Anonymous Referee #2

POME model: I would still like to have some more information about the model. It only requires surface soil moisture and soil profile mean soil moisture as input information and assumes that moisture is either monotonically increasing or decreasing. If this is not the case, an inflection point that is located in the soil layer with the highest field capacity is assumed

1. How does the POME model consider several layers of different texture? They might exhibit rather different soil moisture contents with distinct "jumps" between layers. In addition, infiltration fronts might induce further "inflection points". I cannot really imagine how this can be estimated from surface soil moisture and mean profile water con-tent only. Will there be just one optimal soil moisture profile or might there be several (concept of equifinality).

Response: The referee makes an excellent point about the behavior of soil moisture in real world situations. First, the POME model uses effective SM to develop a profile (eq. 4, Line 280), the boundary conditions and mean are first computed in effective SM and the model is applied. Finally, the developed profile in effective SM is converted to volumetric soil moisture values based on layer soil texture. However, one assumption made here is that the mean effective SM (available from the ALEXI model) is a composite of all the layers with different textures.

Now, as to the observation made by the reviewer, profiles can certainly be very irregular due to the different characteristics of the multiple layers that make up the soil column. As discussed in the manuscript and in the earlier paper by Mishra et al., (2015), the POME method as currently formulated envisions the profile as either monotonically increasing or decreasing or as possessing a prominent inflexion point. However, the method is a statistical procedure that ensures the minimum variance unbiased profile given the input data. In short, this ensures that the profile will be the best fit possible given what we know *i.e.*, the surface and lower boundary values and the mean. As shown in multiple earlier studies (Al-Hamdan and Cruise, 2010; Mishra et al., 2015, 2013; Singh, 2010a, 2010b) the resulting profile will normally be the best fit line through irregular points of a natural profile if the input data are approximately correct. We believe that this is the best any analytical method can achieve. We will add an appendix with more description of the POME model.

2. How is the lower boundary condition parameterized?

Response: We consider the lower boundary to potentially be a calibration parameter. There are various ways it can be estimated. For example, it could be considered a soils parameter or it can be used to link the climatology of the POME profile to a land surface model. In this study, the lower boundary was merely parameterized at 50% of available water content. As shown in past analyses (e.g., Mishra et al. (2013)) moisture content in the deeper layers is often fairly constant over the year, depending on the soil texture, and can thus can sometimes be set as the lower boundary on SM. We felt since the present study was a proof of concept in many ways, that parameterizing the lower boundary in this way was appropriate.

As the authors state correctly, both the Noah and the POME model will be affected by model errors and consequently may provide erroneous soil moisture profiles while the in situ data were measured at a much smaller measurement scale and the measurement site may not be representative for the entire pixel. Nevertheless, for a soil hydrologist, the time series shown in Figure 6 provide the most valuable information for identifying model errors and weaknesses of models and data. Unfortunately, this figure is almost not discussed within the manuscript. Observations to be addressed are e.g.

3. Except some sites where the SCAN data show some bias (mostly towards the dry range), SCAN and NOAH data appear to agree rather well, both in absolute soil moisture content and in the amplitude of the annual dynamics whereas POME often shows a very strong dynamics (especially towards the wet range). Might this cause problem with the upper boundary condition?

Response: We agree with the referee that we did not make sufficient use of the SM series shown in Figure 5. We thought that the salient points could be made through the statistical analyses and ignored the fact that perhaps the issues could be better illuminated through the figure itself. We assume that the referee is referring in this comment primarily to stations 2027, 2053, 2078, 2037, and 2013 where the POME SM estimates show a pronounced cycling effect in the upper layer not evident in the SCAN or NOAH data. We note here that the surface SM from POME is primarily set by the boundary condition provided by the MW data and that the overall correlation among all stations in this layer was about 0.55. However, as the referee states, those particular 5 stations showed anomalies that were not in sync with either the SCAN data or the NOAH simulations. From Figure 1 and Table 1 it can be observed that all of these stations are located in agricultural or mixed crop land coverages. In addition, the stations in North Alabama and southwest Georgia are in heavily irrigated areas. Obviously, the SCAN station would not be irrigated and the NOAH model also does not include it. The ability of the microwave instrument to sense the moisture from irrigation accounts for the seasonal cycle evident in the POME profiles at those sites. In these cases, it is probable that the POME profiles are more accurate over the 5-km spatial grid than are the SCAN or NOAH data. We failed to make this point anywhere in the manuscript and we greatly appreciate the referee pointing it out to us.

Further, the other two sites are located in areas where quite a bit of surface water is present in the remotely sensed pixels. It is possible that the seasonal cycle of water levels in the area account for the behavior seen at these locations.

We will revise the manuscript to add the above discussion to Section 4.3 where Figure 5 is first raised. The later statistical analyses can then be used to support the observations raised there.

4. The same strong dynamics occur in the Noah model at the lower boundary condition at many sites whereas, in this layer, POME and SCAN data better correspond to each other.

Response: We completely agree and as mentioned several times throughout the manuscript, this observation provides further evidence of how the POME model tends to improve relative to the SCAN data in the deeper layers of the soil column. It is also evidence that for most of the SCAN sites, the lower boundary condition (at 50% of available water content) seems to be a reasonable assumption for the POME model.

5. In some cases, the SCAN data sometimes show strong (or strange) soil moisture dynamics in the lower part of the profile (2013, 2115) while dynamics in the upper part of the profile is much less pronounced. Please explain.

Response: We too were struck by the behavior at these two sites and conducted an extensive investigation. The SCAN site SM at these locations showed highly seasonal dynamics at the lower depths. Site 2115 is characterized mostly as sandy soil from 0-45 cm depth. These soils have a much lower water holding capacity that leads to increased infiltration to the lower depths. Having sandy soils in the upper layers in part can explain the seasonal variations at the lower depths. Similarly, at site 2013 the upper two layers (0-33 cm) are recognized as sandy loam although the lower layer at the SCAN site exhibits high clay content.

Specific comments and technical corrections:

1. L5: please correct: ALEXI
   Response: Thank you for pointing out this mistake.

2. L39: replace "and" by "that"
   Response: We appreciate the correction.

3. L43: define CONUS
   Response: Thank you. We will make this correction

4. L67-84: In my view, these two paragraphs would better fit into the methods section
   Response: We placed this material at the end of the Introduction to define the objectives of the study and to provide a brief overview of what was done. If the editors think it appropriate, we are certainly open to removing it from this section.

5. L153: typo: consistent
   Response: Thank you. We will make this correction.

6. L159: yes – please define which meteorological forcing was applied in Noah. Was the model calibrated and if yes, to which data?
   Response: A real-time version of the Land Information System (LIS) has been maintained by NASA Short-term Prediction Research and Transition Center (SPoRT) for use in experimental operations by both domestic and international operational weather forecasters (Case et al., 2016, 2008). The basis of the SPoRT-LIS is a 33-year soil moisture climatology simulation spanning 1981–2013 and extended to the present time, forced by atmospheric analyses from the operational North American Land Data Assimilation System-Phase 2 (Xia et al., 2012). We will clarify this in the revised manuscript.

7. L162-165: Yes but then it must be proven that the POME-derived soil moisture profiles are correct. How will they be validated if not in a similar approach as applied in this manuscript?
Response: We appreciate this point. The POME approach has been applied under strictly controlled laboratory conditions (Al-Hamdan and Cruise, 2010; Singh, 2010a), field scale applications (Mishra et al., 2013) and compared to a detailed mathematical model of soil moisture movement (Mishra et al., 2015). In all of these instances, the method has been shown to be highly accurate (error on the order of 3%) when the input data are known accurately. In addition, entropy theory (Jaynes, 1957) indicates that the method will yield the optimal profile subject to the input data.

8. L170: Please provide reference for the MW soil moisture depth? I think at X-band it should be even less than 2-2.5 cm
Response: Thank you for pointing out this oversight. The penetration depth of the X-band microwaves is indeed 0-2 cm.

9. L183-185: No sentence
Response: Thank you for pointing it out, it will be replaced by "A time differential application of the ALEXI model was performed to monitor the rise in land surface temperature (LST) from morning to local noon. The early-day rise in LST is used to diagnose the partitioning of net radiation into sensible; latent and soil heat fluxes."

10. L337: How were the POME based profiles aggregated?
Response: The initial POME profiles were generated at 5 cm layer depths. A simple unweighted (as all layers being aggregated are of equal depth) mean was used to aggregate the SM values from 5 cm layer depths to represent a layer depth consistent with Noah LSM layer depths.

11. L424: Don't the RS measurements "see" the wet surfaces caused by irrigation?
Response: Exactly, the remotely sensed data are picking up the added water from the irrigation in this area whereas the SCAN site (which is not located in a private irrigated field) is not "seeing" this water and likewise it is not accounted for in the NOAH model. Thus, the positive bias here is not necessarily bad.

12. L 433: please correct: Fig. 4
Response: Thanks for pointing that out. We will make the correction.

13. L 459: How was this aggregation done?
Response: Please refer to response 10

14. L482: Aren't the SCAN observations the "true" SM? The RS soil moisture contents are also estimates.
Response: Thank you for the comment. In triple collocation (TC) analysis the three datasets (including the point SCAN observations) are considered as three independent estimates of the true average soil moisture condition of the pixel. In this analysis there is

no way to know the “true” soil moisture. Rather the error in the three datasets is computed relative to the unknown “truth” so that they can be compared to one another.

References:

Al-Hamdan, O.Z., Cruise, J.F., 2010. Soil Moisture Profile Development from Surface Observations by Principle of Maximum Entropy. J. Hydrol. Eng. 15, 327–337. doi:10.1061/(ASCE)HE.1943-5584.0000196

Case, J.L., Crosson, W.L., Kumar, S. V., Lapenta, W.M., Peters-Lidard, C.D., 2008. Impacts of High-Resolution Land Surface Initialization on Regional Sensible Weather Forecasts from the WRF Model. J. Hydrometeorol. 9, 1249–1266. doi:10.1175/2008JHM990.1

Case, J.L., Mungai, J., Sakwa, V., Zavodsky, B.T., Srikishen, J., Limaye, A., Blankenship, C.B., 2016. Transitioning Enhanced Land Surface Initialization and Model Verification Capabilities to the Kenya Meteorological Department (KMD).

Jaynes, E.T., 1957. Information Theory and Statistical Mechanics I. Phys. Rev. 108, 171–190.

Mishra, V., Cruise, J., Mecikalski, J., Hain, C., Anderson, M., 2013. A Remote-Sensing Driven Tool for Estimating Crop Stress and Yields. Remote Sens. 5, 3331–3356. doi:10.3390/rs5073331

Mishra, V., Ellenburg, W., Al-Hamdan, O., Bruce, J., Cruise, J., 2015. Modeling Soil Moisture Profiles in Irrigated Fields by the Principle of Maximum Entropy. Entropy 17, 4454–4484. doi:10.3390/e17064454

Singh, V.P., 2010a. Entropy theory for movement of moisture in soils. Water Resour. Res. 46, n/a–n/a. doi:10.1029/2009WR008288

Singh, V.P., 2010b. Entropy theory for derivation of infiltration equations. Water Resour. Res. doi:10.1029/2009WR008193

Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Lettenmaier, D., Koren, V., Duan, Q., Mo, K., Fan, Y., Mocko, D., 2012. Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. J. Geophys. Res. Atmos. 117, n/a–n/a. doi:10.1029/2011JD016048