

1                    **Understanding and Modeling the Dynamics of**  
2                    **Storm-time Atmospheric Neutral Density using**  
3                    **Random Forests**

4                    **K. Murphy<sup>1,2</sup>, A.J. Halford<sup>3</sup>, V. Liu<sup>4</sup>, J. Klenzing<sup>3</sup>, J. Smith<sup>5</sup>, K.**  
5                    **Garcia-Sage<sup>3</sup>, J. Pettit<sup>3</sup>, I. J. Rae<sup>2</sup>**

6                    <sup>1</sup>Lakehead University, Thunder Bay, Ontario, Canada  
7                    <sup>2</sup>Northumbria University, Newcastle upon Tyne, UK  
8                    <sup>3</sup>NASA Goddard Space Flight Center, Maryland, USA.  
9                    <sup>4</sup>Johns Hopkins University, Maryland, USA  
10                    <sup>5</sup>Catholic University of America, DC, USA

11                    **Key Points:**

- 12                    • The differences in storm-time vs quiet-time density variations are the result ge-  
13                    omagnetic processes  
14                    • Random Forest models are capable of capturing storm-time atmospheric density  
15                    variation  
16                    • A combined solar irradiance and geomagnetic activity Random Forest provides  
17                    high-cadence and robust modeling of storm-time density

---

Corresponding author: Kyle Murphy, [kylemurphy.spacephys@gmail.com](mailto:kylemurphy.spacephys@gmail.com)

18 **Abstract**

19 Atmospheric neutral density is a crucial component to accurately predicting and  
 20 tracking the motion of satellites. During periods of elevated solar and geomagnetic ac-  
 21 tivity atmospheric neutral density becomes highly variable and dynamic. This variabil-  
 22 ity and enhanced dynamics make it difficult to accurately model neutral density lead-  
 23 ing to increased errors which propagate from neutral density models through to orbit  
 24 propagation models. In this paper we investigate the dynamics of neutral density dur-  
 25 ing geomagnetic storms. We use a combination of solar and geomagnetic variables to de-  
 26 velop three Random Forest machine learning models of neutral density. These models  
 27 are based on (1) slow solar indices, (2) high cadence solar irradiance, and (3) combined  
 28 high-cadence solar irradiance and geomagnetic indices. During quiet-times all three mod-  
 29 els perform well; however, during geomagnetic storms the combined high cadence solar  
 30 irradiance/geomagnetic model performs significantly better than the models based solely  
 31 on solar activity. Overall, this work demonstrates the importance of including geomag-  
 32 netic activity in the modeling of atmospheric density and serves as a proof of concept  
 33 for using machine learning algorithms to model, and in the future forecast atmospheric  
 34 density for operational use.

35 **1 Plain Language Summary**

36 Even though satellites are in space they still experience drag or friction as they fly  
 37 through what little atmosphere there is along their orbit. This drag causes satellite or-  
 38 bits to decay overtime. During periods of enhanced space weather, such as solar flares  
 39 or geomagnetic storms, this drag increases which can make it difficult to track and pre-  
 40 dict the motion of satellites. In this work we develop a new model for atmospheric den-  
 41 sity, they key contributor to satellite drag, utilizing combined solar and geomagnetic data.  
 42 This new model performs better then models based only on solar data especially dur-  
 43 ing geomagnetic storms, periods of extreme space weather. Overall this work highlights  
 44 the importance of near Earth processes in enhancing satellite drag during geomagnetic  
 45 storms.

46 **2 Introduction**

47 The Sun-Earth system is a highly dynamic and extremely coupled environment.  
 48 The physical processes coupling and driving the dynamics of the solar wind-magnetosphere-  
 49 ionosphere-thermosphere system can affect critical ground- and space-based technolog-  
 50 ical infrastructure (e.g., Blake et al., 2016; Cassak et al., 2017; Morley, 2020; Licata et  
 51 al., 2020; Bodeau & Baker, 2021; Chakraborty et al., 2022; Klenzing et al., 2023). For  
 52 example, intense ionospheric currents can cripple ground-based power systems (Oughton  
 53 et al., 2018; Cid et al., 2020), highly energetic electrons in the Earth’s radiation belt can  
 54 lead to satellite anomalies and even complete failures (e.g., Green et al., 2017; Berthoud  
 55 & Agass, 2022), ionospheric irregularities can affect GNSS signal propagation and hin-  
 56 der communications and ionosphere-thermosphere heating can increase atmospheric den-  
 57 sity leading to increased satellite drag, shorter satellite lifetimes, and even the complete  
 58 loss of satellite infrastructure (e.g., Carter et al., 2020; Thayer et al., 2021; Fang et al.,  
 59 2022; Carter et al., 2023). Mitigating these effects requires high-fidelity models capable  
 60 of capturing the dynamic processes adversely affecting technological infrastructure (e.g.,  
 61 Y. Zhang et al., 2018; Sutton, 2018; Licata & Mehta, 2022; Ponder et al., 2023). Such  
 62 models can be used in operational environments to aid stakeholders in making key de-  
 63 cisions to protect various technologies and infrastructure.

64 Of the processes and impacts described above, accurately modeling atmospheric  
 65 density is particularly interesting to space weather forecasters and stakeholders (e.g., Berger  
 66 et al., 2020). Robust models capable of forecasting the dynamics of atmospheric den-

67 sity increase the fidelity of orbit propagation, allowing for more accurate tracking of satel-  
68 lites and debris in low-Earth orbits (LEO). As the number of satellites and orbital de-  
69 bris in LEO continues to grow, such tracking will become increasingly important as it  
70 is key for identifying potential collisions and defining collision avoidance maneuvers.

71 The density of the ionosphere-thermosphere system is driven by a combination of  
72 external forcing from the Sun (Lilensten et al., 2008) and the magnetosphere (Knipp et  
73 al., 2004) and internal processes in the lower atmosphere (Liu, 2016). Generally, Extreme  
74 Ultra Violat (EUV) and Ultra Violet (UV) emissions from the sun are the dominant sources  
75 of the dynamics of atmospheric density driving variations on time scales of the order of  
76 several days, a solar rotation, and over a solar cycle, (e.g., Qian & Solomon, 2011). How-  
77 ever, during geomagnetic storms, energy input and forcing from the magnetosphere are  
78 the dominant drivers of the dynamics of atmospheric density (e.g., Knipp et al., 2004;  
79 Zesta & Oliveira, 2019) driving rapid enhancements on time scales from several hours  
80 (and potentially shorter), which can last for several days (e.g., Liu & Lühr, 2005; Oliveira  
81 & Zesta, 2019). During periods of quiet solar and geomagnetic activity, internal processes  
82 such as atmospheric waves can contribute significantly to the dynamics and redistribu-  
83 tion of atmospheric density (Liu, 2016). Together, solar, magnetospheric, and internal  
84 forcing drive a complex set of dynamics in the ionosphere-thermosphere system across  
85 a broad range of temporal scales, spatial scales, and spatial regions including global and  
86 local variations with latitude, longitude, and altitude. In this work, we focus on quan-  
87 tifying and modeling the storm-time dynamics of atmospheric density, a key challenge  
88 for space weather modeling and forecasting.

89 During geomagnetic storms, energy input into the ionosphere-thermosphere sys-  
90 tem in the form of field-aligned currents (e.g., Lühr et al., 2004), particle precipitation  
91 (Deng et al., 2013, e.g.), and joule heating (e.g., Kim et al., 2006) can lead to rapid changes  
92 in atmospheric density ranging from 50-800% (Forbes et al., 1996; Liu, 2016; Oliveira  
93 & Zesta, 2019). During storms, density enhancements are first observed at higher mag-  
94 netic latitudes, quickly migrating to lower latitudes over a few hours (Zesta & Oliveira,  
95 2019). They are typically scaled with the storm’s size, such that the largest changes in  
96 density are observed during the most extreme geomagnetic storms (Oliveira & Zesta, 2019).  
97 In general, existing thermospheric models have difficulty capturing the dynamic spatiotem-  
98 poral evolution of atmospheric density during geomagnetic storms. This is partly because  
99 the models’ cadence and spatial resolution are insufficient to capture storm-time ther-  
100 mospheric dynamics (e.g., Bruinsma et al., 2018). Recent model developments incorpo-  
101 rating higher cadence solar and geomagnetic inputs have helped address this; however,  
102 additional research and model development are required to accurately simulate storm-  
103 time atmospheric density and, more importantly, accurately forecast atmospheric den-  
104 sity for use in operational space weather.

105 In this work, we investigate the solar and geomagnetic drivers of atmospheric den-  
106 sity changes during geomagnetic storms (storm-time) and geomagnetic quiet periods (quiet-  
107 time). Building on this, we develop three Random Forest machine learning models of at-  
108 mospheric density, one using low-cadence solar indices, a second using high-cadence so-  
109 lar spectra, and a third using combined high-cadence solar spectra and geomagnetic in-  
110 dices. During quiet-times all three models perform well; however, during geomagnetic  
111 storms the combined high-cadence solar/geomagnetic model performs significantly bet-  
112 ter than the models based solely on solar activity. Overall, this work demonstrates the  
113 importance of accurately capturing geomagnetic activity in the modeling of atmospheric  
114 density and serves as a proof of concept for using machine learning algorithms for hind-  
115 casting, nowcasting, and eventually forecasting atmospheric density for operational use.

116 In the subsequent sections, we detail the data sets used to study and quantify the  
117 drivers of storm- and quiet-time atmospheric density. We then detail the analysis of the  
118 relation of solar indices, solar irradiance, and geomagnetic activity to atmospheric den-  
119 sity during storms and quiet times. Following this, we describe the development of three

120 Random Forest models, the quantification of the performance of each model, as well as  
 121 the relative importance of each feature used within each model. The three models are  
 122 then compared during four increasingly active periods of geomagnetic activity and the  
 123 model errors are quantified as a function of storm-time and geomagnetic activity. These  
 124 results are summarized, and we conclude with future work and directions for extending  
 125 the machine learning models developed here.

### 126 3 Data Sets

127 In this work, we use a combination of in-situ neutral density measurements from  
 128 the dual Gravity Recovery and Climate Experiment (GRACE A and B) and the CHAL-  
 129 lenging Minisatellite Payload (CHAMP) satellites, solar irradiance data from the Flare  
 130 Irradiance Spectral Model 2 (FISM2, Chamberlin et al., 2020; Solomon, 2005), solar in-  
 131 dices used in atmospheric models (Bowman et al., 2008; Tobiska et al., 2008), and so-  
 132 lar wind data and geomagnetic indices from the OMNI dataset (King & Papitashvili, 2005).

133 CHAMP was launched in 2000 (Reigber et al., 2002), and shortly after, the dual  
 134 spacecraft GRACE mission was launched in 2002 (Wahr et al., 2004). Both missions were  
 135 launched into near-polar low-Earth circular orbits to altitudes of a radius of  $\sim 460$  km and  
 136  $\sim 500$  km, respectively. This work utilizes neutral densities derived from high-precision ac-  
 137 celerometers onboard each spacecraft (Sutton et al., 2005; Sutton, 2009). The along-track  
 138 density is then normalized to an altitude of 400 km using the empirical global reference  
 139 atmosphere model NRLMSIS-00 (Picone et al., 2002). This normalization allows us to  
 140 remove altitude as an independent variable when characterizing the dynamics of atmo-  
 141 spheric neutral density as a function of solar and geomagnetic activity. The neutral den-  
 142 sity data is available through the University of Colorado Boulder Space Weather Data  
 143 Portal.

144 The FISM2 and solar indices are used as proxies for solar energy input to the up-  
 145 per atmosphere, leading to variations in neutral density. The FISM2 flare data set is an  
 146 empirical model of solar spectral irradiance from 0.01-190 nm in 0.1 nm spectral bins with  
 147 a 60-second cadence (Chamberlin et al., 2020). Here, we use a reduced FISM2 flare data  
 148 set comprised of 23 spectral bands (Solomon, 2005). These bands are commonly used  
 149 in global time-dependent thermosphere-ionosphere models as they reduce both the di-  
 150 mensionality of model input data and the computational overhead of models without ex-  
 151 cessive loss of model accuracy (Solomon, 2005). The solar indices used in this study are  
 152 the F10, S10, M10, and Y10 indices and their 81-day centered averages. These indices  
 153 are used in the semi-empirical thermosphere model JB2008 and have a 24-hour cadence  
 154 (Bowman et al., 2008). The indices correspond to different portions of the solar irradi-  
 155 ance spectrum spanning UV to EUV to X-Ray; a detailed description of the indices can  
 156 be found in Tobiska et al. (2008). OMNI data from NASA’s Space Physics Data Facil-  
 157 ity provide solar wind and geomagnetic observations (King & Papitashvili, 2005). These  
 158 observations can be related to physical processes that drive magnetosphere and ionosphere  
 159 dynamics, including geomagnetic storms, substorms, and enhanced precipitation. Here,  
 160 we use OMNI to quantify the solar wind and geomagnetic drivers of elevated neutral at-  
 161 mospheric density during both quiet and storm-time conditions. Finally, we use a database  
 162 of geomagnetic storms between 2002-2012, inclusive, so that the data sets can be sep-  
 163 arated by quiet-time, storm-time, and storm phase (main or recovery). The database of  
 164 storms is developed using the methodology outlined in Murphy et al. (2018, 2020).

165 The CHAMP, GRACE, FISM2, solar, and OMNI data have varying cadences and  
 166 time stamps. The CHAMP and GRACE data have a cadence of  $\sim 50$ s, the solar indices  
 167 and FISM2 flare data have a cadence of 24h and 60s (respectively), and the OMNI data  
 168 has a 5m cadence. These data sets must have similar cadences and timestamps to per-  
 169 form any relational study between atmospheric density and solar and geomagnetic ac-  
 170 tivity. This is typically achieved by interpolating the data sets to a common abscissa.

171 However, interpolation routines perform poorly for data that rapidly vary, in this case,  
 172 the CHAMP and GRACE density data sets. Here, we use a nearest-neighbor approach  
 173 matching the density and solar data sets to the time stamps of the OMNI data. Each  
 174 satellite is independently matched to the driver datasets (solar, FISM2, OMNI), creat-  
 175 ing a total of three databases: GRACE-A, GRACE-B, and CHAMP. The time stamps  
 176 of each database are then tagged as either quiet or storm-times, with storm-time further  
 177 tagged by storm phase using the storm list Murphy et al. (2018, 2020). These databases,  
 178 spanning 2002-2012, are used to investigate the dynamics of neutral density as a func-  
 179 tion of solar and geomagnetic activity and subsequently develop a random forest model  
 180 of neutral density. In developing the random forest models, the GRACE-B database is  
 181 used to train the model, and the GRACE-A and CHAMP databases are used as out-of-  
 182 sample validations.

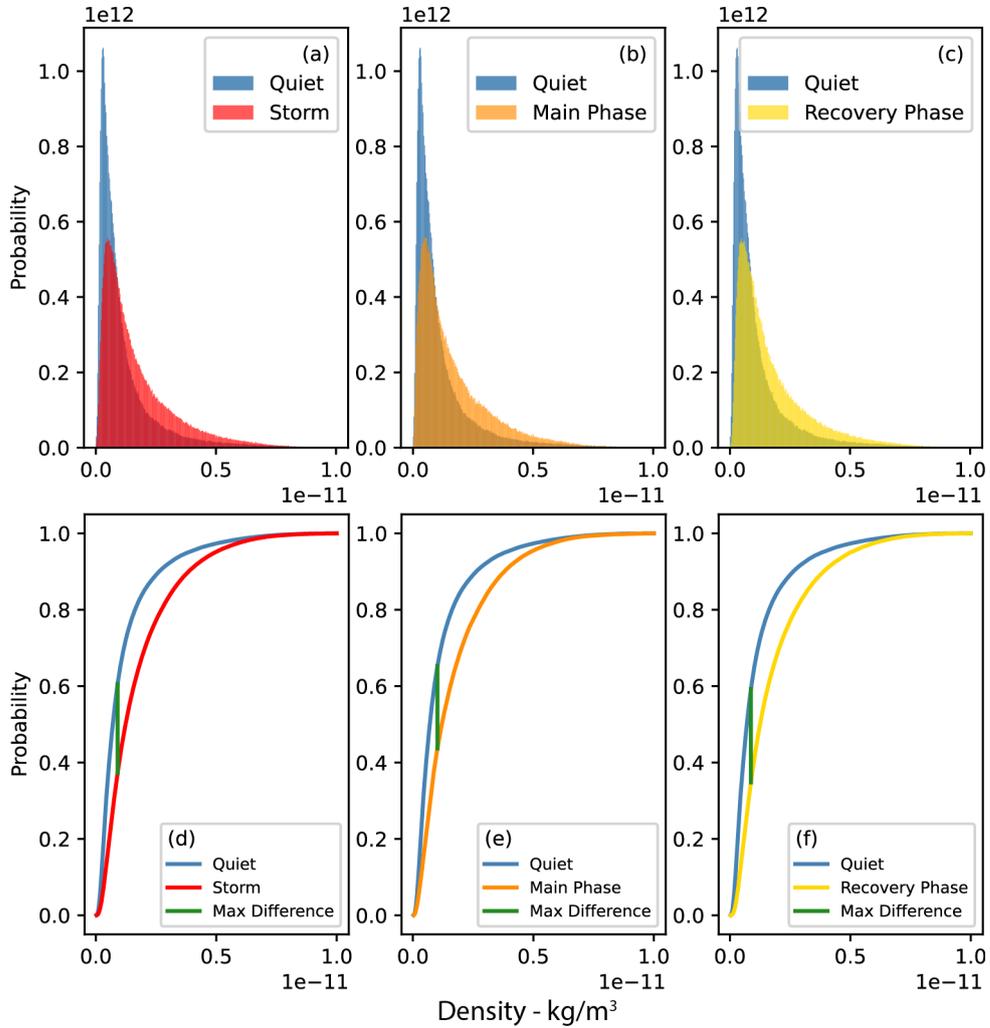
#### 183 4 Atmospheric Density vs Solar and Geomagnetic Activity

184 The dynamics of atmospheric neutral density resulting from solar and geomagnetic  
 185 forcing is complex, responding to a combination of solar drivers and varying geomagnetic  
 186 processes, including geomagnetic storms, substorms, field-aligned currents, and energetic  
 187 particle precipitation. In this section, we investigate the dynamics of atmospheric den-  
 188 sity observed by the GRACE-B satellite as a function of quiet and storm-times, solar ir-  
 189 radiance, solar wind activity, and geomagnetic activity. This analysis is used to inform  
 190 the development of a random forest model of neutral atmospheric density and identify  
 191 key features (independent variables) for the model.

192 Figure 1 shows the distribution of atmospheric neutral density at GRACE-B as a  
 193 function of quiet-times and storm-times. The top row shows the probability distributions  
 194 (integrates to unity), and the bottom row shows the cumulative distributions; quiet times  
 195 are shown in blue, storm-times in red, main phase in orange, and recovery phase in yel-  
 196 low. Evident in both the probability and cumulative distributions is that atmospheric  
 197 density is enhanced during geomagnetic storms. The probability distributions (a-c) show  
 198 that quiet-time densities are concentrated at lower values with a sharp peak and a rapid  
 199 decay. In contrast, storm-time densities have smaller peaks at low densities and a clear  
 200 enhancement in atmospheric density as compared to quiet times. The cumulative dis-  
 201 tributions (d-e) show the same trend; quiet-time densities rapidly reach the asymptotic  
 202 limit of 1 at significantly lower densities than storm-time and storm phase such that higher  
 203 densities are observed more often during storms than quiet times.

204 The green lines on the cumulative distributions (d-e) show the maximum difference  
 205 between the quiet and storm-time distributions. This value can be used in the Kolmogorov-  
 206 Smirnov (KS) test to determine whether two data sets are consistent with being drawn  
 207 from the same distribution. Here, the KS test is used to quantify that the quiet-time den-  
 208 sity distribution is statistically different from the storm-time distribution. In the case  
 209 of storms, the difference between the quiet-time and storm-time and storm phase den-  
 210 sities is large, and the p-value is small. This suggests that the distribution of storm-time  
 211 atmospheric density is statistically and significantly different than the quiet-time distri-  
 212 bution of atmospheric density (for brevity, the values from the KS statistic are not shown).

213 Expanding on the analysis shown in Figure 1 we use correlation matrices to inves-  
 214 tigate the solar and geomagnetic drivers of atmospheric density during quiet- and storm-  
 215 times. Figure 2 (a-c) shows the correlation matrices of atmospheric density and solar in-  
 216 dices, atmospheric density and the FISM2 dataset, and atmospheric density and the OMNI  
 217 dataset (y-axis) as a function of all-times, quiet-times, storm-times, storm main phase,  
 218 and storm recovery phase (x-axis). Figure 2 (a) shows that each solar index and its 81-  
 219 day centered average correlate well with atmospheric density. The highest correlations  
 220 are observed during quiet-times (0.80-0.85), while the lowest is during storm-times and  
 221 specifically the main phase of storms ( $\bar{0}.8$ ). The correlations between atmospheric den-



**Figure 1.** Top, probability distributions of atmospheric density at GRACE-B as a function of (a) quiet- and storm-times, (b) quiet-times and storm main phase, and (c) quiet times and storm recovery phase. Bottom, cumulative distributions of atmospheric density as a function of (d) quiet- and storm-times, (e) quiet-times and storm main phase, and (f) quiet-times and storm recovery phase. The green line in the cumulative distributions shows the maximum difference between each plot's quiet-time distribution and storm distribution.

222 sity and the M10 index are also generally the largest. Of note, the similarity in the cor-  
 223 relations between the day of and 81-day centered average correlations suggest that so-  
 224 lar driving is important for long term variations in atmospheric density on the order of  
 225 several months, as opposed to short term variations on the order of hours and days, time-  
 226 scales associated with geomagnetic storms.

227 The correlation between the 23 spectral bands from FISM2 and atmospheric den-  
 228 sity is shown in Figure 2 (b). Here there are clear differences between quiet and storm-  
 229 times for several bands; several shorter wavelengths between 1.300 – 18.950 *nm* and  
 230 select longer wavelengths 85.550<sup>C</sup>, 94.440<sup>C</sup>, 103.850<sup>C</sup> *nm* correlate well during quiet  
 231 times, while the 85.550<sup>A</sup> *nm* correlates well during quiet and storm intervals. The cor-  
 232 relations in these bands are comparable to those of the solar indices, the largest rang-  
 233 ing from 0.77-0.81 during quiet-times and 0.65-0.73 during storm-times. Compared to  
 234 panel (a), the results in panel (b) suggest that key spectral bands, 1.3, 2.5, and 85.5 *nm*,  
 235 are important to the dynamics of atmospheric density during both quiet- and storm-times.

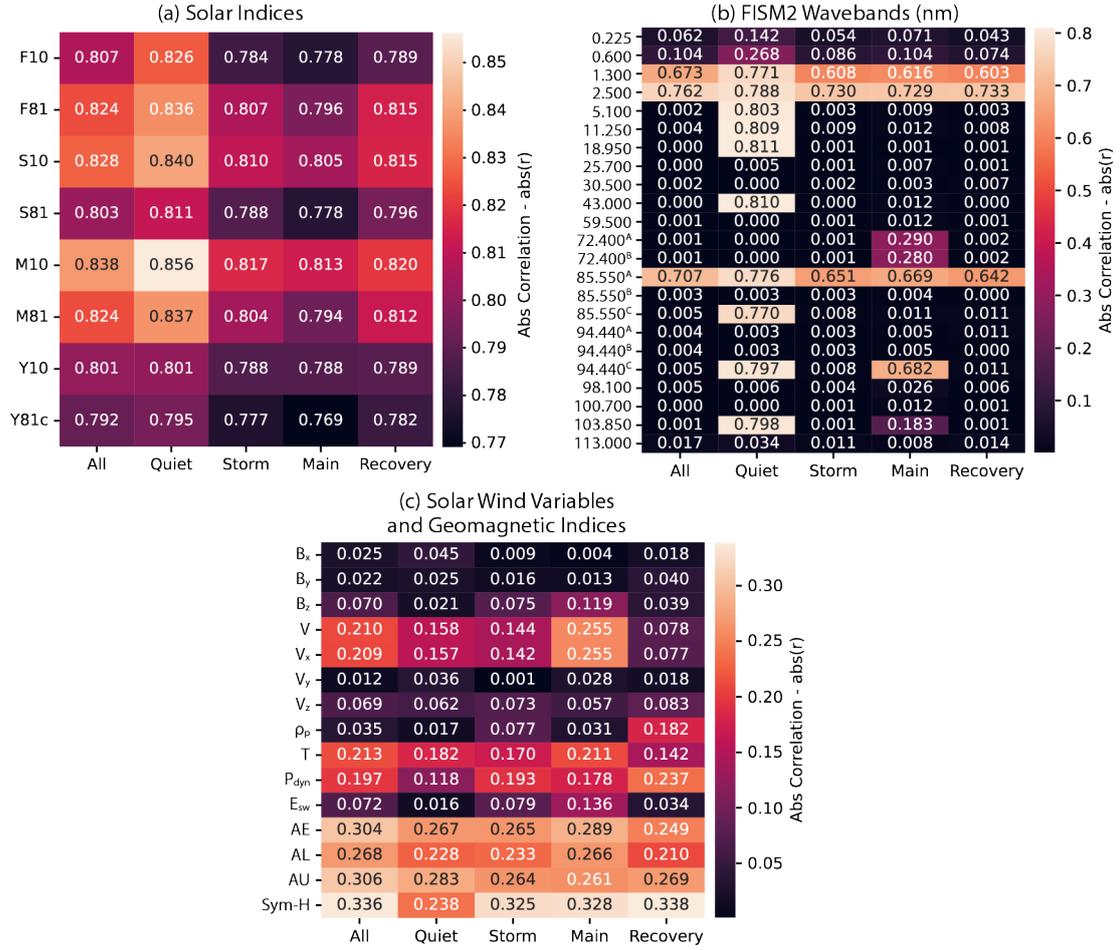
236 Finally, Figure 2 (c) shows the correlations of atmospheric density with solar wind  
 237 variables and geomagnetic indices. These correlations are lower than those of both the  
 238 solar indices and FISM2 wavebands. However, the correlations peak with auroral activ-  
 239 ity as measured by AE, AU, and AL, and storm activity as measured by Sym-H. The  
 240 correlations in Figure 2 (c) are lowest for solar wind variables, the largest being 0.255  
 241 between solar wind velocity and main phase atmospheric density.

242 Taken together, Figures 1 and 2 demonstrate two key points. First, solar activity  
 243 is the key factor controlling the background level of atmospheric neutral density, as demon-  
 244 strated by the high correlations between solar indices and select spectral bands from the  
 245 FISM2 database. Second, storm-time atmospheric neutral density has a different distri-  
 246 bution than quiet times with increased higher density values and proportionally fewer  
 247 lower density values. Previous research has suggested that the difference between storm-  
 248 time and quiet-time densities is likely the result of increased geomagnetic activity lead-  
 249 ing to enhanced joule heating, field-aligned currents, and auroral precipitation during  
 250 geomagnetic storms (Knipp et al., 2004). These results are used to develop and compare  
 251 three random forest atmospheric density models. The goal is to develop a high-cadence  
 252 model of an atmospheric density capable of capturing both quiet- and storm-time dy-  
 253 namics.

## 254 5 Atmospheric Density and Random Forests

255 Machine learning has proven to be a vital resource in Heliophysics. It has been used  
 256 to develop models of magnetospheric dynamics (Bortnik et al., 2018; Li et al., 2023), in  
 257 space weather forecasting (Hua et al., 2022; Iong et al., 2022), and as a tool for scien-  
 258 tific discovery (Camporeale et al., 2022). Here, we utilize Random Forests, an ensem-  
 259 ble machine-learning algorithm based on Decision Trees. In short, Decision Trees cre-  
 260 ate a model that predicts the value of a target, in this case, atmospheric density, by learn-  
 261 ing simple decision rules inferred from the data features or independent variables, here  
 262 solar indices and FISM2 and OMNI data. A Random Forest trains several Decision Trees,  
 263 averaging the target from each Tree to obtain a single ensemble target.

264 Random Forests are particularly useful in model development and model compar-  
 265 isons as there are several methods to investigate and quantify the relative importance  
 266 of features within a model. Here, we use the mean decrease in accuracy (MDA, also re-  
 267 ferred to as permutation importance). The MDA measures the average decrease in ac-  
 268 curacy when a feature vector is randomly shuffled. Randomly shuffling a feature decreases  
 269 model accuracy, the larger the decrease in accuracy of the model the more important the  
 270 feature is. In this methodology, a Random Forest model’s accuracy can be measured by  
 271 one or several metrics such as correlation ( $r$ ) or mean squared error (Morley et al., 2018).



**Figure 2.** Correlation matrices for atmospheric density and (a) solar indices, (b) the FISM2 dataset and (c) solar wind data and geomagnetic indices (y-axis) as a function of all-time, quiet-time, storm-time and storm main and recovery phases (x-axis). The color and number indicate the absolute value of the correlation.

272 The square of the correlation coefficient, median absolute error, mean absolute error, and  
 273 mean absolute percent error were used to measure model performance (below we present  
 274 a subset of these results). The MDA determines the overall importance of features in the  
 275 final models; in the MDA analysis, the square of the correlation coefficient ( $r^2$ ) is used  
 276 to measure feature importance.

277 In this work, we develop three random forest models: one using solar indices, one  
 278 using FISM2 data, and a final model combining FISM2 and OMNI data. We determine  
 279 the most important features for each model and compare the overall accuracy using the  
 280 metrics described in the previous paragraph. However, before developing the three Ran-  
 281 dom Forest models, a subset of data is used to determine the nominal hyperparameters  
 282 or model settings. This optimization helps reduce the chance of overfitting in the mod-  
 283 els and ensures that the models generalize well, that is they work well on not only the  
 284 training data but the test and out of sample (or validation) data as well. In Random Forests,  
 285 the model hyperparameters include the number of trees in the forest, the number of bins  
 286 (or leaves) a tree can end up with, the minimum number of samples in a bin before split-  
 287 ting and creating a new bin, and the number of features to consider when making a de-  
 288 cision. To determine the optimal set of hyperparameters, a number of values is defined  
 289 for each hyperparameter, each combination of hyperparameters is then looped through,  
 290 and a Random Forest fits a subset of data and features. The combination of hyperpa-  
 291 rameters, which maximizes model performance, defines the optimal model setup. Here,  
 292 the model hyperparameters are determined using a subset of the FISM2 and OMNI data  
 293 as features, and GRACE-B density, model performance is measured using the mean ab-  
 294 solute error. An excellent example of this framework is described and illustrated in Bentley  
 295 et al. (2020).

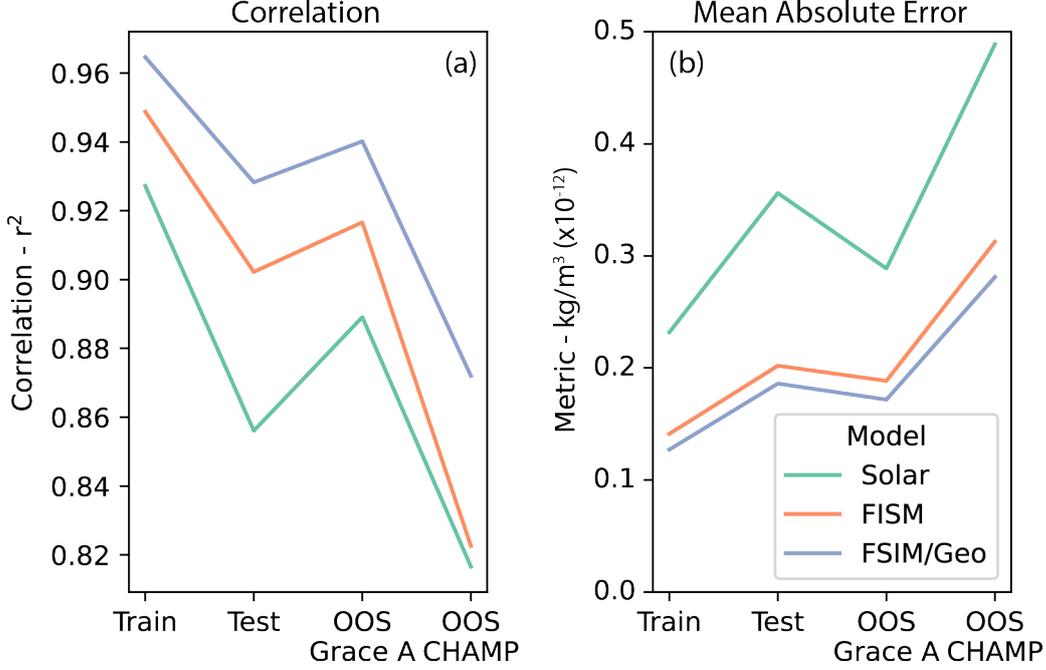
296 Using the nominal set of hyperparameters, three Random Forest models are trained  
 297 using the (i) solar indices, (ii) FISM2, and (iii) FISM2/OMNI as features. In each model,  
 298 the target data is the GRACE-B neutral density and select features from each dataset.  
 299 These features are determined using the correlation matrices shown in Figure 2 and the  
 300 MDA feature importance. Each model's features and target data are separated into a  
 301 train/test dataset using a 70/30 random split. Each model is trained on the training data  
 302 set. The MDA is then used to identify and remove features that add little to the model's  
 303 overall performance. This helps ensure only key features are included and the final model  
 304 is lean (e.g., reduce complexity). The test data set and the out-of-sample GRACE-A and  
 305 CHAMP data sets are used to validate model performance and ensure the model gen-  
 306 eralizes well to inputs it was not trained on, e.g., the model does not overfit to the train-  
 307 ing data. The training and out-of-sample data sets are also used to investigate model  
 308 performance during quiet-times, storm-times, and select case studies. Finally, note that  
 309 all datasets are taken the similar time period, 2002-2012.

310 Table 1 shows the final set of features for each of the three models. Magnetic lo-  
 311 cal time (MLT) and latitude are the base features in each model. The solar indices model  
 312 uses the hourly indices (but not the 81-day centered averages), the FISM2 model uses  
 313 four key wavelengths, and the FISM2/OMNI model uses the same wavelengths as the  
 314 FISM2 model along with the Sym-H and AE indices. Figure 3 shows the performance  
 315 of each model as measured by the square of the correlations coefficient ( $r^2$ ) and the mean  
 316 absolute error. The metrics are calculated for the GRACE B train and test data sets and  
 317 GRACE B and CHAMP the out-of-sample data sets.

318 Overall, each model performs well with correlations between 0.82-0.96 and errors  
 319 on the order of  $0.1 - 0.5 \times 10^{-12} km/m^3$ . However, for each metric and data set, the  
 320 combined FISM2/GEO model performs best; it has the highest correlations and lowest  
 321 errors. This is followed by the FISM2 model and then the solar indices model. In terms  
 322 of data sets, unsurprisingly, the train data set performs best, followed by the test and  
 323 GRACE A data sets, which have very similar performances. The out-of-sample CHAMP  
 324 data set has the lowest correlation and largest errors of all data sets, though, for the FISM2/GEO

**Table 1.** Features used in the random forest models

Base Features (all models)	Solar Features	FISM2 Features	FISM2/GEO Features
MLT	F10, S10	1.30 <i>nm</i>	FISM2 features
$\cos(2\pi \times MLT/24)$	Y10, M10	43.00 <i>nm</i>	Sym-H
$\sin(2\pi \times MLT/24)$	F81, S81	85.55 <i>nm</i>	AE
latitude	Y81, M81	94.40 <i>nm</i>	



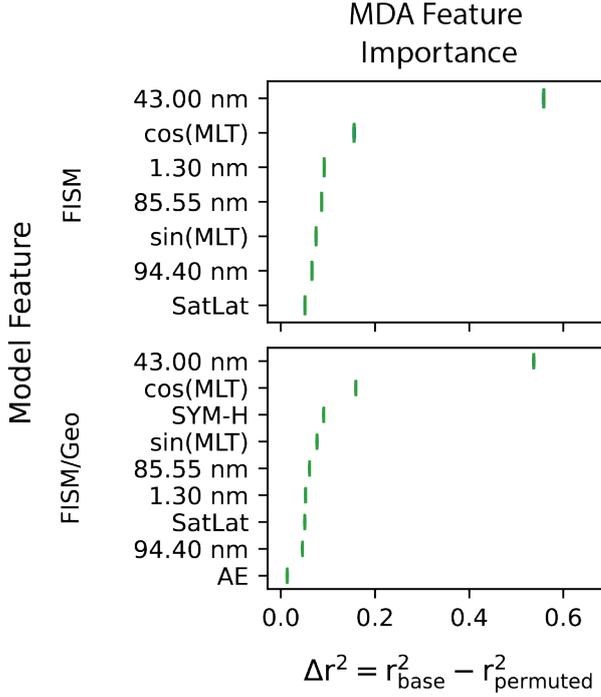
**Figure 3.** Metrics for the three random forest models as a function of data set; train, test, and GRACE A and CHAMP out of sample (OOS). (a) The square of the correlation coefficients. (b) The mean absolute error.

325 model, the correlation remains high  $\tilde{0.88}$  as compared to the FISM2 and solar models.  
 326 The mean absolute error is also low  $0.1 \times 10^{-12} \text{km/m}^3$ , about an order of magnitude  
 327 smaller than typical values observed during geomagnetic storms ( $> 0.1 \times 10^{-11} \text{km/m}^3$   
 328 Figure 1).

### 329 5.1 Feature Importance

330 As described in the previous section, the FISM2/OMNI model performs best, fol-  
 331 lowed by the FIMS2 model and then the solar indices model. However, in this study, we  
 332 also aim to quantify how adding features improves model performance, specifically the  
 333 incorporation of geomagnetic data. In this section, we use the MDA to investigate the  
 334 relative importance of model features in the FISM2 and FISM2/GEO models. The so-  
 335 lar model is ignored as the common features are limited; more importantly, though, the  
 336 previous section demonstrated that more accurate models could be developed using FISM2  
 337 and GEO indices.

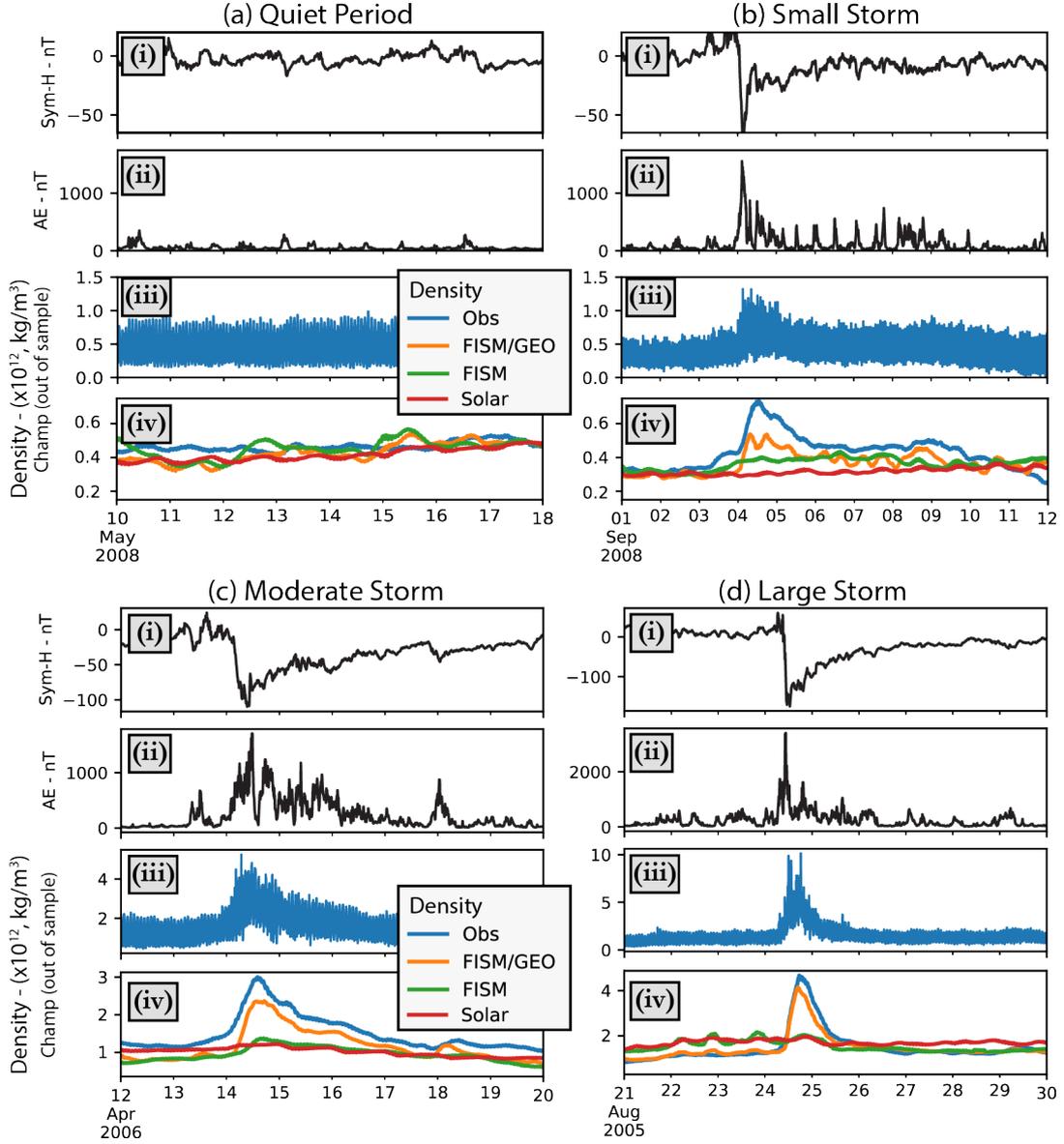
338 Figure 4 shows the MDA values calculated for each feature in the FISM2 and FISM2/OMNI  
 339 models using the out-of-sample CHAMP data set. The out-of-sample data set is used



**Figure 4.** The MDA feature importance for the FISM (top) and FISM /GEO models (bottom). In both panels, the features are ranked from most important (top) to least important (bottom).

340 as it provides data that the model has not seen and allows for a more robust determi-  
 341 nation of feature importance. In Figure 4, the MDA of each feature is calculated using  
 342 a k-folds technique. A feature vector is randomly shuffled and used to predict the tar-  
 343 get value in a given model and calculate a measure (or score) of the models' accuracy.  
 344 This is performed k-times for each feature. The MDA is then calculated as the differ-  
 345 ence between the base score and the average of the shuffled scores,  $\text{MDA} = \delta r^2 = r_{\text{base}}^2 -$   
 346  $\bar{r}_{\text{shuffled}}^2$ . Here, we use the correlation squared as the model score,  $r^2$ .

347 Evident in Figure 4 is that in both the FISM2 and FISM2/OMNI models, the most  
 348 important feature is the 43.00 nm spectral band. Shuffling of this feature reduces  $r^2$  by  
 349 nearly 0.6. This is followed by magnetic local time as characterized by  $\cos(MLT)$ , shuf-  
 350 fling of which reduces  $r^2$  by about 0.2 in both models. In the FISM model, this is fol-  
 351 lowed by the remaining spectral bands and  $\sin(MLT)$ . In the FISM2/GEO model, the  
 352 next important feature is Sym-H, followed by the  $\sin(MLT)$ , the remaining spectral bands,  
 353 and AE. Note in both models, the satellite latitude (SatLat) contributes very little to  
 354 the overall importance of each model, and in the FISM2/GEO model, AE is the least  
 355 important feature. This suggests that while atmospheric density is highly dependent on  
 356 magnetic local time (e.g., day vs night) and Sym-H, there is less variation with latitude  
 357 and possibly nightside activity (as measured by AE), indicating that global phenomena  
 358 such as geomagnetic storms may play a more important role in enhancing atmospheric  
 359 density than more localized phenomena such as substorms. In the next section, we in-  
 360 vestigate model performance during select case studies and statistically over both quiet-  
 361 and storm times.



**Figure 5.** Select case studies comparing observed density from the out-of-sample CHAMP data set and that derived from the three random forest models during (a) geomagnetically quiet period, (c) small geomagnetic storm, (c) moderate geomagnetic storm, and (d) large geomagnetic storm. From top to bottom, each panel shows (i) Sym-H, (ii) AE, (iii) Champ observed density, and (iv) model-data comparison. In panel (iv) the densities have been averaged with a 90 minute rolling window to make comparisons easier and highlight the background change in density during each storm. Observed densities are shown in blue, FISM/GEO modeled densities in orange, FISM modeled densities in green, and solar-modeled densities in red.

362

## 5.2 Case and Statistical Studies

363

364

365

366

367

368

369

370

371

372

373

374

375

376

This section reviews model results during a select quiet period and three increasingly severe geomagnetic storms (as measured by Sym-H). This is followed by a statistical investigation of model residuals as a function of quiet- and storm-times. Figure 5 shows the four case studies (a) a geomagnetically quiet period, (b) a small geomagnetic storm, (c) a moderate storm, and (d) a large storm. Each event shows the same four panels, from top to bottom: (i) Sym-H, (ii) AE, (iii) Champ density normalized to 400 km, and (iv) comparison of Champ and the Random forest modeled densities along the Champ trajectory. Overall, the observed density is highly variable (panels iii), though it typically follows a background trend, especially during storms (b-d). The quiet-time densities are typically low,  $< 10^{12} \text{ km}/\text{m}^3$ , and increase with the geomagnetic storm intensity by a factor of 2 during the small storm and  $\tilde{10}$  during the large storm. The storm-time density enhancements peak during the main phase of each storm as Sym-H decreases and AE activity increases. As the storm recovers and Sym-H and AE trend toward zero, the density enhancements decay toward quiet-time levels.

377

378

379

380

381

382

383

384

385

386

387

388

389

Panel (iv) shows the out-of-sample data-model comparisons. Note that the high variability in the density time series makes any visual comparison difficult; thus, the modeled and observed densities are smoothed with a 90-minute rolling average - the approximate orbital period for a low Earth orbit satellite. Further, we compare the out-of-sample model results and data to get a better idea of the true performance of the three models as models perform better on data sets used in training. Evident in panel (iv) is that during geomagnetic storms (b-c), the combined solar-geomagnetic model (FISM/GEO - orange) performs best, capturing the rapid density enhancement and slow decay density as well as the amplitude of the density enhancement (especially during the moderate and large storm). The two solar models (FISM - green, Solar - red) perform poorly during storms as they are unable to capture the background trend in the variation in atmospheric density during storms. During quiet times (a), all three models generally capture the background variation.

390

391

392

393

394

395

396

397

398

399

400

Figure 6 shows a statistical analysis of the out-of-sample CHAMP residuals for each model as a function of quiet- and storm-times. Panels (a) and (b) show probability distributions of the residuals during geomagnetic quiet periods and storms, respectively (note panels a and b share a y-axis). During quiet-times (a) all three models perform well, the residuals are peaked around zero with similar probability distributions and a slight bias toward the models underestimating the actual density (positive residuals). However, during storm-times (b) the FISM/GEO model (green) performs better than the FISM (red) and Solar (blue) models. The FISM/GEO model highly peaked around zero, while the FISM and Solar models have smaller peaks around zero and larger tails toward larger positive and negative residuals. Again, during storms, each model underestimates the observed density (shift toward positive residuals).

401

402

403

404

405

406

407

408

409

410

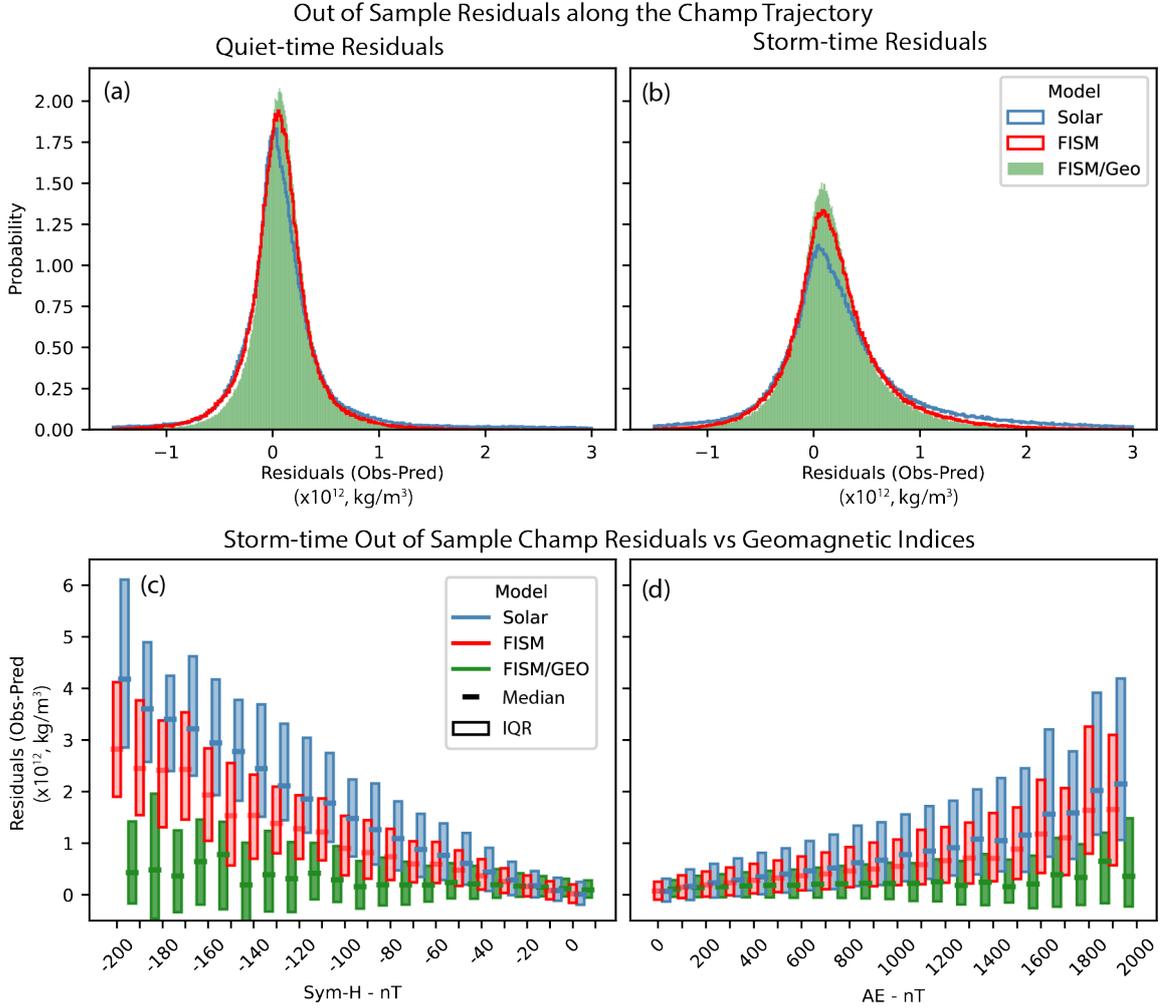
411

412

413

414

Figure 6 (c) and (d) show the storm-time model residuals as a function of geomagnetic activity as measured by Sym-H and AE, respectively (note panels c and d share a y-axis). Here, the residuals are binned by geomagnetic activity, and the residuals are plotted similarly to a box-and-whisker plot: the median is shown by the solid line, and the boxes show the inter-quartile range (bottom of the box is the first quartile, and the top of the box is the third quartile). These panels very clearly highlight the importance of storms and geomagnetic activity in quantifying the dynamics of atmospheric density. In particular, as geomagnetic activity increases during storms and Sym-H becomes more negative and AE more positive, the residuals in the Solar (blue) and FISM (green) models rapidly increase with very large interquartile ranges. However, the residuals of the combined FISM/GEO model remain low, with the median  $< 1$  and upper quartile  $< 2$ . Overall, as storm activity increases, the solar models can have errors up to  $\tilde{8}$  times larger than the model that combines both solar and geomagnetic data and, further, has significant spread as a function of geomagnetic activity such that model accuracy decreases



**Figure 6.** Out of sample Champ residuals as a function of quiet-time and storm-times. Panels (a) and (b) show the probability distributions of the residuals during quiet times and storm times, respectively. Panels (c) and (d) further break down the storm-time residuals as a function of geomagnetic activity measured by Sym-H and AE. In (c) and (d), the residuals are binned by geomagnetic activity, and the median of the residuals is plotted as a solid line and the interquartile range (IQR) as a box for each bin. The top of the boxes represents the third quartile, and the bottom of the boxes represents the first quartile. In panel (c), Sym-H is binned in 10 nT increments. In panel (d), AE is binned in 100 nT increments. In each panel, the Solar model is shown in blue, FISM in red, and FISM/Geo in green.

415 with increasing geomagnetic activity. These differences agree with the case studies high-  
 416 lighted in Figure 5.

## 417 6 Discussion and Conclusions

418 As the number of satellites in low Earth orbit increases, it becomes increasingly  
 419 important to track and predict their orbits accurately. This is especially true with the  
 420 advent of mega-constellations like Starlink, Globalstar, OneWeb, Telesat Lightspeed, and  
 421 Project Kuiper, which are each composed of hundreds to thousands of small satellites.  
 422 Additionally, countries around the world have plans for LEO mega constellations; it is  
 423 expected in the next decade, that nearly 100,000 constellation satellites will be launched  
 424 (J. Zhang et al., 2022), a number which exceeds the total of satellites launched in the  
 425 first half century of the space age by over a factor of 16. While these satellites have im-  
 426 portant societal benefits, including increasing access to high-speed internet in remote ar-  
 427 eas, the increase in LEO satellites has exponentially increased the number of close en-  
 428 counters between satellites, which in-turn increases the chances of collisions. Mitigat-  
 429 ing collisions and monitoring/forecasting close encounters requires accurate knowledge  
 430 and prediction of satellite trajectories.

431 Of all the factors controlling satellite trajectories, drag is the key factor in achiev-  
 432 ing high-fidelity orbit determination. The biggest factor in determining satellite drag is  
 433 atmospheric density and its spatial and temporal variations. The dynamics of atmospheric  
 434 density are driven by a combination of external forcing from the Sun (Lilensten et al.,  
 435 2008) and the magnetosphere (Knipp et al., 2004) and internal processes in the lower  
 436 atmosphere (Liu, 2016). During quiet geomagnetic conditions, the dominant source of  
 437 variations in atmospheric density is solar activity; however, during geomagnetic storms,  
 438 energy input from the magnetosphere can lead to rapid changes in atmospheric density  
 439 ranging from 50-800% (Forbes et al., 1996; Liu, 2016; Oliveira & Zesta, 2019). Here we  
 440 investigated the dynamics of atmospheric density observed by GRACE-B during geo-  
 441 magnetic quiet periods (quiet-times) and geomagnetic storms (storm-time) as function  
 442 of solar and geomagnetic activity and developed, tested, and contrasted three Random  
 443 Forest models of atmospheric density based on low-cadence solar spectral irradiance (those  
 444 used in JB2008), high-cadence solar irradiance (from the FISM2 dataset), and combined  
 445 high-cadence solar irradiance and geomagnetic activity (from the Omni dataset). The  
 446 models were validated for train and test data sets and two out-of-sample data sets, GRACE-  
 447 A and CHAMP. The CHAMP out-of-sample data set was further used to test model per-  
 448 formance during select case studies and statistically investigate model residuals during  
 449 storms as a function of geomagnetic activity.

450 As described above, atmospheric density can vary considerably during geomagnetic  
 451 storms (Forbes et al., 1996; Liu, 2016; Oliveira & Zesta, 2019). While it is known that  
 452 this is the result of energy input from the magnetosphere, little work exists quantifying  
 453 storm-time atmospheric density and investigating the difference between quiet- and storm-  
 454 times. Recent case studies examining several geomagnetic storms with and without ac-  
 455 companying flares proposed that the flares only contributed a minor amount to the re-  
 456 sulting atmospheric disturbances (Qian et al., 2020). The work presented here examines  
 457 the relative contributions of geomagnetic inputs and solar irradiance over a large statisti-  
 458 cal dataset for both storm- and quiet-time conditions. Figure 1, shows the PDF and  
 459 CDF of atmospheric density as a function of storm-times, storm phase, and quiet-times.  
 460 Figure 2 shows the correlations between the low-cadence solar irradiance indices (a), the  
 461 higher-cadence FISM2 irradiance data set (b), and solar wind and geomagnetic activi-  
 462 ty (c) with atmospheric density. Taken together, Figures 1 and 2 demonstrate that while  
 463 solar driving is a key factor in the baseline or long term dynamics of atmospheric den-  
 464 sity, fast changes and magnetospheric processes are a vital component storm-time at-  
 465 mospheric dynamics as evidenced by the correlations of atmospheric density during storms  
 466 with the high cadence FISM2 and OMNI data sets.

467 To explore this in more detail and develop a clearer understanding of the dynam-  
 468 ics and drivers of storm-time atmospheric density, and more importantly, develop a ro-  
 469 bust model of atmospheric density capable of capturing storm-time dynamics we sub-  
 470 sequently developed Random Forest machine learning models of neutral density. Three  
 471 models were developed which shared base features (column 1 of Table 1) but were trained  
 472 on the low-cadence solar wind irradiance indices, that high-cadence FISM2 solar irra-  
 473 diance bands, and a final model which combines features from the FISM2 solar irra-  
 474 diance bands and OMNI geomagnetic data. The features from each model were selected  
 475 based on the correlations shown in Figure 2 and feature importance as measured by the  
 476 mean decrease in accuracy (MDA). The selected features for each model are summarized  
 477 in columns 2-4 of Table 1, respectively. The models were compared using accepted and  
 478 appropriate metrics on the train and test data sets (Grace-B observations) and two out-  
 479 of-sample data-sets, GRACE-A and CHAMP. In all cases the model combining high-cadence  
 480 data from the FISM2 and OMNI datasets performed best, followed by the FISM2 model,  
 481 and then by slow cadence solar indices model (c.f., Figure 3). Figure 4, further inves-  
 482 tigated the relative importance of model features in the two high-cadence models (FISM  
 483 and FISM/Geo) using the mean decrease in accuracy (MDA). This analysis helps to quan-  
 484 tify the relative importance of solar and geomagnetic drivers of atmospheric density dy-  
 485 namics. In both high-cadence models, the 43.00 nm solar irradiance waveband is the most  
 486 important feature, followed by position; however, in the FISM/Geo model the third most  
 487 important feature is Sym-H, often a measure of the strength of geomagnetic storms. This  
 488 supports the conclusion that magnetospheric processes are a fundamental driver of storm-  
 489 time atmospheric dynamics.

490 The metrics and MDA analysis in Figures 3 and 4 provide important insight into  
 491 density dynamics; however, it is important to note that neither of these separated the  
 492 data into quiet- or storm-times. In order to understand and quantify the importance of  
 493 magnetospheric forcing in atmospheric dynamics, Figures 5 and 6 present an analysis  
 494 of select case studies and a detailed investigation of model residuals for each of the three  
 495 models as a function of quiet-times, storm-times, and geomagnetic activity and using only  
 496 the out-of-sample CHAMP data. In the select case studies presented in Figure 5 all three  
 497 models do well during quiet times (panel a); however, as geomagnetic activity increases,  
 498 both solar models do poorly while the FISM/Geo model does very well, capturing the  
 499 shape and time scale of the enhancement though slightly underestimating the peak. Fig-  
 500 ure 6 further quantifies the residuals (observations-predictions) as a function of quiet-  
 501 times (a), storm-times (b), and geomagnetic activity (c and d). Similar to the case stud-  
 502 ies all three models do well during quiet-times while the FISM/Geo model does best dur-  
 503 ing storm-times. Most interestingly, panels (c) and (d) demonstrate that as geomagnetic  
 504 activity increases the errors (or residuals) in the two solar models increase at an almost  
 505 exponential rate. In contrast, the errors in the FISM/Geo model remain flat. Overall,  
 506 Figures 5 and 6, very clearly demonstrate the importance of magnetospheric forcing dur-  
 507 ing storms in atmospheric density, and highlight the necessity of including and consid-  
 508 ering magnetospheric dynamics in atmospheric models.

509 As noted prior, several studies have demonstrated the variation of atmospheric den-  
 510 sity during storms. Thus, it is not surprising that the solar models are not able to cap-  
 511 ture the dynamics of atmospheric density during storms. What is important to note is  
 512 that is that during storms the initial enhancement of density is rapid ( $\lesssim 24$  hours), and  
 513 the decay can occur over several days. In order to capture such dynamics it is imper-  
 514 ative to use higher cadence data sets such as the FISM2 and OMNI datasets, slower ob-  
 515 servations, especially those on the order of days will be unable to capture such variations  
 516 in the atmospheric density. These enhancements and decay timescales have important  
 517 implications when quantifying the performance of models, those here, as well as mod-  
 518 els in general. If one considers only storm-times or storm phase one can incorrectly as-  
 519 sert that in general model errors are small and well behaved, for example, when calcu-  
 520 lating the mean or median error (e.g., Figure 6 b). However, if you consider the full time

521 history during storms (Figure 5) or errors as a function of geomagnetic activity (Figure  
 522 6 c and d), it becomes very clear that solar indices alone are not able to capture the storm-  
 523 time dynamics of atmospheric density. This is quite surprising and very clearly illustrated  
 524 in Figure 6. Errors computed on the out-of-sample data increase nearly exponentially  
 525 with geomagnetic activity in the solar models. In contrast, the errors in the combined  
 526 solar-geomagnetic model remain flat as a function of geomagnetic activity.

527 Overall, the work in this paper has demonstrated and quantified the importance  
 528 of magnetospheric process and geomagnetic activity in storm-time atmospheric density  
 529 dynamics. Future work will investigate the two-dimensional distribution and variation  
 530 in atmospheric density during storms as simulated by the FISM/Geo model, introduc-  
 531 ing additional datasets and features in the FISM/Geo model to improve performance,  
 532 expanding the FISM/Geo model to include altitude, and finally working toward transi-  
 533 tioning this novel research model to operations and developing outputs of use to key  
 534 stakeholders.

## 535 7 Open Research

536 All data used in this manuscript is freely available online. The solar indices were  
 537 obtained from Space Environment Technologies via <https://sol.spacenvironment.net/JB2008/>.  
 538 The FISM2 dataset was obtained from the LASP Interactive Solar Irradiance Datacenter  
 539 (LISIRD) (Laboratory for Atmospheric and Space Physics, 2005) via <https://lasp.colorado.edu/lisird/data>.  
 540 The solar wind and geomagnetic data were obtained from NASA Space Physics Data Fa-  
 541 cility (SPDF) via <https://omniweb.gsfc.nasa.gov/>. The neutral densities were obtained  
 542 from the University of Colorado Boulder Space Weather Data Portal (University of Col-  
 543 orado Boulder and Space Weather Technology, 2019) via [https://lasp.colorado.edu/space-  
 544 weather-portal/](https://lasp.colorado.edu/space-weather-portal/) AGU requires an Availability Statement for the underlying data needed  
 545 to understand, evaluate, and build upon the reported research at the time of peer review  
 546 and publication.

## 547 Acknowledgments

548 The Space Precipitation Impacts (SPI) Heliophysics internal funding model par-  
 549 tially funded K.R.M., A.J.H. K. G-S., J. K., and J. S. V. L. Was funded through the He-  
 550 lioanalytics summer internship.

## 551 References

- 552 Bentley, S. N., Stout, J. R., Bloch, T. E., & Watt, C. E. J. (2020). Random  
 553 forest model of ultralow-frequency magnetospheric wave power. *Earth  
 554 and Space Science*, 7(10), e2020EA001274. Retrieved from [https://  
 555 agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2020EA001274](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2020EA001274)  
 556 (e2020EA001274 10.1029/2020EA001274) doi: [https://doi.org/10.1029/  
 557 2020EA001274](https://doi.org/10.1029/2020EA001274)
- 558 Berger, T. E., Holzinger, M. J., Sutton, E. K., & Thayer, J. P. (2020). Flying  
 559 through uncertainty. *Space Weather*, 18(1), e2019SW002373. Retrieved  
 560 from [https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/  
 561 2019SW002373](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2019SW002373) (e2019SW002373 2019SW002373) doi: [https://doi.org/  
 562 10.1029/2019SW002373](https://doi.org/10.1029/2019SW002373)
- 563 Berthoud, L., & Agass, S. (2022). Identifying space threats for spaceaware resilience-  
 564 a spacecraft and satellite service resilience model. In *2022 IEEE Aerospace Con-  
 565 ference (Aero)* (p. 1-9). doi: 10.1109/AERO53065.2022.9843343
- 566 Blake, S. P., Gallagher, P. T., McCauley, J., Jones, A. G., Hogg, C., Campaña,  
 567 J., ... Bell, D. (2016). Geomagnetically induced currents in the Irish power  
 568 network during geomagnetic storms. *Space Weather*, 14(12), 1136-1154.

- Retrieved from <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2016SW001534> doi: <https://doi.org/10.1002/2016SW001534>
- 569  
570  
571 Bodeau, M., & Baker, D. N. (2021). Effects of space radiation on contemporary space-based systems ii. In *Space weather effects and applications* (p. 13-61). American Geophysical Union (AGU). Retrieved from <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/9781119815570.ch2>  
572  
573  
574  
575 doi: <https://doi.org/10.1002/9781119815570.ch2>
- 576 Bortnik, J., Chu, X., Ma, Q., Li, W., Zhang, X., Thorne, R. M., ... Baker, D. N.  
577 (2018). Artificial Neural Networks for Determining Magnetospheric Con-  
578 ditions. In *Machine learning techniques for space weather* (pp. 279–300).  
579 Elsevier. Retrieved from [https://linkinghub.elsevier.com/retrieve/pii/](https://linkinghub.elsevier.com/retrieve/pii/B9780128117880000111)  
580 <https://doi.org/10.1016/B978-0-12-811788-0.00011-1>
- 581 Bowman, B., Tobiska, W. K., Marcos, F., Huang, C., Lin, C., & Burke, W. (2008,  
582 aug). A New Empirical Thermospheric Density Model JB2008 Using New So-  
583 lar and Geomagnetic Indices. In *Aiaa/aas astrodynamics specialist conference*  
584 *and exhibit*. Reston, Virginia: American Institute of Aeronautics and Astro-  
585 nautics. Retrieved from <https://arc.aiaa.org/doi/10.2514/6.2008-6438>  
586 doi: [10.2514/6.2008-6438](https://doi.org/10.2514/6.2008-6438)
- 587 Bruinsma, S., Sutton, E., Solomon, S. C., Fuller-Rowell, T., & Fedrizzi, M. (2018).  
588 Space Weather Modeling Capabilities Assessment: Neutral Density for Orbit  
589 Determination at low Earth orbit. *Space Weather*, *16*(11), 1806–1816. doi:  
590 [10.1029/2018SW002027](https://doi.org/10.1029/2018SW002027)
- 591 Camporeale, E., Wilkie, G. J., Drozdov, A. Y., & Bortnik, J. (2022, jul).  
592 Data-Driven Discovery of Fokker-Planck Equation for the Earth’s Radi-  
593 ation Belts Electrons Using Physics-Informed Neural Networks. *Jour-*  
594 *nal of Geophysical Research: Space Physics*, *127*(7). Retrieved from  
595 <https://onlinelibrary.wiley.com/doi/10.1029/2022JA030377> doi:  
596 [10.1029/2022JA030377](https://doi.org/10.1029/2022JA030377)
- 597 Carter, B. A., Currie, J. L., Dao, T., Yizengaw, E., Retterer, J., Terkildsen, M., ...  
598 Caton, R. (2020). On the assessment of daily equatorial plasma bubble oc-  
599 currence modeling and forecasting. *Space Weather*, *18*(9), e2020SW002555.  
600 Retrieved from [https://agupubs.onlinelibrary.wiley.com/doi/abs/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2020SW002555)  
601 [10.1029/2020SW002555](https://doi.org/10.1029/2020SW002555) doi: <https://doi.org/10.1029/2020SW002555>
- 602 Carter, B. A., Pradipta, R., Dao, T., Currie, J. L., Choy, S., Wilkinson, P., ... Har-  
603 ris, T. J. (2023). The ionospheric effects of the 2022 hunga tonga volcano  
604 eruption and the associated impacts on gps precise point positioning across  
605 the australian region. *Space Weather*, *21*(5), e2023SW003476. Retrieved  
606 from [https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2023SW003476)  
607 [2023SW003476](https://doi.org/10.1029/2023SW003476) doi: <https://doi.org/10.1029/2023SW003476>
- 608 Cassak, P. A., Emslie, A. G., Halford, A. J., Baker, D. N., Spence, H. E., Avery,  
609 S. K., & Fisk, L. A. (2017). Space physics and policy for contemporary so-  
610 ciety. *Journal of Geophysical Research: Space Physics*, *122*(4), 4430-4435.  
611 Retrieved from [https://agupubs.onlinelibrary.wiley.com/doi/abs/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017JA024219)  
612 [10.1002/2017JA024219](https://doi.org/10.1002/2017JA024219) doi: <https://doi.org/10.1002/2017JA024219>
- 613 Chakraborty, S., Boteler, D. H., Shi, X., Murphy, B. S., Hartinger, M. D., Wang,  
614 X., ... Baker, J. B. H. (2022, October). Modeling geomagnetic induction in  
615 submarine cables. *Frontiers in Physics*, *10*. Retrieved from [https://doi.org/](https://doi.org/10.3389/fphy.2022.1022475)  
616 [10.3389/fphy.2022.1022475](https://doi.org/10.3389/fphy.2022.1022475) doi: [10.3389/fphy.2022.1022475](https://doi.org/10.3389/fphy.2022.1022475)
- 617 Chamberlin, P. C., Eparvier, F. G., Knoer, V., Leise, H., Pankratz, A., Snow,  
618 M., ... Woods, T. N. (2020, dec). The Flare Irradiance Spectral  
619 Model-Version 2 (FISM2). *Space Weather*, *18*(12). Retrieved from  
620 <https://onlinelibrary.wiley.com/doi/10.1029/2020SW002588> doi:  
621 [10.1029/2020SW002588](https://doi.org/10.1029/2020SW002588)
- 622 Cid, C., Guerrero, A., Saiz, E., Halford, A. J., & Kellerman, A. C. (2020). Develop-  
623 ing the ldi and lci geomagnetic indices, an example of application of the auls

- 624 framework. *Space Weather*, 18(1), e2019SW002171. Retrieved from [https://](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2019SW002171)  
 625 [agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2019SW002171](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2019SW002171) doi:  
 626 <https://doi.org/10.1029/2019SW002171>
- 627 Deng, Y., Fuller-Rowell, T. J., Ridley, A. J., Knipp, D., & Lopez, R. E. (2013,  
 628 may). Theoretical study: Influence of different energy sources on the cusp  
 629 neutral density enhancement. *Journal of Geophysical Research: Space Physics*,  
 630 118(5), 2340–2349. Retrieved from [https://onlinelibrary.wiley.com/doi/](https://onlinelibrary.wiley.com/doi/10.1002/jgra.50197)  
 631 [10.1002/jgra.50197](https://onlinelibrary.wiley.com/doi/10.1002/jgra.50197) doi: 10.1002/jgra.50197
- 632 Fang, T.-W., Kubaryk, A., Goldstein, D., Li, Z., Fuller-Rowell, T., Millward, G.,  
 633 ... Babcock, E. (2022). Space weather environment during the spacex star-  
 634 link satellite loss in february 2022. *Space Weather*, 20(11), e2022SW003193.  
 635 Retrieved from [https://agupubs.onlinelibrary.wiley.com/doi/abs/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003193)  
 636 [10.1029/2022SW003193](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003193) doi: <https://doi.org/10.1029/2022SW003193>
- 637 Forbes, J. M., Gonzalez, R., Marcos, F. A., Revelle, D., & Parish, H. (1996, feb).  
 638 Magnetic storm response of lower thermosphere density. *Journal of Geo-*  
 639 *physical Research: Space Physics*, 101(A2), 2313–2319. Retrieved from  
 640 <http://doi.wiley.com/10.1029/95JA02721> doi: 10.1029/95JA02721
- 641 Green, J. C., Likar, J., & Shprits, Y. (2017). Impact of space weather on the satel-  
 642 lite industry. *Space Weather*, 15(6), 804–818. Retrieved from [https://agupubs](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017SW001646)  
 643 [.onlinelibrary.wiley.com/doi/abs/10.1002/2017SW001646](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017SW001646) doi: [https://](https://doi.org/10.1002/2017SW001646)  
 644 [doi.org/10.1002/2017SW001646](https://doi.org/10.1002/2017SW001646)
- 645 Hua, M., Bortnik, J., Kellerman, A. C., Camporeale, E., & Ma, Q. (2022). Ensemble  
 646 modeling of radiation belt electron flux decay following a geomagnetic storm:  
 647 Dependence on key input parameters. *Space Weather*, 20(8), e2022SW003051.  
 648 Retrieved from [https://agupubs.onlinelibrary.wiley.com/doi/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003051)  
 649 [abs/10.1029/2022SW003051](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003051) (e2022SW003051 2022SW003051) doi:  
 650 <https://doi.org/10.1029/2022SW003051>
- 651 Iong, D., Chen, Y., Toth, G., Zou, S., Pulkkinen, T., Ren, J., ... Gombosi, T.  
 652 (2022, aug). New Findings From Explainable SYM-H Forecasting Us-  
 653 ing Gradient Boosting Machines. *Space Weather*, 20(8). Retrieved from  
 654 <https://onlinelibrary.wiley.com/doi/10.1029/2021SW002928> doi:  
 655 [10.1029/2021SW002928](https://doi.org/10.1029/2021SW002928)
- 656 Kim, K.-H., Moon, Y.-J., Cho, K.-S., Kim, H.-D., & Park, J.-Y. (2006, jun). Atmo-  
 657 spheric drag effects on the KOMPSAT-1 satellite during geomagnetic super-  
 658 storms. *Earth, Planets and Space*, 58(6), e25–e28. Retrieved from [https://](https://earth-planets-space.springeropen.com/articles/10.1186/BF03351968)  
 659 [earth-planets-space.springeropen.com/articles/10.1186/BF03351968](https://earth-planets-space.springeropen.com/articles/10.1186/BF03351968)  
 660 doi: 10.1186/BF03351968
- 661 King, J. H., & Papitashvili, N. E. (2005). Solar wind spatial scales in and com-  
 662 parisons of hourly Wind and ACE plasma and magnetic field data. *Journal of*  
 663 *Geophysical Research*, 110(A2), A02104. Retrieved from [http://doi.wiley](http://doi.wiley.com/10.1029/2004JA010649)  
 664 [.com/10.1029/2004JA010649](http://doi.wiley.com/10.1029/2004JA010649) doi: 10.1029/2004JA010649
- 665 Klenzing, J., Halford, A. J., Kellerman, A., & Thompson, B. (2023, March). Using  
 666 application usability levels to support tracking the health of heliophysics. *Fron-*  
 667 *tiers in Astronomy and Space Sciences*, 10. Retrieved from [https://doi.org/](https://doi.org/10.3389/fspas.2023.1144053)  
 668 [10.3389/fspas.2023.1144053](https://doi.org/10.3389/fspas.2023.1144053) doi: 10.3389/fspas.2023.1144053
- 669 Knipp, D. J., Tobiska, W. K., & Emery, B. A. (2004, October). Direct and Indirect  
 670 Thermospheric Heating Sources for Solar Cycles 21–23. , 224(1–2), 495. doi: 10  
 671 .1007/s11207-005-6393-4
- 672 Laboratory for Atmospheric and Space Physics. (2005). *Lasp interactive so-*  
 673 *lar irradiance datacenter. laboratory for atmospheric and space physics*  
 674 [dataset]. Retrieved from <https://lasp.colorado.edu/lisird> doi:  
 675 <https://doi.org/10.25980/L27Z-XD34>
- 676 Li, J., Bortnik, J., Chu, X., Ma, D., Tian, S., Wang, C.-P., ... Lanzerotti, L. J.  
 677 (2023). Modeling ring current proton fluxes using artificial neural network  
 678 and van allen probe measurements. *Space Weather*, 21(5), e2022SW003257.

- 679 Retrieved from [https://agupubs.onlinelibrary.wiley.com/doi/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003257)  
 680 [abs/10.1029/2022SW003257](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003257) (e2022SW003257 2022SW003257) doi:  
 681 <https://doi.org/10.1029/2022SW003257>
- 682 Licata, R. J., & Mehta, P. M. (2022, May). Uncertainty quantification techniques for  
 683 data-driven space weather modeling: thermospheric density application. *Scien-*  
 684 *tific Reports*, *12*(1). Retrieved from [https://doi.org/10.1038/s41598-022-](https://doi.org/10.1038/s41598-022-11049-3)  
 685 [11049-3](https://doi.org/10.1038/s41598-022-11049-3) doi: 10.1038/s41598-022-11049-3
- 686 Licata, R. J., Tobiska, W. K., & Mehta, P. M. (2020). Benchmarking forecasting  
 687 models for space weather drivers. *Space Weather*, *18*(10), e2020SW002496.  
 688 Retrieved from [https://agupubs.onlinelibrary.wiley.com/doi/abs/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2020SW002496)  
 689 [10.1029/2020SW002496](https://doi.org/10.1029/2020SW002496) doi: <https://doi.org/10.1029/2020SW002496>
- 690 Lilensten, J., Dudok de Wit, T., Kretschmar, M., Amblard, P.-O., Moussaoui, S.,  
 691 Aboudarham, J., & Auchère, F. (2008, feb). Review on the solar spectral vari-  
 692 ability in the EUV for space weather purposes. *Annales Geophysicae*, *26*(2),  
 693 269–279. Retrieved from [https://angeo.copernicus.org/articles/26/269/](https://angeo.copernicus.org/articles/26/269/2008/)  
 694 [2008/](https://doi.org/10.5194/angeo-26-269-2008) doi: 10.5194/angeo-26-269-2008
- 695 Liu, H. (2016, September). Variability and predictability of the space envi-  
 696 ronment as related to lower atmosphere forcing. *Space Weather*, *14*(9),  
 697 634–658. Retrieved from <https://doi.org/10.1002/2016sw001450> doi:  
 698 [10.1002/2016sw001450](https://doi.org/10.1002/2016sw001450)
- 699 Liu, H., & Lühr, H. (2005, August). Strong disturbance of the upper thermospheric  
 700 density due to magnetic storms: CHAMP observations. *Journal of Geophys-*  
 701 *ical Research: Space Physics*, *110*(A9). Retrieved from [https://doi.org/10](https://doi.org/10.1029/2004ja010908)  
 702 [.1029/2004ja010908](https://doi.org/10.1029/2004ja010908) doi: 10.1029/2004ja010908
- 703 Lühr, H., Rother, M., Köhler, W., Ritter, P., & Grunwaldt, L. (2004, mar). Ther-  
 704 mospheric up-welling in the cusp region: Evidence from CHAMP observa-  
 705 tions. *Geophysical Research Letters*, *31*(6), n/a–n/a. Retrieved from [http://](http://doi.wiley.com/10.1029/2003GL019314)  
 706 [doi.wiley.com/10.1029/2003GL019314](http://doi.wiley.com/10.1029/2003GL019314) doi: 10.1029/2003GL019314
- 707 Morley, S. K. (2020). Challenges and opportunities in magnetospheric space weather  
 708 prediction. *Space Weather*, *18*(3), e2018SW002108. Retrieved from [https://](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2018SW002108)  
 709 [agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2018SW002108](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2018SW002108) doi:  
 710 <https://doi.org/10.1029/2018SW002108>
- 711 Morley, S. K., Brito, T. V., & Welling, D. T. (2018). Measures of Model Perfor-  
 712 mance Based On the Log Accuracy Ratio. *Space Weather*, *16*(1), 69–88. doi:  
 713 [10.1002/2017SW001669](https://doi.org/10.1002/2017SW001669)
- 714 Murphy, K. R., Mann, I. R., Sibeck, D. G., Rae, I. J., Watt, C., Ozeke, L. G., ...  
 715 Baker, D. N. (2020). A framework for understanding and quantifying the  
 716 loss and acceleration of relativistic electrons in the outer radiation belt during  
 717 geomagnetic storms. *Space Weather*, *18*(5), e2020SW002477. Retrieved  
 718 from [https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2020SW002477)  
 719 [2020SW002477](https://doi.org/10.1029/2020SW002477) (e2020SW002477 2020SW002477) doi: [https://doi.org/](https://doi.org/10.1029/2020SW002477)  
 720 [10.1029/2020SW002477](https://doi.org/10.1029/2020SW002477)
- 721 Murphy, K. R., Watt, C. E. J., Mann, I. R., Jonathan Rae, I., Sibeck, D. G.,  
 722 Boyd, A. J., ... Fennell, J. (2018). The global statistical response of the  
 723 outer radiation belt during geomagnetic storms. *Geophysical Research Let-*  
 724 *ters*, *45*(9), 3783–3792. Retrieved from [https://agupubs.onlinelibrary](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017GL076674)  
 725 [.wiley.com/doi/abs/10.1002/2017GL076674](https://doi.org/10.1002/2017GL076674) doi: [https://doi.org/10.1002/](https://doi.org/10.1002/2017GL076674)  
 726 [2017GL076674](https://doi.org/10.1002/2017GL076674)
- 727 Oliveira, D. M., & Zesta, E. (2019, November). Satellite Orbital Drag Dur-  
 728 ing Magnetic Storms. *Space Weather*, *17*(11), 1510–1533. doi: 10.1029/  
 729 [2019SW002287](https://doi.org/10.1029/2019SW002287)
- 730 Oughton, E. J., Hapgood, M., Richardson, G. S., Beggan, C. D., Thomson,  
 731 A. W. P., Gibbs, M., ... Horne, R. B. (2018, November). A risk as-  
 732 sessment framework for the socioeconomic impacts of electricity trans-  
 733 mission infrastructure failure due to space weather: An application to

- 734 the united kingdom. *Risk Analysis*, 39(5), 1022–1043. Retrieved from  
 735 <https://doi.org/10.1111/risa.13229> doi: 10.1111/risa.13229
- 736 Picone, J. M., Hedin, A. E., Drob, D. P., & Aikin, A. C. (2002, dec). NRLMSISE-  
 737 00 empirical model of the atmosphere: Statistical comparisons and scientific  
 738 issues. *Journal of Geophysical Research: Space Physics*, 107(A12), SIA 15–1–  
 739 SIA 15–16. Retrieved from <http://doi.wiley.com/10.1029/2002JA009430>  
 740 doi: 10.1029/2002JA009430
- 741 Ponder, B. M., Ridley, A. J., Goel, A., & Bernstein, D. S. (2023). Improving fore-  
 742 casting ability of gitm using data-driven model refinement. *Space Weather*,  
 743 21(3), e2022SW003290. Retrieved from [https://agupubs.onlinelibrary](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003290)  
 744 [.wiley.com/doi/abs/10.1029/2022SW003290](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022SW003290) doi: [https://doi.org/10.1029/](https://doi.org/10.1029/2022SW003290)  
 745 [2022SW003290](https://doi.org/10.1029/2022SW003290)
- 746 Qian, L., & Solomon, S. C. (2011, August). Thermospheric density: An overview  
 747 of temporal and spatial variations. *Space Science Reviews*, 168(1-4), 147–  
 748 173. Retrieved from <https://doi.org/10.1007/s11214-011-9810-z> doi:  
 749 [10.1007/s11214-011-9810-z](https://doi.org/10.1007/s11214-011-9810-z)
- 750 Qian, L., Wang, W., Burns, A. G., Chamberlin, P. C., & Solomon, S. C. (2020). Re-  
 751 sponses of the thermosphere and ionosphere system to concurrent solar flares  
 752 and geomagnetic storms. *Journal of Geophysical Research: Space Physics*,  
 753 125(3), e2019JA027431. doi: <https://doi.org/10.1029/2019JA027431>
- 754 Reigber, C., Lühr, H., & Schwintzer, P. (2002, jul). CHAMP mission sta-  
 755 tus. *Advances in Space Research*, 30(2), 129–134. Retrieved from  
 756 <https://linkinghub.elsevier.com/retrieve/pii/S0273117702002764>  
 757 doi: 10.1016/S0273-1177(02)00276-4
- 758 Solomon, S. C. (2005). Solar extreme-ultraviolet irradiance for general cir-  
 759 culation models. *Journal of Geophysical Research*, 110(A10), A10306.  
 760 Retrieved from <http://doi.wiley.com/10.1029/2005JA011160> doi:  
 761 [10.1029/2005JA011160](http://doi.wiley.com/10.1029/2005JA011160)
- 762 Sutton, E. K. (2009, jan). Normalized Force Coefficients for Satellites with Elon-  
 763 gated Shapes. *Journal of Spacecraft and Rockets*, 46(1), 112–116. Retrieved  
 764 from <https://arc.aiaa.org/doi/10.2514/1.40940> doi: 10.2514/1.40940
- 765 Sutton, E. K. (2018, June). A new method of physics-based data assimilation for the  
 766 quiet and disturbed thermosphere. *Space Weather*, 16(6), 736–753. Retrieved  
 767 from <https://doi.org/10.1002/2017sw001785> doi: 10.1002/2017sw001785
- 768 Sutton, E. K., Forbes, J. M., & Nerem, R. S. (2005, sep). Global thermospheric  
 769 neutral density and wind response to the severe 2003 geomagnetic storms from  
 770 CHAMP accelerometer data. *Journal of Geophysical Research: Space Physics*,  
 771 110(A9). Retrieved from <http://doi.wiley.com/10.1029/2004JA010985>  
 772 doi: 10.1029/2004JA010985
- 773 Thayer, J. P., Tobiska, W. K., Pilinski, M. D., & Sutton, E. K. (2021). Remain-  
 774 ing issues in upper atmosphere satellite drag. In *Space weather effects and*  
 775 *applications* (p. 111-140). American Geophysical Union (AGU). Retrieved  
 776 from [https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/9781119815570.ch5)  
 777 [9781119815570.ch5](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/9781119815570.ch5) doi: <https://doi.org/10.1002/9781119815570.ch5>
- 778 Tobiska, W. K., Bouwer, S. D., & Bowman, B. R. (2008). The development  
 779 of new solar indices for use in thermospheric density modeling. *Jour-  
 780 nal of Atmospheric and Solar-Terrestrial Physics*, 70(5), 803–819. doi:  
 781 [10.1016/j.jastp.2007.11.001](https://doi.org/10.1016/j.jastp.2007.11.001)
- 782 University of Colorado Boulder and Space Weather Technology. (2019). *Swx trec*  
 783 *space weather data portal* [dataset]. Retrieved from [https://lasp.colorado](https://lasp.colorado.edu/space-weather-portal)  
 784 [.edu/space-weather-portal](https://lasp.colorado.edu/space-weather-portal) doi: [https://lasp.colorado.edu/space-weather](https://lasp.colorado.edu/space-weather-portal/doi)  
 785 [-portal/doi](https://lasp.colorado.edu/space-weather-portal/doi)
- 786 Wahr, J., Swenson, S., Zlotnicki, V., & Velicogna, I. (2004, jun). Time-variable  
 787 gravity from GRACE: First results. *Geophysical Research Letters*, 31(11),  
 788 n/a–n/a. Retrieved from <http://doi.wiley.com/10.1029/2004GL019779>

- 789           doi: 10.1029/2004GL019779  
790       Zesta, E., & Oliveira, D. M. (2019, November). Thermospheric heating and cool-  
791           ing times during geomagnetic storms, including extreme events. *Geophysical*  
792           *Research Letters*, *46*(22), 12739–12746. Retrieved from [https://doi.org/](https://doi.org/10.1029/2019gl085120)  
793           10.1029/2019gl085120 doi: 10.1029/2019gl085120  
794       Zhang, J., Cai, Y., Xue, C., Xue, Z., & Cai, H. (2022). Leo mega constellations:  
795           Review of development, impact, surveillance, and governance. *Space: Science*  
796           *& Technology*, *2022*. Retrieved from [https://spj.science.org/doi/](https://spj.science.org/doi/abs/10.34133/2022/9865174)  
797           abs/10.34133/2022/9865174 doi: 10.34133/2022/9865174  
798       Zhang, Y., Paxton, L. J., & Jones, J. C. (2018). Introduction to nasa living with  
799           a star institute special section on low earth orbit satellite drag: Science and  
800           operational impact. *Space Weather*, *16*(8), 939-945. Retrieved from [https://](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2018SW001983)  
801           agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2018SW001983 doi:  
802           <https://doi.org/10.1029/2018SW001983>

Figure 1.

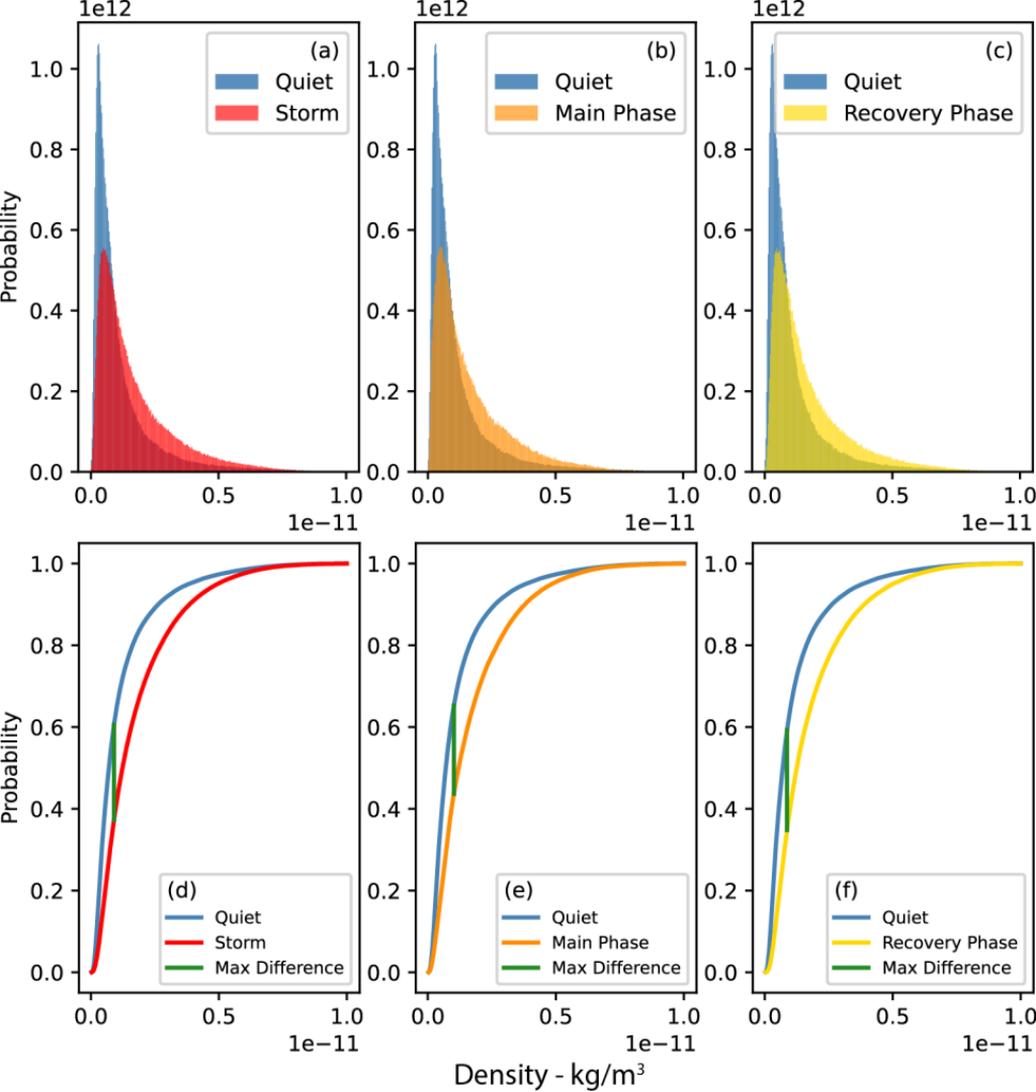
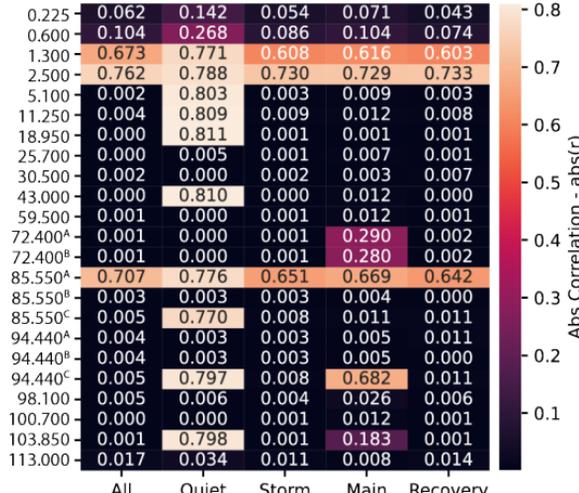


Figure 2.

(a) Solar Indices



(b) FISM2 Wavebands (nm)



(c) Solar Wind Variables and Geomagnetic Indices



Figure 3.

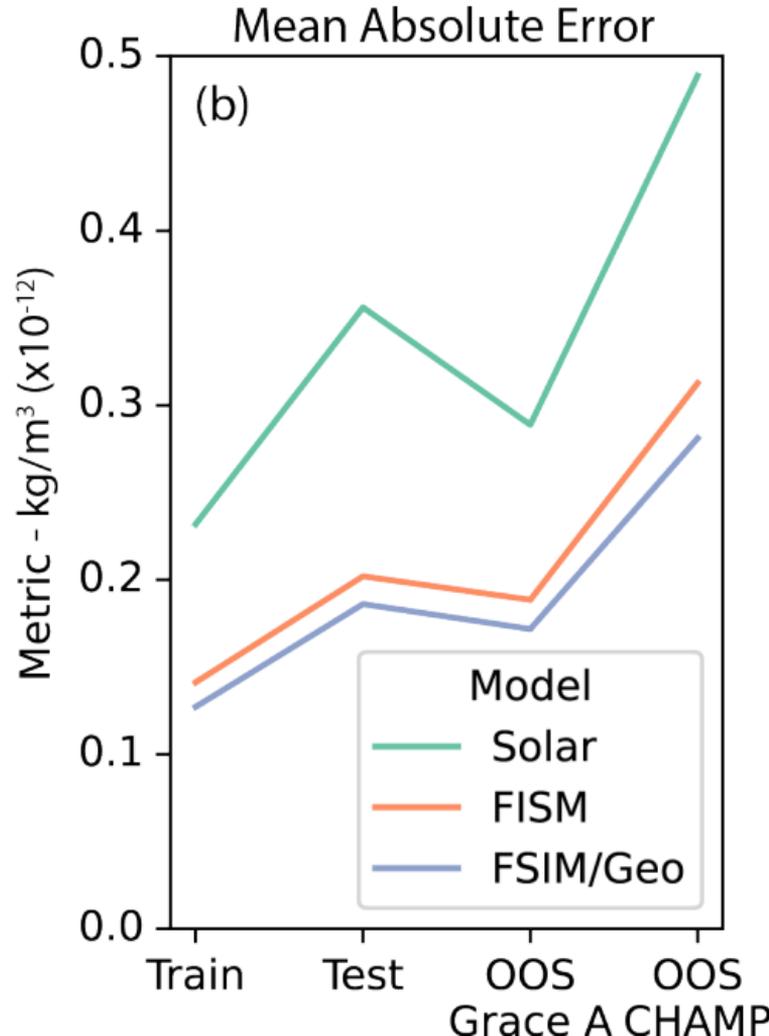
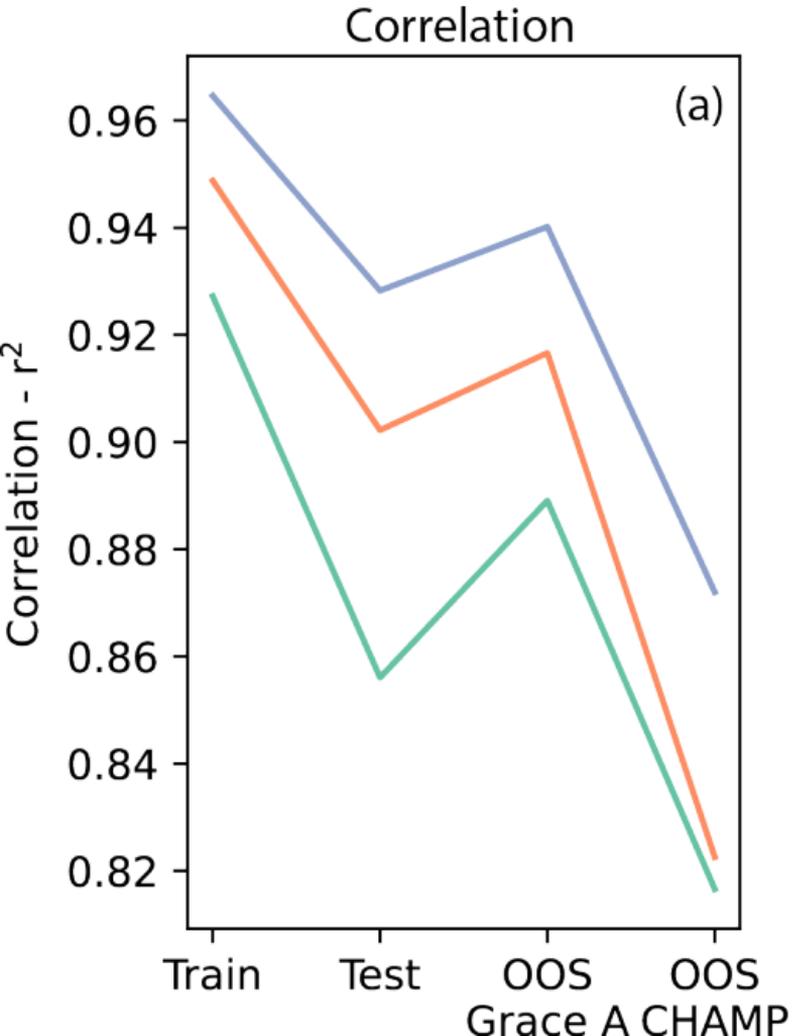


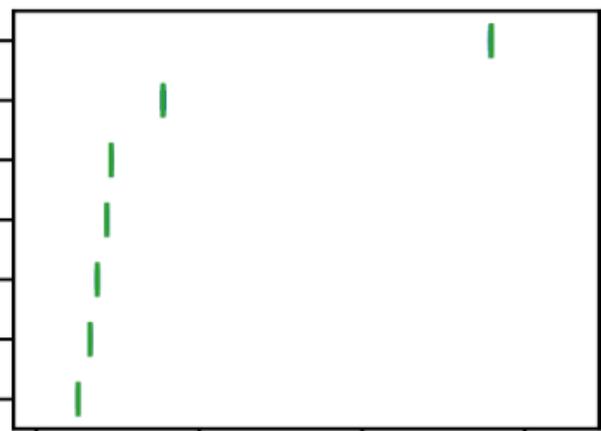
Figure 4.

Model Feature

MDA Feature Importance

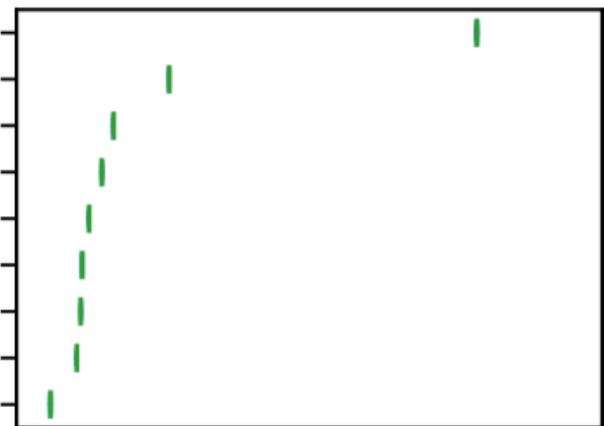
FISM

43.00 nm  
cos(MLT)  
1.30 nm  
85.55 nm  
sin(MLT)  
94.40 nm  
SatLat



FISM/Geo

43.00 nm  
cos(MLT)  
SYM-H  
sin(MLT)  
85.55 nm  
1.30 nm  
SatLat  
94.40 nm  
AE

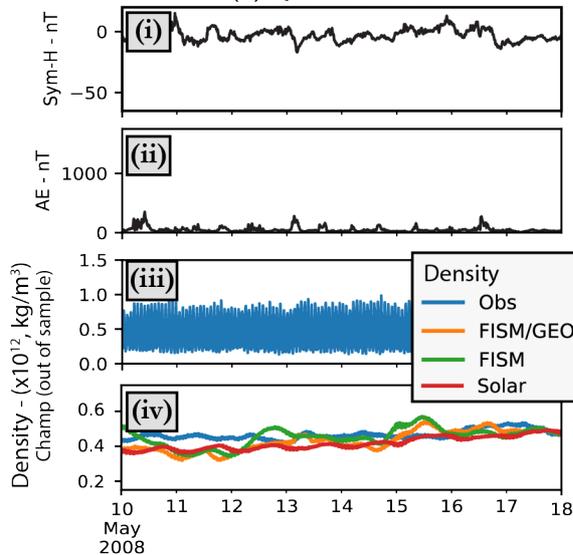


0.0 0.2 0.4 0.6

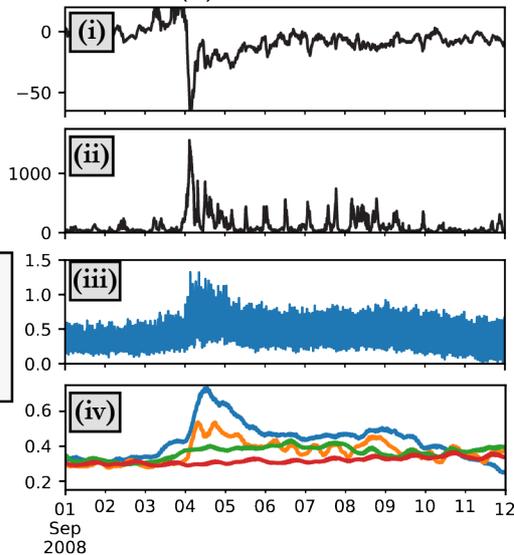
$$\Delta r^2 = r^2_{\text{base}} - r^2_{\text{permuted}}$$

Figure 5.

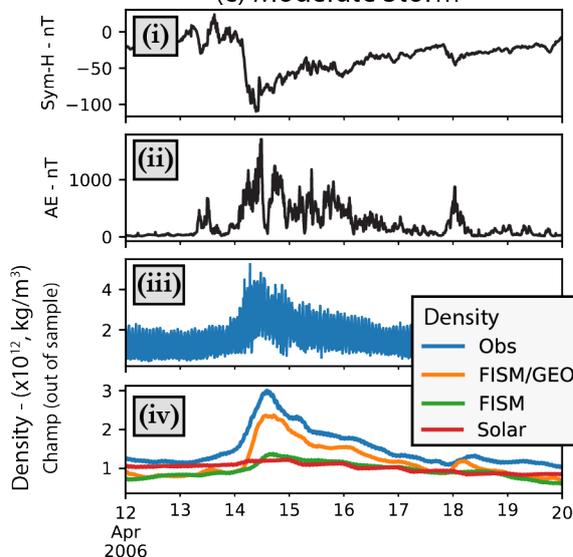
(a) Quiet Period



(b) Small Storm



(c) Moderate Storm



(d) Large Storm

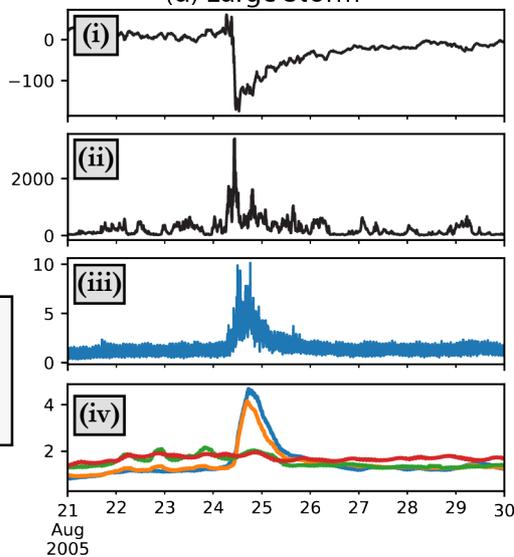
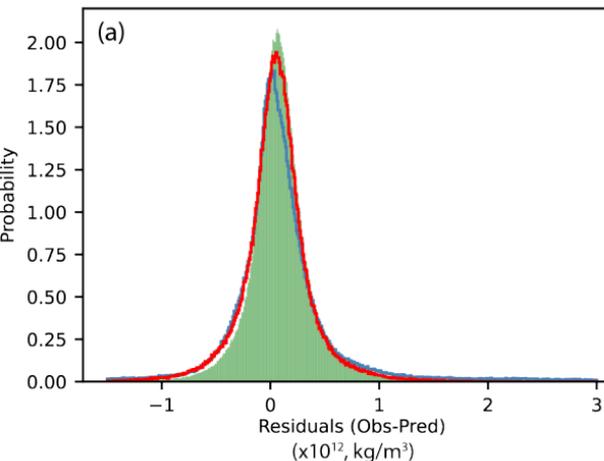


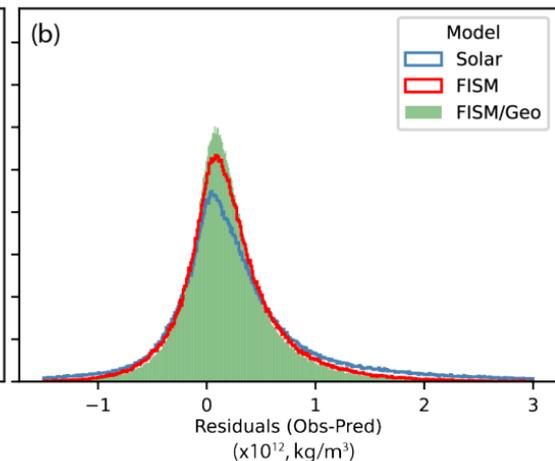
Figure 6.

# Out of Sample Residuals along the Champ Trajectory

## Quiet-time Residuals



## Storm-time Residuals



## Storm-time Out of Sample Champ Residuals vs Geomagnetic Indices

