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Evaluation of satellite soil moisture retrieval algorithms using AMSR-E data

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Since soil moisture is a key variable in interactions between land surface and atmosphere it is important to create large-scale, long-term soil moisture datasets. Microwave remote sensing can be an important tool to do this. In this study, three soil moisture retrieval algorithms designed to retrieve soil moisture from AMSR-E are evaluated using two validation datasets. Two of these algorithms only use AMSR-E brightness temperature as input, the third one uses an additional vegetation dataset. The amount of parameters needed for validation differed strongly between the algorithms. Results indicated that all algorithms yielded reasonable results, but the use of extra vegetation data proved to be an essential advantage and significantly improved the overall estimations. However, additional datasets and validation parameters make it hard to apply an algorithm at large scales.

Introduction Soil moisture is a key variable in the interaction of land surface and atmosphere. Therefore, to monitor environmental changes like climate change, soil moisture needs to be monitored over extensive areas and periods of time. Spaceborne passive microwave remote sensing can be a powerful tool to achieve this and therefore various sensors of this type and algorithms to retrieve soil moisture from them have been proposed (Njoku *et al.*, 2003; Koike *et al.*, 2000). In this work three retrieval algorithms using brightness temperature data of the Advanced Microwave Scanning Radiometer (AMSR) (Kawanishi *et al.*, 2003) are evaluated and tested on two different validation datasets.

Microwave remote sensing and soil moisture Microwave remote sensing is suitable for large-scale soil moisture remote sensing because it is independent of cloud cover and solar illumination. Due to the higher sensitivity to soil moisture and larger penetration depth, sensors operating at low frequencies are the most suitable for soil moisture remote sensing. Also, there is less influence of atmosphere and vegetation. Soil moisture retrieval is based on the Radiative Transfer Equation (Jackson, 1993):

$$T_B = \Gamma \cdot e_r \cdot T_S + (1 - \omega)T_C(1 - \Gamma) + (1 - e_r)(1 - \omega)T_C(1 - \Gamma)\Gamma \quad (1.1)$$

where T_B is the brightness temperature, T_S and T_C are temperatures of soil and canopy respectively (all in K), ω is the single scattering albedo [-], e_r is the surface emissivity [-] and Γ is the canopy transmissivity [-] that can be described by:

$$\Gamma = \exp\left(\frac{-\tau}{\cos(\theta)}\right) \quad (1.2)$$

where τ is the optical depth of the vegetation and θ is the viewing angle of the satellite. ω is very small at microwave wavelengths and can be neglected. e_r depends on surface roughness and soil moisture content. The first is corrected for by means of the approach of (Choudhury *et al.*, 1979) and soil moisture can be derived from the corrected emissivity by the Fresnel equation and a dielectric mixing model such as Wang and Schmugge (1980). Three retrieval algorithms are evaluated in this work:

- the Jackson algorithm (Jackson, 1993) solves the inverted version of (1.1) and needs extra vegetation information (e.g. a vegetation index) to estimate τ . Temperatures of surface and canopy are assumed equal and derived empirically from a high frequency AMSR-E channel (de Jeu, 2003).
- the de Jeu algorithm (de Jeu, 2003) solves (1.1) iteratively using two T_B channels for vegetation optical depth and surface emissivity simultaneously. Temperatures are derived similar to the Jackson algorithm.
- the Wen algorithm (Wen *et al.*, 2003) also solves (1.1) iteratively, however the solved quantities in this case are surface temperature and surface emissivity.

Validation datasets The first validation dataset that was used was the Mongolia Match-up dataset (Kaihatsu, 2003). The dataset covered an $2.5^\circ \times 2.5^\circ$ area in central Mongolia and ran from 1 July 2002 to 21 September 2002. Ground observations were available on a daily base at 12 locations at a depth of 3 cm and for the Jackson algorithm vegetation information was derived from MODIS EVI*.

The second dataset, from SMEX02 (HRSL, 2002), took place in a study area around Ames, Iowa, USA between 25 June 2002 and 12 July 2002. In this case daily ground observations at 47 locations for the upper 6 cm of the soil profile were available. For the Jackson algorithm observations of the Vegetation Water Content were used to derive the transmissivity. Since Iowa is relatively densely populated the C-band of AMSR-E interfered with radio traffic (Li *et al.*, 2004). Therefore for this dataset the X-band channel of AMSR-E was used.

Results As far as the Mongolian dataset is concerned, from Table 1.4 it appears that observations were mostly overestimated. As can be seen in Figure 1.18, this was mainly due to peaks in the estimations that corresponded to rainfall events. The reaction to these events was different; the effects of rainfall were longer visible in the observations than in the estimations. A possible explanation for this is the fact that observations took place at a depth of 3 cm, while the observing depth at C-band is only in the order of ± 1 cm. The rainfall peaks also explain the low errors of the Wen algorithm: the values at the peaks were lower than for the other algorithms. To the end of the simulation the estimations of the de Jeu and Wen algorithms increased compared to the Jackson algorithm and the observations: this is due to a decrease in T_B values. However, also the vegetation density dropped steeply. This explains the lower values of the Jackson algorithm which reacted also to changes in vegetation, while the other algorithms merely responded to T_B input.

For the SMEX02 dataset, there was a large difference in performance between daytime and nighttime (Table 1.4). Especially the de Jeu and Wen algorithms performed better at night, which is surprising because observations took place at daytime. However, from Figure 1.19 it appears that most of the error in the daytime overpasses came from days at the end of the period. Again, this was due to the high vegetation density; the Jackson algorithm used vegetation information, therefore its bias and SEE were lower. The fact that the algorithms performed better at night can be

*<http://tbrs.arizona.edu/project/MODIS/evi.php>

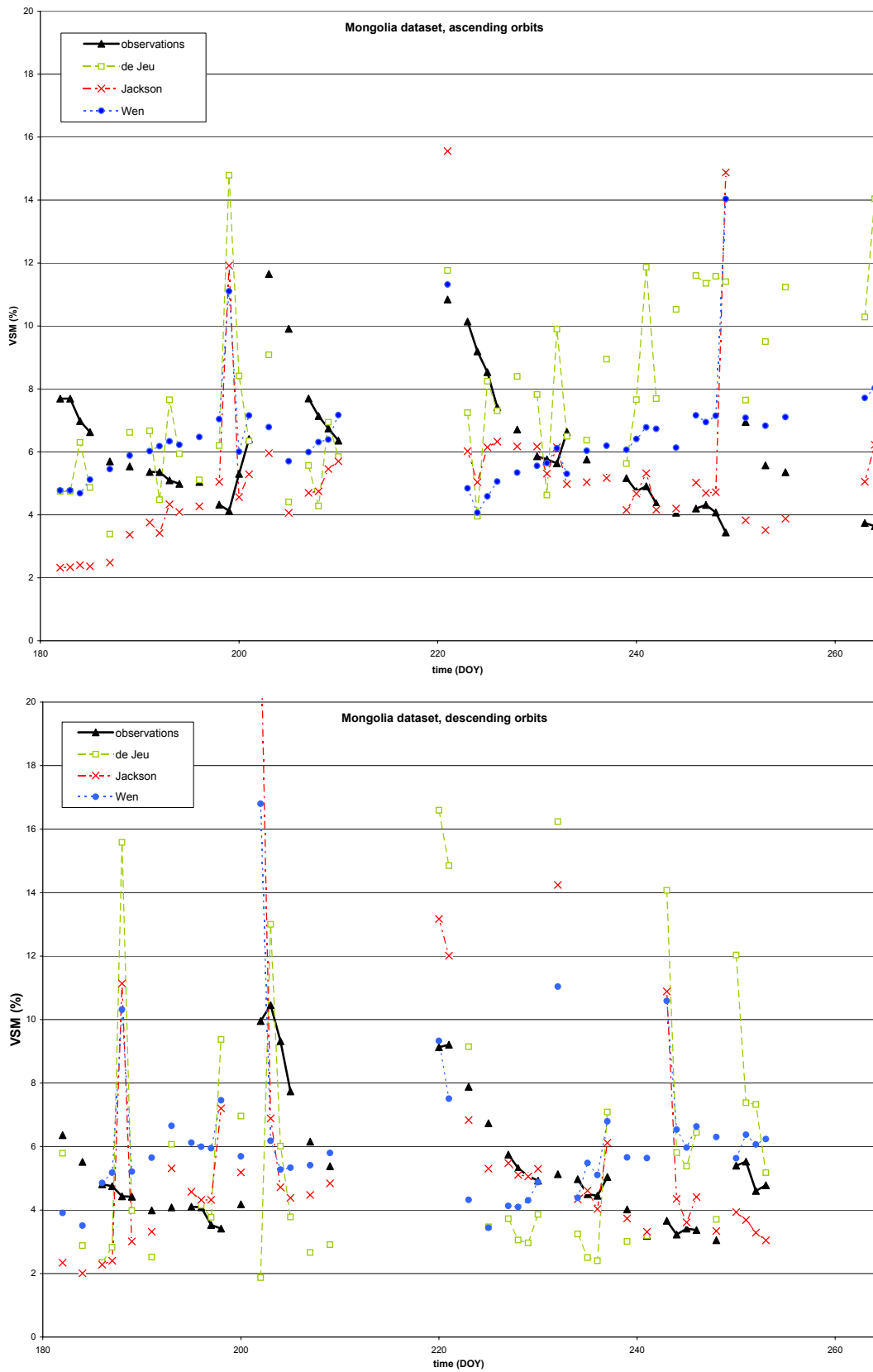


Figure 1.18: Observed and estimated soil moisture content for the Mongolian data. The upper plot shows daytime (ascending) overpasses, the lower plot nighttime (descending) overpasses.

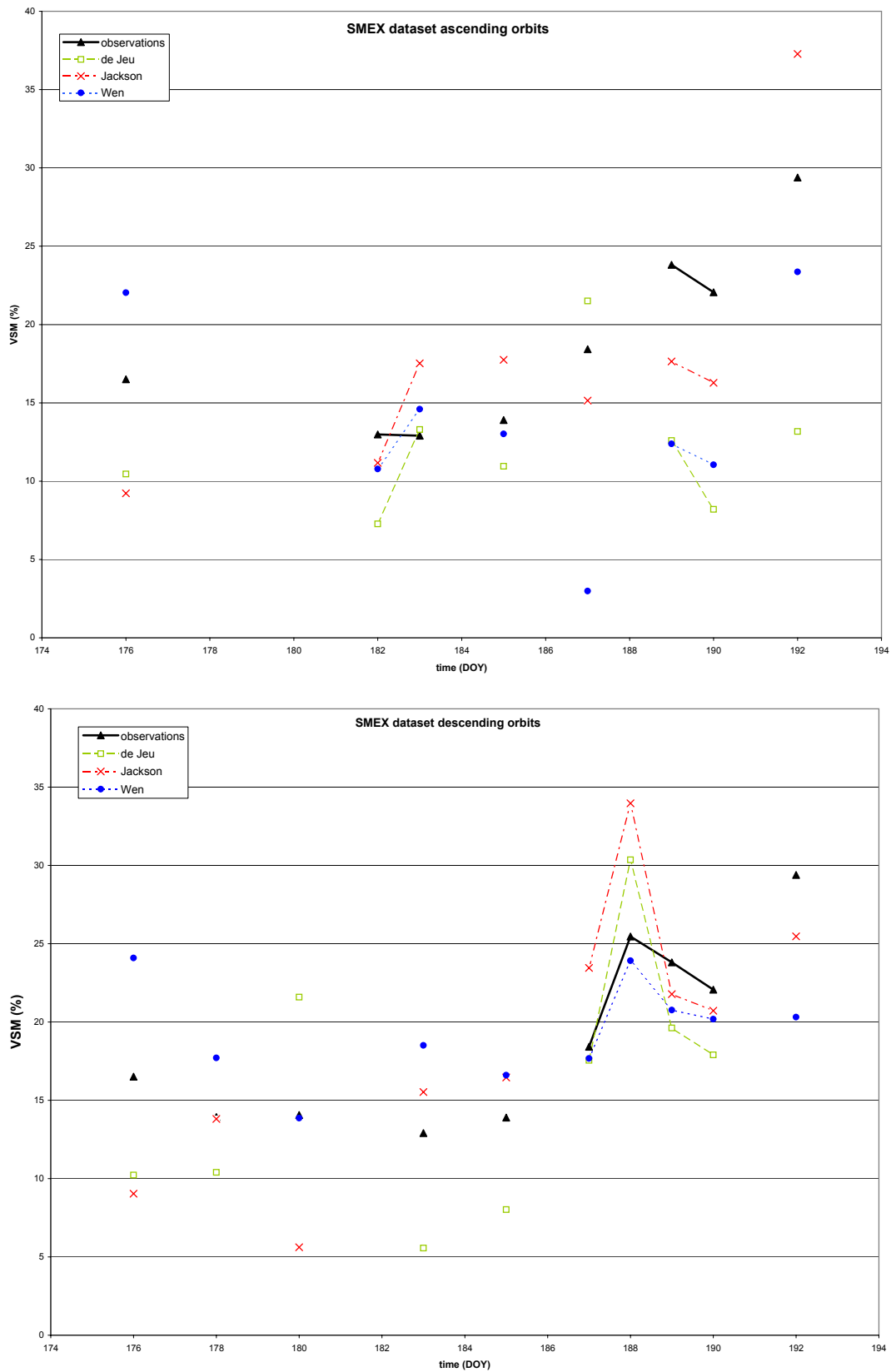


Figure 1.19: Observed and estimated soil moisture content for the SMEX02 data. The upper plot shows daytime (ascending) overpasses, the lower plot nighttime (descending) overpasses.

Table 1.4: Standard Error of Estimation (SEE) and Bias of estimated soil moisture content (estimation minus observation) for the three algorithms, for both daytime and nighttime observations and both datasets.

Mongolia	Daytime overpasses		Nighttime overpasses	
	Bias	SEE	Bias	SEE
Jackson	-0.9144	3.2350	0.3605	3.3799
de Jeu	1.6498	4.1958	0.8072	4.1643
Wen	0.3803	2.9482	0.8995	2.8369
SMEX02	Daytime overpasses		Nighttime overpasses	
	Bias	SEE	Bias	SEE
Jackson	-0.9989	5.4405	-0.4636	5.0948
de Jeu	-6.5661	9.1403	-2.2169	5.1203
Wen	-4.9727	8.4073	0.3156	4.5683

explained by the shallow viewing depth at the frequency used to determine the surface temperature (Ka-band): considering the dense vegetation the canopy temperature was measured rather than the surface temperature. In daytime the surface temperature was higher than the canopy temperature, at night the difference was smaller and the estimates were therefore more accurate.

Conclusions Overall it can be concluded that all algorithms gave reasonable results after validation to each dataset, but the additional vegetation information appeared to be an essential input to a retrieval algorithm. The Jackson algorithm yielded better overall results (considering both datasets at day- and nighttime) because of this advantage. The amount of validation to obtain good results differed strongly per algorithm, especially the Wen algorithm required many frequency and area specific parameters, while the de Jeu algorithm required hardly any validation at all. Also the Jackson algorithm made use of several parameters in addition to the vegetation data. This makes the de Jeu algorithm the most applicable for large-scale (global) applications. Finally, the datasets that were used were not ideal for soil moisture retrieval, but they were very different in terms of vegetation density which made them suitable testcases.

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