Forecasting Global Geophysical States using a Deep Learning Model for Spacecraft Constellation Scheduling and Planning

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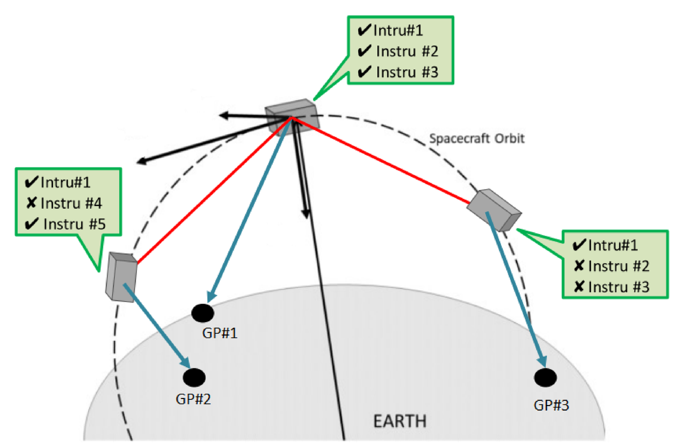
1. Motivation

- Modelling and prediction of geophysical states that have complex structural characteristics and are influenced by meteorological conditions is a challenging task.
- These states often have a high degree of spatial and temporal heterogeneity, that a mathematical model cannot be practically used for their estimation with high accuracy.
- In this work we take advantage of recent developments in **machine learning** domain to **predict global surface soil moisture**, from antecedent observations and forcing factors like precipitation.

2. Background – D-SHIELD

- We develop soil moisture predictor as part of the "Science Simulator" within Distributed Spacecraft with Heuristic Intelligence to Enable Logistical Decisions (D-SHIELD) project.
- D-SHIELD consists of a suite of software tools designed to plan and schedule spacecraft payloads and operations focussing on measuring global surface soil moisture via various microwave remote sensing assets.
- The Simulator predicts surface soil moisture and its prediction error, within a finite variable forecast horizon, which enables D-SHILED constellation planner to determine optimum payload and instrument configurations for soil moisture observations.

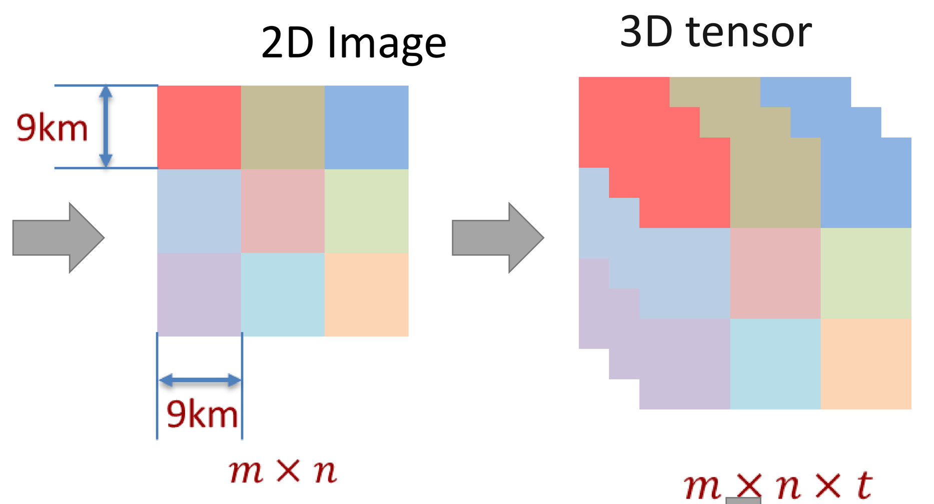


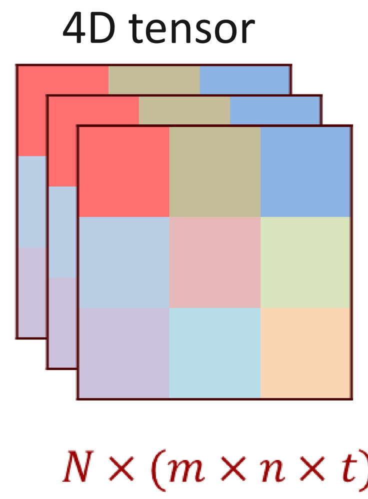
3. Data and pre-processing

Soil Moisture Active Passive (**SMAP**) L4 data
Spatial resolution: $9km \times 9km$
Temporal resolution: 3 hours

NSIDC SMAP SOIL MOISTURE ACTIVE PASSIVE

Lat	Long	SM
49.4876	-124.87	0.23311
49.4876	-124.777	0.355455
49.4876	-124.684	0.345821
49.4876	-124.59	0.355642
49.4876	-124.497	-9999
49.4876	-124.404	0.239824
49.4876	-124.31	0.216903
49.4876	-124.217	0.233664
49.4876	-124.123	0.239641





Data Split

Training Input (X_{train})
$X_1 \coloneqq Soil\ Moisture$ — t-3 | t-2 | t-1
$X_2 \coloneqq Precipitation$ — t-3 | t-2 | t-1

Training Output (Y_{train})
$Y \coloneqq Soil\ Moisture$ — t | t+1 | t+2

MODEL

PERFORMANCE METRICS

RMSE: Root Mean Squared Error

$$RMSE = \sqrt{\frac{1}{n}\sum(y_{predicted} - y_{true})^2}$$

Bias

$$Bias = \frac{1}{n}\sum y_{predicted} - \frac{1}{n}\sum y_{true}$$

References:

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[2] Z. Chao, F. Pu, Y. Yin, B. Han, and X. Chen, "Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting," *J. Sensors*, vol. 2018, pp. 1–9, 2018, doi: 10.1155/2018/6184713.

[3] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," *J. Mach. Learn. Res.*, vol. 15, pp. 1929–1958, 2014, doi: 10.1016/0370-2693(93)90272-J.

[4] Y. Gal and Z. Ghahramani, "Dropout as a Bayesian Approximation: Representing Model Uncertainity in Deep Learning," *Proc. 33rd Int. Conf. Mach. Learn. New York, NY, USA, 2016. JMLR W&CP*, vol. 48, pp. 1022–1034, 2016, doi: 10.1109/TKDE.2015.2507132.

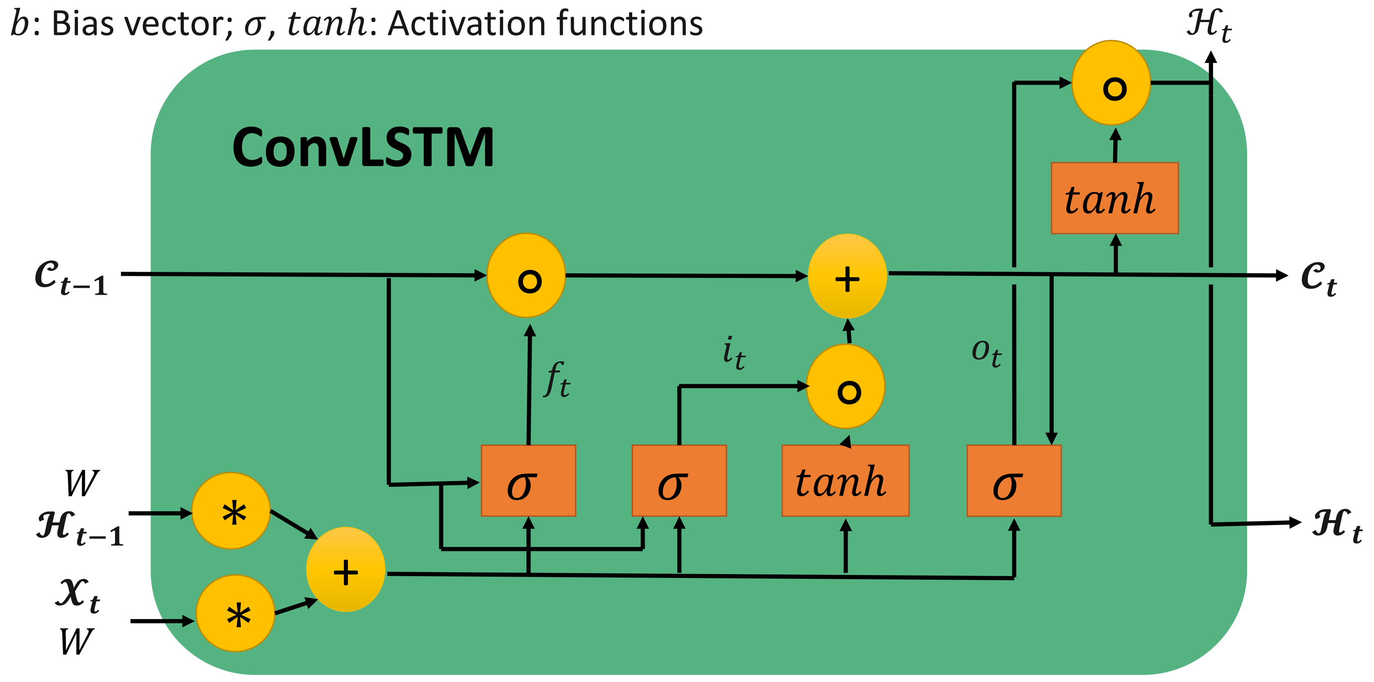
4.Model

- Convolutional Long Short Term Memory(convLSTM) is a type of Recurrent Neural Network(RNN) architecture for spatiotemporal prediction, using images.
- The architecture is very similar to that of LSTM, but instead of multiplication between the transitions, there is convolution.
- The ConvLSTM determines the future state of a certain cell in the grid by the inputs and past states of its local neighbours.

$$i_t = \sigma(W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1} + W_{ci} \circ \mathcal{C}_{t-1} + b_i)$$
$$f_t = \sigma(W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1} + W_{cf} \circ \mathcal{C}_{t-1} + b_f)$$
$$\mathcal{C}_t = f_t \circ \mathcal{C}_{t-1} + i_t \circ \tanh(W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1} + b_c)$$
$$o_t = \sigma(W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1} + W_{co} \circ \mathcal{C}_t + b_o)$$
$$\mathcal{H}_t = o_t \circ \tanh(\mathcal{C}_t)$$

$*$ – Convolution
$\circ$ – Hadamard product

Key: $\mathcal{C}$: Memory cell; $\mathcal{H}$: Final state cell; i: Input gate; o: output gate; f: forget gate; W: Weight matrix; b: Bias vector; σ, $tanh$: Activation functions



- The convolutional LSTM model is being implemented using Tensorflow keras API

ConvLSTM2D layer:
- A LSTM like layer, but the input transformations and recurrent transformations are both convolutional.

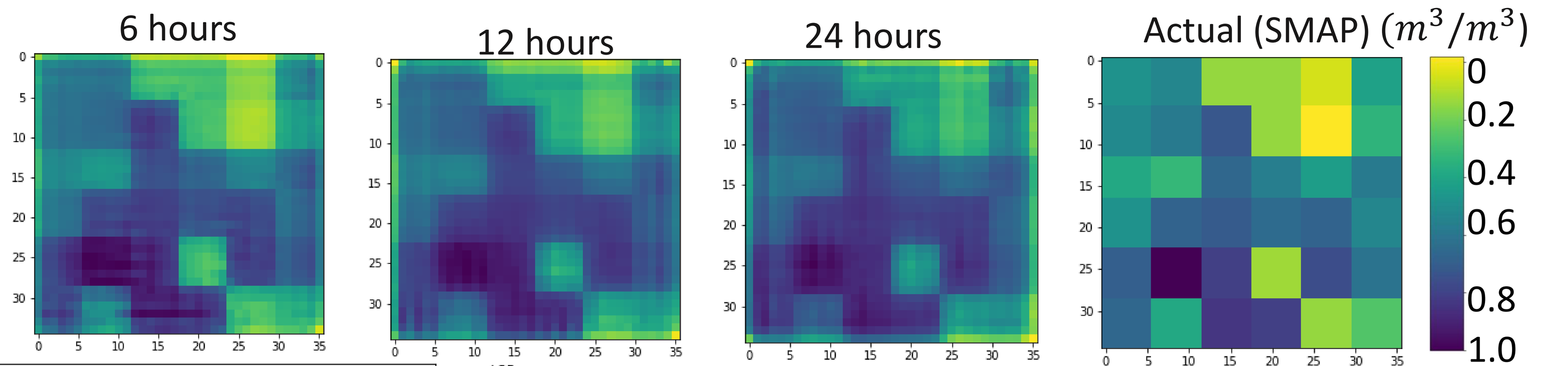
Conv3D layer:
- This layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs.

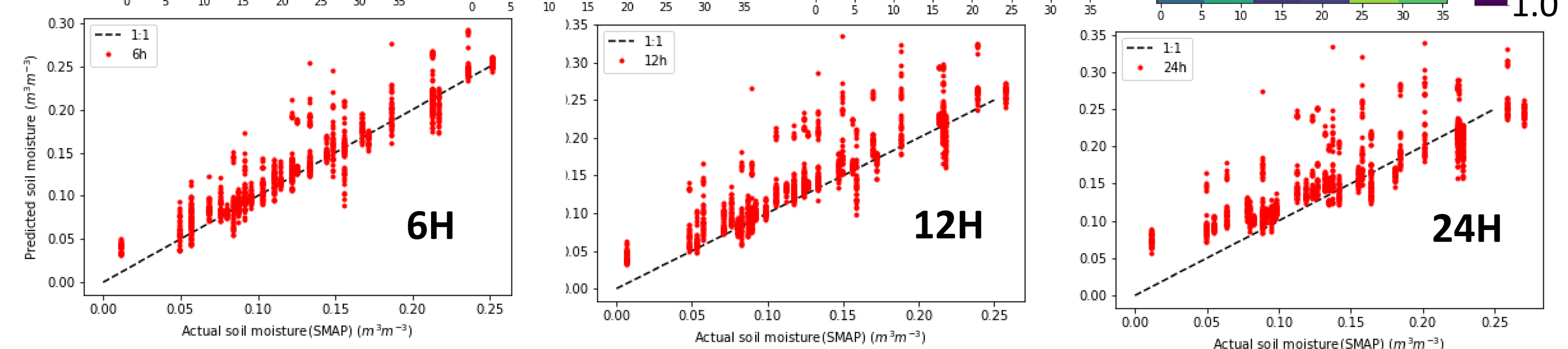
Concatenate layer:
- This layer concatenates multiple inputs, such as soil moisture and forcing factors like precipitation ready for training as a single layer.

Dropout layer:
- This regularization Monte Carlo Dropout layer randomly drop units (along with their connections) from the neural network to remove stochasticity and avoid overfitting during the training phase.
- This dropout layer also provides a Bayesian approximation to estimate a prediction uncertainty during the forecasting phase.

5.Choosing prediction interval window

- Experimented with multiple prediction windows to find the optimal interval



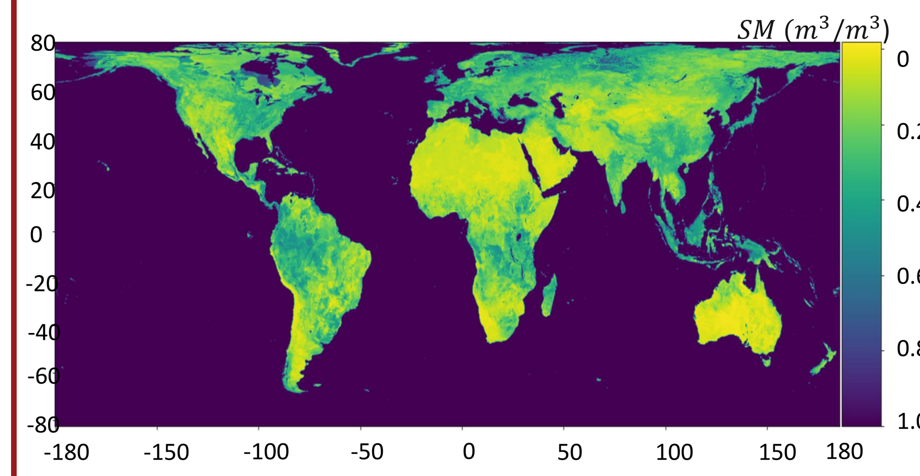


Interval	RMSE	Bias
6 hours	0.0213	0.00178
12 hours	0.0324	0.00217
24 hours	0.0383	0.00284

Local experiment: $54km \times 54km$
Site info: Tonzi Ranch, CA, USA, centered at 30.3°N, 120.9°W with Woody savanna land cover (IGBP classification)

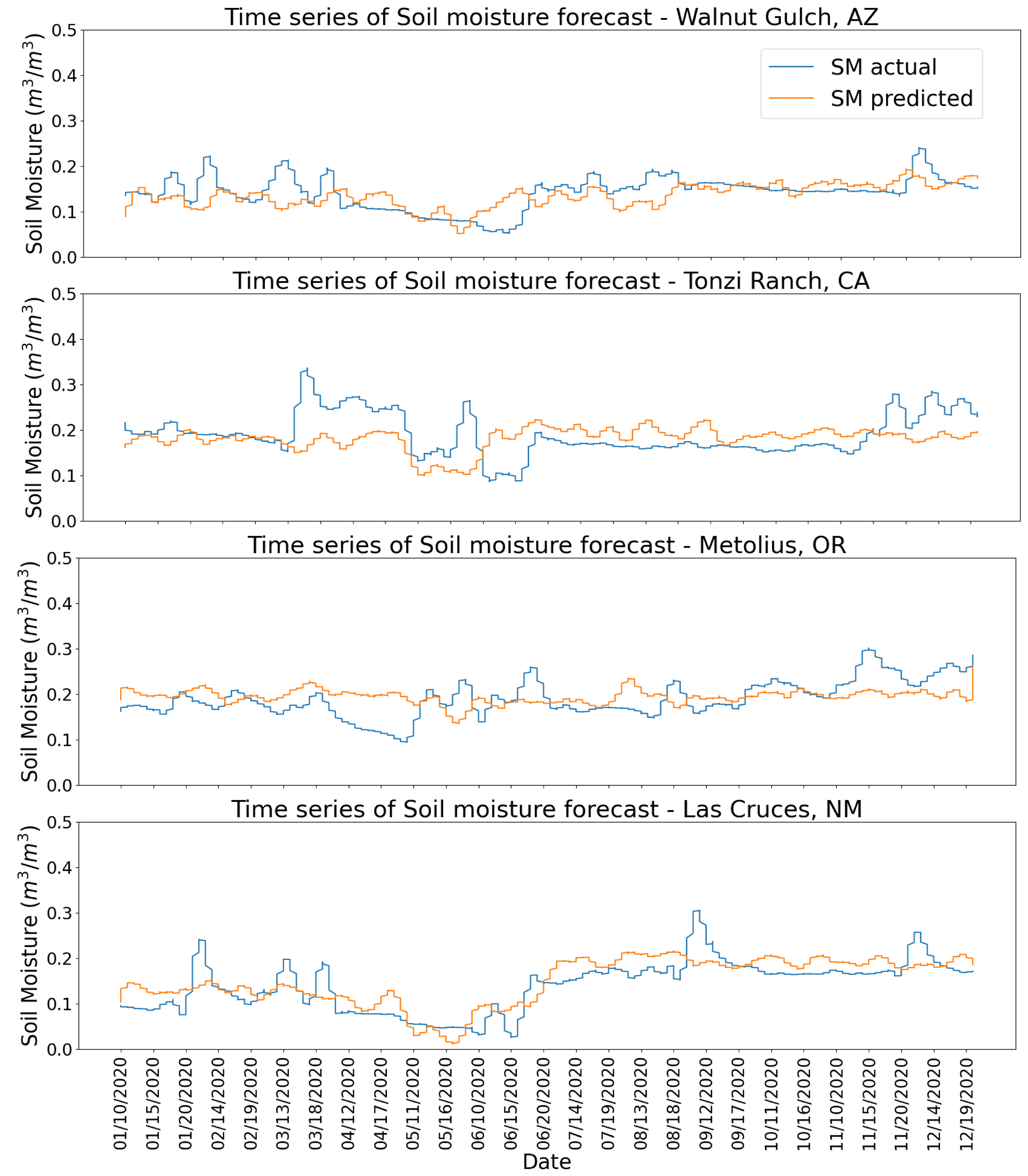
Choosing 6 hours prediction interval

6. Forecast results



Location	Biome type	RMSE	Bias
Walnut Gulch, AZ	Shrubland	0.0348	0.0067
Tonzi Ranch, CA	Woody savanna	0.0544	0.0086
Metiolius, OR	Evergreen forest	0.0429	0.0043
Las Cruces, NM	Bare surface	0.0363	0.0093

The adjacent figure shows a predicted soil moisture image by the convLSTM model for a single timestamp



7. Discussions and future work

- Soil moisture was predicted globally for the year of 2020 and compared with the SMAP L4 soil moisture product. Soil moisture being an AR(1) process, the model was developed to predict with the previous day data. In order to accommodate the SMAP L4 data frequency, the prediction takes place for 3 days ahead with a given soil moisture.
- Four locations with different landcover type were chosen to study the dynamics of the predictions. The model behaves well for minimal fluctuations in the soil moisture. In other words, predictor performed well for continuous dry or continuous wet soil. Sudden soil moisture variations (e.g., due to rainfall, snow melting) were not well captured by the DL model.
- A global average of 0.04 (m^3/m^3) RMSE was observed in the predictions.
- The future work comprises of incorporating more features and forcing factors to better learn the variability of soil moisture. Other time series forecast methods would be explored.