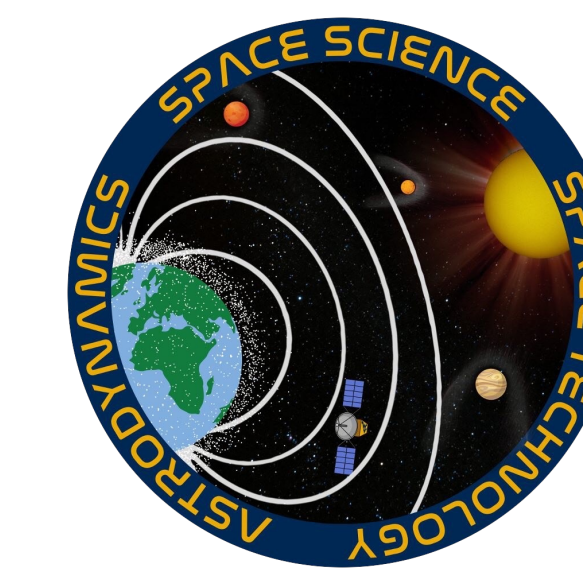


# Bridging High-Fidelity Modeling and Operations with Reduced-Order Thermospheric Data Assimilation

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## Introduction

### Motivation

- Thermospheric density uncertainty drives large errors in LEO orbit prediction
- Accurate, low-latency density estimates are essential for space operations
- See [Poster 4](#) in this session by Nijanthan Vasudevan

### Variability & Forcing

- Dominant forcing from solar EUV irradiance causes order-of-magnitude density changes over the solar cycle, additional variability occurs on diurnal, seasonal, and geomagnetic storms
- Even small density errors accumulate rapidly in low Earth orbit propagation

### Modeling Gap & Deep Learning efforts

- Empirical models lack event-scale responsiveness
- Physics-based models are accurate but too expensive for real-time use<sup>[2]</sup>
- See [Poster 6](#) in this session by Immanuel Ulifun

### Reduced-Order Modeling

- ROMs capture dominant thermospheric variability in a low-dimensional space<sup>[3]</sup>
- Enable fast propagation while retaining key physical structure (**10000x speedup**)
- See [Poster 7 & 10](#) in this session by Nathaniel Michek & Harshitha Challa

### Data-Driven Dynamics

- Linear (DMDc) and sparse nonlinear basis (SINDyc) models capture forced dynamics<sup>[1]</sup>
- Autoregressive terms incorporate memory and state-driver interactions
- See [Poster 8](#) in this session by Daniele Sicoli

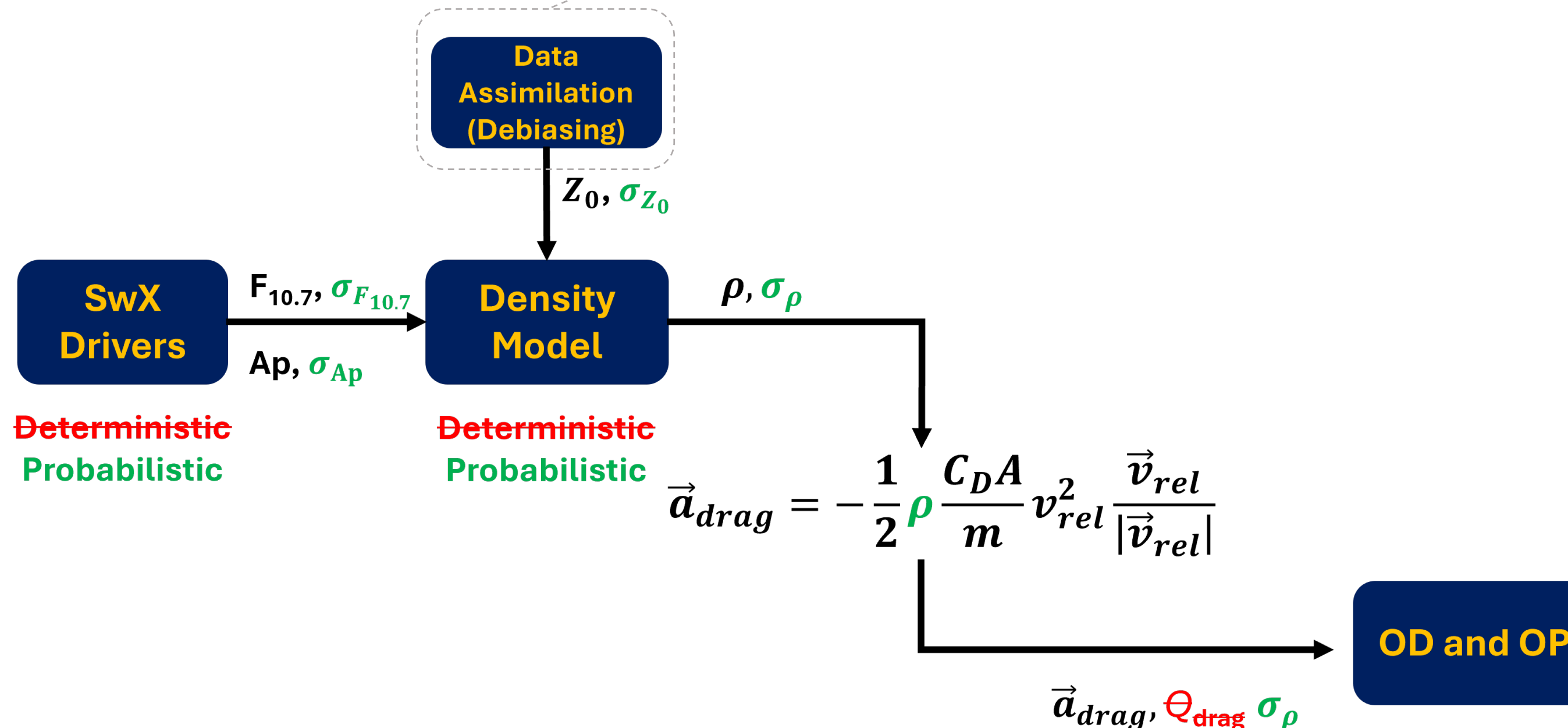
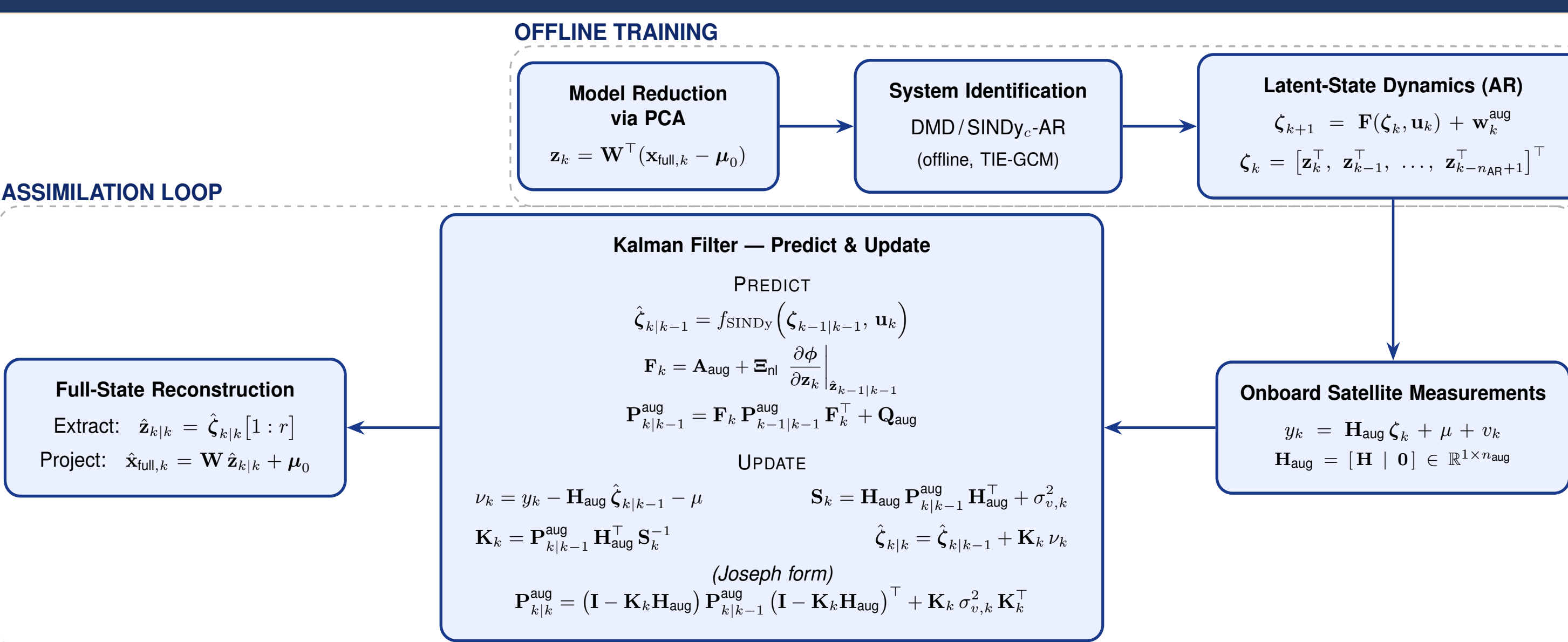
### Data Assimilation

- Kalman filtering combines ROM dynamics with sparse in-situ density data<sup>[4]</sup>

### This Work

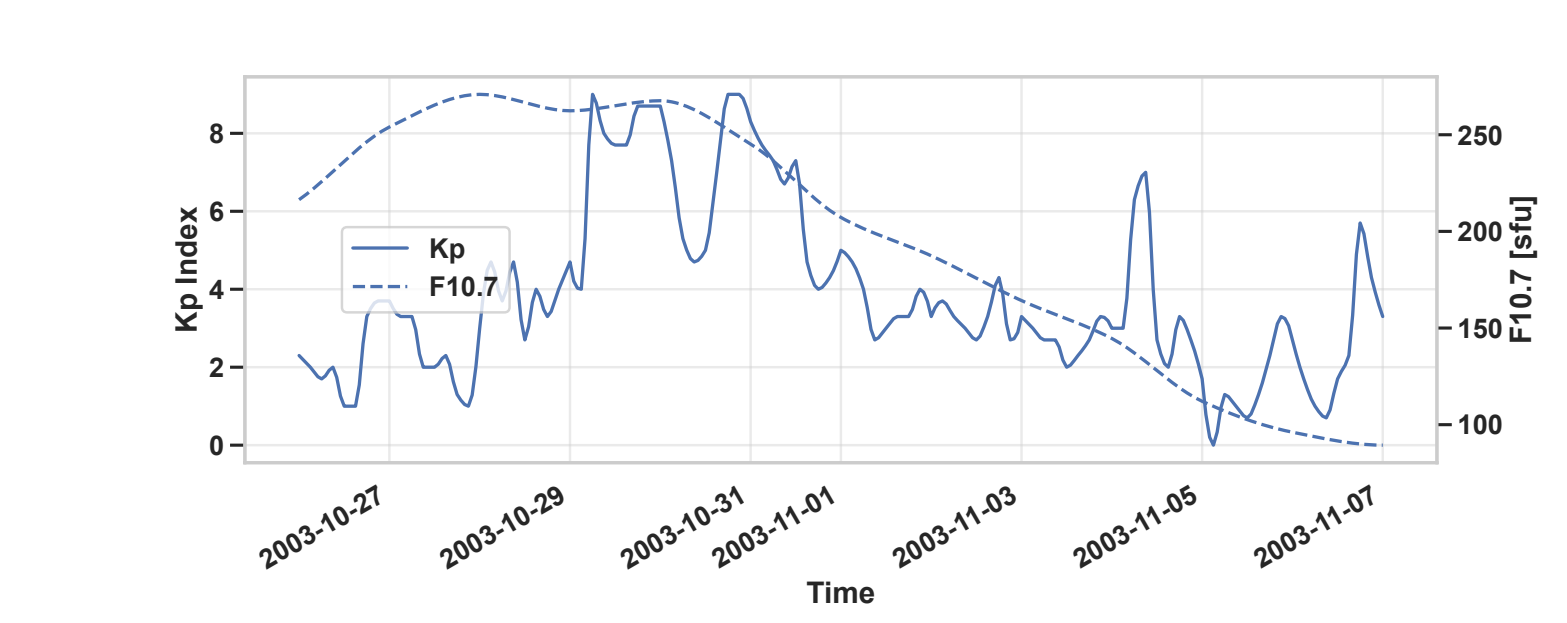
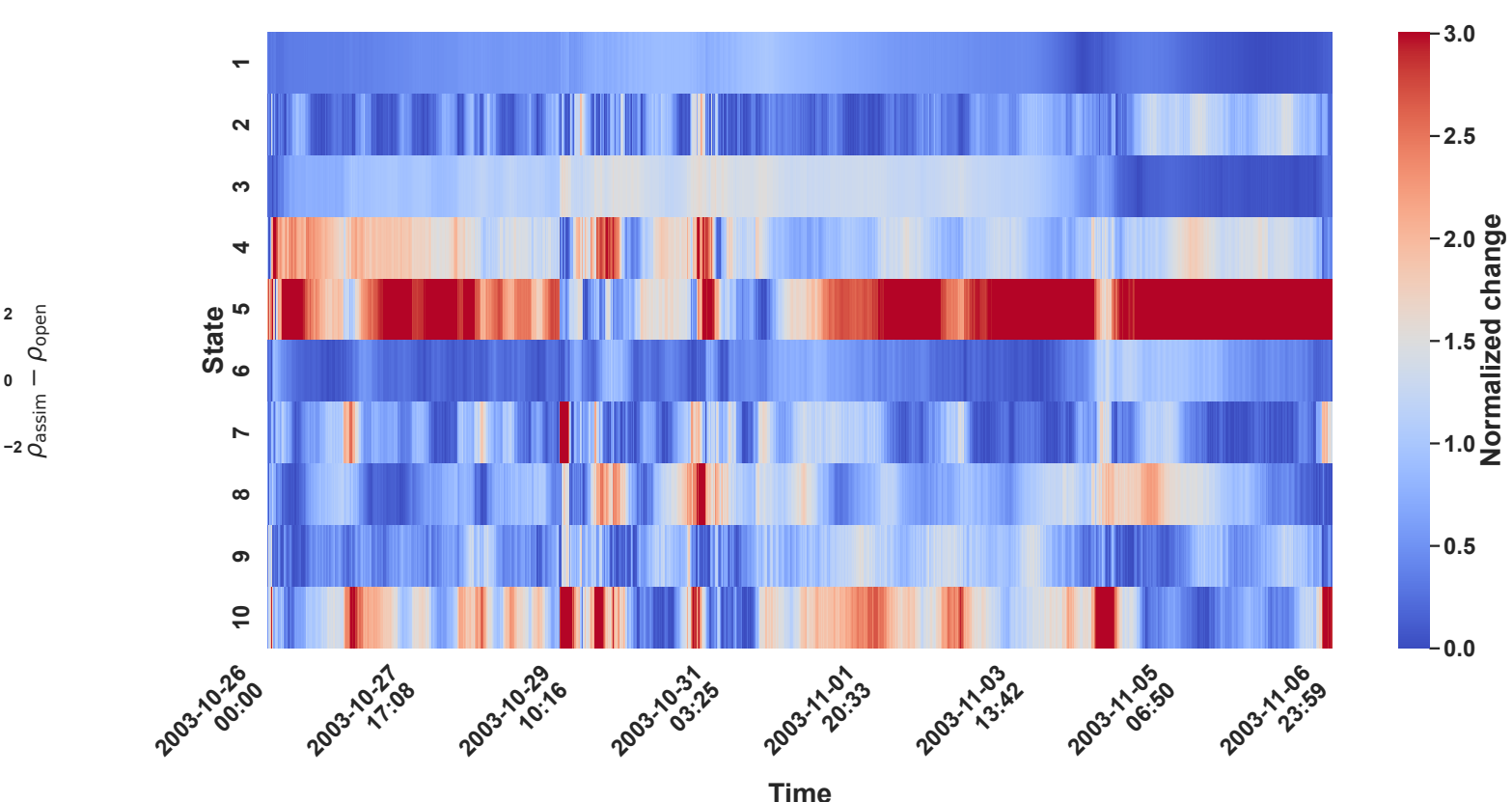
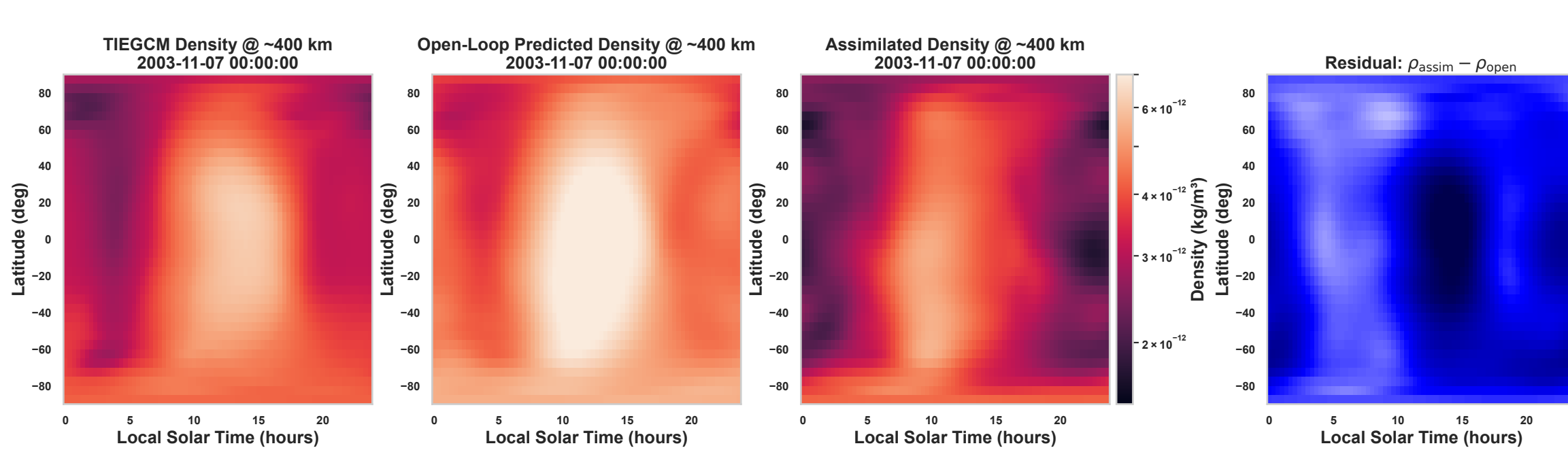
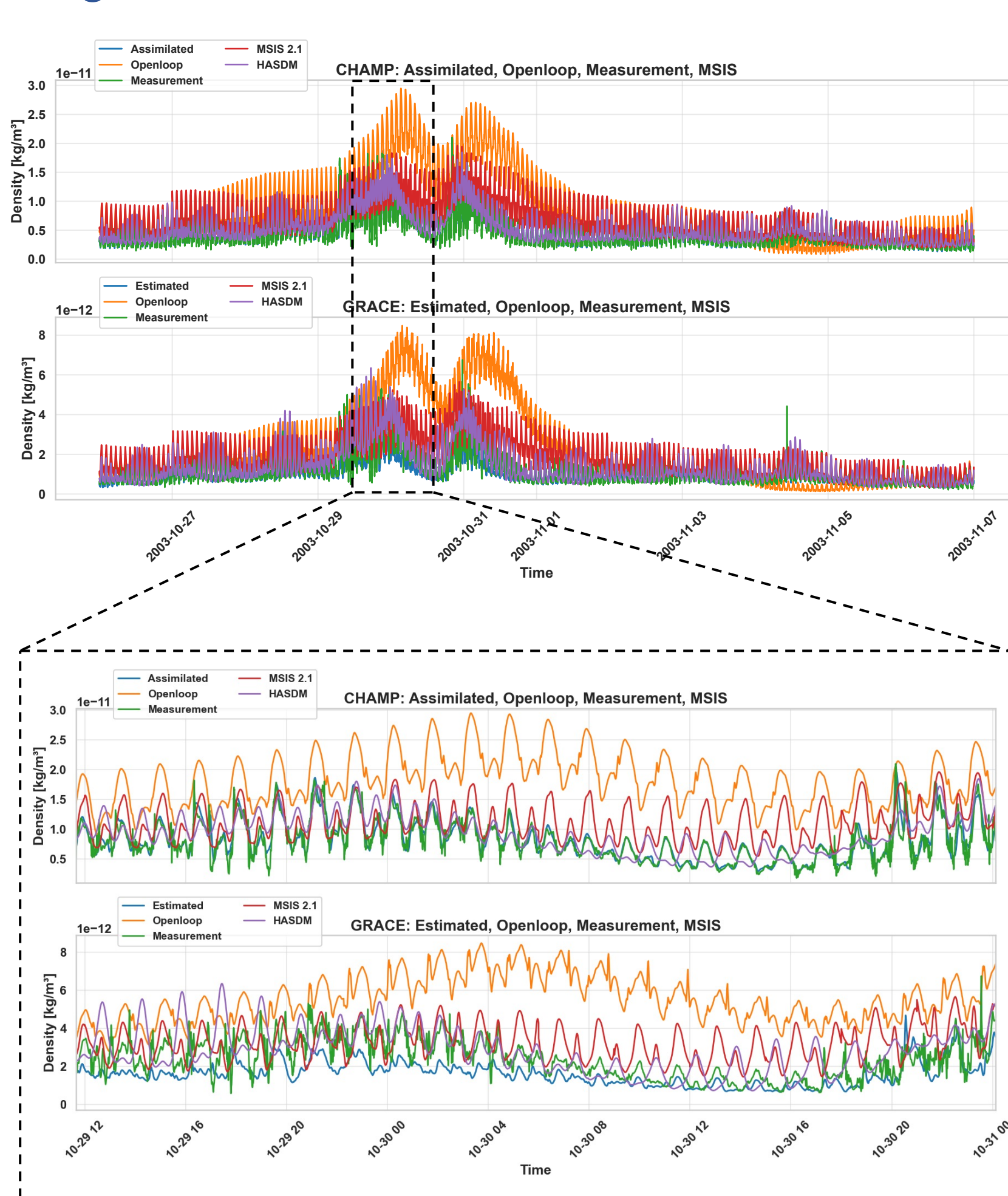
- Combines interpretable ROMs with multi-satellite density assimilation
- Validated across quiet and disturbed geomagnetic conditions
- Improved density estimates and released 2000–2025 assimilated dataset

## Assimilation Framework



## Applications

### Single-Satellite Assimilation: Halloween Storm



$$MAPE = \frac{100}{N} \sum_{k=1}^N \left| \frac{\hat{\rho}_k - \rho_k^{TIEGCM}}{\rho_k^{TIEGCM}} \right|$$

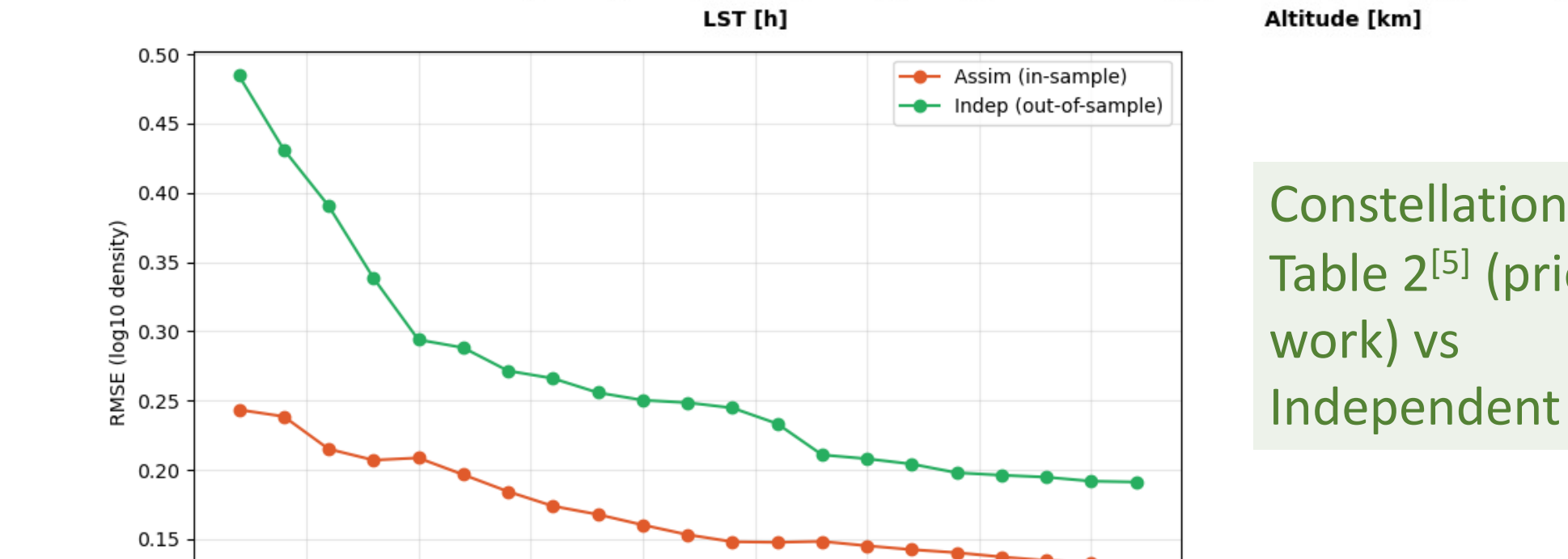
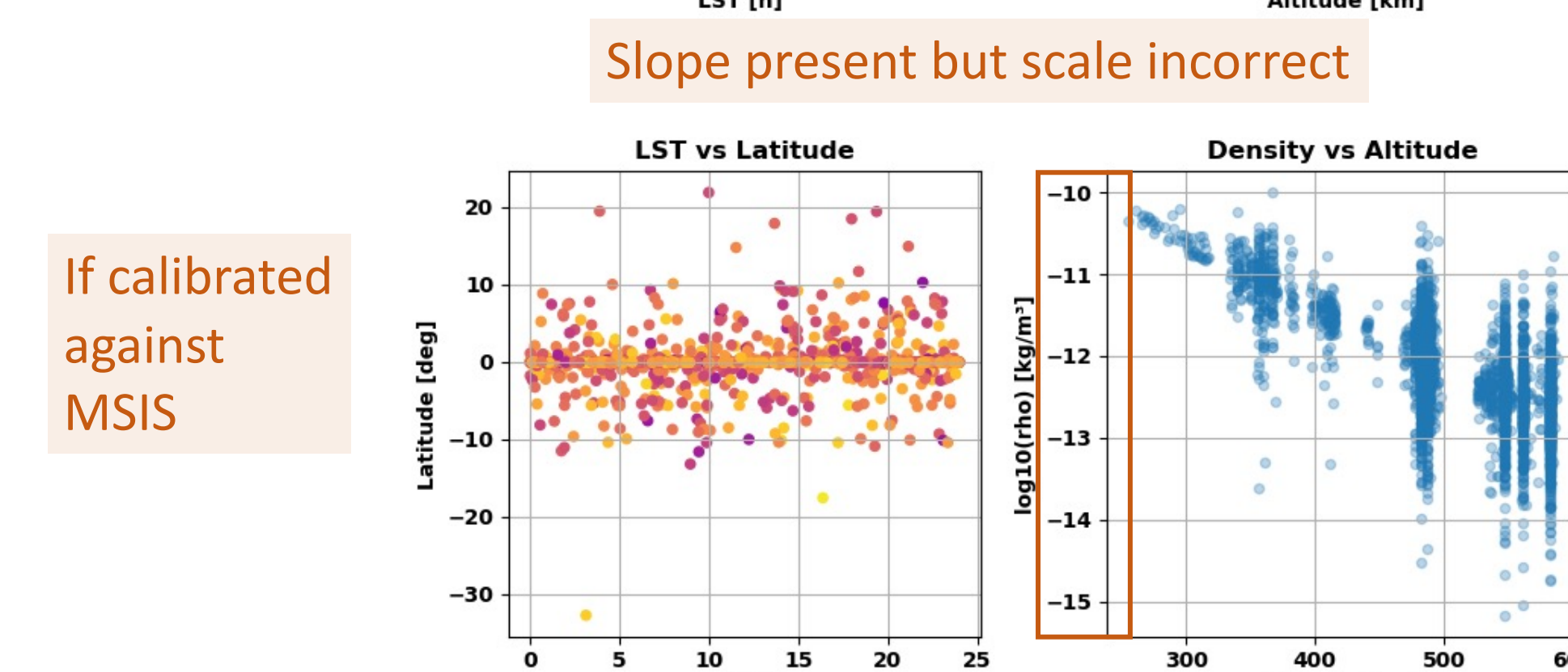
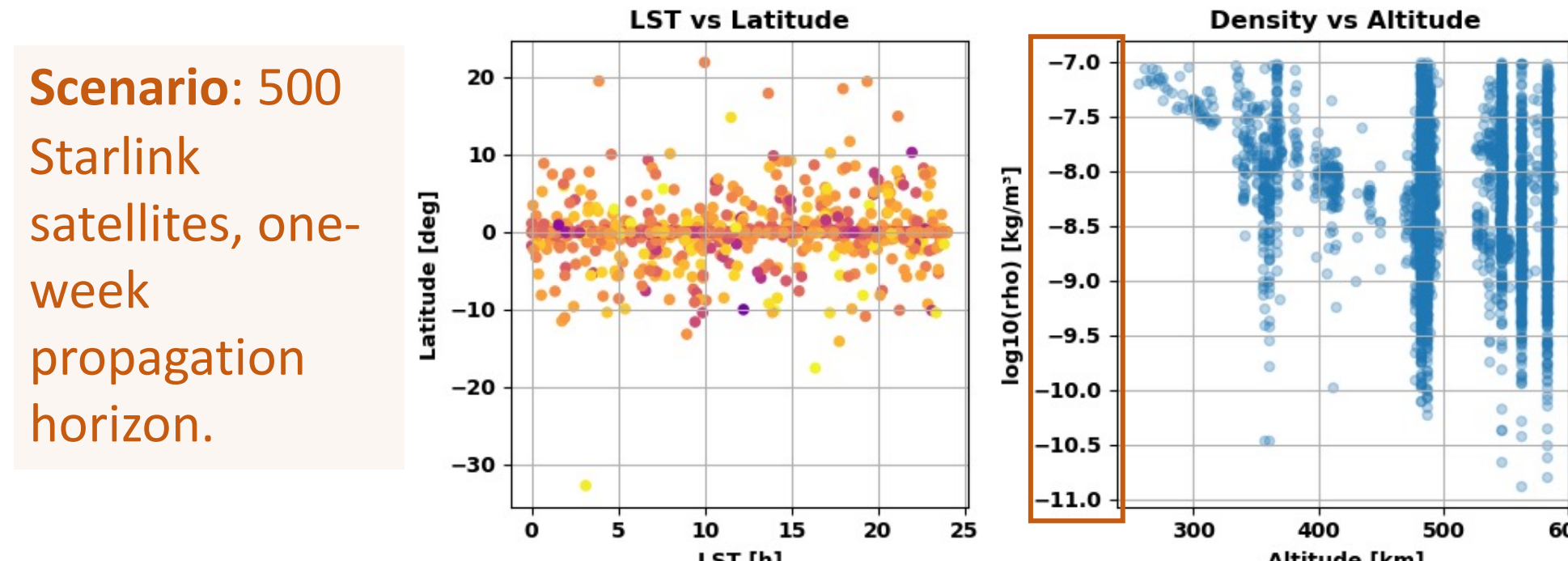
### Orbital Parameters for Measurement Satellites

Mission	Operational period	Alt. range (km)	Inc. (deg)	Ecc.	Period (min)
CHAMP	2000-07 – 2010-09	456 – 250	87.18	0.004	93.6
GRACE	2002-03 – 2017-10	500 – 330	89.00	0.0025	94.5
GRACE-FO	2018-05 – present	490 – 475	89.00	0.002	94.0
GOCE	2009-03 – 2013-11	255 – 224	96.70	0.001	88.4
Swarm-A	2013-11 – present	462 – 430	87.35	0.001	93.7
Swarm-B	2013-11 – present	511 – 505	87.75	0.001	94.9
Swarm-C	2013-11 – present	462 – 430	87.35	0.001	93.7

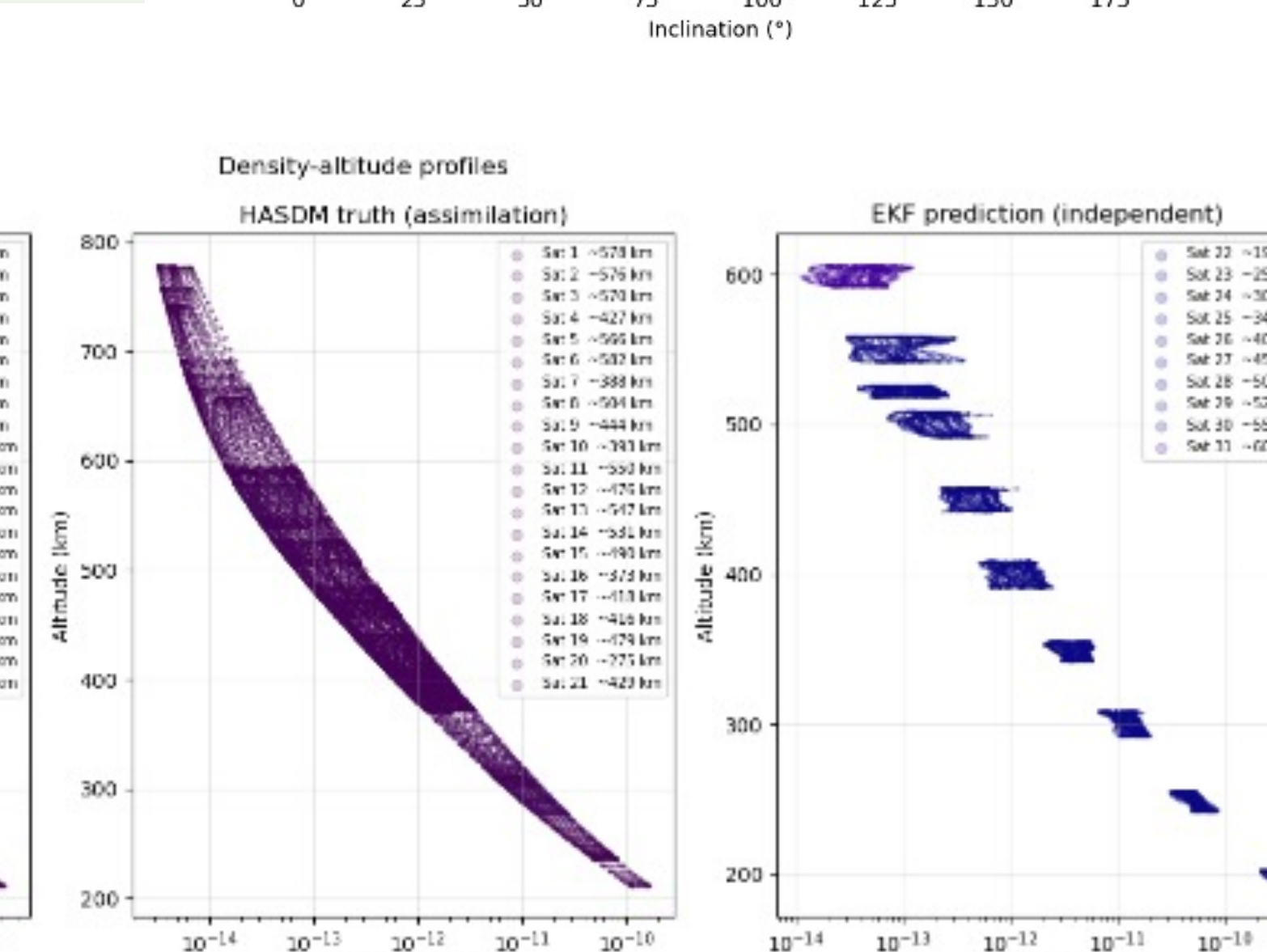
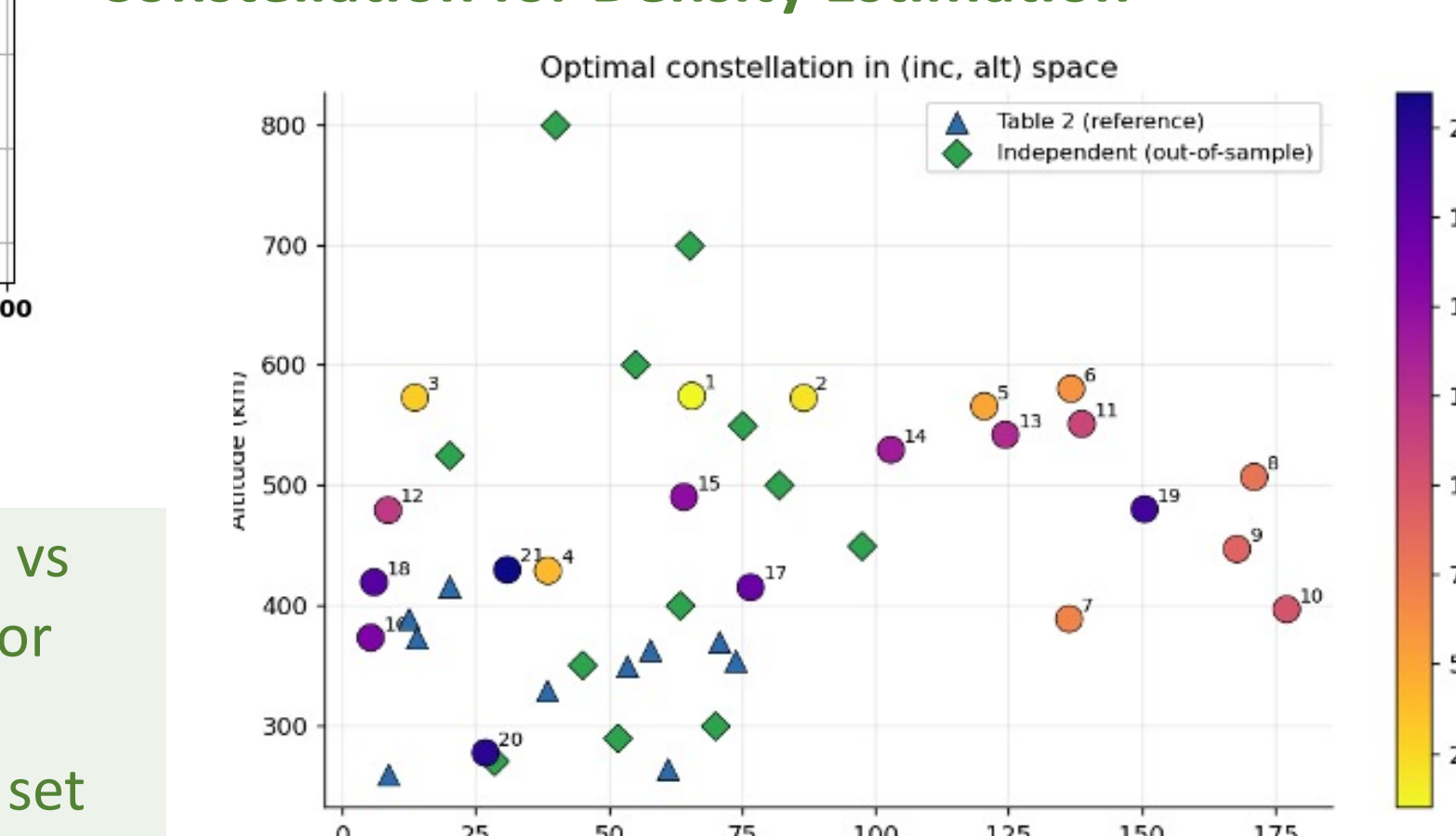
### All Assimilation Scenarios Considered

Scenario	Orbit	Role	SINDyc-AR	DMDc	Open-loop	MSIS	HASDM
<i>Single-satellite — 2003 Halloween storm</i>							
CHAMP to GRACE	CHAMP	A	9.24	6.07	85.92	49.00	36.74
	GRACE	V	22.08	40.09	98.80	58.72	51.78
<i>Single-satellite — 2024 geomagnetic storm</i>							
GRACE-FO to Swarm-C	GRACE-FO	A	8.73	12.44	94.79	58.46	—
	Swarm-C	V	51.65	43.71	94.04	57.37	—
<i>November 2009 — single-satellite baseline</i>							
CHAMP to GOCE	CHAMP	A	6.40	11.72	59.94	24.54	40.70
	GOCE	V	29.98	92.92	73.88	15.67	31.80
<i>November 2009 — dual-satellite</i>							
CHAMP + GRACE to GOCE	CHAMP	A	5.12	18.75	59.94	24.54	40.70
	GRACE	A	6.19	12.18	44.96	29.20	48.29
	GOCE	V	24.54	67.12	73.88	15.67	31.80
<i>November 2009 — multi-satellite (three satellites)</i>							
CHAMP + GRACE + GOCE	CHAMP	A	10.57	8.46	59.94	24.54	40.70
	GRACE	A	13.03	10.78	44.96	29.20	48.29
	GOCE	A	3.47	4.61	73.88	15.67	31.80

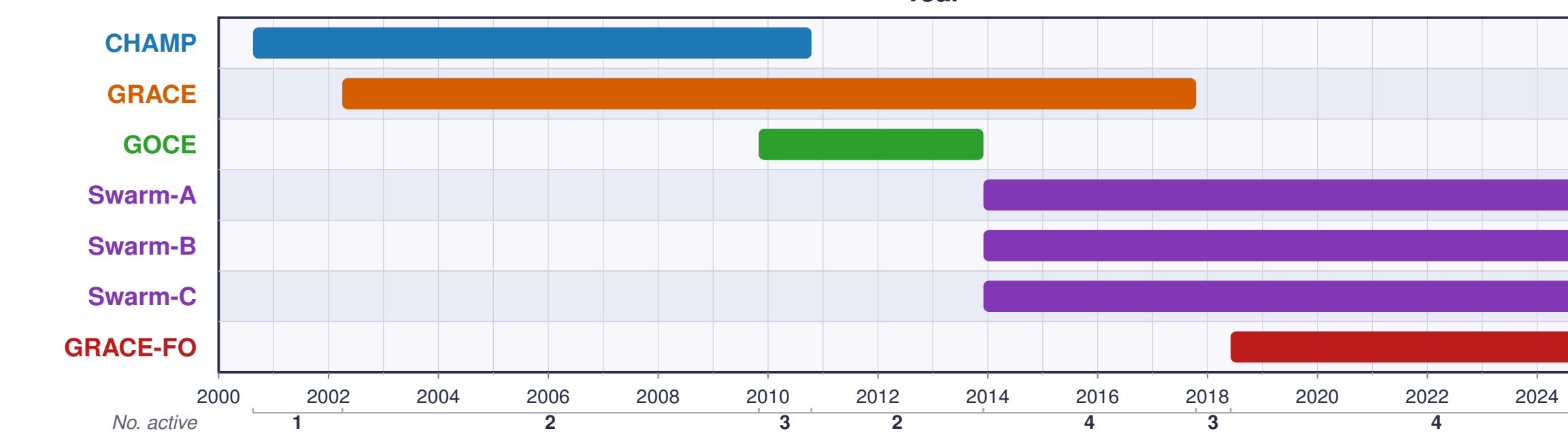
### TLEs as measurements: Density from Energy Dissipation Rate



### Constellation for Density Estimation



### Long-Term Assimilated Density Dataset



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