



A Novel Data Assimilation Model for the Plasmasphere

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Objective and Motivation

■ Objective:

- Apply the idea of data assimilation to the plasmasphere
- To develop a plasmaspheric data assimilation technique to produce time-evolving global maps of plasmasphere electron density structures.

■ Motivation

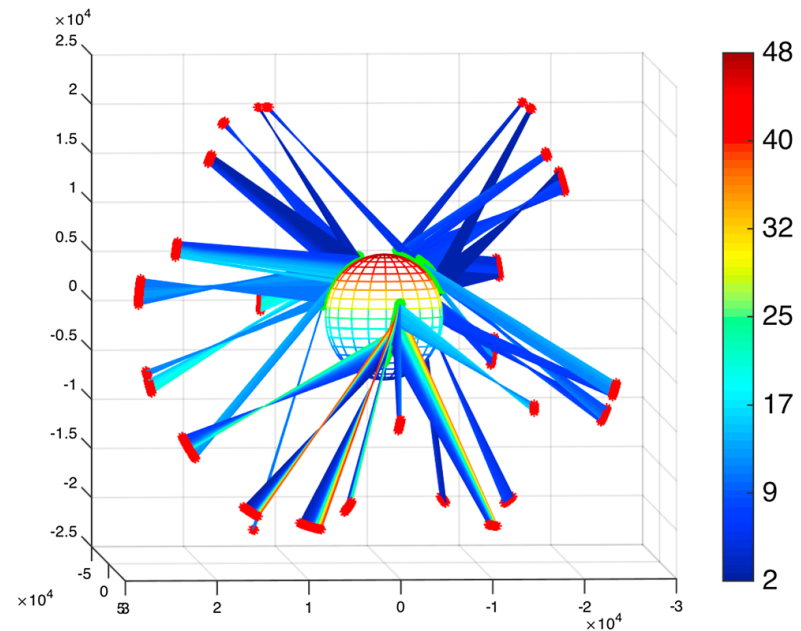
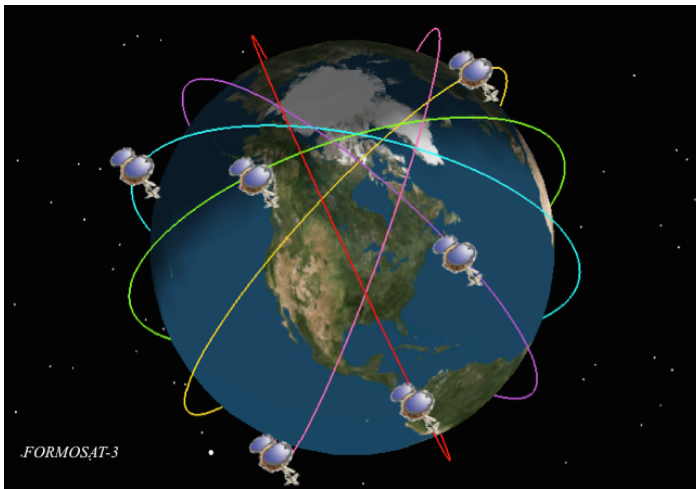
- Understanding magnetosphere/ionosphere coupling requires understanding the dynamics of the transition region between the two, Earth's **plasmasphere**.
- Plasmaspheric dynamics is poorly characterized due to the paucity of in-situ data available, making it difficult to construct a global plasmasphere picture.
- Earlier tomographic imaging efforts were necessarily limited to 2D electron density slice within the LEO orbit plane.
- Data assimilation is a mathematical framework for the statistical union between observations and empirical or physics-based models.

Methodology – Data Assimilation

▪ Based on Ionosphere Data Assimilation 4D (IDA4D) [Bust et al. 2004]

➤ Data:

- COSMIC/FORMOSAT-3: Total electron content (TEC)
- Precise Orbit Determination
 - Overhead GPS TEC signals



Methodology – Data Assimilation

➤ Forward model:

- Relating observations to state variables (electron density)
 - Line-of-sight integration

$$TEC = \int N_e(z) dz + \varepsilon_k \quad \text{or} \quad y_k = H_k x_k + \varepsilon_k$$

➤ Inverse model:

- **Statistical framework:**

- $\varepsilon_k \sim \mathcal{N}(\mathbf{0}, R_k)$, $p(y_k | x_k) \sim \exp\left(-\frac{1}{2} \left(\|y_k - H_k x_k\|_{R_k^{-1}}^2\right)\right)$

- **Maximum-Likelihood (ML) estimate** : $x_k^{ML} = \max p(y_k | x_k)$

$$x_k^{ML} = \arg \min_{x_k} \frac{1}{2} \left(\|y_k - H_k x_k\|_{R_k^{-1}}^2\right)$$

- H is ill-conditioned, in general. Cannot solve directly via $x_k = H_k^{-1} y_k$

Methodology – 3D-VAR

1) Analysis: Compute the estimate at each time step

▪ Bayesian Approach (*a priori* information):

➤ Model:

- Global Core Plasma (GCP) Model [Gallagher et al., 2000]
- Empirical, Kp-driven

➤ $x_k \sim \mathcal{N}(x_k^b, P_k^b)$

➤ Maximum *a posteriori* Estimate: $x_k^a = \arg \max_{x_k} p(y_k | x_k) p(x_k)$

- Objective function combining the deviation from the data and the model
- **3D-VAR:** estimate 3D structure of the unknown state

$$x_k^a = \arg \min_{x_k} \frac{1}{2} \left(\|y_k - H_k x_k\|_{R_k}^2 + \|x_k - x_k^b\|_{P_k^b}^2 \right)$$

- Analytical expressions for the solution exist:

$$x_k^a = x_k^b + P_k^b H_k^T [R_k + H_k P_k^b H_k^T]^{-1} (y_k - H_k x_k^b)$$

$$P_k^a = P_k^b - P_k^b H_k^T [R_k + H_k P_k^b H_k^T]^{-1} H_k P_k^b$$

Methodology – Plasmasphere Data Assimilation (PDA)

- We find that with the ingestion of upward looking data alone, the problem remains ill-posed.

- Hence, we further constrain the solution to be vertically smooth.

- $x_k \sim \mathcal{N}(x_k^b, [P_k^{-1} + \lambda^2 D^T D]^{-1})$

$$x_k^{aMAP} = \arg \min_{x_k} \frac{1}{2} \left(\|y_k - H_k x_k\|_{R_k^{-1}}^2 + \|x_k - x_k^b\|_{P_b^{-1}}^2 + \lambda^2 \|D(x_k - x_k^b)\|_I^2 \right)$$

Where D and λ are the regularization functional and regularization parameter, respectively.

- How to solve this analytically?

$$x_k^{aMAP} = \arg \min_{x_k} \frac{1}{2} \left(\lambda^2 \|D(x_k - x_k^b)\|_I^2 + \|x_k - x_k^a\|_{P_a^{-1}}^2 + C \right)$$

- 3-D VAR: $x_k^a = \arg \min_{x_k} \frac{1}{2} \left(\|y_k - H_k x_k\|_{R_k^{-1}}^2 + \|x_k - x_k^b\|_{P_b^{-1}}^2 \right)$

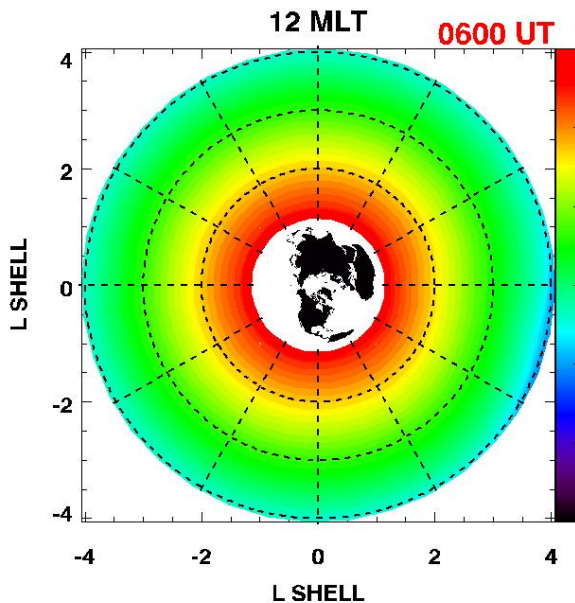
- PDA Two-stage analysis:

i. $x_k^a = x_k^b + P_k^b H_k^T [R_k + H_k P_k^b H_k^T]^{-1} (y_k - H_k x_k^b)$

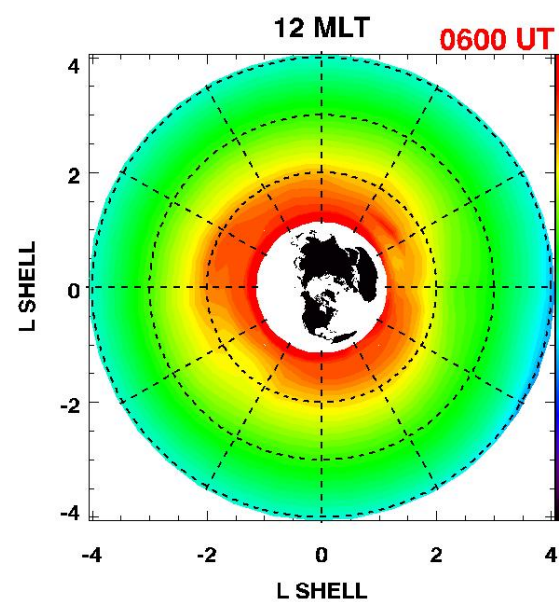
ii. $x_k^{aMAP} = x_k^a + P_k^a D^T [I + D P_k^a D^T]^{-1} (x_k^b - D x_k^a)$

2) Prediction: Moving the state forward in time via Gauss-Markov Kalman.

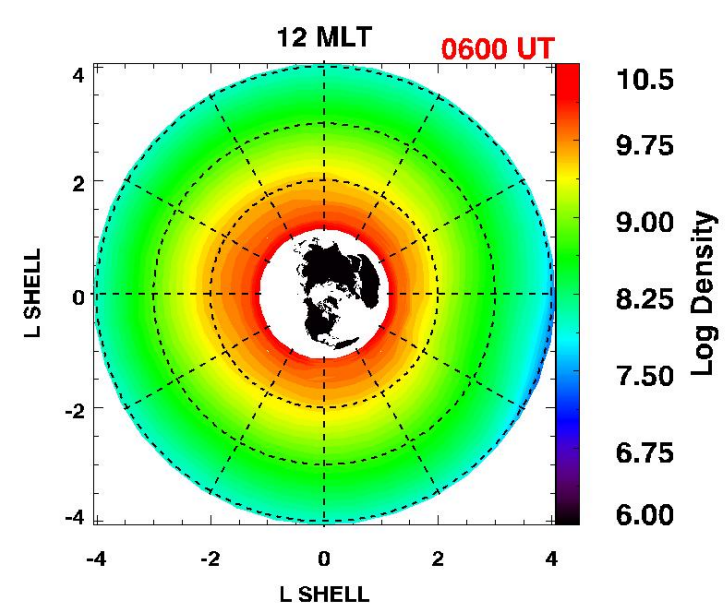
Model



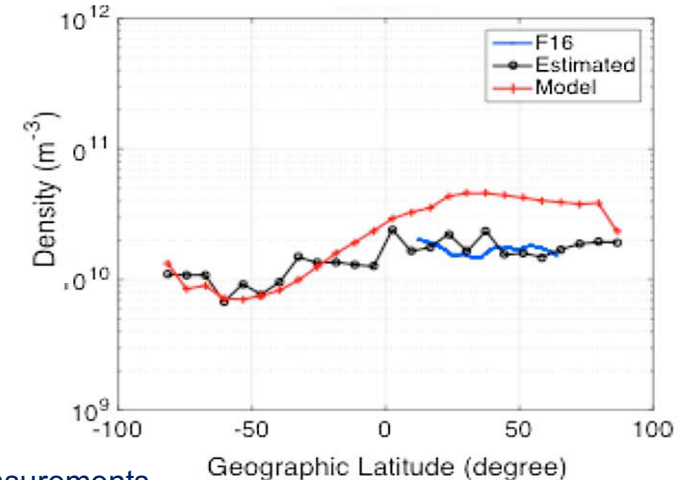
3D-VAR



PDA



- Equatorial cross sections of the plasmasphere electron density (m^{-3}).
- The cross sections extend to $L=4$ (20,000 km).
- Sun is at the top of the image, dawn to the right.
- PDA eliminates unrealistic altitude gradients.
- A good agreement is demonstrated between DMSP-F16 in-situ densities and PDA estimated densities.

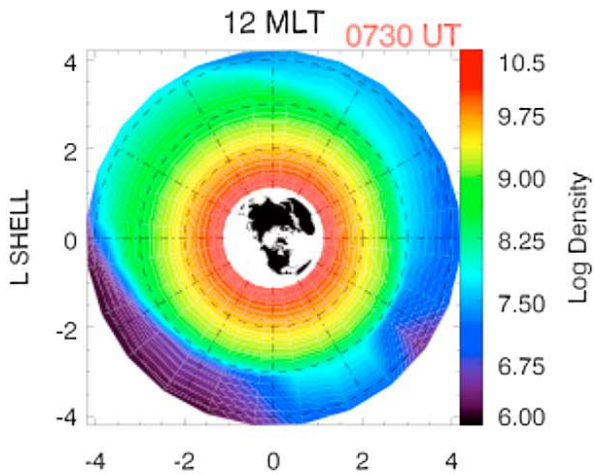


The authors are grateful to Dr. Hairston from UT Dallas for providing DMSP density measurements

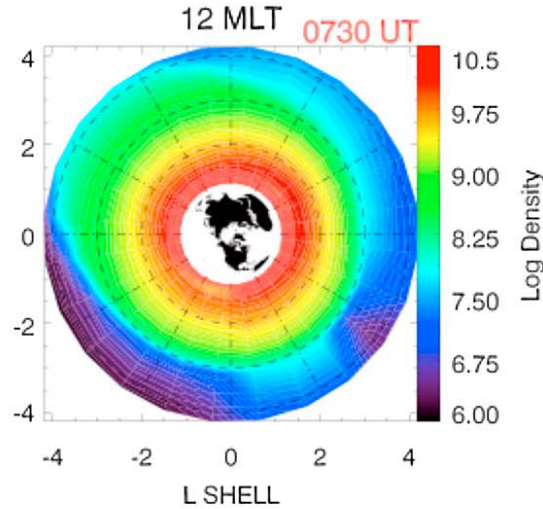
PDA Estimation results – 2

Storm Day, 03/17/2013

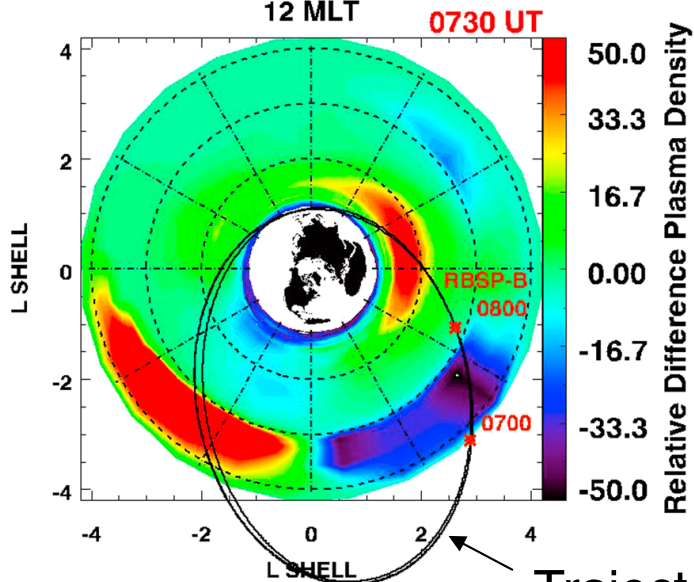
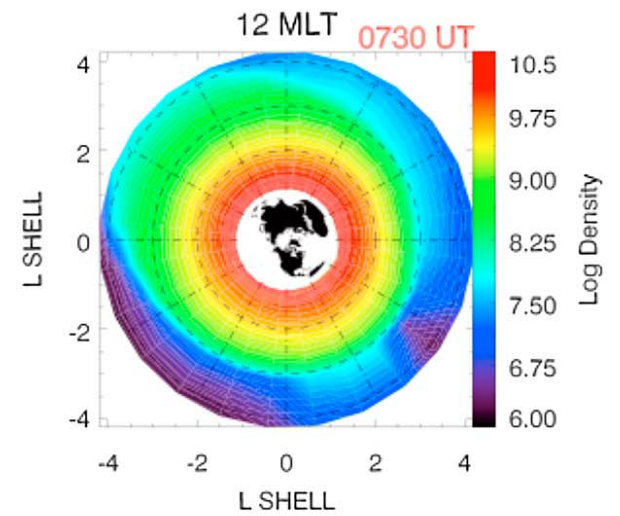
Model



3D-VAR

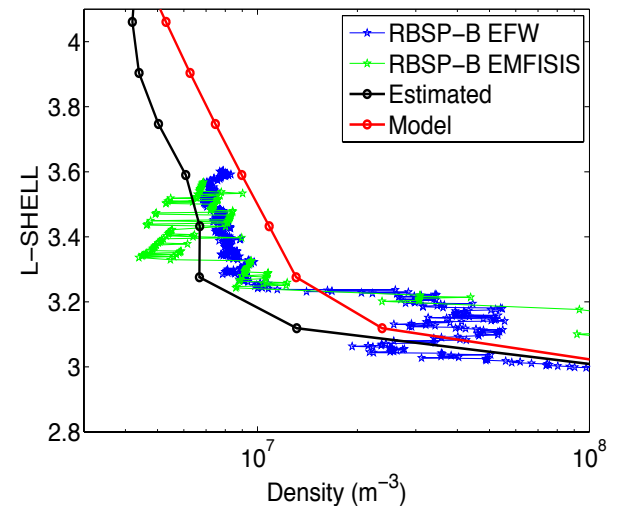


PDA



Absolute difference between the background model and the PDA estimate weighted by model density on 17 March 2013, 0730 UT.

Trajectory of the RBSP-B



Summary and Future Directions

- **An assimilative model that provides global 3D maps of electron density in the plasmasphere.**
- **For plasmasphere data assimilation, it is necessary to impose a smoothness constraint to avoid non-physical gradients.**
- **A coupled ionosphere-plasmasphere data assimilation model****
 - **The extension of the PDA grid to lower ionospheric heights**
 - Ground-based GPS TEC
 - ISR measurements
 - FUV measurements
 - COSMIC-2 GPS TEC
 - **Inclusion of physics-based model such as RCM-E and SAMI**
 - ❖ **3D Evolution of the system during geomagnetic storms (plumes, SED [Foster et al, 2002])**
- **An integrated ionosphere-plasmasphere assimilative model for more accurate specification, nowcast, and forecast of the upper atmosphere**

* NASA-HSR grant #NNX16AG65G, R. Bishop, A. Coster, G. Bust, R. Nikoukar, D. Turner, and C. Lemon, Storm-time Dynamics of the Plasmopause and the Ionosphere/Magnetosphere System, 2016-2018.

** G. Bust, A. Chartier, R. Schaefer, R. Nikoukar, E. Miller, IDA2017: A Next-Generation Coupled Modular Assimilation Package, JHU/APL.



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