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SENTINEL-1/SENTINEL-2-DERIVED SOIL MOISTURE PRODUCT AT PLOT SCALE (S^2MP)

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ABSTRACT

The objective of this paper is to present an operational approach for mapping soil moisture at high spatial resolution over agricultural areas with vegetation cover. The developed approach uses the neural network (NN) technique based on coupling Sentinel-1 radar data and Sentinel-2 optical data. The neural networks were developed and validated using synthetic and real databases. To operationally map the soil moisture, the developed NN uses the C-band SAR signal in VV polarization, SAR incidence angle, and the Normalized Differential Vegetation Index "NDVI" as the inputs. To optimize the automatic production of soil moisture maps a pipeline using the Orfeo Toolbox is implemented.

Index Terms – Soil Moisture, Sentinel-1, Sentinel-2, Orfeo Toolbox

1. INTRODUCTION

Frequent and accurate estimation of soil moisture at high spatial resolution is required for the prediction of the water cycle behavior and agricultural management such as irrigation and water requirements of agricultural areas [1]. The arrival of Sentinel-1 (S1) satellite have encouraged the development of an operational algorithm for soil moisture mapping over agricultural areas with high revisit time (up to 6 days) and high spatial resolution (up to plot scale). The S1 mission from the European Space Agency (ESA) is a constellation of two polar orbiting SAR satellites (Sentinel-1A and Sentinel-1B) operating in the C-band (~5.4 GHz). Recently, several studies tend to use the neural network (NN) technique to invert backscattering models and estimate soil moisture. To estimate soil moisture and roughness from the C-band polarimetric radar data, Baghdadi et al. [2] trained NN using the synthetic database backscattering coefficients generated for a wide range of bare soil conditions (Hrms between 0.3 and 3.6 cm and mv between 5 and 45 vol.%) using the Integral Equation Model IEM. The validation of the trained neural network with real database shows an accuracy of 7 vol.% for soil moisture estimation when considering priori information about soil moisture and surface roughness.

Recently, El Hajj et al. [3] developed an operational method to map soil moisture at the plot scale over agricultural areas based on coupling S1-SAR data and Sentinel-2 (S2) optical data using the neural network technique (S^2MP). The Sentinel-1/Sentinel-2 derived soil moisture product at plot scale (S^2MP) provides soil moisture estimation at plot scale based on the synergic use of radar (Sentinel-1) and optical (Sentinel-2) data. The aim of this paper is to present the practical operational mapping of soil moisture by coupling Sentinel-1 and Sentinel-2 data. In this paper, section 2 describes the proposed methodology for soil moisture estimation using the neural network technique. Section 3 then describes the optimization of the soil moisture estimation algorithm for operational automatic mapping of soil moisture at plot scale and Section 4 presents the main conclusions.

2. S1-SSM ALGORITHM

To estimate soil moisture over vegetated areas, the Water Cloud Model (WCM) developed by Attema and Ulaby [4] is commonly used. In the WCM the radar backscattering signal is the sum of the direct vegetation contribution and the soil contribution multiplied by the attenuation factor. Thus, to estimate soil moisture values, the radar backscattering signal and a descriptor for vegetation are required.

To invert the radar backscattering signal and estimate soil moisture values the approach uses the neural networks (NN) technique [3]. To obtain the final NN that allows the estimation of soil moisture values, several steps are previously performed. In fact the development of the inversion method consists of the following steps:

- Generate a synthetic database of backscattering coefficients using a parameterized WCM [4] combined with the modified IEM [5];
- Noise the synthetic SAR C-band database and NDVI values to obtain synthetic database close to the real SAR and NDVI data;

- Train and validate the neural networks using the synthetic dataset;
- Finally, apply the trained neural networks to S1 and S2 images to map the soil moisture.

Incidence angle, noisy radar signal at VV polarization, and noisy NDVI are the inputs of the NN. The synthetic database was simulated using *Hrms* (Height root mean square) values between 0.5 and 3.8 cm. The NN was trained using the Levenberg-Marquardt algorithm with two hidden layers. The number of neurons for each hidden layer is 20. Linear and tangent-sigmoid transfer functions were associated with the first and second hidden layers, respectively.

A priori knowledge on the soil moisture state is introduced in order to improve the soil moisture estimates. Indeed, using weather forecasts such as precipitation and temperature, it is easy to define if the state of the soil being either dry to slightly wet (no precipitation for many days before SAR acquisition) or very wet (heavy rainfall preceding SAR acquisition). In fact, the integration of a priori information about the soil state leads to a better estimation of the soil moisture because it constrains the range of possible soil moisture parameter values estimated by the neural networks. Therefore, two cases could be obtained:

- Dry to Slightly Wet Soil: The soil is supposed to be dry to slightly wet according to expertise based mainly on precipitation and temperature data. In this case, soil moisture values are assumed to vary between 2 and 25 vol. %.
- Very Wet Conditions: The soil is supposed to be very wet according to the expertise of the meteorological data (precipitation and temperature). The *mv* values are assumed to vary between 25 and 40 vol. %.

For a priori information that the soil is dry to slightly wet (case 1), the NN was developed using the training database elements with the *mv* between 2 and 30 vol. %. For a priori information that soil is very wet (case 2), the NN was developed using the training database elements with the *mv* between 20 and 40 vol. %. An overlap of 10 vol. % on the *mv* is considered between the databases used for the training of the dry (case 1) and the wet (case 2) neural networks.

Finally, to operationally map the soil moisture, the developed NN requires the C-band SAR signal in VV polarization, SAR incidence angle, and the Normalized Differential Vegetation Index “NDVI” as the inputs. While the SAR signal and incidence angle are derived from the S1 data, the NDVI value is derived from S2 images. Therefore, over a given study site and for a given Sentinel-1 acquisition, the soil moisture estimation could be obtained using the Sentinel-1 image accompanied with one or a mosaic of Sentinel-2 images (depending on the area of the study site) acquired on date near the date of the S1 acquisition. In this case, the three input parameters (VV SAR signal, incidence angle, and NDVI) required by the NN are available and a soil moisture map could be generated.

To assess the accuracy of the soil moisture estimation, the soil moisture values estimated have been compared to in situ measurements over a study site located near Montpellier, France. The root mean square error (RMSE) of the comparison between estimated and in-situ soil moisture values reaches 5 vol.% [3]. Moreover, for better assessment of the S^2MP product, the S^2MP was also compared to similar soil moisture products such as SMOS (Soil Moisture and Ocean Salinity), SMAP (Soil Moisture Active Passive), and ASCAT (Advanced Scatterometer)[6]. The results show that the S^2MP provides the most accurate SSM estimation when compared to a wide range of in situ measurements. The S^2MP was also compared to the recent Copernicus surface soil moisture (C-SSM) provided by the European space agency. The comparison performed over a wide region of south France [7] revealed that the S^2MP provides more accurate SSM estimations than the C-SSM estimations when compared to in-situ measurements. The S^2MP was also compared with the precipitation records obtained from the Global Precipitation Mission (GPM) showing high consistency between the SSM estimations derived from the S^2MP and the precipitation records at 0.1° x 0.1° grid scale [8].

3. OPTIMIZATION FOR OPERATIONAL MAPPING OF SOIL MOISTURE

The optimization project was accomplished using iterative software development process framework. It starts with the study of the functional needs of the end users, analyses of the technologies that will be used, and then building a prototype. Eventually we obtain a processing pipeline that fully meets the end-users needs.

3.1. Functionalities and used technologies

The functionalities retained by the study of end-users needs are summarized in table 1.

Functionality
Optimizing the Neural Network model inversion
Creation of agricultural plot scale mask
Segmentation of NDVI
Rasterization of vectorized agricultural plot scale
Automatic calibration of Sentinel 1&2 imagery
Temporal series processing
Automatic download of Sentinel 1&2 imagery
Portability with Docker

Table 1: Pipeline functionality offered by the study

The technologies used in this project are the Orfeo Toolbox (OTB) to optimize image processing, the TensorFlow (TF) for the neural network inversion, Python scripting for processing pipeline connections and Docker for portability. OTB is open-source project for processing remote-sensing images at large scale. It is developed in C++ programming language using the Integration Tool Kit Application Programming Interface (ITK-API) originally created for medical imaging. The great originality of OTB applications is that it uses a streaming technology that allows processing an image by regions lowering computational time and memory usage. It also allows piping multiple applications without creating temporary files. TensorFlow is an open-source platform for machine learning. It has stable API release in Python and C++, and allows development on multiple kind of platform based on Central or Graphic Processing Units. OTBTF (OTB TensorFlow) is a module developed by Cresson [9] to bind OTB capabilities with TensorFlow deep machine learning resources. OTB also contains a Python API, thus, batch processing and files manipulation have been scripted in Python. Docker is a tool that can wrap applications and their dependencies in an isolated container and it can be deployed on any server. The other benefit of Docker is that the container uses images of operational system, which are versioned.

3.2. Workflow

3.2.1 Downloading Sentinel-1/2 time series

Based on an Area of Interest (AOI), a request is performed on Sentinel data provider website (Sentinel1 https://scihub.copernicus.eu/, Sentinel2 https://theia.cnes.fr/atdistrib/rocket/#/home). An xml file containing the links to download the requested images is obtained and downloaded with a simple script.

3.2.2 Sentinel Image calibration

The calibration of the Sentinel-1 and Sentinel-2 images is performed by ESA Sentinel Application software (SNAP) (http://step.esa.int/main/toolboxes/snap/). Both radiometric and geometric calibrations are performed on the S1 images. The radiometric calibration aims to convert the digital number values of the S1 images into backscattering coefficients (σ°) in linear units. The aim of the geometric correction is to ortho-rectify the S1 images using the 1 arc-second SRTM (Shuttle Radar Topography Mission) which is automatically downloaded by SNAP. A Docker image has been created containing this application with a batch script that processes all the images.

In the case where Sentinel-2 images are only available in level-1, the Sentinel-2 images are calibrated into level-2 images using the sen2cor extension of the SNAP software. However, for different AOI worldwide, the French land data center (Theia) provides level-3 images corresponding to a monthly synthesis from weighted mean of clear sky observations. In this case, these level-3 synthesis images are used.

3.2.3 NDVI calculation

From level 2 or level 3 Sentinel-2 images, a python script was developed using OTB applications to calculate the NDVI values. This script computes the NDVI, applies the cloud mask to the NDVI, manages the nodata values and finally creates an unsigned 8 bit (uint8) NDVI image. The temporal gap filling (cloud filling) for time series images, proposed by the Centre d'Etudes Spatiales de la Biosphère (CESBIO), is used to create monthly spread NDVI over the whole period.

3.2.4 Segmentation and agricultural mask

In order to consider only agricultural plots for soil moisture estimation, two options are available. First, if the precise limits of agricultural plot are available in vector format, then this vector shapefile is rasterized to obtain a pseudo-segmented image. The soil moisture estimation is then performed for each agricultural plot. Otherwise, if the precise limits of the plots are not available, the second option uses a stack of monthly NDVIs to perform segmentation in order to obtain plots with homogeneous NDVI values.

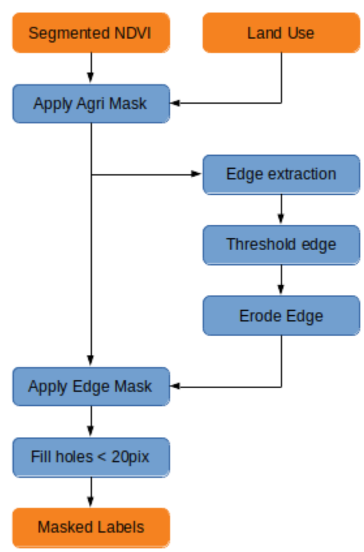

Figure 1 : Processing details of the Segmentation OTB application (SoilMoistureSegmentationFiltering)

The segmentation is very high machine resource consuming, so depending of the AOI size, you may need to deport this computation on a high RAM cluster. In the case of default segmentation, an agricultural mask is required to remove non-agricultural segments.

3.2.5 Soil moisture inversion and batch time series

Figure 2 shows the processing details of OTB application used to invert the SAR signal into soil moisture values (SoilMoistureInvertSARModel).

Figure 2 : Processing details of the SAR inversion OTB application (SoilMoistureInvertSARModel)

A python script will perform the soil moisture estimation at each SAR date using the S1-VV and incidence angle images, the NDVI image corresponding to the S1 acquisition date (e.g. NDVI of October 2017 is used for all SAR images acquired in October 2017), a masked labels image obtained from the segmentation, and a slope image from SRTM. A batch processing is applied over the whole time series.

3.2.6 Portability with Docker

The entire pipeline is enclosed in two Docker images. One Docker image is with OTBTensorFlow and the other is with SNAP application from ESA. Thus, the pipeline can be easily installed on any server. While Linux platform is highly recommended, the pipeline could be also installed on Mac or Windows.

4. CONCLUSION

The present study aimed to present an operational approach for soil moisture mapping in agricultural areas at a high spatial resolution (up to plot scale). Our approach is based on a synergic use of Sentinel-1 and Sentinel-2 images. Our approach for soil moisture estimates used the neural networks technique to invert the radar signal and estimate the soil moisture.

For operational production of soil moisture maps, we designed an optimized soil moisture pipeline using Orfeo Toolbox. This optimization of soil moisture mapping significantly reduced the time required for obtaining soil moisture maps. For the core application of inversion, an image used to be processed in 30 min, requires now less than 5 min using the proposed pipeline. A time series for a given AOI over one year used to be processed in 2 weeks now takes between 3 to 4 days.

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