Targeted Observation Strategy for Space-weather Forecasting During a Geomagnetic Storm

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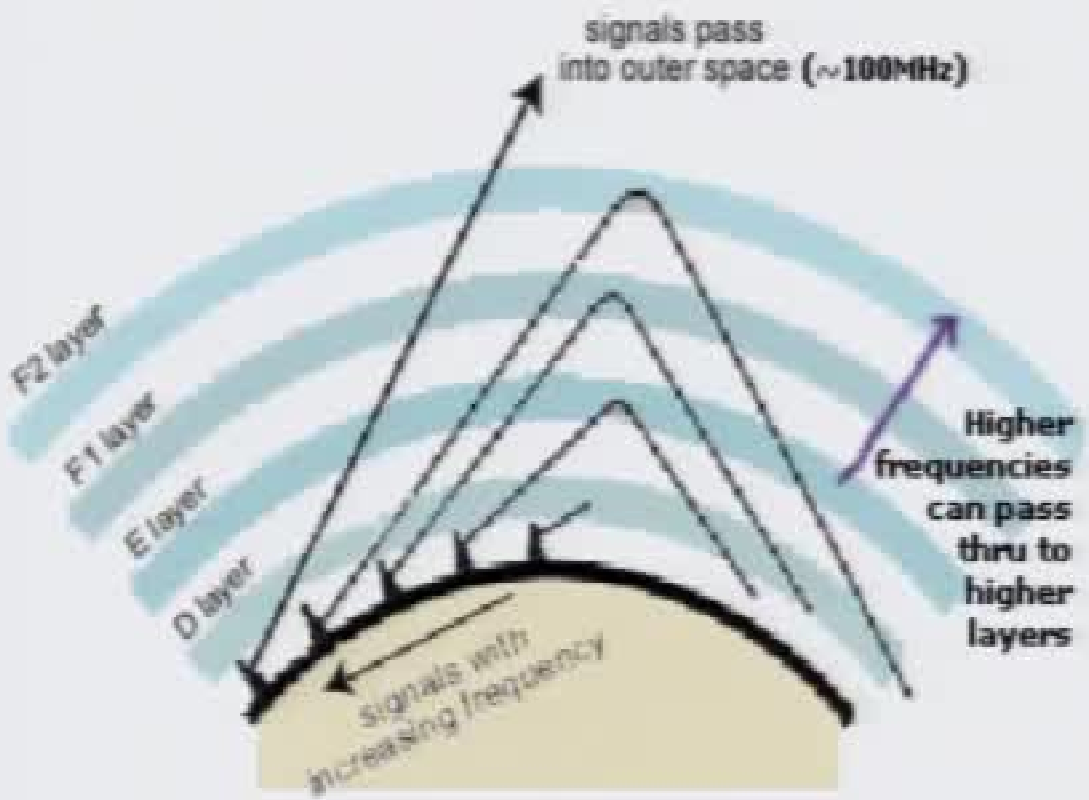
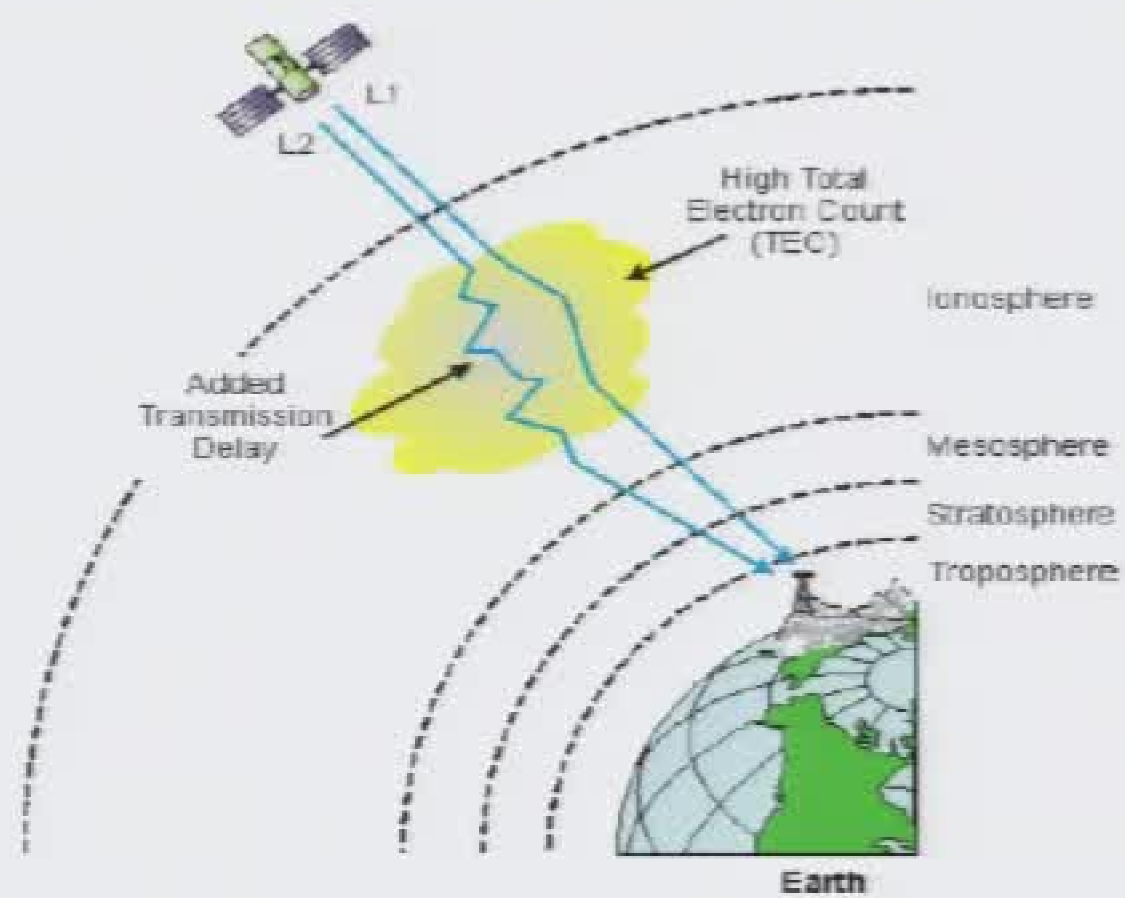
Why is the ionosphere important?

- Electron population affects radio and satellite communication
- Special interest in F-layer



http://selfstudyhistory.com/2015/04/10



http://www.wirelessdictionary.com

Ionospheric Uncertainty

Goal: Estimate/forecast time-varying 3D electron density field

- Challenges: Ionosphere reacts quickly to external drivers:
  - Complex solar radiation influx (ex. solar flares)
  - Distribution of neutral atmospheric composition
  - Geomagnetic activity
  - Atmospheric winds
- Predictability: Infer ionospheric state and its drivers using data assimilation
- Special interest in extreme events

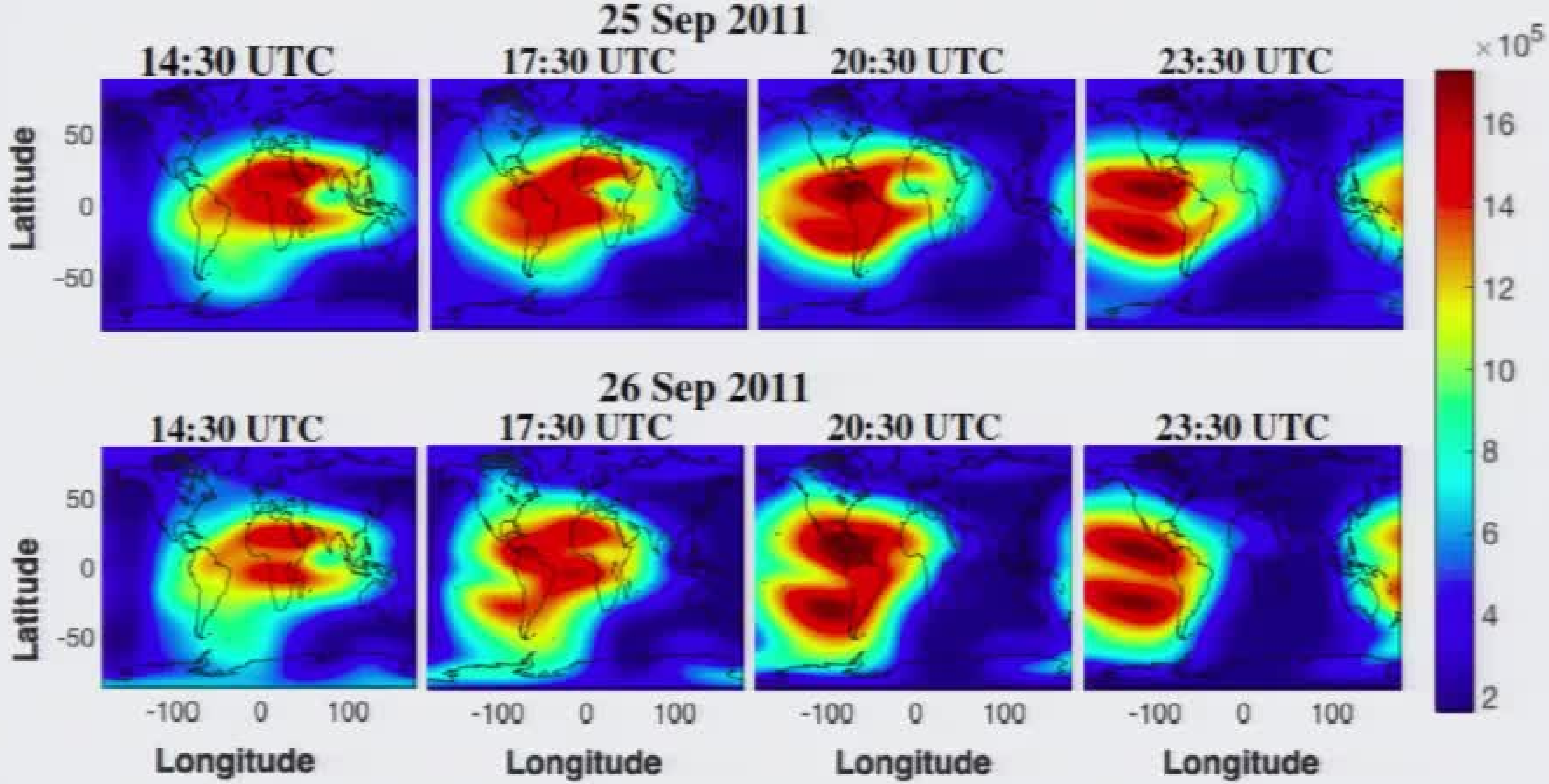
http://www.land-of-kain.de/docs/spaceweather

Representation of Ionospheric Drivers

- Ionosphere's coupling with the thermosphere is represented explicitly
- Effects of solar conditions (ionization, heating, re-combination) rates are represented with external empirical models.
  - Typically parameterized with $F_{10.7}$ index
- High-latitude, magnetospheric input (Energy precipitation, electric field pattern) is also empirical
  - Geomagnetic disturbance characterized with Kp index
  - Kp is used to calculate Hemispheric Power (Hp) and Cross-Tail Potential (Cp) indices
  - Hp and Cp are the inputs of the default high-latitude magnetospheric model
- Historical database provided by the National Oceanic and Atmospheric Administration (NOAA): www.noaa.gov

Electron Density Distribution

Electron density (el/cm^3) averaged over ~ 250–450 km. altitudes



Observation Influence for DA 2

- The observation influence is given by

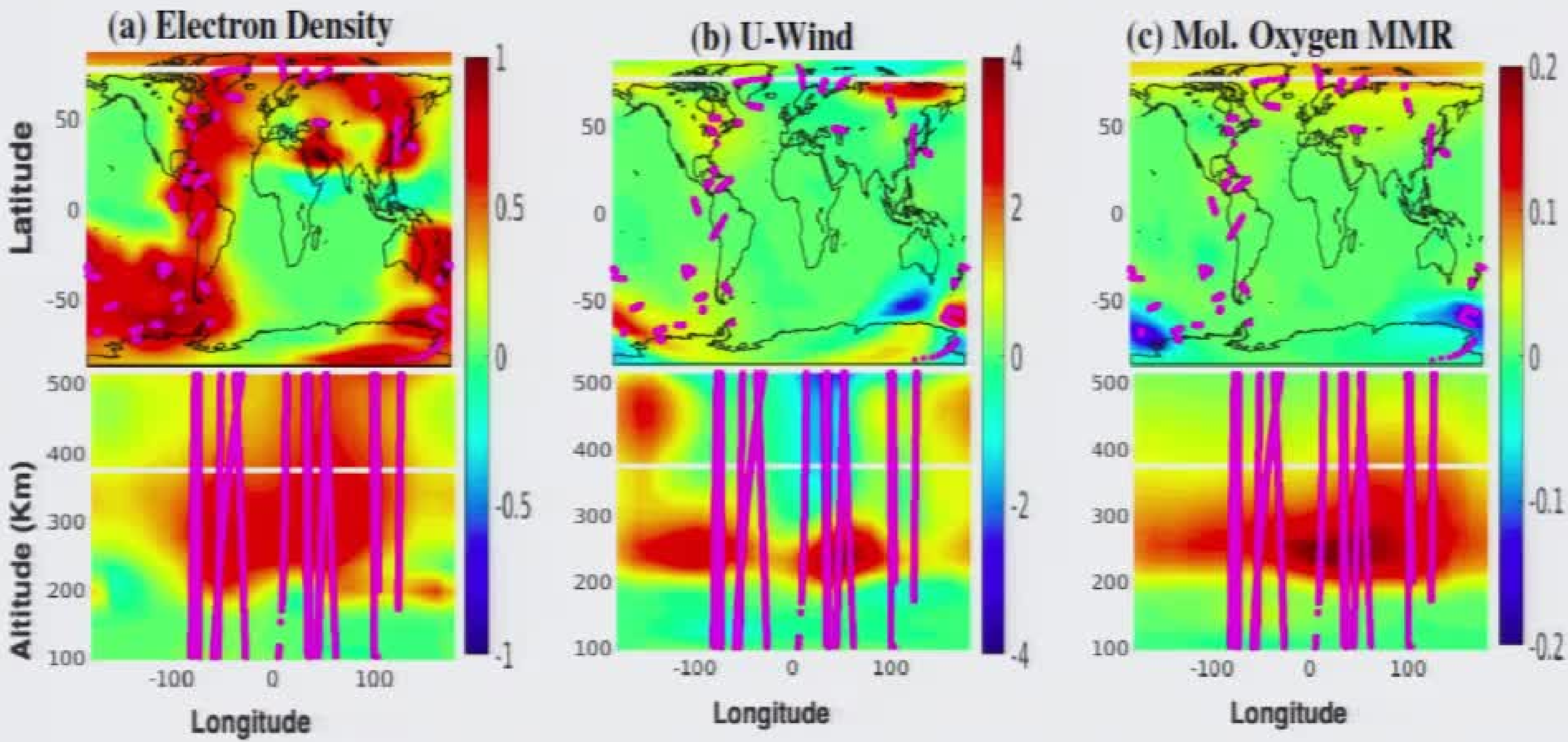
$$\mathbf{S} = \frac{\partial \widehat{\mathbf{z}}}{\partial \mathbf{z}} = \begin{bmatrix} \frac{\partial (\mathbf{H}\bar{\mathbf{x}}^a)}{\partial \mathbf{y}^o} & \frac{\partial (\mathbf{H}\bar{\mathbf{x}}^a)}{\partial \bar{\mathbf{x}}^b} \\ \frac{\partial \bar{\mathbf{x}}^a}{\partial \mathbf{y}^o} & \frac{\partial \bar{\mathbf{x}}^a}{\partial \bar{\mathbf{x}}^b} \end{bmatrix} = \begin{bmatrix} \mathbf{H}\mathbf{P}^a\mathbf{H}^\mathrm{T}\mathbf{R}^{-1} & \mathbf{H}\mathbf{P}^a(\mathbf{P}^b)^{-1} \\ \mathbf{P}^a\mathbf{H}^\mathrm{T}\mathbf{R}^{-1} & \mathbf{P}^a(\mathbf{P}^b)^{-1} \end{bmatrix}. \quad (6)$$

- For the LETKF, $\mathbf{P}^a = \mathbf{X}^b\widetilde{\mathbf{P}}^a(\mathbf{X}^b)^\mathrm{T}$ and $\mathbf{Y}^b = \mathbf{H}\mathbf{X}^b$, which yields

$$\frac{\partial (\mathbf{H}\bar{\mathbf{x}}^a)}{\partial \mathbf{y}^o} = \mathbf{H}\mathbf{P}^a(\mathbf{H})^\mathrm{T}\mathbf{R}^{-1} = \mathbf{Y}\widetilde{\mathbf{P}}^a\mathbf{Y}^\mathrm{T}\mathbf{R}^{-1}$$
$$\frac{\partial \bar{\mathbf{x}}^a}{\partial \mathbf{y}^o} = \mathbf{P}^a(\mathbf{H})^\mathrm{T}\mathbf{R}^{-1} = \mathbf{X}^b\widetilde{\mathbf{P}}^a\mathbf{Y}^\mathrm{T}\mathbf{R}^{-1} \quad (7)$$

Distribution of Observation influence for state variables

- Observation influence for N_e, U_n and O_1



Methodology

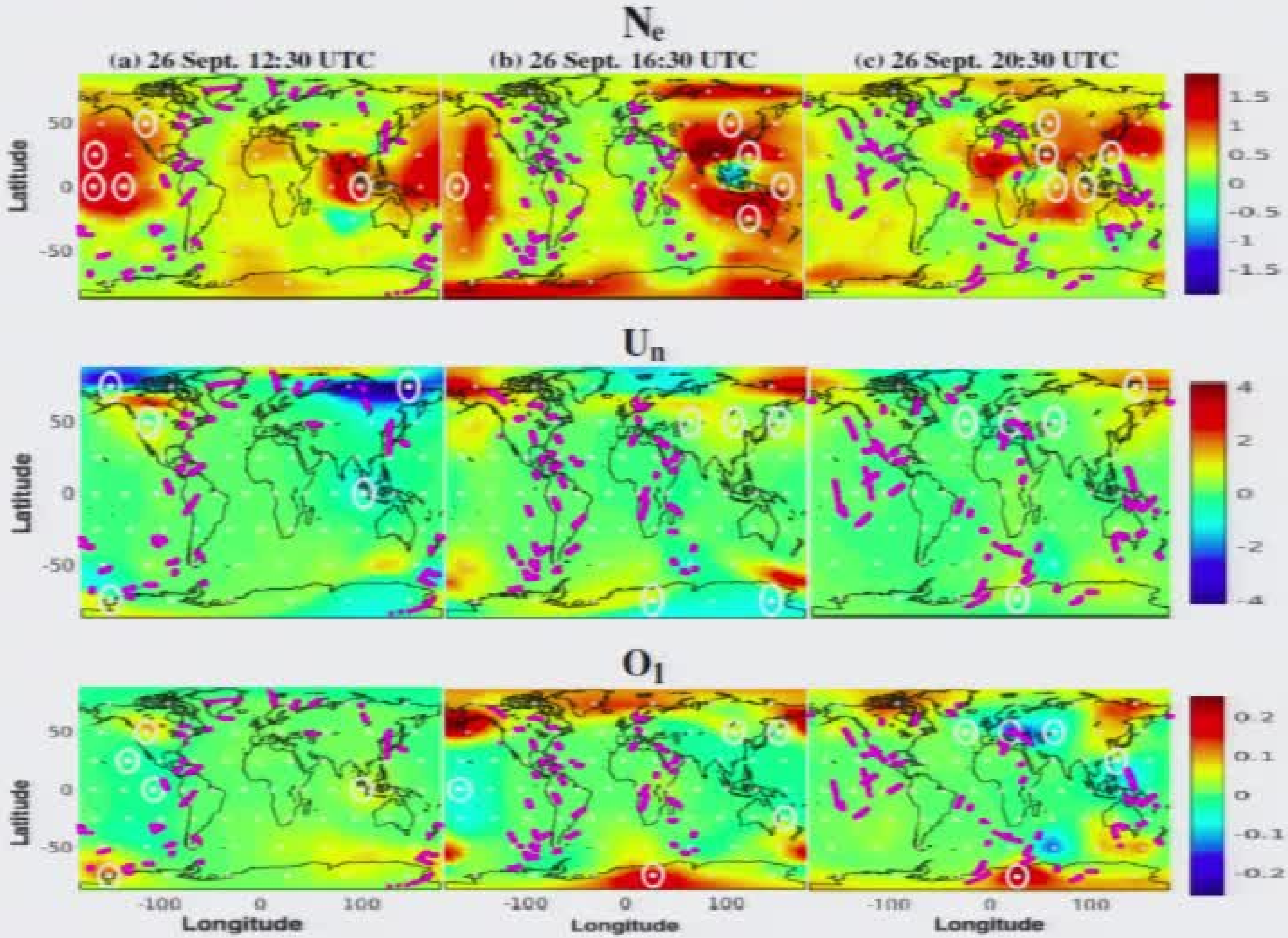
- Partition the observation vector, $\mathbf{y}^F = \left[(\mathbf{y}^C)^\mathrm{T}\ (\mathbf{y}^A)^\mathrm{T}\right]^\mathrm{T}$
- The associated partitions on $\mathbf{Y}_L^F$ and $\mathbf{R}_L^F$ are given by $\mathbf{Y}_L^F = \left[(\mathbf{Y}_L^C)^\mathrm{T}\ (\mathbf{Y}_L^A)^\mathrm{T}\right]^\mathrm{T}$ and $\mathbf{R}_L^F = \begin{bmatrix} \mathbf{R}_L^C & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_L^A \end{bmatrix}$.
- Influence matrices $\mathbf{S}_L^{XF} = \dfrac{\partial \bar{\mathbf{x}}^a}{\partial \mathbf{y}^F}$ and $\mathbf{S}_L^{FF} = \dfrac{\partial (\mathbf{H}\bar{\mathbf{x}}^a)}{\partial \mathbf{y}^F}$ are partitioned as

$$\mathbf{S}_L^{XF} = \left[\mathbf{S}_L^{XC}\ \mathbf{S}_L^{XA}\right] = \left[\mathbf{X}_L^b\widetilde{\mathbf{P}}_L^{a(F)}(\mathbf{Y}_L^C)^\mathrm{T}(\mathbf{R}_L^C)^{-1}\ \mathbf{X}_L^b\widetilde{\mathbf{P}}_L^{a(F)}(\mathbf{Y}_L^A)^\mathrm{T}(\mathbf{R}_L^A)^{-1}\right] \quad (9)$$

$$\mathbf{S}_L^{FF} = \begin{bmatrix} \mathbf{S}_L^{CC} & \mathbf{S}_L^{CA} \\ \mathbf{S}_L^{AC} & \mathbf{S}_L^{AA} \end{bmatrix} = \begin{bmatrix} \mathbf{Y}_L^C\widetilde{\mathbf{P}}_L^{a(F)}(\mathbf{Y}_L^C)^\mathrm{T}(\mathbf{R}_L^C)^{-1} & \mathbf{Y}_L^C\widetilde{\mathbf{P}}_L^{a(F)}(\mathbf{Y}_L^A)^\mathrm{T}(\mathbf{R}_L^A)^{-1} \\ \mathbf{Y}_L^A\widetilde{\mathbf{P}}_L^{a(F)}(\mathbf{Y}_L^C)^\mathrm{T}(\mathbf{R}_L^C)^{-1} & \mathbf{Y}_L^A\widetilde{\mathbf{P}}_L^{a(F)}(\mathbf{Y}_L^A)^\mathrm{T}(\mathbf{R}_L^A)^{-1} \end{bmatrix} \quad (10)$$

Targeted Observations

Observation influence distribution averaged over 250–450 km. altitudes for electron density (N_e), U-wind (U_n) and atomic oxygen (O_1)



References

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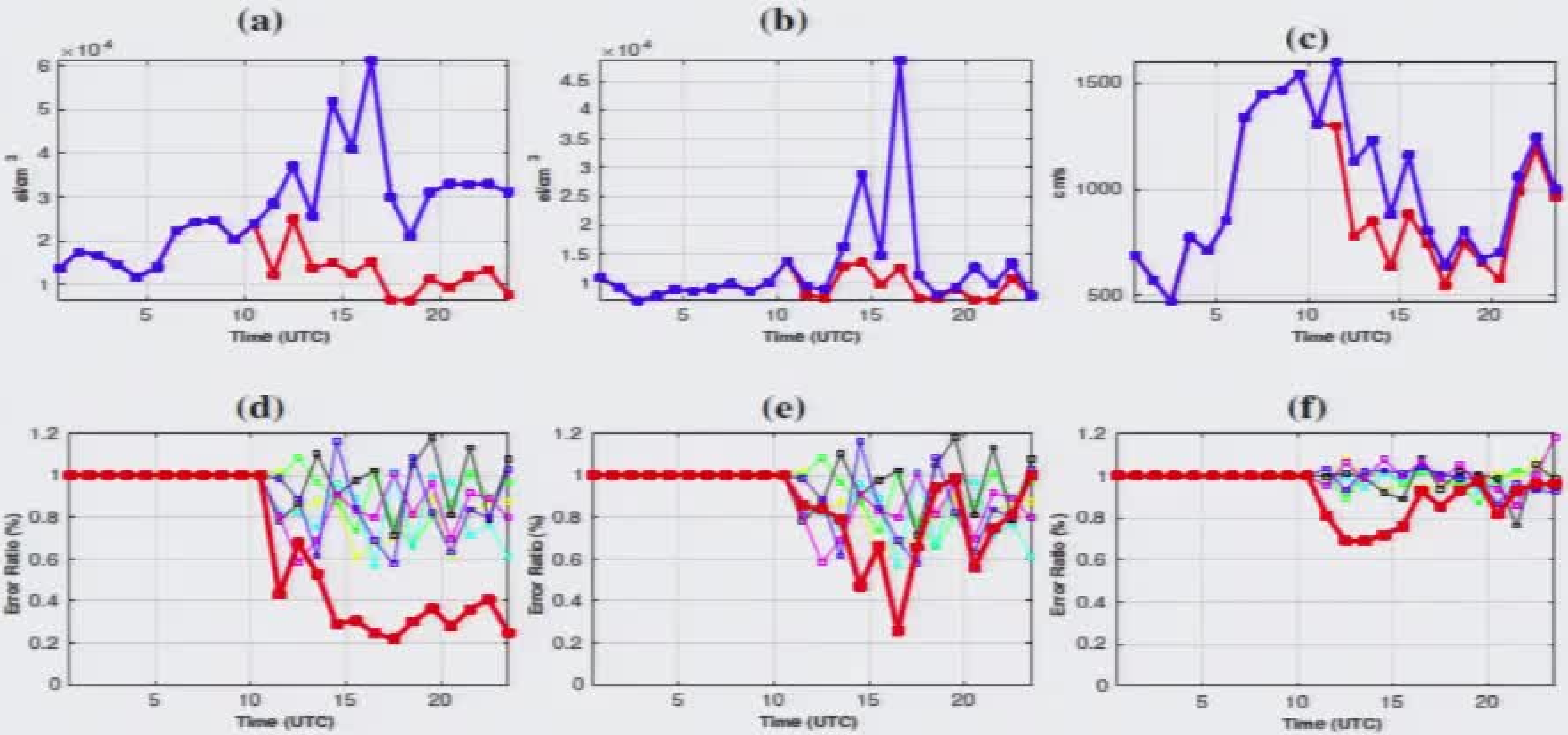
Thank you!:

Questions? Suggestions? Comments?

Benefit of Targeting Observations

- RMS error with and without augmented vertical profiles.
- RMS is averaged over 600 km regions centered around augmented vertical profiles



Outline

1. Ionosphere introduction
   - Motivation
   - Ionosphere Model Overview
2. Data assimilation and observation influence
   - Local ensemble transform Kalman filter (LETKF)
   - Observation influence formulation
3. Application to the ionosphere
   - Targeted Observation Strategy

Distribution of Observation influence for state variables

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