Classification of Magnetosheath Jets using Neural Networks and High Resolution OMNI (HRO) data

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Introduction

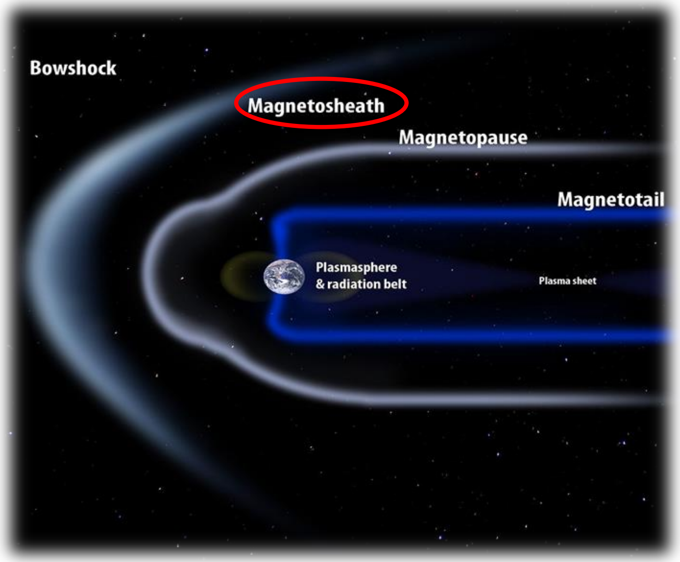
Magnetosheath Jets

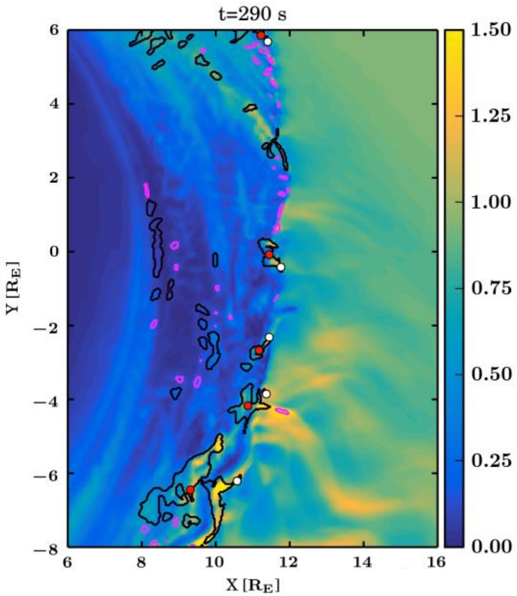
Where: Magnetosheath

What: Enhancements of dynamic pressure above the general fluctuation level

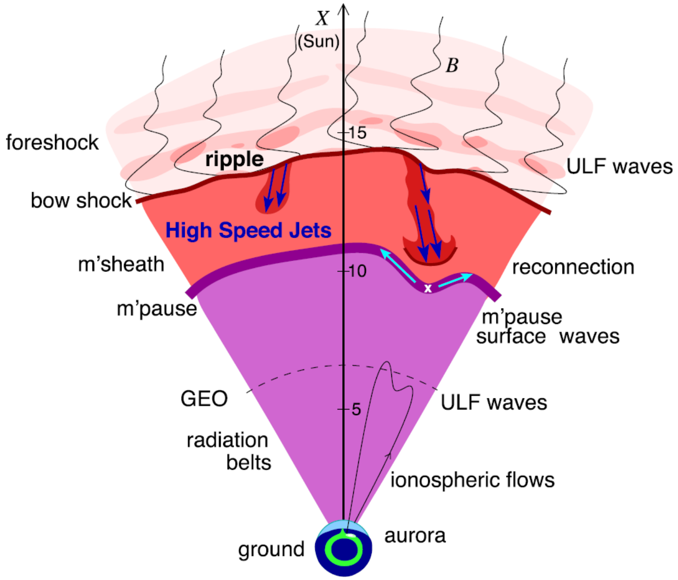
How: MMS (Magnetosheath) – OMNIweb database (Solar Wind)

Why: Interaction of SW & Magnetosphere, magnetopause reconnection, radiation belts, auroral features…



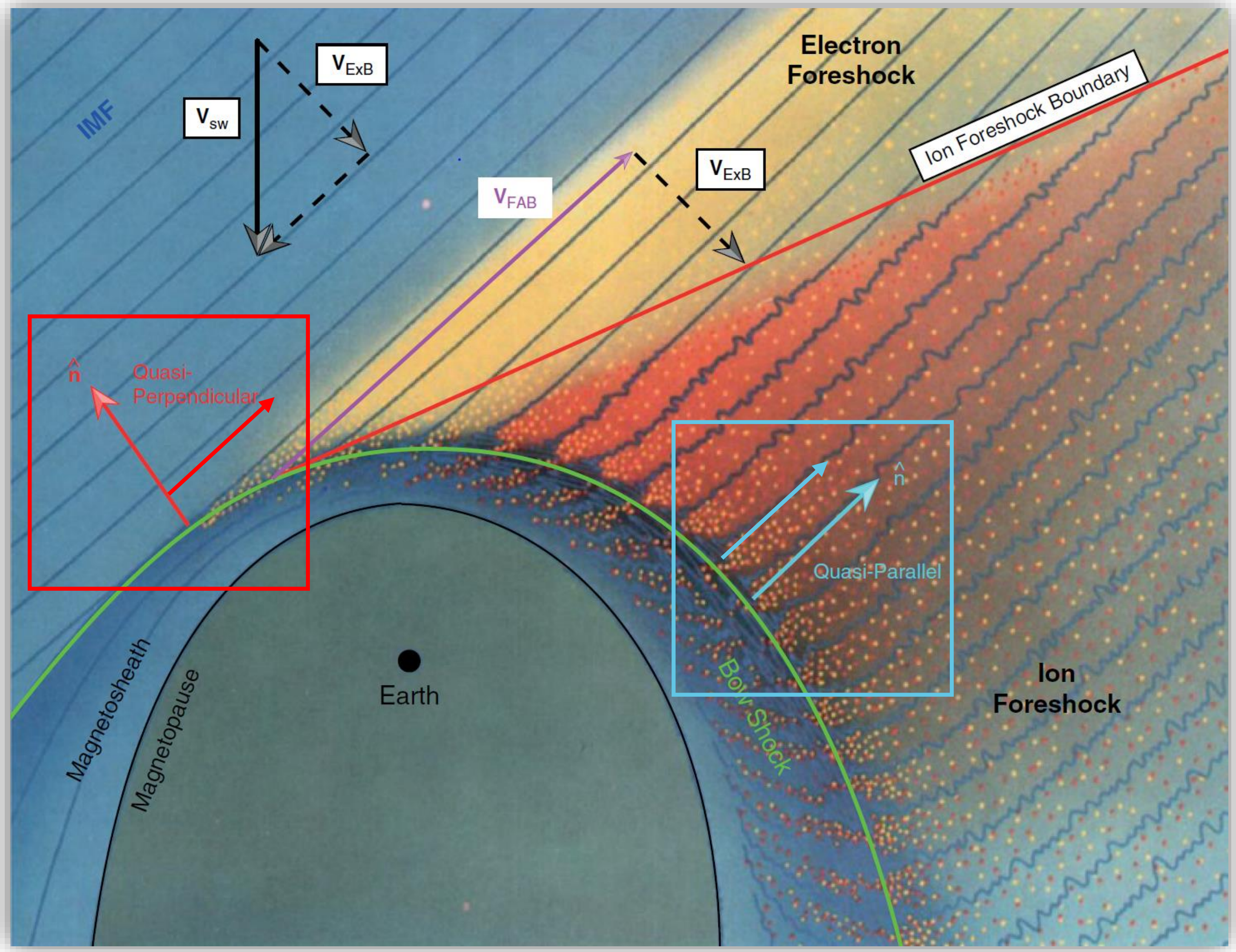


Palmroth Minna et al. (2018)



Plaschke F. et al. (2018)

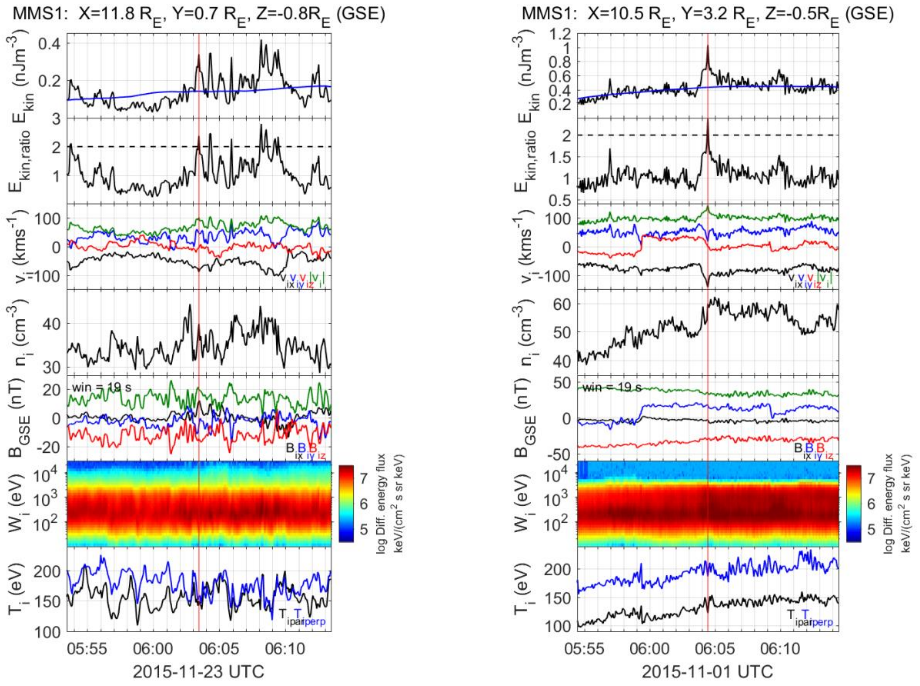
Classes of Magnetosheath Jets



L. B. Wilson (2016)

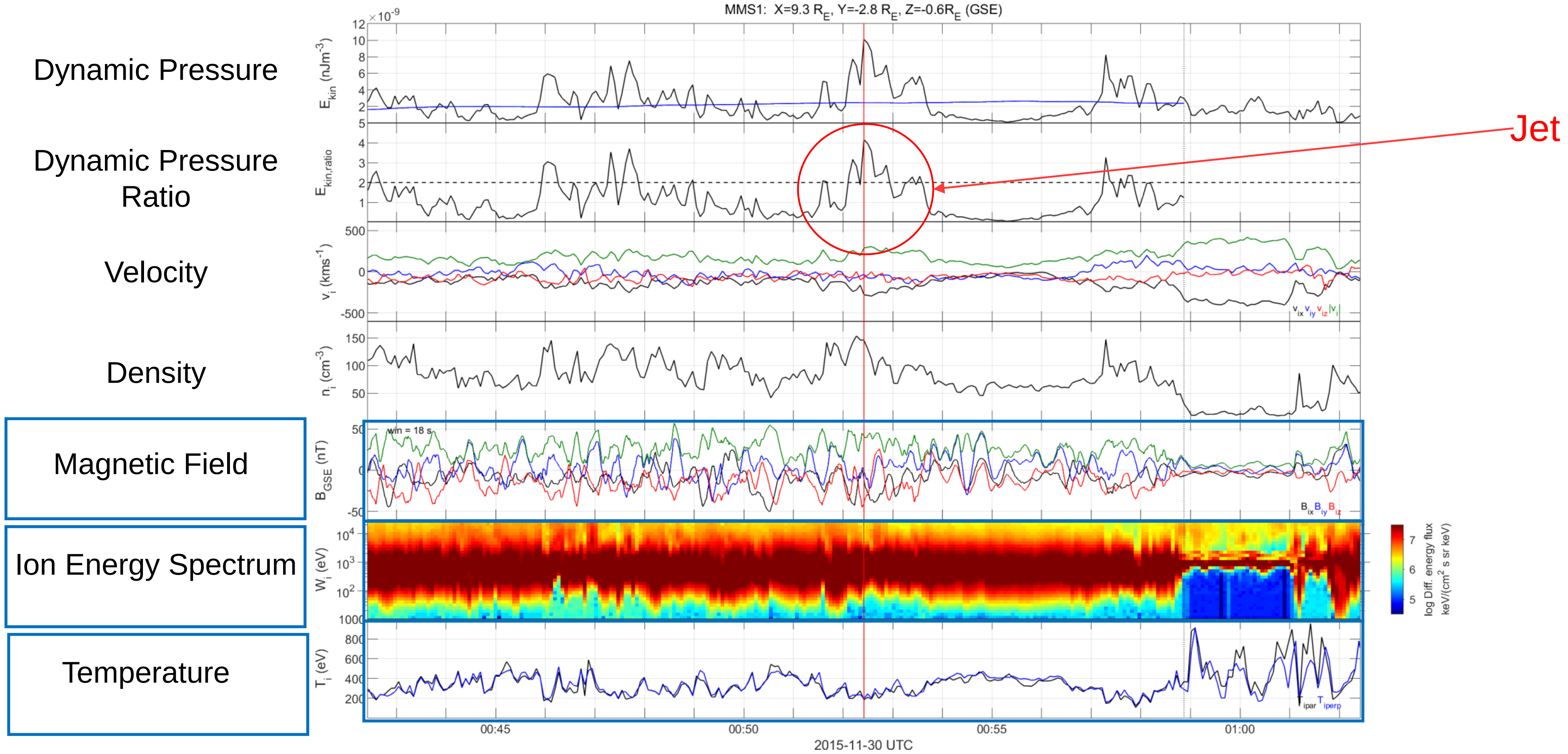
Jets are found mainly in quasi-parallel shock ($\theta_n < 45°$). However, fluctuations also found in quasi-perpendicular regions.

Q_{par}	Q_{per}



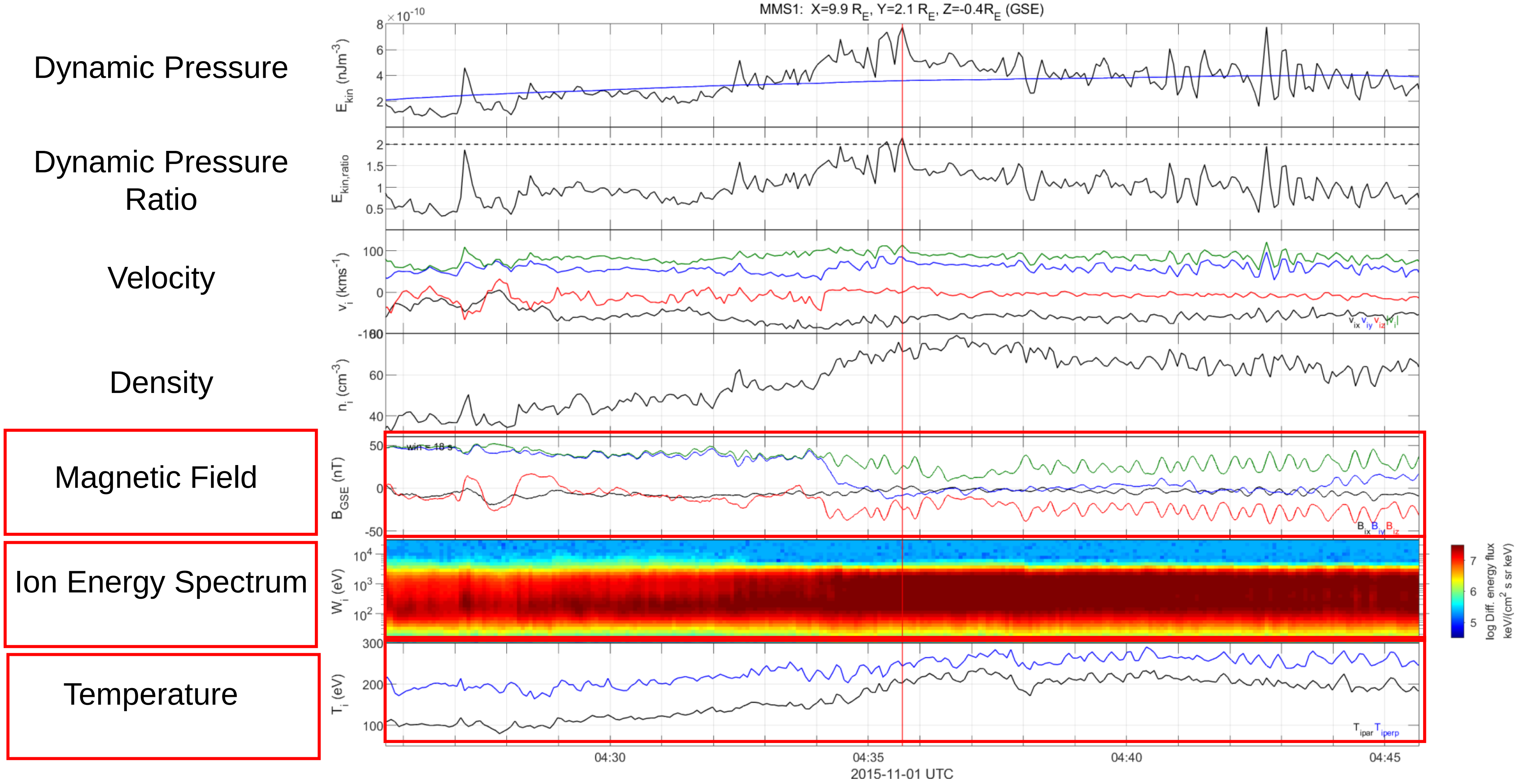
Quasi-parallel jet using MMS

High B Variance, High Energetic Particles, Low Anisotropy



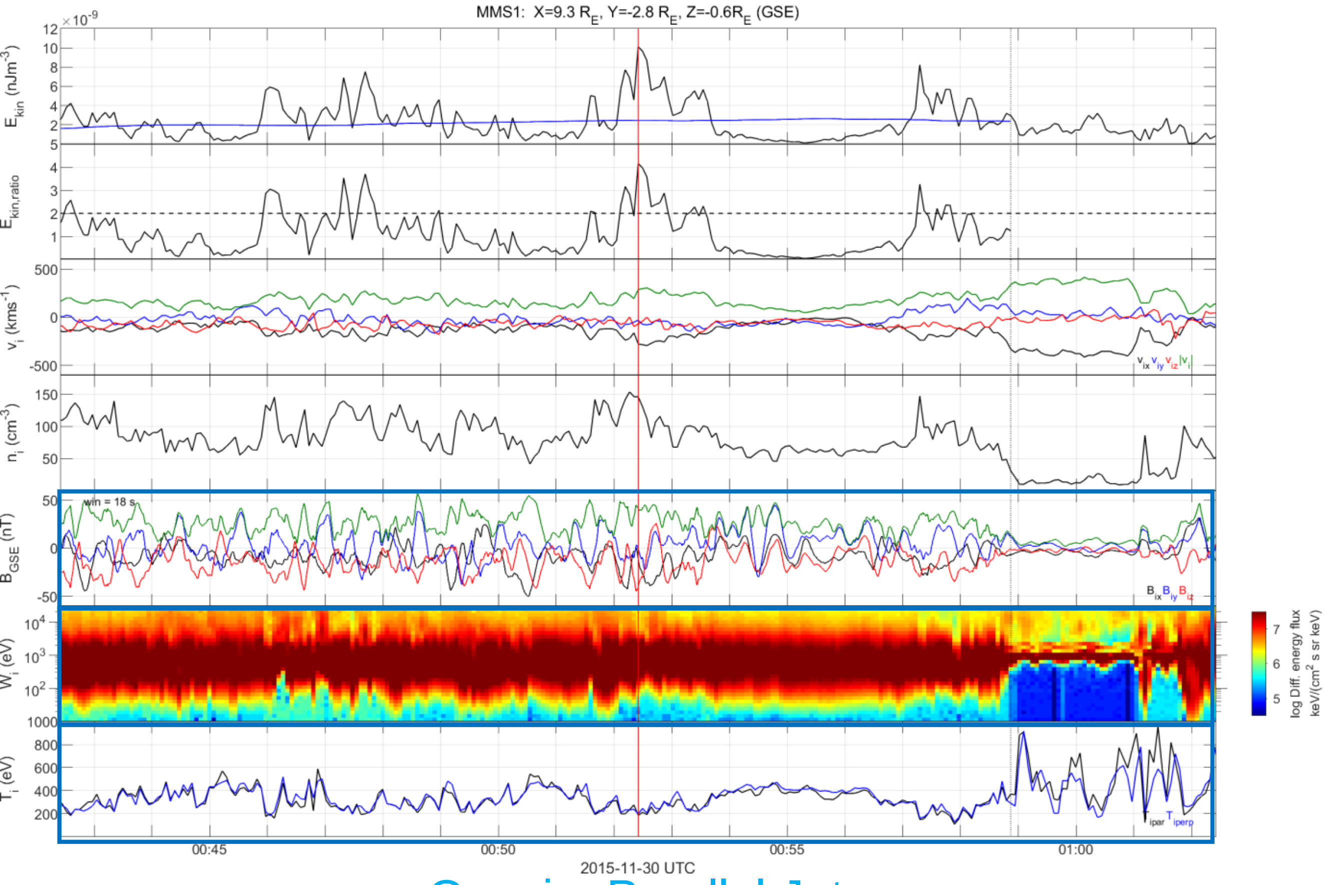
Quasi-perpendicular jet using MMS

Low B Variance, Low Energetic Particles, High Anisotropy



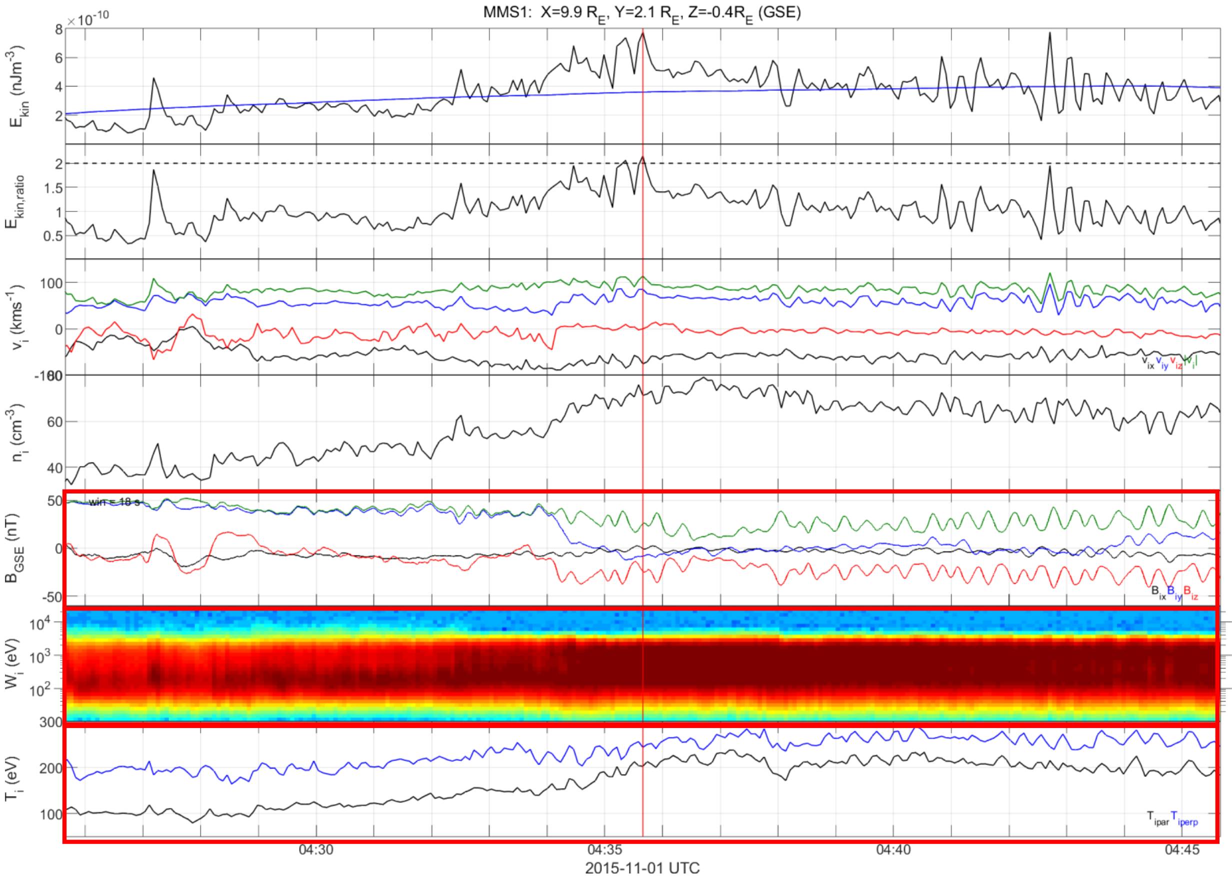
Differences of each class

High Variance, High Energetic Particles, Low Anisotropy



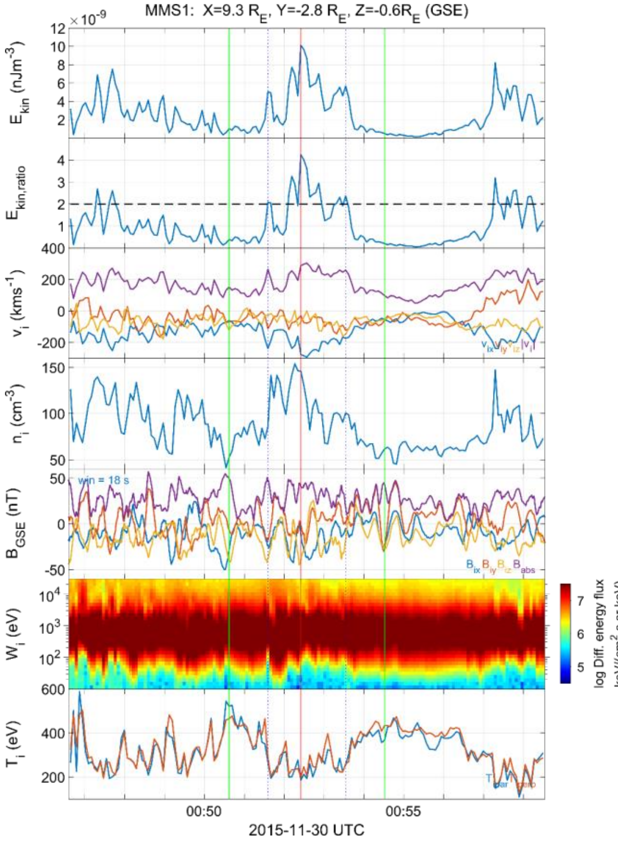
Quasi – Parallel Jet

Low Variance, No Energetic Particles, High Anisotropy

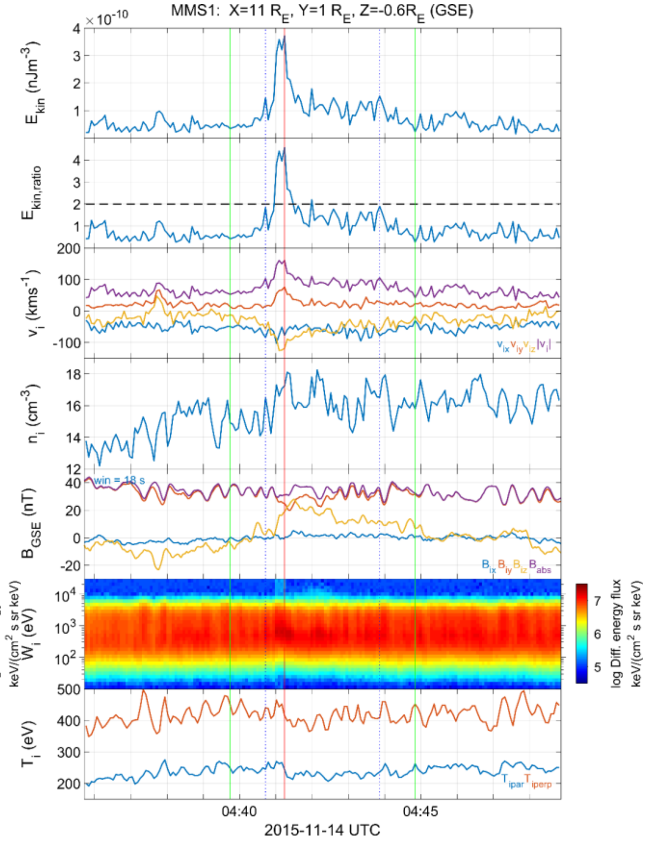


Quasi – Perpendicular

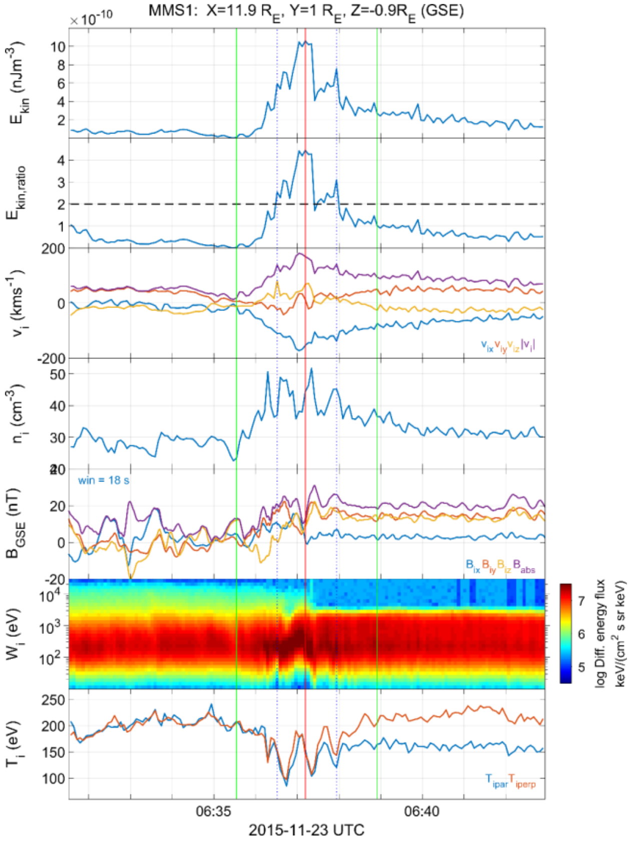
Main Categories



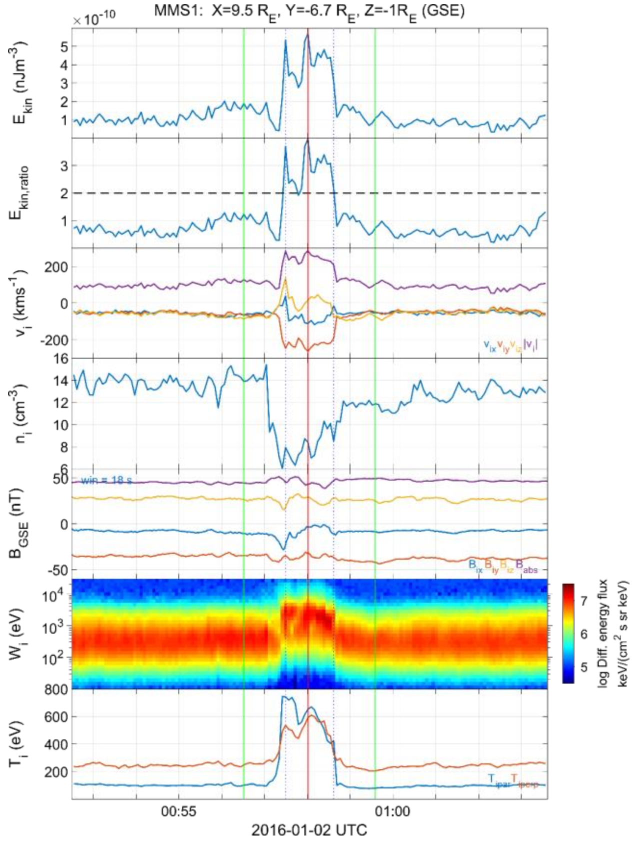
Qpar Jet



Qperp Jet



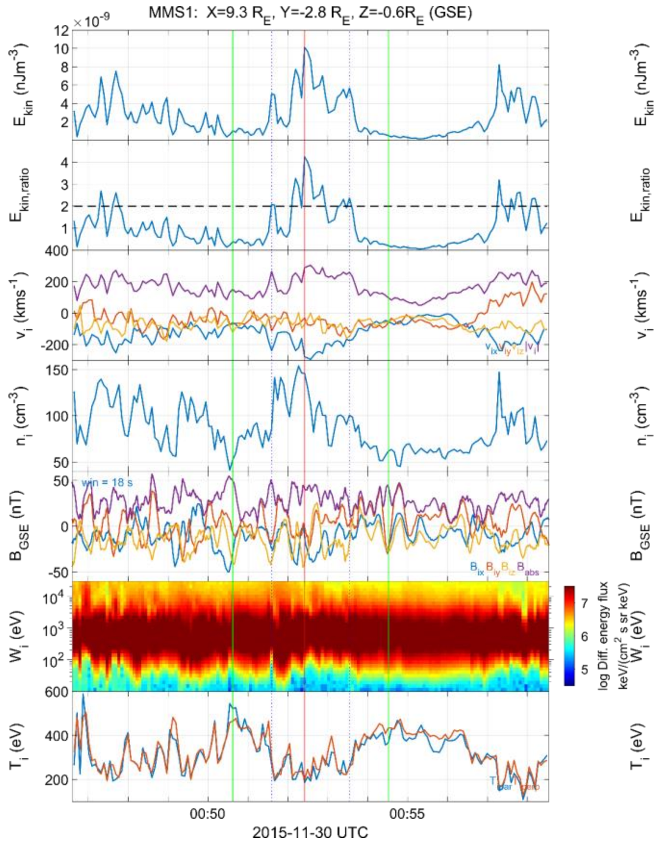
Boundary Jet



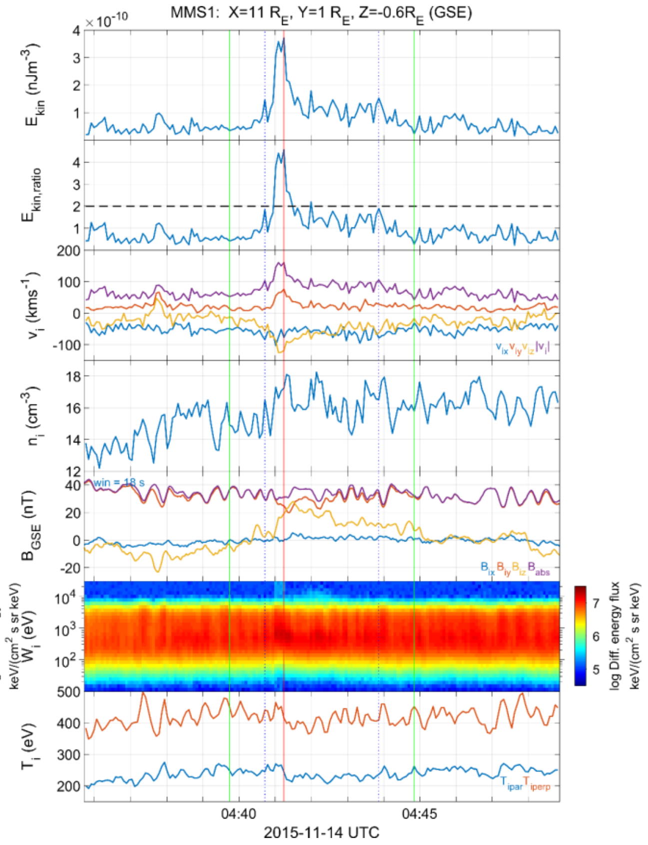
Encapsulated Jet

Raptis S., et al. 2019 (In progress)

Main Categories

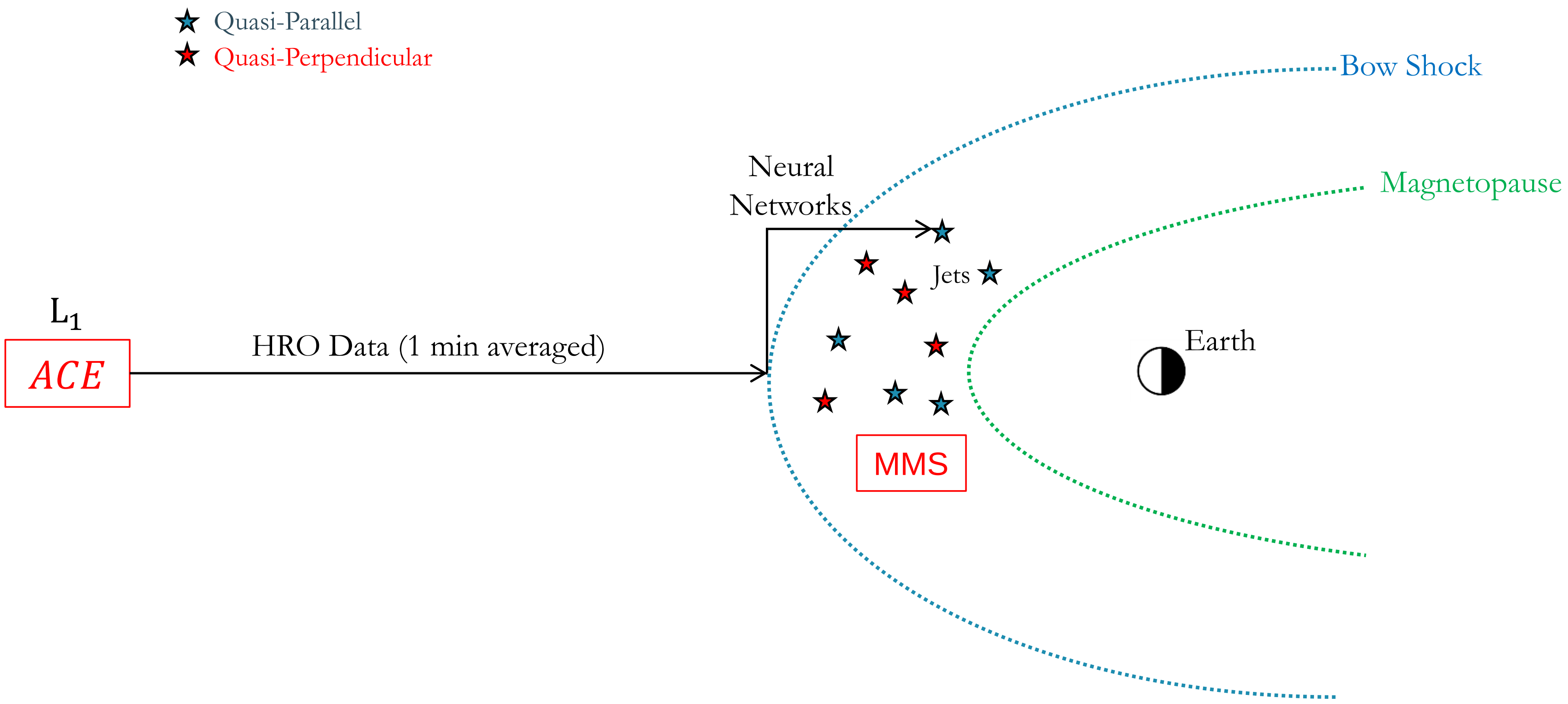


Qpar Jet



Qperp Jet

Motivation


Quasi-Parallel
Quasi-Perpendicular
Bow Shock
Magnetopause
Neural
Networks
Jets
L_1
ACE
HRO Data (1 min averaged)
Earth
MMS

Main Goal

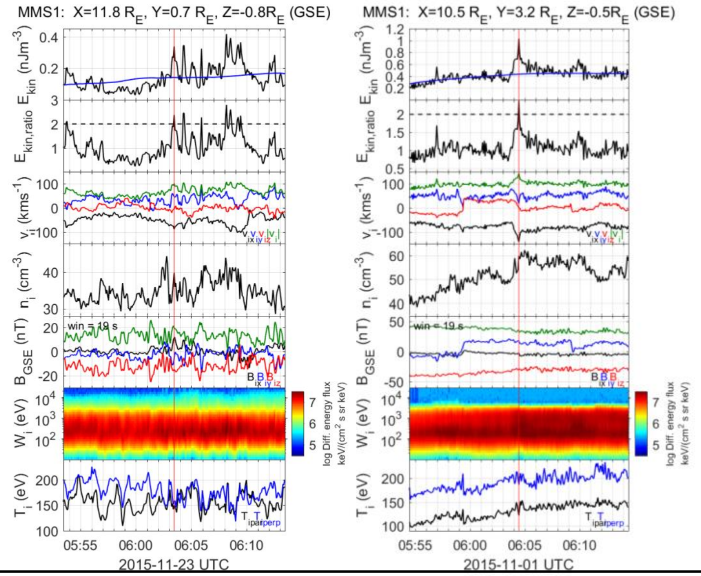
Find class of magnetosheath jet found by MMS using OMNIweb SW data

<u>Input</u>
Solar Wind Data (OMNIweb)

- Absolute Magnetic Field
- Dynamic Pressure
- Mach Number
- Beta Parameter
- Electric Field
- Velocity
- Density
- Temperature
- *Magnetic Field Components…*

<u>Output</u>
Magnetosheath Jet Class (MMS)

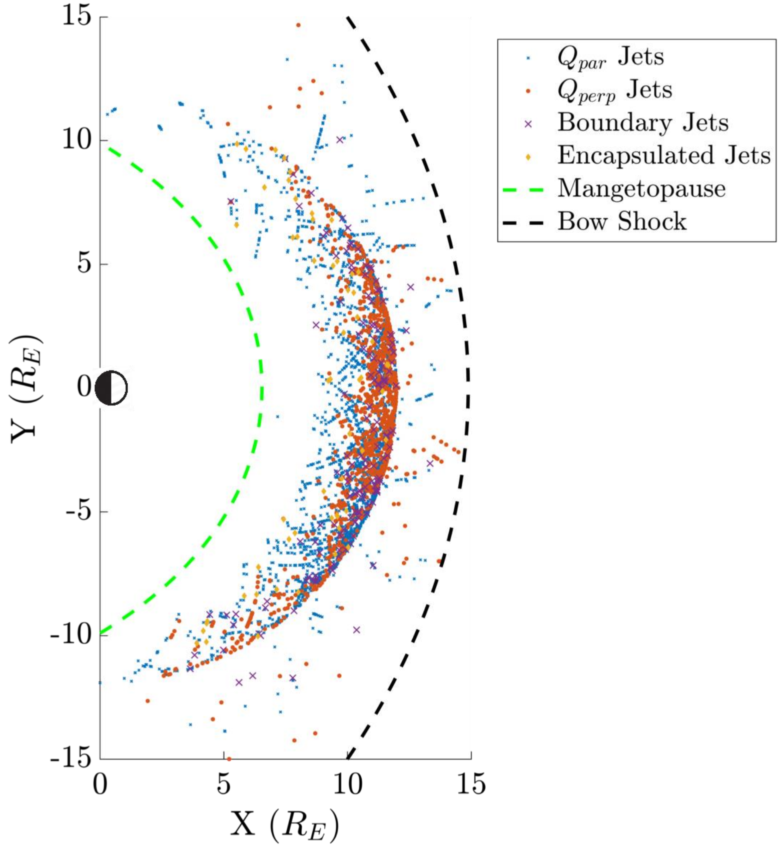
Q_{par}	Q_{per}



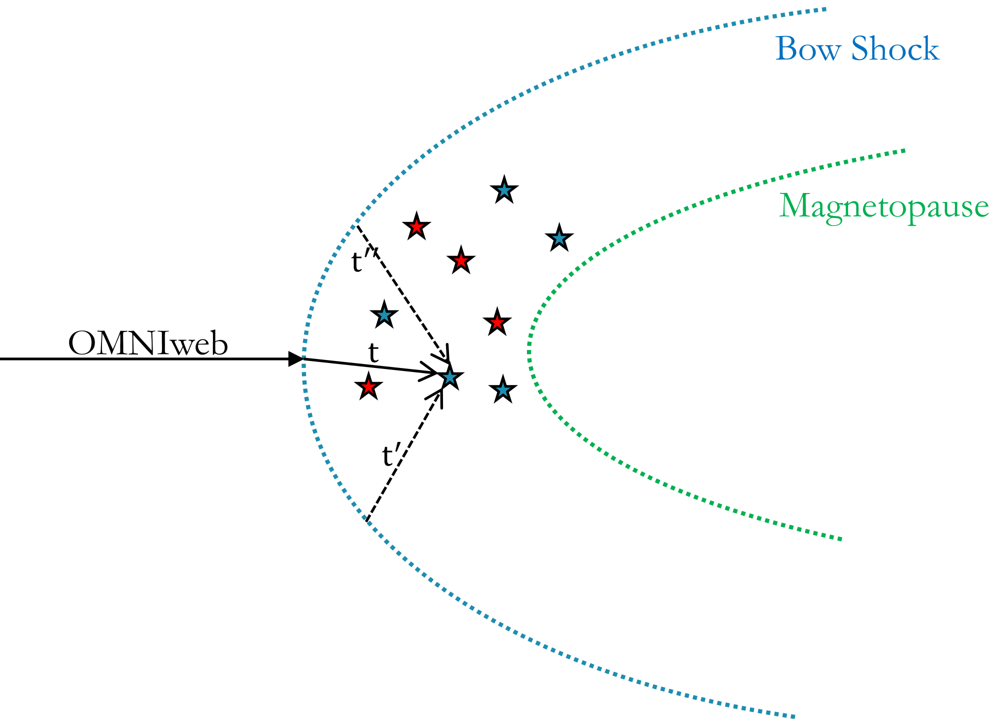
Output Jet list

Table 3. Classified dataset of the magnetosheath jets for the period 10/2015 - 04/2019.

Subset	Number	Percentage (%)
Quasi-parallel	2284	26.9
Certain	860	10.1
Quasi-perpendicular	504	5.9
Certain	211	2.5
Boundary	744	8.8
Certain	154	1.8
Encapsulated	77	0.9
Certain	57	0.7
Other	4890	57.5
Unclassified	3499	41.2
Border	1346	15.8
Data Gap	45	0.5



Input (Solar Wind)



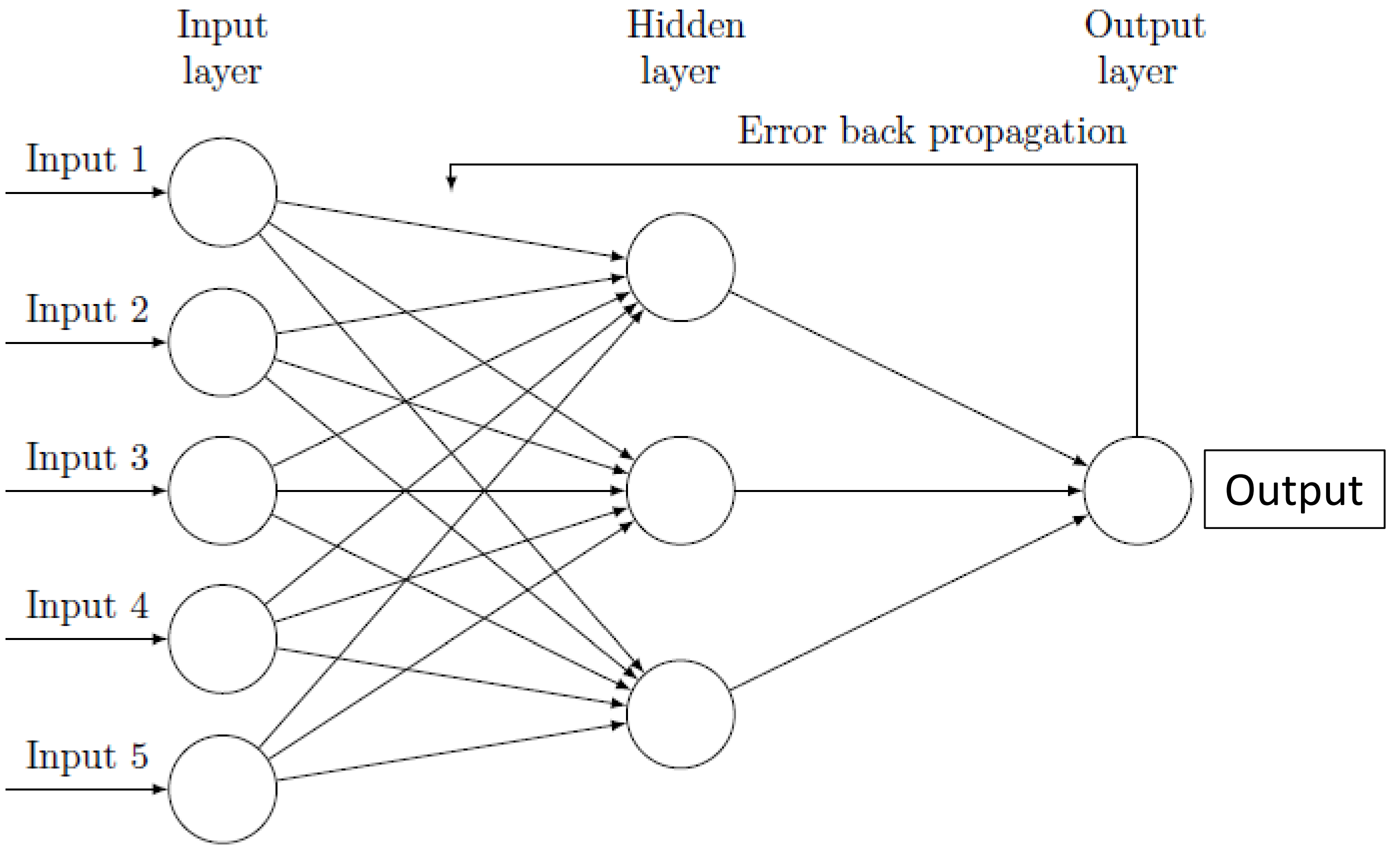
- Solar Wind at $t_0 = t_{MMS}$ ✗
- Mean Solar Wind $(t_0 - 10, t_0 + 5)$ ✗
- Mean Solar Wind $(t_0 - 5, t_0)$ ✓
- Max Solar Wind $(t_0 - 5, t_0)$ ✓

Why Connect SW to jets?

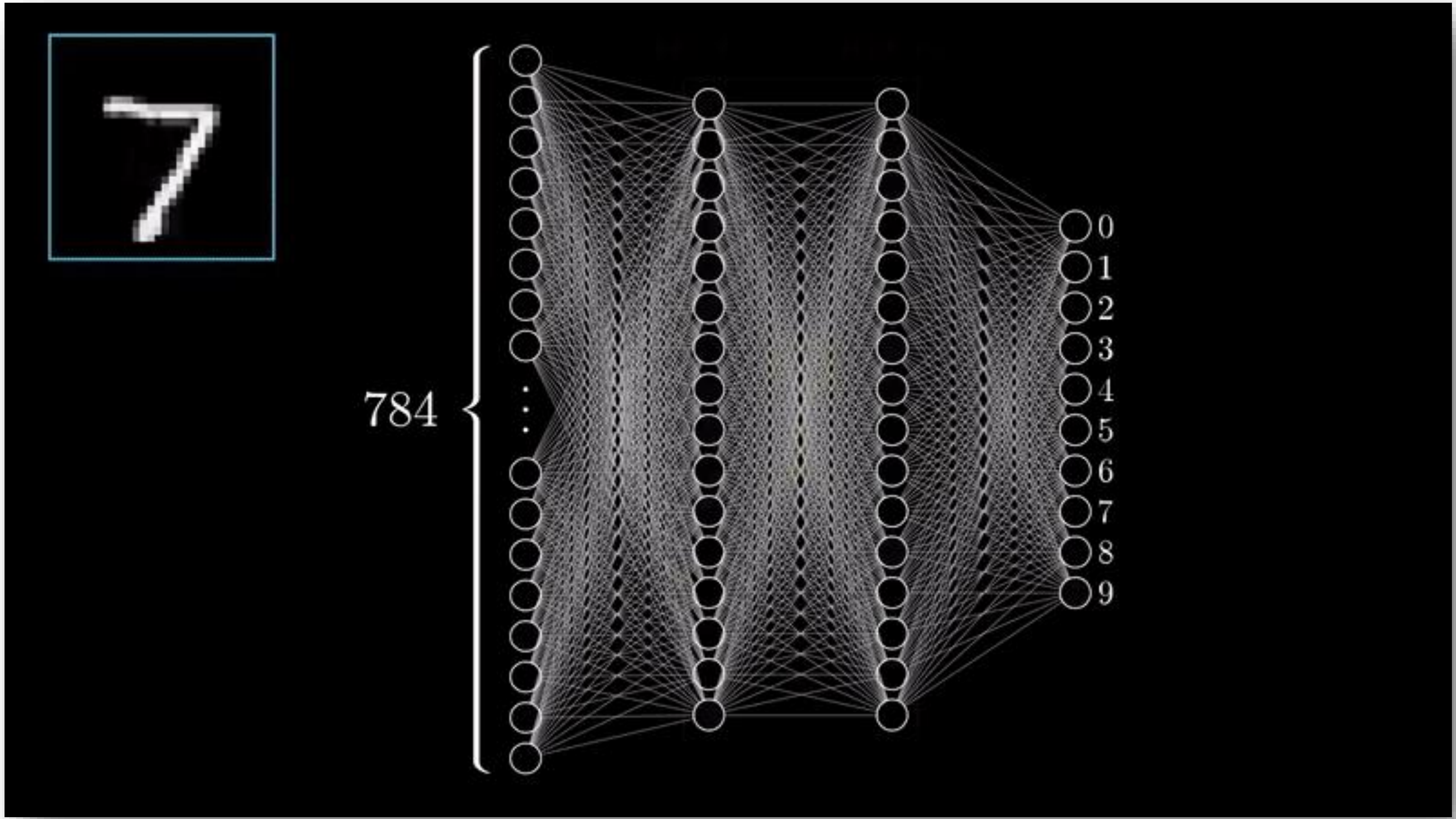
Associate Solar Wind parameters and Jets (SW → MSH)	Assist initial classification based on SW conditions	Work towards jet prediction & generation mechanism
<u>Known</u> Mach Number = Increased Frequency <u>To be determined</u> Temperature Absolute Magnetic Field Density Velocity Electric Field Plasma beta …	<table><tr><td>Other</td><td>4890</td><td>57.5</td></tr><tr><td>Unclassified</td><td>3499</td><td>41.2</td></tr><tr><td>Border</td><td>1346</td><td>15.8</td></tr><tr><td>Data Gap</td><td>45</td><td>0.5</td></tr></table> Provide percentages for unclassified jets	<u>Prediction of Jets</u> Probabilities of jet occurrence, total dynamic pressure, etc. <u>Generation Mechanism</u> Bow shock ripples ? IMF discontinuities ? …

Method

Neural Networks & Backpropagation

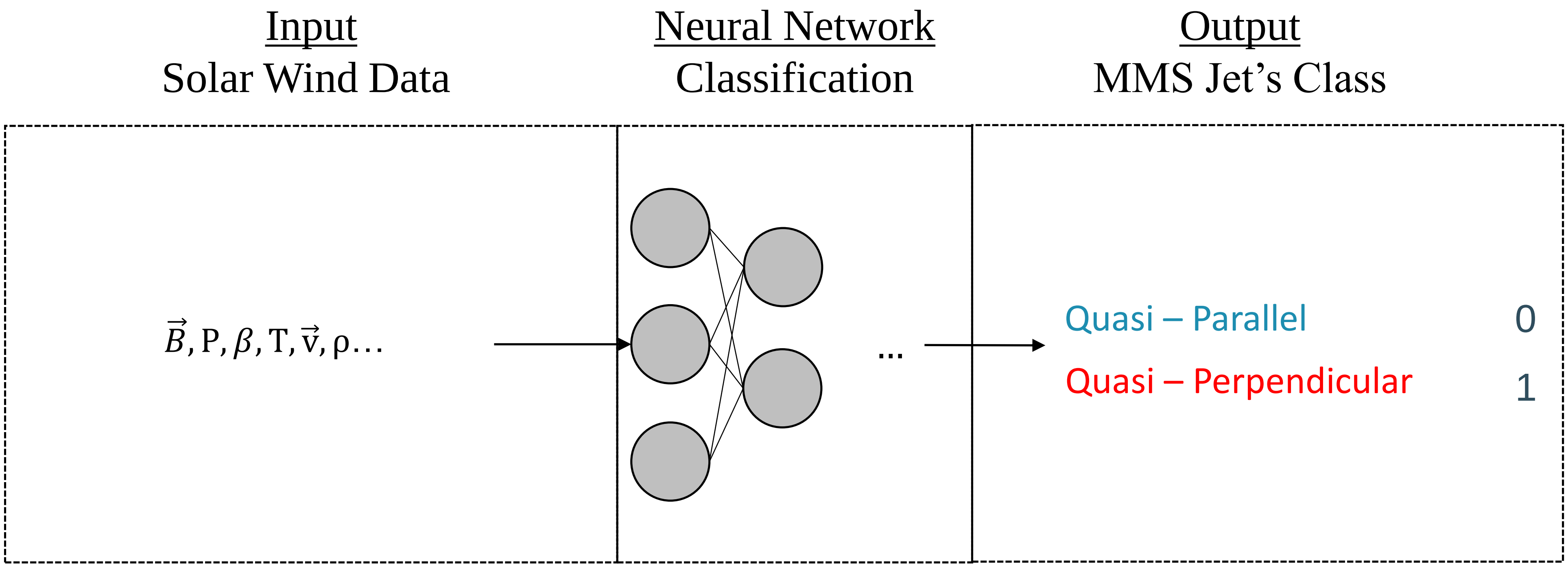


A Trained Neural Network



*Video Courtesy**: 3Blue1Brown** (Check him on YouTube!)

Schematic of Procedure



Results

Best parameters

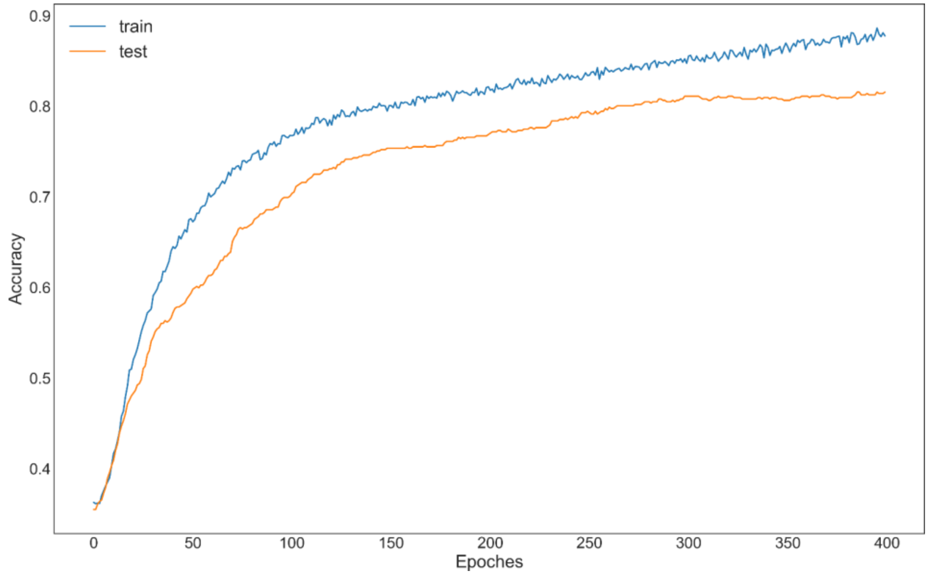
Neural Network Parameters

Training – Test set : 80 – 20%

Optimizer: Nadam

Activation Function: (P)ReLu, Softmax

Extra: Batch Normalization, Class Weight



Input Evaluation

Most important:

Alfvenic Mach Number
Magnetosonic Mach Number
Temperature
Beta parameter
Velocity
Density

Results – Example

$[train, test]$
$[C1, C2]$

	All Jets [2651, 662] [458, 213]		
Mean$(t_0 - 5, t_0)$	360	89	80%
	32	181	86%

Results – Example

Input

	All Jets [2651, 662] [458, 213]		
Mean$(t_0 - 5, t_0)$	360	89	80%
	32	181	86%

Results – Example

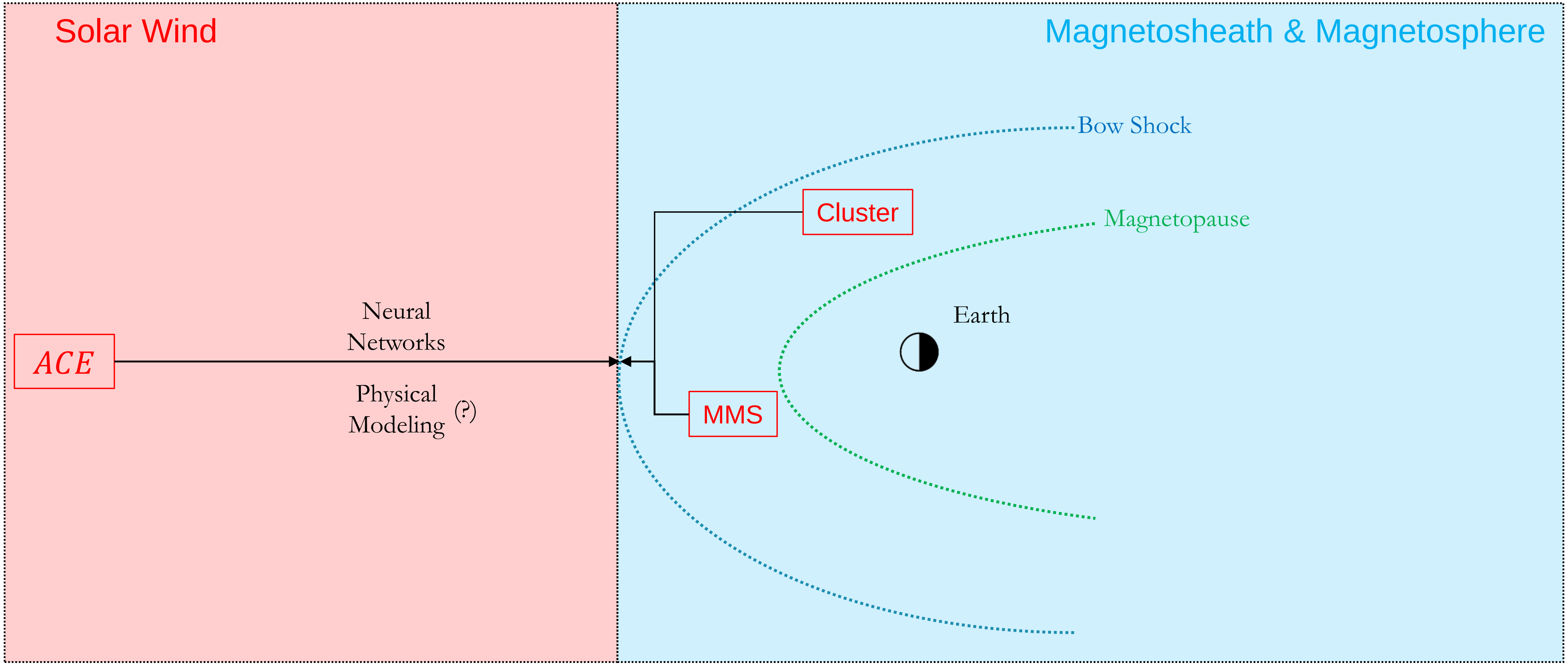
	<u>All Jets</u> [2651, 662] [458, 213]		
Mean$(t_0 - 5, t_0)$	360	89	80% / 86%
	32	181	

True	False	$\frac{Acc_1}{Acc_2}$
False	True	

Results – Classification Accuracies

		All Jets [2651, 662] [458, 213]			Certain Jets [728, 181] [139, 42]		
✓	Mean$(t_0 - 5, t_0)$	360	89	80%	135	4	97%
		32	181	86%	2	40	95%
✗	Max$(t_0 - 5, t_0)$	345	104	77%	131	8	94%
		55	158	74%	4	38	90%

Work in progress …



Conclusion

Summary

- Investigated different solar wind parameters and found the best combination for jet classification.
- Successfully classified part of the jets from our initial dataset with accuracy 80 – 96%
- Provided support to initial dataset from achieving a classification using different satellite data.

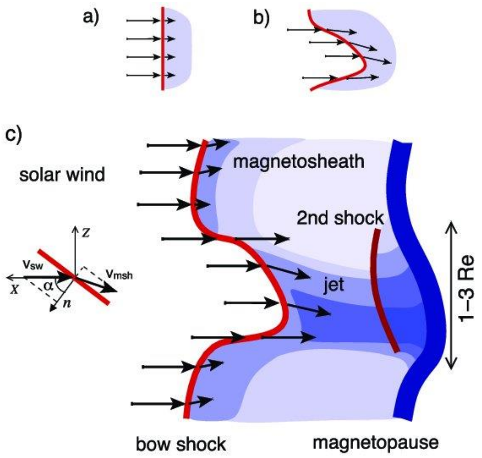
Future Work

- Add more categories of jets from the initial dataset (e.g. “boundary” Jets : Associated with IMF rotation)
- Try to classify unknown jets that could not be determined using initial algorithm.
- Revaluate classification based on the results.
- Work towards finding the dominant features of SW for jet phenomena and prediction.

Extra

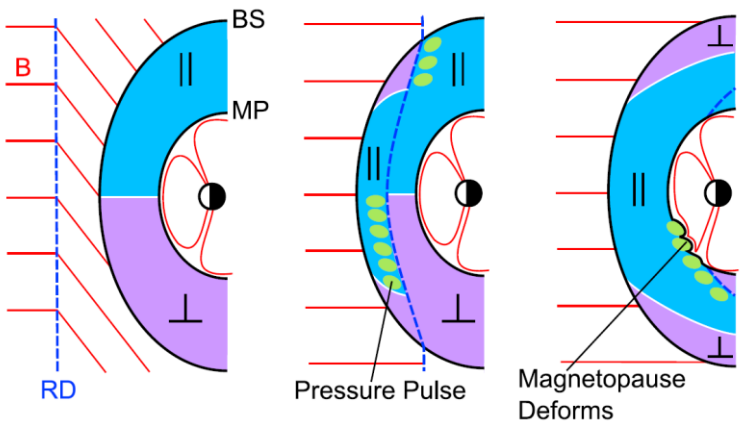
Mechanisms ideas for each jets

Quasi – Parallel



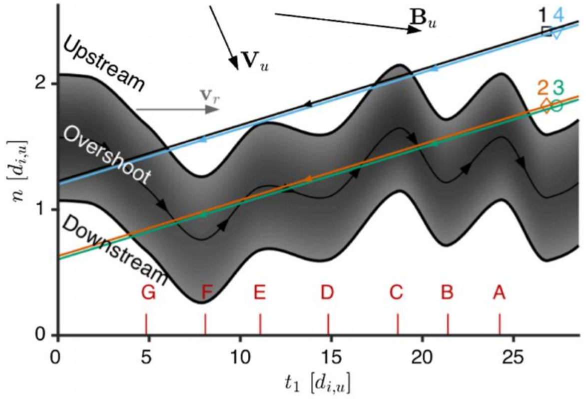
Hietala et al. (2012)

Boundary



Archer et al. (2012)

Quasi – Perpendicular



Johlander et al. (2016)