Characterizing Earth's Magnetosheath and High-Speed Downstream Jets using Machine Learning

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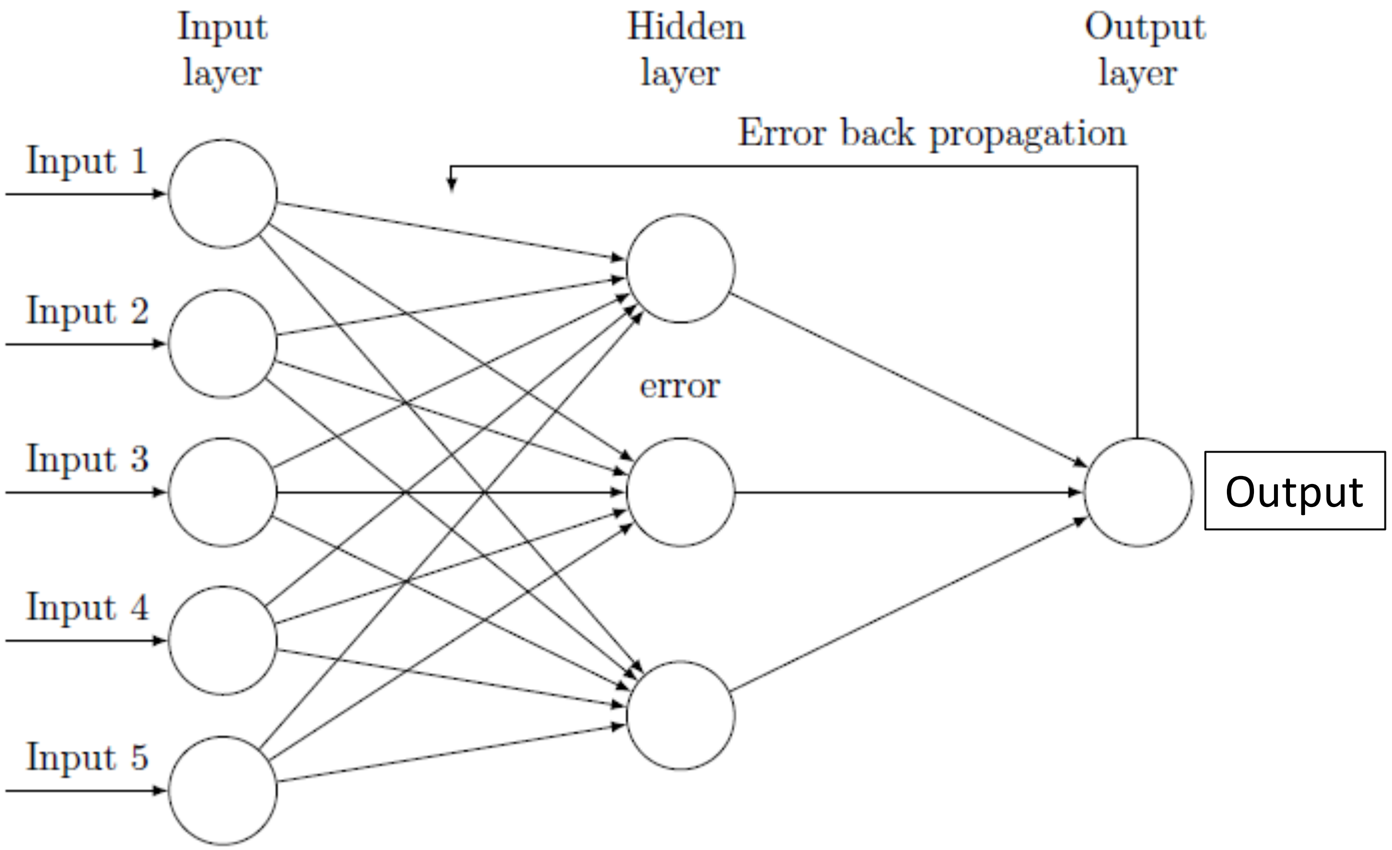
CENTER FOR GEOSPACE STORMS

Introduction
(Neural Networks)

Neural Networks & Backpropagation

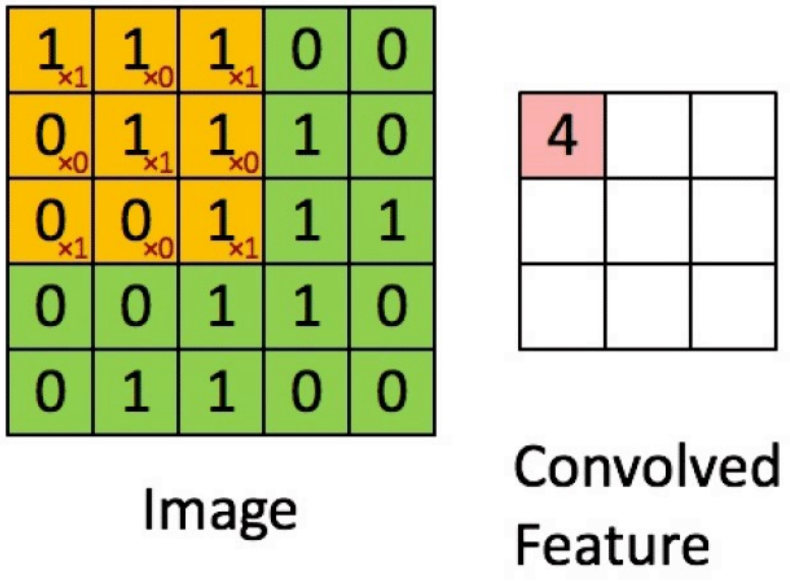
Supervised Learning

- Labeled data
- Known input/output
- Unknown map/relationship



Convolutional Neural Network (CNN) Layers

Convolution
Extract features & keep spatial relationship



Pooling/Subsampling
Reduce dimensionality & retain information

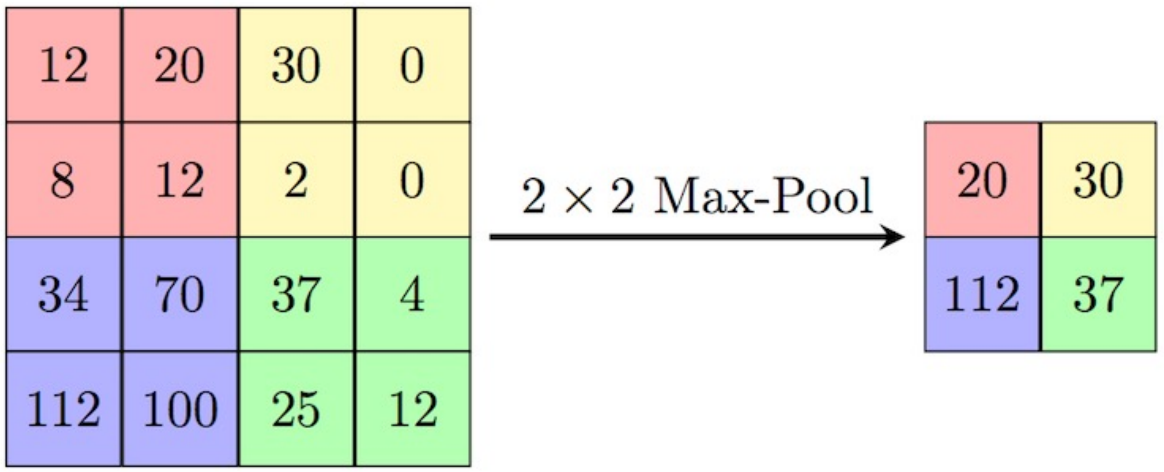


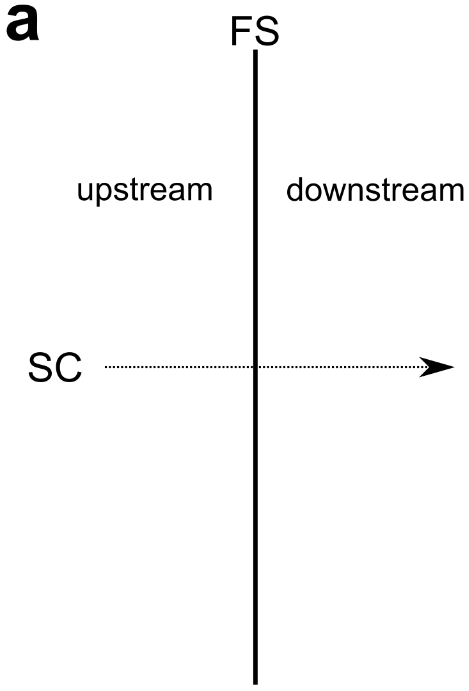
*Figure Courtesy: Erik Reppel

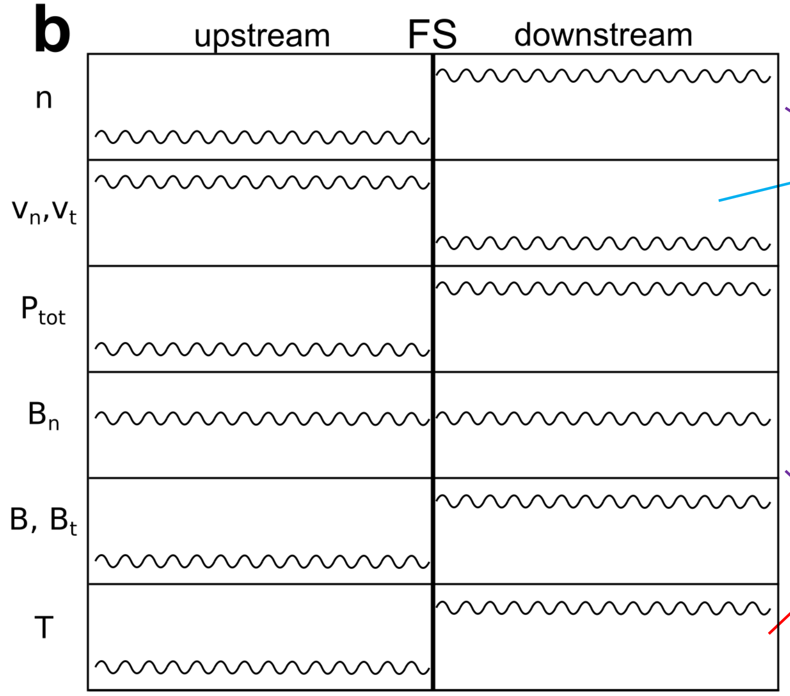
*Figure Courtesy: Cambridge Spark Ltd

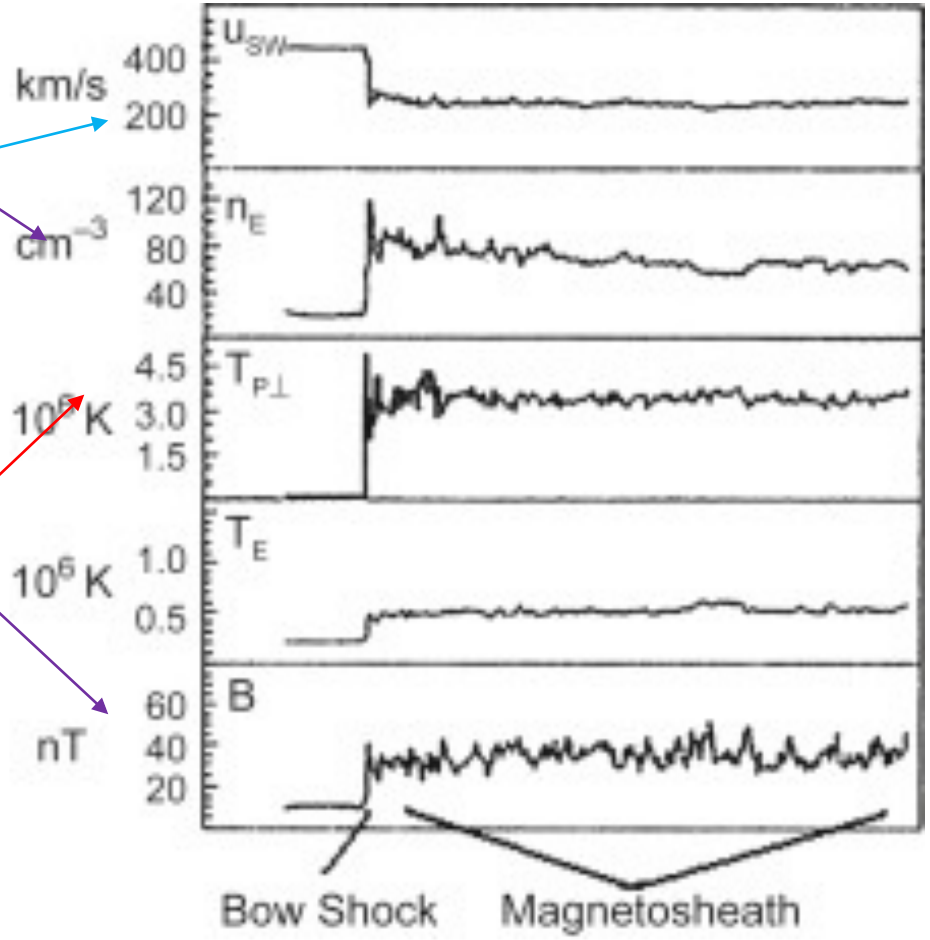
Introduction

(Earth’s Shock & Magnetosheath)

Shock transition (Theory & “initial” data)







Rankine Hugoniot relations / Jump Conditions

Thermalization, Compression, Breaking

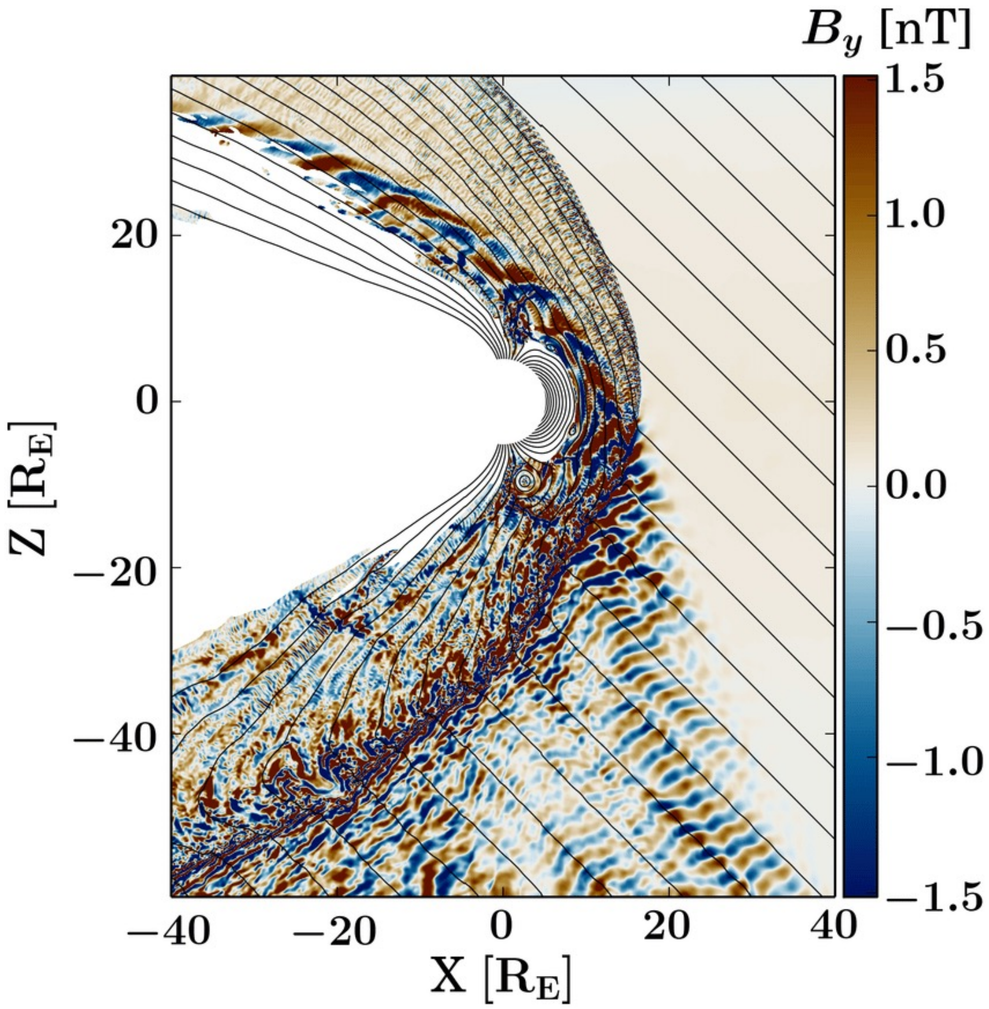
1D Isotropic and adiabatic one fluid plasma shock transitions

1964. Initial results of IMP-1 magnetic field experiment.

Bow shock transition (reality)

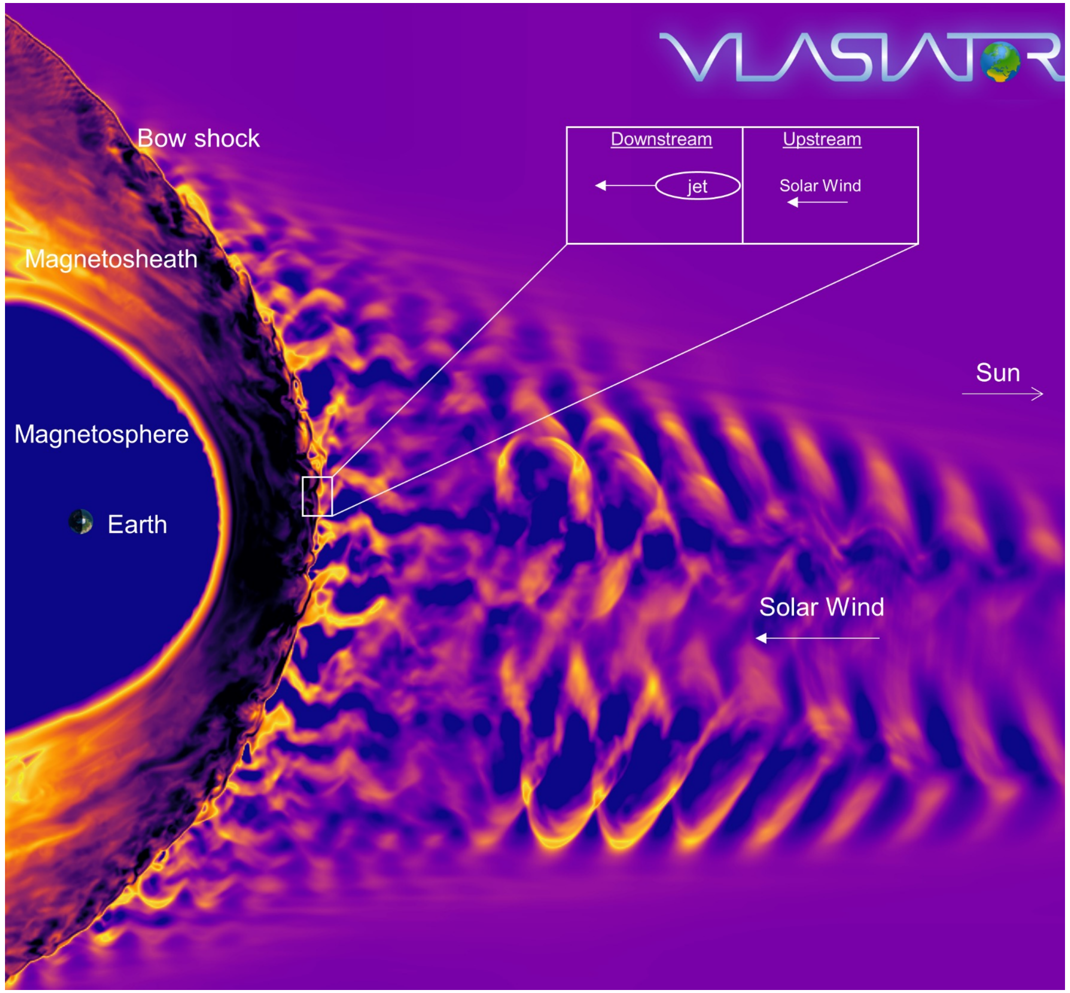
- Reality though is more complicated (as expected…):

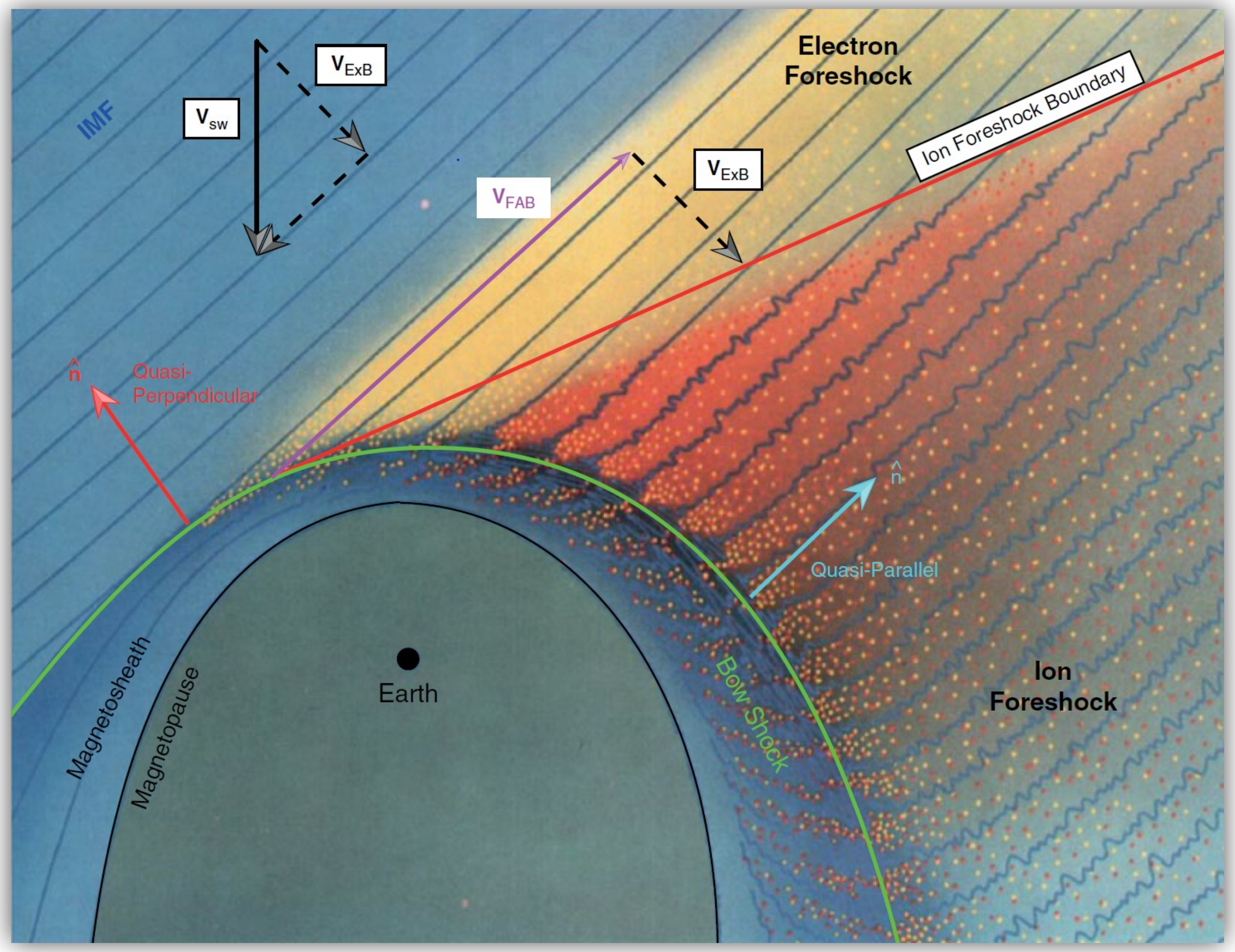
- 3D & kinetic effects
- Foreshock
- Turbulence
- Reconnection
- Non linear effects
- Evolution of plasma waves
- SLAMS, Shocklets, Magnetosheath Jets etc.
- Solar wind condition variability
- Transient phenomena (e.g. CMEs)



Credits: VLASIATOR team

Earth’s shock and magnetosphere

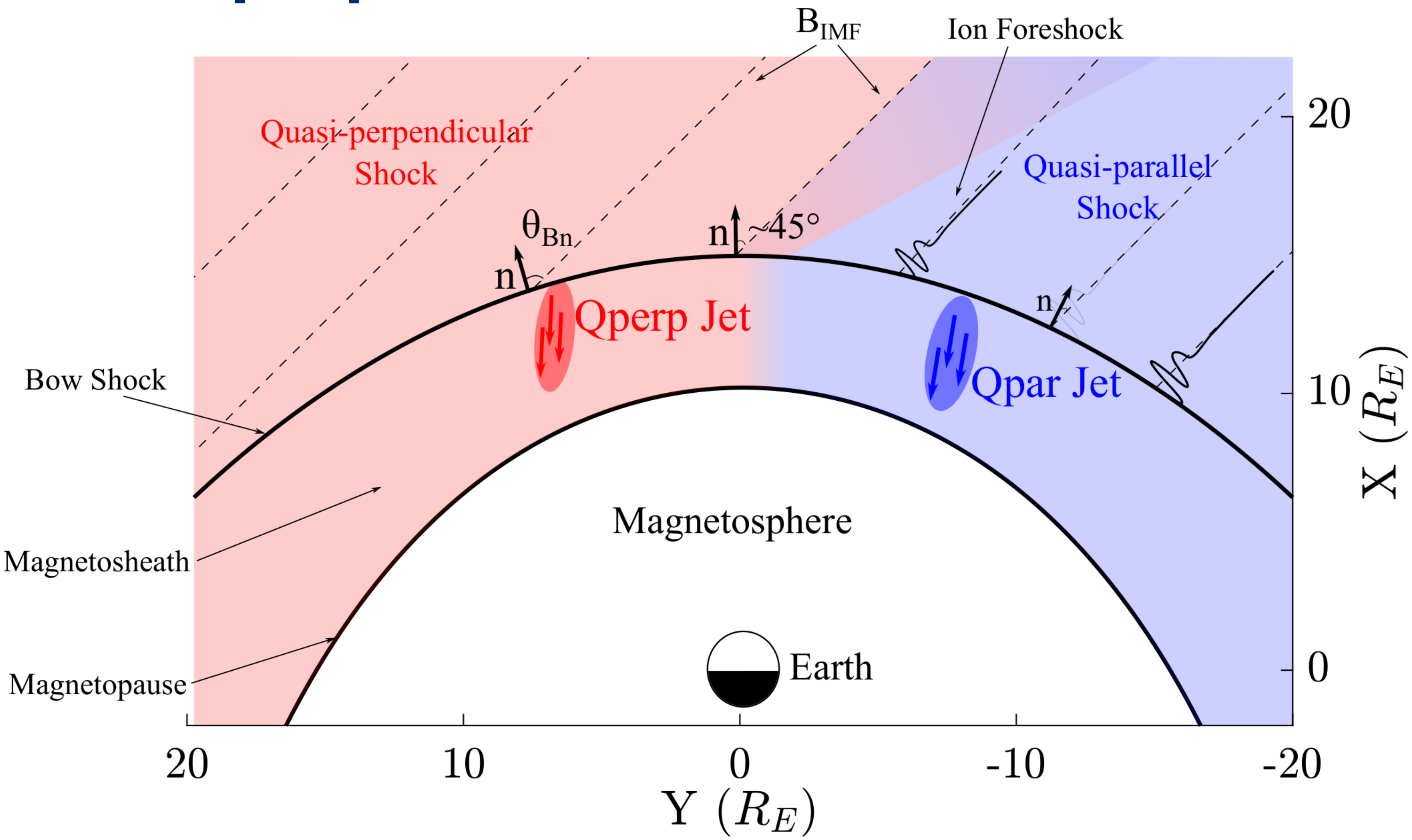




Courtesy of M. Palmroth, U Helsinki / Edited by S. Raptis

L. B. Wilson (2016)

Qpar & Qperp shocks



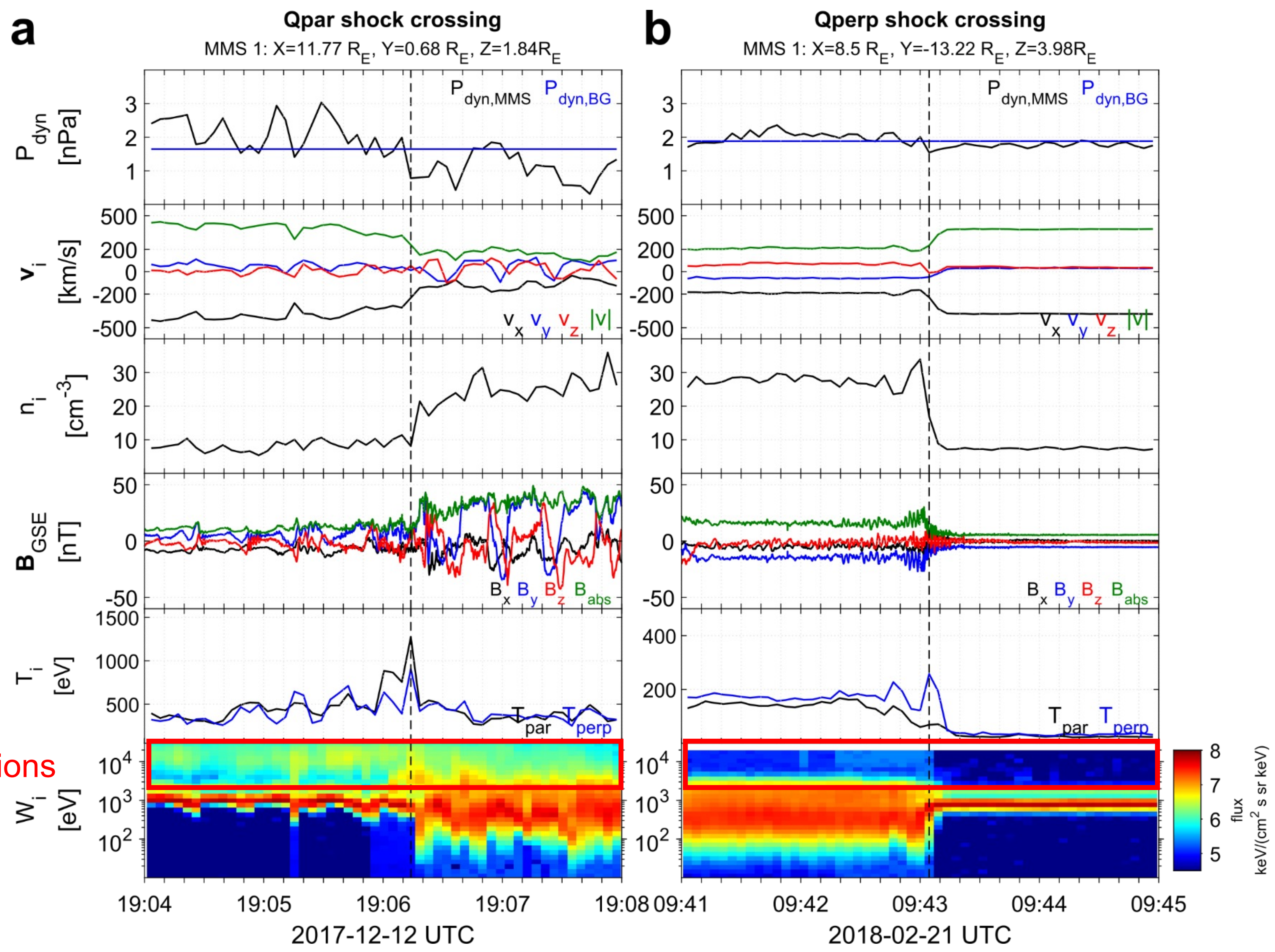
"Θ_{Bn} is the angle between the IMF and the shock's normal vector"

Qpar = $\Theta_{Bn} \lesssim 45°$
Qperp = $\Theta_{Bn} \gtrsim 45°$

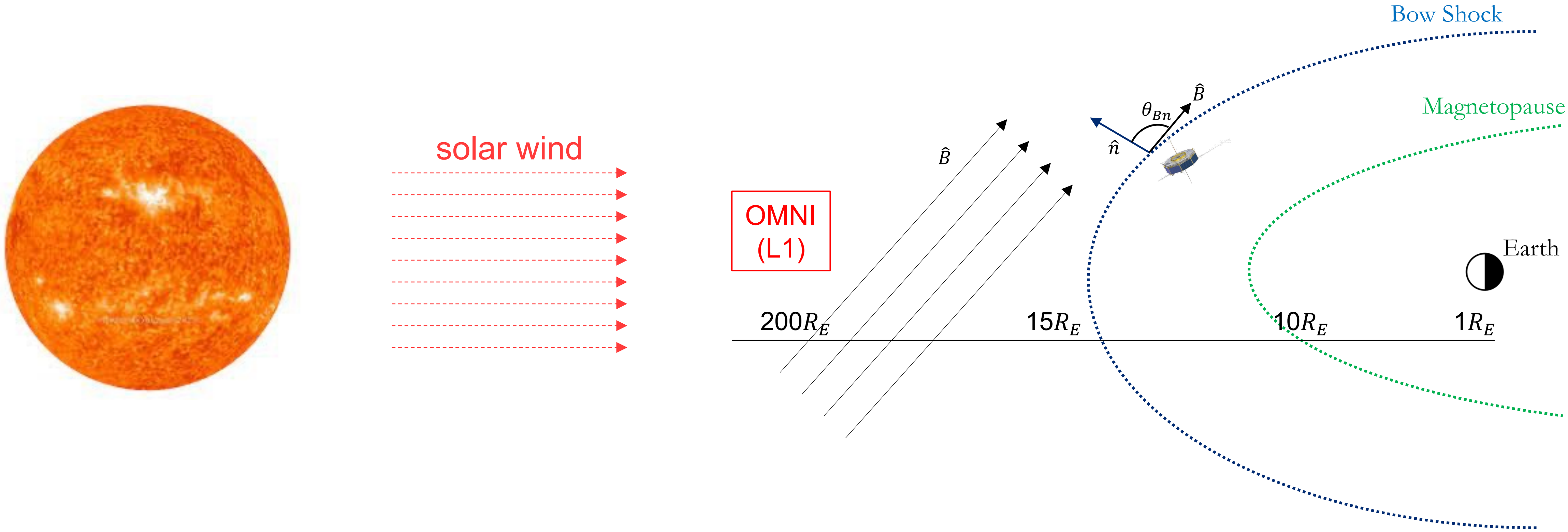
Raptis, Aminalragia-Giamini et al. (2020) | Front. Astron. Space Sci

Shock transitions with MMS

high-energy ions



A common problem

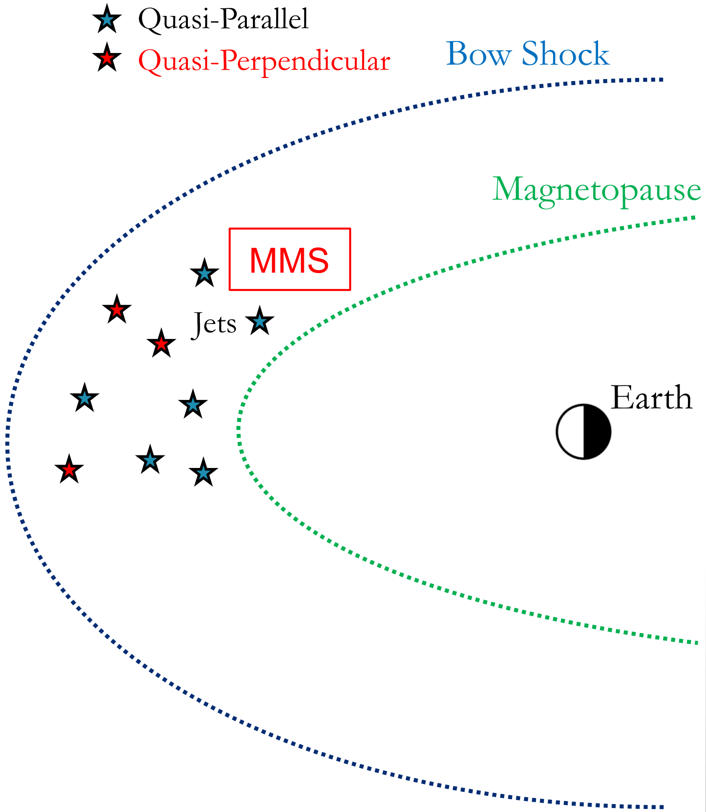


$R_E = 6371.2\ [km]$

Previous Results

Big picture

Paper #1

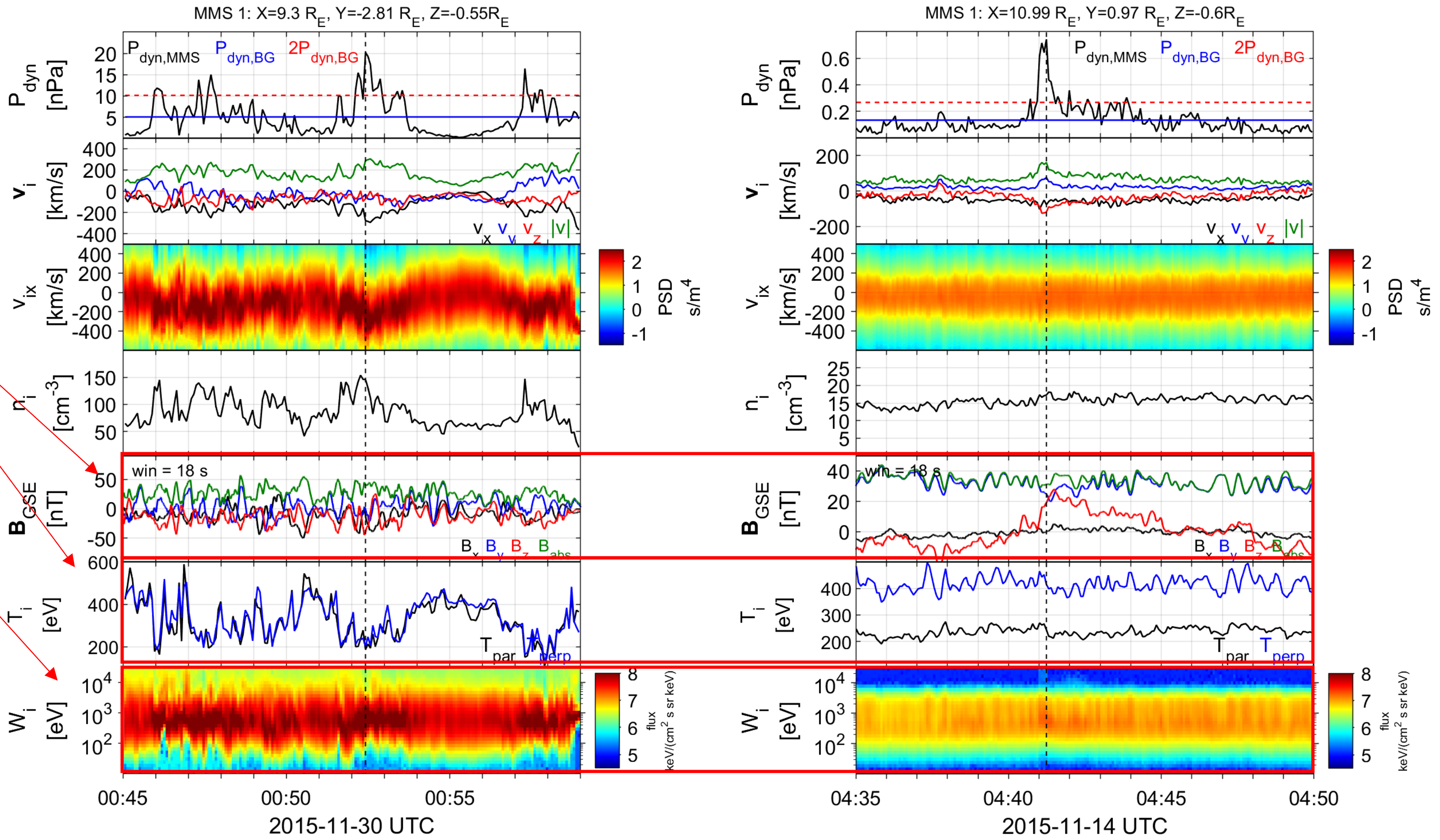


Raptis S., Karlsson T., et al. (2020) | JGR

Relevant Paper #1

<u>Classify jets with *in-situ* data</u>

- ❖ Magnetic field variance
- ❖ Temperature anisotropy
- ❖ High-energy flux



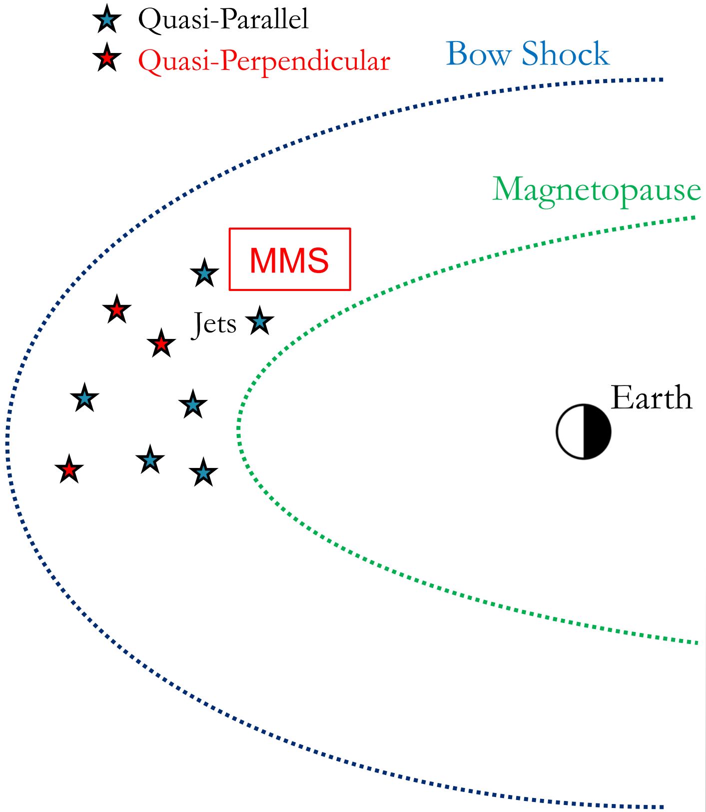
Qpar jet

Qperp Jet

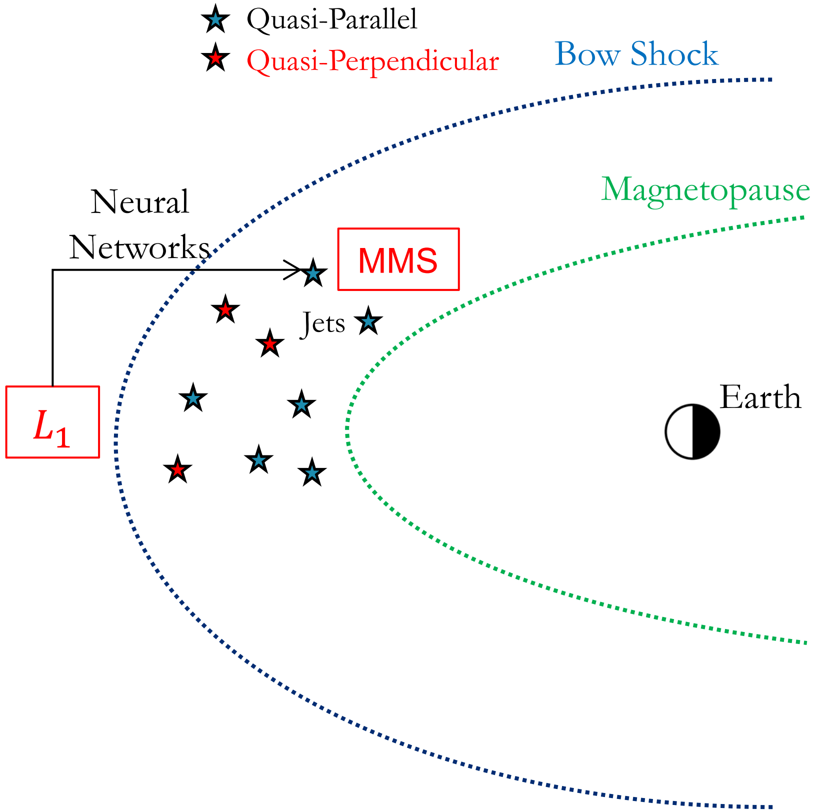
Raptis S., Karlsson T., et al. (2020) | JGR

Big picture

Paper #1	Paper #2



Raptis S., Karlsson T., et al. (2020) | JGR

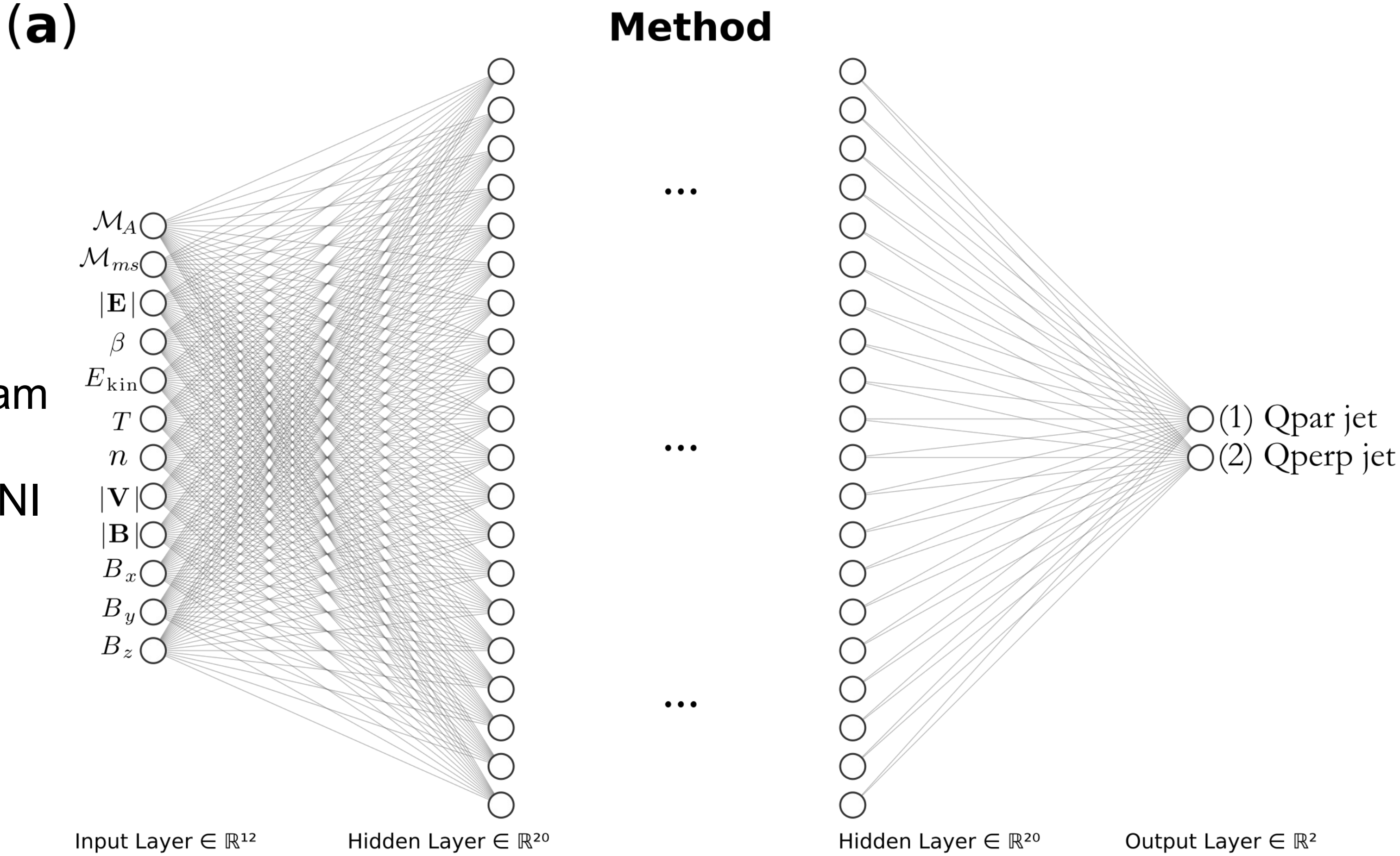


Raptis S., Aminalragia-Giamini et al. (2020) | Front. Astron. Space Sci

Relevant Paper #2

* www.imbalanced-learn.org

Upstream SW L1 OMNI



Downstream MSH MMS

Raptis, Aminalragia-Giamini et al. (2020) | Front. Astron. Space Sci

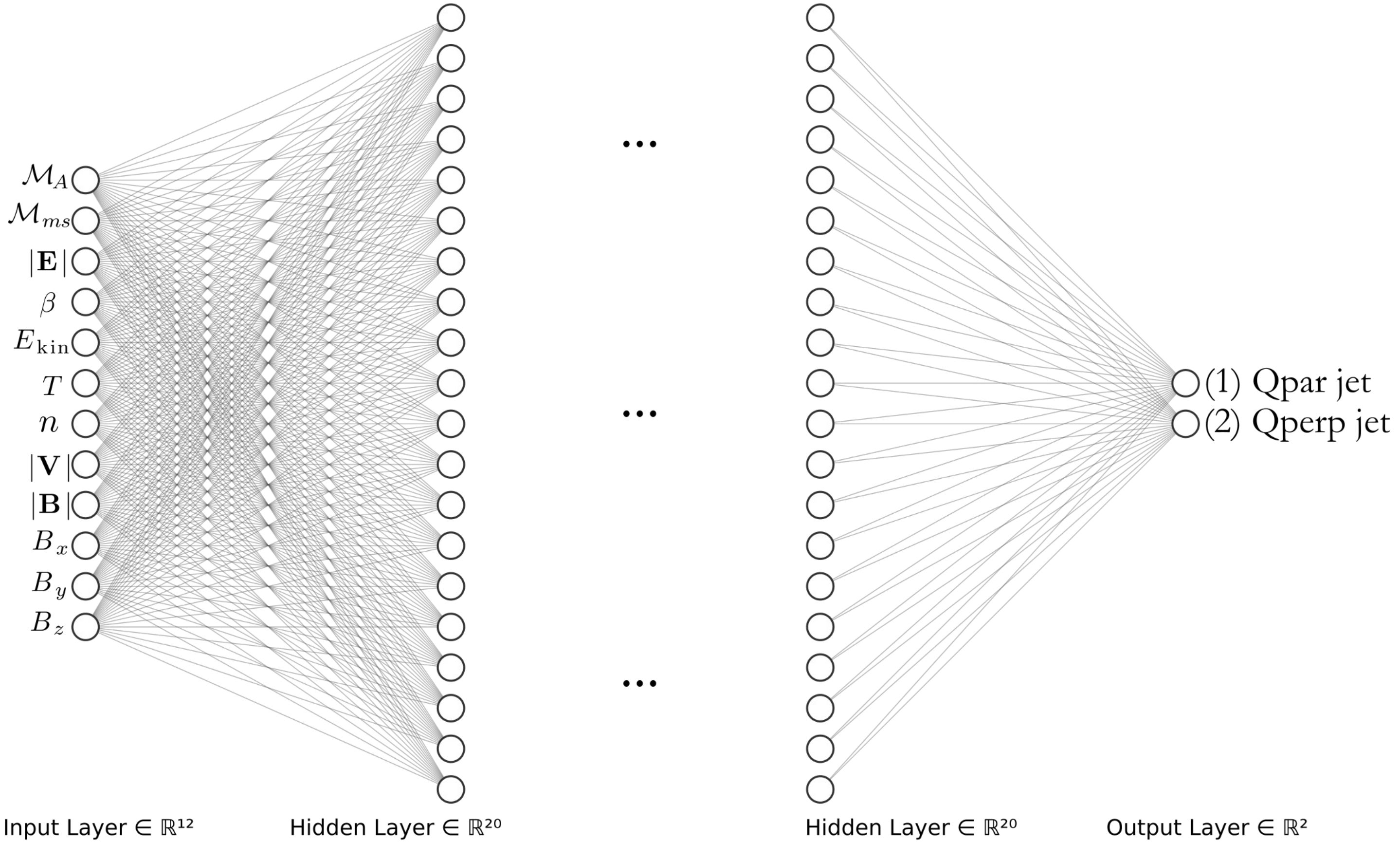
Relevant Paper #2

Classify with NN & OMNI

- NNs > classic methods
- Still in-situ better (?)
- Information upstream

Upstream SW L1 OMNI

(a) **Method**



Downstream MSH MMS

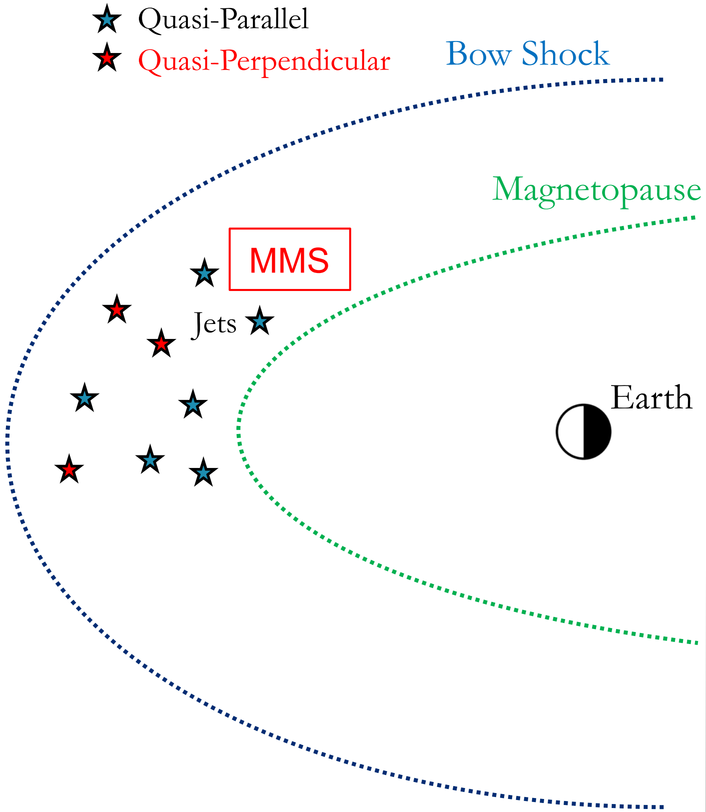
(b) **Results**

	ML		Standard		
Class	**Neural network (B) (%)**	**Neural network (No - B) (%)**	**θ_{cone} (%)**	**Coplanarity (%)**	**Modeling (%)**
Qpar	98	95	61	81	74
Qperp	88	87	94	79	86

Raptis, Aminalragia-Giamini et al. (2020) | Front. Astron. Space Sci

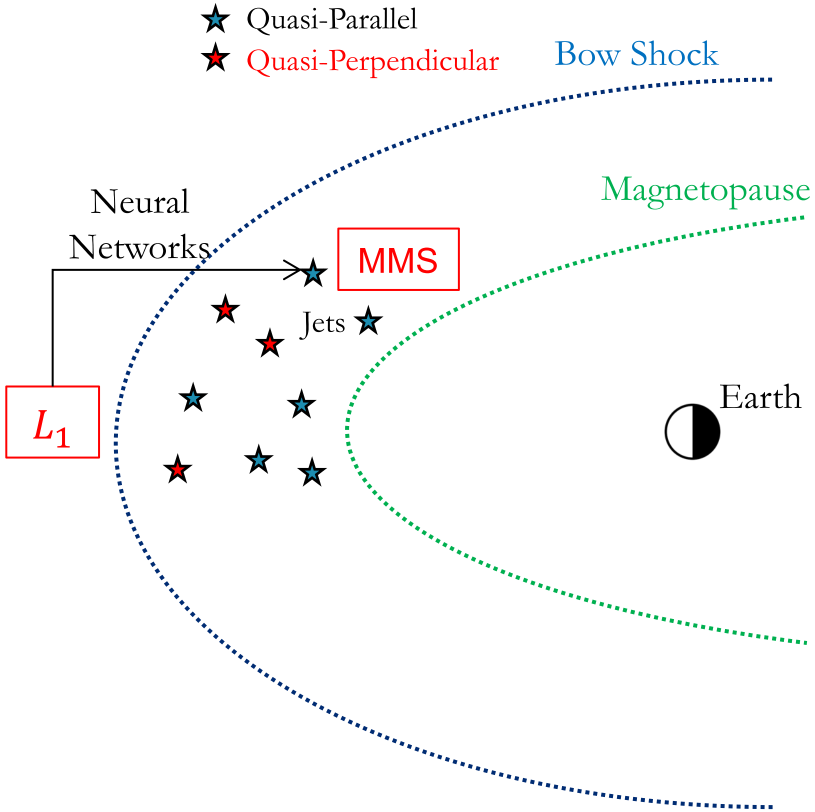
Big picture

Paper #1



Raptis S., Karlsson T., et al. (2020) | JGR

Paper #2



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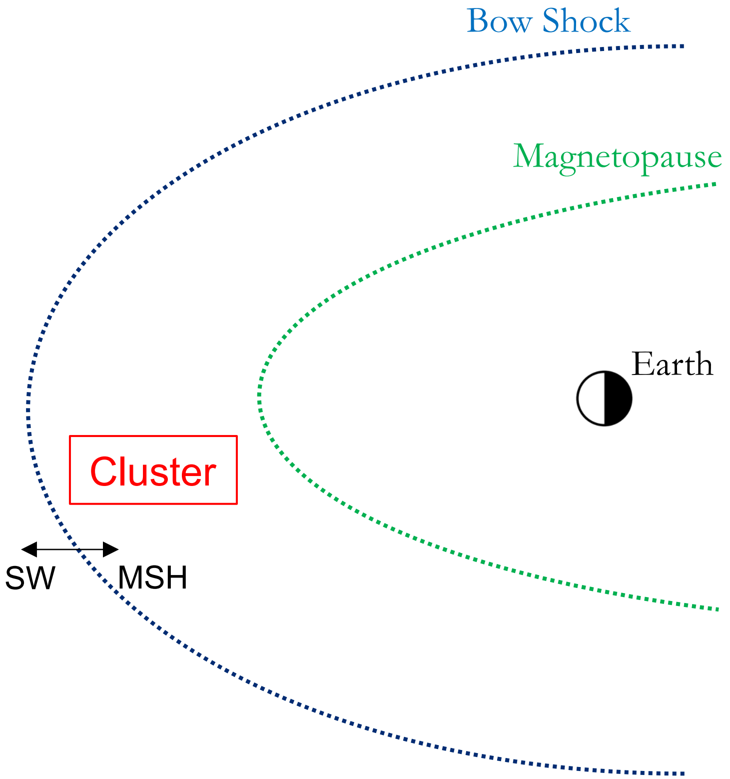
Paper #3

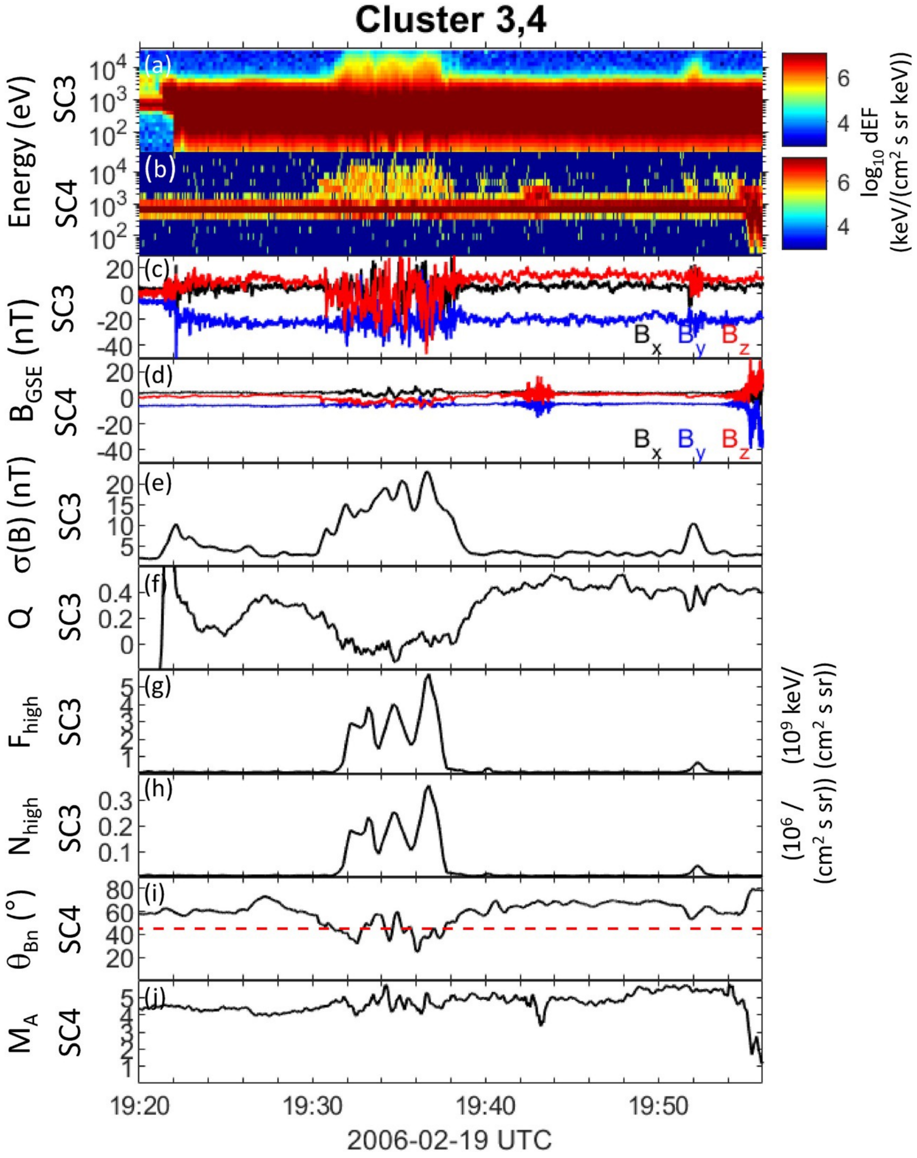


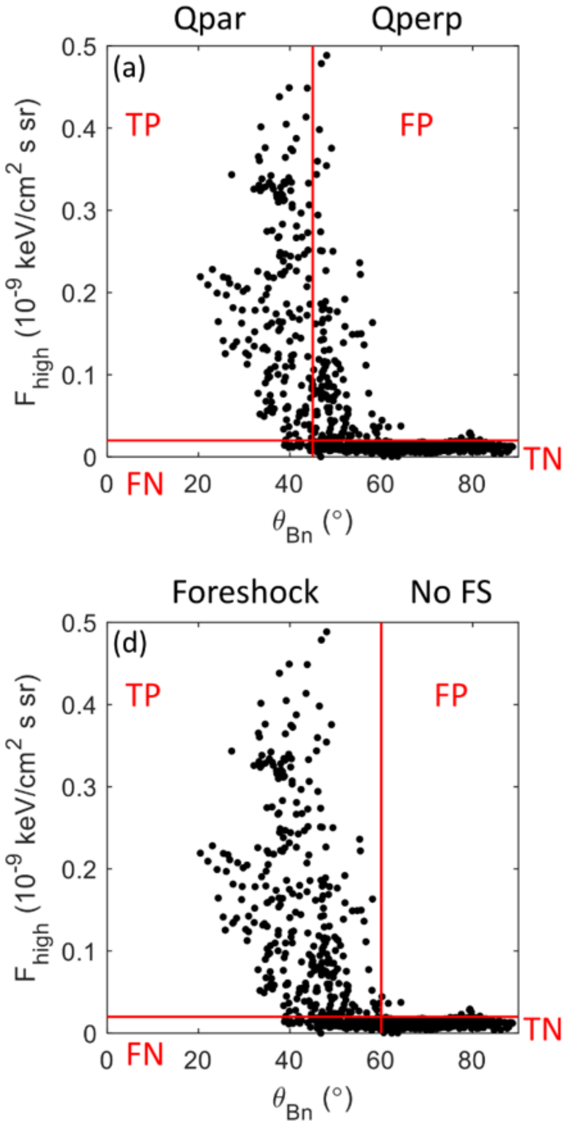
Karlsson T., **Raptis S.**, et al. (2021) | JGR

Relevant Paper #3

SC3 = Downstream satellite

SC1 = Upstream satellite



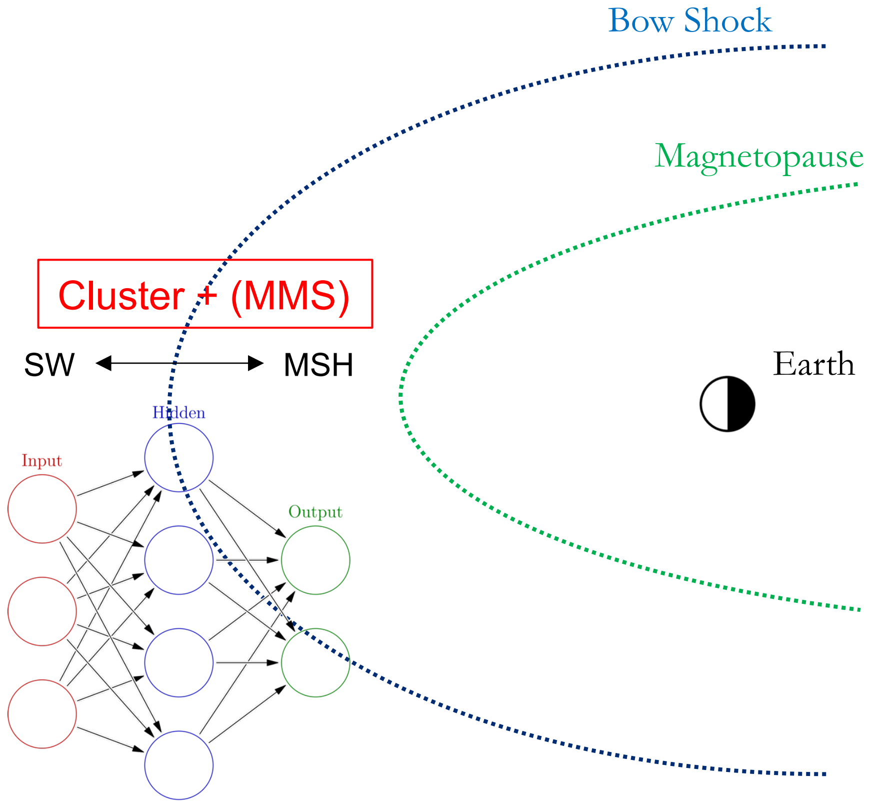


Confirm Paper #1 with CL

- Confirmed*
- Relation energetic ions
- Flux & B variance > Q

Karlsson T., **Raptis S.**, et al. (2021) | JGR

New Results

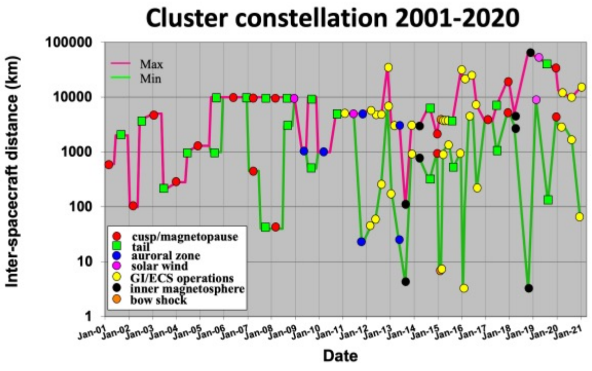


Bow Shock
Magnetopause
Cluster + (MMS)
SW
MSH
Earth
Hidden
Input
Output

Dataset & caveats

CLUSTER

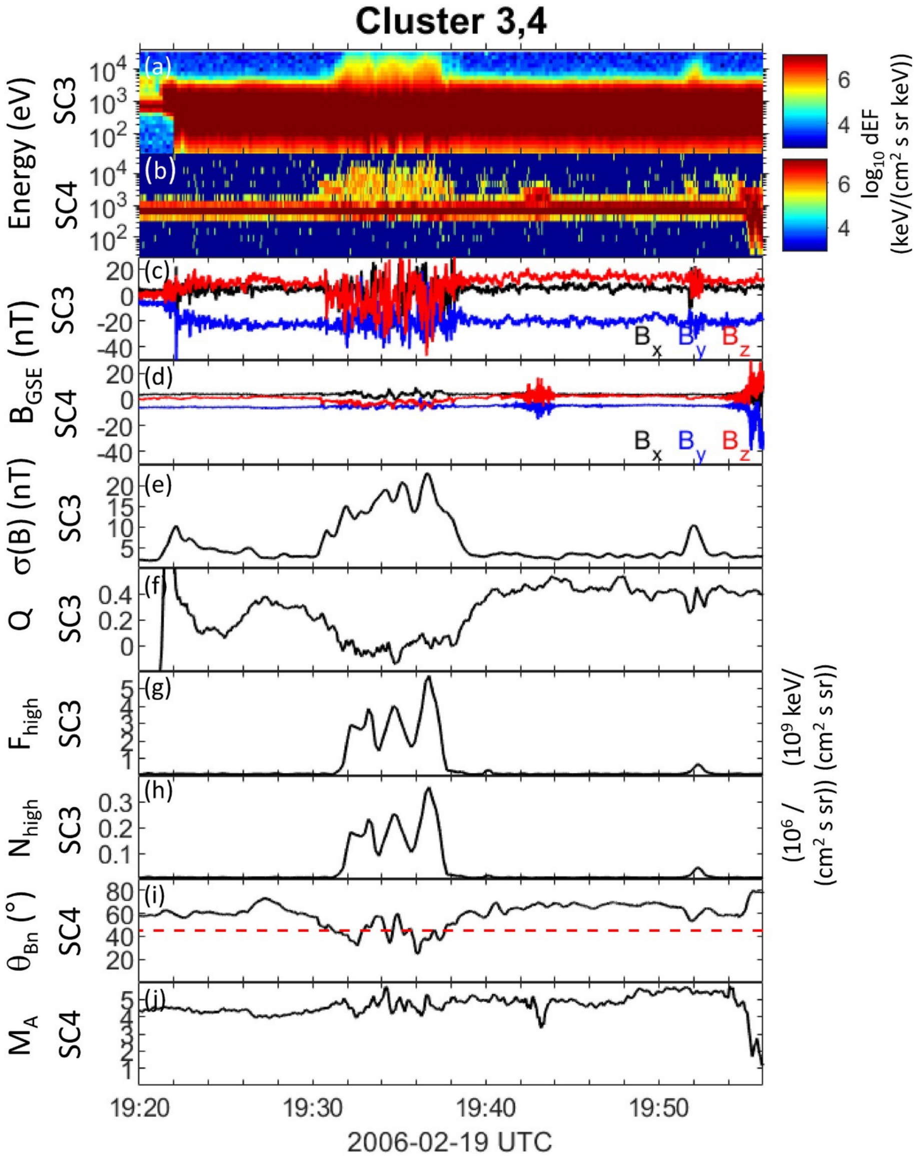
2000 – now



Varying separation, multi-spacecraft analysis (i.e., timing, curlometer etc.

Relevant campaigns

- near solar wind monitor campaign (2019)



Dataset

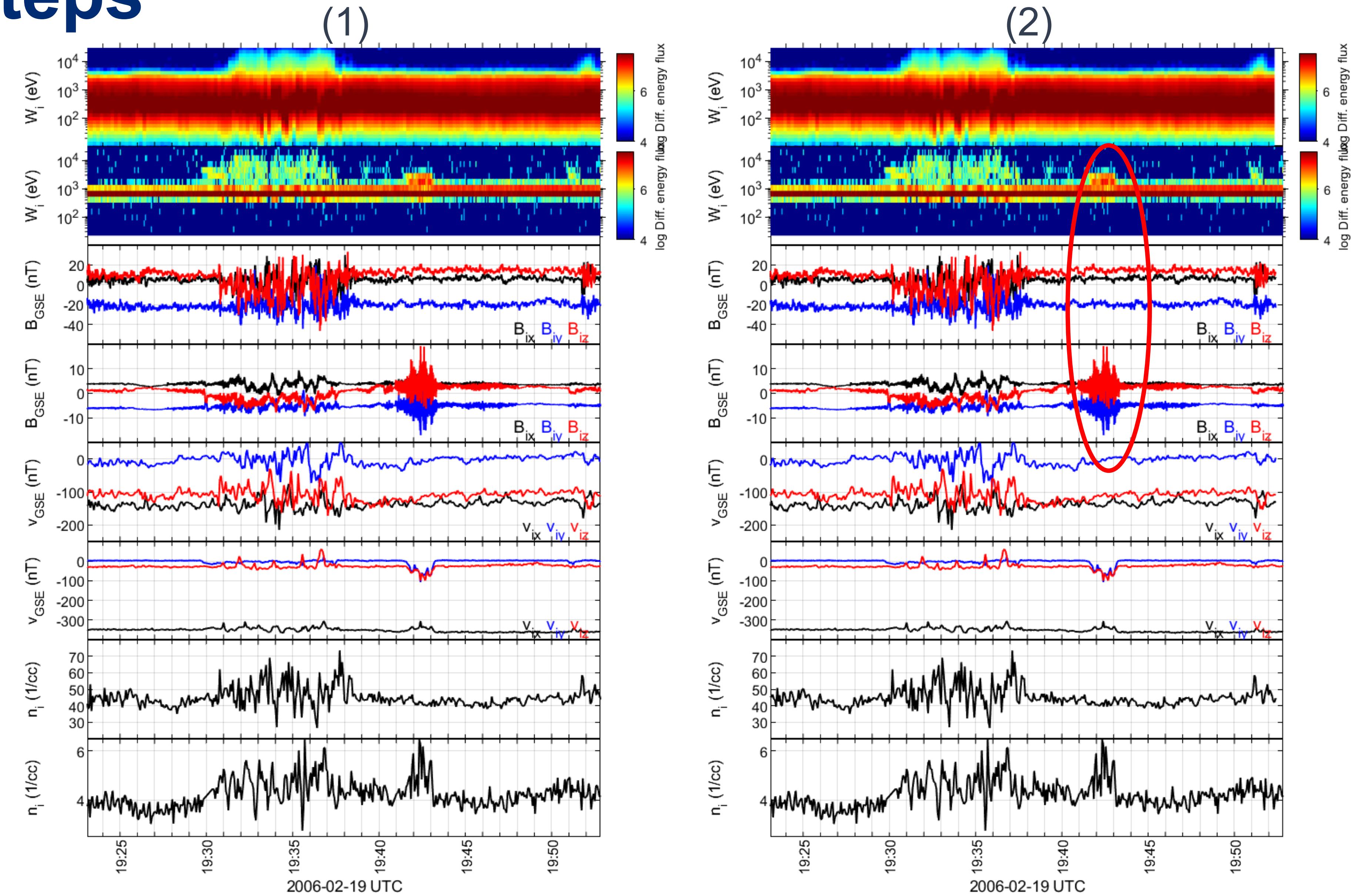
- ~10k points (~10s res)
- 2 instruments
  - Hot Ion Analyzer (HIA)
  - Composition Distribution Function (CODIF) analyzer
- Time lag (upstream – downstream) ~10s – 2min
- Transient localized events (e.g., MSH jets, shocklets, SLAMS, etc.)

GOAL: Can we use info from SC3 to characterize SC4 & create a synthetic energy spectrum ?

Pre-process steps

Steps

1. Raw Data
2. Time-Shift (cross-corr normalized B)

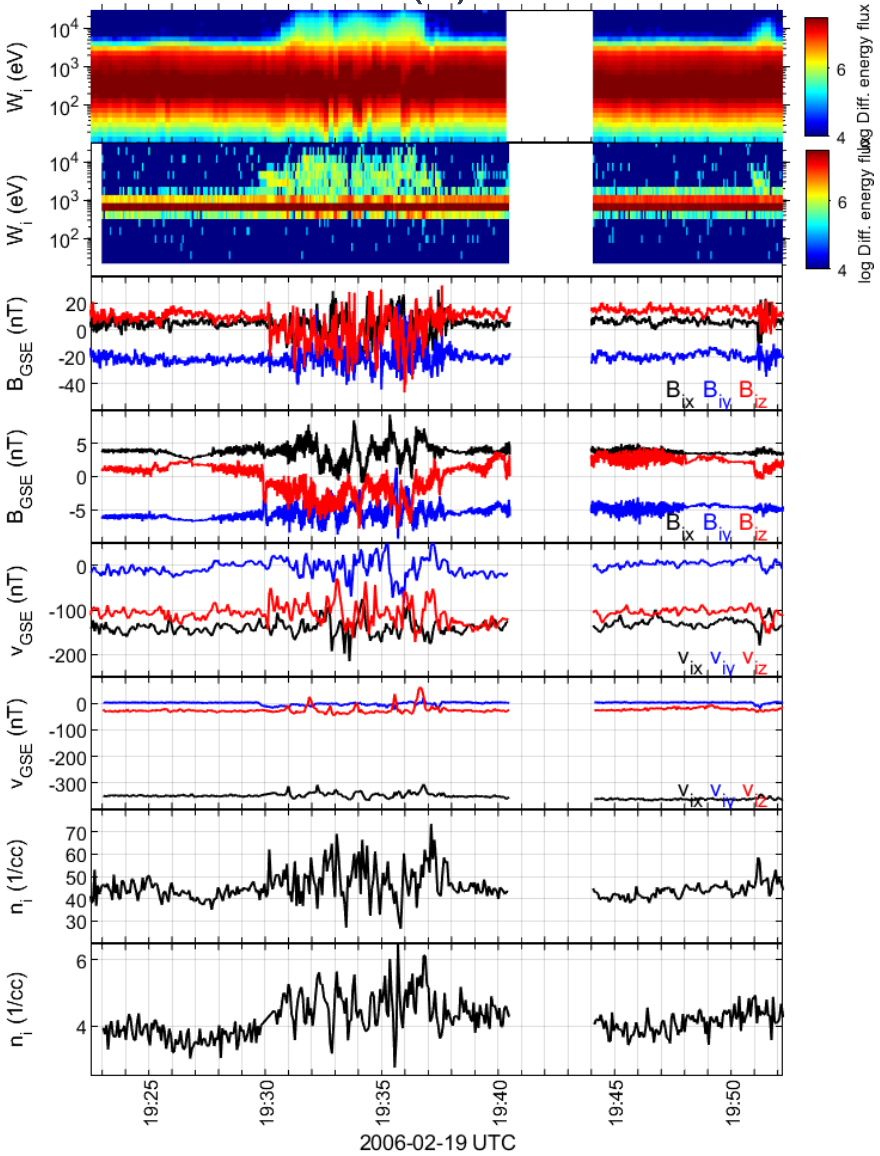


Pre-process steps

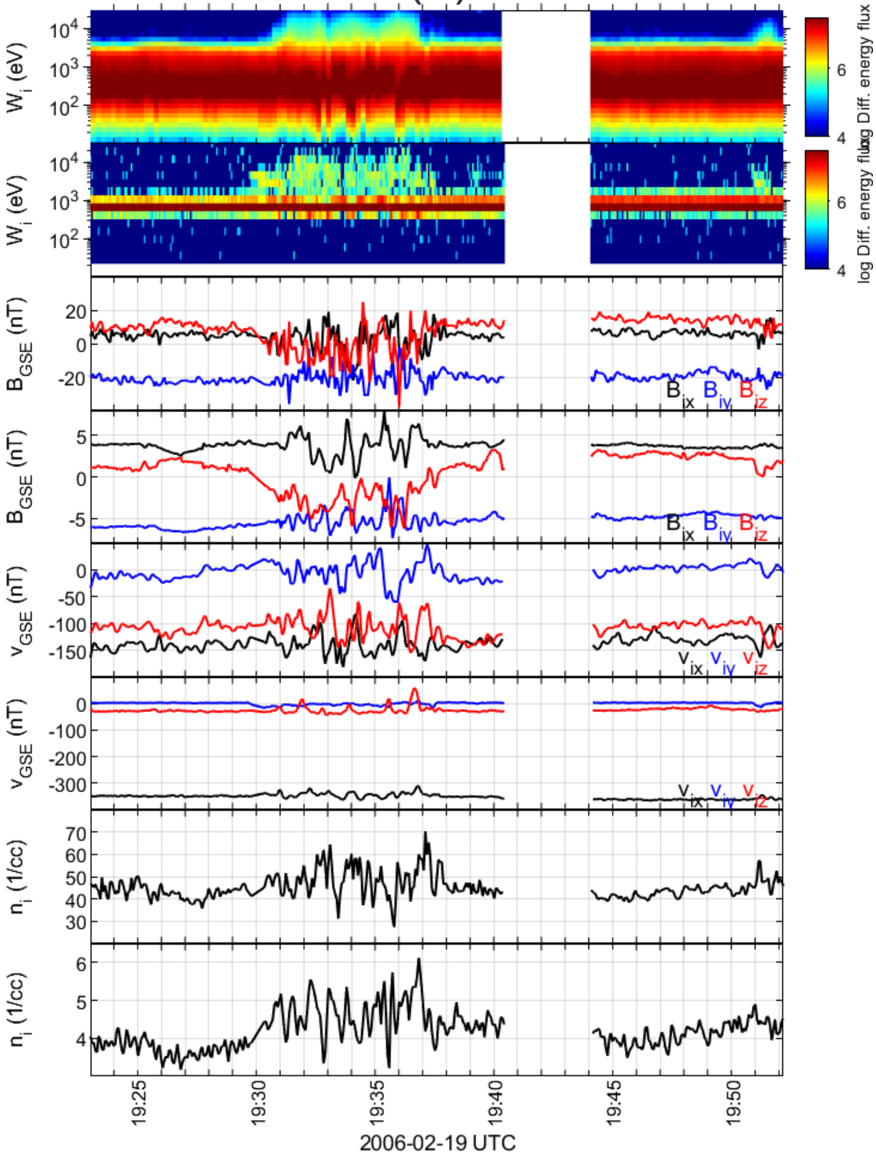
Steps

1. Raw Data
2. Time-Shift (cross-corr normalized B)
3. Remove transients
4. Resample & Rebin

(3)



(4)

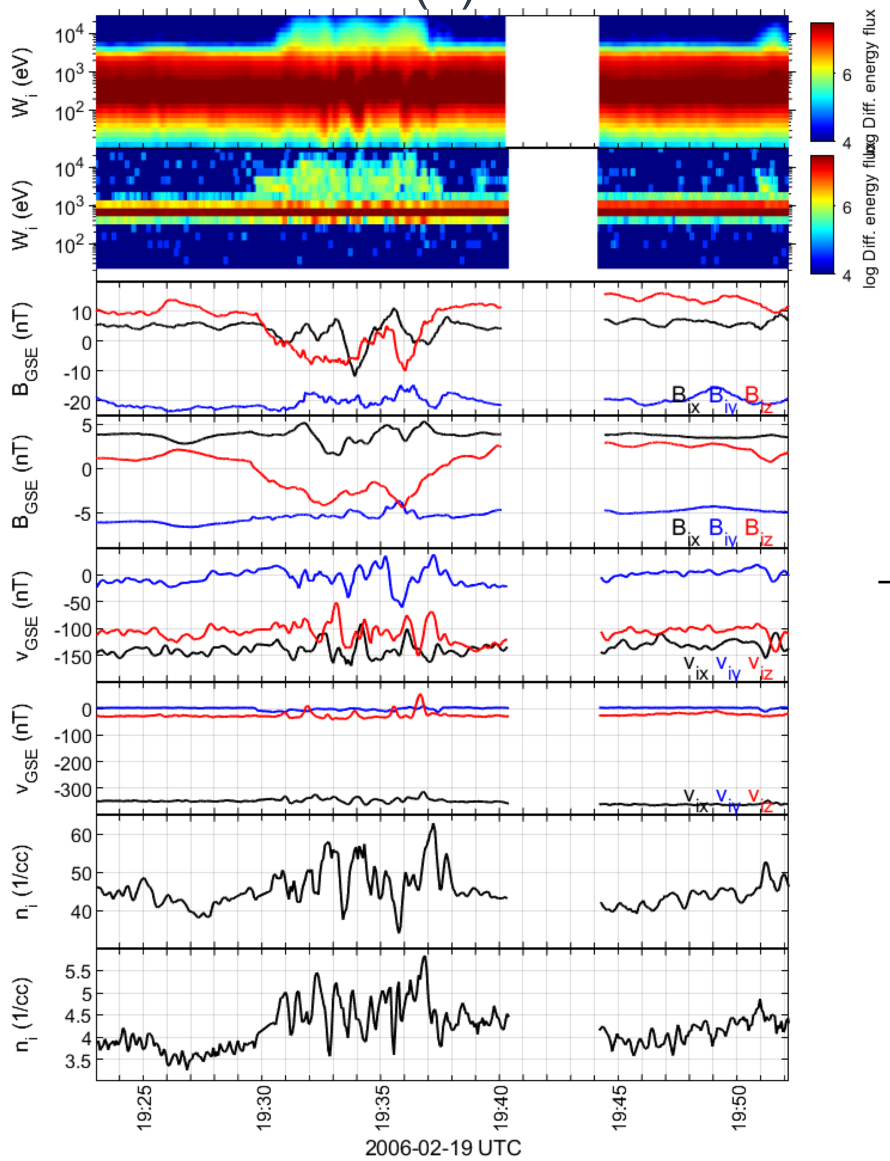


Pre-process steps

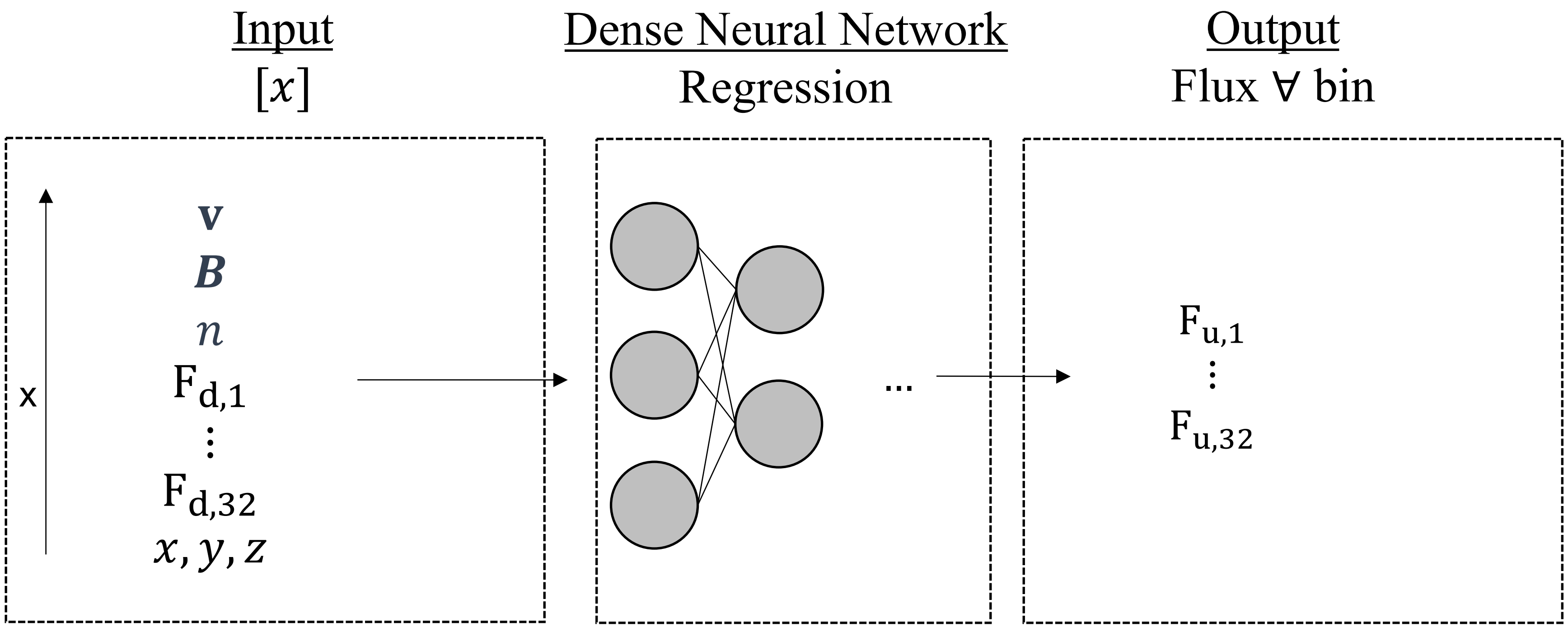
(5)

Steps

1. Raw Data
2. Time-Shift (cross-corr normalized B)
3. Remove transients
4. Resample & Rebin
5. Filter (optional)

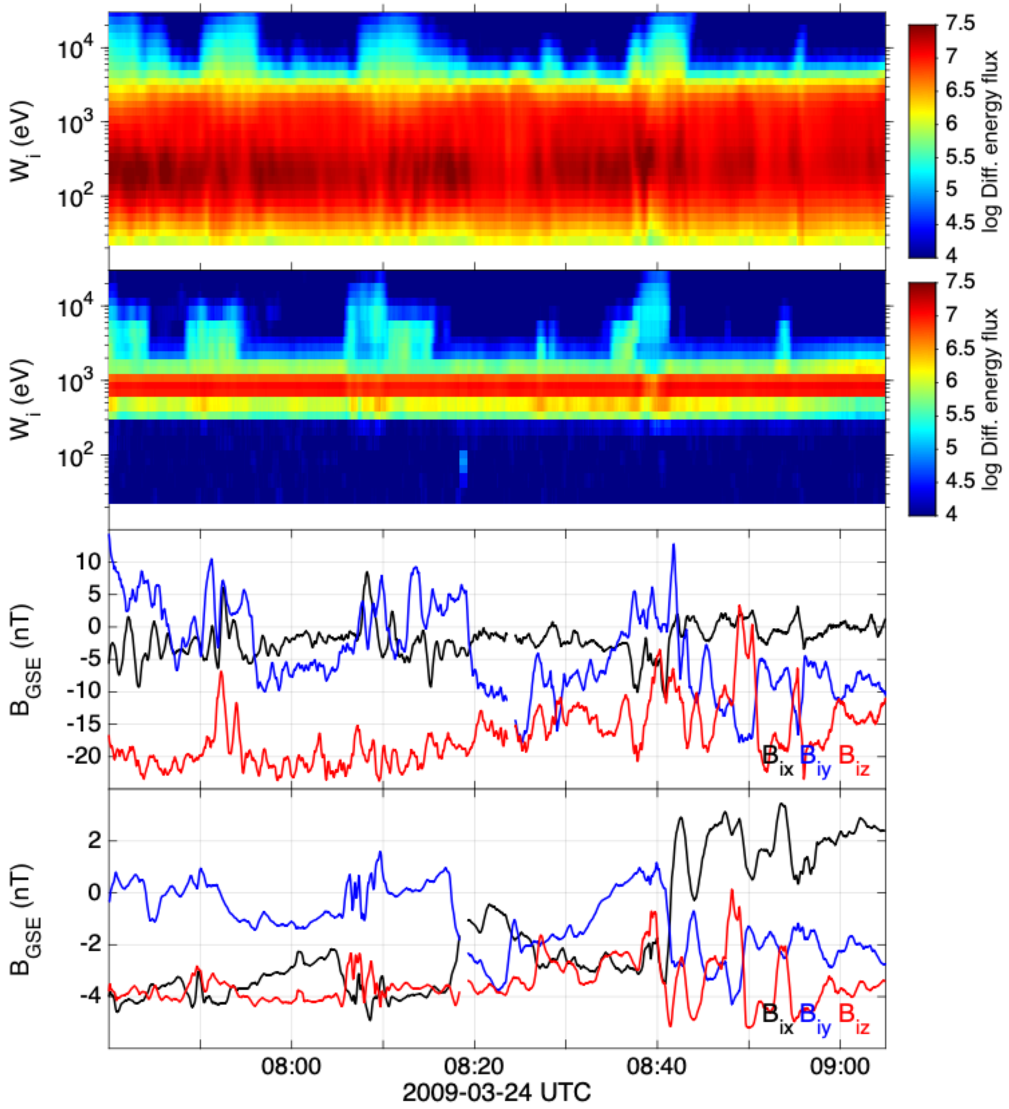


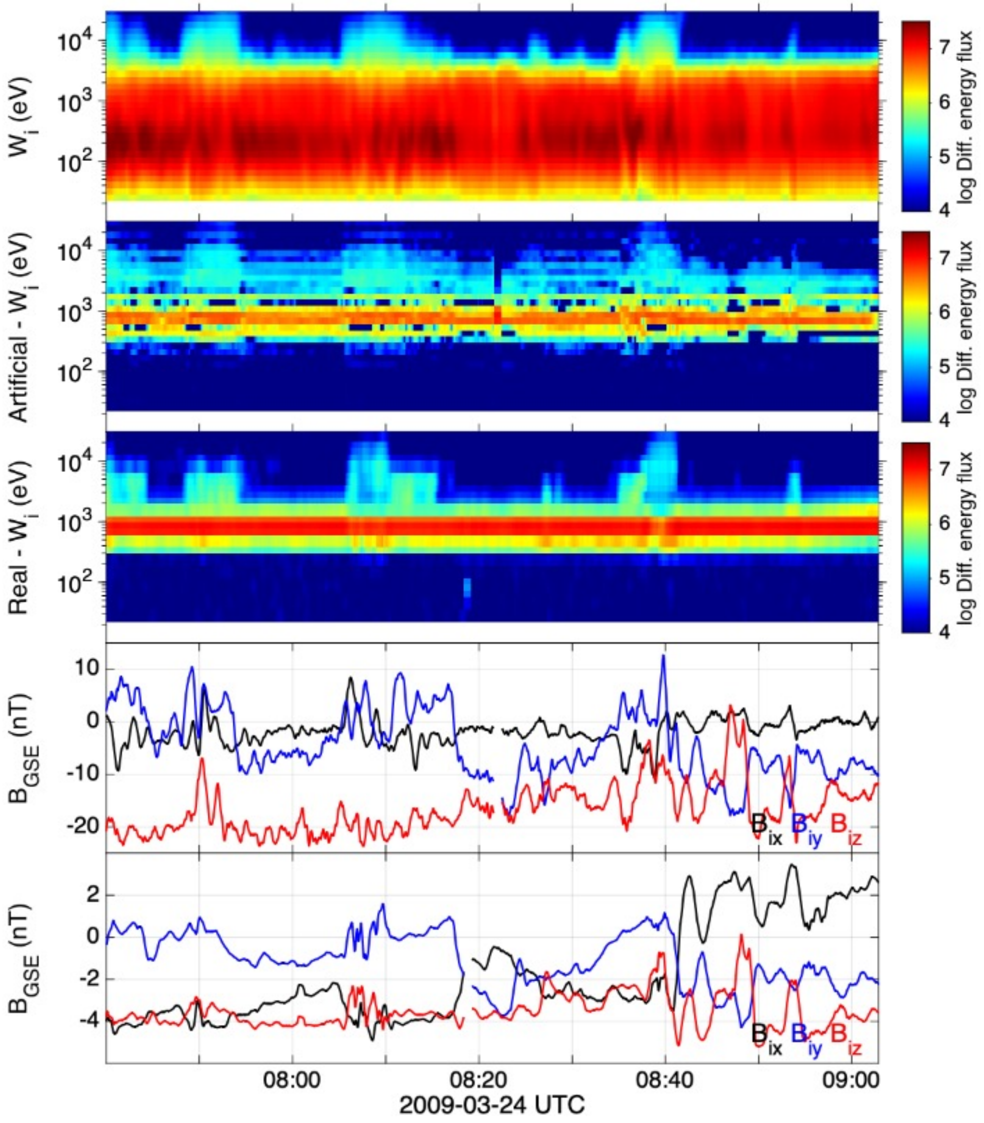
Basic idea (NN)



Input:
x: Different downstream features (e.g., n, B, etc.)

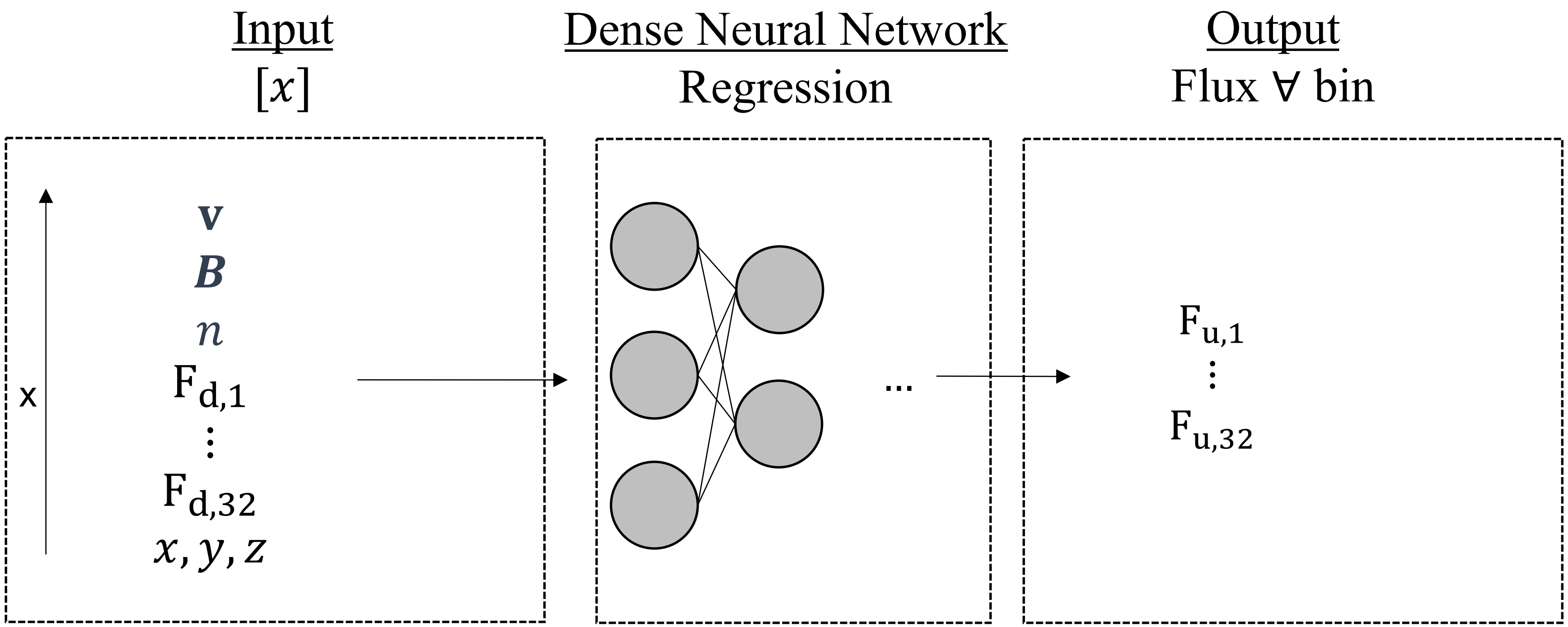
Preliminary results (test set)





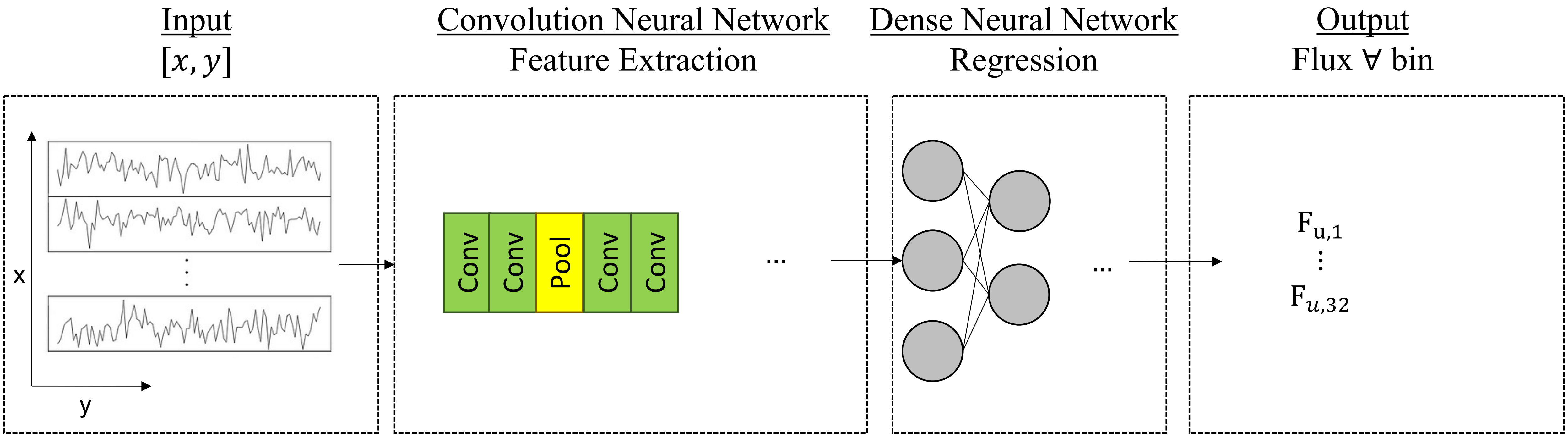
Karlsson T., **Raptis S.,** et al. (2021) | JGR

Basic idea (NN)



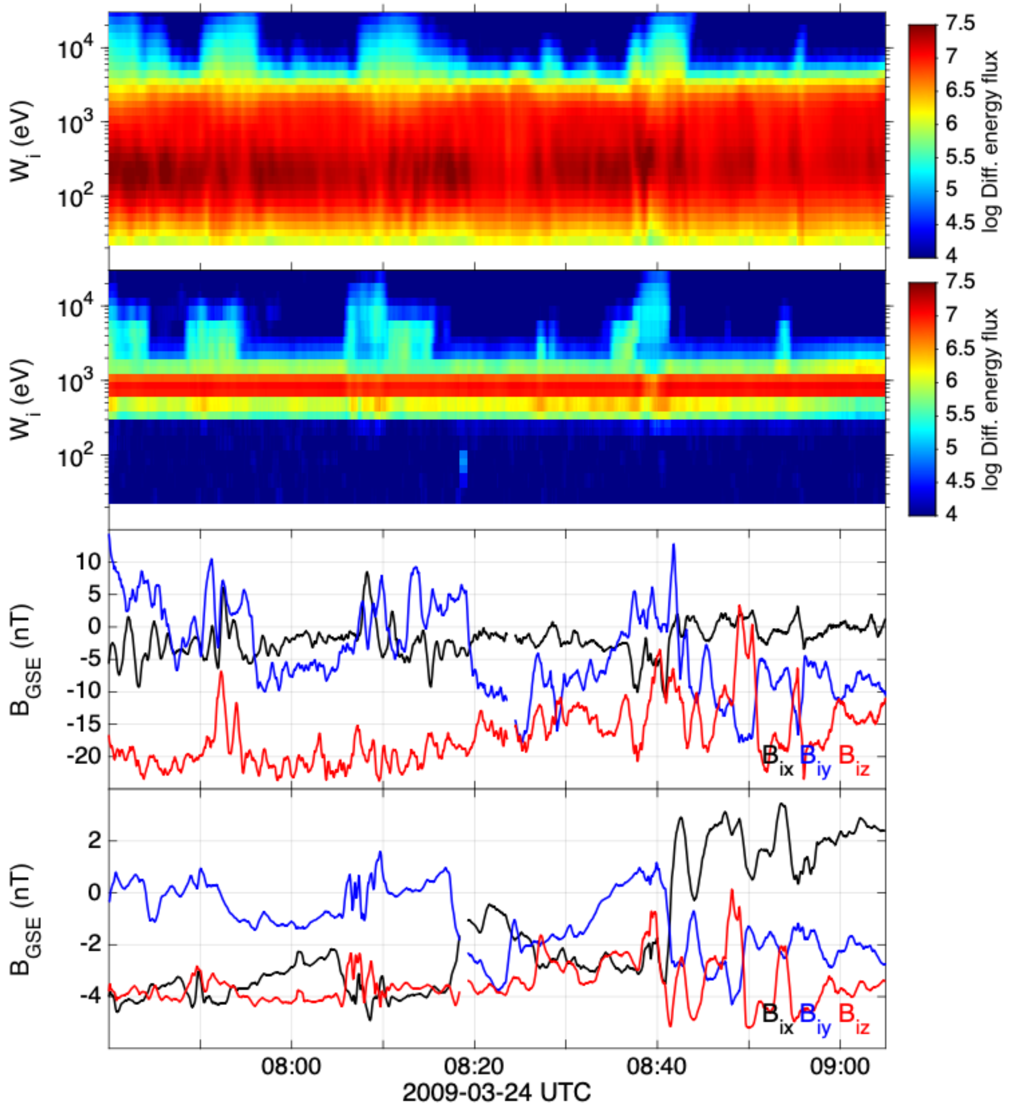
Input:
x: Different downstream features (e.g., n, B, etc.)

Basic idea (CNN)



Input:
x: Different downstream features (e.g., n, B, etc.)
y: Information forward in time (e.g., +10 points with 10 sec resolution) – Skip cross-correlating signals

Preliminary results (test set)



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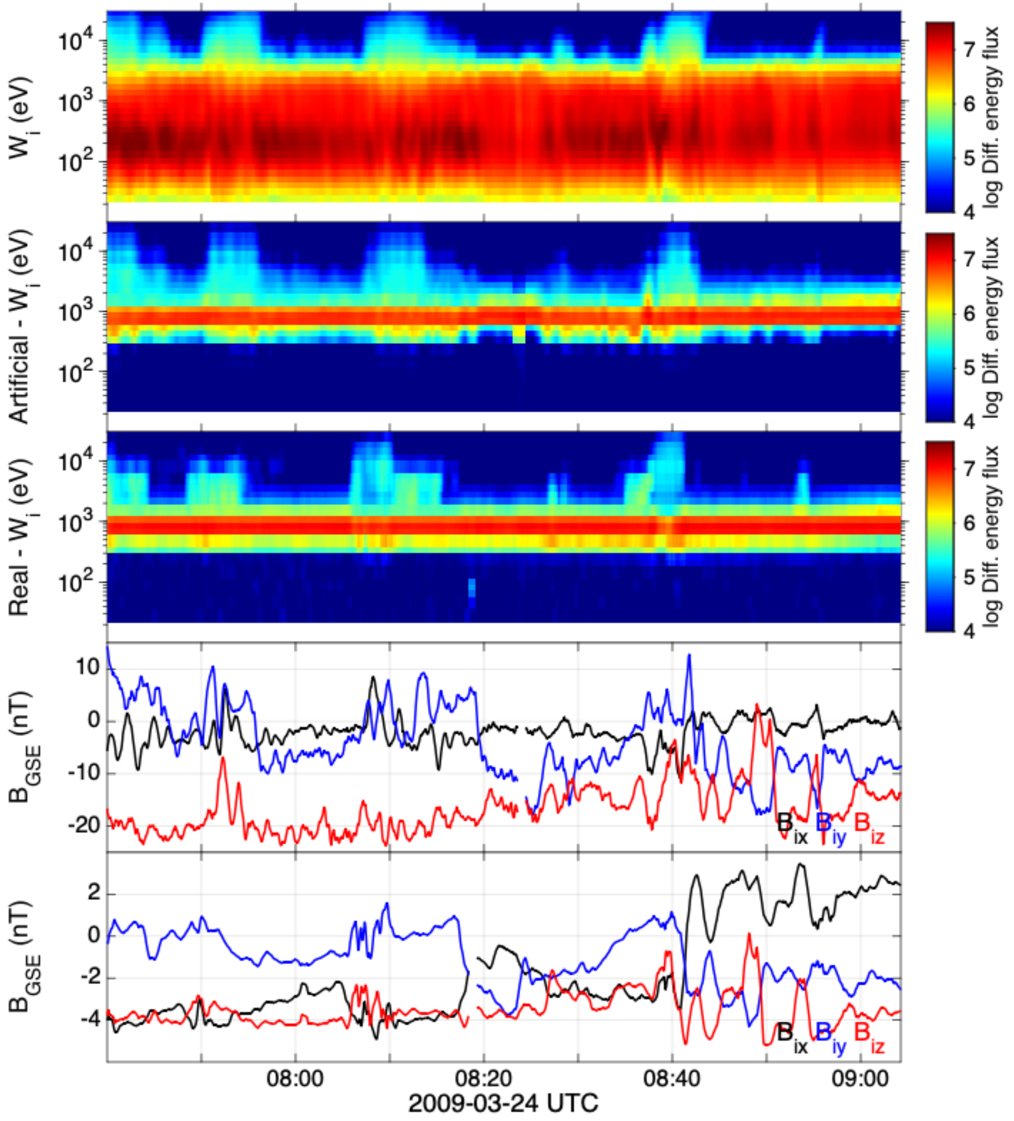


Raptis et al. (ongoing)

Discussion & Conclusion

- Preliminary results: generate upstream data by training a ML model with downstream (*the same applies for upstream to downstream*).

Future

- More data are needed (hard to get, manual labor involved)
- Many things to be done (data cleaning, better architectures, better validation, metrics etc. etc.)
- Smarter problem definition (not produce whole spectra but parts of it, specific bins using multiple models etc.)
- Can we combine our knowledge of shocks to generate synthetic data (e.g., using Physics-informed machine learning)
- Include other missions/objectives (THEMIS, MMS, etc.)

Extra

Model Basic Properties

Metrics:
(normalized)

RMSE_{train} : 0.007
RMSE_{train} : 0.07
R^2_{train}: 0.8

MSE_{test} : 0.01
RMSE_{test}: 0.08
R^2_{test} : 0.7

Basic Architectures:

- Neural Network (60-80-100-80-60-1)
- CNN (16/[4,4] – 8/[2,2]–400–200–100–1)
- XGBoost (various variations)

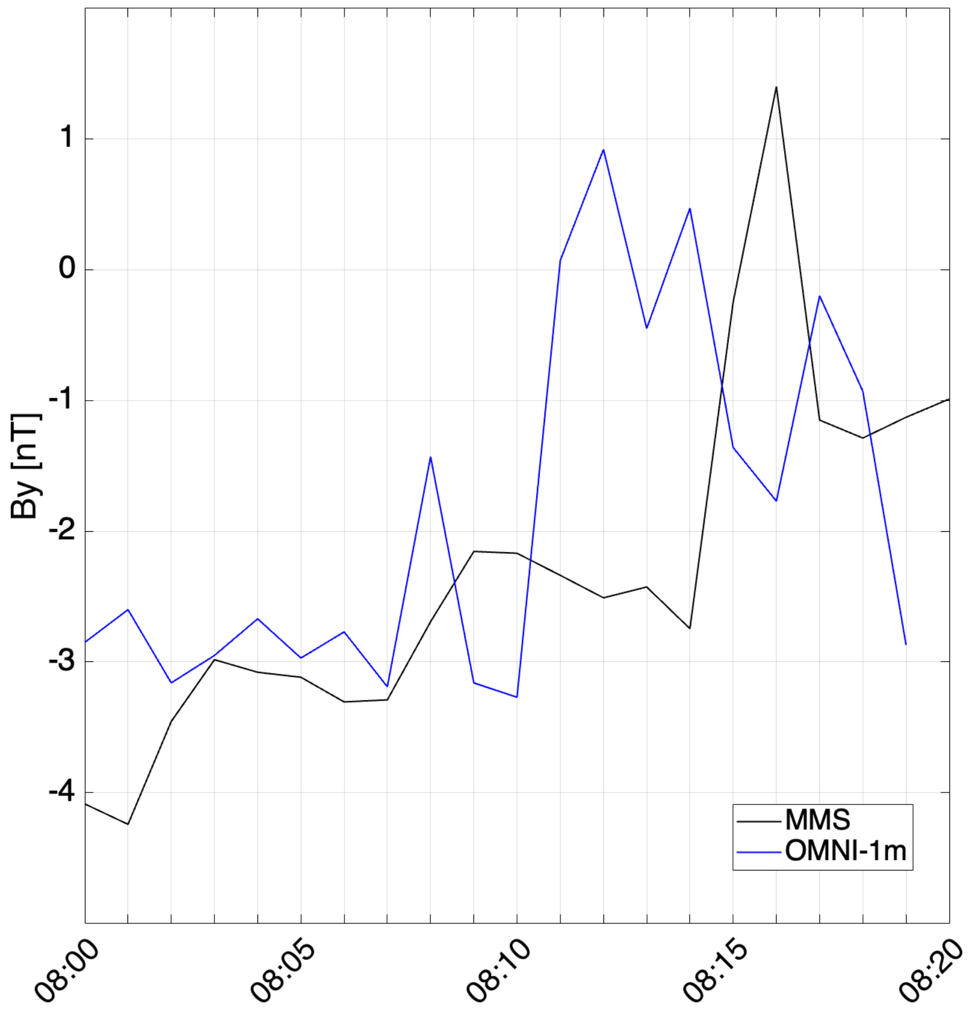
Extras:

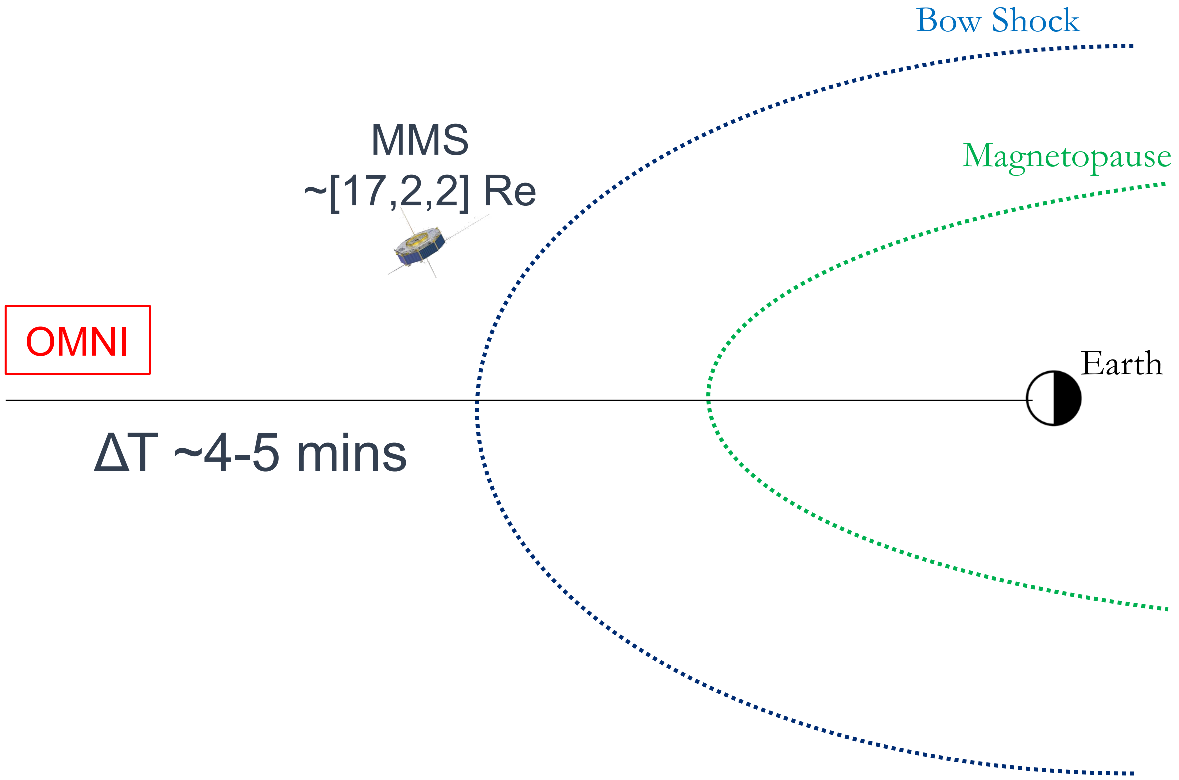
early-stopping based on training loss.

Hyperparameters (NN/CNN):

- Epochs (based on extra)
  - ≈ 50 (batch ~128),
  - ≈ 500 (batch ~length(x_train))
- Optimizers: Adam/Nadam/SGD
- Activation function : Relu (+)
- Loss function minimization: MSE
- Train/Test split: Manual (few variations)

Example of OMNI miss-match





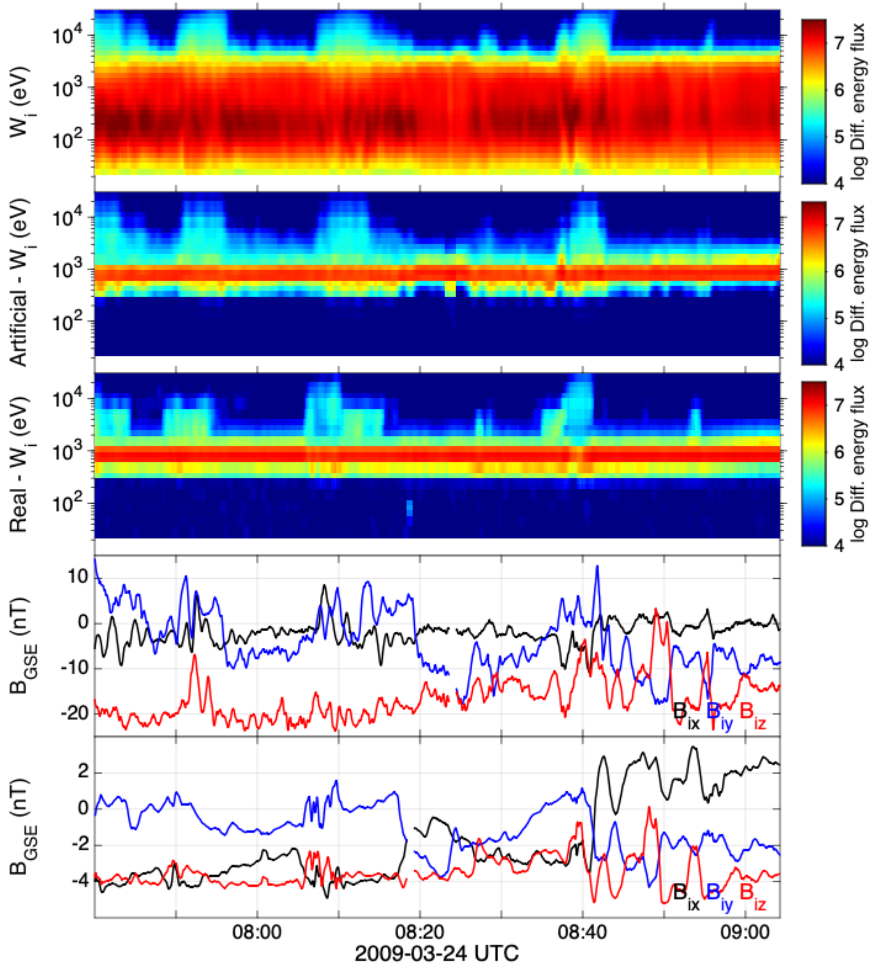
Preliminary results (moments)

Density:

Real = 3.92
NN = 4.039

Interesting results with XGboost

CNN



XGboost