# 7 YEARS OF ASAR GM 1 KM SURFACE SOIL MOISTURE OVER AFRICA

**A. Hegyiová [(1)], M. Doubková [(2)], D. Sabel [(1)], B. Bauer-Marschallinger [(1)], W. Wagner [(1)]**

*[(1)] Vienna University of Technology, Gußhausstraße 27-29, 1040, Vienna, Austria, Email: alena.hegyiova@ipf.tuwien.ac.at, daniel.sabel@geo.tuwien.ac.at, wolfgang.wagner@geo.tuwien.ac.at, bernhard.bauer-marschallinger@geo.tuwien.ac.at*

*[(2)] ESA, ESRIN, Via Galileo Galilei, I-00044 Frascati, Italy, Email: marcela.doubkova@esa.int*

## ABSTRACT

A surface soil moisture (*SSM*) product at 1 km spatial resolution derived from the ENVISAT ASAR GM data series was evaluated over Africa using coarse spatial resolution *SSM* acquisitions from the AMSR-E radiometer and GLDAS-NOAH model. A good ability (R=~0.6) of ASAR GM product to detect spatio-temporal variability of *SSM* was found over region with low to medium dense vegetation and yearly rainfall >250 mm. These findings agree with previous evaluation studies over Australia and further strengthen understanding of the quality of the product and its possible use in data assimilation. Problems were detected in the ASAR GM algorithm over arid regions. Their solutions are being considered and are expected to bring further improvement to the algorithm.

## 1. INTRODUCTION

The ability of coarse resolution (~25-50km) microwave remote sensing products from both, passive and active satellites to demonstrate the variability of soil moisture was demonstrated by numerous studies (e.g. [1,2]). As a result, the products became commonly accepted in the past years. Their benefits in many research fields, such as numerical weather forecasting [3] , runoff modelling [4, 5] or studies of land atmospheric feedbacks [6] were demonstrated.

SSM products with improved spatial resolution were expected to broaden the number of applications and allow the product data usage in regional, higher spatial resolution, models. Motivated by the latter, the use of SAR ScanSAR 1 km data to monitor SSM was suggested by [7,8]. The ScanSAR ASAR GM mode was selected [7] as it provides a trade-off between spatial (1 km) and temporal resolution (4 to 8 days) and allows so for monitoring dynamic processes such as soil moisture [8]. The previous evaluation studies over Oklahoma and Australia proved the ability of the product to resolve the spatial details in the soil moisture patters that were not observable with the coarse resolution scatterometers or radiometers, although spatial averaging to roughly 3–10km was recommended [9,10].

Here, the ASAR GM SSM product produced over Africa from a complete archive of the ASAR GM data available from December 2004 to April 2012 is introduced and evaluated. The ASAR GM product relies on the TU-WIEN change detection algorithm [9]. The initiative started within the ESA's SHARE and was finalized within the ESA's TIGER NET project.

The production and evaluation of the ASAR GM product over the African continent is especially valuable given the variability of the climatological, biogeographical, pedological and lithological characteristics over the continent that is expected to reveal new challenges and opportunities for improvements of the TU WIEN algorithm. For instance, prior studies using scatterometer demonstrated some unexpected backscatter behaviour and negative correlations between the SSM estimates from active and passive sensors over very dry areas [1]. Identical divergences were expected to occur also in the SAR SSM products. Higher resolution of SAR data may improve understanding of the regionalization of such phenomena and link it to other parameters such as soil types, lithology, vegetation or combination of all.

The evaluation step is performed using the SSM data from the Advanced Microwave Scanning Radiometer (AMSR-E) as well as from the GLDAS-NOAH model. At the time of writing this paper, the evaluation with in-situ and medium resolution datasets was impossible at continental scale due to a lack of such data over African continent. The evaluation considers absolute (root mean square error - RMSE) as well as relative (Pearson correlation coefficient - R) measures. Given the recommendations of preceding studies, the input SSM product was spatially averaged to 5km spatial resolution. Evaluation measures were computed always with the nearest corresponding pixel of the coarse resolution products. The results were compared separately for different land cover classes.

## 2. USED DATA

### 2.1. 1 km ASAR GM surface soil moisture

The dataset was retrieved using a change detection algorithm and represents the relative surface soil moisture in the upper soil layer (<3cm) at 1 km spatial resolution. The algorithm was originally developed for data from ERS and ASCAT scatterometers [11] and is based on the scaling of the normalized backscatter values between wet and dry references, representing the wilting point and saturation of the soil, respectively. The unit of the resulting product represents the degree of

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saturation [%].
Over all, more than 18000 ASAR GM images were processed and quality checked. The resulting data coverage is shown at Fig. 1.

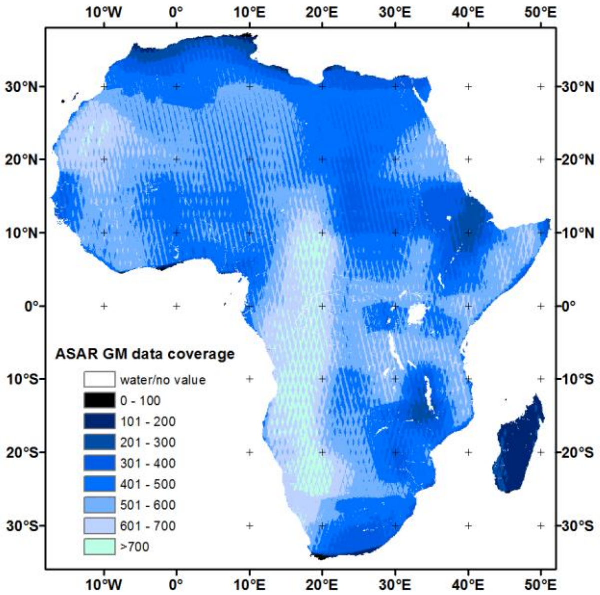


*Figure 1. The number of ASAR GM SSM measurements between December 2004 and April 2012*

### 2.2. Reference datasets

Two independent dataset sources were used for evaluation and are in this publication referred to as reference datasets. These included the SSM derived from the AMSR-E satellite and the SSM from the GLDAS-NOAH model.

#### 2.2.1. AMSR-E VUA SSM

The ASMR-E SSM is derived from the C-band brightness temperature using Version 3 of the Land Parameter Retrieval Model [12] by the VU Amsterdam. It represents the volumetric soil moisture [$m^3/m^3$] in the near-surface soil layer (<3cm) at the original spatial resolution of 56km (resampled to a grid with resolution 0.25°). Only the descending (night-time) orbit data were used as these were addressed as more relevant than daily acquisitions for soil moisture retrievals [13].

#### 2.2.2. GLDAS-NOAH SSM

The GLDAS-NOAH model contains land surface parameters simulated from the NOAH model in the Global Land Data Assimilation System [14]. The SSM dataset represents the modelled soil moisture information in upper soil layer (approx. 0–10cm) at the spatial resolution of 0.25°.

#### 2.2.3. Ancillary datasets

Mean yearly precipitation was computed from the TRMM monthly rainfall data [15]. The land cover information is retrieved from the USGS GLCC Land Use/Land Cover System (Data available from the U.S. Geological Survey)[16].

## 3. METHODS

Each validation metric is robust with respect to some attributes and relatively insensitive or incomplete with respect to others. For example, if there is no variation in the real soil moisture content, there may not be any linear correlation between soil moisture datasets, even though the datasets may be accurate in absolute terms. On the other hand, the retrievals can be biased in their mean and dynamic range but still well reproduce the time variability [17] and be useful in data assimilation In this study, both, the Pearson correlation coefficient as a measure of the relative agreement and the RMSE as a measure of the absolute agreement were used.
To reduce the radiometric noise and provide a better signal-to-noise ratio, the ASAR GM SSM dataset was spatially averaged to 5 km resolution. The product was masked for multiple land cover classes (urban areas, water bodies and densely vegetated areas according to the USGS GLCC Land Use/Land Cover System) where the soil moisture retrieval is not possible.
The R and RMSE were computed between the ASAR GM 5 km pixel and the nearest acquisition of the AMSR-E and GLDAS-NOAH, respectively. A maximum difference of 12 hours between the satellite acquisitions was allowed for temporal matching. To remove bias and to overcome the problem of different units (%, $m^3/m^3$, $kg/m^3$) , the datasets were linearly matched to the ASAR GM SSM dataset. The resulting bias-corrected RMSE highlights the random errors between the datasets. The RMSE was computed only for the areas with $R > -0.1$.
The evaluation metrics were assessed for different land cover classes. Based on our results, the mask of the soil moisture product was adapted.

## 4. RESULTS AND DISCUSSION

The correlation results are shown in Fig. 2, the white colour represents masked regions and, in case of AMSR-E maps, also areas with insufficient number of temporally corresponding data pairs for both satellites. The mean $R$ for the entire continent equals 0.35 and 0.34, respectively for AMSR-E and GLDAS-NOAH. The correlation map strongly corresponds to the precipitation patterns (Fig. 2, bottom). In detail, high correlations are found over areas with yearly rainfall exceeding 250 mm/year (mean $R$ = 0.58 for both reference datasets) whereas weak correlation (mean $R$ = 0) dominates over dry areas (precipitation < 250 mm/year). Even strongly negative correlation values are found over very dry areas. These corresponded to those with negative correlation between scatterometer and modelled SSM, yet the physical explanations remain unknown.

Apart from precipitation, the correlation results appear clearly stratified also by land cover classes. Tab. 2 shows the *R* values computed over different land cover types based on the USGS GLCC Land Use/Land Cover System. Strong mean correlation (R=~0.6) dominates over savannas, croplands or, in case of GLDAS-NOAH, over deciduous broadleaf forest. Savannas and croplands are characterized by less dense vegetation and regular rainfall, and therefore forms an ideal environment for remotely sensed soil moisture datasets. These results correspond very well to our findings over the Australian continent [10].

The *R* values close to 0 are found over desert area and also over the class 'Irrigated Cropland and Pasture'. A significant portion of this class is composed of the Nile Delta. Not surprisingly, a weak correlation (R < 0.3) is found also over wetlands where the change detection algorithm is hampered by regular flooding. The scrubland class according to USGS GLCC is very heterogeneous as it spreads over areas with average yearly rainfall between 100 and 500 mm/year. This causes the large range of *R* values between 0 to 0.6.

The mean unbiased RMSE value for both reference datasets equals to 12%. The white masked areas represent masked areas as well as areas that demonstrated R values < -0.1. The overall patterns of the RMSE (Fig. 3.) correspond to the precipitation forcing at a large scale and vegetation and geomorphological structures at medium (~1 km) scales. The RMSE values increase towards tropics and remain < 8% over dessert areas.

Expectedly, the *R* values remain low or insignificant over most of the desert areas due to the lack of soil moisture variability. RMSE thus appears to be a better evaluation measures over these areas.

| Land cover class | $R_{AMSR}$ | $R_{GLDAS}$ |
|---|---|---|
| Dryland Cropland and Pasture | 0.61 | 0.62 |
| Irrigated Cropland and Pasture | -0.06 | -0.15 |
| Cropland/Grassland Mosaic | 0.58 | 0.52 |
| Cropland/Woodland Mosaic | 0.59 | 0.60 |
| Grassland | 0.63 | 0.55 |
| Scrubland | 0.39 | 0.28 |
| Mixed Scrubland/Grassland | 0.56 | 0.57 |
| Savannas | 0.64 | 0.67 |
| Deciduous Broadleaf Forest | 0.44 | 0.66 |
| Evergreen Needleleaf Forest | 0.41 | 0.36 |
| Mixed Forest | 0.47 | 0.61 |
| Herbaceous Wetland | 0.17 | 0.30 |
| Wooded Wetland | 0.25 | 0.25 |
| Barren or Sparsely Vegetated | 0.01 | -0.06 |

*Table 2. The mean correlation coefficient between ASAR GM SSM and reference datasets for land cover classes from the USGS GLCC Land Use/Land Cover System.*

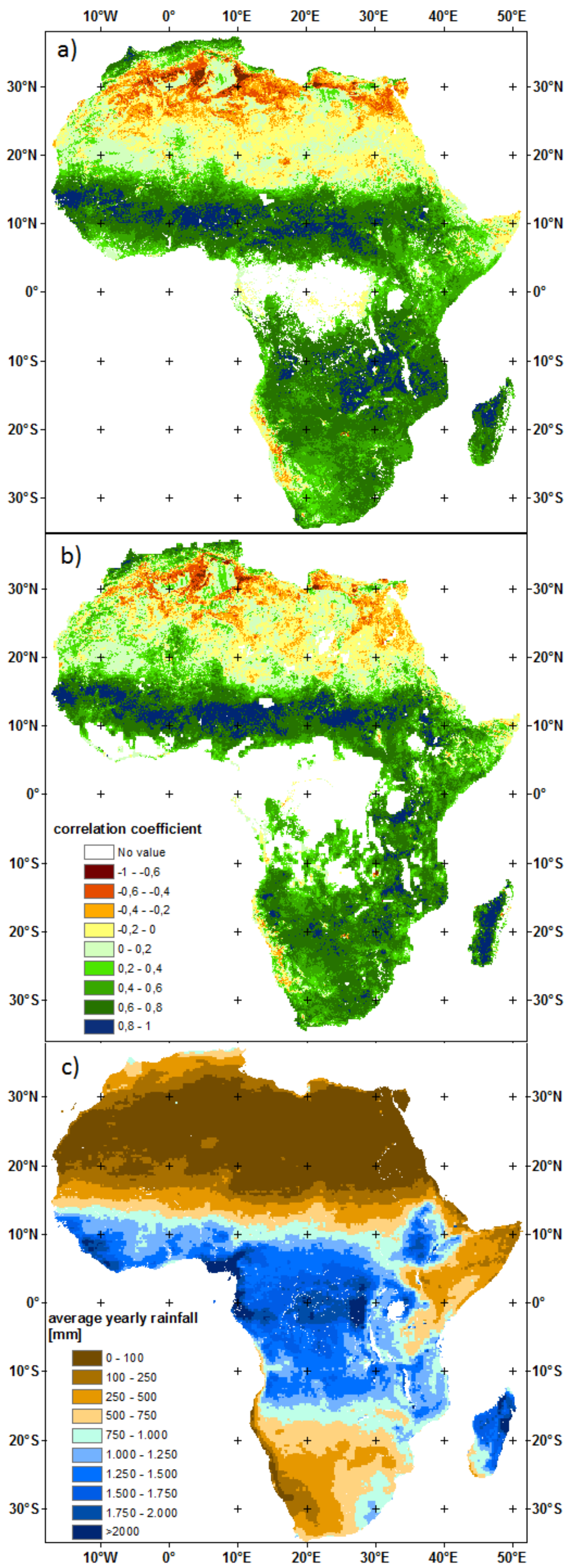


*Figure 2. The correlation coefficient between ASAR GM SSM and (a) GLDAS-NOAH SSM and (b) AMSR-E VUA SSM and (c) the average yearly rainfall computed from the TRMM monthly rainfall over years 2005-2011.*

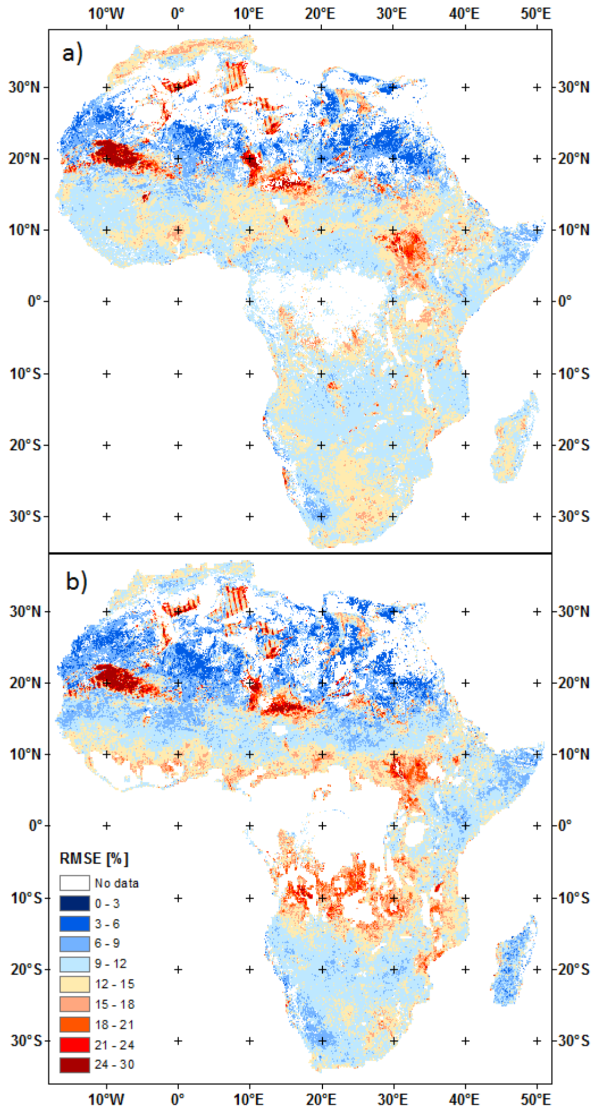


*Figure 3. The RMSE between ASAR GM SSM and (a) GLDAS-NOAH SSM and (b) AMSR-E VUA SSM.*

A high variation of RMSE over dessert regions is evident in Fig. 3. While in some desert regions the unbiased RMSE remains low as expected given the low soil moisture variations (< 8%, marked dark blue in Fig. 3.), the RMSE values can reach up to 20 to 35% elsewhere in the dessert (marked dark red in Fig. 3.). These variations are expected to be related to the geometrical distortions and noise of the ASAR GM data. To investigate this hypothesis, the analyses of the backscatter dependence on the local incidence angle are performed over both, areas with low RMSE (Fig. 4c.) as well as over areas with high RMSE (Fig. 4a. and 4b.) values. Fig 4a. represents an area with computed RMSE = 31%. Clearly, the backscatter from the descending and ascending modes of the ASAR GM suffer a bias that devaluates the data normalization fit and adds noise to the normalised data. Next, the exceptional high RMSE (23%) in Fig. 4b. is due to the sudden increases in the backscatter that occur at around 30° incidence angles and can be explained by the bragg scattering effect due to distinct geometry of the sandy dunes. Finally, the Fig. 4c. shows backscatter over desert region with unbiased RMSE < 8% where none of the above problems occurs. The same region is represented in Fig. 5 in form of time series and compared to the GLDAS-NOAH model. At this point, the R and RMSE between ASAR and GLDAS SSM equal 0.01and 4.2%, respectively. The time series reveals practically no variation in SSM in both modelled and the ASAR GM dataset.

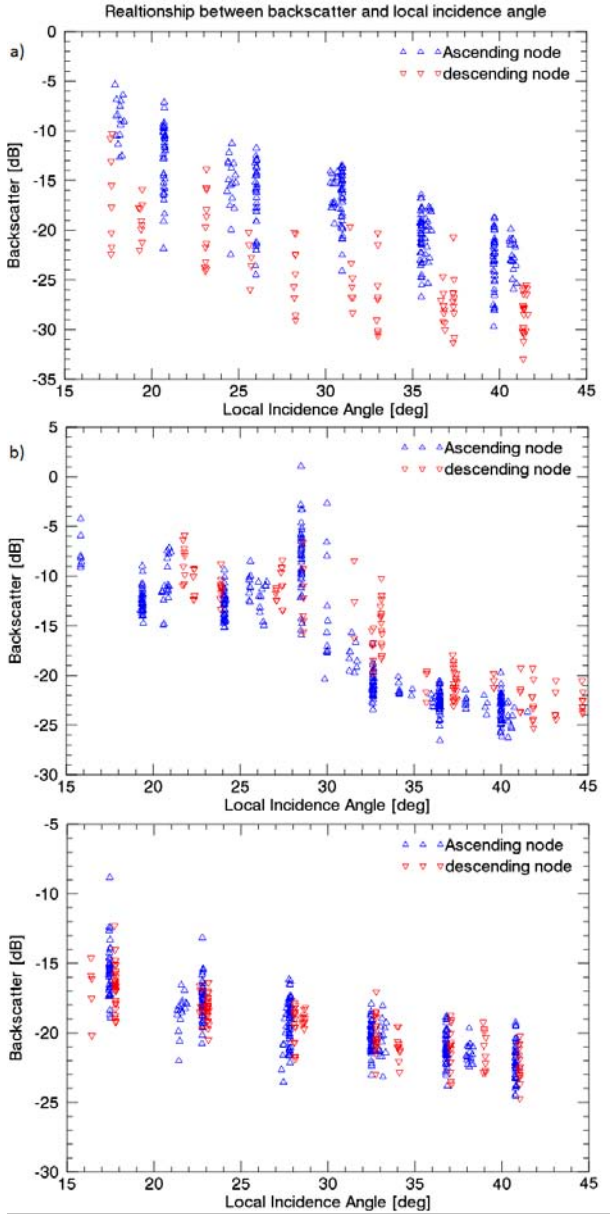


*Figure 4. The relationship between measured backscatter and local incidence angle of the SAR signal showing problems in the desert environments: a) dependency of the backscatter value on the orbit node, b) Bragg scattering from the sandy dunes and c) point without any of the mentioned geometrical distortions.*

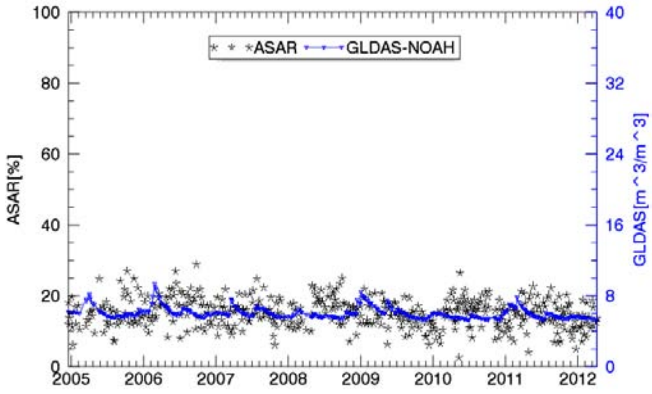


*Figure 5. Time series of ASAR GM SSM and GLDAS NOAH soil moisture at the point with R=0.01 and RMSE=4%.*

To resolve the two detected problems further investigations are needed. Meanwhile, one possible solution of the differing backscatter acquisitions between modes may be to perform the normalization procedure separately on both modes.

Motivated by the results of this study, we extended the mask of the ASAR GM SSM product by two additional classes: a) the regions with R < -0.2, computed using GLDAS-NOAH as a reference and b) the areas with strong geometric distortions defined using a mask derived from the ERS dataset based on the azimuthal anisotropy of the data. For area below 15° N, also mask based on scaling layer traditionally used for TU WIEN ASAR GM 1km SSM product was used. The scaling layer represents the measure of the temporal correlation between the backscatter intensities on the local (1km) and the regional (25km) scales [18]. The resulting masked surface soil moisture maps are shown in Fig. 6.

## 5. CONCLUSIONS

The evaluation of more than six years of ASAR GM SSM data over the African continent was performed for a large diversity of land cover classes and meteorological conditions using coarse resolution SSM datasets from the AMSR-E radiometer and GLDAS model as a reference. Over 18000 ASAR GM scenes were processed to achieve the spatio-temporal coverage. As expected, the best correspondence of the data was

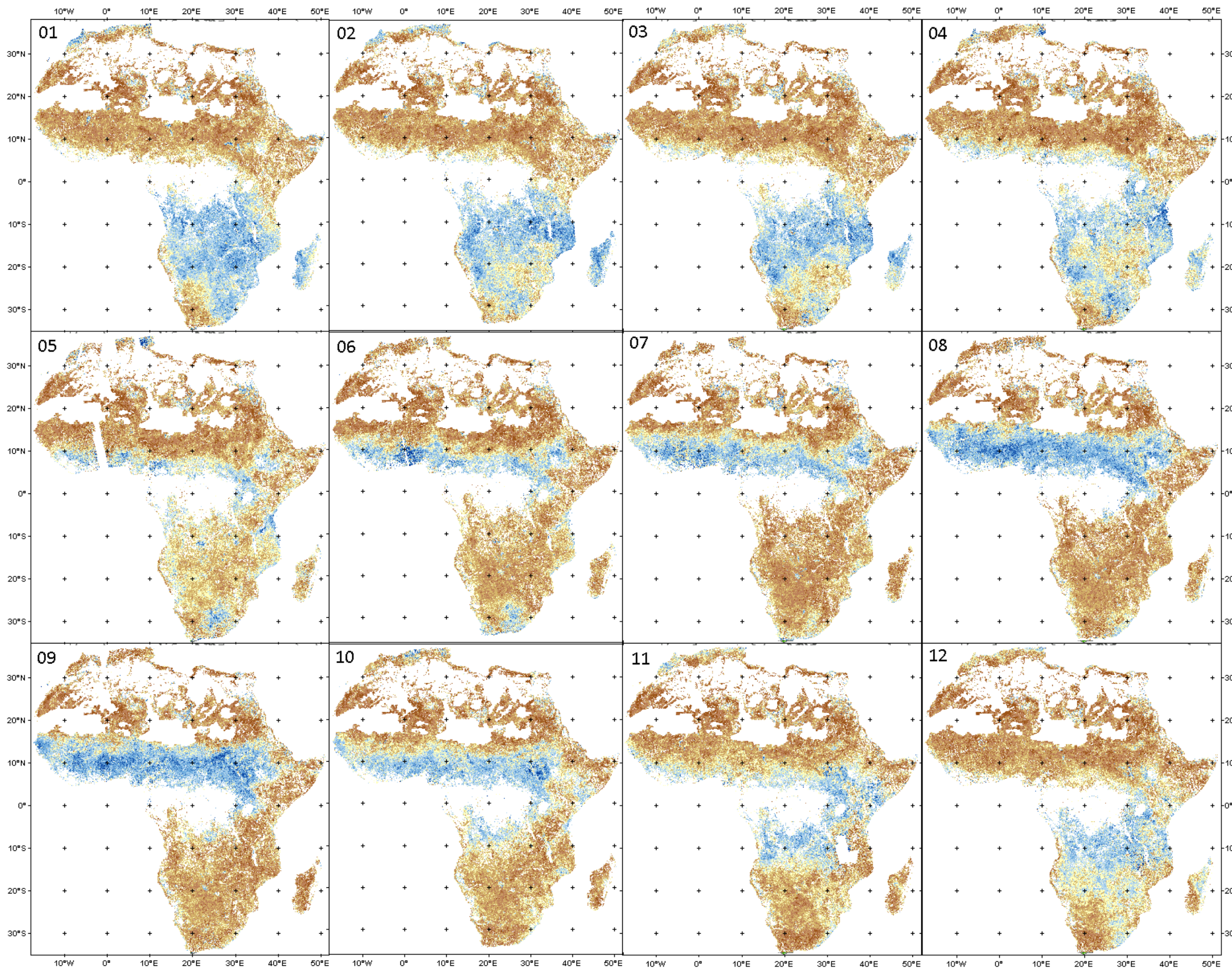


*Figure 6. The 1km ASAR GM surface soil moisture monthly composites from year 2011*

found over moderately vegetated regions with a strong annual precipitation cycle (e.g. savannas). Low or even negative correlation coefficients were found in extremely dry environments. This is in accordance with the global validation results of the scatterometer data as well as with prior evaluation studies of the ASAR GM SSM.

Three distinct problems in the ASAR GM SSM algorithm were detected during the evaluation process over Sahara. These include: a) an inverse behaviour of the ASAR GM backscatter to the reference causing negative correlation with both reference data, b) differences between the backscatter from the descending and ascending mode and c) a sudden increase in the backscatter around 30° due to the bragg scattering effect. These phenomenon require further research and are expected to bring improvements to the ASAR GM algorithm. Furthermore, the first problem was previously detected with scatterometer data. It is thus expected that the ASAR GM SSM data may bring better understanding of the problem also to the scatterometer SSM algorithm considering the high spatial resolution of the product that clearly defines the boundaries of the problematic areas.

The detected problematic areas were masked in the final product. Advanced methods will be investigated that are expected to improve the existing algorithm, overcome the addressed problems and consider also some of the currently masked data.

## 6. ACKNOWLEDGMENTS

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