Response to comments of Referee #2

Please find in Black the reviewer's comments and in blue our answers.

Comment: "This paper discusses the relationship between surface moisture and moisture at depth in the soil layer occupied by roots. This is an important issue for analyzing the time series of surface moisture observed by satellite by providing much more relevant information to characterize the functioning of ecosystems. Indeed, deep moisture has a very important impact on water fluxes by controlling both transpiration and deep drainage. The proposed approach is to use neural networks trained on a large dataset as offered by the ISMN. The main innovation is to introduce variables into the network training that can account for factors impacting the relationship between surface moisture and humidity in the RZSM. I find that the introduction does not insist enough on the processes that govern this relationship. Indeed, it is strongly linked to 1) root uptake, which depends on the canopy and the root profile in interaction with the climate and 2) capillary rise, which means that, depending on the properties of the soil, the water that evaporates from the surface layer is more or less compensated. This very important process, especially for lightly covered soils, is never mentioned. This knowledge of physical processes could have been put forward to justify the process based variables."

Reply: We would like to thank the reviewer for his constructive comments that helped us enhance the quality of the paper.

We agree with the reviewer that the aforementioned processes govern the relationship between SSM and RZSM. In the revised paper, the introduction has been updated to describe in summary the relation governing SSM and RZSM as follows :*«RZSM is nonlinearly related to SSM through different hydrological processes, such as diffusion processes. The root-zone soil moisture may be extracted by evaporation at the surface, through root extraction or by capillary rises (Calvet et Noilhan, 2000).»*

Comment: "I remain a little dubious about the choice of process based variables."

Reply: We changed the term «process-based» to «process-related» in order to avoid any confusion.

Comment: "NDVI: for me there is no doubt that this variable must be taken into account. On the other hand, the use of ndvi modis variable does not seem to me to be adapted to the sites used. Indeed, many measuring stations are placed on sites where the vegetation is not representative of the nearby environment. SMOSMANIA is placed on a meteorological station with a non-irrigated fallow land placed in the middle of an agricultural zone (probably dominant at the scale of the modis pixel). The stations of the plain of Kairouan are on bare soil (probably to simplify the management of sensors) while the plain is an agricultural area. So I think there may be a big difference between the modis ndvi and the ndvi on the representative area of the measurement. This is illustrated in table 4 where the model including the ndvi led to degraded results in comparison to ANN-SSM."

Reply: We agree with the reviewer that it is important to consider NDVI and also that the use of MODIS NDVI has a scale mismatch with point observations. Actually, higher resolution optical remote sensing products at high revisit are available (i.e. Sentinel-2 NDVI), but we privileged the MODIS dataset in order to combine the NDVI and the potential evapotranspiration from the same plateforme. In the revised paper, we have added a paragraph to discuss this point as follows:

«The presence of clouds in the MODIS NDVI and potential evapotranspiration products could explain this observation at sites of South-India and North-Italy. In South-India, for instance, the maximum variability in soil moisture occurred during the monsoon season, which is characterized by a large amount of clouds. Moreover, the coarse resolution of MODIS NDVI product makes it sometimes not adapted to the considered site. (Chen et al., 2016) investigated the impact of sample impurity and landscape heterogeneity on crop classification using coarse spatial resolution MODIS imagery. They showed that the sample impurity such as mixed crop types in a specific sample, compositional landscape heterogeneity that is the richness and evenness of land cover types in a landscape, and configurational heterogeneity that is the complexity of spatial structure of land cover types in a specific landscape are sources of uncertainty affecting crop area mapping when using coarse spatial resolution imagery. High resolution NDVI from sensors like Sentinel-2 could have been used in this exercise to mitigate the spatial resolution issue, however, MODIS data were privileged in order to provide NDVI and PET from the same sensor.»

A sentence has also been added to the conclusion as follows: *«In India and Italy, the correlations were already high with the reference model ANN_SSM. The change in correlation after the addition of process-related features, namely NDVI, is about -0.04 which is nonsignificant, and is potentially because of the cloudy conditions in India and noisy MODIS products. Also the crop heterogeneity and sample impurity makes MODIS NDVI products not adapted to all sites.»*

Comment: "The evaporative fraction as calculated is directly related to the surface moisture. There is therefore no introduction of information except via LEP which acts as a second order factor on the evaporative fraction."

Reply: We agree. Even though the evaporation efficiency formulation is related to surface soil moisture, it is still a new source of information for the neural network via the PET normalization. As mentioned by the reviewer, it acts as a second order factor in the analytical model.

The text related to this section was updated as follows based on the all the reviewers comments:

«-P, a proxy of parameter P (cf. appendix C), represents an equilibrium state controlled by retention forces in the soil, which increase with the thickness L of considered soil and by evaporative demands at the soil surface.*

-PET is the potential evapotranspiration (PET) extracted from the MODIS 500-m 8-day product (MOD16A2).

The soil evaporative efficiency predicted by model 3 by (Merlin et al., 2010) decreases when PET increases. Retention force and evaporative demand make the term P increase (replaced by P), as if an increase of LEp (here PET) at the soil surface would make the retention force in the soil greater. Merlin et al. (2010) tested this approach at two sites in southwestern France using in situ measurements of actual evaporation, potential evaporation, and soil moisture at five different depths collected in summer. Model 3 was able to represent the soil evaporation process with a similar accuracy as the classical resistance-based approach for various soil thicknesses up to 100 cm. Merlin et al. (2010) affirm the parameterization of P as a function of LEp (here PET) indicates that β cannot be considered as a function of soil moisture alone since it also depends on potential evaporation. Moreover, the effect of potential evaporation on β appears to be equivalent to that of soil thickness on β. This equivalence is physically interpreted as an increase of retention forces in the soil in reaction to an increase in potential evaporation.»*

Comment: "The recursive exponential filter completes the filtering by averaging over 10 30 and 90 days. It would have been interesting to compare them in order to identify to what extent these filters are complementary."

Reply: In order to clarify, we didn't apply the recursive exponential filter on the 10, 30 and 90-day averages.We have separated inputs for the 10, 30 , 90 day rolling averages and the recursive exponential filter outputs. This being said, in (Souissi et al, 2020) we investigated the impact of temporal parametrization of SSM inputs, namely the use of hourly, daily or rolling averages over 10, 30 and 90 days. In this paper, we were focused on the study of the impact of the exponential filter which has been identified as a simplified analytical solution for RZSM prediction.

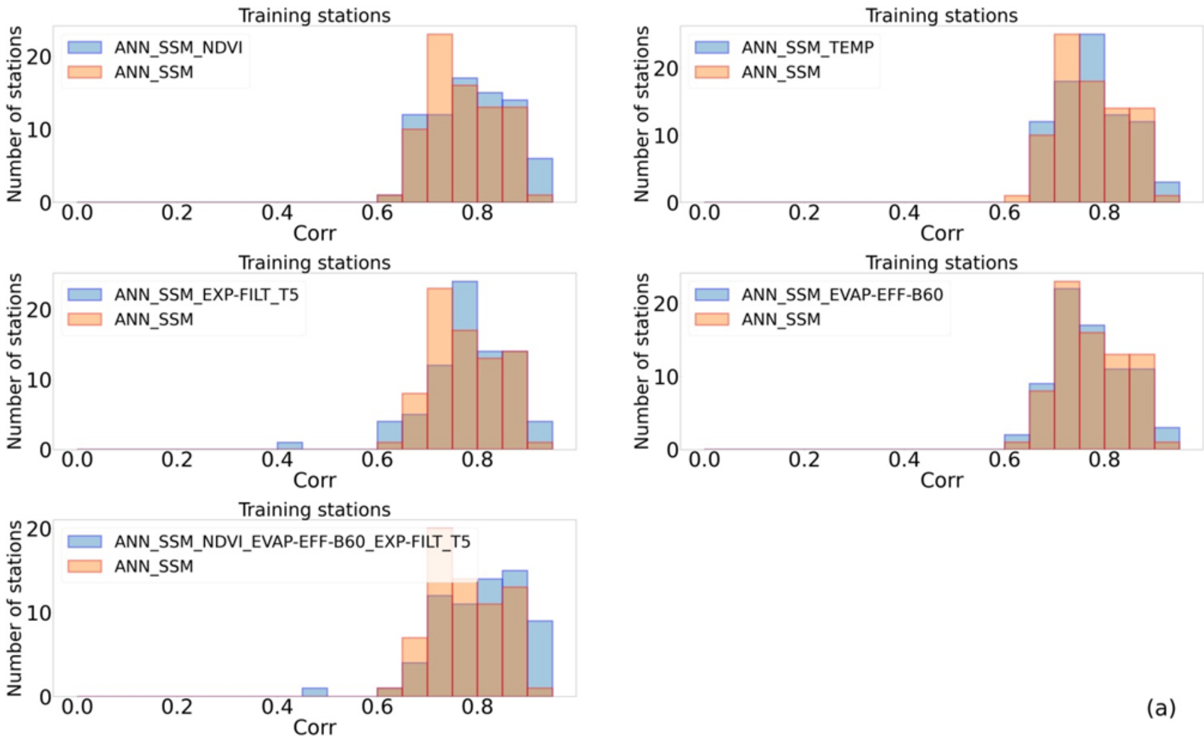
Comment: "The surface temperature could have been an indicator of the evaporative intensity. However, below the vegetation cover, the interpretation is far from obvious and requires knowledge of the air temperature in the canopy. Here it is not clear at what depth it is measured (probably at the depth of the first sensor). In this case the only interest seems to me to be to be able to flag the periods of freezing to eliminate the data which do not have a physical meaning. I would make this cleaning before training the neural networks."

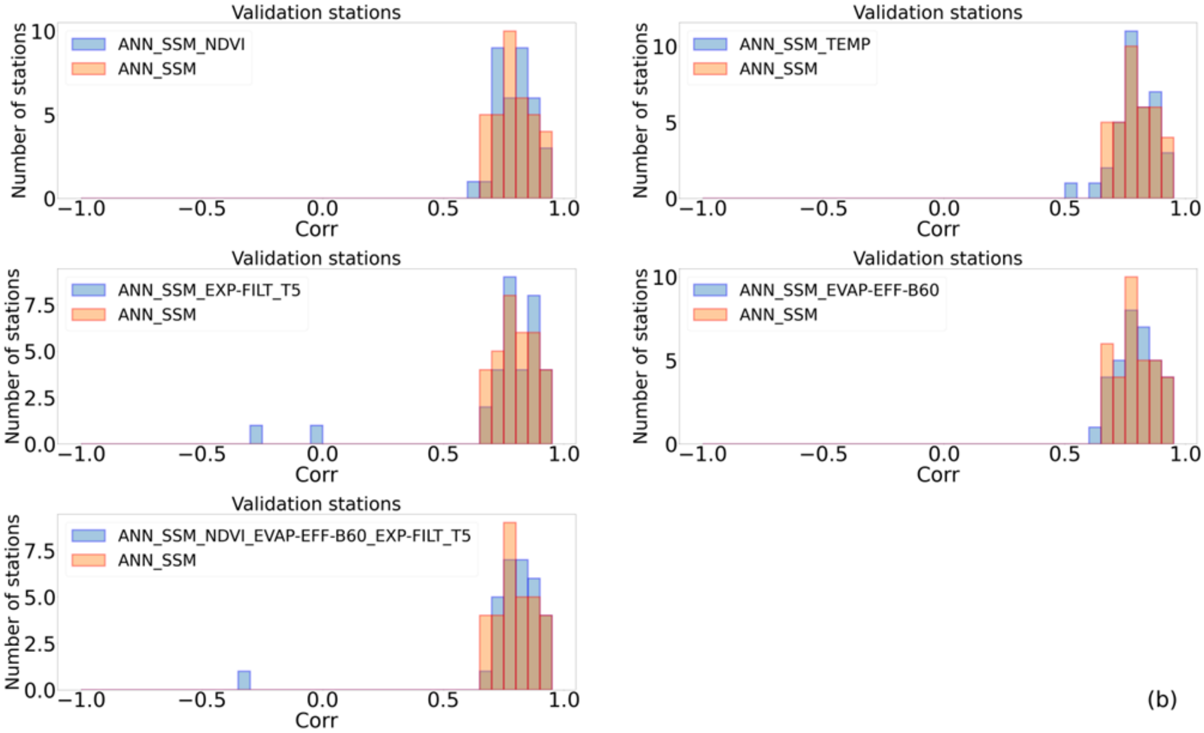
Reply: We thank the reviewer for this point. We have made the following clarification in the ISMN soil moisture dataset description: *«For each selected station, the root zone soil moisture observation point is located between 30 and 55cm (Table 2). For each soil moisture hourly acquisition, ISMN provides quality flags. Quality flags can be marked as 'C' (exceeding plausible geophysical range),' D' (questionable/dubious), 'M' (missing), or 'G' (good) (Dorigo et al.,2011). Category 'D' has subset flags namely 'D01' for which in situ soil temperature < 0°C, 'D02' that flags points at which in situ air temperature < 0°C as well as 'D03' that also flags areas where GLDAS soil temperature < 0°C. In our study, only soil moisture data with a 'G' labeled quality flag 'G' were retained.»*

Comment: **"**A more thorough discussion of the process based variables would be necessary, showing in particular on examples how they allow a better understanding of the relationship between surface and depth."

Reply: We agree with the reviewer. More results and discussions have been added to the manuscript. Time series have also been added in appendix E to compare the quality of fits of the least and the most complex models. As also inquired by reviewer 1, we have enriched the results section. In the revised paper, section (3.2 Intercomparison of the ANN models) has been modified such that there is a separation of training, validation and test datasets. Also, a comparison between the independent dataset quality of predictions (Tunisia) and training quality of fit over ISMN has been conducted. Section 3.2 now reads:

«The distribution histograms for training, validation and test stations (Fig. 3) show that the integration of the considered process-related features improved the prediction accuracy in certain cases compared to the reference. Time series of good and less good quality of fit were provided in appendix E for training, validation and test stations using reference model ANN_SSM and the most complex ANN model.





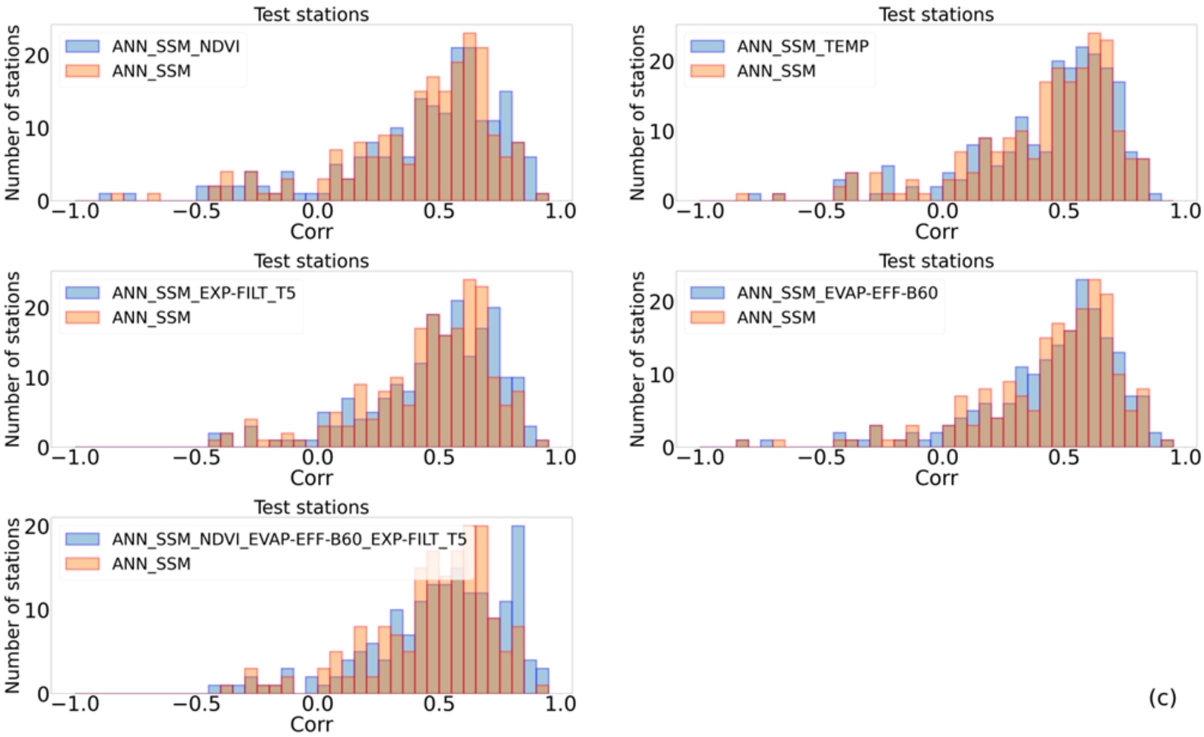


Figure 3. *Correlation histograms of all tested ANN models compared to ANN_SSM (a) on training stations (b) on validation stations (c) on test stations (cf. appendix D for RMSE histograms)*

In terms of the NDVI, 65.82%, 45.71% and 55.22% stations attained better correlation values with ANN_SSM_NDVI than those obtained with ANN_SSM for the training, validation *and test stations, respectively. RMSE decreased for 44.3%, 40.0% and 40.3% of the stations with ANN_SSM_NDVI compared to model ANN_SSM for training, validation and test stations, respectively (Table 3).*

In regard to the ANN_SSM_TEMP model that integrates the soil surface temperature, 49.4%, 55.56% and 59.35% of the training, validation and test stations exhibited higher correlation values than those obtained with the ANN_SSM model, respectively.

RMSE decreased with ANN_SSM_TEMP compared to model ANN_SSM for 25.3%, 38.89% and 42.99% of the training, validation and test stations, respectively.

In addition, model ANN_SSM_EXP-FILT-T5 that integrates the simplified infiltration based features yielded slightly better correlations, and 64.56%, 60.61% and 63.68% 62.62% of the training, validation and test stations attained better correlations than those obtained with model ANN_SSM, respectively.

Besides, RMSE decreased for 36.71 %, 42.42 % and 50.25% of the training, validation and test stations with ANN_SSM_ EXP-FILT-T5 compared to model ANN_SSM, respectively.

Regarding the evaporation efficiency, we considered different values of fitting parameter B (Eq. 4) such that B remained within the [50,60] interval. This parameter can be fitted using different variables, such as the wind speed or relative humidity. Comparisons based on the correlation values provided by the different models for each B value indicated that the performance was insensitive to the B value. Thus, we fixed the B value to 60 W m-^{2}. Comparison of models ANN_SSM and ANN_SSM_EVAP-EFF-B60 revealed that 54.55%, 52.94% and 52.33% of the training, validation and test stations attained higher correlation values with the latter model, respectively. RMSE was reduced for 28.57%, 41.18% and 48.19% of the training, validation and test stations with ANN_SSM_ EVAP-EFF-B60 compared to model ANN_SSM, respectively.

Finally, we investigated the impact of the joint application of the NDVI, recursive exponential filter (T= 5 days) and evaporation efficiency (B=60 W m-^{2}) in the ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 model. The surface soil temperature was not included, as its effect is included in the evaporation process. At 84.06%, 61.29% and 62.07% of the training, validation and test stations, the correlation value obtained with this model was higher than that obtained with the ANN_SSM model, respectively. In addition, RMSE was minimized for 62.32%, 54.84% and 54.02% of the training, validation and test stations with ANN_SSM_ NDVI_EVAP-EFF-B60_EXP-FILT-T5 compared to model ANN_SSM, respectively.»

Section (3.3 Robustness of the approach) now reads:

«However, the consideration of additional features, namely, the NDVI, evaporation efficiency and SWI in the ANN models resulted in a good agreement between the in situ and predicted RZSM values (Fig. 4). The correlation values were improved by 60.04%, 169.5%, 112.02%, 80.23% and 53.7% at stations Barrouta-160, Hmidate_163, Barrage_162, Bouhajla_164 and P12, respectively, with the ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 model over ANN_SSM model values. Similarly, RMSE values were reduced (Table 5). As shown in figure 4, the most complex ANN model is able to capture the variations of RZSM. This finding highlights the added value of our hybrid approach based on an association of a machine learning method with process-related variables. Instead of injecting uncertain information in physical models, such as soil properties, we used a nonparametric method

related to physical processes without using forcing data that may be subject to errors and potentially lead to inaccurate tracking of the long-term evolution of soil moisture.

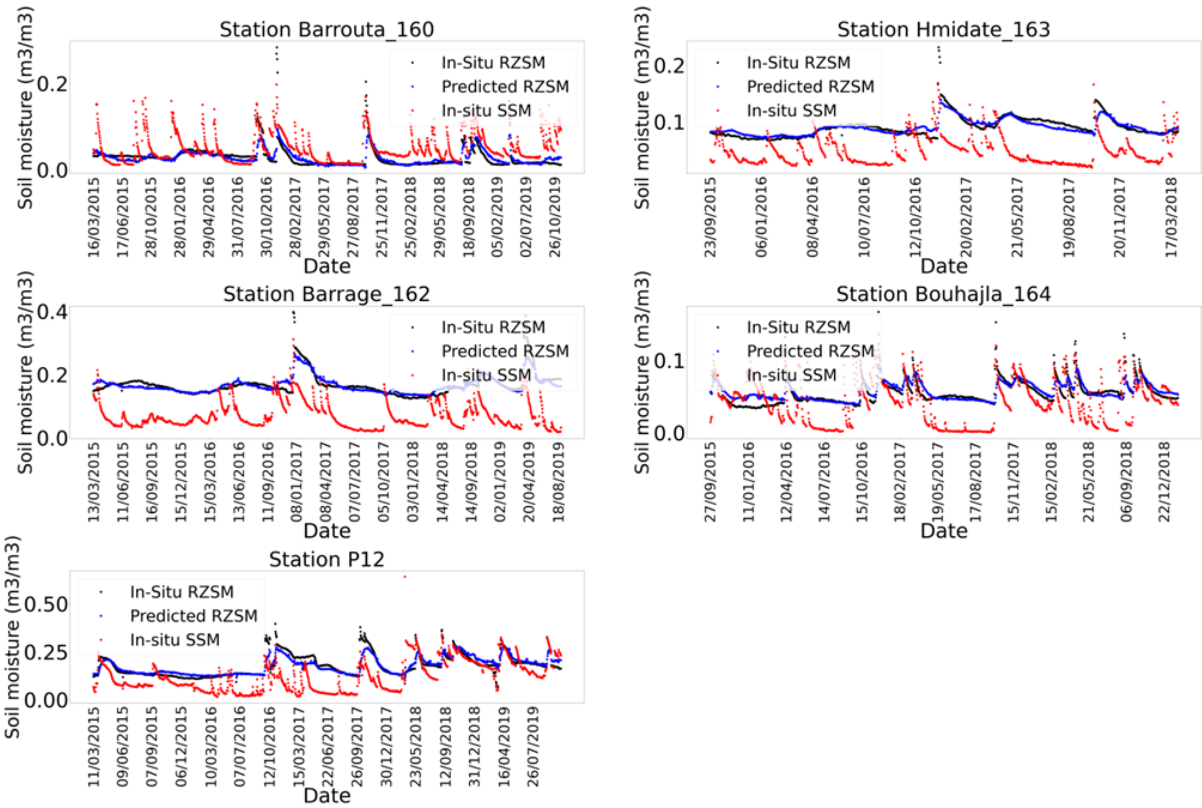


Figure 4. *In situ SSM, in situ RZSM, and predicted RZSM series at the stations in the Kairouan Plain (Tunisia) with model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 (cf. appendix G for larger figure format).*

A second comparison can be conducted between the quality of fit of these independent datasets and training datasets. Actually, the climate class of the Tunisian stations is 'Bsh' (cf. appendix A). At the training stage, no station falls into the climate class 'Bsh' (cf. appendix A). However, some training stations fall under a similar climate class which is 'Bsk' (cf. appendix B). Table 5 presents correlation and RMSE values for these training stations and Tunisian sites with both models ANN_SSM and ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5. For all training stations, performance metrics are slightly enhanced with the most complex ANN model compared to reference model ANN_SSM, except for stations GrouseCreek, Harmsway and Lind#1 which performance decreases. Overall, the range of correlation values is similar for training and external validation stations with model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 and RMSE is well reduced for Tunisian stations compared to training stations. Given the results on unseen datasets, namely on Tunisia, the performance of the most complex ANN model is good as it is able to generalize the patterns present in the training dataset.

Table 5. *Performance metrics of models ANN_SSM and ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 at training stations of climate "Bsk" and Tunisian stations of climate "Bsh".*

Model	*ANN_SSM*	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*

Training stations (climate class 'Bsh')				
Station	Correlation	RMSE	Correlation	RMSE
Banandra (OZNET)	0.701	0.05	0.764	0.046
DRY-LAKE (OZNET)	0.674	0.031	0.692	0.03
CPER (SCAN)	0.691	0.032	0.695	0.032
EPHRAIM (SCAN)	0.758	0.051	0.791	0.046
GrouseGreek (SCAN)	0.818	0.033	0.802	0.035
HarmsWay (SCAN)	0.705	0.034	0.622	0.038
Lind#1 (SCAN)	0.605	0.055	0.483	0.022
External test stations (Tunisia)				
Station	Correlation	RMSE	Correlation	RMSE
Barrouta_160	0.463	0.021	0.714	0.016
Hmidate_163	0.318	0.019	0.834	0.011
Barrage_162	0.416	0.035	0.864	0.019
Bouhajla_164	0.435	0.016	0.733	0.01
P12	0.581	0.047	0.861	0.029

Comment: "I would now focus on the results. Are the results presented in table 3 qualitatively good? For example, for the RMSE, the introduction of co-variables has a positive impact in only 57% of cases at best. This also means that in 43% of the cases the results are worse. I think that a more rigorous statistical analysis would be necessary to decide whether or not the gain is significant."

Reply: In the revised paper, the text has been modified to separate between training, validation and test stations as suggested by reviewer 1. New rates were provided accordingly. Indeed, not all stations undergo an improvement when process-related variables are added. As we have clarified in the revised text, a small percentage of stations undergo a decrease in correlation of more than 0.1 and an increase in RMSE of more than 0.01. Section 3.2 Intercomparison of ANN models now reads:

«Considering model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5, only one training station had a decrease in correlation by more than 0.1 namely station 'Lind#1' (network 'SCAN') compared to reference model ANN_SSM. All inputs were not available at the same dates which implied a significant reduction in data points (cf. appendix F). The decrease in correlation and increase in RMSE didn't exceed 0.1 and 0.01 m3/m3 for the rest of stations of lower performance metrics with the most complex ANN, respectively.

Similarly for validation stations, only one station had a decrease in correlation above 0.1, namely station 'PineNut' (network 'SCAN'), with model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5. This decrease can be also explained because of data shortage (cf. appendix F). The decrease in correlation and increase in RMSE didn't exceed 0.1 and 0.01 m3/m3 for the rest of stations of lower performance metrics with the most complex ANN, respectively.

Regarding test stations , correlation decrease by more than 0.1 and RMSE increase by more than 0.01 m3/m3 with model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 compared to model ANN_SSM was detected for only 2 stations. Both stations, namely station 'S-Coleambally' and 'Widgiewa' which belong to network 'OZNET', significantly lose in data volume when process-related variables are integrated in ANN and more precisely because of NDVI data availability (cf. appendix F). For the rest of test stations, correlation decreased and RMSE increased simultaneously by less than 0.1 and 0.01 m3/m3 with model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5, respectively.

Table 3. Proportion of the stations which performance enhances using the ANN models enriched with process-related features compared to model ANN_SSM (: % of stations at which the correlation improves over the model ANN_SSM level; **: % of stations at which RMSE improves over the model ANN_SSM level)*

Model	Training stations		Validation stations		Test stations	
	% of stations (corr ↑)*	% of stations (RMSE ↓)**	% of stations (corr ↑)*	% of stations (RMSE ↓)**	% of stations (corr ↑)*	% of stations (RMSE ↓)**
ANN_SSM_NDVI	65.82	44.3	45.71	40.0	55.22	40.3
ANN_SSM_TEMP	49.4	25.3	55.56	38.89	59.35	42.99
ANN_SSM_EXP-FILT-T5	64.56	36.71	60.61	42.42	63.68	50.25
ANN_SSM_EVAP-EFF-B60	54.55	28.57	52.94	41.18	52.33	48.19
ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5	84.06	62.32	61.29	54.84	62.07	54.02

Table 4. Proportion of the stations which correlation decreases using the ANN models enriched with process-related features compared to model ANN_SSM (Δ_{corr}=$corr_{ANN\_SSM}$ − $corr_{ANN\_SSM\_X}$, X denotes a or a combination of process-related variables)*

Model	Training stations		Validation stations		Test stations	
	% of stations corr ↓ and 0.05<Δ_{corr}*< 0.1	% of stations corr ↓ and Δ_{corr}*>0.1	% of stations corr ↓ and 0.05<Δ_{corr}*< 0.1	% of stations corr ↓ and Δ_{corr}*>0.1	% of stations corr ↓ and 0.05<Δ_{corr}*< 0.1	% of stations corr ↓ and Δ_{corr}*>0.1
ANN_SSM_NDVI	3.8	0	2.86	0	9.95	5.97
ANN_SSM_TEMP	0	1.2	0	2.78	4.67	3.27
ANN_SSM_EXP-FILT-T5	6.33	1.27	3.03	9.09	6.97	3.48
ANN_SSM_EVAP-EFF-B60	10.39	1.3	0	2.94	6.74	5.7
ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5	4.35	1.45	6.45	3.23	9.2	6.9

Comment: **“**Looking at Figure 4, I am impressed with the quality of the results. Using complex process models and measuring all the soil properties, I have never been able to simulate the water dynamics in different layers with such realism. I am impressed that a neural network trained with data from all over the world is able to reproduce with such fidelity the moisture levels between layers and the temporal variations in deep layers. No spurious variations are observed while the surface signal is particularly impacted by many rain events. If we can highlight the association of variables that allows such quality results, we have a major result for the understanding of water dynamics. This point must absolutely be highlighted.”

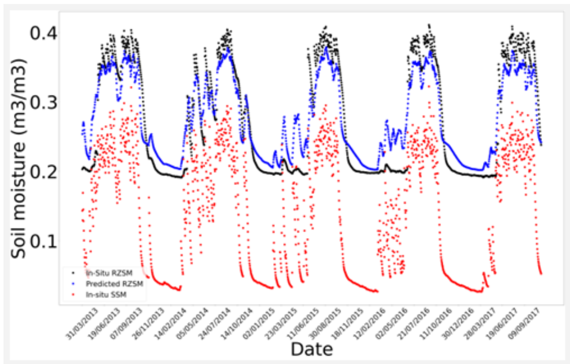
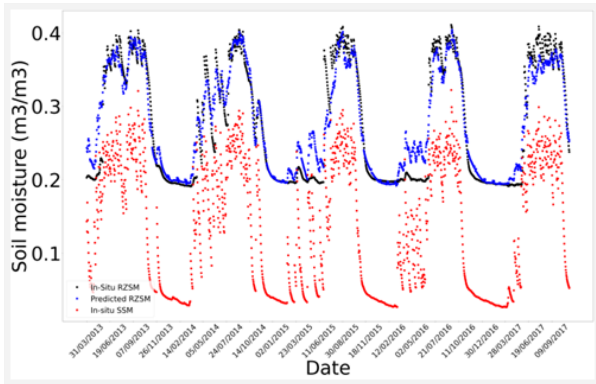
Reply: As the reviewer mentioned, the ANN model was trained on a wide set of areas across the world having different climates and soil textures as described in (Souissi et al., 2020). This coverage across variable conditions contributes to making the model more generalizable. We didn’t make a direct comparison of the outputs of the machine learning approach we used here to the predictions of complex physically-based models for water flow in variably saturated soils using for example the Richards-equations. We agree that it may be difficult to calibrate the pedotransfer functions for variably saturated flow in the soil and for the energy budget. This is mainly because of the sheer heterogeneity and unconsidered phenomena like hysteresis in the soil. This is also the main motivation of this paper.

In the revised paper, a paragraph has been added as follows: *«As shown in figure 4, the most complex ANN model is able to capture the variations of RZSM. This finding supports the added value of our hybrid approach based on an association of a machine learning method with process-related variables. Instead of injecting uncertain information, such as soil properties, in physical models, we used a nonparametric method that is related to physical processes without using forcing data going that may be subject to errors and potentially lead to inaccurate tracking of the long-term evolution of soil moisture.»*

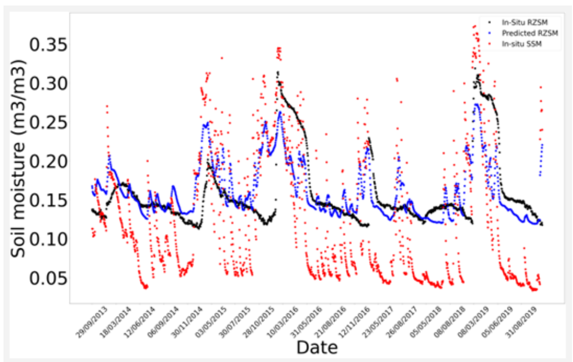
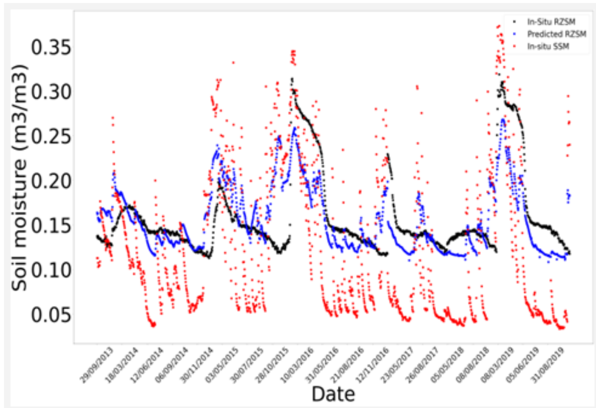
Even though the results we obtain are of good quality over a given set of stations, this is not the case in all conditions. Time series of good and less good quality of fit have been added in appendix E for training, validation and test stations separately using models ANN_SSM and ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 . Appendix E now reads:

«<u>Training stations:</u>

Station 'Beloufoungou Mid' (network 'AMMA-CATCH')

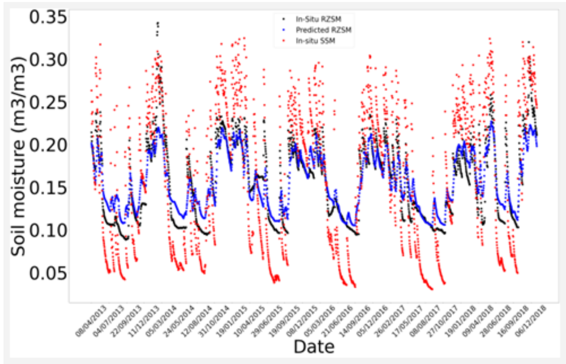
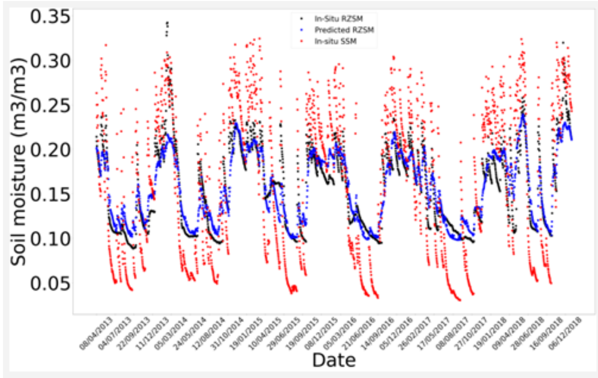
ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

Station 'HarmsWay' (network 'SCAN')

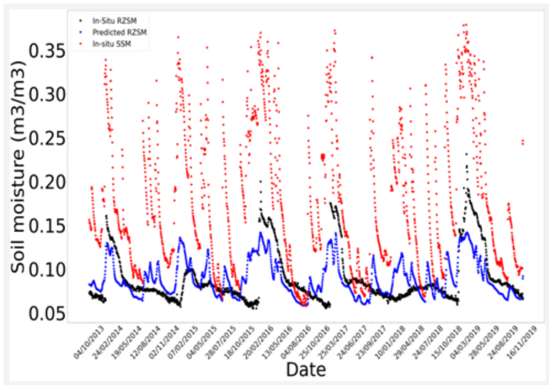
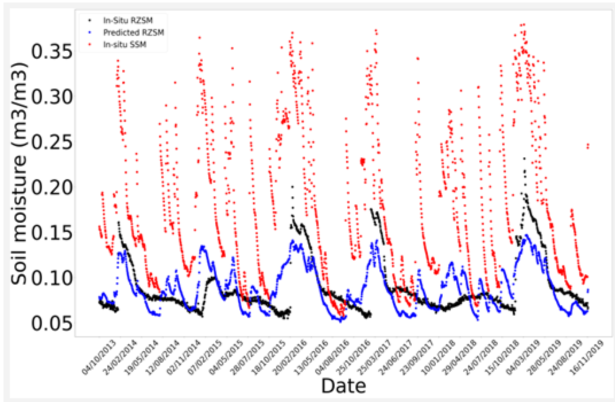
ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

[Validation stations](#)

Station ‘Cabrieres D’Avignon’ (network ‘SMOSMANIA’)

ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

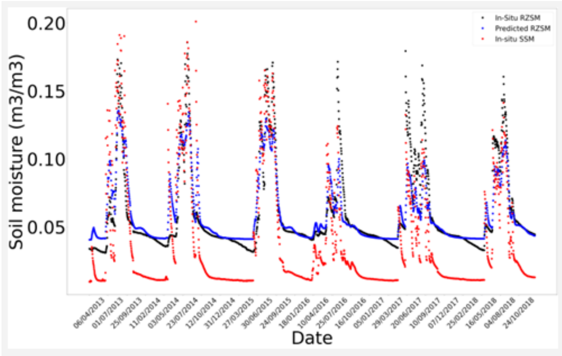
Station ‘Nephi’ (network ‘SCAN’)

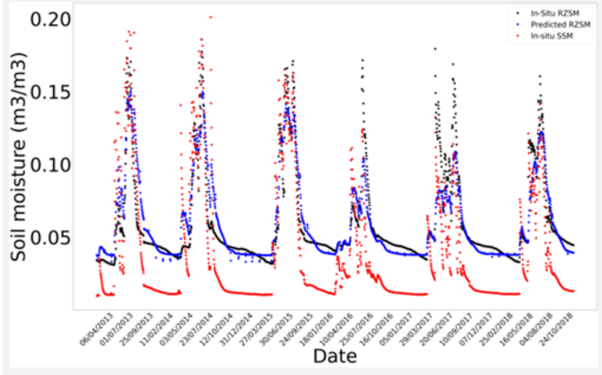
ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

[ISMN test stations](#)

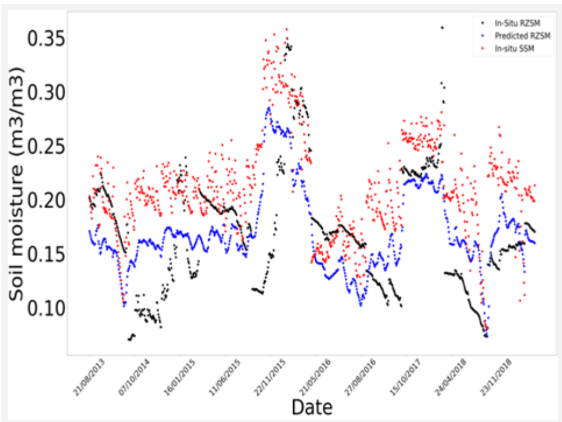
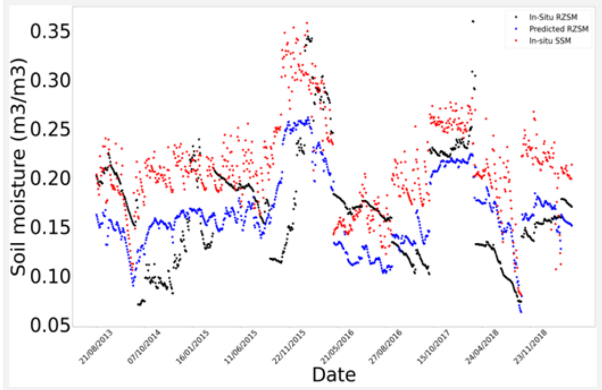
Station ‘Wankama’ (network ‘AMMA-CATCH’)

ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*





Station ‘2.04’ (network ‘HOBE’)

ANN_SSM	*ANN_SSM_NDVI_EXP-T5_EVAP-B60*
	

We have enhanced the discussion of the results obtained in this study with respect to outputs from previous studies by adding the following paragraph:

«Always in terms of the general performance of model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5, about 75% of the stations have an RMSE less than 0.05 m^3/m^3 and around half of the stations have an RMSE less than 0.04 m^3/m^3. This accuracy is consistent, for instance, with the target value in SMAP (Entekhabi et al., 2010) and SMOS (Kerr et al., 2010) missions which is equal to 0.04 m^3/m^3 and also to the average sensor accuracy adopted by Dorigo et al. (2013) which is equal to 0.05 m^3/m^3. Overall, the most complex model ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 can successfully characterize the soil moisture dynamics in the root zone since half of the stations have a correlation value greater than 0.7. Pan et al. (2017) developed different ANN models to estimate RZSM at depth of 20cm and 50cm over the continental United States using surface information. They found that half of the stations have RMSE less than 0.06 m^3/m^3 and more than 70% of stations have correlation above 0.7 when predicting RZSM at 20cm. However, the developed ANN was less effective in RZSM prediction at 50cm which is also in accordance with (Kornelsen and Coulibaly, 2014). In our study, the densest soil moisture network is ‘SCAN’, located in the USA. Soil moisture was predicted at a depth of 50cm over this network. Around half of the stations have a correlation value of above 0.6 and RMSE less than 0.04 m^3/m^3 after the integration of process-related inputs. Pan et al.,

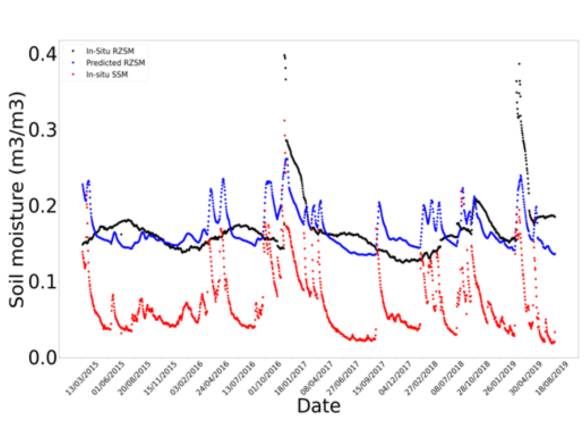
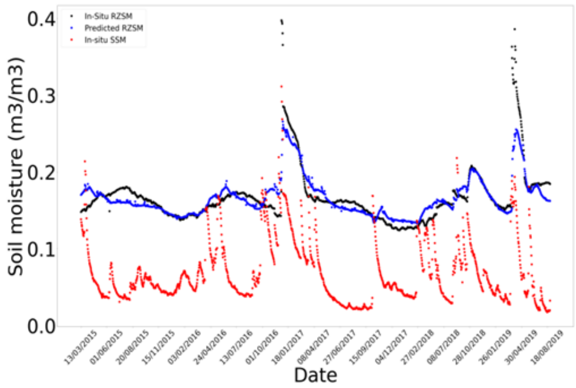
(2017) suggests that the use of only time-dependent variables may not be sufficient for the ANN models to accurately predict RZSM and suggests adding soil texture data.»

Also, the training experiments were designed to detect the impact of each process on the prediction quality. The association of variables is highlighted in figure (cf. figure 6).

Figure 4 shows the prediction results in Tunisia which sites fall into climate class 'Bsh'. Stations of similar climates, namely climate class 'Bsk' , were used in the training process. Table 5 was added in section 3.3 Robustness of the approach (please see Table 5 and updated section 3.3 above).

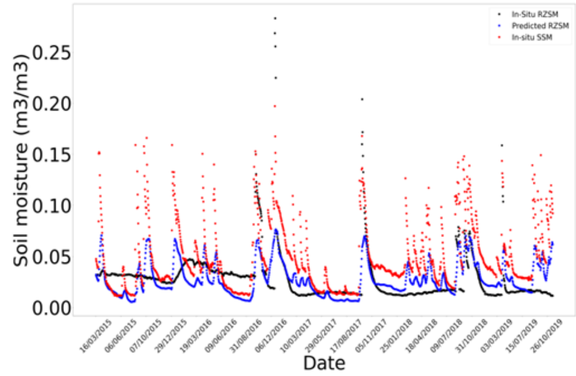
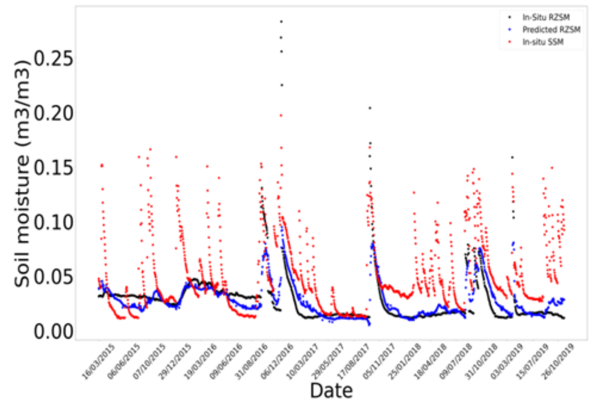
Also, time series over the Tunisian sites, with models ANN_SSM and ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*,* were added in a bigger format in appendix G as follows:*«*

Station Barrage-162 (Tunisia)

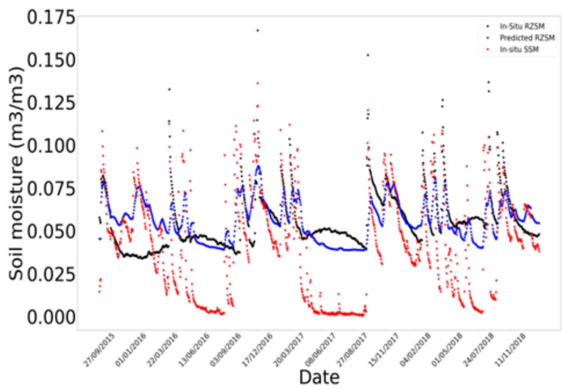
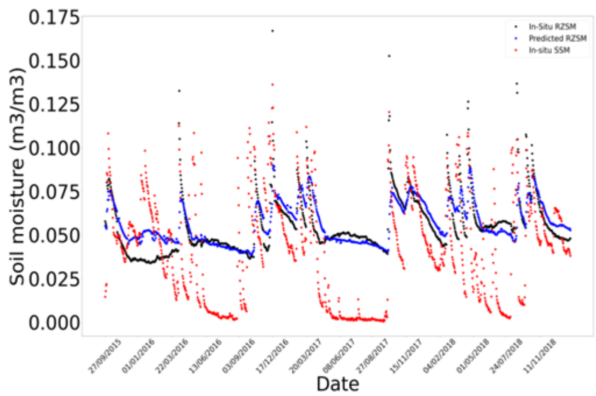
ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

Station Barrouta_160 (Tunisia)

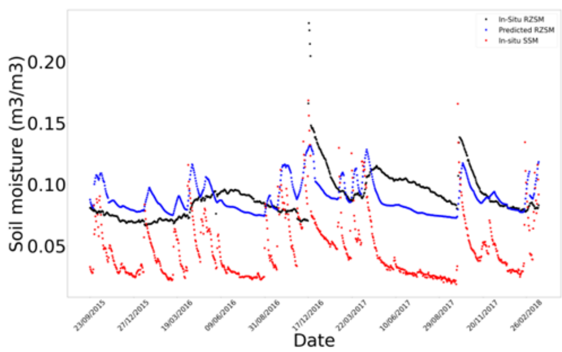
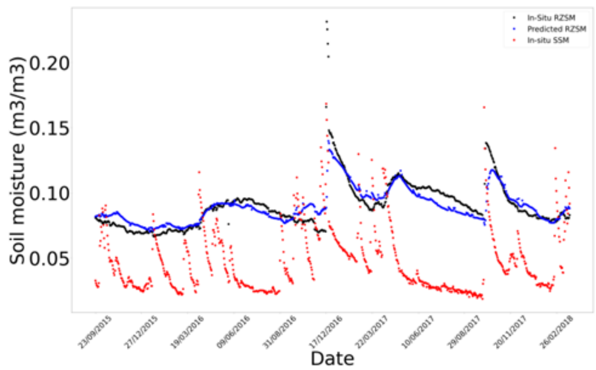
ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*

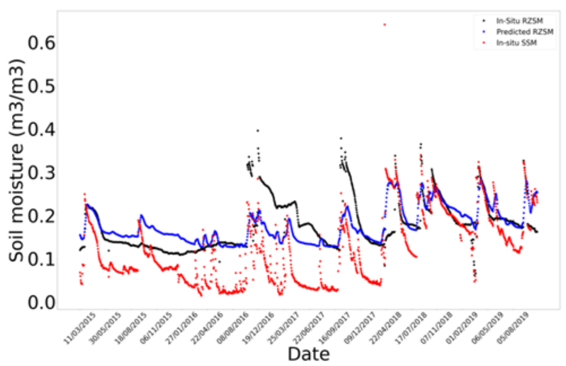
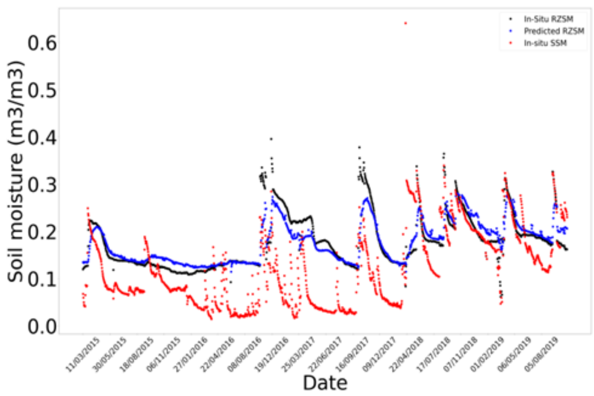
Station Bouhajla_164 (Tunisia)

ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

Station Hmidate_163 (Tunisia)

ANN_SSM	*ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5*
	

Station P12 (Tunisia)

<table>
<tr><th>ANN_SSM</th><th>ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5</th></tr>
<tr><td>
</td><td>
</td></tr>
</table>

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Comment: "Finally, on the form, the article does not seem to me well written. Not being an English speaker, I find the English not very good and the text not always clear. An subtancial editing work is for me essential."

Reply: The submitted manuscript was reviewed by the AJE English editing service (the invoice is attached). The current submitted one has been greatly enhanced and modified and was thoroughly reviewed.

Comment: "In conclusion, I find the submitted draft article has not reached a stage of maturity allowing a publication. Some of the results are potentially extremely important and I therefore invite further analysis."

Reply: We thank the reviewer for taking the time to review our manuscript. We appreciate the suggestions for additional results and further analysis which helped us clarify some points and overall improve the quality of the paper. We believe that the aforementioned modifications will enrich the paper and we hope that all the reviewer's concerns have been addressed. More results and discussions were added to the revised paper. The appendices were also developed to include for instance more time series of good and less good quality of fit for training, validation and test stations separately using models ANN_SSM and ANN_SSM_NDVI_EVAP-EFF-B60_EXP-FILT-T5 (cf. appendix E).

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