Automated Detection of Weather Fronts Using a Deep Learning Neural Network

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August 19, 2020

Motivation

- The Goal – Understand how Precipitation Frequency estimates across North America (NA) will change as the climate changes.
- Extreme precipitation associated with weather fronts is the dominant contributor over most of North America.
- We need to understand how weather front behavior will change as the climate changes.
- Automated front detection will be required.

The Problem Space

- Weather front detection is still a manual process.
- Visual recognition problems are often good candidates for Neural Network solutions.
- A ”supervised learning” neural network approach requires truth data.

Training Data

- We used NASA Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) with data from 1980-2018 for our inputs. We used pressure difference from a moving 30-day mean, near-surface air temperature, specific humidity, and vector wind velocity.
- Used the Coded Surface Bulletin (CSB) digitized front polyline dataset with data from 2003-2018 for our labels to train against.

Training Data

- Used a 1x1° data grid centered over North America (10–70N x 171–31W).
- Converted the CSB polylines to gridded maps with lines drawn 3 grid cells wide.
- CSB data grid layers:
  - Cold fronts
  - Warm fronts
  - Stationary fronts
  - Occluded fronts
  - No front

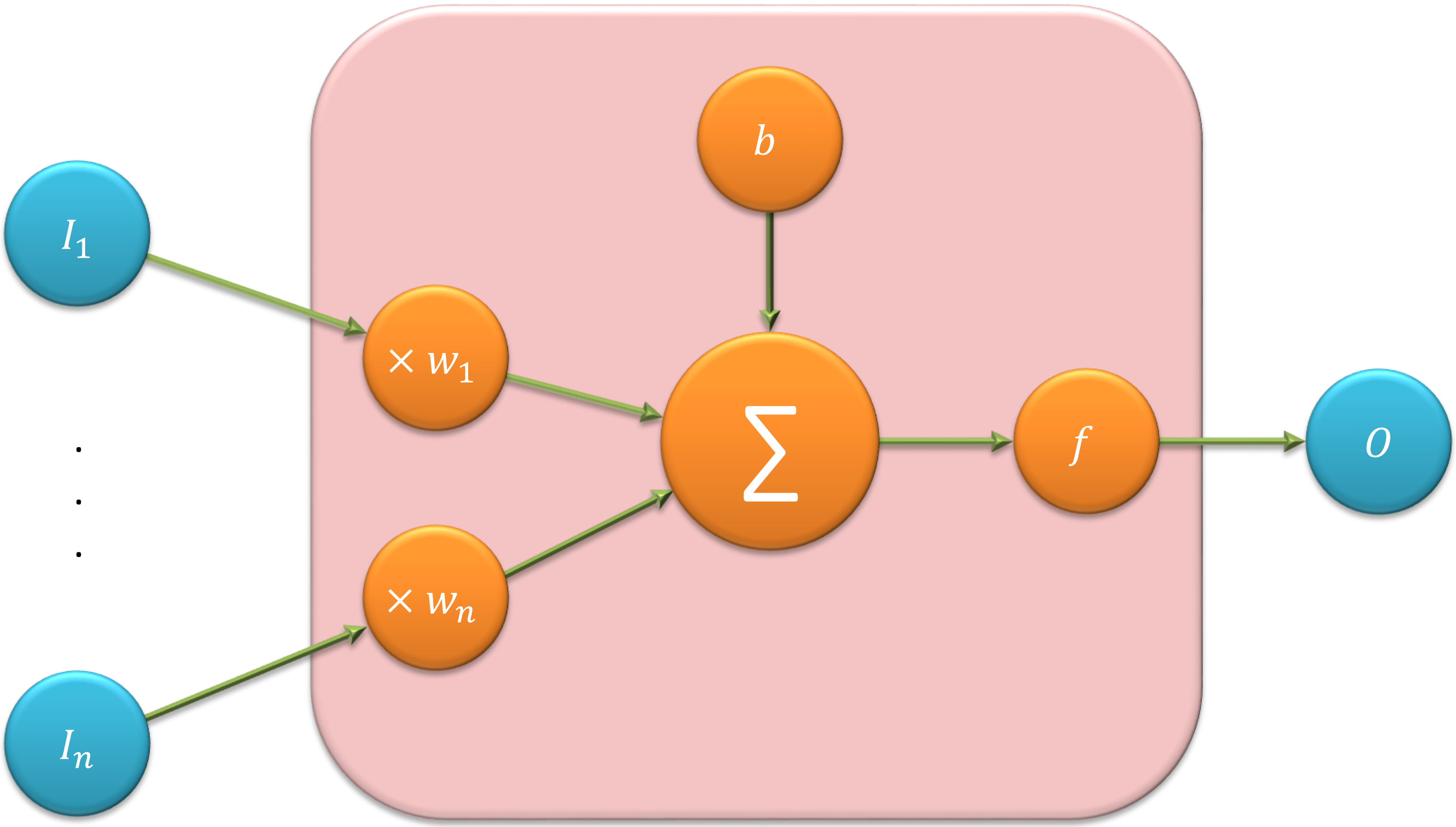
Neural Networks

- Neural networks are composed of simplistic analogs of biological neurons organized in layers.
- Here is the basic structure of a machine learning neuron.

$$O = f\left(b + \sum_i w_i \, I_i\right)$$

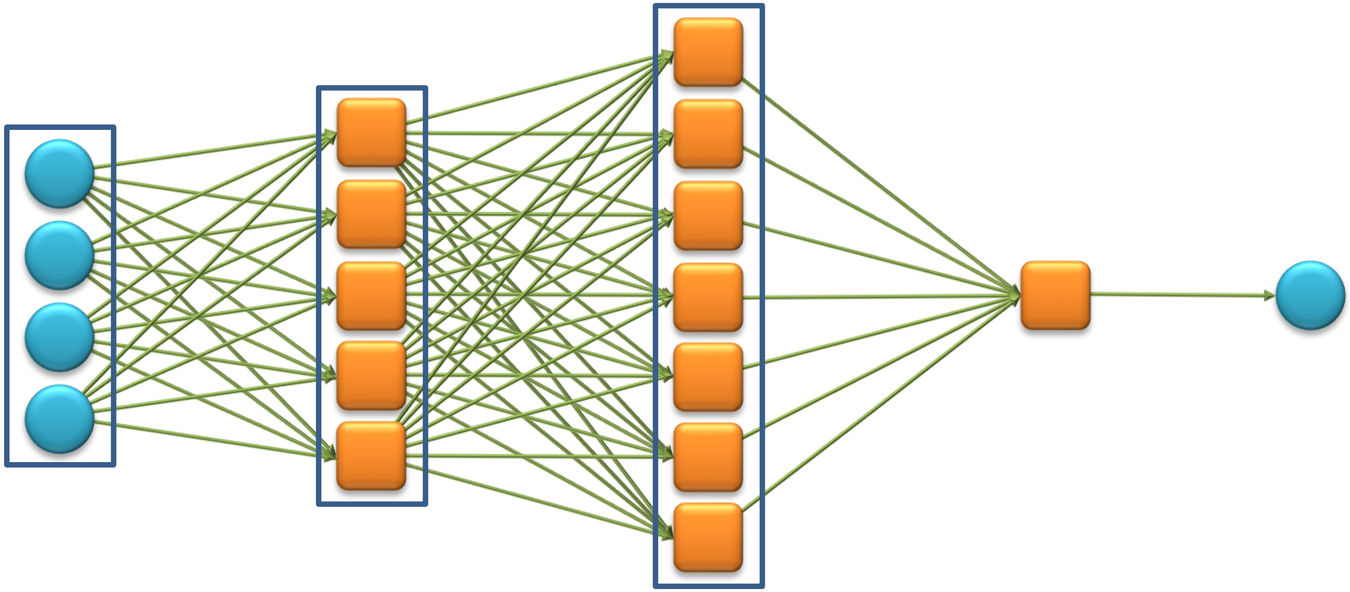
- A non-linear function of a linear superposition of a set of input values.

Neural Networks



Neural Networks

- A neural network is formed by building layers where the outputs from one set of neurons are used as inputs to another set.



Neural Networks

- In the 1960s, mathematicians proved that any complex function of multiple inputs can be decomposed into a combination of linear superpositions and simple non-linear functions applied to the inputs.
- This is, in essence, a neural network with one interior (hidden) layer.
- The problem is finding the appropriate functions and weights!

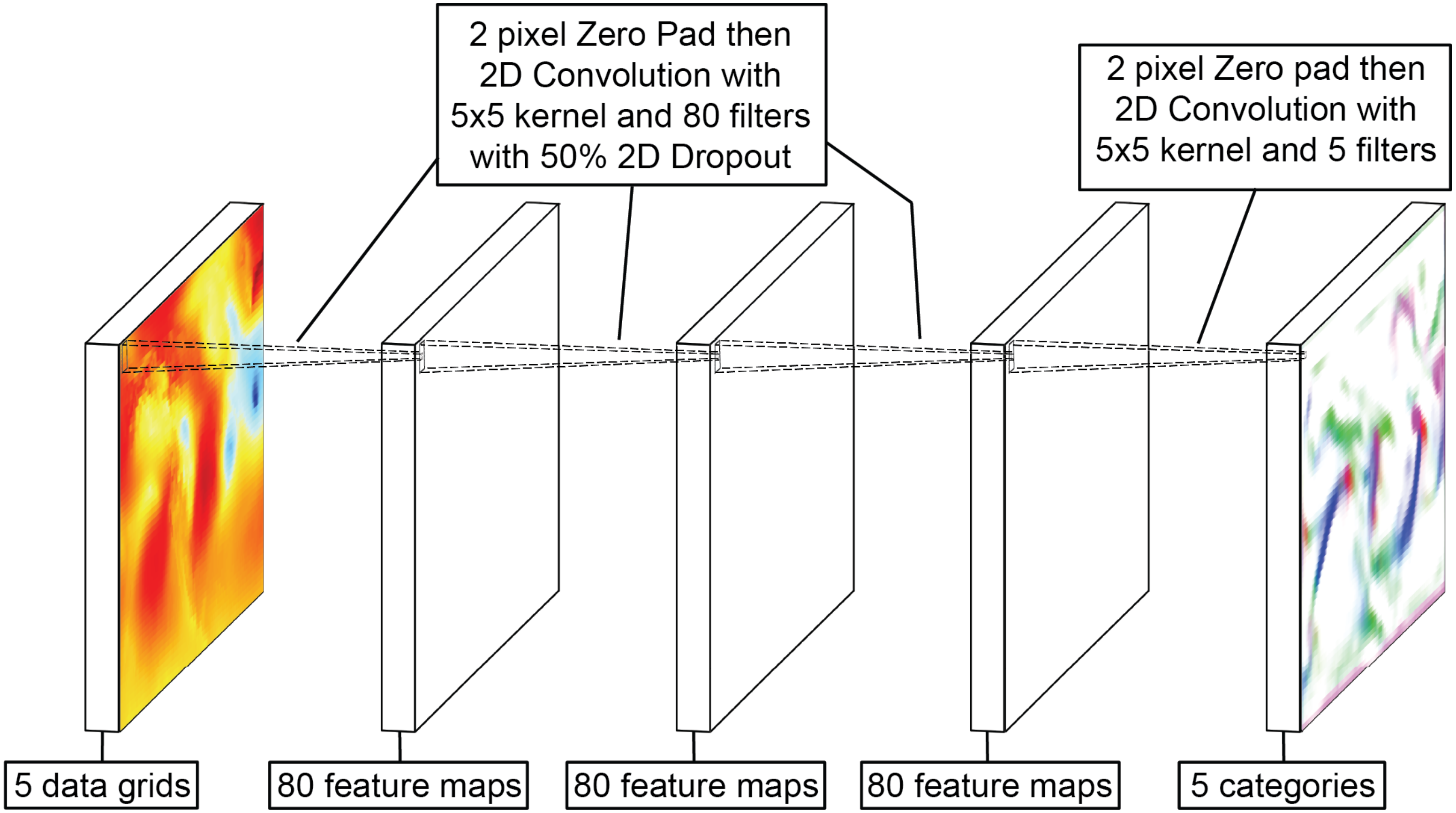
Neural Networks

- In supervised machine learning, the weights are found through hyper-dimensional gradient descent.
  - Produce outputs for a number of inputs with a network initialized with random weights and biases.
  - Use the discrepancy between network outputs and "truth" outputs to update the weights and biases to minimize the difference.
  - Repeat many times.

Neural Networks

- Finding a good network design for your problem is an art.
- Take care, because it is possible to memorize the right answer for each input rather than learn the underlying functional relationships (overfitting).

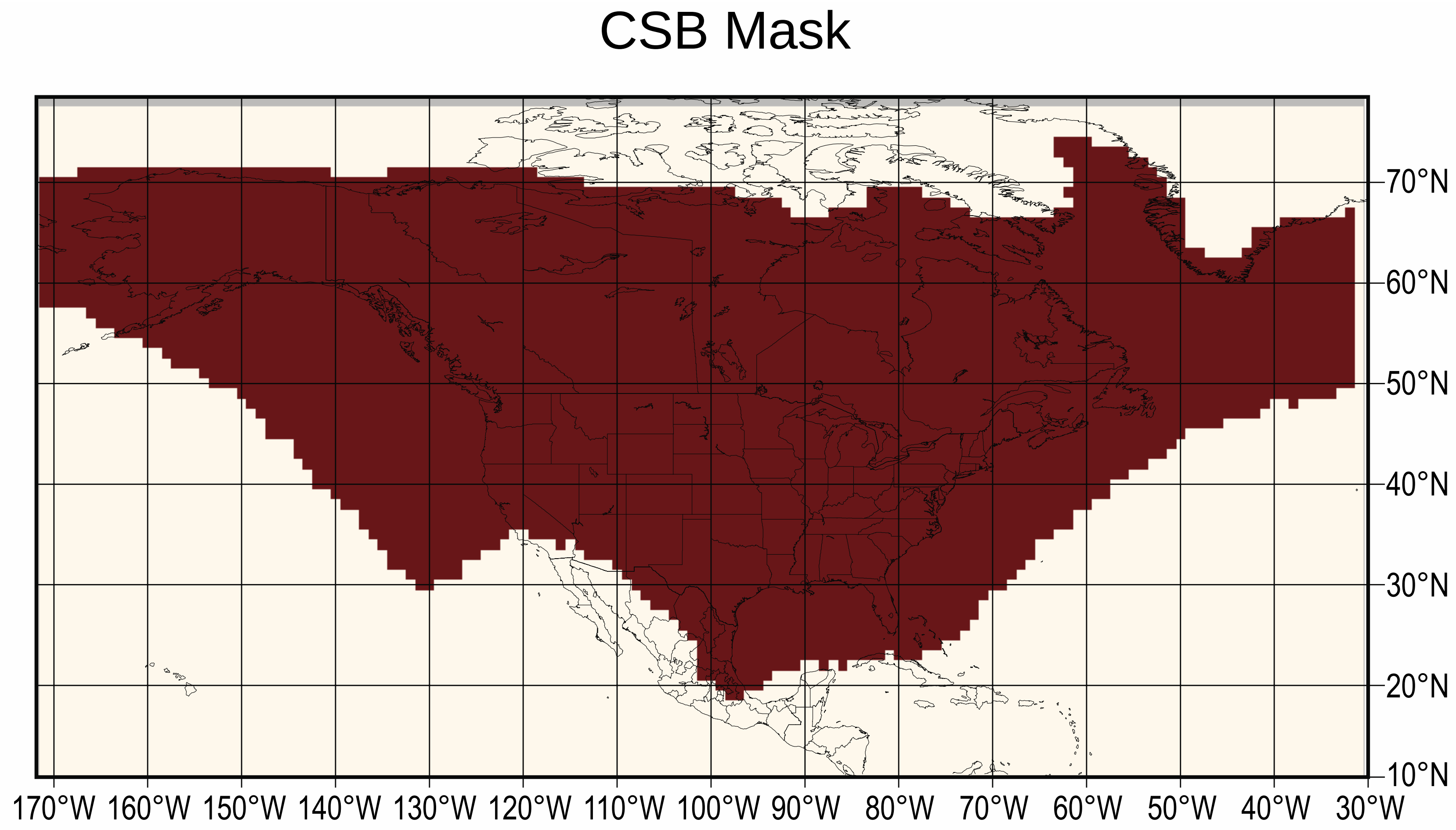
Network Design



Training

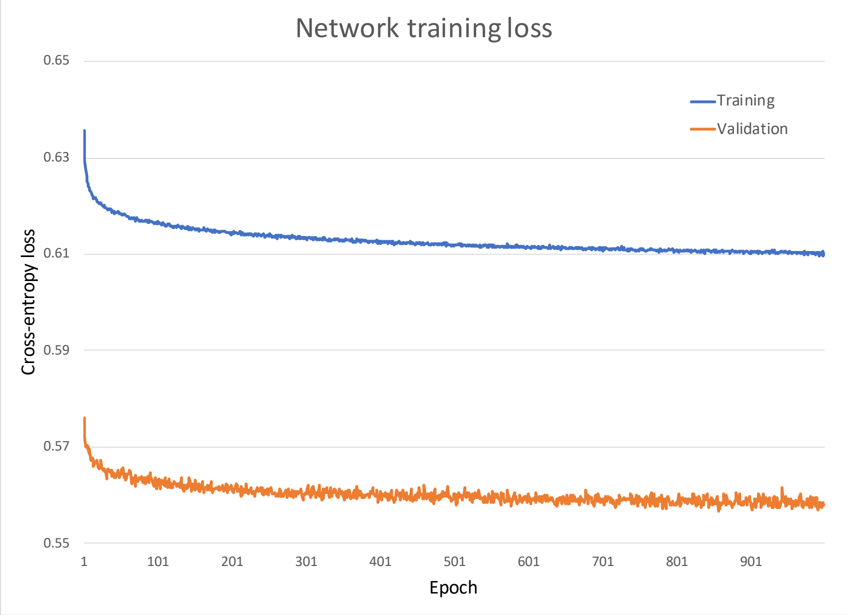
- Trained with data from 2008-2012.
- Randomly selected ¼ of the possible 17x17 grid cell input patches while also ensuring that there were twice as many “no front” patches as “front” patches.
- Limited training and testing to region around CONUS where the rate of front crossings was 40/year or better.
- Training took ~3 days on a NERSC GPU node.

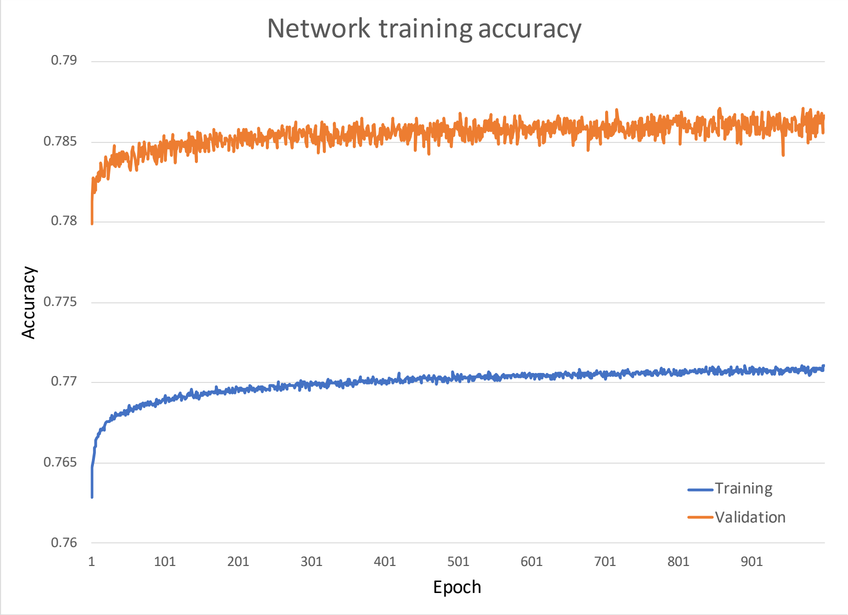
Training



CSB Mask
70°N
60°N
50°N
40°N
30°N
20°N
10°N
170°W 160°W 150°W 140°W 130°W 120°W 110°W 100°W 90°W 80°W 70°W 60°W 50°W 40°W 30°W

Training Results





Training Results

CSB Labels 2003 - 2018						
	Cold	**Warm**	**Stationary**	**Occluded**	**None**	**Total**
Counts	8,551,914	4,631,517	12,797,269	3,893,614	182,795,286	212,669,600
Percent	4.02%	2.18%	6.02%	1.83%	85.95%	

MERRA-2 Predictions 2003 - 2018						
	Cold	**Warm**	**Stationary**	**Occluded**	**None**	**Total**
Counts	8,950,546	2,785,315	10,867,527	4,098,013	185,968,199	212,669,600
Percent	4.21%	1.31%	5.11%	1.93%	87.44%	

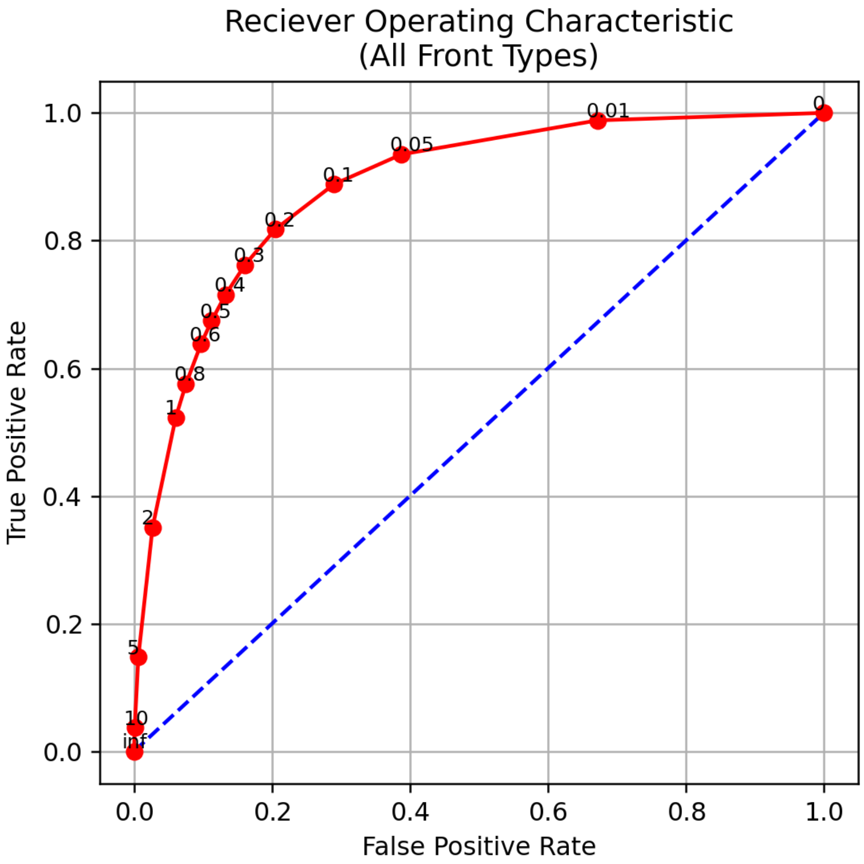
Training Results

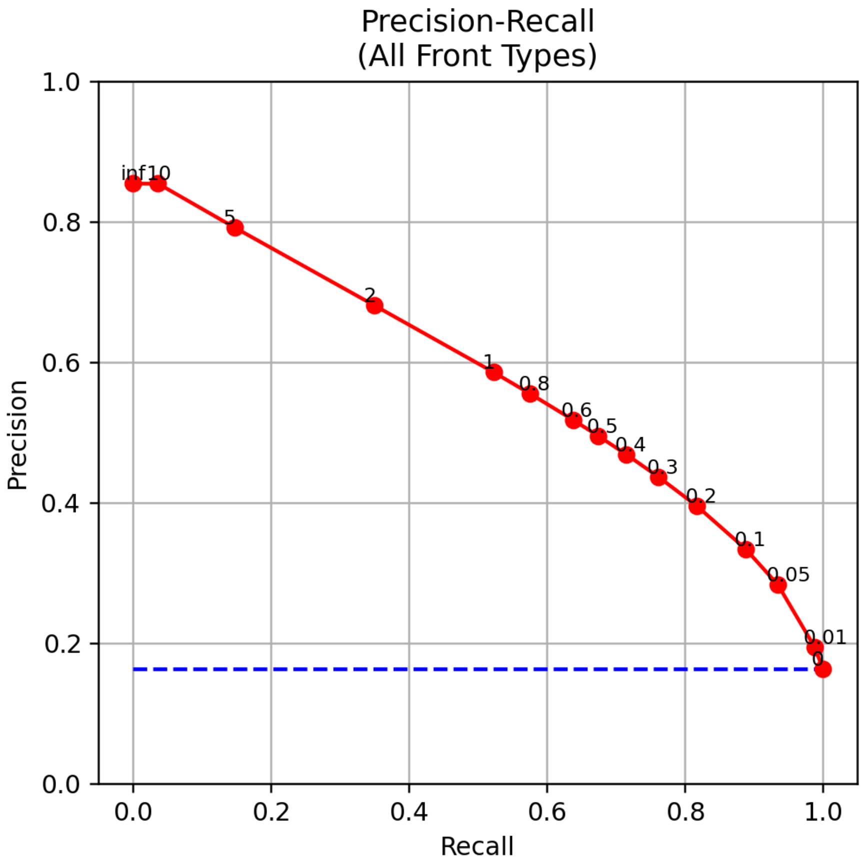
Confusion Matrix 2008-2015						
		Predicted				
		Cold	**Warm**	**Stationary**	**Occluded**	**None**
	Cold	4,118,370	166,264	754,909	231,514	3,280,857
	Warm	214,405	1,104,025	743,101	300,147	2,269,839
Actual	**Stationary**	990,596	244,167	4,464,480	127,063	6,970,963
	Occluded	194,304	128,904	201,375	1,643,822	1,725,209
	None	3,432,871	1,141,955	4,703,662	1,795,467	171,721,331

Training Results

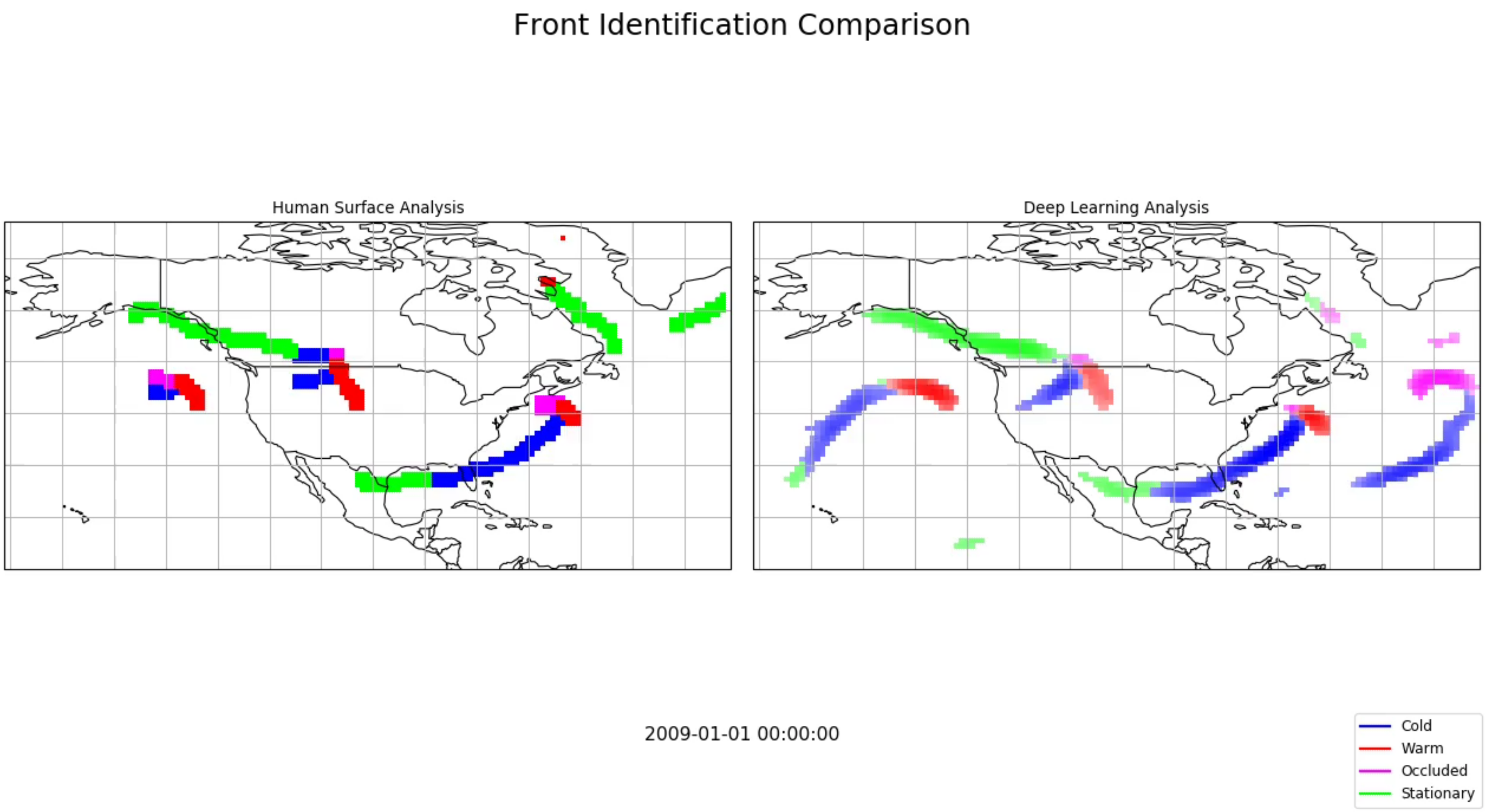
Front/No-Front Confusion Matrix 2003-2018			
		Predicted	
		Front	None
Actual	Front	15,627,446	14,246,868
	None	11,073,955	171,721,331

Training Results





Training Results



Training Results

- The performance of the network may be better than the metrics suggest.
- It may be more conservative about drawing weak fronts.
- Slight geographic offsets count as misses.
- Differences in type of front count as misses.

Front Climatologies

- Goal of the front detection work was to develop front climatologies.
- Decided to measure the rate at which fronts of each type crossed each 1°x1 ° grid cell.
- Also measured the rate at which fronts of any type crossed each cell.
- Calculated climatologies for CSB and for MERRA-2 network outputs.

Front Climatologies

- For MERRA-2, extracted polylines from the front probability data grids produced by the network.
- Produced hard-edged 3-cell-wide data grids on 3-hourly time steps.
- Stacked the data grids to produce a “front event” time series for each front type for each grid cell.

Front Climatologies

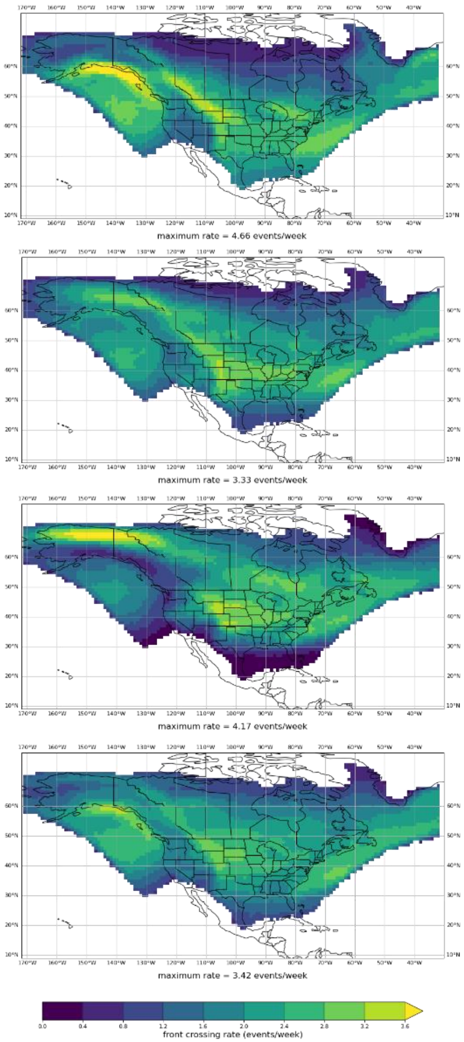
- Filtered each time series by removing the front events that were within 24 hours after each initial event to prevent overcounting.
- Produced front-crossing rates by month and season from the counts.
- Averaged the rates by month and season over years to produce monthly and seasonal front crossing rate climatologies.

MERRA-2 vs CSB Climatology

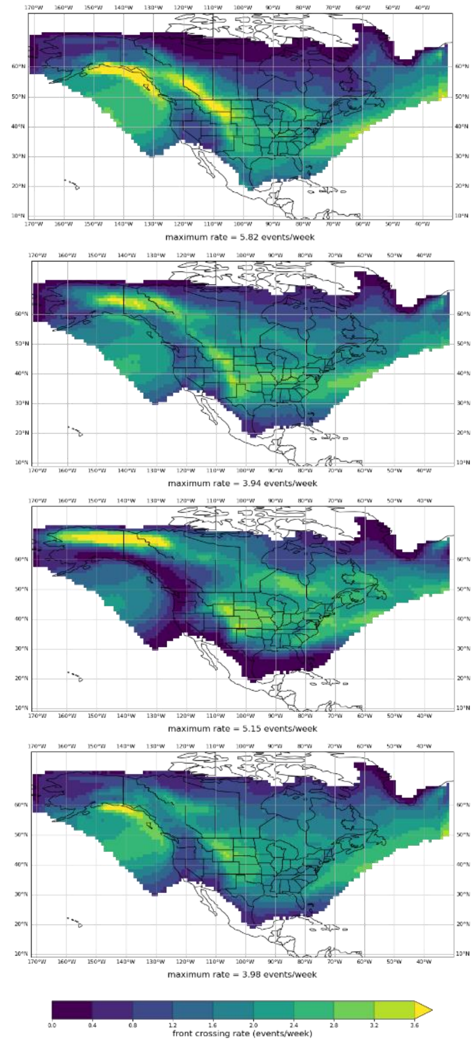
- Produced climatologies as described for MERRA-2 network outputs.
- Produced climatologies the same way for the CSB dataset.
- Used the 2003-2018 overlapping time frame for each.
- Also averaged the results over a CONUS-centered region spanning 20N – 50N, 125W – 65W.

MERRA-2 vs CSB Climatology

CSB



MERRA-2



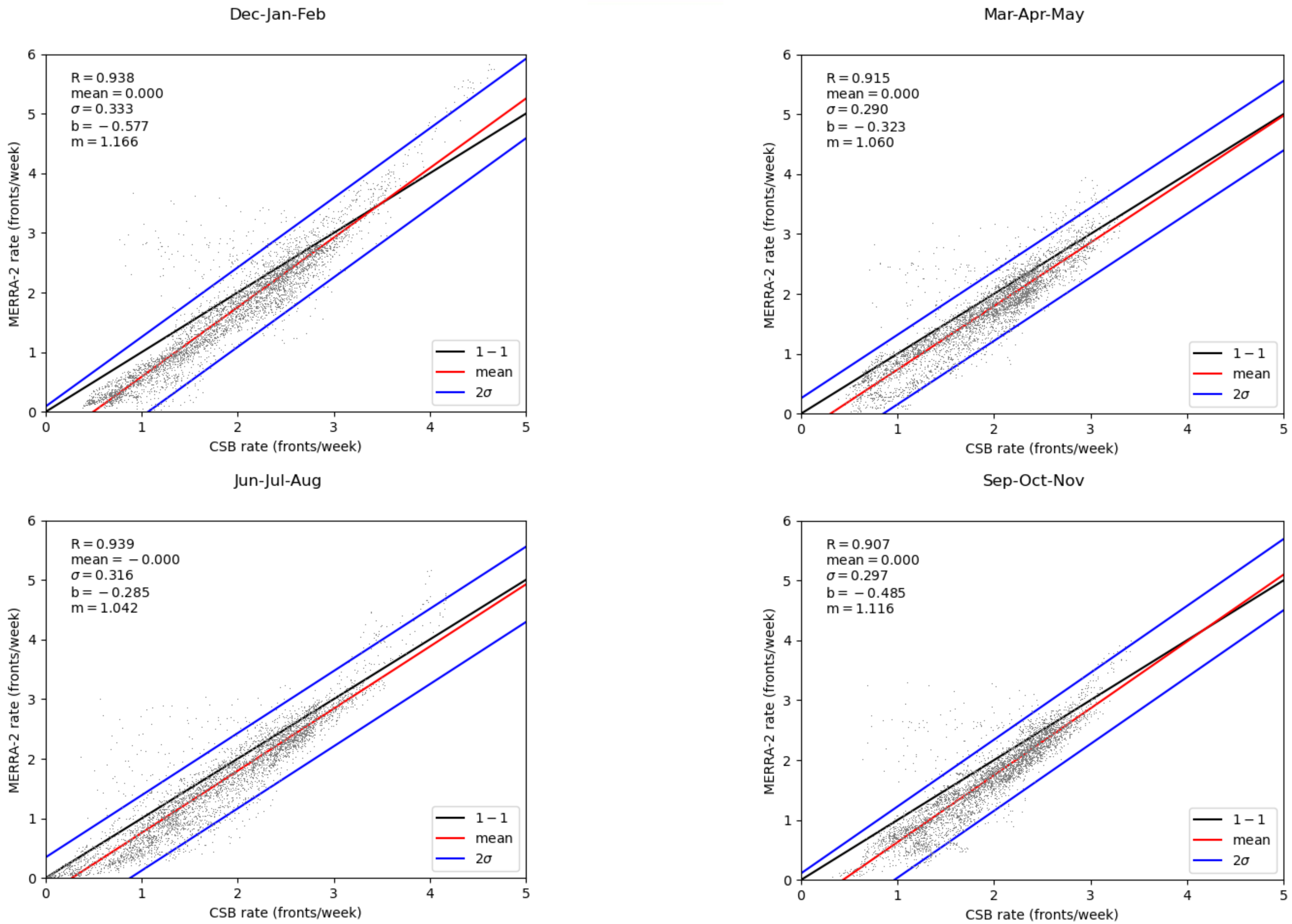
Dec-Jan-Feb

Mar-Apr-May

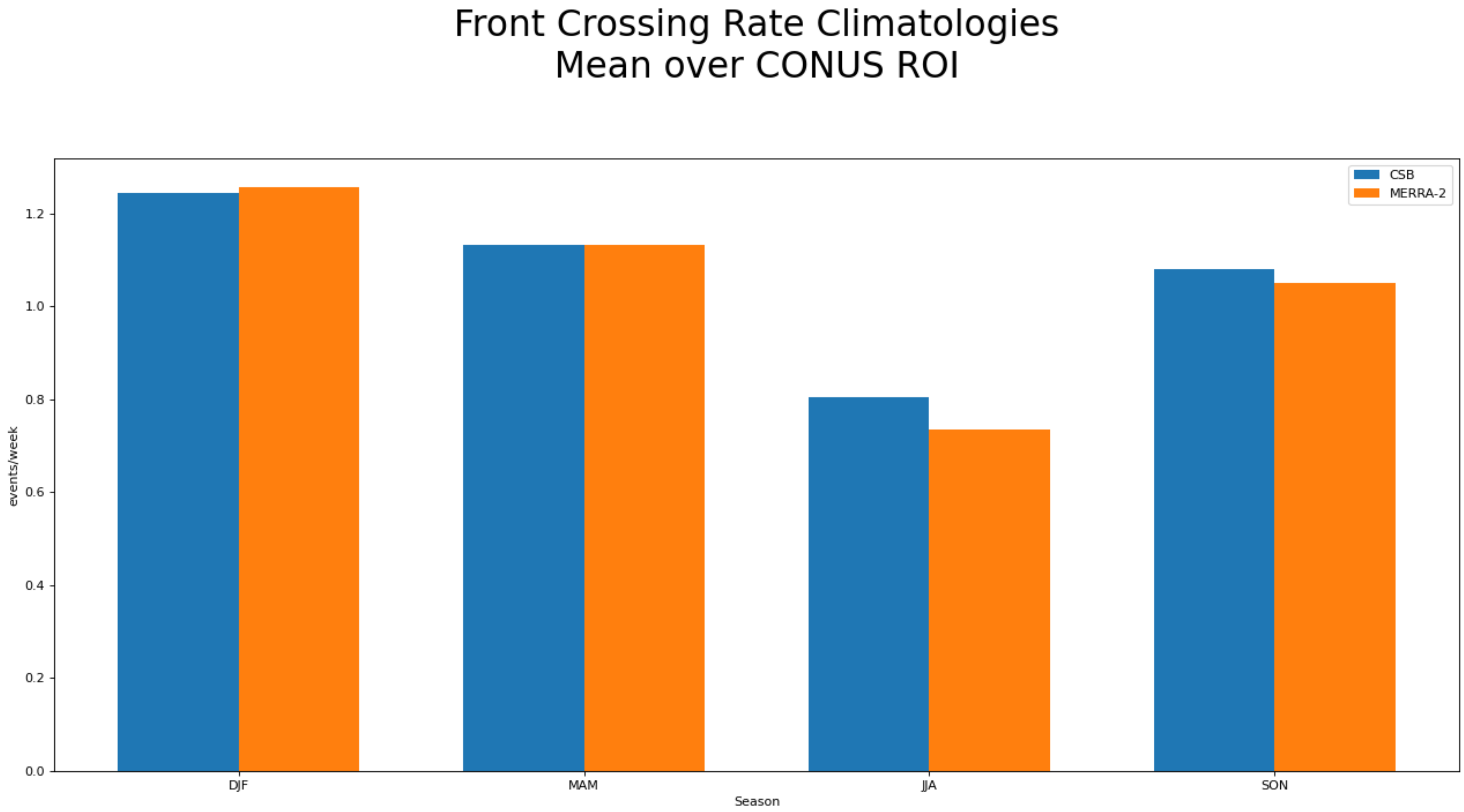
Jun-Jul-Aug

Sep-Oct-Nov

MERRA-2 vs CSB Climatology



MERRA-2 vs CSB Climatology



Conclusions

- The network appears to perform well.
- Hard to determine if further training is warranted.
- Need to try different network architectures.

Questions?

Support for this project was provided by the U.S. Department of Defense Strategic Environmental Research and Development Program Contract # W912HQ 15-C-0010