KERNEL METHODS IN SOIL MOISTURE ESTIMATION FROM REMOTELY SENSED IMAGERY - CASE STUDIES

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ABSTRACT:

We address the problem of top soil moisture estimation by using kernel methods for different scenarios.
In the first, we estimate soil moisture in six agricultural bare soils in Delmarva Peninsula, USA. We use hyperspectral imagery (HyperSpecTIR) and estimate moisture via the support vector regression (υ-SVR) [1] algorithm. All cases examined provided model fits with correlation coefficient, R^2 higher than 0.73 and error (RMSE) smaller than 3 % Vol.
In the second scenario, soil moisture is estimated from L-band simulated backscatter obtained by the discrete model [2] using υ-SVR regression. υ-SVR was trained on the simulations and tested on real measurements acquired by E-SAR. The full growth cycle of winter wheat, maize and sugar beet was examined. For all fields, R^2 was equal or higher than 0.7 and RMSE smaller than 5.9 % Vol.
The remaining scenarios consider soil moisture estimation in grassland mountain areas of South Tyrol (Italy) using Gaussian Process Regression [3].
First, a time series of ASAR Wide Swath images, acquired in snow-free periods of 2010 and 2011, was simulated using the model [2]. For inversion, GPR was trained with the simulated backscattering from the 2010 data and tested on the radar measurements of 2011. RMSE was 5.9 % Vol. and the corresponding R^2 0.85.
In the last scenario, the joint use of GPR, ASAR, MODIS daily reflectances and topographic data acquired in 2010 was tested. Combinations of different data sources were examined. The best soil moisture prediction was obtained when reflectance at 1640 nm was jointly used with SAR data and the utmost important DEM features. In this case, RMSE and R^2 were 5.4 % Vol. and 0.85, respectively.
These case studies are success stories advocating for stronger links between data mining techniques and physical models. We hope fostering discussion on this aspect during the conference.

REFERENCES

[1] B. Scholkopf, A. J. Smola, R. C. Williamson, and P. L. Bartlett, "New support vector algorithms", *Neural Computation*, 12: 1207-1245, 2000.
[2] M. Bracaglia, P. Ferrazzoli, L. Guerriero, "A fully polarimetric multiple scattering model for crops", *Remote Sensing of Environment,* vol. 54, pp. 170-179, 1995.
[3] J. Verrelst, L. Alonso, G. Camps-Valls, J. Delegido and J. Moreno, "Retrieval of Vegetation Biophysical Parameters using Gaussian Processes Techniques", *IEEE Transactions on Geoscience and Remote Sensing*, 50 (5), 1832 - 1843, 2012.

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