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USING PYTHON® LANGUAGE FOR THE VALIDATION OF THE CCI SOIL MOISTURE PRODUCTS VIA SM2RAIN

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ABSTRACT

Remote sensing techniques provide a new way to obtain hydrological variables (i.e. rainfall and soil moisture), mainly in poorly instrumented areas that are fundamental for natural hazard assessment and mitigation. The even increasing availability of satellite derived products characterized by high temporal and spatial coverage requires the development of techniques and instruments for big data volume managing. Moreover, the use of open source systems is highly encouraged in order to increase their use by the scientific community. In this study, the application of the SM2RAIN algorithm to the CCI soil moisture product is proposed as case study. A number of Python® classes and methods have been developed for this purpose, with the aim of creating an open-source web validation tool for SM dataset, within the Earth Observation Data Centre for Water Resources Monitoring (EODC).

INTRODUCTION

Accurate estimates of rainfall and soil moisture are of paramount importance for geo-hydrological (floods and landslides) risk assessment. These variables are usually obtained through a monitoring network or by running land surface models. The first method is impacted by spatial representativeness issues (Kidd and Levizzani, 2011) and requires a big effort in the set up and maintenance phases. The second method instead suffers from some issues like the spatial resolution and seasonal dependent performance (Ebert et al., 2007, Dee et al., 2011).

To overcome these issues, satellite-derived precipitation and soil moisture products may be a valuable alternative. The retrieval of rainfall from satellite is obtained through the inversion of the atmospheric signals reflected or radiated by atmospheric hydrometeors (Kucera et al., 2013). However, if microwave sensors do not pass when it rains, these algorithms are unable to capture the rainfall events thus providing a significant bias in the estimates. Indeed, these methods provide underestimation of the frequency of light rainfall (Huffman et al., 2000, Tapiador et al., 2012) and the overestimation of the frequency of heaviest precipitations which determine a large bias especially for near-real-time products (that do not use gauge observations for bias adjustment).

The even increasing availability of satellite estimates, their increasing spatial and temporal resolution and the development of long-term products, however, involve the use of big data volume analysis and managing platforms and software. As way of example, the European Space Agency Climate Change Initiative (ESA-CCI) developed and provided three different satellite soil moisture (SM) products, by merging several satellite estimates (Liu et al., 2012). These three datasets, namely, “Active”, “Passive” and “Combined” (obtained by combining the SM information retrieved from active, passive and active plus passive sensors), provide daily SM estimates on a global scale, with 0.25° of spatial resolution from 1978 to 2014. The big data volume poses a serious problem and can limit the use of such products for climatological and natural hazards related studies. A way to overcome this issue could be the use of cloud computing environments that allow to manage and analyse huge volumes of data. With this aim, the Earth Observation Data Centre for Water Resources Monitoring (EODC) was recently established in Vienna. The EODC provides a powerful open-source cloud computing environment for Earth Observation (EO) data analysis and is now used for Sentinel 1 data pre-processing and provision. On this basis, the main purpose of this study is to present a new set of open-source tools for analyse long-term (>30 years) SM datasets within the EODC platform. However, a long term validation of the products is challenging since ground soil moisture observations are scarce and, except some cases, lack of long term recording.

To overcome this issue, Brocca et al. (2013, 2014) have developed a method – SM2RAIN – that allows to estimating rainfall using only satellite SM observations. The method has shown to be particularly suitable for estimating accumulated rainfall amount. Indeed, at each satellite overpasses SM2RAIN records the SM value and relates it to the amount of water fallen into the soil via the inversion of the soil water balance equation. After been developed and applied worldwide (Brocca et al., 2013, 2014) the method has been successfully tested in flood prediction applications (Massari et al., 2014 and Ciabatta et al., 2016) and for rainfall correction (Ciabatta et al., 2015). These studies have shown that the accuracy of the retrieved rainfall is strictly dependent on the quality of the soil moisture dataset used as input into SM2RAIN. Given that, since different long-term rainfall products are available worldwide, the retrieved rainfall obtained through soil moisture via SM2RAIN offers a unique opportunity to evaluate the quality of the soil moisture observations. In this respect, SM2RAIN is a valuable tool for testing the accuracy of the ESA-CCI SM products. Indeed, by providing SM for three main different products, SM2RAIN has the chance to evaluate their relative performance in an alternative way. In addition, this is a chance for testing the capability of SM2RAIN to producing rainfall by using a continuous, homogenous, long-term SM time series.

DATA AND METHODS

In this study, SM2RAIN is applied to the ESA-CCI SM datasets. These satellite products are characterized by daily temporal resolution and 0.25° of spatial resolution. The Passive and Combined datasets span from 1^{st} November 1978 to 31^{st} December 2014, while the Active dataset from 5^{th} August 1991 to 31^{st} December 2014. The SM2RAIN algorithm is based on the inversion of the soil water balance equation and uses three parameters which are calibrated by using rainfall from the Global Precipitation Climatology Centre (GPCC) full data daily product at 1° of resolution (Schamm et al., 2015) during the period 2008-2010. SM2RAIN has been calibrated on a pixel-by-pixel basis by selecting the closest land GPCC pixel selected with the Nearest Neighbour Algorithm. The algorithm parameters have been estimated by minimizing the Root Mean Square Error (RMSE) between the estimated and the observed rainfall for 5 days of accumulated rainfall. For a detailed description of the SM2RAIN algorithm the reader is referred to Brocca et al. (2013, 2014).

The performances are assessed in terms of correlation coefficient (R) and RMSE, for five days of accumulated rainfall during the calibration period. The estimated rainfall datasets are then assessed by considering their native resolution (0.25°) and by regridding them at 1° of resolution, in order to perform the evaluation on the same grid of the considered benchmark. The regridding procedure has been carried out by averaging the 25 closest pixels to each 1° grid centroid. Python® language has been used to create classes and methods for the geographical, statistical and cal/val analysis steps and has been chosen for the availability of packages for geographical analysis and big data handling and for the strong support provided by the vast Python scientific community. The developed routines take advantages of the analysis libraries developed by the TUWIEN Remote Sensing Research Group, like the Python Toolbox for the Evaluation of Soil Moisture Observations (pytesmo, https://pypi.python.org/pypi/pytesmo, Paulik et al., 2014). All the developed routines will be implemented into the EODC platform in order to create a valuable satellite SM data validation tool. Figure 1 draws the analysis framework highlighting the used Python® packages.

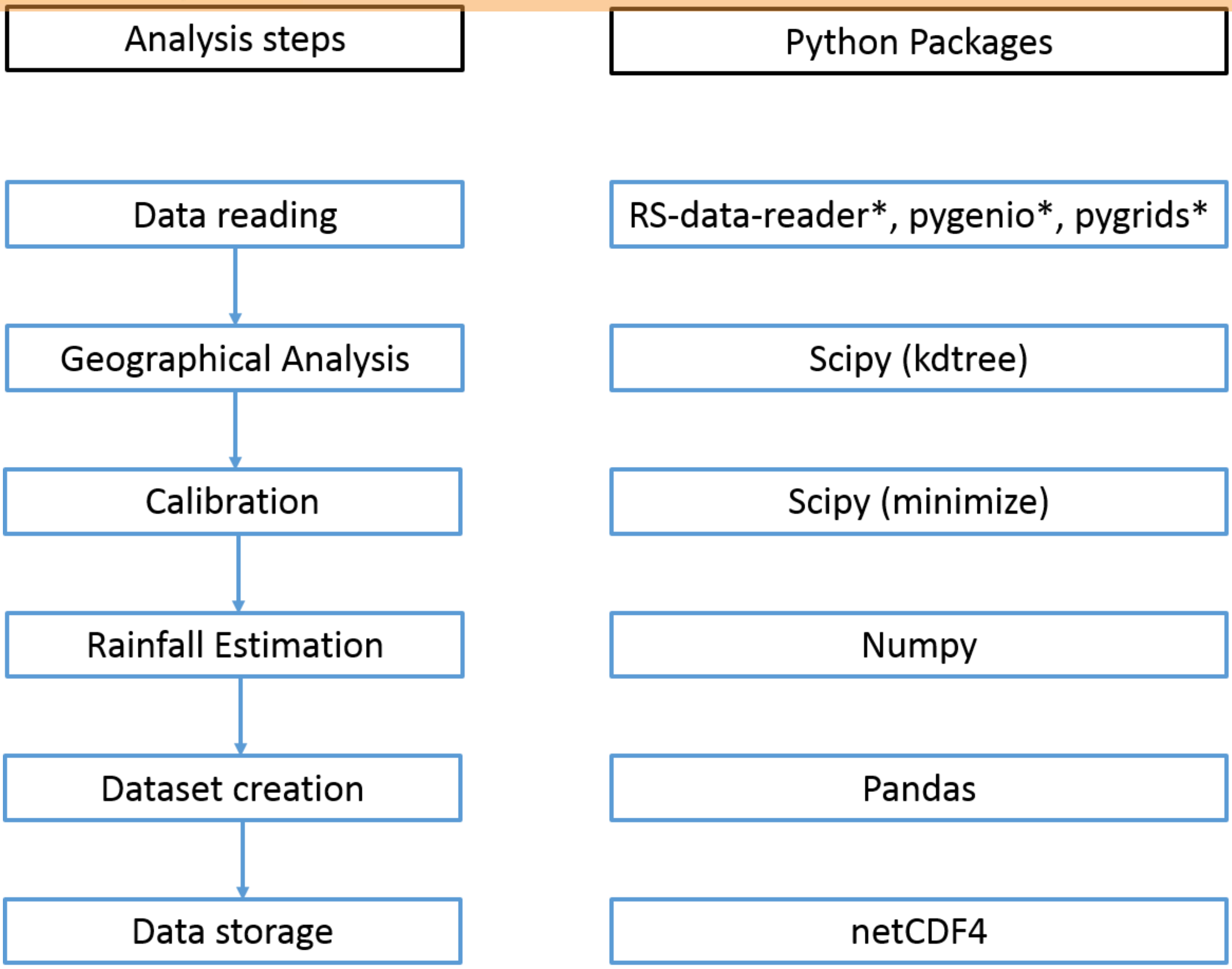

Figure 1 – Analysis framework and Python packages used for each steps. The * indicates Python packages developed by the TUWIEN Remote Sensing Research Group.

RESULTS AND CONCLULSIONS

The SM-derived rainfall datasets are in good agreement with the observed benchmark. As it can be seen in Figure 2, the performances are depending on the SM input data quality, i.e. the correlation is lower over deserts, over vegetated areas, over mountainous regions and over areas characterized by frozen soil. The rainfall obtained from the passive dataset shows the lowest correlation, due to the quality of the input data, while the “active” and the “combined” rainfall show similar patterns and R median values. The passive dataset seems to perform better over the desert areas and over Australia than the other two rainfall estimates. The combined product shows the highest R values, taking advantages of the two different parent datasets. In terms of RMSE the three rainfall datasets provide a different scenario, with the “active” rainfall showing the best score and the “combined” showing the highest RMSE error. The analysis of the 1° datasets (not shown for the sake of brevity) provides the same trend, with better performance values, probably due to an averaging effect during the regridding procedure. Table 1 summarizes the results obtained for the analysed datasets.

Product	R		RMSE	
	0.25°	1°	0.25°	1°

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Active dataset	0.42	0.56	9.48	8.77
Passive dataset	0.32	0.44	9.72	9.24
Combined dataset	0.46	0.57	12.02	10.74

Table 1 – Correlation coefficient (R) and Root Mean Square Error obtained for the Active, Passive and Combined ECV-SM derived rainfall during the calibration period, at 0.25° and 1° of spatial resolution and for 5 days of accumulated rainfall.

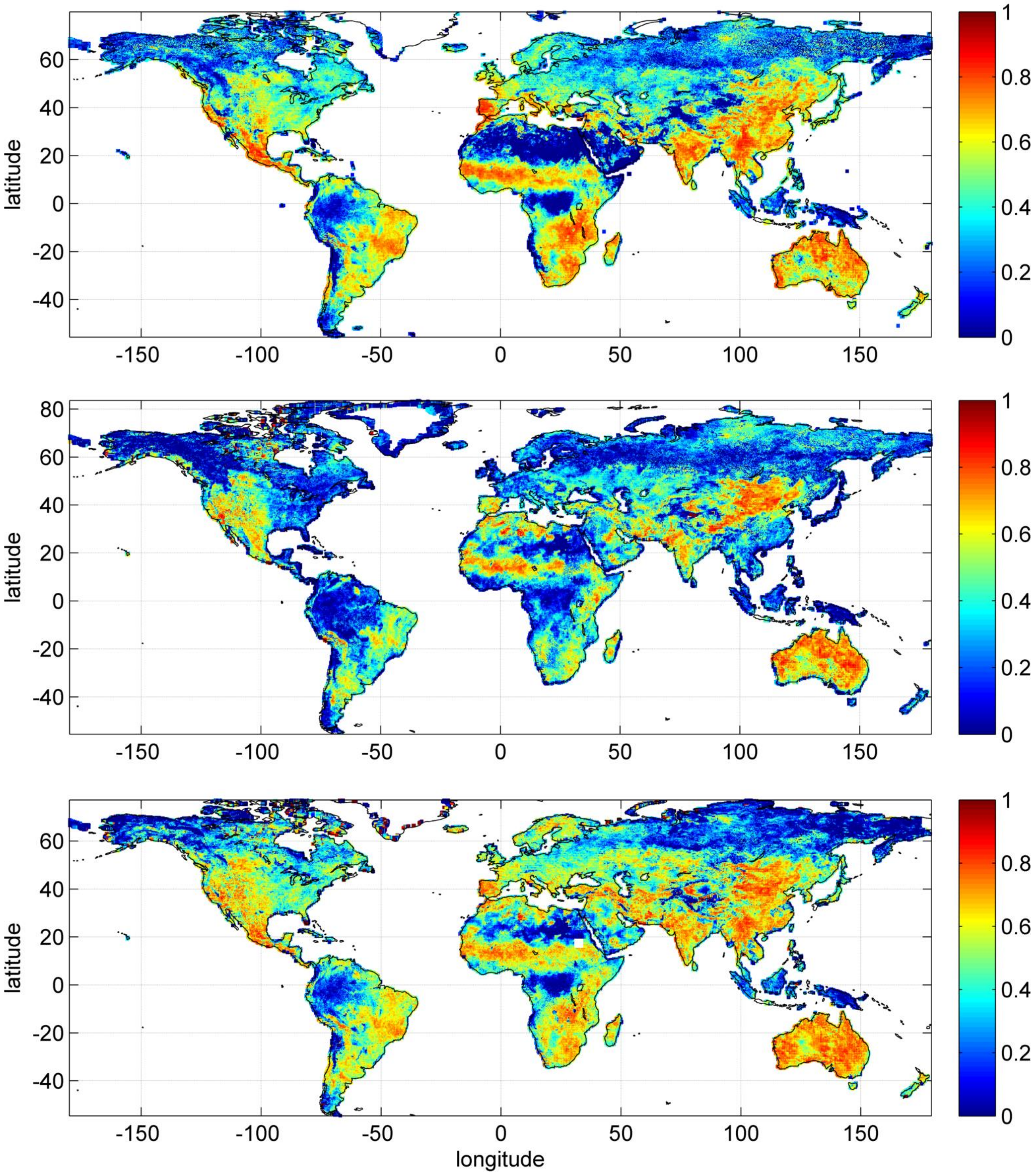

Figure 2 – Correlation maps for 5 days of accumulated rainfall obtained for the active (up), passive (middle) and combined (down) ECV-SM dataset.

Base on the results obtained in this analysis the following conclusion can be drawn:

- Cloud computing facilities cam be very beneficial for analyzing huge amount of data;
- Python® has proven to be very useful for validation and big data analysis procedure implementation;
- SM2RAIN algorithm can be used for estimating rainfall and for assess the quality of SM dataset;
- During the analysis period, the “combined” rainfall outperforms the “active” and the “passive” estimates;

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