INFERRING SOIL MOISTURE AND VEGETATION PARAMETERS FROM AIRBORNE AND SPACEBORNE RADAR DATA

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ABSTRACT

Most of the emphasis in active remote sensing of soil moisture has focused on higher resolution SAR data. We critically examine the existing soil moisture algorithms, and compare the performance of the different algorithms. In addition to these applications, we also examine the utility of low spatial resolution, high temporal resolution data from the dual polarization SeaWinds instrument on QuikSCAT satellite for soil moisture mapping. This instrument covers 92% of the globe in one day, with a resolution of 7 km by 25 km. Meteorological events derived from the QuikSCAT data will be compared with in-situ precipitation data.

INTRODUCTION

Soil moisture is a key parameter in numerous environmental studies, including hydrology, meteorology, and agriculture. It plays an important role in interactions between the land surface and the atmosphere, as well as in the partitioning of precipitation into runoff and ground water storage. In spite of its importance, soil moisture has not found a widespread application in the modeling of hydrological and biogeochemical processes and related ecosystem dynamics, in part because soil moisture is a difficult parameter to measure on a large area, cost-effective, and routine basis.

Several algorithms for inverting multi-parameter radar data for soil moisture and surface roughness from bare soil surfaces have been published in the past [1-3]. The algorithm proposed by Oh *et al.* [1] was derived empirically from data measured with a truck mounted scatterometer, and involves ratios of various polarization combinations. Dubois *et al.* [2] used the same data, plus data from truck mounted scatterometers measured by the University of Berne [4] over bare surfaces with a wide range of surface roughnesses to derive an empirical algorithm that uses HH and VV polarization combinations at L-band. Shi *et al.* [3] generated a synthetic data set using the Integral Equation Method (IEM) model [5] and then derived a set of coefficients to parameterize their synthetic data set. These parameters were then used to invert AIRSAR and SIR-C data. As in the case of Dubois *et al.,* [2], the algorithm proposed by Shi *et al.* [3] uses a pair of measured radar cross-sections to estimate the surface dielectric constant and a roughness parameter. Both these algorithms have been applied to data acquired from space during the SIR-C mission, and have shown accuracies on the order of 4% when estimating volumetric soil moisture from SAR data.

High resolution SAR data allow the detailed study of small-scale soil moisture variations. The drawback, however, is that SAR data, especially spaceborne SAR data, are typically not acquired with the temporal frequency that would allow the study of the temporal evolution of soil moisture. To address this aspect of soil moisture measurement, we investigated the use of spaceborne scatterometer data for soil moisture inversion.

The QuikSCAT satellite was successfully launched at 7:15 p.m. Pacific Daylight Time on 19 June 1999 from the Vandenberg Air Force Base in California. The satellite carries the SeaWinds scatterometer for ocean wind measurements. The scatterometer has been collecting data at 13.4 GHz on both ocean and land. Backscatter data, at a radiometric resolution of 7 km x 25 km, are acquired with the vertical polarization at a constant incidence angle of 54°

over a conical-scanning swath of 1800 km, and with the horizontal polarization at 46 ^{o} over a 1400-km swath. The large swath can cover almost the entire globe in 2 days even at low latitudes and equatorial regions. The satellite orbit was stabilized, the scatterometer performance was verified, and the calibrated science data have been obtained since 19 July 1999 [6].

COMPARISON OF SOIL MOISTURE ALGORITHM PERFORMANCE

We compare the accuracy of the inversions from the three algorithms mentioned earlier by using a synthetic data set generated using the IEM model published by Fung *et al.* [5]. The characteristics of the data set are as follows:

1. Incidence angle is arbitrarily fixed at 40 degrees
2. Frequency is L-band
3. Soil moisture is varied in 5% steps between 2.5% and 37.5%
4. Four different values of kh are used: 0.1, 0.5, 1.0 and 2.0

The inversion results are shown in Figure 1 below. For smooth surfaces, both the small perturbation model and the Shi *et al.* model show excellent accuracy. However, when the surfaces become rough, both these models significantly underestimate the moisture, giving poor results. The model by Oh *et al.* seems to underestimate the moisture consistently for wetter surfaces, and overestimates the moisture consistently for drier surfaces. For the extreme rough surface case, this model fails to produce any results.

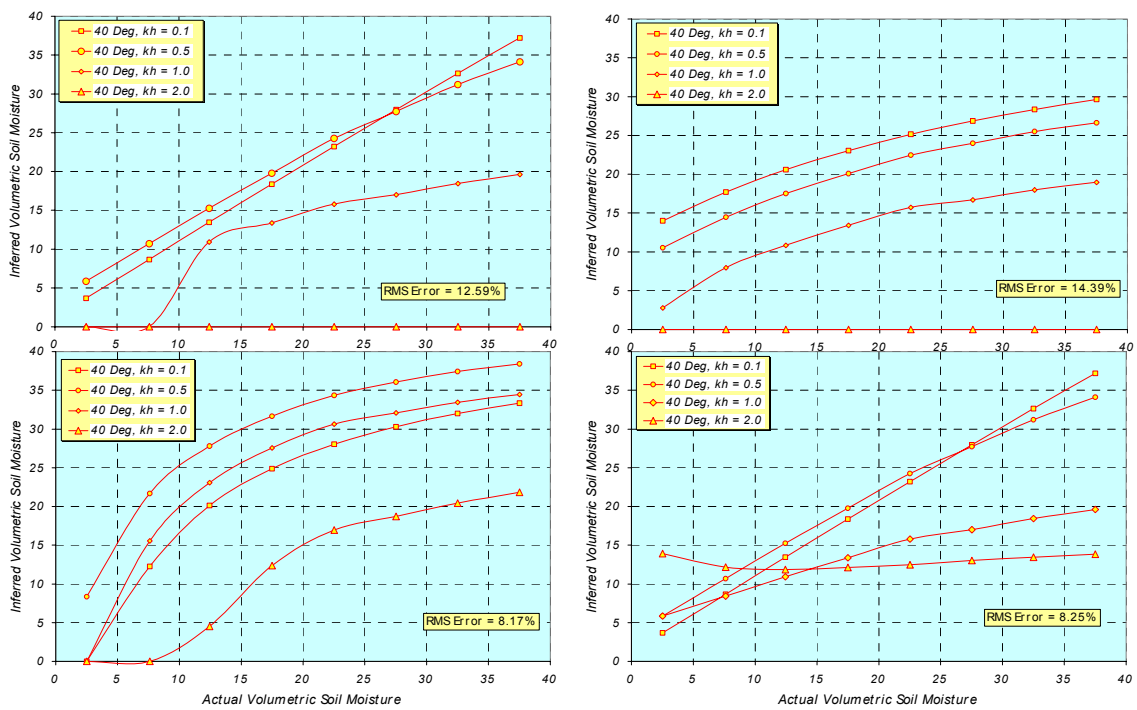

Figure 1. Comparison of the inversion results suing a synthetic data set. The upper right figure shows the results for the Oh *et al.* model, the lower left those for the Dubois *et al.* model, and the lower right those for the Shi *et al.* model. For comparison, the upper left graph also shows the results for the small perturbation model.

The Dubois *et al.* model in essence is a linear approximation to the non-linear variation of the radar cross-section with moisture. As a result, the estimated moisture clearly shows this residual non-linearity as a function of moisture. This model is also a linear approximation to the non-linear variation of radar cross-section with roughness, and as a result, there is a non-linear residual error with roughness. Overall, though, this model provides reasonable results over all the parameters used in the simulation. This model provides the best accuracy when the surface is rough, while either the small perturbation model or the model by Shi *et al.* provides the best accuracy for smooth surfaces.

SCATTEROMETER DATA

As an illustration of the utility of the SeaWinds data to soil moisture measurements, we compare the observed scatterometer data to measured precipitation data at Station Pietersburg in South Africa. The backscatter in Figure 2 shows an unchanging low level from July to early October 1999 corresponding to the dry period as indicated by the precipitation data. In late October 1999, a backscatter peak is observed in correlation with precipitation events as observed in Figure 2. Then the backscatter increases and maintains at a high level until February and March 2000 corresponding to the rain season there. After March 2000, the backscatter shows some decreasing trend, which agrees with decreasing precipitation during the same time period. Figure 2 shows that the transient short-time scale events such as those in early June are seen in both backscatter and precipitation data.

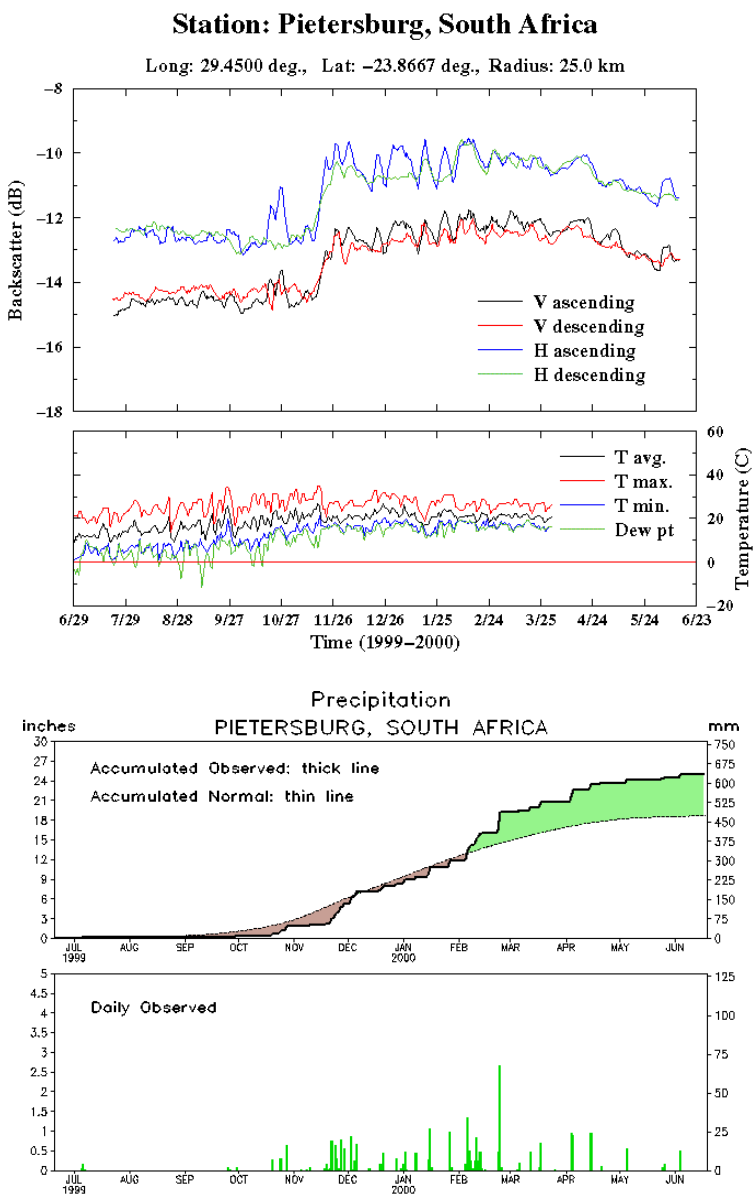

Figure 2: Time-series backscatter and *in-situ* precipitation data at Pietersburg, South Africa.

The results in Figure 2 show a number of important aspects. First, and quite surprising, the Ku-band scatterometer data show significant correlation with *in situ* precipitation data. Conventional scattering models suggest that the Ku-band signals will be severely attenuated by even a moderate vegetation canopy, and hence one would expect little to no sensitivity to the underlying soil moisture. We are quite confident that the observed backscatter spikes are not due to

increased vegetation water content, as there is no observable time delay between the observed precipitation event and the backscatter spike. That the Ku-band backscatter is affected by the presence of the vegetation is also observed in Figure 2. Note that during the summer rainy season, the backscatter signal is generally elevated. This is most likely due to scattering by a combination of the increased amount of vegetation and the elevated vegetation water content. At the same time, we observe that during this period, the backscatter spikes due to precipitation events are significantly smaller in magnitude compared to those at the end of the dry season in late September and October. We conclude that even though the Ku-band signal is attenuated by the vegetation, a large enough fraction of the area covered by a resolution cell has a thin enough vegetation cover so that the resulting backscatter still shows significant sensitivity to soil moisture. There is no question, though, that the sensitivity to moisture is diminished during the rainy season.

The second aspect that is clear from Figure 2 is that the effect of a precipitation event on the radar backscatter is only on the order of a few days, most of the time less than about three to four days. It is therefore possible to decompose the total backscatter time series into two components; a short-term transient response to meteorological events, and a longer term seasonal component that is governed by both seasonal variations in soil moisture and vegetation water content. A complete understanding of these different components can only be gained by frequent temporal sampling such as that provided by the QuikScat satellite.

SUMMARY

We compared the accuracy of soil moisture inversion algorithms using data simulated by the IEM model. The results show that the algorithm proposed by Shi *et al.* are the most accurate when the surface is relatively smooth, although the results in that case are quite similar to that of the small perturbation model. For rougher surfaces, the algorithm proposed by Dubois *et al.* seems to be the most accurate.

We also showed some examples illustrating strong correlation between the observed backscatter from the SeaWinds instrument on the QuikScat satellite and *in situ* data at Pietersburg, South Africa. While space permits us only to show that one example, we have seen similar correlations at many other stations where *in situ* data are available. Future work will concentrate on separating short term meteorological information from longer term seasonal information in the SeaWinds backscatter data.

ACKNOWLEDGMENT

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