EVALUATION OF THE ASAR GM SOIL MOISTURE PRODUCT

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ABSTRACT

With the increasing number of remotely sensed soil moisture products a need for their standardized evaluation becomes necessary. This work comprises of two major parts. First, it provides a brief overview on three advanced evaluation measures commonly used to evaluate soil moisture products. Second, it investigates the performance of the triple collocation (TC) and error propagation (EP) methods when these are used to evaluate the medium resolution ASAR GM soil moisture product. The study highlights the fact that each evaluation method has limitations and presumptions that may not always be fully achievable. It further demonstrates that a combination of only two evaluation methods can shed more light on the performance quality of the methods and may lead to an improved understanding of the error structures of the product.

Index Terms— soil moisture, evaluation, triple collocation, error propagation, ASAR GM

1. INTRODUCTION

The ENVISAT satellite has been keeping watch over our planet for over a decade starting in 2002. The development of the soil moisture service from the Global Mode (GM) of the ENVISAT's Advanced Synthetic Aperture Radar (ASAR) is only one of its many achievements. The service demonstrated the potential of C-band observations at high temporal and moderate spatial resolution to monitor variations in soil moisture on a quasi-operational basis [1].

Evaluation of the ASAR GM soil moisture product, much like of any other soil moisture product, is critical for its successful application. In the last decade a large amount of global coarse resolution soil moisture datasets have become available [2–5] that allowed for numerous cross-evaluation studies world wide. The results showed that each of these datasets contains different error structures of varying amplitudes.

This study provides a brief overview of advanced evaluation methods commonly used in remote sensing of soil moisture. Furthermore, it uses two advanced evaluation methods – the triple collocation (TC) and error propagation (EP) – to evaluate the ASAR GM medium resolution soil moisture dataset.

This work is innovative in that it applies TC, amply applied only to coarse resolution (~25 km) datasets, to evaluate the ASAR GM medium resolution dataset. The errors retrieved from the TC method are then compared to the error structures as retrieved by the EP method. The potential reasons for the discrepancies between the two maps are discussed. The other two datasets used in the TC are the modeled surface soil moisture retrieved from the grid-based landscape hydrological model (AWRA-L) [6] and remotely sensed AMSR-E C-band soil moisture [12].

2. ADVANCED EVALUATION METHODS

An increasing number of the coarse resolution soil moisture datasets triggered the development of new evaluation techniques as well as the transfer of the existing advanced evaluation techniques from other fields of remote sensing to the remote sensing of soil moisture [7].

The EP method determines the error of a model in that it propagates the impact of the errors of the individual model parameters [8]. By doing so the EP method accounts for the effect of random errors in the final model but it cannot evaluate if the model itself is correct.

The estimated root mean square difference (eRMSD) [9] uses a simplified version of the EP technique to estimate the RMSD between two independent datasets by applying their individual error estimates. If the individual errors are well known the retrieved eRMSD can be assumed to be unbiased. The inversed version of the method can estimate the error of one of the datasets using the eRMSD and the error of the second dataset.

Finally, the TC method estimates the error variances of three calibrated soil moisture products *x*, *y* and *z* by computing their cross-calibrations with respect to each other according to:

$$\langle \varepsilon_x \rangle^2 = \langle x - y \rangle \langle x - z \rangle, \qquad \text{Eq. 1}$$

where the angle brackets represent the mean over time and the ε_x represents the error of the dataset *x*. Analogical equations can be derived also for ε_y and ε_z. Importantly, the TC method provides an estimate of the deviation relative to two independent datasets. In particular, the method assumes that the closer together are the independent estimates the higher is the probability that these represent the studied phenomena and that the lower is the resulting error ε_x.

The TC method requires that a) the residual errors are uncorrelated, b) there is no bias between the independent datasets and c) the different datasets observe the same physical phenomenon. The removal of the systematic bias and the significance of the relationship between the datasets can be assured using the CDF matching and tests of significance of correlation. The independency of the residual errors is however strenuous to access and is often accepted only considering the different retrieval strategies.

3. THEORY

Some of the introduced evaluation methods commonly assume that one system is much more accurate (i.e., is truth) than the other. This has been demonstrated to potentially lead to substantial pseudobias effects [10]. Furthermore, advanced evaluation methods have limitations and presumptions (i.e. absolute independency of the soil moisture residual errors or number of triples in the TC method) that were found not always realizable [11]. These findings lead to a conclusion that no single evaluation method should be given an absolute preference. More accurate evaluations may be achieved with a careful combination of several evaluation methods that comprehend more than two independent datasets

As an example, the EP and TC methods are here implemented to estimate the error of the ASAR GM soil moisture product. The former method refers to the random error of the dataset and avoids any judgement about the systematic error related to the quality of the model. The latter method removes any systematic bias prior to the analyses and estimates the combined effect of a random error and systematic error related to the quality of the model. A good correspondence of the EP and TC error maps would indicate a complete fulfilment of the TC presumptions (especially the independency of the residual errors) and a good understanding of the propagated errors in the EP. On the contrary, discrepancies would indicate that the residual errors are not completely independent, that the estimates of the input variables errors in EP are not correct or that there is a missing variable in the EP method.

4. DATASETS AND PREPROCESSING

4.1. ASAR GM soil moisture

The algorithm used to retrieve soil moisture from the C-band ASAR GM observations is similar to the soil moisture algorithm for the Earth Resource Satellite (ERS) scatterometer [2]. The approach is based on a change detection method and assumes a) sufficiently long time series to cover a full range of soil moisture values from the wilting point to saturation and b) variations in soil moisture to be tracked by the temporal change in backscatter. The final product represents relative soil moisture product with the expected depth less than 5 cm.

4.2. AWRA-L soil moisture

The AWRA-L landscape hydrological model [6] estimates the soil water balance at a daily step for four different layers: the surface top soil, the shallow root zone, the deep root zone and the saturated ground water store. The top soil moisture is expressed in % and corresponds to 0–*z* cm of the top soil layer, where *z* ranges between 5 to 10 cm.

4.3. AMSR-E

The brightness temperatures measured by the AMSR-E are converted to volumetric soil moisture using the Land parameter Retrieval Model [12]. The method uses a forward modelling optimization procedure to solve a radiative transfer equation for both soil moisture and vegetation optical depth.

The AMSR-E soil moisture derived from the C-band was used in this study as this is expected to represent soil depth corresponding to that represented by the ASAR GM soil moisture product. The original resolution of the footprint measurements at C-band is 56 km; this was resampled to 0.25 degree grid. Only night-time acquisitions were used as these were shown better suited for retrieving soil moisture than day-time observations [13].

4.4. Pre-processing

The three datasets rely on different retrieval strategies and represent different soil depths. Furthermore, the ASAR GM and AWRA-L datasets are expressed in relative units ranging from 0-100% while the AMSR-E dataset is expressed in volumetric units. To mitigate these differences the Cumulative Distribution Function (CDF) matching was applied [14]. The CDF matching was preferred over linear matching because of the demonstrated non-linear relationship between the modelled and the remotely sensed datasets (not displayed). Given the aim of the study to evaluate the error of the ASAR GM dataset, the AMSR-E and AWRA-L soil moisture datasets were matched to the dynamics of the ASAR GM data.

The final analyses were performed at the spatial resolution of the AWRA-L dataset (5 km). The ASAR GM data were averaged over the corresponding AWRA-L footprint; the AMSR-E data were resampled to the same.

5. RESULTS AND DISCUSSIONS

First, the significance of the relationship between the three independent soil moisture datasets was tested that is a prerequisite for the triple collocation method. The one-tailed T test was implemented; areas with insignificant correlation are masked in the Figure 1.

Second, the TC method was computed according to the equation 1 using the ASAR GM, AWRA-L and AMSR-E datasets; ASAR GM representing the reference. The resulting ASAR GM error (ε_{TC}) is displayed in the Figure 1 (above). The selection of the reference doesn't influence the relative patterns of the residual errors [15]. Finally, the retrieved error was compared to the EP error estimate (ε_{EP}) [1] (Figure 1, below).

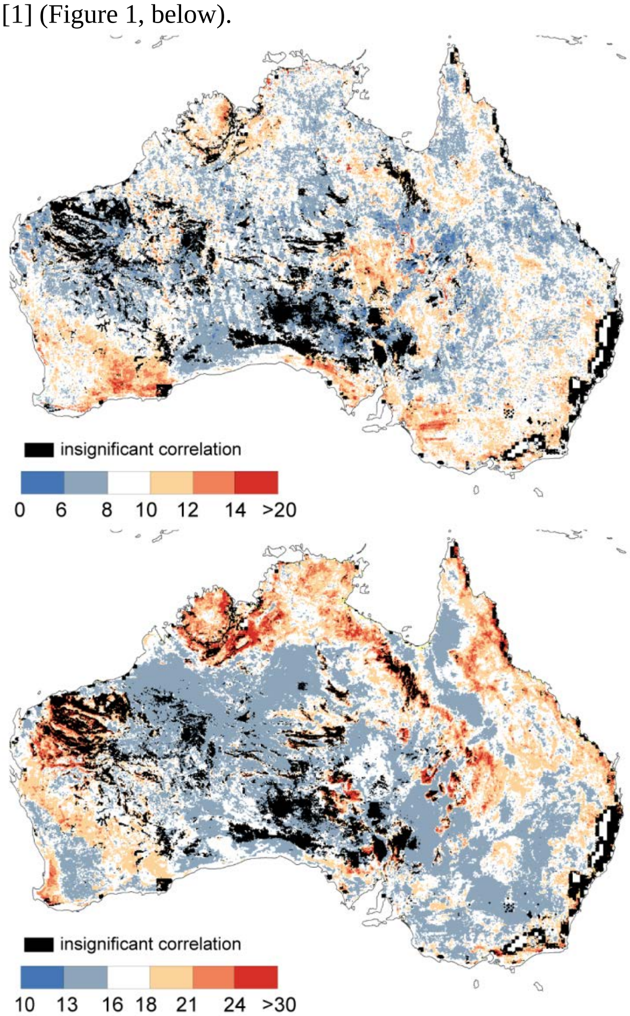

Figure 1 – The estimates of the ASAR GM soil moisture error at 5 km scale using triple collocation (ε_{TC}) (above) and the error propagation (ε_{EP}) (below).

Both error estimates appear to be affected at large (>100 km) as well as at medium scales (<5 km). While the large scale patterns reflect mainly the differences in atmospherical forcing, the medium scale patterns correspond to the vegetation and soil roughness patterns or to the geomorphological features. The effects of medium scale vegetation patterns are more evident in ε_{EP}. This can be explained by the smoothing role of the AMSR-E coarse resolution dataset in the computation of the TC cross-correlations (equation 1).

The absolute values of ε_{EP} are significantly higher than ε_{TC}. This was expected given that ε_{EP} refers to the maximum effect of the propagated errors. The relative patterns of highs and lows in ε_{TC} and ε_{EP} maps correspond only in southwestern, western and northwestern Australia reflecting the lows over areas with low soil moisture variation, medium values over croplands and alluvial areas and highs over the forested areas, rock outcrops and steep slopes.

On the contrary, severe differences between the ε_{TC} and ε_{EP} are evident in northeastern and northern Australia, in the central desert regions and southeastern Australia. While ε_{TC} is higher than ε_{EP} in the desert regions and in southeastern Australia, the opposite trend is evident in eastern and northern Australia.

The possible reason for the high ε_{TC} over desert regions may be the high ASAR GM sensitivity (S) [1] to soil moisture in the central desserts caused by the severe but exceptional rains. The high sensitivity propagates into the EP model and decreases the final ε_{EP} without considering the high seasonal variance of S. Also, the parameter S is derived from the reference probabilities of the ERS scatterometer [1]. Some inaccuracies in the references should be therefore expected given the differences in the sensitivity of the SAR and scatterometer to roughness effects of soils and vegetation. Similarly, the higher values of ε_{EP} in northern and northeastern Australia may be explained by the potential underestimation of S.

Furthermore, the discrepancies in ε_{EP} and ε_{TC} may be caused by the fact that the residual errors of the ASAR GM, AWRA and AMSR datasets are not fully independent (see the theory section). To gain a better understanding on the latter further analyses would need to be performed comparing the results of the separate error propagation schemes.

In addition, the spatial resolution of the original datasets may play a role in interpreting the discrepancies between ε_{TC} and ε_{EP}. For instance, the high values of ε_{TC} in southeastern Australia may indicate that the ASAR GM is more sensitive to the vegetation and roughness effects at 1 km scale when compared to the AWRA and AMSR-E datasets. This would terminate in high correlation between the AWRA and AMSR-E soil moisture datasets and in higher ε_{TC}.

Finally, it is important to note that the AWRA soil moisture dataset follows a non normal distribution. Furthermore, large portions of the data clouds are located in the very dry and very wet ranges respectively (not displayed). This makes it difficult to assign the correct cumulative fraction of the AWRA retrievals to the corresponding ASAR retrievals using the CDF matching. It is expected that such affects may introduce significant biases in the TC results.

7. CONCLUSION

An overview of commonly used evaluation methods for remotely sensed soil moisture datasets has been provided. Each evaluation method has limitations and presumptions that may not always be achievable. Violation of some of these may lead to false error estimates. It is suggested in this study that a combination of several evaluation methods may help to assess effects of the latter limitations and violations on the retrieved error estimate.

As an example, the errors of the ASAR GM data derived using the TC (ε_{TC}) and the EP (ε_{EP}) methods were here compared. Areas with a good correspondence demonstrated a good fulfillment of the prerequisites of the TC method (especially the independency of the residual errors) and a good understanding of the propagated errors. However, severe discrepancies in the ε_{EP} and ε_{TC} maps were found. While it could not be clearly distinguished where the differences originate several hypothesis were provided. These include an inaccurate understanding on the errors of the input variables in the EP technique, non-independency of the separate error structures, different spatial scale of the TC input parameters and biases introduced by an inappropriate usage of the CDF matching.

At this preliminary stage there seem to be more questions than answers related to the performance of the advanced evaluation methods for soil moisture datasets. Nevertheless, assessments similar to those presented here are expected to lead to a better understanding and more appropriate use of these evaluation methods.

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