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Physics-Informed ML Framework for Thermosphere Density Prediction

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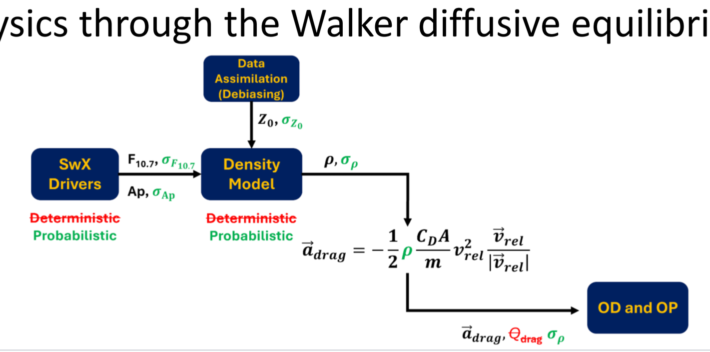
Introduction

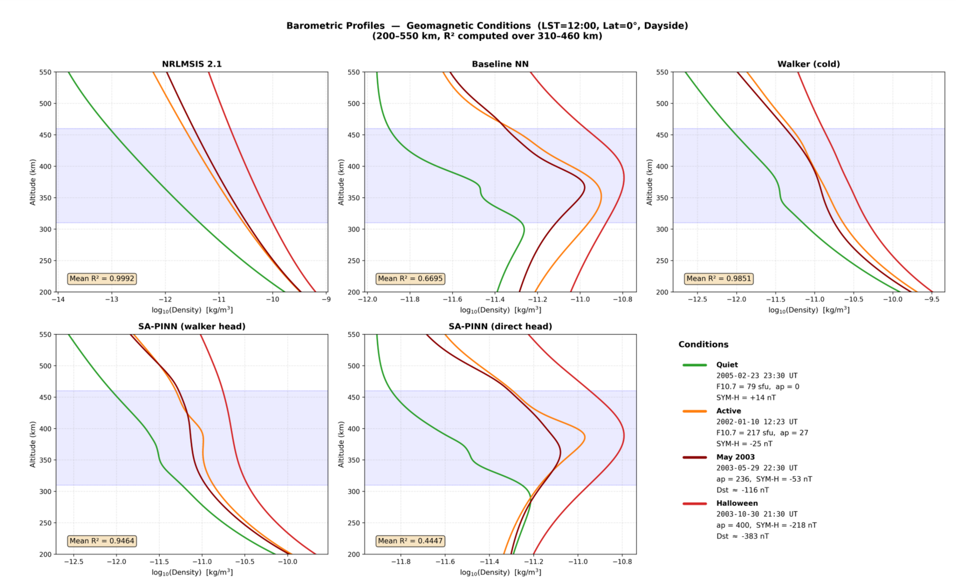
- Atmospheric drag driven by thermospheric density variations is a leading cause of satellite de-orbits, especially during geomagnetic storms
- Physics-based density models are computationally expensive and degrade when equilibrium assumptions break during storms.
- Physics-Informed Neural Networks (PINNs) embed governing equations into the training process, giving solutions that are both data-consistent and physically plausible
- Our approach enforces physics through the Walker diffusive equilibrium equation as an additional loss constraint



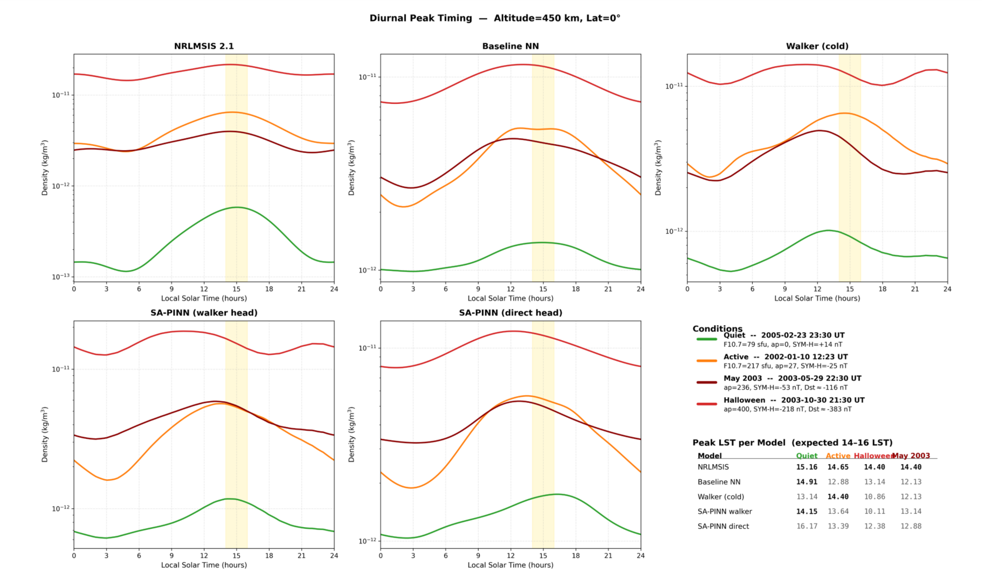
Motivation

- A model that fits data but violates physics has memorized, not learned
- Physics-informed hybrids offer improved generalization to unseen conditions, capture nonlinearities that degrade empirical models, and maintain low computational cost relative to first-principles solvers
- Our framework: two competing paths to density (data-driven and physics-constrained) balanced by a self-adaptive minimax game that discovers the optimal weighting automatically

Physics Compliance

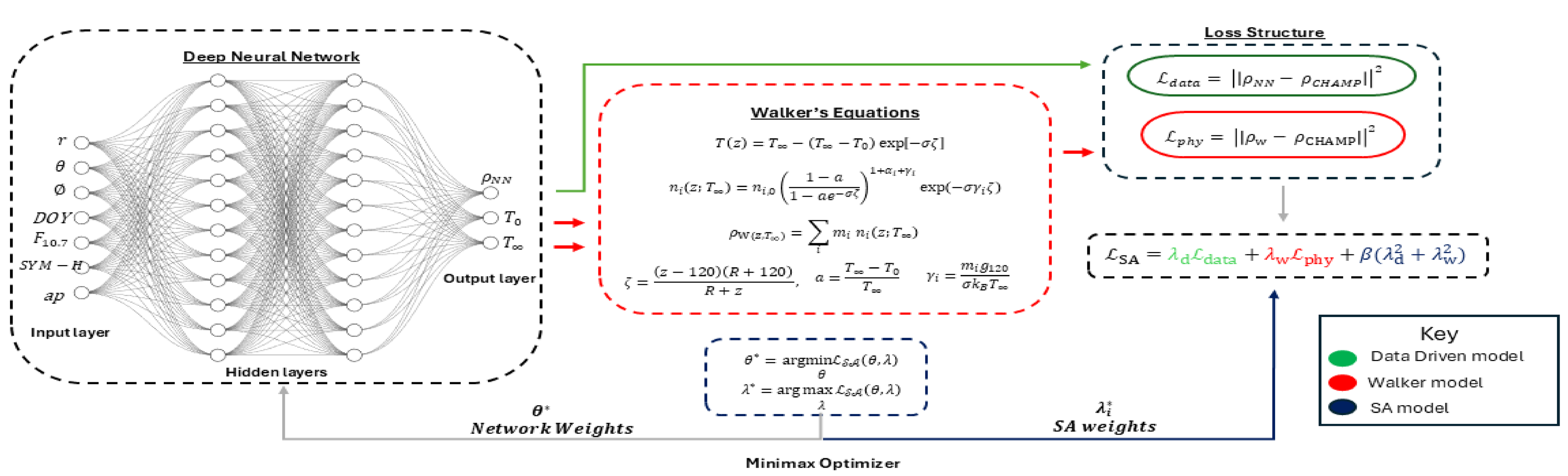


- Quiet conditions show the expected dayside bulge across all models. During Halloween, density increases by an order of magnitude with the physics-informed models capturing finer spatial structure than the baseline



- MSIS and Walker cold produce smooth exponential density decay across all conditions. Baseline and SA-PINN direct head show weakened altitude structure outside the training range

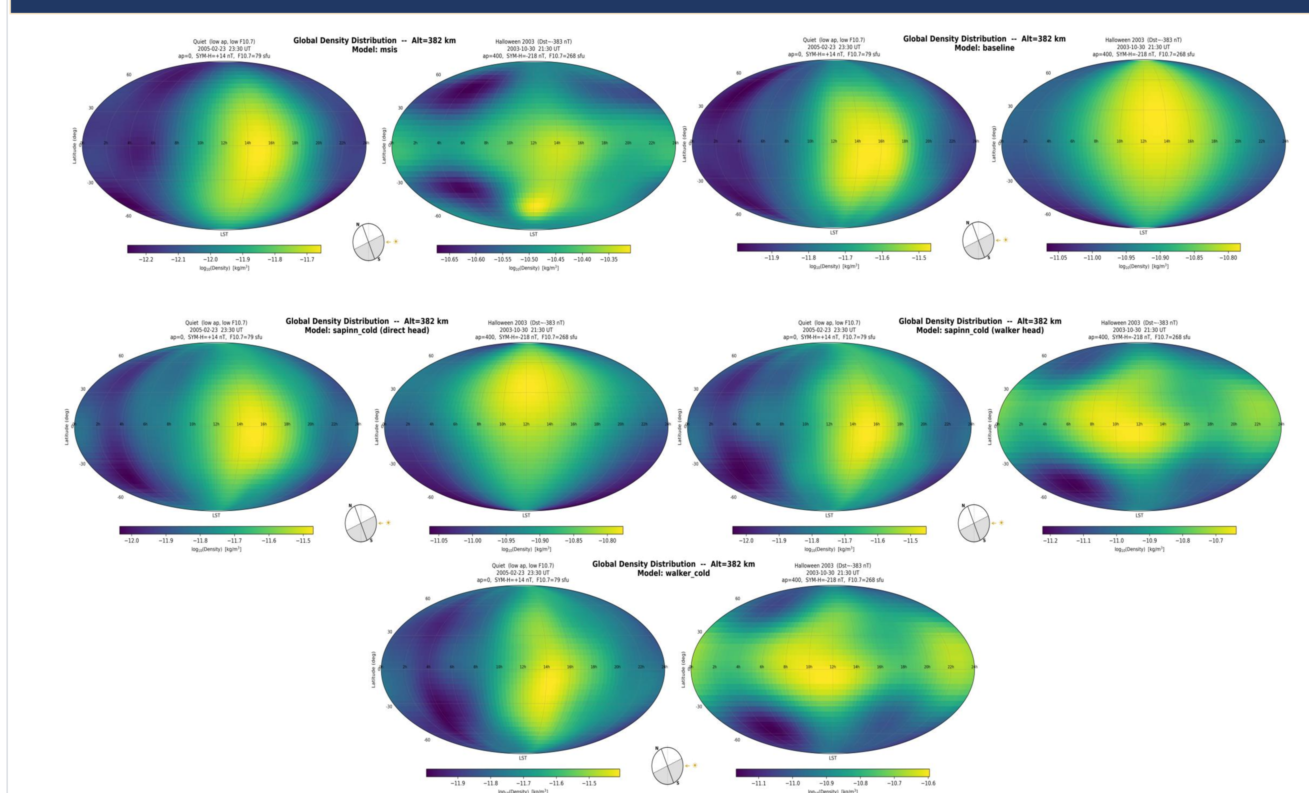
Model Frameworks



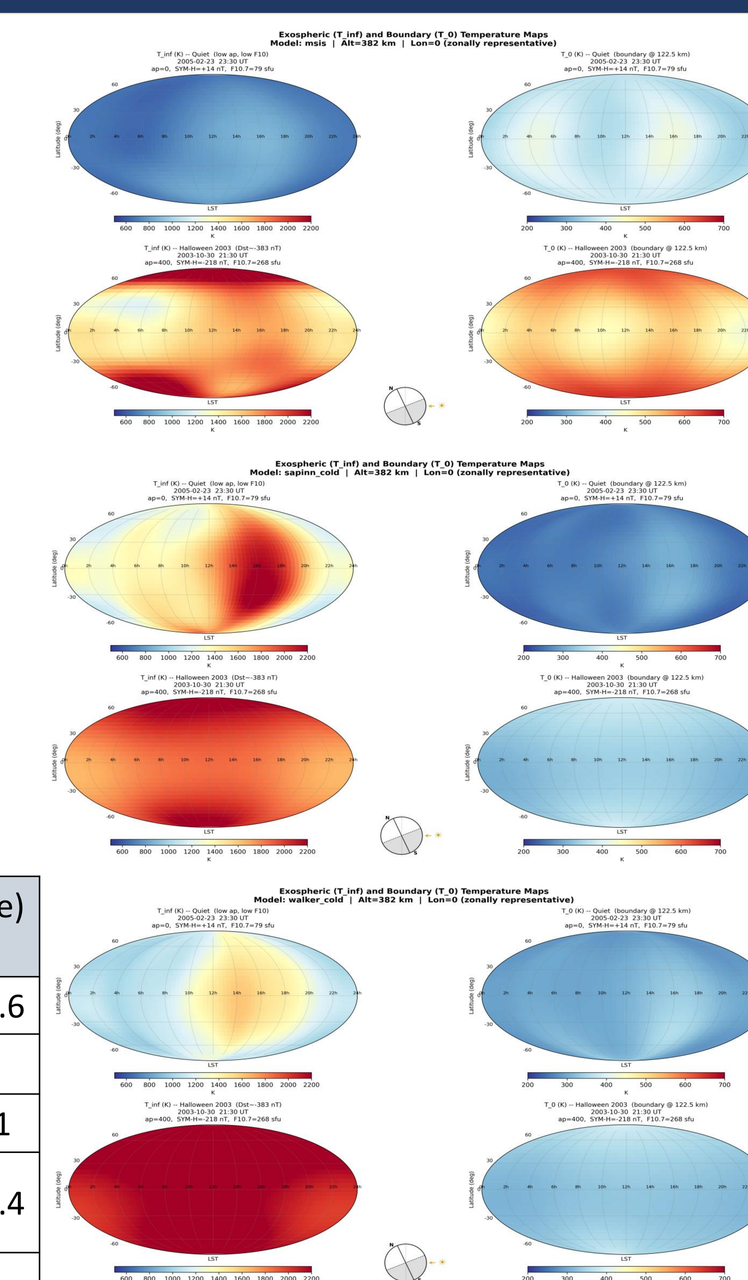
- Baseline: direct density prediction from network output, trained on CHAMP observations only
- Walker: network predicts exospheric temperature T_∞ and boundary temperature T_0, which feed into the Walker diffusive equilibrium equations to compute neutral density
- SA-PINN (green + red + blue): both heads active simultaneously. A self-adaptive minimax optimizer learns weights that balance both losses, At equilibrium, the harder constraint receives a higher weight automatically
- All physics-informed models discover their own temperature profiles without supervision

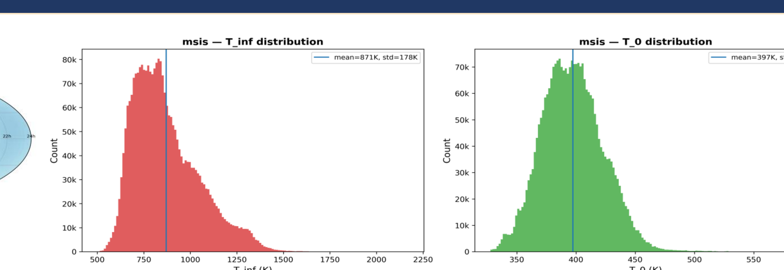
Feature class	Description	Parameters
Spatial	Orbital Position	
Temporal	Seasonal encodings	DOY
Geomagnetic	Storm indices + history	ap, symh,symh-lags
Solar	EUV proxy	F10.7

Results

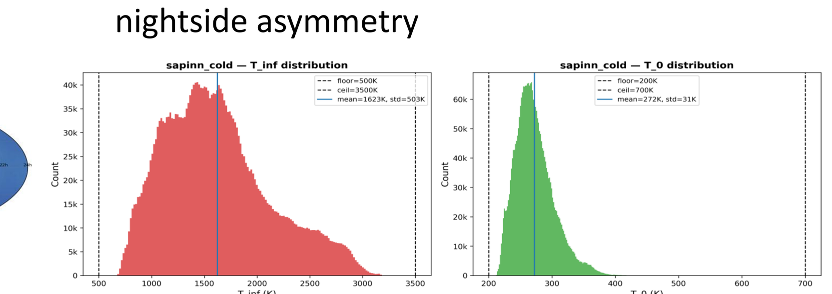


Model	R^2	MAPE (%)	$T_\infty(\mu/\sigma)$ K	T_∞(range) K	$T_0(\mu/\sigma)$ K	T_0 (range) K
MSIS	0.7920	22.46	875/172	1762-518	398.3/25.42	530-328.6
Baseline	0.8589	17.06	-	-	-	-
Walker-cold	0.8540	17.02	1137/407	3077 - 546	332/23.65	438-211
SA-PIINN(walker)	0.8707	16.60	1622/503	3233-674	272.4/30.62	449-211.4
SA-PINN(direct)	0.8704	16.68	-	-	-	-

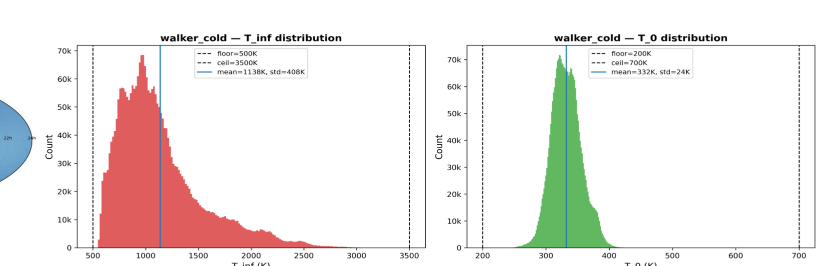




- Shows expected polar heating signatures from auroral energy deposition, with dayside-nightside asymmetry

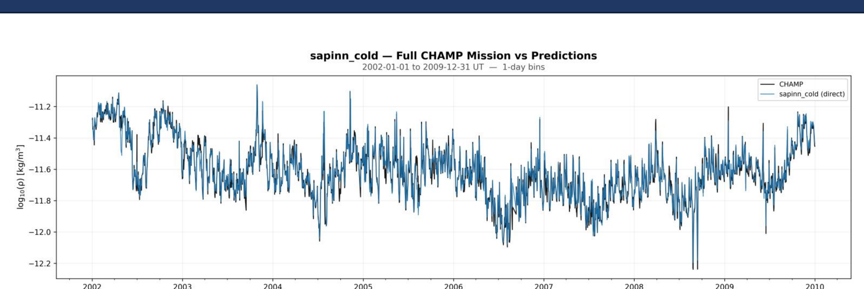


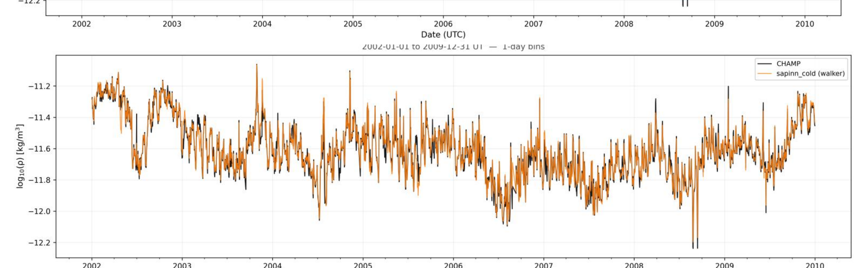
- Discovers higher T_∞ and lower T_0 than MSIS, wider T_∞ spread reflects greater sensitivity to geomagnetic variability across conditions.

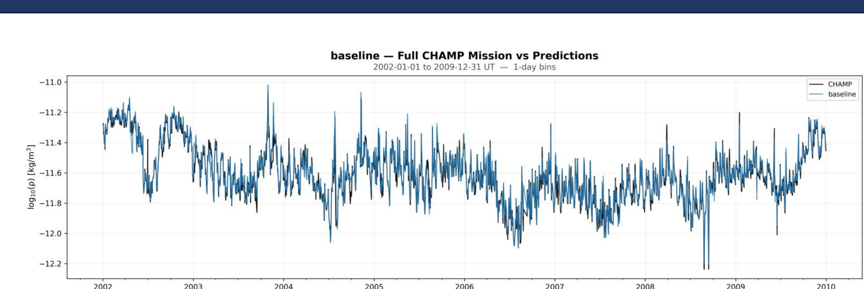


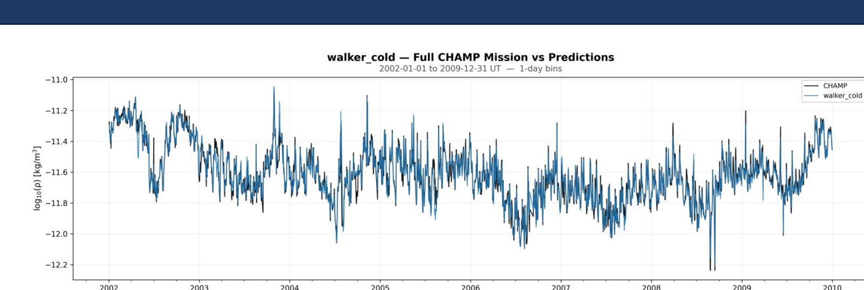
- The dual-head architecture allows the Walker chain to explore a wider temperature manifold than Walker cold being less constrained since direct head shares fitting burden.
- Temperature distributions are computed on the full test set (~2.5M samples). Each variant discovers its own (T_∞ , T_0) manifold

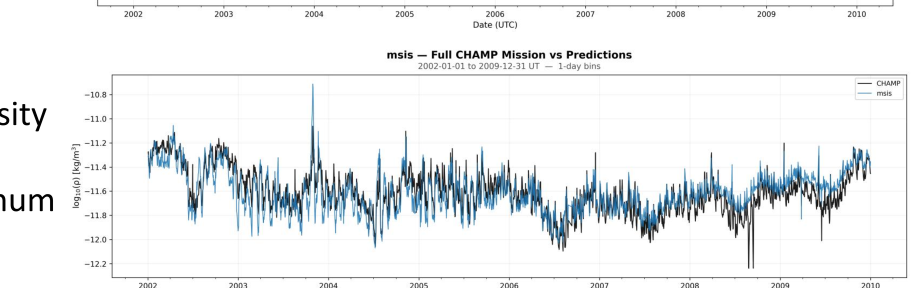
Timeseries predictions











- All neural network models track the solar cycle decline and storm-time density spikes. MSIS shows systematic bias during high solar activity.
- The SA-PINN walker head shows slightly higher variance during solar minimum but maintains tracking throughout

Conclusion and Future Work

- We presented a self-adaptive physics-informed neural network (SA-PINN) for thermosphere density prediction that combines a data-driven head with a physics-constrained head through a minimax optimization framework
- The SA mechanism automatically discovers the optimal balance between data fit and physics compliance; the Walker constraint received a higher weight, beating baselines and MSIS
- Improvements would be integration of continuity and momentum equations from first-principles models (e.g. TIEGCM) as additional physics constraints for a more complete representation of the thermosphere

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