Evaluation of Flash Drought Identification with Machine Learning Techniques, Part 2: Deep Learning Machine Learning Algorithms

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Motivation

Following from part 1 (traditional machine learning techniques), various studies in droughts and other environmental sciences have found that deep learning (DL) methods have frequently outperformed other traditional machine learning (ML) methods. This part carries on from part 1 to investigate the abilities of neural networks to represent flash drought (FD) events.

Goal:
Determine if and how well DL models improve from traditional ML in FD representation

Neural Network Models and Methods

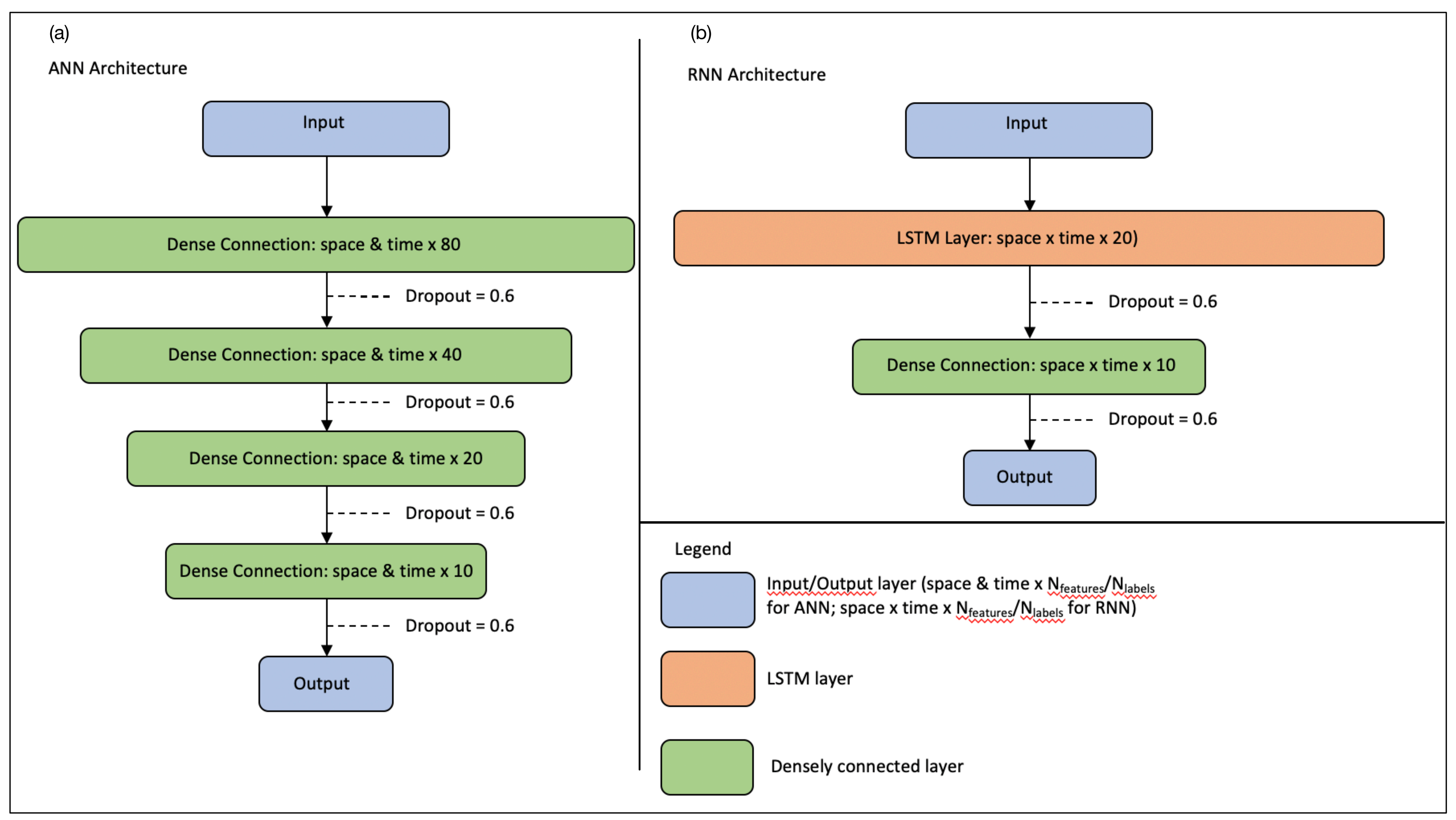

Fig. 1: Frequency of FD occurrence for each month for (a) C23, (b) N20, (c) P20, (d) L20, (e) O21.

Experiment design:

- Same dataset (North American Regional Reanalysis) and setup as part 1
- NN experiments setup using Keras, and structure varies with the type of NN
  - ANN experiments: each grid point and pentad was an example
  - RNN experiments: each grid point was an example (LSTM module was recursively trained along the time axis)
- Convolutional NNs were experimented with, but failed to produce realistic results
  - CNNs were thus omitted from this part of the study
- Target labels remain the same as Part 1 (Identify FD for different FD identification methods):
  - Christian et al. 2023 (C23)
  - Nogeura et al. 2020 (N20)
  - Pendergrass et al. 2020
  - Liu et al. 2020 (L20)
  - Otkin et al. 2021 (O21)

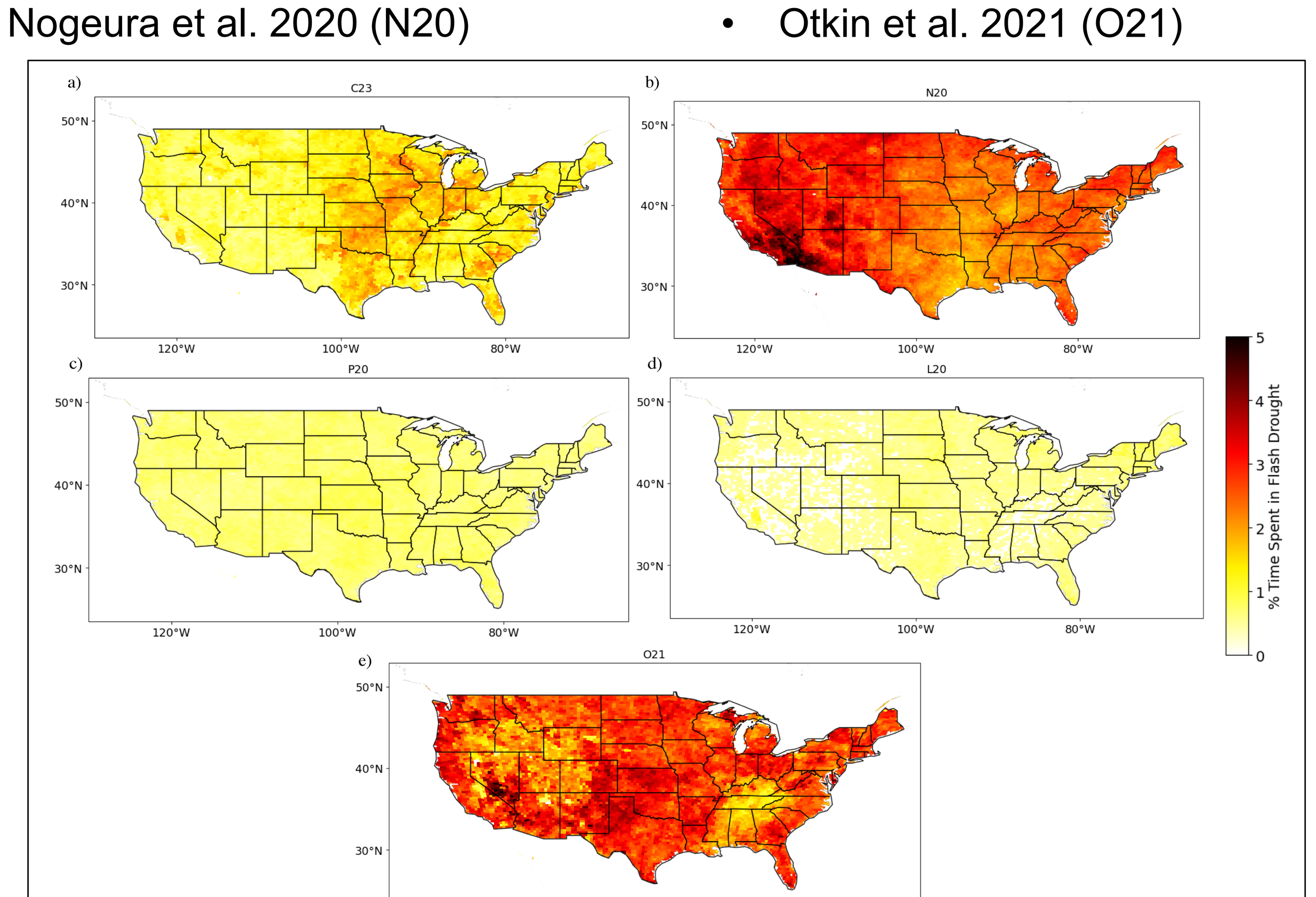

Fig. 2: Percentage of pentads spent in FD for the NARR dataset from 1979 – 2021.

Model Performance

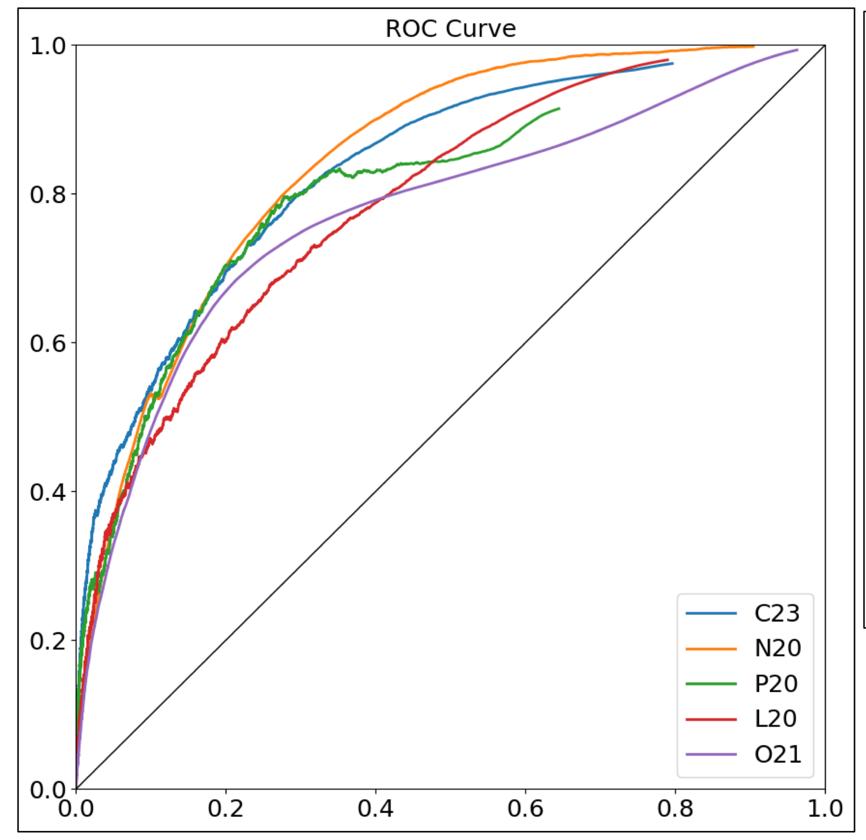

Fig. 3: ROC curve for RNNs for each FD identification method.

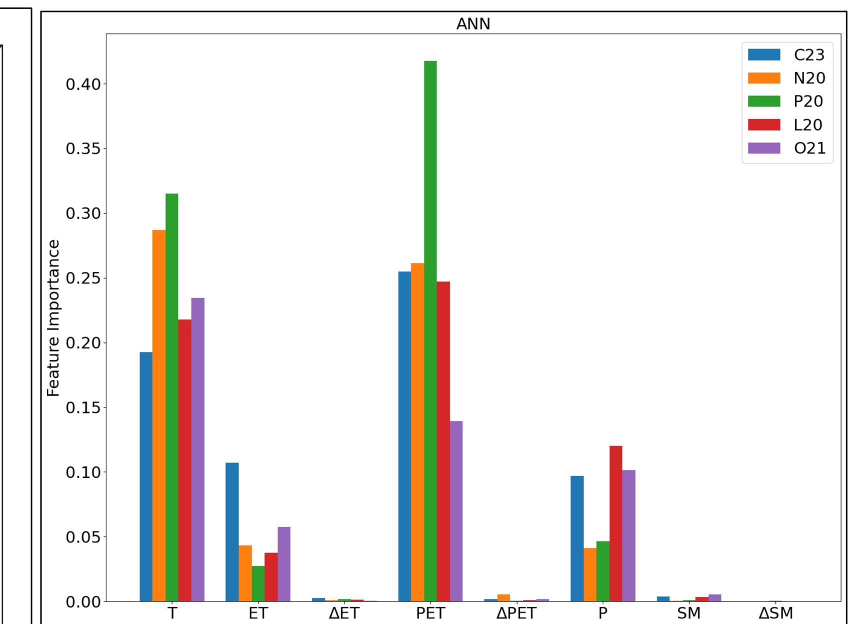

Fig. 4: Feature importance – based on SHAP values – for the ANNs for each FD identification method.

Table 1: True Skill Statistic.

	ANNs	RNNs
C23	0.03	0.24
N20	0.00	0.24
P20	0.00	0.09
L20	0.05	0.16
O21	0.14	0.02

- RNNs show improved performance over Ada boosted trees in part 1
  - Exception for O21 method, where RNNs struggle to make positive FD predictions
- ANNs struggled to learn surface processes, relying on simpler temperature and precipitation based variables

Case Studies

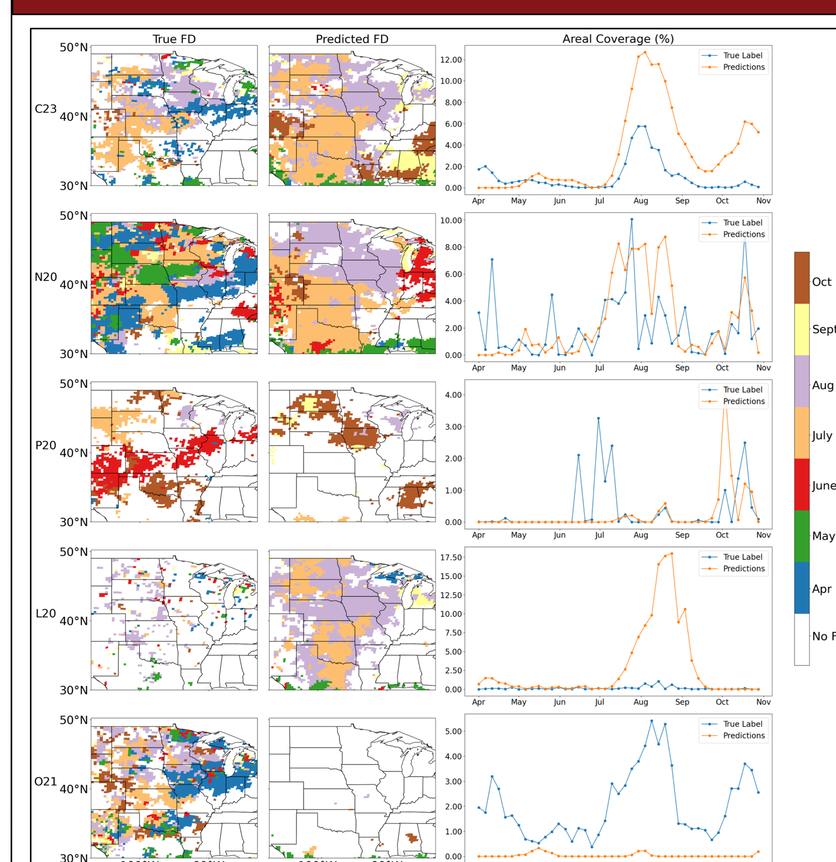

Fig. 5: Case study 2003. Colors indicate month of FD onset. Predictions by RNNs.

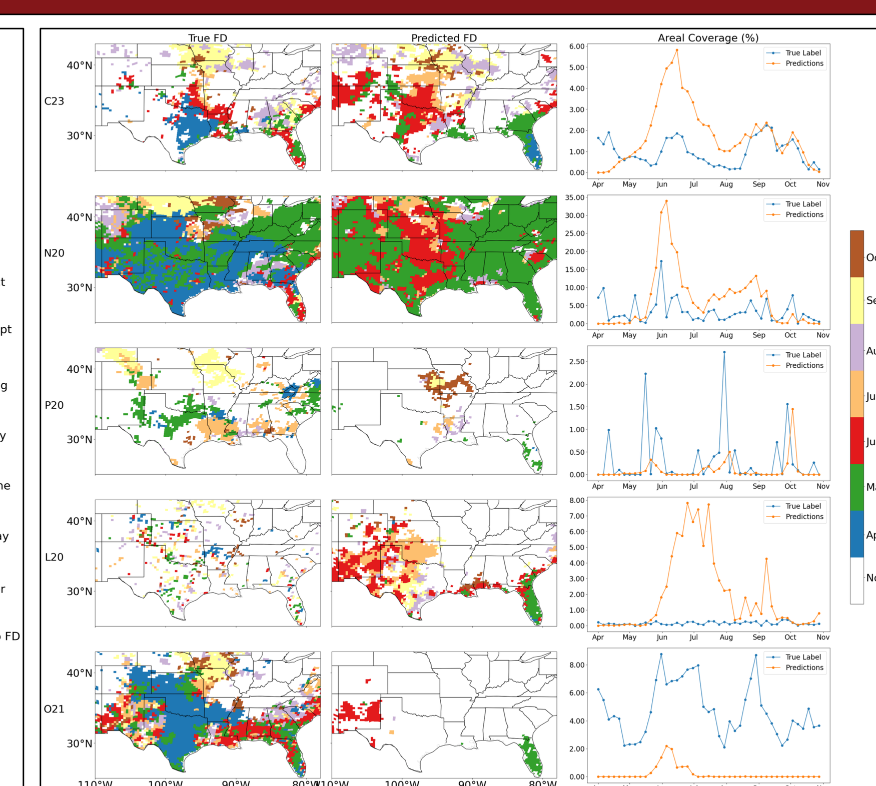

Fig. 6: Case study 2011. Colors indicate month of FD onset. Predictions by RNNs.

- RNNs were able to largely reproduce the coverage of FD events
  - Extent to which FD coverage was overpredicted was reduced from boosted trees
- RNNs still struggled with the timing of FD onset
  - RNNs frequently identified FD 1 – 2 months late

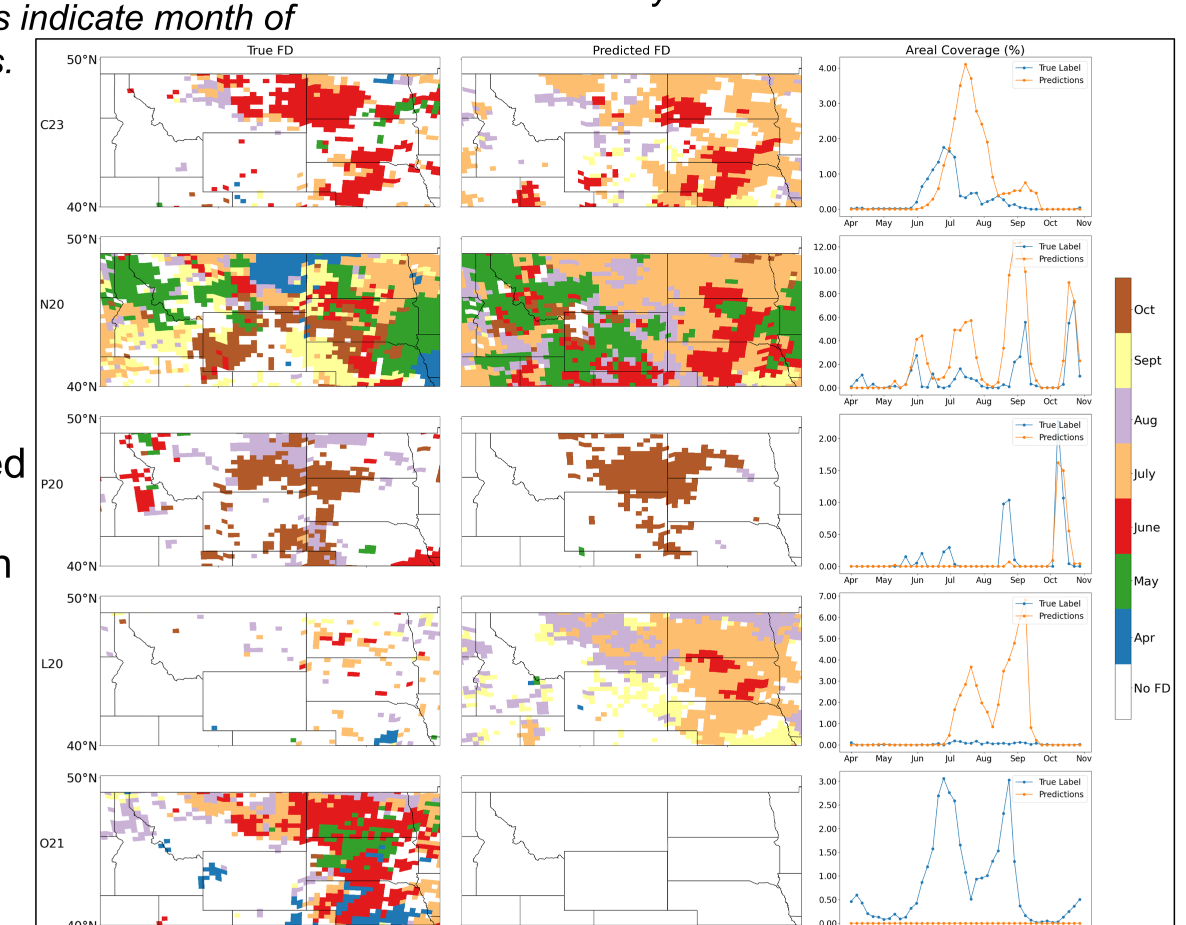

Fig. 7: Case study 2017. Colors indicate month of FD onset. Predictions by RNNs.

Test Predictions

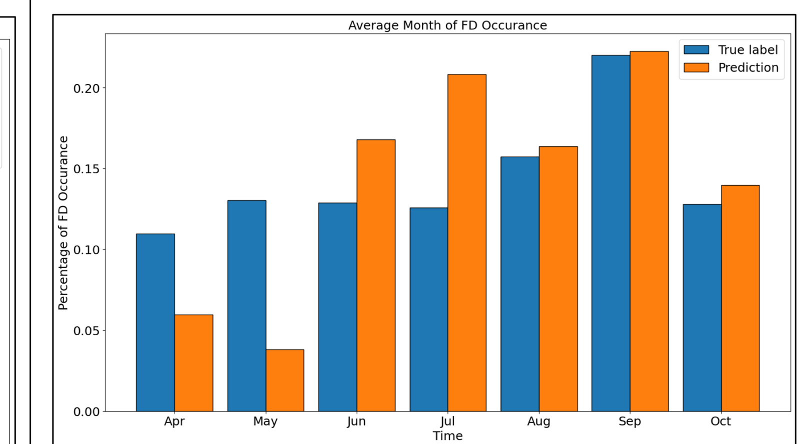

Fig. 8: Average frequency of FD onset occurrence for each growing season month for true labels and RNN predictions for the C23 method. Seasonality bias pattern occurs for N20 and L20 methods.

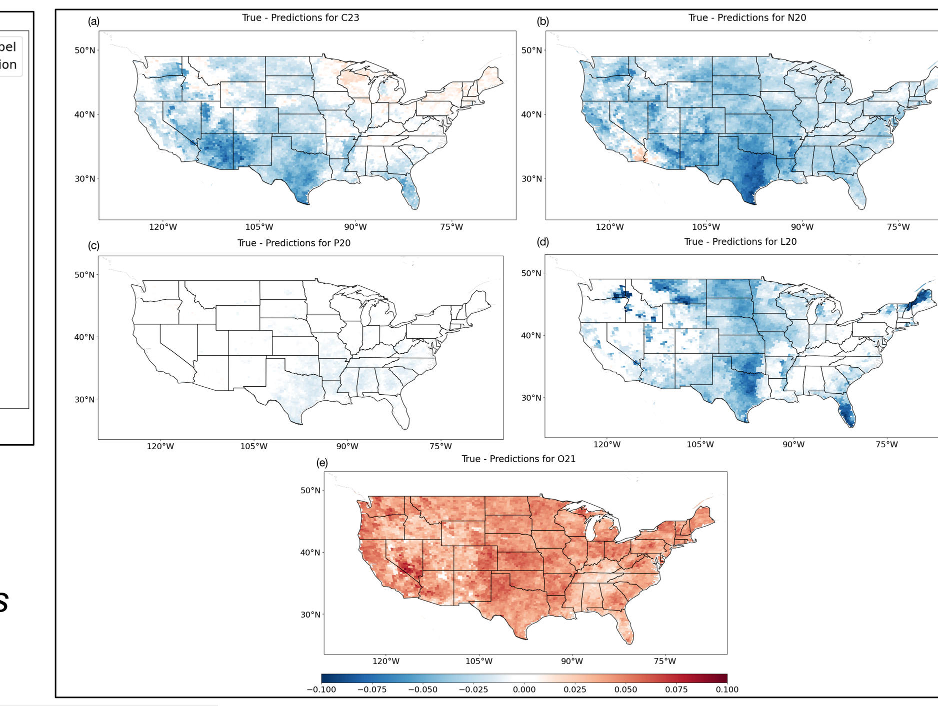

Fig. 9: Composite mean difference between the truth labels and RNN predicted labels.

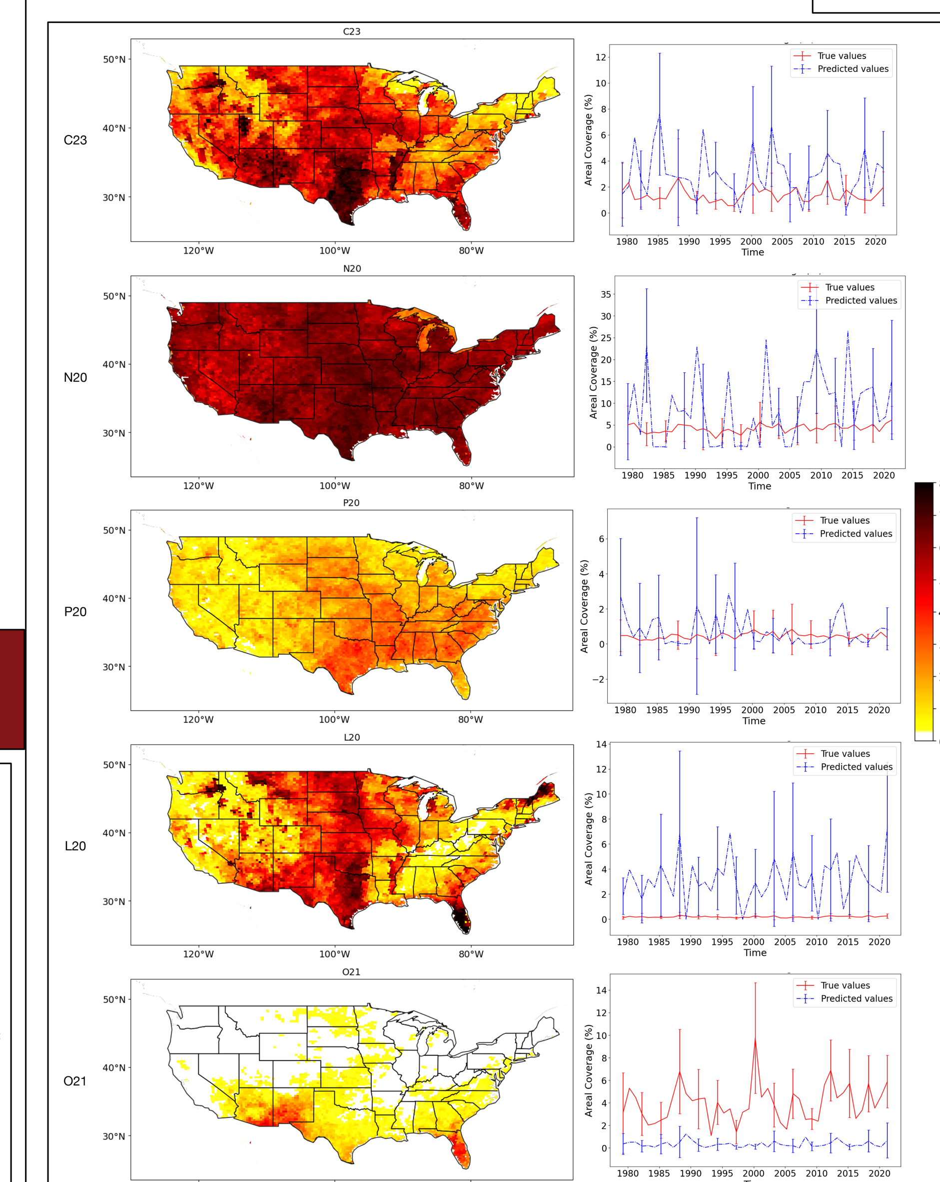

Fig. 10: Predicted frequency climatology (left) and areal coverage (right) of RNN predictions of and true FD labels.

- RNNs notably reduced over predictions of FDs compared to traditional ML methods
  - RNNs struggled more with the O21 method
  - RNNs had a reduced degree to which seasonality is overemphasized (though it had issues capturing seasonality for the P20 and O21 methods)
- RNNs also learned climatological hotspots, but also captured some additional regions
  - ML models picked up regions of rapid intensification without drought (Southwest)
  - ML models detected other irrigation regions (eastern Washington, Great Salt Lake, Central Valley)
  - ML models made up some hotspots (Florida)

Conclusions

- Use of NNs did not guarantee improved model performance
  - ANNs struggled to learn surface interactions, and potentially suffered from oversampling
  - NNs did not always converge to a non-trivial solution
  - CNNs failed to produce realistic FD predictions
  - Complex NNs (many parameters) often over generalized and failed to identify FD
- Despite these, RNNs with LSTMs were able to outperform traditional ML methods with most (though not all) FD identification methods
  - RNNs improved climatological predictions, reducing the issue of over predicting climatological hotspots, and improved predictions for specific case studies
- This (and the previous part) also highlight some of the differences in FD identification methods
  - FD identification methods often have similar spatial patterns in FD frequency, but have different durations of FD and seasonalities, and timing and spatial coverage for specific events

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