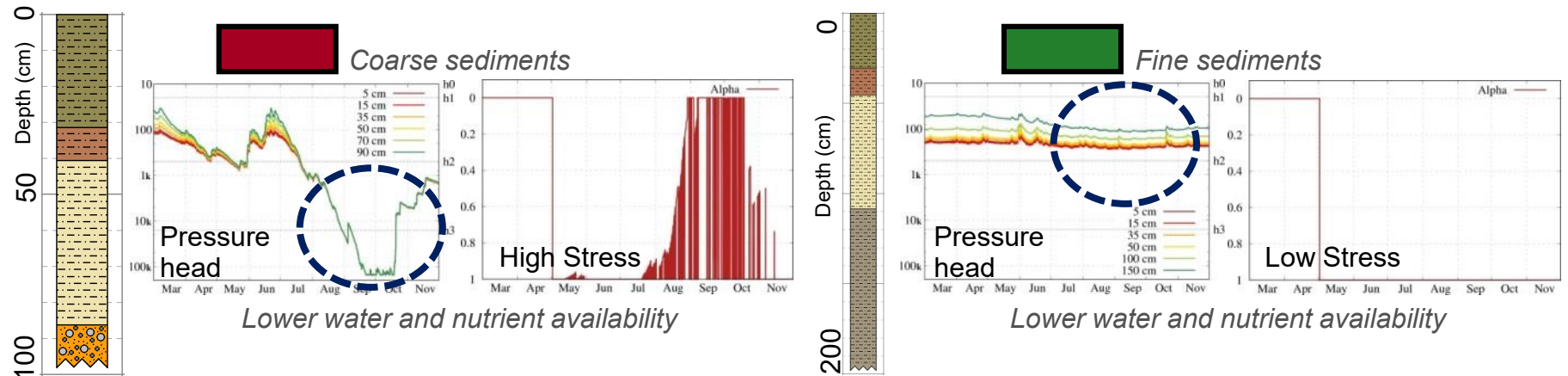


Horizonation and soil hydraulic parameters of each horizon are used in AgroC to simulate soil water content dynamics given an atmospheric input.

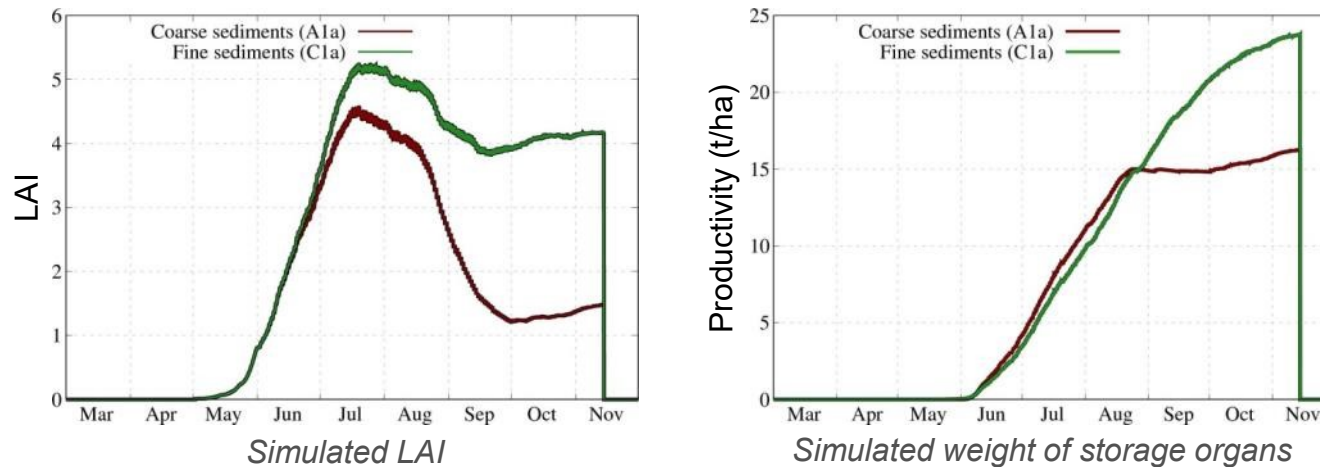


Agro-ecosystem stress simulation

Simulations of sugar beet in 2016 with different soil profiles



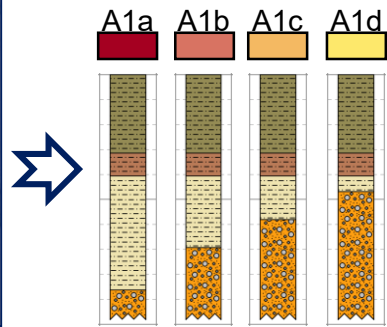
Clear difference in leaf area index (LAI) and weight of storage



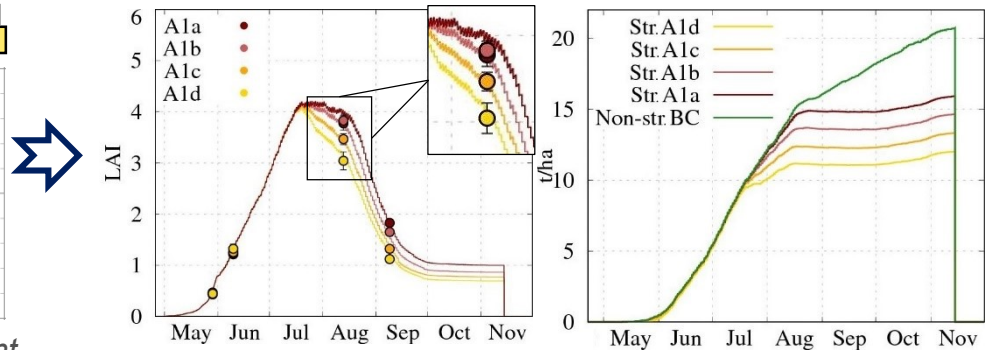
Field-scale simulation of sugar beet



Patterns in sugar beet and soil classes

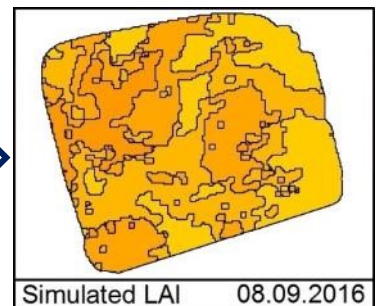
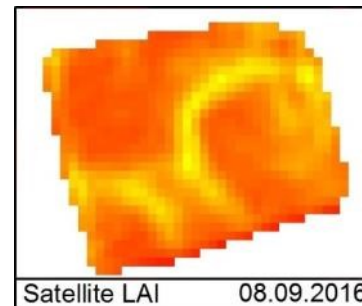
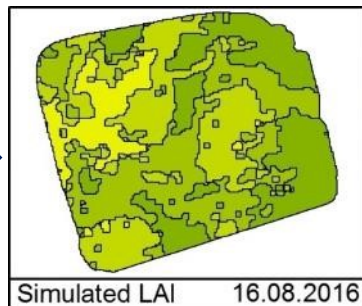
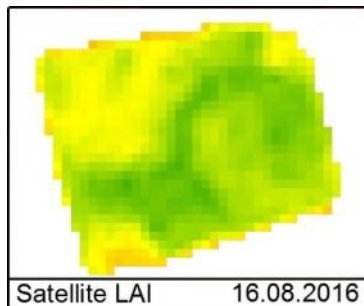


Four soil units present in the analyzed field



Simulated LAI (lines) vs satellite LAI_{NDVI} (dots) and productivity on the four soils

Compared with LAI_{NDVI} obtained from RapidEye satellite images for 2016 (Ali et al. 2014).



Satellite derived LAI and simulated LAI at two different dates

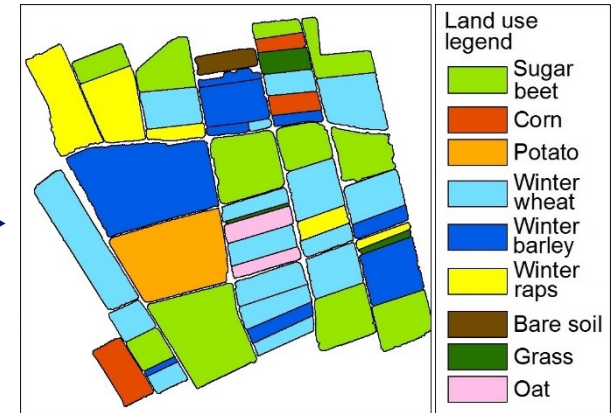
Simulated LAI well matches observed LAI_{NDVI} from satellite.

Simulation of LAI (km² scale)

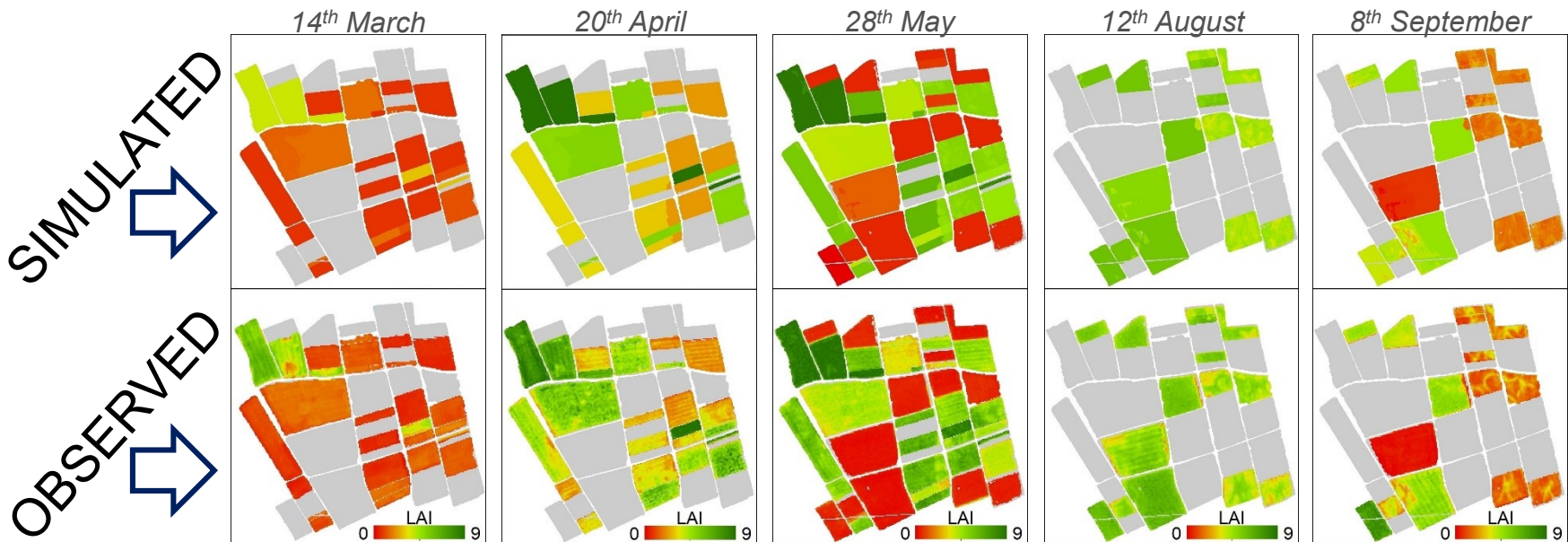
AgroC simulation of six crop types:

■ Sugar beet ■ Potato ■ Winter raps
■ Corn ■ Winter barley ■ Winter wheat

Simulated LAI well match observed LAI_{NDVI}.



Land use in 2016



Satellite derived LAI and simulated LAI throughout the 2016 growing season

Maps of simulated yield



- 100% = not limited by water
- Sugar beet and winter barley match well actual harvest data
- Corn and winter wheat correspond to literature values

Received: 6 September 2019 | Accepted: 10 January 2020
DOI: 10.1002/vzj2.20009

ORIGINAL RESEARCH ARTICLE

Simulation of spatial variability in crop leaf area index and yield using agroecosystem modeling and geophysics-based quantitative soil information

C. Brogi¹ | J. A. Huisman¹ | M. Herberichs¹ | L. Weihermüller¹ | A. Klosterhalfen^{1,2} | T. Montzka¹ | T. G. Reichenau³ | H. Vereecken¹

More info in this manuscript

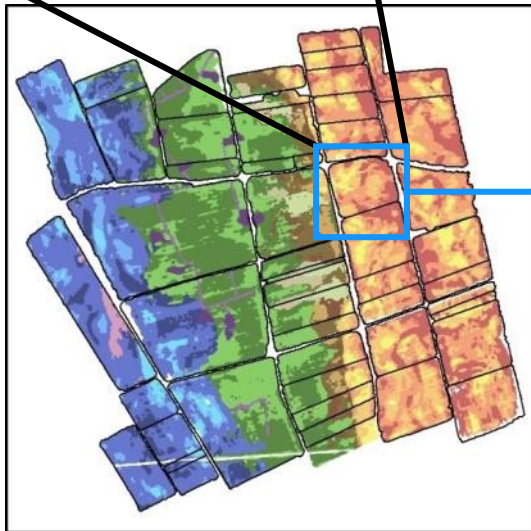
What is the added value of geophysics-based compare to commonly-available maps?

Added value compared to conventional soil maps



A geophysics-based soil map provides:

- Quantitative information allows large-scale simulation
- Identify and simulate small-scale patterns



Geophysics-based soil map



Soil taxation map



Soil map 1:5000

Further AgroC simulations were set-up using information from two commonly available soil maps and compared to the EMI-based.

Added value in simulation of LAI_{NDVI}

Date	Geophysics-based		1:5000 Soil map		Soil taxation map	
	RMSE	R ²	RMSE	R ²	RMSE	R ²
March	0.62	0.84	0.63	0.83	0.79	0.72
April	1.07	0.72	1.09	0.72	1.84	0.45
May	0.64	0.93	0.67	0.92	1.01	0.81
June	0.64	0.89	0.69	0.88	0.86	0.84
August	0.64	0.47	0.89	0.39	0.70	0.38
September	0.56	0.78	0.78	0.65	1087	0.50

Winter crops

Summer crops

RMSE and R² of the 1km² simulations of LAI

- Slight improvements for winter crops at the km² scale.
- Strong improvements in summer and over soil heterogeneities.

Fields	Geophysics -based	1:5000 map	Taxation map
F-12	0.72	0.73	0.73
F-47	0.51	0.45	0.43
F-01	0.45	0.53	0.88
F-13	0.56	0.73	0.73
F-48	0.62	0.78	0.90

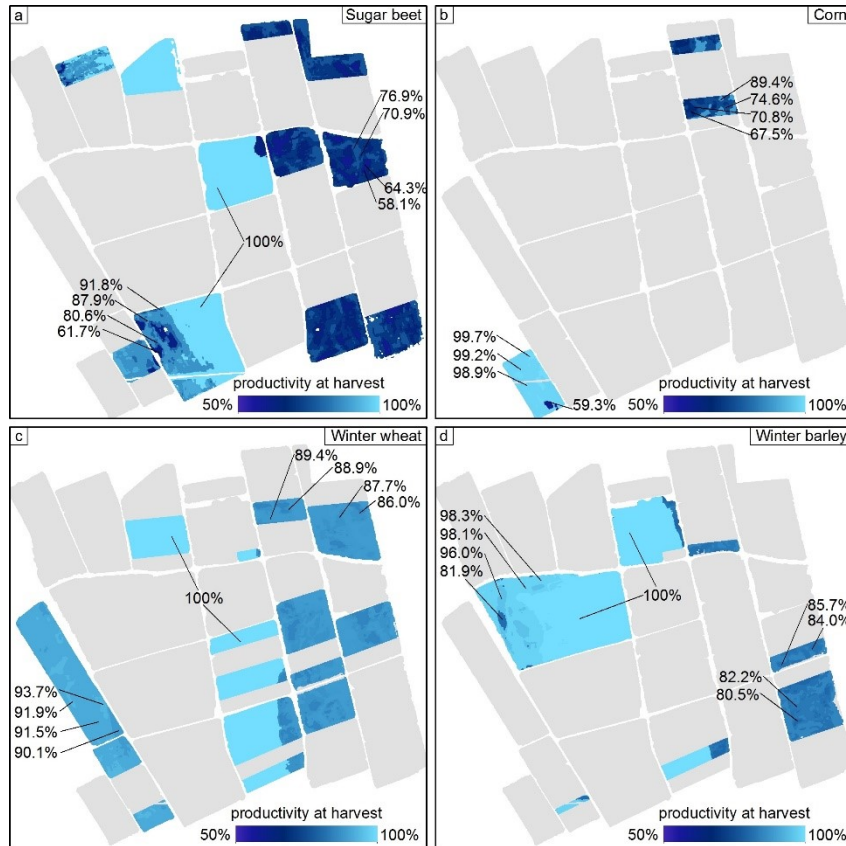
Relatively homogeneous soils

Heterogeneous soils

With Geophysics-based soil map, average reduction of RMSE of 25% and 31% in heterogeneous areas and for summer crops.

Added value of geophysics-based soil mapping

Image classification of EMI produces high resolution and large-scale soil maps provided with quantitative layering and texture.



Simulated water-limited productivity of four crops in 2016 within the study area

Simulate time series of:

- Productivity at harvest
- Stress (caused by water scarcity)
- LAI that matches satellite LAI_{NDVI}

Agricultural applications:

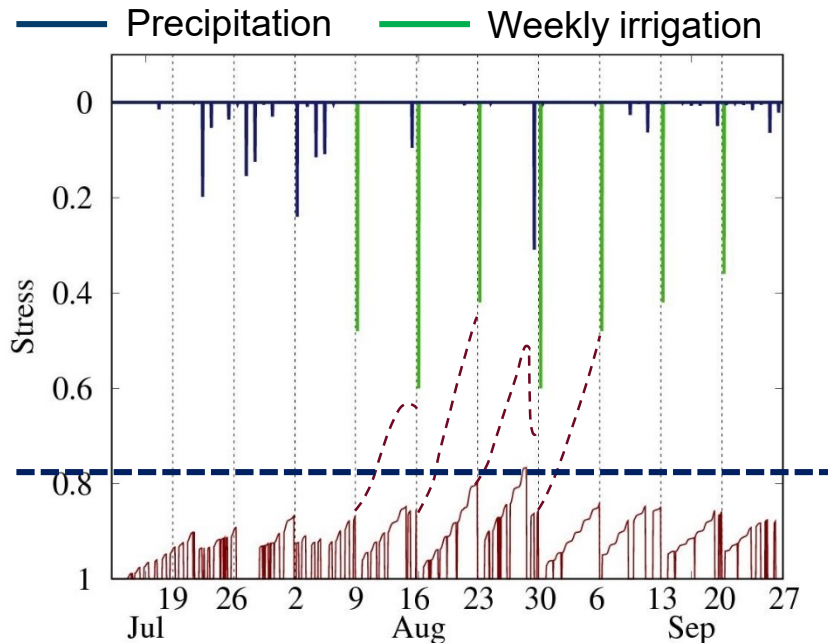
- Optimize irrigation
- Maximize productivity
- Evaluate management practices
- Costs/benefits estimation

Environmental applications:

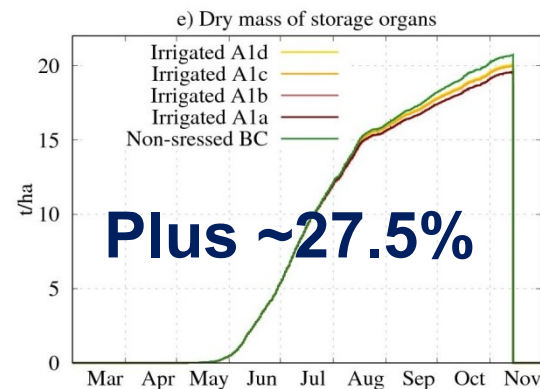
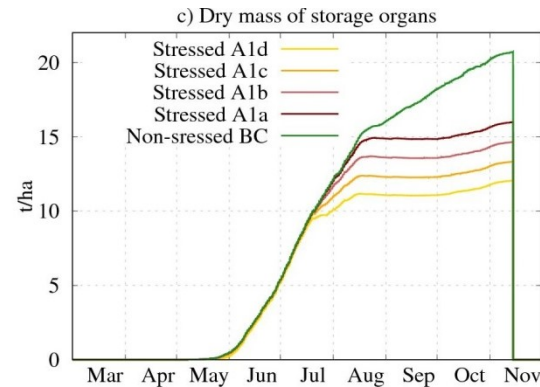
- Estimate carbon sequestration

Optimize irrigation with perfect 7-day forecast

By adding irrigation water, we can decrease water stress and increase crop productivity.



Add weekly irrigation to keep water stress below a certain level considering seven days of forecasted precipitation



$\sim 2200 \text{ m}^3/\text{ha}$

 $=$

 $+23.3 \text{ t/ha}$

wet beets

- Economical and environmental irrigation cost (€ & CO₂ emissions)

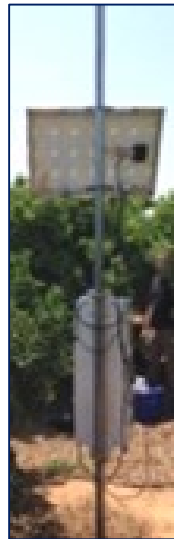
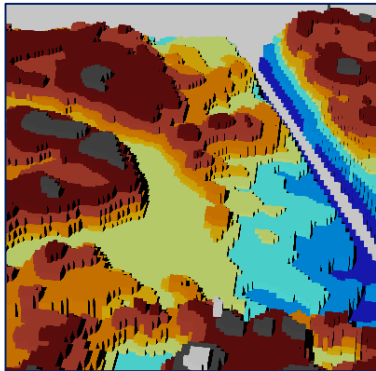
ATLAS: real-time optimized irrigation



Experimental apple orchards
plots in Agia (Greece)

+

Digital Soil Mapping
(EMI & ground truth)



Network of:
- SoilNet sensors
- Cosmic Ray
Neutron Probes



Combination of:
+ Near real-time monitoring
of soil moisture and
matrix potential
+ Weather forecast
+ Hydrological modelling
+ Crop modelling
= **Optimized irrigation
scheduling**



Make our farmers happy!