

PHYSICS-CONSTRAINED DEEP LEARNING MODELS FOR MICROWAVE RETRIEVAL OF HIGH-RESOLUTION SOIL MOISTURE

Archana Kannan ^{*,1}, Grigorios Tsagkatakis², and Mahta Moghaddam¹

¹Ming Hsieh Department of Electrical and Computer Engineering,
University of Southern California, Los Angeles, CA, USA;

²Foundation for Research and Technology - Hellas (FORTH),
Institute of Computer Science, Heraklion, Greece

* kannana@usc.edu

ABSTRACT

Soil moisture is an essential climate variable that directly influences many hydrological, agricultural, and water-cycle processes. Many satellites have been launched and are still being launched to map soil moisture accurately at a global scale. Motivated by the coarse resolution of existing satellite products, many statistical, physics-based, and machine learning-based methods have been proposed to downscale soil moisture to much finer spatial scales. In this paper, we propose a novel deep learning approach that is constrained by the *Tau-omega* radiative transfer model to enhance the resolution of surface soil moisture. We demonstrate the proposed framework by downscaling Soil Moisture Active Passive (SMAP) L-band brightness temperature (TB) with C-band synthetic aperture radar (SAR) backscattering coefficient (σ_0) imagery from Sentinel-1A/B and subsequently retrieving high spatial resolution (1 km) soil moisture.

Index Terms— Physics-constrained deep learning, *Tau-omega* model, Soil moisture, Downscaling

1. INTRODUCTION

Soil moisture (SM) knowledge is crucial for various applications, including precision agriculture, water resource management, flood forecasting, and climate change impact assessment. To comprehensively map SM, various satellite missions, such as Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP) missions, have been launched. There are also ongoing efforts, e.g., NASA-ISRO Synthetic Aperture Radar (NISAR), to enhance SM resolution. A notable challenge lies in the coarse scale (current SMAP products are at 36 km and assimilated products at 9 km resolution) of satellite observations, limiting their applicability to finer-resolution environmental assessments. Many critical applications, including agriculture, disaster management, and mitigation, necessitate higher-resolution (1 km or finer) SM data.

Efforts to enhance the spatial resolution of SM measurements have been made through the exploration of various methodologies [1], [2], including statistical approaches, physics-based models, and, more recently, machine learning (ML) techniques [3], [4]. Physics-based models face challenges in generalizability and require region-specific geophysical parameters. On the other hand, data-driven methods depend on substantial volumes of training and validation datasets, which may not be consistently available. In response to these challenges, some studies have proposed hybrid approaches, where physics-based models serve as initial disaggregated estimates for subsequent ML predictions [5], [6]. Another approach involved leveraging physics to guide the selection of inputs for ML models [7]. In this paper, we propose a novel method, bridging the gap between physics-based and deep learning methods, to downscale SM using a conditional generative adversarial network (cGAN) model incorporated with physical constraints from the *Tau-omega* ($\tau - \omega$) model.

2. PHYSICS-CONSTRAINED DEEP LEARNING MODEL FOR RESOLUTION ENHANCEMENT

The proposed physics-constrained neural network for resolution enhancement is realized by incorporating the $\tau - \omega$ model within the cGAN [8] architecture. The generator model of cGAN is trained to predict brightness temperature (TB) at a 1 km scale, and then the SM is retrieved at the same scale. By adding a discriminator model to compare the predicted-retrieved SM with validation SM, we build a constraint on predictions of the generator model to be as close as possible to the validation dataset.

The generator part of cGAN is a modified U-Net architecture with an encoding path, a decoding path, and skip connections built with convolutions, normalization, and dropout layers. The neural network output is passed through a rectified linear unit (ReLU) to get real-valued TB. The inputs to the generator are coarse-resolution TB maps and 1 km radar

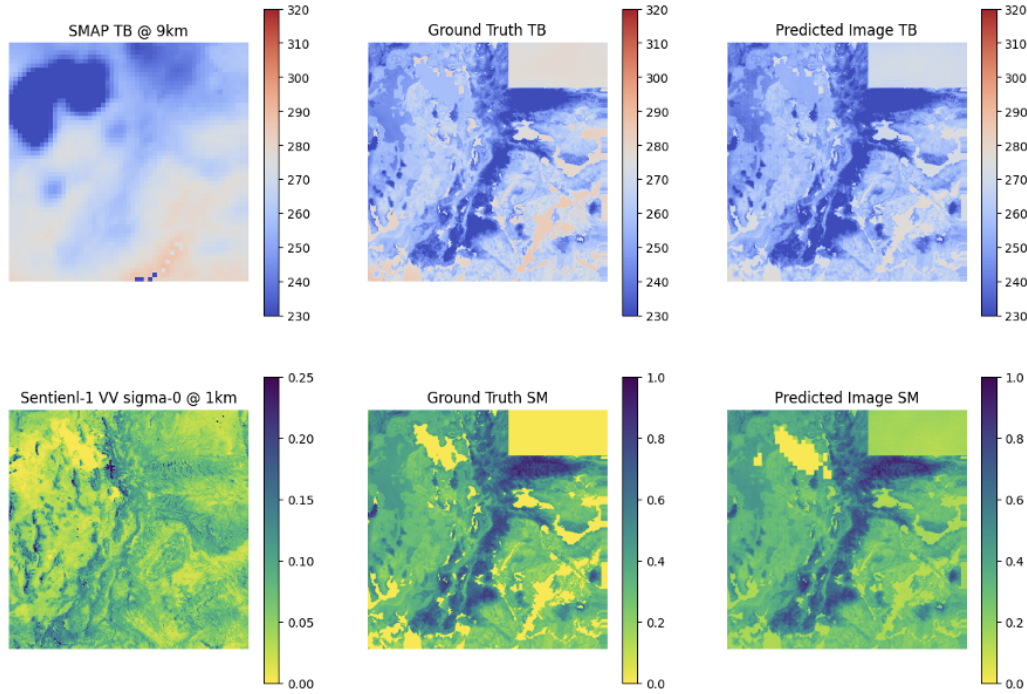


Fig. 1. An example of downscaled SM image from SMAP brightness temperature (TB) at 9 km and Sentinel-1 radar backscattering coefficient (σ_0) at 1 km using the proposed physics-constrained deep learning model.

backscattering coefficient (σ_0) maps. The output is the 1 km TB maps.

The discriminator model is a convolutional neural network (CNN) based model with convolutions and normalization layers. Unlike the generator, the output of CNN is passed through a sigmoidal activation function to restrict output to be within 0 and 1. The inputs to the discriminator are predicted-retrieved SM and true SM at 1 km. The output of the discriminator is a value in the range [0, 1], with 0 indicating that the two input images given are highly varied and one indicating both images are the same.

The $\tau - \omega$ model comprises computing transmissivity from vegetation optical depth, sequentially calculating emissivity, reflectivity, and soil dielectric. The SM is retrieved using the Mironov model [9] from soil dielectric and clay fraction. The detailed equations of $\tau - \omega$ model can be found in [10].

3. MATERIALS

Utah, USA (centered at 39.3210° N, 111.0937°W) was chosen as the study site. Utah has relatively heterogeneous land cover types, comprising shrublands, grasslands, and mixed forests with dry, semi-arid, and desert climates, but also experiences monsoon rains.

The SMAP TB is the primary variable for retrieving high-resolution SM. The TB layer is accessed from the

NASA SMAP Enhanced L3 Radiometer Global and Polar Grid Daily 9 km EASE-Grid Soil Moisture product. For the physics-based model, ancillary data layers, vegetation optical depth (τ), clay fraction, surface temperature (TS), albedo (ω), and roughness parameter (h) were also downloaded from the SMAP Enhanced L3 product. The SMAP TB is disaggregated with σ_0 accessed from Sentinel-1. A radiometric terrain correction is applied to the raw synthetic aperture radar (SAR) images using a Hybrid Pluggable Processing Pipeline (HyP3) [11] to remove the geometric and radiometric distortions of the SAR instrument.

4. RESULTS AND DISCUSSION

The proposed framework is validated using upscaled SM from *in-situ* networks. The surface SM (top 5 cm) sensor networks in the study area, SNOTEL, SCAN, PBO H2O, COSMOS, and USCRN, are accessed from the International Soil Moisture Network (ISMN) [12]. Upscaling is done using the Random Forest approach [13].

The root mean squared error (RMSE) was computed to assess the performance of the proposed framework against the validation dataset. The RMSE with and without the addition of σ_0 is tabulated in Table 4. An example of a downscaled product for a day in May 2021 is demonstrated in Figure 1.

The impact of integrating physical constraints within the neural network framework was studied to assess the effective-

	Without σ_0		With σ_0	
RMSE	Training	Test	Training	Test
TB [K]	3.1255	3.4191	2.0943	2.3393
SM [m^3/m^3]	0.0632	0.0776	0.0595	0.0654

Table 1. Performance metrics of the proposed methodology compared with and without the σ_0

ness of the proposed framework. The physics-based model, $\tau - \omega$, was moved out of the cGAN loop, and the RMSE of predicted TB was studied. Figure 2 shows the scatter and bias plot of the two cases with the same training setup. The proposed methodology showed a 60% error reduction in fewer epochs, indicating lesser usage of resources and training time. In general, there was an overestimation of soil moisture in vegetated regions of the study area.

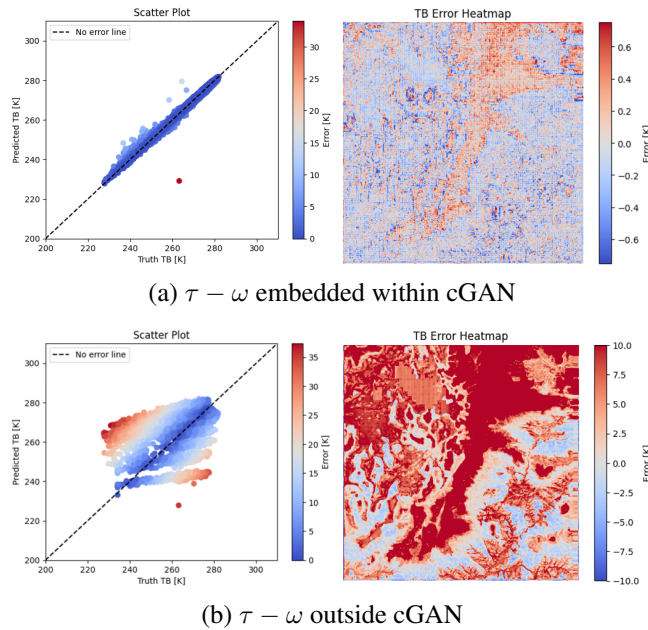


Fig. 2. Scatter plots of predicted vs true TB (Left) and error heatmap at 1 km of TB (Right) for two different case studies.

5. CONCLUSION

In this paper, we propose a physics-constrained deep learning model to enhance the resolution of surface SM to a 1 km scale. The SMAP TB was downsampled with Sentinel-1 σ_0 , and subsequently $\tau - \omega$ model embedded within a cGAN architecture was utilized to retrieve high resolution SM product. A cGAN based architecture provided neural network implicit dependence on the physics-based model. The enhanced product was validated with upscaled ISMN data. The proposed framework demonstrated a $0.06 m^3/m^3$ and $3 K$ RMSE for SM and TB, respectively. This framework can be

extended to downscale various low-resolution products with high-resolution observations relevant to the specific geophysical variable of interest.

6. REFERENCES

- [1] Jian Peng, Alexander Loew, Olivier Merlin, and Niko EC Verhoest, "A review of spatial downscaling of satellite remotely sensed soil moisture," *Reviews of Geophysics*, vol. 55, no. 2, pp. 341–366, 2017.
- [2] Sabah Sabaghy, Jeffrey P Walker, Luigi J Renzullo, Ruzbeh Akbar, Steven Chan, Julian Chaubell, Narendra Das, R Scott Dunbar, Dara Entekhabi, Anouk Gevaert, et al., "Comprehensive analysis of alternative downsampled soil moisture products," *Remote Sensing of Environment*, vol. 239, pp. 111586, 2020.
- [3] Grigorios Tsagkatakis, Anastasia Aidini, Konstantina Fotiadou, Michalis Giannopoulos, Anastasia Pentari, and Panagiotis Tsakalides, "Survey of deep-learning approaches for remote sensing observation enhancement," *Sensors*, vol. 19, no. 18, pp. 3929, 2019.
- [4] Maria Sdraka, Ioannis Papoutsis, Bill Psomas, Konstantinos Vlachos, Konstantinos Ioannidis, Konstantinos Karantzalos, Ilias Gialampoukidis, and Stefanos Vrochidis, "Deep learning for downscaling remote sensing images: Fusion and super-resolution," *IEEE Geoscience and Remote Sensing Magazine*, vol. 10, no. 3, pp. 202–255, 2022.
- [5] Hao Sun, Xiaohan Zhang, and Xiang Zhao, "Series or parallel? an exploration in coupling physical model and machine learning method for disaggregating satellite microwave soil moisture," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–15, 2022.
- [6] Pei Leng, Zhe Yang, Qiu-Yu Yan, Guo-Fei Shang, Xia Zhang, Xiao-Jing Han, and Zhao-Liang Li, "A framework for estimating all-weather fine resolution soil moisture from the integration of physics-based and machine learning-based algorithms," *Computers and Electronics in Agriculture*, vol. 206, pp. 107673, 2023.
- [7] Qianqian Han, Yijian Zeng, Lijie Zhang, Chao Wang, Egor Prikaziuk, Zhenguo Niu, and Bob Su, "Global long term daily 1 km surface soil moisture dataset with physics informed machine learning," *Scientific Data*, vol. 10, no. 1, pp. 101, 2023.
- [8] Mehdi Mirza and Simon Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, 2014.
- [9] Valery L. Mironov, Lyudmila G. Kosolapova, and Sergej V. Fomin, "Physically and mineralogically based spectroscopic dielectric model for moist soils," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 7, pp. 2059–2070, 2009.
- [10] Peggy O'Neill, Rajat Bindlish, Steven Chan, Julian Chaubell, Eni Njoku, and Tom Jackson, "Soil Moisture Active Passive (SMAP) Algorithm Theoretical Basis Document Level 2 & 3 Soil Moisture (Passive) Data Products," *Jet Propulsion Laboratory*, 2020.
- [11] Kirk Hogenson, Heidi Kristenson, Joseph Kennedy, Andrew Johnston, James Rine, Thomas Logan, Jiang Zhu, Forrest Williams, Jake Herrmann, Jacquelyn Smale, and Franz Meyer, "Hybrid pluggable processing pipeline (hyp3): A cloud-native infrastructure for generic processing of sar data [computer software]," 2020.
- [12] Wouter Dorigo, Irene Himmelbauer, Daniel Aberer, Lukas Schremmer, Ivana Petrakovic, Luca Zappa, Wolfgang Peimesberger, Angelika Xaver, Frank Annor, Jonas Ardo, et al., "The international soil moisture network: serving earth system science for over a decade," *Hydrology and earth system sciences*, vol. 25, no. 11, pp. 5749–5804, 2021.
- [13] Daniel Clewley, Jane B Whitcomb, Ruzbeh Akbar, Agnelo R Silva, Aaron Berg, Justin R Adams, Todd Caldwell, Dara Entekhabi, and Mahta Moghaddam, "A method for upscaling in situ soil moisture measurements to satellite footprint scale using random forests," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 10, no. 6, pp. 2663–2673, 2017.