An Observing System Simulation Experiment (OSSE) for the Aquarius/SAC-D soil moisture product

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Abstract— An Observing System Simulation Experiment for the Aquarius/SAC-D mission is being developed for assessing the accuracy of soil moisture retrieval from passive and active Lband remote sensing. The implementation of the OSSE is based on: a 1-km land surface model over the Red-Arkansas River Basin, a backscatter model and a forward microwave emission model to simulate the radiometer and scatterometer observations, a realistic orbital and sensor model to resample the measurements, and an inverse soil moisture retrieval model. The simulation implements zero-order radiative transfer model for emission and Dubois model for backscattering. Retrieval is done by direct inversion.

The Aquarius OSSE attempts to capture the influence of different error sources: land surface heterogeneity, instrument noise and retrieval ancillary parameter uncertainty. In order to assess the impact of these error sources on the estimated volumetric soil moisture, a quantitative error analysis is performed through the comparison between of footprint-scale synthetic soil moisture product and high spatial resolution degraded at coarse resolution 'true' soil moisture product. The root mean squared errors are evaluated for all the conditions.

Keywords- Aquarius; Observing System Simulation Experiment; soil moisture.

I. INTRODUCTION

An Observing System Simulation Experiment (OSSE) is a simulation designed to mimic as closely as possible a given satellite mission, in order to study one or several characteristics of its operation. In general, OSSEs are developed to study final product characteristics as a function of system characteristics. They are a useful tool to analyze the error budget of a given sensor from a system theory point of view, in order to identify areas where the error is large and can be reduced by relatively inexpensive means. In this paper, we used an OSSE of the Aquarius radiometer and scatterometer as an instrument to study soil moisture product errors as a function of the characteristics of the retrieval algorithm.

This OSSE includes four elements: 1) a land surface model (LSM) to generate 1-km resolution geophysical data fields; 2) a microwave emission and backscatter model (MEBM) to

simulate soil surface brightness temperature (Tb) and radar backscatter (σ^0) from soil properties at 1 km; 3) a system and orbital model (SOM) to simulate Aquarius measurements at 100 km (which includes instrument and acquisitions strategy artifacts); and 4) a retrieval model (RM) to estimate soil moisture from Aquarius measurements at 100 km and aggregated ancillary data.

Generally speaking, there are four different types of errors captured by the OSSE, which corresponds to four reasons why estimated soil moisture does not match the original ground soil moisture:

- 1) **Heterogeneity effects** i.e. sampling and nonlinearity effects associated with land surface heterogeneity and running the retrieval model at a coarser spatial resolution than forward model. These errors include gridding effects associated with the gain function and will occur even if no synthetic noise is added to any block of the OSSE system.
- 2) **Observation noise effects** errors that arise when adding synthetic noise to the footprint-scale Tb and σ^0 observations. These errors correspond mainly to system measurement errors.
- 3) **Retrieval parameter error effects** errors that arise when adding synthetic noise to the footprint-average retrieval parameters. These errors are related to uncertainties on the ancillary parameters needed in the retrieval block (e.g. vegetation water content, VWC).
- 4) **Forward/retrieval model incompatibilities** errors that arise when the retrieval model is structurally inadequate (e.g. use an advanced theoretical model as the forward model and then apply a retrieval based on the zero-order radiative transfer model).

Of course, real retrievals are degraded by all four effects. Nevertheless, using OSSEs outputs it is possible to study how simulated retrievals errors increase as each source is incrementally turned on. In this paper, we focused in the simulations corresponding to land surface heterogeneity effects (1), observation noise effects (2) and retrieval parameter error effects (3). Simulations are presented for all the cases, and a description of how errors evolve from case-to-case is also offered.

II. METHODOLOGY

A. Land Surface Model

High resolution geophysical variables used as the reference "true" fields needed for the simulation were generated via a land surface model (LSM) at 1 km spatial resolution within 250,000 km² Red-Arkansas River Basin (south-central US) for 4 months in summer of 1994. The static dataset used for the nature run include some microwave emission parameter variables (e.g. vegetation water content, *VWC*, and the assumed single scattering albedo). The three LSM predictions are: 0 to 5 cm integrated surface soil moisture in volumetric (m³/m³) units, surface "skin" temperature and 5-cm soil temperature. Outputs were generated at 6 p.m. local time in the Central US, corresponding to Aquarius ascending overpass time. Therefore, only ascending results were simulated and analyzed.

B. Microwave Emission and Backscatter Model

Radar backscattering and radiometer observations were simulated at Aquarius frequencies (1.26 GHz for scatterometer and 1.413 GHz for radiometer), polarization (h and v for radiometer and hh, hv and vv for scatterometer) and incidence angles (28.7° , 37.8° and 45.6° for inner, middle and outer beam) at 1-km spatial resolution. Radiometer brightness temperature was computed based on a zero-order radiative transfer model that includes vegetation and soil components as

where *p* refers to polarization, T_S is soil temperature, T_C is vegetation temperature, r_p is the soil reflectivity, θ is the look angle, τ is the nadir vegetation opacity and ω is the vegetation single scattering albedo. Vegetation opacity is assumed to be unpolarized and is defined as $\tau = bW$, where b is a land cover depending coefficient and W is vegetation water content (kg/m²).

The surface roughness effect over the modeled brightness temperature was approximated as $r_p=r_{sp}\exp(-h)$ where *h* is related to the root mean square surface height and r_{sp} is the reflectivity of the equivalent smooth soil surface. The radar backscatter model implemented is based on the sum of three components as [1]:

$$\sigma_{pq}^{t} = \sigma_{pq}^{s} \exp(-2\tau) + \sigma_{pq}^{v} + \sigma_{pq}^{sv}.$$
 (2)

where σ_{pq}^{t} represents the total radar scattering cross section, σ_{pq}^{s} is the soil scattering cross section two way attenuated by the vegetation, σ_{pq}^{v} is the vegetation volume scattering cross section and σ_{pq}^{sv} is the scattering interaction between soil and vegetation.

Inland water pixels were masked for the analysis.

C. Sensor and Orbital Model

The orbital model is based on a Matlab routine [2] that implements SGP4 orbit propagation. The synthetic 1-km Tb and σ are weighted by a sinc² function, a theoretical approximation of the Aquarius antenna patterns with matching 3 dB footprints. For each of the three beams, 1-km resolution gain patterns were projected on the ground. Patterns were rotated and located to move along with the satellite motion. Geolocation of observations was associated to the latitude and longitude of the center of the footprint. Spatially independent Gaussian noise with standard deviation of 1K for brightness temperature and 0.5 dB for backscatter was added to measurements at this stage when accounting for radiometer and scatterometer instrumental noise effect. Radiometer and scatterometer observations were then averaged to a time step of 1.44 s (i.e. 12 Tb samples and 8 σ^0 samples).

D. Retrieval Model

The OSSE implements a single channel retrieval algorithm to invert simulated brightness temperature and backscatter. This is accomplished by directly inverting radiative transfer model. Auxiliary data for estimating soil moisture are the ancillary parameters at footprint scale. These values are derived by aggregating high resolution layers used as inputs to the simulation.

To evaluate the effect of subfootprint-scale land surface heterogeneity, two methods of aggregating VWC were evaluated. Impact of linear averaging VWC and an aggregation alternative on soil moisture estimation was assessed through comparison of root mean square errors on retrieved values. Alternative aggregated VWC equation derived analytically from theoretical brightness temperature function [3] results as follows

$$VWC_{agg} = \left[\ln\left(\sum_{i=1}^{n} A^{VWC_i}\right) - \ln n\right] / \ln A.$$
 (3)

where A=exp(-2/cos θ), with θ Aquarius incident angle.

Uncertainties in footprint-scale ancillary parameters were accounted for by adding Gaussian noise to some OSSE's runs with standard deviation of 1K for T_S and T_C , 1% for *sand*, *clay* and *VWC*, and 0.005 for *b* and *h* (cm). Finally, soil moisture was achieved from reflectivity coefficient via Fresnel equations and Hallikainen soil dielectric empirical model.

E. Composite

To mimic Aquarius Level 3 processing, measurements at center of footprints location for the three beams were mapped onto a fixed 1° grid. Image pixels values were derived from sample points within 1° x 1° grid boxes. The sampling methods implemented to resample the data were nearest neighbor and a weighing function which depends upon the spatial location of each observation. Composite pixels may arise from observations of different beams.

III. RESULTS

Soil moisture was retrieved from April 2nd to July 30th 1994. Since Aquarius has a 7 days repeat pass, 17 weekly product images were obtained. Each 7-day retrieved soil moisture image was obtained through composing observations from 7 different days.

A. Total Error Analysis

OSSE's runs were done with single channel retrieval for the five Aquarius channels for the three different beams, with two alternatives aggregation strategies of VWC and two different soil moisture composites. For every run alternative, three outputs were obtained: no noise, adding Gaussian noise to temperature brightness and backscatter observations and finally adding Gaussian noise to ancillary parameters as well. For assessing the impact of these different error sources and be able to quantify their influence over the final product (weekly soil moisture at coarse spatial resolution), error metrics were taken into consideration.

For every output, correlation (ρ) between synthetic soil moisture and weekly-averaged "true" soil moisture degraded at coarse resolution, as well as root mean square error, *RMSE* (4), were computed.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (sm_{synthetic} - sm_{true\,aggregated})^2}$$
(4)

B. Averaged VWC vs. Aggregated VWC

Estimation of soil moisture was calculated via two different methods: linear averaging *VWC* among the $1^{\circ}x1^{\circ}$ grid box and an alternative aggregation (see Eq. (3)). Synthetic soil moisture was then gridded for the three beams and compared with degraded $1^{\circ}x1^{\circ}$ 'true' soil moisture.

Results suggested that linear aggregation of vegetation water content produced overestimation of soil moisture for heavily vegetated surfaces. Though, an alternative aggregation strategy gives rise to lower *VWC*, which turns over lower retrieved soil moisture. Nevertheless, this method resulted on an underestimation of the retrieved product with higher bias than linear averaging *VWC*.

Errors on synthetic soil moisture retrieved from radiometer and scatterometer observations due to vegetation water content were particularly different. Unlike radiometer results that showed biases on heavily vegetated areas, retrieval with scatterometer observations did not seem to have such strong dependency with *VWC*.



Figure 1. Error Metrics

C. Nearest Neighbor interpolation vs. Weighing Interpolation

The two different methods to obtain soil moisture imagery were evaluated for a weighing function such that,

$$Pixel value = \frac{\sum_{i=1}^{n} \frac{1}{dist_{i}} observ_{i}}{\sum_{i=1}^{n} \frac{1}{dist_{i}}} .$$
(5)

Furthermore, while the composite through many samples smoothed soil moisture, nearest neighbor was more sensitive to noise on retrieved soil moisture. Thus, composite through weighing function exhibited higher correlation between retrieved soil moisture and coarse resolution "true" soil moisture.

IV. CONCLUSIONS

Using an OSSE for Aquarius, this study evaluated the accuracy of retrieving soil moisture from radiometer and scatterometer simulated observations and the potential impact of different error sources over the final product. Nevertheless, product performance depends on interpretation of OSSEs results and error analysis. Different error metrics, as well as different objectives on the characteristics of the obtained imagery, will lead to different soil moisture maps. These latter should agree with users expectations.

After evaluating error metrics (correlation and RMSE), it has been showed that synthetic soil moisture retrieved from radiometer observations exhibited higher accuracy than retrieval from backscatter for all Aquarius channels (Fig. 1). In addition, error analysis of synthesized soil moisture among Aquarius three incidence angles suggested that middle beam with 38° incidence angle has highest accuracy. On the other hand, overpasses of the beams were at different locations and vegetation density over each ground track varied. In general, middle beam ground track passed over the center of the domain of the OSSE, where vegetation is less dense.

On the basis of this study, it can be concluded that single channel algorithm for retrieving soil moisture from brightness temperature observations displays high sensitivity to optical depth and vegetation water content aggregation technique. Moreover, results exhibited a bias on highly vegetated areas for synthetic soil moisture retrieved from passive microwaves. Aggregation of vegetation water content impact was stronger at denser vegetation, thus the bias on the retrieval is influenced by the aggregation strategy chosen for this parameter.

As regards radiometer channel polarization, soil moisture retrieved from vertical polarization brightness temperature showed highest accuracy than horizontal polarization. Presumably, this effect is due to the fact that the unpolarized vegetation parameter b layer used on the OSSE agrees better with vertical polarized b [4] which was higher than horizontal as a consequence of vegetation structure.

Concerning accuracy obtained through backscatter measurements, an analysis of variance between synthetic soil

moisture and aggregated at footprint-scale resolution 'true' soil moisture pinpointed vegetation water content had not substantial influence on radar sensitivity as did on radiometer. Soil moisture accuracy is most likely to be degraded by surface roughness and vegetation parameters in a complex manner [5].

Under the scope of this paper, both parameter uncertainty and instrumental were considered in both active and passive simulations. In both cases, the retrieval was found to be more sensitive to ancillary parameter errors than to added footprint-scale noise over observations.

This study focused the analysis on capturing the influence of different error sources over the retrieved soil moisture. OSSE's results were highly dependent on the retrieval algorithm used and its sensitivity to the parameters. However, errors arising from the fact that the retrieval model is a simplified approach to reality were not considered since the algorithm is the inverse of the forward model used as the 'truth'. In order to account for errors contribution of the single channel algorithm zero order radiative transfer model, a forward model different from the one used to retrieve soil moisture should be implemented.

The OSSE also attempted to evaluate and compare two different composing methods to obtain product imagery. Results suggest that, even though nearest neighbor interpolation kept the pixels values intact, this method is noisier than one that would smooth soil moisture over the 7days period of each image.

Finally, future work will focus on testing further composing and aggregation alternatives to improve obtained soil moisture quality.

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