New ML Approaches for Nowcasting of Global Auroral Particle Precipitation

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(Heliosphere to Earth Atmosphere Rendering Through Building Excellent Artificial-Intelligence Training)

Outline

- Past work:
  - Energy Flux
  - ML, Ovation
- ML model improvements
  - Dropout, more layers, custom loss function
- Auroral Boundary/Region Models
  - Regions, model separation, multi-task models
- Number Flux Modeling
  - Total and Channel based
- Conv2d_Transpose Modeling
- New Database
  - Selection of Time scales
- New Ideas

Overview

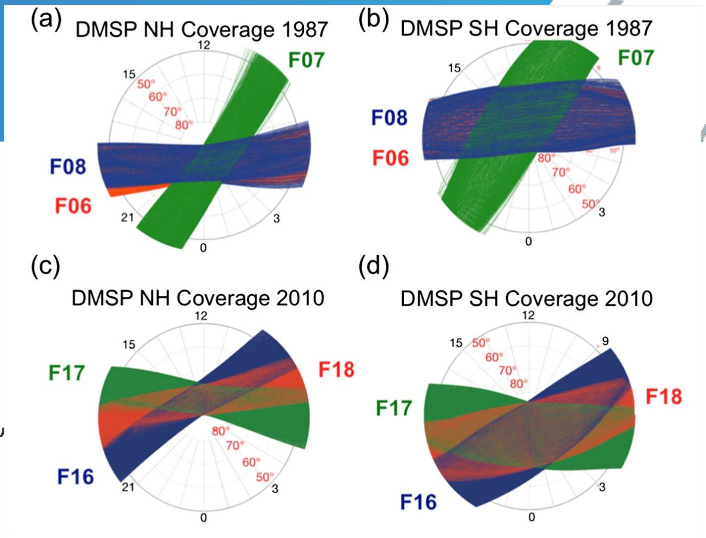
- Total Electron Energy(Number) Flux

  Full problem:

  Precipitation(time, Mlat, Mlocaltime)

  = *function*[mlat, mlocaltime, Magnetic_indices(time),

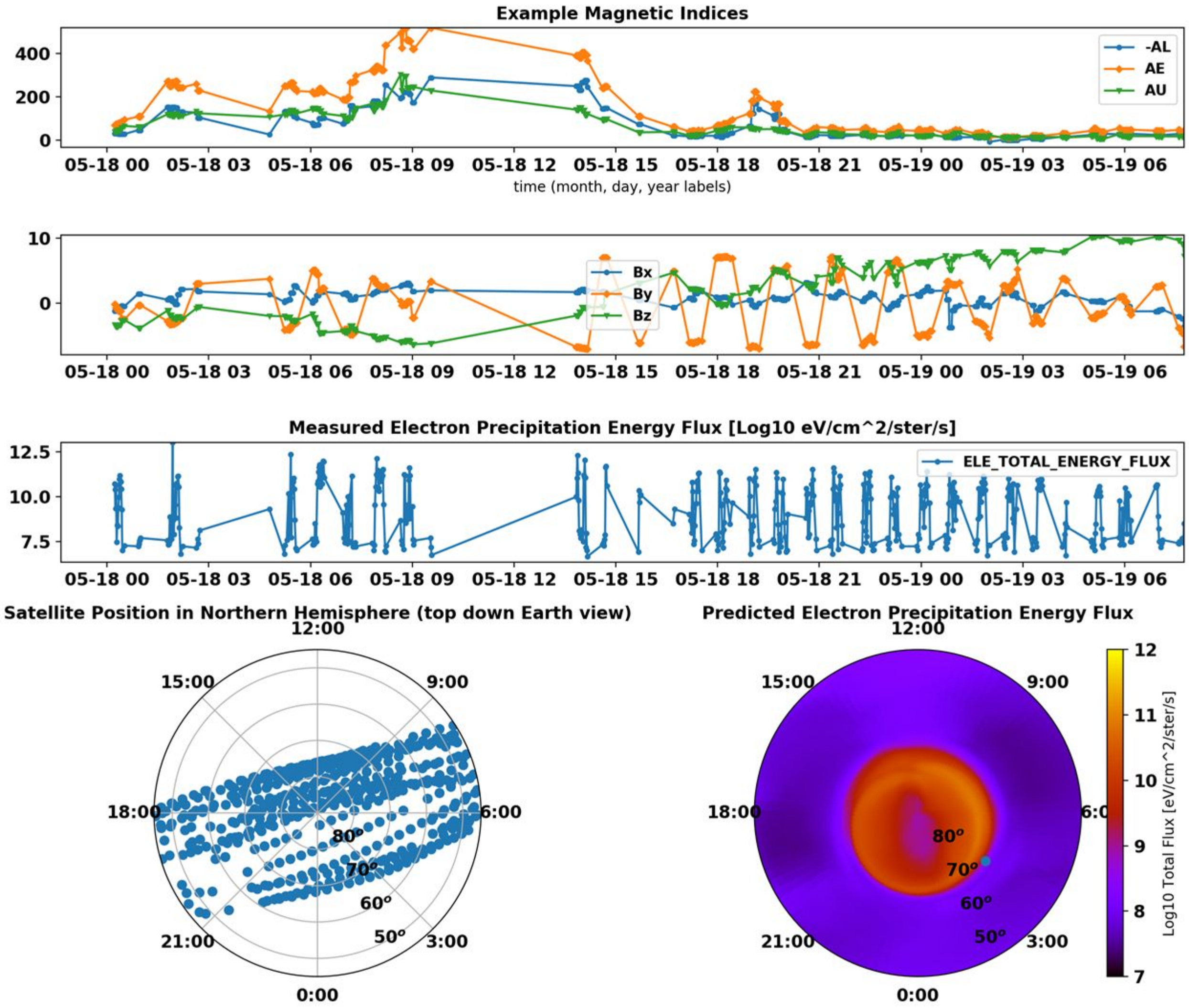
  solar_wind(time)]



Satellites from "multiple generations of sensors" from 1987 to 2018. 150 total "satellite years"

- DMSP Measurements
  - ML Modeling Challenges
  - Regression instead of time-series

- Inputs and outputs
  - Inputs: M_Lat, M_Local_time, date and Magnetic indice history
    - (5 min cadence)
  - Outputs: Total Energy flux at current time as function of MLat and MLT
    - (using 1 min cadence (sub-sampled, not averaged), 1 second cadence available)


Example Magnetic Indices
-AL
AE
AU
time (month, day, year labels)
Bx
By
Bz
Measured Electron Precipitation Energy Flux [Log10 eV/cm^2/ster/s]
ELE_TOTAL_ENERGY_FLUX
Satellite Position in Northern Hemisphere (top down Earth view)
Predicted Electron Precipitation Energy Flux
12:00
15:00
9:00
18:00
6:00
21:00
3:00
0:00
80°
70°
60°
50°
Log10 Total Flux [eV/cm^2/ster/s]

Past Work

PrecipNet

- Solves 2D time series problem as a regression problem with the target transformed to a log10 scale

For HEARTBEAT System: We use only the input features that the HB system provides.

- These are our 'existing HB low energy precipitation models' - i.e., the ones that will be integrated.

HEARTBEAT'S 33 Inputs:

'SC_AACGM_LAT','SC_AACGM_LTIME', 'ID_SC', 'sin_ut',
'cos_ut', 'sin_doy', 'cos_doy', 'sin_SC_AACGM_LTIME', 'cos_SC_AACGM_LTIME',

'F107', 'AE', 'AL', 'AU', 'SymH',
'F107_6hr', 'AE_6hr', 'AL_6hr', 'AU_6hr', 'SymH_6hr',
'F107_5hr', 'AE_5hr', 'AL_5hr', 'AU_5hr', 'SymH_5hr',
'F107_3hr', 'AE_3hr', 'AL_3hr', 'AU_3hr', 'SymH_3hr',
'F107_1hr', 'AE_1hr', 'AL_1hr', 'AU_1hr', 'SymH_1hr'

ML Model Improvements

New Model:

- Twice as many and larger layers overall
- Massive increase in batch size to 32,768
- Dropout layer
- GPU usage
- Layer size testing ->
    - 2x larger than input, 50% dropout, smaller layer, larger layer, and then smaller layers

Custom loss function for tail

8 Hidden layers:

256 node dense

50% dropout layer

64 node dense

32 node dense

256 node dense

1024 node dense

256 node dense

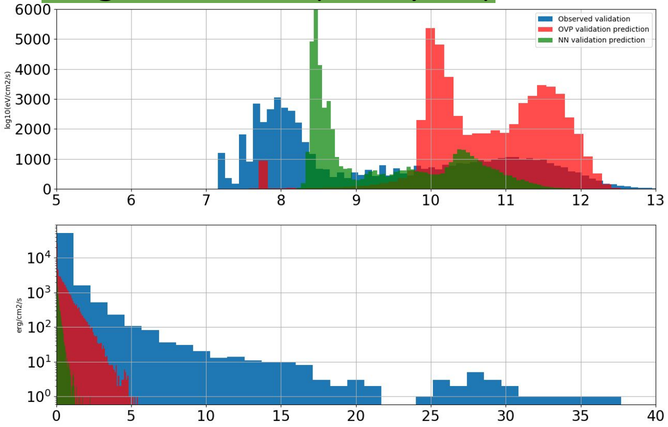
32 node dense

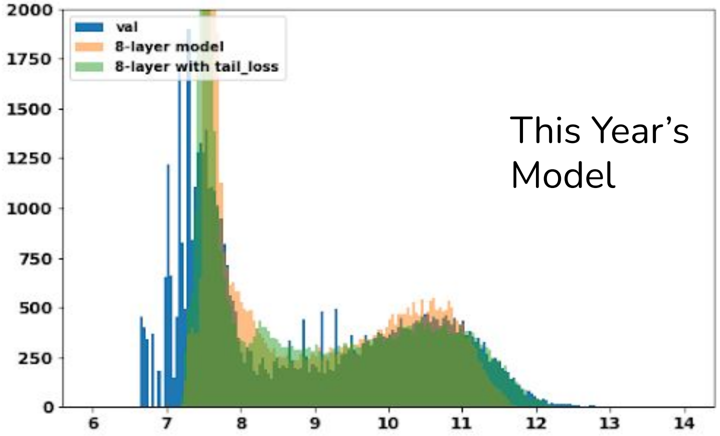
4 node dense

Output layer:

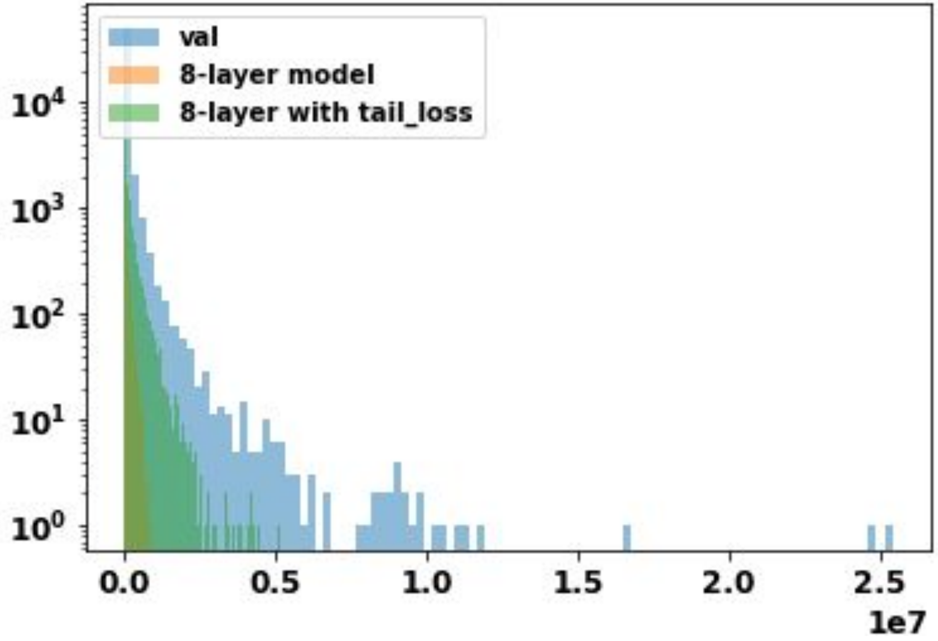
1 node dense

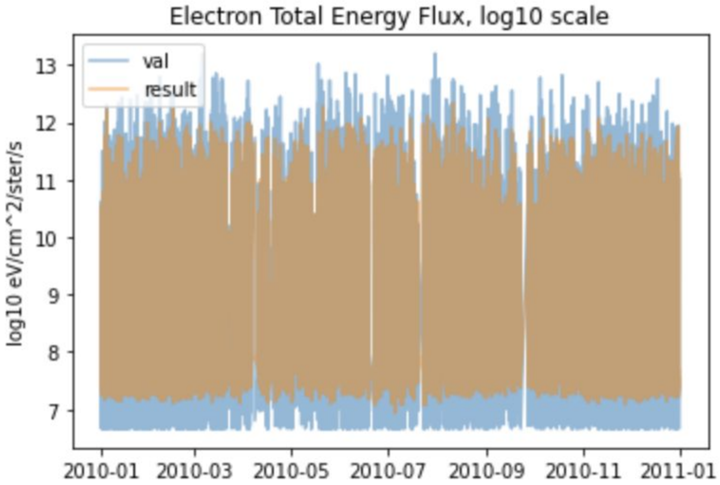
Original Model (Last year)

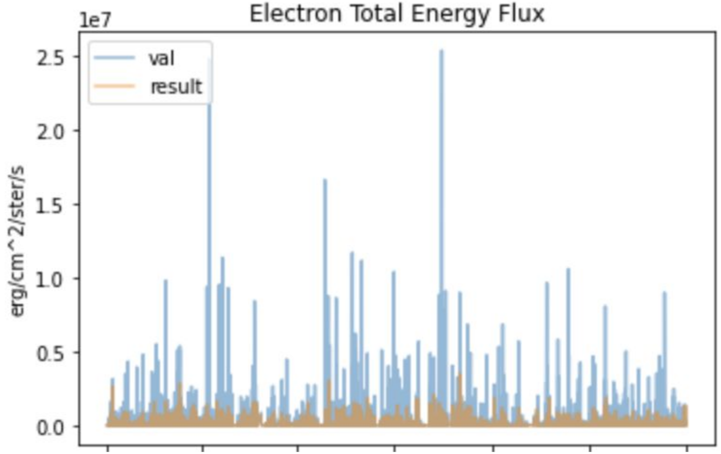




This Year's Model







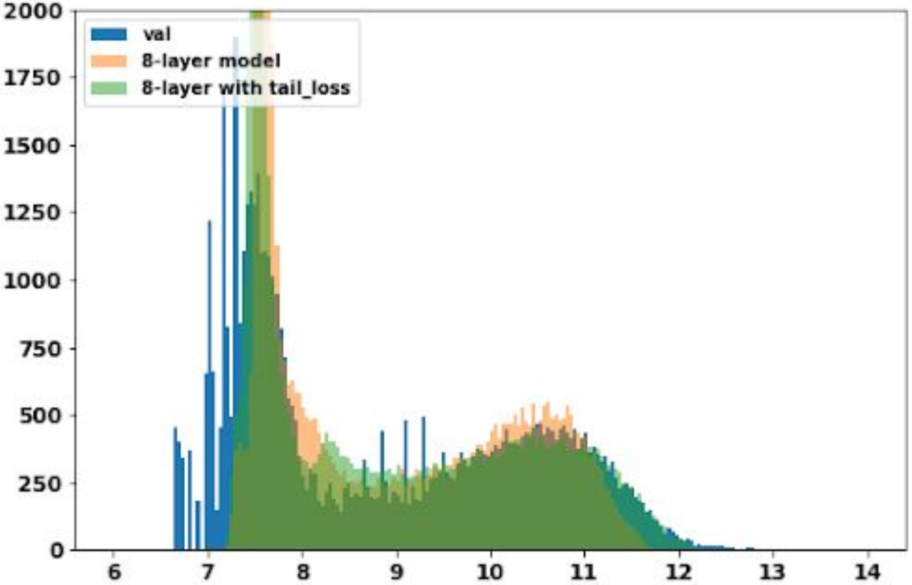
Tail loss function

$$\left[\frac{1}{N}\sum_{i=1}^{N}|obs - pred|\right]^{2} * \left[1 + \sum_{j}^{M}\gamma_j\right]$$

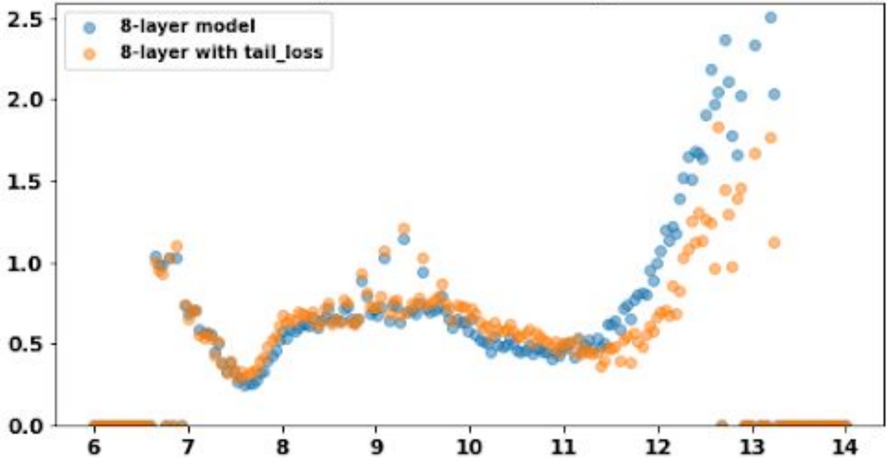
Where $\gamma_j(obs, pred) = w \quad \text{if obs} > \text{tail limit} \quad \& \quad \text{pred} < \text{tail limit}$

$\gamma_j(obs, pred) = 0 \quad \text{otherwise}$

Log10 Scale



val
8-layer model
8-layer with tail_loss
2000
1750
1500
1250
1000
750
500
250
0
6
7
8
9
10
11
12
13
14

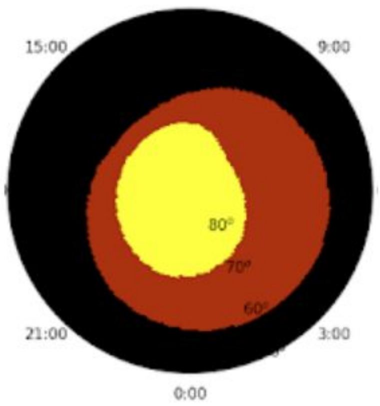


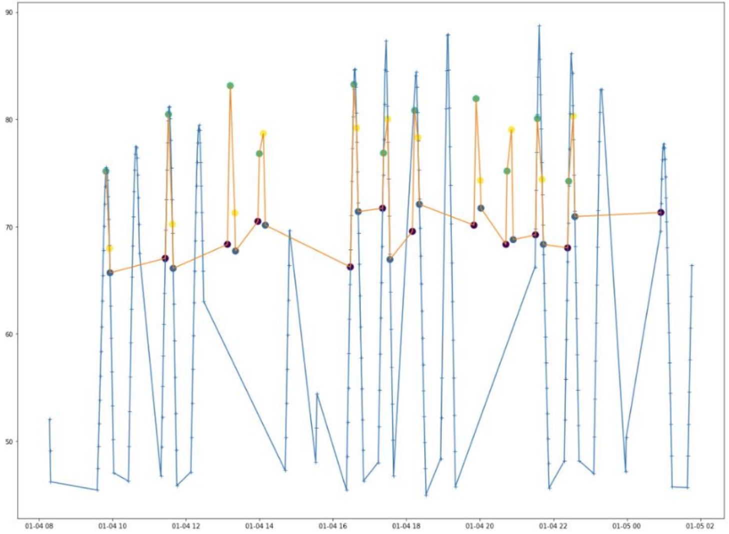
Average Validation Error over target Bins
8-layer model
8-layer with tail_loss
2.5
2.0
1.5
1.0
0.5
0.0
6
7
8
9
10
11
12
13
14

Auroral Boundaries

- 3 class classifier
  - (90% accurate over 45 to 90 M_lat)
- Extended to a three model method
  - (one model for each region)
- Also a dual classifier and regression model
  - 6 outputs,(3 classes and 3 regions)
    - Only the predicted region is used for final result
    - Combined loss function

Region	Train samples	Test samples	Test MSE
Equatorial	925,990	26,821	0.45
Auroral	496,715	14,856	0.55
Polar	415,578	13,533	0.84



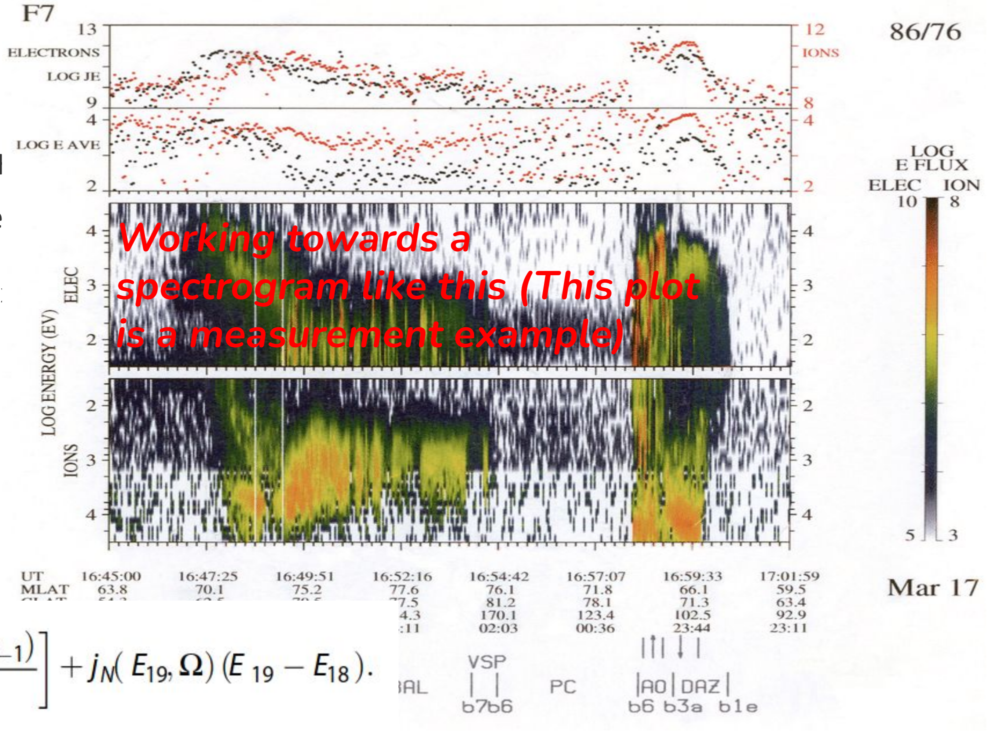


Number Flux Modeling

- Calculated from “electron counts” from 19 total energy channels
  - Each spacecraft has a different “geometric factor” thougl
- Total Number Flux is a scalar representation of all these values
  - Calculated in a way that is very similar to total energy flu

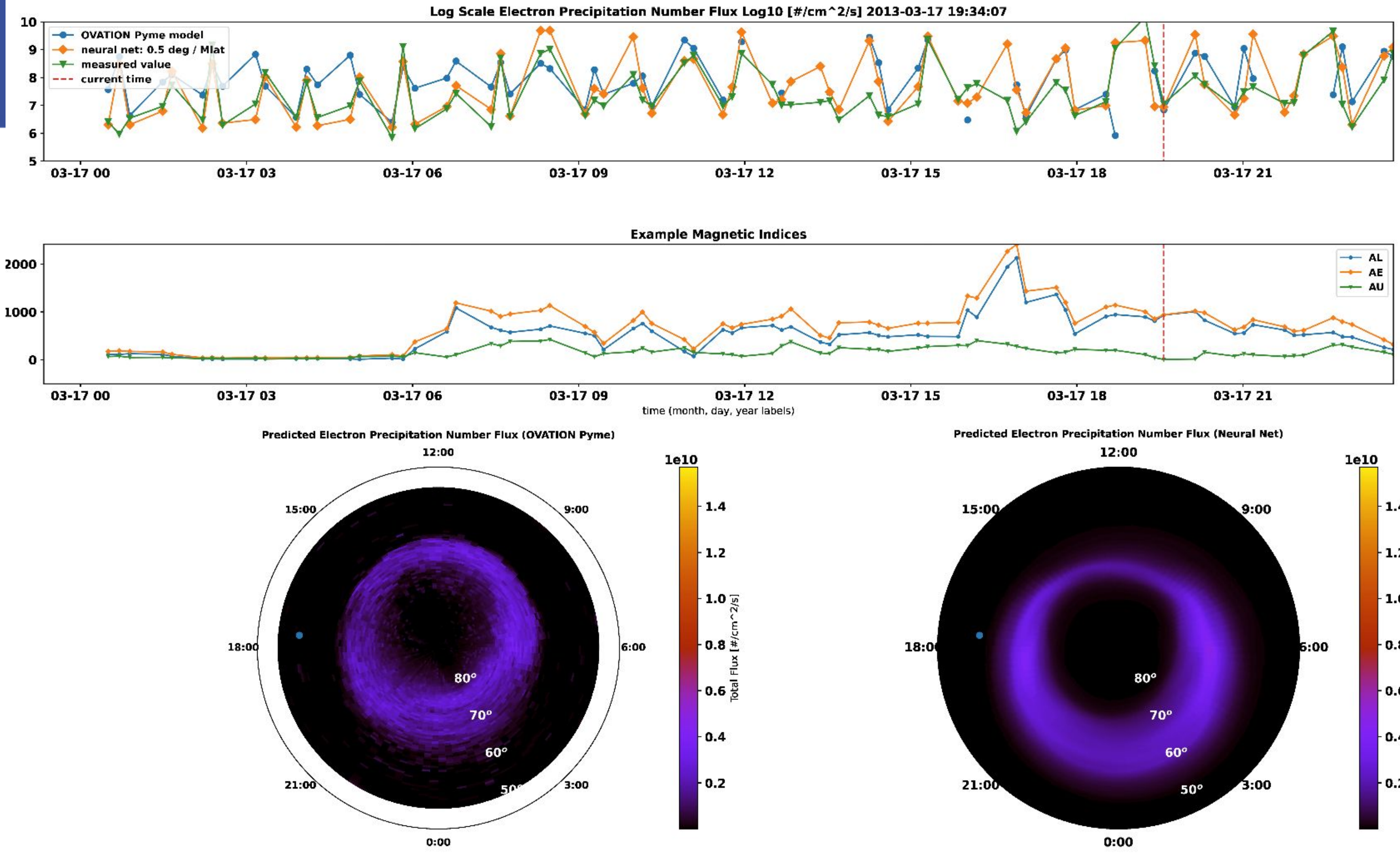
We have models for Total number flux and a 19 Channel output number flux

Uses same network structure as total energy flux

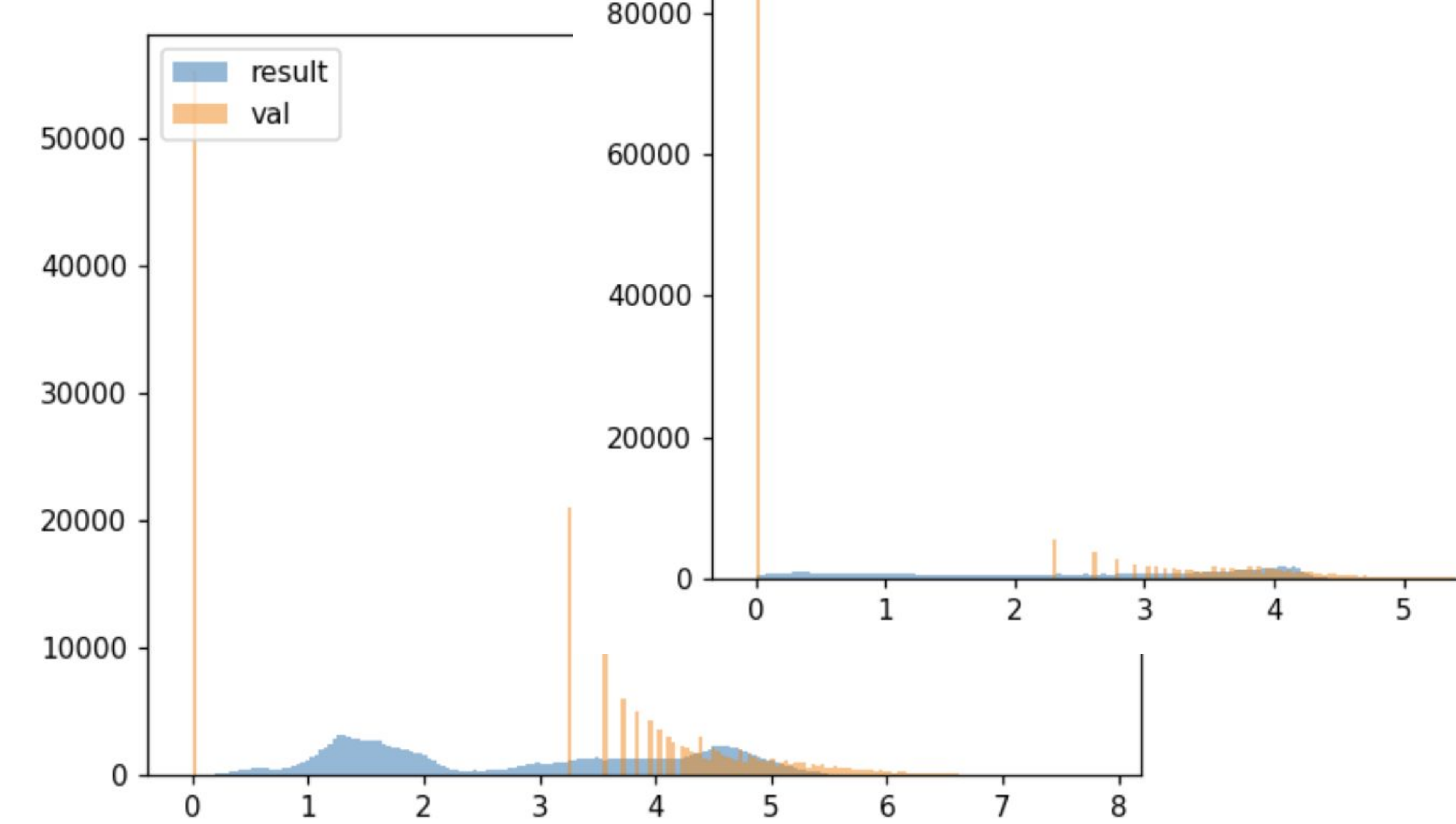


$$J_{N,\mathrm{Total}}(\Omega) = j_N(E_1,\Omega)\,(E_2 - E_1) + \left[\sum_{i=2}^{18} j_N(E_i,\Omega)\frac{(E_{i+1} - E_{i-1})}{2}\right] + j_N(E_{19},\Omega)\,(E_{19} - E_{18}).$$

units: $\dfrac{1}{cm^2 \cdot s \cdot ster}$



Log Scale Electron Precipitation Number Flux Log10 [#/cm^2/s] 2013-03-17 19:34:07
OVATION Pyme model
neural net: 0.5 deg / Mlat
measured value
current time
03-17 00
03-17 03
03-17 06
03-17 09
03-17 12
03-17 15
03-17 18
03-17 21
Example Magnetic Indices
AL
AE
AU
time (month, day, year labels)
Predicted Electron Precipitation Number Flux (OVATION Pyme)
Predicted Electron Precipitation Number Flux (Neural Net)
12:00
15:00
9:00
18:00
6:00
21:00
3:00
0:00
80°
70°
60°
1e10
Total Flux [#/cm^2/s]

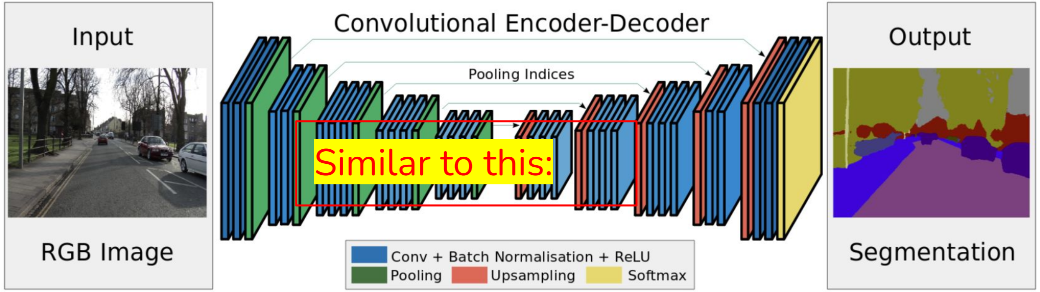

result
val
50000
40000
30000
20000
10000
0
0
1
2
3
4
5
6
7
8
80000
60000
40000
20000
0
0
1
2
3
4
5

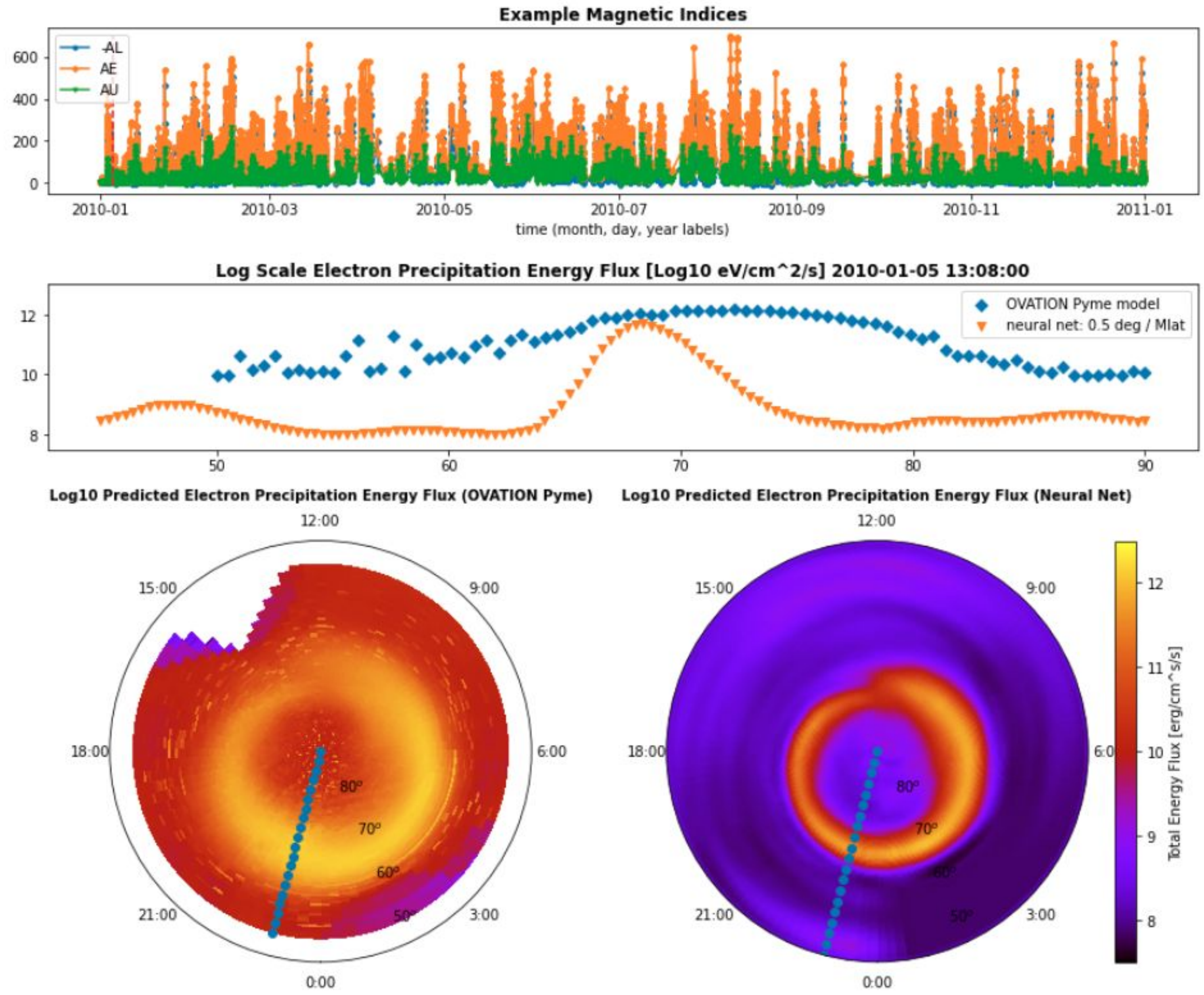
Conv2D_transpose Formulation

Inputs: 'ID_SC', 'sin_ut','cos_ut', 'sin_doy', 'cos_doy',
'F107', 'AE', 'AL', 'AU', 'SymH',
'F107_6hr', 'AE_6hr', 'AL_6hr', 'AU_6hr', 'SymH_6hr',
'F107_5hr', 'AE_5hr', 'AL_5hr', 'AU_5hr', 'SymH_5hr',
'F107_3hr', 'AE_3hr', 'AL_3hr', 'AU_3hr', 'SymH_3hr',
'F107_1hr', 'AE_1hr', 'AL_1hr', 'AU_1hr', 'SymH_1hr'

```
model1 = Dense(256, activation='relu')(input1)
model1 = model1 = Dropout(0.5)(model1)
model1 = Dense(int(64),   activation='relu')(model1)
model1 = Dense(int(32),   activation='relu')(model1)
model1 = Dense(int(256),   activation='relu')(model1)
model1 = tf.keras.layers.Reshape((16, 16, 1))(model1)
# 16x16 to 16 32x32 feature map
model1 = tf.keras.layers.Conv2DTranspose(4, (9,9),
                strides=(2,2), padding='same')(model1)
model1 = tf.keras.layers.Conv2DTranspose(4, (5,5),
                strides=(4,4), padding='same')(model1)
# 4 128x128 feature map to 1 128x128
model1 = model1 = Dropout(0.5)(model1)
model1 = PeriodicPadding2D(3)(model1)
model1 = tf.keras.layers.Conv2D(1, kernel_size=(7,7),
                              padding='valid')(model1)
```

```
Layer (type)                 Output Shape
=================================================================
input_1 (InputLayer)         [(None, 145)]

dense (Dense)                (None, 256)

dropout (Dropout)            (None, 256)

dense_1 (Dense)              (None, 64)

dense_2 (Dense)              (None, 32)

dense_3 (Dense)              (None, 256)

reshape (Reshape)            (None, 16, 16, 1)

conv2d_transpose (Conv2DTran (None, 32, 32, 4)

conv2d_transpose_1 (Conv2DTr (None, 128, 128, 4)

dropout_1 (Dropout)          (None, 128, 128, 4)

periodic_padding2d (Periodic (None, 134, 134, 4)

conv2d (Conv2D)              (None, 128, 128, 1)
=================================================================
Total params: 65,281
```





2010-01-05 23:27:00

```python
class DataGenerator_train(keras.utils.Sequence):
    'Generates data for Keras'
```

MLat

0	0	0	0	0
0	0	0	0	0
0	0	(Ytrue-Ypred)^2	0	0
0	0	0	0	0
0	0	0	0	0

MLocalTime

Left-right Periodic Padding
(not yet implemented)

Loss function for each time step and target value

Note: 2048 are combined for each batch

```python
def custom_mse(y_true, y_pred):


    mse = K.sum( K.cast(K.greater(y_true, 0),'float32')*(
        K.square(y_true-y_pred)) )/params['batch_size']
    return mse
```

```python
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model1 = tf.keras.layers.Reshape((16, 16, 1))(model1)
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# 4 128x128 feature map to 1 128x128
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model1 = PeriodicPadding2D(3)(model1)
model1 = tf.keras.layers.Conv2D(1, kernel_size=(7,7),
                                     padding='valid')(model1)
```

Time dependent inputs are only changing every 5 min (from NASAOMNI)

One min available (but not as accurate)

Idea: use all traced data (collected at 1 sec cadence) within a 5 minute window for each 5 min cadence input

Also use multiple SC_IDs at once for satellites

```python
history = model.fit(training_generator,
                    validation_data=validation_generator,
                    batch_size=2048,epochs=400,#verbose=2,
                   callbacks=[tf.keras.callbacks.EarlyStopping(moni
              patience=50)], use_multiprocessing=True,
                     workers=6)#
```

- Uses tf.keras Data_generator class which creates batches as needed
    - Save all 160 GB data in data files and load dynamically, each epoch still can use all data at once

```python
class DataGenerator_train(keras.utils.Sequence):
    'Generates data for Keras'
```

New Idea,
For each 2D target use all Spacecraft at that time step as well as data from nearby times.
This assumes time scale changes are >> 1 second

MLat

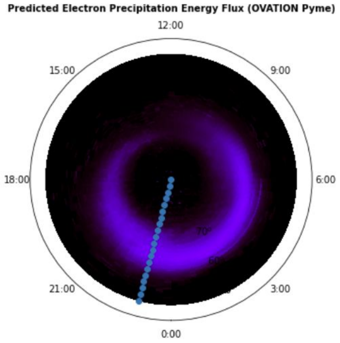
0	0	0	0	0	0	0	0	0	0
0	F16 Spacecraft	0	Y ti+1	0	0	0	0	0	0
0	0	Y ti	0	0	0	0	Y ti+1	0	0
0	Y ti-1	0	0	0	0		0	Y ti	Y ti-1
0	0	0	0	0	0	0	F17 Spacecraft	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

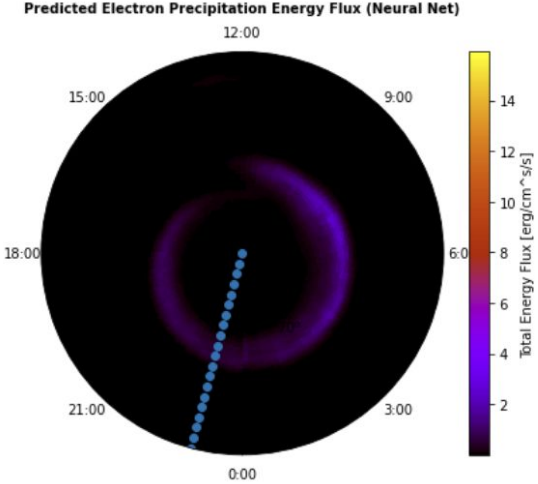
MLocalTime

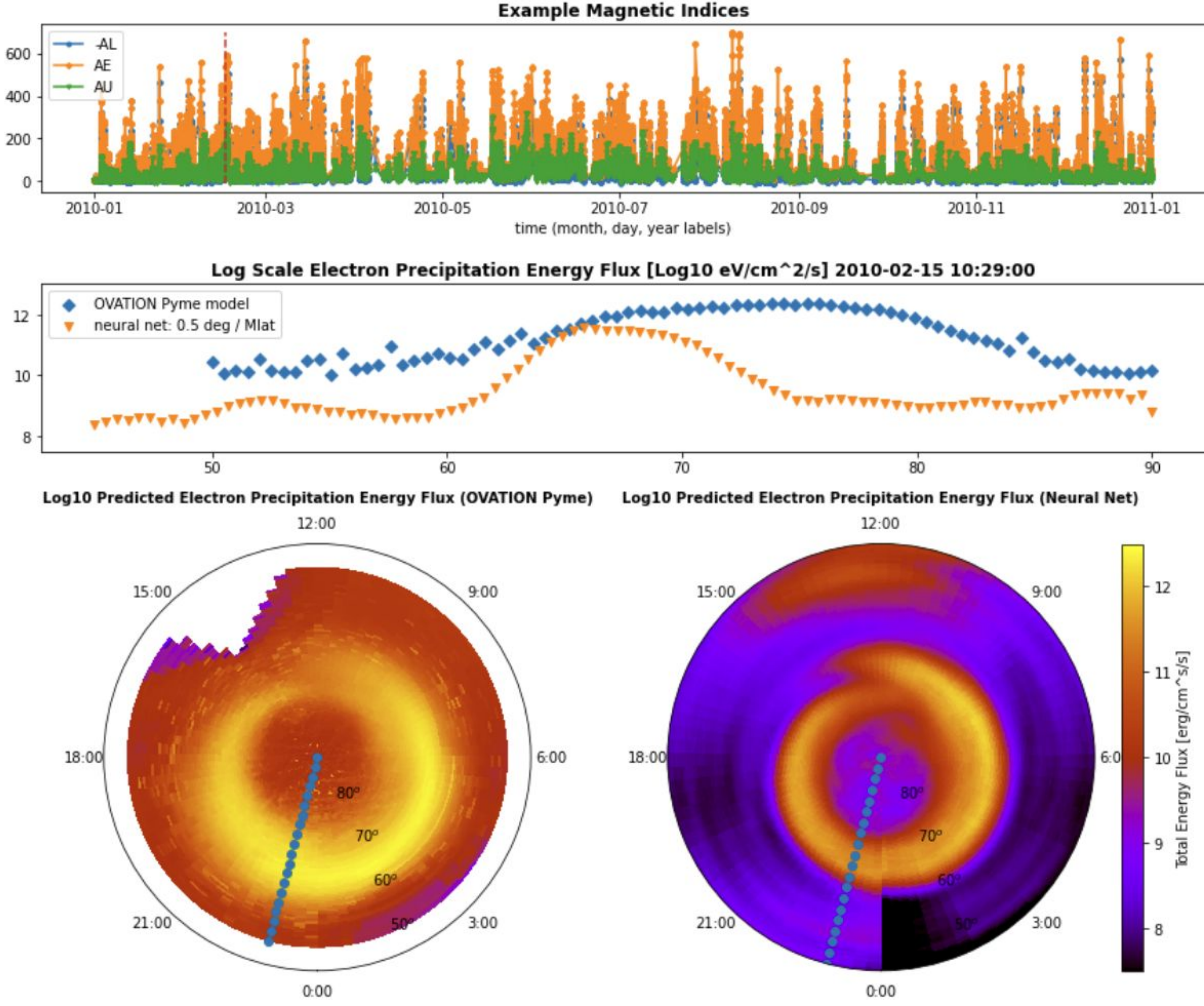
Loss function for each "time step" and 2D target value

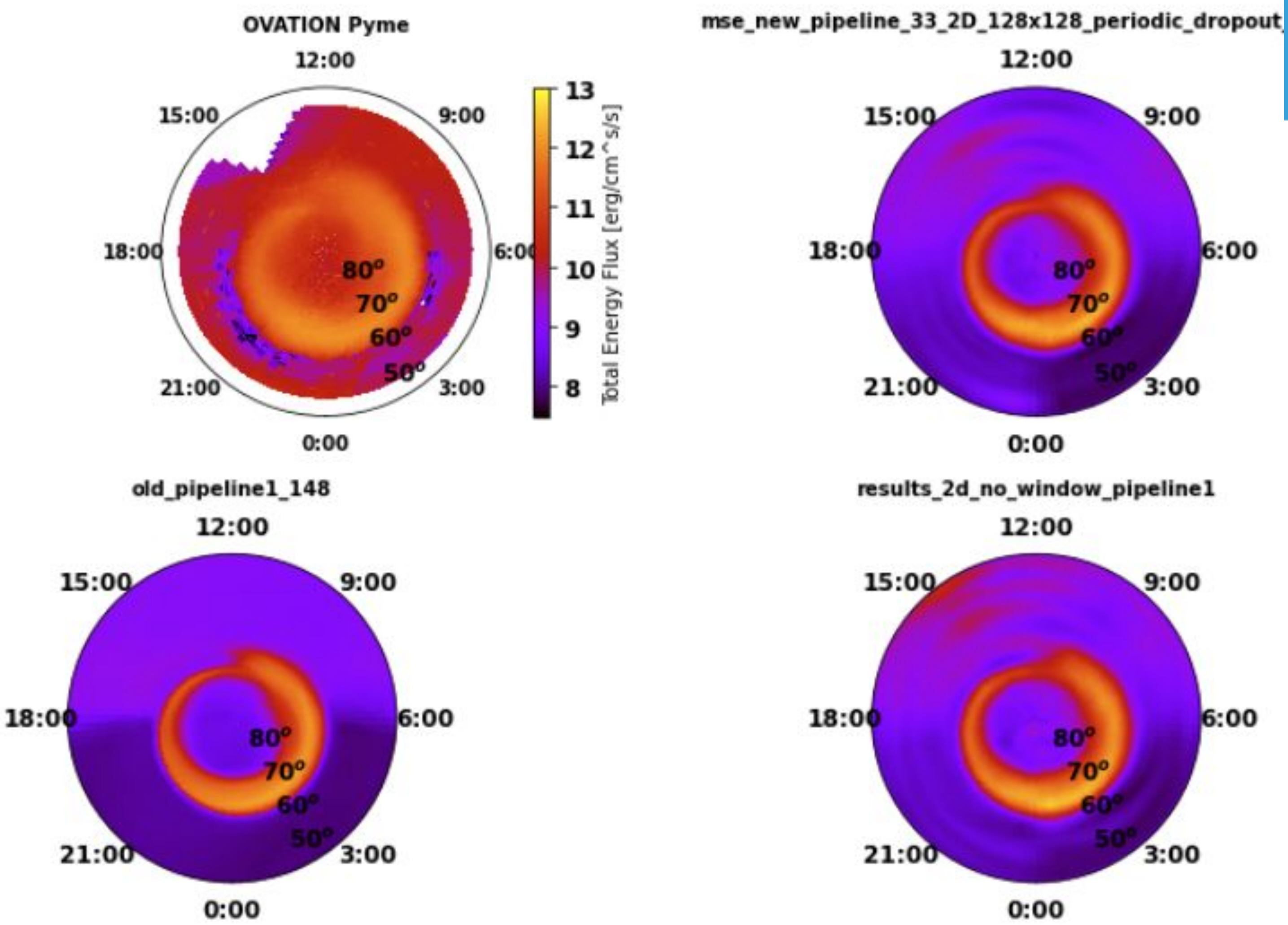
Note: 1024 are still combined for each batch

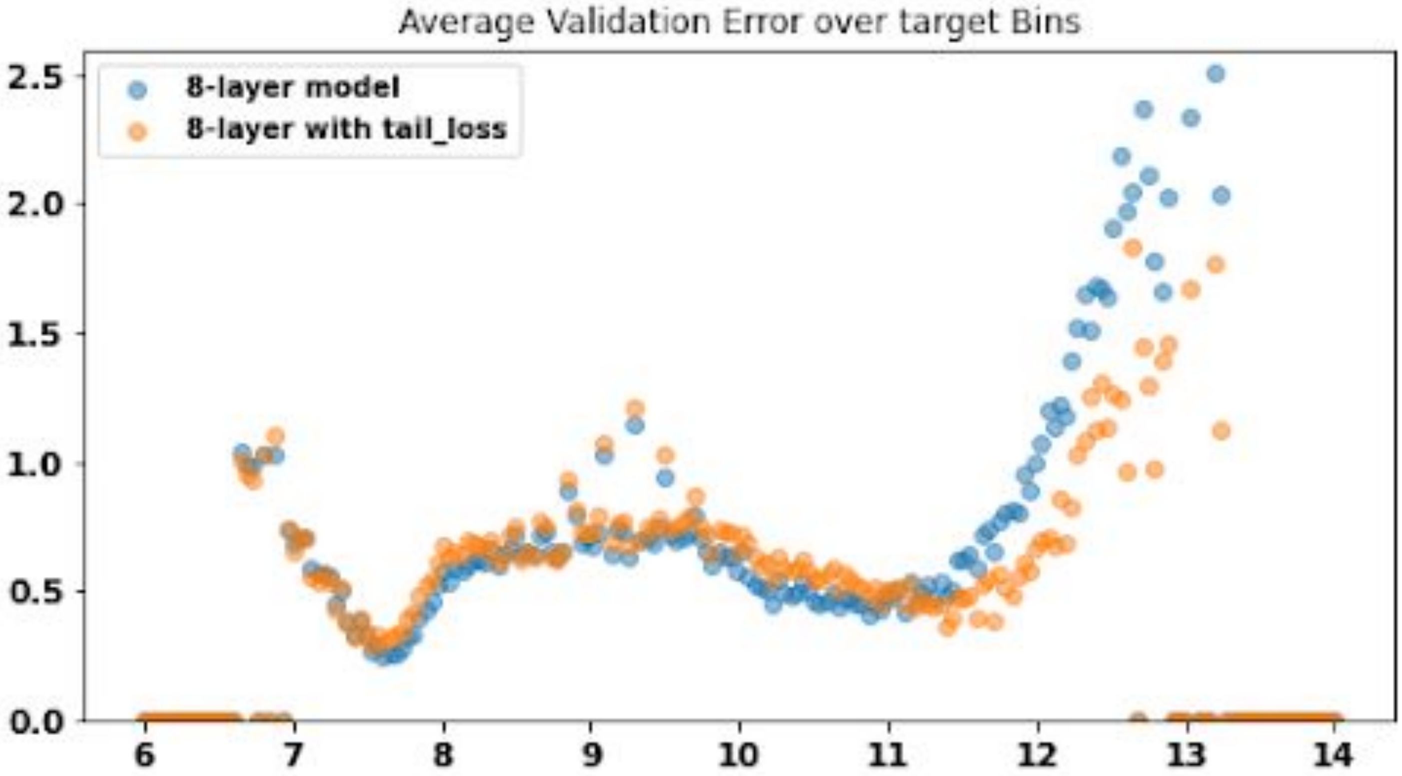
145 Inputs (with solar wind)








OVATION Pyme
mse_new_pipeline_33_2D_128x128_periodic_dropout
old_pipeline1_148
results_2d_no_window_pipeline1
12:00
15:00
9:00
18:00
6:00
21:00
3:00
0:00
80°
70°
60°
50°
Total Energy Flux [erg/cm^s/s]
13
12
11
10
9
8



Average Validation Error over target Bins
8-layer model
8-layer with tail_loss
2.5
2.0
1.5
1.0
0.5
0.0
6
7
8
9
10
11
12
13
14

https://github.com/rmcgranaghan/HEARTBEAT

New Database

- Full DMSP dataset is > 100 GB, cadence is 1 second
    - Currently using every 60th point (1 minute data)
- Still using indices at 5 minute cadence

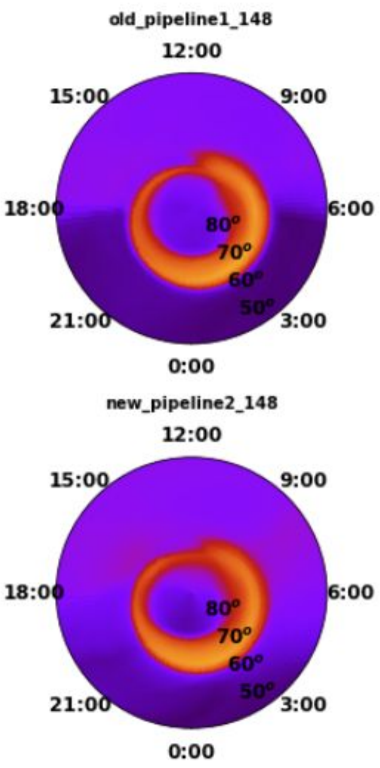
- All DMSP data is saved to CDF files locally
- Indices and solar wind data is access online and moving averages over time a formed

- Can very rapidly create ranges of 1 second data to test for validation (a few days

  - Great for testing single storms

Goal: Create new custom datasets from 1 second data (currently using 1 minute data)

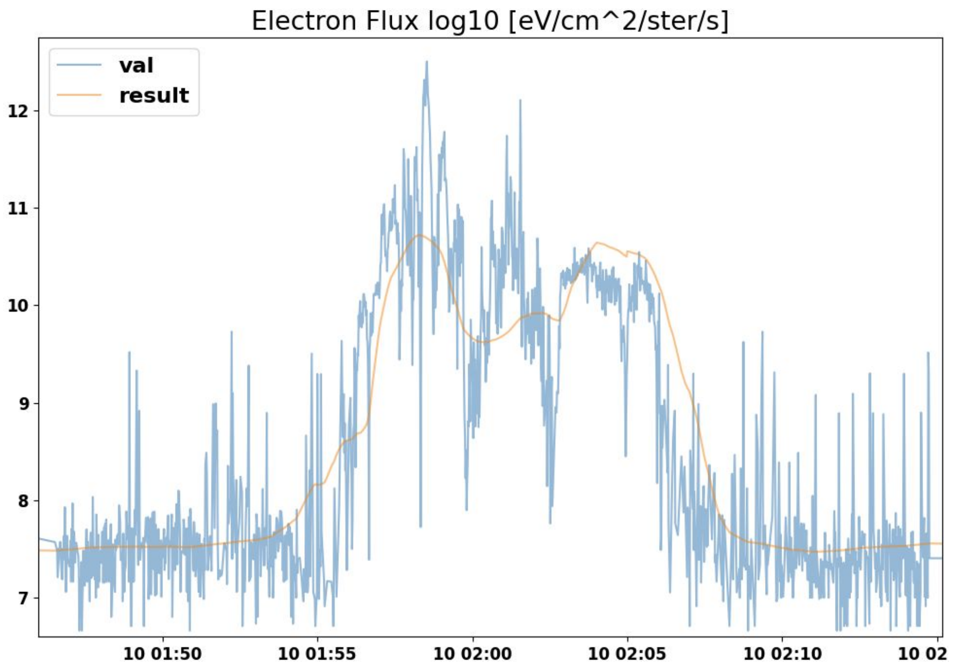
- Our mesoscale interest needs 15 second cadence to get appropriate spatial resolution
- Whole database create is slow,
    - ideal to parallelize and store NASAOmni time histories locally to run faster



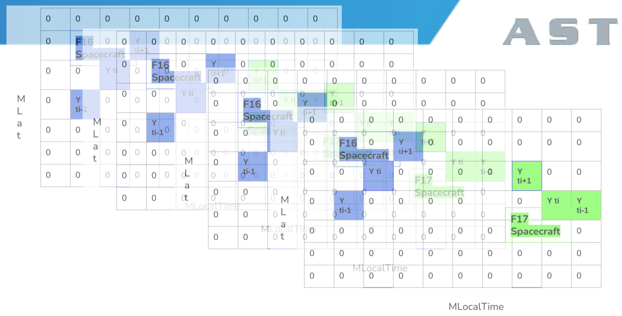
1 second data comparisons

Current issues

- 60x more data than 1 min cadence
- First tries of training on a subset using dense neural network (PrecipNet) averages out the variations
- 1 second data appears very random, hard to separate out “mesoscale” and “smaller scales”
  - Maybe use an approach similar to turbulence modeling??



Future work and Ideas



- Simultaneous Spacecraft 2d model
  - Adding in multiple timestep predictions from one input time
    - Would work like predicting multiple movie frames
- Channel-based Energy Flux (similar to number flux)

$$J_{TOT} = j(E_1)(E_2 - E_1) + \sum_{i=2}^{15} j(E_i)\frac{E_{i+1} - E_{i-1}}{2} + j(16)(E_{16} - E_{15})$$

the integral energy flux in units of keV/cm^2 s sr defined as

$$JE_{TOT} = E_1 j(E_1)(E_2 - E_1) + \sum_{i=2}^{15} E_i j(E_i)\frac{E_{i+1} - E_{i-1}}{2} + E_{16} j(E_{16})(E_{16} - E_{15})$$

- Improving mesoscale identification
  - Simple solution: running at higher resolution
  - Extended solution: use 1-second resolution data (right now using 60-second sub-sampled data samples)
- Tail Loss function exploration
- Phase II ideas
  - Multi-task learning (auroral region + energy and number flux)
- The challenges:
  - Computational burden of developing the full-map model? Of using one-second data?

https://github.com/rmcgranaghan/HEARTBEAT