WAM ROPE – Part I: Dimensionality reduction using dual encoder autoencoder

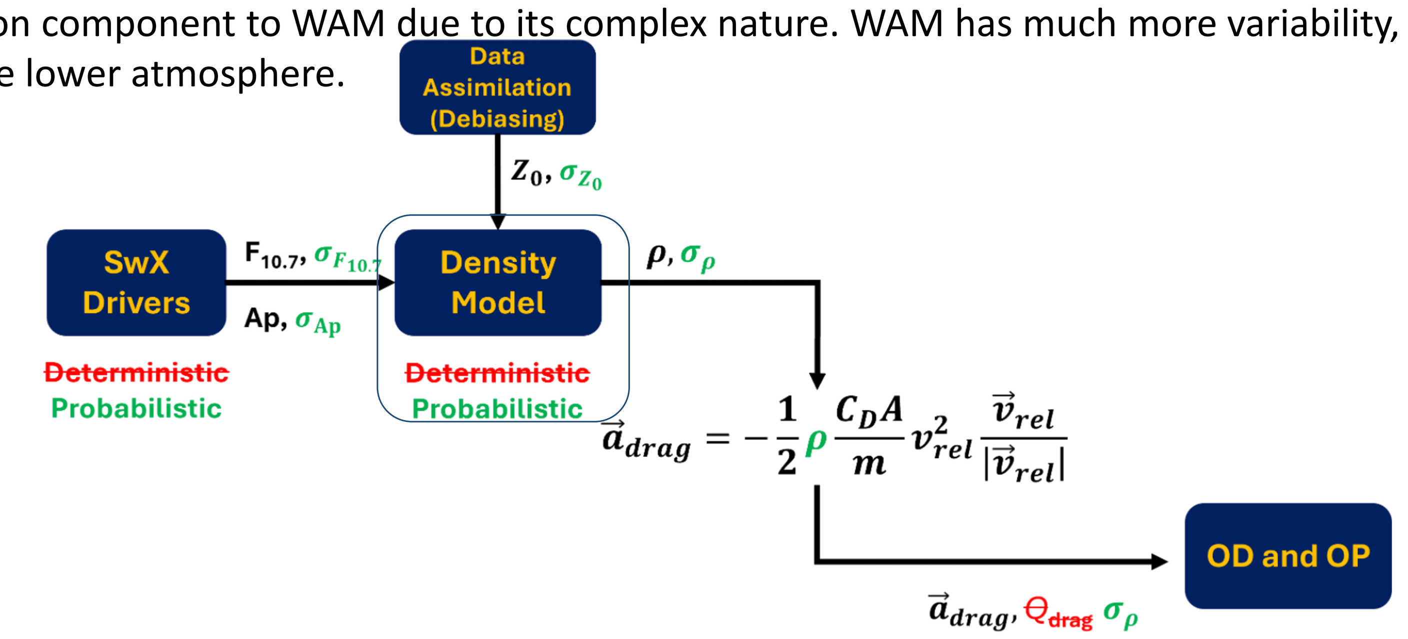
Harshitha Challa[1] . Zhuxiao Li[2,3] . Anirudh Tapedia[1] . Tim Fuller-Rowell[2,3] . Tzu-Wei Fang[3] . Piyush M. Mehta[1]
[1] ASSIST Lab, West Virginia University , [2]CU/CIRES , [3]NOAA/SWPC

Introduction

- A major source of uncertainty in satellite orbit prediction in Low Earth Orbit (LEO) is atmospheric drag, and existing operational frameworks for drag modeling are based on empirical models.
- Many high-fidelity physics-based ionosphere-thermosphere models have been developed over the years but cannot be operational due to their high computational complexity.
- We have recently developed a **reduced order probabilistic emulator (ROPE) framework** which addresses these concerns, using the TIE-GCM (thermosphere ionosphere electrodynamics - general circulation model) model.
- In this work, we develop a major component of ROPE using WAM (Whole Atmospheric Model) which is a physics-based model extending the MSIS empirical model.
- WAM is a key component of the coupled **Whole Atmosphere Model–Ionosphere Plasmasphere Electrodynamics (WAM-IPE) Forecast System (WFS)**, which was transitioned into operations at the NOAA Space Weather Prediction Center (SWPC) in 2021.

ROPE Framework

- The ROPE framework acts as a surrogate density model and encompasses three major components: **(a) dimensionality reduction, (b) dynamic time-series modeling in the reduced state space, and (c) uncertainty quantification using ensemble approaches**.
- We successfully developed this surrogate model for TIEGCM model, with minimum MAPE of 3.15%. However, we could not directly apply TIEGCM's dimensionality reduction component to WAM due to its complex nature. WAM has much more variability, compared to TIEGCM, and is also coupled to the lower atmosphere.
- In this work we focus on the first step, **dimensionality reduction**, for **WAM**.
- This work provides a foundation to build **ROPE framework using WAM**.



WAM Description

- The **Whole Atmosphere Model (WAM)** is an extension of the altitude domain to ~600 km of the NOAA National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS).
- In this study, the neutral density data are drawn from **16 years (2008–2023)** with the output interpolated onto fixed geometric altitudes at 10 km intervals from 100 to 1000 km.
- The output is provided with an hourly cadence and a horizontal resolution of approximately 180 km in latitude–longitude.

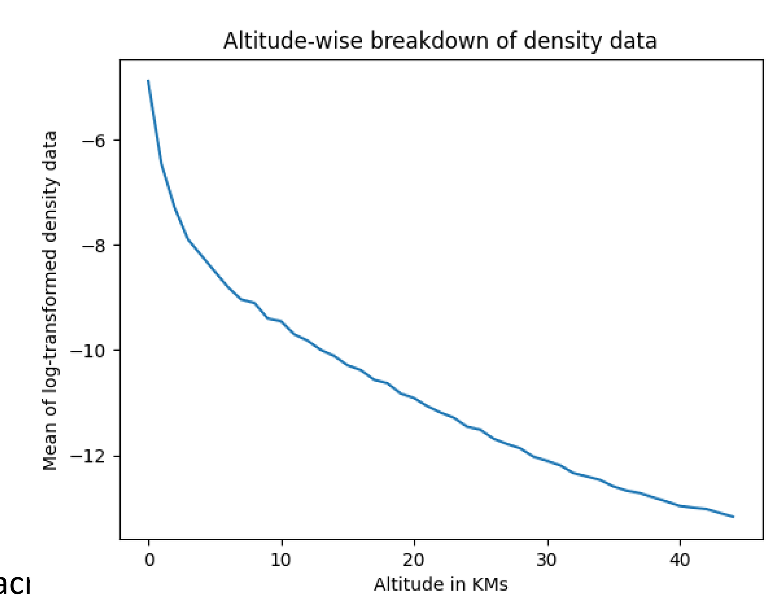
Data Preprocessing and Challenges

- The original density grid of size (91, 89, 90) is compressed to **(72, 36, 45)** by linear interpolation for machine learning model training.
- Data is **log-transformed**
- **Median-based standardization** is performed (instead of mean and standard deviation) because of the skewed nature of the dataset:

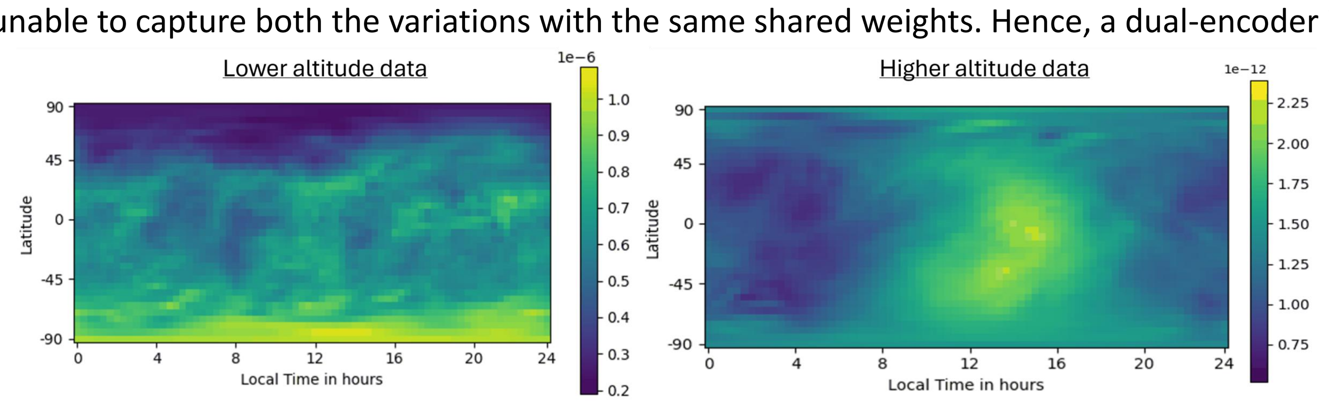
$$x_i^{\text{scaled}} = \frac{x_i - Q_2(x)}{Q_3(x) - Q_1(x) + \epsilon},$$

where $Q_j(x)$ is the jth quantile of x

- Kp based sampling to ensure good performance across all geomagnetic activity levels.

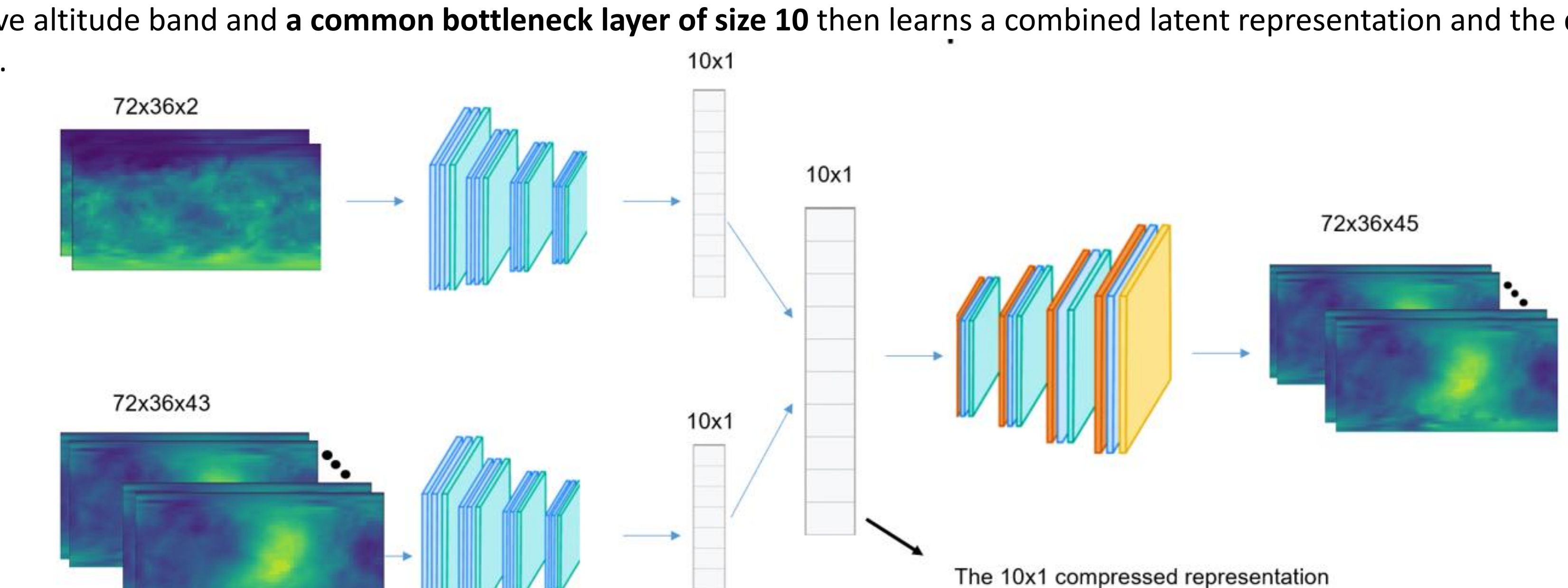


- <u>CHALLENGES:</u>
- Data is skewed altitude-wise, with different altitudes exhibiting different range of values as shown in figure.
- Lower altitude data has much less variance (constant across timesteps) compared to higher altitude data (changes acı
- A single encoder is unable to capture both the variations with the same shared weights. Hence, a dual-encoder is employed



Model Architecture

The input is partitioned along the altitude dimension to capture distinct statistical and physical characteristics of the data. The lower (first two altitude bands) and upper altitude regions exhibit different variability, motivating the use **of two independent encoders** without shared weights. Each encoder learns latent representations of its respective altitude band and **a common bottleneck layer of size 10** then learns a combined latent representation and the data is reconstructed through one **single decoder.**



Encoder/Decoder Architecture:

- Four 3-D conv layers
- Channel dimensions increasing from 16 to 128.
- Kernel size: (3x3x3)
- Unit stride and padding of 1
- Act. Fn: LeakyReLU.
- Optimizer: Adam
- Batch size: 64

Loss function:

$$\mathcal{L}_{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \; ; \; \mathcal{L}_{log-cosh} = \frac{1}{2}\sum_{i=1}^{2}\log(\cosh(y_i - \hat{y}_i))$$

$$\mathcal{L}_{ortho} = (Z^T Z - I)^2 \; ; \; \mathcal{L}_{weighted} = \frac{1}{N}\sum_{i=1}^{N} w_i|y_i - \hat{y}_i| \, ; w_i \in [10, 4], \quad i = 1, \ldots, 45$$

$$\mathcal{L}_{total} = 1.25\,\mathcal{L}_{MAE} + 0.3\,\mathcal{L}_{log-cosh} + 0.25\,\mathcal{L}_{ortho} + 0.25\,\mathcal{L}_{ortho-enc1} + 0.15\,\mathcal{L}_{weighted}$$

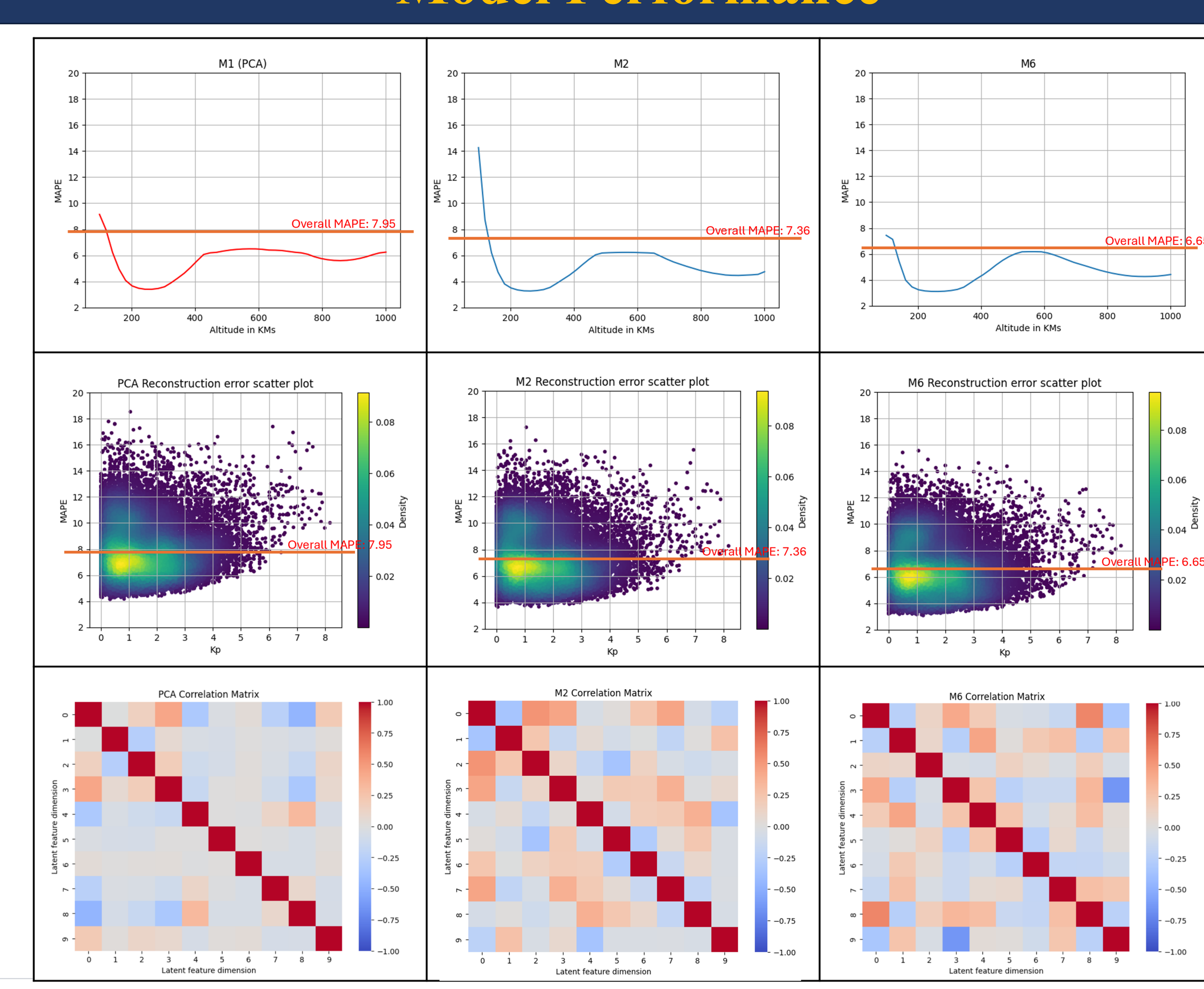
Metric used and results

Metric:

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

Model	Standardization	Low altitude MAPE	Overall MAPE
M1: PCA (Theoretical baseline)	Mean-based	8.70	7.95
M2: Single Encoder with $\mathcal{L}_{MAE}$ and $\mathcal{L}_{ortho}$ (Autoencoder baseline)	Mean-based	11.49	7.36
M6: Dual encoder with $\mathcal{L}_{total}$	Median-based	**7.28**	**6.65**

Model Performance



Conclusion and Future Work

- This work extends our previous work of developing a ROPE framework using TIEGCM data, by developing the **first component of ROPE for WAM data** (dimensionality reduction).
- This work introduces a new customized dual-encoder autoencoder model specifically designed for WAM.
- The introduction of dual-encoder setup does not alter the ROPE framework and can be seamlessly integrated.
- We also designed a customized loss function to reduce the error for low-altitude data.
- We achieved an **overall MAPE of 6.65**, with the average MAPE of lower altitude data being 7.28.
- Our model **surpassed the performance of PCA** and showed more variability for altitudes above 120 km, in **all geomagnetic conditions**.
- This is major progress in operationalization of physics-based models for drag modeling.

- While this work presents the dimensionality reduction of WAM data, it is only the first component of the complete ROPE framework.
- Our future work includes developing the next component**, dynamic modeling**, where the latent vectors (with reduced dimensions) produced by the autoencoder model will be used for forecasting and modeling the **temporal dynamics using time-series modeling**.
- Further steps also include building the final component of the framework, probabilistic uncertainty quantification.

ACKNOWLEDGEMENTS

- *This research is based upon work support in part by the Office of the Director of National Intelligence (ODNI), Intelligence Advance Research Projects Activity (IARPA), via 2023–23060200005.*
- *This work is also supported by OSC (via CU CIRES)*

CONTACT

Harshitha Challa, Computer Vision Scientist
ASSIST Lab, West Virginia University
Email: harshitha.challa@mail.wvu.edu