Poster 13: Development of Gap-agnostic Machine Learning techniques for Earth Science applications

Soni Yatheendradas[1,2], Sujay Kumar[2], Christa Peters-lidard[2], and David Mocko[2,3]

[1]UMD ESSIC, [2]NASA GSFC, [3]SAIC

1. Introduction

- Input data gaps hamper machine learning
- Current gap-agnostic technique of partial convolution can handle pixels where all inputs have valid values
- But not effective for earth sciences where data gaps vary across inputs!
- For full gap-agnosticity, we developed generalized versions of partial convolution, partial neural network layer, and input relevance calculation
- Our example applications:
  - Regression: Gap-filling remotely-sensed snow cover fraction (SCF) through downscaling
  - Classification: Using Climate Prediction Center (CPC) Experimental Objective Blend inputs for predicting United States Drought Monitor (USDM) categories

2. Data and methododology

A. SCF gap-filling using Super-Resolution Convolutional Neural Network

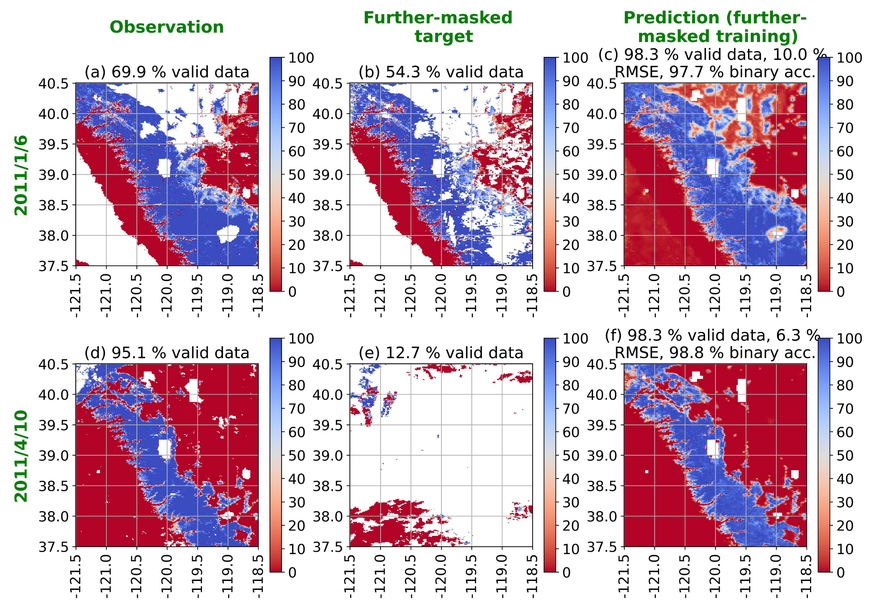
- Target: MOD10A1 C5 SCF (1-km version)
- Core input/s: 5-km MOD10A1 C5 SCF: SCF, Cloud Cover Fraction (CCF), Confidence Index (CI)
- Auxiliary inputs (1 km resolution):
  - static terrain: elevation, slope, aspect
  - Land Surface Model dynamics (Noah-MP): Precip, Snow Water Equivalent (SWE), surface radiative temperature, Leaf Area Index (LAI)
  - Satellite-based: C5: MOD10A1 snow albedo, MOD11A1 land surface temperature (LST)
- 3° X 3° domain centered over Lake Tahoe (CA-NV border), 3- year training (2009-2011), 2012 for validation, 2005-2007 for further synthetic cloud masking

B. Input relevances in USDM classification

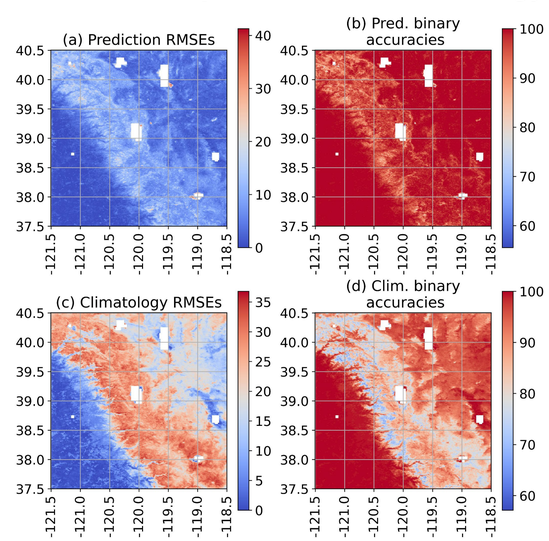
- Data resolved to US Climate Division polygons
- CPC Blends' Short- and Long-Term inputs: Z-index; 60-month Z-index; Modified and Hydrologic Palmer Drought Indices (PMDI, PHDI); Precipitations for 1, 3, 6, 12, 24 and 60 months; CPC soil moisture
- Training years 2006-2018, Validation 2019
- 1 intermediate layer of 16 neurons
- Our modified Softmax-Gradient Layer-wise Relevance Propagation (SGLRP) for better input contrast and relevance conservation

3a. Results (SCF gap-filling)

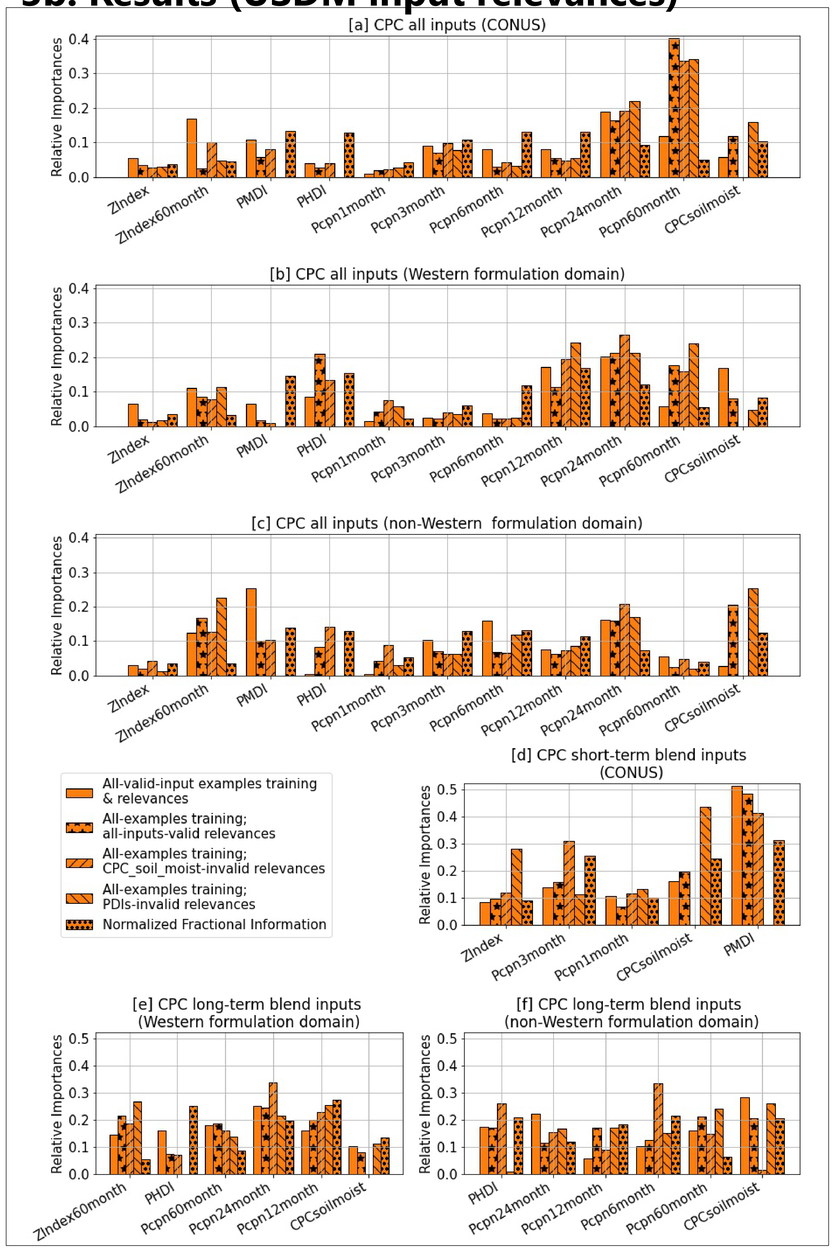
- **Example-day predictions**



- **Spatial error: ML-based prediction vs. climatology**



3b. Results (USDM input relevances)



4. Summary

- SCF gap-filling:
  - Our generalized technique successfully recreates synthetically masked-out areas much better than the climatology baseline
- USDM input relevances:
  - Regular training bars (no-hatch) and fully gap-agnostic ones (star and diagonal hatchings) show different information
- These advancements provide the earth science community with a gap-agnostic Machine Learning infrastructure tool

5. References

- Iwana, B. K. et al (2019), Explaining Convolutional Neural Networks using Softmax Gradient Layer-wise Relevance Propagation, arXiv:1908.04351
- Liu, G., et al. (2018), Image Inpainting for Irregular Holes Using Partial Convolutions, arXiv:1804.07723
- Vandal, T., et al. (2017), DeepSD: Generating High Resolution Climate Change Projections through Single Image Super-Resolution, DOI: http://dx.doi.org/10.1145/3097983.3098004