Passive Microwave Brightness Temperature Simulation with Physics-informed Machine Learning

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INTRODUCTION

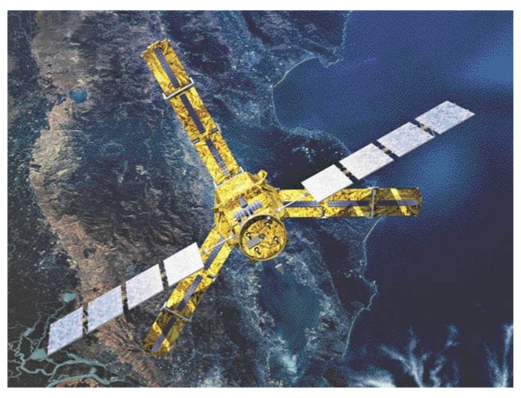

Figure 1. SMOS satellite image

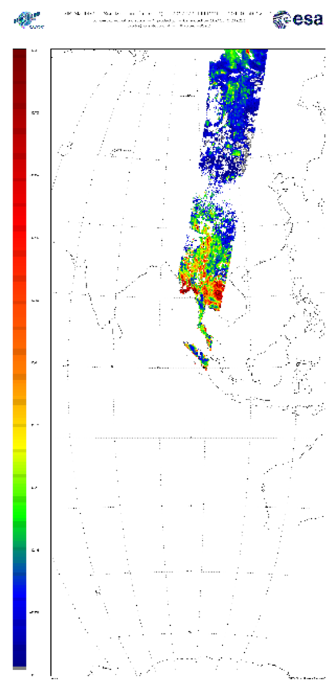

Figure 2. SMOS brightness temperature L2 image covering the Maqu site

- Soil moisture is an essential variable in the hydrological cycle and exhibits a strong connection to weather and climate change.
- The comprehensive understanding of the physical mechanism underlying brightness temperature enables more accurate estimation of soil moisture.
- The integration of physical theory into machine learning models has the potential to leverage the advantages of both methods, but this area hasn't been extensively explored in brightness temperature simulation.

METHODS

- This research conducted several experiments on the Alpine Meadows at the Maqu site, located in the Eastern Tibetan Plateau (33°30′ - 34°15′N, 101°38′ - 102°45′E)
- The model predictors include meteorological data, soil moisture measurements, soil temperature measurements and vegetation parameters. In total 42 predictors were used for model training.
- The Random Forest regression model (RFR) and Support Vector Regression (SVR) model were trained to emulate ELBARA-III L-band Brightness Temperature.

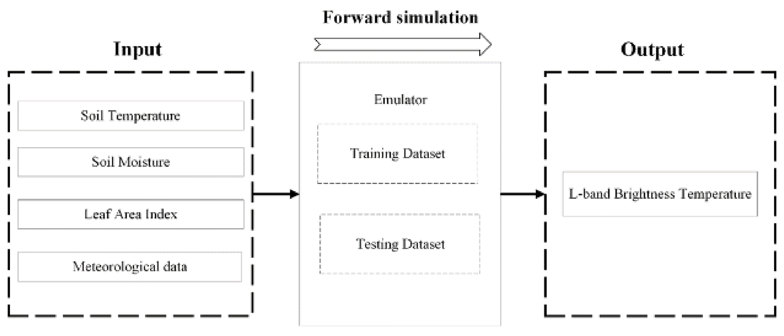

Figure 3. Flowchart of the research

CONCLUSION

After exploring various predictor combinations, the optimal model for predicting horizontal polarization incorporates predictors such as day of year (DOY), year, longwave radiation, and TBV, resulting in a cross-validation correlation coefficient (R) of 0.918. In the case of vertical polarization, the best combination involves surface temperature, TBH, and other predictors, excluding longwave radiation, DOY, and year, yielding a cross-validation R of 0.867.

ACKNOWLEDGE

This research would like to acknowledge the WUNDER project (grant no. KICH1. LWV02.20.004) and Water JPI project "iAqueduct" (Project number: ENWWW.2018.5)

RESULTS

1. Generally, the horizontal polarization exhibits better performance compared to the vertical polarization.
2. The model predictions can capture the general trend of variation in observations. However, during certain time periods, such as the transition season of October and November, the model predictions appear smoother and can't fully capture all the fluctuation present in the signal.
3. The soil temperature, soil moisture and vegetation parameters exhibit a strong correlation with the target brightness temperature. Furthermore, soil temperature at deeper layers exerts a greater influence on the prediction of TB.
4. In order to capture the dynamics of the observed processes, the research explored the inclusion of TB at vertical (TB_V) and horizontal (TB_H) polarization as additional predictors, with the aim of predicting TB at horizontal (TB_H) and vertical polarization (TB_V), respectively. Notably, there was a significant enhancement in performance after incorporating the observed data for model training.

Feature Type	Predictors
Time	DOY (Day of year) Year
Solar radiation	Shortwave upwelling Shortwave downwelling Longwave upwelling Longwave downwelling
Meteorological	Air temperature Relative humidity Wind speed Wind direction Precipitation Air pressure
Vegetation descriptor	MODIS LAI
Soil Moisture	At 2.5, 5, 7.5, 10, 12.5, 15, 17.5, 20, 25, 70, 80, 90 and 100cm depth
Soil Temperature	At 2.5, 5, 7.5, 10, 12.5, 15, 17.5, 20, 25, 70, 80, 90 and 100cm depth
Incidence angle	40, 45, 50, 55, 60, 65, 70

Figure 4. Input predictors in forward simulation model of Brightness Temperature

Prediction Year	Training Data	MAE	RMSE	R
2016	2016	2.182	4.158	0.994
	2017	21.898	26.593	0.801
	2018	21.290	26.135	0.831
	2019	33.088	41.066	0.223
	3 years	21.365	26.430	0.795
2017	2017	1.939	4.333	0.994
	2016	14.267	21.333	0.861
	2018	16.310	21.498	0.885
	2019	34.980	43.030	0.269
	3 years	19.547	25.512	0.866
2018	2018	1.982	4.011	0.995
	2016	32.960	41.323	0.447
	2017	29.881	43.294	0.496
	2019	36.189	43.626	0.555
	3 years	21.340	29.832	0.727
2019	2019	2.111	3.978	0.991
	2016	64.181	67.327	0.629
	2017	59.630	62.775	0.650
	2018	14.881	20.064	0.750
	3 years	17.537	23.148	0.690

Figure 5. Evaluation metrics of model prediction in horizontal polarization

Group number	DOY	Year	Longwave upwelling	Longwave downward	Surface temperature	TB_V
1	√	√	√	√		√
2	√	√	√	√		
3			√	√		√
4			√	√		
5	√	√			√	√
6	√	√			√	
7					√	√
8					√	

Figure 6. The different combinations of predictors in horizontal polarization using year 2016 data for training (the same combinations are also used for other years and three years cooperation, in total 64 combinations for each polarization)

Prediction Year	Training Data	MAE	RMSE	R
2016	2016	0.755	1.312	0.996
	2017	19.751	22.51	0.507
	2018	16.14	18.476	0.368
	2019	25.661	28.71	0.331
	3 years	16.483	18.554	0.351
2017	2017	0.691	1.432	0.998
	2016	10.545	21.408	0.454
	2018	12.7	21.958	0.453
	2019	28.877	34.744	0.04
	3 years	8.642	19.43	0.562
2018	2018	0.71	1.34	0.998
	2016	20.891	25.021	0.099
	2017	15.601	35.628	0.122
	2019	25.486	30.316	0.236
	3 years	19.933	38.328	0.051
2019	2019	0.638	1.098	0.993
	2016	36.229	38.706	0.198
	2017	30.886	32.028	0.422
	2018	4.594	6.222	0.817
	3 years	4.711	0.381	0.8

Figure 7. Evaluation metrics of model prediction in vertical polarization

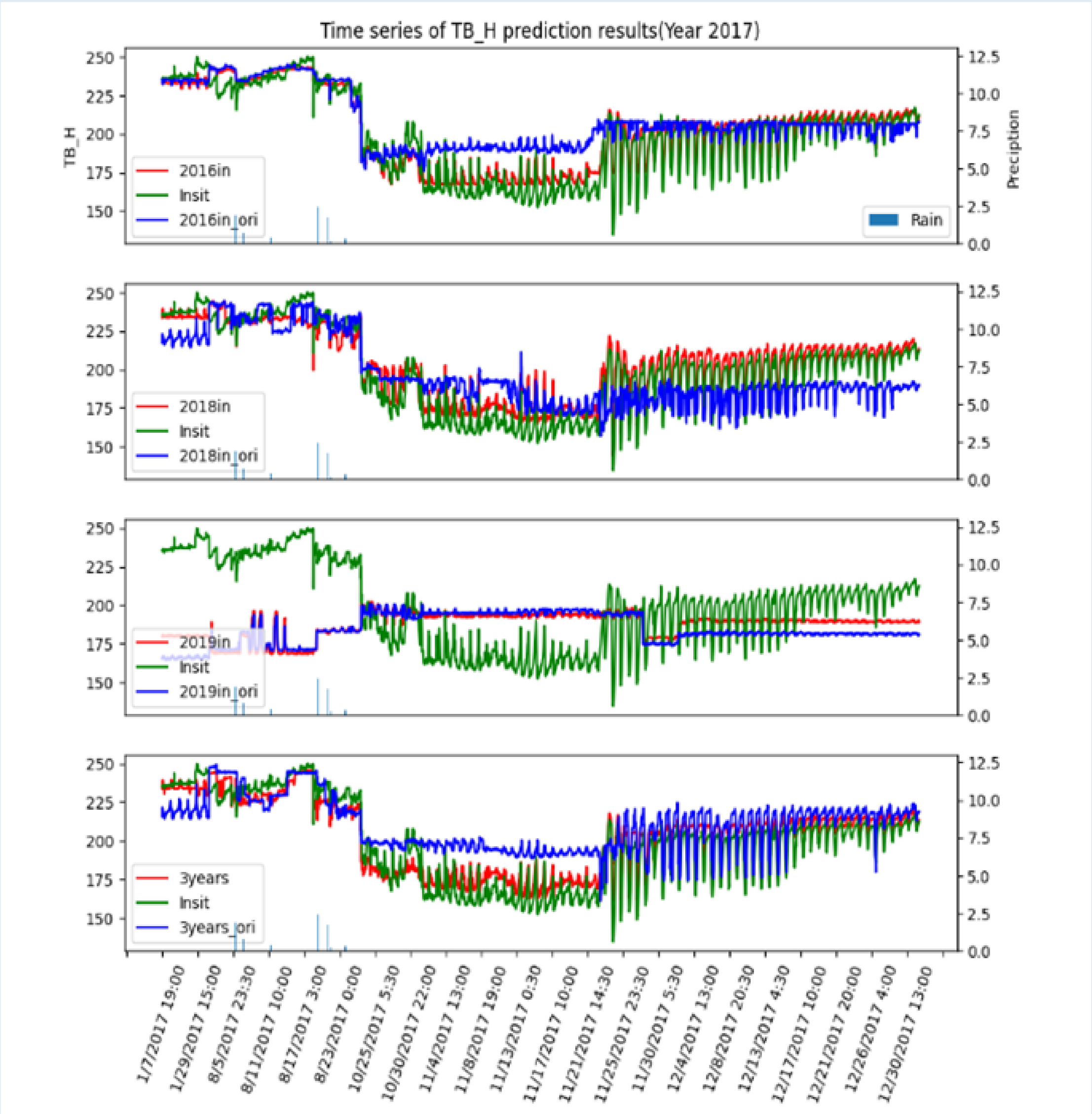

Figure 8. Predictions of TB_H in year 2017 using different input combinations (for top to bottom: year 2016, year 2018, year 2019 and corporation of these three years) with RFR. Green lines present the in-situ observations. Red lines show the results with TB_V for training. The blue lines show the results without TB_V as input.

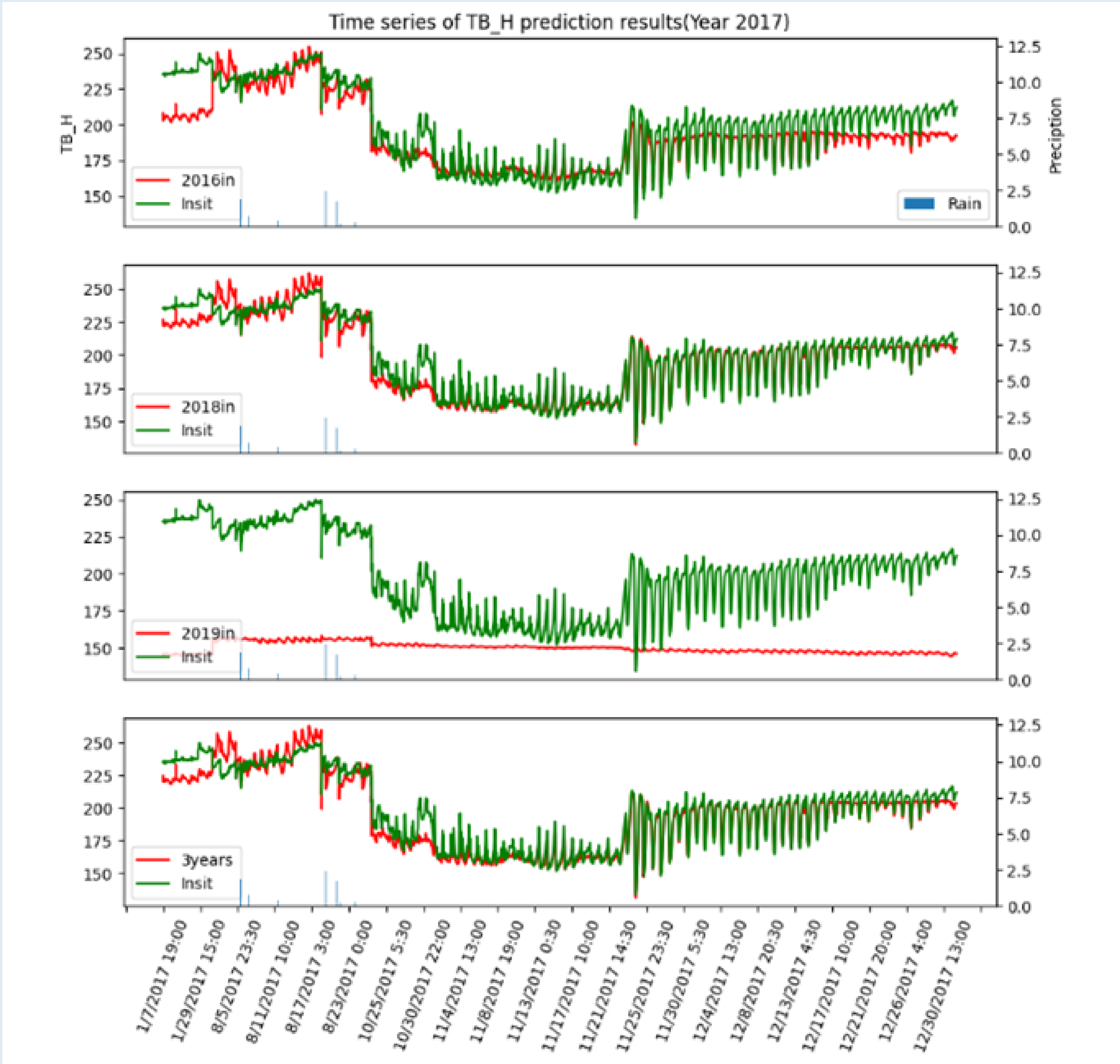

Figure 9. Predictions of TB_H in year 2017 using different input combinations (for top to bottom: year 2016, year 2018, year 2019 and corporation of these three years) with SVR. Green lines were in-situ observations. Red lines show the model predictions.

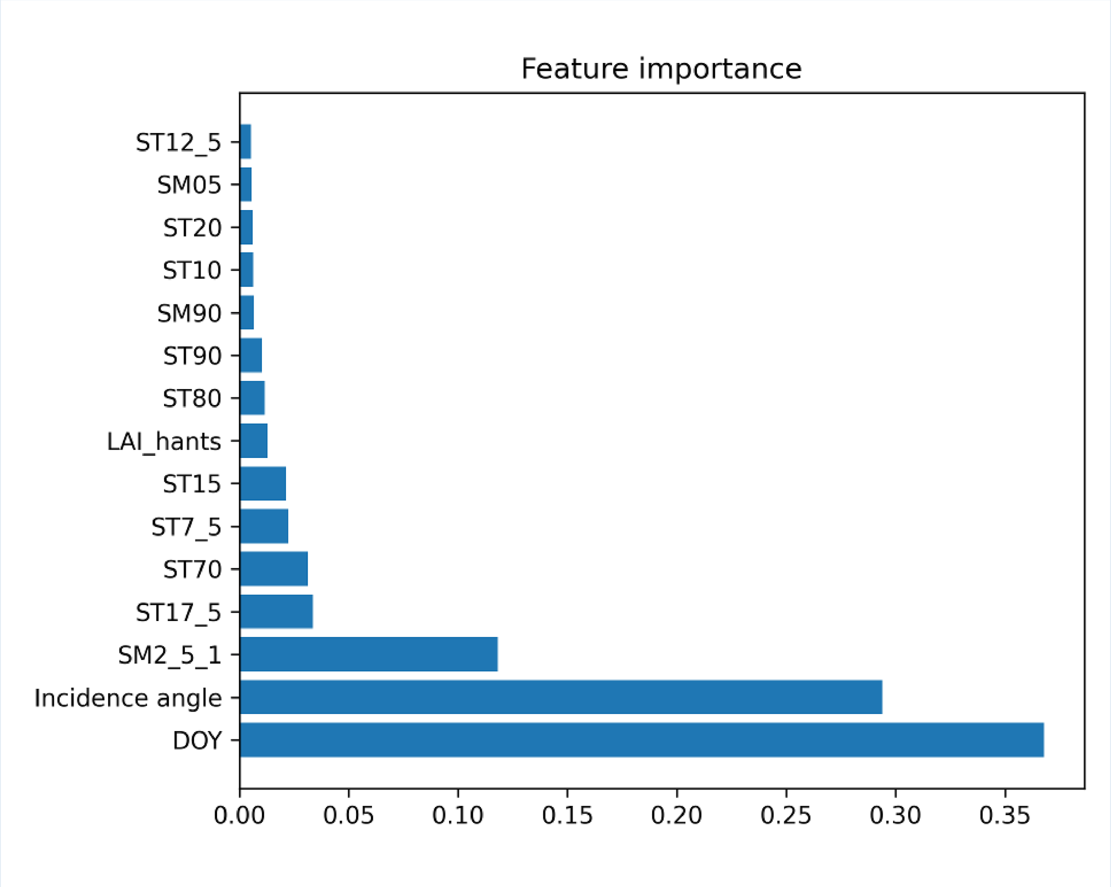

Figure 10. Evaluation metrics of model prediction in horizontal polarization

- However, despite removing the time stamp (DOY and year), replacing longwave radiation with surface temperature, and employing separate seasonal models, minimal improvements were observed in the model.
- Additionally, SVR can be used to provide predictions, but its computation complexity limits its capability to handle large volumes of data compared to RFR. The best model performance for horizontal polarization is a testing R2 of 0.869 and a validation R2 of 0.765, while for vertical polarization, it is a testing R2 of 0.732 and a validation R2 of 0.521. Notably, SVR demonstrates the ability to address certain anomalies observed in RFR, suggesting its potential as a suitable candidate for the emulator.

1. Su, Z., Wen, J., Zeng, Y., Zhao, H., Lv, S., van der Velde, R., Zheng, D., Wang, X., Wang, Z., Schwank, M., Kerr, Y., Yueh, S., Colliander, A., Qian, H., Drusch, M., & Mecklenburg, S. (2020). Multiyear in-situ L-band microwave radiometry of land surface processes on the Tibetan Plateau. Scientific Data, 7(1), Article 317. https://doi.org/10.1038/s41597-020-00657-1