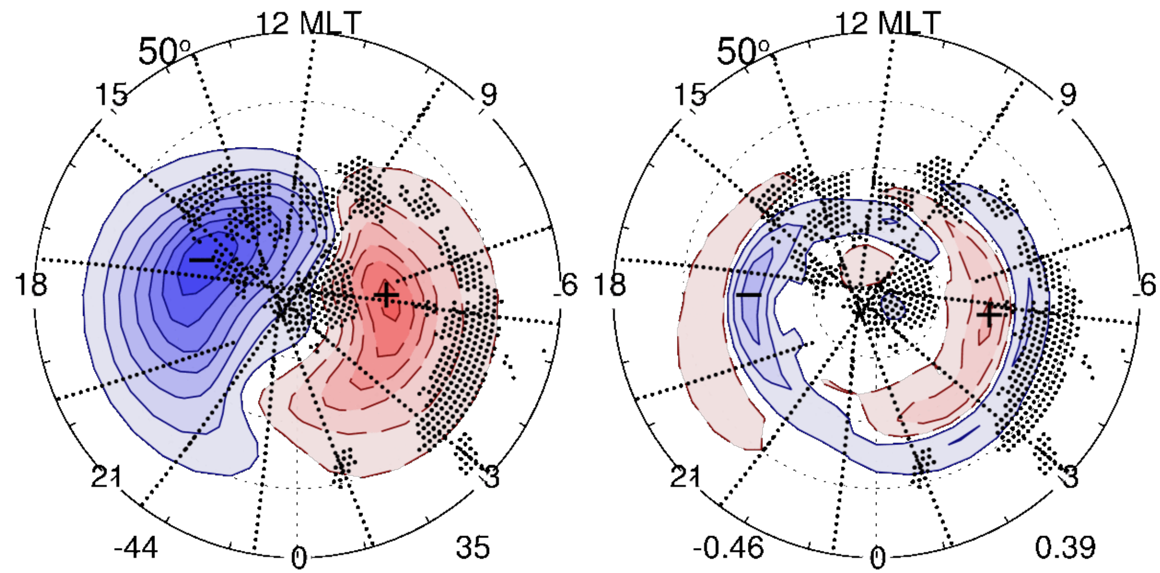
Mapping ionospheric electrodynamics with AMPERE and SuperDARN data

Ellen Cousins[1], Tomoko Matsuo[2,3], Art Richmond[1]
[1]NCAR-HAO, [2]CU-CIRES, [3]NOAA-SWPC

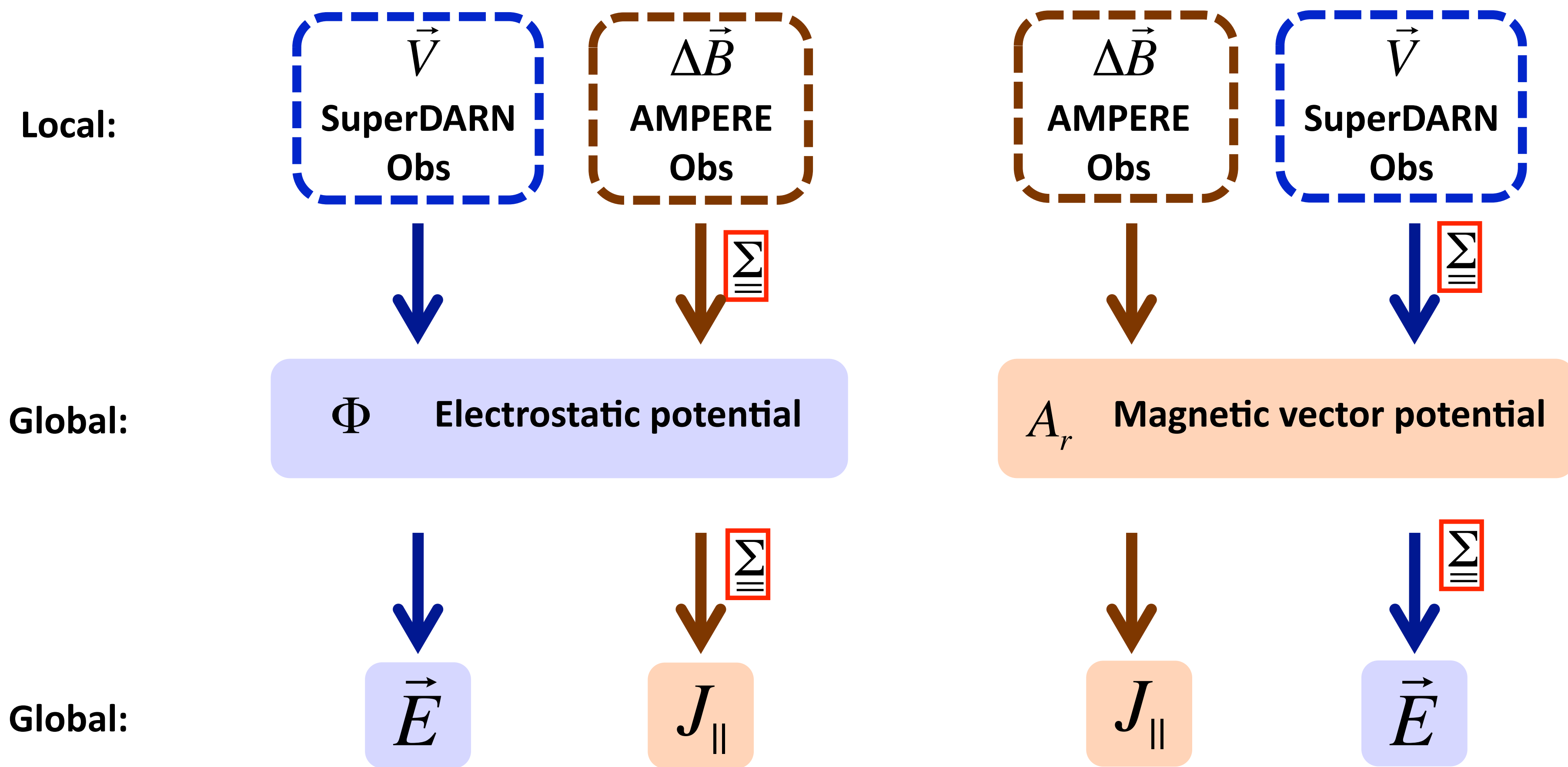
Challenges

- Uncertainty quantification
- Specifying conductance
- Validation of results



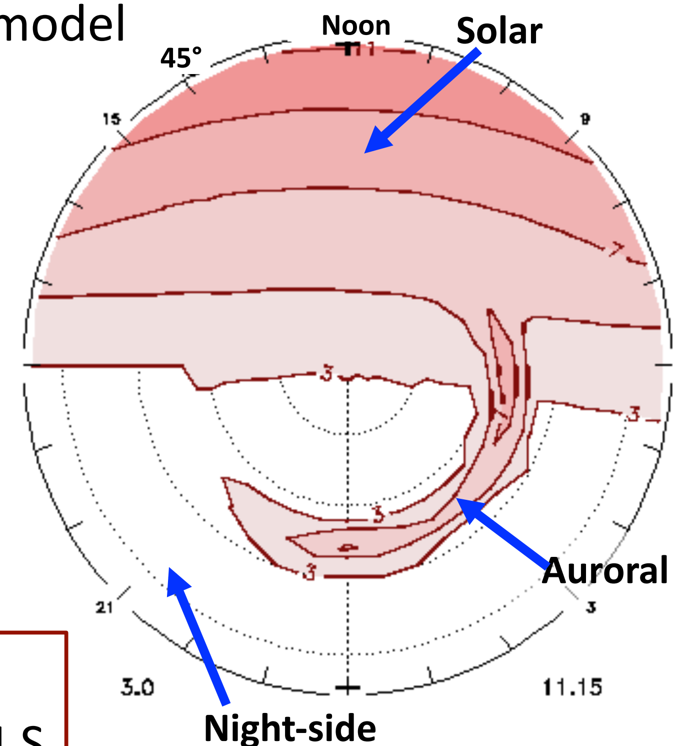
Mapping Procedure

- Assimilative technique with Empirical Orthogonal Function (EOF) – based error covariance
- Traditionally solved in terms of electrostatic potential; can also be solved in terms of magnetic vector potential



Evaluating Conductance Models

- Want quantitative metric for selecting 'best' conductance model
- Evaluate by using mapping procedure with just one data type, predict observations of other type
  - e.g., fit electrostatic potential with SuperDARN data, predict AMPERE observations (using assumed conductance),
  - Compare predictions with actual observations
- Pick conductance model that minimizes discrepancy between **E** obs & **ΔB** obs

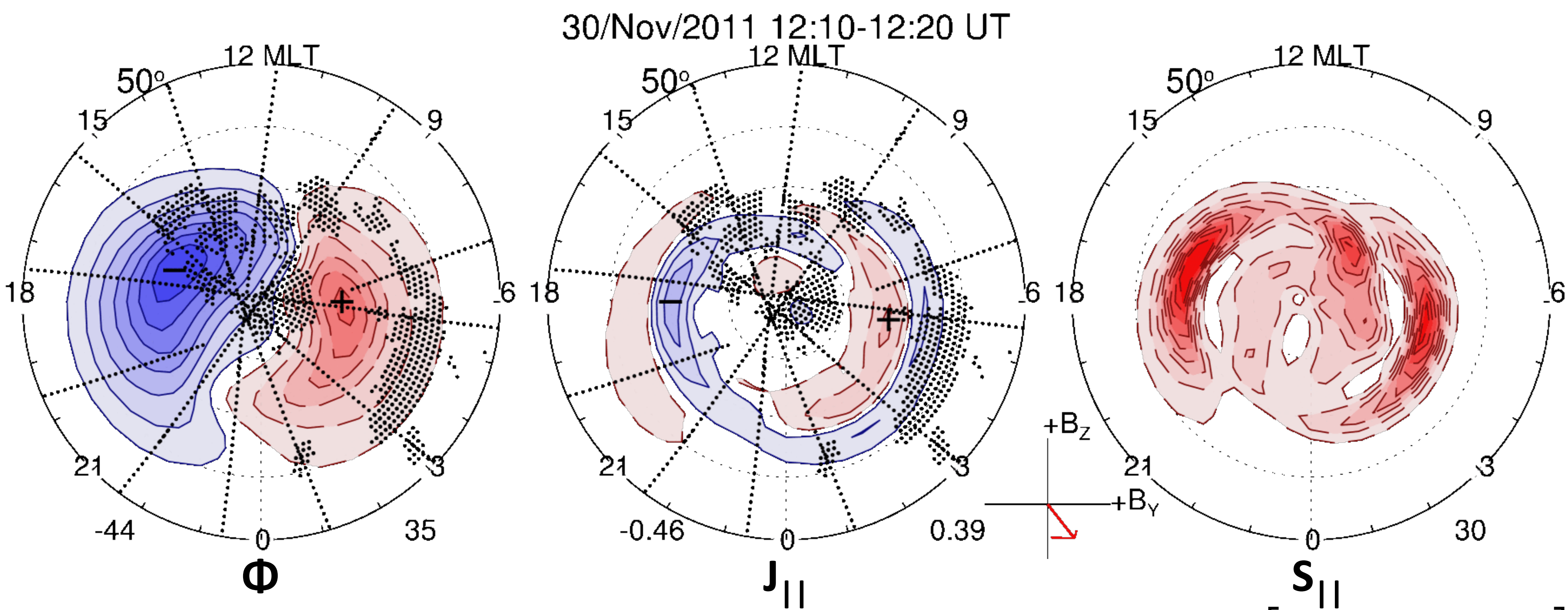


Best results: diffuse aurora from Ovation Prime or SM [*Newell et al.*, 2010; *Mitchell et al.*, 2013], w/ night-side Σ_p= 4 S

		O-P	FAC adj	>2, O-P	>4, O-P	>4, O-SM	>4, no aur	>6, O-P
ΔB ➔ E:	Med |err| [m/s]	523	513	172	147	146	147	142
E ➔ ΔB:	Med |err| [nT]	33.2	33.3	33.5	34.7	34.6	34.7	36.7

Assimilative Mapping Example

- Solving with both data sets together
- Electrostatic potential map based on solving in terms of electrostatic potential (more weight for SuperDARN data)
- Field-aligned current map based on solving in terms of magnetic vector potential (more weight for AMPERE data)



$$\left[S_{\parallel} = \vec{E}_{\perp} \times \Delta\vec{B}_{\perp} / \mu_0 \right]$$

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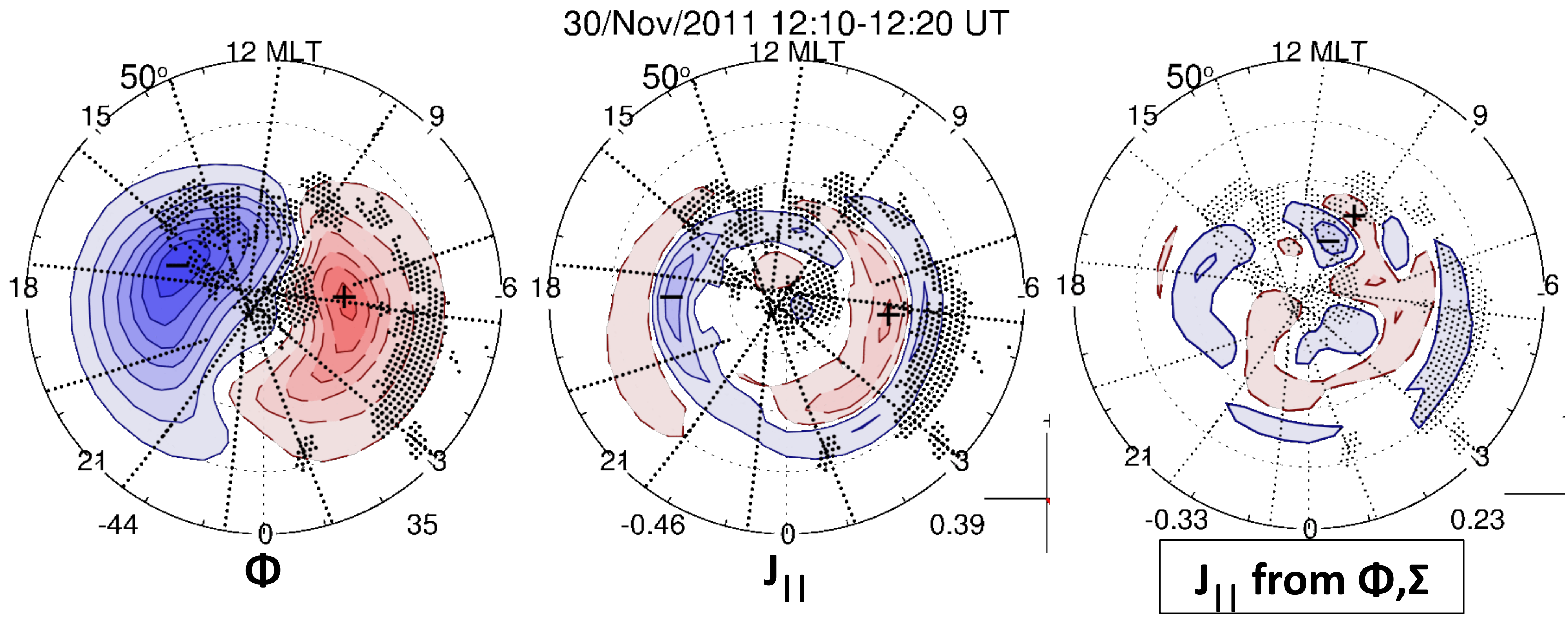
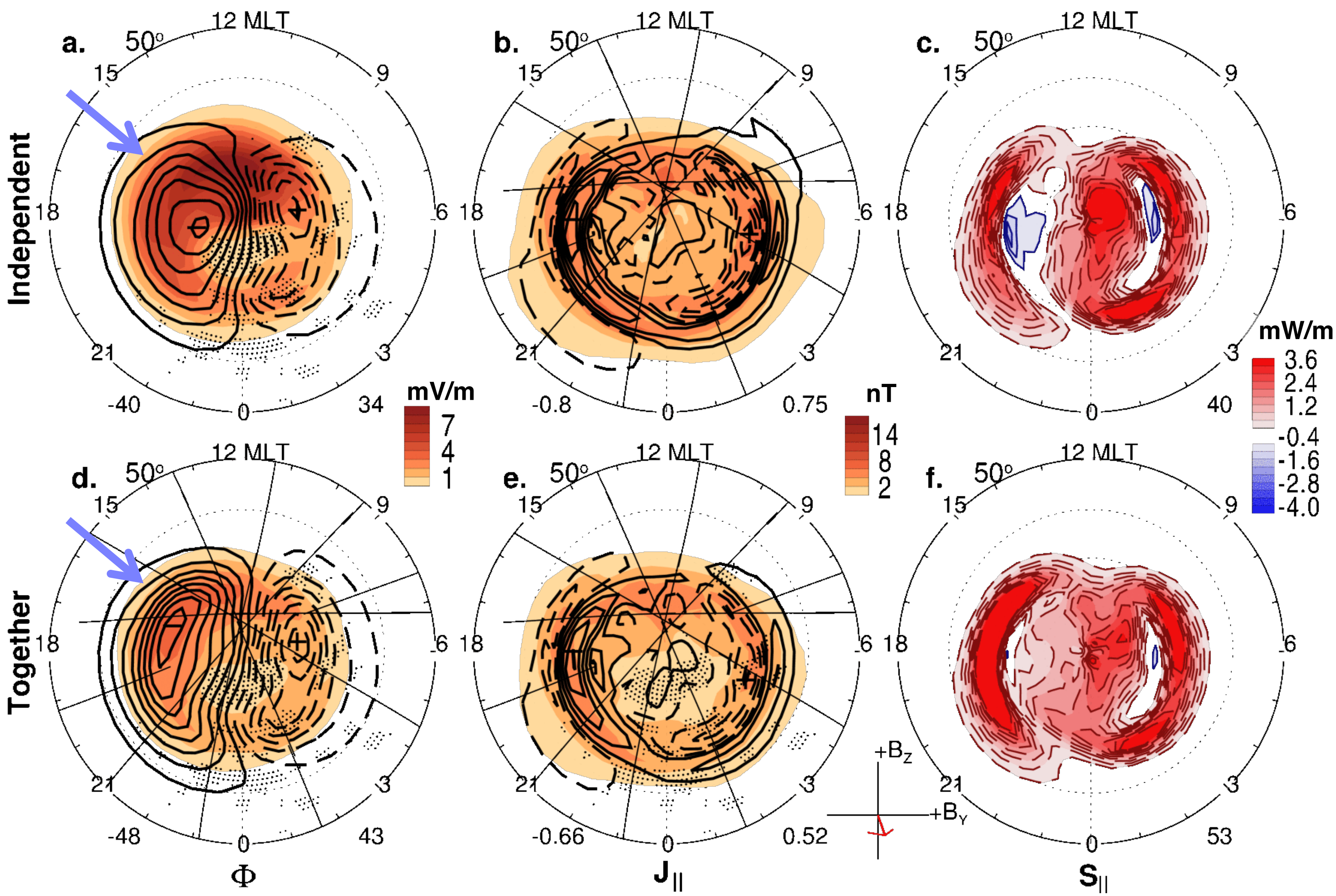


Assimilative Mapping – Benefits of using data sets together

- Analysis error decreases by 10% for **Φ**, 40% for **A**
- AMPERE fills in SuperDARN coverage gaps & vice versa
- Electric potential & FAC maps more compatible?
  - feature correspondence



Summary of SuperDARN-AMPERE Mapping

- Mapping ionospheric electrodynamics using optimal interpolation data assimilation method with SuperDARN & AMPERE data
  - Solving for both electrostatic potential & magnetic vector potential
    - Using magnetic potential improves specification of FACs

Challenges

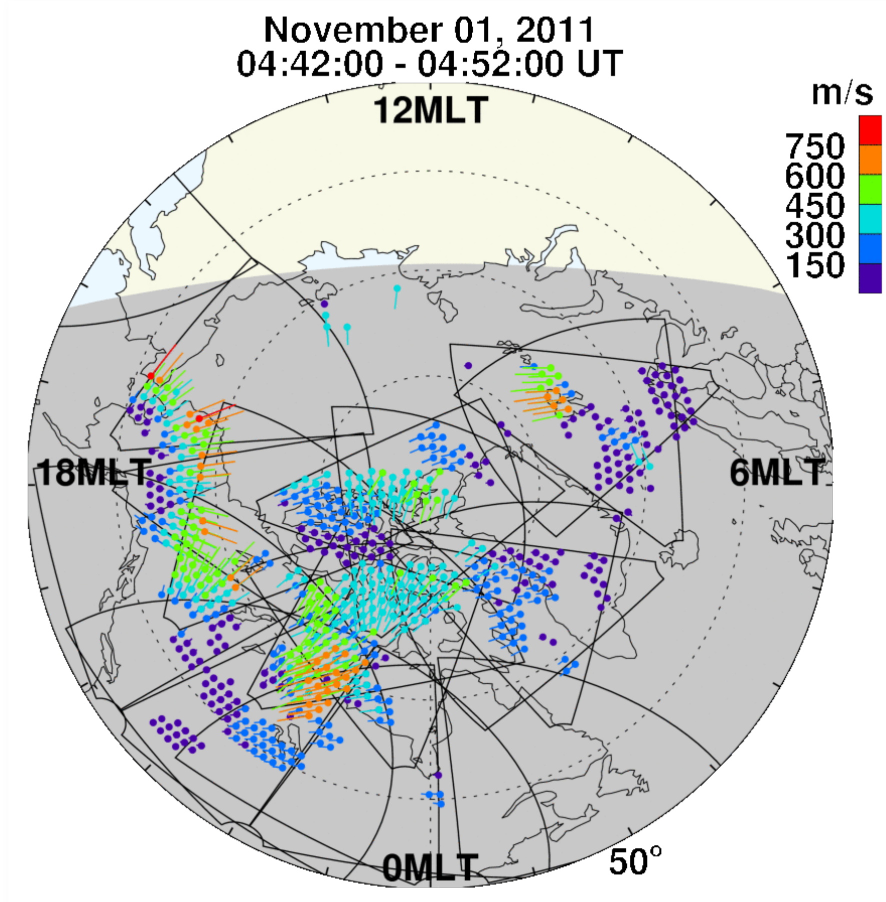
- Uncertainty quantification
  - EOF analysis of model errors
  - Sub-resolution variance of obs. (but what about biases?)
- Specifying conductance
  - Empirical models & obs.-based adjustments tested quantitatively
  - Best results w/ Ovation Prime (or SM) diffuse aurora & night-side $\Sigma_P = 4$ S
  - But even 'best' model is not representative of instantaneous reality…
- Validation of results
  - Improvement in qualitative appearance
  - Quantitative reduction in analysis error
  - Other approaches to validation?

We thank the AMPERE team and the AMPERE Science Data Center for providing the Iridium-derived data products.

[Extra Slides]

SuperDARN data

- 19 radars in the Northern Hemisphere, ~50° and poleward
- 'Grid' level data
  - Spatial resolution: 110 km
  - Temporal resolution: 2 min
- Line-of-sight (LOS) observations of **ExB** plasma drifts at ~300 km altitude



AMPERE

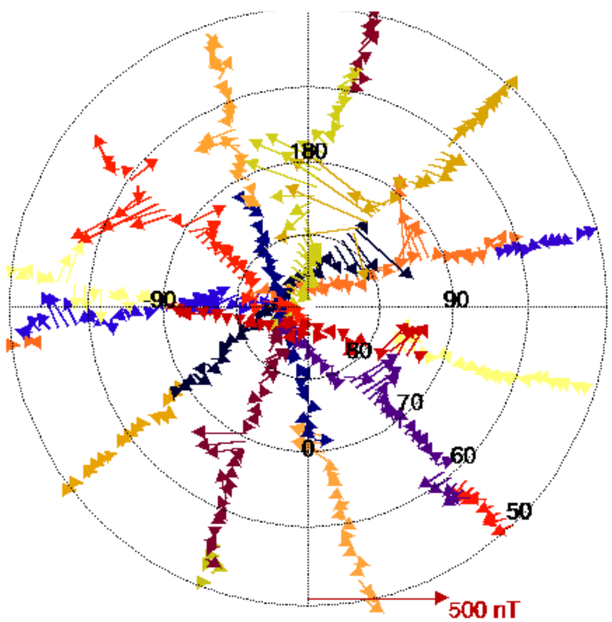
Active Magnetosphere and Planetary Electrodynamics Response Experiment

Iridium for Science

- **Magnetometer on every satellite**
- **6 orbit planes (12 cuts in local time) ~11 satellites/plane**
- **9 minute spacing - re-sampling cadence**
- **780 km altitude, circular, polar orbits**

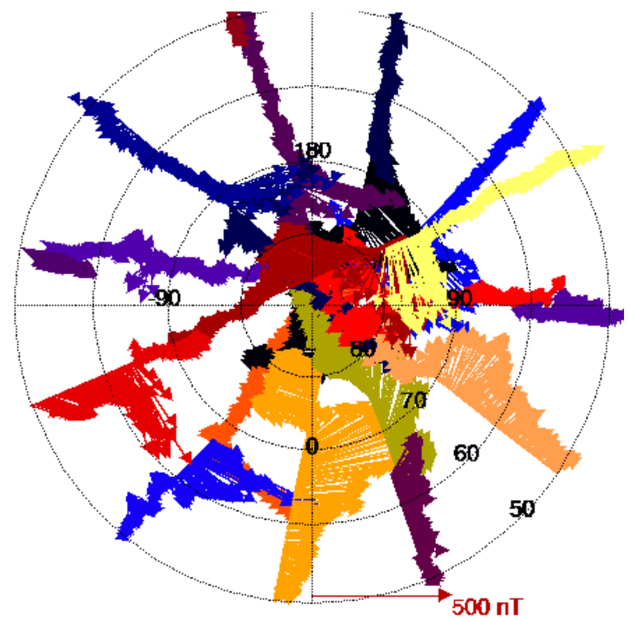
AMPERE: Standard

~1° lat. res.



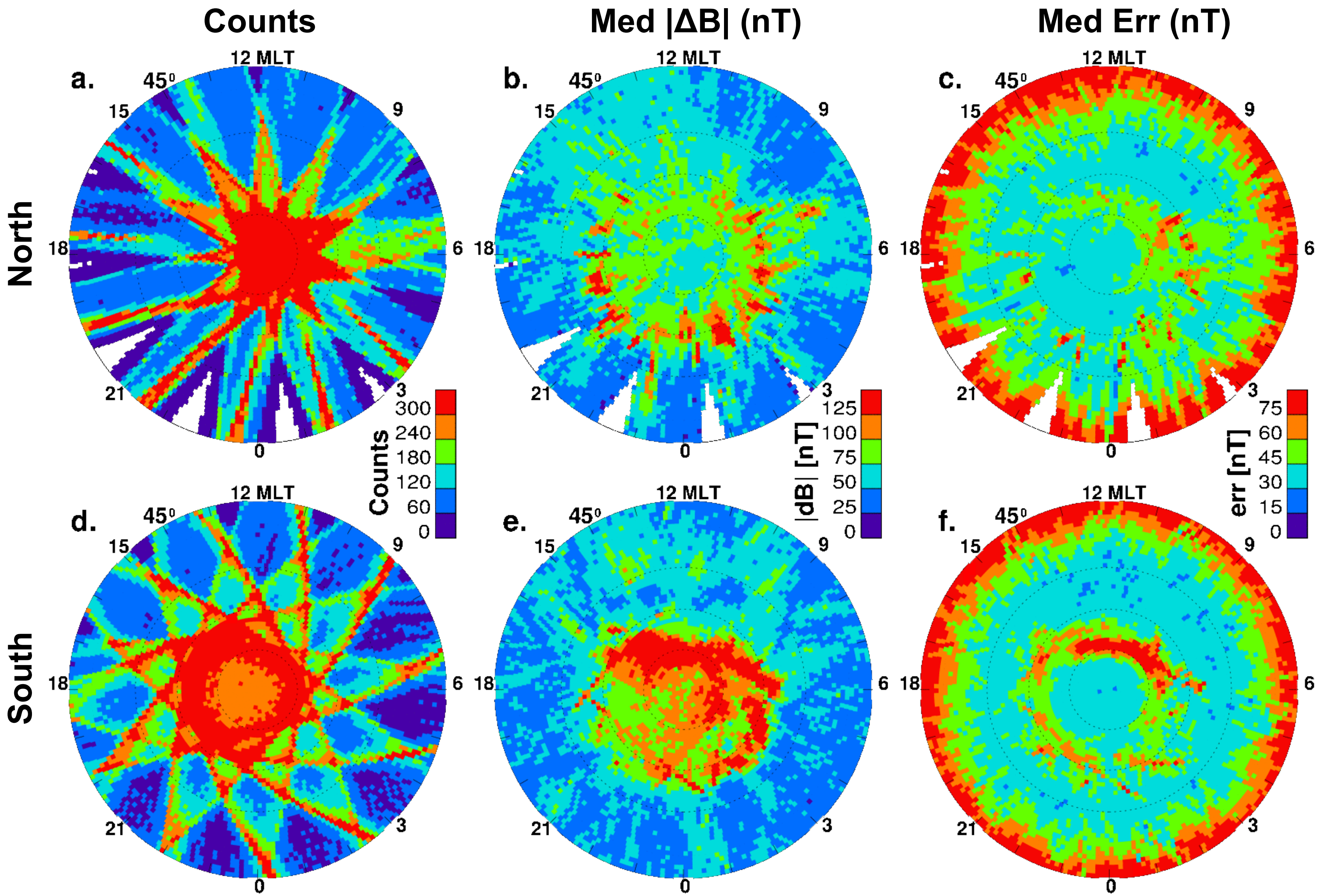
AMPERE: High

~ 0.1° lat. res.



[Brian Anderson]

AMPERE Data: 26 Nov – 2 Dec, 2011



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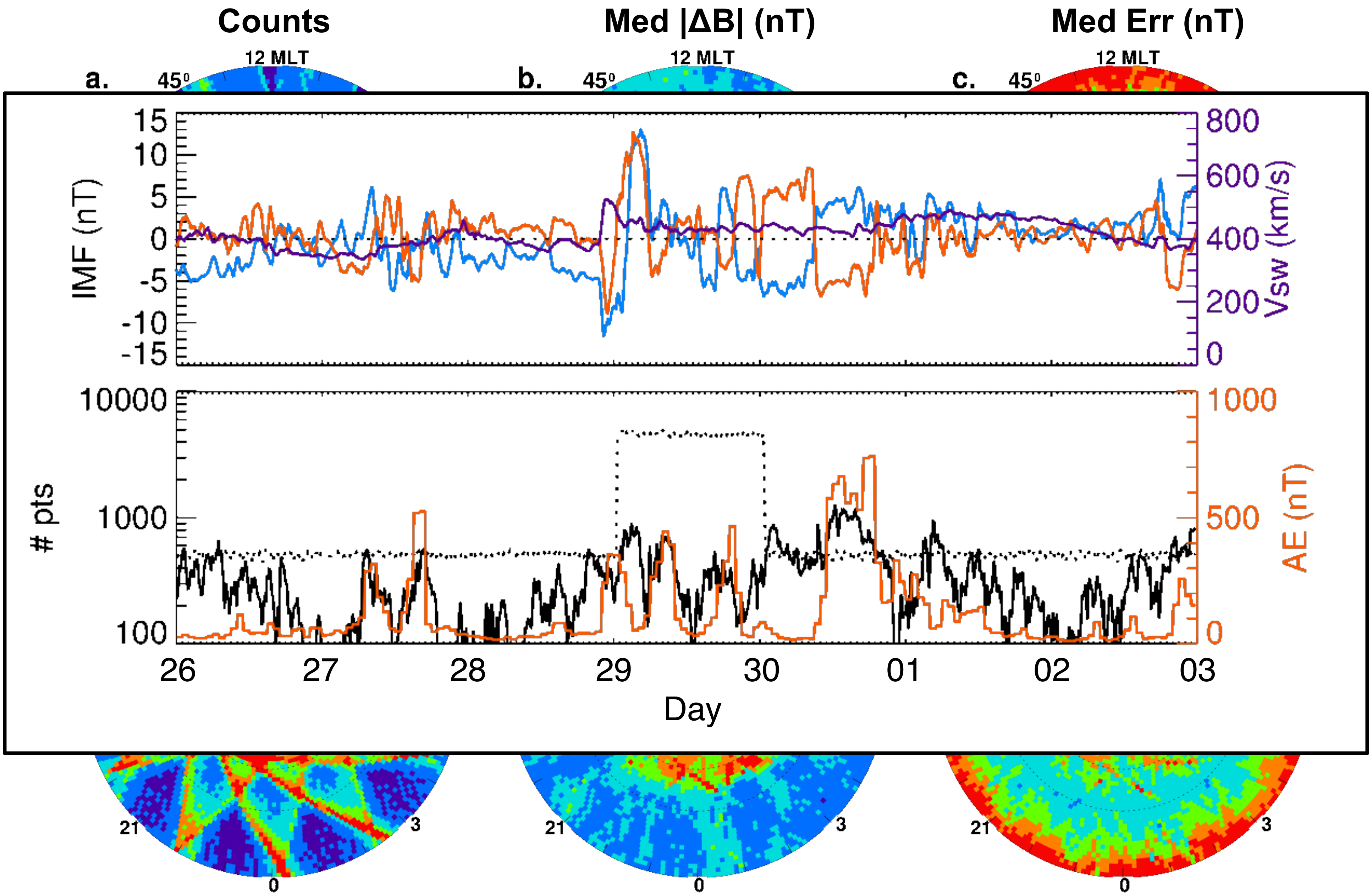


Assimilative Mapping Procedure

- Use the optimal interpolation (OI) method of data assimilation
  - Optimally combine information from **observations** and a **background model**, taking into account **error properties** of both
- **Background model:**
  - Electrostatic potential: SuperDARN CS10 empirical convection model
  - Magnetic vector potential: AMPERE mean
- **Error properties** of background models estimated using Empirical Orthogonal Function (EOF) analysis
- **Observational errors** based on local small-scale variance values

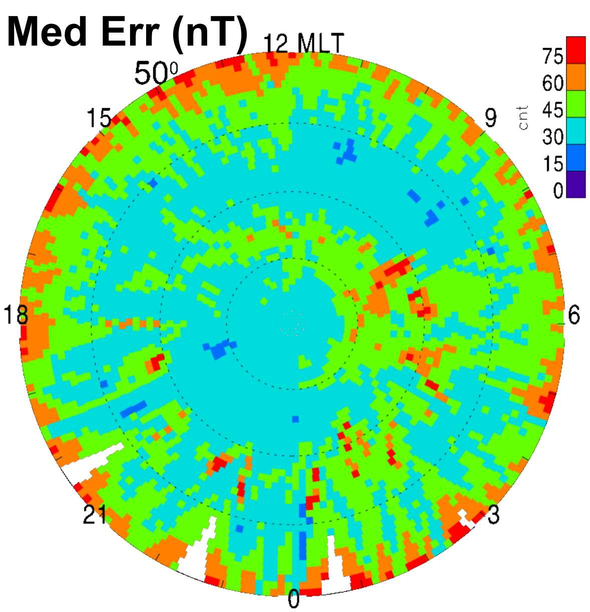
$$x_a = x_b + K(y - H x_b)$$

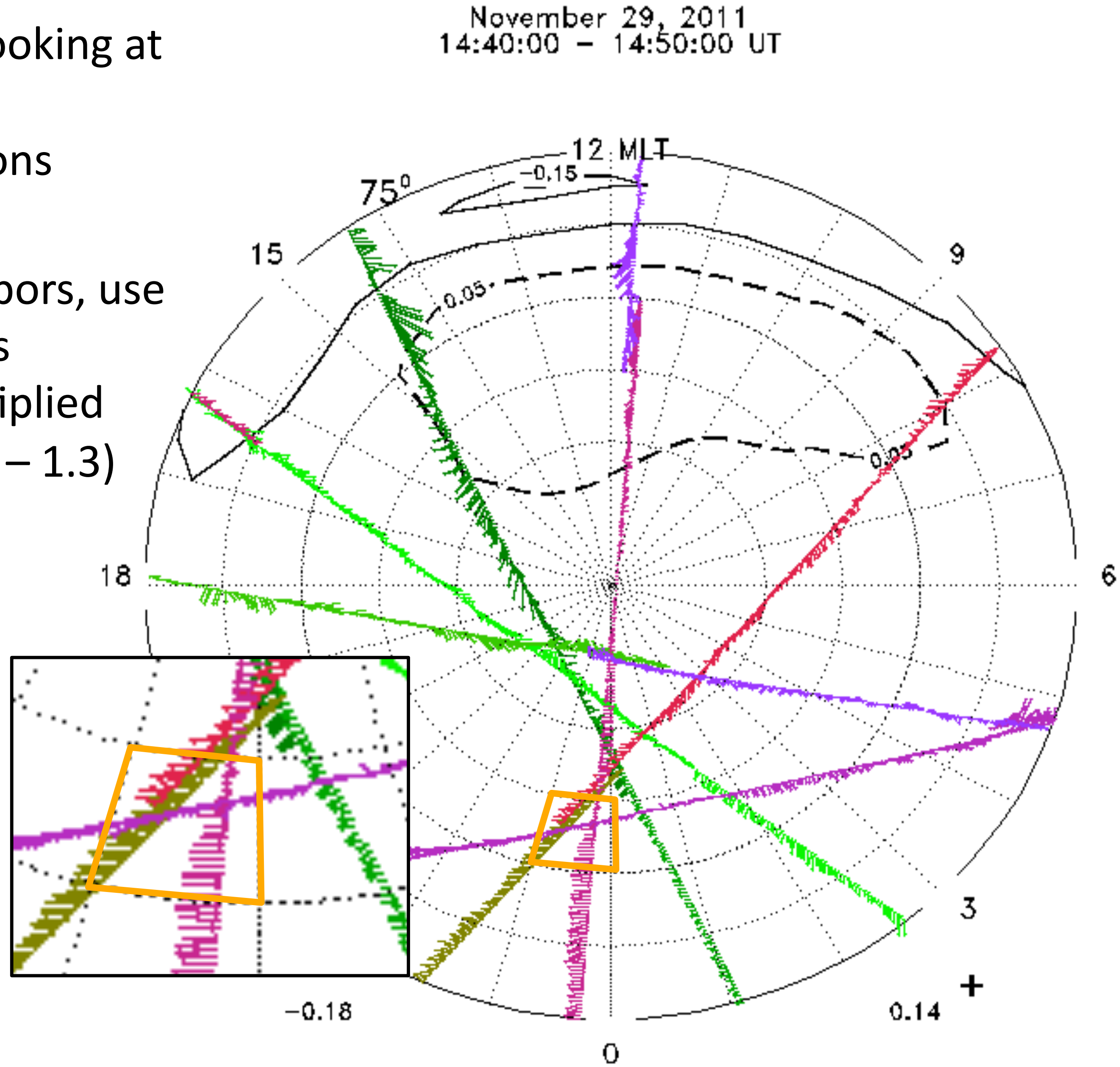
$$K = P_b H^T (H P_b H^T + R)^{-1}$$

$\mathbf{x}_a$ – analysis
$\mathbf{y}$ – observations
$\mathbf{x}_b$ – background model
$\mathbf{H}$ – forward operator [physics + Σ]
$\mathbf{K}$ – Kalman gain
$\mathbf{P}_b$ – background model error covariance
$\mathbf{R}$ – observational error covariance

AMPERE data: Uncertainty Estimation

- Estimate uncertainty by looking at variation in values below resolution of basis functions (~2.5°Λ, 1h MLT)
- For vectors with <5 neighbors, use median of variance values calculated as above, multiplied by data quality flag (~0.7 – 1.3)

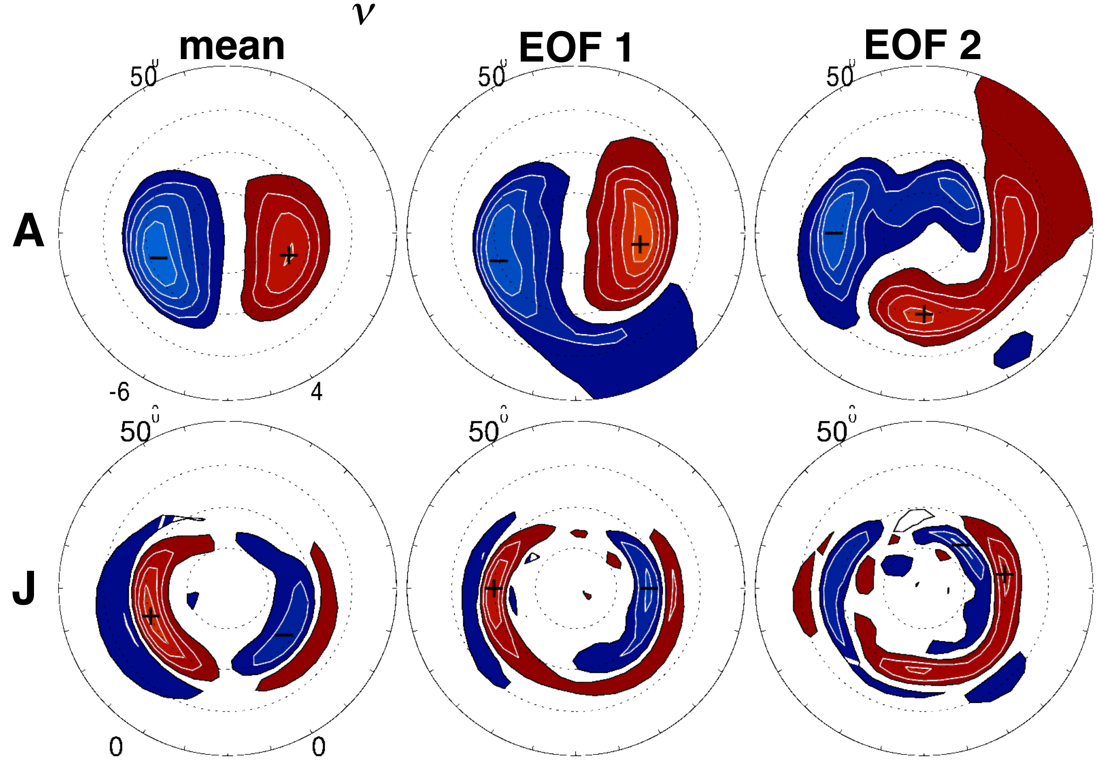




Empirical Orthogonal Function (EOF) analysis

- A variant of principal component analysis (PCA)
- Technique to estimate dominant modes of variability in a data set (Decompose into eigenmodes & eigenvalues)
- Calculated in terms of magnetic vector potential: $\Delta \vec{B}_{hor} = \nabla \times \vec{A}_r$

$$A_r(\mathbf{x},t) \approx A_r^{mean}(\mathbf{x}) + \sum_{\nu} \alpha^{(\nu)}(t) EOF^{(\nu)}(\mathbf{x})$$

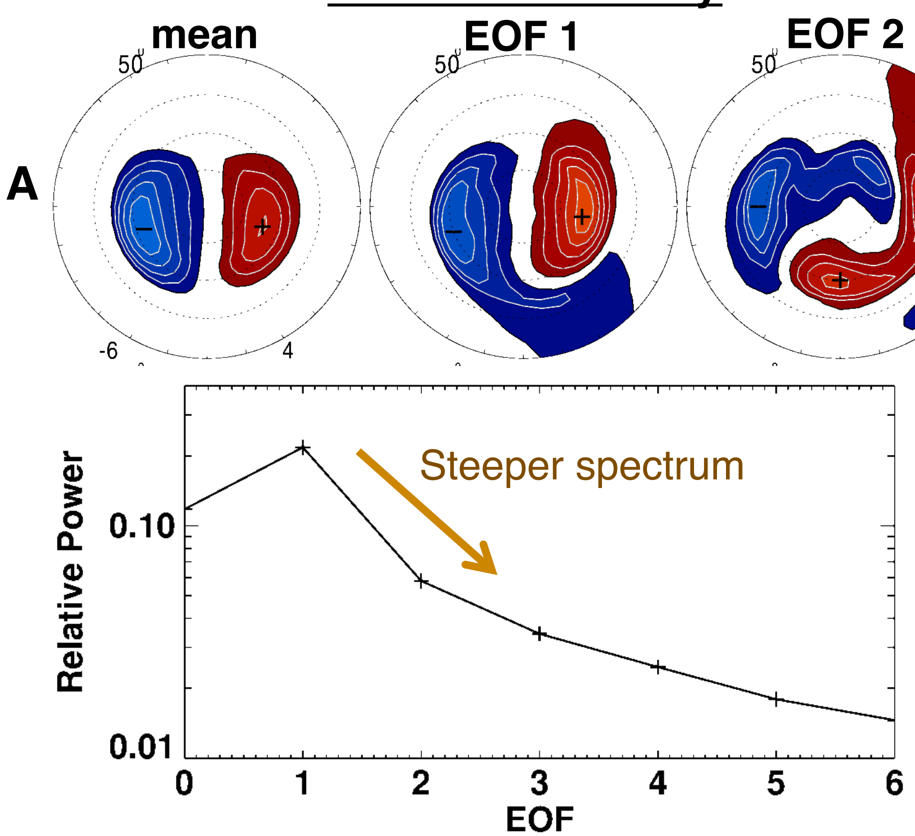


$$\vec{J}_r = \nabla \times \Delta \vec{B}_{hor}$$
$$= -\nabla^2 A_r$$

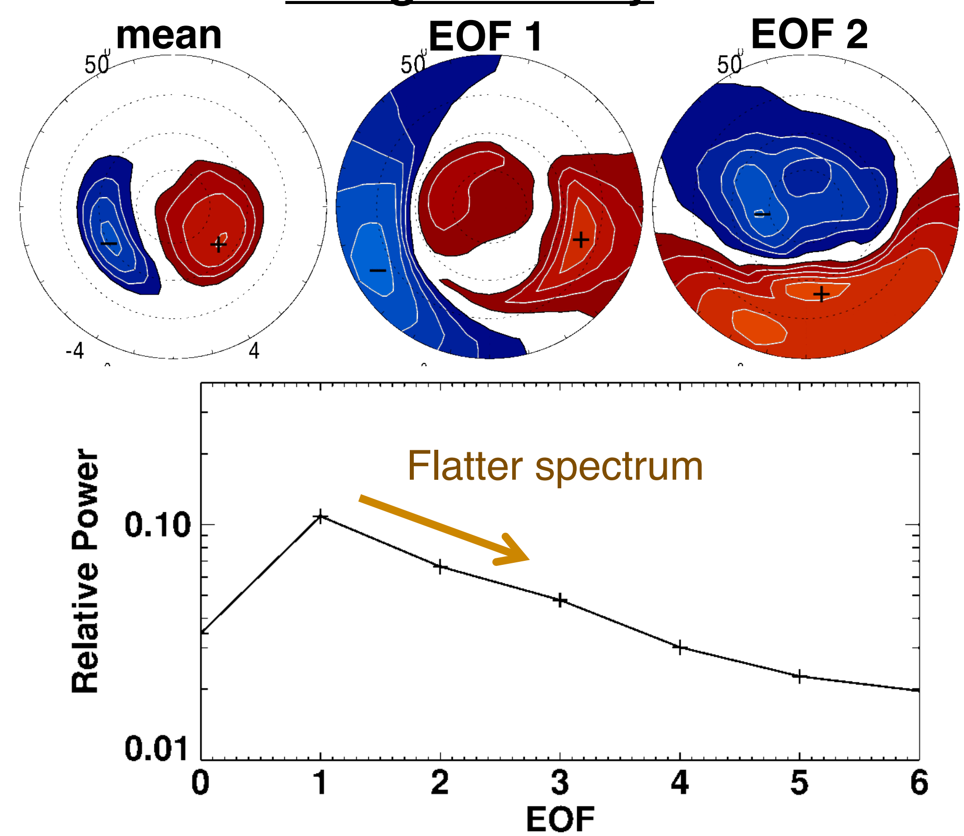
Data quality issues

- Difficult to obtain clean EOFs using just 1 week of data with low SNR
- Higher quality data in across-track direction vs. along-track direction (likely due to attitude determination errors)
- Better EOFs using just across-track data

Across-track only

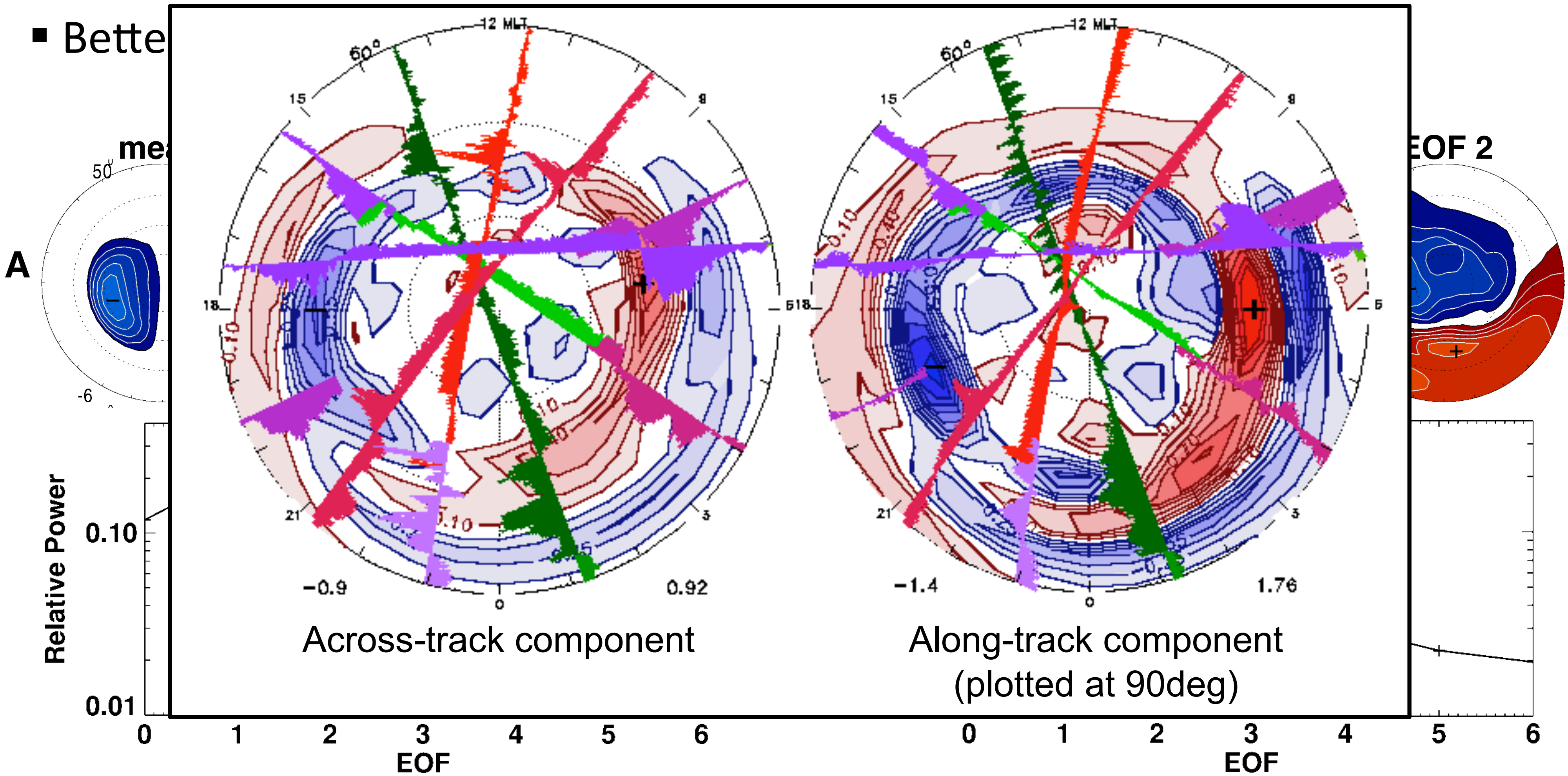


Along-track only



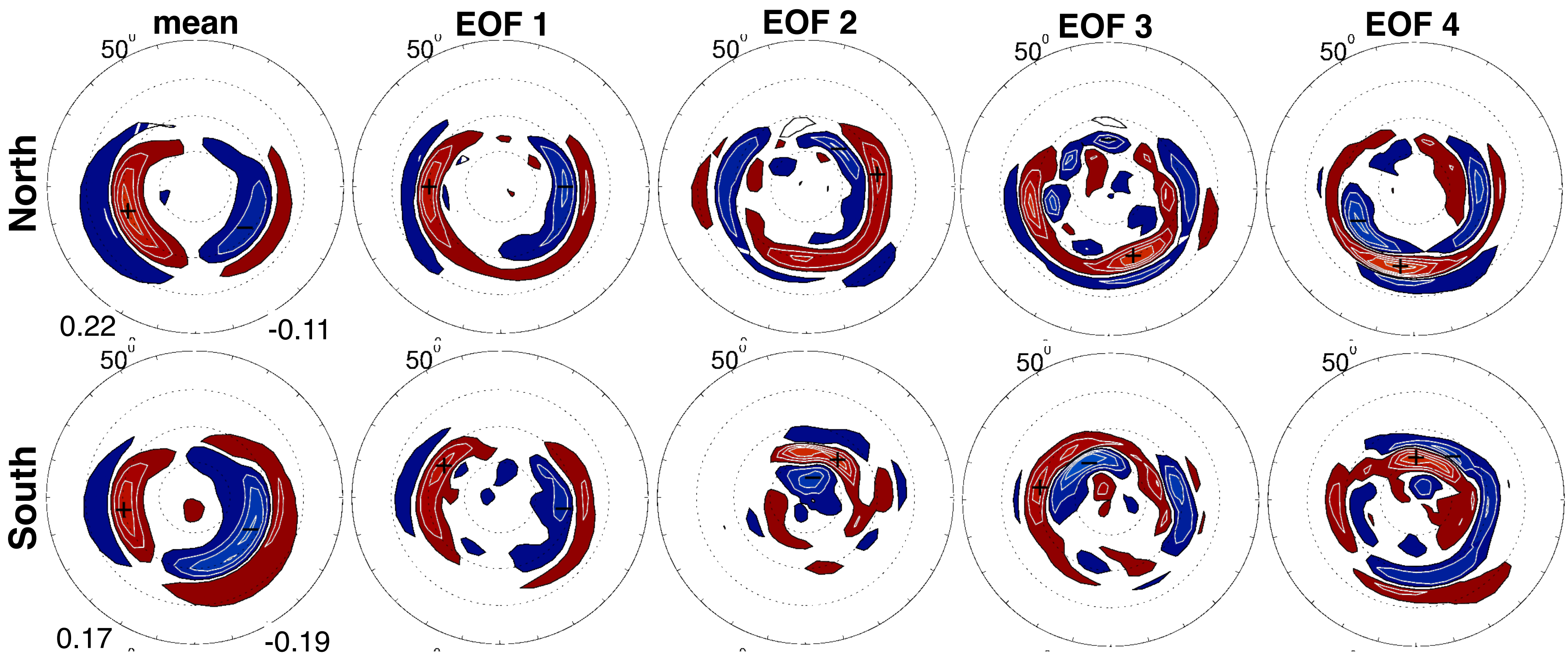
Data quality issues

- Difficult to obtain clean EOFs using just 1 week of data with low SNR
- Higher quality data in across-track direction vs. along-track direction (likely due to attitude determination errors)
- Bette



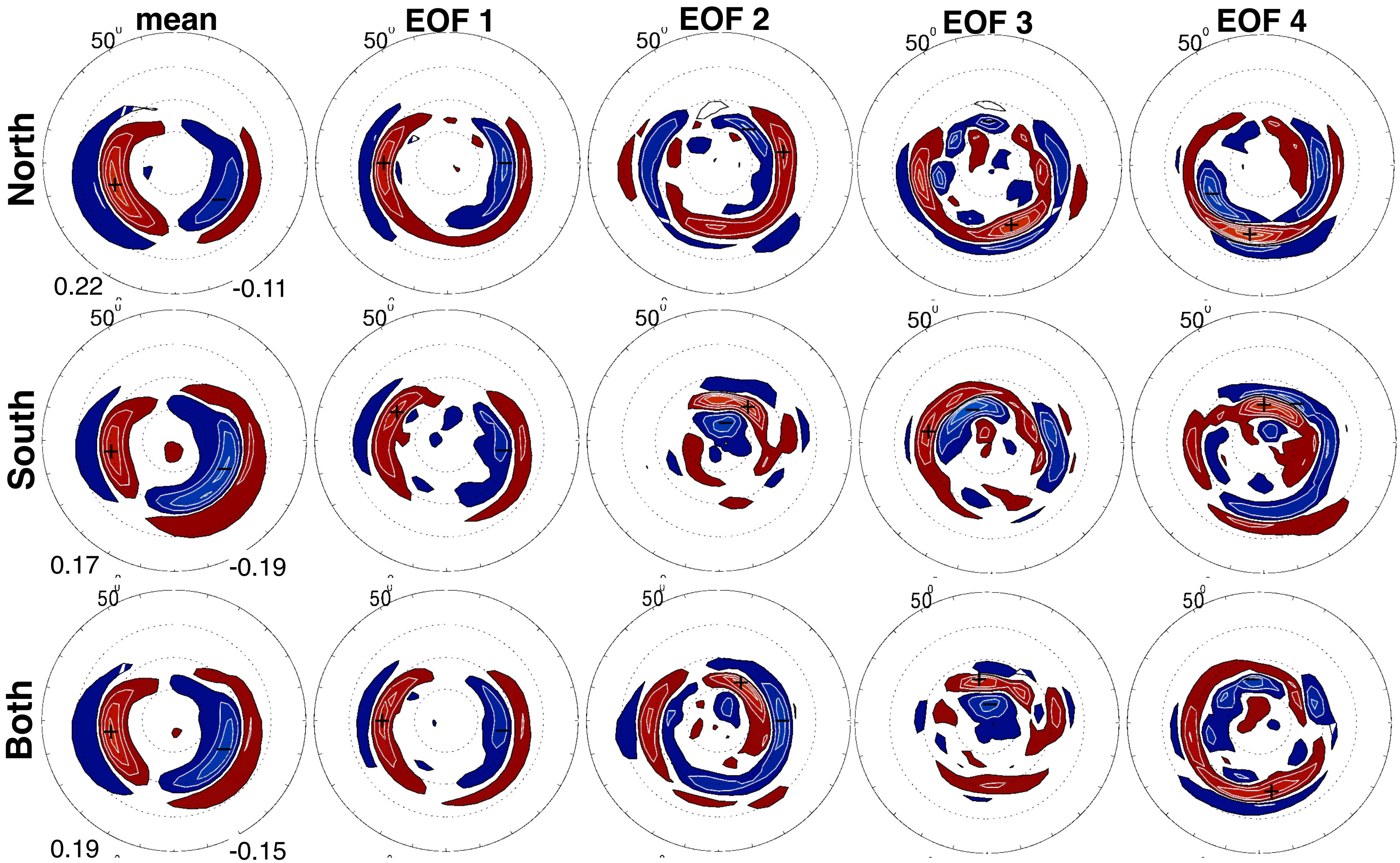
EOF Properties: Winter/Summer

- EOFs calculated independently for North/Winter & South/Summer hemispheres
- Dawn-dusk asymmetry in mean – different in two hemispheres
- Winter hemi. shows more night-side features, summer more day-side



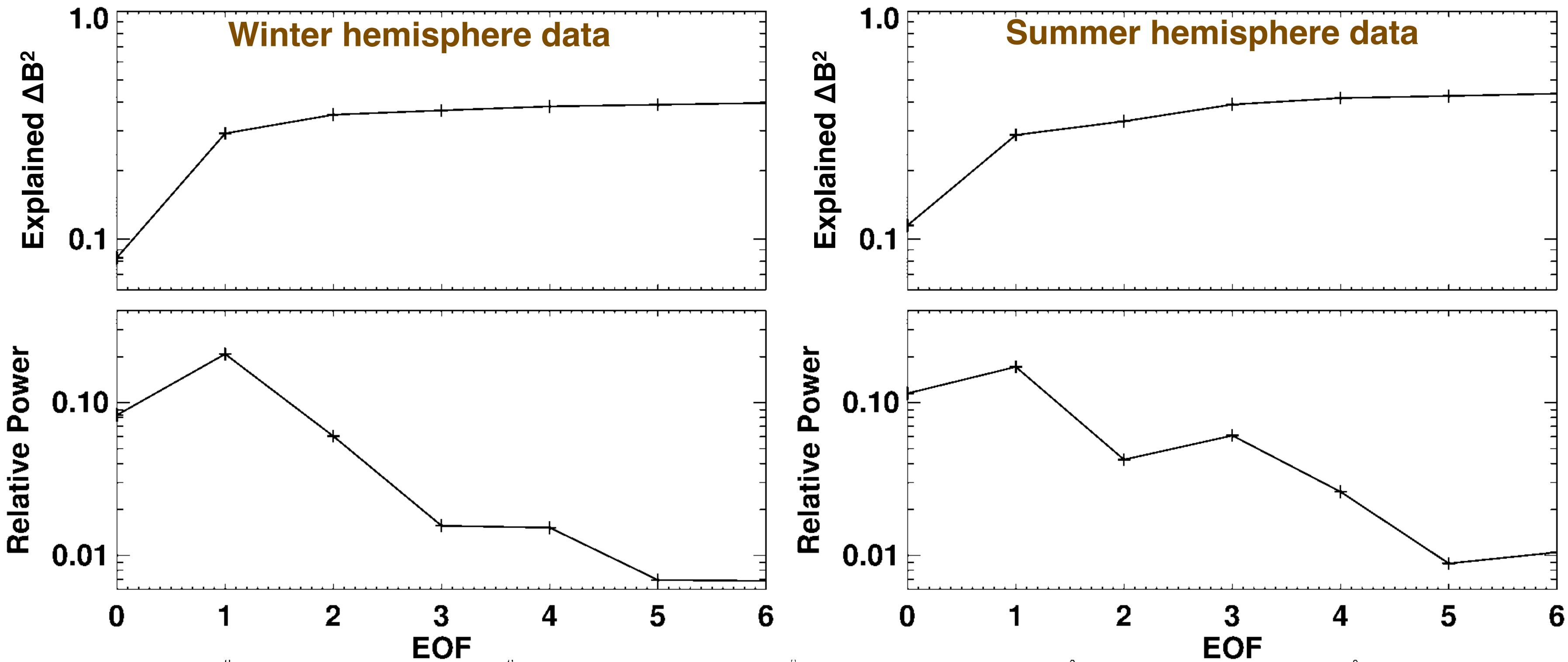
Universal EOFs

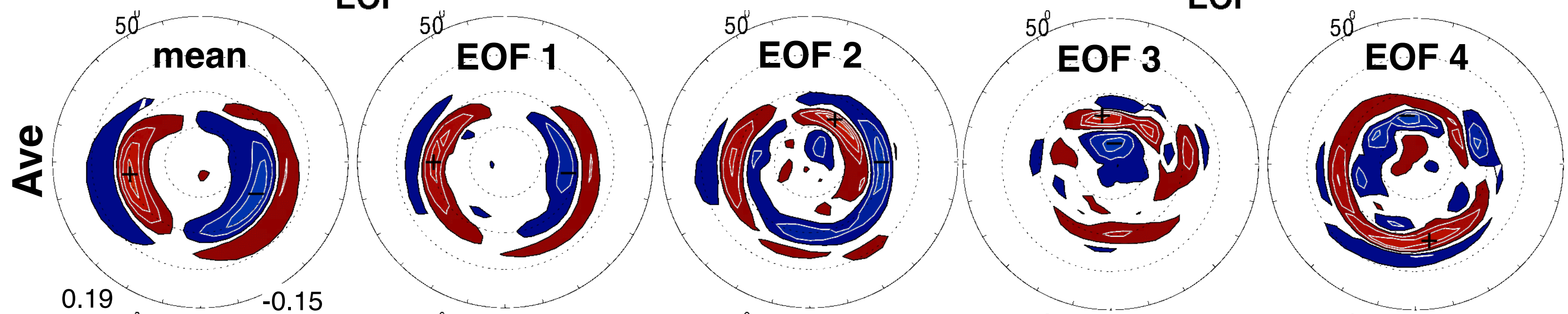
- Ideal to have set of universal EOFs that can be used to describe any AMPERE data
  - Obtained by combing results from North/Winter & South/Summer



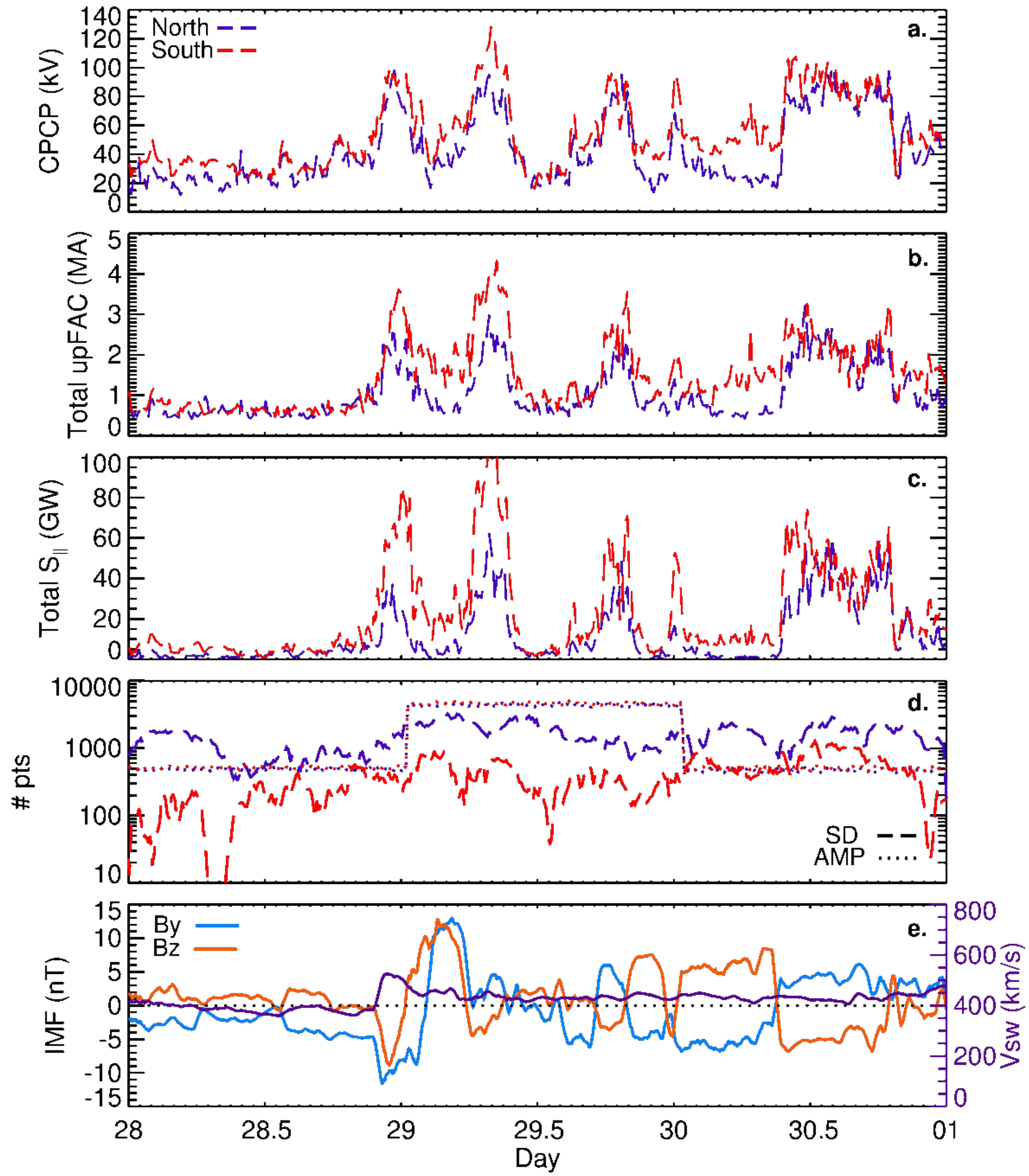
EOF properties: Power Spectrum

- Mean accounts for more of total ΔB^2 in summer than in winter
- Mean + 6 EOFs accounts for < 50% of total ΔB^2
  - ➔Significant amount of small-scale variability &/or noise in data





Example Results



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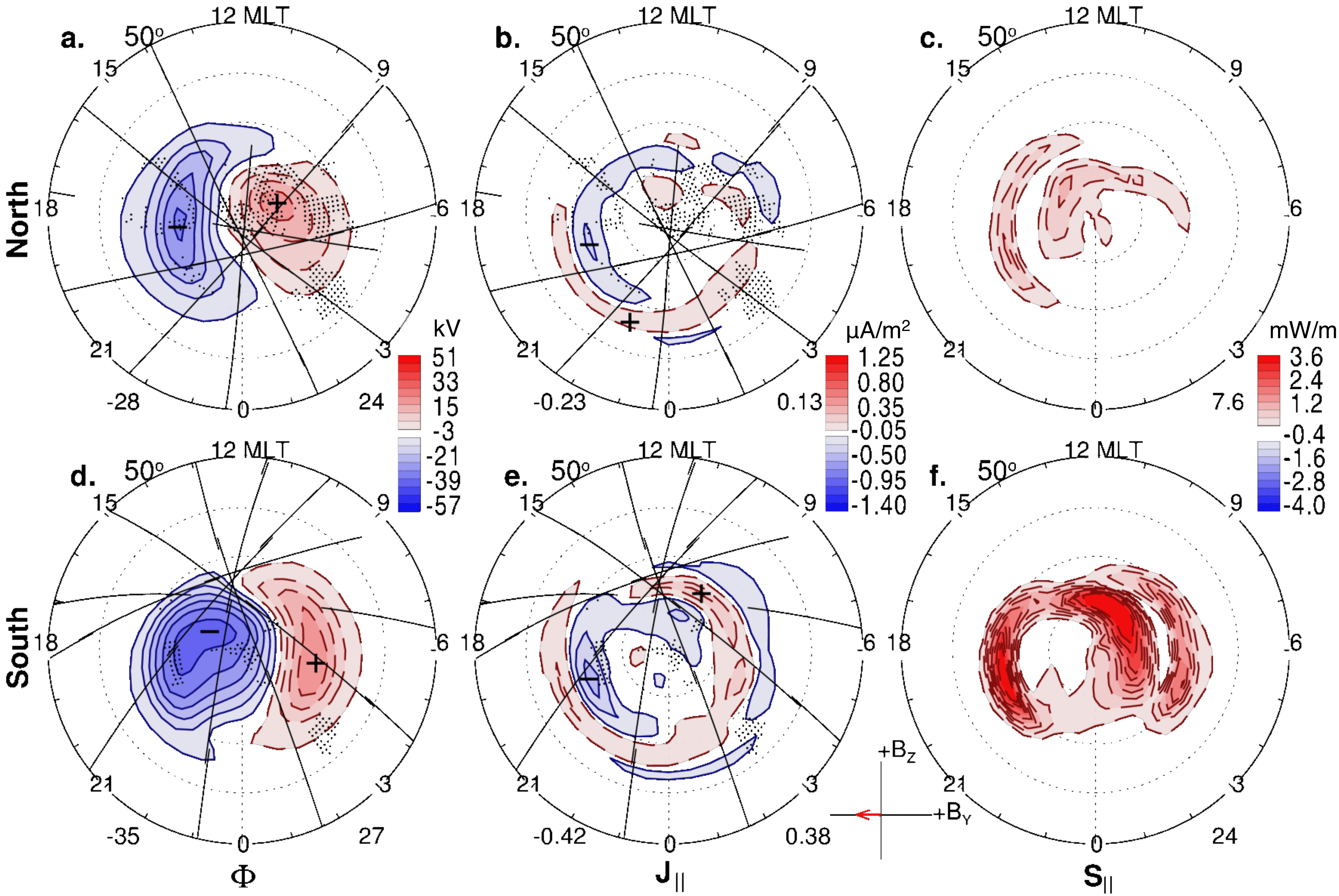

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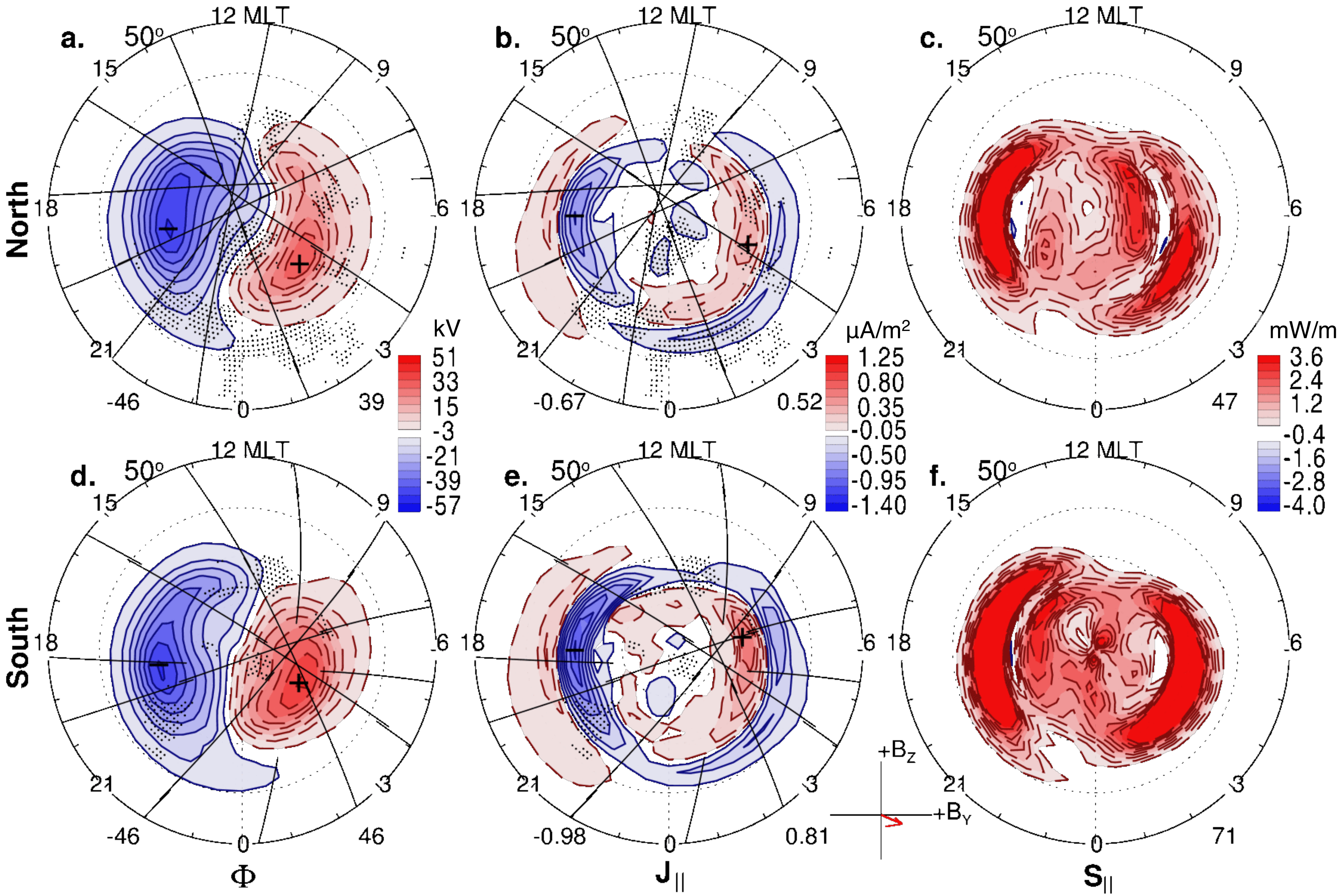

Example Results