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Estimation of soil moisture using radar and optical images over Grassland areas

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The purpose of this study was to develop an inversion approach to estimate soil moisture over Grassland areas by coupling SAR and optical data. A time series of radar (TerraSAR-X and COSMO-SkyMed) and optical (SPOT 4/5, LANDSAT 7/8) images were acquired over an agriculture region in southeastern France. In most cases, the optical and radar images were not separated by more than four days. Ground-truth measurements of volumetric soil moisture and vegetation descriptors were performed simultaneously with image acquisitions.

In this study, the semi-empirical water-cloud model (WCM) was used to model the total backscattering coefficient in HH and HV polarizations as a function of soil moisture and vegetation descriptor. WCM was fitted against in situ measurements to estimates WCM parameters according to each vegetation descriptor and each radar polarization (HH and HV). The parameterized water cloud model was then used to generate one synthetic dataset using wide range of soil moisture and NDVI values. Next, a noise was applied to both simulated radar responses and NDVI.

An inversion technique based on Multi-Layer Perceptron (MLP) neural networks (NN) were used to invert the radar signal in order to estimate the soil moisture. Three inversion configurations were defined using in addition to one vegetation descriptor: (1) HH polarization, (2) HV polarization, and (3) both HH and HV polarizations. The neural networks were trained and validated on the noisy synthetic dataset. Next, the inversion approach was then conducted on real dataset comprised observed SAR data, soil moisture and NDVI.

The best soil moisture estimates were obtained with the use of HH (in addition to one vegetation descriptor). For NDVI (Normalized Difference vegetation index) lower than about 0.8 the RMSE (Root Mean Square Error) between measured and estimated soil moisture is about 0.05 cm^3/cm^3. However, for NDVI greater than about 0.8 the RMSE on estimated soil moisture is about 0.08 cm^3/cm^3.