Evaluating Thermospheric Nowcast and Forecast Performance of an Assimilative Density Specification Tool

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Introduction

A significant increase in orbital congestion in low Earth orbit (LEO) is motivating research into enhanced orbit prediction and conjunction analysis (CA) capabilities. In LEO, this includes predictions of satellite drag perturbations that are proportional to the atmospheric neutral density (ND) which is highly variable and difficult to predict, degrading the accuracy of orbital forecasts.

Recently developed data assimilation (DA) techniques such as Dragster (Pilinski et al., 2016) and IDEA (Sutton et al., 2018) have the ability to determine atmospheric model forcing and (in the case of Dragster) density corrections using physics-based and empirical models. The results are then most compatible with the observed satellite drag, effectively making a “model driver correction” at each time step. Because the Thermosphere is a strongly forced system, these drivers are critical to determining the global distribution of neutral density. The techniques above use ensembles of atmospheric models to assimilate satellite drag data and have been shown to significantly reduce ND specification errors. However, it is not clear at the present time how existing forecast of Thermospheric forcing should be correlated with the corrected drivers estimated by DA techniques. One approach is to compute the offset between each estimated forcing parameter and its zero-day forecast then to apply that offset to the predictions at each step of the forecast. Another method involves the linear regression between the zero-day forcing forecasts and the DA estimates over a moving analysis window. The results of the regression are then applied to subsequent forecasts. The latter approach also results in an estimate of uncertainty in the mapping parameters between the available forecasts of model drivers and their DA estimates. This uncertainty can be used to generate an ensemble of ND forecasts leading to an estimate of the evolving errors in satellite drag that are necessary for improved CA.

Conclusions

- Dragster is capable of multi-point and multi-source assimilation
- Good agreement between drag-based assimilation and occultation data
- Ability to accommodate a broad set of temporal sampling characteristics is required to accommodate existing operational datasets along with newly developed observations
- Validation metrics demonstrate performance improvements over several other models, including current operational DA, esp. at higher altitudes

References

Pilinski, M.D, G. Crowley, E. Sutton, M. Codrescu (2016), Improved Orbital Determination and Forecasts with an Assimilative Tool for Satellite Drag Specification, https://amostech.com/TechnicalPapers/2016/Poster/Pilinski.pdf

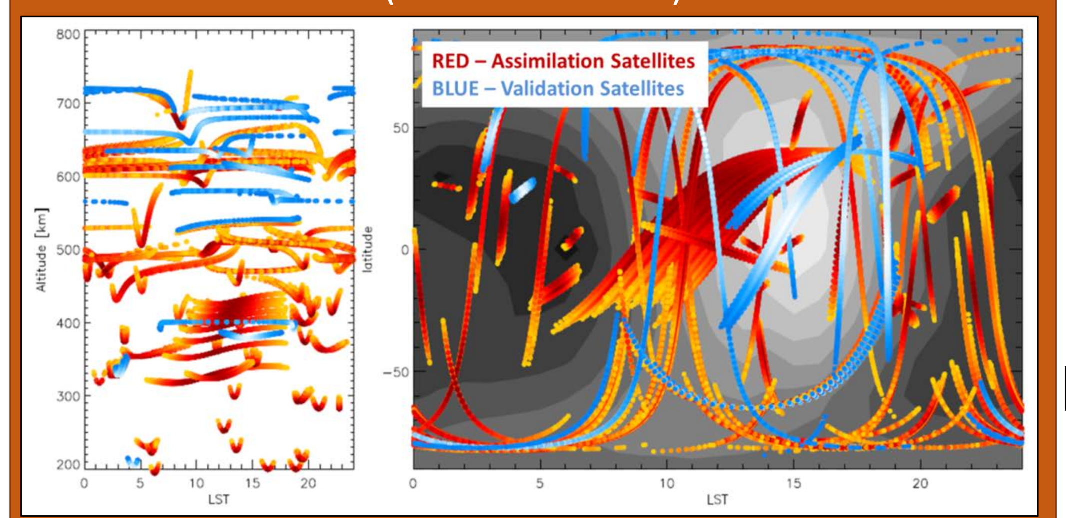
Sutton, E. K. (2018), A new method of physics-based data assimilation for the quiet and disturbed thermosphere, https://doi.org/10.1002/2017SW001785

Sutton, E. K., Thayer, J. P., Pilinski, M. D., Mutschler, S. M., Berger, T. E., Nguyen, V., & Masters, D. (2021). Toward accurate physics-based specifications of neutral density using GNSS-enabled small satellites. https://doi.org/10.1029/2021SW002736

Thiemann, E. M. B., Dominique, M., Pilinski, M. D., & Eparvier, F. G. (2017). Vertical thermospheric density profiles from EUV solar Occultations made by PROBA2 LYRA for solar cycle 24. https://doi.org/10.1002/2017SW001719

Thermospheric Data Assimilation

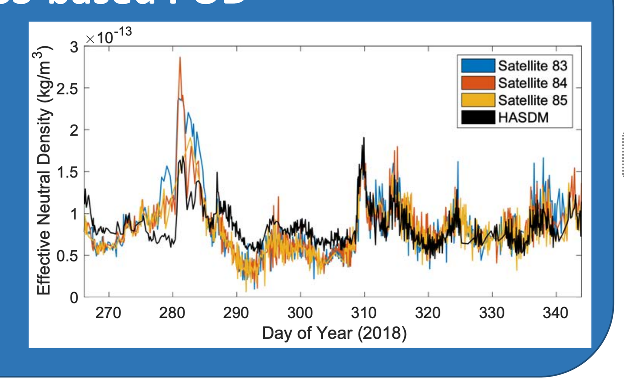
Orbit Average (OA) Densities
(50-90 satellites)



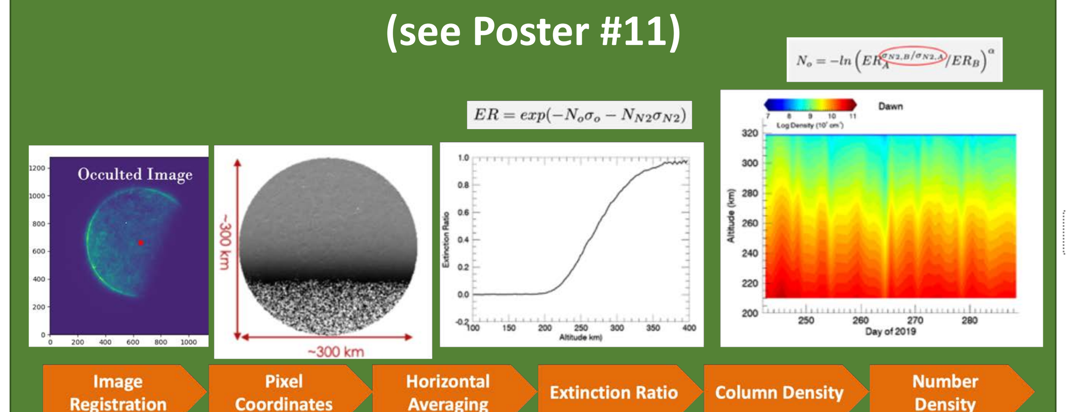
Above: Sections of orbits where each satellite experiences 90% of drag along its orbit. Line shade indicates amount of drag. Blue corresponds to validation satellites (not assimilated) and red corresponds to assimilation satellites.

GNSS-based POD

Densities derived from Spire CubeSat POD shown as an example of this data-type (Sutton et al. 2021)



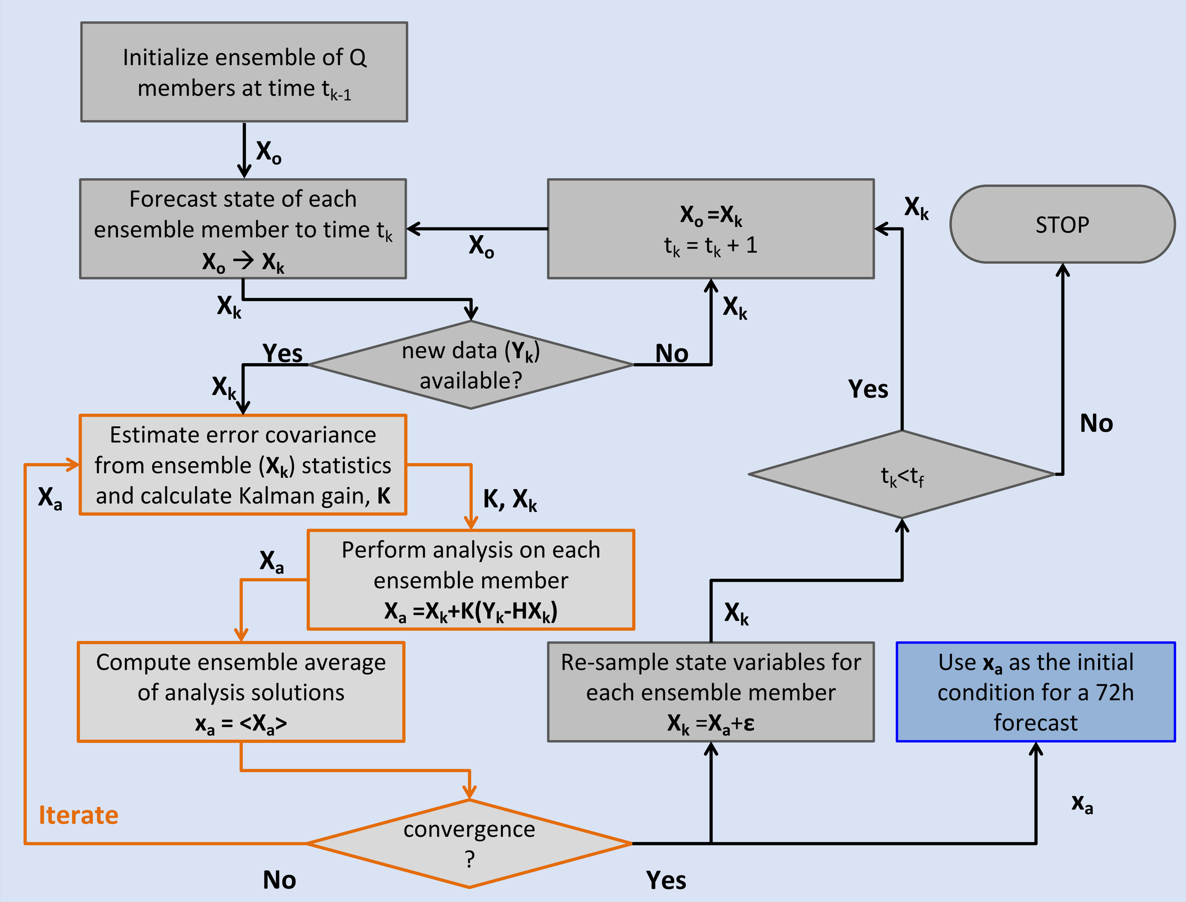
Solar Occultation Measurements
(see Poster #11)



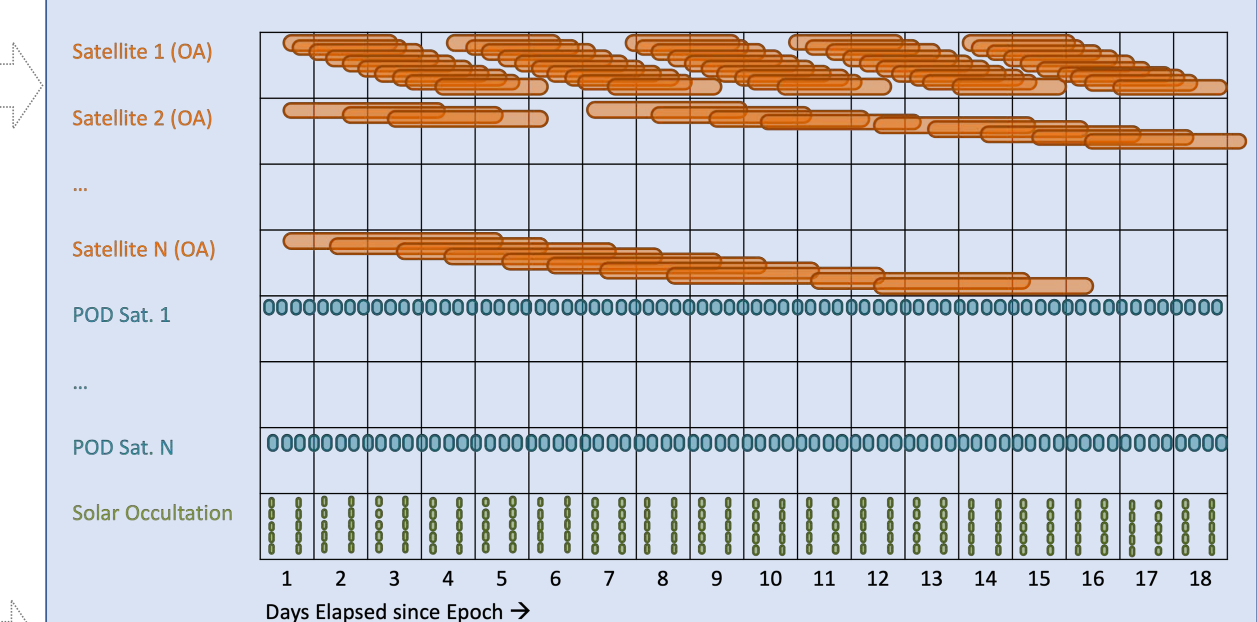
- Method developed from occultation processing on the Lyra instrument on Proba II
- Retrieval integrates the solar disk over reference atmosphere to find a column density
- See Thiemann et al. 2017 for a full description

Existing Capability — In Development & Testing

Dragster Ensemble DA Engine



Dragster DA flowdiagram



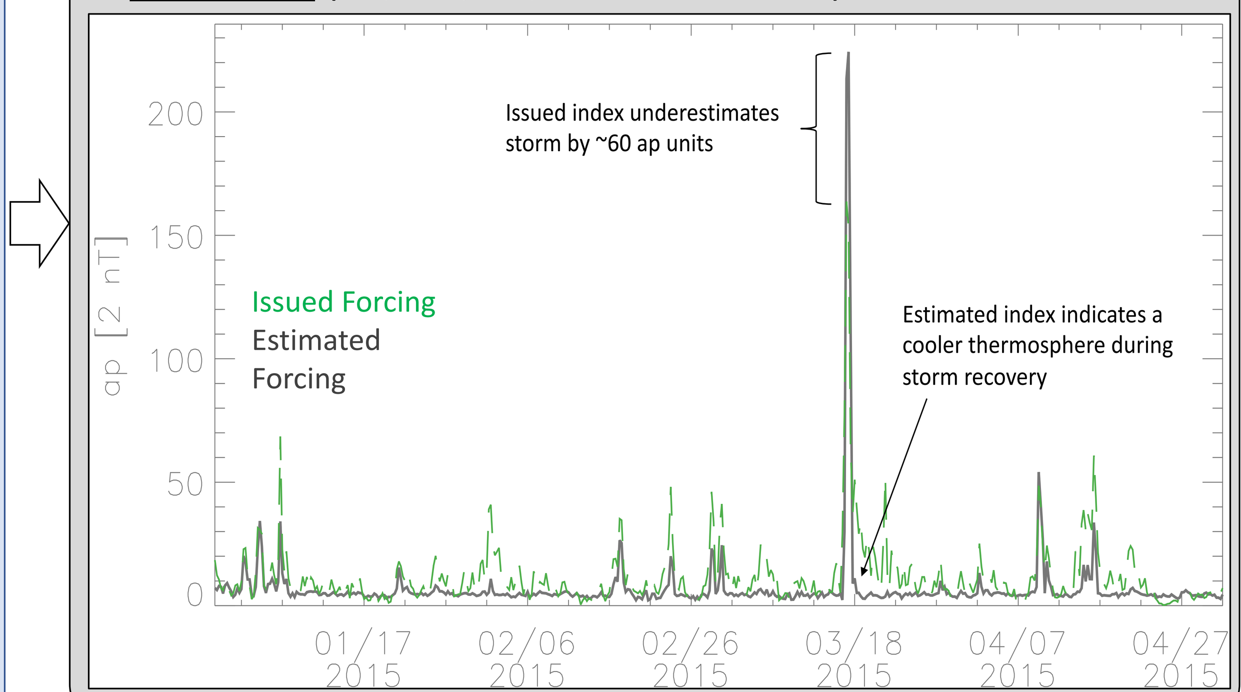
Temporal sampling of potential Dragster data sources. The DA approach is to iteratively analyze data in a 3-6 day moving window.

Atmospheric Model Manager
(30-90 Ensemble Members)

NRLMSISE-00 (empirical) — TIE-GCM 2.0 (physics-based)

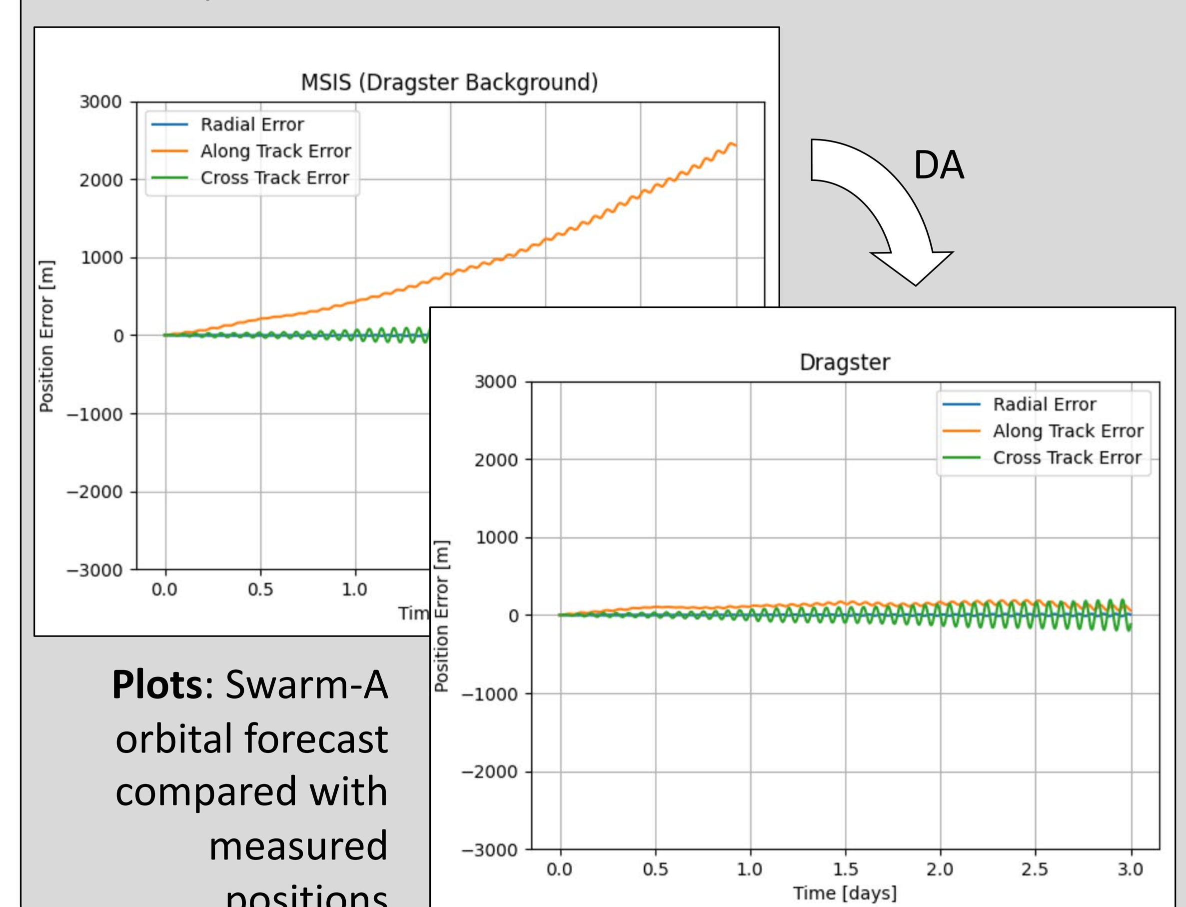
Thermospheric State Estimates

- Geomagnetic forcing (3-6 hour cadence)
- Solar Forcing (6-24 hour cadence)
- Output Fields include density, composition, temperature, and winds (lat, LST, alt, 6 hour cadence)



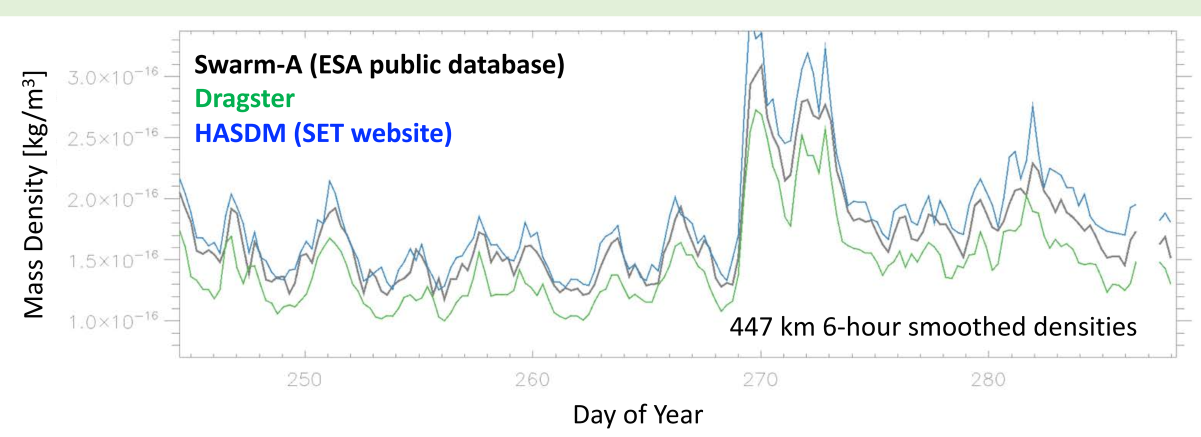
Thermospheric Forecasts

- Linear regression used to map DA forcing estimates to issued Ap and F10.7
- Mapping used to interpret solar and geomagnetic forecasts
- 3-7 day forecast duration, launched at 6-12 hour cadence



Plots: Swarm-A orbital forecast compared with measured positions

Validation



Left: Time series of ESA Swarm densities compared with two assimilative models.

Lower Left: Tables showing model performance metrics. Both linear and log standard deviation metrics are shown. Log metrics use Swarm density observations (O) and model-computed densities (C):

$$SD\left(\frac{O}{C}\right) = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\ln\frac{O_n}{C_n} - \ln \text{Mean}\left(\frac{O}{C}\right)\right)^2}$$

$$\text{Mean}\left(\frac{O}{C}\right) = \exp\left(\frac{1}{N}\sum_{n=1}^{N}\ln\frac{O_n}{C_n}\right)$$

- Green indicates best performance (lower value=better)
- High values during 2017 are a result of increased Swarm density noise above 500 km
- Dragster input data was similar to that of HASDM for this time

2015 ¼ Orbit Average - Validation Results 2015, SD Logarithmic (Linear), 5 storms with Kp>5+

	Dragster	HASDM*	JB-08	NRLMSISE-00
Swarm-A (450km)	0.115 (0.101)	0.117 (0.133)	0.180 (0.202)	0.267 (0.318)
Swarm-B (515km)	0.198 (0.202)	0.219 (0.295)	0.258 (0.329)	0.340 (0.497)

2016 ¼ Orbit Average - Validation Results 2016, SD Logarithmic (Linear), 1 storm with Kp>5+

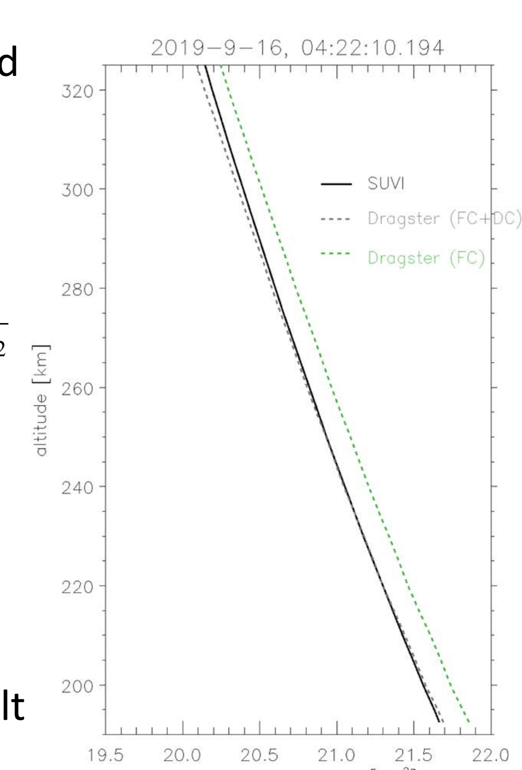
	Dragster	HASDM*	JB-08	NRLMSISE-00
Swarm-A (450km)	0.166 (0.164)	0.157 (0.202)	0.236 (0.278)	0.274 (0.413)
Swarm-B (515km)	0.384 (0.871)	0.369 (1.065)	0.425 (0.930)	0.456 (1.563)

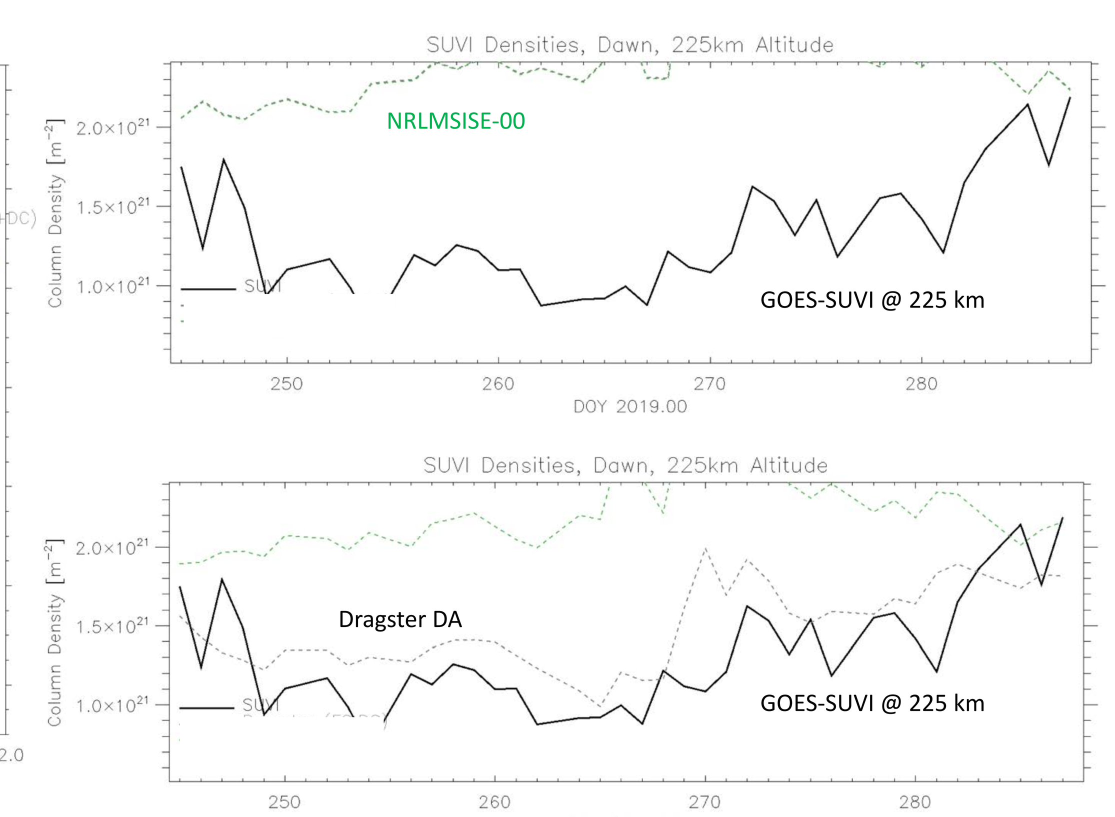
2017 ¼ Orbit Average - Validation Results 2017, SD Logarithmic (Linear), 2 storms with Kp>5+

	Dragster	HASDM*	JB-08	NRLMSISE-00
Swarm-A (450km)	0.176 (0.160)	0.188 (0.220)	0.259 (0.303)	0.278 (0.442)
Swarm-B (515km)	0.377 (0.616)	0.389 (0.724)	0.440 (0.740)	0.437 (1.227)

**HASDM is the DoD operational High Accuracy Satellite Drag Model*

Below: Dragster validation using GOES-SUVI occultations including a single altitude profile (left) and dawn density comparisons at a 225 km altitude.





Poster # 17