Data fusion and classification of electromagnetic induction and remote sensing data for management zone delineation in sustainable agriculture

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Introduction and motivation

High-resolution soil characterization is vital in precision agriculture because of the critical role of soils in crop growth and productivity (Brogi et al., 2019).

Proximal soil sensing through geophysical and remote sensing methods has shown promising results, yet there is untapped potential in effectively combining these techniques across large and complex agricultural fields.

We aim to derive agricultural management zones from a combination of electromagnetic induction (EMI) and remote sensing measurements, thereby bridging existing methodological gaps and addressing the challenges of scale and temporal variation.

Highlights

- EMI is a fast mapping method (multiple ha per hour).
- Comprehensive understanding of the spatial and temporal variability by combining with remote sensing.
- Process and analyze data from different environmental conditions.
- Aid in soil profile sampling and investigation.
- Reduce operator influence by using unsupervised clustering.

Study area and EMI measurements

The PatchCROP experimental site is located in Tempelberg, Brandenburg (**Fig. 1**). It Includes 30 experimental patches of 72 x 72 m. EMI measurements were collected in three campaigns from Aug 2022 to Aug 2023 with two EMI instruments in HCP and VCP configuration (**Fig. 2**)

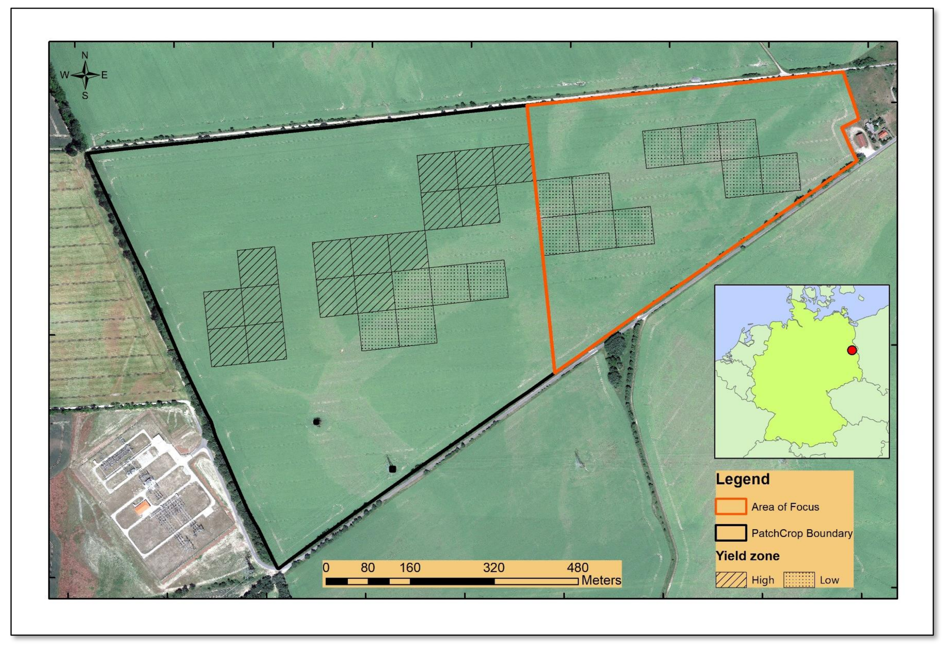
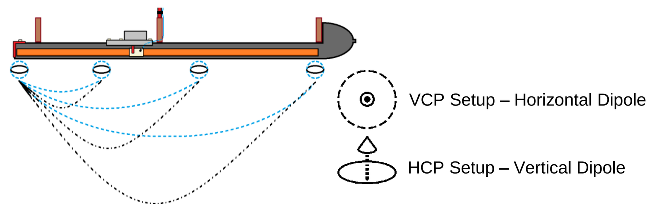


Fig. 1 PatchCROP experimental site with 30 patches

Fig. 2 EMI Instruments in the field.



Normalization of EMI Measurements

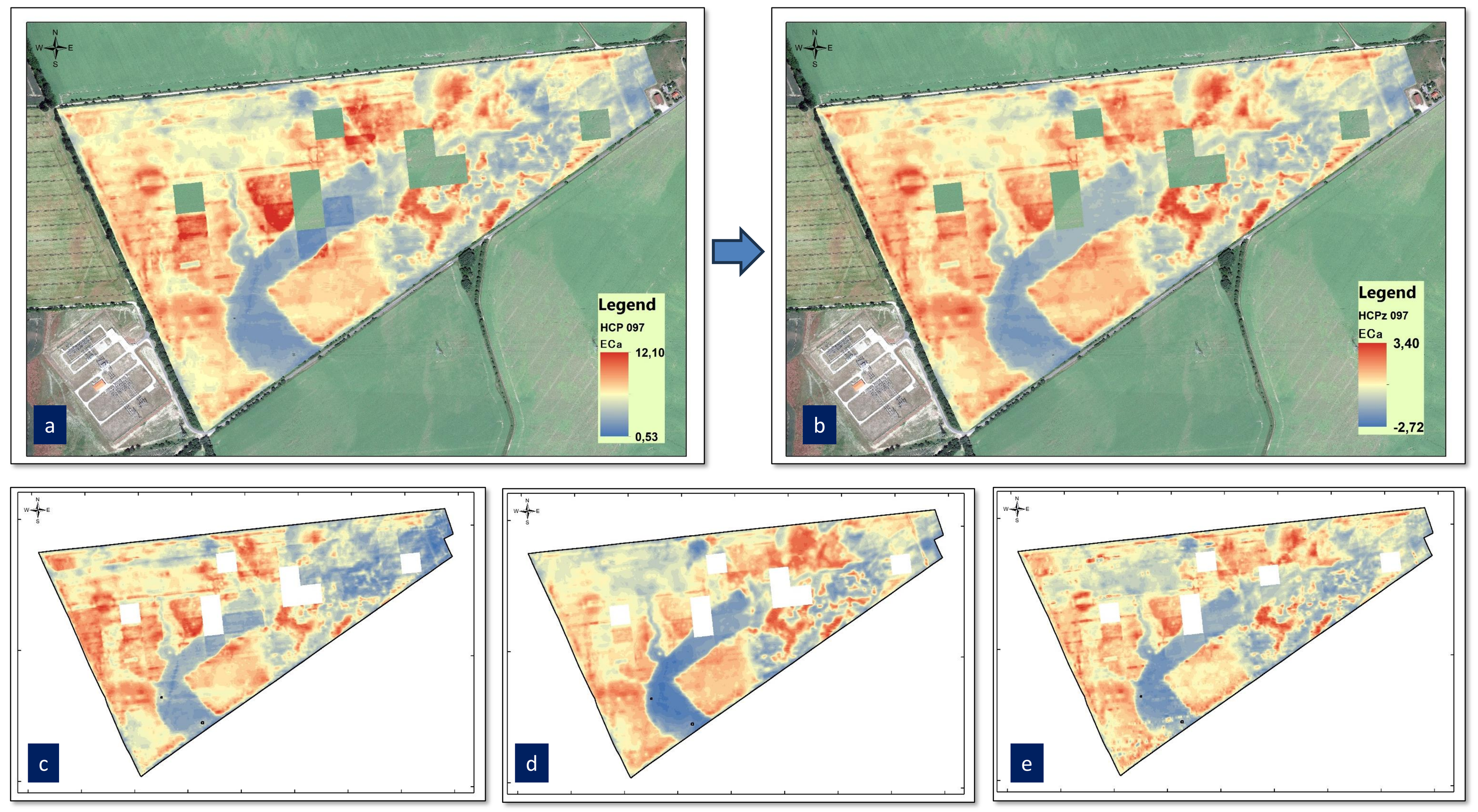
The Z-transformation was applied to EMI measurements to ensure uniformity on a consistent scale for further processing. The following equation was used for normalization. After normalization, a multiband raster was created using 9 apparent electrical conductivity (ECa) maps with increasing coil separation.

$$ECa_Z = \frac{ECa - \mu_{ECa}}{\sigma_{ECa}}$$

- ECα = Original ECα value
- μECα = Mean of ECα
- σECα = Standard deviation of ECα

Data processing (proximal and remote sensing)

Normalization of ECa Maps (1 m resolution)

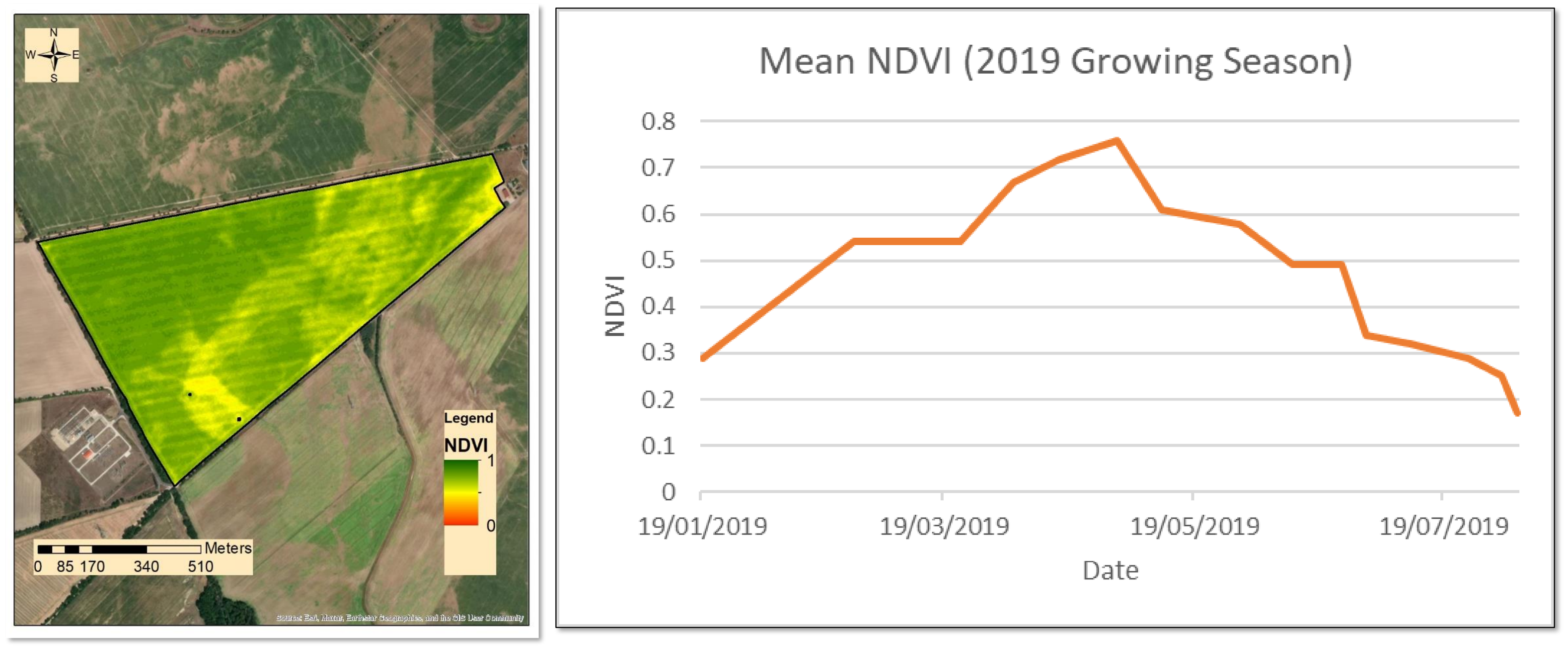


a) Filtered ECa map (HCP mode coil-3 with DOI up to 108 cm), b) ECa map after Z-transformation normalization. This highlights the intra-field variability and removes the influence of temporal changes in environmental conditions. c) Normalized ECa map of HCP 0-52 cm, d) HCP 0-270 cm, e) VCP 0-118 cm

PlanetScope NDVI (3 m resolution)

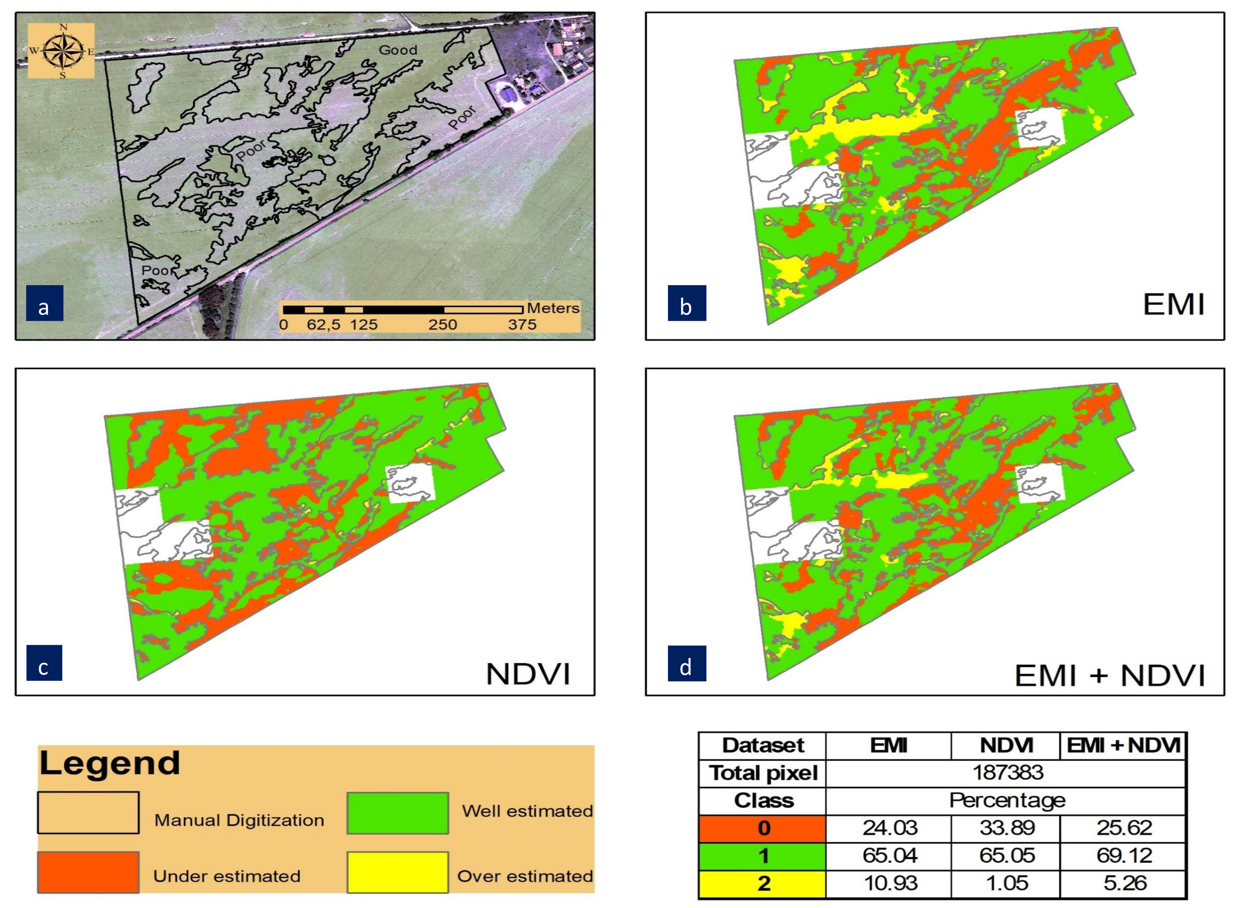
High-resolution PlanetScope imagery was used to derive the Normalized Difference Vegetation Index (NDVI) to analyze crop development for the 2019 winter rye growing season.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$



NDVI maps for the 2019 growing season were processed in ArcMAP. A total 19 NDVI maps were processed. 7 specific NDVI maps were selected based on the temporal NDVI changes in crop phenology.

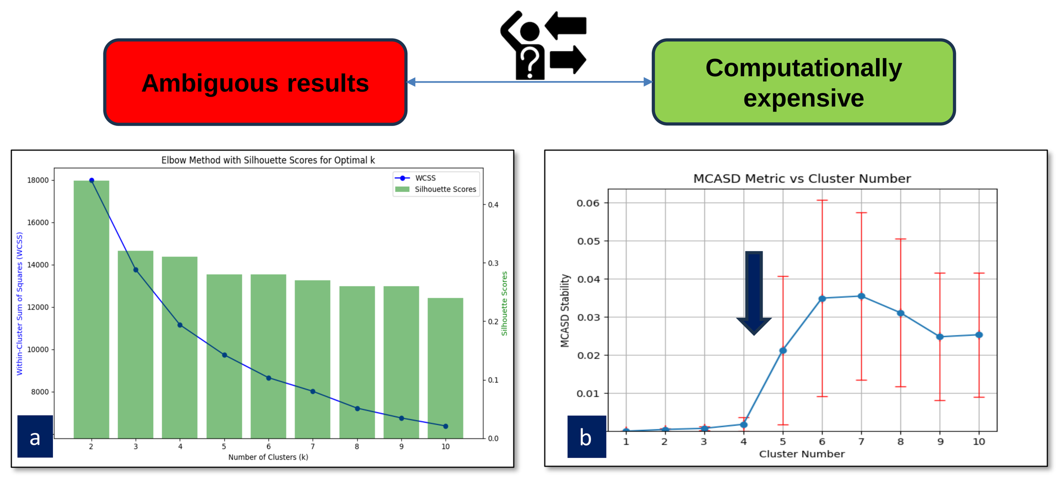
Image classification of the study area

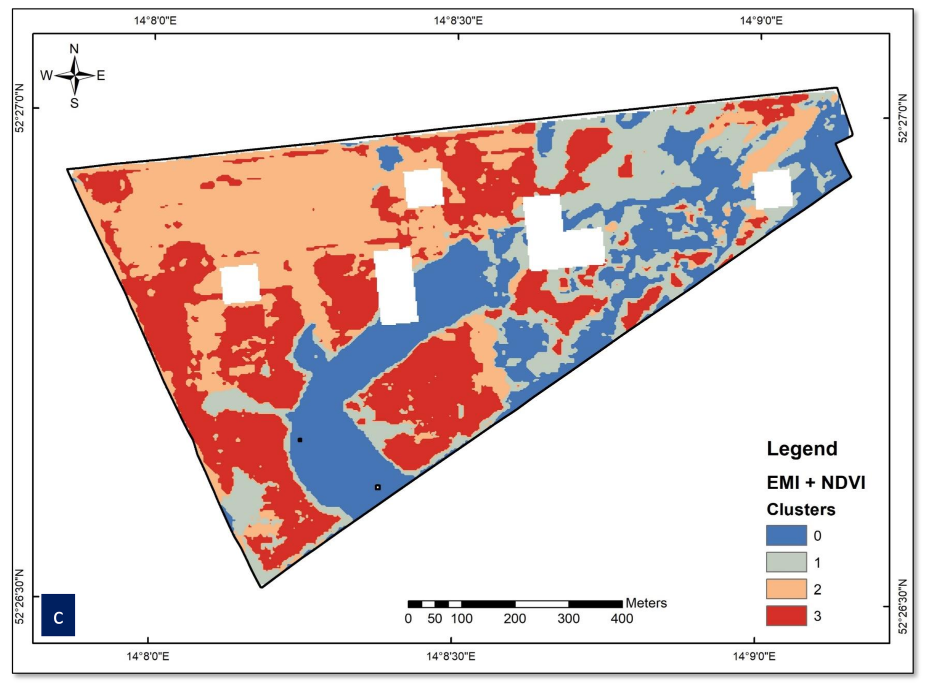


Dataset	EMI	NDVI	EMI + NDVI
Total pixel	187383		
Class	Percentage		
0	24.03	33.89	25.62
1	65.04	65.05	69.12
2	10.93	1.05	5.26

Overview of 2 cluster classification and validation with digitized patterns in heterogeneous areas in the northeast part of the field. a) Satellite image (ESRI, 2018) of the study area with digitized patterns are shown in two classes good and bad. b) EMI-based clusters vs digitized pattern, c) NDVI-based cluster, d) combined EMI and NDVI-based clusters.

- Homogeneous zones created with ISODATA and K-means.
- Principal component analysis (PCA) applied to reduce the dimensionality of the data while retaining important information.
- Clusters validated against a manually digitized satellite image.
- Elbow and Silhouette methods are used to find the optimum number of clusters.
- The new computational method MCASD developed by (O'Leary et al., 2023) analyzed and the results were compared.





Testing various clustering techniques to determine the optimal number of clusters on a single patch from the PatchCROP field. a) Elbow and Silhouette methods for cluster analysis, b) MCASD analysis involving 100 iterations for each cluster, c) Mapping of 4 clusters by combining EMI and NDVI using MCASD.

Conclusions

- ECa maps unveiled intriguing patterns of subsurface soil texture variability.
- Integrating NDVI with EMI can enhance classification accuracy.
- MCASD analysis can facilitate the identification of the optimal number of clusters.
- Future work includes assessment of cluster accuracy and the relationship between yield and soil information.
- We will also conduct patch-level and field-level assessments to analyze soil textural changes with ECa maps.

References and acknowledgments

Large-scale soil mapping using multi-configuration EMI and supervised image classification. *C. Brogi et al., (2019)*

Observations of intra-peatland variability using multiple spatially coincident remotely sensed data sources and machine learning. *D. O'Leary et al., (2023)*

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For more information

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