Evaluation of Flash Drought Identification with Machine Learning Techniques, Part 1: Standard Machine Learning Algorithms

Stuart Edris[1*], Jeffrey Basara[1,2], Jordan Christian[1], Jason Furtado[1], Amy McGovern[1,3], Xiangming Xiao[4]
[1]School of Meteorology, University of Oklahoma, [2]School of Civil Engineering and Environmental Science, University of Oklahoma, [3] School of Computer Science, University of Oklahoma, [4]Department of Microbiology and Plant Biology, University of Oklahoma, *Contact: sgedris@ou.edu

Introduction

Flash droughts (FD) are rare climatological extremes in which the moisture conditions and vegetative health deteriorates on a relatively rapid timescale (~1 month). The recent advancements in machine learning (ML) in earth sciences have shown its ability to improve on current methods of drought identification and prediction. However, investigation of flash droughts with machine learning remains scarce, nearly untouched except for a few studies. This study is one of two parts seeking investigate the ability of ML models to identify flash drought events, using variables known to drive or show signs of flash drought. This part focuses on ML models found in the sci-kit learn toolbox (random forests, RF; Ada boosted decision trees, Ada; and linear kernel support vector machines, SVMs), while part 2 focuses on deep learning with the Keras and Tensorflow package.

Data

- The following data was incorporated from the North American Regional Reanalysis (NARR) dataset, focused on growing seasons from 1979 – 2021:
  - Temperature (T)
  - Precipitaiton (P)
  - Evaporation (ET)
  - Change in Evaporation (ΔET)
  - Potential evaporation (PET)
  - Change in potential evaporation (ΔPET)
  - Soil moisture (0 – 40 cm layer; SM)
  - Change in soil moisture (ΔSM)
- K-Fold validation with 43 folds (one for each growing season)

- Five different methods identifying FD were investigated:
  - Christian et al. 2019 (C19)
  - Nogeura et al. 2020 (N20)
  - Pendergrass et al. 2020 (P20)
  - Liu et al. 2020 (L20)
  - Otkin et al. 2021 (O21)
- The ML models were trained to identify FD with each identification method
- Identical parameters and class weights were used for each method

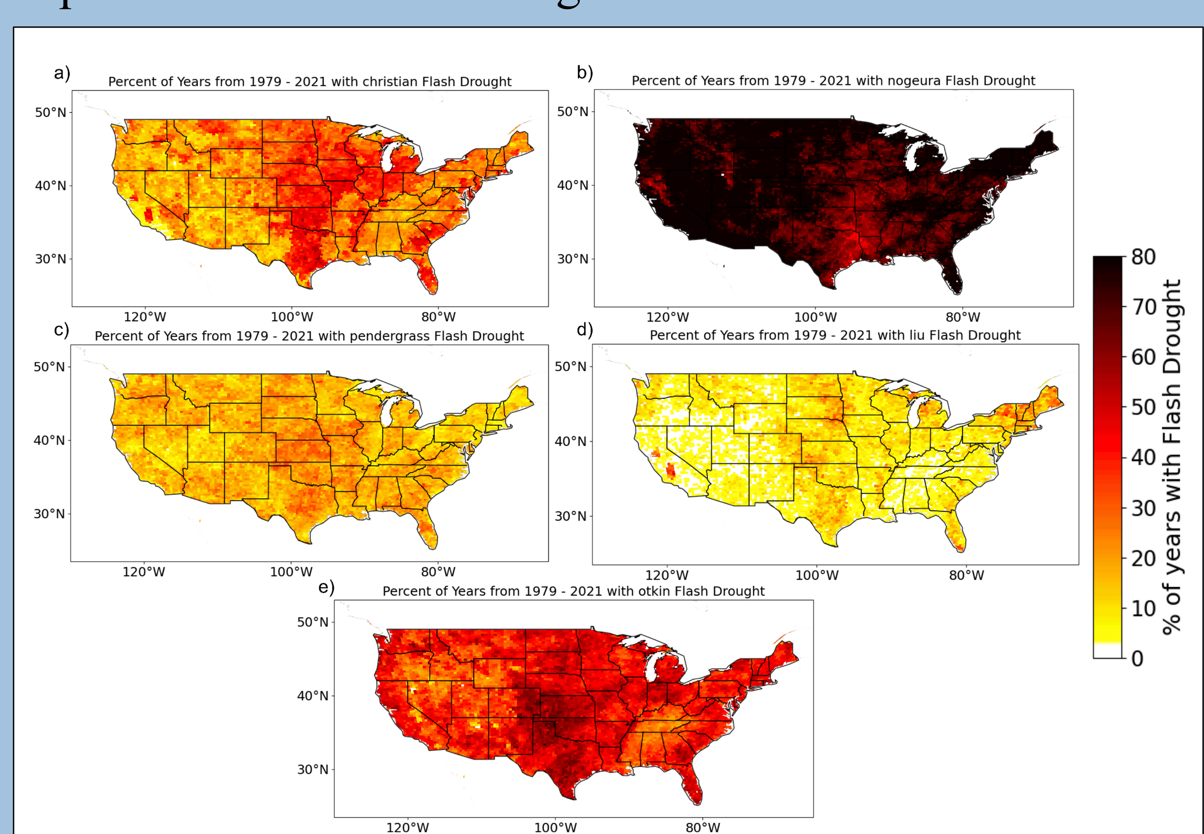

Figure 1. Average frequency of FD according to the, (a) Christian, (b) Nogeura, (c) Pendergrass, (d) Liu, and (e), Otkin identification methods.

Results

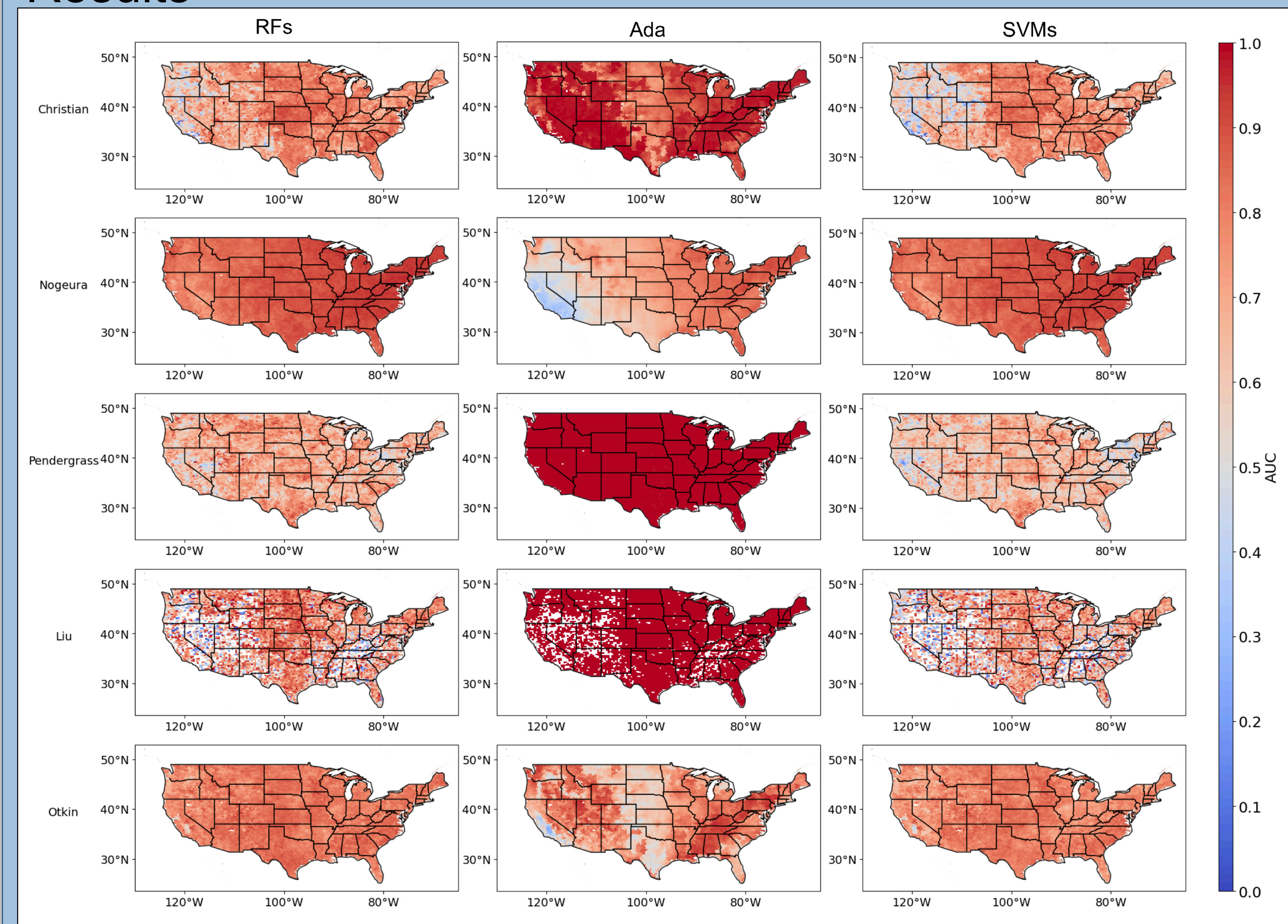

Figure 2. Area Under the Curve (AUC) metric evaluated for every grid point for (left) RFs, (center) Ada, (right) SVMs, and trained on each FD identification method.

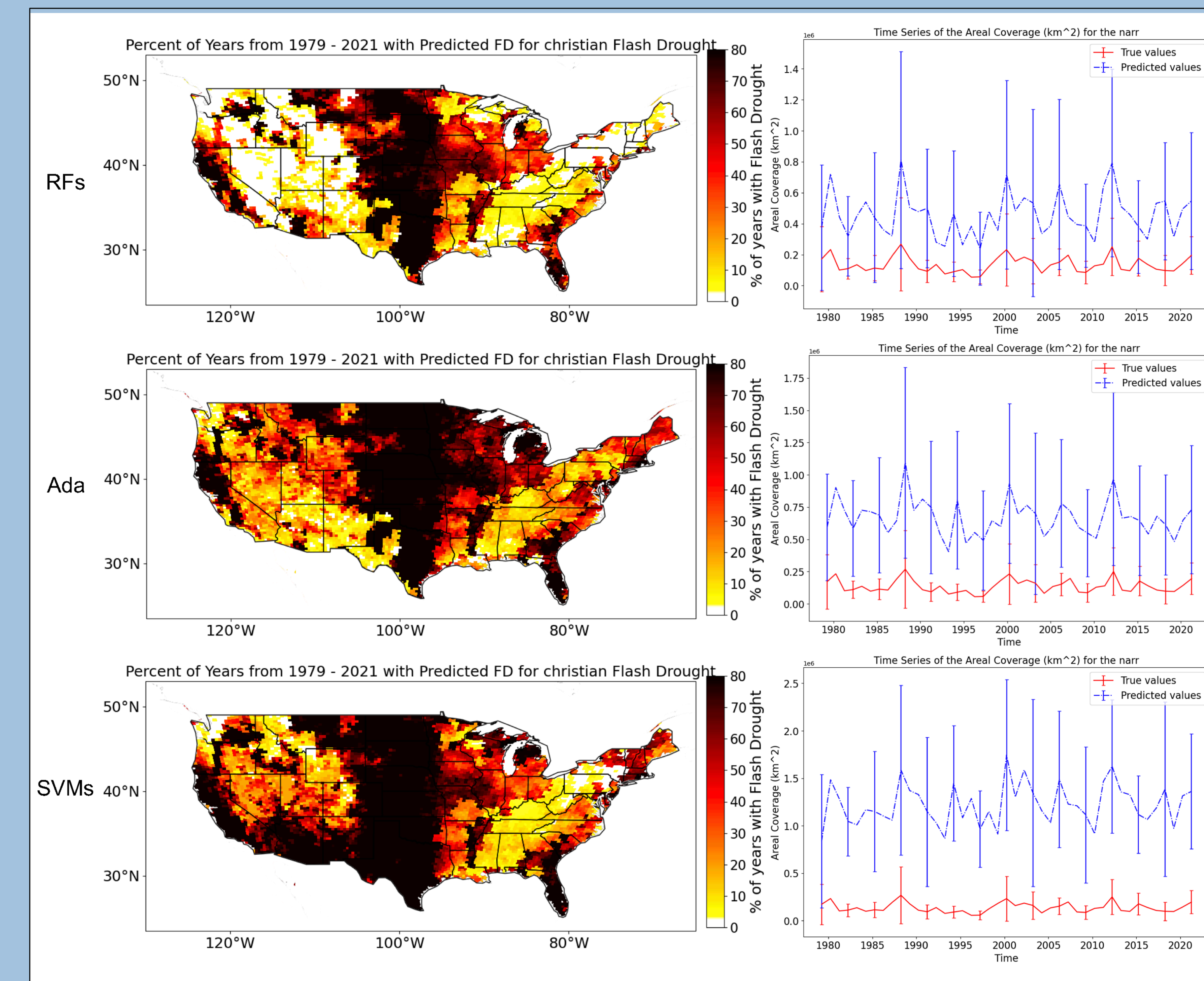

Figure 3. (left) Predicted climatological frequency of C19 FD, and (right) true (red) and predicted (blue) areal coverage of C19 FD. Predictions are from (top) RFs, (center) Ada, and (bottom) SVMs

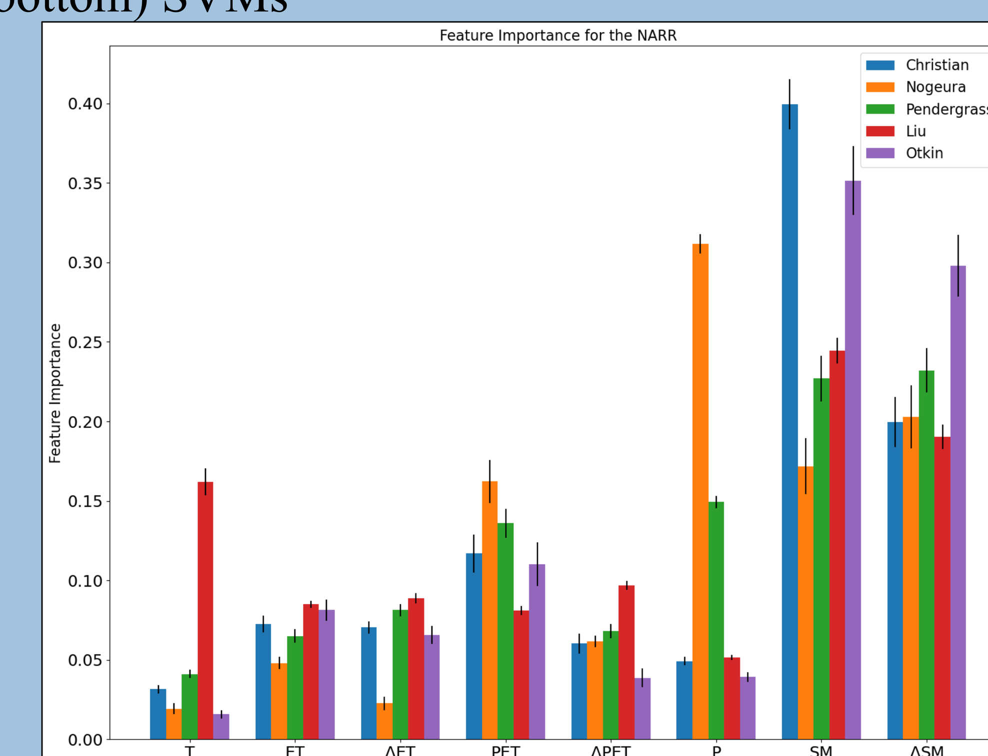

Figure 4. Average feature importance (over all rotations) of each variable used by the RFs to identify FD for each FD identification method.

Case Studies

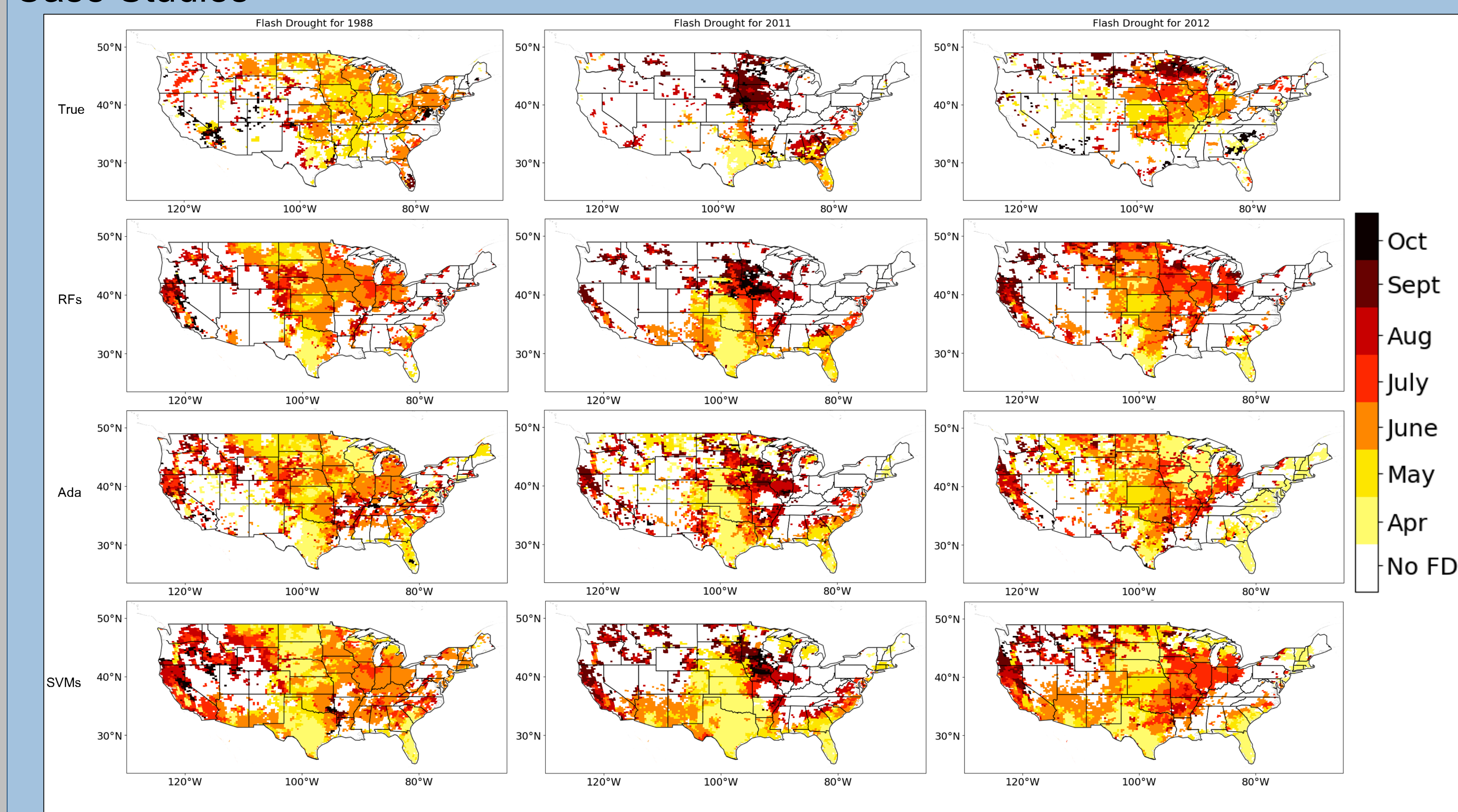

Figure 5. Case studies of C19 FD for (left) 1988, (center) 2011, (right) 2012, for (top) true labels, and each ML model.

Concluding Remarks

- Results showed varying results with each FD identification method.
  - Each method is not the same and finds different features of FD.
  - ML models need to be individually tuned to each FD identification method.
- ML models were able to reproduce the spatial and temporal patterns of FD.
  - FD hotspots were overpredicted, and regions with few FDs were underpredicted (sans SVMs).