Forecasting soil moisture using a deep learning model integrated with passive microwave retrieval

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University of Southern California

Outline

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- Soil moisture forecast model
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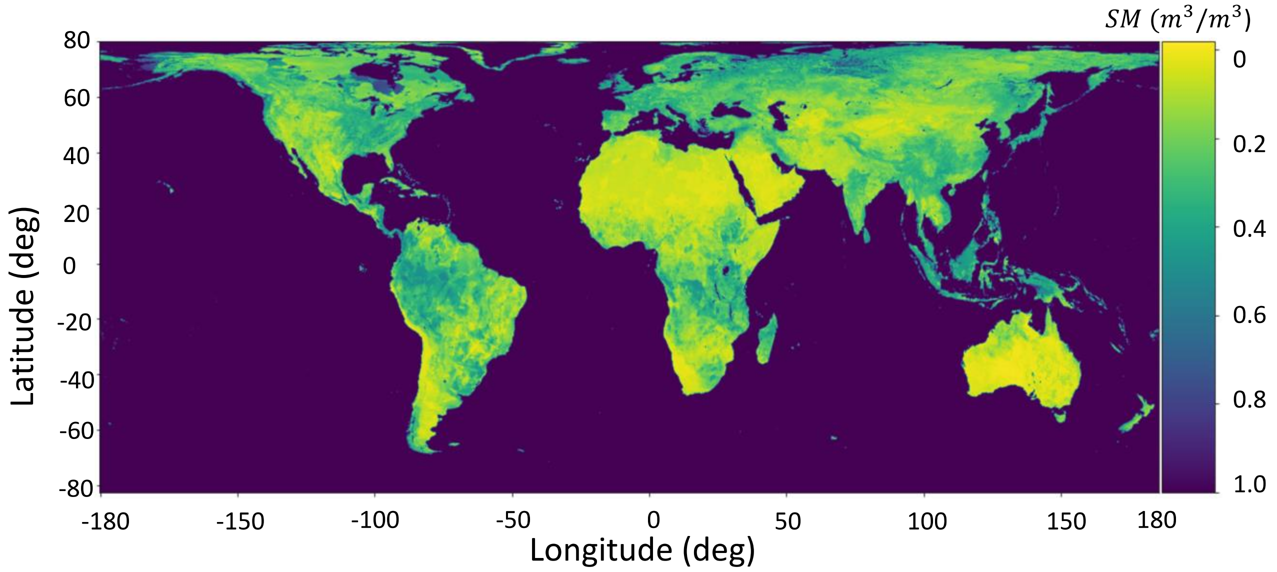


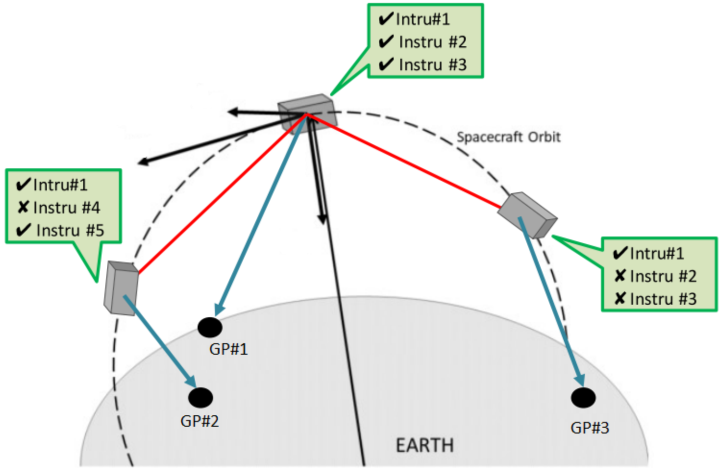
Fig. convLSTM predicted soil moisture

D-SHIELD Background

(Distributed Spacecraft with Heuristic Intelligence to Enable Logistical Decisions)

Predictions Run001 → Plannar →

(Jan 4th, 2020)



→ Assimilated images → ConvLSTM model → Predictions Run002

(Jan 5th, 2020)

- The predictions are from the convLSTM deep learning model
- The prediction uncertainty for global GPs for 24-hour period is given to the plannar

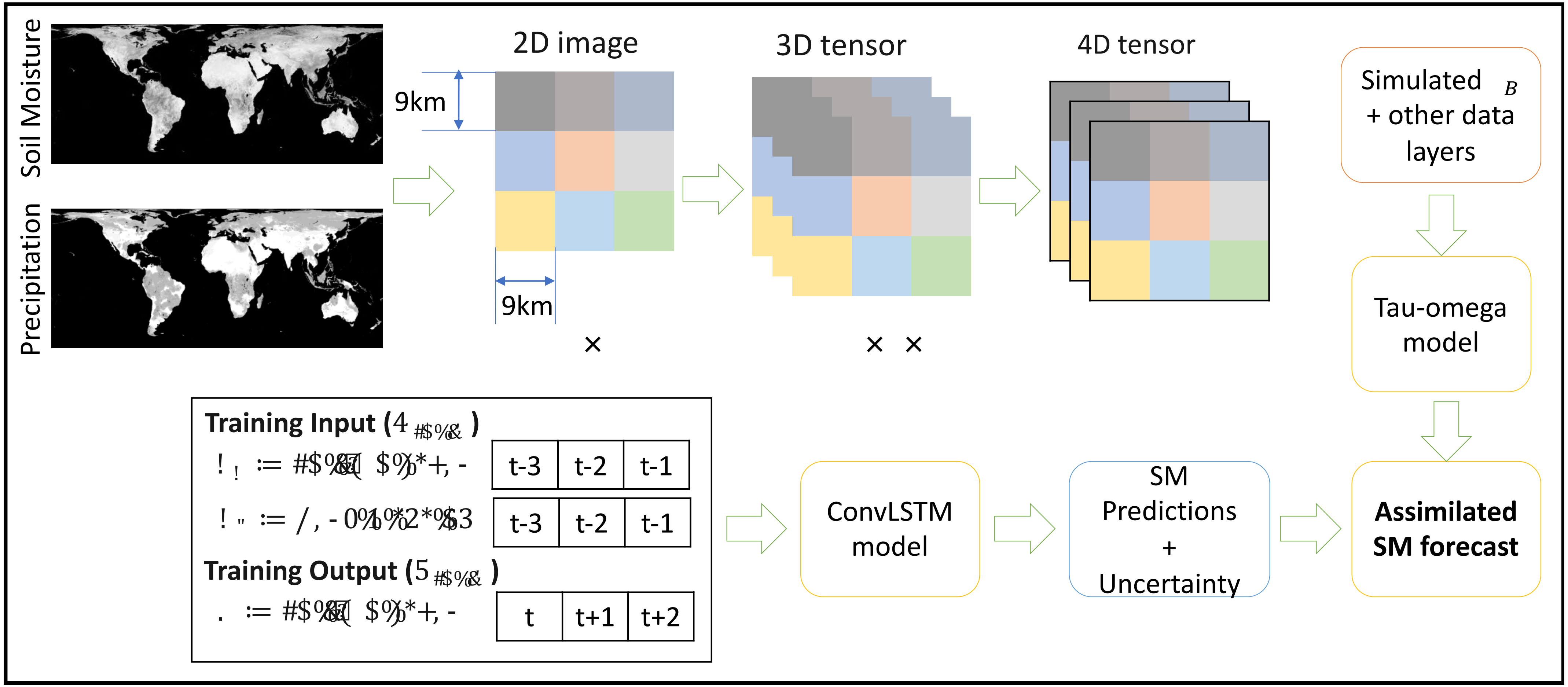
- The plan of observing GPs with high uncertainty over a horizon is executed by the Science Simulator.
- The soil moisture is retrieved using radiometer retrieval procedures.

- The observed soil moisture are then fused with the predictions from previous run.
- The next day predictions are based on both SMAP L4 and predictions assimilated with the satellite observed values.

References:

[1] Sreeja et al, "D-SHIELD: Distributed Spacecraft with Heuristic Intelligence to Enable Logistical Decisions", IGARSS 2020.

Soil moisture forecast model



ConvLSTM model

Soil Moisture: InputLayer	input	(None, 3, 1624, 3856, 1)
	output	(None, 3, 1624, 3856, 1)

Precipitation: InputLayer	input	(None, 3, 1624, 3856, 1)
	output	(None, 3, 1624, 3856, 1)

ConvLSTM2D	input	(None, 3, 1624, 3856, 1)
	output	(None, 3, 1624, 3856, 2)

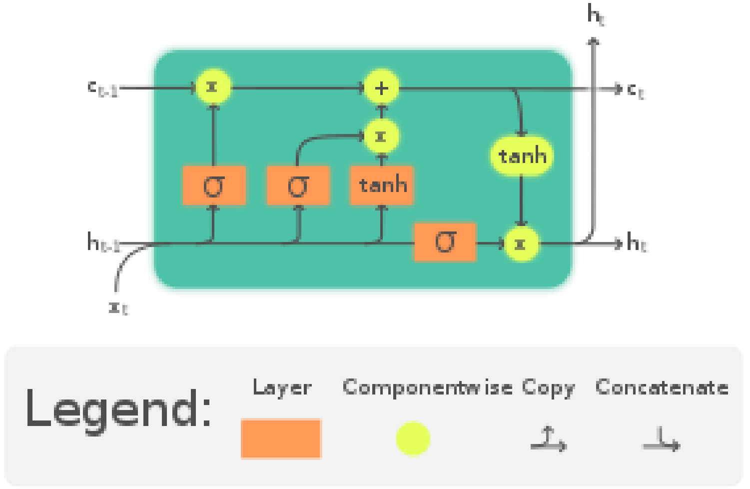
ConvLSTM2D	input	(None, 3, 1624, 3856, 1)
	output	(None, 3, 1624, 3856, 2)

Concatenate	input	(None, 3, 1624, 3856, 2), (None, 3, 1624, 3856, 2)
	output	(None, 3, 1624, 3856, 4)

ConvLSTM2D	input	(None, 3, 1624, 3856, 4)
	output	(None, 3, 1624, 3856, 2)

Dropout	input	(None, 3, 1624, 3856, 2)
	output	(None, 3, 1624, 3856, 2)

Conv3D	input	(None, 3, 1624, 3856, 2)
	output	(None, 3, 1624, 3856, 1)



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

C: Memory cell; H: Final state cell
i: Input gate; o: output gate; f: forget gate

Tau-omega model

Vegetation parameter (b)

Vegetation water content (VWC)

Brightness Temperature (T_B)

Surface Temperature (T_S)

Dielectric constant[2], $\varepsilon = \frac{\sin^2\theta}{cos\theta}\left[\frac{(1+r)cos\theta}{(1+r)-(1-r)cos\theta}\right]$

Optical depth, $\tau = b \times VWC$

Reflectivity[1], $r = \frac{T_S(1-\omega+\omega\gamma)-T_B}{T_S\gamma(\gamma+\omega-\omega\gamma)}$

Clay

Mironov Model

Transmissivity, $\gamma = \exp(-\tau sec\theta)$

Single Scattering Albedo (ω)

Incidence Angle (θ)

Soil Moisture

1 – Reflectivity from Tau Omega model

2 – Dielectric constant from Fresnel equations(vertical polarization)

Single Channel Algorithm

References:
[1] Entekhabi et al, “SMAP Algorithm Theoretical Basis Document L2 & L3 Radar/Radiometer Soi oisture (Passive) Data Products”, 2020.
[2] Mironov et al, “Physically and mineralogically based spectroscopic dielectric model for moist soils”, 2009.

Performance metrics

RMSE: Root Mean Squared Error

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

Bias

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

Uncertainty

$$Uncertainty = RMSE = \sqrt{Variance + Bias^2}$$

Results and analysis

Run001 – Predicted Jan 4th ,2020 data assimilated with observed values

Uncertainty	1:30	4:30	7:30	10:30	13:30	16:30	19:30	22:30
Prediction before assimilation	0.0035	0.0129	0.0294	0.0441	0.0650	0.0941	0.1227	0.1522
Prediction after assimilation	0.0034	0.0124	0.0275	0.0402	0.0576	0.0822	0.1047	0.1265
% decrease	**2.8596**	**3.8976**	**6.3482**	**8.7593**	**11.3255**	**12.6230**	**14.6393**	**16.8508**

- *Assimilation* corresponds to replacing the predicted soil-moisture values at the observed grid-points by the Tau-omega model estimated ("simulating observing of ground points") soil-moisture values.

$$\%\ Decrease = \frac{Before\ assimilation\ uncertainty - After\ assimilation\ uncertainty}{Before\ assimilation\ uncertainty} \times 100$$

Results and analysis

Run002 – Different model runs of Jan 5th ,2020

S.NO	Uncertainty	1:30	4:30	7:30	10:30	13:30	16:30	19:30	22:30
1	Model run (a)	0.0040	0.0134	0.0299	0.0446	0.0655	0.0946	0.1233	0.1527
2	Model run (b)	0.0033	0.0127	0.02922	0.0438	0.0648	0.0939	0.1225	0.1520
3	(b) + observations	0.0032	0.0122	0.0273	0.0400	0.0576	0.0822	0.1050	0.1271
4	% decrease (1&2)	**19.0419**	**5.7619**	**2.5898**	**1.7396**	**1.1843**	**0.8205**	**0.6299**	**0.5084**
5	% decrease (1&3)	**21.2214**	**9.4448**	**8.8265**	**10.2877**	**12.1861**	**13.0965**	**14.8291**	**16.7724**

Model run (a)

- This model run is driven entirely based on SMAP L4 data.
- No observations are used during this run.

Model run (b)

- This model run is based on predictions which are triggered by SMAP L4, the intermediate inputs are assimilated with observed values.

Results and analysis

Run003 – Different model runs of Jan 6th ,2020

Uncertainty	1:30	4:30	7:30	10:30	13:30	16:30	19:30	22:30
Model run (a)	0.0040	0.0134	0.0300	0.0446	0.0656	0.0946	0.1233	0.1527
Model run (b)	0.0032	0.0127	0.0292	0.0438	0.0648	0.0939	0.1225	0.1520
% decrease	**19.3449**	**5.8651**	**2.6374**	**1.7718**	**1.2063**	**0.8358**	**0.6417**	**0.5179**

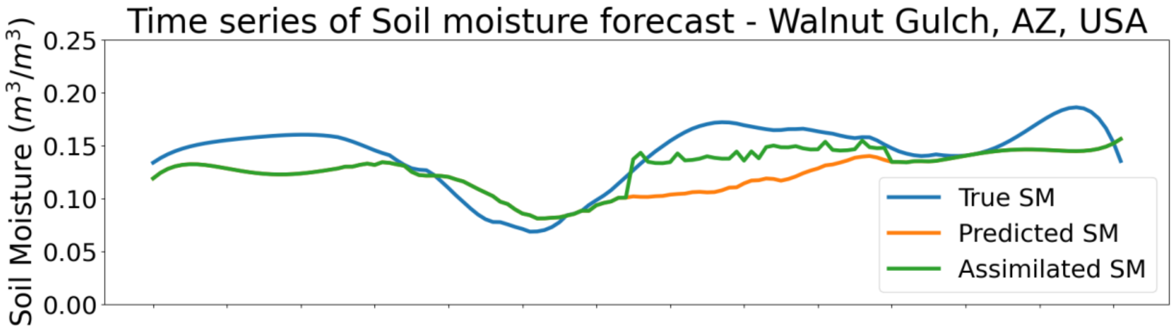
Model run (a)

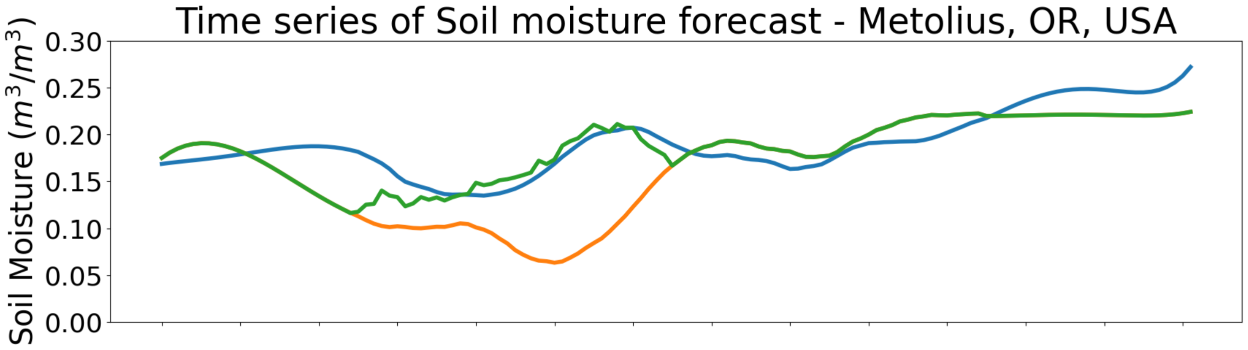
- This model run is driven entirely based on SMAP L4 data.
- No observations are used during this run.

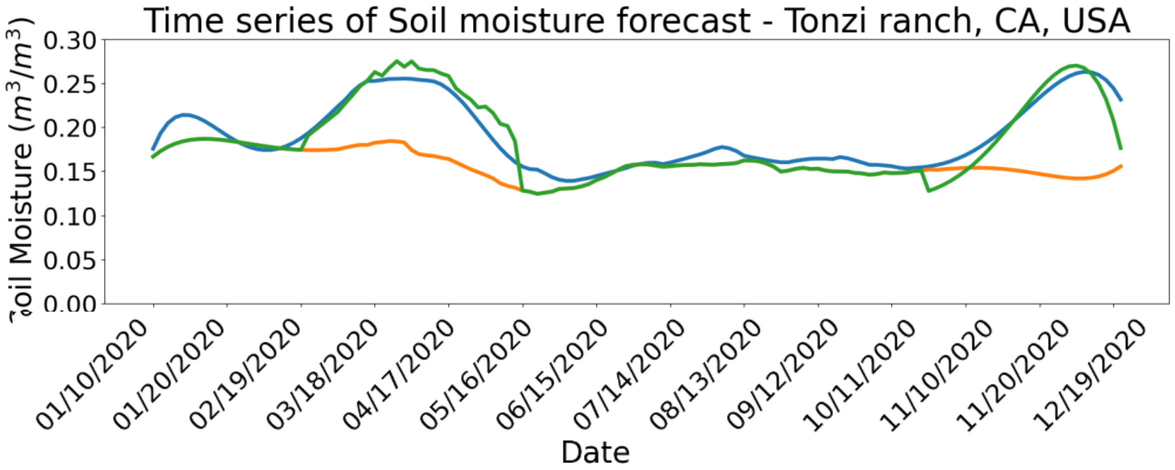
Model run (b)

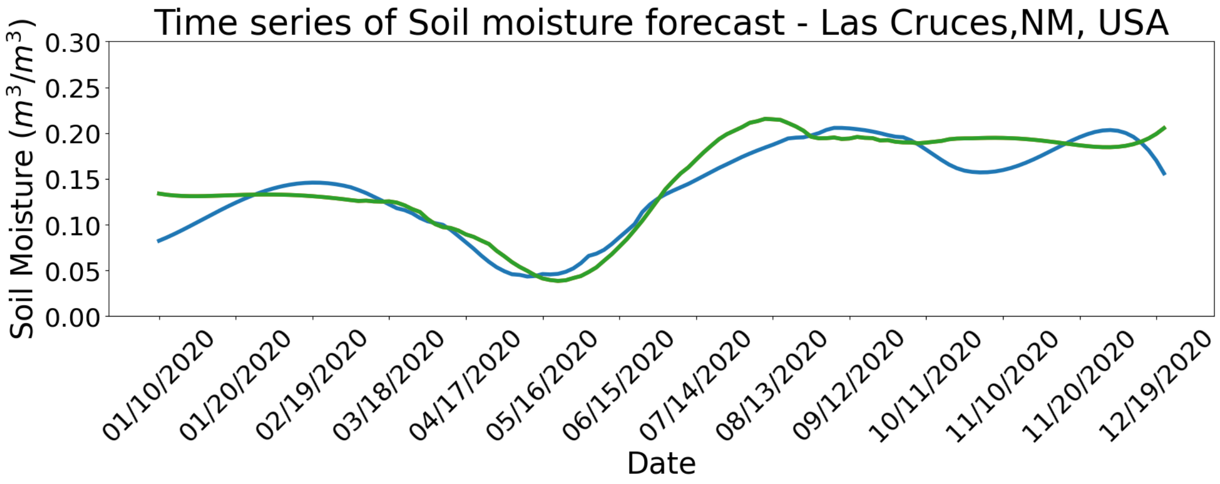
- This model run is based on predictions which are triggered by SMAP L4, the intermediate inputs are assimilated with satellite observed values.

Results and analysis









Conclusion

- This paper proposes a convLSTM model to predict soil moisture at high spatiotemporal resolution. This paper also deals with a science simulator using Tau-omega model that acts as tool of observing true soil moisture at ground points with high uncertainty.

- The experiments show a 19% error reduction in the predictions with the assimilations.

- Future work will be focused on improving this error reduction by exploring more data layers and other microwave remote sensing resources.

Thank You