

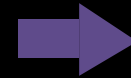
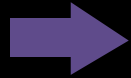
**Observationally-driven  
Ionospheric Conductivity:  
Where we are, where we need to be,  
and how to get there**

**June 22, 2019**

**Ryan McGranaghan**

Atmosphere and Space Technology Research  
Associates (ASTRA)

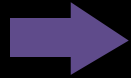
## Agenda



Why is progress slow?

Why is there hope?

What are the *trends*?



**Why is progress slow?**

**Why is there hope?**

**What are the *trends*?**

# Conductivity is...challenging

Why? - Where are we now? - What's next?

## Need to know:

- **Magnetic field strength**
- **Neutral composition**
- **Temperature**
- **Ion & electron densities**





Why is progress slow?

Why is there hope?

What are the *trends*?

# Progress

## Conductivity assimilation

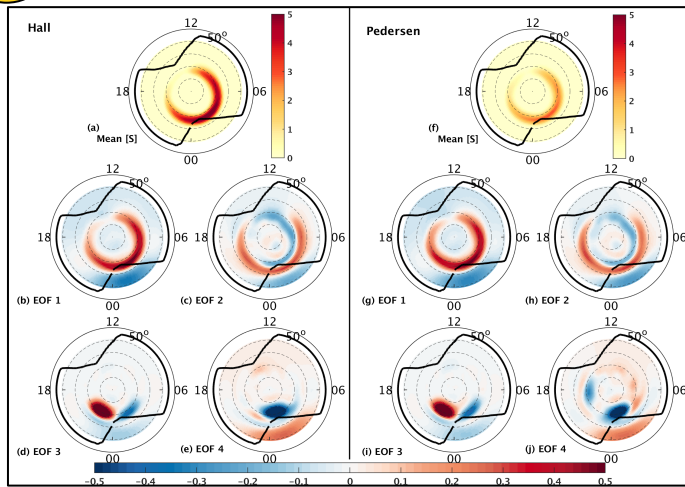
Why? - **Where are we now?** - What's next?

# Progress

## Conductivity assimilation

Why? - Where are we now? - What's next?

### 1 Characterize the variability



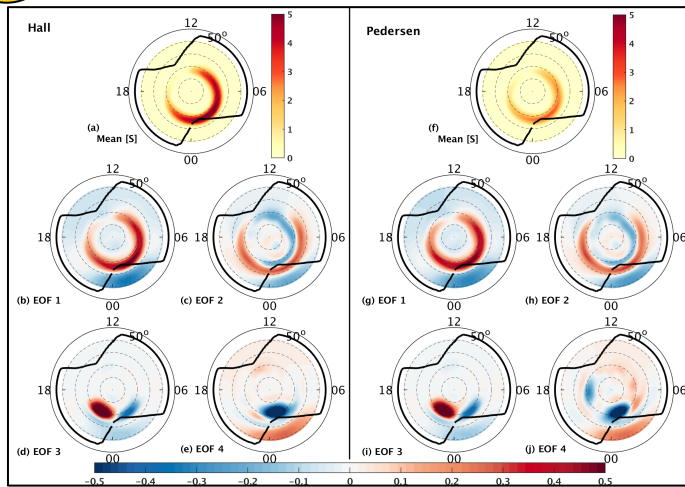
McGranaghan, R. et al. (2015), Modes of high-latitude conductance variability derived from DMSP energetic electron precipitation observations: Empirical Orthogonal Function (EOF) analysis. *J. Geophys. Res. Space Physics*, 120, 11,013–11,031, doi:[10.1002/2015JA021828](https://doi.org/10.1002/2015JA021828).

# Progress

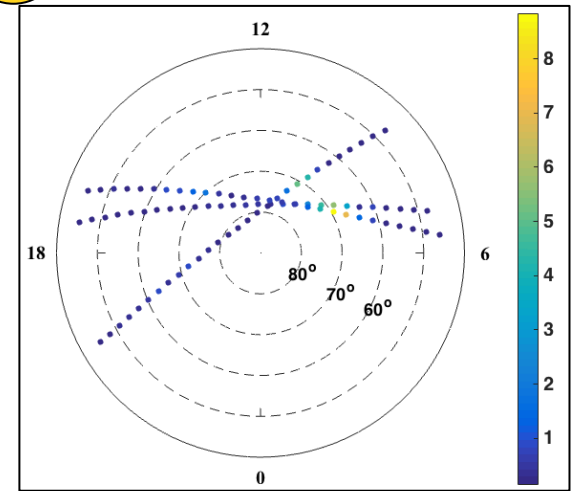
## Conductivity assimilation

Why? - Where are we now? - What's next?

### 1 Characterize the variability



### 2 Accumulate observations



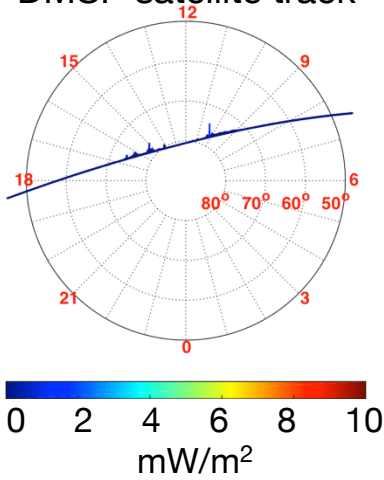
McGranaghan, R., D. J. Knipp, T. Matsuo, and E. Cousins (2016), Optimal interpolation analysis of high-latitude ionospheric Hall and Pedersen conductivities: Application to assimilative ionospheric electrodynamics reconstruction, *J. Geophys. Res. Space Physics*, 121, 4898–4923, doi:[10.1002/2016JA022486](https://doi.org/10.1002/2016JA022486).

# Progress

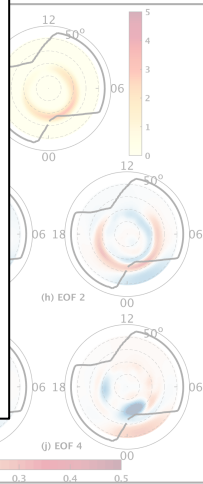
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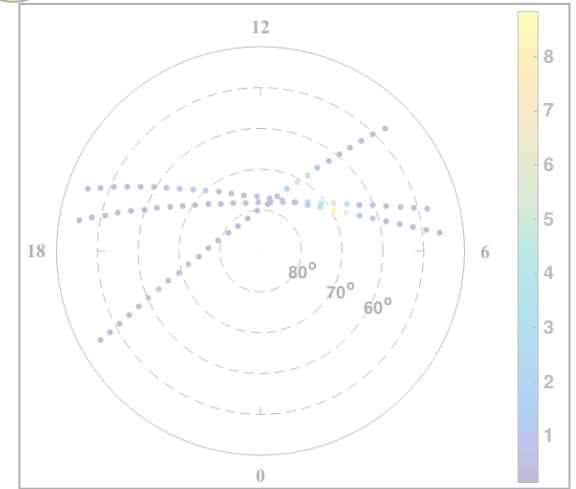
Total electron energy flux along  
DMSP satellite track



ability



## 2 Accumulate observations



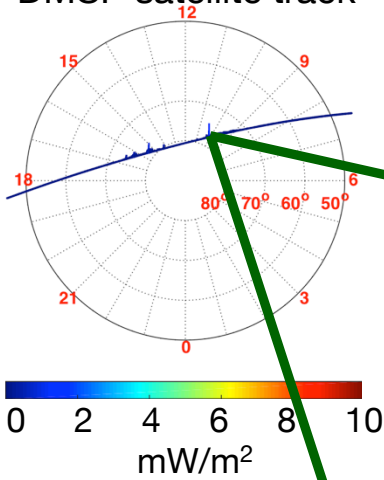
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# Progress

## Conductivity assimilation

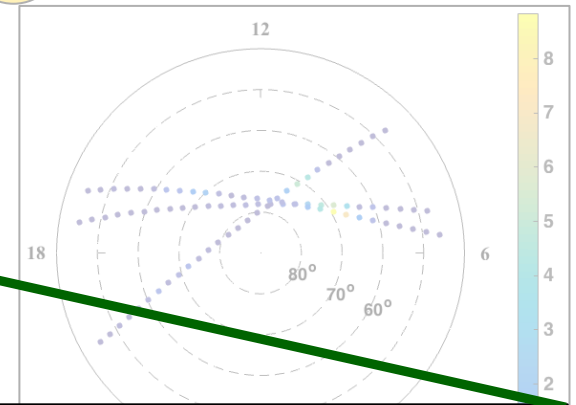
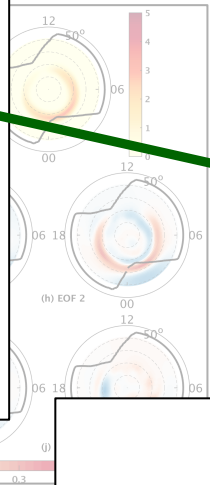
Why? - Where are we now? - What's next?

Total electron energy flux along DMSP satellite track

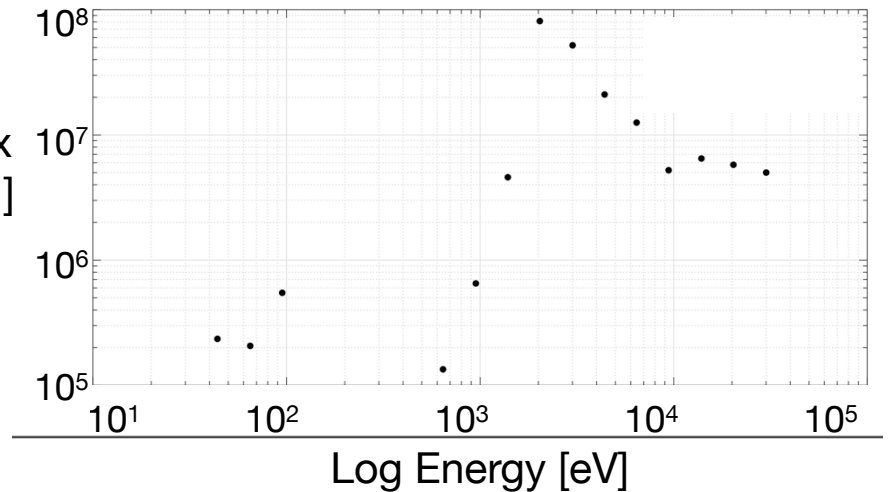


ability

2 Accumulate observations

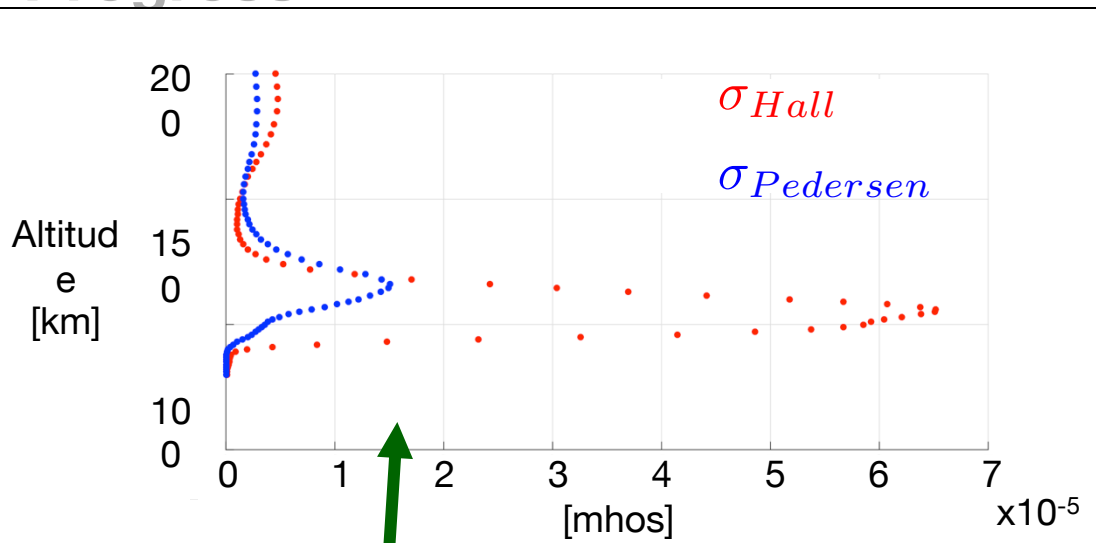
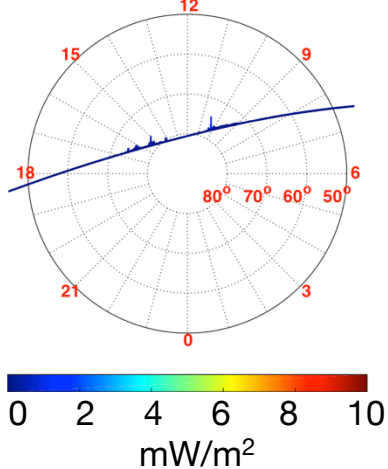


Log Energy Flux [eV cm<sup>-2</sup> sr<sup>-1</sup> s<sup>-1</sup>]



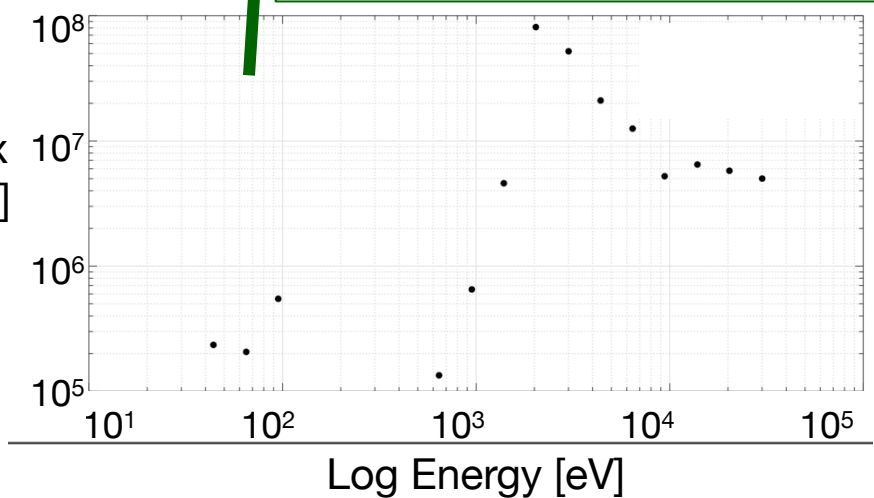
# Progress

Total electron energy flux along DMSP satellite track



**GLobal AirglOW + Conductivity (GLOWcon) model**

Log Energy Flux [eV cm<sup>-2</sup> sr<sup>-1</sup> s<sup>-1</sup>]

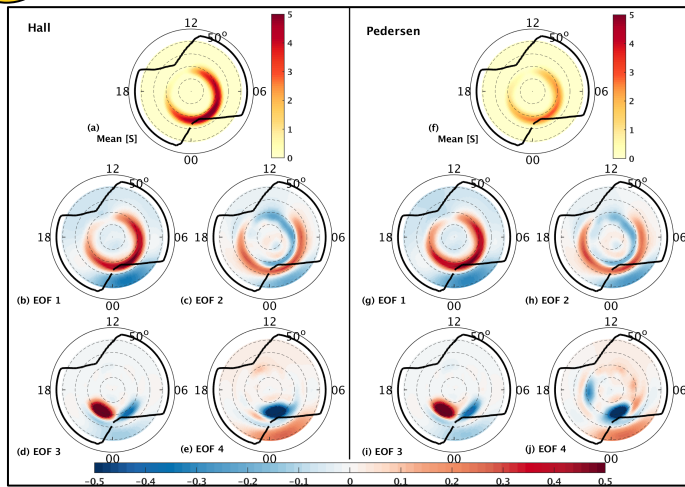


# Progress

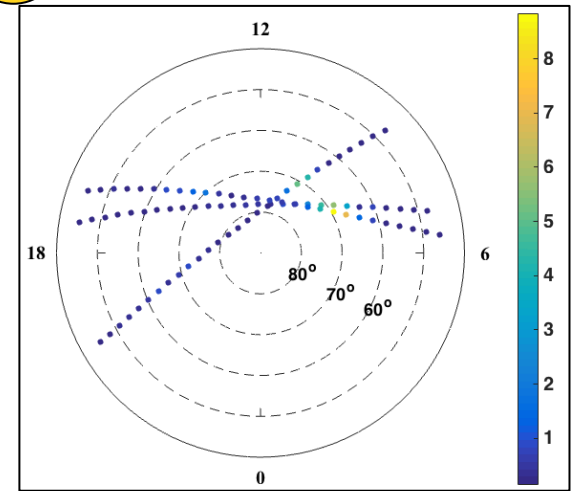
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Why? - Where are we now? - What's next?

### 1 Characterize the variability



### 2 Accumulate observations



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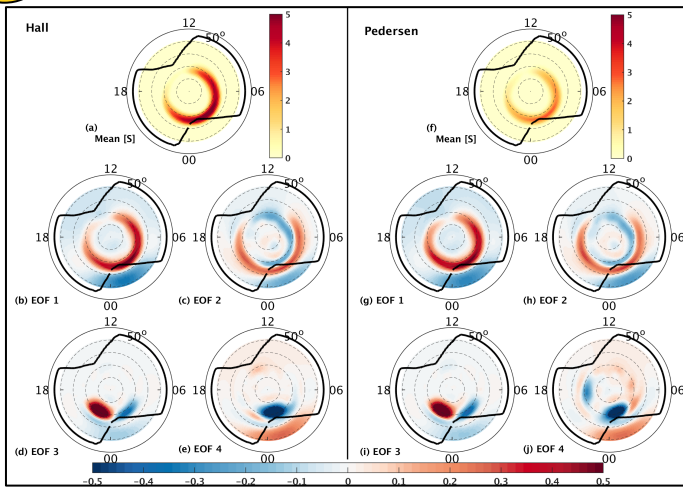


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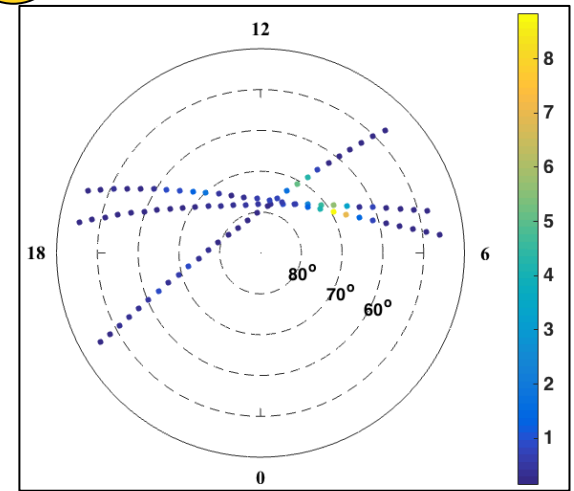
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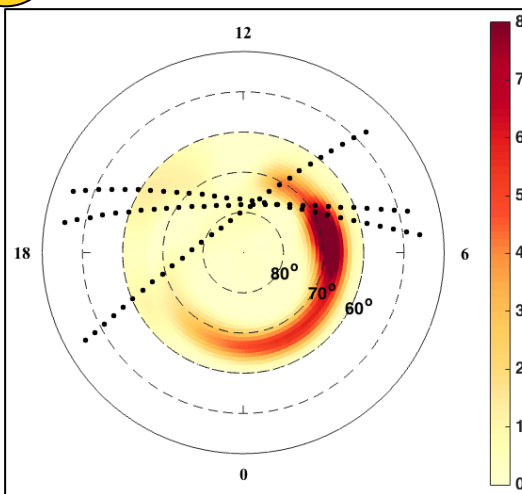
### 1 Characterize the variability



### 2 Accumulate observations



### 3 Optimal interpolation



McGranaghan, R., D. J. Knipp, T. Matsuo, and E. Cousins (2016), Optimal interpolation analysis of high-latitude ionospheric Hall and Pedersen conductivities: Application to assimilative ionospheric electrodynamic reconstruction, *J. Geophys. Res. Space Physics*, 121, 4898–4923, doi:[10.1002/2016JA022486](https://doi.org/10.1002/2016JA022486).

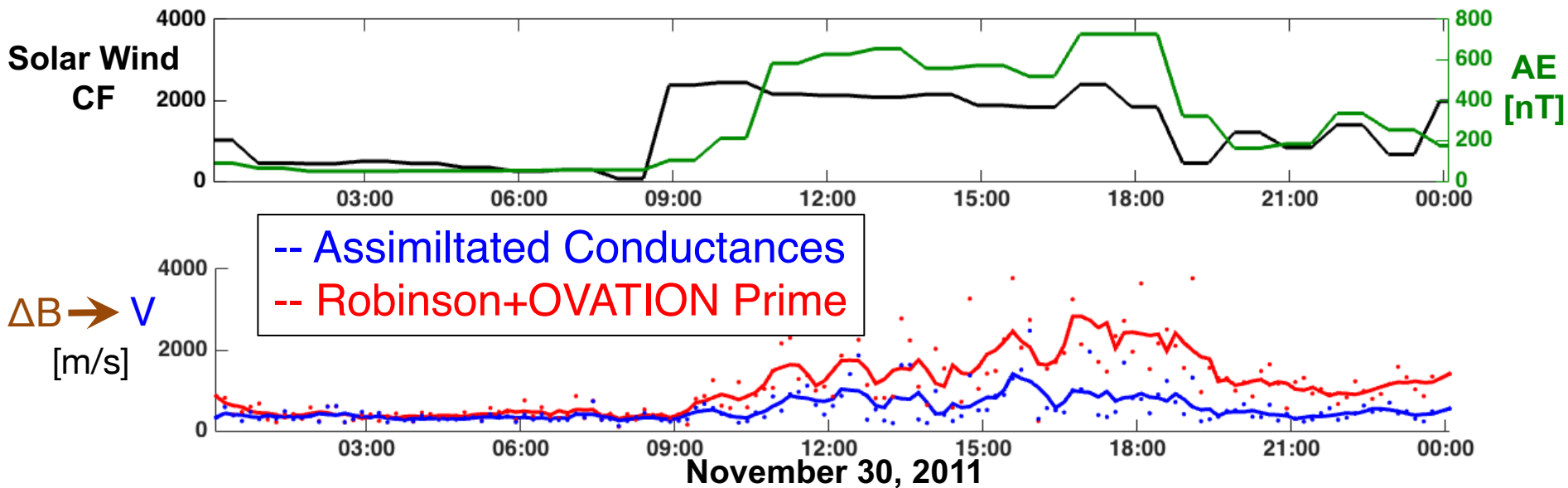
# Progress

## Conductivity assimilation

Why? - Where are we now? - What's next?

$\Delta B \rightarrow V$

### Median Absolute Deviations (MADs)



Total  $\Delta B \rightarrow V$  MADs [m/s]

Robinson+OVATION Prime: 684.2  
Assimilated Conductances : 382.7

~50% better prediction of SuperDARN observations

# Progress

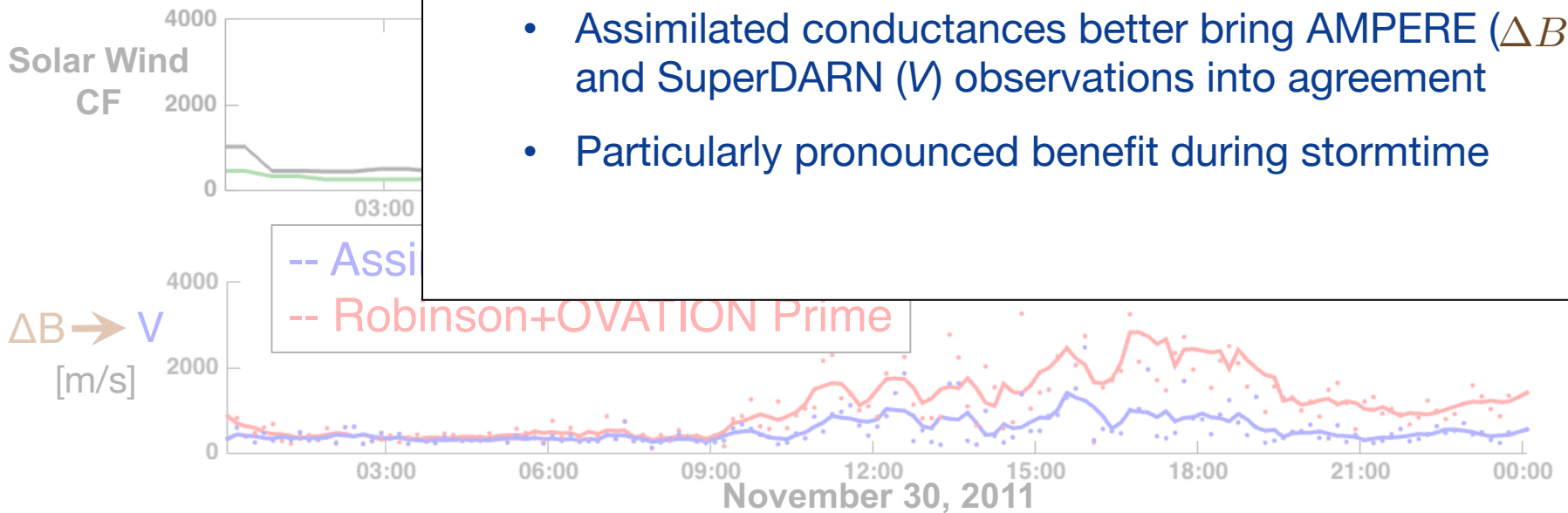
## Conductivity assimilation

Why? - Where are we now? - What's next?

$\Delta B \rightarrow V$

### Bottom line:

- Assimilated conductances better bring AMPERE ( $\Delta B$ ) and SuperDARN ( $V$ ) observations into agreement
- Particularly pronounced benefit during stormtime



Total  $\Delta B \rightarrow V$  MADs [m/s]

Robinson+OVATION Prime: 684.2  
Assimilated Conductances: 382.7

~50% better prediction of SuperDARN observations

# Progress

## PFISR – AMPERE

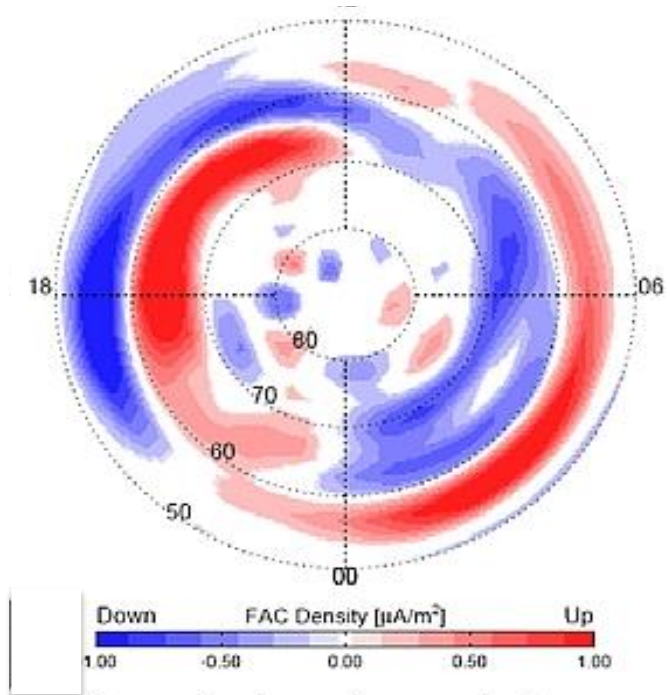
Why? - **Where are we now?** - What's next?

# Progress

## PFISR – AMPERE

Why? - Where are we now? - What's next?

### Active Magnetosphere and Planetary Electrodynamics Response Experiment (AMPERE)



### Poker Flat Incoherent Scatter Radar (PFISR)



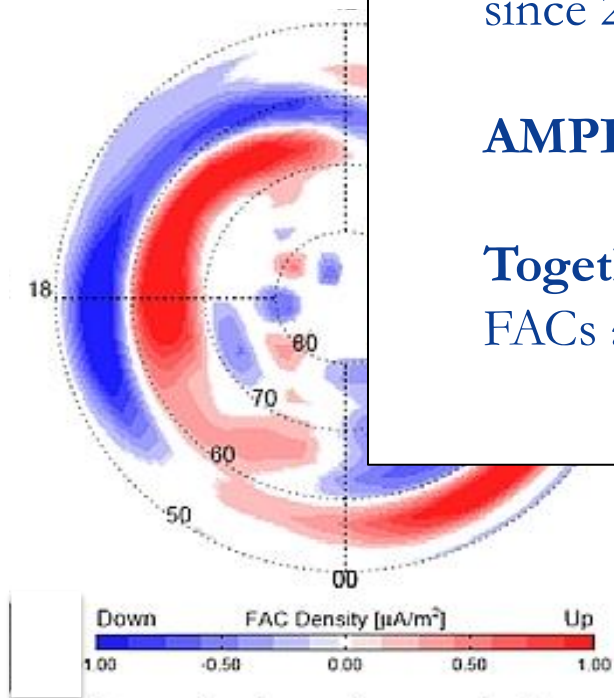
Courtesy: Bob Robinson & Katie Garcia-Sage

# Progress

## PFISR – AMPERE

Why? - Where are we now? - What's next?

### Active Magnetospheric and Planetary Electrodynamic Response Experiment



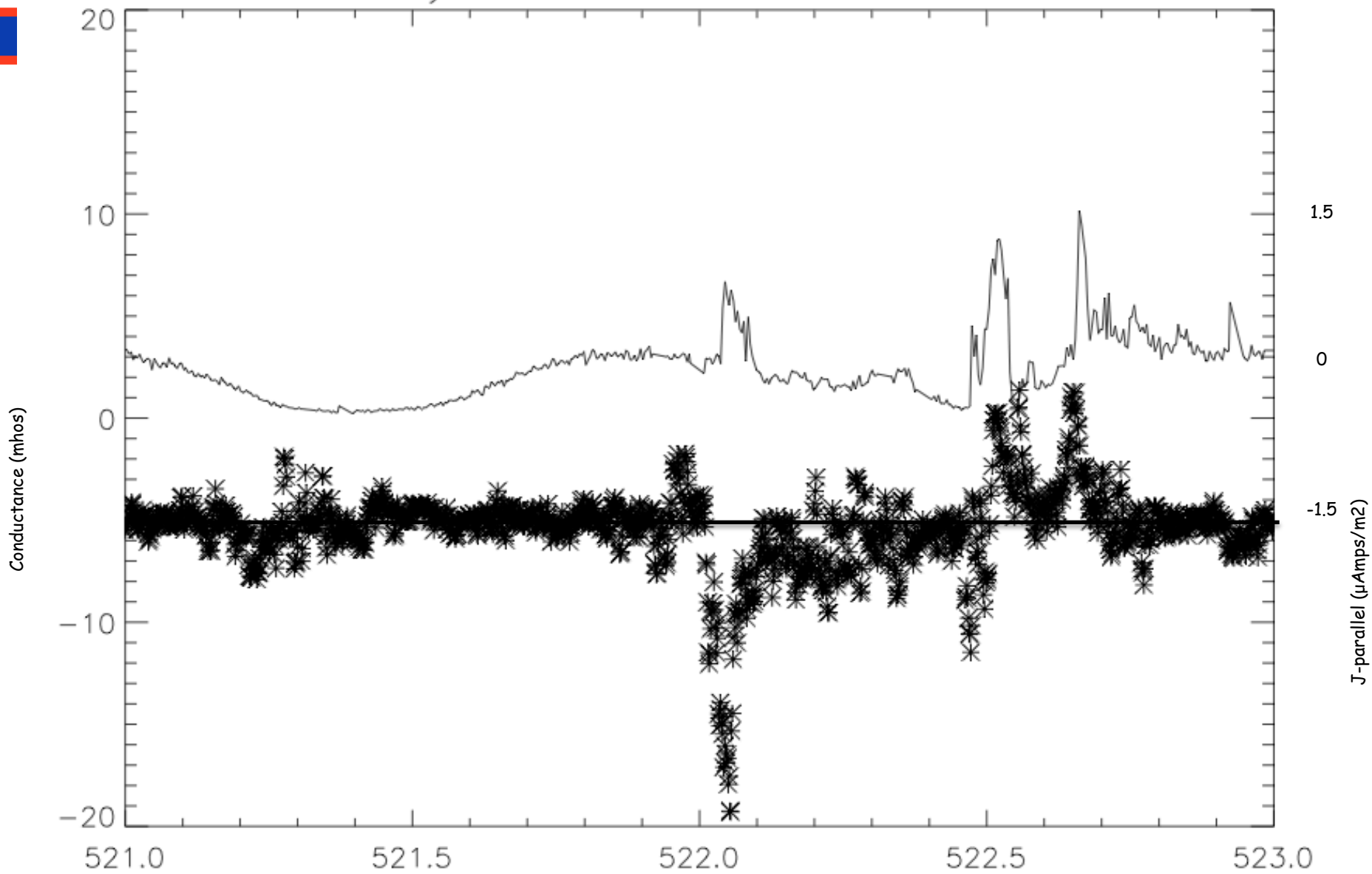
**PFISR** = ionospheric conductivity data every 10 minutes since 2009

**AMPERE** = FACs since 2010

**Together** = ~1.5 million simultaneous measurements of FACs and ionospheric conductivities



Day number: 521 to 523



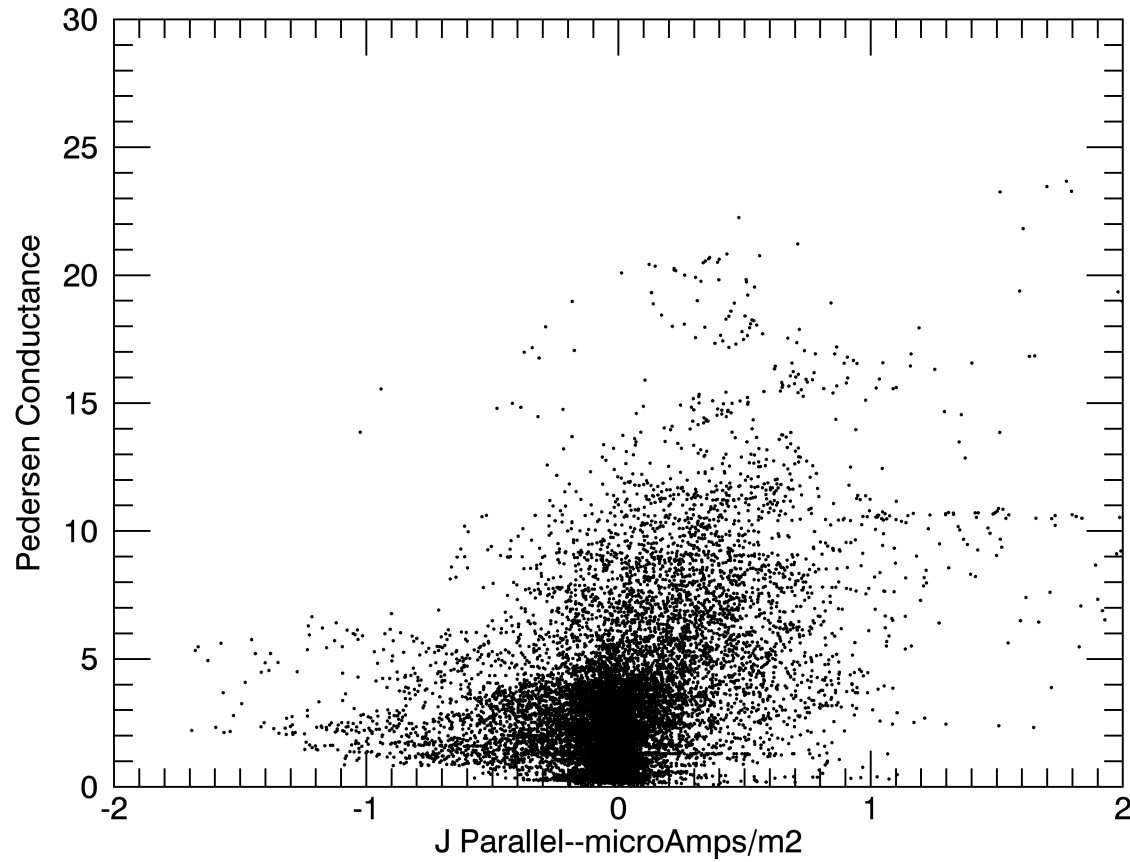
Courtesy: Bob Robinson & Katie Garcia-Sage



# Progress

## PFISR – AMPERE

Why? - Where are we now? - What's next?





# Progress

## PFISR – THEMIS ASI








Why? - **Where are we now?** - What's next?

# Progress

## PFISR – THEMIS ASI

Why? - Where are we now? - What's next?

### How Well Can We Estimate Pedersen Conductance From the THEMIS White-Light All-Sky Cameras?

M. M. Lam<sup>1</sup> , M. P. Freeman<sup>2</sup> , C. M. Jackman<sup>1</sup> , I. J. Rae<sup>3</sup> , N. M. E. Kalmoni<sup>3</sup> ,  
J. K. Sandhu<sup>3</sup> , and C. Forsyth<sup>3</sup> 








<sup>1</sup>Department of Physics and Astronomy, University of Southampton, Southampton, UK, <sup>2</sup>British Antarctic Survey, Cambridge, UK, <sup>3</sup>Mullard Space Science Laboratory, University College London, London, UK

# Progress

## PFISR – THEMIS ASI

Why? - Where are we now? - What's next?

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<sup>1</sup>Department of Physics and Astronomy, University of Southampton, Southampton, UK, <sup>2</sup>British Antarctic Survey, Cambridge, UK, <sup>3</sup>Mullard Space Science Laboratory, University College London, London, UK

**PFISR** = ionospheric conductivity data every 10 minutes since 2009

**THEMIS ASI** = Wide field-of-view since 2006








**Together** = Expand conductivity specification over ASI FOV through empirical relationship between PFISR-ASI

# Progress

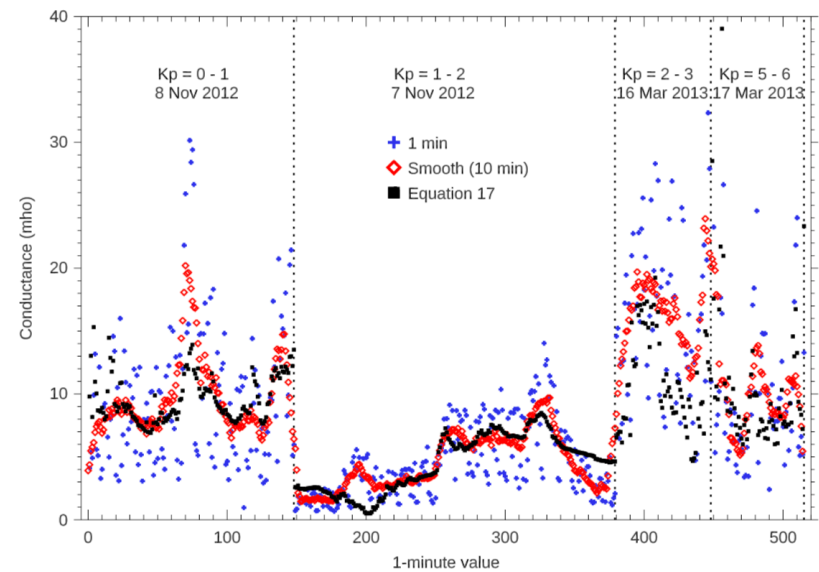
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Why? - Where are we now? - What's next?

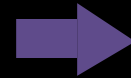
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<sup>1</sup>Department of Physics and Astronomy, University of Southampton, Southampton, UK, <sup>2</sup>British Antarctic Survey, Cambridge, UK, <sup>3</sup>Mullard Space Science Laboratory, University College London, London, UK



**Figure 8.** Time-domain comparison of the all-sky imager-derived Pedersen conductance with the PFISR-derived value. For each of the four intervals examined (Table 1), we plot the 1-min PFISR values of  $\Sigma_p$  (blue crosses), the 1-min PFISR values smoothed over 10 min (red diamonds), and the 1-min values of  $S_p$  (equation (16)) derived from all-sky imager data (black squares). The conductance is only plotted up to a value of 40 mho for clarity (a single 1-min data point exceeds this at ~64 mho). PFISR = Poker Flat Incoherent Scatter Radar.



Why is progress slow?

Why is there hope?

What are the *trends*?

Utilizing available observations



What are the *trends*?

Utilizing available observations

ISR capable of tying data  
together



What are the *trends*?

Utilizing available observations

ISR capable of tying data  
together

Data science to culminate  
efforts



**What are the *trends*?**



Utilizing available observations

ISR capable of tying data together

Data science to culminate efforts



What are the *trends*?

## Analysis Ready Data

|               |           | features |              |              |         |                              |              |            | label   |                    |
|---------------|-----------|----------|--------------|--------------|---------|------------------------------|--------------|------------|---------|--------------------|
|               |           | 'time'   | 'solar wind' |              |         | 'state of the magnetosphere' |              |            |         |                    |
| Training Data | Sample #1 | t1       | Bz (t1-x*dt) | Bz (t1-2*dt) | Bz (t1) | ...                          | AL (t1-2*dt) | AL (t1-dt) | AL (t1) | $\Sigma_p (t1+dt)$ |
|               | Sample #2 | t2       | Bz (t2-x*dt) | Bz (t2-2*dt) | Bz (t1) | ...                          | AL (t2-2*dt) | AL (t2-dt) | AL (t2) | $\Sigma_p (t2+dt)$ |
|               | ⋮         |          |              |              |         |                              |              |            |         |                    |
|               | Sample N  | tN       | Bz (tN-x*dt) | Bz (tN-2*dt) | Bz (tN) | ...                          | AL (tN-2*dt) | AL (tN-dt) | AL (tN) | $\Sigma_p (tN+dt)$ |

Utilizing available observations

ISR capable of tying data together

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What are the *trends*?

**Analysis Ready Data**

**Robust quantification**

|               |           | features |              |              |         |                              |              |            | label   |                    |
|---------------|-----------|----------|--------------|--------------|---------|------------------------------|--------------|------------|---------|--------------------|
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|               | ⋮         |          |              |              |         |                              |              |            |         |                    |
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Utilizing available observations

ISR capable of tying data together

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What are the *trends*?

Analysis Ready Data

Include informative, available data

|               |           | features |              |              |         |                              |              |            | label   |                    |
|---------------|-----------|----------|--------------|--------------|---------|------------------------------|--------------|------------|---------|--------------------|
|               |           | 'time'   | 'solar wind' |              |         | 'state of the magnetosphere' |              |            |         |                    |
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Utilizing available observations

ISR capable of tying  
together

Data science to culminate  
efforts

### Enables:

- Rapid exploration
- Identification of complex relationships
- Widespread investigation

What are the *trends*?

## Analysis Ready Data

|               |           | features |              |              |                              |     |              |            | label   |                    |
|---------------|-----------|----------|--------------|--------------|------------------------------|-----|--------------|------------|---------|--------------------|
|               |           | 'time'   | 'solar wind' |              | 'state of the magnetosphere' |     |              |            |         |                    |
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## NOVEL APPROACHES to MULTISCALE GEOSPACE PARTICLE TRANSFER

Improved understanding and prediction through uncertainty quantification and machine learning

ISR capable of tying  
together

Data science to culminate  
efforts

### Enables:

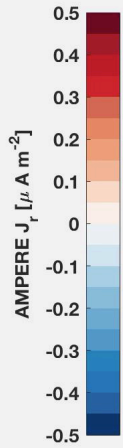
- Rapid exploration
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What are the *trends*?

# Analysis Ready Data

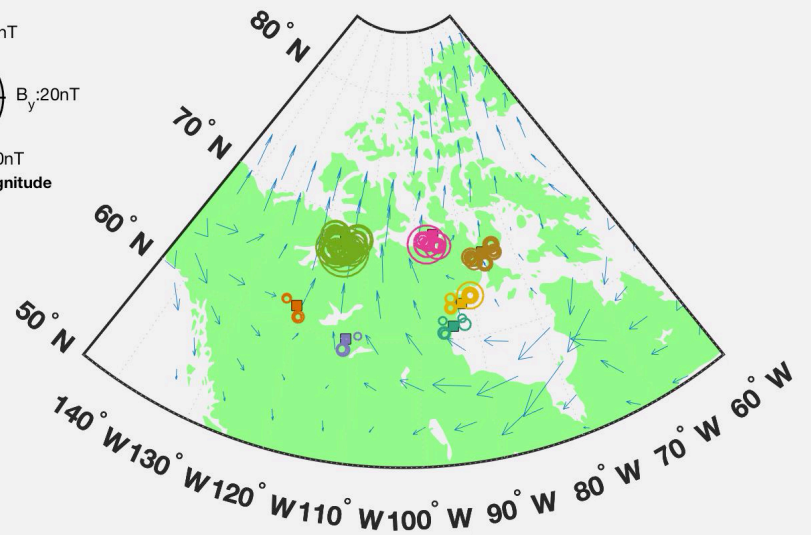
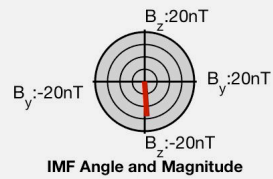
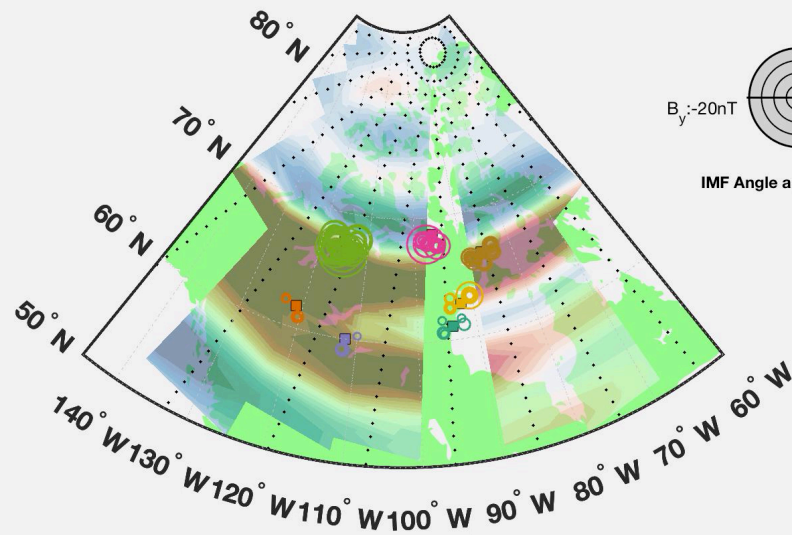
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|               | ⋮         |          |              |              |                              |     |              |            |         |                    |
|               | Sample N  | tN       | Bz (tN-x*dt) | Bz (tN-2*dt) | Bz (tN)                      | ... | AL (tN-2*dt) | AL (tN-dt) | AL (tN) | $\Sigma_p (tN+dt)$ |

**Backup slides**



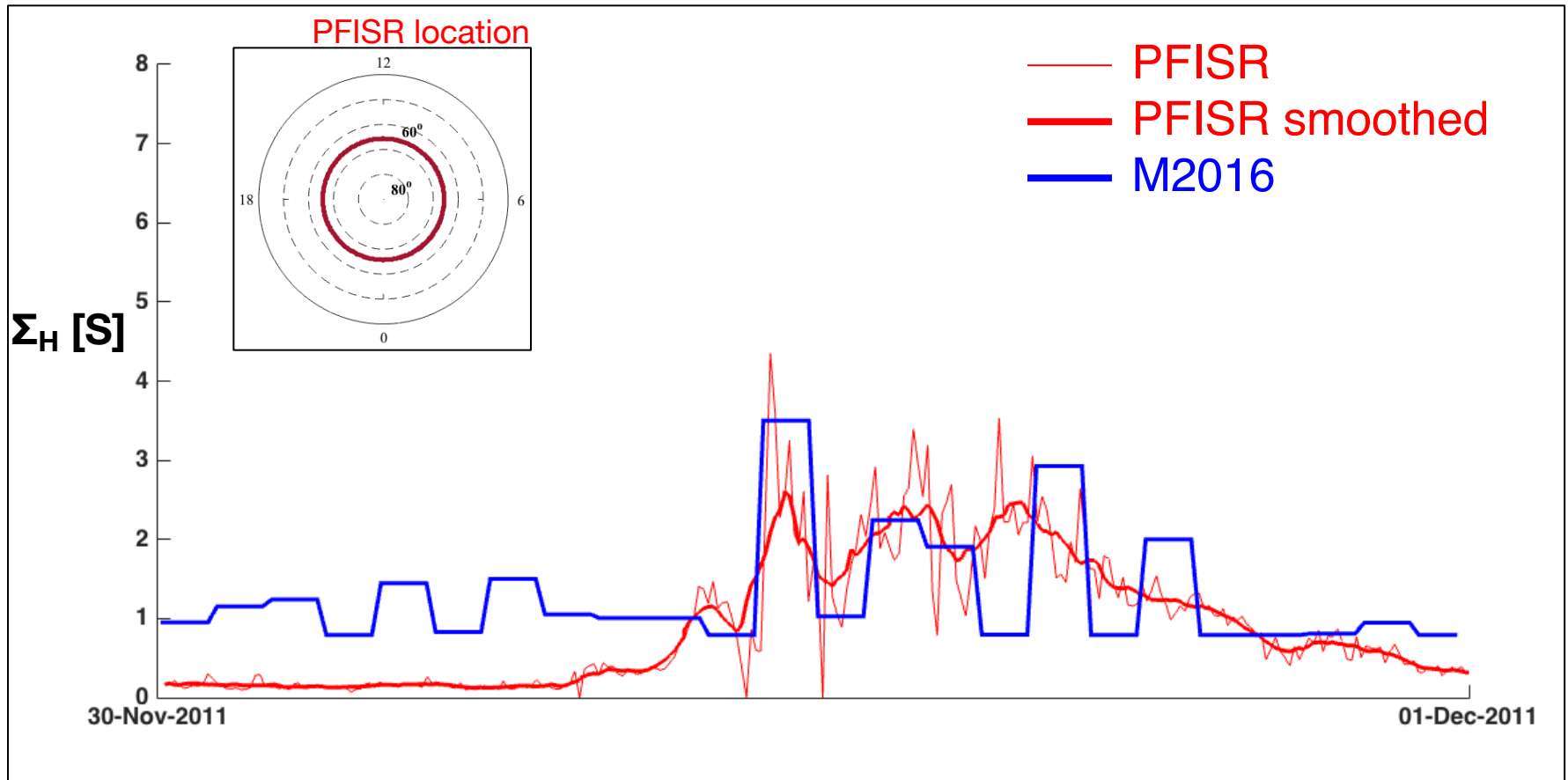
UT =6:00

MLT range<sub>140 W-60 W</sub> = 19.0 - 3.0 hrs



# Comparison with PFISR

Why? - Where are we now? - What's next?

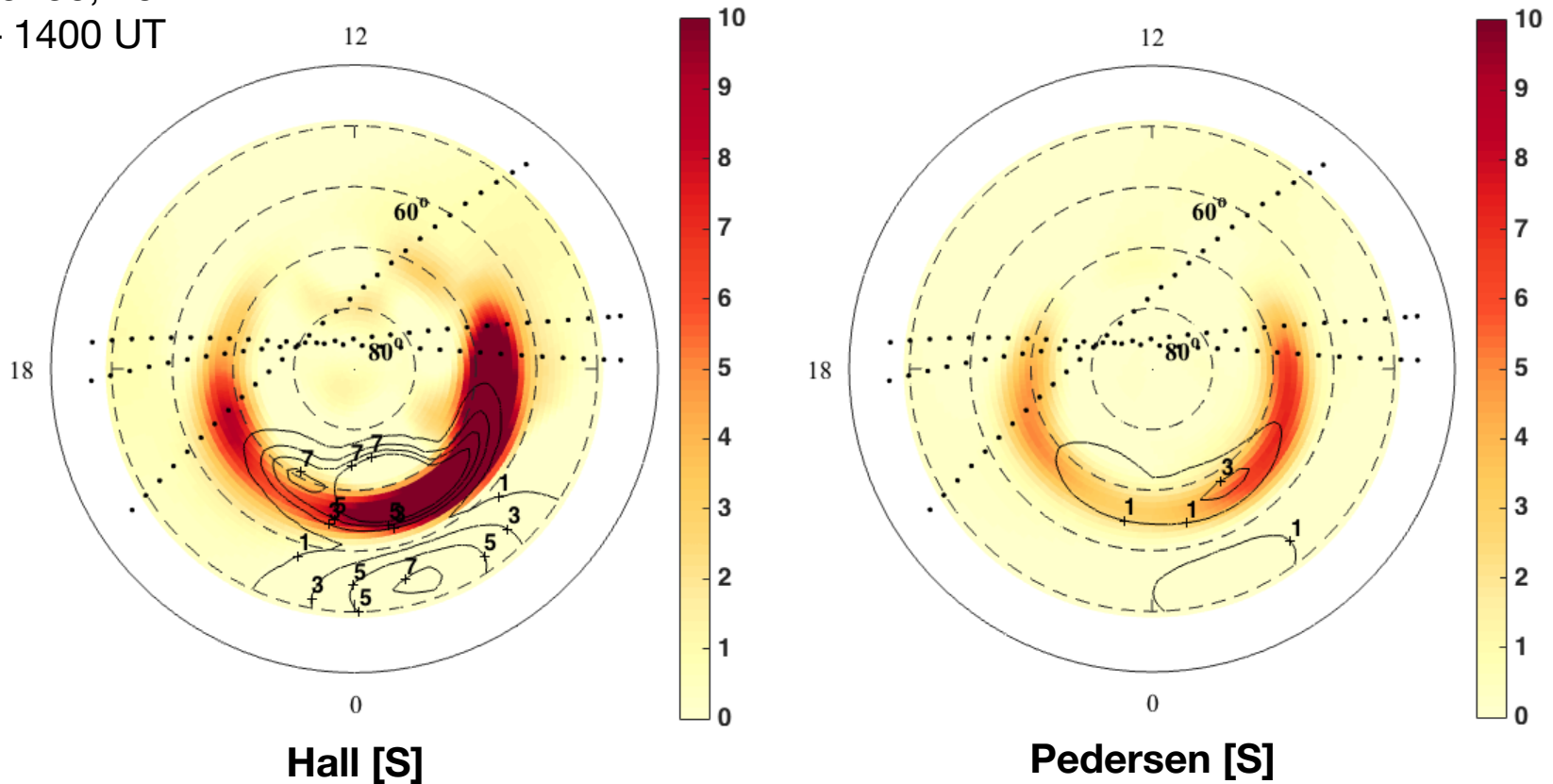




# At times, uncertainty on estimates can be large...

Why? - Where are we now? - What's next?

November 30, 2011  
1300 - 1400 UT

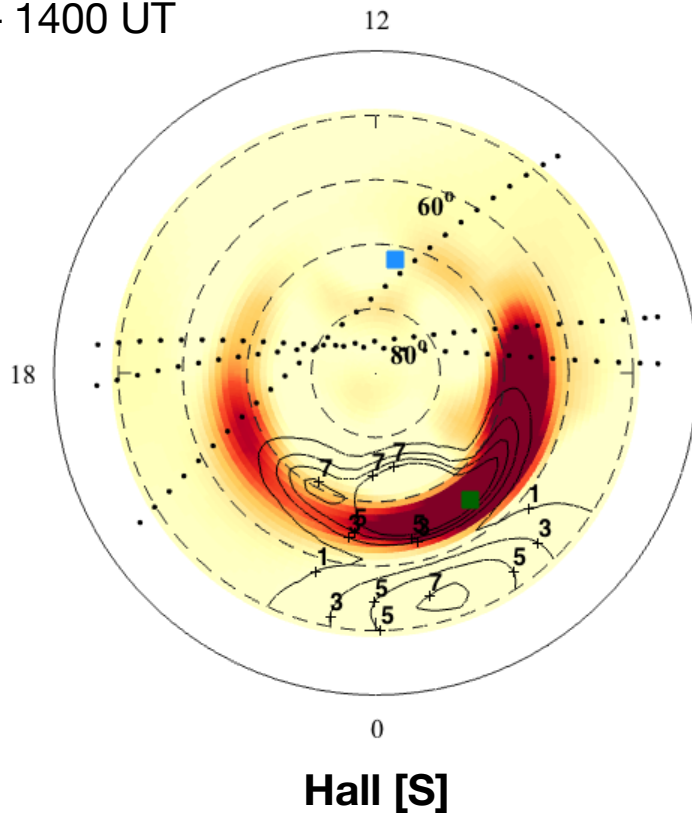


Contours = uncertainties  
Color Map = estimates

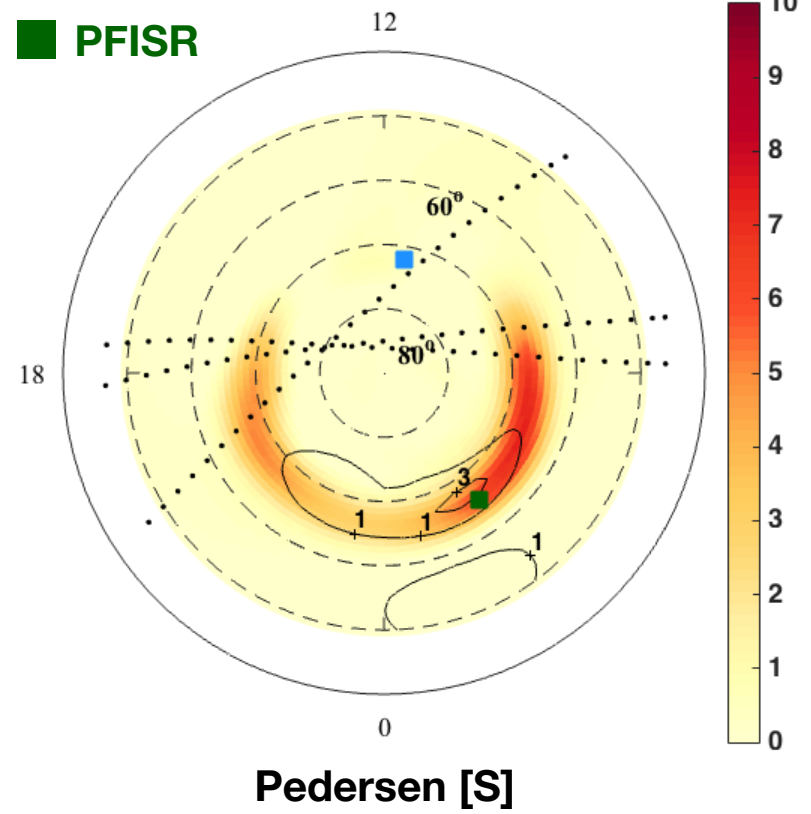
# At times, uncertainty on estimates can be large... But ISR data provide opportunity to supplement observations

Why? - Where are we now? - What's next?

November 30, 2011  
1300 – 1400 UT



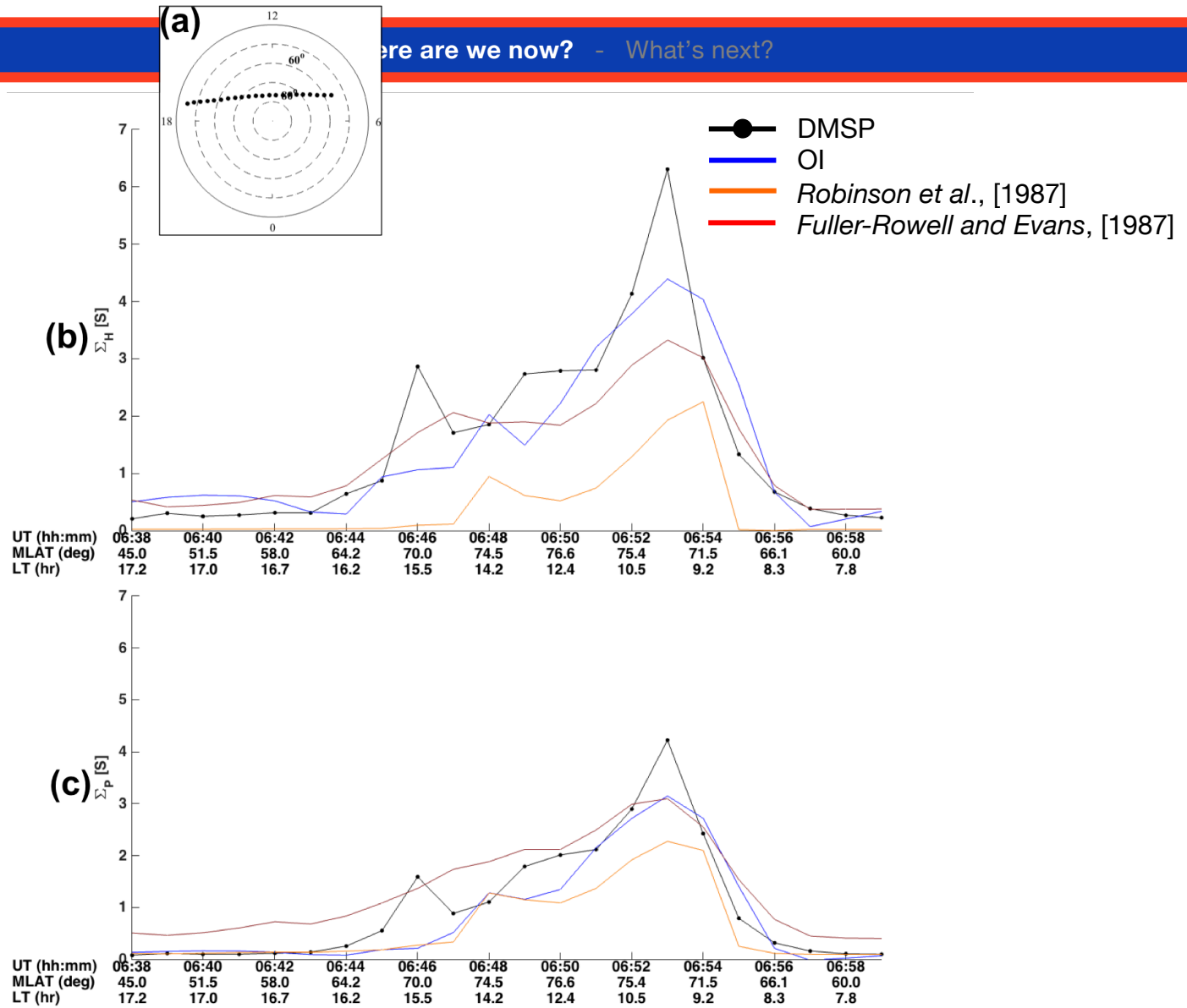
■ Sondrestrom ISR  
■ PFISR

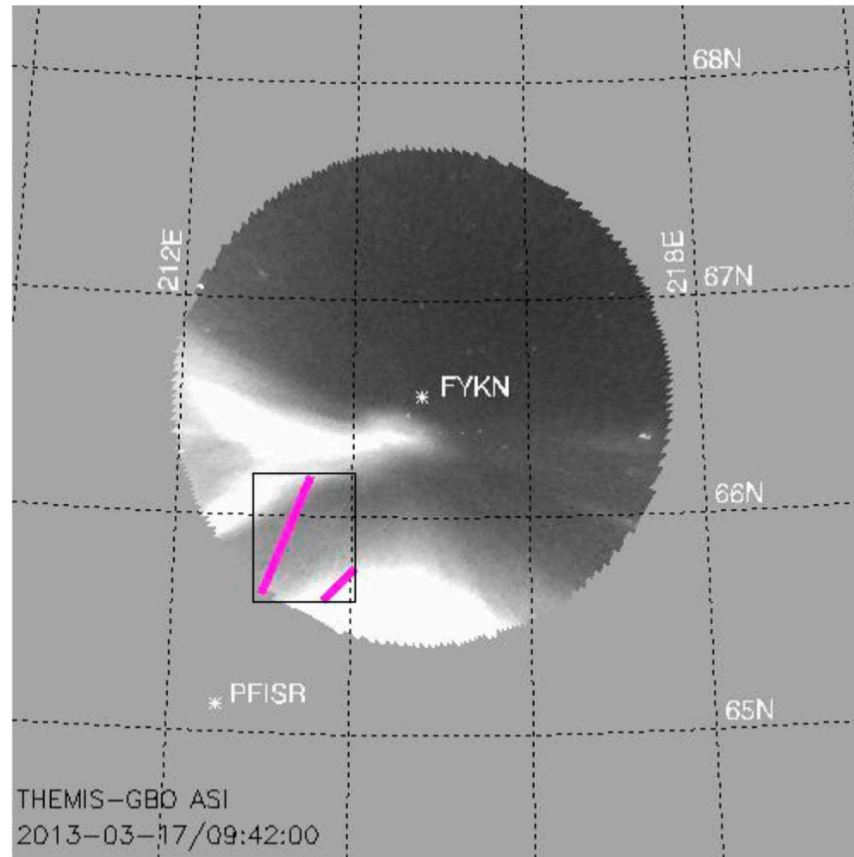


Contours = uncertainties  
Color Map = estimates

# Cross-validation results: M2016 models vs. *Robinson et al., [1987]* and *Fuller Rowell and Evans, [1987]* models

Where are we now? - What's next?





**Figure 1.** Location of experiment. The location of the PFISR (white asterisk) and of the beams of the 1-min PFISR data used (pink solid lines); the location of the FYKN ASI (white asterisk) and the field of view for elevation angles  $\alpha \geq 48^\circ$ . The solid black box represents the latitudes and longitudes of the data used. FYKN = Fort Yukon; PFISR = Poker Flat Incoherent Scatter Radar; THEMIS = Time History of Events and Macroscale Interactions during Substorms; GBO = Ground-Based Observatory; ASI = all-sky imager.