Earth Observation Summer Term 2025

Project Topic 1
Detecting smallholder farming dynamics in Mozambique from Sentinel-2 time series

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Globally, smallholder farms under 2 ha produce 30–34% of the food supply in 24% of the agricultural area. While small farms operate at high productivity and harbor higher levels of crop and non-crop biodiversity as compared to larger farms, the dynamics in smallholder agriculture cause high rates of land change. Mapping and monitoring of smallholder agriculture using satellite remote sensing is challenging due to the high degrees of landscape fragmentation, within-field heterogeneity, rapid change dynamics, and the prevalence of short-term fallows as an integral component of the agricultural system. Global products on cropland extent thus often explicitly disregard smallholder systems characterized by shifting cultivation. Consequently, the extent of smallholder cropland, and the dynamics thereof are only weakly understood for many world regions, and for Sub-Saharan Africa in particular. Generally, only Landsat (30m) and Sentinel-2 (10m) provide an unbiased global acquisition strategy, a consistent and frequent revisit time, adequate spatial and spectral resolutions, as well as high-quality pre-processing that facilitate detecting surface dynamics such as smallholder systems across the globe.

The overall idea of this project is to explore opportunities to map smallholder cropland using Sentinel-2 10m surface reflectance time series for four growing seasons in Northern Mozambique to better understand land use of the region. A small set of reference data (cropland / non-cropland) exists for the growing season 2020/21 (Sep-Aug).
As an initial step, you will explore the spectral-temporal appearance of these classes across space and then train a Random Forest model that predicts active cropland against other land cover classes for the growing season 2020/21 (Sep-Aug). In this project, particular methodological emphasis should be put on developing an approach that can work with a limited amount of reference data. Accordingly, for efficient collection of additional training data, you may use an Active Learning approach, a model-based estimate for optimal training point selection. This should ultimately strengthen the capabilities for temporal generalization of the models.
Once established, a global (i.e. time-independent/calibrated) cropland/non-cropland model shall be used to predict active cropland for the different growing seasons. This will allow generating a change product indicating the onset and duration of smallholder farming at the pixel level. The maps should ideally be validated and map-based cropland estimates be compared to existing land cover/cropland products.

Provided data

- Sentinel-2 L2A (surface reflectance) interpolated (gap-free) time series of Tasseled Cap features covering the growing seasons 2019/20, 2020/21, 2021/22, 2022/23
- A small, initial set of cropland/non-cropland reference samples for 2020/21
- A cropland extent product by Potapov et al. (2021) for 2019

Selected literature

Remote Sensing of smallholder cropland

Rufin et al. (2022): Large-area mapping of active cropland and short-term fallows in smallholder landscapes using PlanetScope data. International Journal of Applied Earth Observation and Geoinformation 112, 102937. https://doi.org/10.1016/j.jag.2022.102937

Bey et al. (2020): Mapping smallholder and large-scale cropland dynamics with a flexible classification system and pixel-based composites in an emerging frontier of Mozambique. Remote Sens. Environ. 239, 111611. https://doi.org/10.1016/j.rse.2019.111611

Active Learning

Tuia et al. (2011): Using active learning to adapt remote sensing image classifiers. Remote Sensing of Environment 115, 2232–2242. https://doi.org/10.1016/j.rse.2011.04.022

Land system science: smallholder systems

Heinimann et al. (2017): A global view of shifting cultivation: Recent, current, and future extent. PLOS ONE 12, e0184479. https://doi.org/10.1371/journal.pone.0184479

Pendrill et al. (2022): Disentangling the numbers behind agriculture-driven tropical deforestation. Science 377, eabm9267. https://doi.org/10.1126/science.abm9267