General comments

The paper provides an important contribution to the research on data assimilation in land surface modelling. The paper considers assimilation of cosmic-ray soil moisture data and land surface temperature in the Community Land Model (CLM). Assimilation of the data sources individually and jointly as well as in combination with estimation of leaf area index are evaluated with respect to soil moisture, evapotranspiration, and latent and sensible heat flux. The paper is, in general, well written and technically sound. However, some elaborations are needed; especially on the Kalman filter setup and evaluation (see detailed comments below).

Response: Thanks for the recommendation. We will improve the manuscript according to the responses below.

Detailed comments

1. Page 9031, line 10-13. Not clear. Inclusion of bias in the Kalman filter is usually defined either as a bias in the system equation or a bias in the observation equation. The specific source of error need not be known.

   Response: Before we estimate the bias, we should determine whether the bias comes from the model, observation, or both. If the source of bias is not attributed to the right source, model predictions are not improved. A comprehensive overview of bias estimation is given by Dee (2005). According to them, “By design, bias–aware assimilation requires assumptions about the nature of the biases: first, the attribution of a bias to a particular source, and second, a characterization of the bias in terms of some well-defined set of parameters”. In this paper, no explicit model for observation bias or model bias was assumed, and no explicit bias estimation was done for simplicity. Nevertheless, model states are corrected by the observations. We will improve the description in the revision.

   1) Dee, D. P. (2005). "Bias and data assimilation." Quarterly Journal of the Royal Meteorological Society **131**(613): 3323-3343.

2. Page 9031, line 13. Not clear what is meant by ‘bias blind assimilation’ and why this is applied for ‘safety’.

   Response: The bias blind assimilation is the traditional data assimilation without bias estimation. Dee et al. (2005) wrote: “If the source of a known bias is uncertain, bias-blind assimilation may be the safest option. The main scientific challenge is to correctly attribute a detected bias to its source, and then to develop a useful model for the bias. When different sources produce similar biases, the assimilation may correct the wrong source.” Because the study area is a very heterogeneous irrigated farmland, both the observation and model could be biased. In CLM, the main bias came from the irrigation input, but the bias could also come from the soil properties and other vegetation parameters. For example, the following three papers studied the sensitivity of latent heat flux to hydraulic parameters (Hou, et al., 2012), vegetation parameters (Bonan, et al., 2011), and soil moisture and leaf area index (Schwinger, et al., 2010) in CLM4. For each analysis, a strong assumption was made that other the other two types of sensitive parameters were correct. We will clarify this in the revision.

1) Hou, Z. S., et al. (2012). "Sensitivity of surface flux simulations to hydrologic parameters based on an uncertainty quantification framework applied to the Community Land Model." Journal of Geophysical Research-Atmospheres 117.
2) Bonan, G. B., et al. (2011). "Improving canopy processes in the Community Land Model version 4 (CLM4) using global flux fields empirically inferred from FLUXNET data." Journal of Geophysical Research-Biogeosciences 116.
3) Schwinger, J., et al. (2010). "Sensitivity of Latent Heat Fluxes to Initial Values and Parameters of a Land-Surface Model." Vadose Zone Journal 9(4): 984-1001.

3. Page 9031, line 17. Define 'CLM'.
Response: CLM is Community Land Model, will include this in the revision.

4. Page 9036, line 8-10. Are the measured data at the station in Switzerland representative for the Chinese case study?
Response: The data are used to remove temporal (secular or diurnal) variations caused by the sunspot cycle. We follow the standard approach applied by the COSMOS network globally, discussed in detail by Zreda, et al. (2012). This reference will be appropriately mentioned in the revision.

1) Zreda, M., et al. (2012). "COSMOS: the COsmic-ray Soil Moisture Observing System." Hydrology and Earth System Sciences 16(11): 4079-4099.

5. Page 9036, line 24-26. Soil moisture from 10 soil layers (does this correspond to the top 10 cm of the soil?) in CLM is used as input to COSMIC. The effective measurement depth of the cosmic-ray probe depends on soil moisture, so why is a fixed depth used here? I expect this will introduce a bias in the simulated soil moisture for comparison with the measurements.
Response: The thickness of top 10 soil layers in CLM is about 4 meters. Because the effective measurement depth of cosmic-ray probe is between 12 and 76 cm, it is unlikely that anything beyond 1 m deep will substantially impact the results. The COSMIC model assumes a more detailed soil profile. In COSMIC, the soil moisture information from ten layers from CLM was interpolated to information for 300 layers based on the soil layer depth for numerical solution. The contribution of each soil layer to the measured neutron flux will change temporally depending on the soil moisture condition. So the effective measurement depth of the cosmic ray probe will also change temporally. The explanation in the manuscript will be improved.

6. Page 9039, line 1. Definition of state vector not clear. Why soil moisture from 10 layers (see previous comment) and soil temperature for 15 layers?
Response: These are the standard CLM layout for both soil moisture and soil temperature. The hydrology calculations are done over the top ten layers, and the bottom five layers aee specified as bedrock. The lower five layers are hydrologically inactive layers. Temperature calculations are done over all layers.

7. Page 9040, line 17-20. How is the leaf area index represented in the augmented system equation? As a persistence model?

   Response: the leaf area index was treated as a parameter and updated with help of the augmented state vector approach, but only changed after each update.

8. Page 9041, line 1-15. The Kalman filter settings are not sufficiently discussed. They seem rather arbitrarily chosen. It is not clear how the standard deviations, spatial and temporal correlations, and cross correlations given in Table 1 are determined. Has sensitivity analysis been applied to analyse the sensitivity of ensemble size and model error statistics on the assimilation results? You can analyse the prediction uncertainty provided by the Kalman filter to evaluate the Kalman filter settings by comparing measurements with predicted confidence bands or analyse the statistical properties of the model innovations. Definition of measurement uncertainty is not described.

   Response: the values of standard deviations and temporal correlations in Table I were chosen based on previous catchment scale and regional scale studies (Kumar, et al., 2009; Reichle, et al., 2010; De Lannoy, et al., 2012). In the 3D-EnKF, the imposed spatial correlation on forcing data is very important for the assimilation (Reichle and Koster, 2003; De Lannoy, et al., 2009). In 1D-EnKF and LETKF (which we used), no horizontal correlation among model grid cells are calculated, so the imposed spatial correlation on forcing data will not influence the assimilation. The impacts of horizontal spatial correlation on the assimilation can be included through the localization technique (Reichle and Koster, 2003; De Lannoy, et al., 2009). The selection of our ensemble size was based on Han et al., 2014, which reported that for more than 30~40 ensemble members, the assimilation results could not be improved too much. Therefore 50 ensemble members were used in this study.

   The observation standard deviation of cosmic-ray probes is equal to the square root of the measured neutron counts (Zreda, et al., 2012) and the observation standard deviation of MODIS land surface temperature was here equal to 1 K (Wan and Li, 2008). We will add this information in the revised version of the manuscript.

1) Kumar, S. V., et al. (2009). "Role of Subsurface Physics in the Assimilation of Surface Soil Moisture Observations." Journal of Hydrometeorology **10**(6): 1534-1547.
2) Reichle, R. H., et al. (2010). "Assimilation of Satellite-Derived Skin Temperature Observations into Land Surface Models." Journal of Hydrometeorology **11**(5): 1103-1122.
3) De Lannoy, G. J. M., et al. (2012). "Multiscale assimilation of Advanced Microwave Scanning Radiometer-EOS snow water equivalent and Moderate Resolution Imaging Spectroradiometer snow cover fraction observations in northern Colorado." Water Resources Research **48**.
4) Reichle, R. H. and R. D. Koster (2003). "Assessing the impact of horizontal error correlations in background fields on soil moisture estimation." Journal of Hydrometeorology 4(6): 1229-1242.
5) De Lannoy, G. J. M., et al. (2009). "Satellite-Scale Snow Water Equivalent

Assimilation into a High-Resolution Land Surface Model." Journal of Hydrometeorology 11(2): 352-369.

6) Han, X., et al. (2014). "Soil moisture and soil properties estimation in the Community Land Model with synthetic brightness temperature observations." Water Resources Research **50**(7): 6081-6105.
7) Wan, Z. and Z. L. Li (2008). "Radiance‐based validation of the V5 MODIS land‐surface temperature product." International Journal of Remote Sensing **29**(17-18): 5373-5395.
8) Zreda, M., et al. (2012). "COSMOS: the COsmic-ray Soil Moisture Observing System." Hydrology and Earth System Sciences 16(11): 4079-4099.

9. Page 9043, line 4. How is measured soil moisture estimated?

   Response: the soil moisture at the same CRS footprint scale was calculated from the arithmetic mean of the 23 SoilNet soil moisture observations. This information will be included in the manuscript.

10. Page 9045, line 4. Same information shown in Figs. 6-8 and Table 3. All results can be included in the table and figures omitted.

    Response: thanks for the suggestion. We will remove the figures in the revision.

11. Page 9045, line 3-25. It is stated that the results for latent and sensible heat flux correspond to the results obtained for soil moisture. However, there are some notable differences that should be elaborated. The effect of inclusion of parameter estimation of LAI on latent and sensible heat flux depends on the type of data being assimilated. For LST assimilation an increase in RMSE is obtained when LAI estimation is included. With assimilation of both LST and CRS lower RMSE is obtained with LAI estimation. In addition, assimilation of LST provides better results than assimilation of both LST and CRS.

    Response: thanks, we will improve the discussion in the revision. In the scenario of only LST assimilation without LAI update, the latent heat flux could not be improved. The single assimilation of LST did not give any improvement for this case.

12. Figure 5. Explain numbers in lower-right corner in figure caption.

    Response: these are the accumulated ET amounts during the study period, we will correct this in the revision.