Reviewer #2, Anonymous
General Comments:

This model attempts to represent soil moisture storage by modifying the model of Pan et al. The model has 6 parameters and includes two exponential functions, which should be sufficient to represent a wide variety of soil moisture response to precipitation, if hydrology is a model. Yet, the model does not consistently reproduce soil moisture patterns at a single depth with this limited information. It is not clear how this is an improvement in modeling soil moisture. The paper does give rise to several questions and concerns.

We thank the reviewer for his/her commentary, and appreciate the opportunity to discuss our findings. The performance obtained by our approach is comparable to the results published by Pan in 2012, despite the fact that we have attempted to generate an hourly estimate (Pan, 2012 predicts daily soil moisture values) and chosen numerous sites where wetting/drying behavior is more nuanced than the predominately drier locations chosen by Pan (2012). Additionally, the fundamental objective of this paper is not to build a better soil moisture model than any of the precursors mentioned in the literature review, but rather, to develop an approach to soil moisture prediction that requires only a precipitation time series for ungauged location.

Major concerns. The authors correctly state that soil heterogeneity poses a substantial challenge for soil moisture modeling. This restricts model application to the relatively homogenous soils. Yet, even in homogenous soils bulk density is commonly regarded to decrease with depth. In the model phi is a singular value for the soil profile, how is phi determined or chosen? Is this physical parameter subject to change from the genetic algorithm, if so, is it a physical parameter or a "degree of freedom" parameter? The authors state that the prediction is made for a specific soil depth, but none of the demonstration figures identify sensor depth, not do they compare performance for multiple depths at a single site. Such comprehensive analysis would be of interest to the reader and perhaps give the authors insight into the model performance, especially near the upper and lower boundaries of the soil.

The reviewer correctly notes that soil density can be a function of soil depth, yet the parameter, φ, is a constant by location. Given the general limitation of our datasets and the fact that shallow-depth soil moisture is most relevant to decision-support, all of our analyses occur with measurements of 2in (~5cm) depth. A note to this effect has been added following equation two, to avoid any subsequent confusion. Phi, as discussed on p.2327, lines 22-26 of the original manuscript, is fit by genetic algorithm. With calibration sets consisting of tens of thousands of hours of data, with only six total parameters, the 'degree of freedom' parameter issue is minimal. Comparisons of performance by depth at each site is a relevant question, but one best left for future research.

The soil moisture conditions of greatest concern to agriculture are excess moisture, which limits soil strength and trafficability in the spring, and excessively wet or dry soils during various stages of crop development. The vertical fluxes to drainage and evaporation differ dramatically under these conditions and would seem to require greater control than a precipitation decay function coupled with a soil water flux resistance term. It will be beneficial to the reader for the authors to explain clearly how their model accomplishes a water balance through a growing season without separate representations of percolation and evaporation. The causal dismissal of the need for farmers to know extent of saturation is disappointing. In this model, and in reality, the time until a farmer can resume field operations is largely dependent on the extent of saturation.

Though percolation and evaporation are not explicitly included, the Eta series, presented in equation three, describes a sinusoidal loss function over a year. This approximates the phenomena discussed in this comment. The diagnostic soil moisture equation, a parsimonious model by design, has been peer-reviewed and published in 2003 and 2012. It was chosen specifically because of its limited data requirements – no doubt there are other hydrologic and agricultural features that would be relevant to soil moisture predictions, but to include them in a model is to require their availability wherever the model is applied.

The KNN correction is intended to allow consistent model biases, but the results show that the model consistently over predicts or under predicts for some case studies. This is not a convincing demonstration.

The KNN approach does achieve results in smoothing systematic biases from the diurnal cycle (see Fig. 6). The following sets of images (created at the behest of reviewer #1) demonstrate the effect of bias correction for time-of-day, day-of-year, soil moisture conditions, or even antecedent precipitation. However, despite all of these adjustments, it is still possible that a validation year is notably wetter/drier than the training data, causing over or under-predictions. Moreover, sensor calibrations are imperfect and dynamic – it would be difficult for any model to avoid such errors. Even NASA's SMAP mission (Soil Moisture Active Passive), during which soil moisture will be remotely sensed and validated with in situ sensors, targets root-mean-squared errors of 4%. Without the satellite images or other information, this approach (after bias correction), is only marginally worse; see the newly created Table 1 (also created at the behest of reviewer #1).

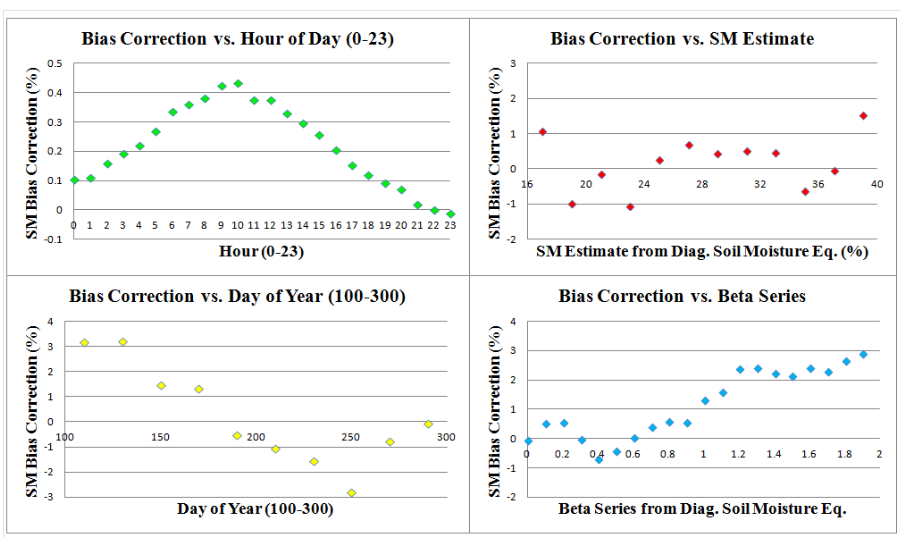

Figure 7, Bias Correction Analysis, SCAN Site 2015 (IAQ, Desert, Loamy Sand)

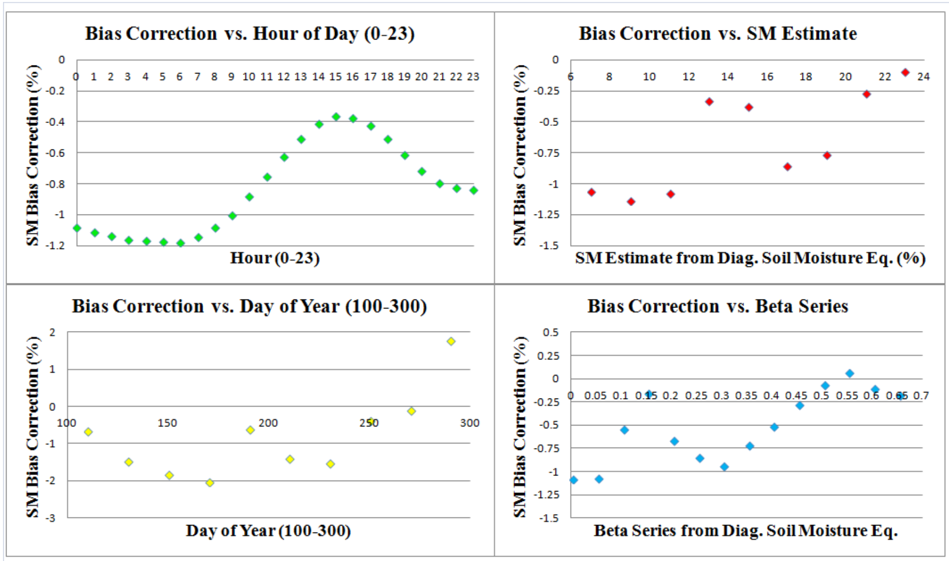

Figure 8, Bias Correction Analysis, SCAN Site 2068 (ISCJ, Plains, Silty Clay Loam)

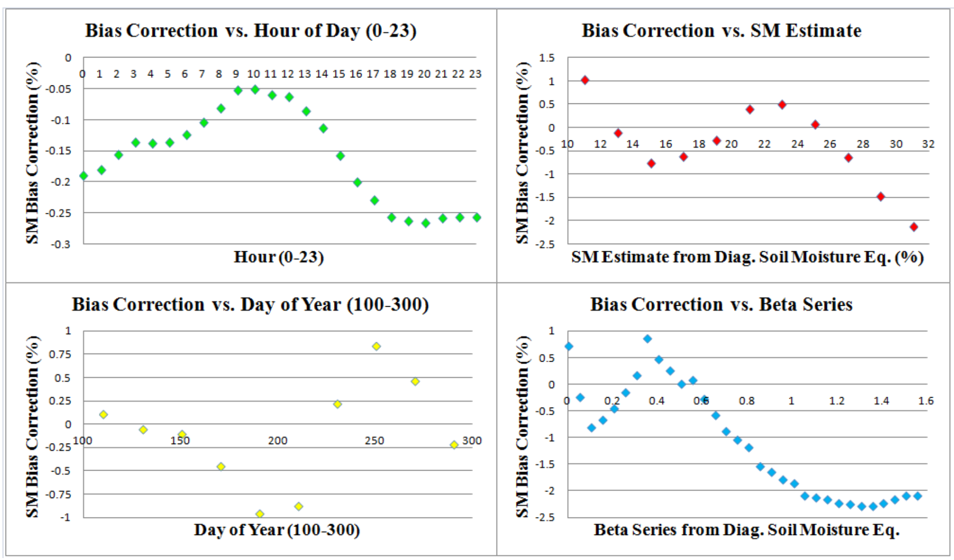

Figure 9, Bias Correction Analysis, SCAN Site 2013 (LWC, Woods, Sandy Loam)

SiteID	Hydro-climate	Soil Information	RMSE	RMSE w/ KNN	R^2	R^2 w/ KNN
2008	LJ	Sandy Loam	8.38	7.69	0.590	0.726
2013	LWC	Sandy Loam	2.16	2.06	0.876	0.885
2015	IAQ	Loamy Sand	3.29	2.37	0.740	0.841
2017	ISQJ	Sandy Loam	3.62	3.27	0.637	0.701
2018	IAQ	Loamy Sand*	2.23	2.16	0.803	0.828
2028	LPC	Loam	4.89	4.71	0.707	0.738
2031	ISQJ	Silty Clay Loam	5.46	6.00	0.687	0.750
2036	LPC	Silt Loam	4.61	3.95	0.635	0.726
2038	LJ	Sandy Loam	4.81	4.51	0.546	0.584
2068	ISCJ	Silty Clay Loam	5.28	4.03	0.716	0.837
2089	LJ	Sandy Loam	6.7	6.31	0.682	0.697
2091	LPC	Silt	8.12	6.89	0.539	0.808
2107	IAQ	Loamy Sand	1.98	1.85	0.790	0.843
2108	IAQ	Loamy Sand/Sand	1.26	1.12	0.828	0.863
2111	ISQJ	Silty Clay Loam	5.38	5.01	0.607	0.796

*Not similar to other sandy soils, see Figure 9.

Table 1, The Fifteen SCAN Sites: Class & Soil Information and Performance

Minor concerns The basis of adding a diurnal cycle to soil moisture is not well supported if prediction for agricultural management is the goal. The benefit of using LT (presumably local time) rather than simply stating the 24 h time is not clear.

We presume the reviewer is referring to p.2328, lines 15, 24, and 28 of the original manuscript. The "LT" can easily be removed. It is superfluous. We believe that including a diurnal cycle is relevant insofar as it may guide agricultural decision-makers to choose one hour rather than another to irrigate their fields or eschew traffic due to the wetter ground conditions.