Soil Moisture Prediction Model from ERA5-Land Parameters using a Deep Neural Networks

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Abstract: In a global context of scarcity of water resources, accurate prediction of soil moisture is important for its rational use and management. Soil moisture is included in the list of Essential Climate Variables. Because of the complex soil structure, meteorological parameters and the diversity of vegetation cover, it is not easy to establish a predictive relationship of soil moisture. In this paper, using the large amounts of data obtained in West Africa, we set up a deep neural network to establish an estimation of soil moisture for the two first layers and its prediction temporally and spatially. We construct deep neural network model which predicts soil moisture layer 1 and layer 2 multiple days in the future. Results obtained for accuracy training and test are greater than 93 %. The mean absolute errors are very low and vary between 0,01 to 0,03 m^3/m^3.

1 INTRODUCTION

The most important resource for the survival and development of the earth's population is water (Schlesinger, 2014). The soil moisture is the amount of water level present in the top layers of the soil. The soil moisture interacts and affects with atmosphere by evaporation and transpiration (Kaleita et al., 2014; Seneviratne et al., 2010). Temperature variability and heatwaves have large dependence on soil moisture feedback on evapotranspiration (Miralles et al., 2014; Mueller and Seneviratne, 2012).

Many instruments and procedures can be used to measure the soil moisture. Then, when the soil moisture measurements are done by using gravitimetric and volumetric procedures, it is called direct method. Indirect method involves using instrument like tensiometers, gypsum blocks, and neutron probes.

The high correlation between soil moisture and reflection spectrum of soil involve that many researchers used remote sensing data to infer soil moisture. The reflectance of soil in visible and infrared bands is highly related to the soil colour, texture, surface roughness and crusting, composition and organic matter.

Reanalysis, that combines model data with observations from across the world into a globally complete and consistent dataset using the laws of physics, offers spatial and temporal coverage (Balsamo et al., 2015).

A good knowledge of soil moisture prediction can be helpful in irrigation water management. It involves better estimation of fertilizers and other input, and better assessment of need and availability of soil water level for crop cultivation. Thus, it is necessary to be able to accurately predict soil moisture in order to be able to save water, especially for farmers.

Empirical formulas, linear regression, and neural networks are currently the most widely used methods for predicting soil moisture.

By the use of daily meteorological records, soil physical properties, basic crop characteristics and topographical data, Vahedberdi et al., (2009) developed the Bridge Event And Continuous Hydrological (BEACH) modelling to provide timely information on the spatially distributed soil moisture content over a given area without the need for repeated field visits.

Using a soil moisture, precipitation and drought prediction model, it was possible to predict drought in a soil several days into the future (Chen et al, 2014).

Cai et al., (2019) use a deep learning regression network, built with a two-layer hidden layer, to

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establish a predictive model between meteorological parameters and soil moisture at a depth of 20 cm in the Yanqing area (Beijing, China) with accuracy of 98%.

The objective of this work is to accurately predict the soil moisture level multiple hours in advance by using deep neural network regression. With few parameters easy to measure and easy to access, the challenge in this work is to successfully predict the evolution in time and space of soil moisture.

The reason for choosing deep learning is that with these methods it was possible to improve the accuracy of soil prediction due to its non-linearity and structure complexity (Veres et al., 2015; Cai et al., 2019).

2 DATASET

We use ERA5-Land hourly dataset with ~9km grid spacing. ERA5-Land has been produced by replaying the land component of the ECMWF ERA5 climate reanalysis. Thus, ERA5-Land is forced by the atmospheric analysis of ERA5 and hence observations indirectly influence the simulations.

This dataset is taken in an area of the West Africa, between 6°N and 24°N and -17°W and 34°W.

West Africa's climate is characterized by a strong latitudinal rainfall gradient that determines production systems. It is also characterized by dramatic fluctuations in rainfall patterns on multi-decadal time scales, amplifying the already substantial annual rainfall variability. These include sub-humid, semi-arid and arid zones.

The climatology of the average annual precipitation cycle can be summarized in a few main phases. The first rains appear on the coasts of the Gulf of Guinea (5°N) in March; they then increase in intensity during the months of April and May; during the month of June, the zone of heavy rainfall moves rapidly towards latitudes close to 10°N (Sultan and Janicot, 2000), remaining almost stationary at this position until the end of August, a period which corresponds to the short dry season in the Guinean zone. Rainfall decreases in August, linked to the relative atmospheric stability on the coasts of the Gulf of Guinea resulting from the drop-in ocean temperatures and a divergence in specific humidity (Philippon and Fontaine, 2002). Finally, there is a gradual withdrawal of the rainy zone towards the coasts between September and November, a period that corresponds to the beginning of the second passage of the ITCZ along the coasts (second rainy season).

The learning dataset describes eight (08) variables and two (02) moisture soil layer. These 08 features are noted by x and the volumetric soil moisture. Volumetric soil moisture is expressed in $m^3.m^{-3}$.

Features x are composed of five meteorological data such as 2 metre temperature (t2m), 2 metre dewpoint temperature (d2m), total precipitation (tp), 10m u-component of wind (u10) and 10m v-component of wind (v10); two parameters related to soil properties such as evaporation from bare soil (evabs) and surface sensible heat flux (sshf); and the initial soil moisture (smli).

Soil moisture is localized in ERA5-Land in 4 layers with depths of 0.07 (0–0.07), 0.21 (0.07–0.28), 0.72 (0.28–1.00) and 1.89 (1.00–2.89) m. The first two layers are of interest to us in this study.

For each ERA5-Land day, we take measurements at 00 h and 12 h. These measurements concern the years from 2012 to 2013 for the months from July to November. This gives a matrix with a dimension of 10 x130000.

For validation dataset, we used combined various single-sensor active and passive microwave soil moisture from Climate Change Initiative (CCI) of the European Space Agency (ESA). These level 3 (super-collated: L3S) dataset are observations combined from multiple instruments into a space-time grid. The soil moisture data for the combined product are provided in volumetric units [m3.m-3]. The products come, among others, from sensor as Scanning Multichannel Microwave Radiometer (SMMR) onboard Nimbus-7, Tropical Rainfall Measuring Mission (TRMM), the Advanced Scatterometer (ASCAT) onboard the Meteorological Operational satellite program (MetOp), the Special Sensor Microwave Imager (SSM/I), the Advanced Microwave Scanning Radiometer — Earth Observing System (AMSR-E) on-board the Aqua satellite.

3 METHODS

The main objective of machine learning is to estimate the unknown relationship between input and target parameters using known examples. For numerical targets, the tasks become a supervised learning. The objective of supervised learning is to build relationships and dependencies model between the target prediction output and the input features such that we can later predict the output values for new data based on the model.

Suppose $\{x_n, y_n\}_{n=1}^{N}$ to be the training dataset with X being the input space and Y being the output space. The objective at the moment is to seek a function *f: X → Y* from a hypothesis space that minimizes the loss associated. The best fit to the underlying function can be chosen by minimizing a cost function.

Consider $\hat{y}_i$ the predicted value, y_i the true value, and the average value, the performance of a model can be measured by:

Mean Absolute Error (MAE):

$$\frac{1}{n}\sum_{1}^{n}\left|(y_i - \hat{y}_i)\right| \tag{1}$$

R Squared (R^2):

$$1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{2}$$

To build supervised learning model, several algorithms, which are developed in different mathematical backgrounds, exist. We can denote, linear regression, ridge regression, decision trees, K-Neighbors regression, Support vector regression, neural networks (Diouf and Seck, 2019).

For this study, we are taken a neural network method. A neural network is a mathematical model used as nonlinear statistical tools in modeling complex relationships between inputs and outputs.

We opt to a two-hidden layer regression neural network. The output of the previous layer is the input of the next layer. It is a deep neural network regression and its mathematical structure is composed by:

- An input layer for which the number of nodes is equal to the number of input parameters.
- Hidden layers node composed of neurons.
- The regression model output layer. The output of the previous hidden layer is multiplied by the weight and is added to a bias on the output node to obtain the regression prediction value.

We use a single model to predict soil moisture for layer 1 and layer 2, so-called 2NNL2. This model is a succession of two networks to form a unique model. The first network has as input the eight parameters and as output the soil moisture of layer 1. The second network have as input the same inputs of the previous network plus the output of network 1. The output is the soil moisture of layer 2.

We use five models to predict the soils moisture level multiple days in advance.

Model 1: The output data of network 1 (*sml1*) is measured two (02) days after the input data. The output data of network 2 (*sml2*) is measured three (03) days after the input data and one (01) day after the sml1.

Model 2: The output data of network 1 (*sml1*) is measured three (03) days after the input data. The output data of network 2 (*sml2*) is measured four (04) days after the input data and one (01) day after the sml1.

Model 3: The output data of network 1 (*sml1*) is measured four (04) days after the input data. The output data of network 2 (*sml2*) is measured five (05) days after the input data and one (01) day after the sml1.

Model 4: The output data of network 1 (*sml1*) is measured five (05) days after the input data. The output data of network 2 (*sml2*) is measured six (06) days after the input data and one (01) day after the sml1.

Model 5: The output data of network 1 (*sml1*) is measured six (06) days after the input data. The output data of network 2 (*sml2*) is measured seven (07) days after the input data and one (01) day after the *sml1*.

This means that for each model, the inputs of network 2 are the same inputs of network 1 plus output of network 1 (*sml1*).

After many attempts, all these models' structure was determined to be 8-150-80-1 followed by 8-100-50-1 respectively for network 1 and network 2.

We train and optimize Model 1, Model 2, Model 3, Model 4 and Model 5.

Several algorithms can be used for optimization. Here we choose Adaptive Gradient Algorithm (AdaGrad) as an optimization algorithm (Duchi et al., 2011). AdaGrad is an optimization algorithm for gradient-based optimization. AdaGrad performs gradient descent with a variable learning rate. Parameters associated with infrequent features are adapted with large gradients and parameters associated with frequently occurring features perform small gradients. Adagrad thus improves on SGD, or stochastic gradient descent, with a per-node learning rate scheduler built into the algorithm.

To optimize gradient descent at time-step t, g_t, an objective function $J(\theta)$ is minimized by updating a parameter θ. The equation of the parameter is:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\varepsilon I + diag(G_t)}} \bullet g_t \tag{3}$$

where θ_t is the parameter to be updated at time-step t, η is the learning rate, ε is some small quantity that used to avoid the division of zero, I is the identity matrix, $diag(G_t)$ is a diagonal matrix containing the squares of all previous gradients, g_t is the vector of gradients for the current time-step and can be expressed, for each training example x^i and label y^i, by:

$$g_t = \frac{1}{n}\sum_{1}^{n} \nabla_\theta J(x^i, y^i, \theta_t) \quad (4)$$

The accuracy on the learning set is 93.8% and the validation accuracy is 92.5% for all models. The mean absolute error turn around 0.015 m^3/m^3 for training phase and 0.02 m^3/m^3 for validation phase. Table 1 summarizes performances measures for all models. We notice that the soil moisture retrieved from training features and its real values are quite good for layer 1 and layer 2. This figure gives us an idea of the accuracy of the model in reproducing the training dataset.

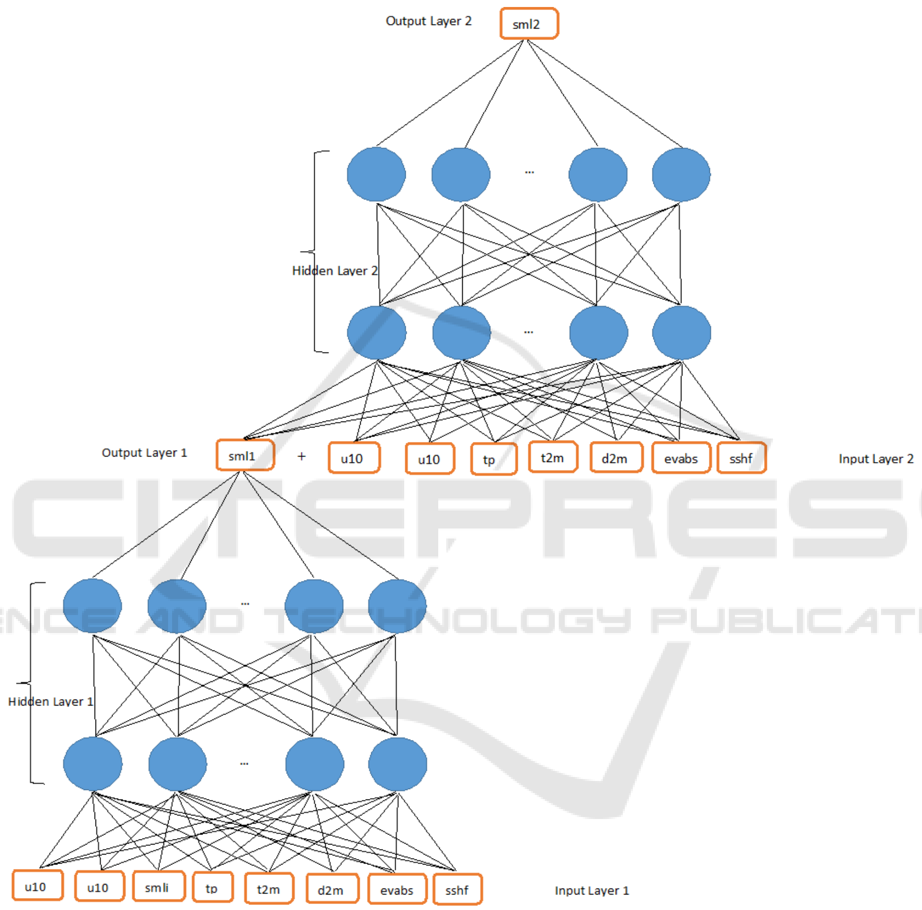

Figure 1: A two connected two-hidden layer regression neural network (2NNL2).

Table 1: Performance measures of 2NNL2 models.

		Train mae	Test mae	Train loss	Test loss	Train R^2	Test R^2
Model 1	Output 1	0.010	0.013	0.0002	0.0005	98.37%	98.43%
	Output 2	0.023	0.026	0.0010	0.0013	93.8%	93.7%
Model 2	Output 1	0.013	0.015	0.0004	0.0006	97.7%	97.2%
	Output 2	0.023	0.026	0.0011	0.0014	93.8%	92.7%
Model 3	Output 1	0.015	0.018	0.0005	0.0007	97.1%	97.1%
	Output 2	0.023	0.027	0.0010	0.0015	93.8%	92.5%
Model 4	Output 1	0.017	0.020	0.0006	0.0009	96.8%	96.5%
	Output 2	0.024	0.027	0.0011	0.0013	93.9%	92.7%
Model 5	Output 1	0.018	0.021	0.0006	0.0010	96.4%	96.4%
	Output 2	0.024	0.027	0.0011	0.0014	93.6%	92.5%

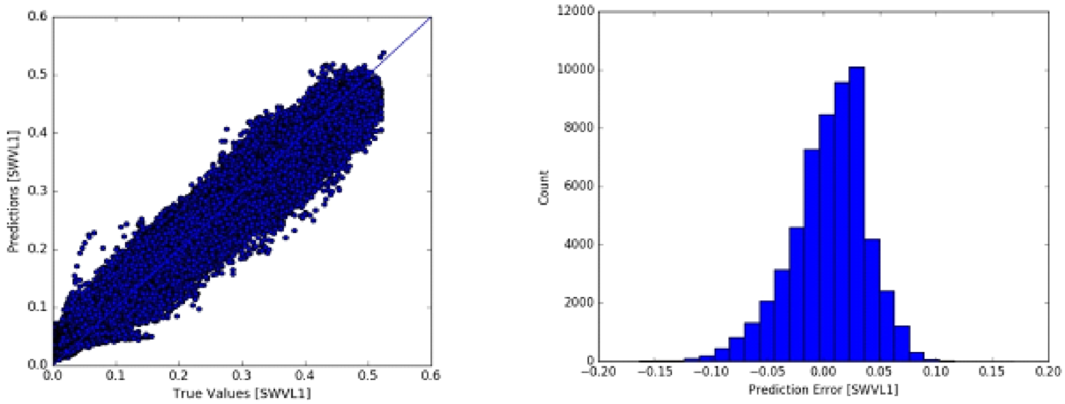

Figure 2: Scatter plot (left) and relative error (right) between predicted and measured values for sml1 in 12 July, 2012.

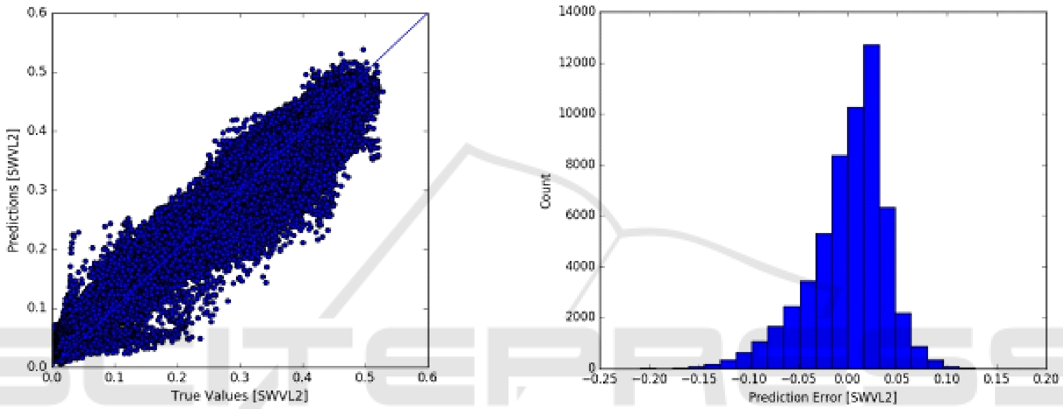

Figure 3: Scatter plot (left) and relative error (right) between predicted and measured values for sml2 in 13 July, 2012.

4 RESULTS

In the training phase, the dataset selected concern sample less than 20% of all measured values from July to December 2012. We compared two data sets of soil moisture that did not participate in training phase to the measure from ERA5-Land at the same date.

Using July 10, 2012 input parameters, we predict *sml1* and *sml2* two days and three days in the future, respectively, i.e. on dates of 12 and 13 July, 2012. Figure 2 and figure 3 show comparisons of soil moisture layer predicted and measured. We can notice that the prediction model was able to retrieve the soil moisture very faithfully. The accuracies of scatter diagrams are 95.6% and 94.4% respectively for *sml1* and *sml2*.

The global mean absolute error between the two data sets is quite small: 0.03 m^3/m^3. Then, the *sml1* retrieval from the Era5-Land features by using neural network are obtained with good accuracy. In the construction of the model, the output *sml1* of the first stage is part of the input of the second stage which models the *sml2*. This means that a good estimate of the output of stage 1 will lead to a good estimate of stage 2. The contrary will also cause the opposite effect. These comparisons on dataset that not participate to the training phase between observed and estimated show the generalization capability of the built model.

Soil moisture obtained from Climate Change Initiative of the European Space Agency (CCI-ESA), which are combination of measurements from various single-sensor active and passive microwave, is used to validate mainly our model and occasionally the ERA5-Land data.

Comparison between the sml1 predicted two days in the future from model with using the ERA5-Land parameters reanalysis (a) and the measured ESA-CCI *sml1* (b) on July 10, 2012 can be seen in figure 4. The soil moisture prediction two days in the future was compared with measurements from ESA-CCI data. A correlation of 87% and a mean absolute error of 0.05 m^3/m^3 were obtained. For the prediction made two days in the future for layer 1 in figure 5 (date of July 12, 2012), we also note good results with a correlation coefficient of 85% and a mean absolute error of 0.06 m^3/m^3. For the two figures shown below, we note that the trends are the same in part (a) and part (b). However, the intensities of soil moisture predicted from Era5-Land features are on average 0.05 $m^3.m^{-3}$ higher than those measured from CCI-ESA.

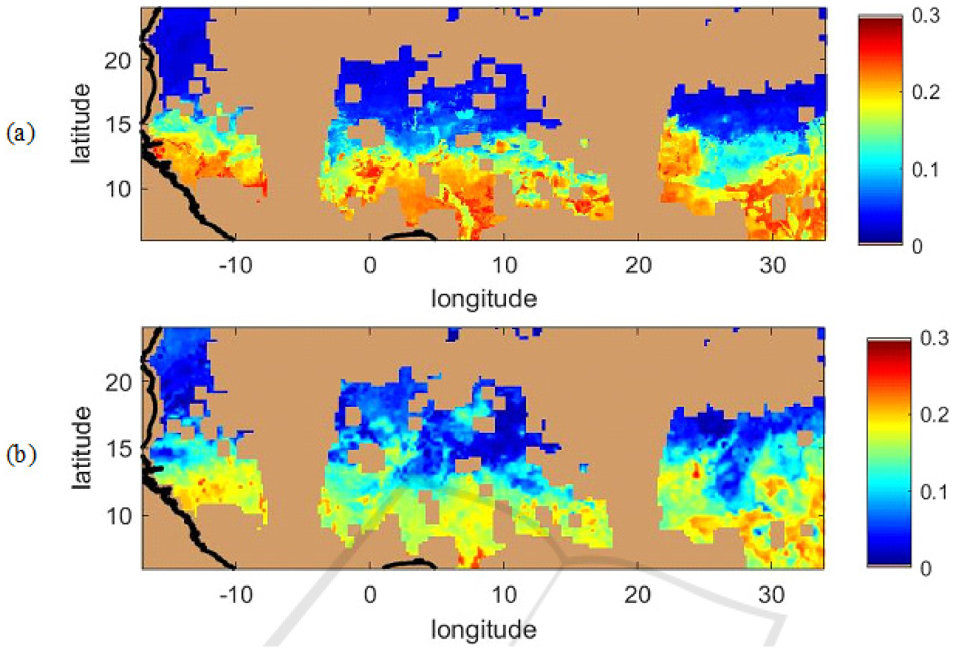

Figure 4: Map of the soil moisture layer 1 predicted from ERA5-Land features with 2NNL2 (a) and CCI-ESA observations data (b) in 10 July, 2012.

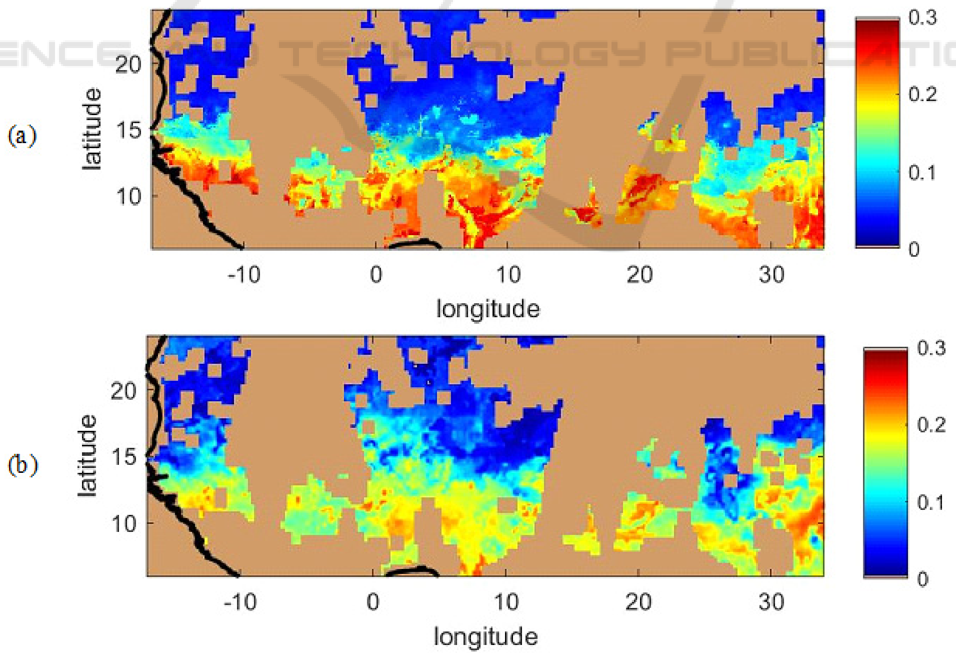

Figure 5: Map of the soil moisture layer 1 predicted from ERA5-Land features with 2NNL2 (a) and CCI-ESA observations data (b) in 12 July, 2012.

5 CONCLUSIONS

In this study, dataset from ERA5-Land were used to build a prediction model by using a deep neural network able to evaluate further soil moisture in the first two layers. The built model, so-called 2NNL2, which is a succession of two-hidden layers, retrieved successfully soil moisture layer 1 and layer 2 for two to seven days in the future. We have analyzed the performance of the model by comparing soil moisture estimated from ERA5-Land features to CCI-ESA soil moisture. We denoted that results are satisfying with low mean absolute error and high correlation.

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