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Biogeosciences Discussions

Interactive comment on "Assimilation of Soil Wetness Index and Leaf Area Index into the ISBA-A-gs land surface model: grassland case study" *by* A. L. Barbu et al.

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The authors thank the anonymous reviewer #2 for his/her review of the manuscript and for the fruitful comments.

COMMENT 1. The paper seems to suggest (cfr. first sentence in the conclusion) that it is the first in its kind in which both variables are assimilated. However, Pauwels et al. (2007) did something very similar. I suggest to the authors to reference to this paper and maybe validate whether similar conclusions can be drawn.

RESPONSE 1:

Indeed, the first sentence of the Conclusion Section may be confusing. We wanted to underline the originality of SWI assimilation and not the combined assimilation of soil moisture and LAI. We shown that the use of the SWI product provided by an exponential filter was a challenging task from the assimilation point of view. In order to clarify this aspect, the sentence will be rephrased.

The work mentioned by Reviewer #2, Pauwels et al. (Water Res. Research, 43, W04421, doi:10.1029/2006WR004942, 2007), consisted in an assimilation study of near-surface soil moisture and LAI using a coupled hydrology-crop growth model. The objective was to assess to what extent the use of both sources of information could lead to an improvement of model results. Pauwels et al. (2007) underlined the positive impact of assimilation on the simulated soil moisture and LAI. The conclusions are similar to other referred studies (Sabater et al., 2008; Albergel et al., 2010), including ours.

An important issue in data assimilation is the characterization of model and observation errors. Pauwels et al. (2007) used synthetic observations with different degrees of uncertainties in order to assess whether a high observational error is still useful for assimilation. The overall conclusion is that even with large uncertainties (0.1 m3/m3 for soil moisture and 1 m2/m2 for LAI), observations from both sources are beneficial to the model simulations.

In our study, in situ data were assimilated in a land surface model that takes into account the dynamic evolution of vegetation. Our approach was to gain insight of the uncertainty settings, under realistic conditions. Several error variances for both the model and the observations were tested and validated by using a posteriori diagnostics. The objective was to calibrate these parameters to achieve the best possible filter performance. However, the choice of the observation errors seems to be in agreement with the limit values proposed by Pauwels et al, 2007 (0.5 m2/m2 and 0.05 m3/m3 for LAI and soil moisture, respectively). Above these limits, changes in observation errors have little impact on the filter performance.

The paper will be cited in the revised Introduction Section.

COMMENT 2: It is not really clear to me why the authors chose for the Extended Kalman Filter. This type of filter is not used very much. In literature, one finds more references to the Ensemble Kalman Filter. Can the authors argument why they chose for this filter (and furthermore why a simplified version)?

RESPONSE 2:

The choice of a specific filtering method was not clearly presented in the manuscript. We will therefore add a number of comments in Introduction and Section 2.3 of the revised manuscript that we think are suitable to support our choice, as follows:

The EKF was used in a number of papers for land data assimilation applications (Walker and Houser, 2001; Sabater et al., 2007 ; Draper et al., 2009; Seuffert et al., 2004, Drusch et al., 2009 ; Albergel, 2010). They show that this filter can produce satisfactory estimates of soil moisture.

The performances of the EKF and of the EnKF for soil moisture estimation were compared by several authors (Sabater et al., 2007 ; Reichle et al., 2001). Results are rather similar, but the computational cost of the EKF is generally lower. The computational effort of a filter is an important aspect for operational applications and monitoring activities. Our LDAS should be able to incorporate near-real time satellite data at regional or global scale. For the EKF, the cost involved in computing the Jacobian for a state vector of dimension 2 (our case) corresponds to an ensemble of 2+1 members. However, for a such small number of ensemble members, the performances of the two filters are comparable (Reichle et al., 2001).

For off-line applications, the EnKF could be a worthy alternative to the EKF due to its larger flexibility in representing various types of model errors. At the same time, the calibration of the EnKF could be a complex issue (size and type of perturbations required for the ensemble generation, number of ensembles, correlation time of the model er-

rors). Tests of an EnKF with the ISBA-A-gs model revealed that filter parameters such as the inflation factor are quite sensitive and need to be carefully tuned (Sabater et al., 2007 ; Mahfouf, 2007).

In this study, we assumed a static behaviour of the background error matrix B, that is considered constant at the beginning of each analysis step. This assumption is based on the fact that the increase in the background error during each forward propagation step is balanced by the decrease of the error through the previous analysis step. Moreover, the results obtained by Sabater et al. (2007) over the SMOSREX site suggested that the analysis is more stable and accurate by using a fixed background error. It resulted in a Simplified Extended Kalman Filter (SEKF) algorithm described by Mahfouf et al. (2009) and successfully used for the assimilation of near-surface soil moisture by several authors, e.g. Draper et al. (2009), Albergel et al. (2010).

COMMENT 3. The paper mentions that there are quite often biases to be seen between observations and model results. However, the filtering algorithm doesn't take a bias correction into account. I suggest that the authors would better comment on this issue and refer to literature in which it is tried to address this problem.

RESPONSE 3

Yes, data assimilation techniques are designed to correct random errors in the model and do not take into account a bias correction.

Many studies involving LSM evaluations indicated the presence of systematic biases between the observations and the model outputs for soil moisture (Walker et al. (2003) ; Walker and Houser (2004), De Lanoy et al. (2007)) and LAI (Jarlan et al. (2008) ; Lafont et al. (2010)).

Several authors pointed out the need of rescaling the information before assimilation (Reichle et al.,2004; Drush et al., 2005 ; Crow et al., 2005).

Even after quality control and calibration, under the conditions of an existing bias-free observational system, incorrect model parameterization and uncertain model inputs cause the presence of a systematic bias in the model forecast for both soil moisture and LAI. This bias should not be neglected since it has been shown by Dee and Da Silva (1998) that a biased forecast causes a biased update. For example, in this study, it was noticed that after the assimilation of an LAI observation, the model tends to drift back to a biased state. On one hand, this suggests that the model itself should be improved through enhanced parameterizations or parameter tuning. On the other hand, this is an indication that the bias should be included in the analysis system as demonstrated by Drécourt et al. (2006), De Lanoy et al. (2006), (2007). This can be a subject for a future work.

In the revised manuscript, Section 4 and Conclusions will be modified (new paragraphs and references will be added) to include this discussion on the bias issue.

Interactive comment on Biogeosciences Discuss., 8, 1831, 2011.