This paper investigates how a simple soil moisture model can be used at sites with no soil moisture measurements available for model training, but with similar climate and/or soil type. Given the sparsity of soil moisture measurements this is an important contribution as it allows to spatially generalize (soil moisture) model calibrations.

We thank the reviewer for his/her compliments, as this was precisely our intention with this work. We hope that our responses to the comments below improve the manuscript and satisfy the reviewer.

General comments:
The paper needs minor revisions. In my opinion the paper is very well written. It is straightforward to understand and clearly structured. There are other simple soil moisture models that do not require soil moisture information for calibration. (Koster and Mahanama 2012, JHM; Orth et al. 2013, JHM) A reference to such approaches (e.g. in the discussion section) could indicate another possible direction in which to apply the derived results. I appreciate the tables and information the authors provided in response to reviewer #1, I agree that these will improve the manuscript.

We thank the reviewer for drawing our attention to the two listed papers. Indeed, these works also provide estimates of soil moisture without antecedent soil moisture information. Following line 13 on p. 2338, the following will be added:

> "The diagnostic soil moisture equation used in this paper (Pan et al, 2003; Pan, 2012) was an appropriate choice due to its ability to generate soil moisture estimates without the need for knowledge of antecedent soil moisture conditions. Koster and Mahanama (2012) and Orth et al. (2013) have developed approaches to estimate soil moisture at the watershed scale by leveraging hydroclimatic variability and long-term streamflow measurements in a water-balance model – also without employing previous soil moisture conditions. If the parameters calibrated and then generalized in this work produce point estimates of soil moisture at a diversity of locations, integration with a water balance approach could help with the up-scaling process.

Specific comments:
Title: Maybe you want to consider simplifying your title such that a broader audience can understand it. I would think of e.g. "Using climate and soil information to generalize soil moisture prediction"

Perhaps a different title would lead to wider appeal. Consider:
"Using similarity of soil texture and hydroclimate to enhance soil moisture estimation"

page 2323, line 7: remove "(precipitation"

Agreed. The change will be made.

page 2326: From equation 1, soil moisture content would never increase. I guess you add (possible) precipitation at each time step?

In equation 1, the β term represents the convolution of previous hours of precipitation. One can observe that if β is equal to zero (no precipitation during the relevant historical window), θ_{est} is *set to θ_{re}, the residual soil moisture of the soil. Should β grow large (saturating the soil), θ_{est} approaches the porosity, φ_e. At each time step, β changes, as its temporal window is fixed – at each time step, the oldest hour of precipitation data used to calculate β is replaced by the most recent hour. In this manner, precipitation in the most recent hour (weighted more heavily in the convolution) increases θ_{est}.*

page 2326, lines 21-25: Why do you use different metrics (objective functions) that are minimized/maximized here?

Does the reviewer refer to lines 21-25 of p.2327? If this is the case, the reviewer's question regards the fact that we maximize correlation for the first three parameters fit by genetic algorithm, yet minimize the sum of squared errors for the three parameters fit during the second stage. The reason for this is that the β-series is characterized by a wholly different numerical scale than the soil moisture series were are ultimately attempting to estimate. Moreover, it is still (at that point in the analysis) missing the three soil-specific parameters. Thus, choosing optimal values for the first three parameters entails developing a β-series whose shape follows the shape of the measured soil moisture values. Once this 'shape' is modeled, choosing a lower-bound for θ_{est} (residual soil moisture, θ_{re}) and an upper-bound(porosity, φ_e), along with a rate of drainage (c_4), allows the generation of a soil moisture series that should have a minimal total sum of square errors with respect to the observed soil moisture series.

page 2333: Please mention that this error correction approach cannot deal with trends in the soil moisture data.

The following sentence will be added, following line 18 of p. 2333:

"This approach to error correction, as it relies on previous errors to predict future errors, will not address long-term trends within the soil moisture record."

page 2333, line 13: add "when considering the entire time series" before "but without flooding events ..."

These sentences will amended at the behest of this and another reviewer. The paragraph that begins on line 7 of p. 2333 will now read:

> "During the validation period, specifically 2010, wetter conditions were observed than were present during calibration. At this SCAN, before 2010, the average soil moisture value observed as 28.55%, with only 25% of values exceeding 35% volumetric soil moisture. However, in 2010, the average soil moisture value measured was 33.16% with 45% of values exceeding 35%. The machine learning driven error correction improves the diagnostic soil moisture equation ($\rho = 0.846$) significantly ($\rho = 0.915$), but fails to raise its forecasts to reach some of the wetter conditions experienced in validation. Underestimations of this nature, although detrimental…"

page 2333, lines 16-18: In terms of droughts this shortcoming has more serious consequences. Wheras it may not matter much if it is wet or very wet, it is important if it is dry (plants may survive) or very dry (plants may die), especially in the context of irrigation management.

Agreed. Small errors in terms matter more during dry conditions than during wet conditions. Generally, the model does make smaller errors, in absolute terms, during dry conditions. Following line 18 of p.2333, the following sentence will be added.

> "It is important to note that small errors are more significant in terms of decision support (specifically when and where to irrigate) during dry conditions. Generally, the model's errors are smaller, in absolute terms, during drier conditions."

page 2336, lines 15-18: Would you say hydro-climate and soil type are about equally important or is it too little data to make such a statement here?

This is an important question – the data seem to suggest that hydroclimatic characteristics are slightly more important than edaphic features (the model performs better when hydroclimates align but soil textures do not than the converse). However, what is not rigorously analyzed (though it could be, in a subsequent paper) is the extent of the hydroclimatic differences vs. the extent of the edaphic differences within those groups respectively. As a result, it would be speculative to say which is ***more*** *important – one can only state that both are important. To this end, after line 18 of p. 2336, the following will be added:*

> "…future modeling work, in which the relative importance of hydroclimates and soil textures can be examined in greater detail."

page 2337: The model may not only benefit from accounting for overland flow but also for subsurface flow/runoff, especially in hilly areas.

Absolutely. Line 19 of p. 2337 will read:

> "…by considering overland and subsurface flows, specifically in areas characterized by more complex topography."

page 2338: What is the soil depth considered in the model? Satellite data represents only the upper centimeters of the soil and may therefore be of limited use to improve total column soil moisture model estimates.

Another reviewer (#2) has raised this question as well. The response to that reviewer is reproduced below:

"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."

Figure 2: Please label the x-axis. You can cut the range of the y-axis such that it starts at 0.3 or so.

The new Figure 2 appears below:

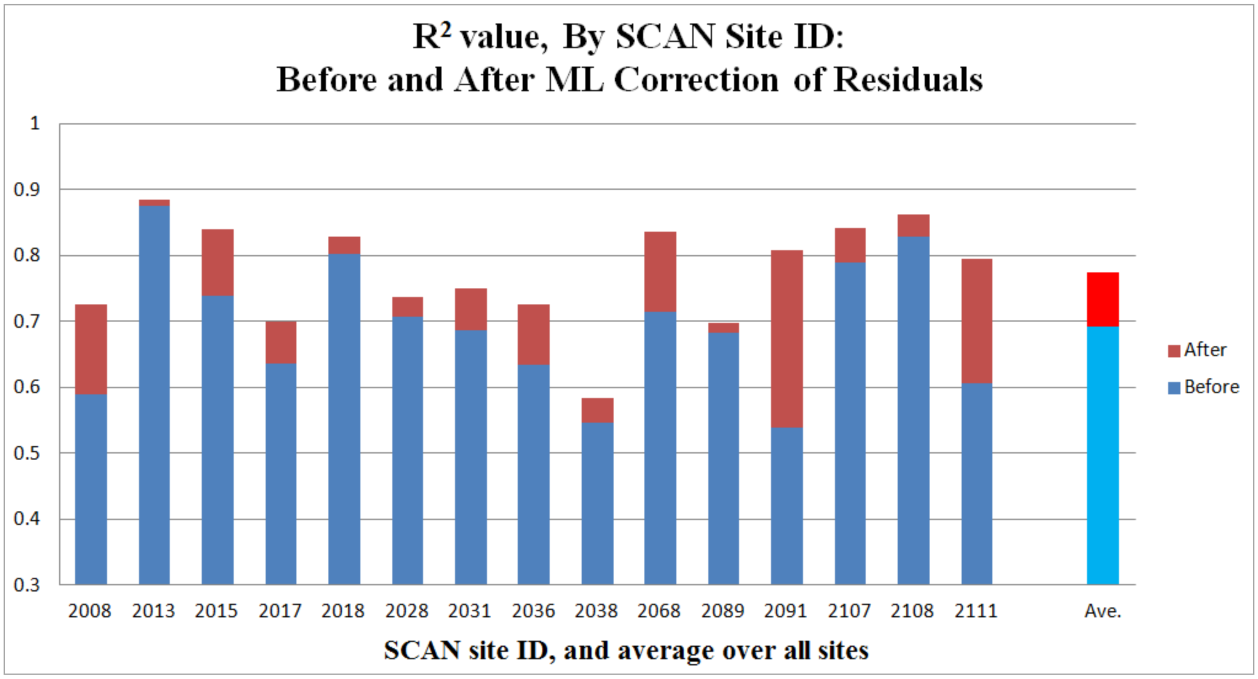

Figure 2, Improvements from machine learning (KNN) models of residuals.

Figures 3-6: Put exact dates/times on x-axis.

In figures 3-6, the only hourly time stamps that appear are those for which the date falls between the 100th and 300th days of the year (to ensure analysis of unfrozen ground) and for which the precipitation and soil moisture values from the relevant sensor are available. Thus, these are not wholly continuous time-series and consequently, it could confuse readers were dates to appear at inconsistent intervals. Figures 3-6 have been updated slightly at the behest of other reviewers, appearing below.

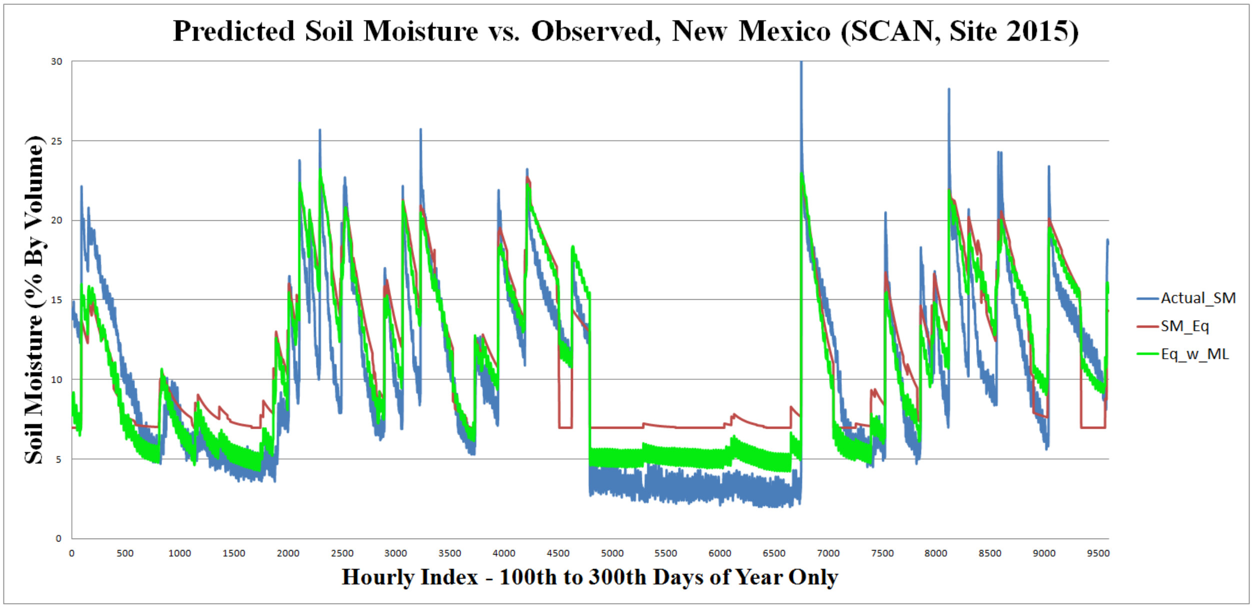

Figure 3, Soil Moisture Time Series, SCAN Site 2015, New Mexico (USA), Actual Soil Moisture (Blue Line), Diagnostic Soil Moisture Equation Estimate (Red Line), and Diagnostic Soil Moisture Equation with Machine Learning Error Correction (Green Line). Hydroclimate: IAQ (Intermediate Seasonality, Arid, Summer Peak Runoff) Soil Texture: Loamy Sand

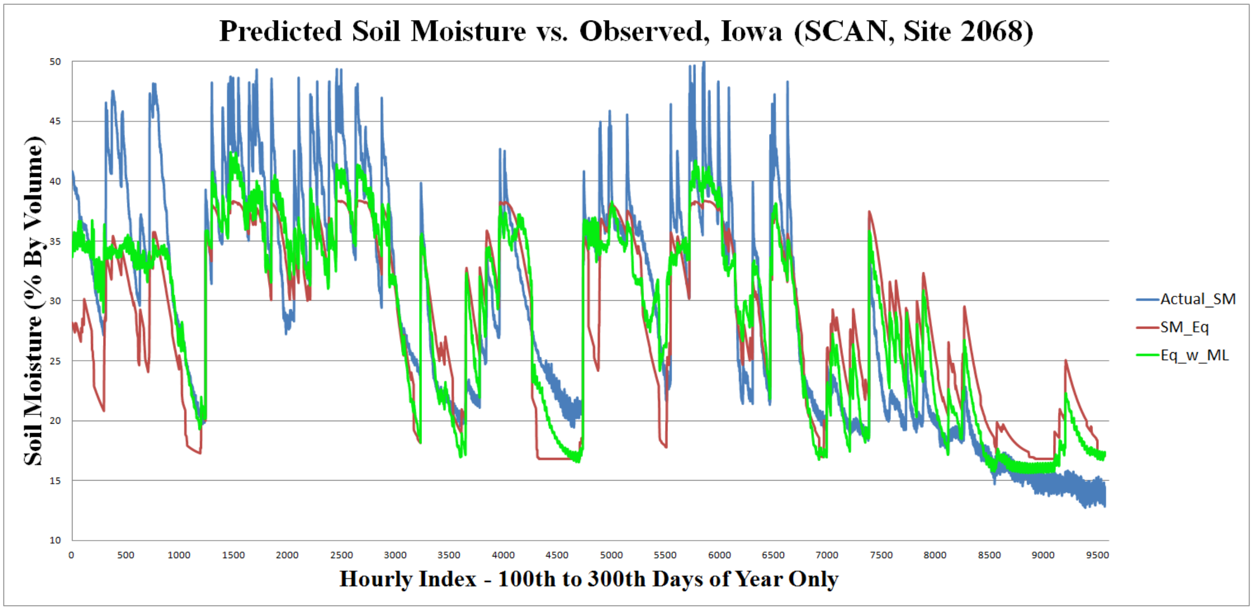

Figure 4, SM Time Series, SCAN Site 2068, Iowa (USA), line colors from Fig. 3 Hydroclimate: ISCJ (Intermediate Seasonality, Semi-Arid, Winter Peak Runoff, Summer Peak Precipitation) Soil Texture: Silty Clay Loam

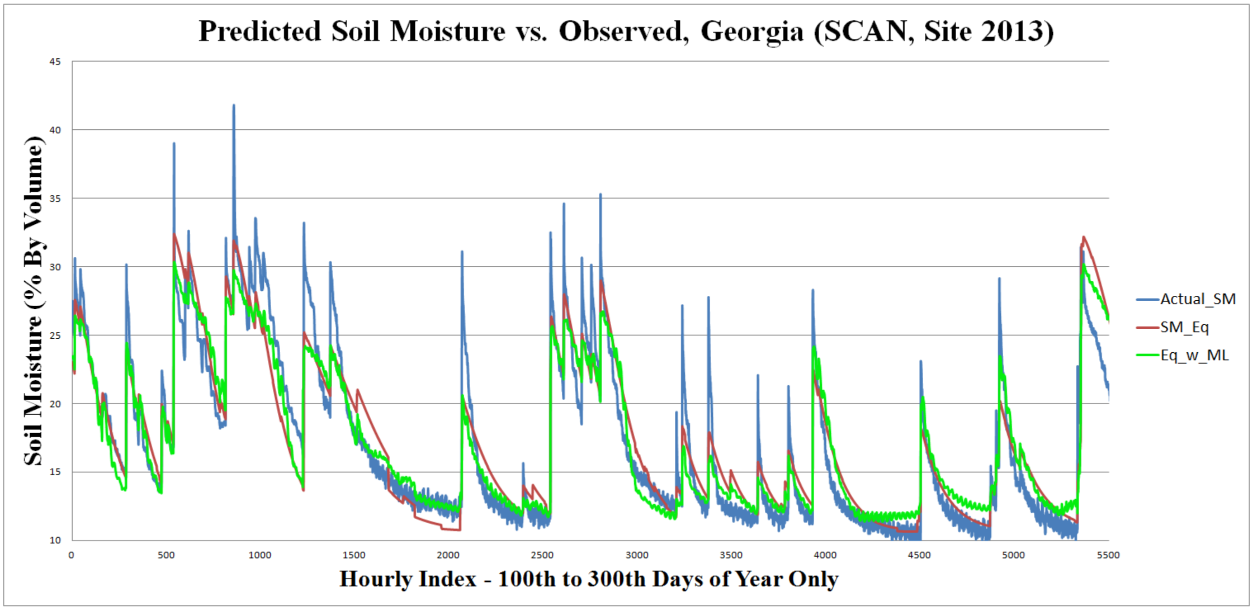

Figure 5, SM Time Series, SCAN Site 2013, Georgia (USA), line colors from Fig. 3
Hydroclimate: LWC (Low Seasonality, Winter Peak Precipitation, Winter Peak Runoff)
Soil Texture: Sandy Loam

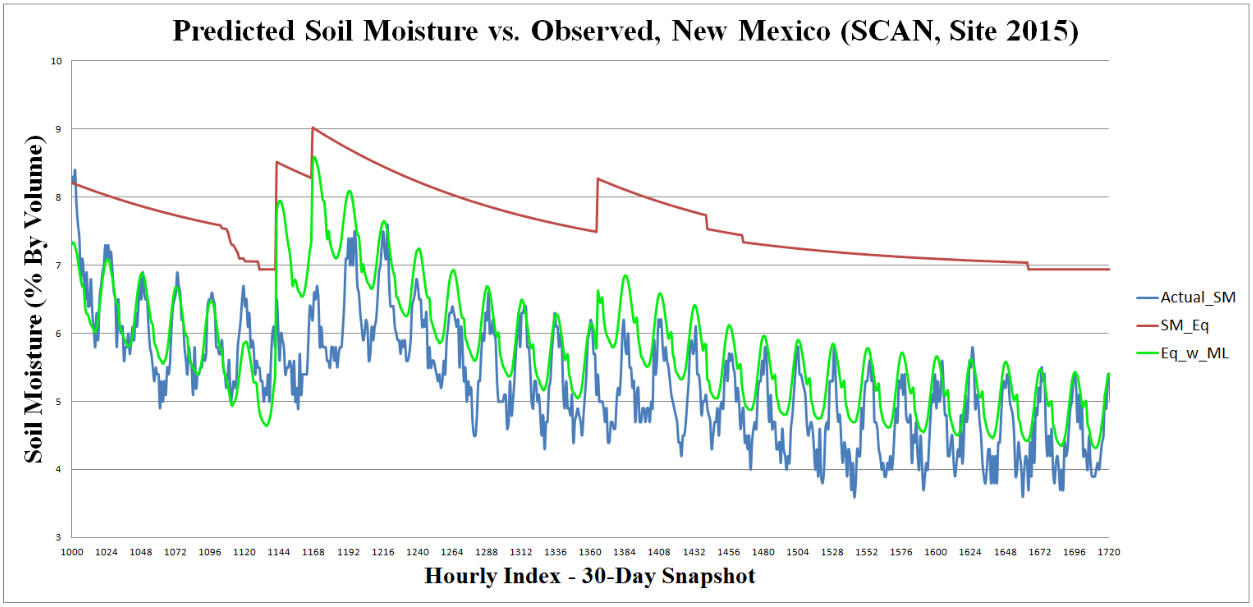

Figure 6, Soil Moisture Time Series, SCAN Site 2015, New Mexico (USA), Actual Soil Moisture (Blue Line), Diagnostic Soil Moisture Equation Estimate (Red Line), and Diagnostic Soil Moisture Equation with Machine Learning Error Correction (Green Line)

Figure 10: Some text is missing in the brown box.

The correction has been made, see below:

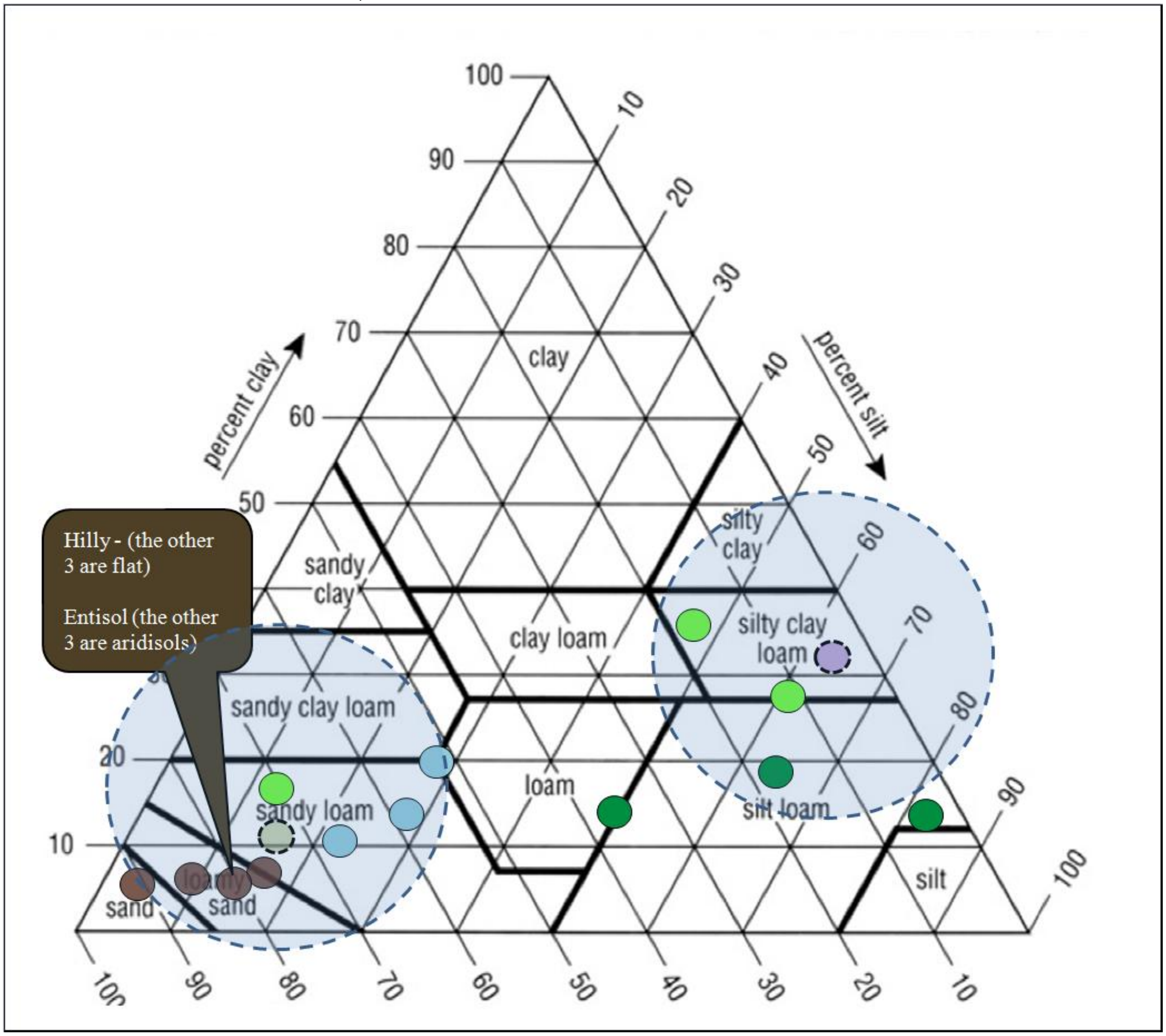

Figure 12, The 15 SCAN sensors, color-coded to match their hydro-climatic class, with similar soil textures shaded.

Figure 11: Has it been referred to in the text? Use different colors for soil texture circle and hydroclimate circle.

Figure 11 is referenced on line 12 of p. 2336. It is reproduced below (it will be Figure 13 in the revised manuscript). Green shades denote hydroclimatic similarity, brown shades denote similarity with respect to soil texture.

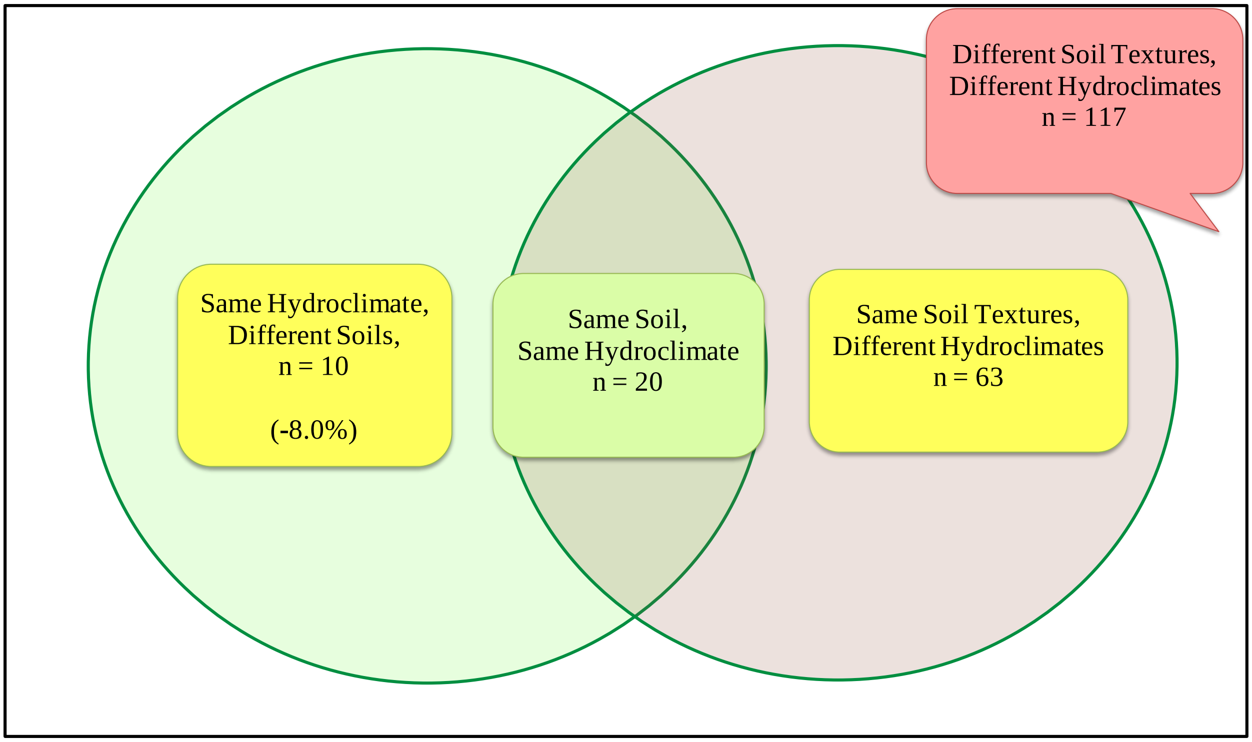

Figure 13 Venn-Diagram of Modeling Errors with Similar and Different Soils and Hydro-climates