

## Introduction

The ability to monitor radiation environment data at aviation altitudes and forecast the dose rates is vital for estimating exposure risks faced by aviation and the spacecraft crews and the impact of space weather disturbances on electronics. As of now, mostly physics-based models driven by various space weather parameters are used for this task.

To test data-driven machine learning (ML) models for aviation radiation forecasting, a multi-variate time series ML-ready dataset has been constructed (Sadykov et al. 2025, in prep).

## Objectives

- To improve the nowcasting of radiation dose rates at aviation altitudes using machine learning
- To explore the importance of various Geospace environment factors with respect to radiation dose rates

## ML-Ready Radiation Dataset

An ML-ready dataset has 3 partitions containing ARMAS flight data and respective Geospace environment properties (energetic particle and SXR fluxes from GOES, solar wind properties from OMNI, Geomagnetic indexes, neutron monitor counts, and global solar activity parameters)

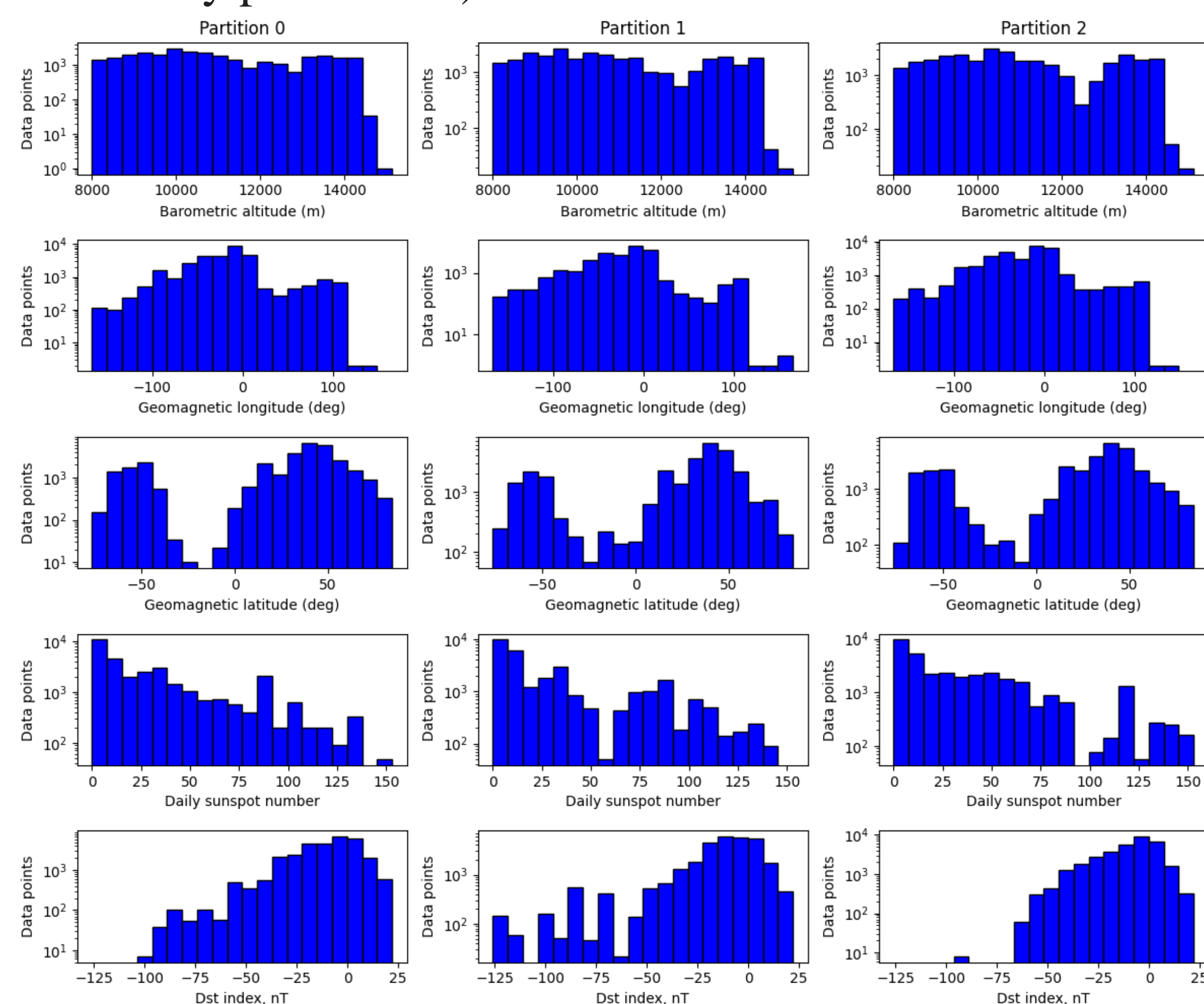


Figure 1. Distribution of the parameters that were used for the partitioning of the dataset (barometric altitude, geomagnetic longitude, geomagnetic latitude, daily sunspot number, and Dst index)

## ML-Driven Predictions

Random Forest (RF) and Lasso regression ML algorithms available at 'Scikit-learn' were used for modeling. Data was standardized for Lasso regression, while RF directly used the ML-ready dataset. Feature importance was extracted, and MSE and  $R^2$  evaluated the model's performance.

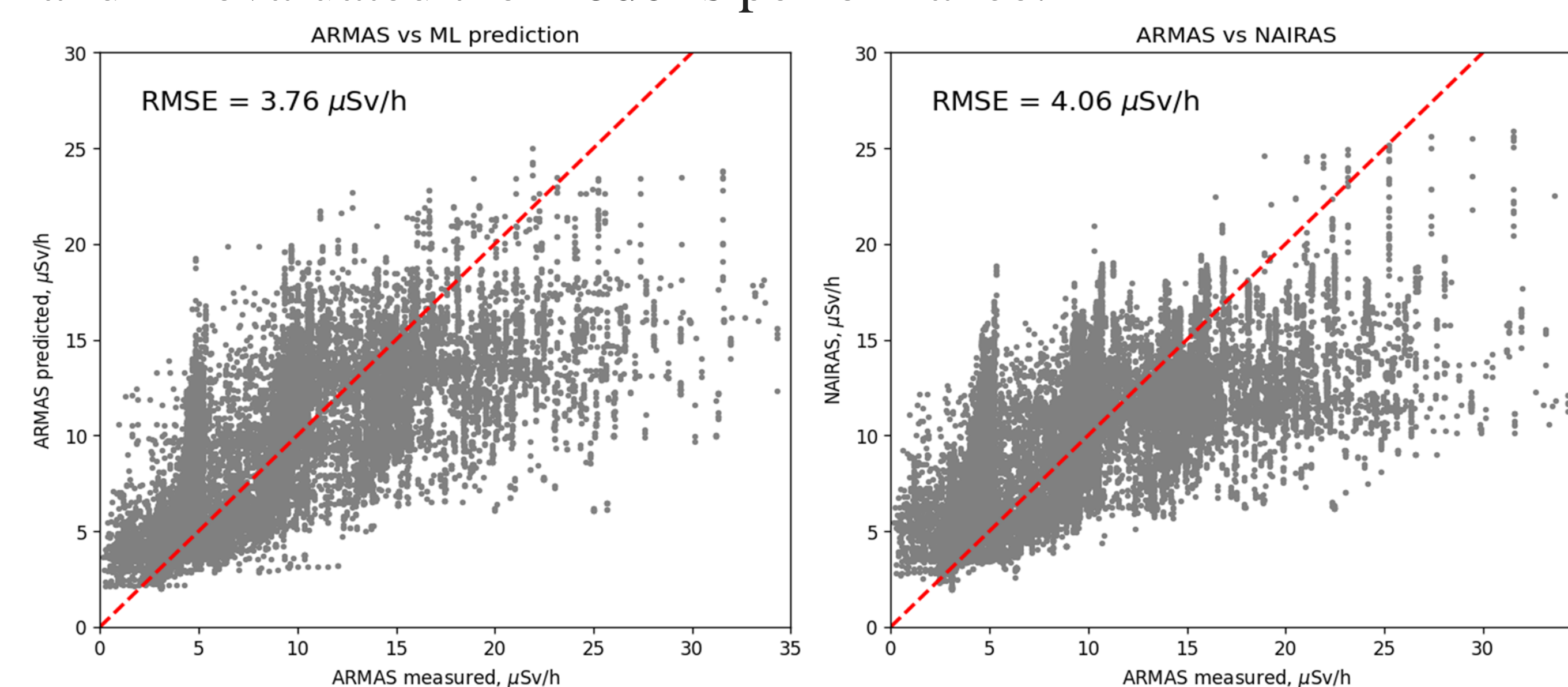


Figure 2. Left: Measured radiation dose rates VS predicted using an ML model (Random Forest Regressor). Right: Measured radiation dose rates VS nowcast of a physics-based NAIASV3 model.

- Figure 2 shows the performance of the hyperparameter-tuned RF regressor trained on Partition 1 and evaluated on Partition 2. Both the ML-based and physics-based forecasts show the 'tail' for the high radiation dose values predicted not correctly.
- Figure 3 illustrates the performance of the RF and Lasso Regression models on different train-validation-test partitions:
  - Random Forest performs better than the Lasso Regression
  - Both ML models perform better than NAIAS V3 physics-based model

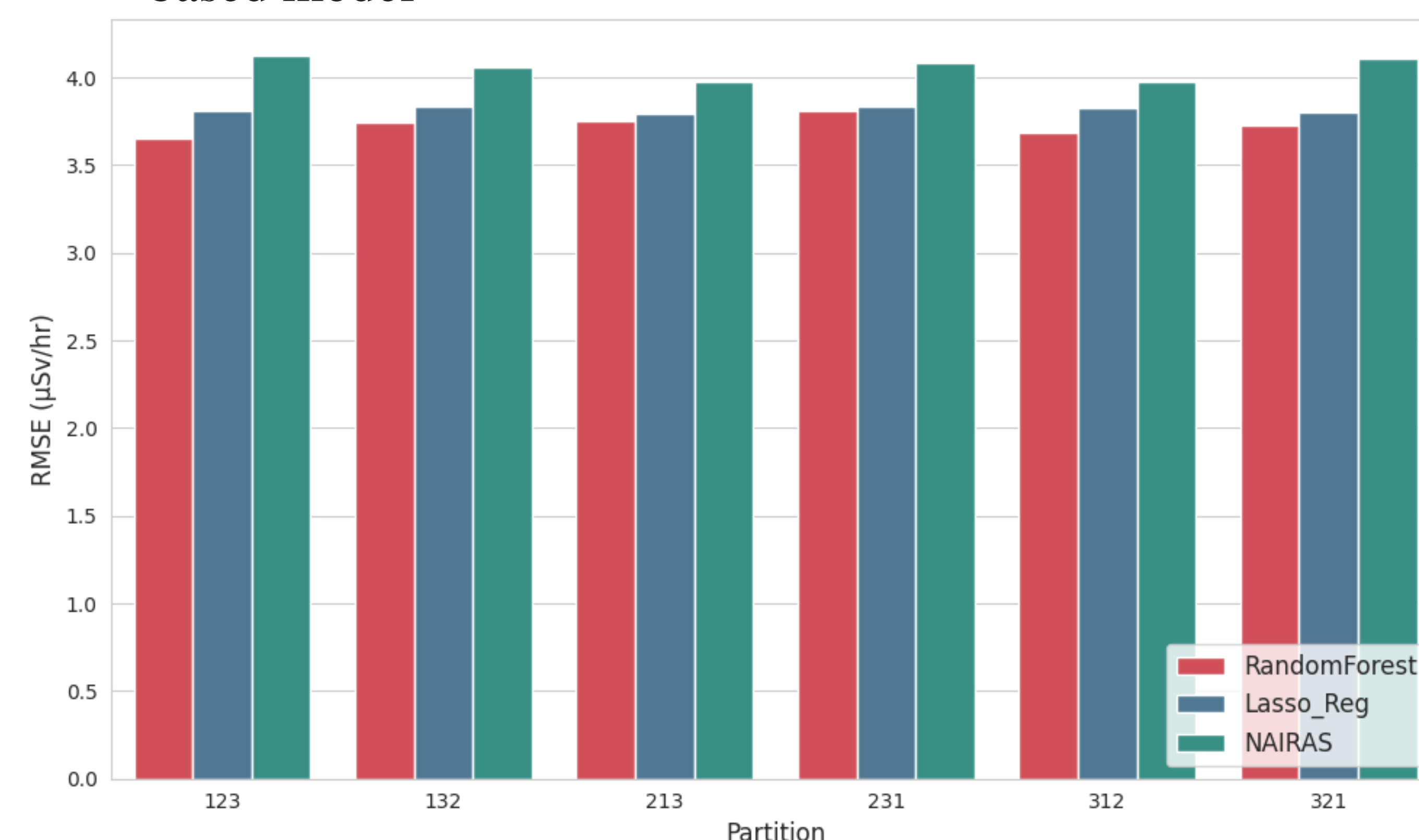


Figure 3. Comparison of the Root Mean Squared Error (RMSE) measures for radiation prediction for different train-validation-test partition combinations.

## Feature Importances

Assessment of feature importances can help to understand what Geospace factors impact the radiation prediction. Importances are calculated using both Lasso and RF regression models.

- Solar wind properties significantly contribute to the prediction.

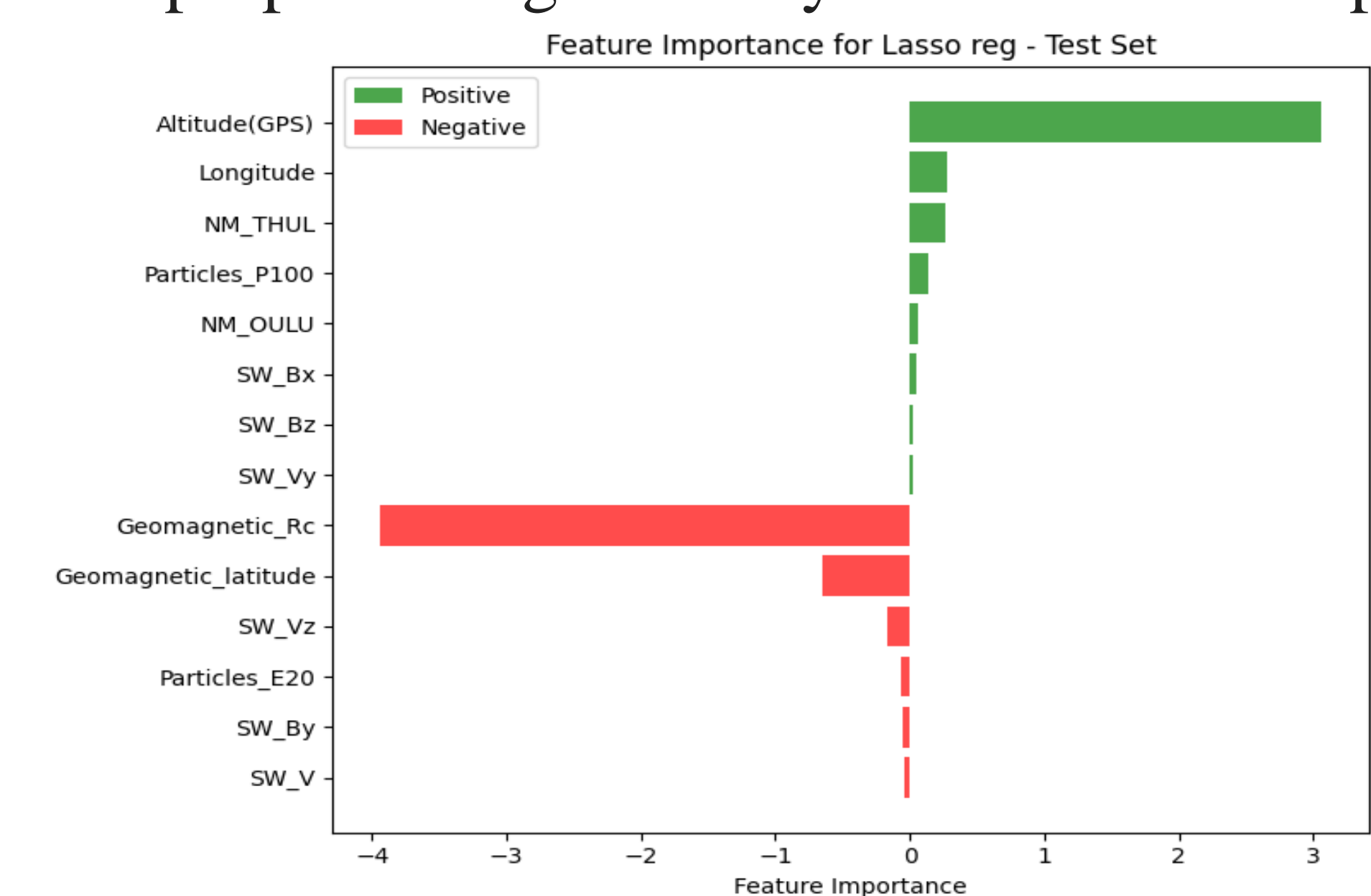


Figure 4. Feature importance from the Lasso regression.

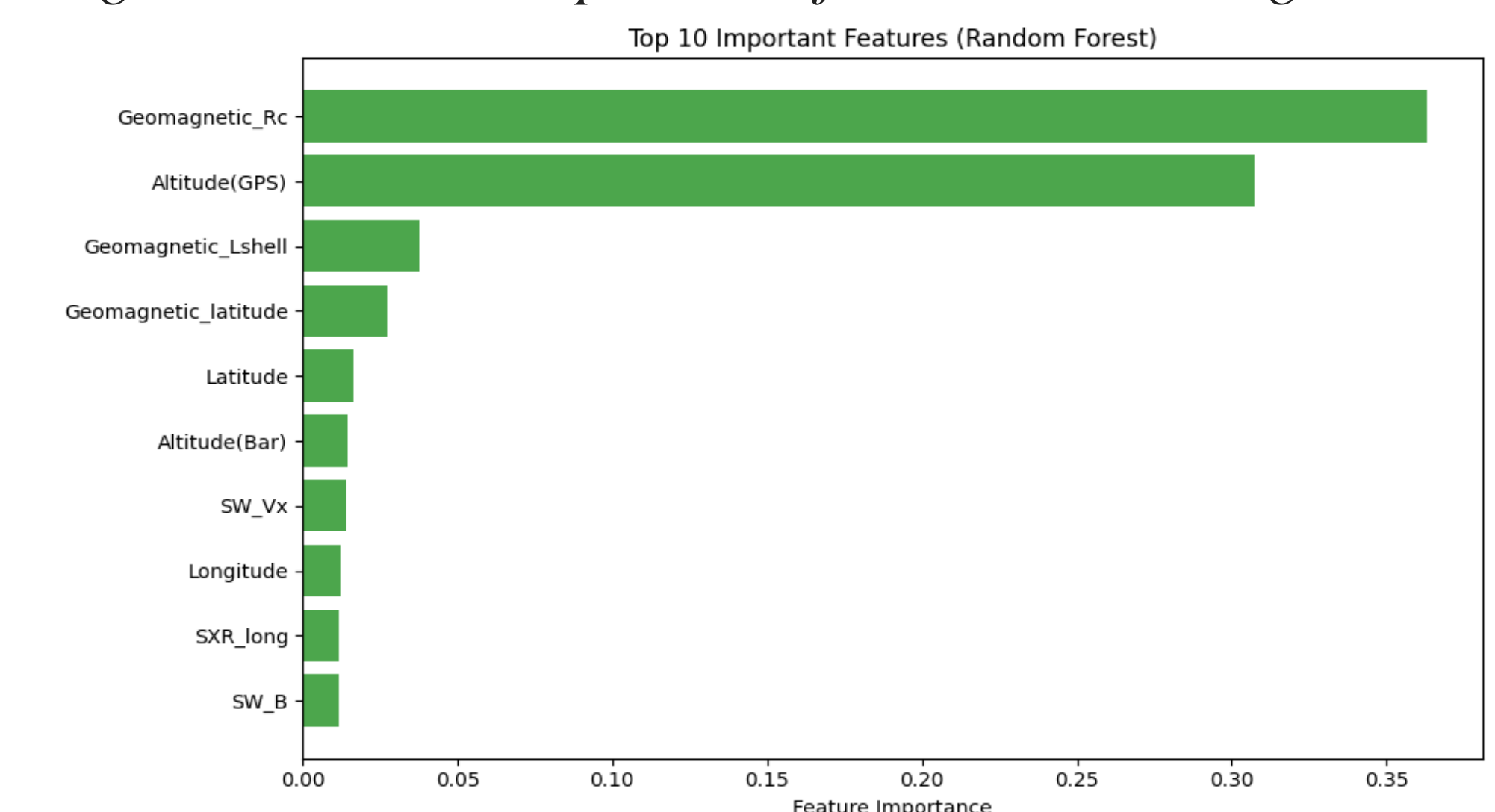


Figure 5. Feature Importance for the Random Forest Regression.

## Conclusions

- This preliminary study demonstrates the ML-driven models for nowcast of atmospheric radiation at aviation altitudes
- ML-driven RF regressor demonstrates improvements over Lasso (linear regression) and of physics-based modeling
- Analysis of feature importances allows to uncover a potentially strong role of the solar wind dynamics in radiation modulation

## Acknowledgements

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- The original ARMAS data are publicly available from the ARMAS Data Archive found at Space Environment Technologies. ARMAS data and corresponding NAIAS model data provided by SET under agreement with NASA LaRC and NAIAS PI Chris Mertens.