New Methods for Physics-Based Neutral Density

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Integrity ★ Service ★ Excellence

Project Goals & Motivation

Goals:

- Blend data and physics-based I-T model to improve accuracy both where and when data is not available
- Identify the obstacles currently hindering physics-based I-T data assimilation techniques and design new ones

Motivation:

- Empirical or climatological I-T models offer limited predictive capabilities
- Physics-based models offer better predictive ability, but significant advances to Data Assimilation techniques are needed first

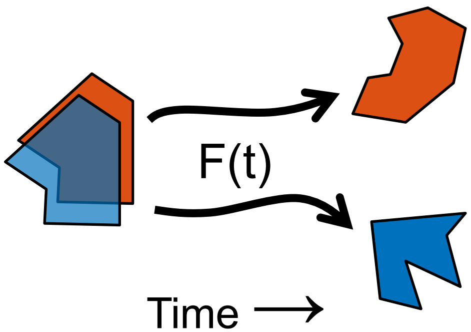
Data Assimilation

Different Approaches for Different Systems

Features of the Ionosphere-Thermosphere (I-T) system:

- Highly driven
- Sparsely observed

Chaotic System
(e.g. tropospheric weather)



Strongly Driven System
(e.g. Ionosphere-Thermosphere)

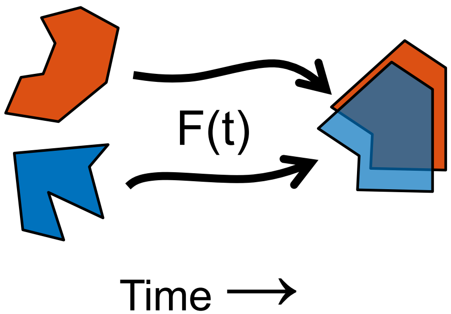


Image credit: S. Codrescu

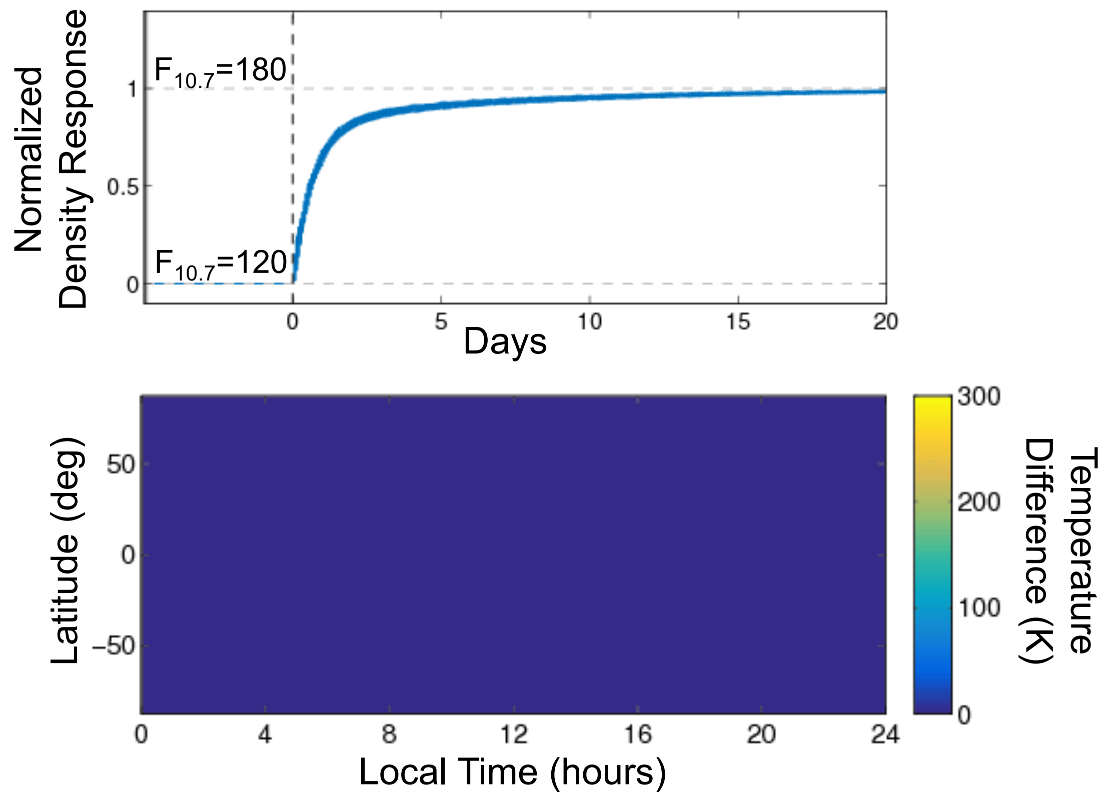
See the method by S. Codrescu et al. [2018, Space Weather]

I-T Response Characteristics

One example

Response of the I-T to a step increase in solar irradiance:

- $F_{10.7}$ increases from 120 to 180 at t=0
- Neutral density response as observed by a circular, polar satellite orbiting at 400 km altitude
- Density is normalized between two steady-state simulations ($F_{10.7}$=120 and 180)
- The increase in temperature across the globe is shown below



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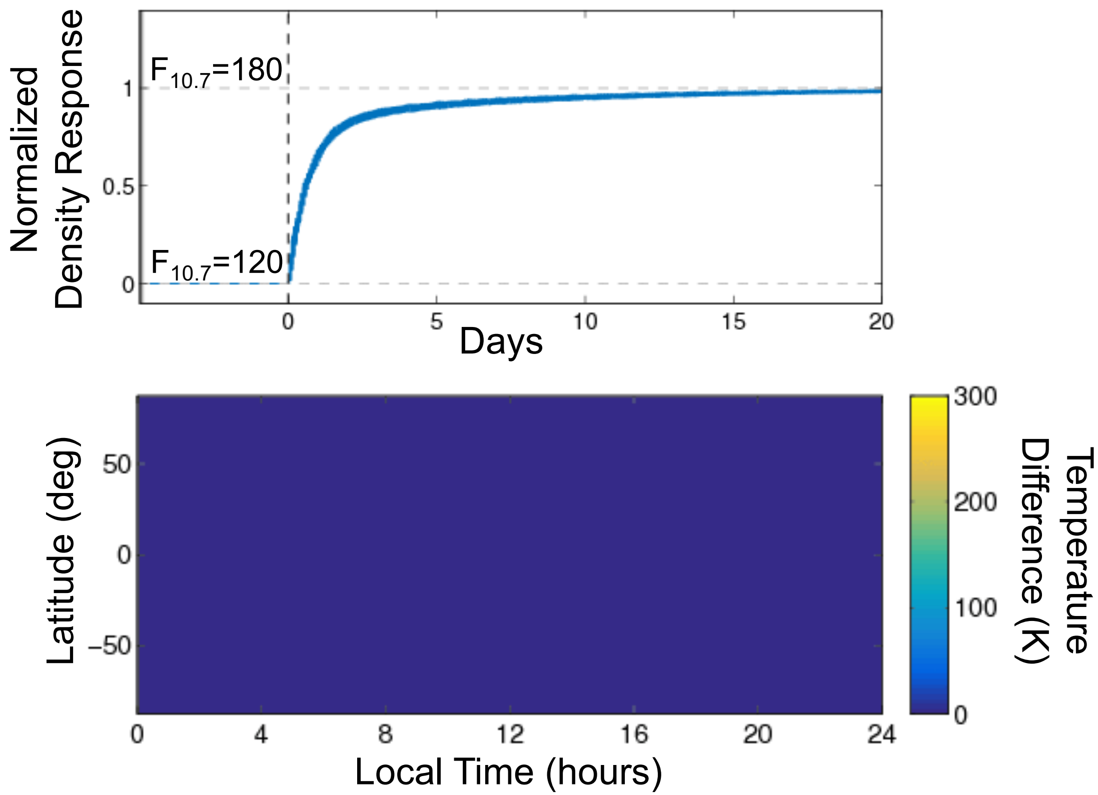
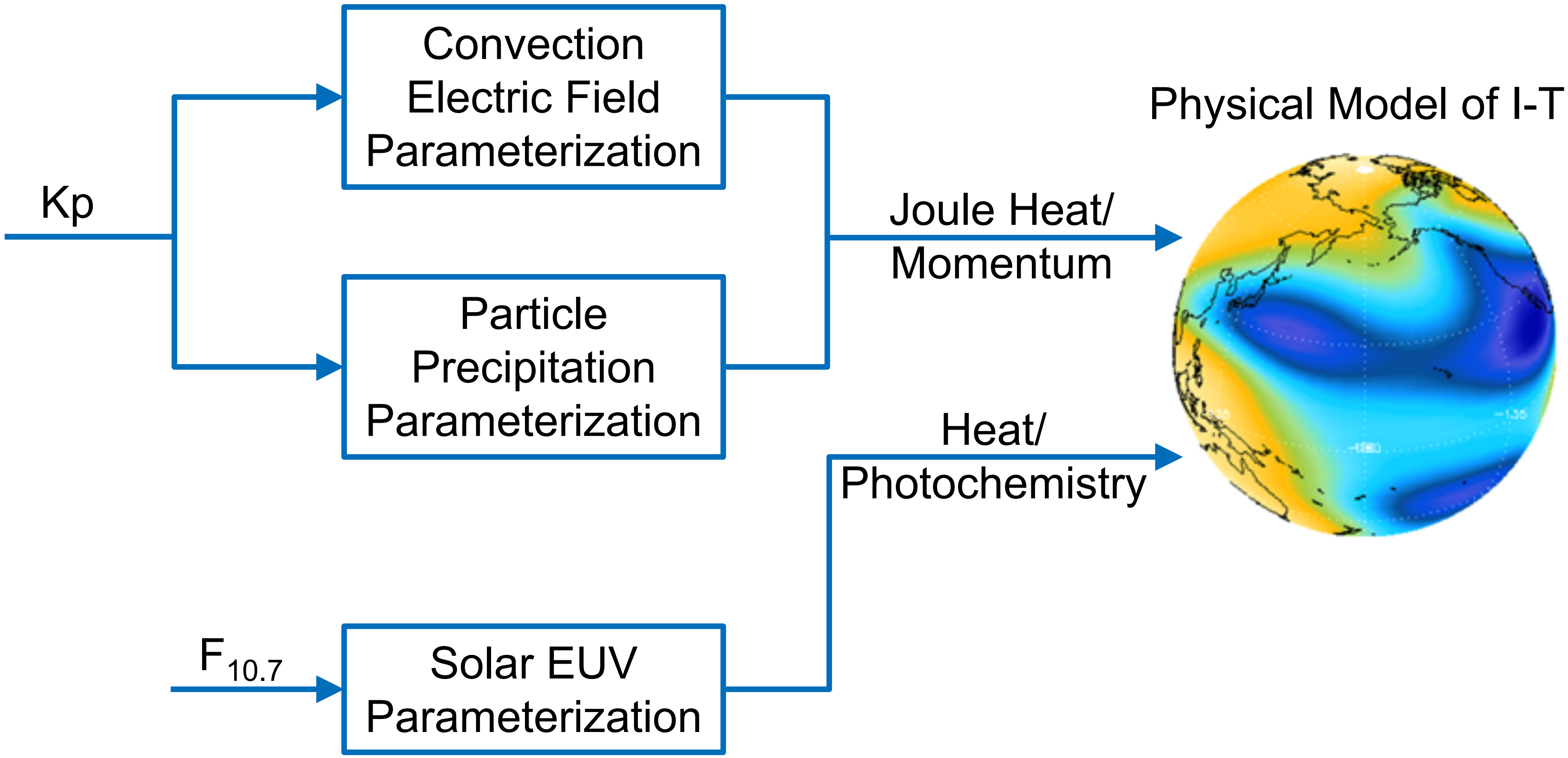


Drivers of an I-T Model



Data Assimilation

Obstacles

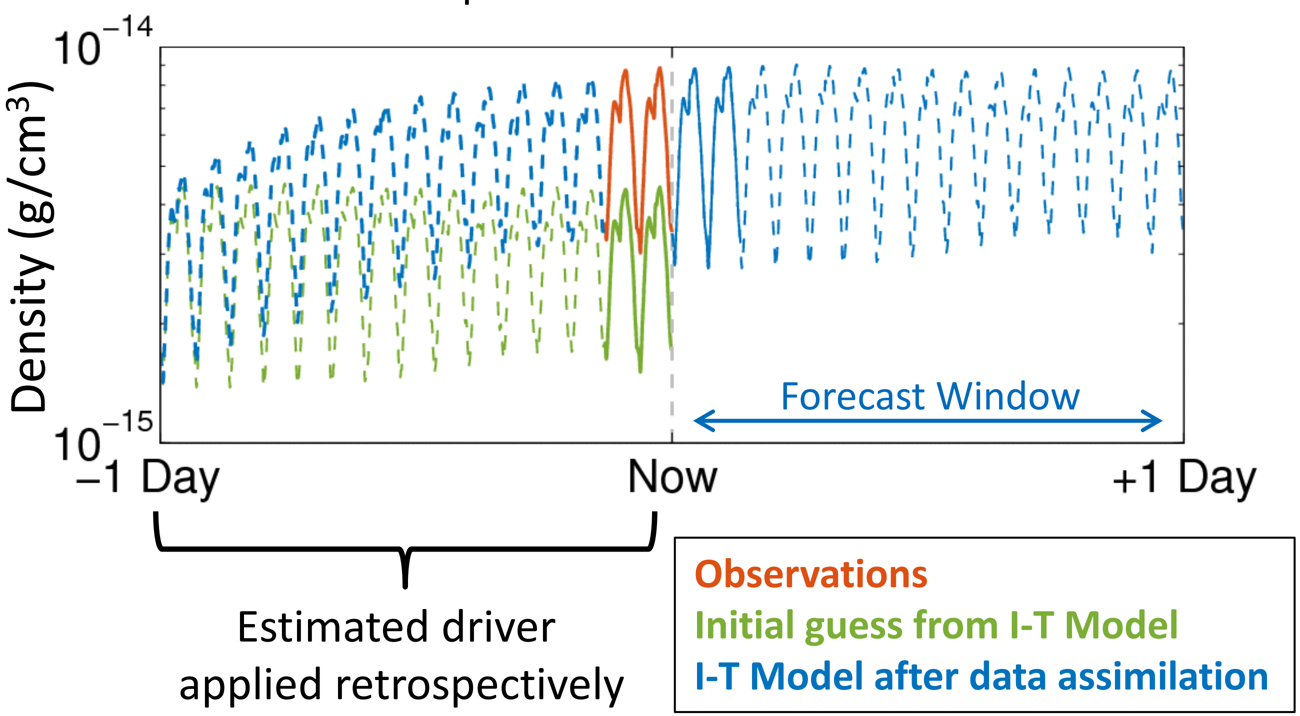
1. **Driven system:** initial conditions less important than conditions of the solar wind and solar flux
2. **Sluggish response:** thermosphere takes some time to responds to drivers
3. **Unknown drivers:** solar flux (EUV) and solar wind/magnetosphere/ionosphere coupling are not always well observed

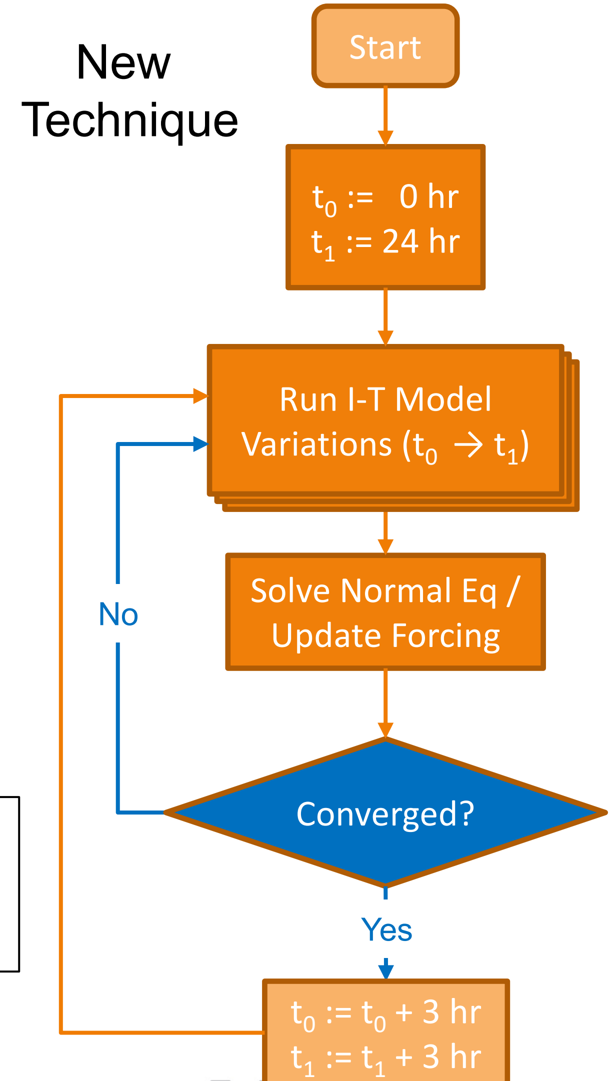
Data Assimilation

New Approach

New approach to data assimilation:

- Calculate what the driver *should* be for I-T model output to match observations
- Apply new estimated driver retrospectively to allow model to equilibrate





More details here: Sutton [2018, doi:10.1002/2017SW001785]

Physics-Based I-T Model

TIE-GCM

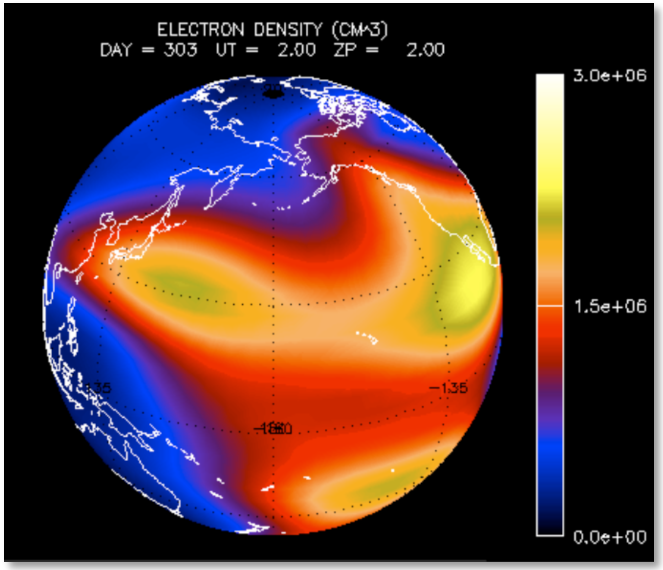
Solves the 3D neutral equations for:

- Energy
- Momentum
- Continuity
- Comp./chem. (O_2, O, N_2, +minor species)

and the ionospheric equations for:

- O^+ production/transport/chemistry
- O_2^+, NO^+, N_2^+, N^+, e^- photochemical equilibrium
- Electric potential
- Ion/elect. Heating

http://www.hao.ucar.edu/modeling/tgcm/tie.php



Thermosphere

$$\frac{\partial T'}{\partial t} = \frac{ge^z}{p_0 c_p}\frac{\partial}{\partial z}\left(\frac{K_T}{H}\frac{\partial T'}{\partial z}\right) - aT' - \mathbf{V}\cdot\nabla T' - w\left(S + \frac{\partial T'}{\partial z} + \frac{RT'}{c_p m}\right) + Q'/c_p$$

$$\frac{\partial u}{\partial t} = \frac{ge^z}{P_0}\frac{\partial}{\partial z}\left(\frac{\mu}{H}\frac{\partial u}{\partial z}\right) + \left(f + \frac{u}{r}\tan\phi - \lambda_{xy}\right)v - \lambda_{xx}u - \mathbf{V}\cdot\nabla u - w\frac{\partial u}{\partial z} - \frac{1}{r\cos\phi}\frac{\partial \Phi'}{\partial \lambda} + (F_\lambda + \lambda_{xy}v_I + \lambda_{xx}u_I)$$

$$\frac{\partial v}{\partial t} = \frac{ge^z}{p_0}\frac{\partial}{\partial z}\left(\frac{\mu}{H}\frac{\partial v}{\partial z}\right) - \left(f + \frac{u}{r}\tan\phi - \lambda_{yx}\right)u - \lambda_{yy}v - \mathbf{V}\cdot\nabla v - w\frac{\partial v}{\partial z} - \frac{1}{r}\frac{\partial \Phi'}{\partial \phi} + (F_\phi + \lambda_{yy}v_I - \lambda_{yx}u_I)$$

$$\partial\Phi'/\partial z = R(T_0 + T')/m \qquad \frac{1}{r\cos\phi}\frac{\partial}{\partial\phi}(v\cos\phi) + \frac{1}{r\cos\phi}\frac{\partial u}{\partial\lambda} + e^z\frac{\partial}{\partial z}(e^{-z}w) = 0$$

Ionosphere

$$\frac{3}{2}N_e k_B\frac{\partial T_e}{\partial t} = -N_e k_B T_e \nabla\cdot \mathbf{u}_e - \frac{3}{2}N_e k_B \mathbf{u}_e\cdot\nabla T_e - \nabla\cdot q_e + \sum Q_e - \sum L_e$$

$$\sin^2 I\frac{\partial}{H\partial Z}\left(\frac{2}{7}\frac{K^0}{H}\frac{\partial G}{\partial Z}\right) - \left(\frac{L_{on} + L_{oi}}{T_e^{5/2}}\right)G = -L_{on}T_n - L_{oi}T_i - Q_e$$

$$\frac{\partial n}{\partial t} - Q + Ln = -\nabla\cdot n\underline{V}$$

$$\underline{V} = \underline{V}_\beta + \underline{V}_\perp$$

$$\underline{V}_\beta = \left\{\underline{b}\cdot\frac{1}{\nu}\left[g - \frac{1}{\rho_i}\nabla\left(P_i + P_e\right)\right] + \underline{b}\cdot\underline{u}\right\}\underline{b}$$

$$\underline{V}_\perp = \frac{1}{|B|}\underline{E}\times\underline{b}$$

$$\nabla\cdot\sigma\cdot\nabla\Phi = \nabla\cdot\sigma\cdot(V_n\times B)/c$$

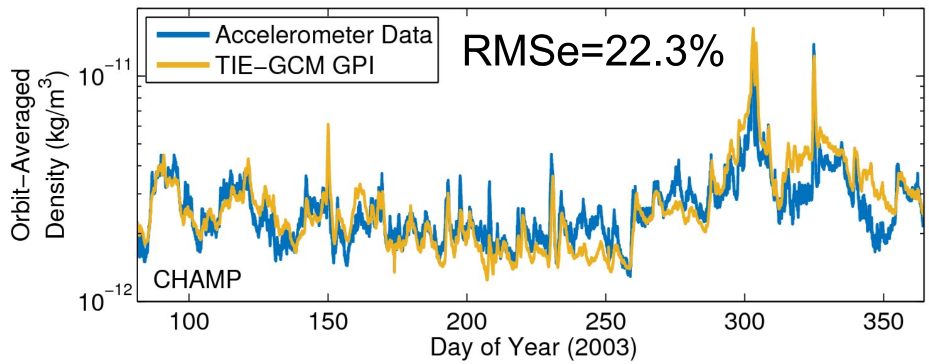
TIE-GCM vs. IRIDEA

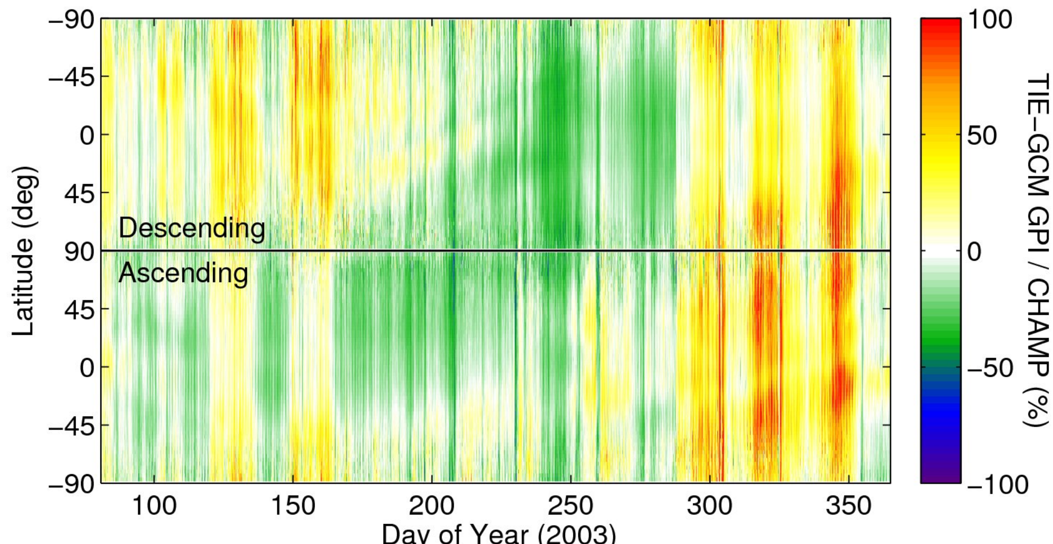
Day 80-365, 2003

Validate new approach, IRIDEA, with real-world scenario

- Simulate the **I-T without data assimilation**
- Simulate the **I-T with IRIDEA data assimilation**
  - Ingest CHAMP/STAR accelerometer observations at ~400 km
  - Estimate corrections to both solar flux and geomagnetic activity drivers
- Compare output of I-T model with observations of **neutral density from CHAMP**

Without Data Assimilation





IRIDEA: Iterative Re-Initialization, Driver Estimation, and Assimilation

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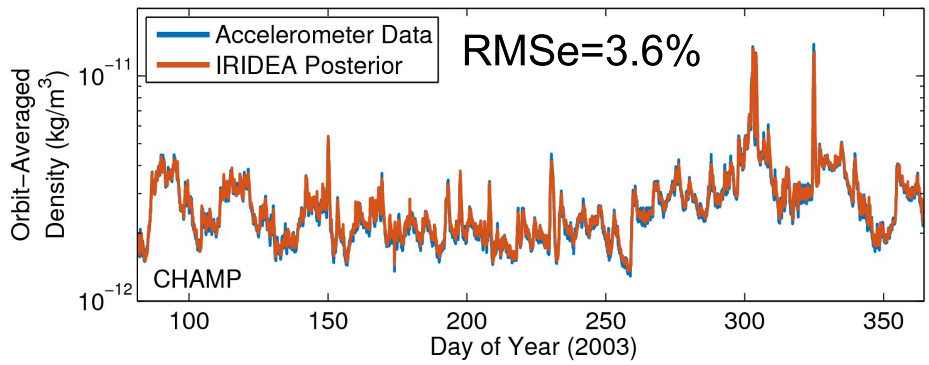
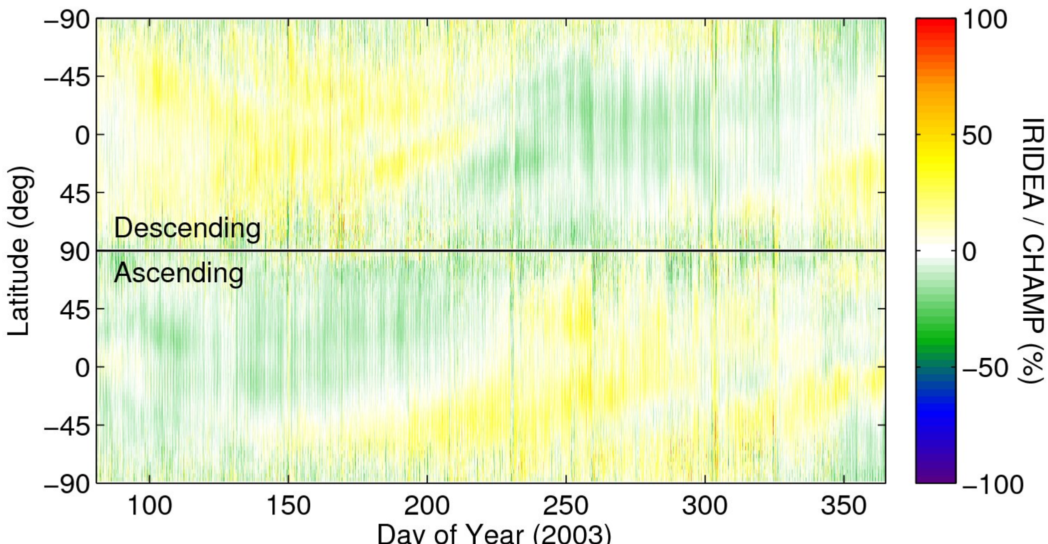
With IRIDEA Data Assimilation





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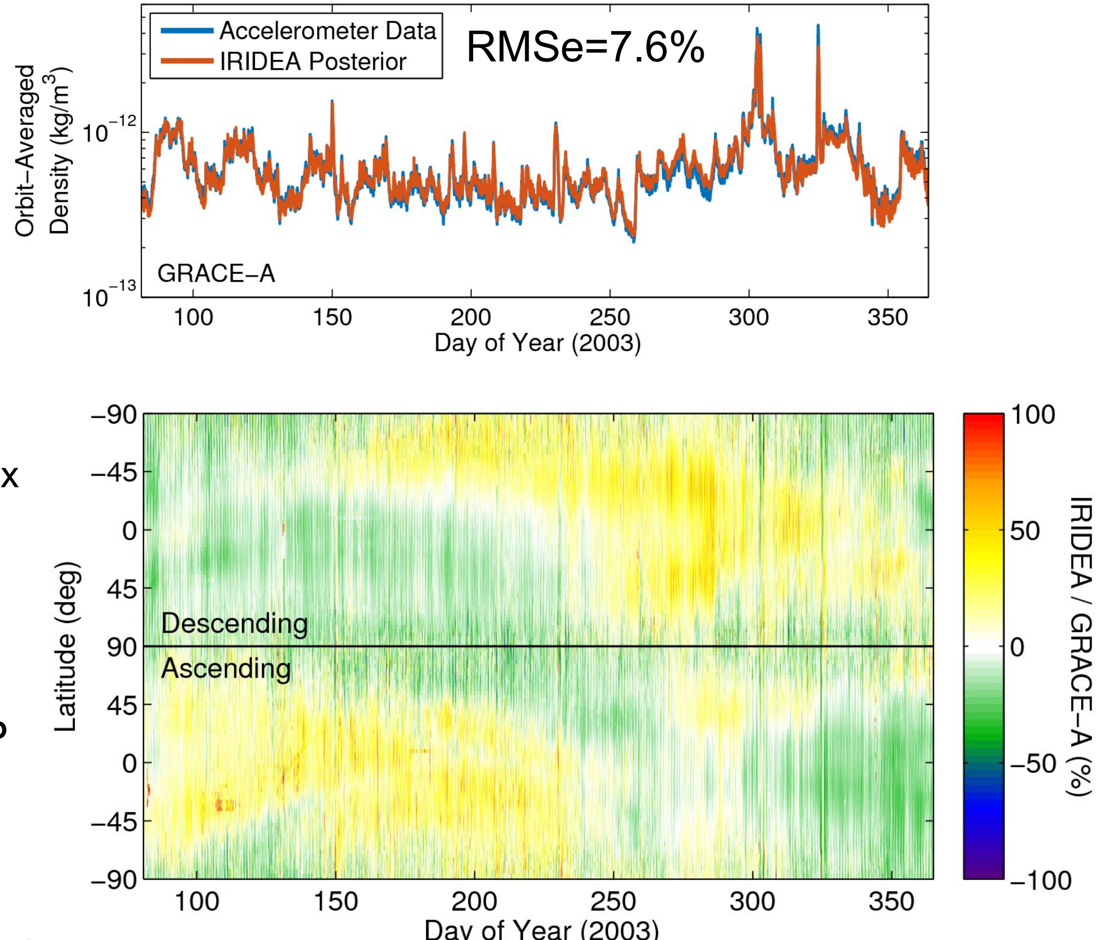
- Compare output of I-T model with observations of **neutral density from GRACE** at ~500 km and separated in local time from CHAMP

With IRIDEA Data Assimilation



IRIDEA: Iterative Re-Initialization, Driver Estimation, and Assimilation

Observed vs. Estimated Drivers

The estimated $F_{10.7}$ time series resembles the actual

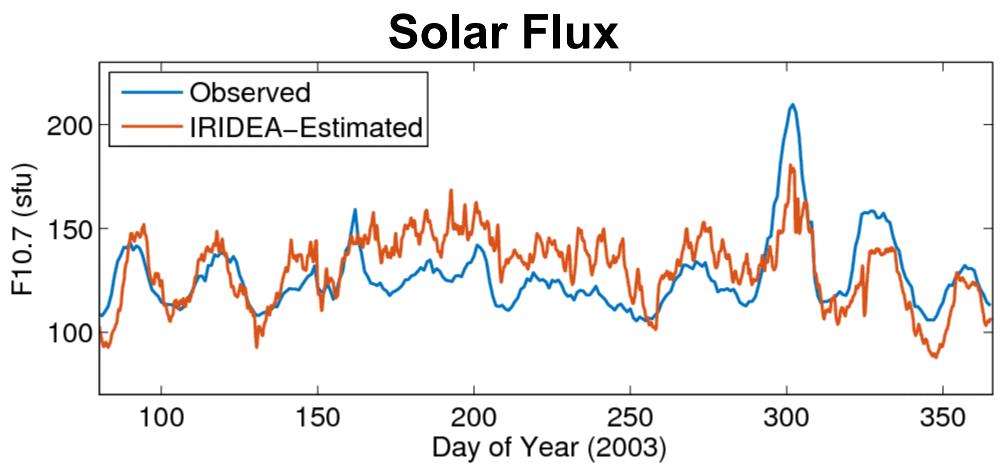
- Solar rotational modulation is evident
- But, the spikes are probably not representative of EUV variations

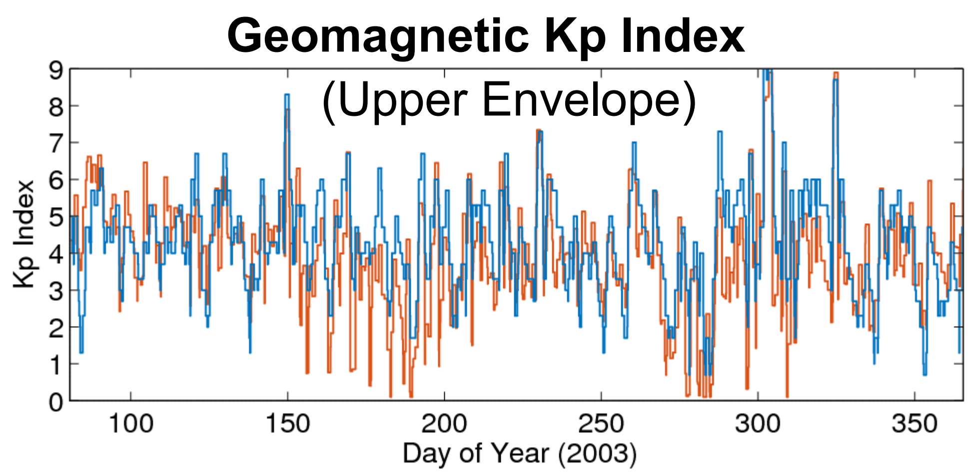
The estimated Kp time series *somewhat* resembles the actual

- Better correlation when a daily running-maximum filter is applied
- Does TIE-GCM have a problem cooling down **or** is correlation of the estimated drivers causing this?

How do we better disentangle solar vs. geomagnetic influences?

- Improve data coverage?
- Incorporate data types with better information content?
- Incorporate actual drivers into the mix?





Summary

A new data assimilation technique has been developed for I-T physics-based models:

- Accounts for the driven I-T system with response time-scales of approximately 1 day
- Able to accurately specify neutral densities in both quiet and disturbed times for the first time

Questions:

- How do we best incorporate actual drivers (e.g., EUV vs. F10.7)?
- How do we best incorporate forecasts of drivers?
- How do we best disentangle solar irradiance vs. geomagnetic driving?
- What measurements would be more ideal for driving this type of a technique?
- Are there analogs throughout Geospace?

Results Recently Published in:

Space Weather
RESEARCH ARTICLE

A new method of physics-based data assimilation for the quiet and disturbed thermosphere

10.1002/2017SW001785

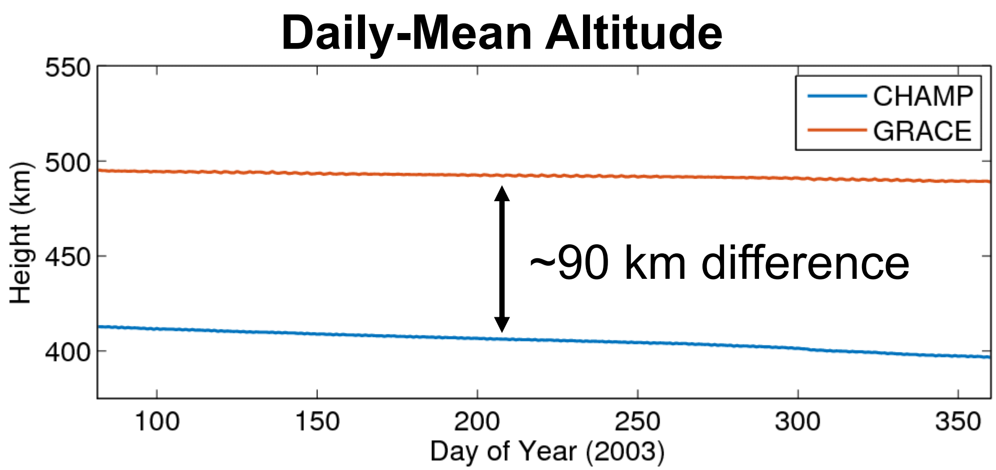
This work was sponsored by the Air Force Office of Scientific Research. Travel was paid for by the NASA LWS Institute on Neutral Density Nowcasting.

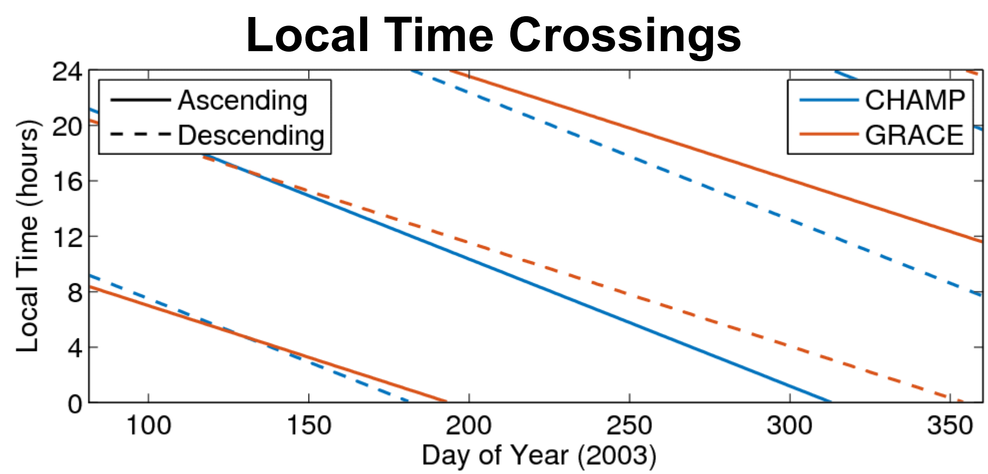
Backup Slides

Data Sets

Assimilation and Validation Data Sets:

- **Ingested data:** neutral densities measured onboard CHAMP satellite
- **Independent Validation Data:** neutral densities measured on-board GRACE-A satellite
- GRACE-A is ~90 km higher than CHAMP during the interval
- Local times align early in the interval, diverging near the end of the interval with a difference of ~4 hours
- Both Satellite orbits are circular and near-polar





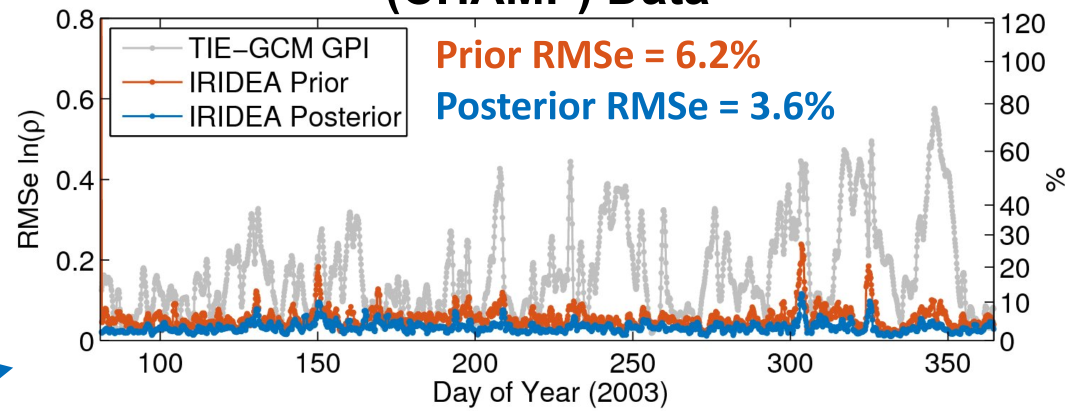
Model Performance Metrics

Day 80-365, 2003

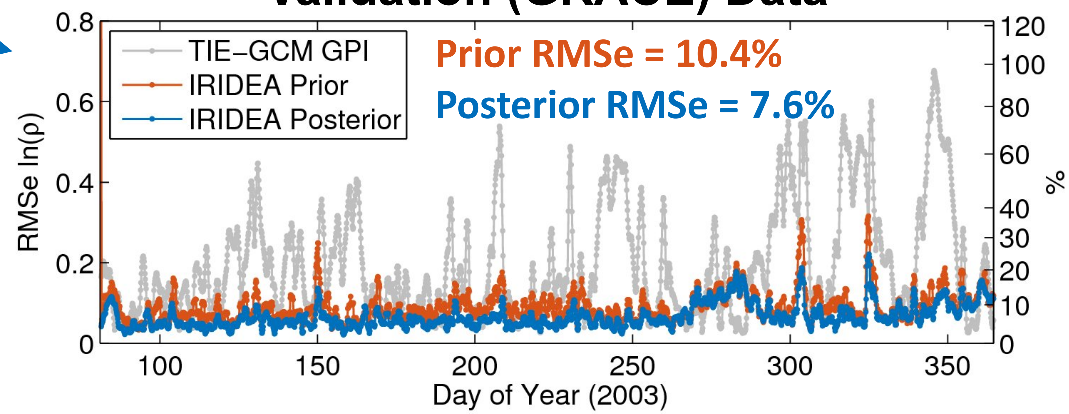
Validate new approach, IRIDEA, with real-world scenario

- Root Mean Squared error (RMSe) of model simulations with respect to:
  - Ingested data
  - Independent validation data

Comparison with the Ingested (CHAMP) Data



Comparison with the Independent Validation (GRACE) Data



Model Performance Metrics

2003

	TIE-GCM GPI	IRIDEA Prior	IRIDEA Posterior	JB-08	MSIS
CHAMP					
$\mu(m/o)$	1.02	1.01	1.01	0.99	1.09
$\sigma(m/o)$	22.2%	6.1%	3.3%	13.1%	17.4%
RMSe	22.3%	6.2%	3.6%	13.1%	20.2%
GRACE-A					
$\mu(m/o)$	1.03	1.00	1.01	0.99	1.13
$\sigma(m/o)$	27.0%	10.3%	7.6%	17.2%	22.4%
RMSe	27.3%	10.4%	7.6%	17.2%	26.6%

Ingested Data (CHAMP)

Independent Validation Data (GRACE-A)

$$\mathrm{RMSe} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\ln\frac{\rho_{m,i}}{\rho_{o,i}}\right)^2}$$

$$\mu(m/o) = \exp\left(\frac{1}{N}\sum_{n=1}^{N}\ln\frac{\rho_{m,i}}{\rho_{o,i}}\right)$$

$$\sigma(m/o) = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\ln\frac{\rho_{m,i}}{\rho_{o,i}} - \ln\mu(m/o)\right)^2}$$

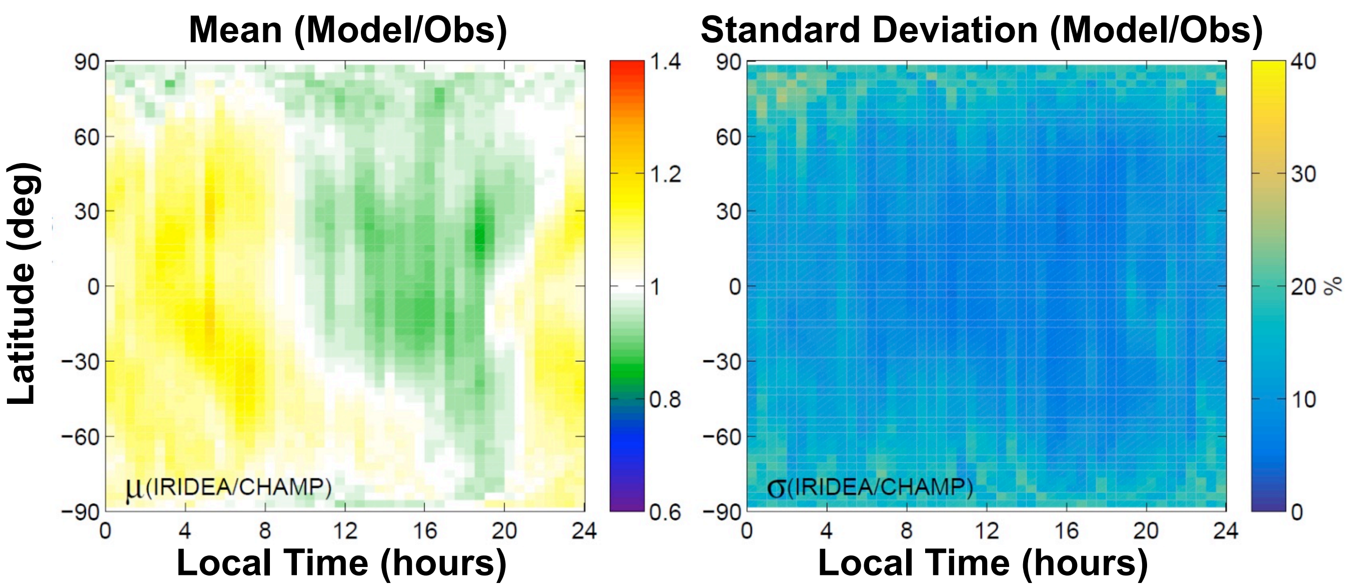
$$\mathrm{RMSe}^2 = \ln(\mu(m/o))^2 + \sigma(m/o)^2$$

Going Forward…

Location-Dependent Errors

Orbit-averaged model output is greatly improved, but how do we minimize the remaining location-dependent errors?

Binned IRIDEA-to-CHAMP Residuals



Need to assess contributions from:

- Lower atmosphere waves and tides
- Lower boundary considerations: TIE-GCM vs. TIME-GCM vs. WACCM-X
- Viscous and ion drag (and many other model parameters)