Reply to RC1

We thank the referee for the very helpful comments. We have revised the manuscript accordingly, below please find our replies to the individual comments.

> The paper applies a deep neural network to build a relationship between 18 predictors (simulations of rain, surface temperature and humidity, location, seasonality, root depth etc.) and a predictand (soil moisture down to about 5 cm). The simulation data was produced by a global atmospheric chemistry-climate model EMAC nudged to reanalysis data. The predictand's reference data was the ESA CCI Soil Moisture product.
> The motivation for the application of a neural network was to replace EMAC's soil moisture parameterization with a better one in a mineral dust emission parameterization. The study shall be seen as a proof of concept (line 195). Yes, it is, but a few issues should be clarified.
> The application has very dry areas in its focus. I have in mind that the soil moisture satellite product is especially uncertain in these areas. This should be discussed a bit. The trained prediction is most uncertain in the most interesting regions (Fig. 4: Sahara, Gobi Desert etc.). Why? Quality of the satellite reference or a training period of only 8 years?

In the driest central desert regions, the soil moisture is not very relevant for the dust emissions because the RHS of Eq. (1) is equal or close to unity. It is most relevant in semi-arid regions at the interface of desert and non-desert regions, which is dry enough to allow dust emissions but with enough moisture to have an effect. Therefore the uncertainty in the very dry regions is of limited concern in this context. Fig. S1 in the new supplement shows an example time series in a dry grid cell on the Arabian Peninsula, where comparison and training with the satellite data are challenging because retrievals are both rare and inaccurate. Fig. S2 shows the time series in a grid cell further north in Mesopotamia where the soil moisture levels are more relevant for dust emissions. Here, the observations and predictions are more reasonable and show good agreement. Other applications than dust emissions may require and extra treatment for the central desert regions. This is now mentioned in the discussion of Fig. 4 in section 3.

> The DNN is built with 512 units and four hidden layers. This parameter selection should be motivated a bit. Of more concern is the DNN performance. With location and seasonality as predictors, I expect a high correlation between prediction and reference soil moisture. What is the benefit of using meteorology/climate simulation in the prediction?

We added some motivation for the DNN dimensions in Section 3, but neither a strict rule can be applied, nor did we perform a systematic optimisation of these paramaters, therefore other choices might work even better. In section 3, we also added a discussion of the importance of the meterological predictors which substantially enhance the temporal correlation and allow the predictions to respond to climatic changes.

> Finally, it would be helpful to have short discussions on the applicability of the chosen approach in a changing climate and an alternative DNN training of EMAC parameters (avoiding two parametrizations predicting soil moisture).

We address the applicability in a changing climate in the new discussion on the importance of the meteorological predictors. Regarding the alternative training, it is true that strictly speaking our approach involves two soil moisture parametrisations, the DNN and indirectly the original EMAC parametrisation which is used to produce the training data. To reduce the effect of the latter, the training could be repeated after generating new training data with an EMAC simulation that uses the DNN. But we are not sure whether this is advantageous at this stage.