Satellite Drag Environment Prediction: Leveraging Data-Assimilative Driver Estimates

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Boulder, CO

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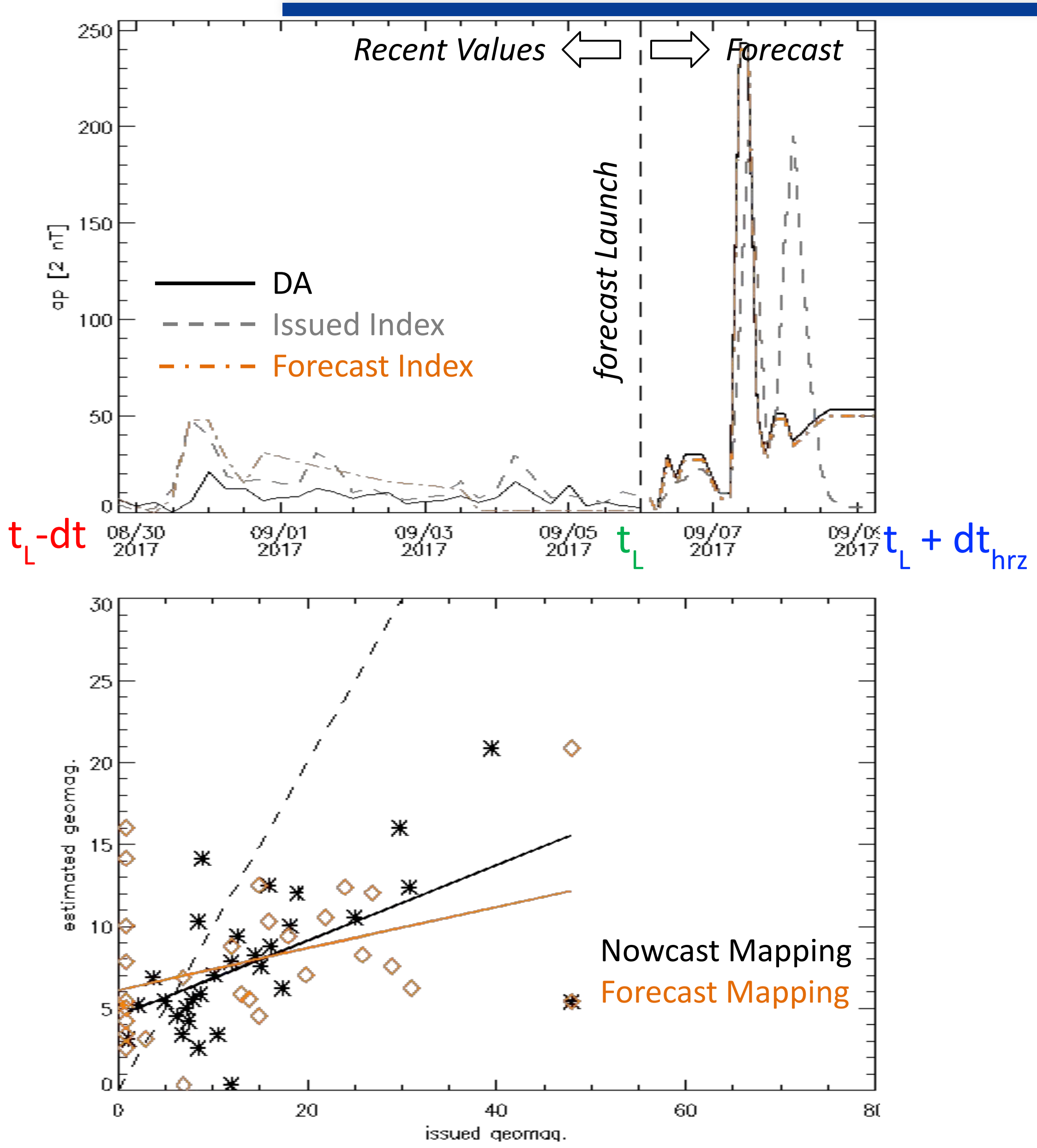
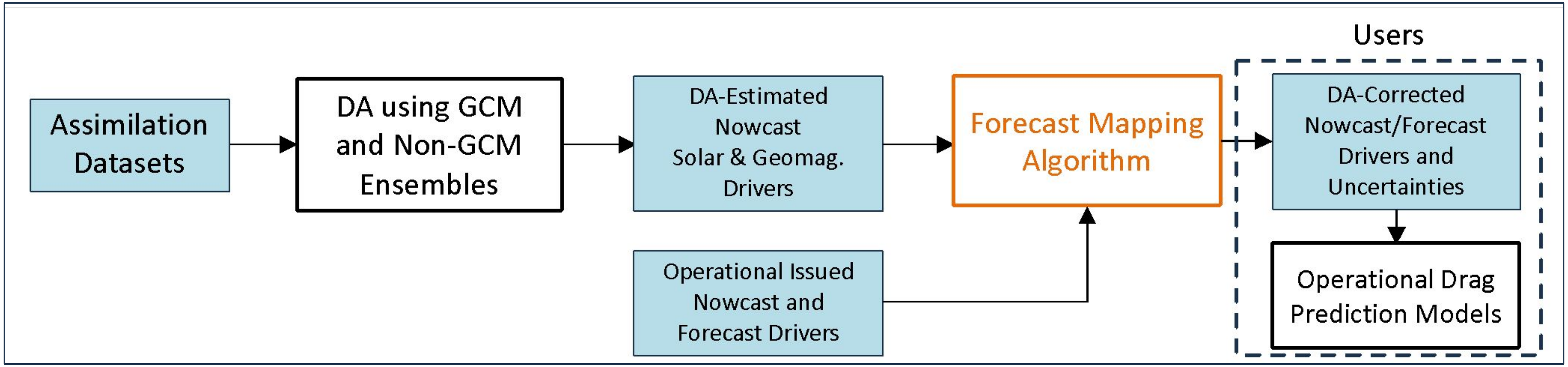
Challenges of Driver Forecast Integration



- Simple approach: remove bias between estimated and nowcast/forecast states at the time of the forecast launch, t_L
- Some neutral density forecasting approaches use bias offset and regression methods to compute forecasts
- The bottom panel illustrates a linear-regression mapping of the recently issued [t_L-dt , t_L] nowcast from (black) and forecast (orange) to the DA-estimated drivers. **This mapping changes with time and conditions**
- ***How best to take advantage of recent DA driver estimates and recent forecast forcing performance?***

Top Level Problem Description



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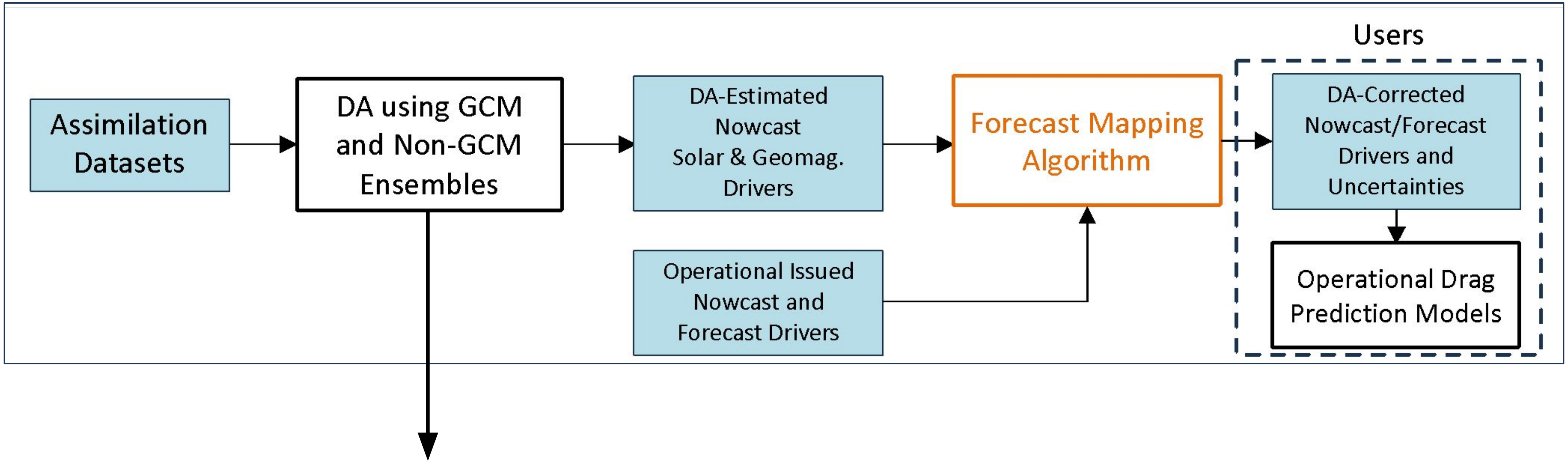
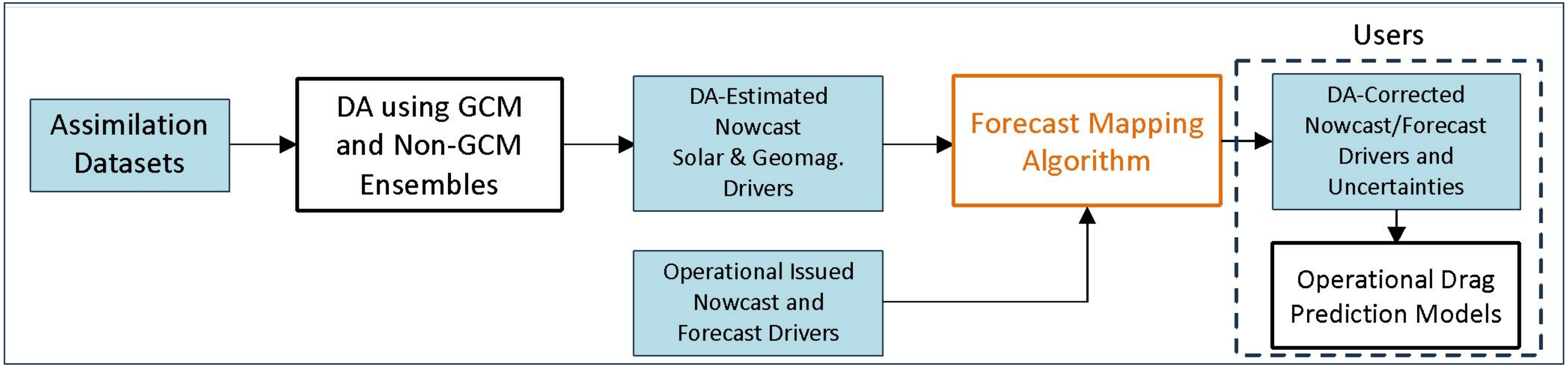


	GCM	Non-GCM
DA Technique	IDEA (TIE-GCM Ensemble)	CAFE (MSIS 2.1 Ensemble)
Assimilated Dataset	GRACE-FO Accelerometers	Orbit-Avg. Drag from ground observations of ~70 calibration objects
Validation	Swarm POD	Swarm POD

Top Level Problem Description

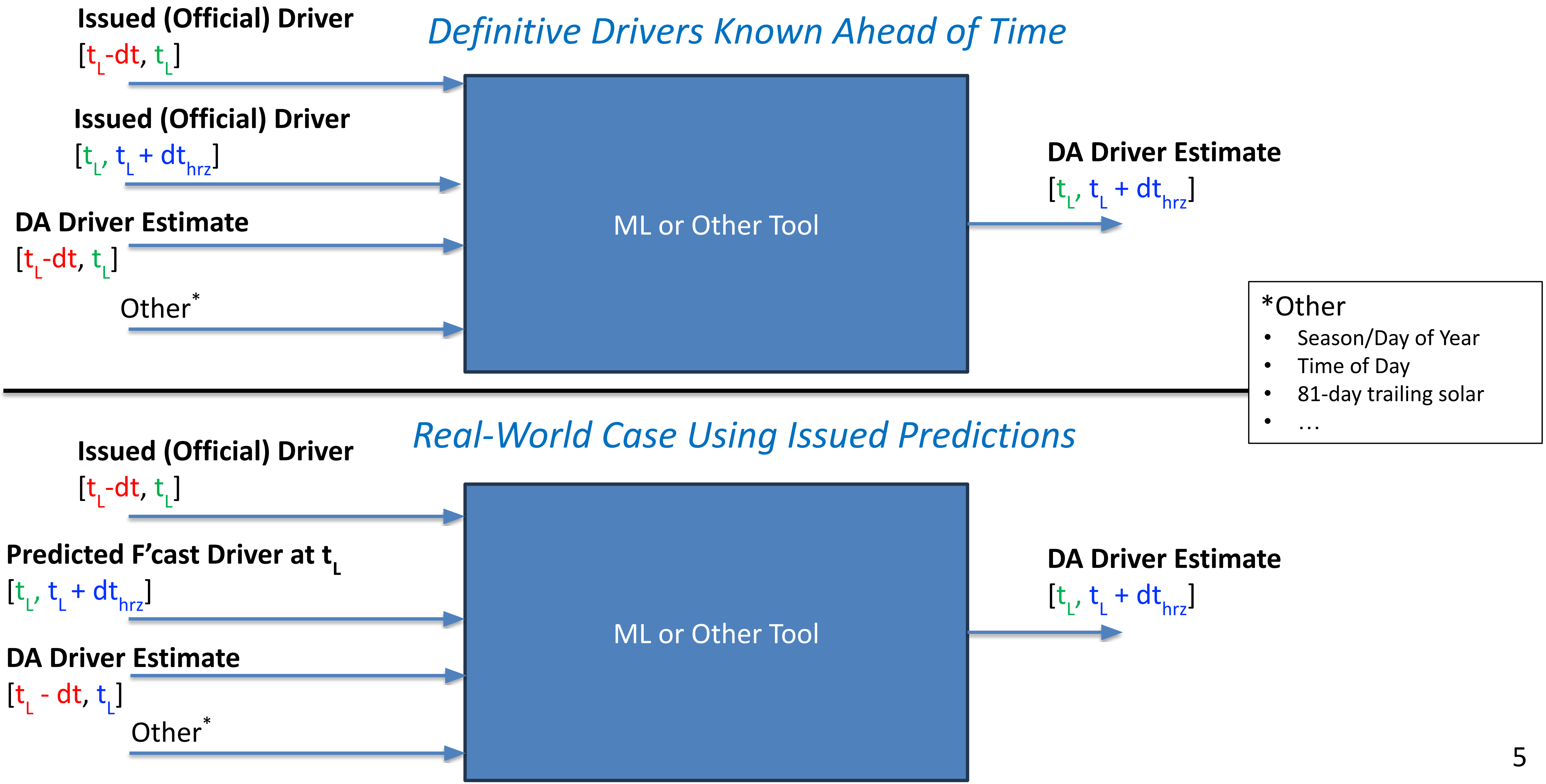


Project Objectives:

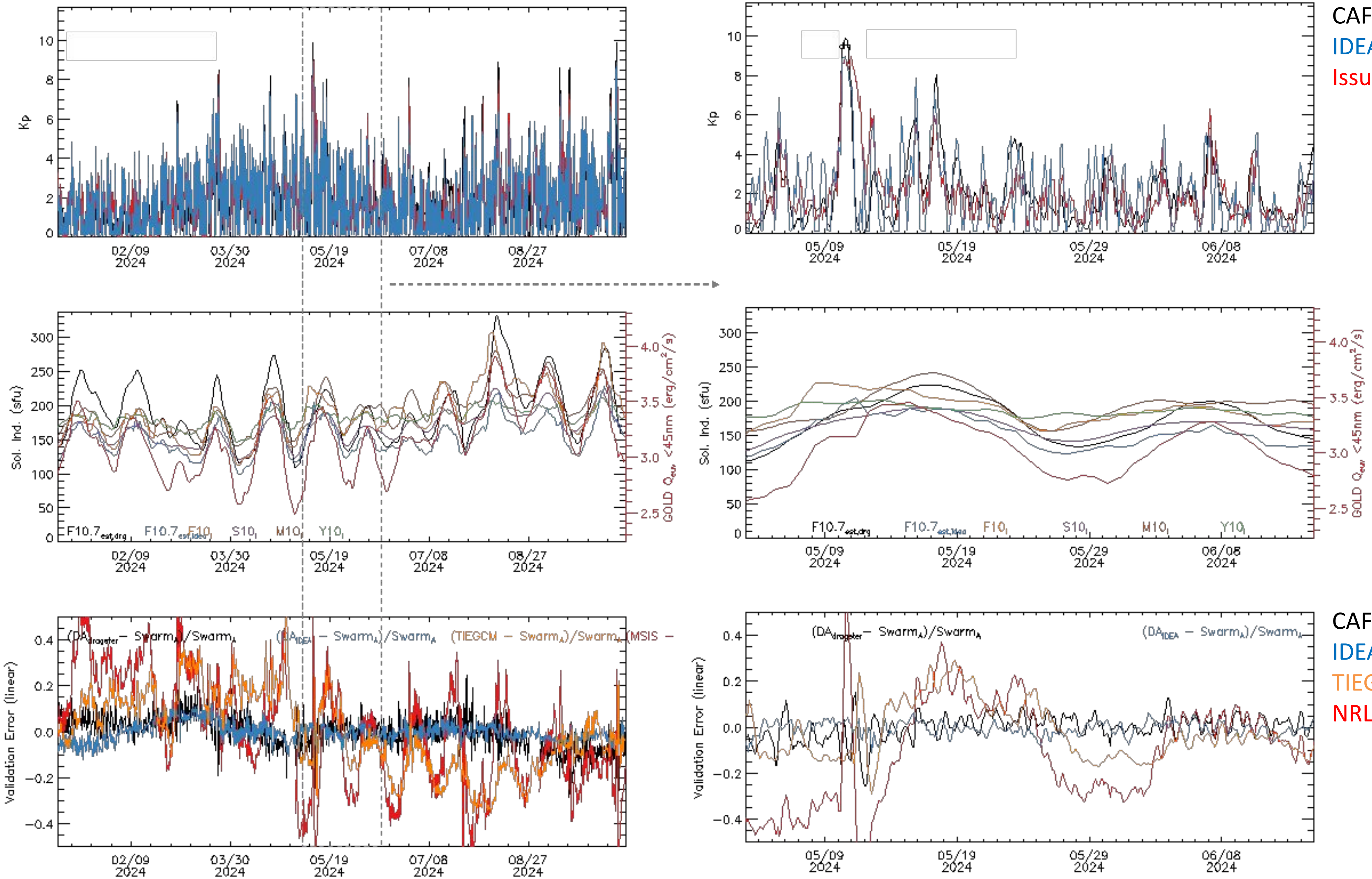
(a) Identify methodologies to map data-assimilative estimates of solar and geomagnetic drivers to operational forecast streams.

(b) Evaluate the results using metrics relevant to LEO orbit forecasting over several years.

Driver Mapping



Examples of Post-Storm Discrepancy



CAFE 1.0 (MSIS)
IDEA (TIEGCM)
Issued Kp

CAFE 1.0 (MSIS)
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$\text{TIEGCM}_{\text{GPI}}$
NRLMSISE-2.1

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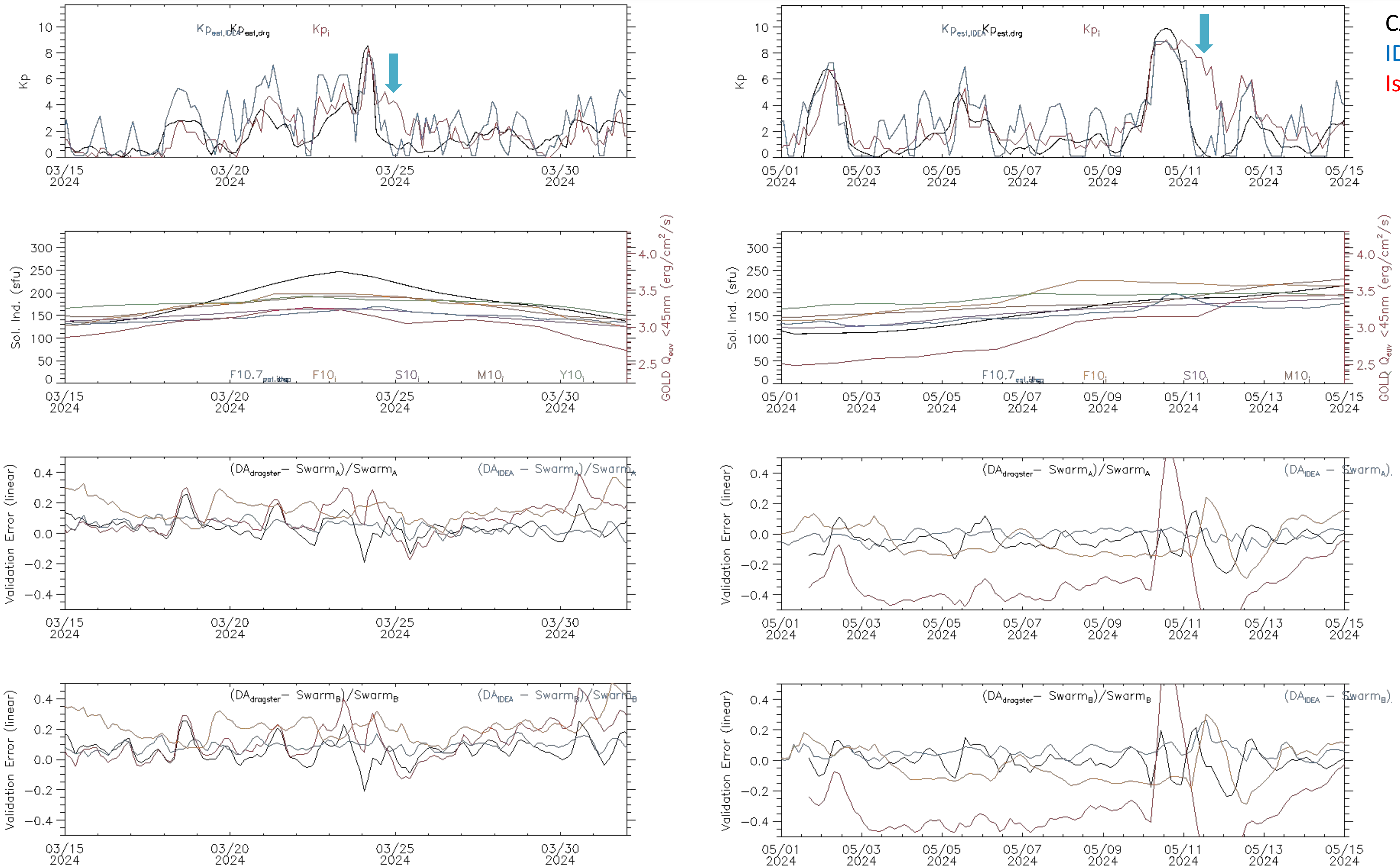

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$TIEGCM_{GPI}$
NRLMSISE-2.1

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Swarm A & B Comparisons

2024 Validation Results, StdDev Logarithmic				
	Swarm-A (~480 km altitude)		Swarm-B (~520 km altitude)	
	1 Orbit	¼ Orbit	1 Orbit	¼ Orbit
IDEA	0.042	0.095	0.078	0.126
Dragster 1.0	0.066	0.107	0.059	0.110
Dragster 1.0 DC*	0.063	0.100	0.057	0.103
TIE-GCM GPI	0.287	0.323	0.311	0.353
MSIS	0.142	0.170	0.144	0.177

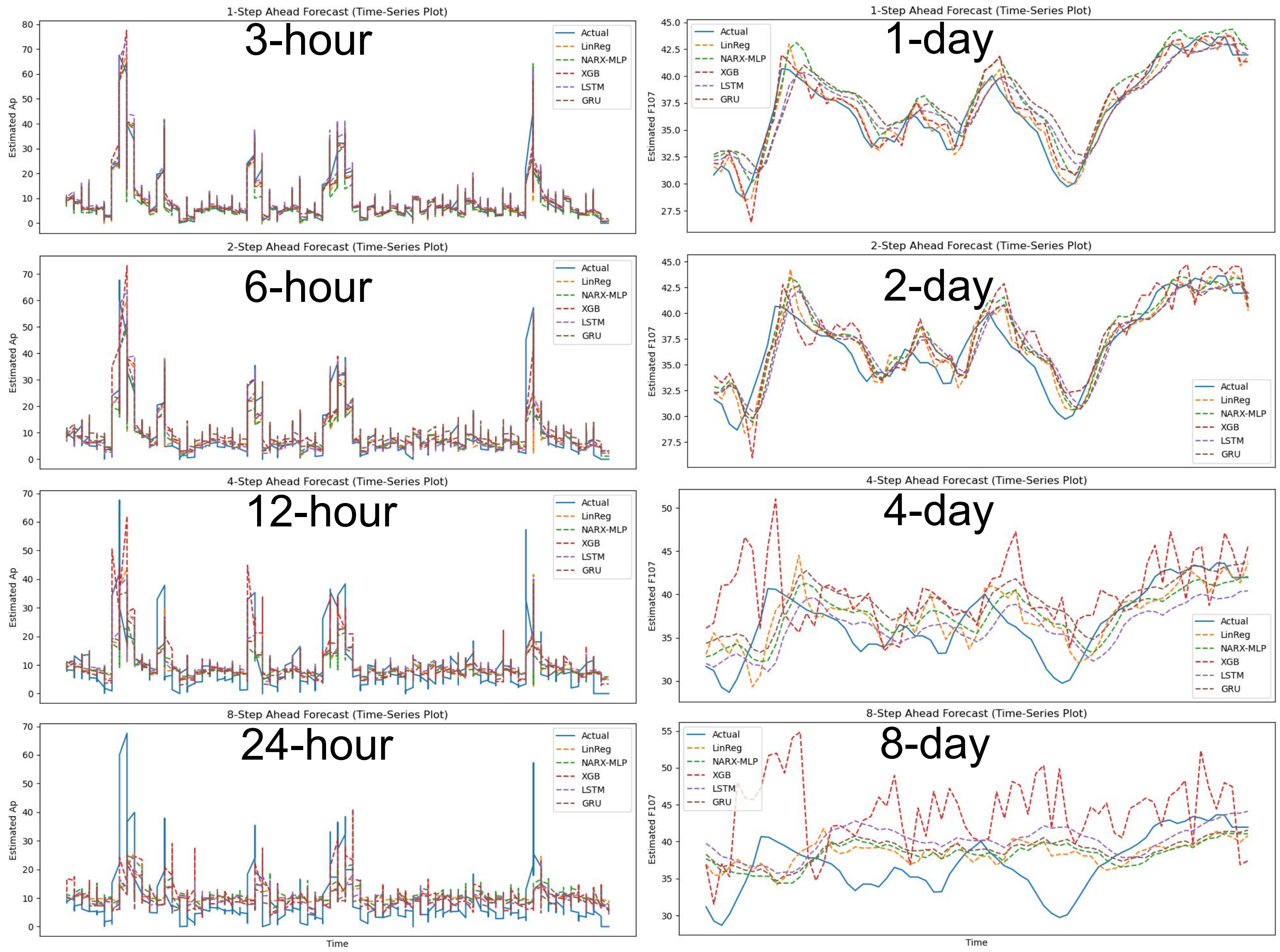
**Density Corrected (DC), estimating both drivers and density corrections*

Examples of Forecast Mapping Approaches

Algorithm	Strengths	Weaknesses
Multiple linear regression	Simple, fast, interpretable Easy to implement & explain Effective when data is near-linear or has strong autocorrelation at lag=1	Only captures linear relationships Struggles with nonlinear, long-lag effects Sensitive to outliers
NARX-MLP (Nonlinear autoregressive with external input)	Capable of modeling nonlinearities Can ingest multiple lagged inputs & exog Flexible architecture (number of layers)	May require careful feature engineering Can overfit if not enough data/regularized
XGBoost (Extreme Gradient Boosting)	Strong performance in many tabular tasks Automatically handles some nonlinearities	Can require extensive hyperparameter tuning May struggle with very long-sequence dependencies
GRU (Gated Recurrent Units)	Similar to LSTM but typically simpler Fewer parameters than LSTM, faster to train	May still be prone to overfitting with insufficient data or poor architecture
LSTM (Long short-term memory)	Designed for sequence data (long lags Remembers patterns across many timesteps	Higher complexity, slower training Tends to require a lot of data

Predictions (CAFE empirical example)

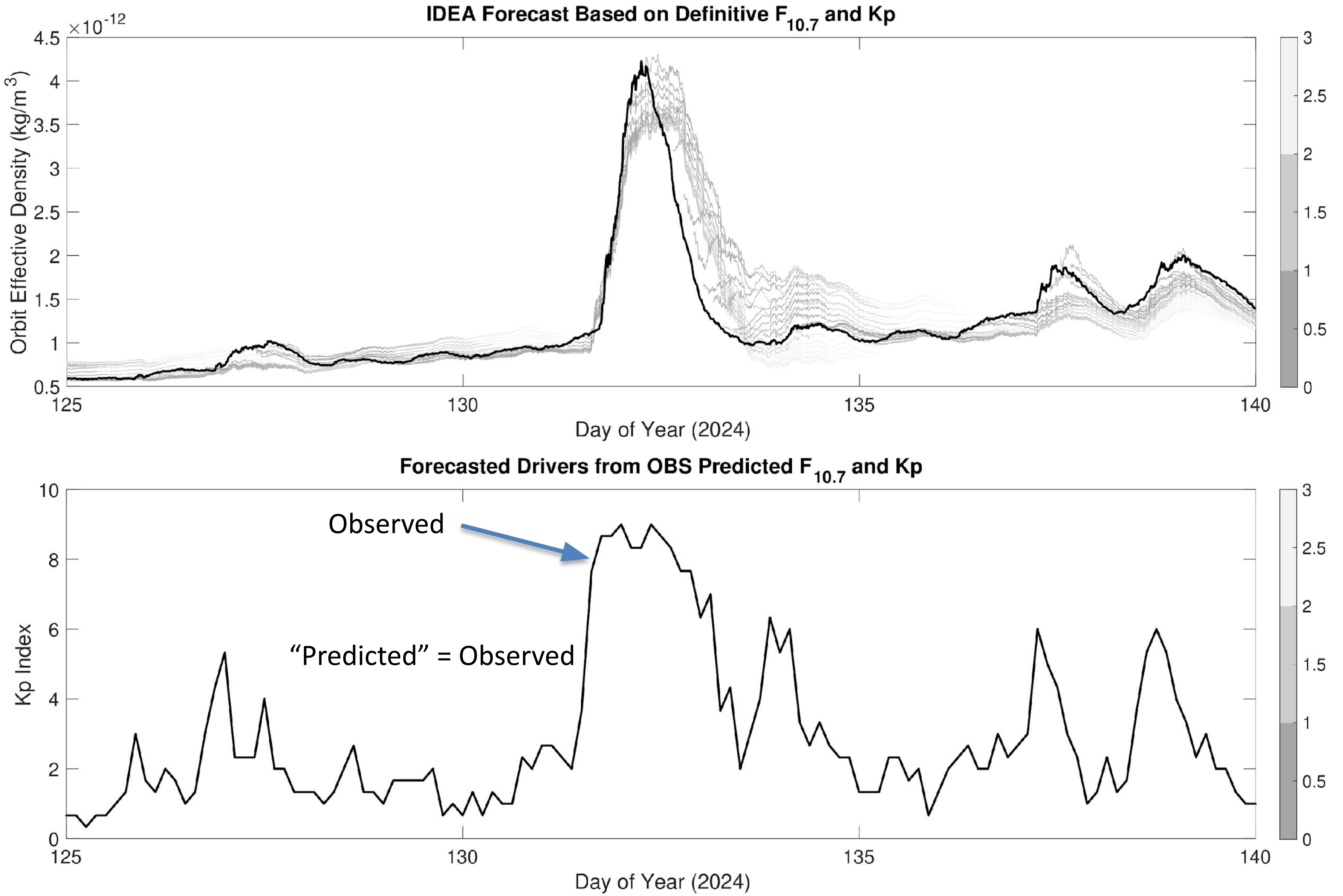
2019 Empirical-DA Predictions



IDEA (TIE-GCM) Forecast Experiments: Definitive Drivers

72-Hour "Forecast" using Definitive Drivers:

EDDYDIF: Fixed
NO Beta2: Fixed



IDEA (TIE-GCM) Forecast Experiments: Definitive Drivers

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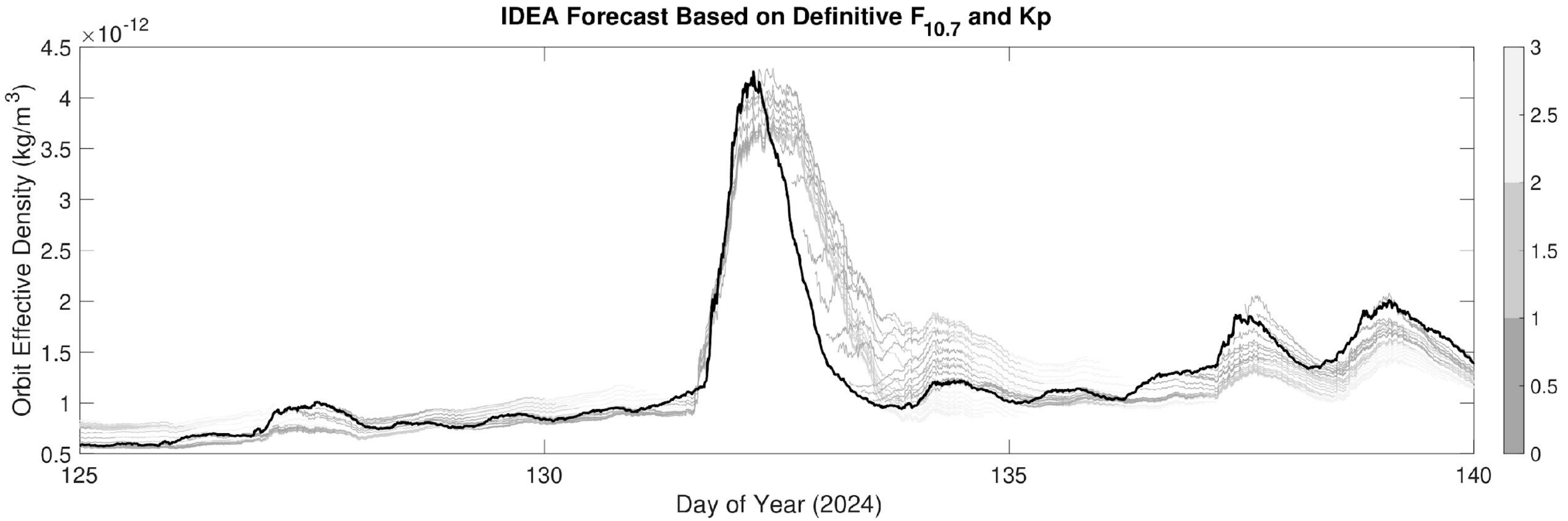

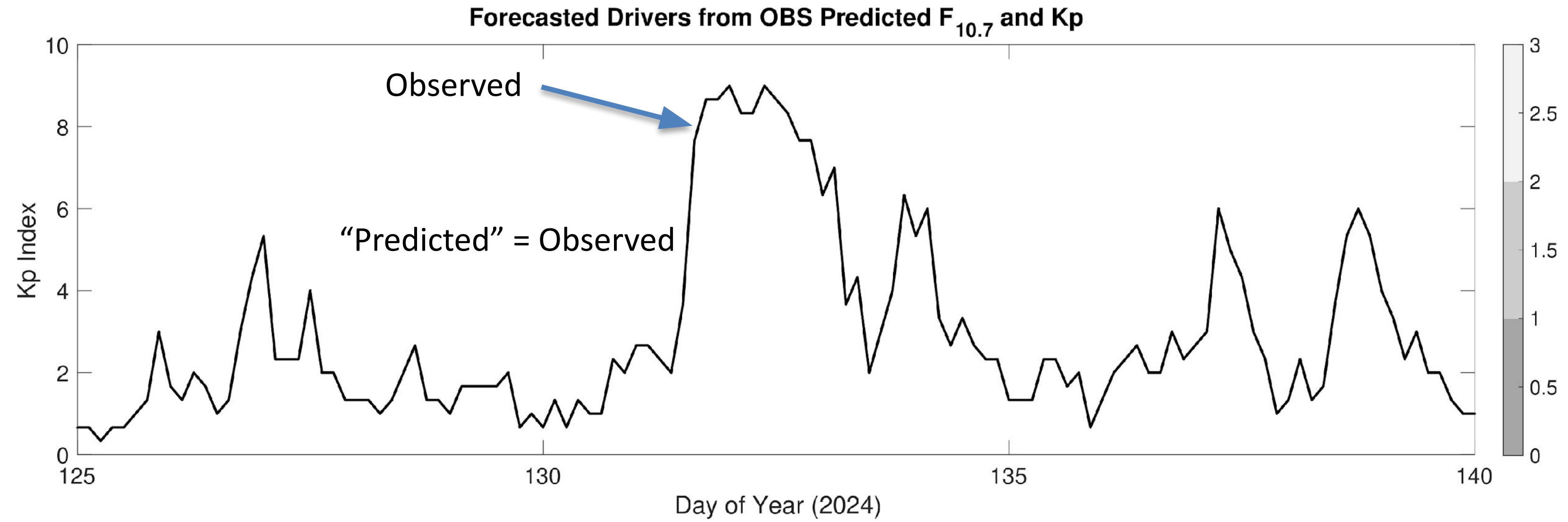

IDEA (TIE-GCM) Forecast Experiments: Definitive Drivers

72-Hour "Forecast" using Definitive Drivers:

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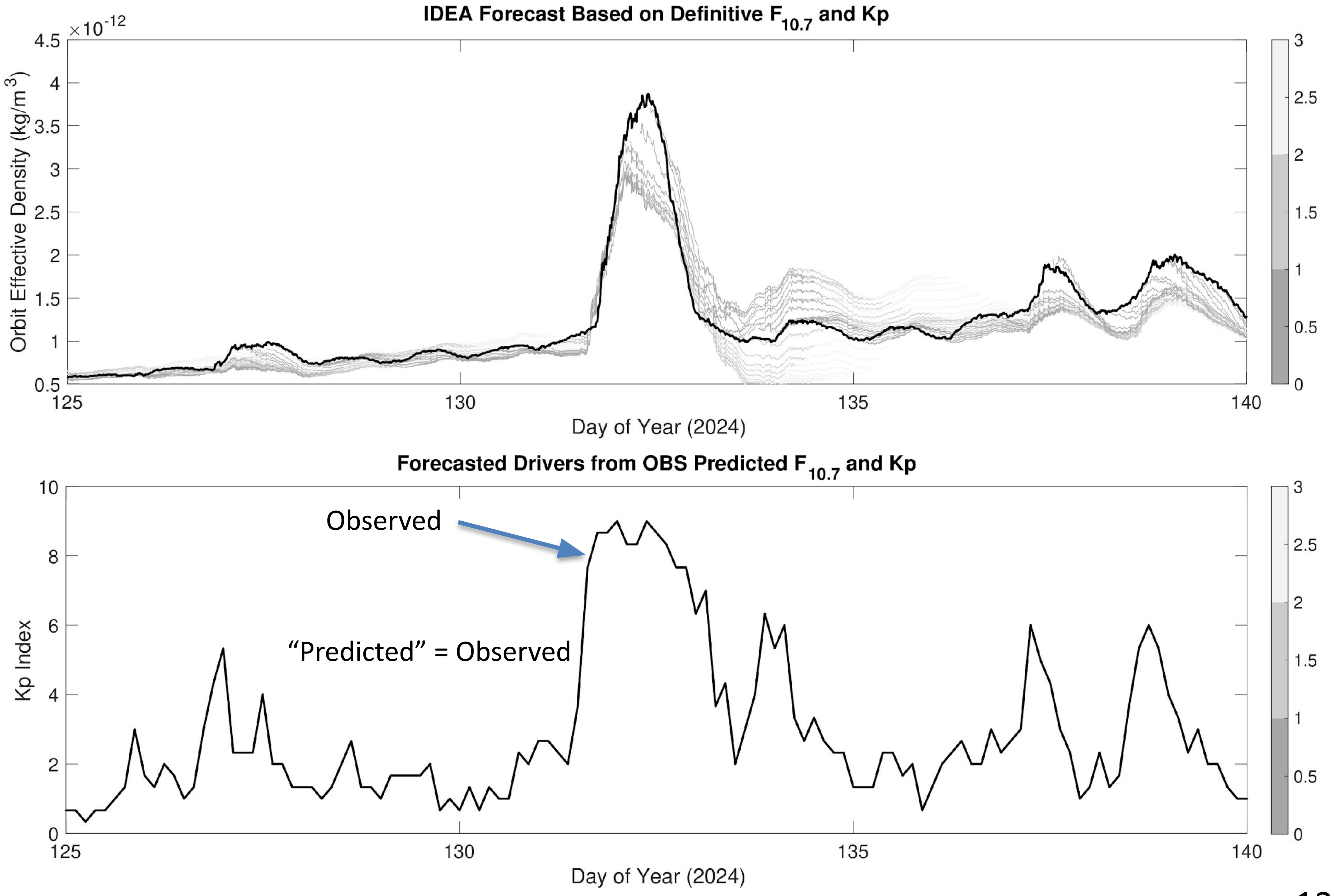
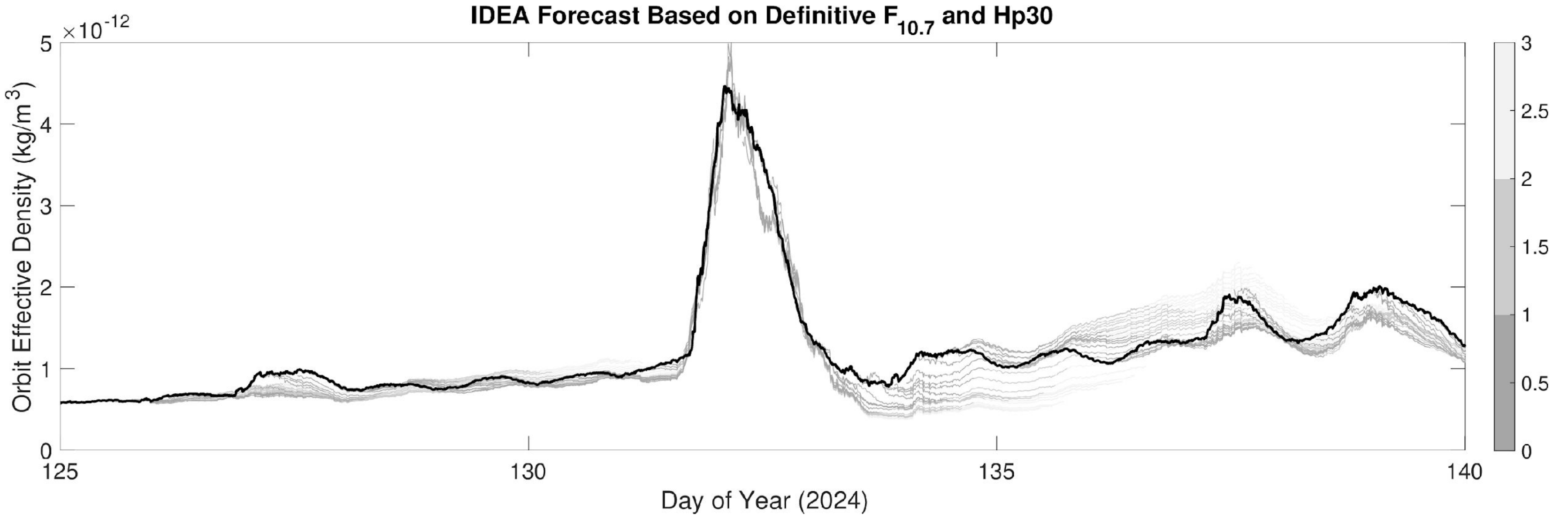
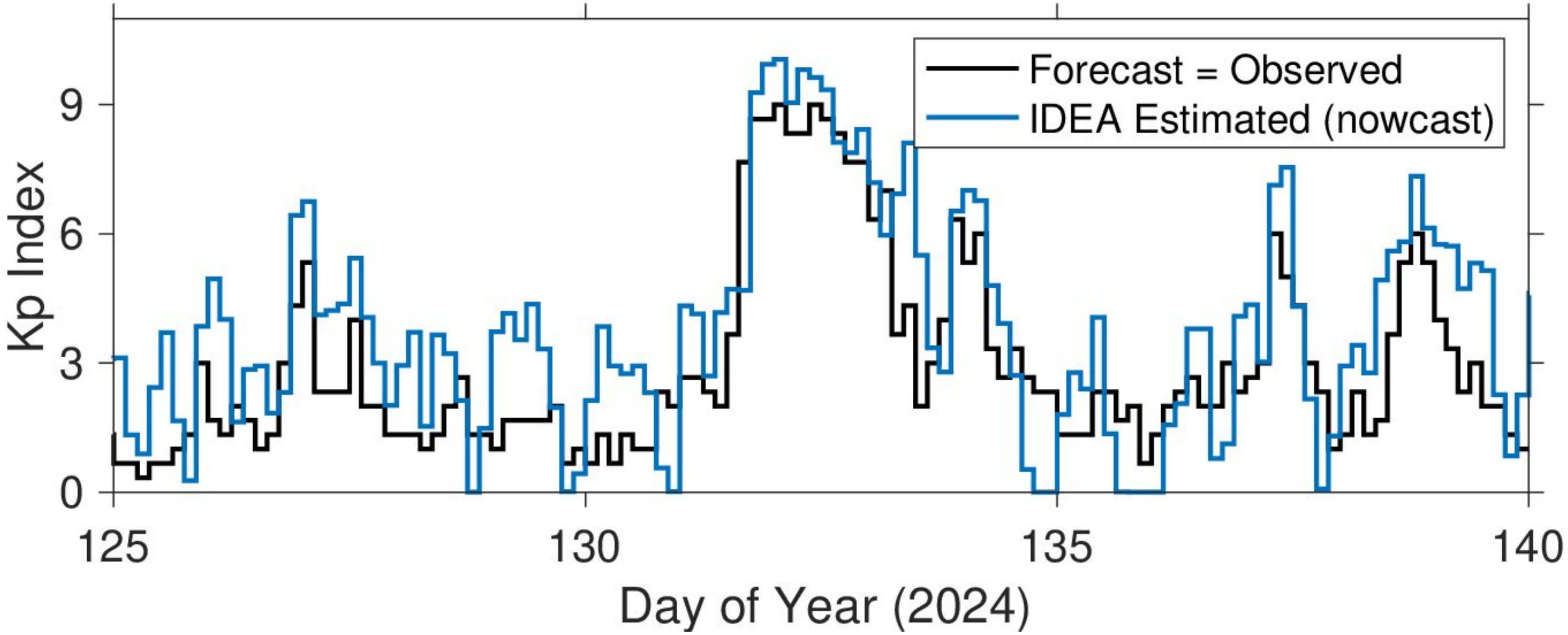


IDEA (TIE-GCM) Forecast Experiments: Definitive Drivers

72-Hour "Forecast" using Definitive Drivers:

EDDYDIF: Variable
NO Beta2: Temperature Dependent
Kp Bounds: Expanded
Geomag F'cst: Hp30





Blue Sky Thinking About Specifying and Forecasting the LEO Drag Environment

- How well do benefits of nowcast performance persist into the forecast?

- At what time scales does the importance of initial conditions (previous states) become relevant to the dynamic evolution of the thermosphere?
  - Under what conditions do GCM’s offer benefits in the forecast over non-GCM’s

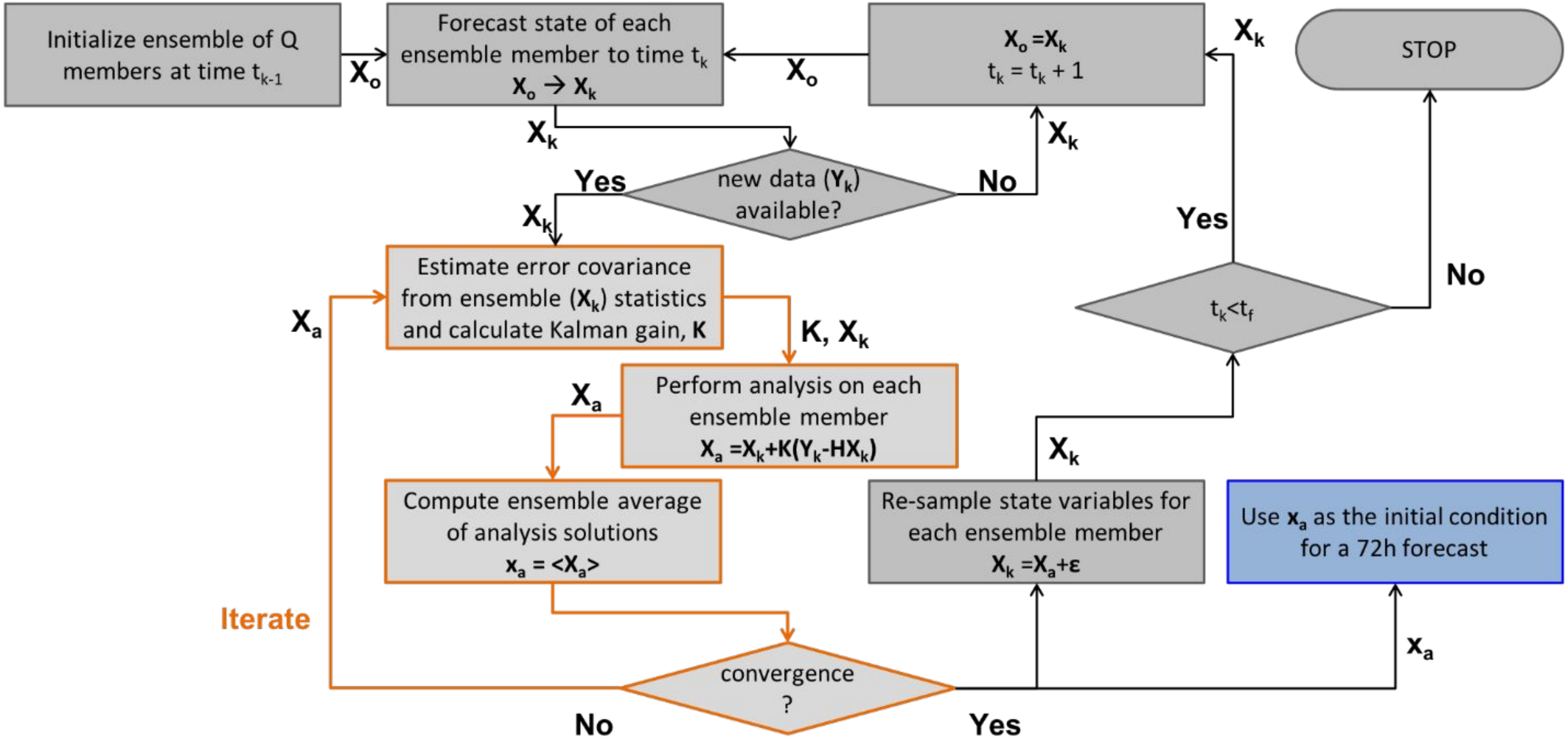
- How do model quality and data coverage change nowcast (and forecast) quality?
  - When/where do we need more data?
  - How do we need to improve the models (and our understanding)?
  - At what time scales?

Thank You!

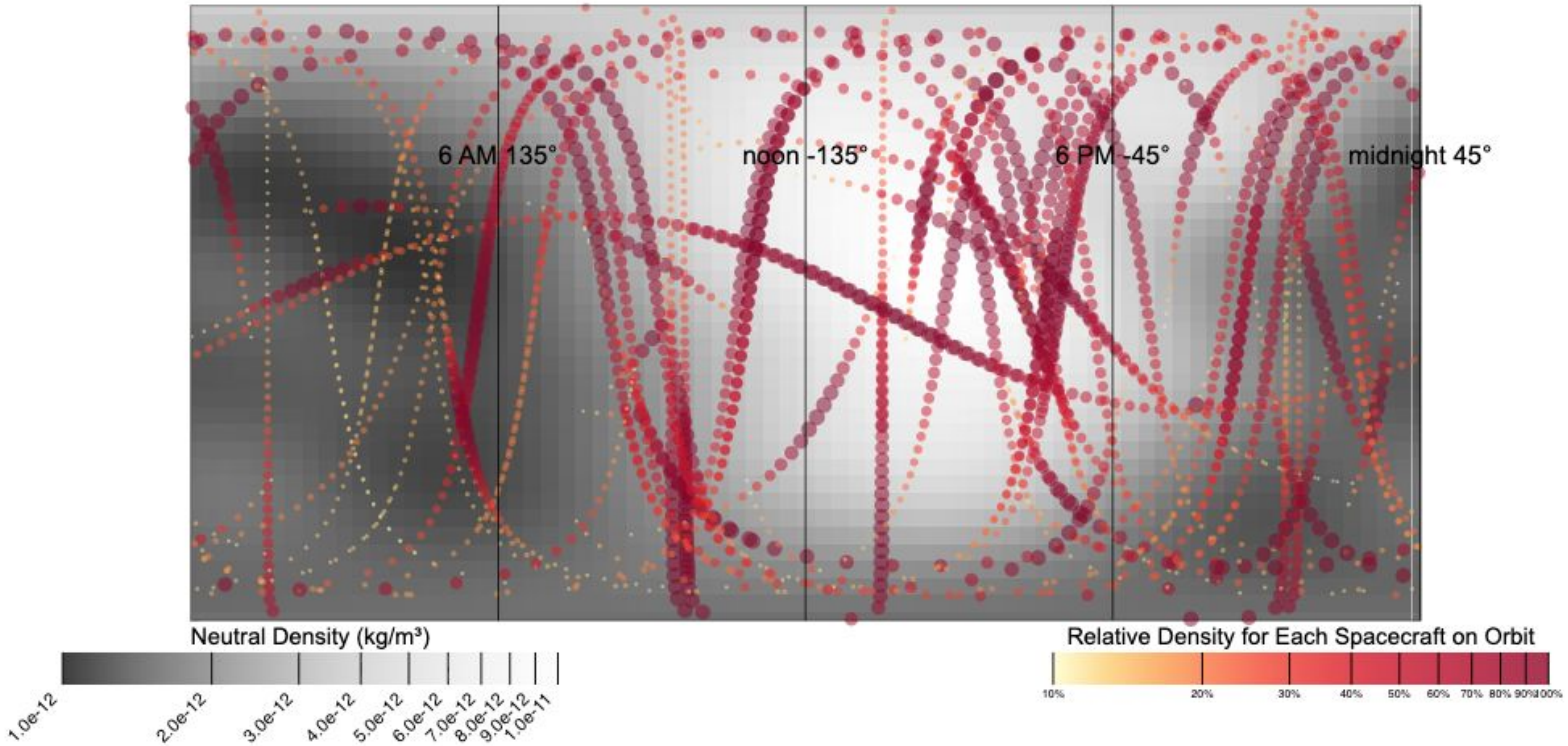
More specifically to this O2R…

- Are the estimated forcing states and their variability physical? To what extent?
- To what extent do they improve upon the operational indices/proxies?
- What are the estimation errors associated with the forcing states? To what extent are the geomagnetic vs. solar energy inputs observable?
- **How can the DA-based forcing estimates be leveraged to produce enhanced forecast inputs?**

CAFE DA Process



Assimilated Data Spatial Information

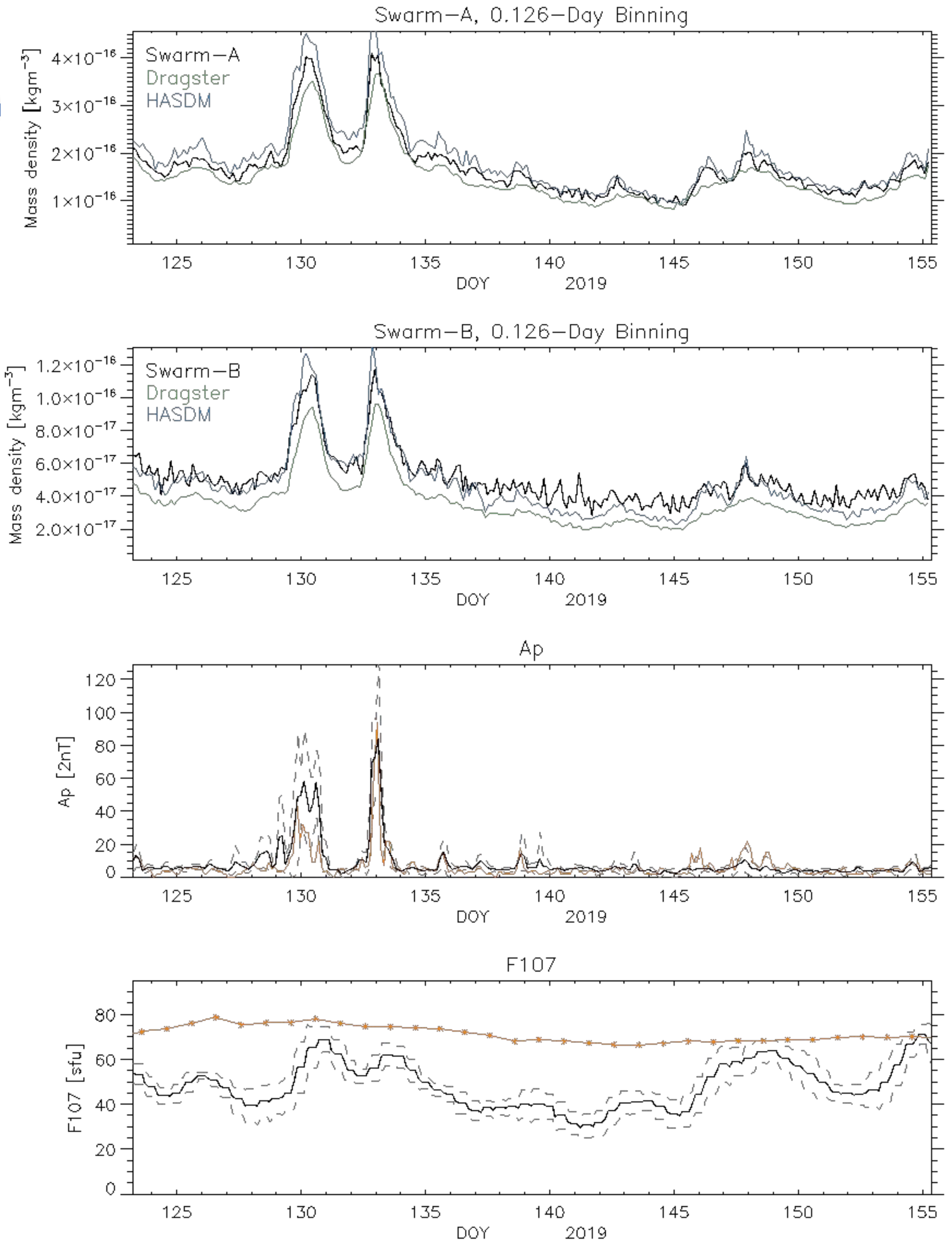


Assimilated Data Temporal Information

Dragster 2019 results

- Running around 20-30 x wallclock (on laptop M3 chipset)
- 50-70 satellites
- MSIS-2.1 background
  - 20 model ensemble members
  - 60 total
- 4-day assimilation windows
  - May want to consider 5
- Forecast launched every 12 hours
  - Changing this to 6 hours for future runs

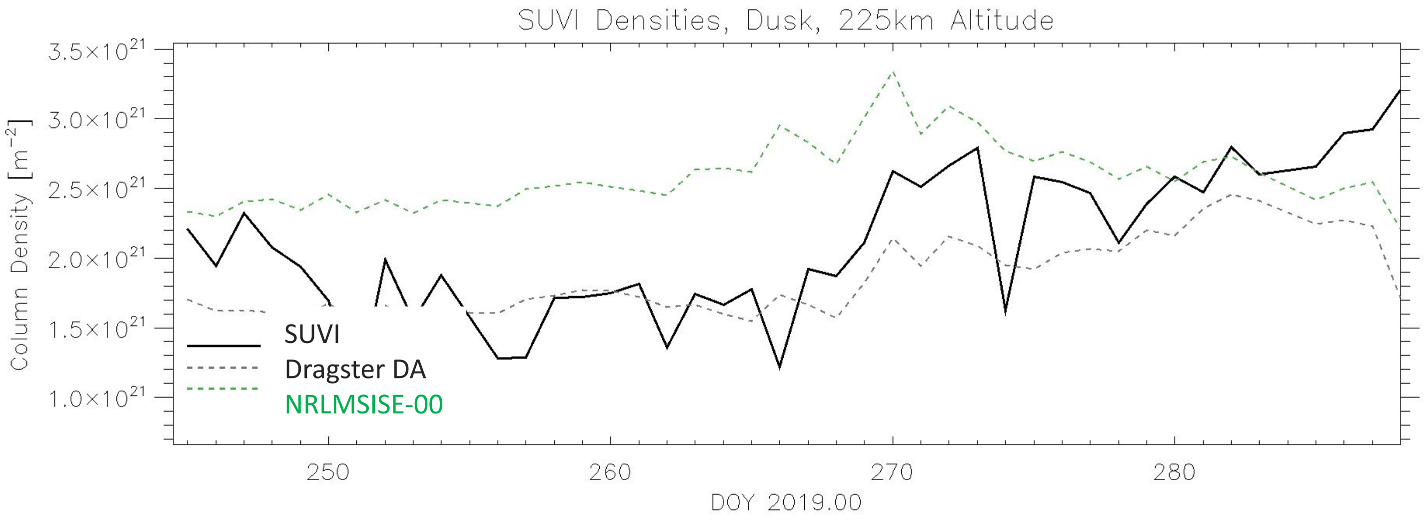
	Dragster log Std	HASDM log Std
Swarm-A	8.6%	8.5%
Swarm-B	20.0%	20.4%

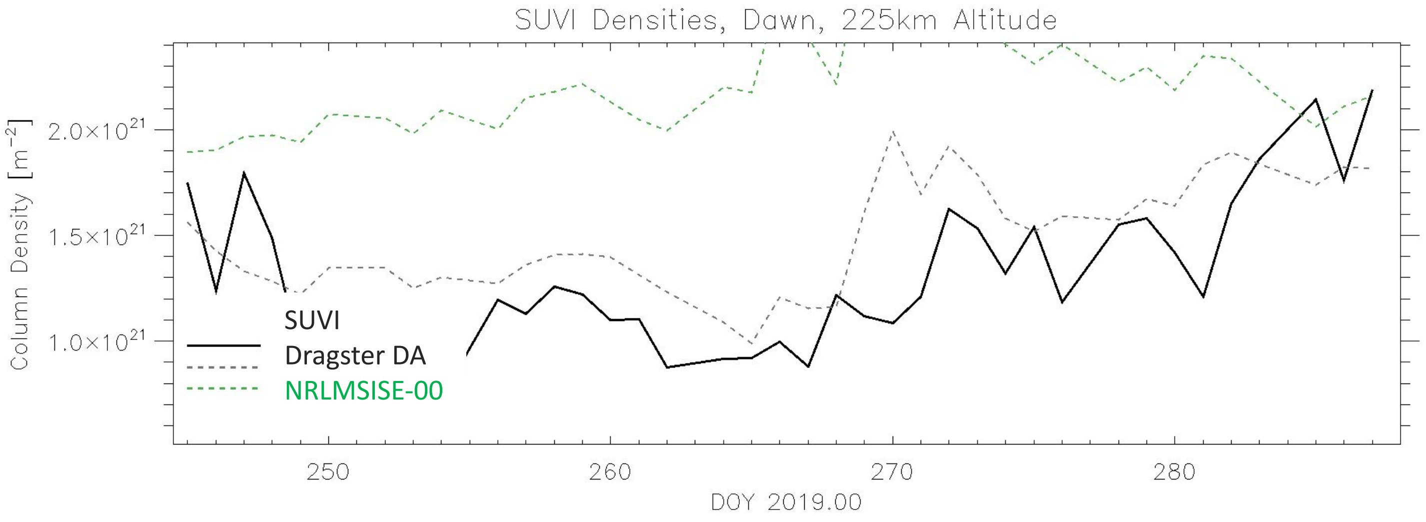


SUVI Densities (Ed Thiemann, PI) and DA

(mod-obs)/obs

Altitude	Dawn MSIS STDEV	Dawn DA STDEV
190 km	54%	23%
195 km	58%	24%
200 km	56%	23%
225 km	53%	23%
250 km	50%	23%
275 km	47%	23%
300 km	47%	24%
325 km	42%	20%
345 km	44%	22%
average:	50%	23%

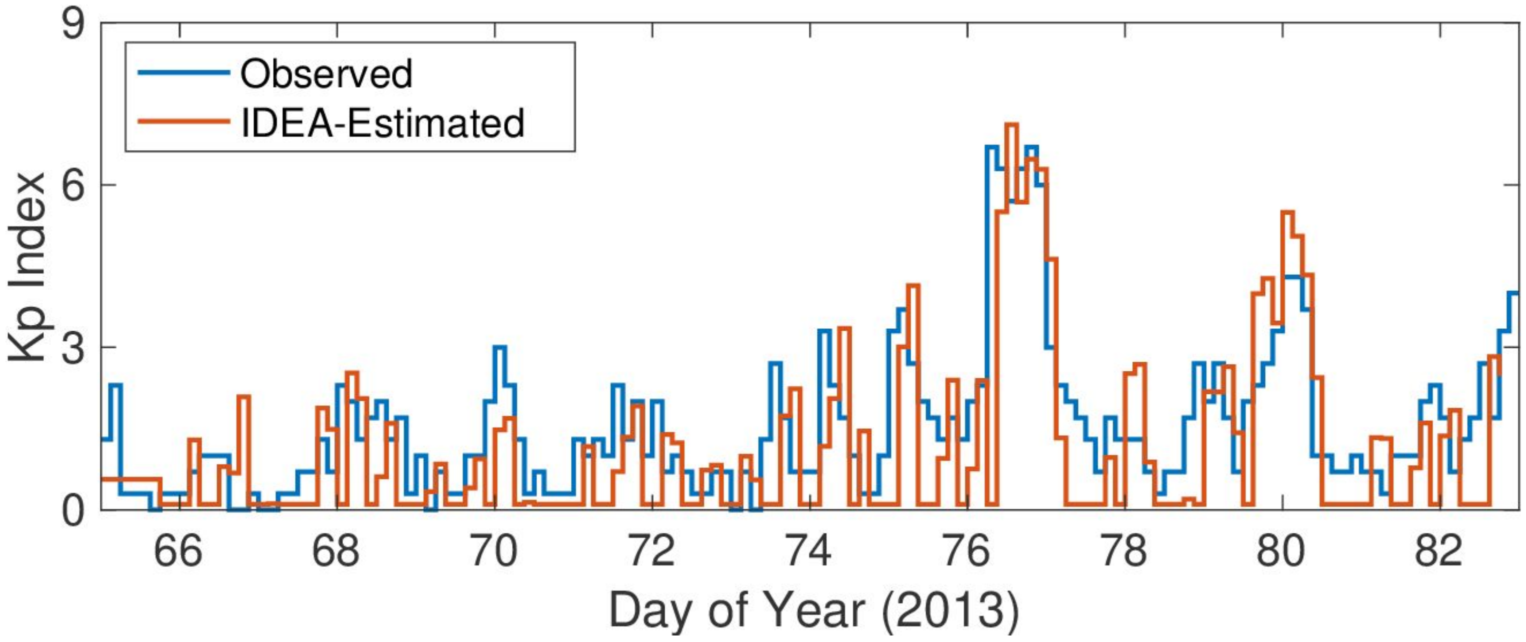




Courtesy of Robert Sewell and Ed Thiemann

IDEA Data Assimilation Method

- Estimates corrections to external solar and geomagnetic drivers
- Ensembles of TIE-GCM models (can also use WAM-IPE)
- Has been shown to provide better or comparable densities to HASDM*

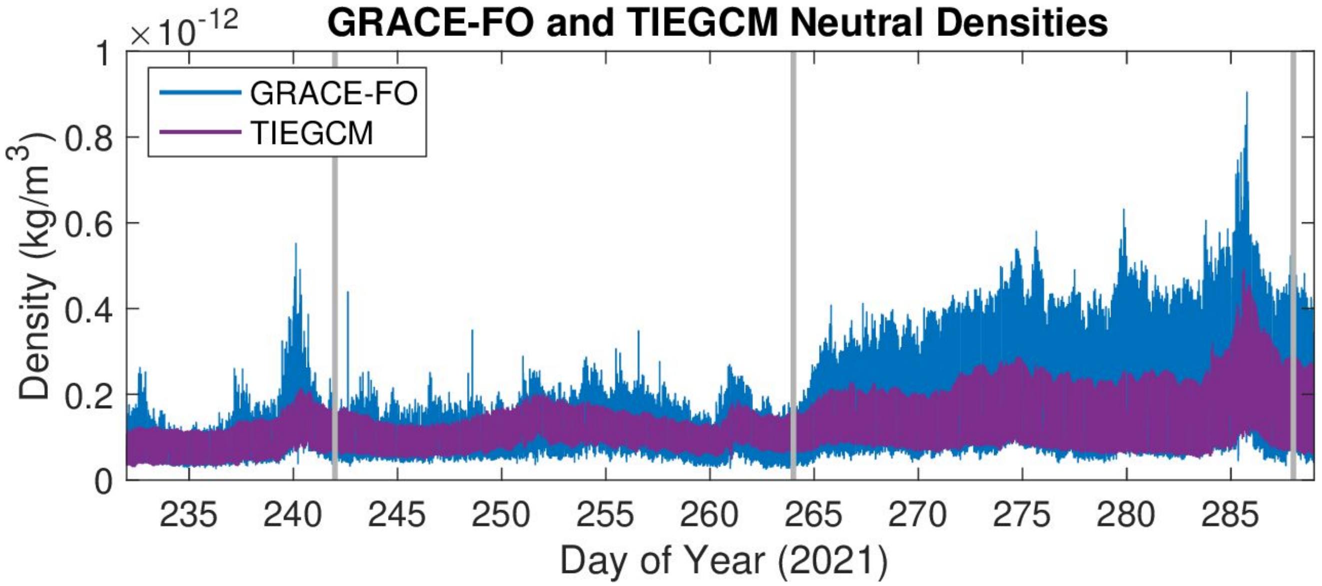


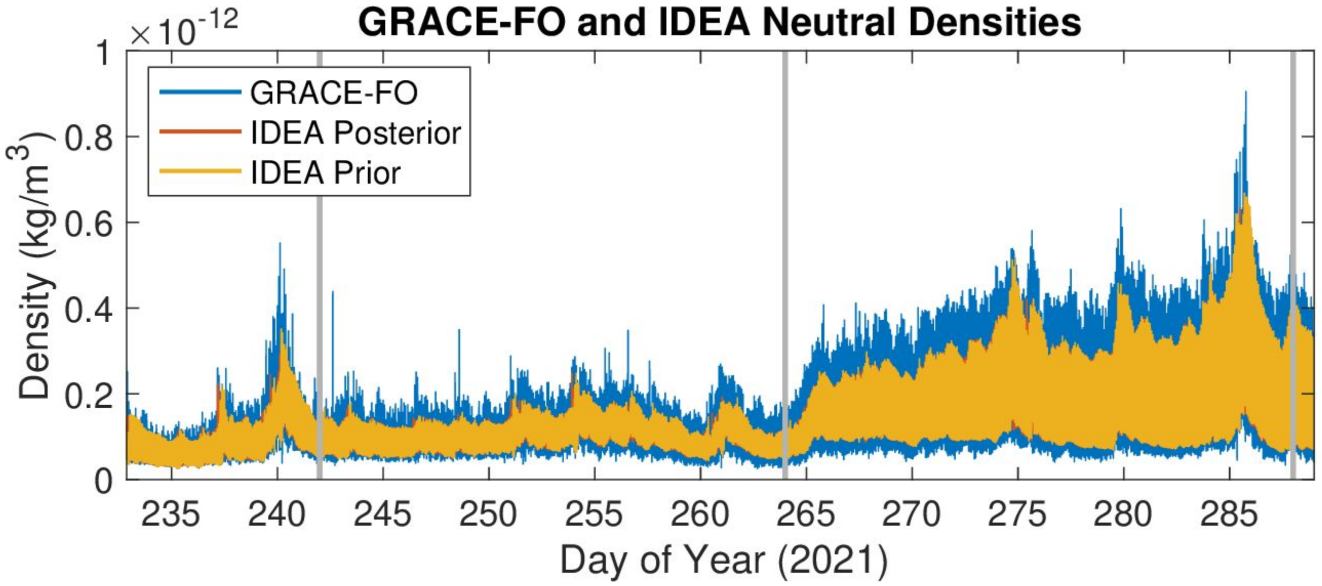
2003 day 80-365, Orbit Average – Ratio Validation Results, RMSe Logarithmic, 1 storm with Kp>5+					
	IDEA	**HASDM***	**TIE-GCM GPI**	**JB-08**	**NRLMSISE-00**
GRACE-A	0.076	0.072	0.273	0.172	0.266

**HASDM is the DoD operational, empirical, and data assimilative High Accuracy Satellite Drag Model*

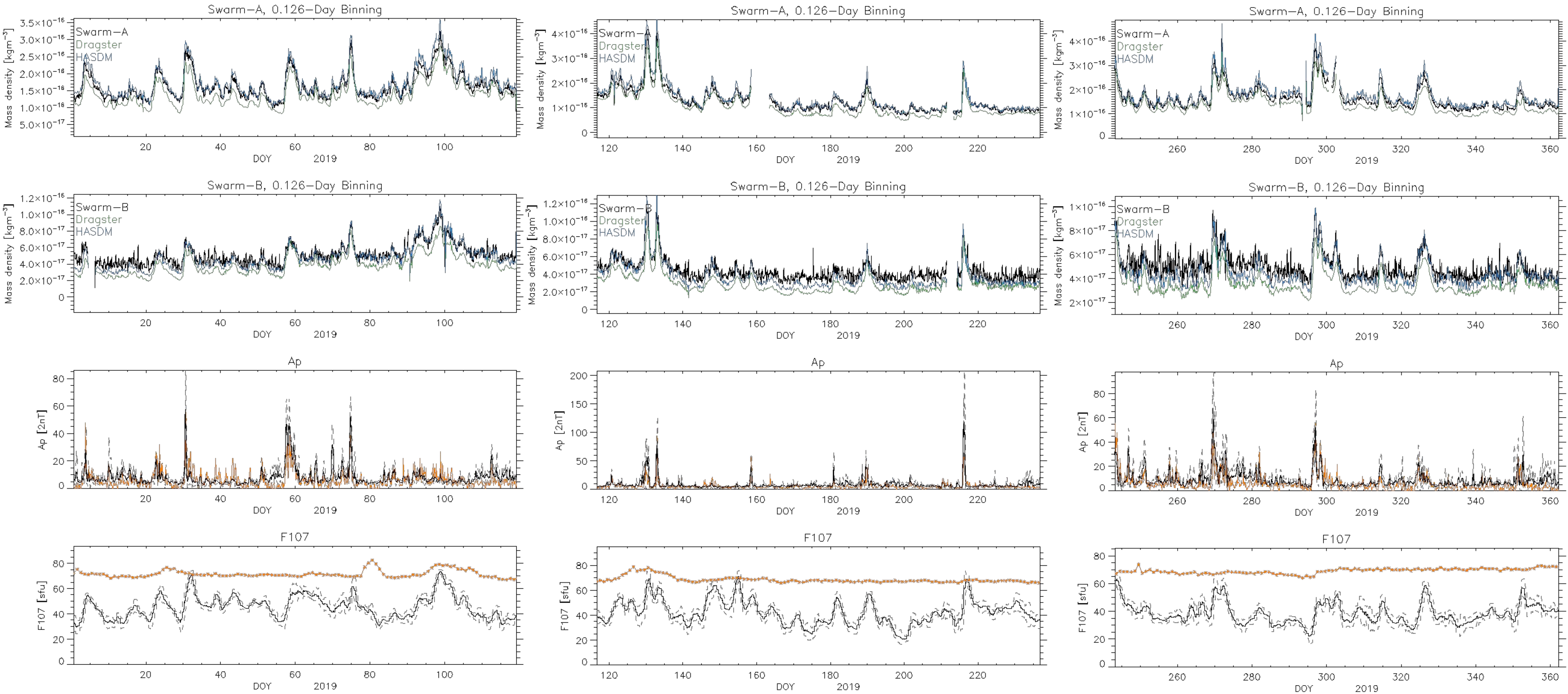
IDEA Assimilating GRACE-FO

Sept. Equinox, 2021

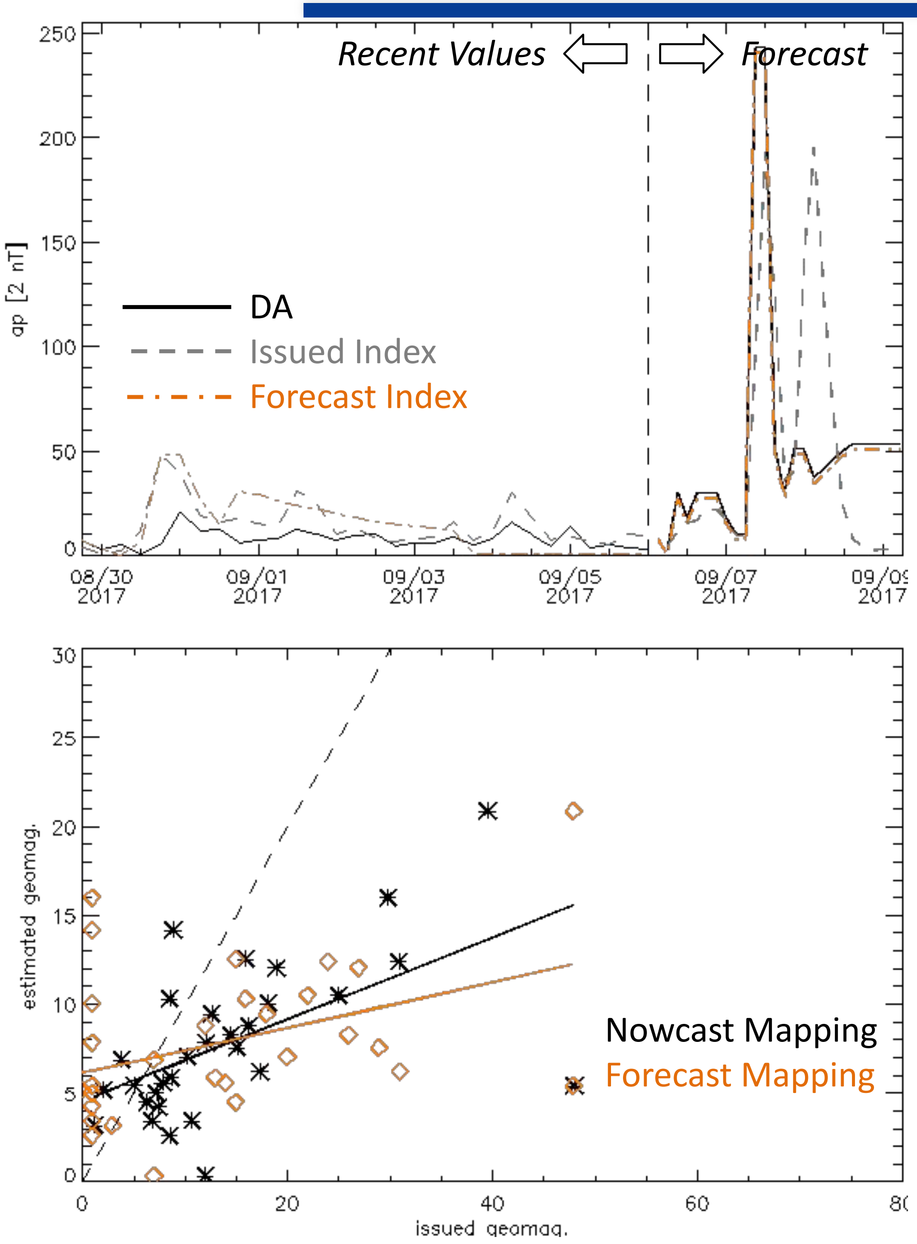




Dragster DA 2019 Results



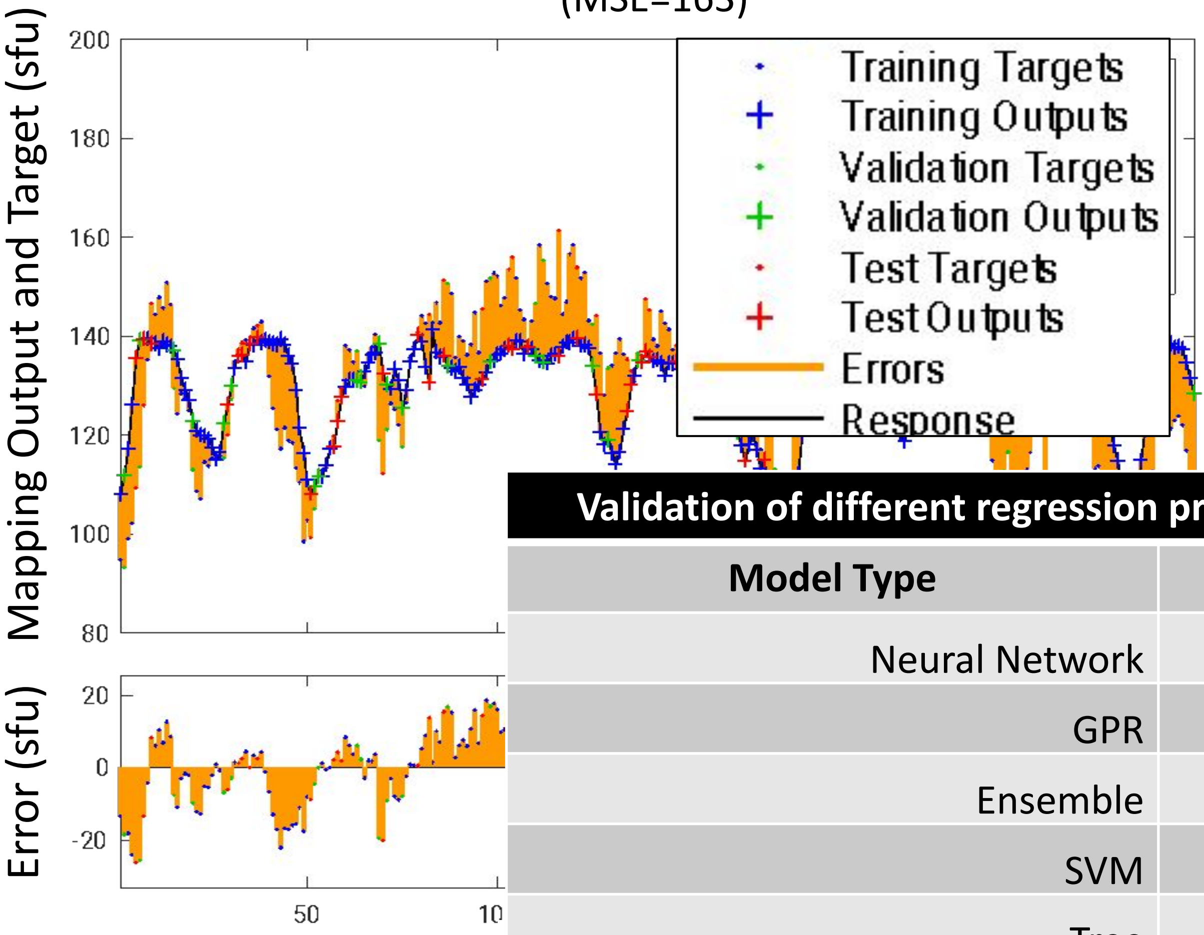
Challenges of Driver Forecast Integration



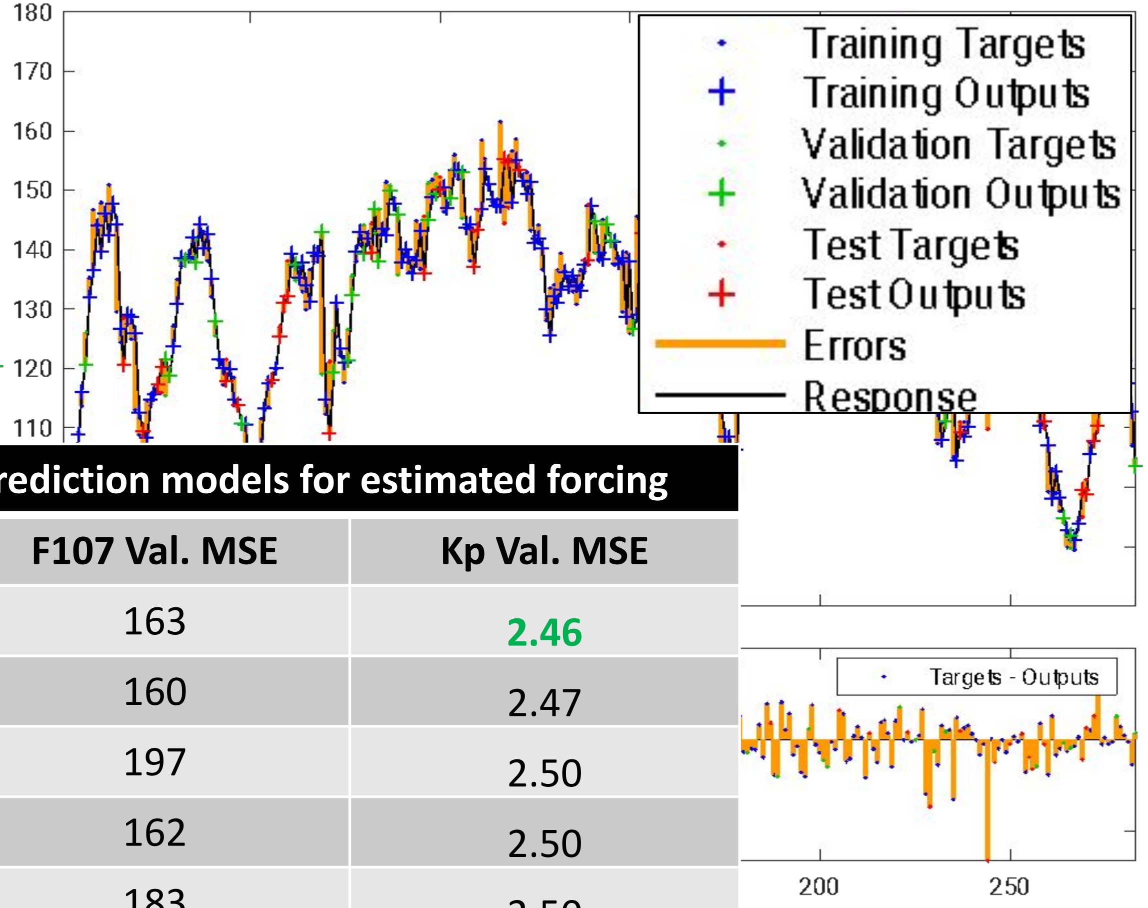
- Dragster and IDEA generate forecasts based on removing a bias between issued and forecast drivers at the time of the forecast launch.
- The bottom panel illustrates a linear-regression mapping of the recently issued nowcast (black) and forecast (orange) to the DA-estimated parameters. **This mapping changes with time and conditions.**
- Other neutral density forecasting approaches use bias offset or regression methods to compute forecasts
- ***How best to take advantage of recent DA driver estimates and recent forecast forcing performance?***

Preliminary Driver Forecast Mapping Study

Nonlinear Autoregressive neural network, NAR (MSE=163)



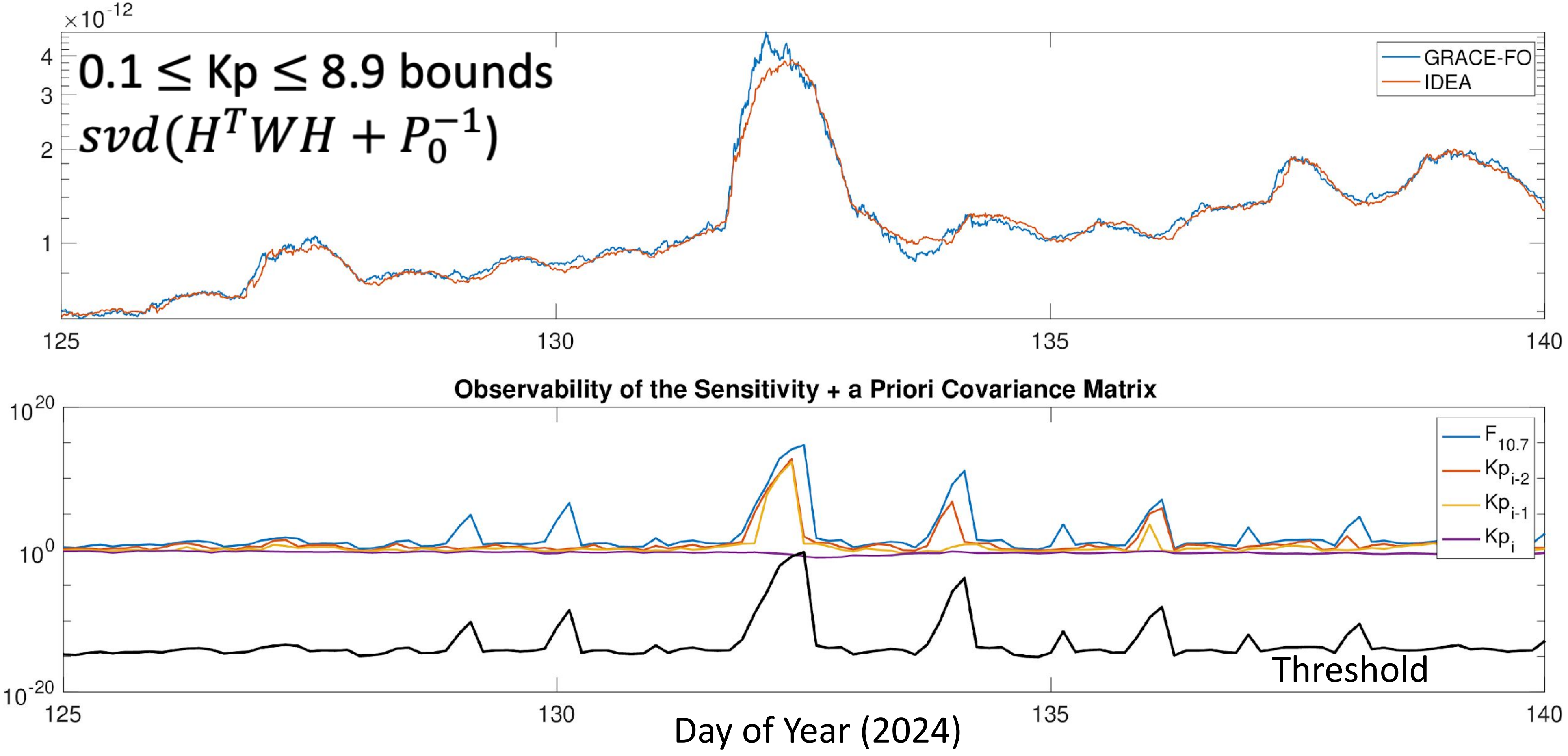
NARX using recent values of DA-estimated forcing (MSE=37)



Validation of different regression prediction models for estimated forcing

Model Type	F107 Val. MSE	Kp Val. MSE
Neural Network	163	**2.46**
GPR	160	2.47
Ensemble	197	2.50
SVM	162	2.50
Tree	183	2.50
Linear Regression	204	2.51
Kernel	294	3.42
NARX using recent DA estimates	**37**	*Under evaluation*

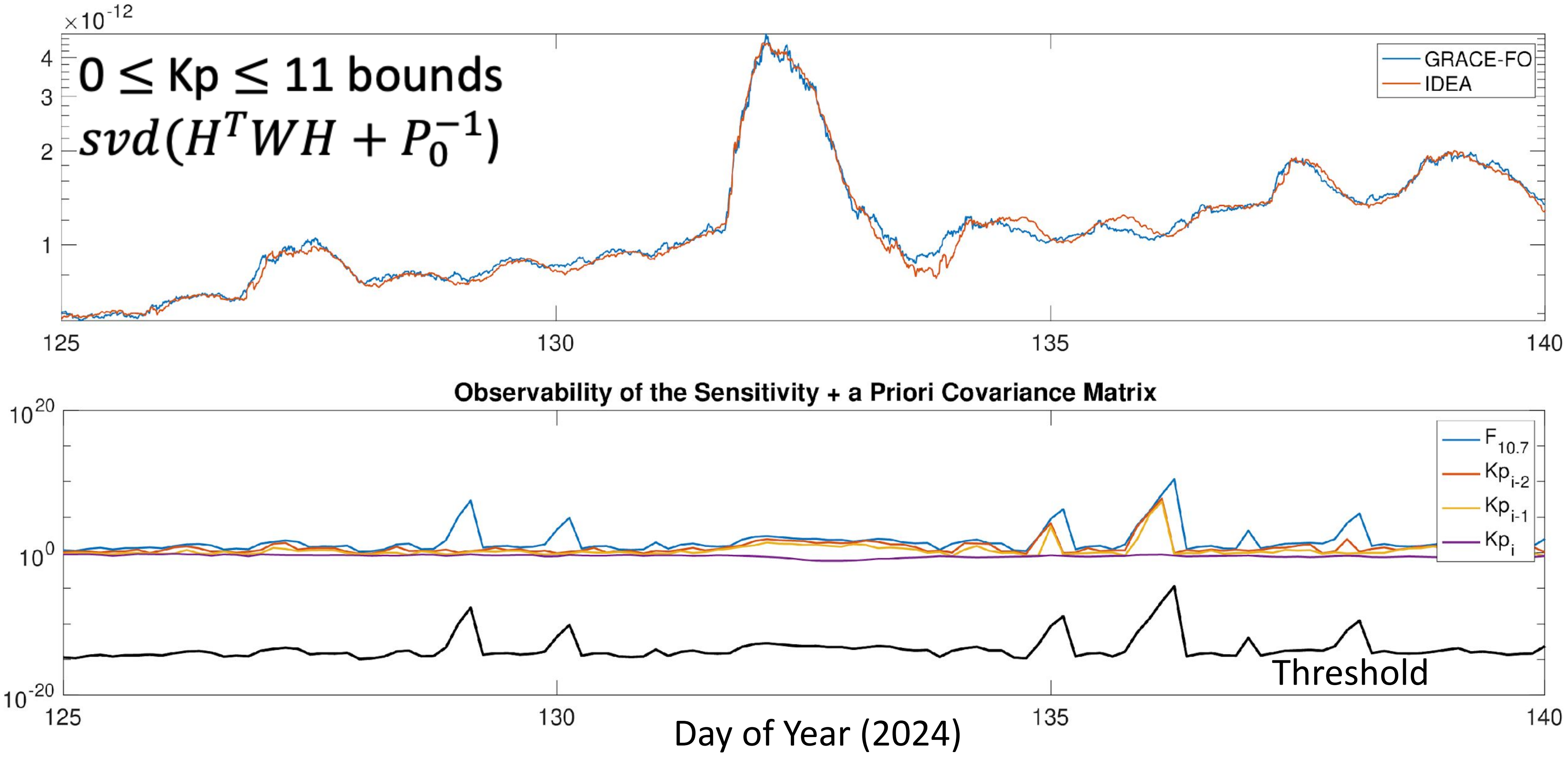
Observability w/ restricted Kp bounds:



Threshold$= \max(svd(M)) * \dim(M) * eps$

where $M = H^T W H + P_0^{-1}$

Observability w/ expanded Kp bounds:



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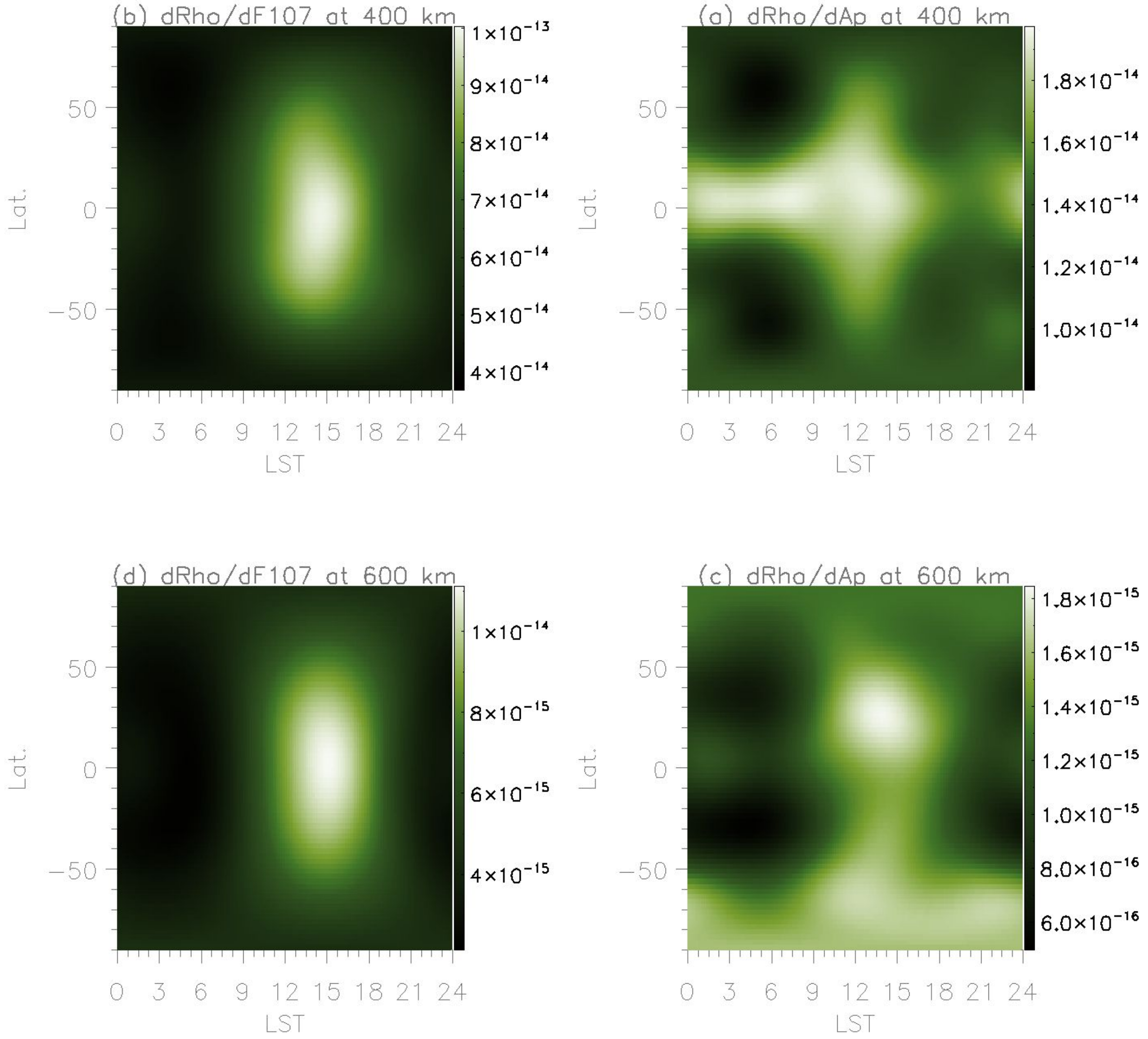
Observability of Driver Estimates



Observability of Driver Estimates