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**Predicting Satellite Anomalies with Solar Weather**

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**Abstract**

Satellite anomalies, often caused by space weather events like solar flares, pose a significant threat to satellite operations. This study aims to develop a predictive model for satellite anomalies using space weather data, specifically focusing on X-ray and EUV irradiances. A logistic regression model was employed to classify the occurrence of anomalies based on key space weather variables. Spearman correlation analysis was conducted to identify the most relevant predictors of anomaly events, including X-ray flux measurements. The model was evaluated using 5-fold cross-validation to ensure robust performance across different subsets of the data. In addition to logistic regression, various other modeling approaches were explored to capture complex relationships in the data, including decision trees and machine learning algorithms. The findings from this research provide a foundation for improving satellite anomaly prediction by leveraging space weather data, with potential applications in satellite operations and space weather forecasting. Future work may involve incorporating more extensive datasets, advanced modeling techniques, and improved space weather predictions to enhance forecasting accuracy.

**Introduction**

The Sun is a massive sphere of plasma whose energy is generated via internal nuclear reactions. The energy generated by these reactions are emitted directly outwards towards the solar system in the form of electromagnetic radiation [[AGU](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2003SW000056)]. Solar emissions cover a broad range of the electromagnetic spectrum, from visible light to x-rays. The intensity and frequency of these emissions vary as the Sun oscillates from solar minimum, when the surface is relatively uninteresting, to solar maximum, when it is most complex.

Certain solar events can create larger spikes in energy emissions. For instance, solar flares and coronal mass ejections (CMEs) are considered solar events, and are classified by unusually intense emissions of high-energy particles and electromagnetic radiation. Solar flares and CMEs are a direct product of the Sun’s random, volatile nature [[NOAA SWPC](https://www.swpc.noaa.gov/phenomena/coronal-mass-ejections), [NASA](https://hesperia.gsfc.nasa.gov/rhessi3/mission/science/the-impact-of-flares/index.html#:~:text=The%20x%2Drays%20from%20flares,atmosphere%2C%20causing%20it%20to%20expand.)].

These emissions, henceforth referred to as ‘solar weather’ in this paper, can have an incredible impact on electronics. This effect is amplified for satellites in Earth’s orbit, who are subject to the brunt of the Sun’s ionized particles and waves. Solar weather can provoke electronic malfunctions, physical drag in the atmosphere, and a loss of communication with a satellite. There are many important reasons for why we want to study solar weather’s impact, especially given that objects sent out to space require a massive amount of money and resources to keep active. As such, learning how solar weather relates to these malfunctions can help us predict and prevent such risks. For example, high bursts of electromagnetic radiation cause the Earth’s atmosphere to react, creating local density which in turn increases high drag for orbiting satellites [[JSWSC](https://www.swsc-journal.org/articles/swsc/full_html/2022/01/swsc220018/swsc220018.html#:~:text=Unexpected%20space%20weather%20causing%20the%20reentry%20of%2038%20Starlink%20satellites%20in%20February%202022,-Ryuho%20Kataoka1&text=The%20accidental%20reentry%20of%2038,broader%20area%20than%20previously%20thought.&text=This%20is%20an%20Open%20Access,original%20work%20is%20properly%20cited.)]. Drag can change a satellite’s intended orbit, or otherwise send it off-course.

Previous research in this area of study also examines what weather can cause extraordinary problems in electronics. Ionized particles from the Sun have been of particular interest because they can cause a “switch” (much like a switch in a circuit that goes from 0 to 1). More specifically, they create a magnetic field within sensitive electronics which cause all sorts of issues. This is a growing problem because as technology becomes more advanced, a greater amount of sensitive electronics are harbored within satellites in outer space, which makes it more prone to such effects. Such incidents can have a significant impact on the long and short term health of a satellite. We call these adverse effects “anomalies,” which are noticeable irregularities in a satellite’s behavior.

The purpose of our project is to create a model that intakes solar weather data from the web via scraping, and outputs a forecast of potential satellite problems under those conditions. If we can predict when a satellite anomaly will occur, we can prepare the satellite to brace for the weather by using some sort of preventative measure. For ionized particles, the satellite may have a “safe mode” where sensitive electronics can retreat behind a countermeasure until the solar weather has passed. For drag caused by solar particles, operators on Earth can give extra thrust to the satellite. Our topic specifically focuses on SEUs, or “single event upsets,” which cause disruption to a satellite.

Furthermore, these correlations are not only important because we want to react to solar weather. Another huge reason for studying solar weather’s impact on satellites is to know when adverse reactions from a satellite may not be caused by solar weather, and instead be caused by a malicious force from somewhere on Earth. Satellite malfunctions are a security concern, and identifying a malicious disruption is vital. If we can predict when solar weather causes a problem, and diagnose it correctly, then we can also predict when solar weather is not the problem, authorities can then take appropriate measures to figure out where the problem lies and if it is malicious.

Our project will be partitioned by two satellite types: Low Earth Orbit satellites (LEO), and Geostationary Earth Orbit satellites (GEO). Satellites orbit Earth at many different altitudes, but solar weather affects these different delineations with different intensities. Consequently, it is important to distinguish them. LEO orbiting satellites orbit below 600 km from Earth, and the most common anomalies on LEO vessels are caused by high drag, since LEO craft are still well within the atmosphere and thus suffer from higher atmospheric density during solar storms [[IEEE](https://ieeexplore.ieee.org/abstract/document/8700141?casa_token=RmGUic_E9S8AAAAA:UGehzv1lPiz3ACIB4MYma9yw0HqQdKKMbJzPJ2FoBLPvhujihVQvwmLoWbFOTs6In0mWxAs)]. Conversely, GEO satellites orbit around 35,700 km about Earth, and are significantly less protected by the Earth’s atmosphere from energy emissions [[IEEE](https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=902228)]. Thus, anomalies aboard GEO satellites are most frequently caused by raw particles and electromagnetic radiation directly from the Sun. Being able to understand and identify the unique anomaly types within each orbit, and how to predict them using solar conditions, is highly relevant to our project.

**Sources**

Our project draws extensively from authoritative sources like National Oceanic and Atmospheric Administration (NOAA), a trusted institution for monitoring and forecasting space weather. NOAA provides detailed information relating to space weather, such as solar flares, geomagnetic storms, and x-ray flux, which are directly linked to satellite anomalies. Data from NOAA is highly relevant because the organization is a leading provider of real-time space weather updates, which are essential for understanding and predicting the effects of solar activity on satellite operations.

In addition, other public websites that compile space weather information, such as NASA’s Space Weather Prediction Center and international satellite data, contribute to the data pool. These sources provide both historical and current observations, allowing for comprehensive analysis of satellite anomaly patterns over time.

NOAA and similar public sources are recognized globally for their scientific accomplishments, ensuring the accuracy and reliability of the data. NOAA’s data collection methods are based on advanced instruments like space-based GEO sensors, satellite monitoring systems, and ground based observatories. This data is updated regularly, as reflected by their Space Weather dashboard which depicts current space weather patterns along with recent solar activity. The abundance of reliable data from NOAA is crucial for examining space weather effects, as satellite anomalies are complex and may have multiple causes.

The data from NOAA typically consists of time-series datasets, which capture space weather variables (e.g., EUV, X-ray flux, geomagnetic activity) alongside timestamps. This structure is suitable for correlating space weather events with satellite anomalies, which are also collected from NOAA. The anomaly data provides details on the date the anomaly occurred, the diagnosis of the issue, the type of anomaly, and the duration. A second type of anomaly data includes only the timestamps of the events. The time-series format allows analysts to compare space weather patterns and anomalies over time, providing valuable information regarding their relationship.

Previous research has emphasized the critical role of space weather events in affecting satellite operations, highlighting the importance of accurately forecasting these events to protect satellite technology. Feynman and Gabriel (2000) identified solar energetic particles (SEPs), geomagnetic storms, and galactic cosmic rays as the primary space weather phenomena that impact satellites, while noting that the solar wind has minimal harmful effects. Their study also found that solar cycles and CMEs are the best predictors of these space weather events, although they pointed out that current forecasting models, with the exception of NASA's, are inadequate for long-term predictions.

Further investigations have shown that the vulnerability of satellites varies depending on their orbital position. Satellites in LEO are more susceptible to communication loss and atmospheric drag due to solar activity, as their lower altitude and greater energy generation increase their exposure to space weather effects. In contrast, GEO satellites face more risks from high-charge particles. These vulnerabilities are compounded by the increasing complexity of satellite electronics, making them more susceptible to anomalies like SEUs, which can disrupt satellite operations for hours, as seen in the Galaxy 4 satellite failure (Baker, 2000).

Moreover, high-energy electromagnetic waves pose additional risks to GEO satellites, while LEO satellites experience increased atmospheric drag from solar activity, further emphasizing the need for accurate space weather predictions to mitigate the impact on satellite systems (Horne et al., 2013). The combination of data from reliable public institutions like NOAA, along with peer-reviewed research from the scientific community, provides a robust foundation for analyzing how space weather causes anomalies in satellites. By carefully selecting and verifying the source of data and research, the study ensures that the insights drawn are credible, relevant, and backed by evidence-based research.

**Methodology**

The process of building this model can be separated into three parts. The first is to gather necessary data and to prepare it for modeling, the second step is to explore the data to determine effective modeling techniques, and the third is to create a model with a high test accuracy.

**Data Collection**

Data for this project came from two sources - the NASA/GOES 16 and 17 satellites, and an internally-provided data set containing anomaly data about GOES satellite anomalies. The primary reason GOES satellite data was chosen over other open-sourced GEO satellite data was simply because the internally-provided data set, mentioned above, contains data from the GOES satellites. This data set contains the exact moments, down to the accuracy of a minute, at which satellite anomalies aboard the GOES 16 and 17 satellites were observed. It is then no question that the most accurate data we can use to analyze the anomalies should come from the GOES satellites themselves, as we can easily overlap this data with our anomaly data set to identify trends. As for the source of the data, the NASA/NOAA GOES 16 and 17 satellites, operational since 2016 and 2017 respectively, are multi-purpose satellites whose functions include high-fidelity weather imaging, state-of-the-art geostationary lightning mapping, and importantly, space weather measurements. This publicly-available data was scraped directly from the NOAA website and downloaded directly into a shared repository. The code for the scrape can be found in the appendix of this paper.

While NOAA provides many different tables of space weather data observations, we singled out two data sets which are of most use to the purpose of this paper - minute extreme ultraviolet (EUV) and x-ray emissions. Prior research has already established a heavy correlation between solar events (CMEs, solar flares) and anomalies, and one of the biggest characteristics of solar events are huge spikes in high-frequency light waves, especially x-rays. Naturally, if we go by prior research, then we can expect to see some sort of relationship between EUV and x-ray emissions and anomalies. As for the physical source, the data itself is collected via the GOES 16 Extreme Ultraviolet and X-ray Sensor (EXIS), an onboard x-ray and EUV sensor that measures changes in extreme ultraviolet irradiances from the sun.

Below is a table documenting the metadata of the two data sets we retrieved from the NOAA website.

Metadata on EUV and X-ray Variables in the Data Used in Research

| EUV Flux | | X-ray Flux | |
| --- | --- | --- | --- |
| time | Time of each observation, measured in minutes | Time | Time of each observation, measured in minutes |
| irr\_256 | Irradiance of light oscillating at 256 nanometers a second | xrsa\_flux\_observed | Raw x-ray detection of wavelengths .05 - .4 nm |
| irr\_284 | Irradiance of light oscillating at 284 nanometers a second | xrsb\_flux\_observed | Raw x-ray detection of wavelengths .4 - .11 nm |
| irr\_304 | Irradiance of light oscillating at 304 nanometers a second | xrsa\_flux\_electrons | Adjusted x-ray detection of wavelengths .05 - .4 nm |
| irr\_1175 | Irradiance of light oscillating at 1175 nanometers a second | xrsb\_flux\_electrons | Adjusted x-ray detection of wavelengths .4 - .11 nm |
| irr\_1216 | Irradiance of light oscillating at 1216 nanometers a second | xrsa\_flag | Flag that indicates status of the X-ray flux in channel A |
| irr\_1335 | Irradiance of light oscillating at 1335 nanometers a second | xrsb\_flag | Flag that indicates status of the X-ray flux in channel B |
| irr\_1405 | Irradiance of light oscillating at 1405 nanometers a second |  |  |

[Table 1]

**Data Cleaning**

After gathering all of the data necessary for our project, we needed to aggregate it into one dataset specifically designed for modeling and measuring how good our model functions. To do this, we first needed to join the datasets by a time ID. We did this by transforming a variety of time measurements into one consistent variable that was accurate to the specified time period (a one minute average) across all of our data. Then, we joined all of our data such that no columns or observations would be lost. There were several anomaly dataset observations that did not match with NOAA data, and a vast majority of NOAA x-ray and EUV values that did not have any anomaly recorded. However, we could not simply do away with all of our NA values, or else we would only have observations where an anomaly occurred that included our prediction data from NOAA.

To create a model that predicts anomalies, we needed a new variable that recorded a binary value based on whether an anomaly occurred (1) or did not occur (0). This would also serve as our response variable, and help declutter the joined dataset by eliminating extra timestamps and NA values in columns where anomalies did not exist. By doing this, we could also filter out the few anomalies that had no NOAA data. To make this new column, we conditioned a new binary variable named “binary” on whether or not a timestamp from the original anomaly dataset existed.

We also decided to trim our model data to an even split between observations when an anomaly happened (binary = 1), and when one did not happen (binary = 0). Model accuracies can be deceptive when using an uneven split of binary values as the response variable, as seen later in our model-building process when we encountered this problem. To make the even split, we first created a dataset filtered only with anomalies (binary = 1) that included NOAA prediction data, then from the remaining dataset consisting of data with no anomalies (binary = 0), we took a random sample of the same size. This meant we ended up with 2590 observations in total: 1295 with an anomaly recorded, and 1295 without, all spanning from the years 2018 to 2021 when we had complete anomaly data. This discarded a massive amount of observations without anomalies (approximately 2 million) from the original NOAA minute-average data. In doing this, we successfully eliminated NA values from our dataset while also creating new clean data that was ready to be fed into our model, and so the model building process began.

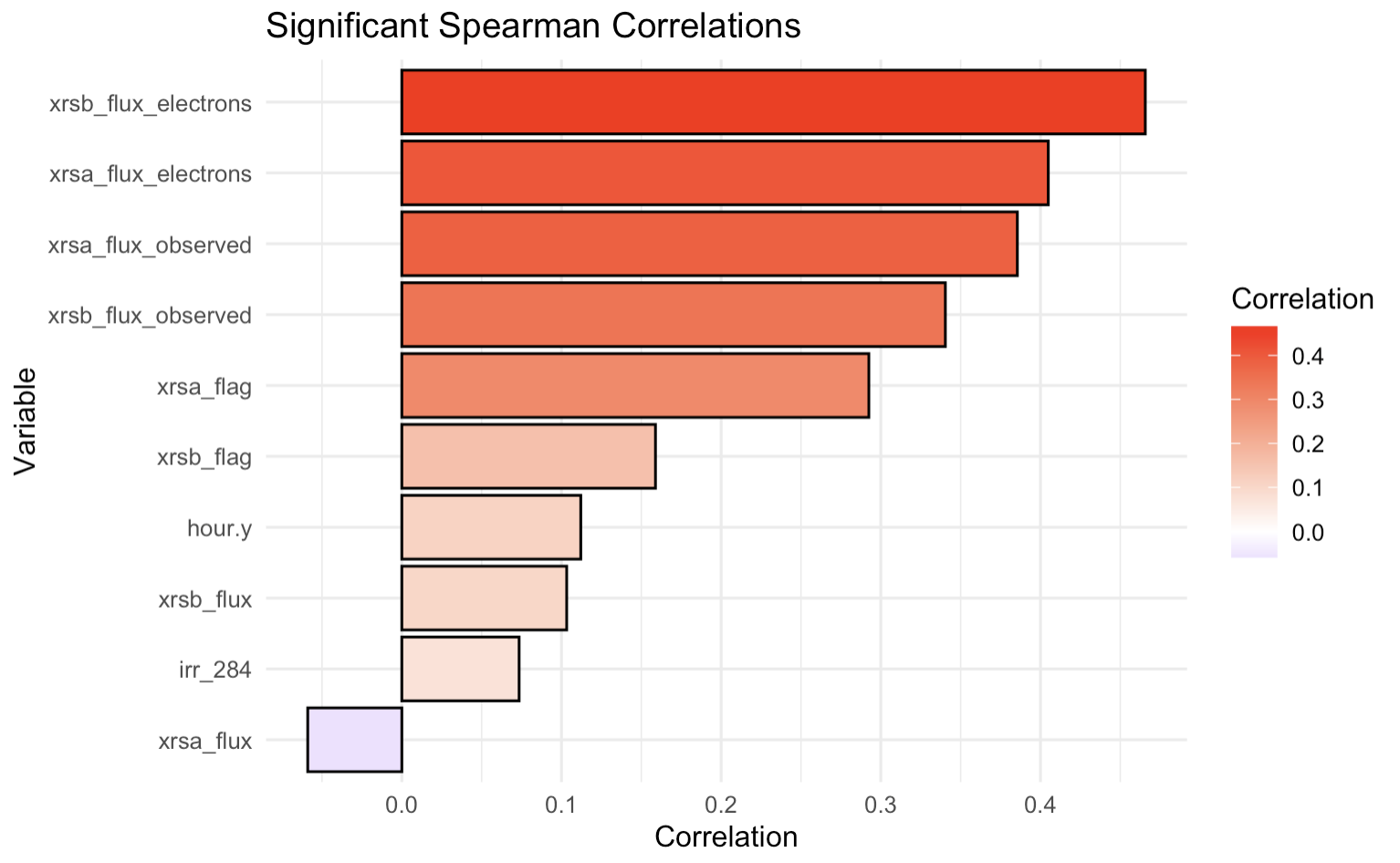
Given the structure of our data, where half of the observations correspond to anomalies and the other half do not, the baseline (null) model reflects a 50/50 probability. This implies that, without any additional information, there is an equal likelihood of an anomaly occurring or not occurring. Our objective is to enhance this baseline model by identifying patterns and developing a predictive model to better determine when anomalies are likely to occur.

**Modeling**

The modeling process aimed to develop a robust framework for predicting satellite anomalies based on patterns in EUV and X-ray irradiance data. We began by assessing the relationships between predictor variables and the binary target (anomaly vs. no anomaly) using Spearman correlation, which is well-suited for identifying monotonic relationships. Logistic regression was chosen as the primary modeling approach due to its effectiveness in predicting binary outcomes. The variables and the interactions between variables were experimented with to improve the model. In addition to logistic regression, we experimented with a variety of alternative models to identify the most accurate and reliable approach. This iterative process of altering and evaluating the best-performing models, ensured meaningful insights and improved predictions over the baseline.

**Correlation**

As a first step in the modeling process, we used Spearman correlation to examine the relationships between each predictor variable and the binary target variable. Spearman correlation was chosen because it measures the strength and direction of monotonic relationships, making it well-suited for our data, which may not have strictly linear associations. The analysis revealed several predictors with strong correlations to the presence of anomalies, particularly *xrsb\_flux\_electrons*, *xrsa\_flux\_electrons*, *xrsa\_flux\_observed, xrsb\_flux\_observed, xrsa\_flag*, and *xrsb\_flag* (Figure 1). These findings align with previous studies highlighting the importance of X-ray and EUV measurements in detecting satellite anomalies (Feynman and Gabriel 2000). By focusing on variables with the strongest correlations, we narrowed down the feature set to those most likely to enhance the model's predictive accuracy.



[Figure 1]

Using these key variables, we developed a logistic regression model to estimate the probability of an anomaly occurring. Logistic regression is ideal for binary classification problems, as it predicts probabilities between 0 and 1. For classification, we adopted the standard threshold of 0.5, where predictions greater than or equal to 0.5 are classified as anomalies (1), and those below 0.5 are classified as non-anomalies (0). This threshold balances the trade-off between false positives and false negatives, serving as a baseline for assessing the model’s performance and accuracy.

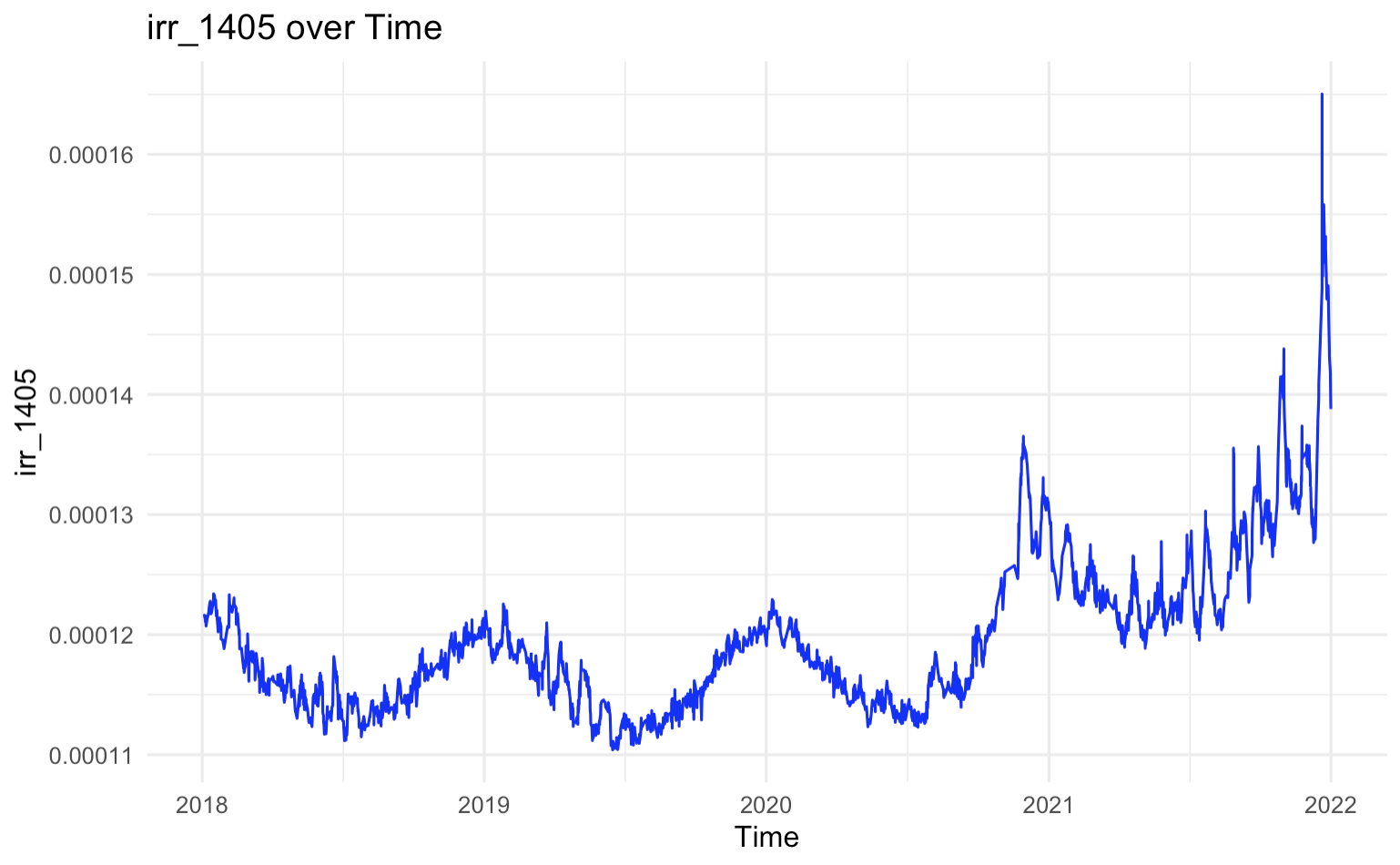
**Addressing Cyclic Behavior in EUV data**

Throughout our exploration of the EUV irradiance data, we observed that many of these irradiances exhibit a sinusoidal, wave-like pattern over multiple years, reflecting the natural oscillations of solar activity. To capture this cyclic behavior in the model, we initially experimented with taking the derivative of the irradiance values, hoping to quantify the rate of change in these fluctuations. However, this approach inadvertently reduced model accuracy, likely due to the added noise and variability introduced by the derivative.

We explored several techniques to enhance the model, including lag variables and rolling averages, to better capture patterns in the data. Lag variables involve using past values of predictors to account for delayed effects, while rolling averages smooth out short-term noise to highlight longer-term trends. Although these methods provided some insight into temporal patterns, they did not significantly improve model performance.

The most impactful change came from introducing a cosine predictor to capture the periodic, sinusoidal patterns we observed, which likely correspond to the 11-year solar cycle. EUV irradiances also demonstrated periodic fluctuations over time. Solar activity, driven by this cycle, influence the levels of radiation emitted by the Sun, resulting in oscillations that affect satellite systems. By incorporating a cyclical pattern into the model, we were able to better align predictions with the regular increases and decreases in solar activity.

To visually illustrate this sinusoidal pattern, we included a graph (see Figure 2), which highlights the cyclical trends in EUV irradiance over time. This addition to the model helped it better recognize the periodic nature of solar fluctuations, enhancing its ability to predict anomalies with greater precision.



[Figure 2]

**Results**

**Model Accuracy**

To assess the performance of our logistic regression model, we utilized 5-fold cross-validation. This approach splits the dataset into five subsets, training the model on four subsets and testing it on the remaining one, repeating this process five times. By averaging the results, we obtain a more robust estimate of the model's performance while reducing the risk of overfitting.

In addition to logistic regression, we experimented with other modeling approaches, including decision trees, ridge regression, lasso regression, and random forests. Each model was evaluated using cross-validation to compare their accuracy and area under the curve (AUC) scores, which will be explained in the next section. The models’ performances are summarized in the table below:

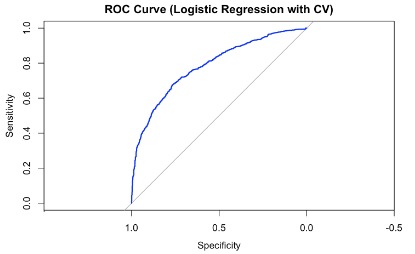
| Model Type | Accuracy | AUC |
| --- | --- | --- |
| Logistic | 72% | 0.78 |
| Decision Tree | 72% | 0.70 |
| Ridge | 71% | 0.77 |
| Lasso | 70% | 0.78 |
| Random Forest | 67% | 0.68 |

[Table 2]

The cross-validated logistic regression model achieved an average accuracy of approximately 72%, meaning it correctly classified 72% of the instances across all folds. However, this indicates that around 28% of cases were misclassified, suggesting potential areas for further model refinement. Additionally, the model’s average AUC score of 0.78 highlights its moderate ability to distinguish between anomalies and non-anomalies, but there remains room for improvement.

**Discriminative Ability**

To further assess the model’s performance, we measured the model’s AUC, which evaluates the model’s ability to distinguish between instances of anomalies versus events without anomalies (See Figure 3). With an AUC of 0.78, our model has a good level of discriminative ability. In practical terms, a higher AUC indicated that the model is better at identifying true anomalies without producing a large number of false positives (events without anomalies incorrectly classified as anomalies). This is particularly valuable for satellite anomaly detection, where minimizing false alarms is essential to ensure accurate predictions and avoid unnecessary responses to non-events.



[Figure 3]

**Sensitivity and Specificity Analysis**

We also examined two important metrics for model performance: sensitivity and specificity. Sensitivity, also known as the true positive rate, measures the model's ability to correctly identify actual anomalies. In our case, the model achieved a sensitivity of 0.77, indicating that it successfully detected 77% of actual anomalies. On the other hand, specificity, or the true negative rate, measures the model's ability to correctly identify non-anomalous events. The model’s specificity was 0.64, meaning it correctly identified 64% of non-anomalous events.

The relationship between AUC, sensitivity, and specificity is key to understanding the model's performance. The AUC represents the overall trade-off between sensitivity and specificity at various thresholds. A higher AUC suggests that the model maintains a good balance, effectively identifying true anomalies (high sensitivity) while also avoiding false positives (high specificity).

Through extensive data manipulation, exploratory analysis, and iterative model testing, we developed a logistic regression model with an accuracy of 72% for predicting satellite anomalies. Our model successfully incorporates key variables through correlation analysis, capturing relevant patterns in EUV and X-ray data, including sinusoidal trends associated with solar activity.

**Discussion**

The ability to predict satellite anomalies caused by space weather events is critical for ensuring the smooth operation of satellite systems, which are essential to communication, navigation, and weather forecasting. In this study, we developed a predictive model based on space weather data, particularly X-ray and EUV irradiances, to classify and anticipate anomalies. The logistic regression model demonstrated a solid foundation for anomaly prediction, with key predictors identified through correlation analysis. While the model achieved a respectable accuracy, there is room for improvement, particularly in reducing false positives (non-anomalous events classified as anomalies) and increasing the specificity of predictions.

From a practical standpoint, professionals in satellite operations and space weather monitoring could use this model to better anticipate periods of increased risk for satellite anomalies. By integrating space weather data with the model, satellite operators could take preventive measures, such as adjusting satellite positioning or temporarily shutting down sensitive equipment during periods of heightened solar activity, ultimately reducing the risk of malfunctions or mission failures.

However, there are important ethical considerations in the use of predictive models like this. The reliance on model predictions could lead to overconfidence or mismanagement if the model’s limitations are not properly understood. For example, in cases where anomalies occur outside the scope of the model's training data or due to unexpected space weather events, the model could underperform. It is crucial that the model is used as a tool for decision-making rather than as a definitive answer. Moreover, the model's predictions should be complemented with expert judgment and continuous monitoring of space weather conditions.

This model should not be used in isolation for mission-critical decisions, especially in high-risk situations where failure could have significant consequences. Limitations stem from the data used to train the model, the availability and accuracy of space weather data, as well as the model’s ability to capture the complex behaviors of the space environment. Future improvements could include incorporating additional data sources and refining the model to account for more complex, non-linear relationships. Furthermore, ethical concerns related to reliance on machine learning in safety-critical fields highlight the need for caution, transparency, and oversight when integrating such models into operation.

In summary, while the predictive model developed here provides valuable insights for satellite anomaly prediction, it is important to acknowledge its limitations. When applied with caution and in combination with expert knowledge, this model can serve as a useful tool in satellite operations and space weather forecasting, contributing to more resilient satellite systems in the face of space weather events.

**Conclusion**

This study set out to answer the question: Can space weather data, specifically X-ray and EUV irradiances, be used to predict satellite anomalies? The answer is yes. Through the development of a logistic regression model, we were able to predict satellite anomalies with reasonable accuracy. The model leveraged key space weather variables, such as X-ray flux measurements, to classify instances of anomalies, demonstrating that space weather patterns can be an effective predictor of satellite performance issues.

Domain experts can use this model to anticipate and mitigate the impact of space weather events on satellite systems. By integrating this model into existing satellite monitoring frameworks, operators can gain early warnings of potential anomalies, allowing for preventive measures such as adjusting satellite positioning, power management, or operational modes during times of heightened space weather activity. This could lead to improved satellite longevity, reduced operational disruptions, and lower risk of costly satellite malfunctions.

However, the model also has its limitations, and future work can enhance its predictive capabilities. Incorporating more comprehensive datasets, including additional space weather variables and satellite performance metrics, could help refine the model's accuracy. Furthermore, exploring more complex modeling techniques, such as machine learning algorithms that capture non-linear relationships, may lead to even better predictions. As satellite systems evolve and space weather forecasting improves, continual updates and fine-tuning of the model will be necessary to maintain its effectiveness.

Ultimately, this work serves as a foundation for more advanced anomaly prediction models. With further data and research, this work has the potential to significantly improve the resilience of satellite systems against space weather events.

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