



Effects of Driving Parameter Filtering on SWPSNN Model Performance

Aaron Johnson¹, Michael Liemohn², Brian Swiger²

¹Department of Physics, Gustavus Adolphus College - St. Peter, MN

²Department of Climate and Space Sciences and Engineering, University of Michigan - Ann Arbor, MI

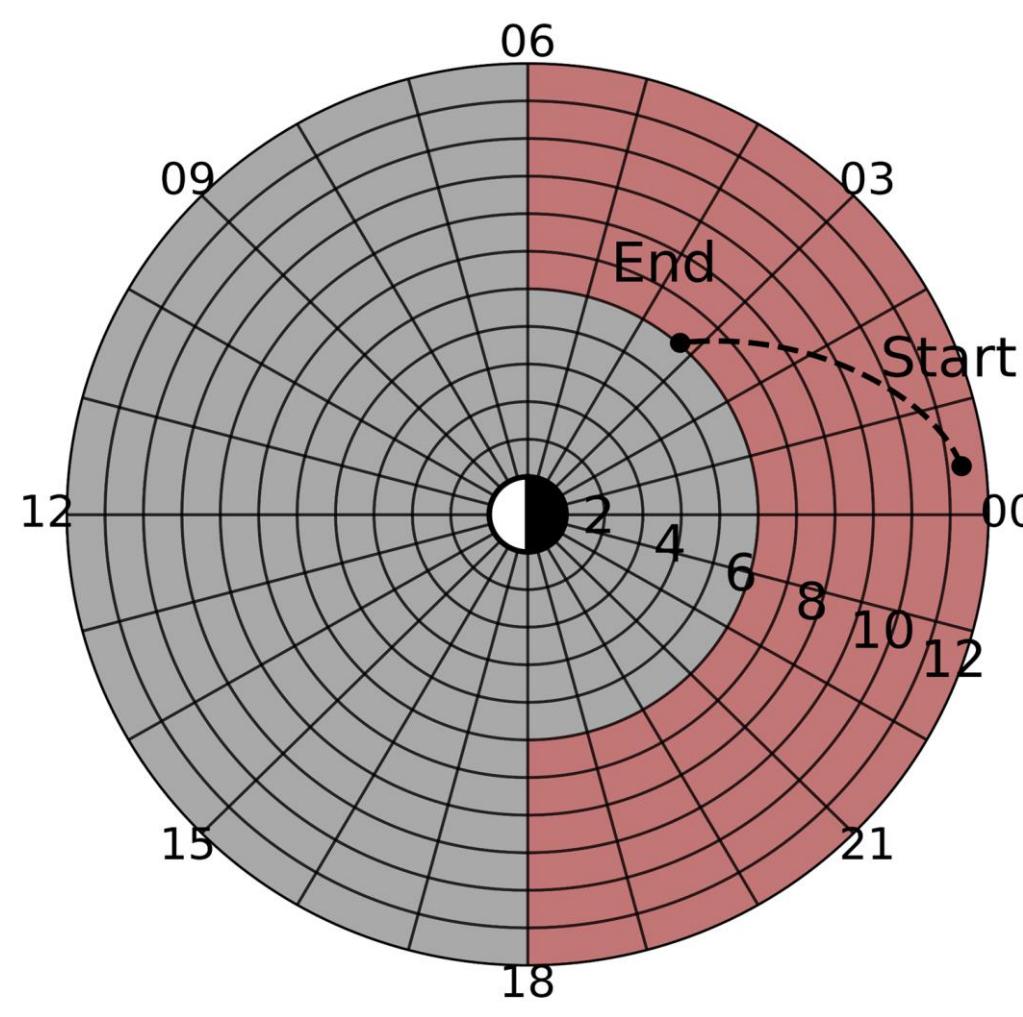
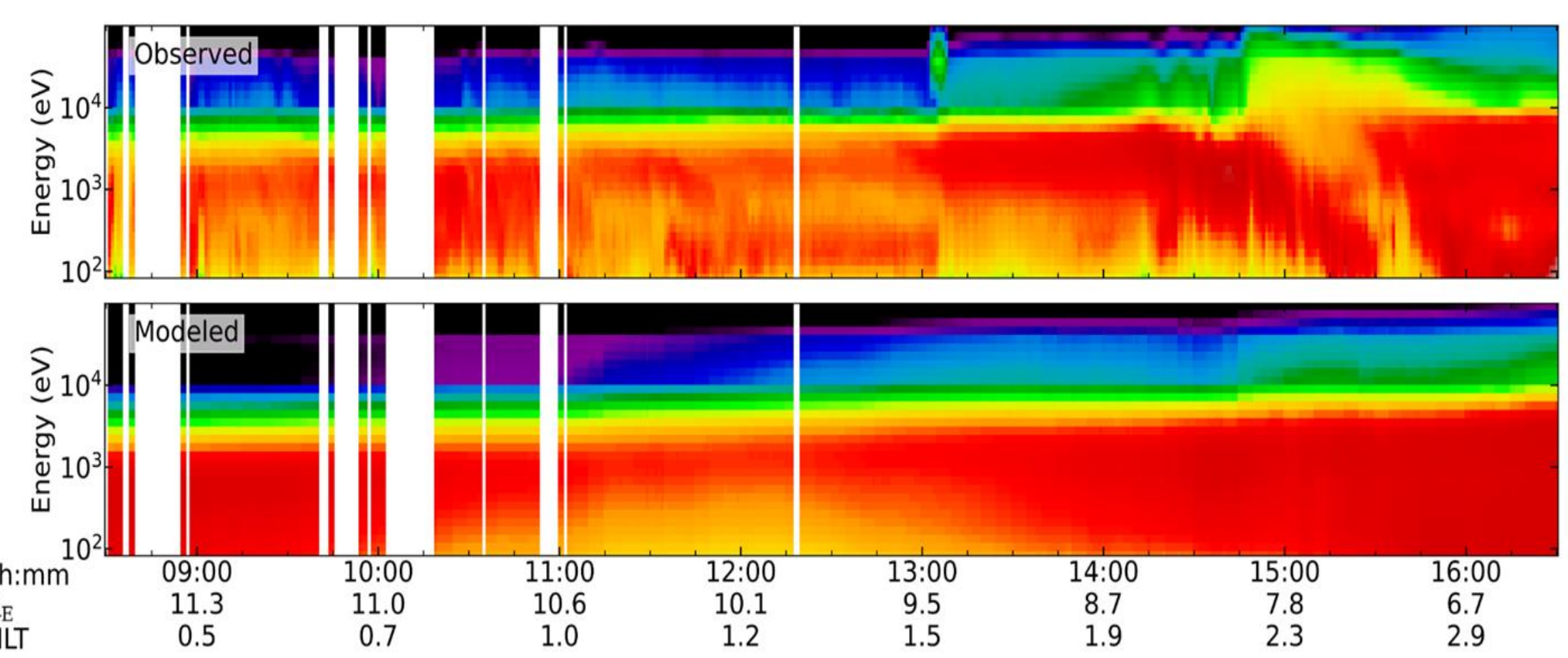


Introduction

The SWPSNN neural network model developed by Swiger et al. is an optimized function that maps between a features (OMNI input) matrix containing various solar wind driving parameters and a targets (THEMIS output) matrix containing differential number flux values for several energy channels [1].

$$F(\bar{X}) = A(\bar{X}W_0 + b)W_1 = \bar{Y}$$

The SWPSNN proved to be an accurate (median symmetric accuracy between 41% and 140%) model of electron flux in the plasma sheet [1]. The objective of this study was to determine if the performance of the model depends on the subset of features (OMNI) data supplied as inputs.

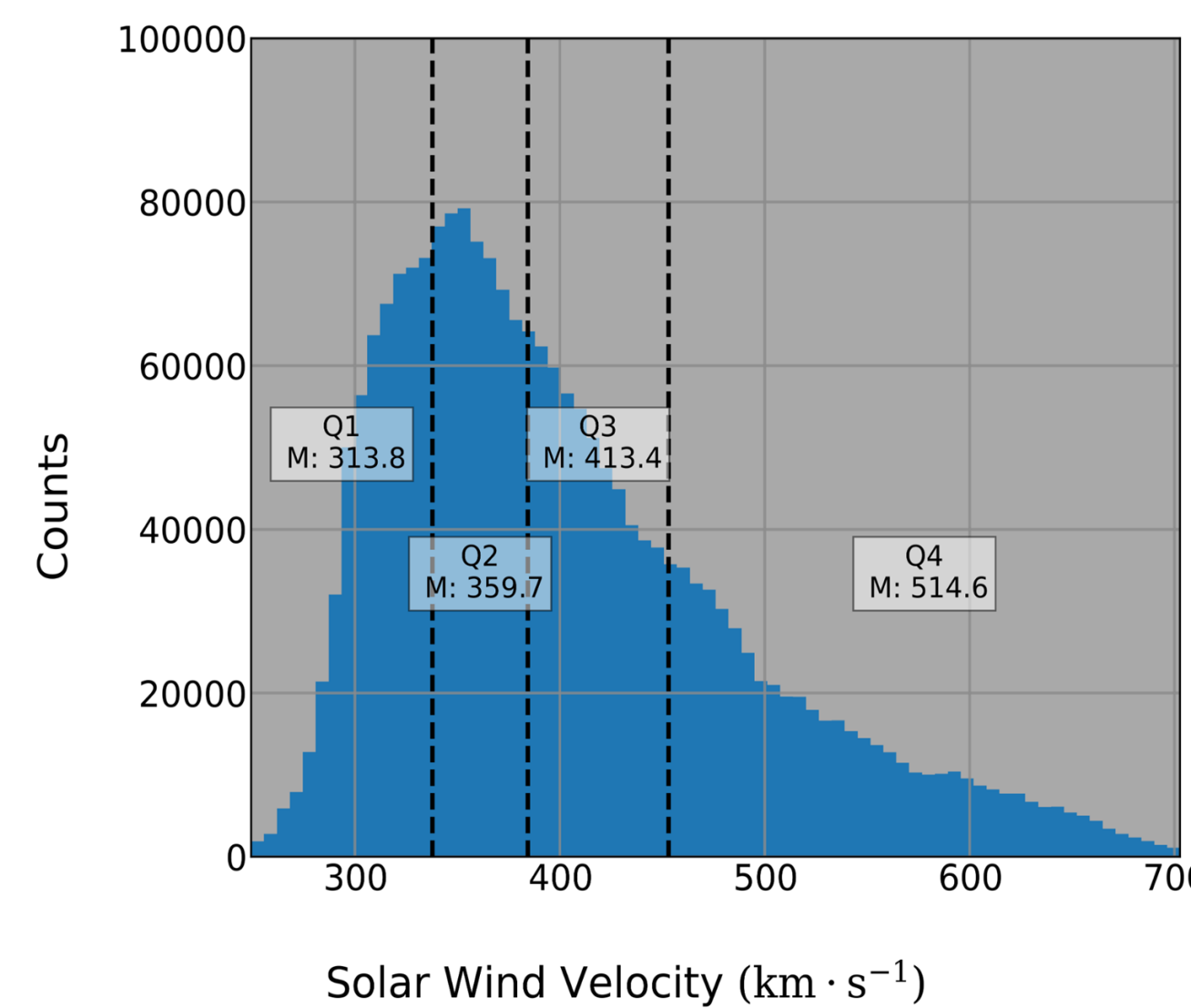
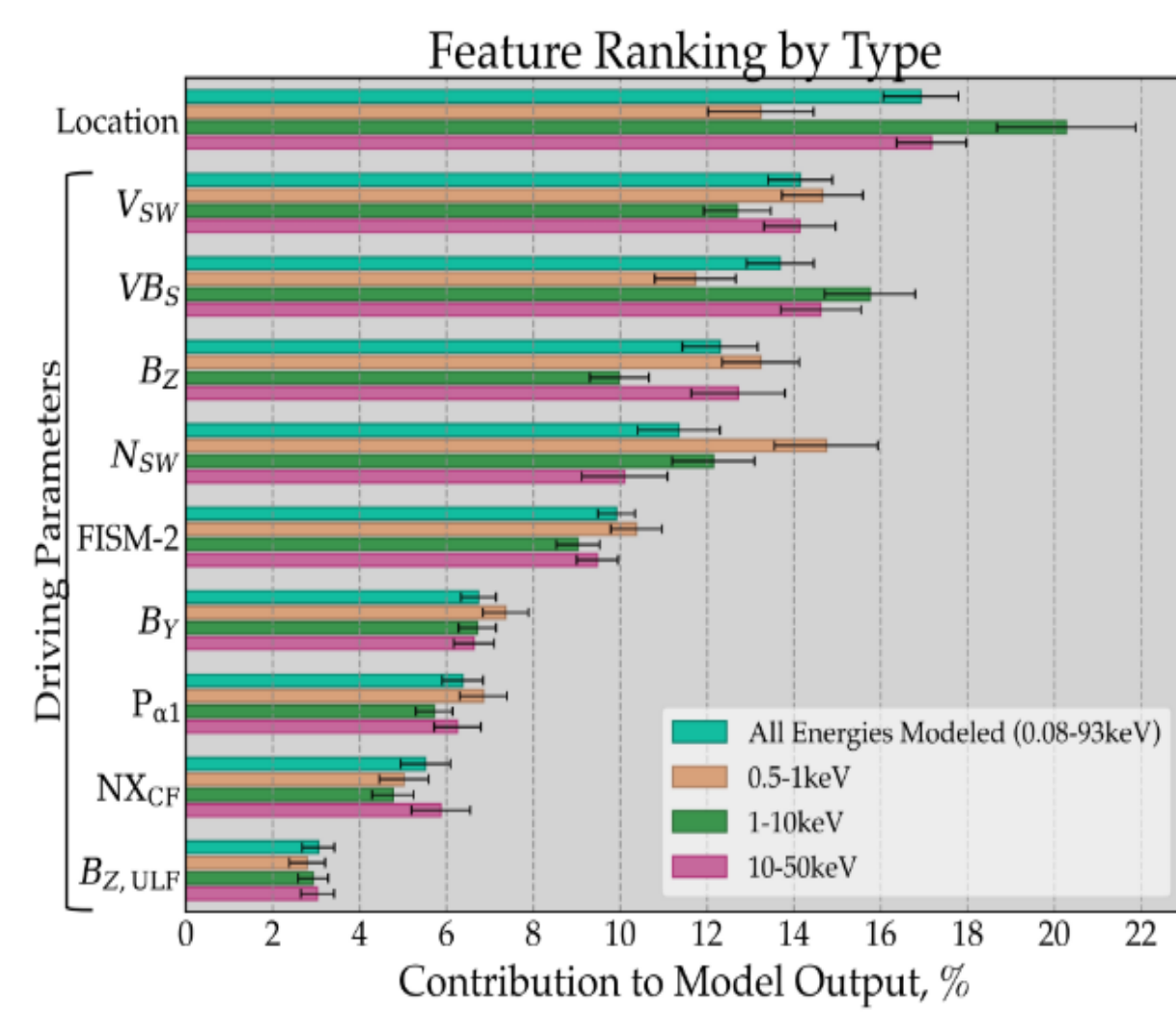


Methods

Using the DeepSHAP algorithm, the OMNI driving parameters were ranked according to their importance in determining the best fit model [1].

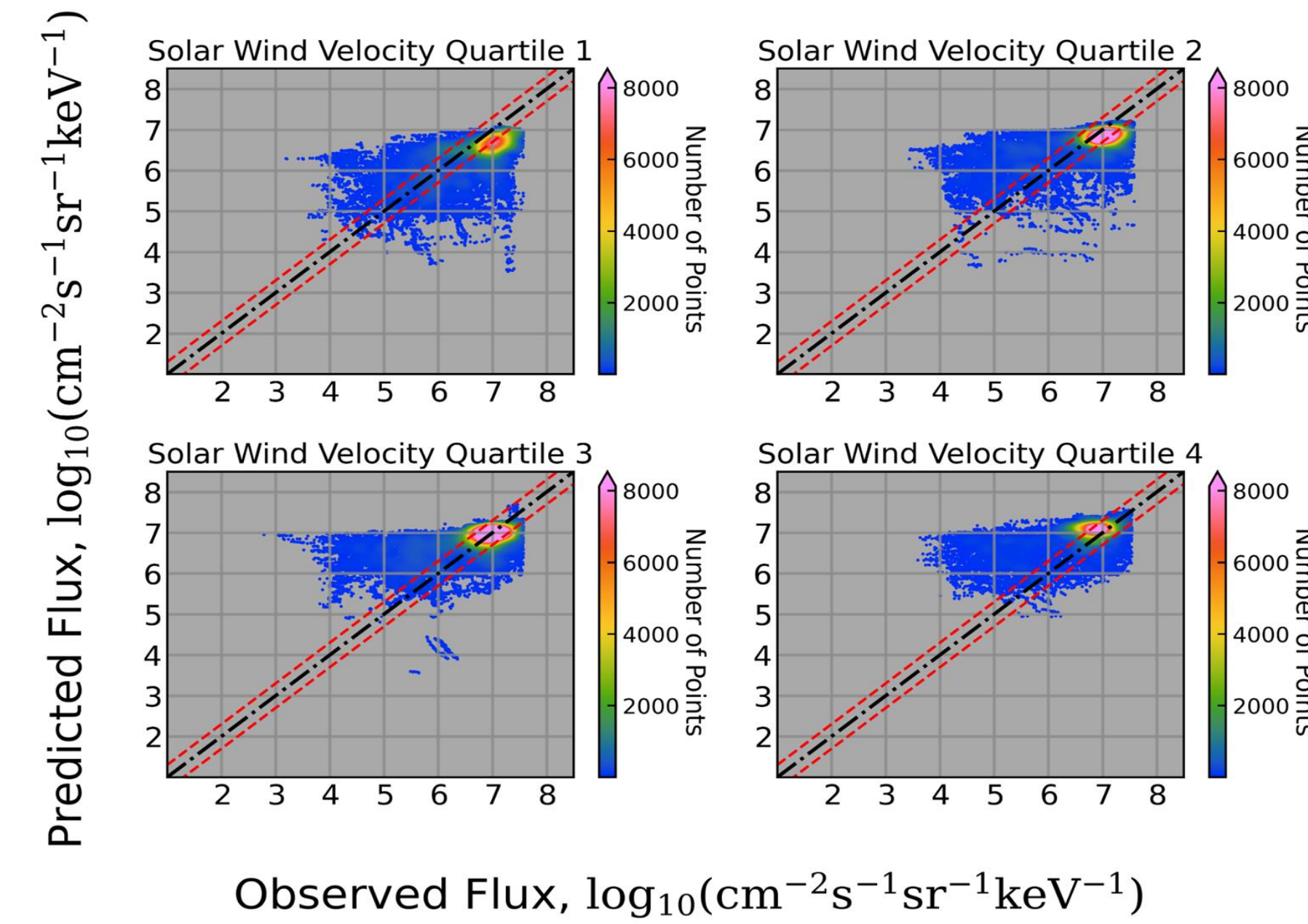
We developed a Python algorithm that sorts the feature data set according to the values of each of the parameters in the figure to the right. First, each driving parameter was divided into quartiles, as shown below. Next, the program iterated through the timestamps of the target matrix, selecting only those times whose corresponding feature values fell inside the specified quartile.

To locate the feature value, we subtracted ten minutes- the average time needed for solar wind conditions to reach the plasma sheet- from the target timestamp [2]. Finally, we ran the model using the filtered feature and target data frames.



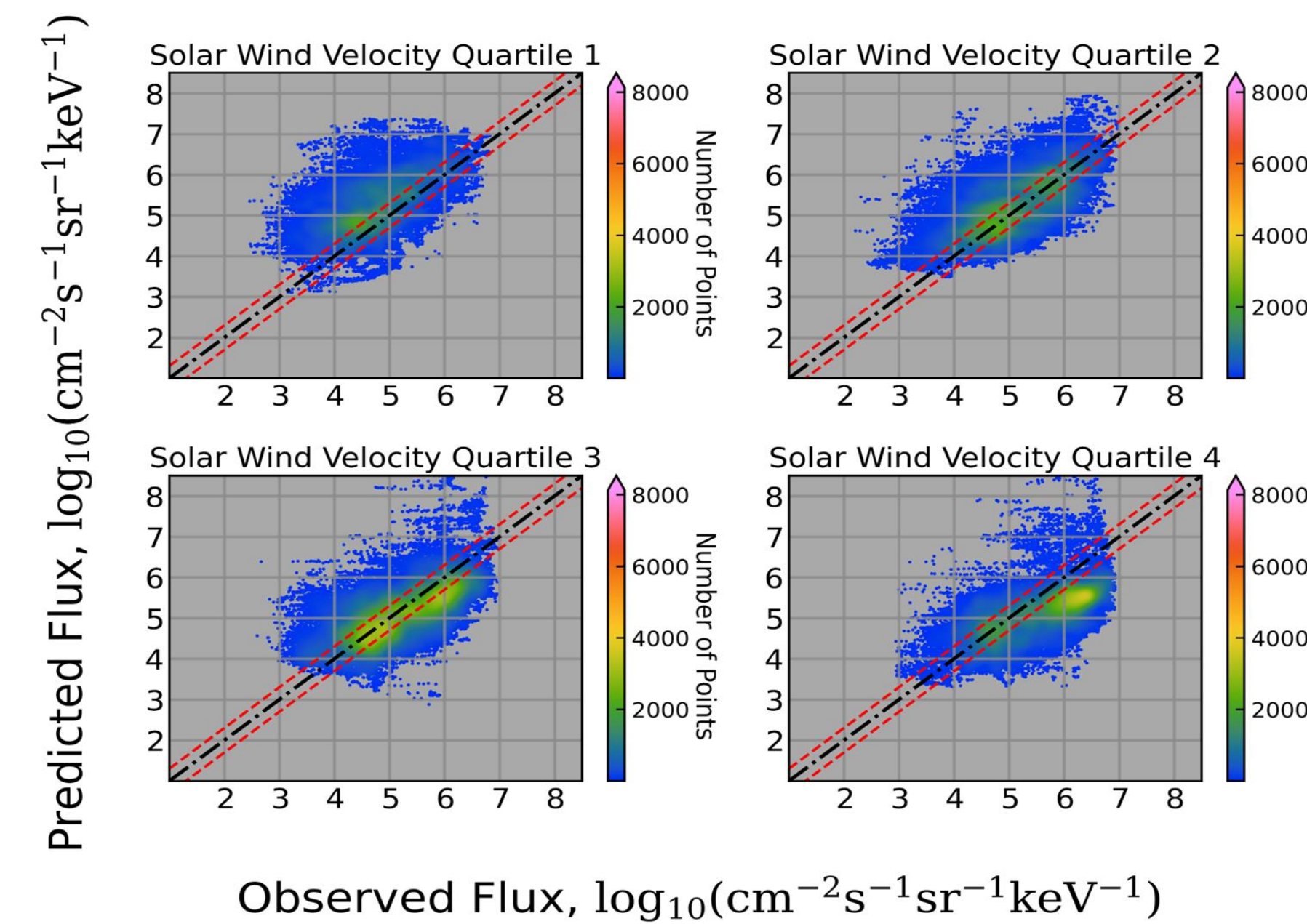
Results

Scatterplot Grid for 3.9 keV Energy Channel



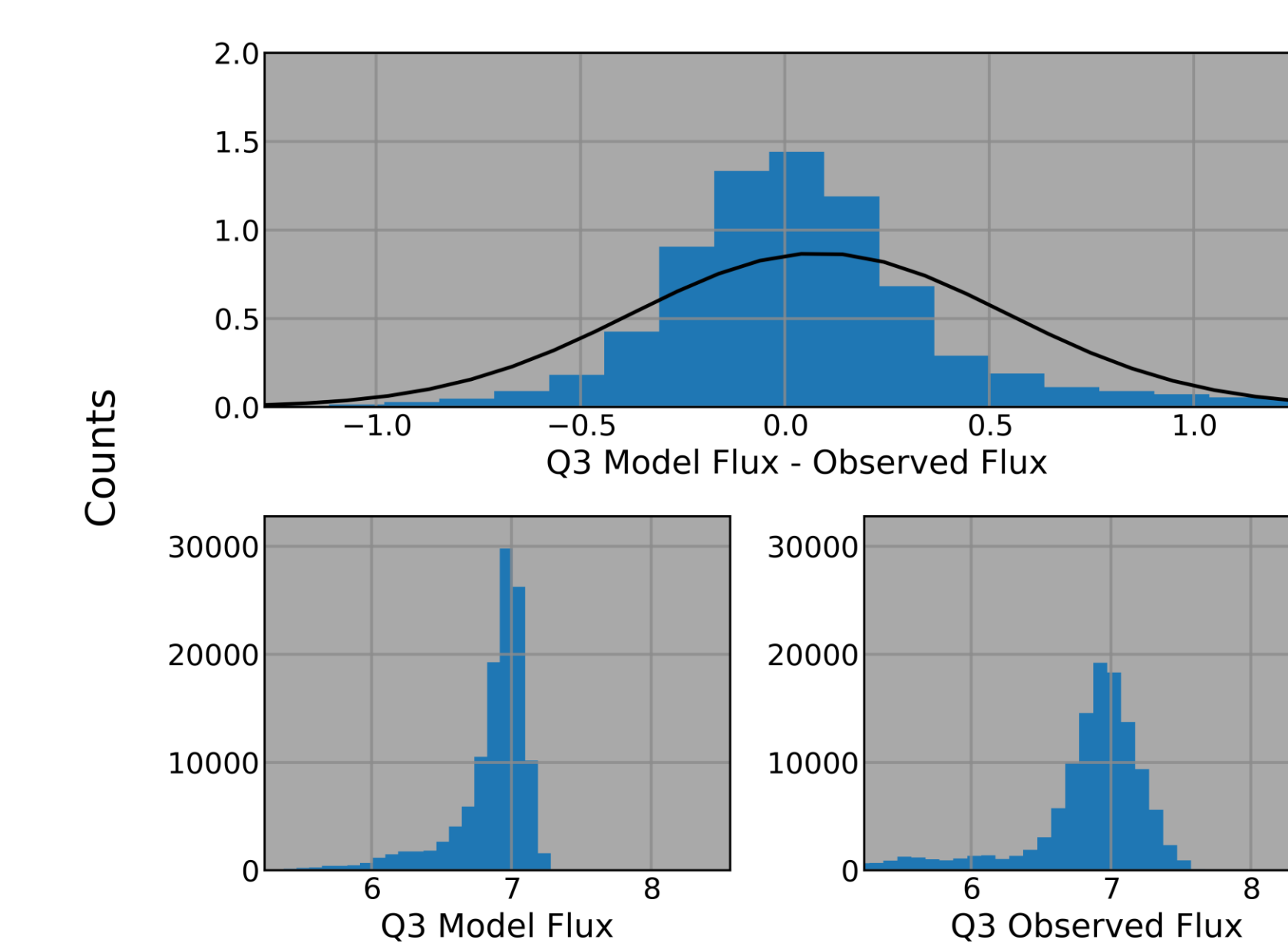
Scatterplots of predicted versus observed differential number flux in the 3.9 keV energy channel for four driving parameter subsets based on solar wind velocity values. MSA is noticeably better than for 20 keV channel.

Scatterplot Grid for 20.0 keV Energy Channel



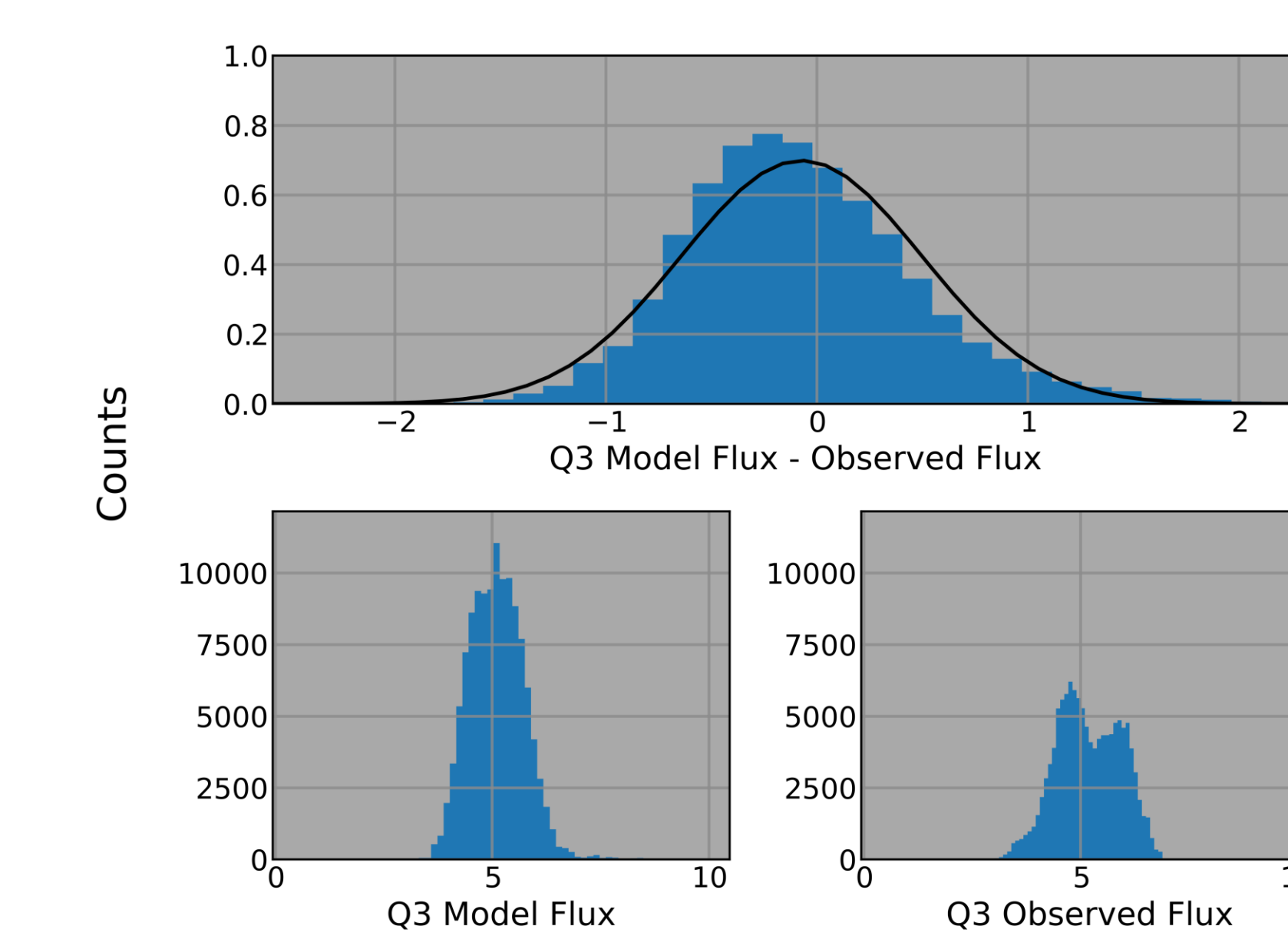
Scatterplots of predicted versus observed differential number flux in the 20 keV energy channel for four driving parameter subsets based on solar wind velocity values. Bimodal distribution in observed flux in Q3 is clearly visible.

Flux Histograms for Solar Wind Velocity, Energy Channel: 3.9 keV



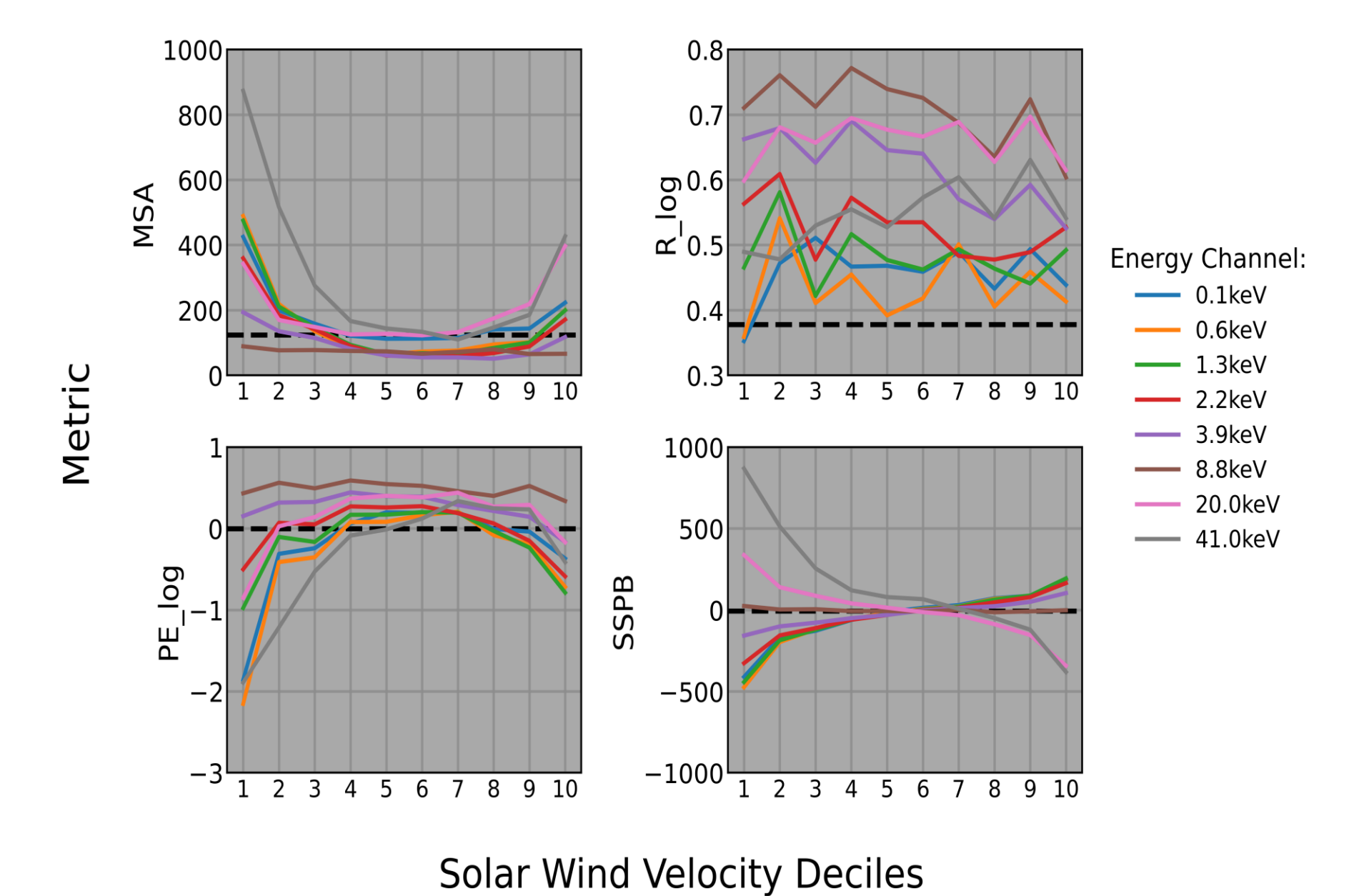
Histograms of flux for quartile three of the feature matrix sorted by solar wind velocity. Despite the skewness of the model and observed flux distributions, the model minus observed histogram is relatively normal.

Flux Histograms for Solar Wind Velocity, Energy Channel: 20.0 keV



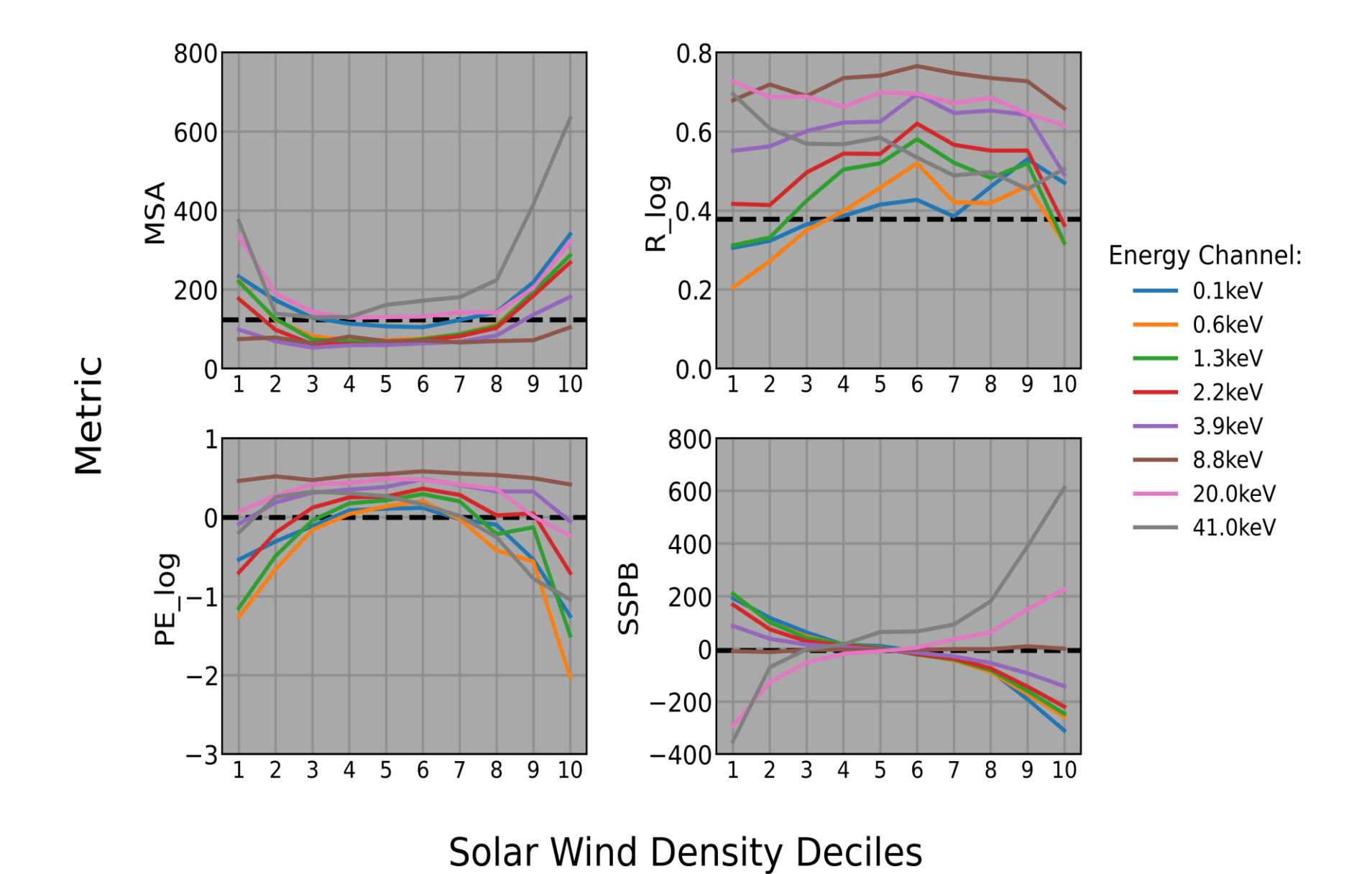
Histograms of flux for quartile three of the feature matrix sorted by solar wind velocity. Despite the bimodal nature of the observed flux histogram, the model minus observed histogram is relatively normal.

Metric Grid for Solar Wind Velocity



Metrics versus solar wind velocity decile for eight energy channels (Deciles used to increase resolution). For the middle four deciles (average solar wind velocity conditions) all metrics are significantly better than they are for extreme solar wind conditions.

Metric Grid for Solar Wind Density



Metrics versus solar wind density decile for eight energy channels. For the middle four deciles, all metrics are significantly better than they are for extreme solar wind conditions. For the same quartiles, the metrics are equal to or better than the control (no sorting) median.

Conclusions

- Model performs best for energy channels in the 1 to 10 keV range.
- Consistently returns a normal distribution for model minus observed flux.
- R_{log} is greater than the median for all energies for VSW and NSW only.
- For all other driving parameters, changing the input subset does not noticeably affect metrics.

References

- [1] Swiger, B.M. et al. (2022). Energetic Electron Flux Predictions in the near-Earth Plasma Sheet from Solar Wind Driving. Space Weather, Submitted
- [2] Wang, C.-P. et al. (2017). Effects of solar wind ultralow-frequency fluctuations on plasma sheet electron temperature: Regression analysis with support vector machine. Journal of Geophysical Research: Space Physics, 122 (4), 4210-4227.

Acknowledgements

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