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Development of a deep learning method for soil moisture estimation at high spatial and temporal resolution using satellite data

Remote sensing is one of the most widely used solutions for estimating soil moisture at a large spatial scale accurately. It has gradually come to replace point-based measurements where spatiality is required but is still providing mostly coarse spatial resolution results. Deep learning provides a novel method for estimating soil moisture at higher resolutions than previously through complex temporal multivariate relationships.

Soil moisture remains one of the most important hydrological and climatic variables used in modelling, forecasting, and analysis within these and many other fields. Microwave-based remote sensing provides an opportunity to measure soil moisture at much greater spatial scales than possible with point-based in situ measurements. This is achieved by calibrating the backscatter signal from the microwave radar with the perceived soil moisture on the ground, as the former varies greatly with changes in the latter due to the dielectric constant of water. Most remote sensing soil moisture products have spatial resolutions of ~25 km with some efforts from recent studies to reduce that to ~1 km by downscaling the products using optical images or other ancillary data sources. However, many applications of soil moisture require spatial resolutions <1 km, such as precision agriculture, which is only met by few products. Deep learning can extract more complex relationships from the data than traditional machine learning and recurrent neural networks are able to create temporal profiles of these relationships, which can greatly increase accuracy in temporally auto-correlated variables like soil moisture.

The model in this thesis is a recurrent neural network consisting of long-short term memory cells and built on the high-level libraries Tensorflow and Keras. The model is implemented in a semi-automatic pipeline that preprocesses and harmonizes the various the datasets, trains the model, and creates a prediction of soil moisture. The output is a spatio-temporal map showing the change in soil moisture of a given region. Several variations of the dataset are tested in this thesis to determine which variables are most meaningful for the model to reduce the parameter space and thus increase the accuracy.

The results show that using a model with only temporally dynamic variables gives the highest accuracy, while including temporally static variables result in lower accuracies. This is likely due to the higher degree of information contained in dynamic variables in a dataset, where the main limitation is spatial representation. The model results also show that soil moisture predictions on densely vegetated and inundated land cover types have a low accuracy, which conforms with previous studies in the field. The performance of the model is tested against two existing remote sensing-based soil moisture products at different spatial resolutions, where it shows higher overall accuracies than both products. This thesis concludes that deep learning is a viable and promising but underexplored method for estimating soil moisture.

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