Physics-informed Machine Learning for Probabilistic Space Weather Modeling and Forecasting: Thermosphere and Satellite Drag

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Introduction

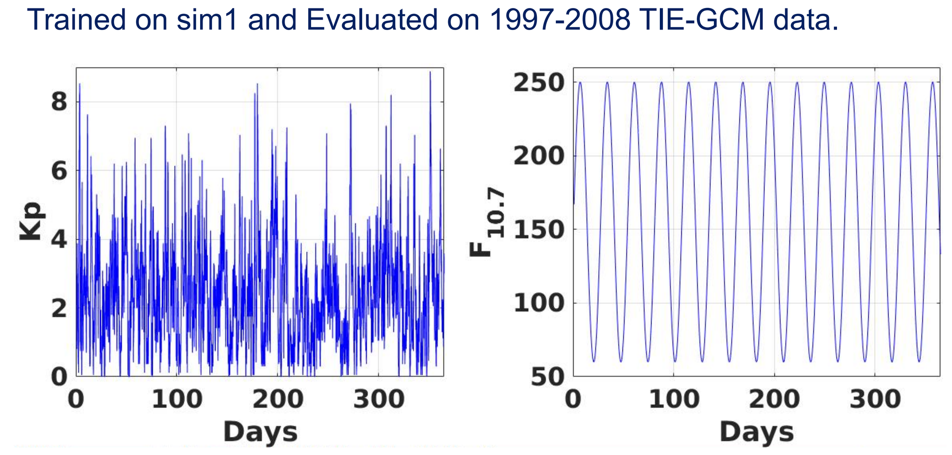
- In low Earth orbit (LEO), atmospheric drag is the largest source of uncertainty in orbit prediction and determination stemming from inaccurate thermosphere models.
- Robust decision making in the context of Space Situational Awareness (SSA) and Space Traffic Management (STM) requires accurate forecasting of mass density and the associated uncertainties.
- Empirical models are fast to evaluate but can be inaccurate and have limited forecasting capabilities.
- Physical models are expected to be more accurate but are limited by their computational cost.
- **Goal**: **Develop a Physics-based, Data-Driven Framework for Modeling and Forecasting Space Weather and Quantification of the Associated Uncertainties.**

Methodology

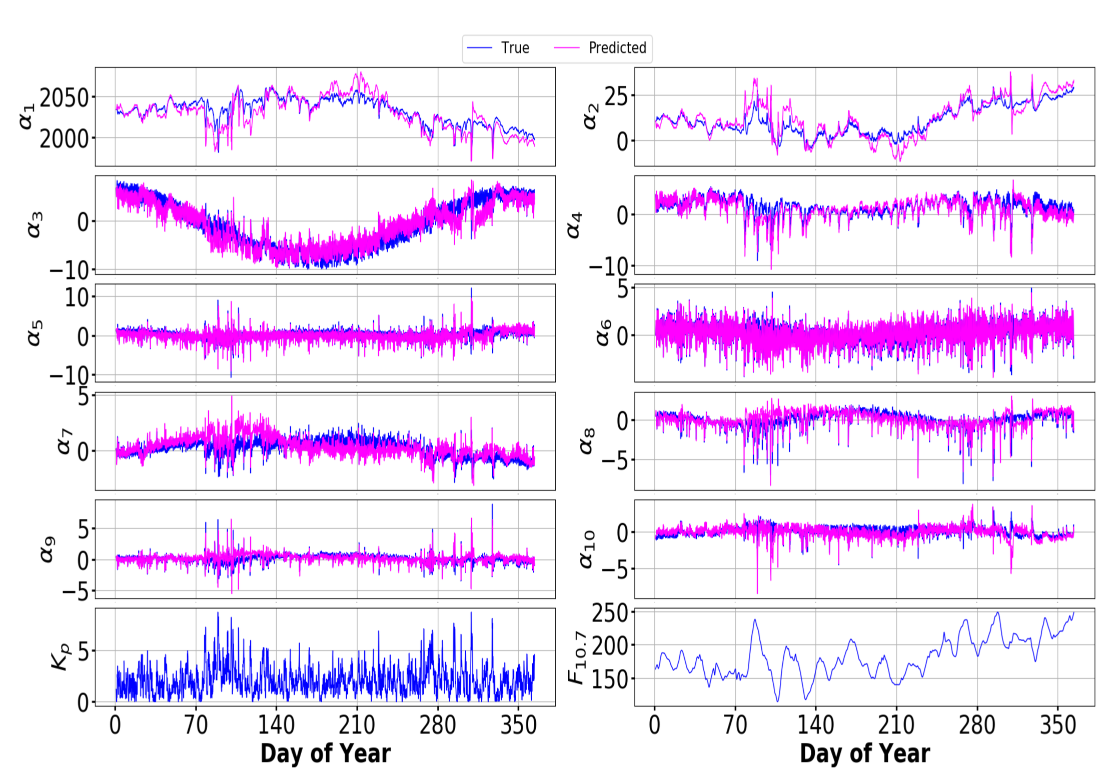
- Dimensionality reduction through Principal Component Analysis (PCA).
- Capturing temporal dynamics using Long-Short Term Memory (LSTM) networks. Identify optimal architecture.
- Characterize and quantify prediction uncertainty the develop Bayesian Emulator.
- *Case Study*: Investigate the impact of input uncertainty on mass density and satellite orbits.

Dataset and Hyperparameter Optimization

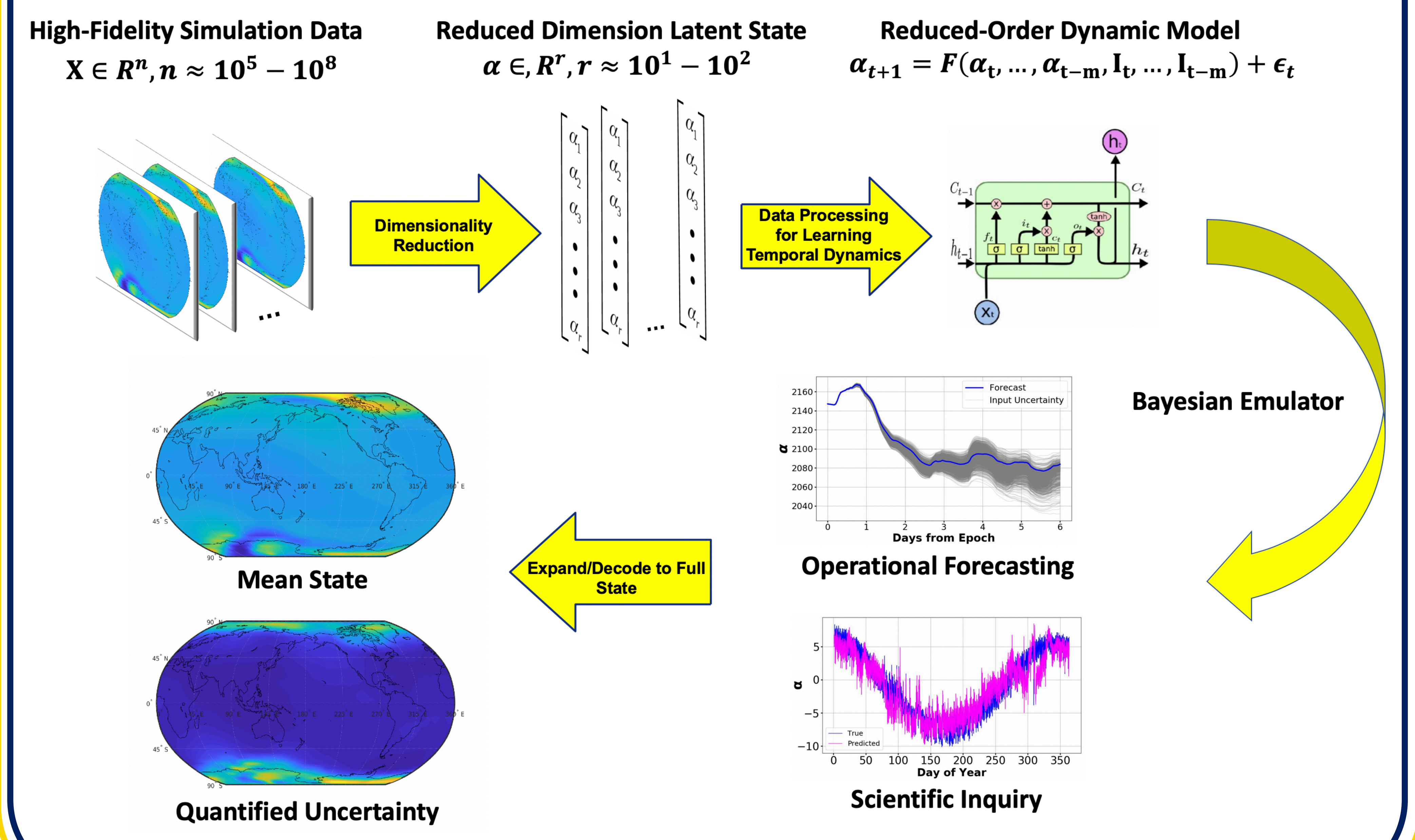
- Sim1 is a density dataset derived from TIE-GCM by Mehta et. al. [1] using simulating inputs to cover a large range of solar and geomagnetic drivers in one year.
- PCA was used to isolate the spatial and temporal variations, reducing the state to size $r = 10$.
  - Trained on sim1 and Evaluated on 1997-2008 TIE-GCM data.



- Given only the initial state and the year-long inputs, it is able to model the coefficients with accuracy as high as 11% (2001) and as low as 23% (2008).



Physics-Informed Machine Learning

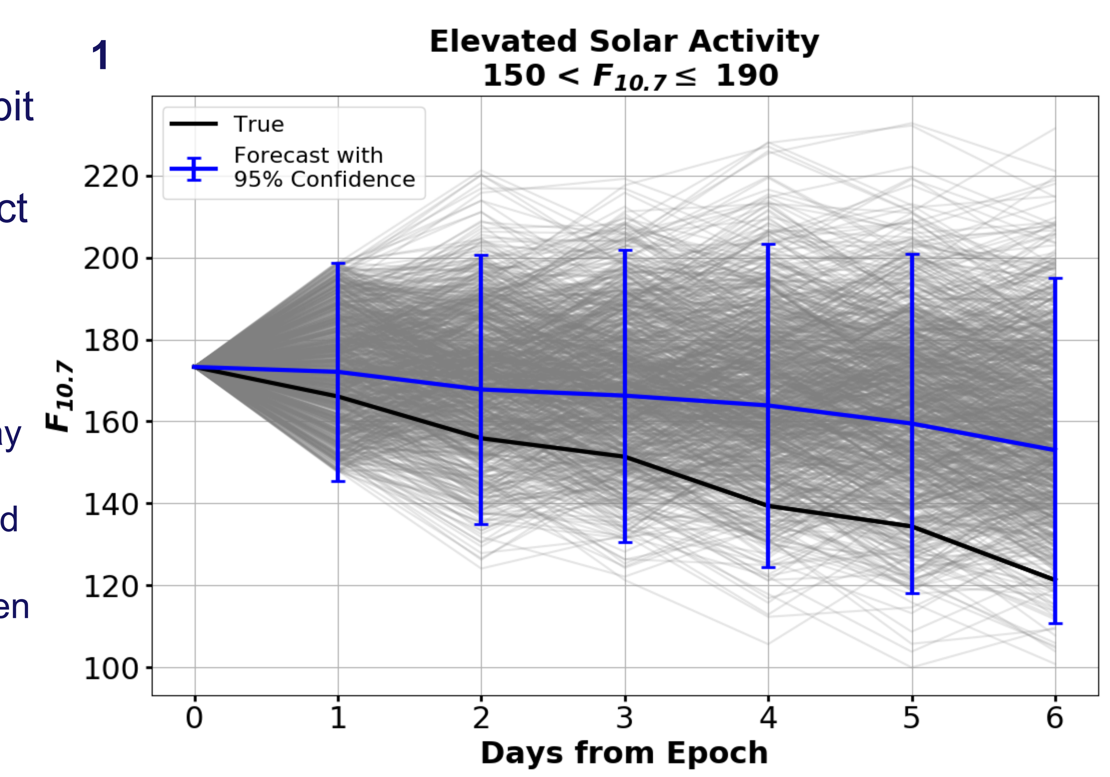


Case Study

- Used the International Space Station's orbit as a case study to assess the effect of uncertain inputs on its position with respect to time.

1. Monte Carlo sampling of the distribution (generated based on six years of historical input data obtained from Space Environment Technologies) for variations in $F_{10.7}$ over a six-day period.
2. Evaluated LSTM on every input sample and used resulting density arrays to propagate orbits. The spatial and nonlinear dynamic effects can be seen in the density variations.
3. Quantified effect of input uncertainty on position six days from epoch. The deterministic in-track prediction has an error of ~7 km with respect to the true position (zero difference). The absence of input uncertainty quantification would result in large errors for operational collision probabilities.

1



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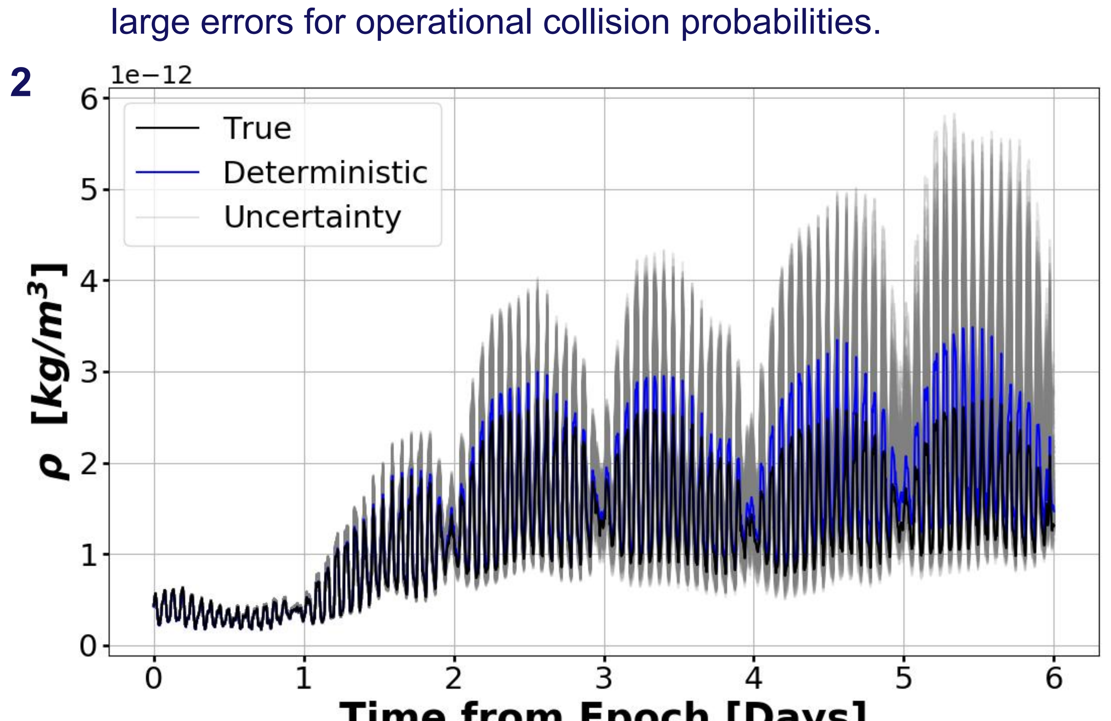

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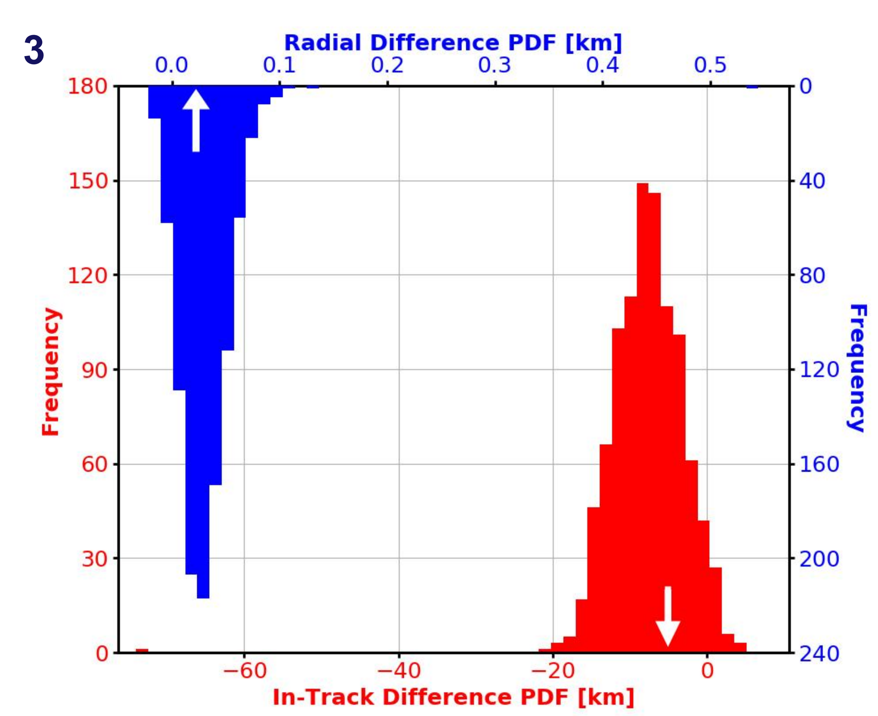
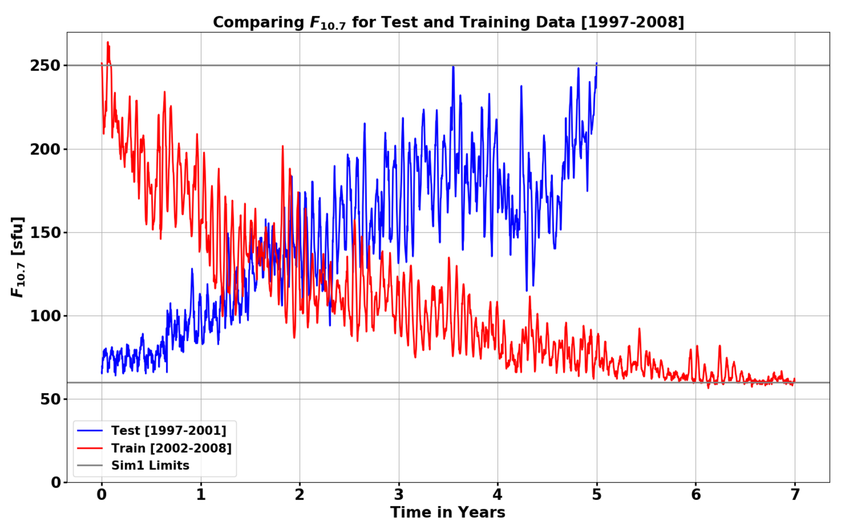


Dataset over a Solar Cycle

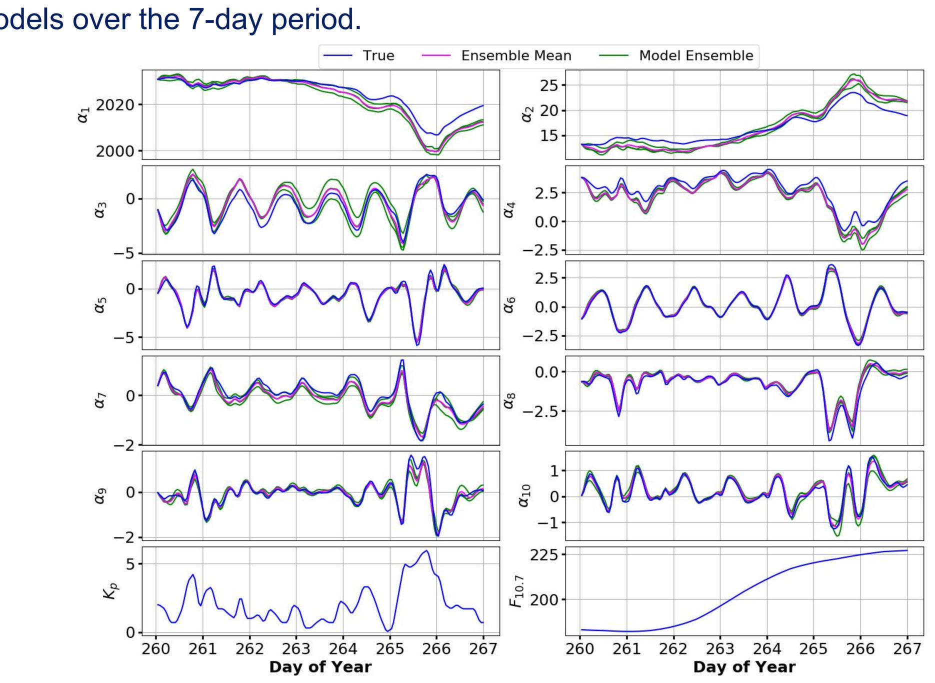
- A seven-year portion during solar cycle 23 was identified that covered the full range of solar radio flux



- The larger dataset results in improved performance with respect to models trained on Sim1 data.

Ensemble Prediction

- Using model ensembles (equally weighted average) improved prediction performance
  - RMSE of just under 3% for ensemble mean as opposed to under 4% for the three individual models over the 7-day period.



Conclusions and Future Work

- LSTMs show great promise for predicting temporal mass density variations as a function of space weather.
- Models trained on Sim1 data portray capability of short and long-term predictions making them useful for operations and science.
- Further research is required to improve performance during abrupt changes in geomagnetic activity.
- Nonlinear dimensionality reduction will also be the focus of future work.

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