Fairbairn *et. al.*, (2016):
http://www.hydrol-earth-syst-sci-discuss.net/hess-2016-195/
Response to comments from Referee 1

July 26, 2016

Firstly, we would like to thank the reviewer for his/her constructive comments. A point by point response is given below.

Response to specific comments:

1. P2 l34 "especially near soil moisture thresholds" do you mean wilting point and saturation values? If so best to expand sentence.

   Response: Yes. We will replace "especially near soil moisture thresholds" with "especially near the wilting point and field capacity thresholds".

2. P5 l17 "The original ASCAT values are converted into SSM values..." My understandiing is that this is not correct, the ascat backscatters are converted into a soil wetness index. Is this what is assimilated in your experiments?

   Response: In order to explain this more clearly, we will replace lines 17-12 (starting with "The original ASCAT values...") with the following: "The original ASCAT values are converted into the surface degree of saturation (SDS, with values between 0 and 1) using a change detection technique, which was developed at the Vienna University of Technology (Tu-Wien) and is detailed in Wagner *et al.* (1999); Bartalis *et al.* (2007). The historically lowest and highest backscatter coefficients are assigned values for dry and saturated soils respectively. The Copernicus Global Land Service then calculates the surface water index (SWI) by applying a recursive exponential filter to these SDS values (Albergel *et al.*, 2008) using a time-scale that may vary between 1 and 100 days. The SWI represents the soil wetness over the soil profile and also has values between 0 (dry) and 1 (saturated). The longer the time-scale of the exponential filter, the deeper the representative soil profile. In this study we use a time-scale of one day (SWI-001 product), which represents the SWI for <5 cm of soil. We then interpolate the SWI-001 data to the 8 km resolution model grid. As in Draper *et al.* (2011) an additional screening step is performed to remove observations with an altitude greater than 1500m, frozen regions and areas with an urban fraction greater than 15%."

As mentioned in lines 24-31, we apply a linear rescaling to the SWI-001 data, which scales them such that the mean and standard deviations match the WG1 layer climatology (Calvet and Noilhan, 2000; Scipal *et al.*, 2008). The rescaling is designed to remove biases between the model and the observations and in the process the SWI-001 data are converted into the same units as the model, expressed in volumetric soil moisture (m^3/m^3). These rescaled SSM observations are assimilated into the WG1 model layer.

3. Section 2.3 Data Assimilation. Good explanation of background and observation errors for LAI, but no mention of the errors assigned to the ASCAT data. In particular, I would be interested to know if you inflate the errors to account for the oversampling issue, i.e. the same ASCAT obs covers several gridpoints.

   Response: On page 7, line 14 we mentioned that the SSM observation error is prescribed a value of $0.4(w_{fc}\text{-}w_{wilt})$, where w_{fc} is the field capacity and w_{wilt} is the wilting point (note there is a typo, we will replace "WG1" with "SSM"). The scaling by $(w_{fc}\text{-}w_{wilt})$ assumes that there is linear relationship between the soil moisture errors and the dynamic range (Mahfouf *et al.*, 2009). Averaged over France, this observation error is equal to 0.034 m^3/m^3. This underestimates the median SDS estimated error of 0.05 m^3/m^3 by Draper *et al.* (2011). We have therefore rerun the LDAS2 experiments, but with a larger SSM observation error standard deviation of $0.65(w_{fc}\text{-}w_{wilt})$. This averages to 0.055 m^3/m^3 over France. We used a slightly larger value than Draper *et al.* (2011) in order to account for the oversampling issue. This is comparable with observation errors expected for remotely sensed SSM observations (de Jeu *et al.*, 2008; Draper *et al.*, 2013). The LDAS2 results for this larger observation error will be included in the revised version of the paper. We will use the following description of the SSM observation error: "The SSM observation error standard deviation was set to $0.65(w_{fc}\text{-}w_{wilt})$, which is about 0.055 m^3/m^3 averaged over France. This value is slightly larger than the median ASCAT-derived SDS error of 0.05 m^3/m^3 estimated by Draper *et al.* (2011) because it also approximates the oversampling issue i.e. the same ASCAT observation covers several gridpoints."

Increasing the observation error standard deviation reduces the impact of the SSM assimilation for the LDAS2 experiments. Table R1.1 (at the end of the document) shows the new WG1 scores (prognosic variable compared with SSM observations) averaged over 2007-2014. The fit of LDAS2 to the observations is slightly reduced relative to the original results (Table 3 in the paper). However, as mentioned by the reviewer, the poor performance of the soil moisture fluxes for the SEKF was explained by the observation operator Jacobians. Therefore changing the SSM observation error does not change the conclusions of the study. Table R1.2 (at the end of this document) will replace Table 4 in the paper and shows the median Nash efficiency scores for the all the experiments. Following a comment from reviewer 2, the median Nash efficiency scores are calculated for all the stations instead of the mean. The median is a more appropriate metric for our experiments as it is less sensitive to extreme outliers and is a better indicator for highly skewed distributions (Moriasi *et al.*, 2007). Following a comment from Dr Jean-Philippe Vidal, the scores are also shown for the 67 stations with low anthropogenic influence (also see response to Dr J.-P. Vidal for details). The relative performances of the experiments in Table R1.2 are very similar to Table 4 in the paper and therefore the conclusions of the experiments remain unchanged.

4. P10 l2 Typo on Figure number should be Fig7?

   Response: Yes, we have changed this.

5. Section 4 Discussion. It seems that the principle problem with the assimilation in the SEKF for this situation is that the LAI assim has little or no sensitivity during winter and the SM jacobians are unrealistically too small. One short term improvement might be to simply increase the variances in the size of the background error covariance matrix in winter which is a realistic response to the known issue of enhanced model and forcing errors. Any thoughts on this?

   Response: These are interesting suggestions. However, we have tried increasing the LAI variances in winter but this does not help. Part of the problem if that the LAI observations are infrequent (every 10 days). We found that the model quickly returns to its underestimated minimum value between cycles, regardless of the size of the analysis increments. Perhaps one way to tackle this problem would be to implement a Kalman smoother with a long assimilation window of 10 days, but this is beyond the scope of this study. The problem with the SSM Jacobians cannot be resolved by simply increasing the estimated background errors in winter. The problem occurs because the SSM Jacobian value is negatively correlated with WG1 itself. This results in large analysis increments when rainfall is detected in the surface soil moisture observations but is missed by the model, and small increments when rainfall is detected by the model but is missed by the soil moisture observations. This problem would still occur with larger background-error variances. A potential solution to this problem is to assimilate the SWI product into a deeper soil moisture layer, which is less sensitive to the model and atmospheric forcing over the 24 hour assimilation window. We are currently testing this idea with the new multi-layer diffusion based model (ISBA-DIF).

Table R1.1: Scores for WG1 (prognosic variable compared with observations) averaged over 2007-2014. The closest fit to the observations are shown in bold font.

Experiment	RMSD (m^3/m^3)	CC	Bias (m^3/m^3)
NIT	0.051	0.77	0.00
NIT_m	0.049	0.77	0.00
NIT_{bc}	0.051	0.77	0.00
LDAS1	0.049	0.77	0.00
LDAS2	**0.048**	**0.78**	0.00
$LDAS1_{bc}$	0.049	0.77	0.00
$LDAS2_{bc}$	0.049	**0.78**	0.00
$LDAS2_{QC}$	**0.048**	**0.78**	0.00

Table R1.2: Median Nash efficiency (NE) and discharge ratio (Qs/Qo) scores over the 546 river gauges over France and for the subset of 67 gauges with low anthropogenic influence, calculated over 2007-2014. Also shown are the % of stations with a Nash score above 0.6. The best scores are shown in bold font.

Experiment	NE for 546/67 stations	Discharge ratio for 546/67 stations	% stations with NE > 0.6 for 546/67 stations
NIT	0.44/0.48	1.19/1.16	26%/44%
NIT_m	0.48/0.54	1.15/1.12	30%/48%
NIT_{bc}	**0.56/0.60**	**1.02/0.99**	**42**%/**59**%
LDAS1	0.44/0.48	1.18/1.15	27%/44%
LDAS2	0.41/0.45	1.21/1.18	23%/40%
$\mathrm{LDAS1}_{bc}$	**0.56/0.60**	**1.02/1.00**	**42**%/**57**%
$\mathrm{LDAS2}_{bc}$	0.53/0.54	1.08/1.06	38%/53%
$\mathrm{LDAS2}_{QC}$	0.40/0.45	1.21/1.18	21%/39%

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