Data-Driven HASDM Density Model using Machine Learning

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Abstract

Space traffic management is difficult. Monitoring and predicting the accurate, real-time position of satellites for collision avoidance in low earth orbit is an engineering challenge. The dominant source of error in satellite prediction tracking models is in the determination of space weather driven atmospheric drag. The High Accuracy Satellite Drag Model (HASDM) (Storz et al., 2005) was developed by the U.S. Air Force Space Command (AFSPC) between 2000–2005 to help solve this problem. It is a data assimilative modeling system using the JB2008 thermospheric density model (Bowman et al., 2008) plus continuously derived densities from several dozens of calibration satellites to achieve <5% density uncertainty at most epochs. The HASDM data is being made available to the community of scientists and operators for the first time. Under authority from the AFSPC, Space Environment Technologies (SET) has extracted two solar cycles of operational High Accuracy Satellite Drag Model (HASDM) data for scientific use and this is called the SET HASDM database. Navigating and extracting information from this database quickly and efficiently to manage satellite space traffic is currently complex and tedious. We present the development of a data-driven model for the HASDM mass density using Machine Learning and an attempt to quantify the associated uncertainties.

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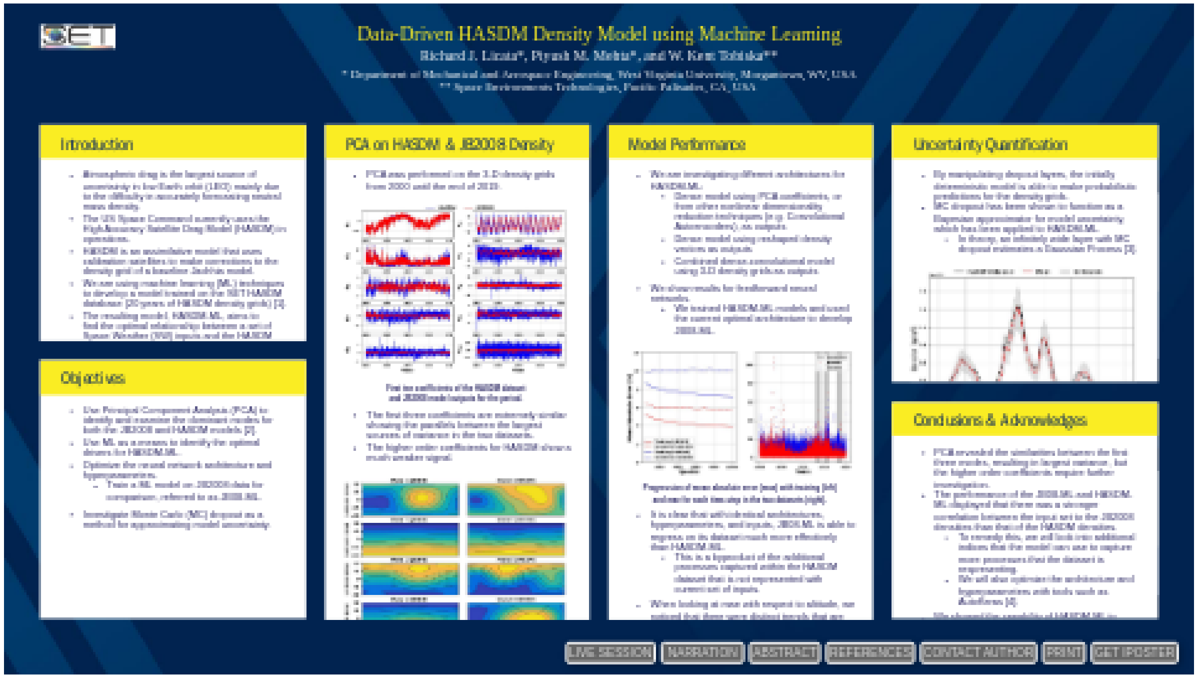

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INTRODUCTION

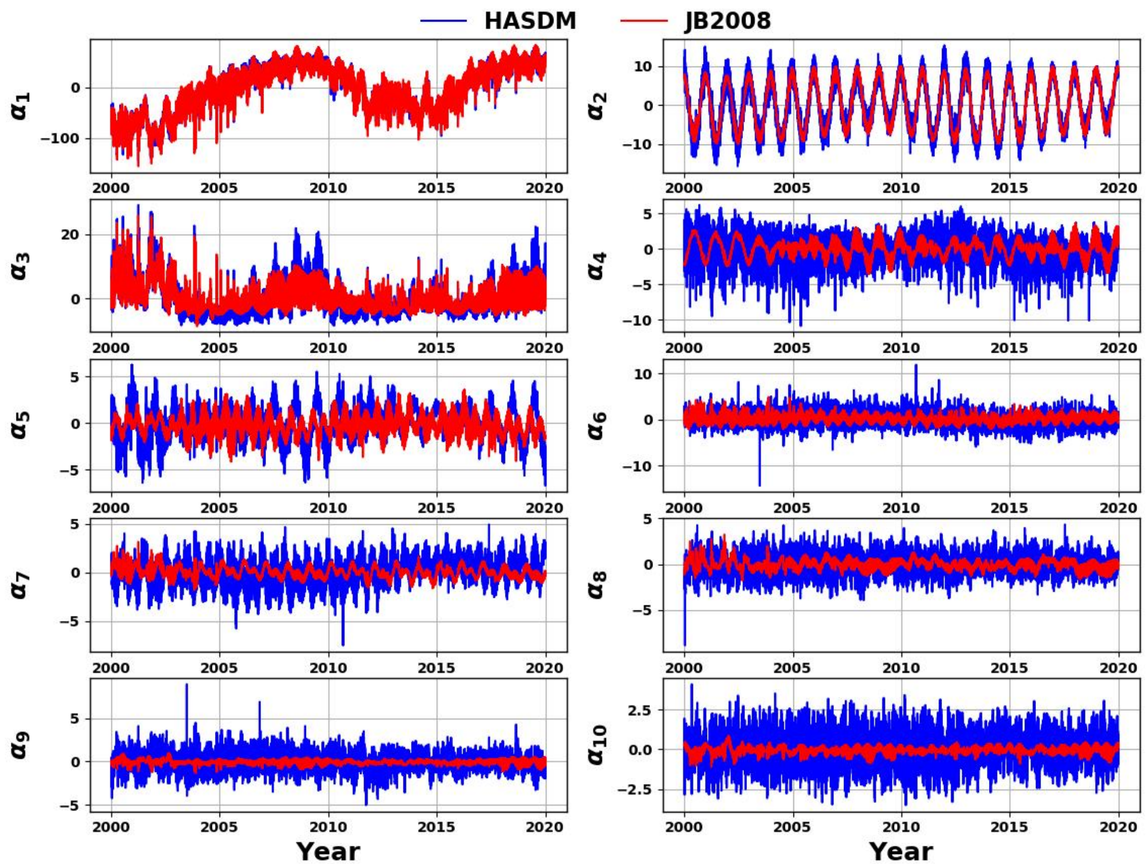
- Atmospheric drag is the largest source of uncertainty in low Earth orbit (LEO) mainly due to the difficulty in accurately forecasting neutral mass density.
- The US Space Command currently uses the High Accuracy Satellite Drag Model (HASDM) in operations.
- HASDM is an assimilative model that uses calibration satellites to make corrections to the density grid of a baseline Jachhia model.
- We are using machine learning (ML) techniques to develop a model trained on the SET HASDM database (20 years of HASDM density grids) [1].
- The resulting model, HASDM-ML, aims to find the optimal relationship between a set of Space Weather (SW) inputs and the HASDM density grid.

OBJECTIVES

- Use Principal Component Analysis (PCA) to identify and examine the dominant modes for both the JB2008 and HASDM models [2].
- Use ML as a means to identify the optimal drivers for HASDM-ML.
- Optimize the neural network architecture and hyperparameters.
  - Train a ML model on JB2008 data for comparison, referred to as JB08-ML.
- Investigate Monte Carlo (MC) dropout as a method for approximating model uncertainty.

PCA ON HASDM & JB2008 DENSITY

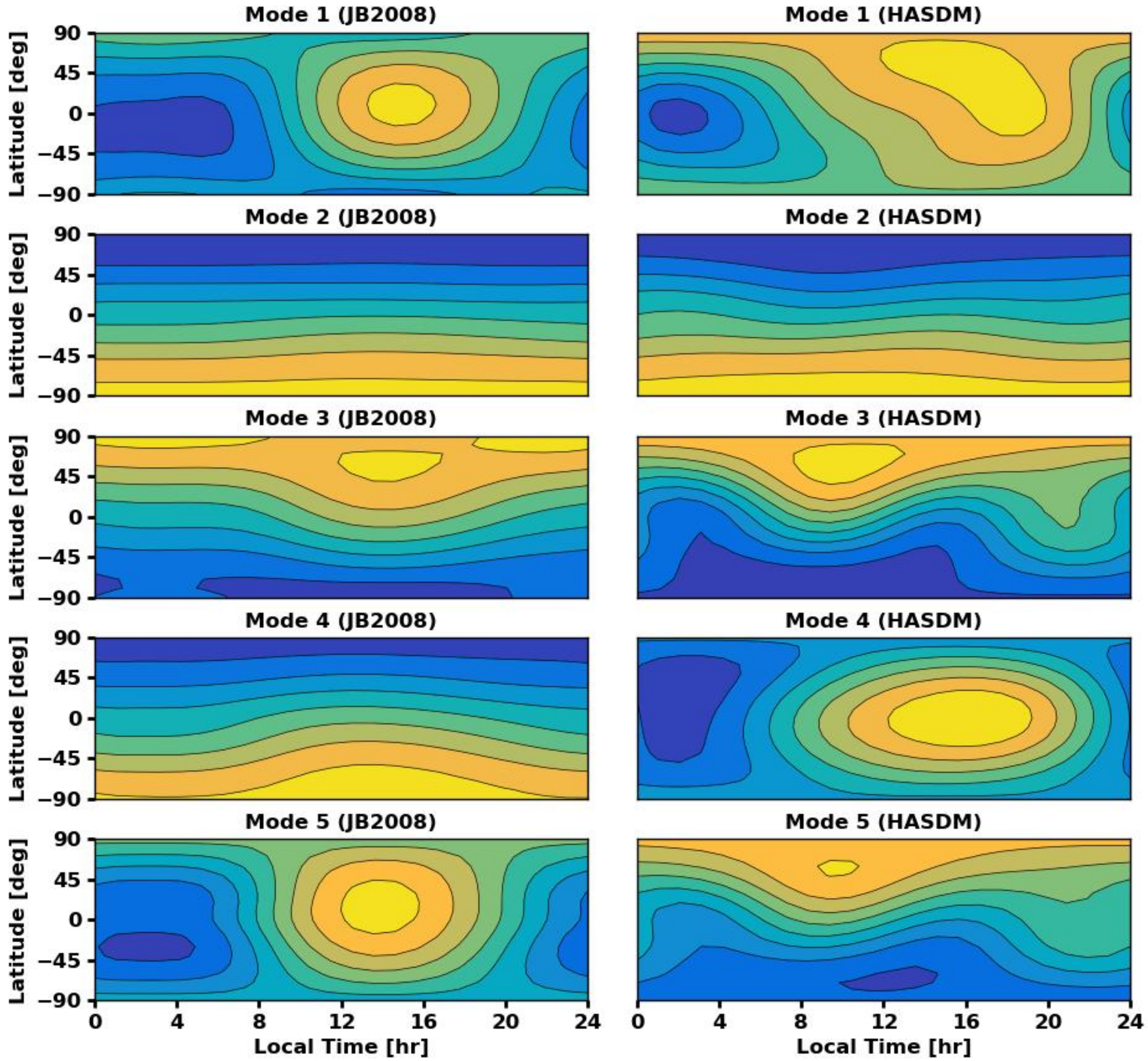
- PCA was performed on the 3-D density grids from 2000 until the end of 2019.



First ten coefficients of the HASDM dataset

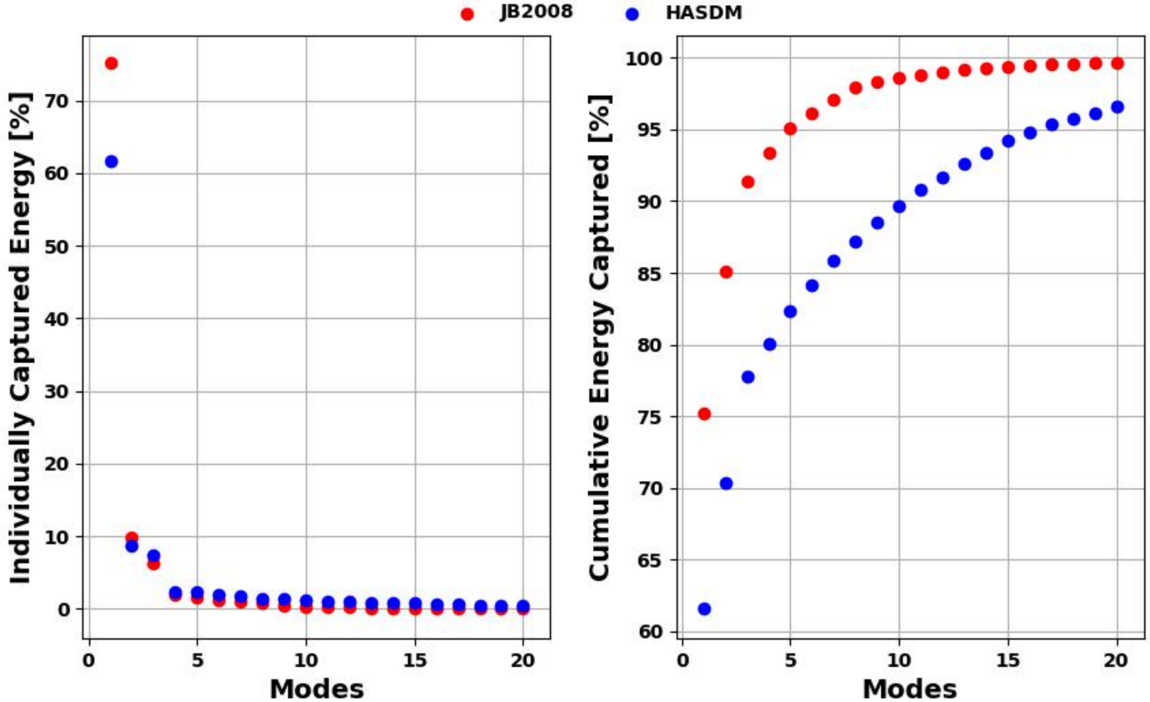
and JB2008 model outputs for the period.

- The first three coefficients are extremely similar showing the parallels between the largest sources of variance in the two datasets.
- The higher order coefficients for HASDM show a much weaker signal.



First five most energetic modes for JB2008 (left) and HASDM (right).

- These similarities are also prevalent in the contours of the first five modes.

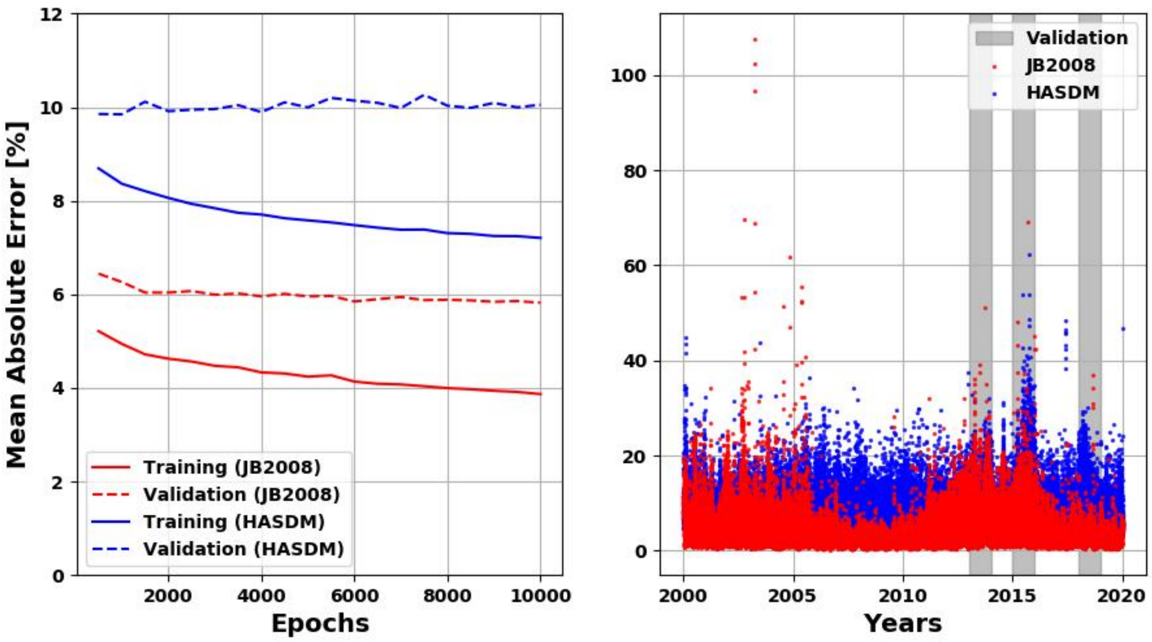


Individual (left) and cumulative (right) energy captured by the first 20 PCA modes for the two density datasets.

- The first mode for JB2008 captures significantly more energy than that of HASDM.
  - For clarification, energy refers to the variance corresponing to the eigenvalues, not physical energy.
- The first ten JB2008 modes capture ~98% of the system's energy while the first ten for HASDM only capture ~90%.

MODEL PERFORMANCE

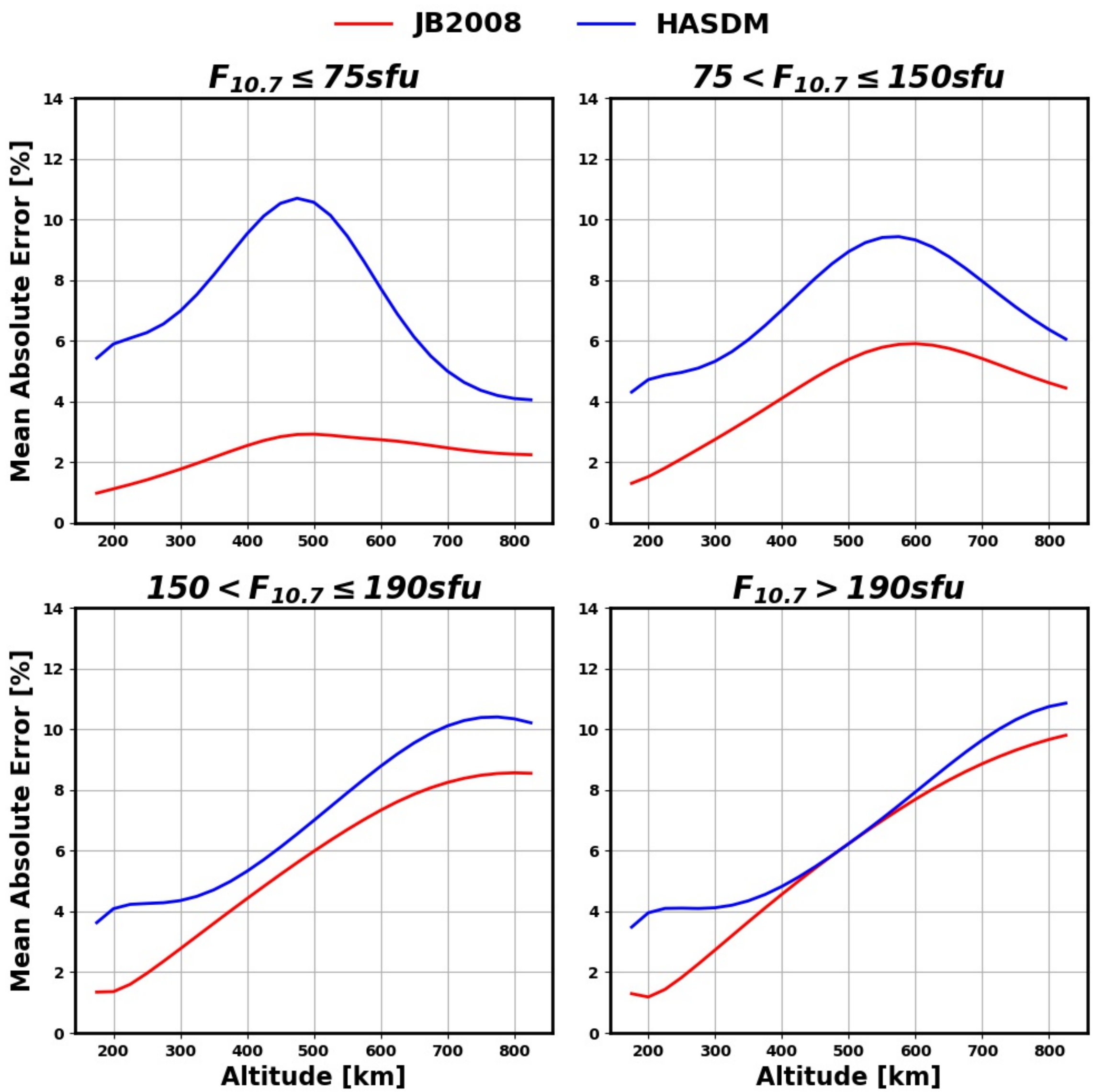
- We are investigating different architectures for HASDM-ML:
  - Dense model using PCA coefficients, or from other nonlinear dimensionality reduction techniques (e.g. Convolutional Autoencoders), as outputs
  - Dense model using reshaped density vectors as outputs
  - Combined dense-convolutional model using 3-D density grids as outputs
- We show results for feedforward neural networks.
  - We trained HASDM-ML models and used the current optimal architecture to develop JB08-ML.



Progression of mean absolute error (mae) with training (left)

and mae for each time-step in the two datasets (right).

- It is clear that with identical architectures, hyperparameters, and inputs, JB08-ML is able to regress on its dataset much more effectively than HASDM-ML.
  - This is a byproduct of the additional processes captured within the HASDM dataset that is not represented with current set of inputs.
- When looking at mae with respect to altitude, we noticed that there were distinct trends that are common between the models.

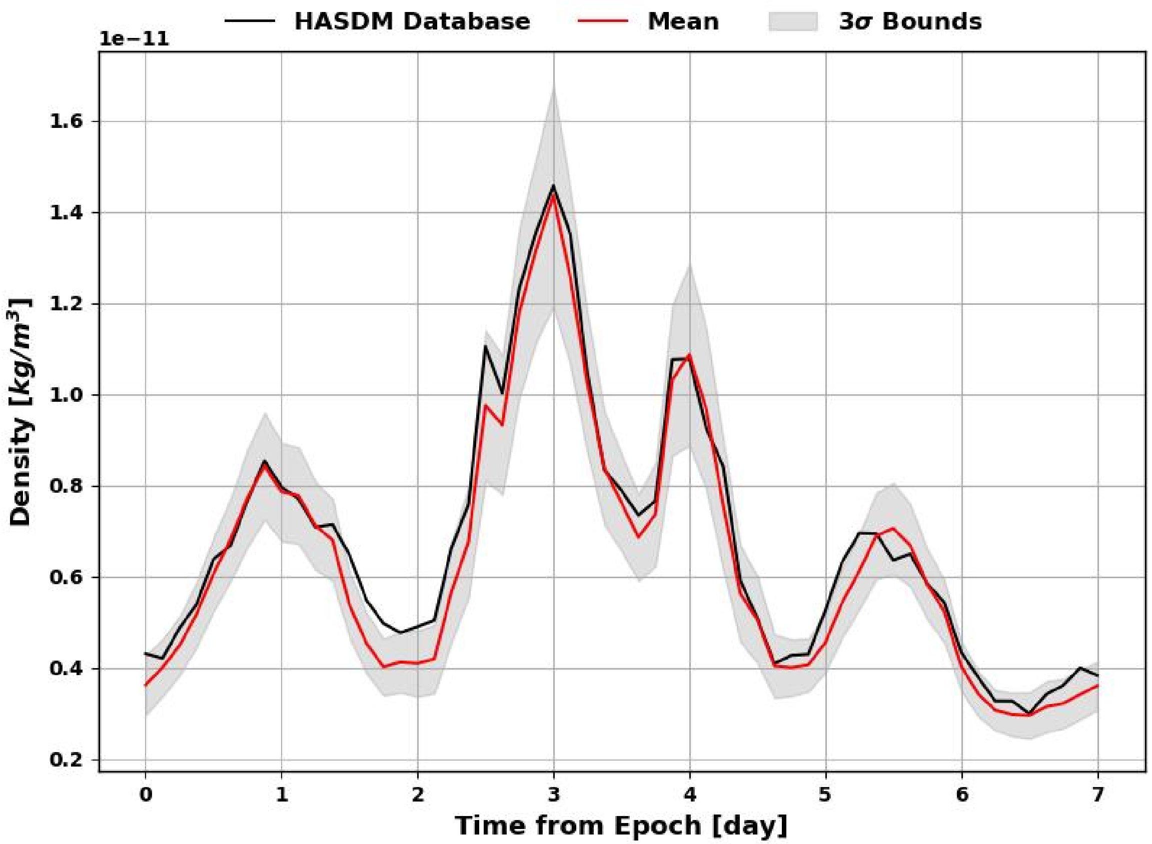


Altitude-error profiles for both HASDM-ML and JB08-ML with different solar activity levels.

- There is a pronounced peak in the lowest solar activity level that resides around 500 km, and it rises in altitude with increasing solar activity.
- We hypothesize that this is likely the models' inability to capture the He-O transition effectively.

UNCERTAINTY QUANTIFICATION

- By manipulating dropout layers, the initially deterministic model is able to make probabilistic predictions for the density grids.
- MC dropout has been shown to function as a Bayesian approximator for model uncertainty, which has been applied to HASDM-ML.
  - In theory, an infinitely wide layer with MC dropout estimates a Gaussian Process [3].



UQ for density encountered along a 400 km circular orbit during the Halloween Storm of 2003 (3-hour cadence).

- The 3σ bounds for the HASDM-ML prediction capture the SET HASDM database densities for nearly the entire 7-day period.
- A key observation is how the uncertainty grows with increased geomagnetic activity.

CONCLUSIONS & ACKNOWLEDGES

- PCA revealed the similarities between the first three modes, resulting in largest variance, but the higher order coefficients require further investigation.
- The performance of the JB08-ML and HASDM-ML displayed that there was a stronger correlation between the input set to the JB2008 densities than that of the HASDM densities.
  - To remedy this, we will look into additional indices that the model can use to capture more processes that the dataset is respresenting.
  - We will also optimize the architecture and hyperparameters with tools such as AutoKeras [4].
- We showed the capability of HASDM-ML to estimate model uncertainty on its predictions and how they vary along a given orbit.

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ABSTRACT

Space traffic management is difficult. Monitoring and predicting the accurate, real-time position of satellites for collision avoidance in low earth orbit is an engineering challenge. The dominant source of error in satellite prediction tracking models is in the determination of space weather driven atmospheric drag. The High Accuracy Satellite Drag Model (HASDM) (Storz et al., 2005) was developed by the U.S. Air Force Space Command (AFSPC) between 2000–2005 to help solve this problem. It is a data assimilative modeling system using the JB2008 thermospheric density model (Bowman et al., 2008) plus continuously derived densities from several dozens of calibration satellites to achieve <5% density uncertainty at most epochs. The HASDM data is being made available to the community of scientists and operators for the first time. Under authority from the AFSPC, Space Environment Technologies (SET) has extracted two solar cycles of operational High Accuracy Satellite Drag Model (HASDM) data for scientific use and this is called the SET HASDM database. Navigating and extracting information from this database quickly and efficiently to manage satellite space traffic is currently complex and tedious. We present the development of a data-driven model for the HASDM mass density using Machine Learning and an attempt to quantify the associated uncertainties.

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