Responses to the comments from Reviewer #2

We thank the reviewer for the useful comments. We have incorporated the review comments and revised the manuscript thoroughly. The review comments and the revision have resulted in a much more complete presentation of the work. While the changes made to the manuscript can be seen in the revised manuscript, we also present here our detailed responses to the review comments (reviewer comments in black, our response in blue).

Manuscript Number: hess-2016-696 Title: Incorporating remote sensing ET into Community
Land Model version 4.5 Authors: Dagang Wang, Guiling Wang, Dana T. Parr,
Weilin Liao, Youlong Xia, Congsheng
Summary
This paper follows the ET bias correction scheme proposed in Parr et al. 2015 and carries out a regional scale (CONUS) study in order to evaluate the effectiveness/performance of this approach over a large domain in terms of estimating ET, runoff, and soil moisture. The main idea I see is to reduce the ET overestimation in CLM 4.5 by rescaling it down and push the reduced ET back into the model to raise the runoff and soil moisture content – this goal is obviously achieved. The data, experiments and analysis in this study are all carefully chosen and the descriptions are very clear too. The overall quality of the research is good though most of the major conclusions are more or less well expected even without these experiments.
I think the paper can be published in HESS with minor revisions.

Major Comments
Unlike true "state" variables like moisture content or temperature, whose current value directly influences the future state of the underlying dynamic system, ET is not a state variable but a flux variable. Therefore, any effort to incorporate ET information effectively into the land surface model needs a way to propagate the change to ET flux across other parts of the dynamic system (e.g., soil moisture, canopy storage, runoff fluxes, etc.). The approach taken in this paper (following Parr et al. 2015) is to re-run the model (CLMET) and force the ET flux to be a value rescaled relative to the initial run (CLM), where the rescaling factor is pre-calibrated for every location and month. This approach is simple and effective, I think. On the other hand, this approach is also awkward as it looks like an enhanced post-processing" for bias correction instead of tackling the ET overestimation from its root cause, e.g., an underestimated surface resistance. The awkwardness comes in also because the "forced" ET in the CLIMET run will considerably disrupt the model physics itself, e.g. breaking the water balance and sustaining wetter soil without letting the plants transpire more. If we adjust the resistance (or some other related process like to make the water easier/faster to drain from the soil), then most of such physical inconsistency would be gone.
Response: the model bias in ET simulations results from inaccurate information of meteorological conditions (Mueller and Seneviratne, 2014), surface-type data (Hwang

and Choi, 2013), model parameters (Ma et al. 2015), and soil water (Decker 2015). Adjusting surface resistance is essentially one of many methods of model parameters calibration, which can reduces model bias as well. However, only making parameter adjustment may results in nonphysical parameter subsets when other inaccurate information is the main cause of the model bias for some regions/seasons (Ray et al. 2015). In this study, we take a different approach to correct simulated ET as a whole instead of adjusting each separate factors, which provide a simple and efficient way to improve model performance in hydrological estimation without improving the model physics itself. We have added a short discussion in the Section 5.
"Model parameter calibration (e.g., tuning surface resistance) is another way to reduce model bias (Ren et al. 2016). However, the parameter space may contain nonphysical parameter subsets (Ray et al. 2015), which is especially an issue when model parameter tuning is used to offset unrelated model deficits. The method used in this study attempts to avoid such issues through improving the model performance without dealing with calibration of model physical parameters." (the last pargragrah of Section 5 in the revised manuscript)

Mueller, B., and S. I. Seneviratne (2014), Systematic land climate and evapotranspiration biases in CMIP5 simulations, Geophysical Research Letter, 41, 128–134, doi:10.1002/2013GL058055.

Hwang, K., and Choi, M. (2013). Seasonal trends of satellite-based evapotranspiration algorithms over a complex ecosystem in East Asia. Remote Sensing of Environment, 244-263.

Ma, N., Y. Zhang, C.-Y. Xu, and J. Szilagyi (2015), Modeling actual evapotranspiration with routine meteorological variables in the data-scarce region of the Tibetan Plateau: Comparisons and implications, Journal Geophysical Research: Biogeosciences, 120, doi:10.1002/2015JG003006.

Decker, M. (2015). Development and evaluation of a new soil moisture and runoff parameterization for the CABLE LSM including subgrid-scale processes. Journal of Advances in Modeling Earth Systems, 7(4), 1788-1809.

Ray, J., Z. Hou, M. Huang, K. Sargsyan, and L. Swiler (2015), Bayesian calibration of the Community Land Model using surrogates, SIAM/ASA Journal on Uncertainty Quantification, 199 – 233, doi:10.1137/140957998.

The authors have a major assumption that the ET biases won't change from year to year (with seasonal variability, though) so that such static errors can be corrected with static correction factors. So, the entire long ET validation section (4.2.1) is really validating the performance of the new estimation system but this stationarity assumption. It'll be interesting if the results can be compared to a pure "post-processing" approach, i.e., to rescale ET then rebalance the water budget between precipitation, ET, soil moisture, and runoff.

Response: It is hard to rebalance water and energy budgets though post processing without model runs after ET is rescaled. The rescaled ET influences simulations of many components of land surface processes, such as infiltration, soil water/energy transport, which cause changes in land surface states. The land surface states at the current time step is the bases of flux variable simulations for the next time step. All these processes and connections between adjacent time steps cannot be tackled in the post processing. To obtain the consistency between different components of land surface processes and connect land surface states between adjacent time steps, we really need to re-run CLM and let model resolve all these issues. That is the reason why Parr et al. (2015) proposed the method and we applied this method in CLM on the regional scale.

Details:

Line 65: model -> models

Response: we have changed to “models”.

Line 88: intense -> intensive

Response: we have changed to “intensive”.

Line 91: past -> historical

Response: we have changed to “historical”.

Line 101: Parr et al. -> Parr et al. (2015); into -> for

Response: we have changed to “Parr et al. (2015)” and “for”.

Line 111: spell out PFT

Response: we have spelled out PFT (plant functional type).

Line 122: “CONUS” was first mentioned in line 115

Response: we have define “CONUS” (Conterminous United States) in line 115.

Line 155: unbalance -> imbalance

Response: we have changed to “imbalance”.

Line 322-334: where does the runoff data come from? GSCD or GRDC? What is GRDS in line 328? And Line 379?

Response: all these should be GSCD (Global Streamflow Characteristics Dataset). We have corrected them.

Line 413: replace -> to replace

Response: we have changed to “to replace”.