NIWA

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Deep learning for Lightning Forecasts and Drought Prediction

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Bureau of Meteorology Annual R&D Workshop

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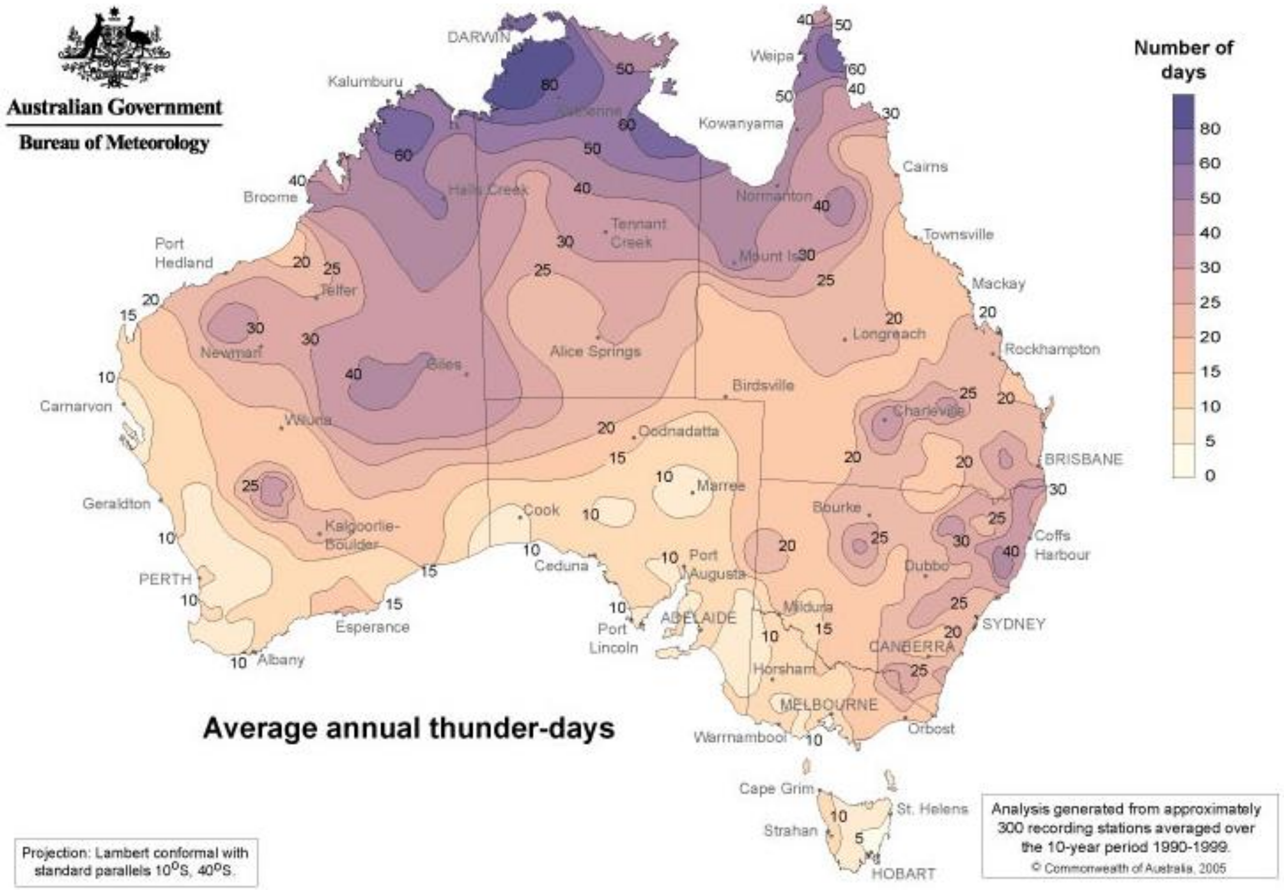
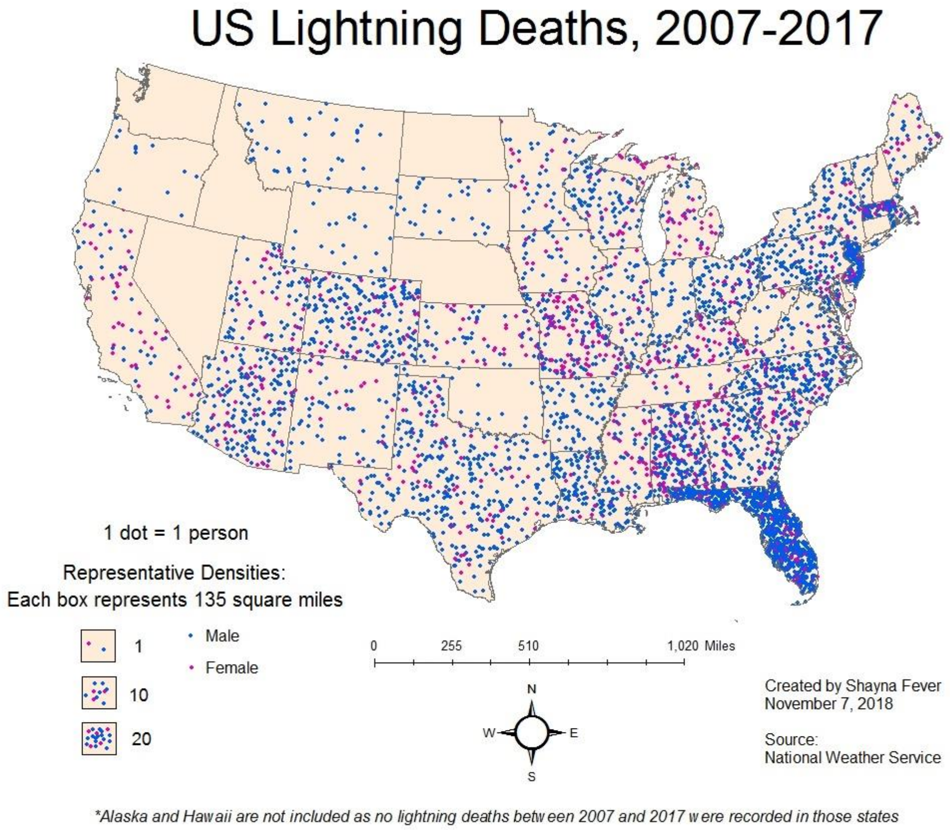
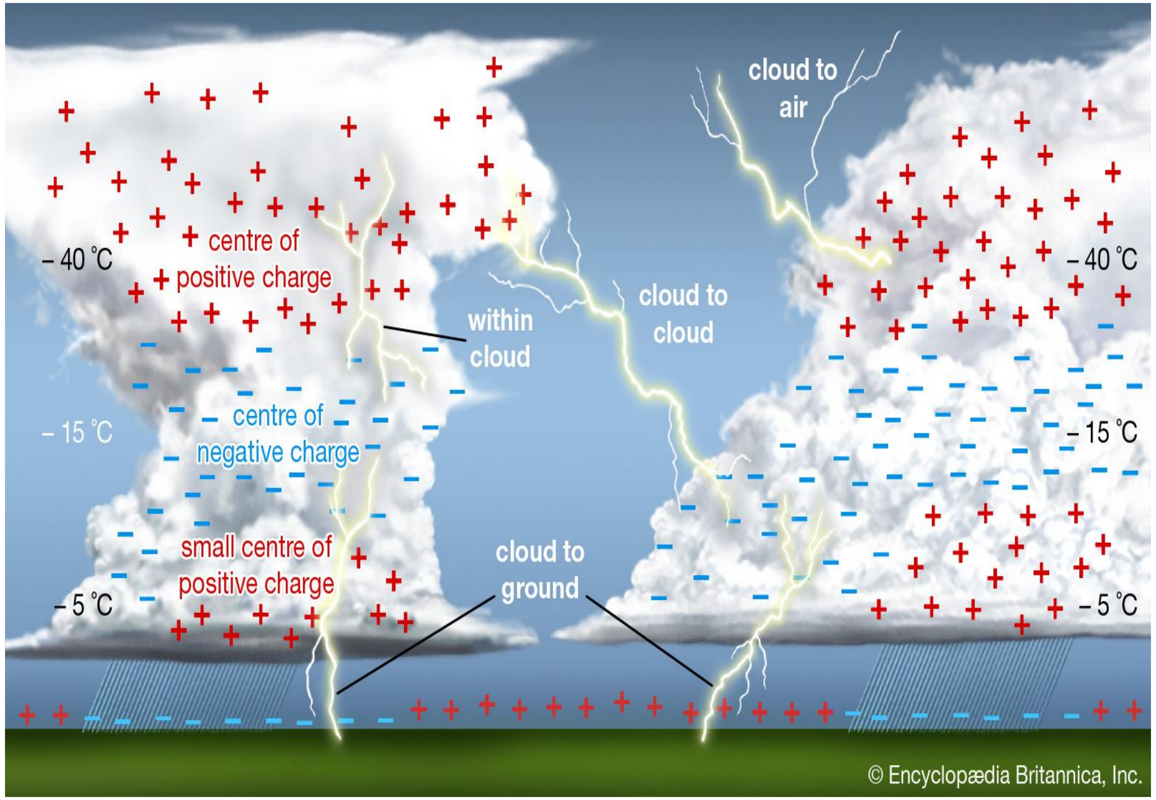
Introduction





How can we resolve events such as Lightning?

- Events such as Lightning are linked to atmospheric process from a spectrum of spatial meteorological scales.
- Discharges of Lightning is linked Cloud Microphysics (e.g. Nucleation, deep convection).

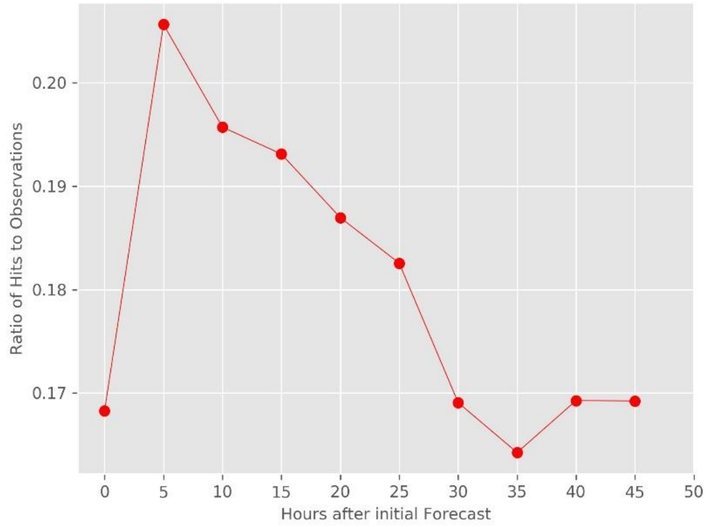


How do we Predict Thunderstorms?

- NWP processes can resolve scales ~ 1.5 km
- **Graupel Flux** - McCaul et al (2009)
- **Lightning Potential Index -** Yair et al. 2010
- **Fierro et al (2013)** – Charging Physics of the Cloud.
- **Large Scale Indices** (Haklander and van Delden 2003; Vujović et al. 2015).
- **Radar Nowcasting** – Links between flash rate and Radar reflectivity.

How accurate are our forecasts?

- There are a variety of useful metrics for validation.
- Probability of Detection (hits) and False Detection (misses).
- We use regional-based accuracy metrics (e.g. the proportion of lightning that was correctly forecasted) for all forecast lead times.
- Accuracies are much better for 1-10 forecasts (not shown).



Northland Region	Auckland Region	Waikato Region	Bay of Plenty Region	Gisborne Region	Hawke's Bay Region	Taranaki Region	Manawatu-Wanganui Region	Wellington Region	West Coast Region	Canterbury Region	Otago Region	Southland Region	Tasman Region	Nelson Region	Marlborough Region
0.16	0.18	0.29	0.24	0.17	0.2	0.23	0.33	0.29	0.44	0.32	0.27	0.43	0.21	0.11	0.2

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Nowcasting lightning occurrence from commonly available meteorological parameters using machine learning techniques

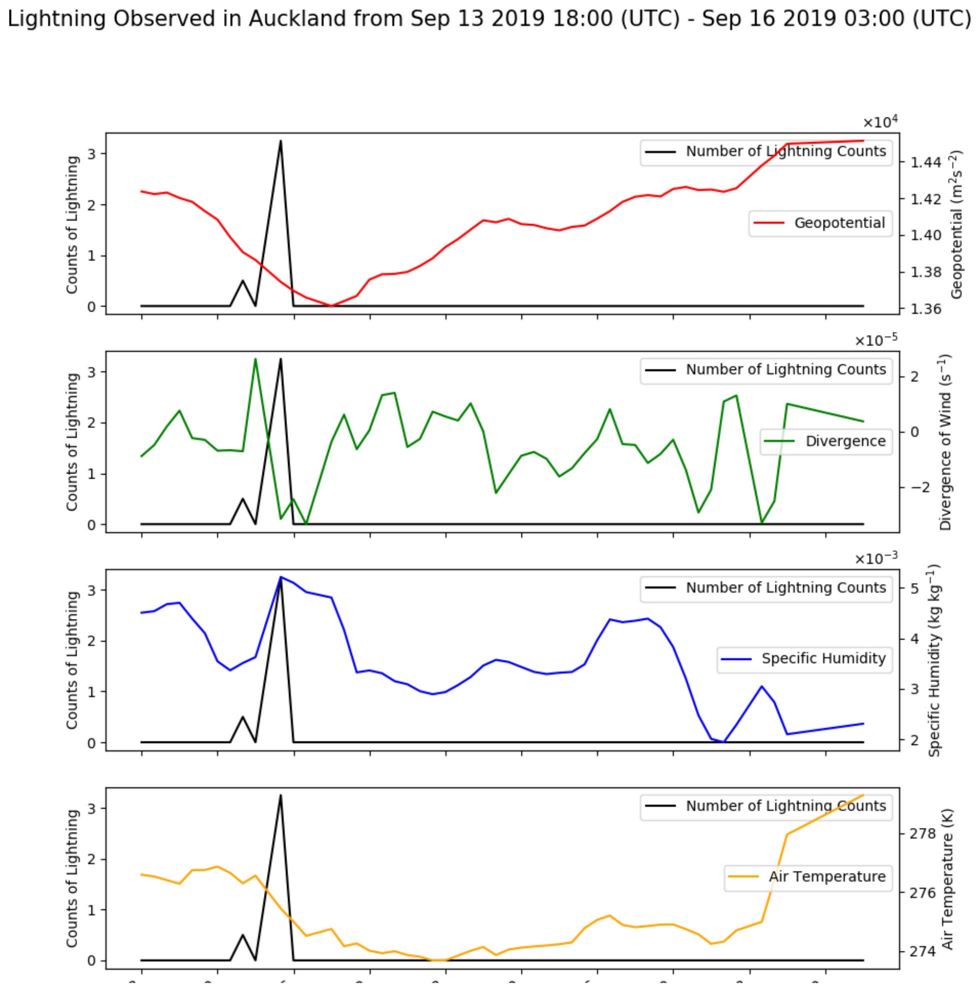
Amirhossein Mostajabi[1], Declan L. Finney[2], Marcos Rubinstein[3] and Farhad Rachidi[1*]

How can we use Machine Learning ?

- Use complex model to capture abstract features that are not captured in linear models.
- 2D Convolutional networks consider spatial variability at a variety of scales (e.g., large-scale flow).
- Techniques such as transfer learning.
- Literature has indicated that rainfall and lightning forecasts can improve with machine learning

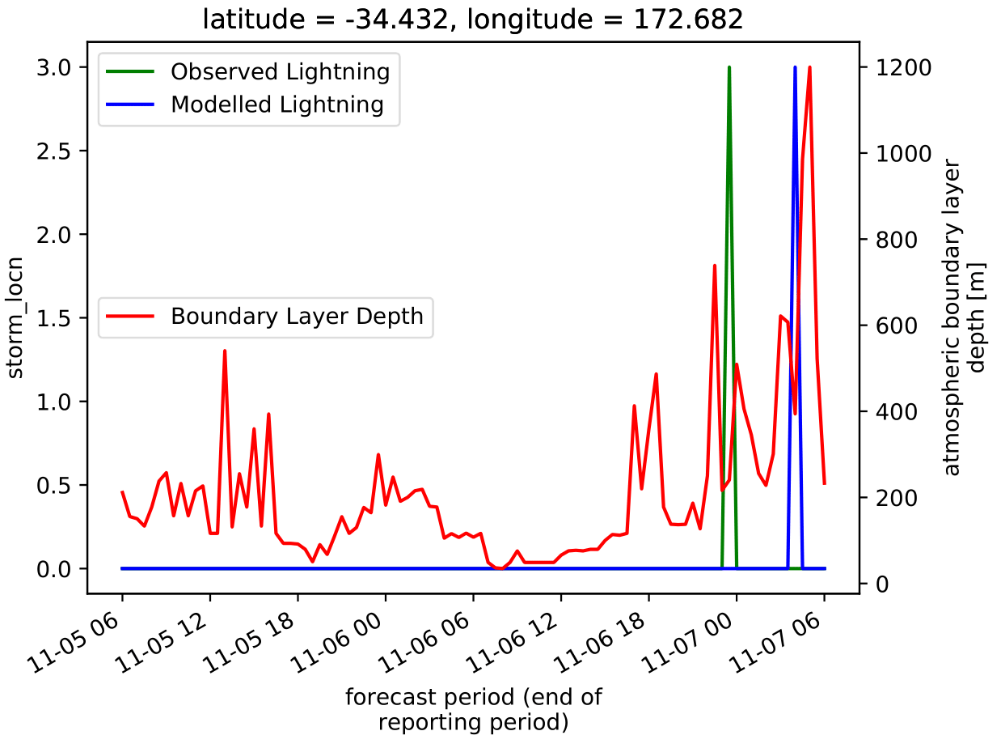
What are we doing differently?

- Model training in real-time, updated with forecasts.
- Using a variety of variables, and a Convolutional Neural network to determin complex relationships.
- Using 2D forecasts (using 6 fields) and 1D forecasts (19+ variables + considering how variables change in time)



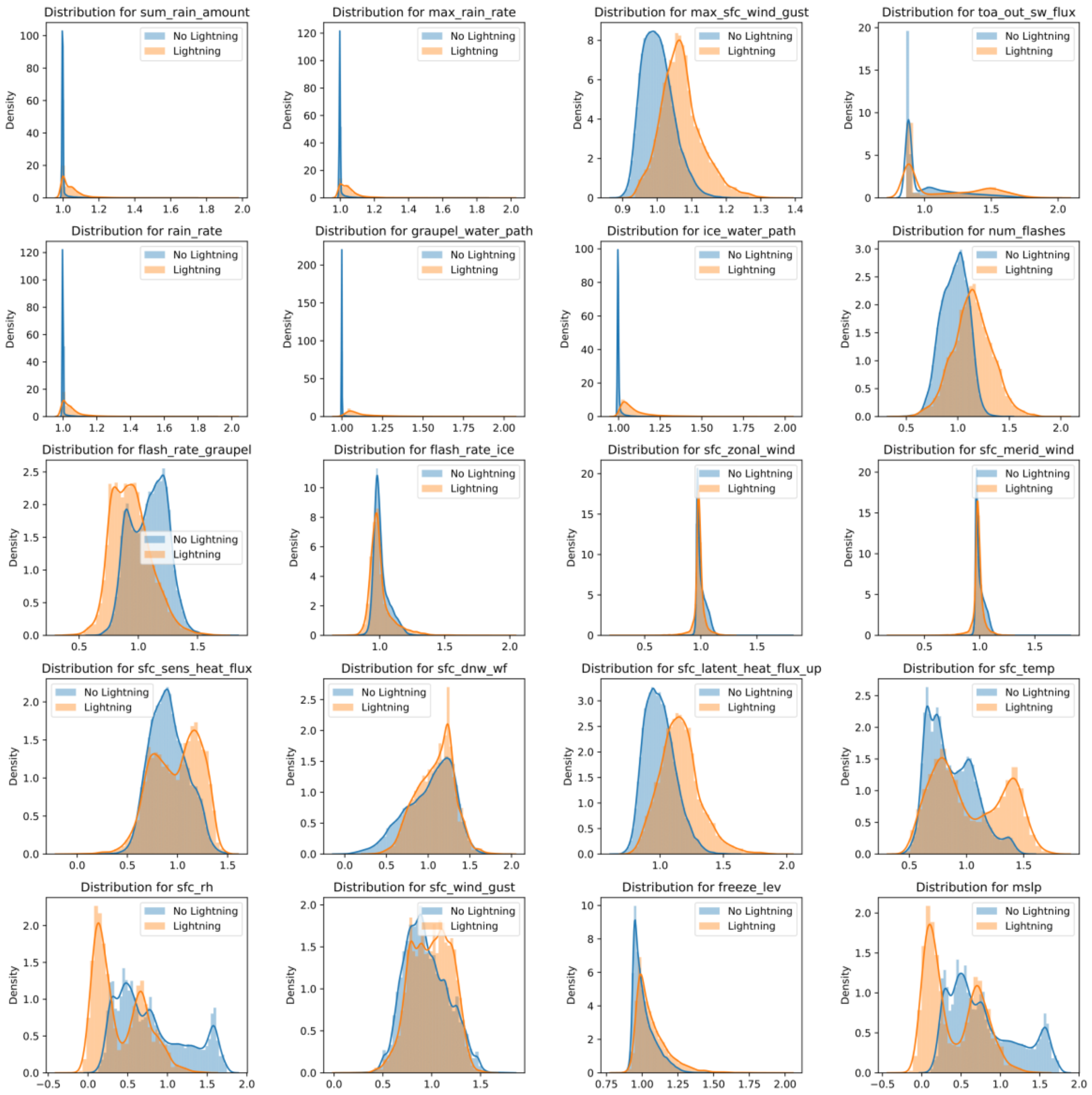
Methods (Lightning Forecasts in time)

- Vaisala Lightning Network (near instantaneous measurements of lightning).
- These are sampled with 10 km from the site and are sampled within a 1-hour window from the forecast (to create a continuous like architecture).
- NZCSM model, sampled at 942 sites for 19 forecasted variables.
- Validated against a baseline forecast.



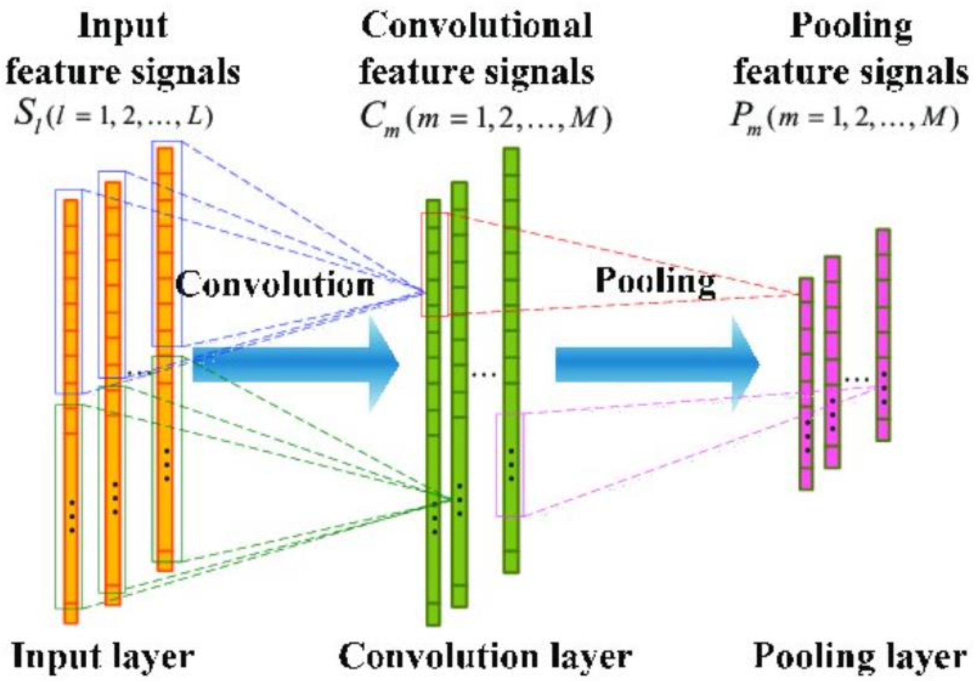
Methods

- Input fields are normalized (relative to the mean for all sites).
- Each site is considered independently to increase the sample size, and to ensure the physics are robust.



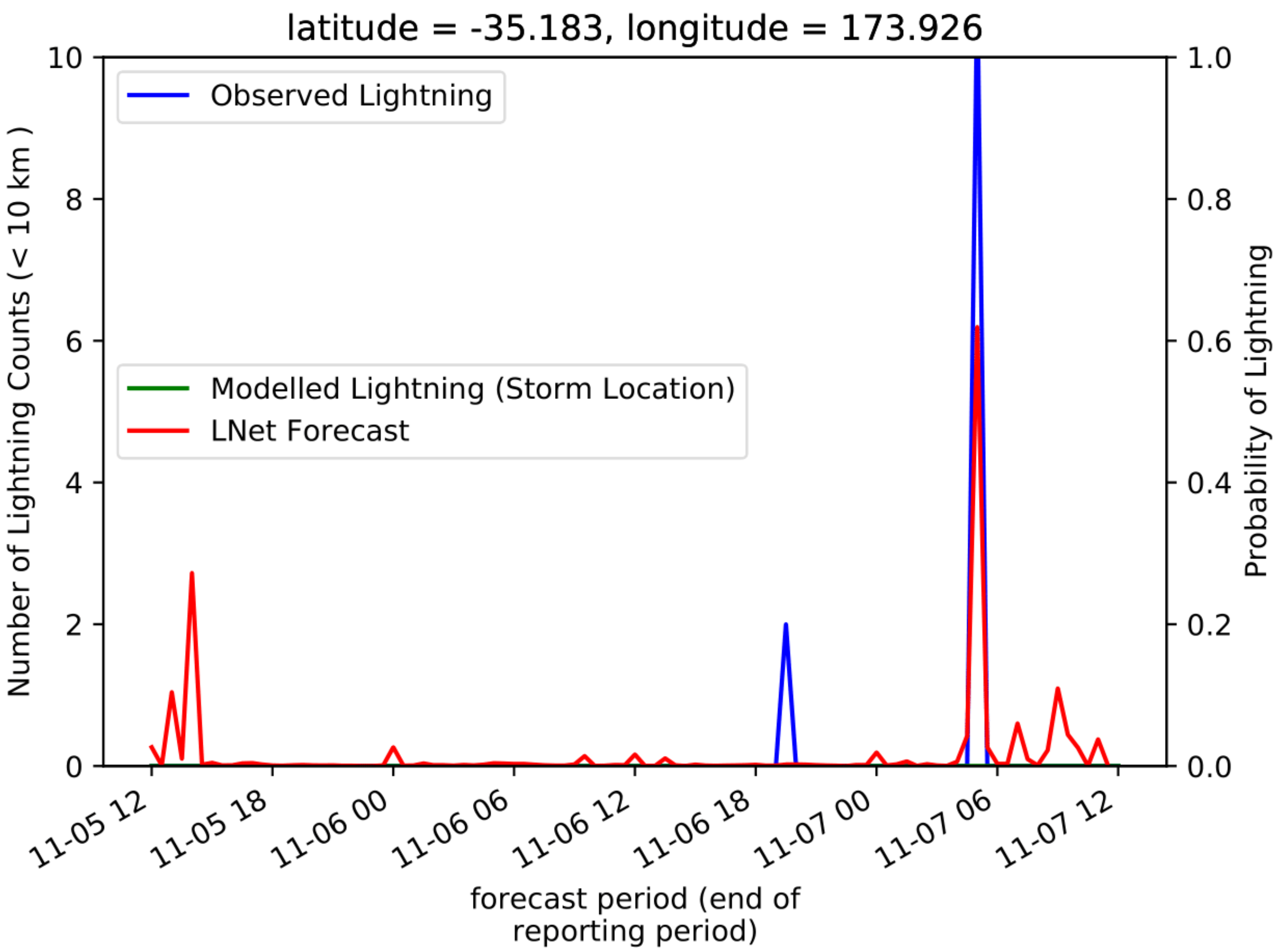
Model (Preliminary)

- 5-layer 1D Convolutional Neural Network.
- 1000 Lightning Events across New Zealand (Even number of North Island and South Island samples).
- 5000 Events without Lightning
- Output: The probably of Lightning for sample (single location).
- Weighted binary cross-entropy loss function (to handle data imbalance).



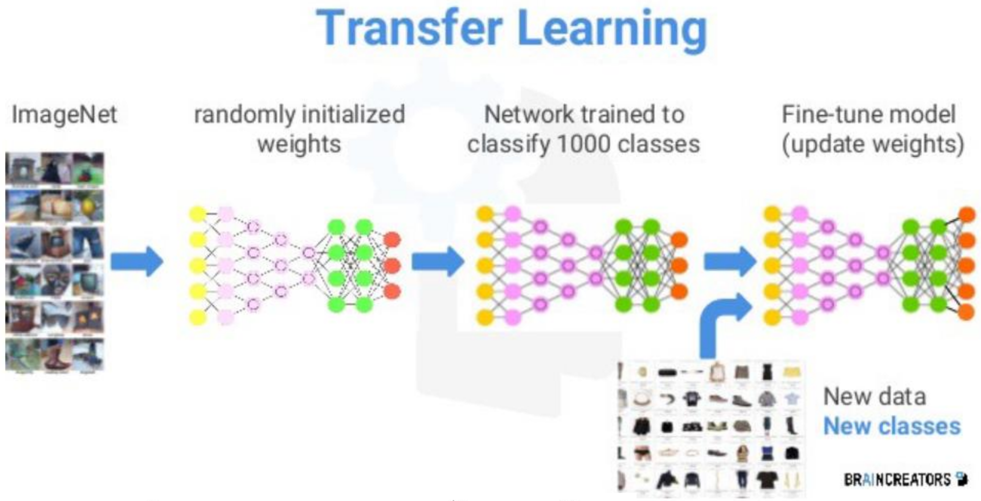
Results (Training Set)

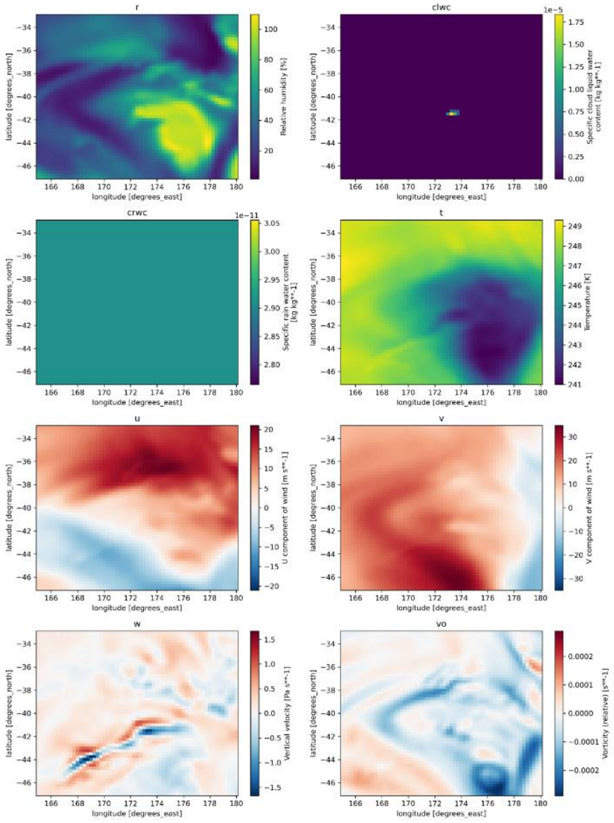
- 60/100 Lightning Events were predicted up to 4 hours in advance.
- Baseline model accuracy predicted 20/100 Lightning events.
- Further model updates will include smoothing the lightning inputs to incorporate the importance of uncertainty in forecasts.



Two Dimensional Model (ERA5)

- Hourly gridded observations: Divergence, temperature, relative humidity, vertical velocity and geopotential height.
- Gridded Lightning Data (25 km)
- ResNET34 Pre-trained model.
- Lightning Observations are spatially smoothed to handle data imbalance.

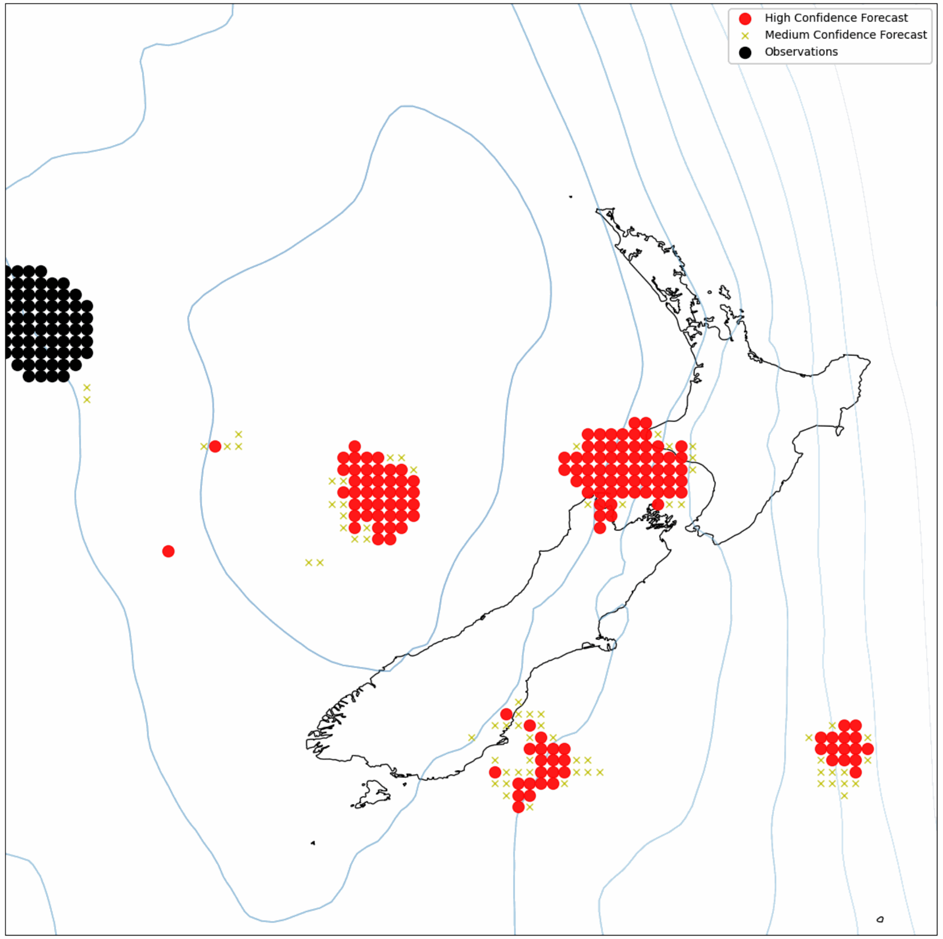




Results (Training Set)

- Success metric – Intersection / Union
- Union: Total area of both observations and forecasts.
- Area of overlap between observations and “AI Forecast” is 15%.
- Machine Learning over estimates the area for which lightning occurs.
- 60% of the area is false positives (AI forecast) and 25% misses.
- In general there is good agreement between the fields.

Forecast Lead Time 14 Hours

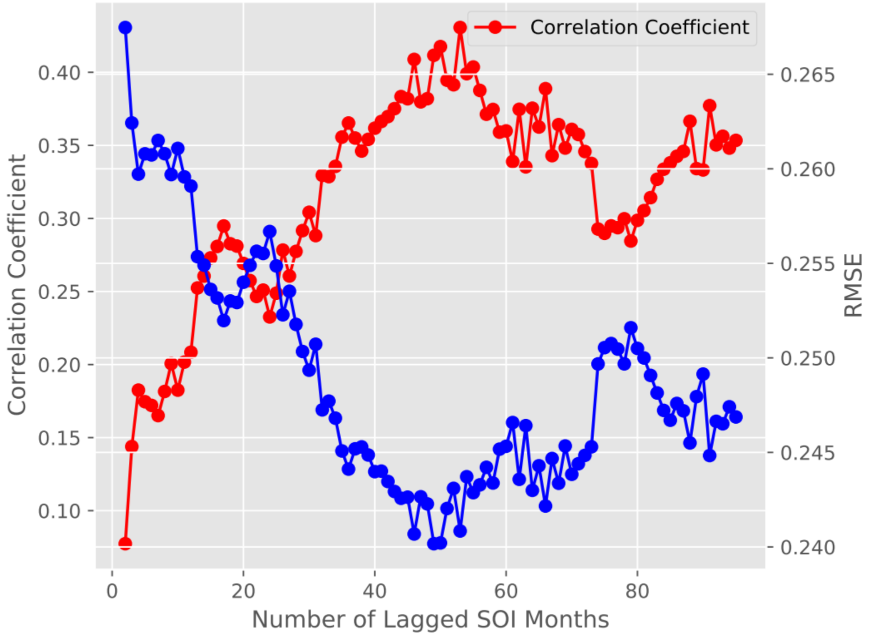


Further work

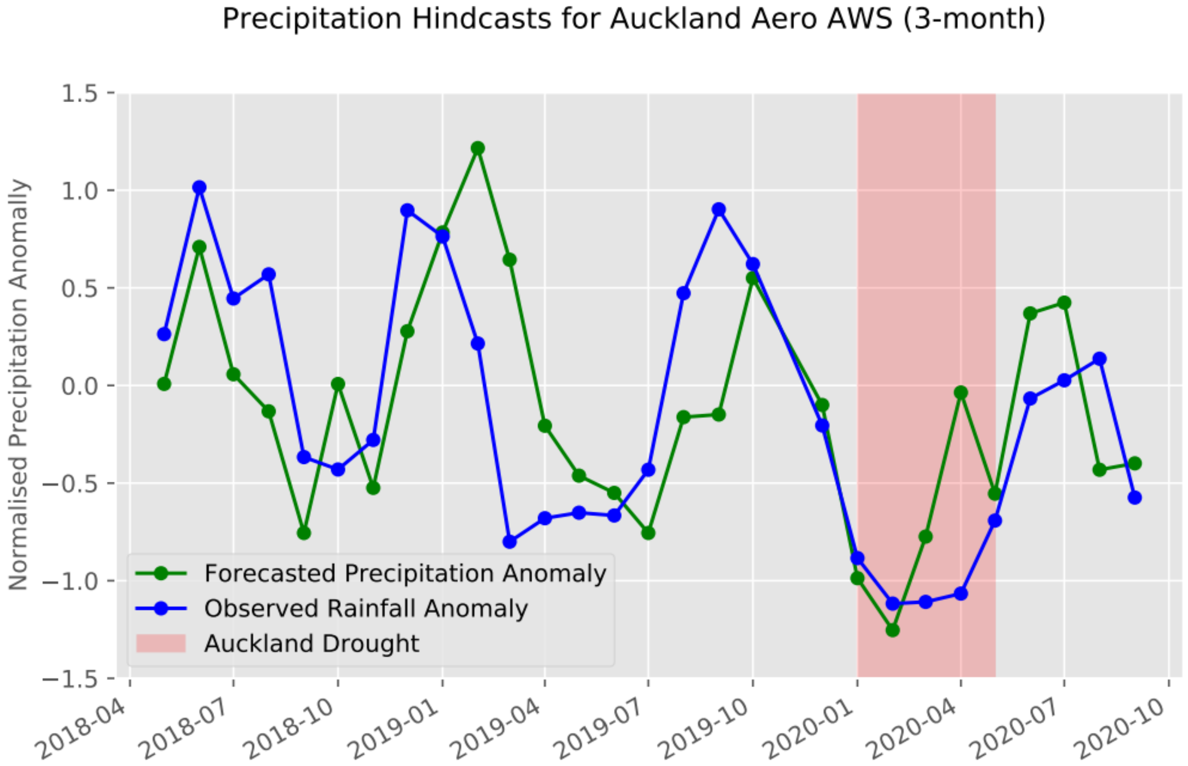
- Use more data for validation techniques
- Use a Convolutional LSTM (CONVLSTM) network, to combine spatial and temporal information to forecast lightning.

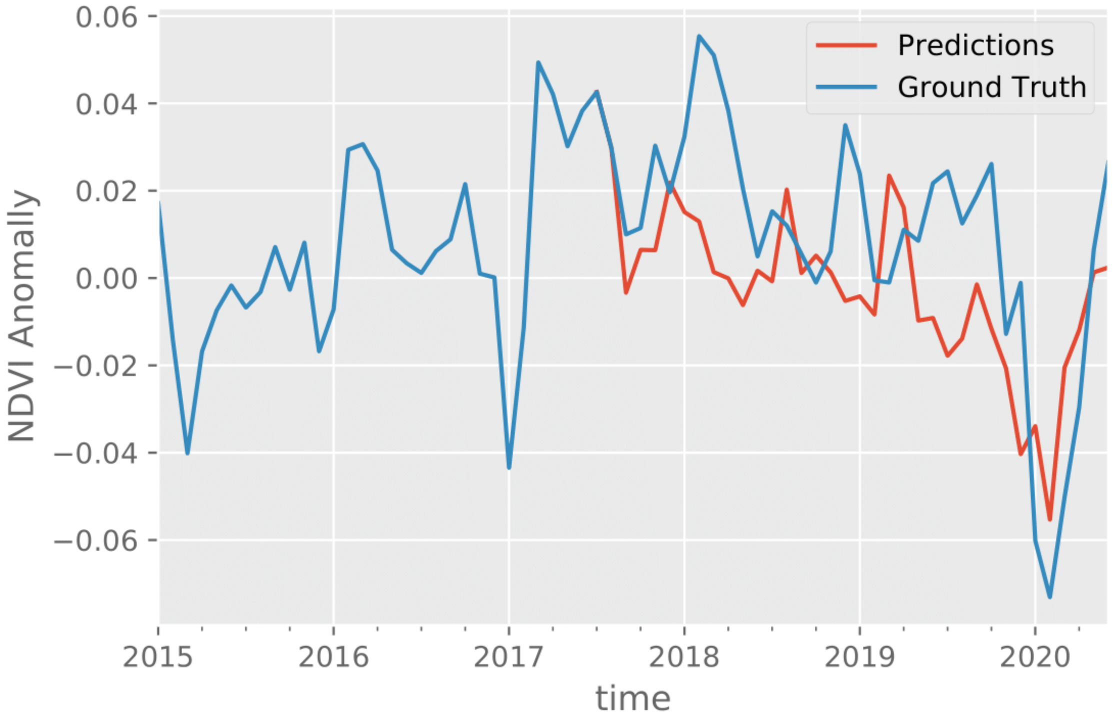
Applications: Transfer Learning for Drought Forecasts

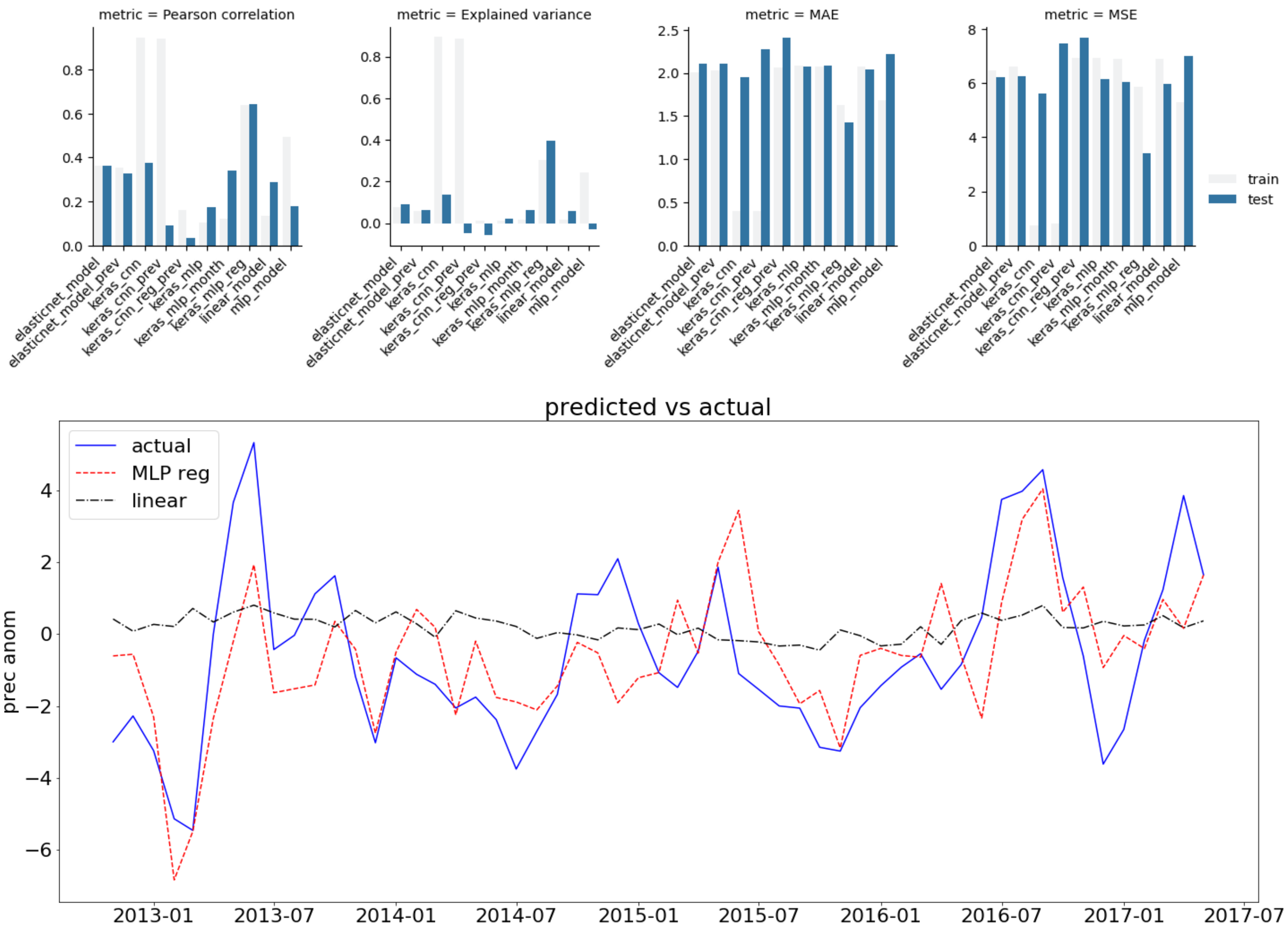
- Training the 1D Convolutional model on monthly precipitation and drought indices for forecasting.
- Using lagged indices of SOI, SAM, Atmospheric flow indices across NZ (64 lagged months).
- We can explain about 50% of the variance in rainfall and predict key drought events.
- Significant improve using linear methods.



Results (Using SOI Alone)







Results (Using SOI Alone)