Space Weather: A Multi-Disciplinary Approach

Lorentz Center, Leiden, the Netherlands

Empirical modeling of the plasmasphere dynamics using neural networks

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OUTLINE

1. Motivation
2. Methodology
3. Model validation
4. Results
5. Conclusions

PLASMASPHERE

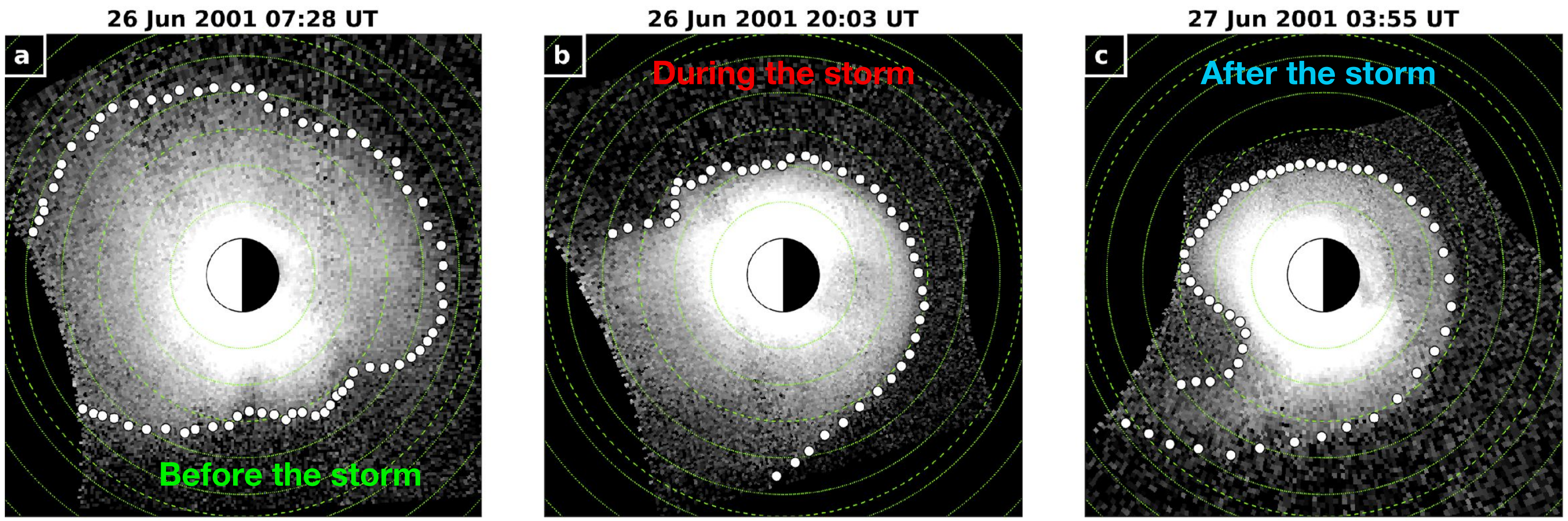


IMAGE EUV images
of He+ distribution.
Spasojevic et al. [2003]

PLASMASPHERE

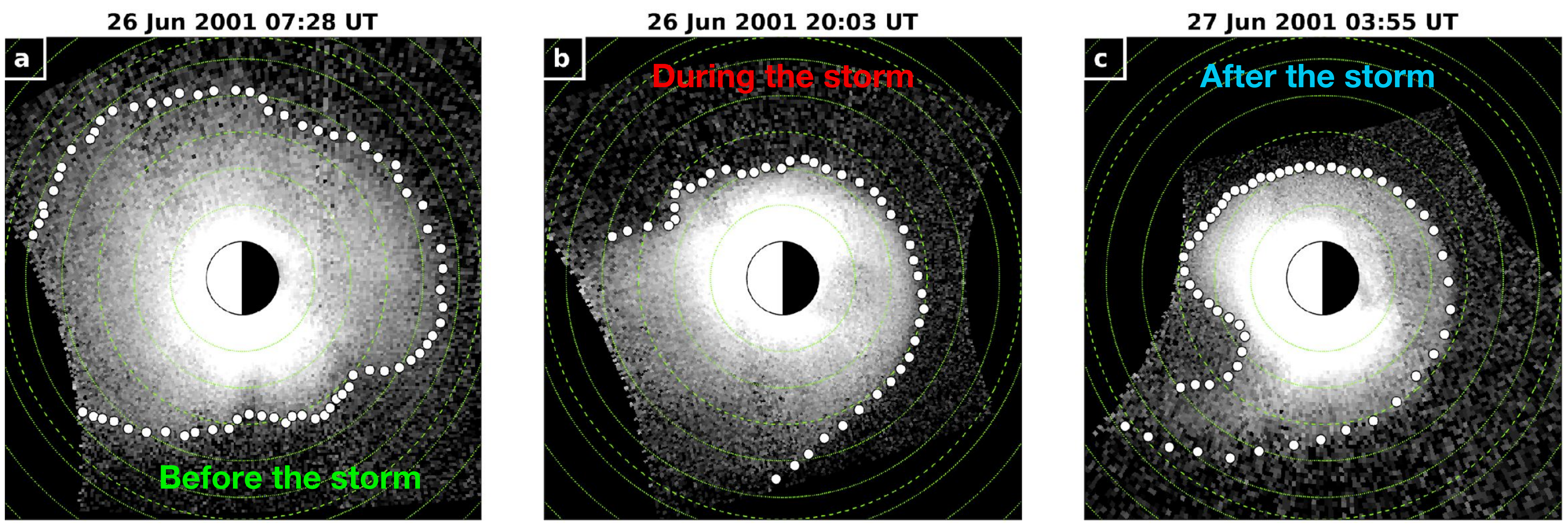
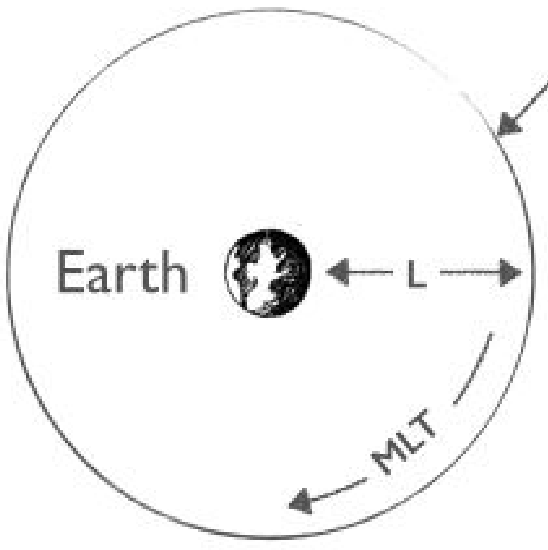


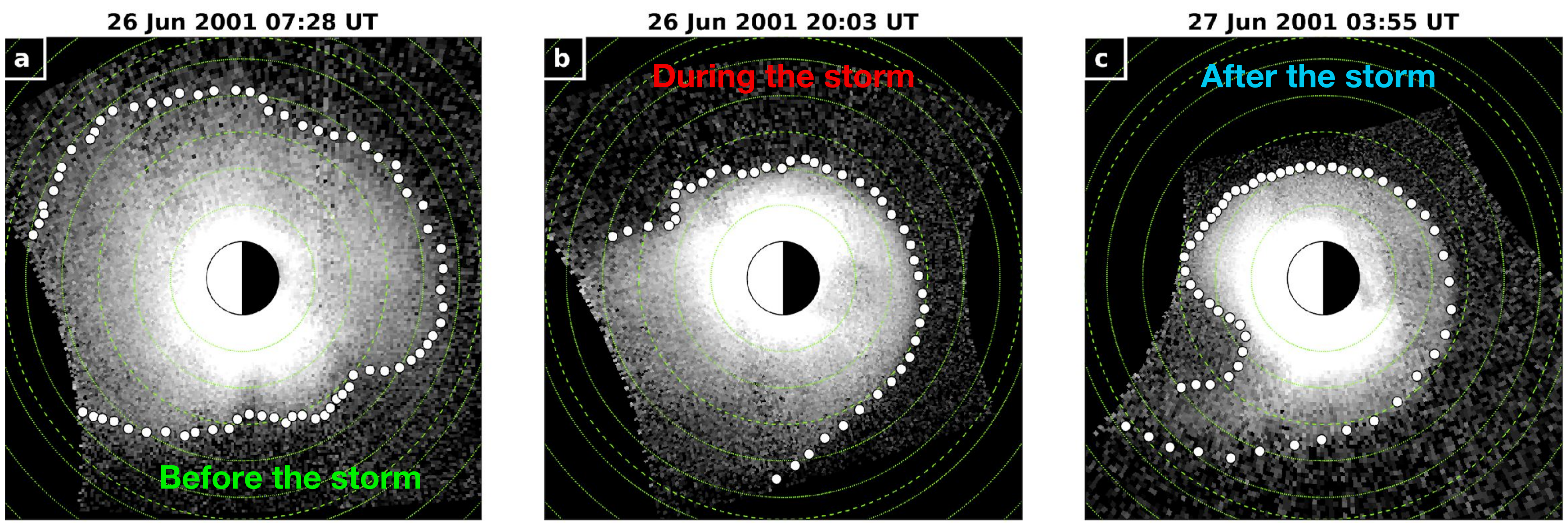
IMAGE EUV images of He+ distribution. Spasojevic et al. [2003]

- Carpenter and Anderson, 1992
- Sheeley et al., 2001

Plasmasphere (model)



PLASMASPHERE



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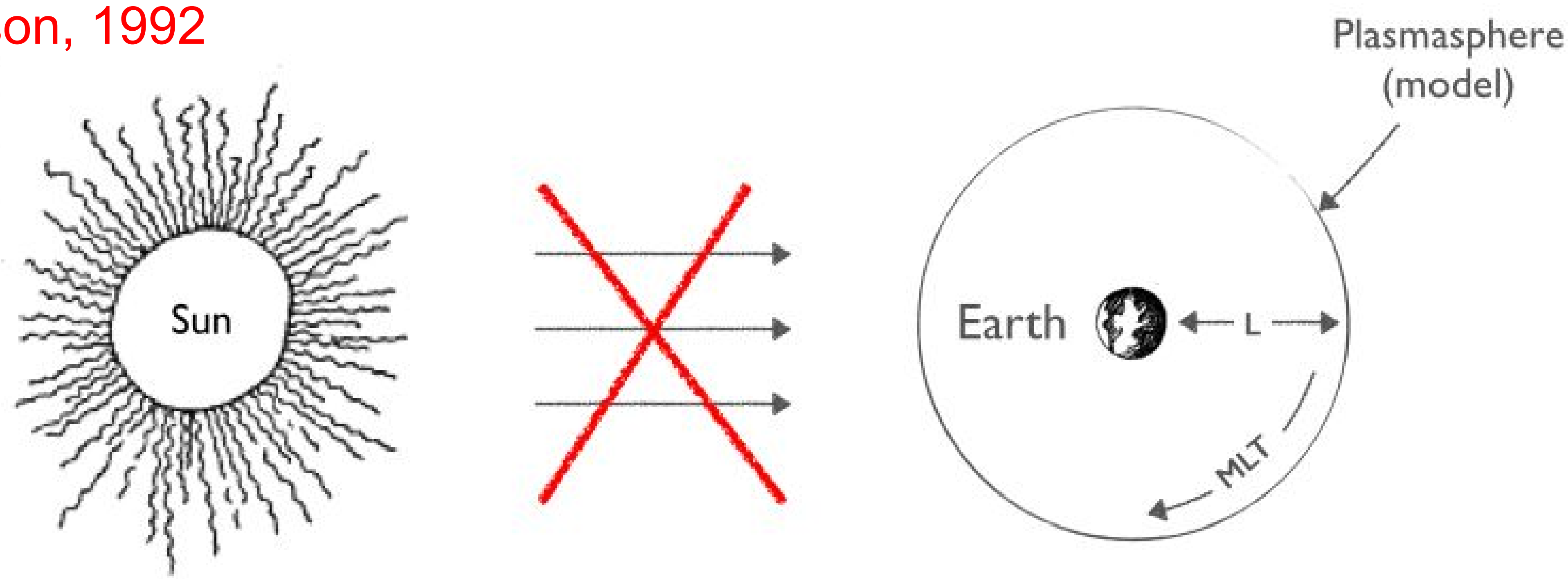


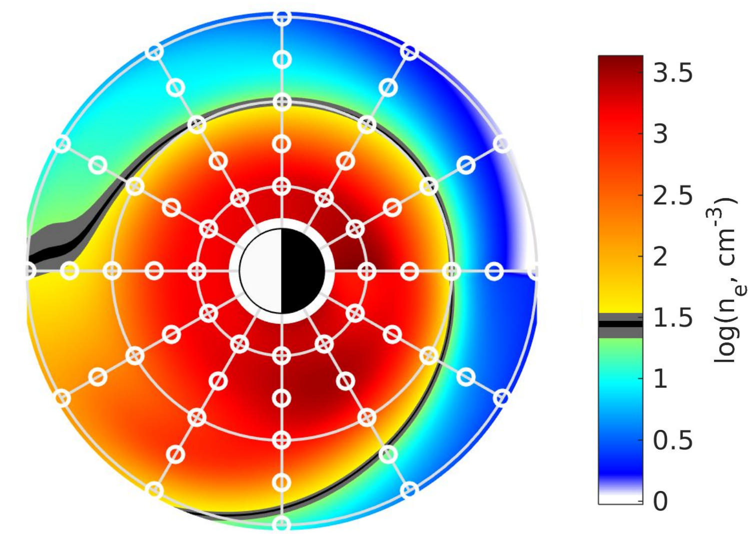
GOAL: GLOBAL DENSITY MODEL

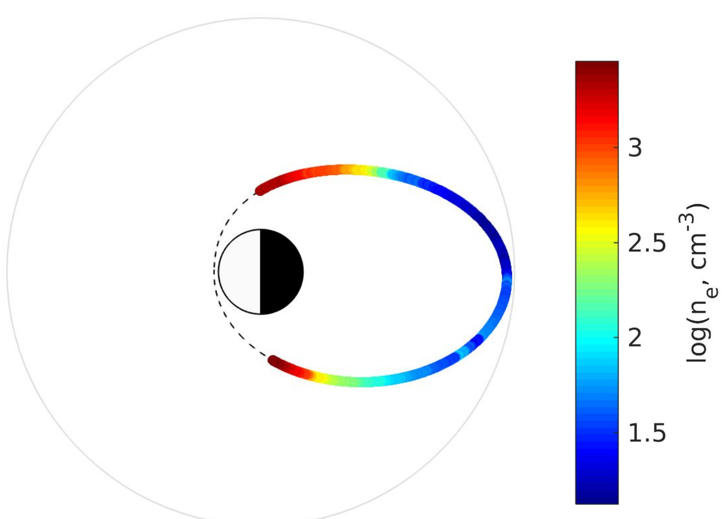
Training data

Input: solar wind and geomagnetic parameters, location

Output: electron density dataset derived using the NURD algorithm for the Van Allen Probes mission [*Zhelavskaya et al.*, 2016]*

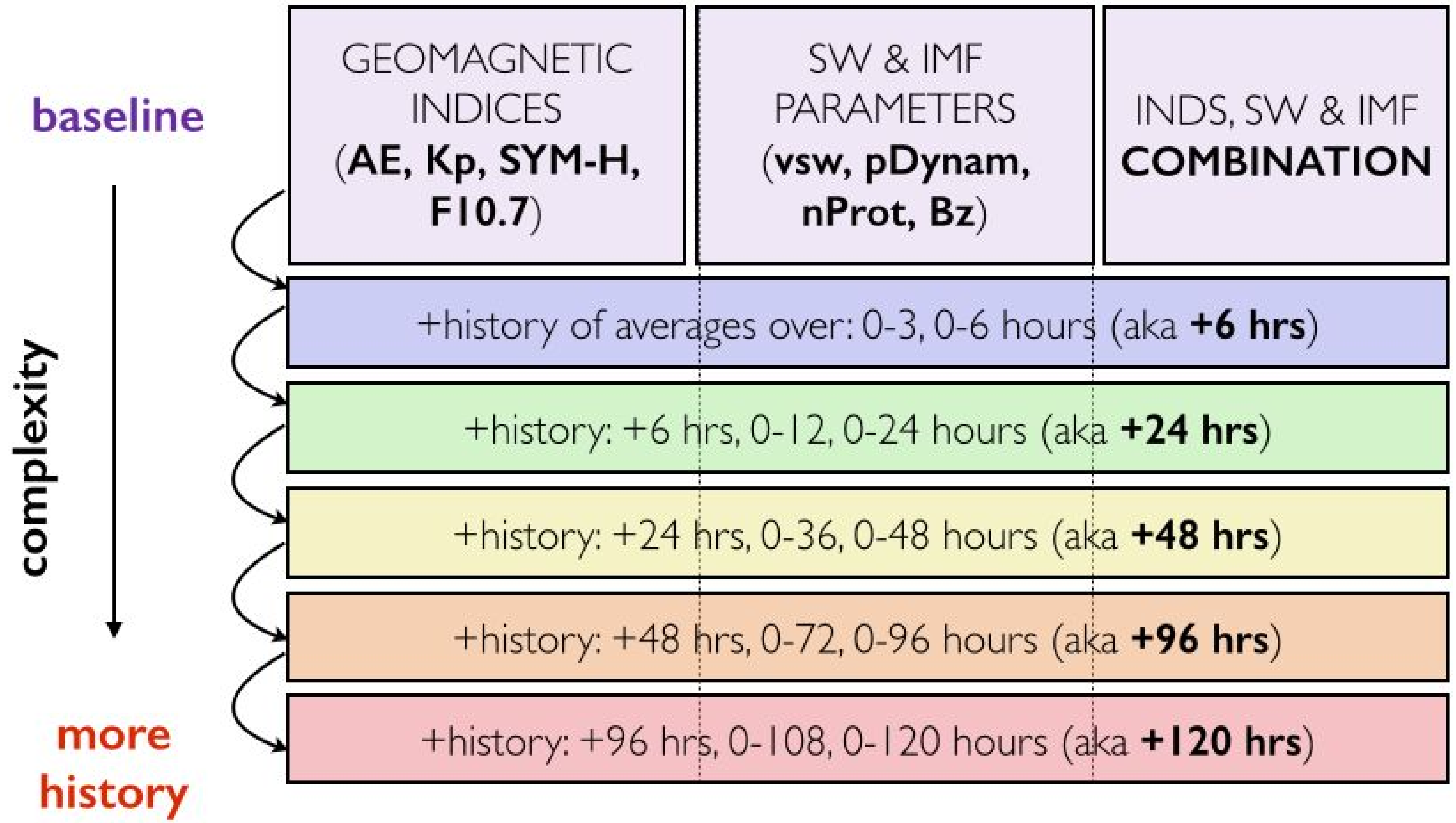
Neural network





* https://tinyurl.com/NURDdensity

INPUTS TO NEURAL NETWORK

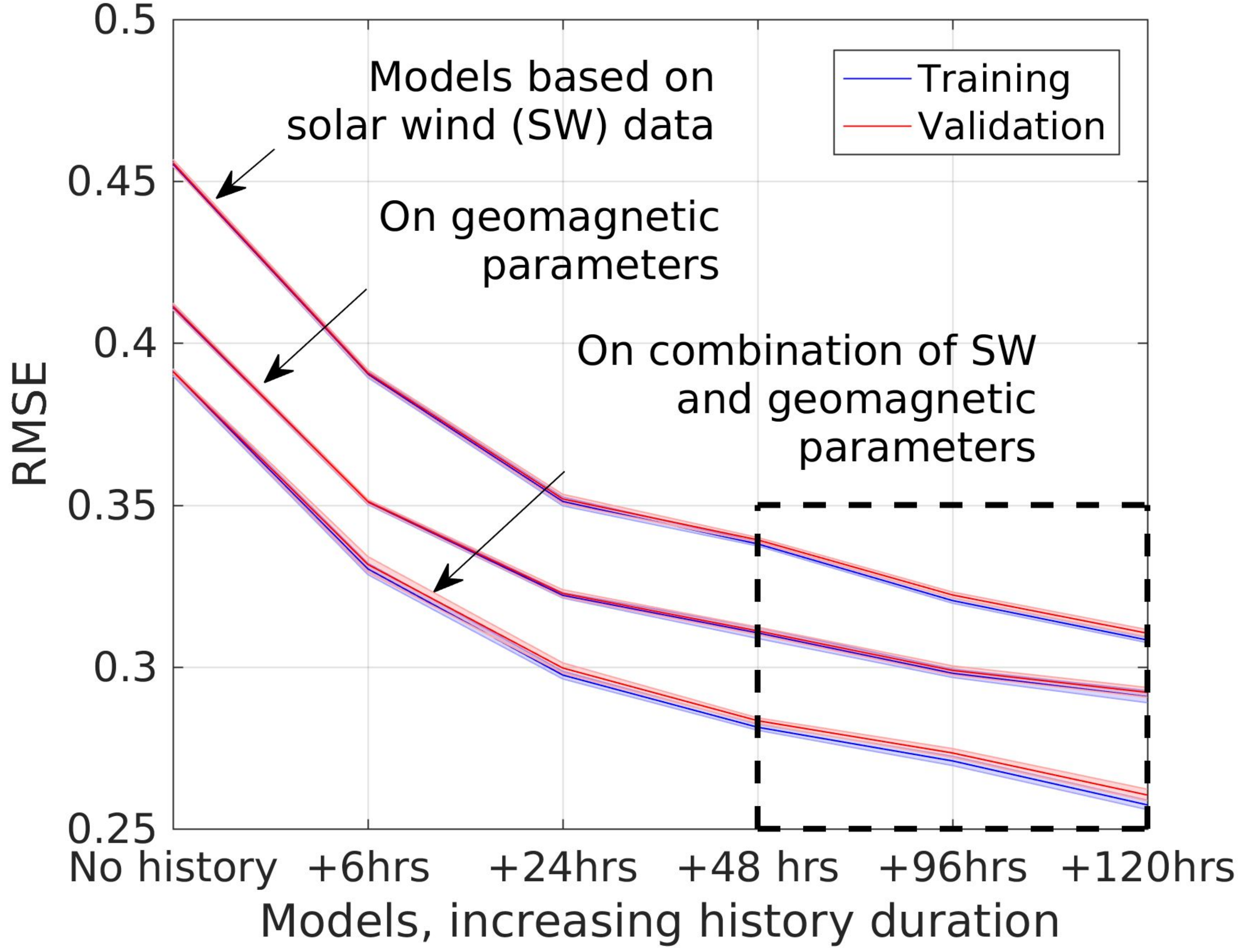


VALIDATION

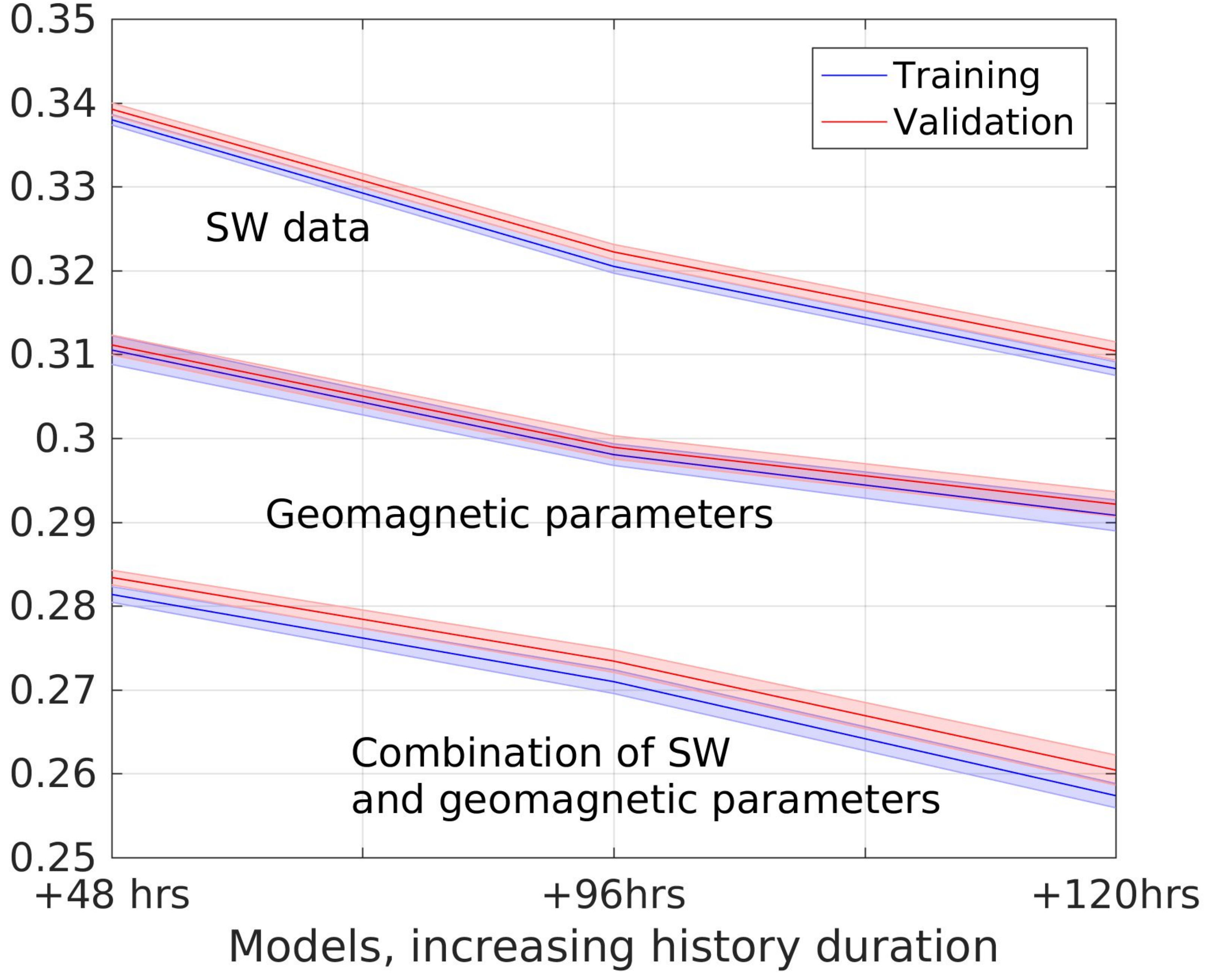
1. K-fold cross validation (K = 5) - *local* validation (quantitative).

2. Comparison with manually selected plasmapause locations from IMAGE EUV satellite images - *global* validation (qualitative).

K-FOLD CROSS VALIDATION

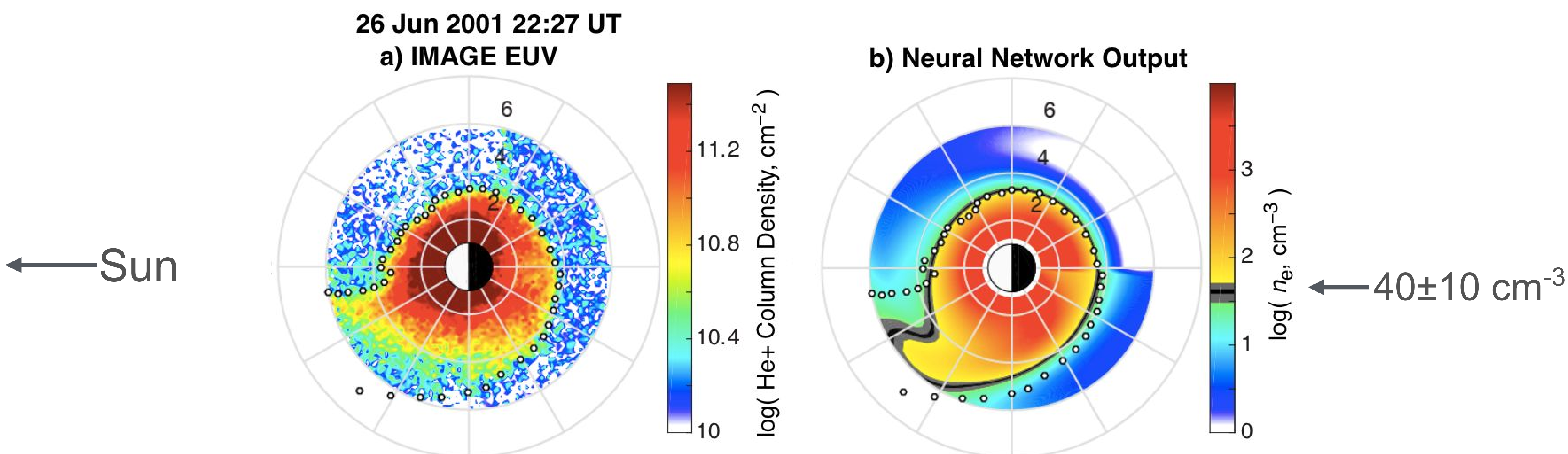


K-FOLD CROSS VALIDATION



GLOBAL VALIDATION

Comparison with manually selected plasmapause locations from IMAGE EUV satellite images (2000 - 2005)



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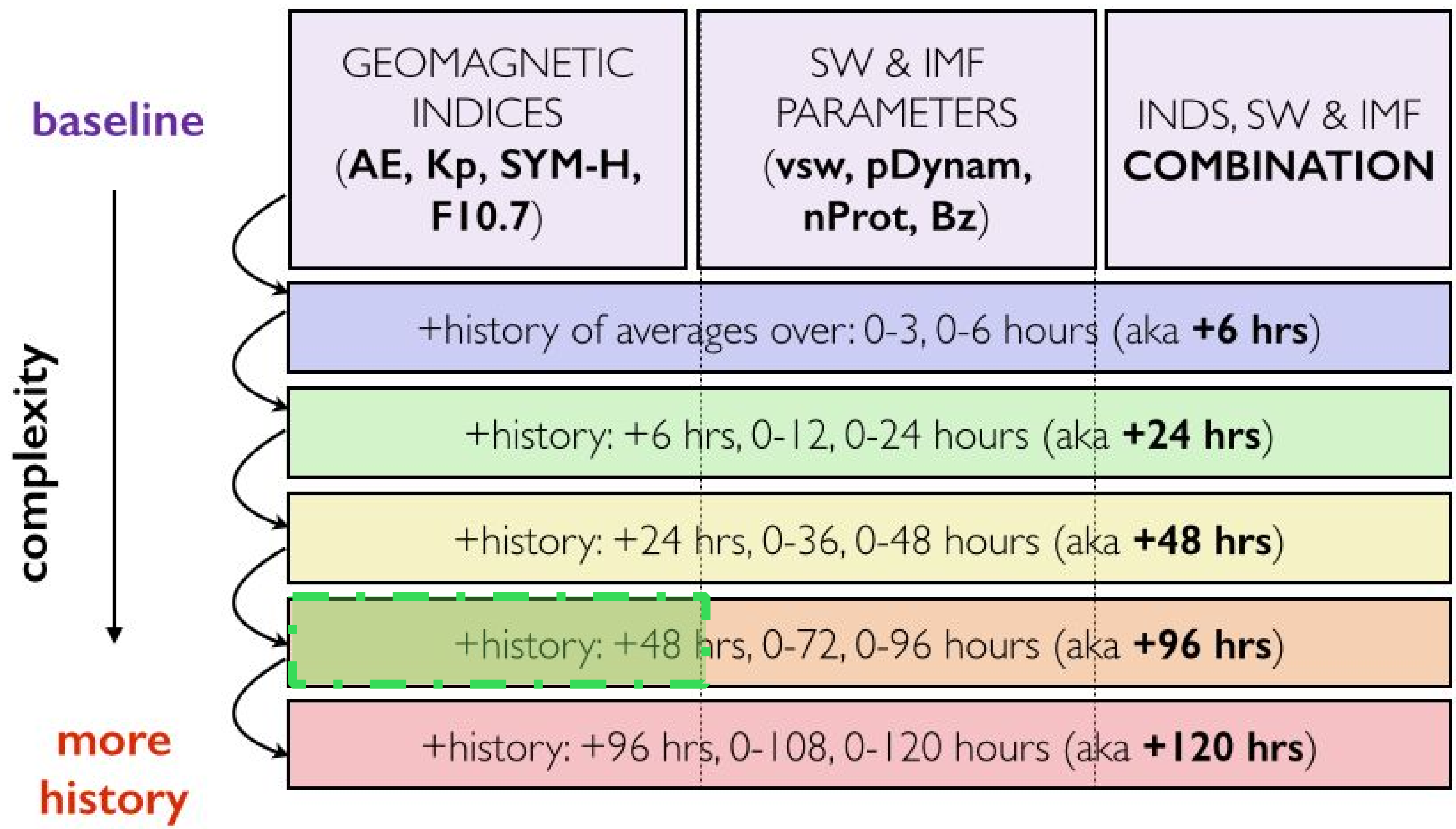
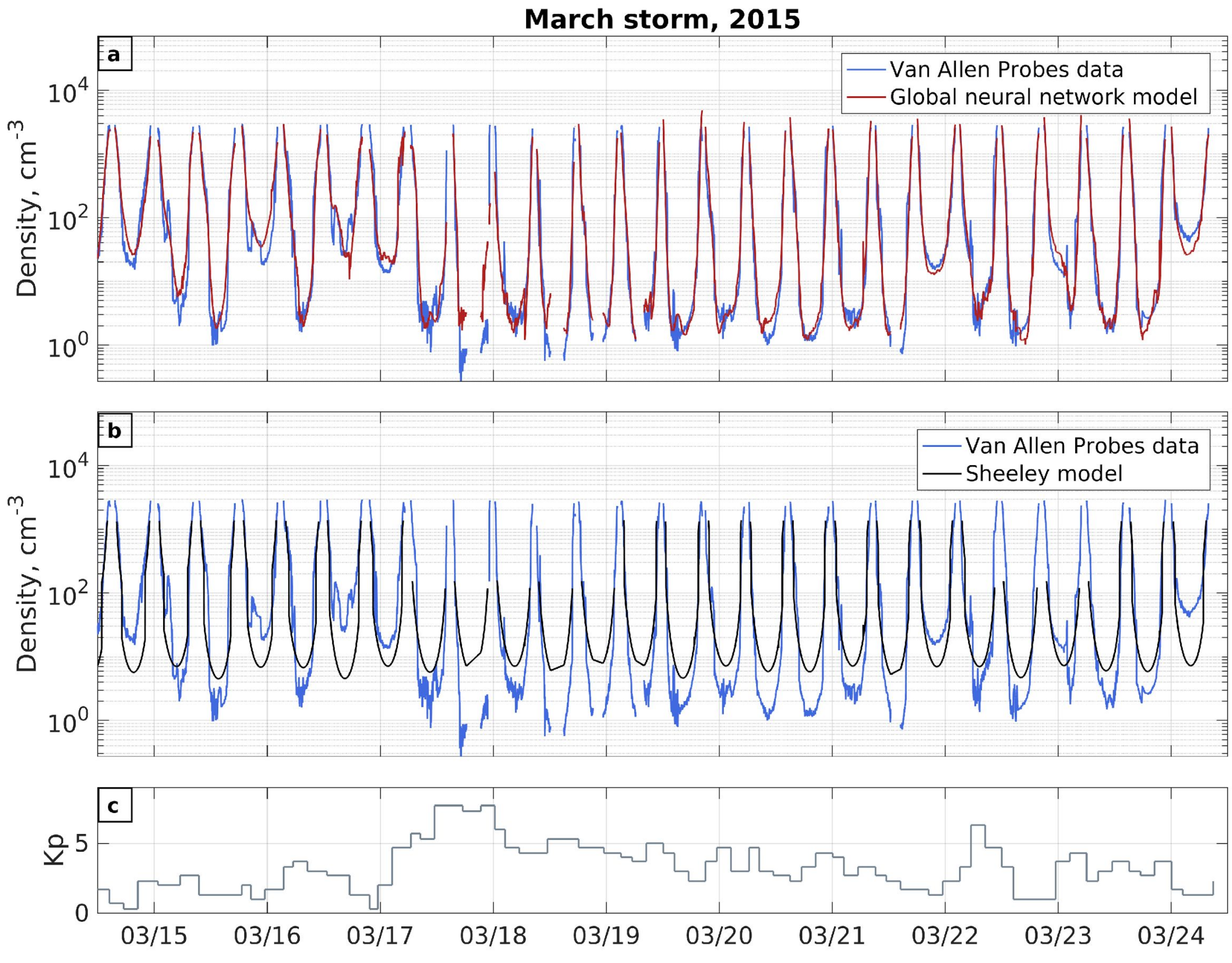
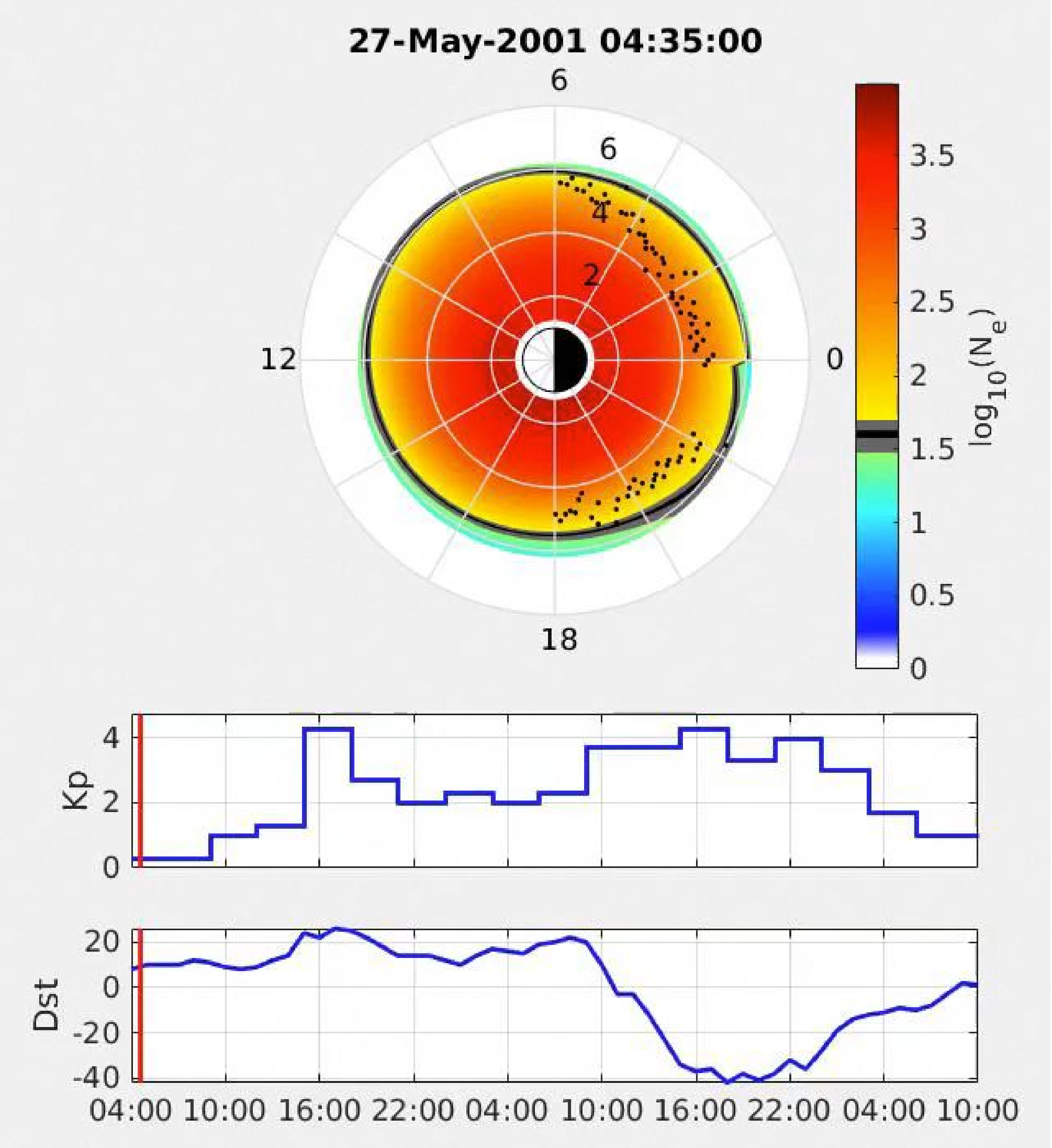


EXAMPLE: MARCH STORM 2015



EXAMPLE: GLOBAL MODEL OUTPUT

Sun



CONCLUSIONS

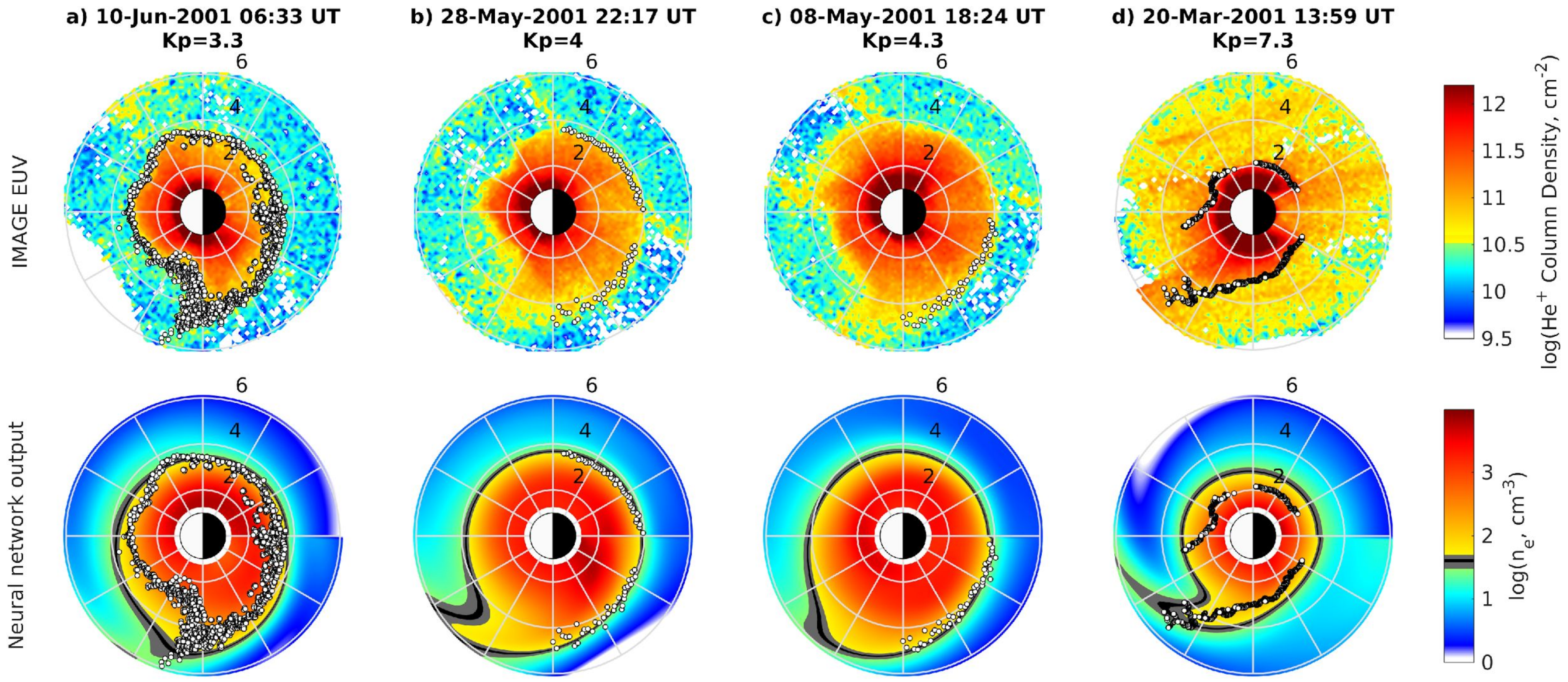
- We developed a dynamic plasmasphere density model by applying neural networks to in situ density measurements and verifying with global images from IMAGE EUV.
- The optimal model takes as input the 96-hour time history of geomagnetic indices.
- The model can reproduce the plasmasphere density and can capture plume formation and evolution (https://tinyurl.com/globalDensity).

THANK YOU!

BACKUP SLIDES

RESULTS

We used feedforward neural network with one layer to reconstruct the plasmasphere dynamics



VALIDATION

- K-fold cross validation

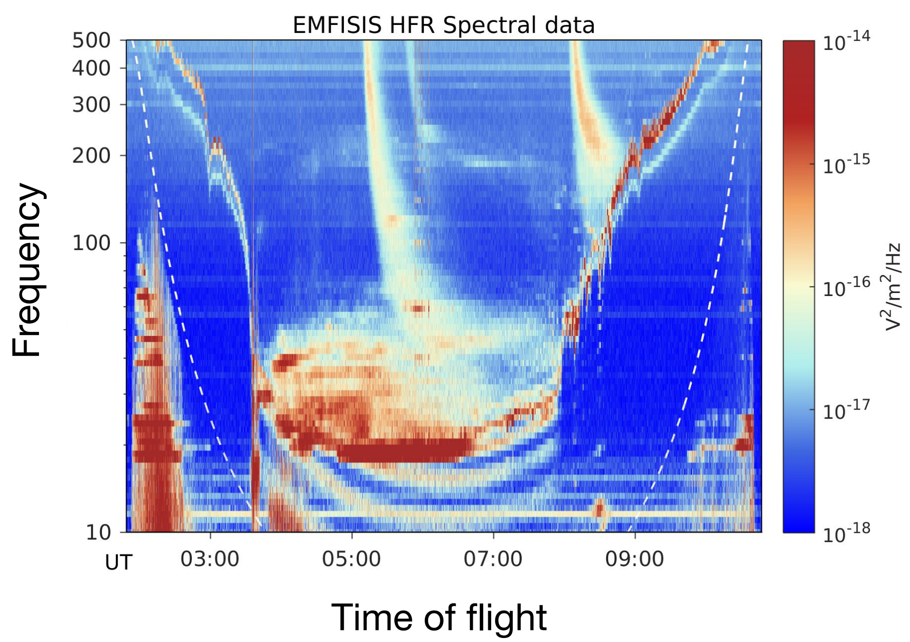
Iteration 1	Validation	Train	Train	Train	Train
Iteration 2	Train	Validation	Train	Train	Train
Iteration 3	Train	Train	Validation	Train	Train
Iteration 4	Train	Train	Train	Validation	Train
Iteration 5	Train	Train	Train	Train	Validation

K = 5

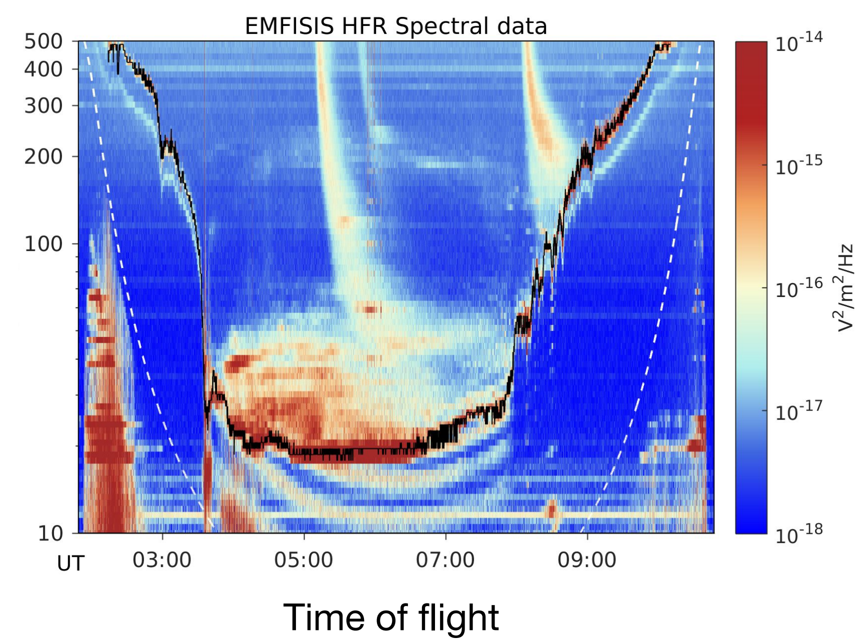
DETERMINING PLASMA DENSITY FROM SATELLITE MEASUREMENTS

Determining the electron density from intense upper-hybrid band emission in dynamic spectrograms:

EMFISIS spectral data for one orbital pass



Upper-hybrid frequency



Plasma density

$$n_e = \frac{f_{uhr}^2 - f_{ce}^2}{8980^2}$$

DETERMINING PLASMA DENSITY FROM SATELLITE MEASUREMENTS

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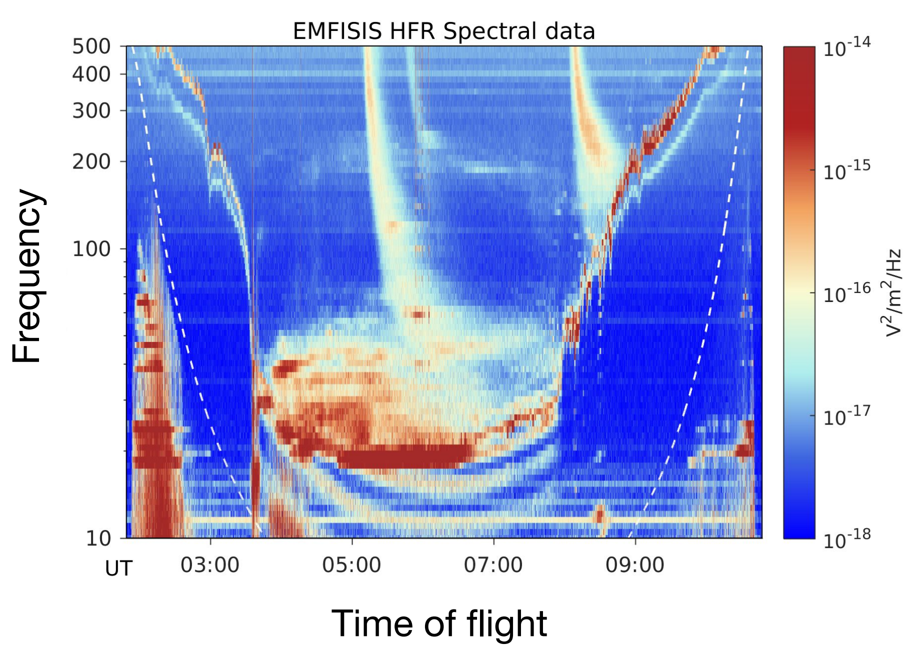
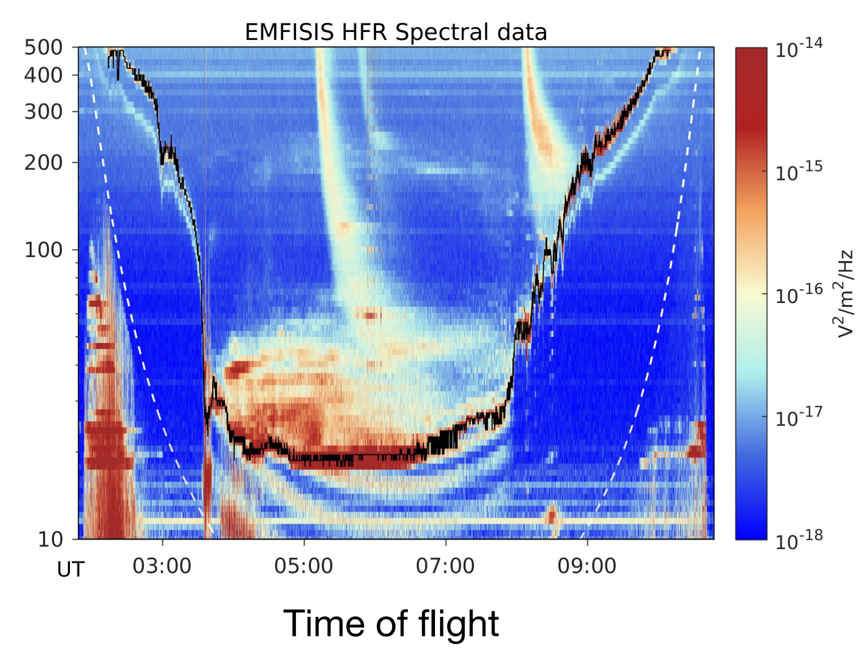
EMFISIS spectral data for one orbital pass

Neural networks

Upper-hybrid frequency





Plasma density

$$n_e = \frac{f_{uhr}^2 - f_{ce}^2}{8980^2}$$

NURD

Neural-network-based **U**pper-hybrid **R**esonance **D**etermination algorithm

Split ratio: 34% ÷ 33% ÷ 33%
training ÷ validation ÷ test

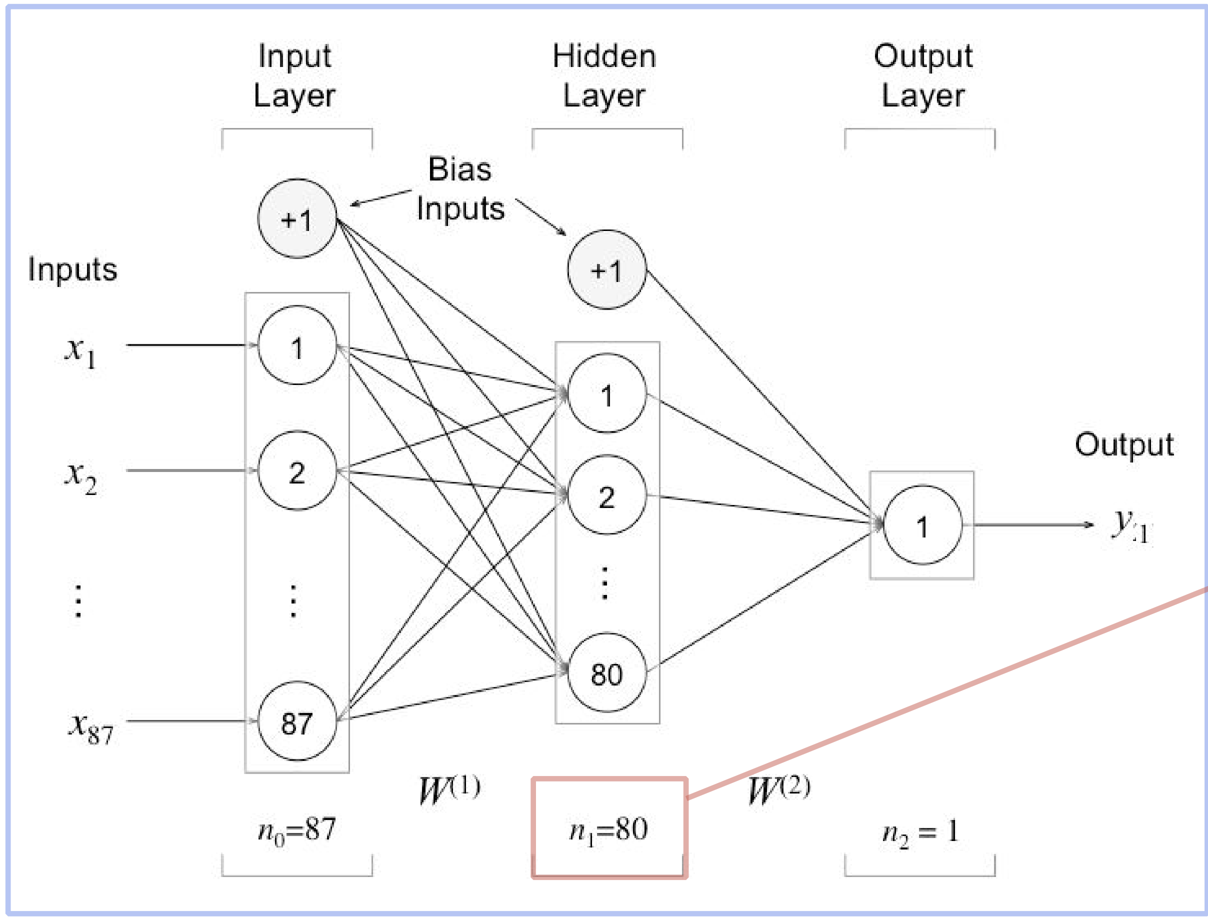
Inputs

1-82	Spectrum
83	f_{ce}
84-85	Location (L, MLT)
86	K_p
87	$fbin_{max}$

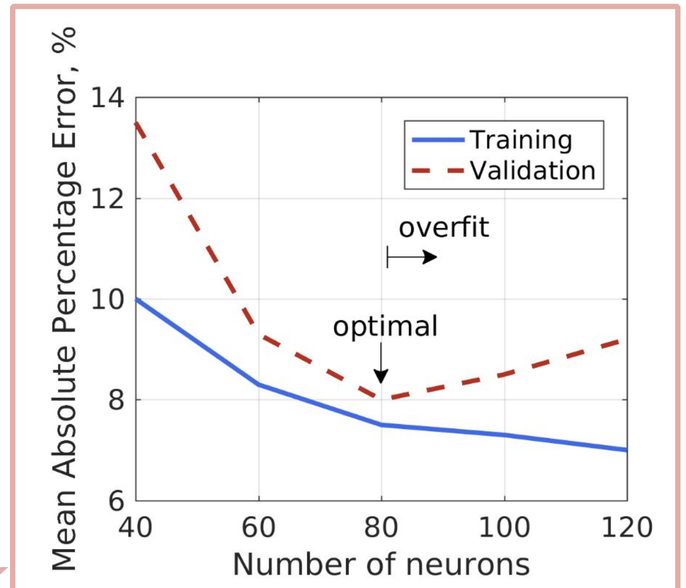
Output

f_{uhr} along the satellite orbit. Training data - 2.5 years of f_{uhr} values derived with AURA algorithm [*Kurth et al.*, 2015].

Feedforward neural network



Configuration selection



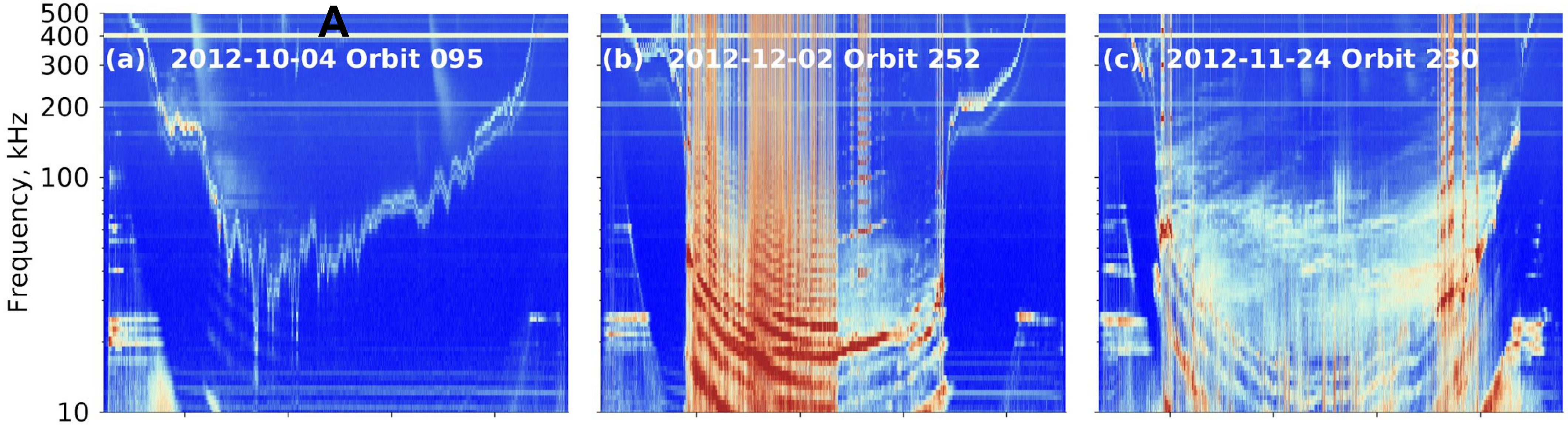
$$\mathrm{MAPE} = \frac{1}{\mathrm{M}} \sum_{i=1}^{\mathrm{M}} \frac{\left| f_i^{\mathrm{AURA}} - f_i^{\mathrm{NURD}} \right|}{f_i^{\mathrm{AURA}}} * 100\%$$

Error on the test set

MAPE = 8%

ORBIT TYPES

Type A | **Type B** | **Type C**

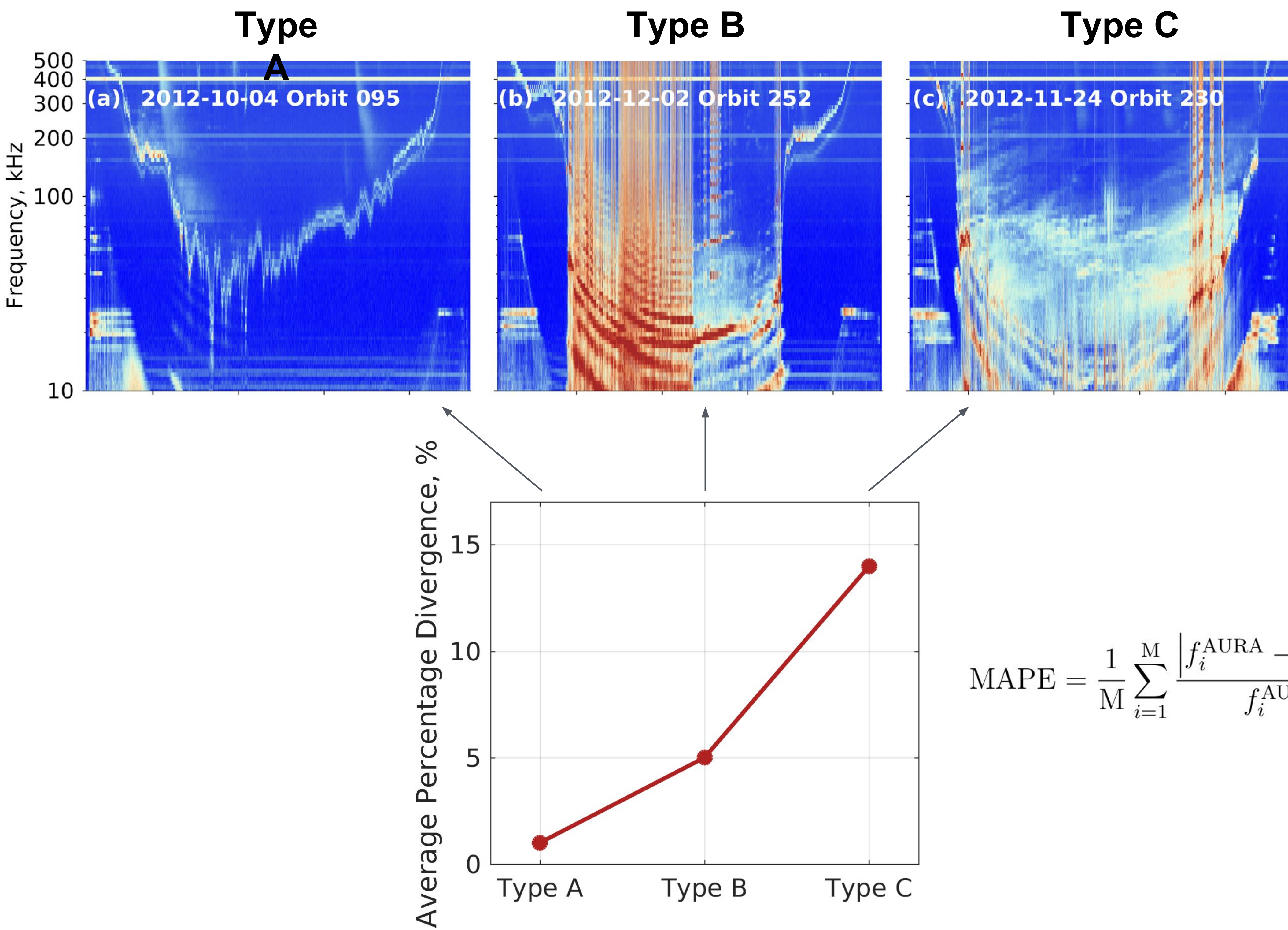


70% of orbits processed by AURA

20% of orbits

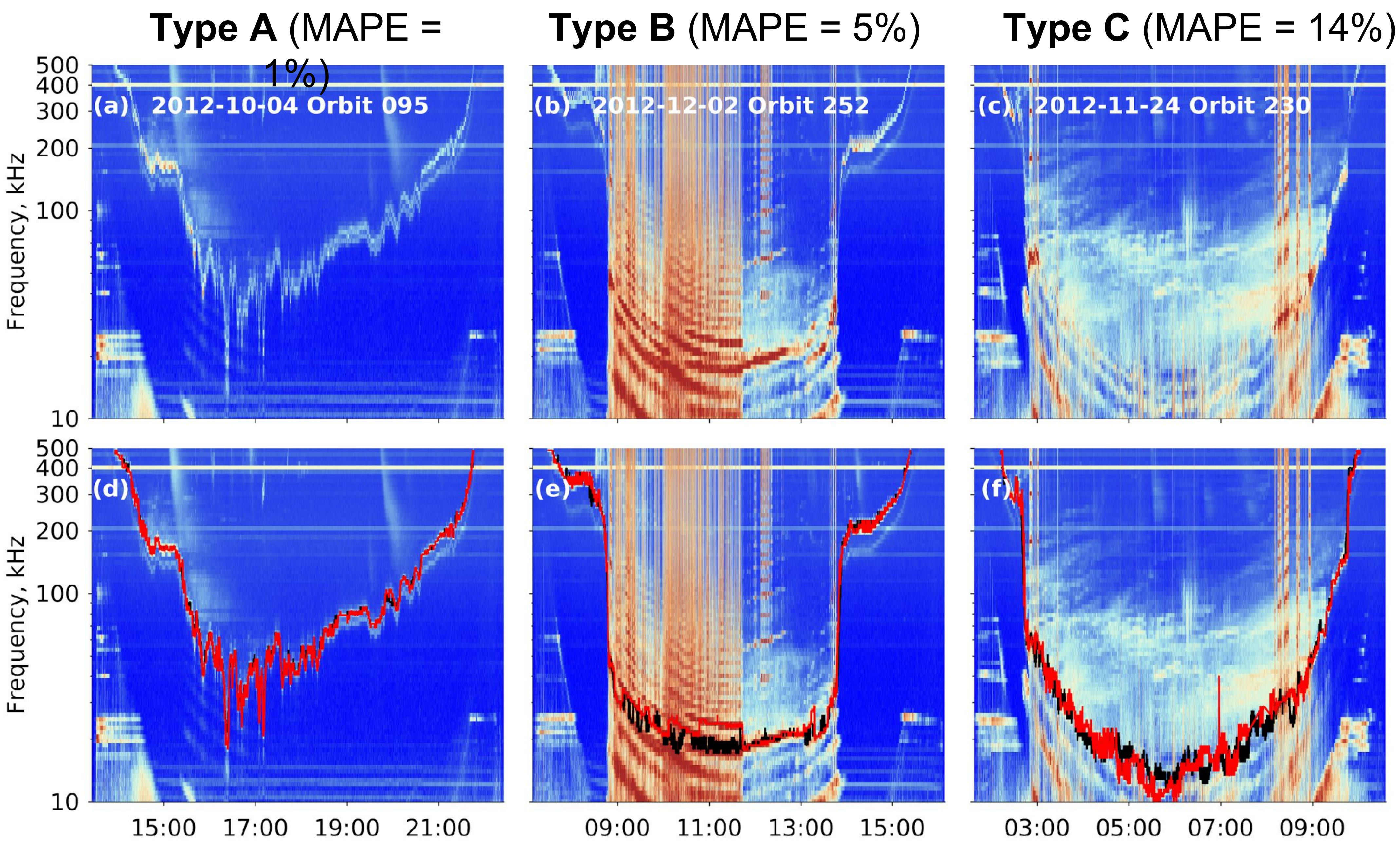
10% of orbits

NURD'S PERFORMANCE



$$\mathrm{MAPE} = \frac{1}{\mathrm{M}}\sum_{i=1}^{\mathrm{M}} \frac{\left|f_i^{\mathrm{AURA}} - f_i^{\mathrm{NURD}}\right|}{f_i^{\mathrm{AURA}}} * 100\%$$

EXAMPLES



red – upper-hyrbid frequency identified using AURA,

black – upper-hyrbid frequency identified using NURD

DENSITY DISTRIBUTION

Plasmasphere and trough empirical density models [*Sheeley et al*., 2001].

Mean of the derived density distribution for the plasmasphere and trough.

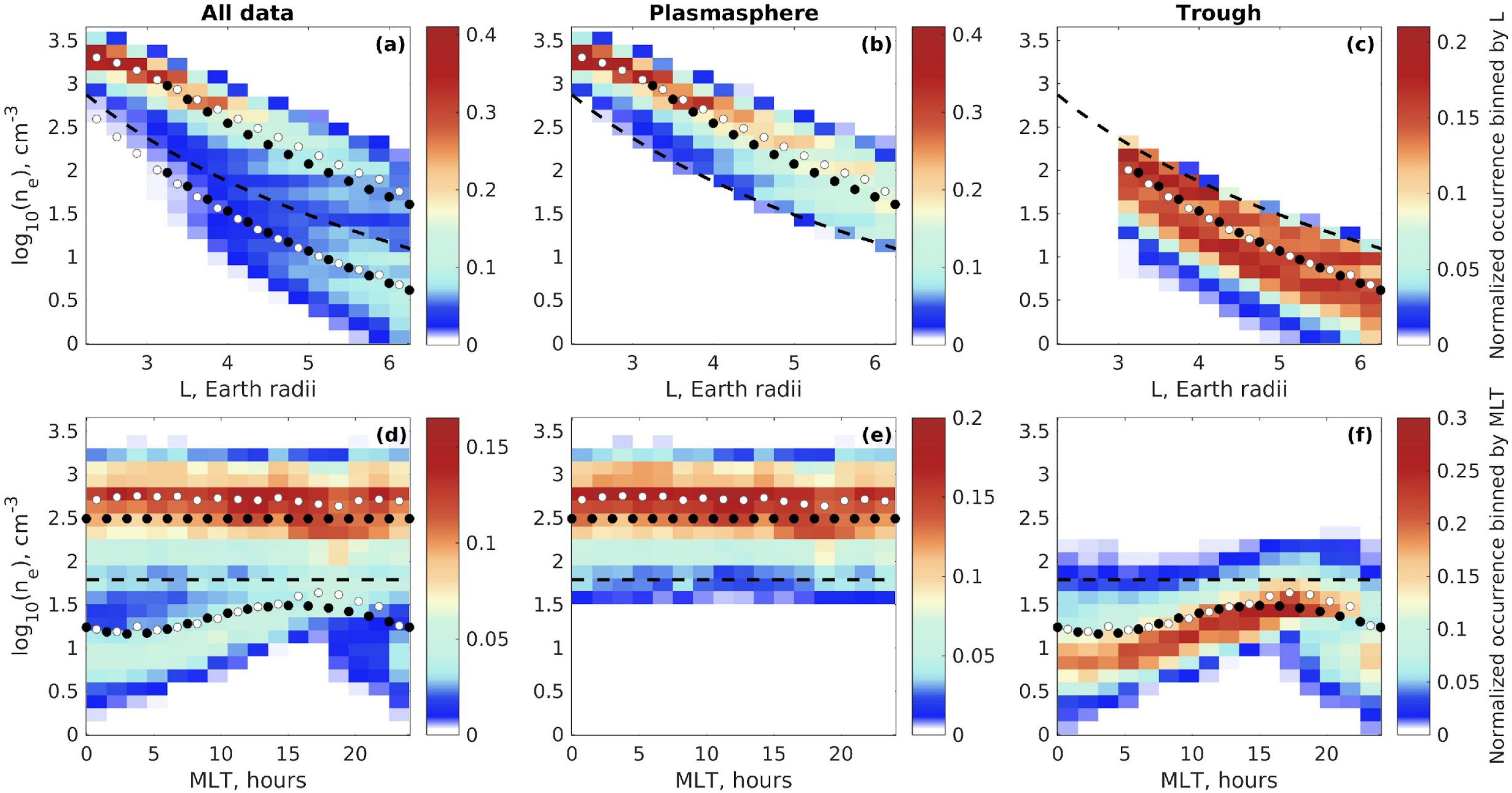
Separation border between plasmasphere and trough:

$$n_\mathrm{b} = 10\left(\frac{6.6}{L}\right)^4$$

(as in *Sheeley et al*. [2001]).

1

2

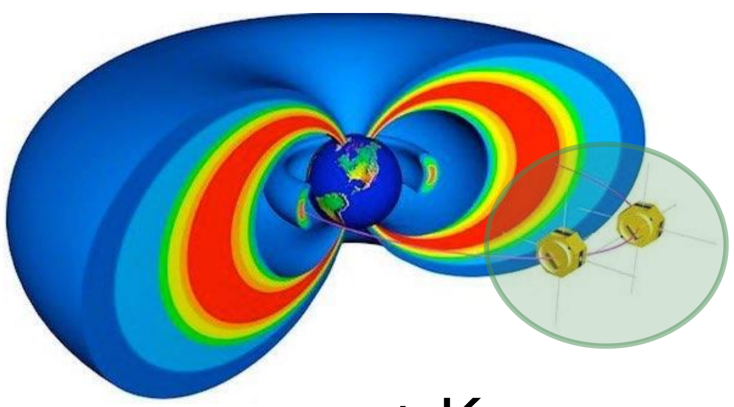


CONCLUSIONS I

- We developed a neural network model to infer the upper hybrid resonance line from plasma wave observations.
- The model is applied to 3750 orbits of Van Allen Probes electric and magnetic field data, and a dataset of electron number density is produced (https://tinyurl.com/NURDdensity).
- Using the developed algorithm, the electron density can be determined to a much finer resolution than using existing empirical models.

NURD: LOCAL DENSITY

Van Allen Probes EMFISIS measurements



+ Kp

Neural network

Local density reconstruction