Leveraging Data Assimilative Models for Enhanced Satellite Drag Predictions

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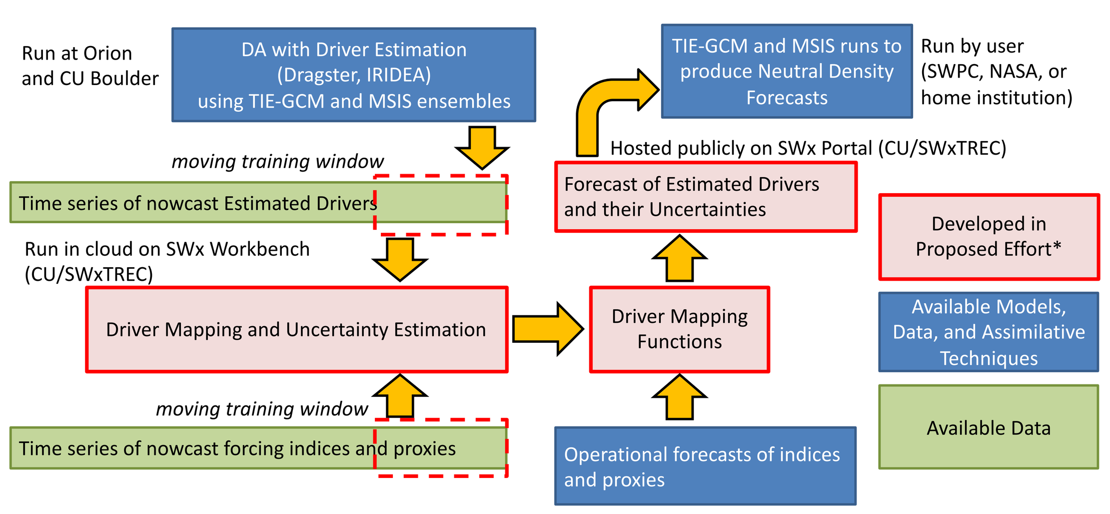
Introduction

- Low Earth Orbit (LEO) satellite drag is a persistent Space Weather (SWx) challenge.
  - Related to errors in air-density predictions and lack of uncertainty specification
  - Leads to inadequately forecasting collisions, with dire consequences
  - Many collision warnings are false positives associated with uncertainties in modeling and forecasting densities in the upper atmosphere
- Drag-validated data assimilation (DA) techniques such as IDEA [Sutton 2018], and Dragster [Pilinski et al. 2016] have the ability to determine the thermospheric model forcing that is most compatible with the observed satellite drag.
- These methods have been the only ones so far shown to outperform the current state of the art in density specification.
- *It is not clear how well DA driver corrections persist into the forecast window nor how best to combine them with existing operational driver forecasts.*
- We therefore evaluate various driver mapping schemes on archived forecast driver indices, estimates, and proxies
  - F10.7, S10(SET), F30, MgII (ADAPT/SIFT)
  - Kp/Ap (SWPC), Anemomilos Dst (SET)
  - Other available forecasts will be considered

Figure 1 (below), A driver-mapping approach to enable DA-based ND forecast capability. Method to provide DA-based forecasts and their uncertainties currently does not exist.



Conclusions

- DA methods that estimate forcing drivers are able to match or exceed HASDM performance
- The relationship between forecast and estimated drivers (mapping) evolves over time
- It is not known how DA driver estimates should be related to forecast drivers to enhance forecast performance
- Mapping regression "models" allow the DA techniques to seamlessly transition from ND nowcast to forecast using the *existing* operational forecast data without sudden changes in the driver offset or scale factor

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

Bishop, C. M. (2006). Pattern recognition and machine learning. New York: Springer.

Zhou, Z.-H. (2021). Machine Learning. Singapore: Springer Singapore.

Camporeale, E., Wing, S., & Johnson, J. R. (2018). Machine Learning Techniques for Space Weather.

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Thermospheric Data Assimilation with Forcing Estimation

Dragster Ensemble DA Engine

- Estimates corrections to external solar and geomagnetic drivers along with direct density corrections on a user-specified grid
- Ensembles of MSIS models (can also use TIE-GCM)
- Has been shown to provide better or comparable densities to HASDM*

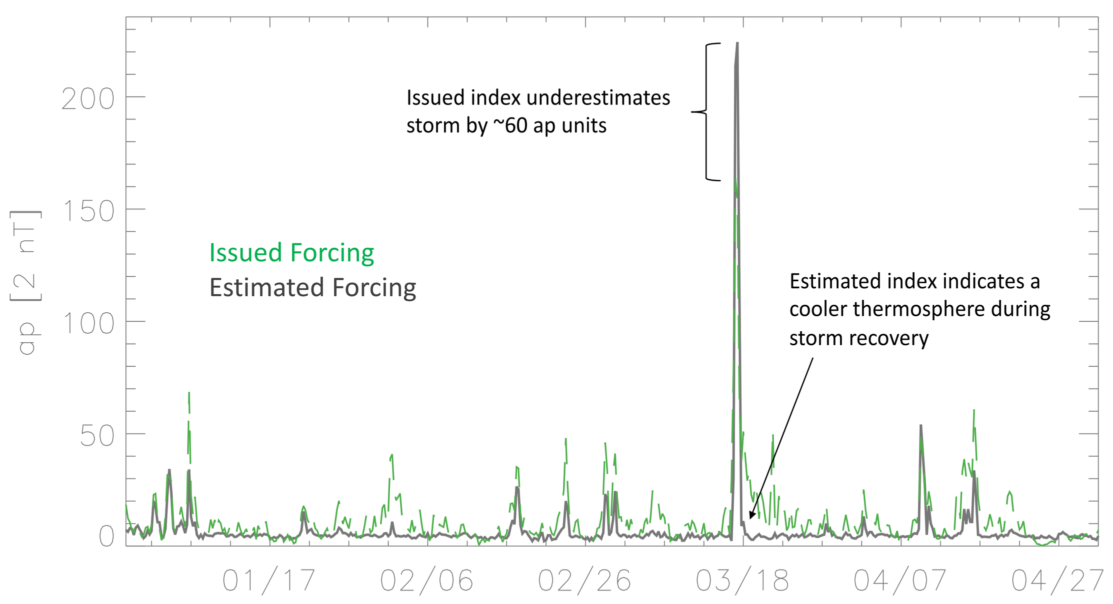

Figure 2 (left) shows a 2015 example of a driver dataset and the corresponding driver estimates determined by assimilating 70 satellite orbits into Dragster.

- Issued data often *overestimated* quiet time forcing during this time
- Forcing was underestimated by the *issued* index during the large storm on 3/17

2015 ¼ Orbit Average - Validation Results, 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)
2017 ¼ Orbit Average - Validation Results, 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)

Table 1 (left) showing Dragster performance metrics over two years. Metrics compare Swarm (not assimilated) density observations and model-computed densities.

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

Iterative Driver Estimation and Assimilation (IDEA)

- 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*

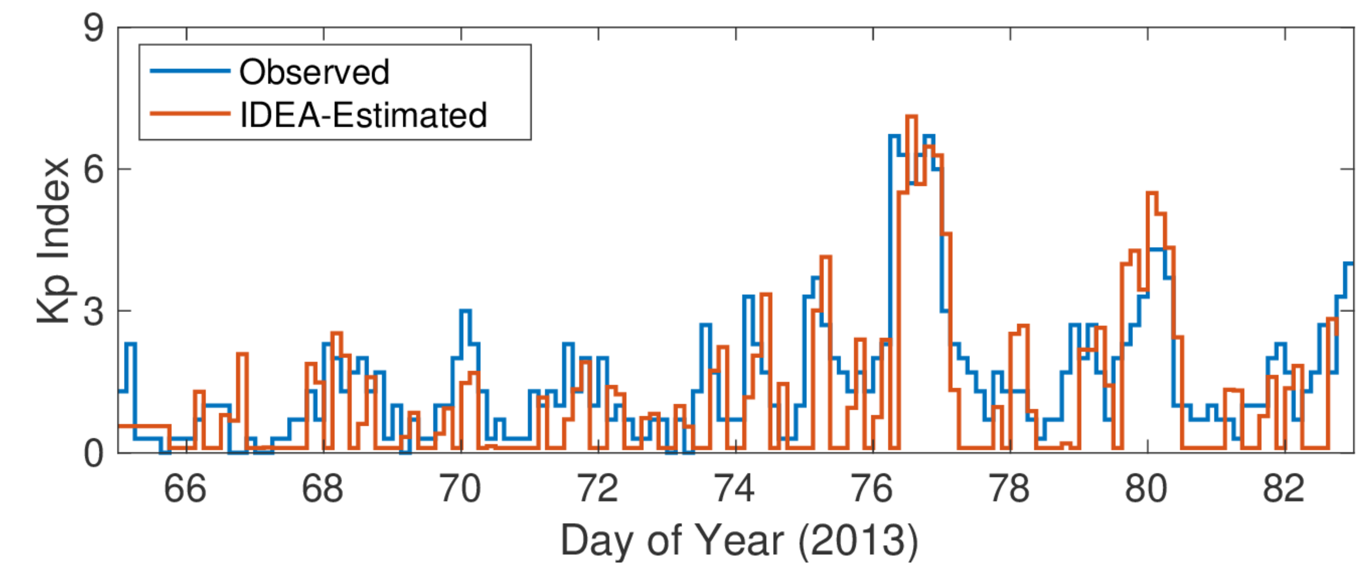

Figure 3 (above) shows an example of a driver dataset and the corresponding driver estimates determined by assimilating GOCE accelerometer data into IDEA

Table 2 (below) showing IDEA performance metrics over 9 months. Metrics evaluate the GRACE (not assimilated) density observations and model-computed densities *ratios*.

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*

Challenges of Driver Forecast Integration with Models

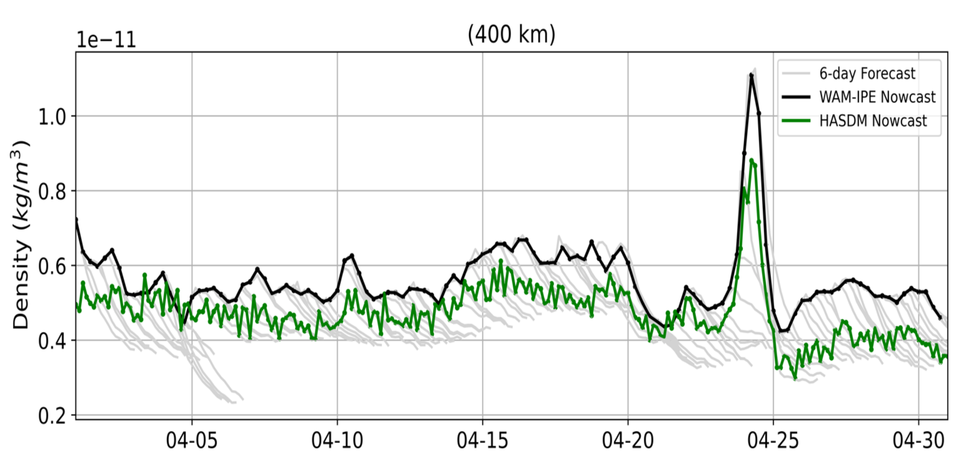

Figure 3 (above), 2023 SWPC WAM-IPE nowcast & forecast

- WAMP-IPE example above used solar wind drivers for nowcast but Kp-driven parametrization for the forecast.
- Without driver-mapping, the differently-generated forecasts can deviate from the model and observed baselines.
- DA without forcing estimates, such as HASDM, reduces forecast offsets by evaluating recent Thermospheric temperature estimates.

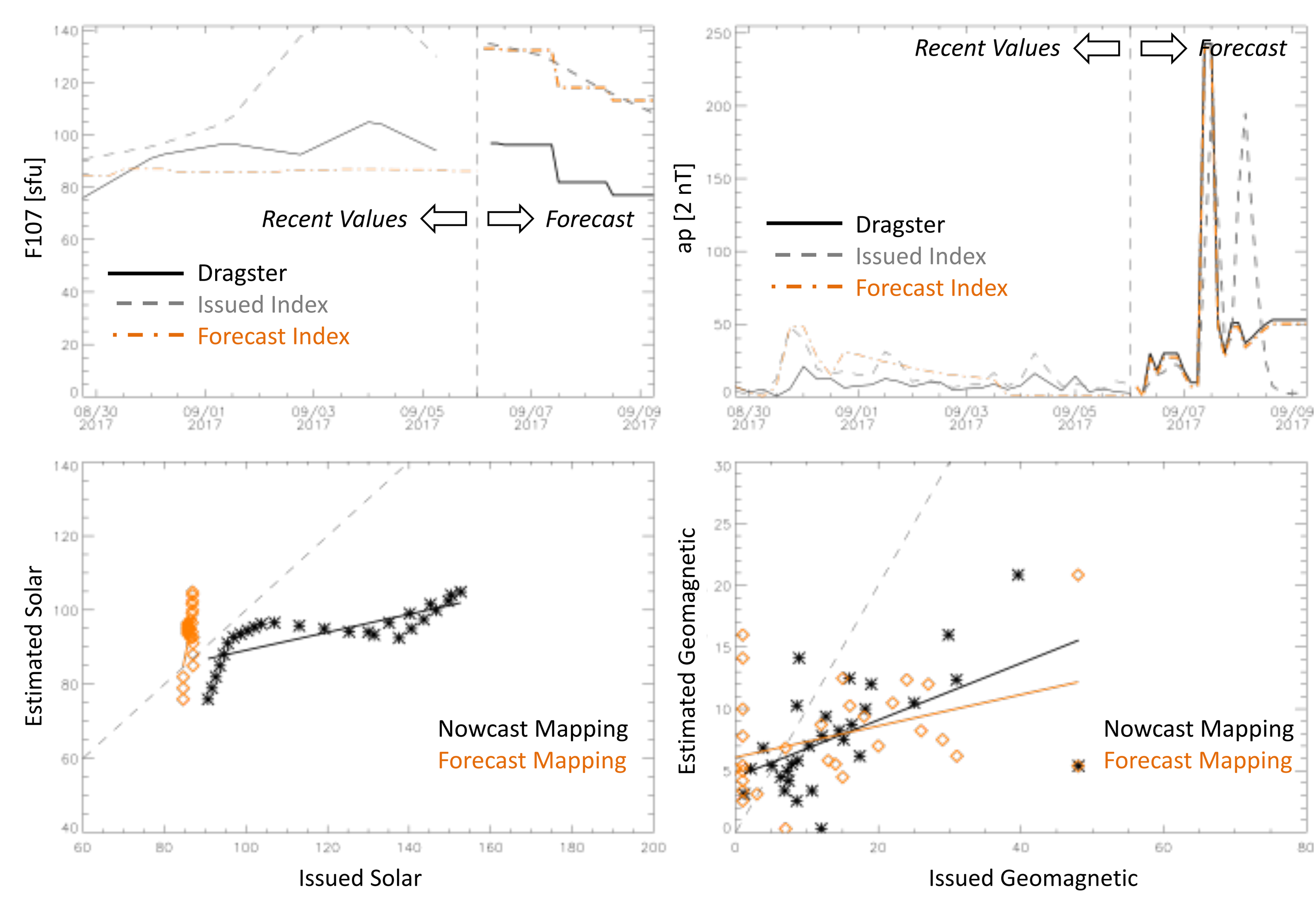

Figure 4 (above), Solar (left) and geomagnetic (right) drivers for the Dragster model. Forecasts occur to the right of the vertical dashed line and are compared to an eventual nowcast. The de-biased forecast used by Dragster is shown using the dark black solid line.

- Dragster and IDEA generate forecasts based on removing a bias between issued and forecast drivers at the time of the forecast launch.
- To the left of the vertical dashed line in Figure 4, the orange line represents a recent forecast launched on 8/30/2017. To the right of the vertical dashed line, the orange represents the "current" forecast launched on 9/7/2017
- Black solid lines are DA-estimated drivers to the left of the vertical dashed line and the de-biased Dragster forecast drivers to the right.
- The bottom panels illustrate a linear-regression mapping of the recently issued nowcast (black) and forecast (orange) indices to the DA-estimated parameters. **This mapping changes with time and conditions.**
- Issued forcing parameters (8/30 to 9/7) over-estimated the energy input to the thermosphere.
- De-biasing at 9/7 leads to an overestimate of storm and post-storm time period geomagnetic forcing.

Forecast Driver Mapping, Preliminary Results

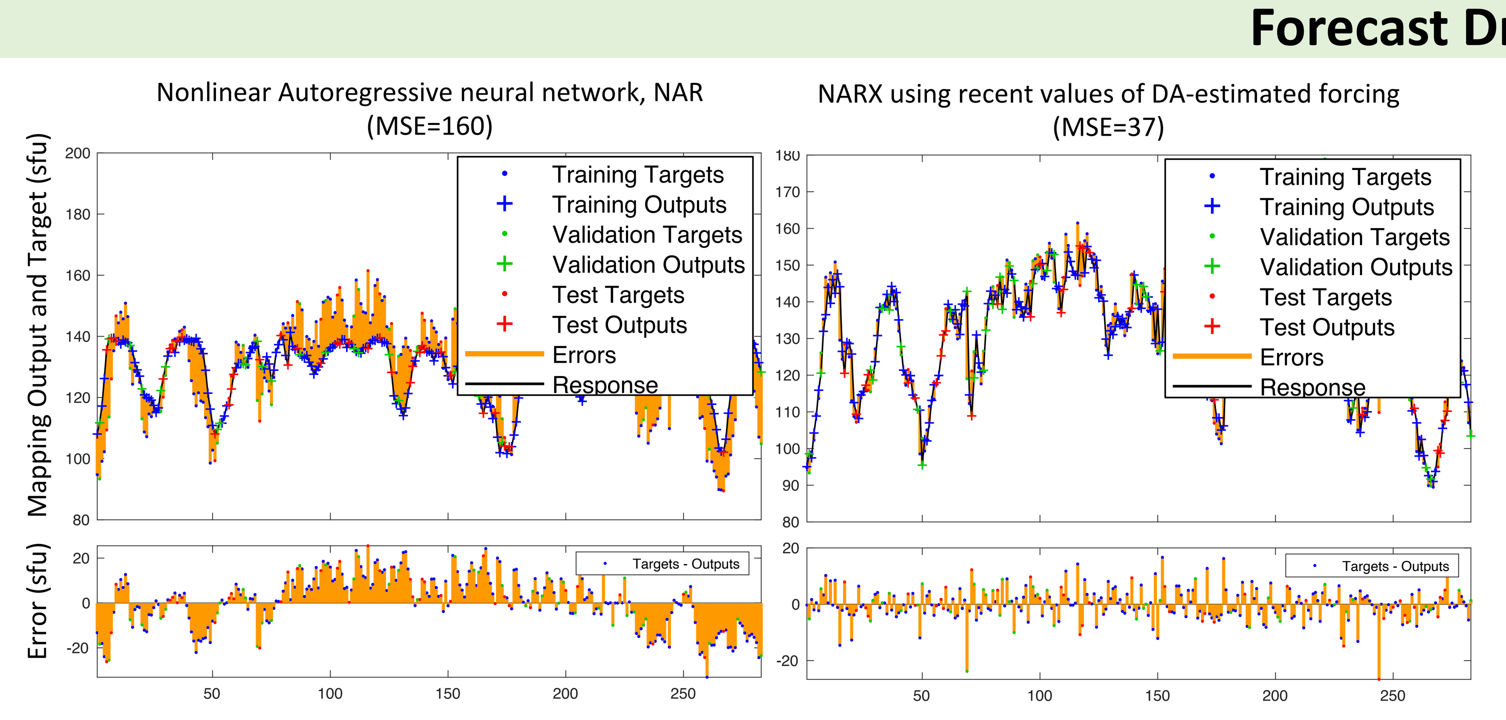

Figure 5 (above), (Left) Mapped F10.7 outputs and the DA-estimated F10.7 "targets" and variation of MSE by using the NAR model. (Right) Mapped F10.7 and DA-estimated F10.7 and variation of MSE by using the NARX model that takes into account recent history.

- Pilot mapping study using driver estimates from IDEA assimilation along with issued F10.7 and Kp indices.
- Tested and compared the performance of different regression models and a nonlinear autoregressive neural network (NAR) model.
- Input was the issued index (such as Kp) and output was the DA-estimated equivalent based on an IDEA run spanning days 80-364 of 2003.
- Gaussian process regression (GPR) performs the best when making predictions for F10.7 and a medium-sized neural network does better when making predictions for Kp.
- Figure 6 indicates that the mapping or "prediction" errors can be reduced by taking advantage of past values of DA-estimated drivers.

Table 3 (below), Validation results of regression prediction models (green is best). Methods described by Bishop [2006], Zhou [2021], Comporeale et al. [2018].

Validation results of different regression prediction models for estimated forcing (green is best). Methods described by Bishop [2006] and Zhou [2021]		
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	37	*Under evaluation*