Convolutional Neural Networks for downscaling SMAP radiometer brightness temperature observations with high-resolution radar

Grigorios Tsagkatakis[1], Mahta Moghaddam[2] and Panagiotis Tsakalides[1]

[1] Institute of Computer Science - Foundation for Research and Technology- Hellas (FORTH), Crete, Greece

[2] Electrical Engineering Department, University of Southern California (USC), Los Angeles, CA, USA

The Soil Moisture Active Passive mission

Environmental research satellite targeting the estimation of surface soil moisture at 9km^2 spatial resolution with a 2-3 days revisit frequency. It is equipped with two instruments, (a) an L-band microwave radiometer imaging at 36km^2 per pixel. And (b) a L-band radar imaging at 3km^2 per pixel.

Challenge

The radar malfunctioned after a few months of operation (July 2015) which led to a significant void in terms of overall observation capabilities.

Project Objective

- Increase spatial resolution of SMAP radiometer observations

Downscale brightness temperature observations from 36km to 9km using radiometer and radar derived observations from April-June 2015.

- Provide high quality estimation of soil moisture using SMAP radiometer only

Utilize soil moisture estimates derived using SMAP radiometer and ESA Sentinel 1 C-band radar from limited overlapping spatial and temporal location for inferring a soil moisture map at any location/time.

Method: Formulate the problem as an inverse imaging problem and employ Deep Machine Learning.

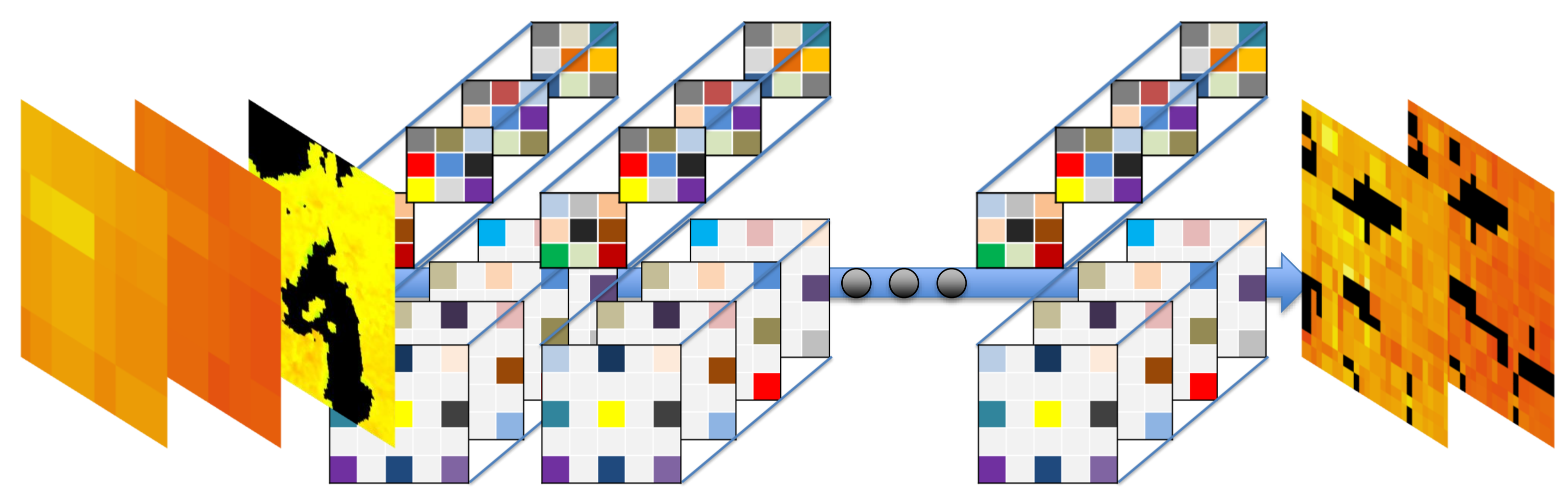
Approach: a limited set of high spatial resolution observations is employed in order to learn a mapping from low resolution inputs to high resolution outputs (training stage). Use this mapping is subsequently used to generalize the estimation to any input observation beyond the ones shown during the training stage (inference stage). In this work, we consider training and validation applied on available observations acquired between April-June 2015.The learned mapped can then be applied to other periods beyond the 2015 failure point.

Convolutional Neural Network (CNN)

- Specifica deep machine learning architecture which has achieved state-of-the-art performance in numerous remote sensing tasks (land use classification, object detection, semantic labeling) in the past two years..

Architectural components

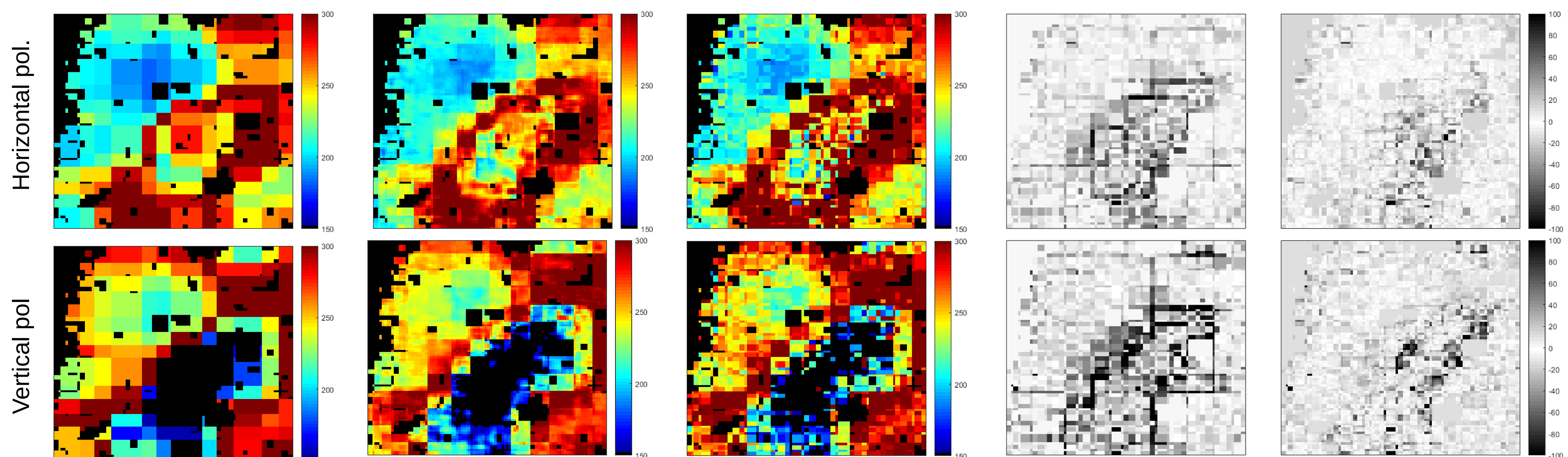
- 7 groups of layers where each layer is composed of 64 [3x3] and 64 [5x5] (dilated) convolutional kernels followed by a Rectified Linear Unit (ReLU) activation function.
- Output of layer 7 convolved with 2 [3x3] kernels, one for each polarization (plus residual connected between input and output).
- Convolutional kernels regularized with respect to l_2 norm.
- Optimization using ADAM optimizer (learning rate 10^{-4}).
- Mean absolute error used a the loss function.



Radiometer & Radar downscaling architecture

- Input: low spatial resolution (36km^2) radiometer (v & h polarization) observations and land surface temperature (1km^2)
- Output: (i) high spatial resolution (9km^2) radiometer (v & h polarization) or (ii) soil moisture estimation

Radiometer downscaling



Input: 36km SMAP radiometer | Output: Estimated 9km SMAP radiometer | SMAP radar guided 9km radiometer observations | Difference between low and high resolution | Difference between CNN and high resolution

Dataset

- Case 1: Input: SMAP radiometer, Output: downscaled SMAP radiometer using radar observations (100x100 km location-specific network).
- Case 2: Input SMAP radiometer and MODIS Land Surface Temperature (LST), Output: Estimated Soil Moisture (SM) derived from SMAP radiometer and Sentinel 1 radar.

Soil Moisture Estimation