EVALUATION OF FLASH DROUGHT IDENTIFICATION WITH MACHINE LEARNING TECHNIQUES, PART 3: GLOBAL PERSPECTIVES

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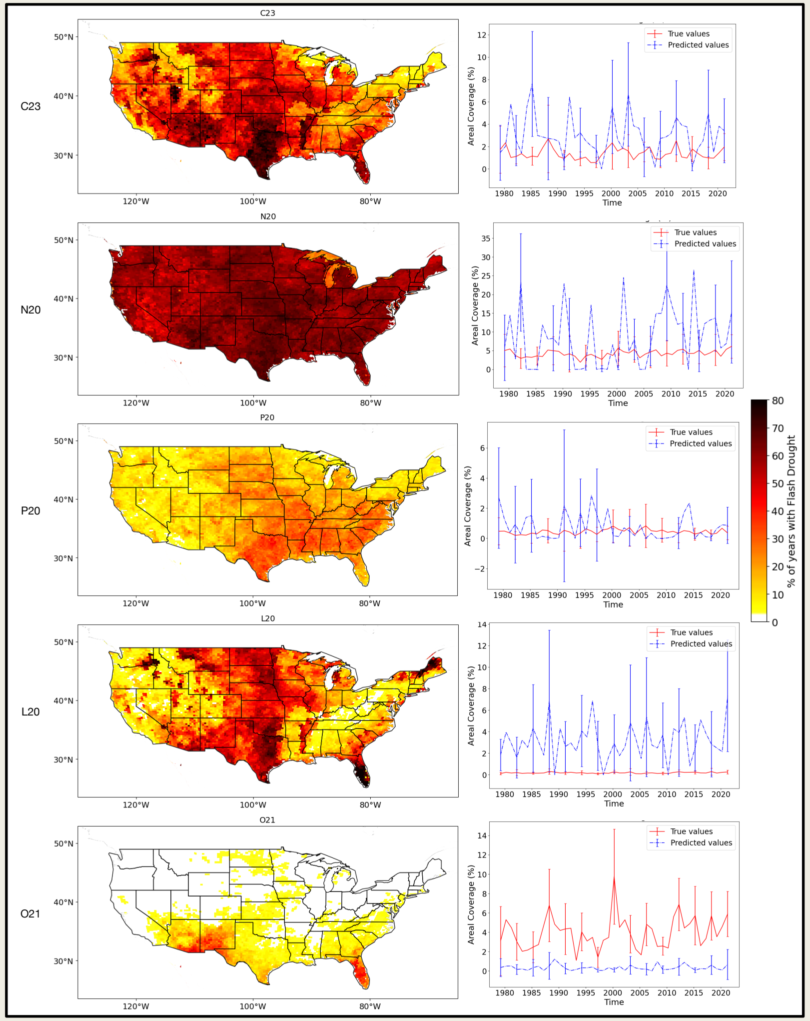
Background

- Advances in flash drought (FD) studies have delivered numerous results
  - *Understanding in FD hotpots and seasonality and the reasons for them*
  - *Numerous different methods to identify and quantify FD*
  - *Parts 1 and 2 used machine learning (ML) to represent FD events*



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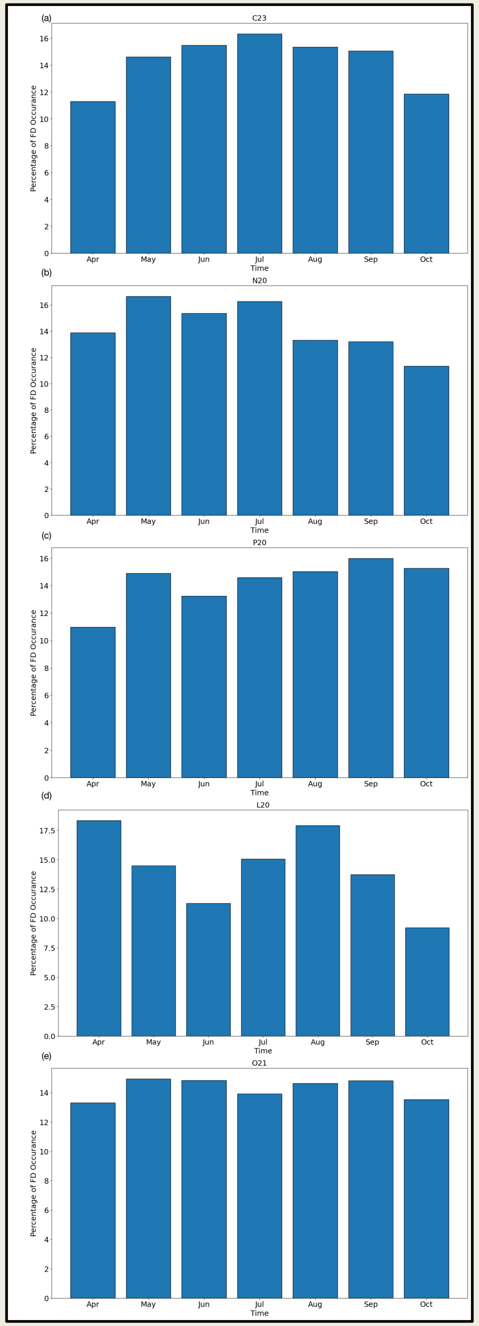

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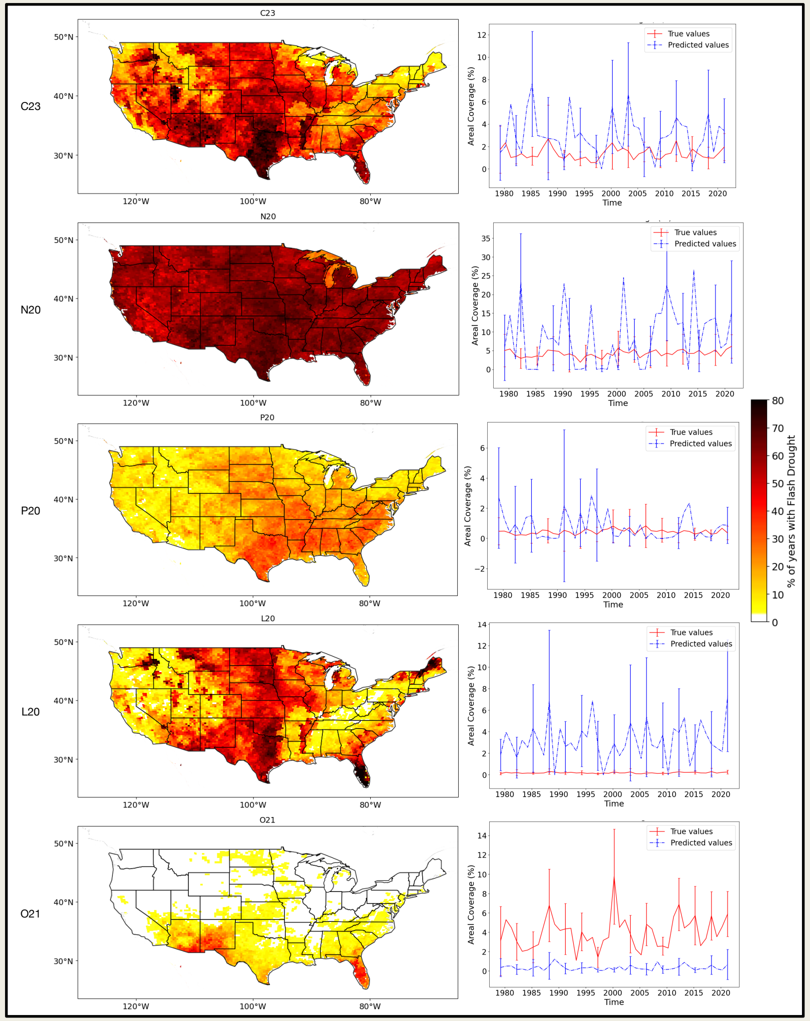
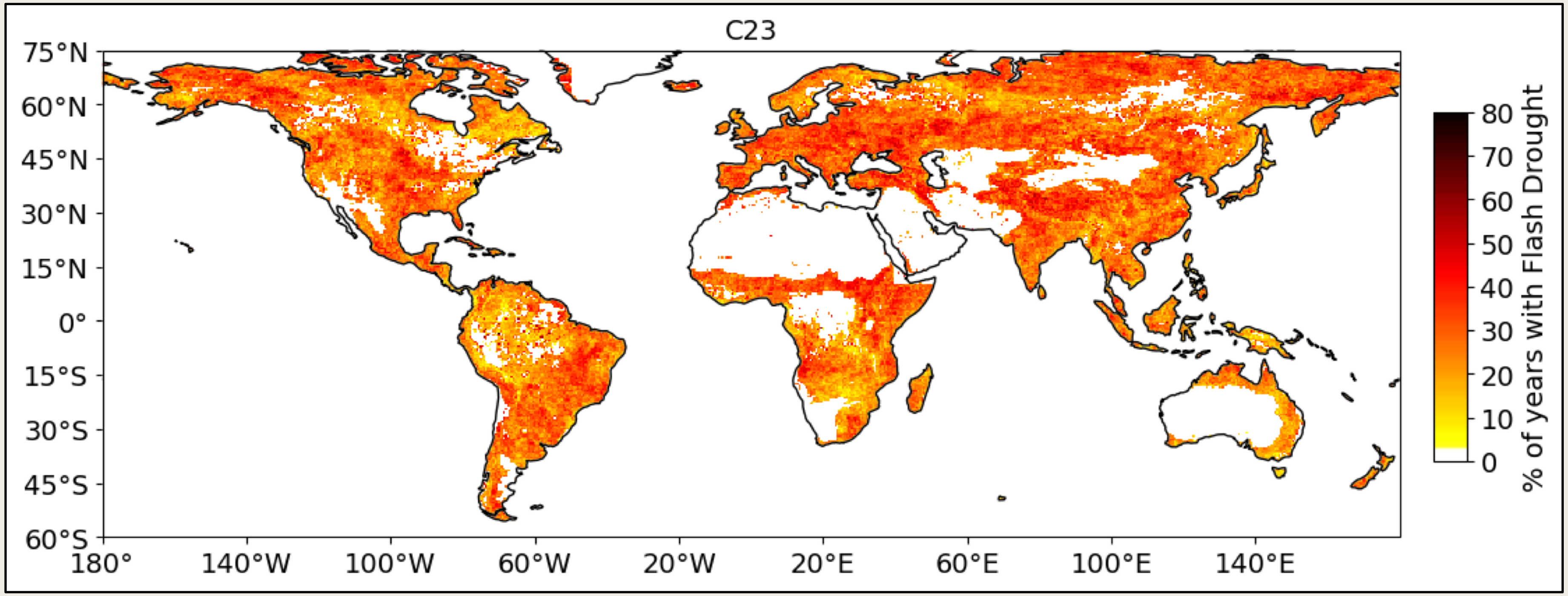
  - *Numerous different methods to identify and quantify FD*
  - *Parts 1 and 2 used machine learning (ML) to represent FD events*
  - *Parts 1 and 2 also highlighted some of the differences in different FD identification methods*
- However, many studies focus on a specific region, with only a handful expanding to global analyses



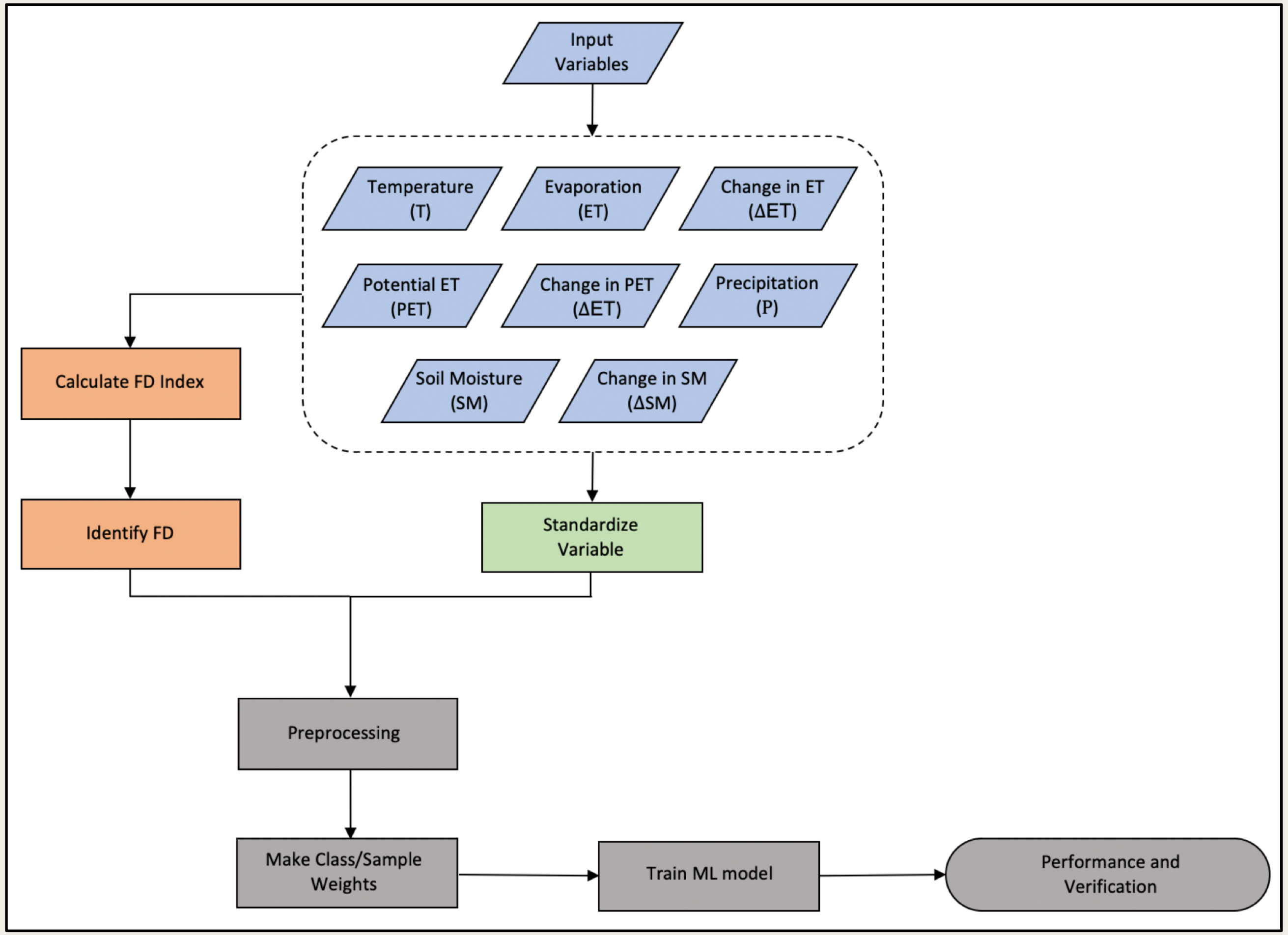
Research Goals

- Expand on parts 1 and 2 and investigate the ability of ML algorithms to generalize and learn global patterns
  - *Can it capture trends in FD in different locations? Different seasonalities? Different hotspots?*
  - *This also allows the opportunity to look at FD events in locations that are not often talked about*



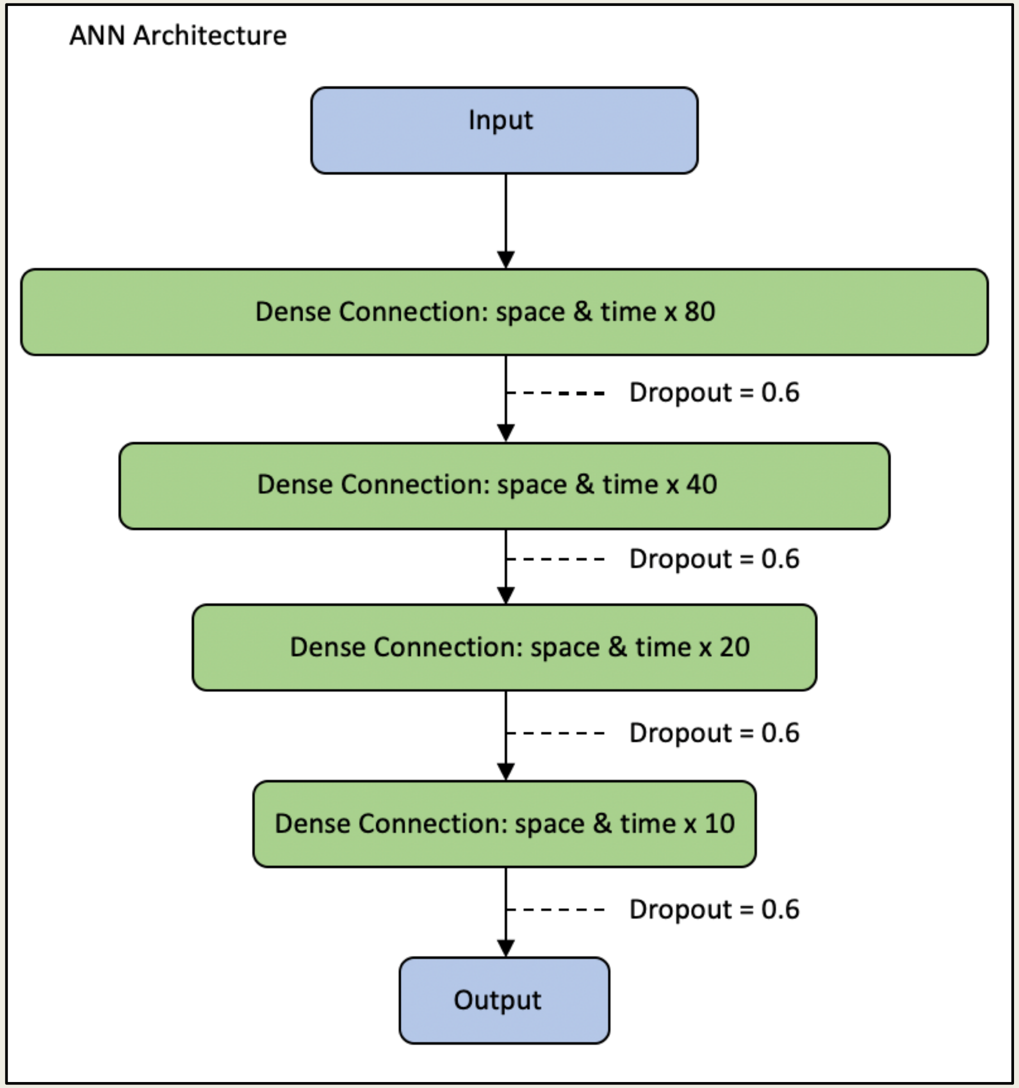
Dataset

- Global data was taken from the ERA5 reanalysis
  - *1979 – 2021 year range to match the previous parts*
  - *Data averaged to the pentad timescale*
  - *Change variables are the 30 day mean in pentad differences*
- Growing season defined as:
  - *Northern Hemisphere: April – October*
  - *Southern Hemisphere: September – March*
- Presented results focus on the FD identification method outlined in Christian et al. 2023 (C23)

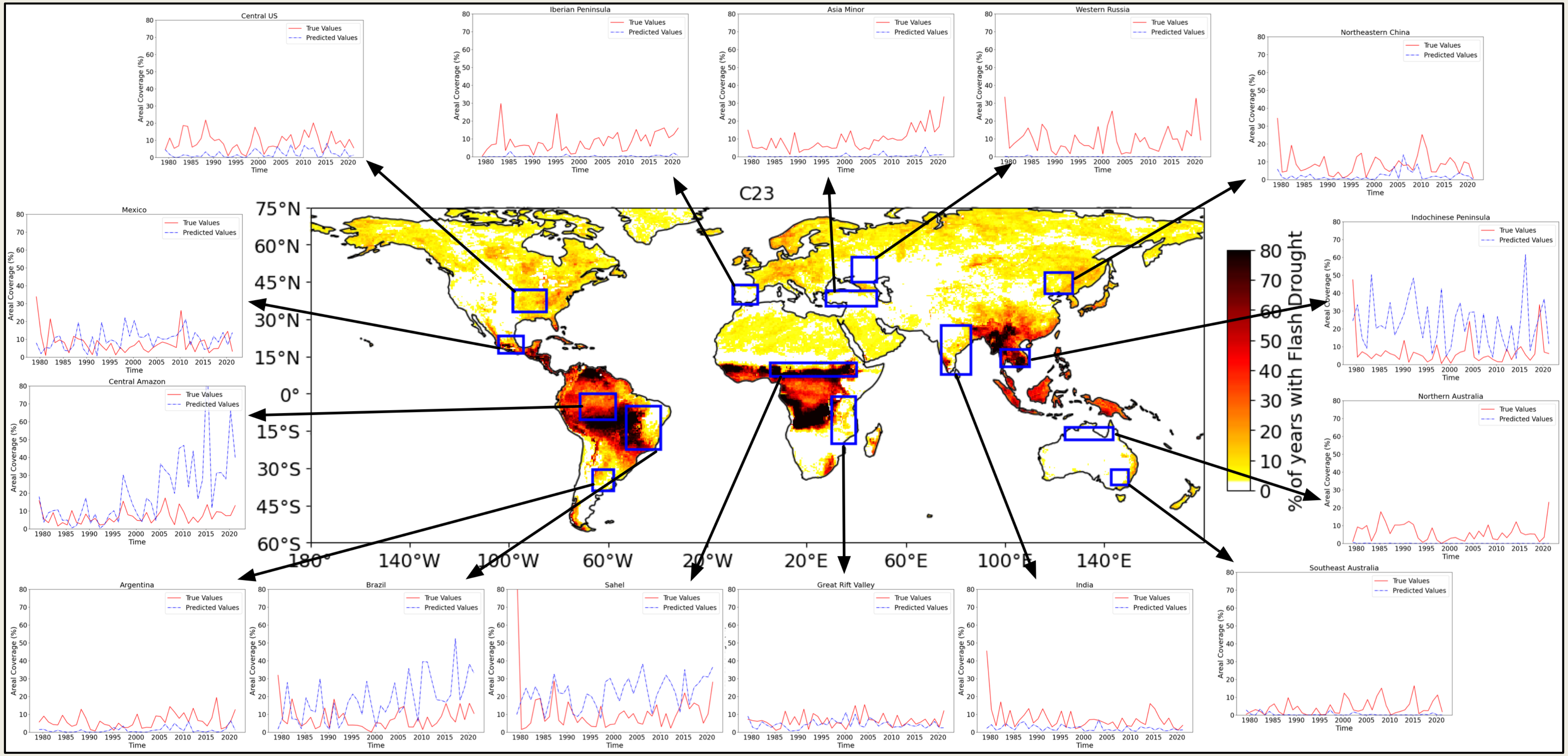


Neural Network Design

- Current results trained on a densely connected artificial neural network (ANN)
  - *Traditional NNs connect each variable/node to in a layer to all the nodes in the next layer*
- Used K-Fold cross validation:
  - *Data was split into 42 folds (1 fold = 1 growing season)*
  - *40 folds were used for training, 1 for validation, 1 for testing*
- Each (land) grid point and pentad was treated as an example
  - *ANN takes in any set of input variables and gives a probability of FD*

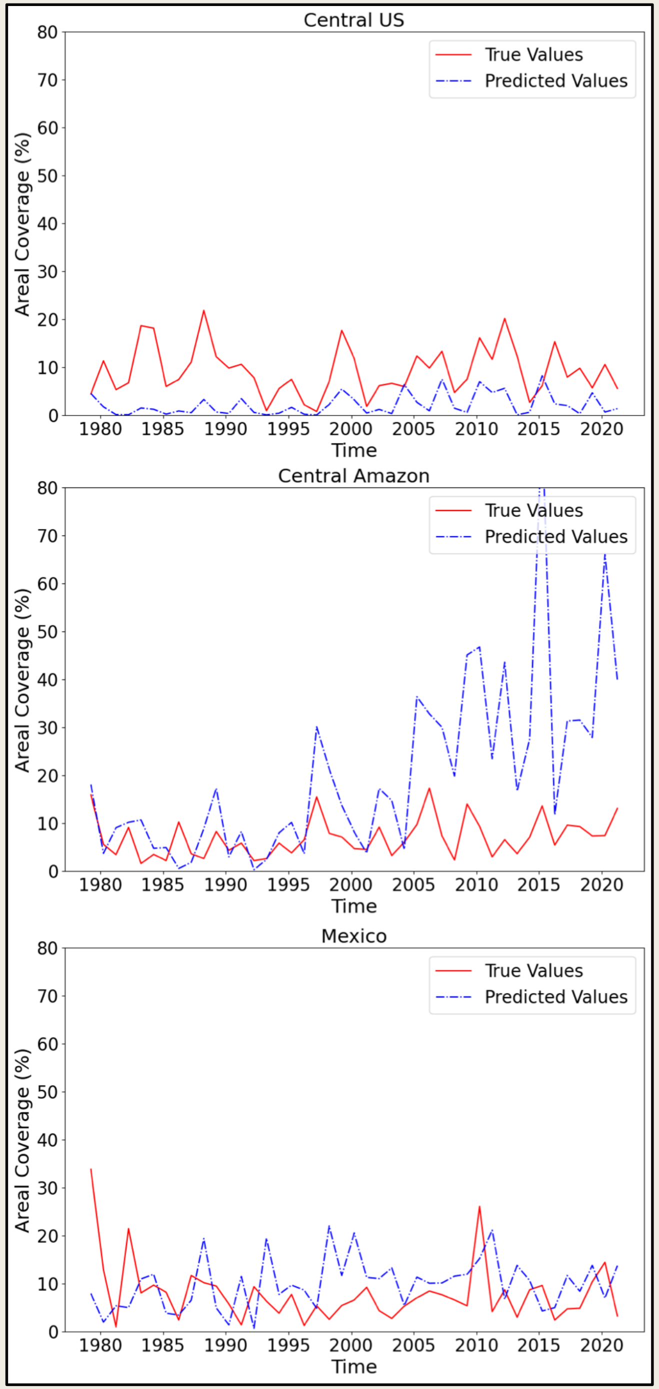


Climatological Predictions



Climatological Predictions

- Three general patterns occur across all regions
  - *ANNs heavily under predict FD coverage (namely happens in higher latitudes)*
  - *ANNs start by performing well, then start to think there is an increasing trend in FD coverage that is not seen in ERA5 (more common for some tropical regions)*
  - *ANNs were able to represent FD coverage reasonably well and learn what year had more widespread events (few transitional zones)*



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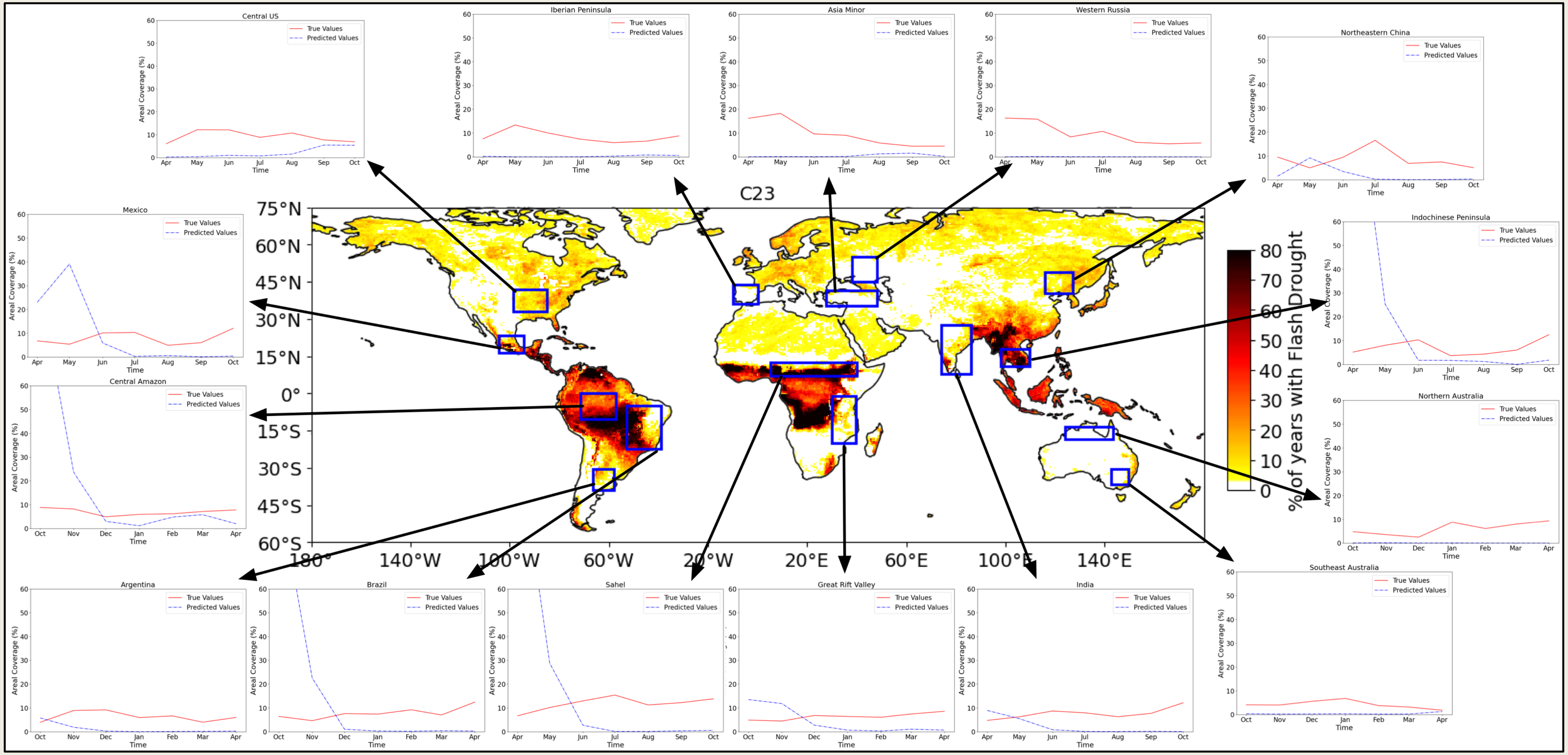
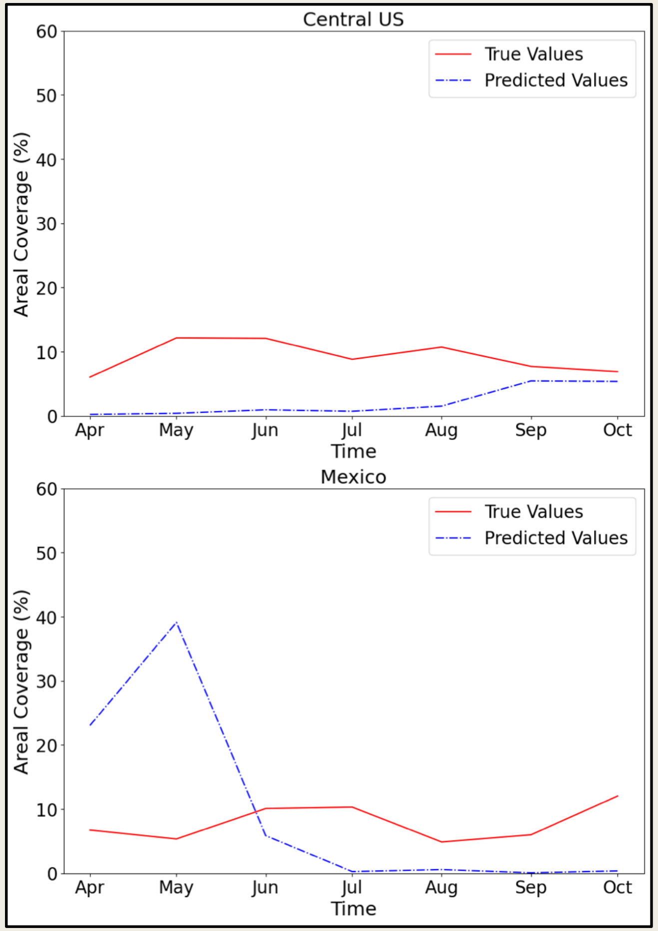
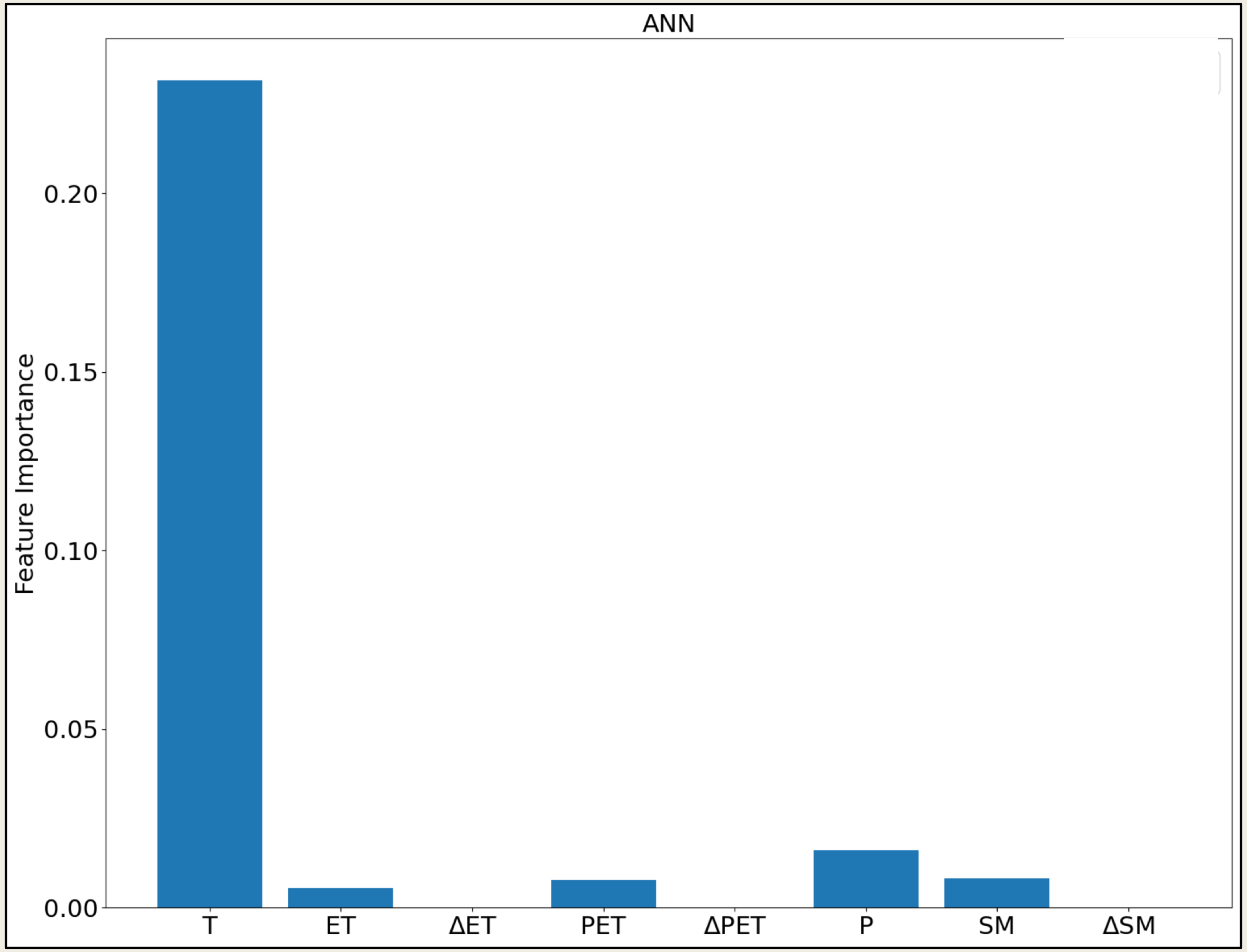


Climatological Predictions

- ANNs struggled with the timing of FD, identifying them either too early or too late
  - *ANN primarily identifies FD primarily at the start or end of the growing season*
  - *Potential reason is the ANN is mainly looking at temperature increases/decreases to capture FD (i.e., it is not learning the surface interactions)*

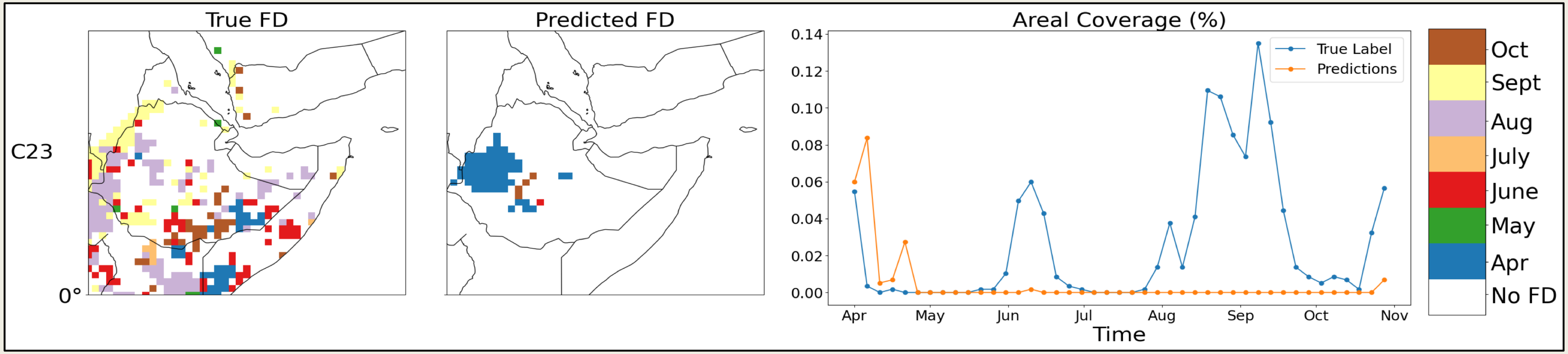


Feature Importance



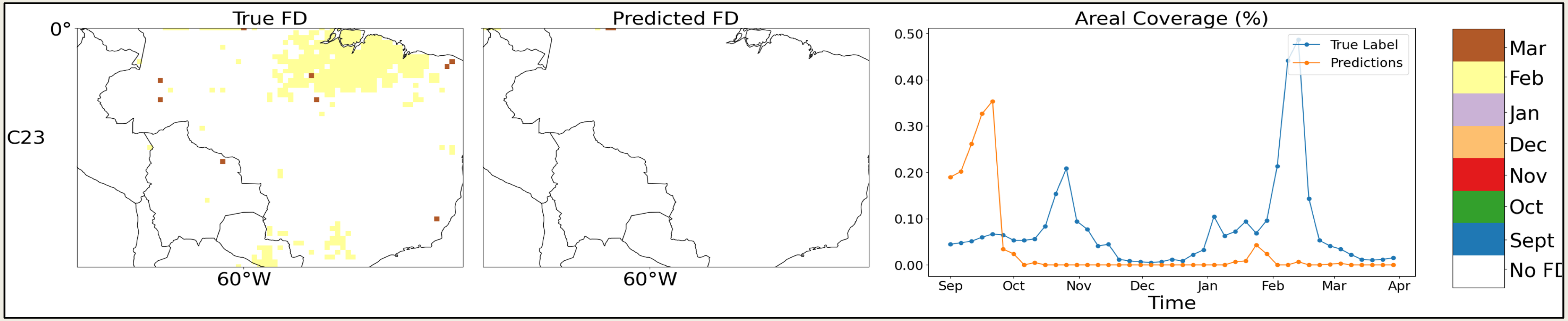
Case Study: Eastern Africa (2016)

- Severe drought that resulted in famine
  - *40% - 80% of the population (depending on country) is employed in and depends on local agriculture*



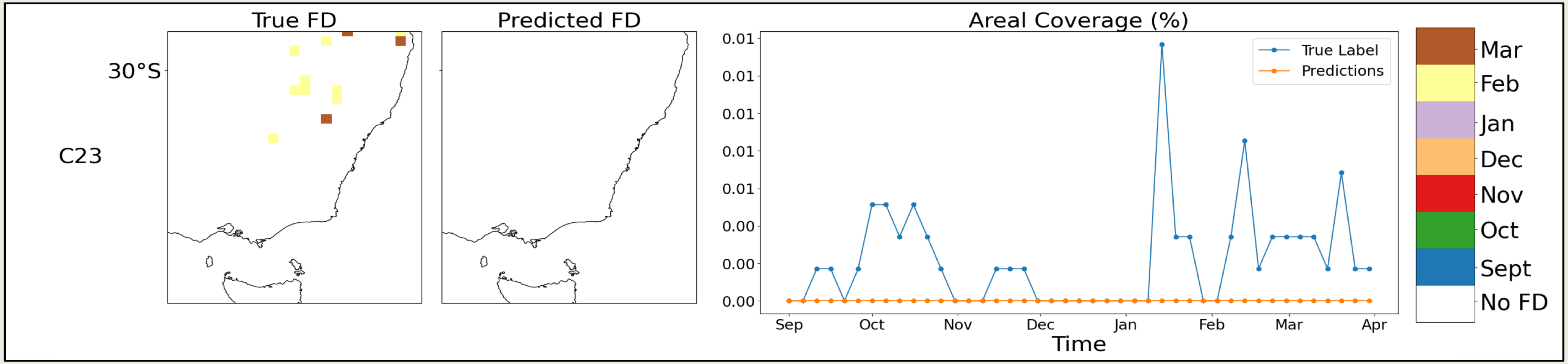
Case Study: Amazon (2015 – 2016)

- Record level drought, primarily impacted vegetations
  - *Estimated CO_2 emissions from killed trees exceed some developed countries*



Case Study: Southern Queensland (2018 – 2019)

- Large drought in southeastern Australia
  - *Heavily devastated ranching*



Summary and Conclusions

- ANNs showed some limited ability to distinguish spatial patterns of global FD
  - *Heavy overemphasis on tropical regions*
- ANNs struggled to generalize the temporal patterns and seasonality of FD
  - *ANNs oversimplified FDs, using primarily temperature to identify them*
- Some of the case studies provided a look at infrequently examined regions
  - *Different locations, ecosystems, and cultures gave different types of impacts for droughts and drought resilience*
  - *There is a human element in determining how impactful or drought resilient a location is*

Future Work

- Perform ML experiments with other FD identification methods
- Expand to other ML models
  - *RNNs outperformed other ML techniques in parts 1 and 2*
- Recommendations for future work include:
  - *Further investigate drought and FD impacts in different parts of the world to better understand how human response effects that impact*
  - *Improve datasets to have better estimates in all parts of the world and be less biased*
  - *Delve deeper into one or two of these ML techniques (including interpretability) to create a fully applicable, usable, and trustworthy ML model*
    - Goal is create a ML model that can be transferred to S2S ensemble models so that FDs can be identified in real time and predicted

Acknowledgements

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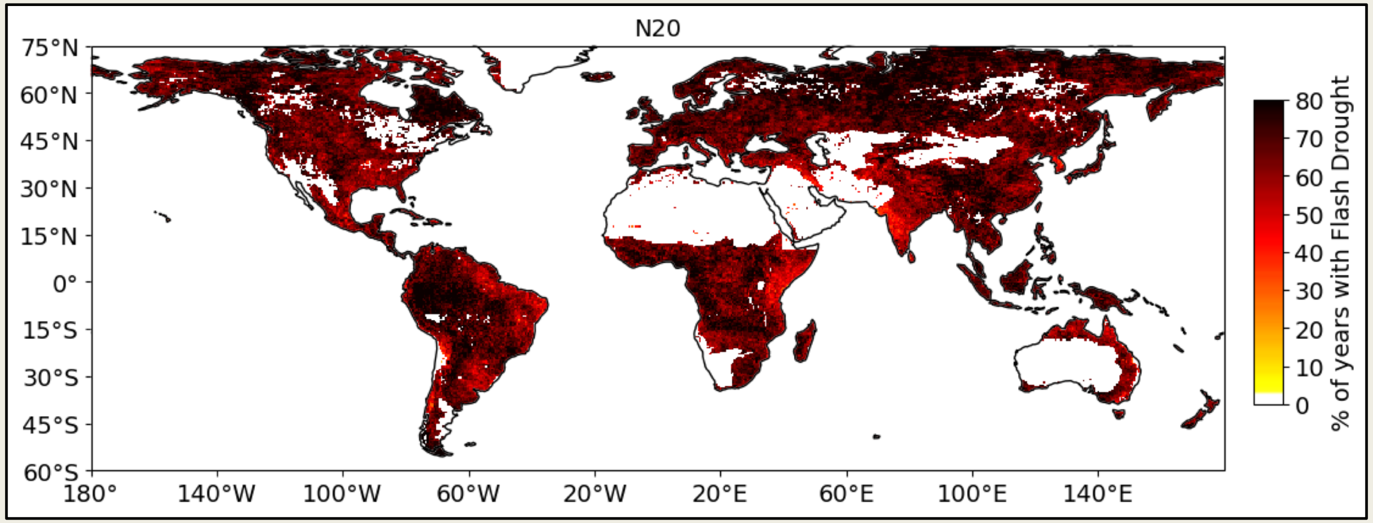
Extra



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140°W
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60°W
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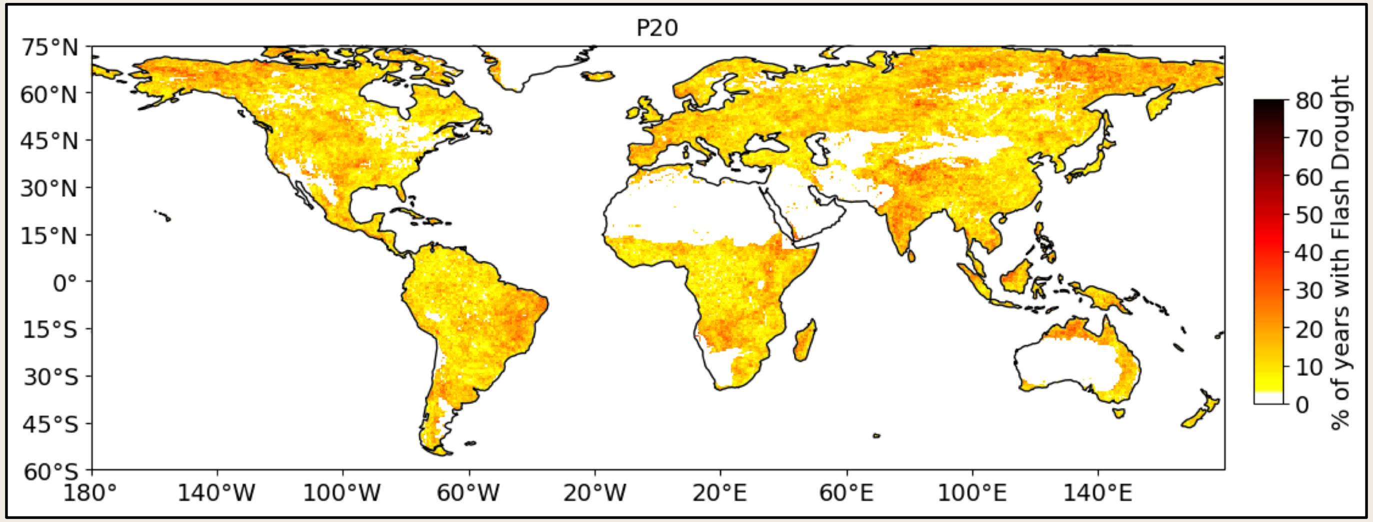
% of years with Flash Drought



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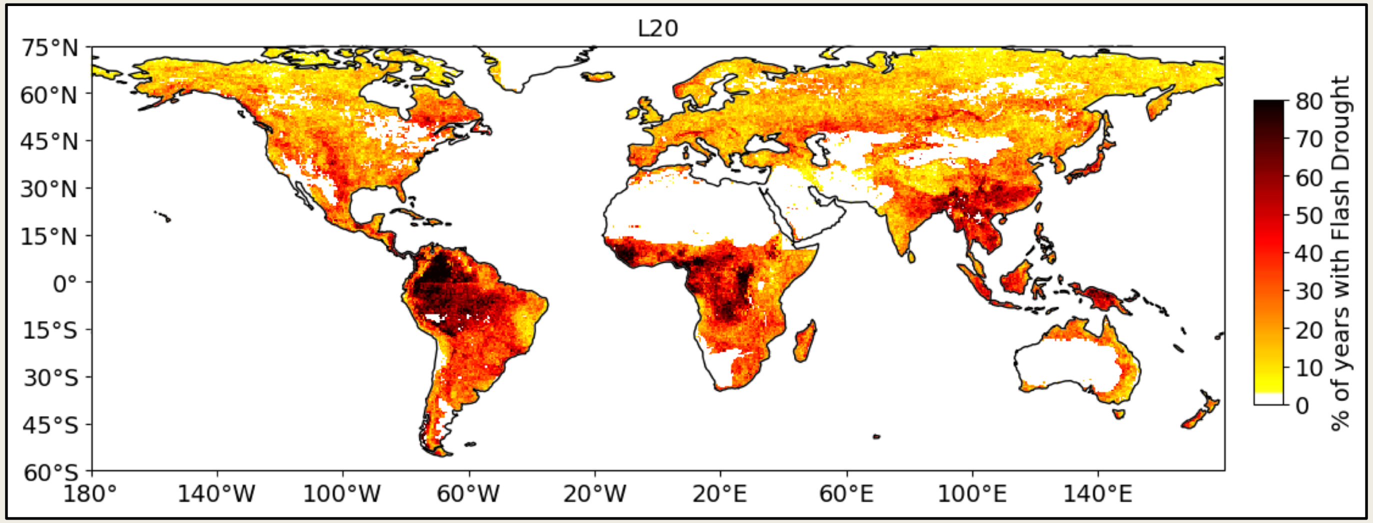
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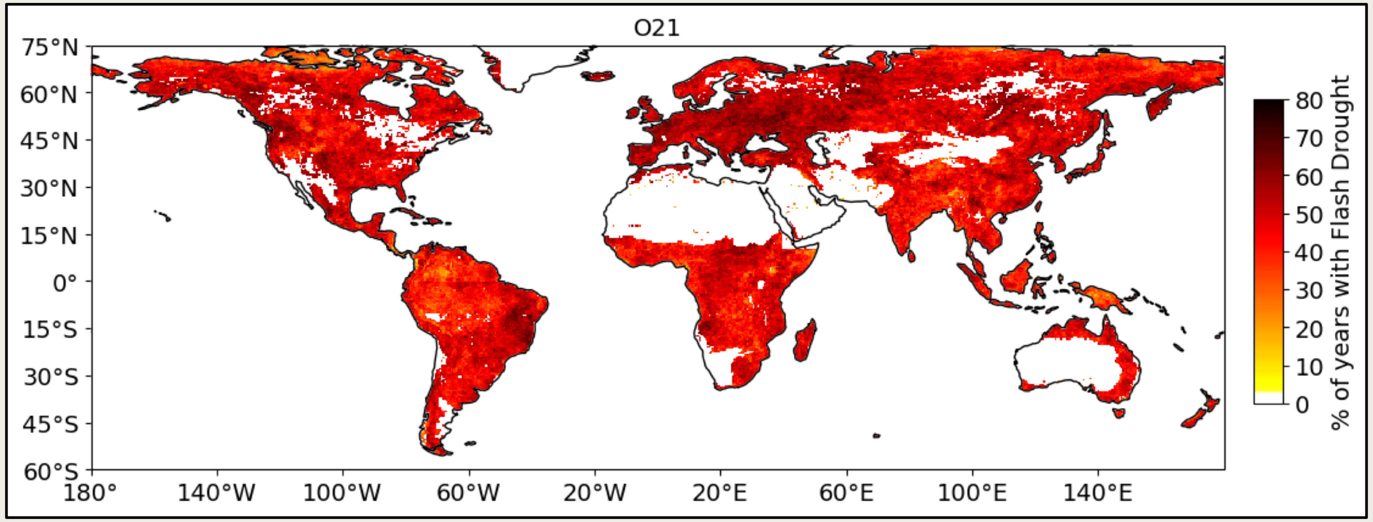
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