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Delineating Agricultural Management Zones using Unsupervised Classification of Electromagnetic Induction and Remote Sensing Data

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An accurate delineation of management zones that reliably characterizes within-field heterogeneity is essential to optimize resources and improve yields in precision agriculture. Non-invasive hydro-geophysical methods, such as electromagnetic induction (EMI), offer a rapid approach to delineating agricultural management zones that are based on subsurface soil characteristics that influence crop growth. Integrating additional data sources, such as remote sensing imagery and yield maps, can further enhance the quality and applicability of these management zones. However, integrating above-ground and subsurface information from multiple datasets for large agricultural fields poses challenges in data harmonization, analysis, and methodological consistency. Additionally, the impact of different dataset combinations on management zone delineation remains underexplored.

In this study, we propose a robust processing workflow that combines unsupervised classification and statistical validation to delineate management zones using proximal and remote sensing. This method was applied to a 70-ha field of the patchCROP experiment in Tempelberg (Germany). Part of this field consists of 30 small patches (0.5 ha each) that are managed separately since 2020. EMI data were collected in four campaigns between 2022 and 2024 by using a CMD Mini-Explorer and a CMD Mini-Explorer Special-Edition (featuring 3 and 6 coil separations, respectively). Maps of measured ECa were standardized using z-score normalization (ECa_z) to reduce the effect of measuring in different environmental conditions. Additionally, seven satellite images of the 2019 growing season with 3 m resolution (PlanetScope) were used to obtain maps of NDVI development. Three dataset combinations were investigated: 1) ECa_z maps, 2) NDVI maps, and 3) a combination of the EMI and NDVI maps. The Self-Organizing Maps (SOM) machine learning technique was used to cluster these three datasets. The optimal number of clusters was determined using the Multi-Cluster Average Standard Deviation (MCASD) method. Nine years (2011-2019) of yield data and detailed soil information up to 100 cm depth were used to refine the cluster numbers by using Tukey's post-hoc analysis and to assess the accuracy of the clustered

maps with two-tailed t-tests in a subsequent step.

The EMI-based clustering resulted in 4 management zones. A comparison of adjacent zones showed that 15 out of 21 soil properties and 23 out of 27 yield combinations were statistically separated. The average p of all these combinations was 0.113 and 0.045, respectively. The NDVI-based clustering resulted in 3 zones with 10 out of 14 soil properties and 18 out of 18 yield combinations showing significant separation (average p of 0.166 and 0.001, respectively). Overall, the EMI-based zones better captured the patterns in soil heterogeneity, whereas the NDVI-based zones better matched yield maps. The combined EMI-NDVI clustering resulted in 3 zones, and all the combinations of soil properties and yield showed significant separation. This EMI-NDVI derived 3 m resolution map better represented soil properties and yield maps, highlighting the potential of integrating multi-source datasets for field management and, ultimately, agricultural productivity. It represents the base for actionable insights not only for precision agriculture applications such as fertilization and irrigation, but also for environmental modelling or to guide future sampling campaigns.