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

The UNIVERSITY of OKLAHOMA

Stuart Edris[1], Jeffrey Basara[2] , Jordan Christian[1], Jason Furtado[1], Amy McGovern[1,3], Xiaoming Xiao[4]

[1]School of Meteorology, University of Oklahoma Norman, Oklahoma, USA; [2]Department of Environmental, Earth, and Atmospheric Sciences, University of Massachusetts Lowell, Lowell, Massachusetts, USA; [3]School of Computer Science, University of Oklahoma, Norman, Oklahoma, USA; [4]Department of Microbiology and Plant Biology, University of Oklahoma, Norman, Oklahoma, USA

Motivation

Flash drought (FD) describes the rapid development of drought conditions in an area. The new subset of drought has gain increased attention in the past decade due to impacts from the rapid desiccation of the landscape. Recent advances have shown the FDs are becoming more frequent and severe in time, and steadily becoming the more common form of drought in some regions. However, research has yet to solidify around a standard, quantitative definition for FD, resulting in a number of different methods for identifying FD based on one or more variables that drive local drying on the pentad to monthly timescale. However, despite machine learning (ML) becoming increasingly prominent in environmental sciences, it has yet to be fully utilized for investigating FD phenomenon, despite ML showing promise in traditional drought identification and prediction.

Goal:
Determine if and how well traditional ML models represent FD

Datasets and Experiment Design

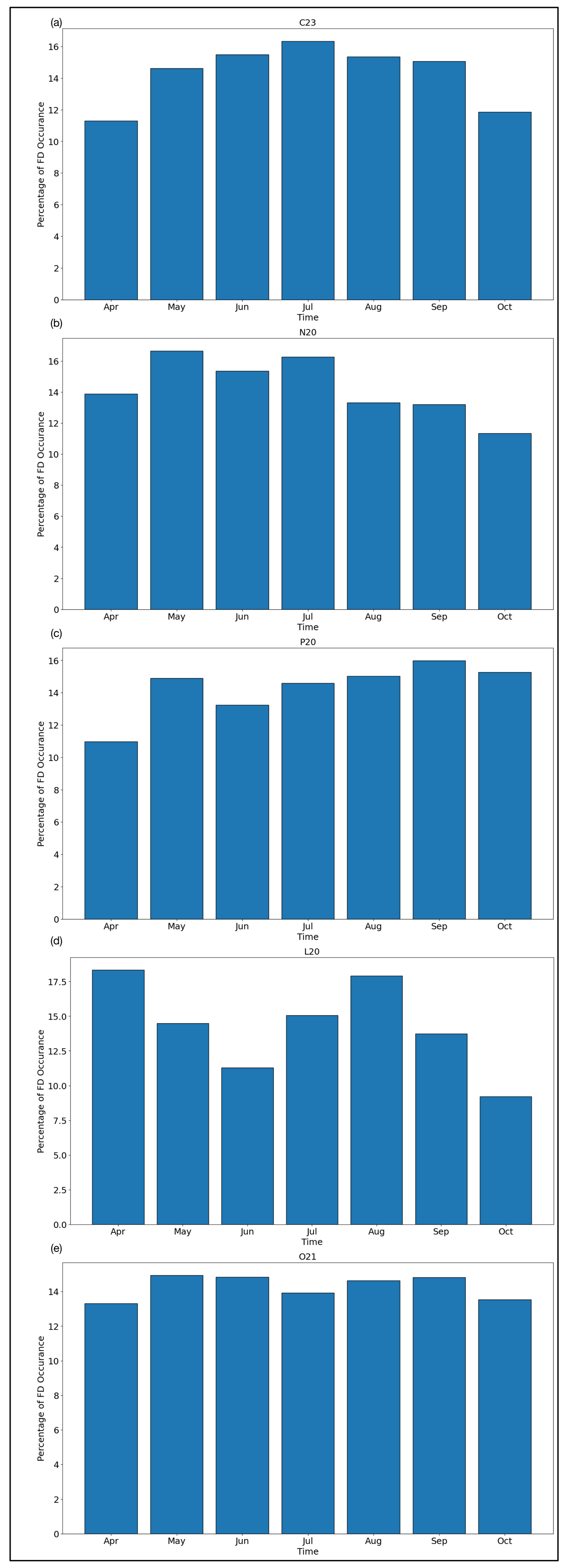

Fig. 1: Frequency of FD occurrence for each month for (a) C23, (b) N20, (c) P20, (d) L20, (e) O21.

North American Regional Reanalysis (NARR)
- 5 day, non-overlapping temporal timescale
- 32 km x 32 km horizontal grid spacing

Experiment design:
- Input features shape: space and time x features
  - Models make an FD prediction for each set of input features
- K-Fold cross validation employed:
  - Training data: 41 folds (1 fold = 1 growing season) per rotation
  - Validation and test data: 1 fold per rotation
- Three sklearn models explored:
  - Random forests (RFs)
  - Ada boosted trees (Ada)
  - Support vector machines (SVMs)

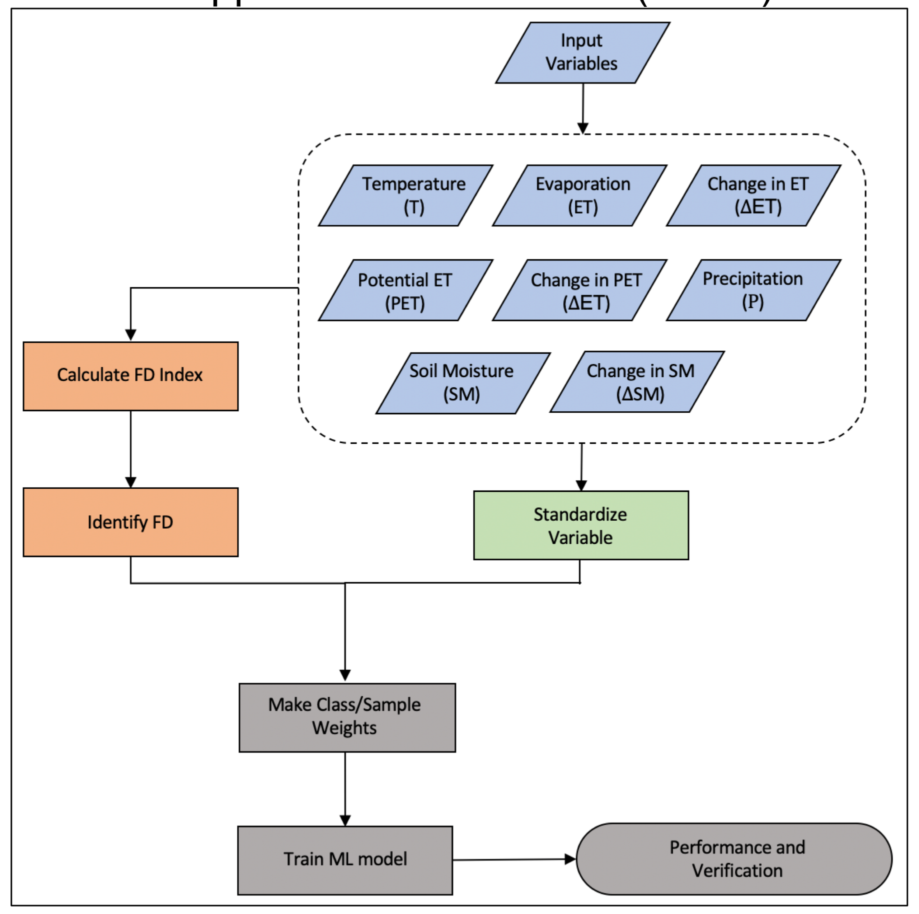

Fig. 2: Data preparation and design for ML experiments.

Output labels:
- 5 separate binary classification for tasks for different FD identification methods:
  - Christian et al. 2023 (C23)
  - Nogeura et al. 2020 (N20)
  - Pendergrass et al. 2020 (P20)
  - Liu et al. 2020 (L20)
  - Otkin et al. 2021 (O21)

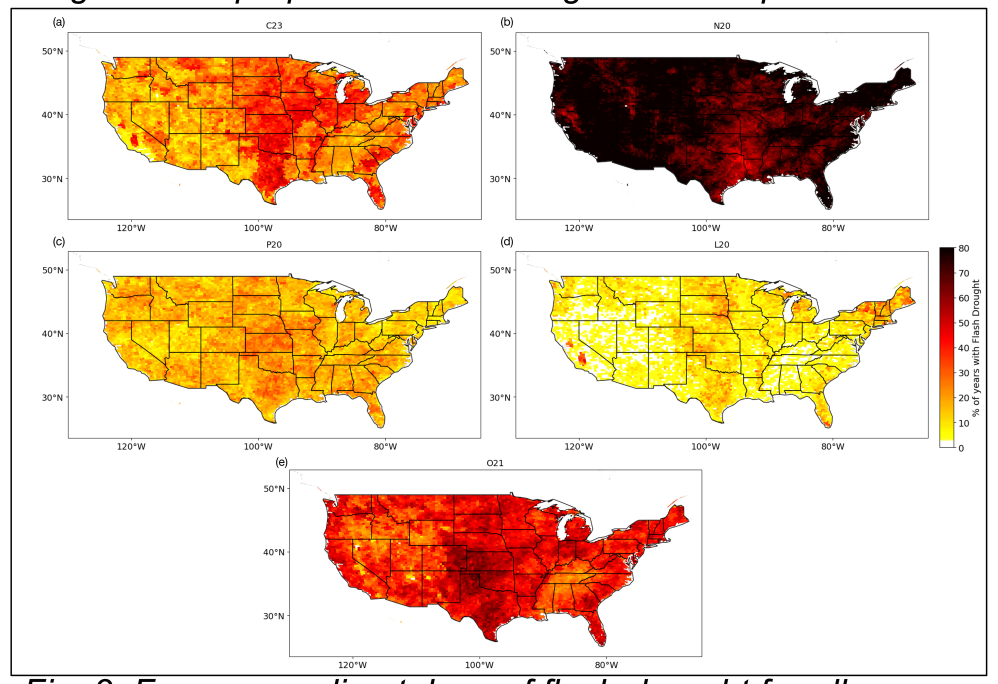

Fig. 3: Frequency climatology of flash drought for all identification methods (truth labels/targets).

Model Performance

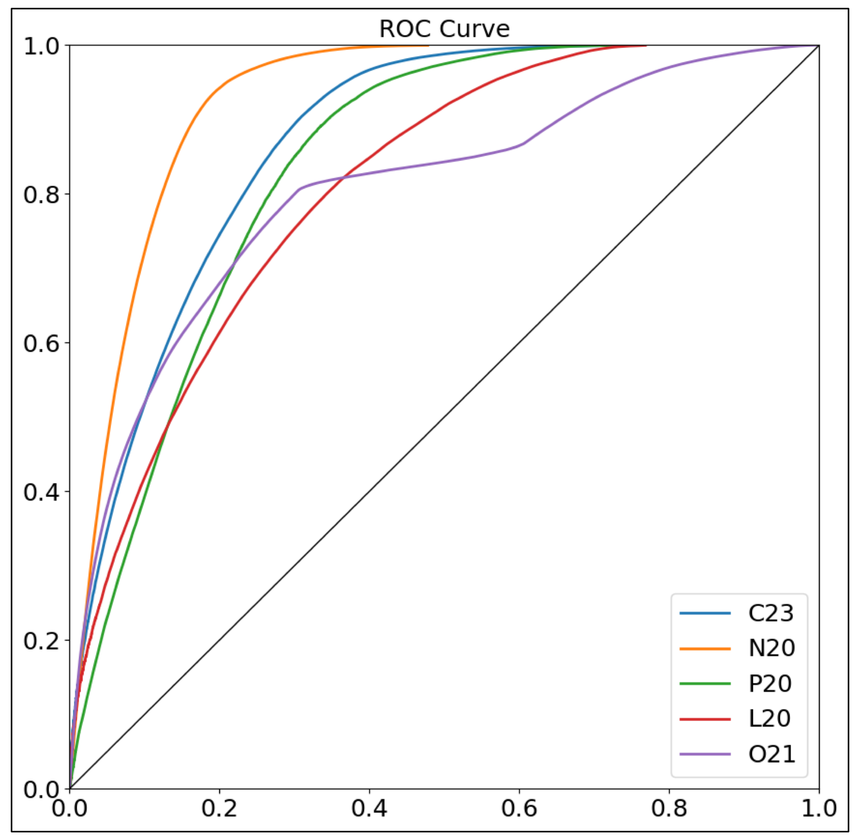

Fig. 4: ROC curve for RFs for each FD identification method.

Table 1: True Skill Statistic/Peirce's Skill Score.

	RFs	Ada	SVMs
C23	0.13	0.32	0.13
N20	0.07	0.13	0.21
P20	0.09	0.06	0.05
L20	0.10	0.27	0.07
O21	0.08	0.08	0.08

- Boosted trees showed the most skill in identifying FD
- Found variability in feature importance with ML model and FD method – only boosted trees incorporated surface variability
- Notable variation in performance with different FD identification methods

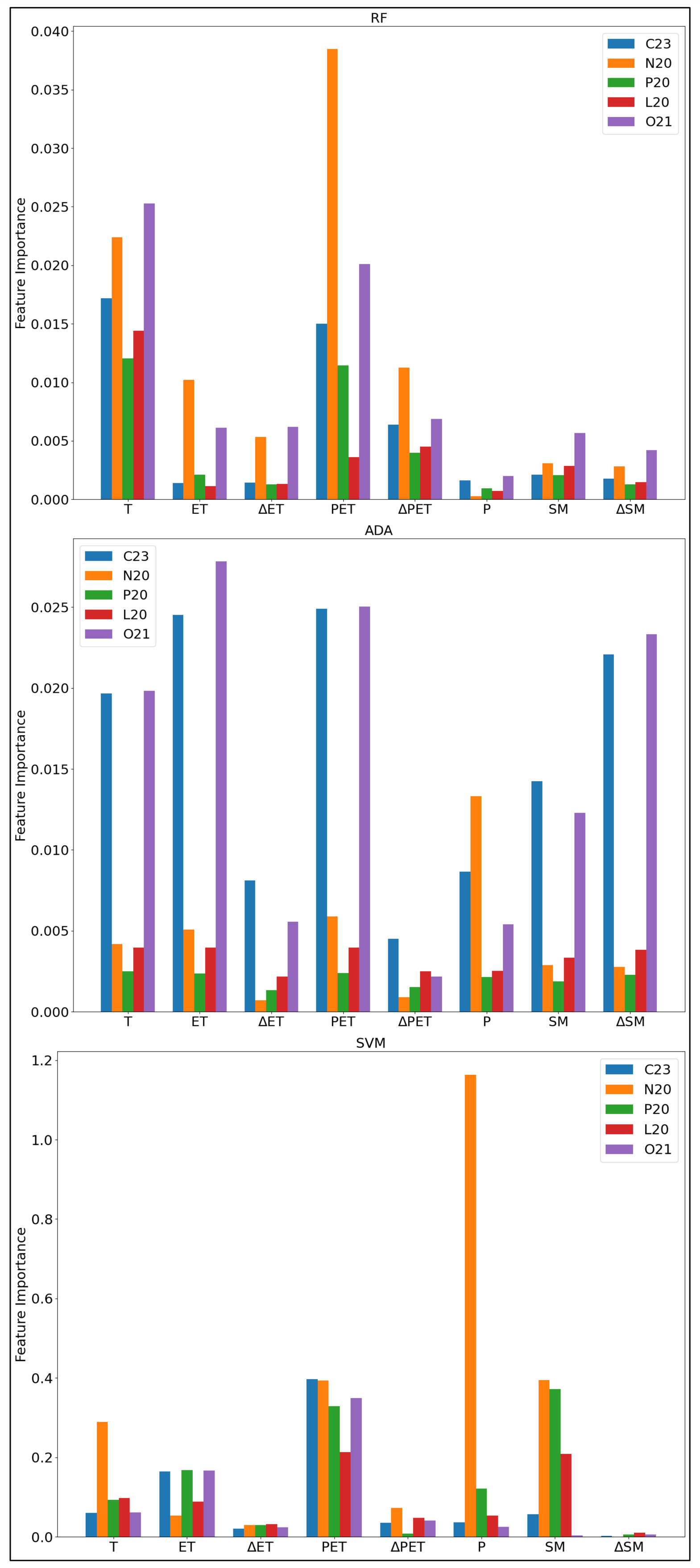

Fig. 5: Feature importance – based on SHAP values – for each ML algorithm and for each FD identification. method.

Case Studies

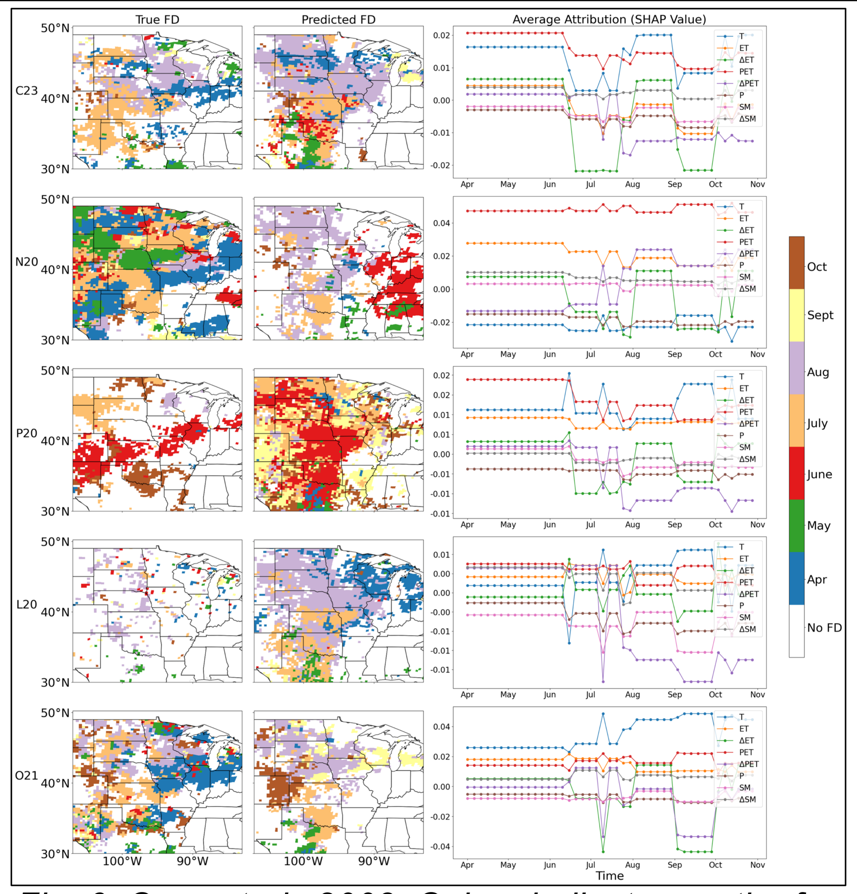

Fig. 6: Case study 2003. Colors indicate month of FD onset. Predictions made by Ada boosted trees

- Boosted trees were able to represent the coverage of the individual cases
- Some issues with timing of FD onset (bias towards seasonal climatology)
- Some bias toward predicting climatology in hotspots

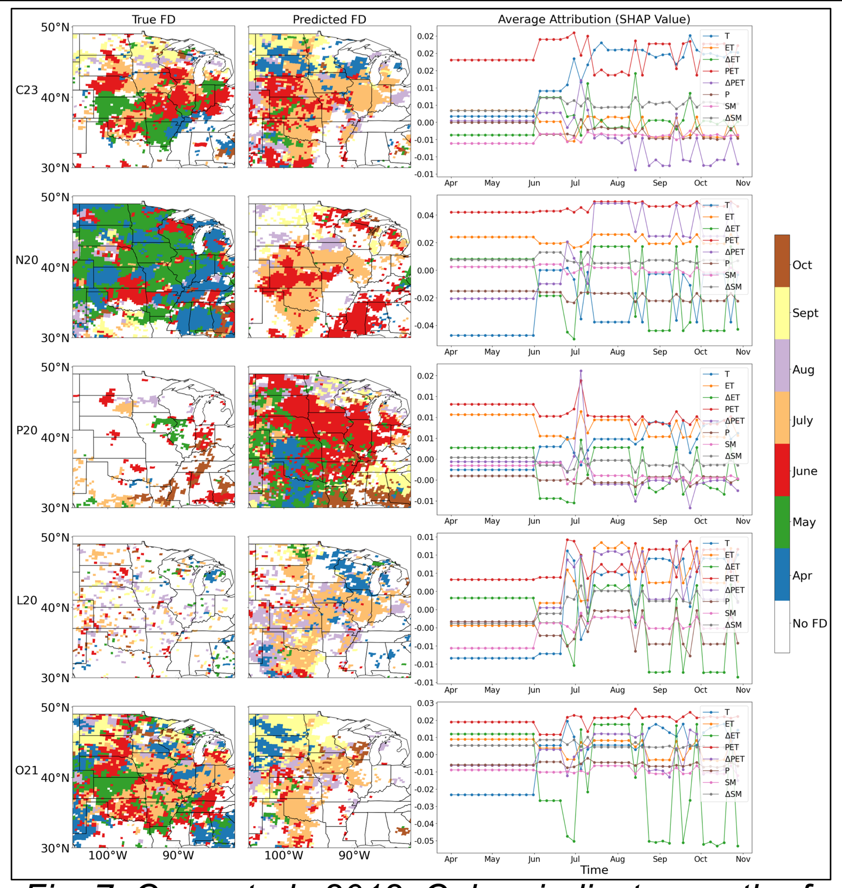

Fig. 7: Case study 2012. Colors indicate month of FD onset. Predictions by Ada boosted trees.

- Predicted coverage of FD generally well represented – ML models like to create contiguous patches of FD if there wasn't one originally
- Notable variability in feature attribution with time
  - E.g., change variables can frequently contribute to a no FD prediction

Test Predictions

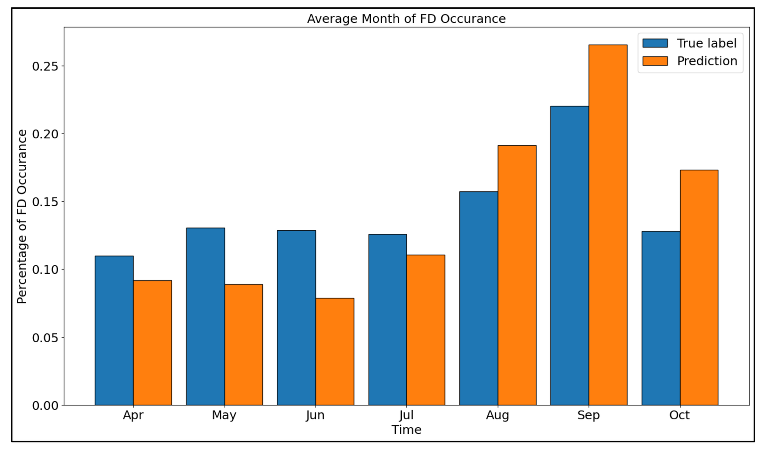

Fig. 8: Average frequency of FD onset occur for each growing season month for true labels and Ada boosted tree predictions for the C23 method. Seasonality bias pattern occurs for other FD identification methods.

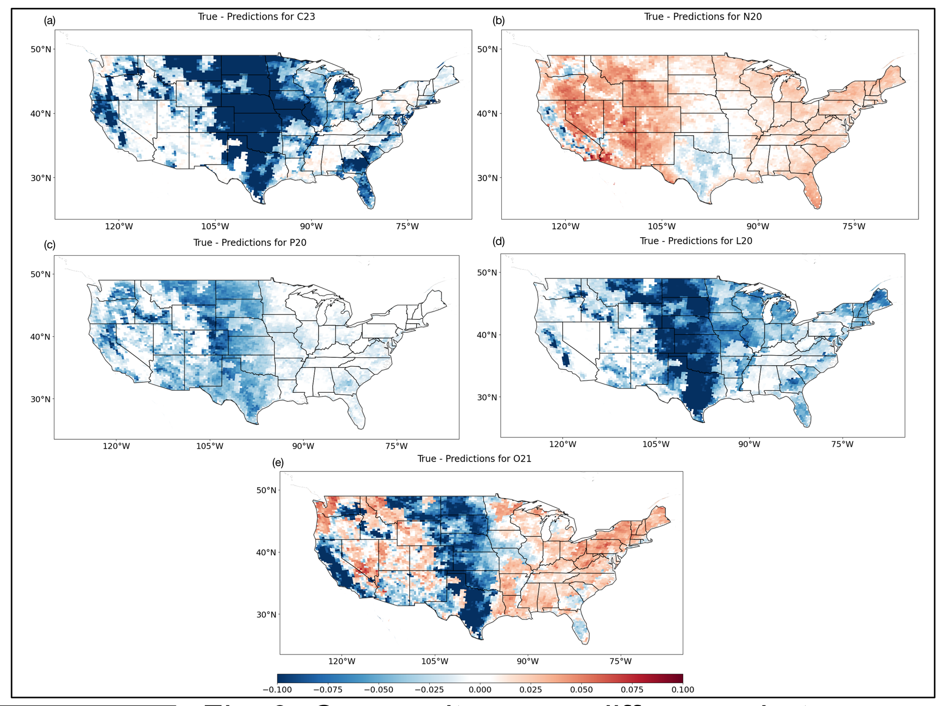

Fig. 9: Composite mean difference between the truth labels and predicted labels from Ada boosted trees.

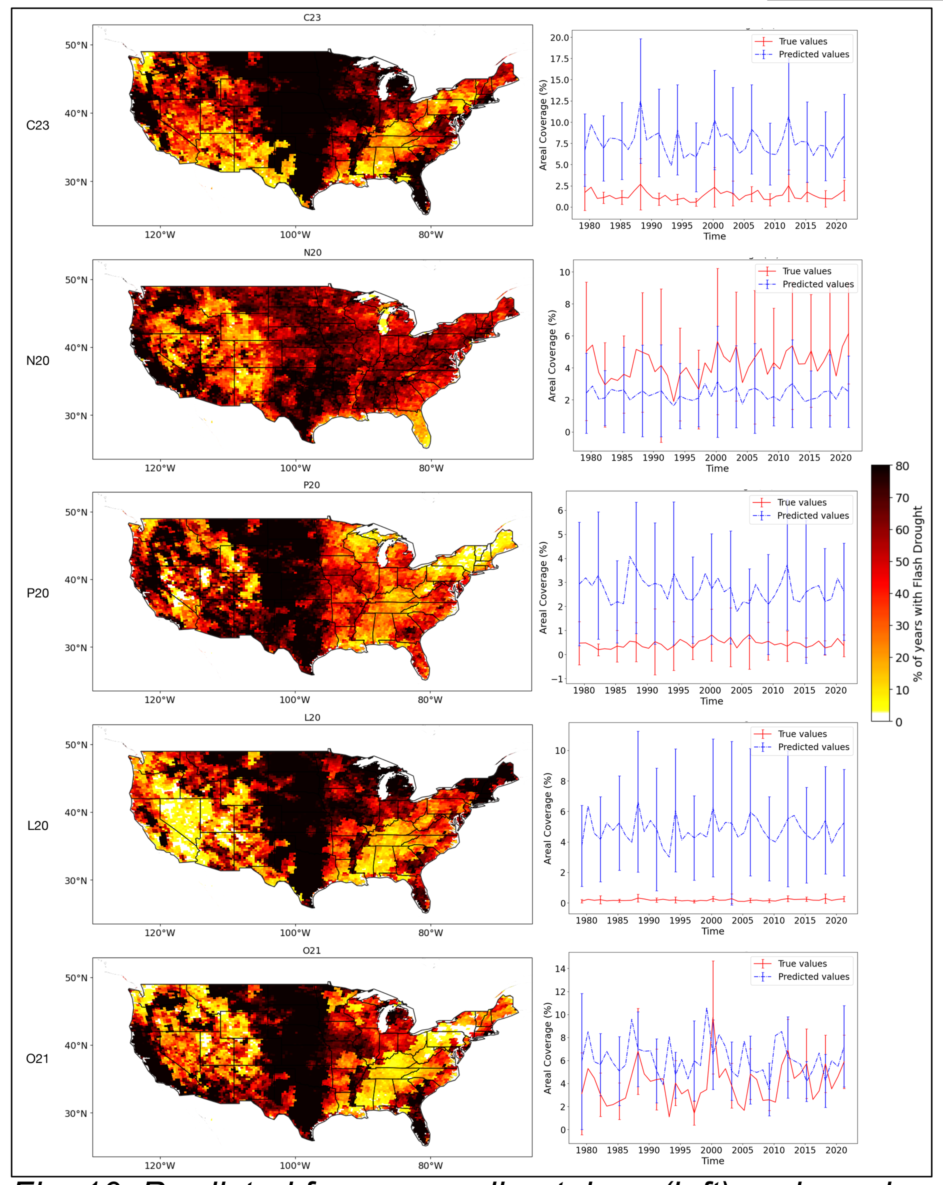

Fig. 10: Predicted frequency climatology (left) and areal coverage (right) of predicted and true FD labels. Predictions from Ada boosted trees.

- Initial predictions capture many of the patterns for FD
  - ML models find hotspots over major agricultural and energy transition regions
  - This includes some agricultural regions not included in the true labels
  - Seasonality of FD is generally captured
  - However, models over emphasize statistical averages (overprediction of hotspots and seasonality)
- ML models had an easier time with some FD identification methods than others
  - E.g., predictions for the N20 method has more positive cases to learn from

Conclusions

- ML models showed some skill in being able to represent FD events and re-create their climatology
- Initial results showed Ada boosted trees possessed the most skill in representing FD spatially and temporally
- Model performance can be dependent on FD identification method
  - N20 method was easiest to learn (most positive cases), however methods with more distinct patterns (C23 and L20) also had higher skill scores
- ML models tend to over-emphasize climatological hotspots (creating many false negatives) and most probable months (creating some FD onset timing issues)
- ML models interestingly use T and PET primarily to identify FD, and remaining variables are more minor (or tend to contribute to a no FD case)
  - Only boosted trees really focused on variables with surface interactions

References

Mesinger, F., and Coauthors, (2006): North American Regional Reanalysis. Bulletin of the American Meteorological Society, 87 (3), 343–360, doi:10.1175/bams-87-3-343

Christian, J. I., and Coauthors, 2023: Global Projections of Flash Drought Show Increased Risk in a Warming Climate. Communications Earth & Environment, 4 (1), doi:10.1038/s43247-023-00826-1

Pendergrass, A. G., and Coauthors, 2020: Flash Droughts Present a New Challenge for Subseasonal-To-Seasonal Prediction. Nature Climate Change, 10 (3), 191–199, doi:10.1038/s41558-020-0709-0

Noguera, I., F. Dom´ınguez-Castro, and S. M. Vicente-Serrano, 2020: Characteristics and Trends of Flash Droughts in Spain, 1961–2018. Annals of the New York Academy of Sciences, 1472 (1), 155–172, doi:10.1111/nyas.14365

Liu, Y., Y. Zhu, L. Zhang, L. Ren, F. Yuan, X. Yang, and S. Jiang, 2020: Flash Droughts Characterization Over China: From a Perspective of the Rapid Intensification Rate. Science of The Total Environment, 704, 135 373, doi:10.1016/j.scitotenv.2019.135373

Otkin, J. A., and Coauthors, 2021: Development of a Flash Drought Intensity Index. Atmosphere, 12 (6), 741, doi:10.3390/atmos12060741

Yuan, X., Y. Wang, P. Ji, P. Wu, J. Sheffield, and J. A. Otkin, 2023: A Global Transition to Flash Droughts Under Climate Change. Science, 380 (6641), 187–191, doi:10.1126/science.abn6301