Dear Editor

Thanks for your help and reviewer's comments. Please find enclosed responses for the final comment and two previous reviewer's comments. Thanks for your help and arrangement in advance,

Editor Decision: **Reconsider** after major revisions (further review by editor and referees) (07 Jul 2021) by Erwin Zehe

Comments to the Author:

I read your paper with **great interest** and agree with both reviewers that this work has **great potential** to evaluate to which extend machine learning methods can help to classify soil moisture events and to search for underlying reasons. Yet, I think in line with the assessment of reviewer 2 that **the manuscript needs major revisions** to fully explore it's potential. In addition to the points raised by the reviewer, I I'd like to bring the following points to your attention.

1. Figure 2 is indeed difficult to digest. Maybe it is better to present boxplots not using the profile names but **their topographical elevation on the x-axis** (more information), **and it might be better to separate different depths into different panels.**

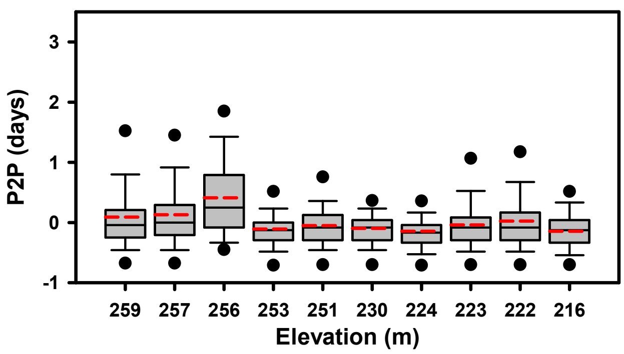
⇨ We revised x-axis of figures using topological elevations and separate different depths into different depths as follows. The order of measuring locations from hilltop to downslope is UP1-UP4-UP2-UP5-UP3-DO1-DO2-DO3-DO4-DO5.

⇨ The tendency of maximum variation is different from that of P2P. Both average of maximum variation is the lowest in the depth of 30cm except for locations UP4, DO1 and DO2. Both standard deviation and average of maximum variation for upslope area are lower than downslope area.

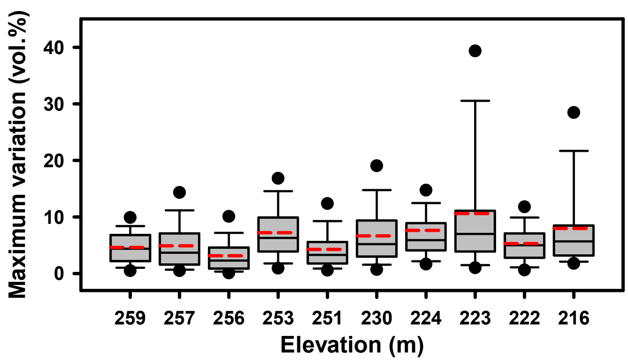
⇨ We revised context to address reviewer's point as follows,

"The statistics of soil moisture response based on the analysis of 30 points are summarized in terms of the P2P and maximum variation, as displayed in Fig. 2(a) - 2(f), which present elevations as an order of locations in x-axis as UP1-UP4-UP2-UP5-UP3-DO1-DO2-DO3-DO4-DO5 (Fig. 1) from the hilltop to downslope. The means of P2P ranged from –0.2 d to +0.5 d, indicating that the maximum soil moisture could be achieved even before the occurrence of the rainfall peak. Both standard deviation and average of P2P tended to increase at deeper depths, except for locations with elevations in 224 m and 216 m (locations of DO2 and DO5 in Fig. 1).

Fig. 2(a), 2(c) and 2(e) indicate while the mean P2P for the upslope area was 0.24 d, that of the downslope area was 0.02 d. The mean values of P2P at depths of 10, 30, and 60 cm were −0.08, 0.04, and 0.011 days for the downslope and were 0.1, 0.24, and 0.38 days for upslope, respectively. The differences in P2P between other points at an identical depth for the downslope were smaller than those for the upslope. This suggests that the soil moisture response in the downslope area is faster and more uniform than that in the upslope area. The accumulated soil water flow from the upslope area to the downslope area seems to be responsible for more rapid and less spatially variable soil moisture responses in the downslope area. As shown in Figs. 2(b), 2(d) and 2(e), both average and standard deviation of maximum variation tend to increase for locations with lower elevation. The average of maximum variations at depths of 10 cm and 60 cm were higher than those for the 30-cm depth, indicating that primary lateral flow tended to be generated along boundaries (surface and subsurface)." .



(a)



(b)

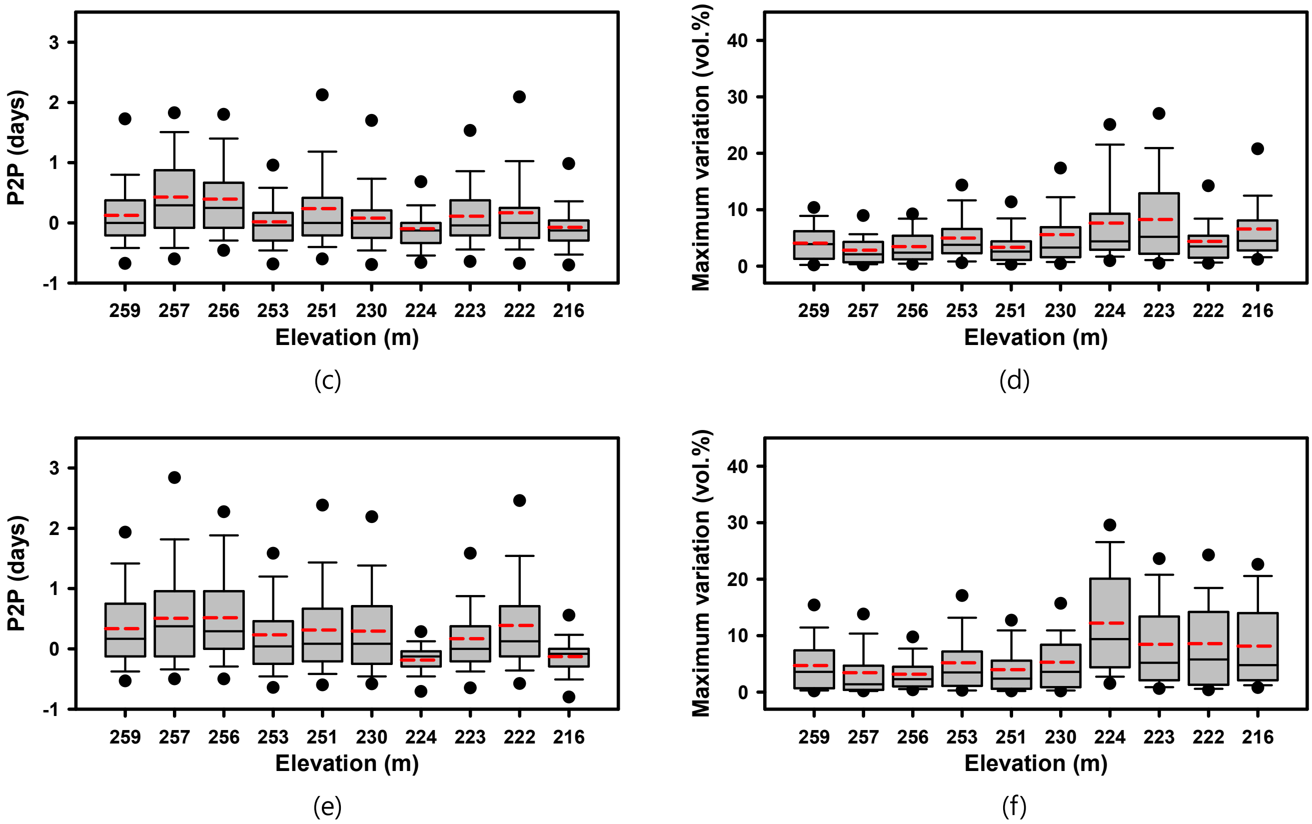
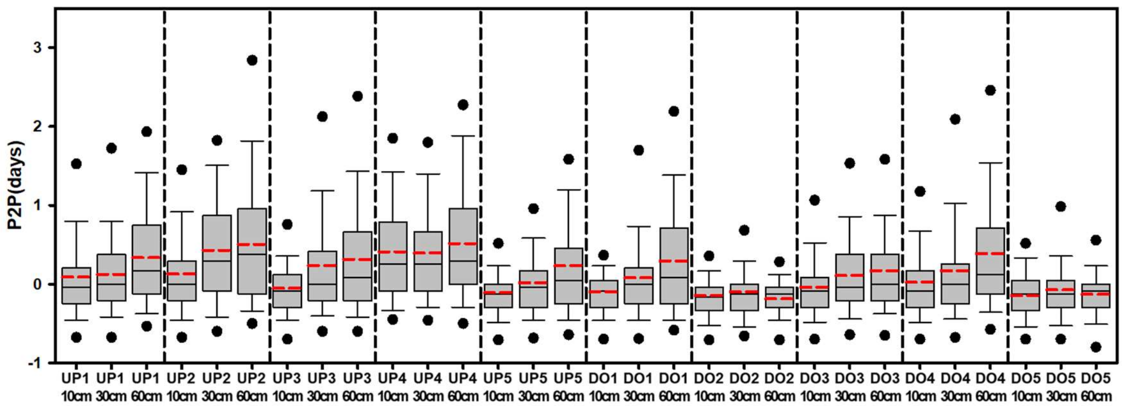
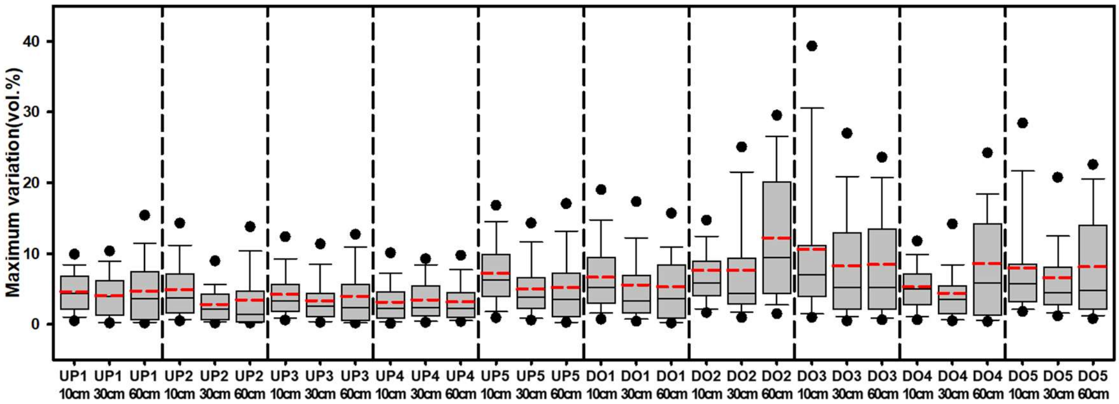


Figure 2: Boxplots illustrating soil moisture responses of P2P and Maximum variation at 10 cm depth (a) (b); those at 30 cm depth (c) and (d); those at 60 cm depth (e) and (f), respectively. Elevations in x-axis are between 260 and 215 m as an order of UP1-UP4-UP2-UP5-UP3-DO1-DO2-DO3-DO4-DO5 shown in Fig. 1.



(a)



(b)

Original form of boxplots of soil moisture responses

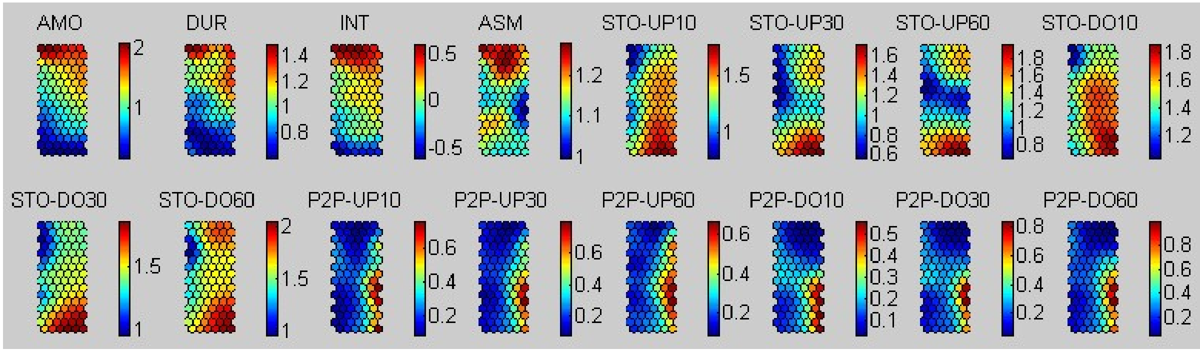
2. I have furthermore problems with the definition of **the maximum soil moisture variation VAR**. A normalization with the antecedent soil moisture is hydrologically misleading. Let me explain this based on two cases:

1) Theta_max = 0.4, Theta_asm =0.3 gives a var of 33%,

2) Theta_max = 0.15, Theta_as = 0.05 gives a var of 200%,

In fact, in the first case the storage change was 200% larger than in the second. I think a normalization with **total precipitation depth** is hydrologically much more appropriate. You could calculate storage changes, for instance **by multiplying changes in theta with the respective depth increments** that are represented by these measurements. VAR will then compare normalized storage changes, and the normalization is constant and not variable due to the variability of ASM between the profiles (see Fig. 3). To me this is a hydrologically much more meaningful index, which relates storage changes to the total forcing. Related to this, I think that Fig. 3b is misleading, as the variations downslope are normalized with systematically elevated antecedent soil moistures. The proposed normalization with total precipitation will rectify this and the downslope var will become likely larger than the upslope var. **And it might change the results of the clustering and will differences more meaningful**.

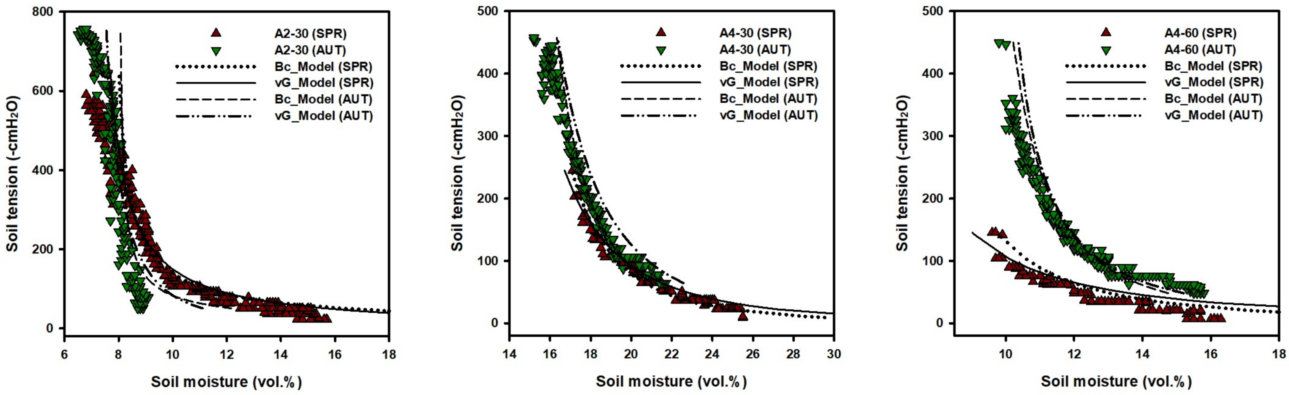
⇨ We partially agree reviewer's point for the normalized index with precipitation depth. Actually, we also considered this point in our initial approach because it looks sound and meaningful before we actually applied SOM. However, this storage coefficient provided substantially skewed measures due to the very wide ranges of precipitation depth (from 1 mm to 360.6 mm as denominator depending on event). The application of the storage coefficient into SOM provide unacceptable and unreasonable results in terms of the relationship between rainfall properties and its outcomes (storage coefficients) as shown following component planes.



Component planes of SOM using the storage coefficient (with precipitation depth)

- ⇨ As shown in component planes of SOM (above Figure) with the storage coefficient, there was no meaningful relationship between any rainfall properties (e.g., rainfall amount(AMO), duration(DUR), and intensity(INT)) and storage coefficients (STO-UP10, STO-UP30, STO-UP60, STO-DO10, STO-DO30, STO-DO60), which make no hydrological sense. Furthermore, the relationships between rainfall properties and P2Ps (standard deviation of peak time) (P2P-UP10, and so on) were also less meaningful. This is because that the storage coefficient is substantially skewed by the precipitation depth that heavily depends on events. The maximum, minimum, median, mean and standard deviation of precipitation depth (mm) were 1, 360.6, 11.7, 27.4 and 44.4. These skewed impact by the precipitation depth was much higher than those by the initial status of soil moisture.

- ⇨ The variation feature of soil moisture substantially depends on the local property of soil texture and its flow path connectivity. The initial status of soil moisture also important, which varied spatially and temporally. Actually, soil moisture variation can be described by soil moisture characteristic curve (SMCC). As shown in following figures (from Lee and Kim, 2019), SMCC varies for depth, location and season. Spatially and temporally different initial soil moisture before wetting or drying is important to express the wetness change.



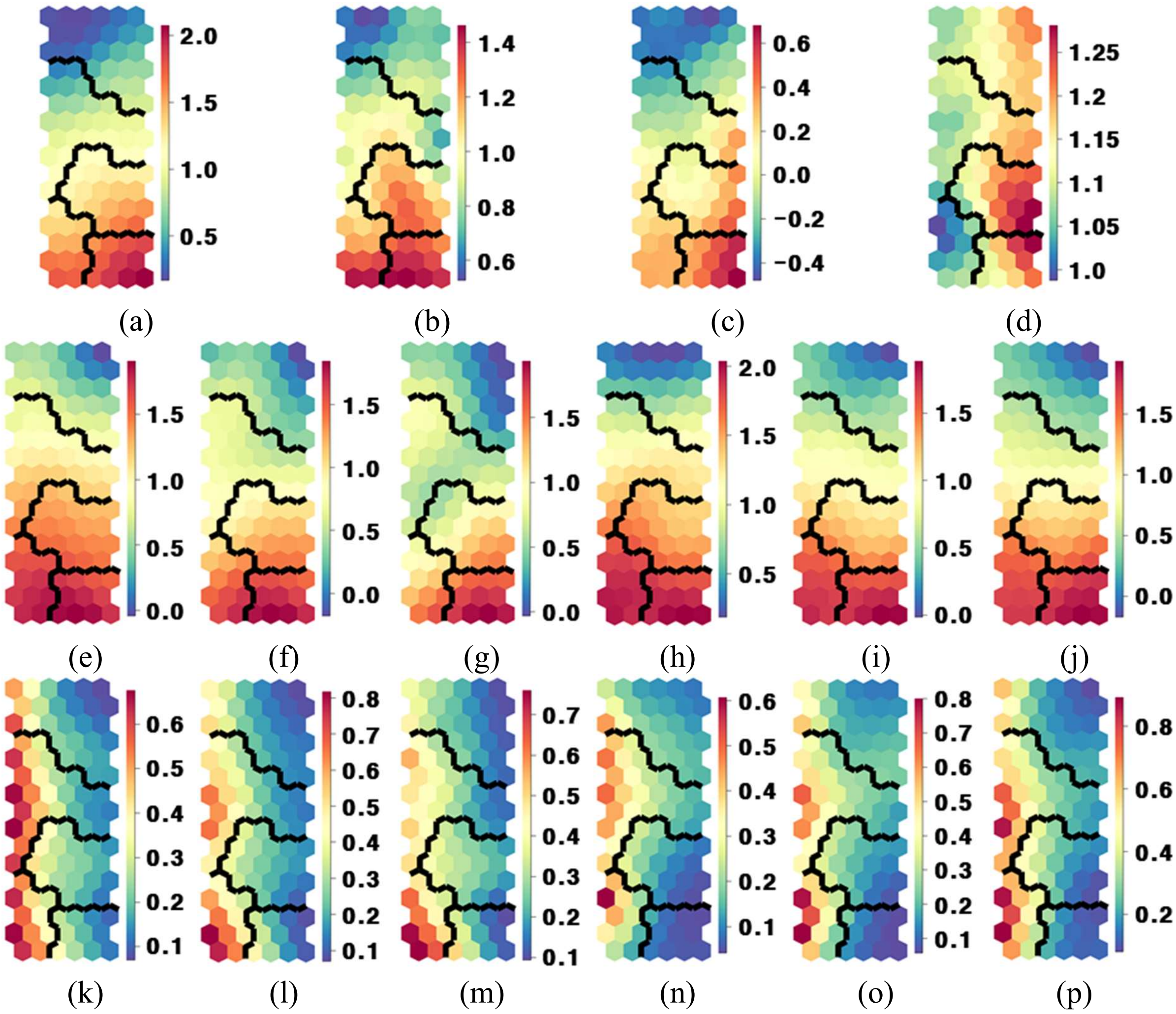
UP1-30cm UP3-30cm UP3-60cm

- Lee, E., Kim S., Seasonal and spatial characterization of soil moisture and soil water tension in a steep hillslope, Journal of Hydrology, 2019, 568, 676-685

https://doi.org/10.1016/j.jhydrol.2018.11.027

⇨ While the storage coefficient is the normalized index based on precipitation, the soil moisture difference index used in this paper addresses spatially and temporally distinct initial soil moisture status. Therefore, the SOM analysis (component planes) using the soil moisture difference index provides more reasonable, and hydrologically meaningful and interpretable results as presented in following Figs. 6.

⇨ Following Figs. 6 show the component planes of SOM using the volumetric soil moisture difference index. The relationships between rainfall properties (AMO, DUR, INT) and soil moisture difference indices at upslope depths and downslope depths were significant and meaningful in hydrological causality. Depending on the cluster (expressed as divided areas), the relationship between rainfall properties and its resulting volumetric soil moisture indices can be distinctly addressed in component planes shown in Figs. 6. Furthermore, the relationship between rainfall properties and standard deviation of peak time was significant only in the cluster 4, which can be explained by the lowest antecedent soil moisture condition.



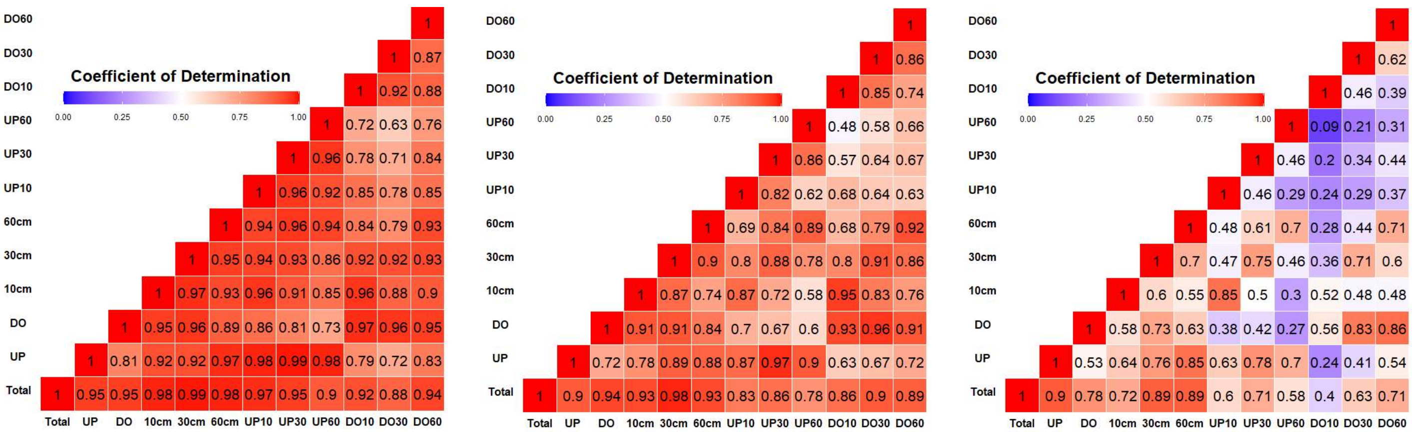
⇨ **Figure 6:** (**a**)–(**p**) Component planes of variable weightings for rainfall amount (AMO) (a); rainfall duration (DUR) (b); rainfall intensity (INT) (c); antecedent soil moisture (ASM) (d); volumetric soil moisture difference indices for the upslope and downslope at depths of 10, 30, and 60 cm (VUP10, VUP30, VUP60, VDO10, VDO30, and VDO60) (e)-(j); standard deviation of peak time for the upslope and downslope at depths of 10, 30, and 60 cm (SUP10, SUP30, SUP60, SDO10, SDO30, and SDO60) (k)-(p).

⇨ Regarding to reviewer's point related to storage coefficient, we addressed the storage changes in Table 2 that showed 5 different clusters well addressed the storage changes, which only used storage as depth change and not normalized by the precipitation depth.

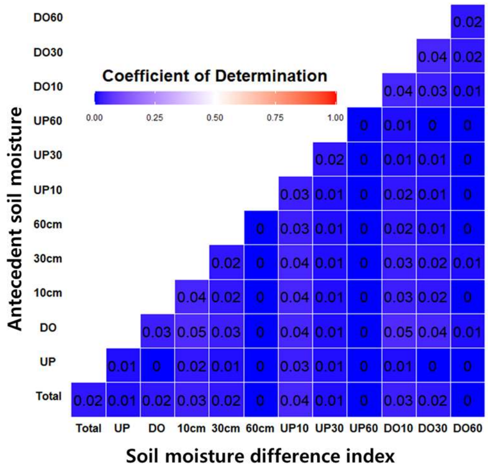
3. **Figure 4 is interesting**, but **the numbers are too small**. Please clarify whether this is the coefficient of determination R2 or the correlation R. The corresponding text mentions both. I also wonder whether you could correlate ASM and optional other predictors with VAR (to explain variations between the profiles).

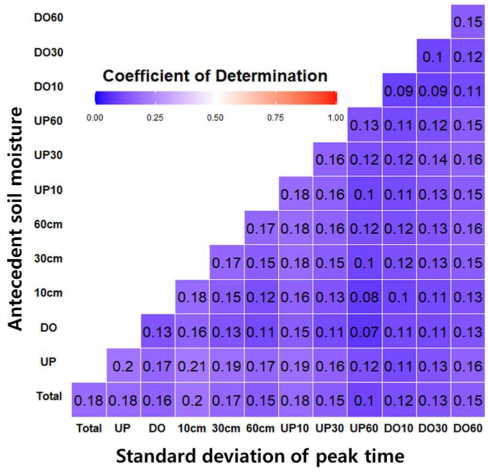
⇨ The numbers in Figure 4 represents the coefficient of Determination, R^2, ranged from 0 to 1. We explicitly noted 'Coefficient of Determination' in Figs.

⇨ We enlarged the size of both numbers and text in Figure 4 compared to previous figures.



⇨ The relationship between ASM and optional other predictors of soil moisture difference index and SDP2P are shown as heatmap below. The ranges of the relationships ranged from 0 to 0.2 in R2 which showed very week impacts of ASM on the other predictors. Therefore, we did not include ASM in analysis.





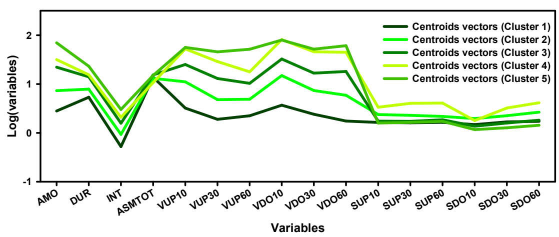
Heatmap for coefficient of determination between soil moisture difference index and ASM

Heatmap for coefficient of determination between SDP2P and antecedent soil moisture

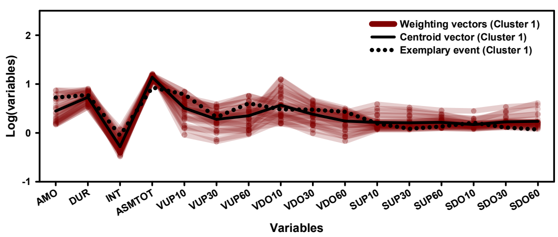
4. Last but not least, I agree with reviewer 2 that **a clear physical interpretation of the clusters is highly desirable.** Boxplots are an **abstract** representation of an event. In a different context (model error classification), Reusser et al. (2009) used typical errors in runoff events and classified those with am SOM. I am sorry to mention my own work in this context, this approach helped to interpret the corresponding error clusters (and to create an imagination how they looks like). **Another option would be to show the events closed to the cluster centroids.**

⇨ Our datasets were generated by the event-based approach. It is unavailable for our dataset to be applied on the comparison between time series data. Therefore, the second option to show the event close to the cluster centroid can be possible option on our dataset.

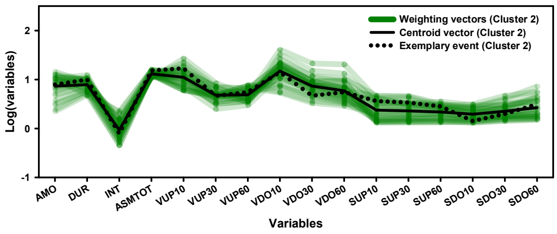
⇨ The centroid for each cluster was calculated by averaging of combinations with weighting vectors in the neurons corresponds to each cluster. The rainfall event with the smallest root mean squared error between input variables of the event and centroid of each cluster was selected as the events closed to the cluster centroids. The combinations of weighting vectors for the neurons, centroids, and the selected rainfall events were displayed below.



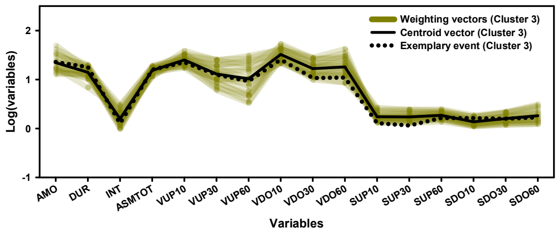
Comparison of average weightings for clusters



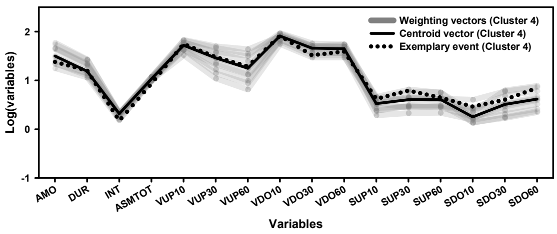
Cluster 1



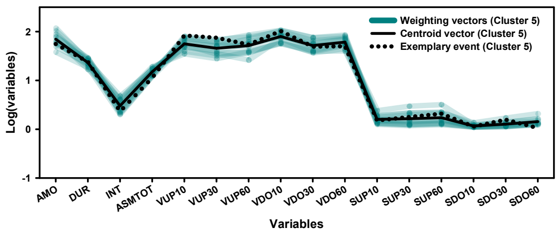
Cluster 2



Cluster 3

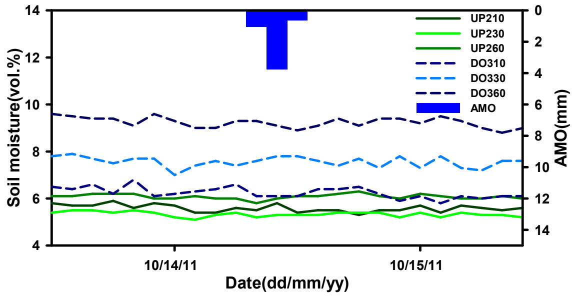


Cluster 4

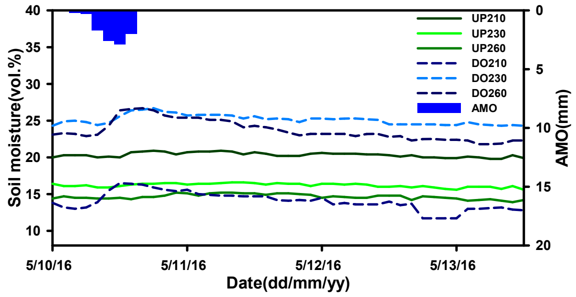


Cluster 5

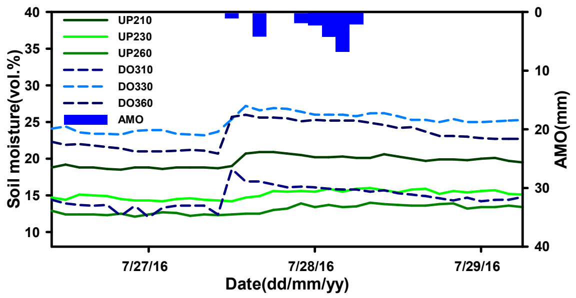
⇨ Since the selected rainfall event can represent the typical features of hydrological processes of each cluster, the exemplary event in appendix were replaced into the selected events based on cluster centroids.



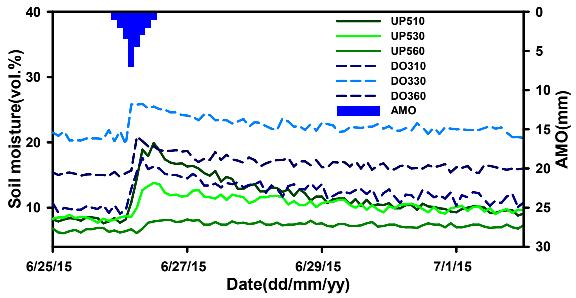
Cluster 1



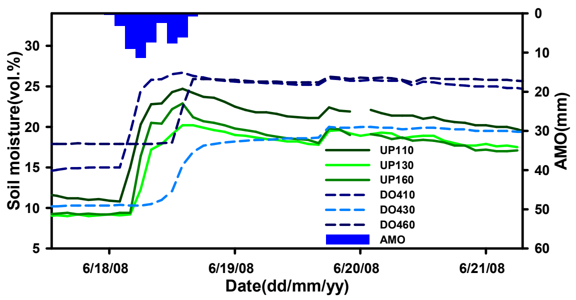
Cluster 2



Cluster 3



Cluster 4



Cluster 5

⇨ Also, following contexts were added to provide process for selection of exemplary events based on centroid of each cluster.

"The centroid for each cluster was calculated by averaging combinations of weighting vectors in the neurons. The event having the smallest root mean squared error between input variables of each event and the centroid of each cluster was selected as the exemplary event for corresponding cluster. Appendix presents exemplary events with rainfall and soil moisture responses at several upslope and downslope points for Clusters 1 to 5. The exemplary event for Cluster 1 showed almost no response to rainfall and that of Cluster 2 resulted into limited responses in designated downslope locations. Both events from Cluster 3 and 4 showed apparent response in many points with a difference in lower antecedent soil moisture condition for Cluster 4. The exemplary event for cluster 5 showed significant recharge impact in soil moisture for most points."

⇨ The reference which you suggested is also added in the sentence as reference.

"The SOM can be considered an effective tool for understanding substantial hydrologic data by reducing the dimensionality of a dataset, which can help provide hydrologic interpretation (Reusser et al., 2009)."

I would like to summarized all revised points for comment of previous reviewers as follows;

We revised paper addressing two comments from Reviewer 1 as follows;

⇨ Figure 7 is mentioned in text as;

"The hydrologic events classified by the SOM can be characterized through a comparative feature presentation for all clusters (Fig. 7)."

⇨ The exemplary events were added in Appendix

Appendix section is added to represent exemplary events.

We revised paper addressing comments from Reviewer 2 as follows;

The manuscript is written with a simple language however it is still very difficult to easily follow the manuscript. I think, although, the use of the English language in formulating the sentences is sufficient however the logical flow of the text is not intuitive and hampers by evolving around the technicalities and repetition.

⇨ We revised paper in many parts with help from professional English edior

1. I think figures can be improved and can be better explained in the text. For example, it is very hard for me to comprehend Figure 2 (and other figures which perhaps has a lot of dense information).
   - Figure 2 and Figure 3 were revised to improve readability (simple way) and corresponding explanations were added.

“3.1 Soil moisture responses of all measuring points during rainfall events

The statistics of soil moisture response based on the analysis of 30 points are summarized in terms of the P2P and maximum variation, as displayed in Fig. 2(a) - 2(f), which present elevations as an order of locations in x-axis as UP1-UP4-UP2-UP5-UP3-DO1-DO2-DO3-DO4-DO5 (Fig. 1) from the hilltop to downslope. The means of P2P ranged from –0.2 d to +0.5 d, indicating that the maximum soil moisture could be achieved even before the occurrence of the rainfall peak. Both standard deviation and average of P2P tended to increase at deeper depths, except for locations with elevations in 224 m and 216 m (locations of DO2 and DO5 in Fig. 1).

Fig. 2(a), 2(c) and 2(e) indicate while the mean P2P for the upslope area was 0.24 d, that of the downslope area was 0.02 d. The mean values of P2P at depths of 10, 30, and 60 cm were −0.08, 0.04, and 0.011 days for the downslope and were 0.1, 0.24, and 0.38 days for upslope, respectively. The differences in P2P between other points at an identical depth for the downslope were smaller than those for the upslope. This suggests that the soil moisture response in the downslope area is faster and more uniform than that in the upslope area. The accumulated soil water flow from the upslope area to the downslope area seems to be responsible for more rapid and less spatially variable soil moisture responses in the downslope area. As shown in Figs. 2(b), 2(d) and 2(e), both average and standard deviation of maximum variation tend to increase for locations with lower elevation. The average of maximum variations at depths of 10 cm and 60 cm were higher than those for the 30-cm depth, indicating that primary lateral flow tended to be generated along boundaries (surface and subsurface).

3.2 Soil moisture response features in measuring locations and depths

The soil moisture response features (e.g., ASM, soil moisture difference index, and SDP2P) were expressed in different spatially averaged responses (Fig. 3), depending on the depth and location. As shown in Fig. 3(a), the ASM in the downslope area was higher than that in the upslope area. It was apparent that the ASM in the downslope area increased with increasing depth; however, ASM for the upslope area did not display any notable trend in the depth profile. This indicated that soil water infiltration in the upslope area did not necessarily occur for all depth profiles.

The soil moisture difference index in the downslope area was higher than that in the upslope area, as shown in Fig. 3(b). The average soil moisture difference index in the downslope area (50.67%) was higher than that of the upslope area (38.73%), and the average soil moisture difference indices at depths of 10, 30, and 60 cm for the upslope area were 44.51%, 34.27%, and 37.39%, while those for the downslope area were 64.49%, 40.83%, and 46.69%, respectively. This indicates higher wetness along both the surface and subsurface boundaries, and this trend is pronounced in the downslope direction.

The SDP2Ps for the soil moisture datasets represent the degree of spatial heterogeneity in the temporal soil moisture response. The statistics of the SDP2P (Fig. 3(c)) revealed that the downslope response varied less than the upslope response. While the SDP2P of the downslope displayed an apparent increasing trend at deeper depths, those for the upslope showed a similar in-depth profile. The difference in the SDP2P profile between the upslope and downslope indicates that the impact of rainfall on soil moisture response timing can be completely different between the upslope and downslope directions.

2. I think the questions which the authors are asking were not directly answered. Perhaps the questions can be better elaborated in the discussions and reflect on the conclusions.

Following contexts were added to provide direct answers for questions in discussion section

"The machine learning algorithm (SOM) can be considered a useful analysis platform not only for elucidating soil moisture response patterns in conjunction with rainfall and ASM (Fig. 7), but also for an effective characterization of soil water storage changes at different locations and depths (Table 2)."
"As presented in Table 3, delineated clusters of hydrologic events can be considered to distinctly explain the combinations of hydrological processes such as vertical and lateral flows (either surface and subsurface boundaries) between the upslope and downslope directions.

- in conclusion section

"The SOM can be considered a useful analysis tool not only to understand the different soil moisture response patterns between the upslope and downslope areas but also to configure particular hydrological processes for delineated clusters. "

3. The key points are very vague please make them more specific to this study and the finding of this study. Title can also be improved; title is very generic and broad.

Key points were revised as follows

"A hydrologic dataset can be classified and characterized by applying a machine learning algorithm.

The self-organizing map is useful to understand the soil moisture response pattern at a hillslope scale.

Five event clusters distinctively represent different combinations of hydrological processes."

Title is revised as follows

"Characterization of Soil Moisture Response Patterns and Hillslope Hydrological Processes Through a Self-Organizing Map"

4. Perhaps reduce the long explanation on the method and wordy results to sharpen the messages.

On order to address reviewer's point, many parts of text in method and results in revised paper was reduced. Thanks.

Eqs. 1 – 3(from old version of paper) were eliminated.

5. I would like to encourage the authors to bring their study into wider hydrological modeling efforts. What is the message of the results for the hillslope hydrology at a larger scale? The hydrological models carry memory (antecedent soil moisture) for example, so the strong correlation the author is showing here is implicitly taken care of in the models that using time-stepping of storage over time. I do not see an important message from this study which is different from the general knowledge that we already have on how hillslope might behave; the findings may not be that different from what it can be inferred from a model. as an example, how Figure 4 would look like if the authors have repeated their study on a hydrological model at hillslope scale rather than the data itself. I would say we would strongly find the same pattern, so what is new? The authors can cite modeling work at catchment scale and try to contextualize their work. The previous studies such as Fang, Clark, et al., 2019 WRR, Loritz et al., 2017 HESS, Gharari et al., 2014 HESS, Gharari et al., 2011 HESS, Gao et al., 2014 HESS among others.

In order to address reviewer's concern following context was added as
"Several studies have been conducted to model the behavior of hillslope hydrology (Fan et al., 2019; Loritz et al., 2017). The SOM analysis for a large dataset showed an apparent distinct pattern in soil moisture response and flow path generation between upslope and downslope

areas depending on antecedent soil moisture and rainfall conditions. This suggests that the performance of the model can be improved as the storage structure of the model (fast and slow reservoirs) (Gao et al., 2014; Gharari et al. 2015) is further classified into upslope and downslope categories. The appearance of Cluster 4 (Table 3) demonstrates nonlinear behaviors in the hydrologic response, which can be explained by the apparent role of macropore flow even under low soil moisture conditions (Beven and Germann, 2013; Nimmo, 2012). The implementation of bypass flow under low ASM and high rainfall conditions into the model structure can help improve the modeling of soil water travel time (Kim, 2014). Further elaboration in modeling to represent dual lateral boundary flows in Cluster 5 can be useful to address multiple drain flow pathways under extreme rainfall conditions."

J.R. Nimmo, Preferential flow occurs in unsaturated conditions. Hydrol. Process. 26, 786-789, https://doi.org/10.1002/hyp.8380 2012.

S. Kim, Hydrometric Transit Times along Transects on a Steep Hillslope. Water Resour. Res. 50(9) 7267-7284. https://doi.org/10.1002/2013WR014746. 2014.

Y. Fan, M. Clark, D. M. Lawrence, S. Swenson, L. E. Band, S. L. Brantley, P. D. Brooks, W. E. Dietrich, A. Flores, G. Grant, J. W. Kirchner, D. S. Mackay, J. J. McDonnell, P. C. D. Milly, P. L. Sullivan, C. Tague, H. Ajami, N. Chaney, A. Hartmann, P. Hazenberg, J. McNamara, J. Pelletier, J. Perket, E. Rouholahnejad-Freund, T. Wagener, X. Zeng, E. Beighley, J. Buzan, M. Huang, B. Livneh, B. P. Mohanty, B. Nijssen, M. Safeeq, C. Shen, W. van Verseveld, J. Volk, D. Yamazaki, Hillslope hydrology in global change research and earth system modeling. Water Resour. Res. 55(2), 1737-1772, https://doi.org/10.1029/2018WR023903 2019

R. Loritz, K.H. Sibylle, J. Conrad, A. Niklas, L.v. Schaik, J. Wienhöfer, E. Zehe, Picturing and modeling catchments by representative hillslopes. Hydol. Earth Syst. Sci. 21, 1225-1249, https://doi.org/10.5194/hess-21-1225-2017, 2017.

H. Gao, M. Hrachowitz, F. Fenicia, S. Gharari, H.H.G. Savenije, Testing the realism of a topography-driven model (FLEX-Topo) in the nested catchment of the Upper Heihe, China. Hydol. Earth Syst. Sci. 18, 1895-1915, https://doi.org/10.5194/hess-18-1895-2014. 2014.

S. Gharari, M. Hrachowitz, F. Fenicia, H. Gao, H.H.G. Savenije, Using expert knowledge to increase realism in environmental system models can dramatically reduce the need for calibration. Hydol. Earth Syst. Sci. 18, 4839-4859, https://doi.org/10.5194/hess-18-4839-2014. 2015

K. Beven, P. Germann, Macropores and water flow in soils revisited. Water Resour. Res. 49(6) 3071-3092, https://doi.org/10.1002/wrcr.20156. 2013.

Thanks for your comments. Revised paper addressed most of reviewer's points. We used the soil moisture difference index because the storage coefficient with precipitation depth from final reviewer resulted into skewed and unreasonable results.

Sincerely,

Sanghyun Kim, Prof.

Pusan National University Busan

South Korea

kimsangh@pusan.ac.kr