Creating high-resolution land use and soil moisture maps from remote sensing data

Key findings

- Optical Sentinel-2 systems provide high-resolution land use/land cover maps that can be improved at higher levels of detail (crop maps) by the integration of SAR-systems such as Sentinel-1.
- A procedure for downscaling the global Soil Water Index from ESA-CCI using Sentinel-1 data is developed.
- Geodata integration and machine-learning workflows can improve the quality of remote sensing-based results, which can serve as additional information for applications in data-scarce regions.

Motivation

Today, land use information and soil and vegetation parameters such as soil moisture or vegetation density are widely used for hydrological modeling or ecosystem services assessments. Particularly in data scarce-regions, remote sensing has become an essential data source (Sheffield et al., 2018). For land cover classifications and the derivation of vegetation parameters, mainly data from the Landsat sensors with a spatial resolution of 30 m have been used. Radar-based analyses have proven essential for accurate estimates of near-surface soil moisture; however, global products are based on coarse resolutions (12.5 km - 25 km pixel size; Peng et al., 2017). Recently, the European Sentinel-1 and 2 systems have provided high-resolution time series which have already demonstrated their potential for new developments in these fields. In MedWater, different remote sensing data was explored to create and provide accurate high-resolution (10 m - 20 m) land use and near-surface soil moisture maps using GIS and machine-learning methods. These maps were developed for the Western Mountain Aquifer (WMA) in Israel and the West Bank, the project's main study site.

Methodology

High-resolution land use mapping relied on multi-temporal data from Sentinel-2 and Sentinel-1 (2016-2018). Google Earth provided training data to distinguish between basic land use classes (e.g., settlement, water, forest, desert, cropland). Crop data was obtained from the Israeli Ministry of Agriculture and Rural Development. Sentinel-2 data was processed with the open source software Sen2Cor. Machine-learning was applied for classification optimization. For the creation of detailed crop distribution maps, Sentinel-1 backscatter was included, as it comprises information on the vegetation structure. The downscaling procedure to estimate near-surface soil moisture integrates different indicators that influence the signal from Sentinel-1. These include terrain parameters, NDVI time series comprising information about vegetation dynamics, and NDWI time series of the vegetation water con-

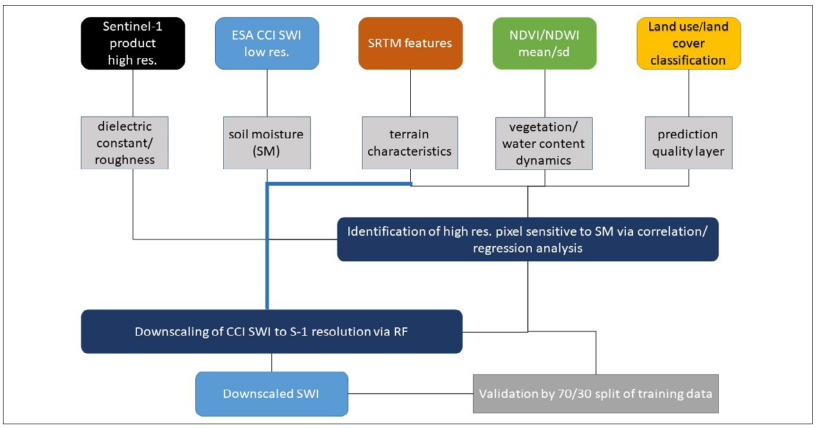

Figure 1: Workflow of the downscaling approach

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tent. It is assumed that constantly increased vegetation water content indicates high soil moisture. Random forest (RF) was used as a machine-learning algorithm to downscale the 12.5 km Soil Water Index (SWI) to a resolution of 20 m. The procedure is described in Figure 1.

Results

Key results are high-resolution land use maps (Figure 2) and downscaled SWI time series (Figure 3). The classification accuracy was almost 70% for the major land cover classes and achieved 65% for the detailed maps. The complexity of land cover in dry climate conditions such as Mediterranean karst areas introduced high spectral confusion between soil and settlement bodies, water and foil cover of fields, and different vegetation classes. Sentinel-1 data enormously improved the quality of the detailed crop maps. The aggregated land use map was directly integrated in the approach to downscale the SWI. The internal validation of the SWI approach resulted in an average coefficient of determination (R^2) of 0.96 and a mean square of variation (RMSE) of 1.5%. Analysis of the resulting time series indicates spatial variations of soil moisture in the study area. However, for some land use classes, prediction quality can be assessed to be reduced, e.g., in the case that water bodies or impervious areas characterize the SWI pixel under consideration. Agricultural use or sparse vegetation that is typical in arid climates, as well as bare soils allow for comparatively good predictions.

Application

In data-scarce regions, remote sensing can contribute valuable data sets such as high-resolution land use and soil moisture maps. They can serve as input to different models and are useful for management purposes, e.g., if integrated in information systems. Land use classifications benefit from SAR data, as they contribute a higher thematic level of detail. In MedWater, land use and soil moisture were relevant information for hydrological analyses and eecosystem services assessments. Difficulties are the SAR-based soil moisture assessment under vegetation cover and validation. Hence, future work should aim for in-situ validation. International activities, such as JECAM (Joint Experiment for Crop Assessment and Monitoring) that includes the German TERENO site DEMMIN, are promising starting points.

Soil Water Index (SWI)

The Soil Water Index approximates the percentage of soil water in relation to the soil water holding capacity in different soil depths (here the top 1 m). Water holding capacities of soils differ mainly with soil structure and are also affected by organic matter. In the ESA-CCI SWI product, remote sensing methods contribute the near-surface soil moisture to a two-layer water balance model. More information about the SWI are provided by Paulik et al. (2014).

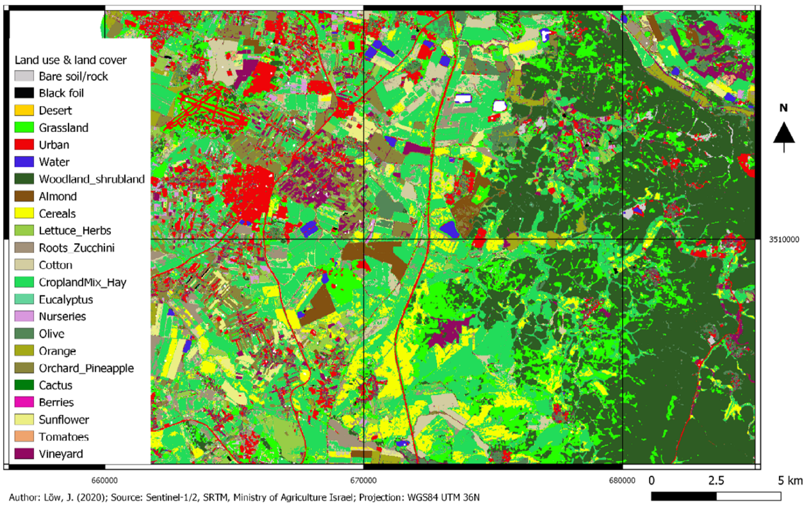

Figure 2: Map of land cover in the study area showing classification information on overview and high-detail levels (2016)

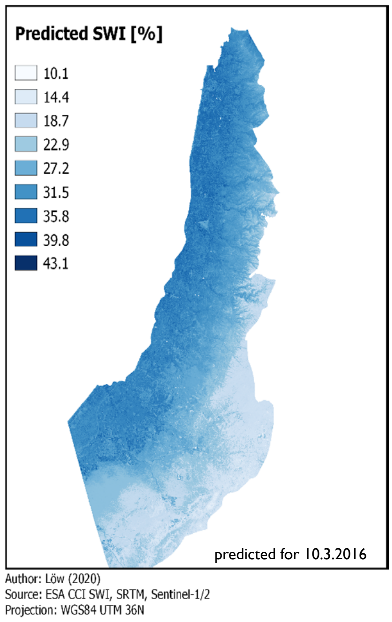

Figure 3: Soil Water Index (SWI) at a pixel resolution of 20 m based on Sentinel-1/2, SRTM, and ESA CCI SWI data

References

Paulik, C., Dorigo, W., Wagner, W., & Kidd, R. (2014). Validation of the ASCAT soil water index using in situ data from the International Soil moisture network. *International Journal of Applied Earth Observation and Geoinformation, 30*(1), 1-8. https://doi.org/10.1016/j.jag.2014.01.007

Peng, J., Loew, A., Merlin, O., & Verhoest, N.E.C. (2017). A review of spatial downscaling of satellite remotely sensed soil moisture, *Reviews of Geophysics, 55*(2), 341-366. https://doi.org/10.1002/2016RG000543

Sheffield, J., Wood, E.F., Pan, M., Beck, H., Coccia, G., Serrat-Capdevila, A., & Verbist, K. (2018). Satellite remote sensing for water resources management: Potential for supporting sustainable development in data-poor regions. *Water Resources Research, 54*(12), 9724-9758. https://doi.org/10.1029/2017WR022437

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