Data Fusion of Historical Space Weather Outliers and Satellite Anomalies

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ABSTRACT

Space operators faced with the challenge of sensemaking and threat assessment for a great many satellites need to understand the significance of current conditions for situational awareness. A key step is to rule out possible explanations in arriving at a characterization. For example, if a satellite begins to exhibit abnormal behavior, this could potentially be due to hostile actions by adversaries, or internal anomalies, or external forces such as space weather. The synthesis of historical space weather and satellite anomaly data can potentially help identify new correlations from past data, and help with operational use cases involving both forensics (of a current or past situation), and forecasting (of an anticipated space weather condition that may have adverse impacts on satellite operations). In a preliminary data fusion experiment, statistical machine learning methods were used to identify historical outlier space weather conditions and uncover correlations with records of known satellite anomalies.

For this experiment, 15 years of historical space weather data were collected for 6 commonly used indicators, from archived resources available from the Space Weather Prediction Center (SWPC) at the National Oceanic and Atmospheric Administration (NOAA). The 6 indicators included F10.7cm radio flux, X-ray flux (indicator of solar flares), proton flux (energetic particles, at two energy levels), electron flux (energetic particles), and Kp index (planetary geomagnetic disturbance). Using the NOAA data sets for these indicators, outlier conditions were identified over the 15-year sample, by detecting deviations from the mean over a specific threshold. The initial source for spacecraft health data was a commercially available database which aggregates publicly sourced data about spacecraft over their entire lifetimes, including records of insurance claims when satellite anomalies occur. Anomaly records include supporting text with details and in some cases causal attributions. There were 151 candidate anomalies, and when synthesized with the space weather analysis, 18 had current or recent outlier space weather conditions. Among the 18 satellite anomalies with a possible space weather correlation, the existing records for 5 of them included attribution to space weather causes, but 13 did not. Although closer examination would be needed to draw conclusions about the remaining 13, this preliminary analysis illustrates the possible results from synthesizing these data sources in a model to support space domain awareness (SDA) decision-making. These findings are the result of initial unsupervised data fusion methods, but give an indication of the potential for much greater insight to be derived using similar methods with higher-fidelity data, and ultimately applied in a model to support space domain awareness decision-making.

1. BACKGROUND

Machine learning techniques have been extensively applied to space weather forecasting, to predict and quantify attributes of phenomena such as geomagnetic disturbances, charged particles at different orbital regimes, solar flares, coronal mass ejections, and solar wind. Camporeale et al [1] and others have surveyed machine learning applications for space weather, while also laying out methods to combine physics-based and machine learning approaches, to help forecasting results account for uncertainties. With the tandem increase in both available data and computing power comes the opportunity to continue making strides in space weather forecasting with an approach that integrates data-driven methods. The subject experiment and analysis were designed to explore avenues to build on this kind of work in space weather forecasting, with the potential for level two data fusion to help operators understand possible space weather effects on the current and future situation affecting space vehicles. In general terms, level two data fusion often involves synthesis across the results of level one data fusion predictions. For example, level one data fusion may be used to predict or characterize space weather phenomena based on multi-sensor data. Level two data fusion may then synthesize these probabilistic characterizations with data for the behavior exhibited by space vehicles, to predict potential impacts from space weather.

An initial unsupervised learning experiment was performed in conjunction with the Sprint Advanced Concept Training (SACT) events conducted at the Catalyst Campus in Colorado Springs, as part of a research effort exploring applications for automated probabilistic reasoning and level two fusion capabilities in support of space domain awareness. The objective of the experiment was to explore the potential to use automated data-driven methods to derive patterns for the interactions between space weather phenomena and satellite anomalies. Ultimately such patterns applied in SDA models can help operators with sensemaking and threat assessment. Initial readily available data sources for modeling included NOAA space weather data from the past 15 years in conjunction, with publicly sourced records of spacecraft anomalies. The database for historical spacecraft health data is from Seradata, a company that gathers public information from insurance claims and other sources to build historical records. Seradata made their SpaceTrak database available for analytics within the context of the SACT event, and for this experiment the database was queried to collect records tagged as being related to space weather or electrical power systems.

2. EXPERIMENTAL RESULTS

The table below summarizes selected noteworthy results from initial analytics. Queries to the SpaceTrak database produced 151 candidate anomalies to be investigated for potential temporal associations with current or recent outlier space weather conditions identified in the NOAA data. 18 of the 151 anomalies could be associated with space weather outliers. The existing records for 5 of those 18 had text annotations attributing anomalies to causes related to space weather. This leaves 13 with potential correlations that may have been previously unidentified. In the table below, each row represents the answer to the following question with regard to a specific anomaly instance:

> *For a historical record of an anomaly on the given date (for spacecraft identified by NORAD ID and with a given orbital regime), how many space weather features had outlier values in time intervals at or before the anomaly, and what was the max outlier deviation?*

Table 1. Noteworthy Satellite Anomalies Correlated with Outlier Space Weather Conditions

Regime	NORAD	Date	Same day	3 day	7 day	SW attribution?
GEO	29644	2017-09-30	1 (E:3)	2 (E:3, Kp:3)	2 (E:3, Kp:3)	NO
LEO - Std	25544	2015-11-13	1 (E:4)	1 (E:5)	1 (E:5)	NO
GEO	29045	2015-10-15	0	0	1 (E:6)	NO
LEO - Std	39678	2014-12-03	0	1 (F:3)	2 (F:3, X:4)	NO
LEO - Sun-sync	40024	2014-10-15	1 (X:3)	1 (X:3)	1 (X:3)	NO
GEO	39728	2014-10-09	0	0	1 (X:3)	NO
GEO	39616	2014-04-16	1 (F:3)	1 (F:3)	1 (F:3)	NO
GEO	27499	2014-01-12	0	2 (F:3, P1:6)	3 (F:5, X:5, P1:10)	NO
LEO - Std	27651	2013-06-30	0	1 (K:3)	1 (K:3)	NO
HELIO	28901	2012-03-07	3 (X:3, P1:10, P2:20)	3 (X:3, P1:10, P2:20)	3 (X:3, P1:10, P2:20)	YES
HELIO	37872	2011-11-08	1 (F:3)	1 (F:3)	1 (F:3)	YES
GEO	26580	2008-10-11	1 (K:3)	1 (K:3)	1 (K:3)	NO
Elliptical - Std	26464	2006-12-13	2 (P1:4, P2:16)	2 (P1:4, P2:16)	2 (P1:11, P2:16)	YES
GEO	26487	2005-08-10	0	1 (E:4)	1 (E:4)	NO
GEO	28622	2005-04-15	0	0	1 (E:3)	NO
GEO	26089	2005-04-05	1 (K:3)	1 (K:3)	1 (K:3)	YES
LEO - Polar	28230	2005-01-26	0	1 (E:3)	4 (P1:9, P2:57, E:3, K:3)	YES
LEO - Std	14780	2005-01-15	1 (X:4)	1 (X:4)	1 (X:4)	NO

Time intervals used to cross-reference space weather outlier conditions are: same day, within the past 3 days, or within the past 7 days. Columns corresponding to these labels in the table above give values describing the total number of outlier conditions, with additional shorthand information providing more details.

The NOAA archived data was analyzed for outlier conditions among the following features (parenthetical terms refer to the shorthand notation used in the table above):

- F10.7cm radio flux (F)
- X-ray flux (X)
- Proton flux >=10MeV (P1)
- Proton flux >=100MeV (P2)
- Electron flux >=2MeV (E)
- Kp index 24 hr max (K)

Example: “P1:10” means the feature P1 (corresponding to proton flux >=10MeV) was measured at a value with 10 sigma deviation from the mean, in the corresponding time interval. Since there are 6 features under analysis, the maximum number of outlier features for any particular interval (i.e., same day, 3 day, or 7 day) is 6. In the table above, the instance with the largest number of outlier features is 28230 on 2005-01-26, having 4 space weather outliers in the 7 day interval prior to the recorded anomaly. This is also the most extreme outlier instance among those identified in the table, having a measured P2 (proton flux >=100MeV) with a 57 sigma deviation from the mean!

The last column in the table (“SW attribution”) identifies whether the selected anomaly was previously attributed to space weather in existing records. For example, the extreme case involving 28230 was in fact already attributed to space weather in the contemporary information for that instance, but there are other significant cases that are not, despite having space weather outlier conditions.

This initial experiment with an unsupervised analysis potentially identifies new correlations in data sets, and demonstrates a possible direction for analytics. Although closer examination would be needed to draw conclusions about the 13 anomaly cases that were not previously attributed to space weather factors despite a temporal correlation, this preliminary analysis illustrates the possible results from synthesizing these data sources in a model to support SDA decision-making. Specifically, for both forensics and forecasting purposes, a derived model for correlations between space weather events and satellite anomalies can be extremely valuable. The following examples discuss specific cases in greater detail, for illustration.

Example Result: Positive Correlation

This example illustrates a case where there is a positive correlation between the detection of outlier space weather conditions, and a record collected from the SpaceTrak database with a satellite anomaly attributed to a solar storm. Information about the anomaly from SpaceTrak is as follows:

Satellite	Date	Category	Description
26464 Cluster II-FM8 (Elliptical, std)	2006-12-13	Power – Electrical Distribution	Solar storm related anomaly. The High Power Amplifier switched itself off. w-esa.int. A major X3 solar flare was detected on 13th December by SOHO's LASCO (Large Angle Spectrometric Coronagraph Experiment). This flare was the forerunner to a large Coronal Mass Ejection of charged particles which arrived at the Earth on 14th December.

Fig. 1 shows a plot of the space weather outlier conditions identified for this anomaly instance.

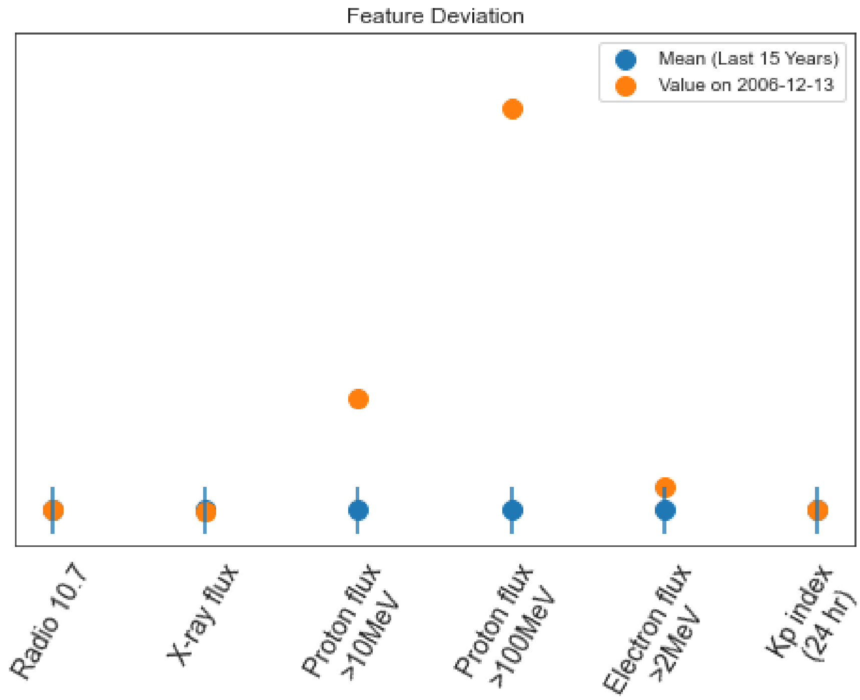

Fig. 1. Plot of Space Weather Outliers for 2006-12-13 Anomaly

In particular for the measure relating to high energy proton flux (at >100MeV), this was the highest value in all of 2006, and the spike was measured on 12-13. This is consistent with the recorded description in SpaceTrak for this anomaly, which notes an X3 class solar flare on the same day. It is reasonable to expect that the 26464 vehicle suffered a single event upset from a solar radiation storm.

Example Result: Possible Correlation

This example illustrates a possible correlation case – that is, one of the instances where there appears to be a temporal correlation between space weather outlier conditions and a satellite anomaly, but no attribution to space weather causes in the existing records for the anomaly. Information about the anomaly from SpaceTrak is as follows:

Satellite	Date	Category	Description
27499 EUTELSAT 70D (GEO)	2014-01-12	Solar Array Operating Anomaly	EUTELSAT 8 WEST C lost the use of its North Solar Array after the array's BAPTA (Bearing and Power Transfer Assembly) failed 12 January 2014. The Spacebus 3000 series has a genetic issue with this fault. An insurance claim for Total Insurance Loss was accepted but the payout was negotiated down as part of insured value was within deductible limits.

The anomaly record is dated 2014-01-12, and this may well have no relation to space weather phenomena, as the SpaceTrak record notes an insurance claim associated with a genetic fault issue with the bus. For this initial analysis there was no attempt to further investigate such cases; rather the purpose was to look for patterns and correlations suggested by level two fusion on the data alone. And in this case, in fact there was an X1 class solar flare 5 days earlier on 01-07, accompanied by outlier space weather conditions in F10.7cm radio flux and X-ray flux as shown below. Fig. 2 shows a plot of the space weather outlier conditions identified for 2014-01-07 on the day of the flare.

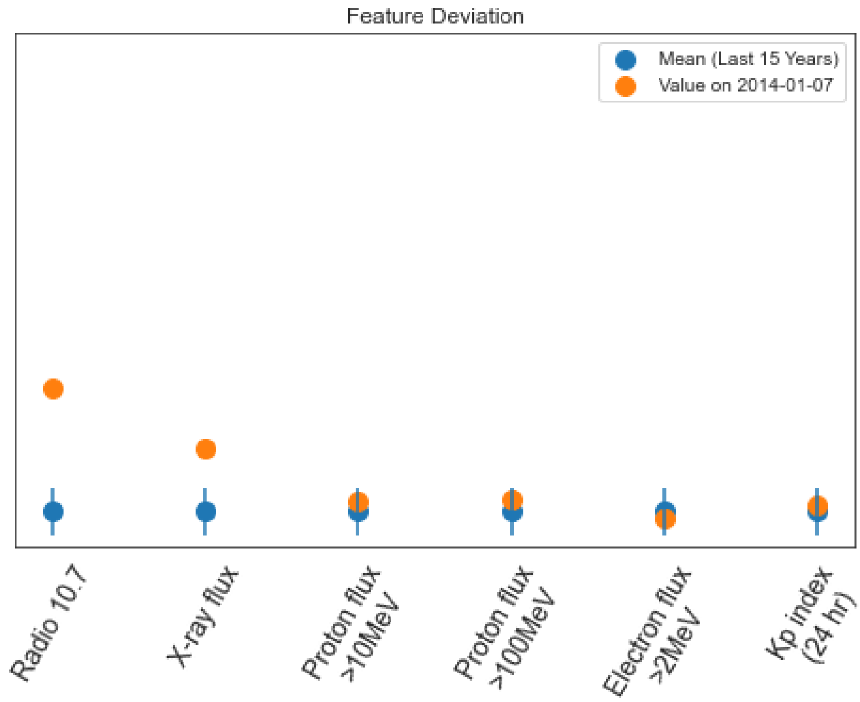

Fig. 2. Plot of Space Weather Outliers on 2014-01-07

Figure 3 below shows the outlier space weather conditions that persisted as of 2014-01-12, the day of the recorded anomaly for 27499. Both the F10.7cm radio flux and X-ray flux are still at outlier levels, and the planetary geomagnetic disturbance index Kp is also somewhat elevated.

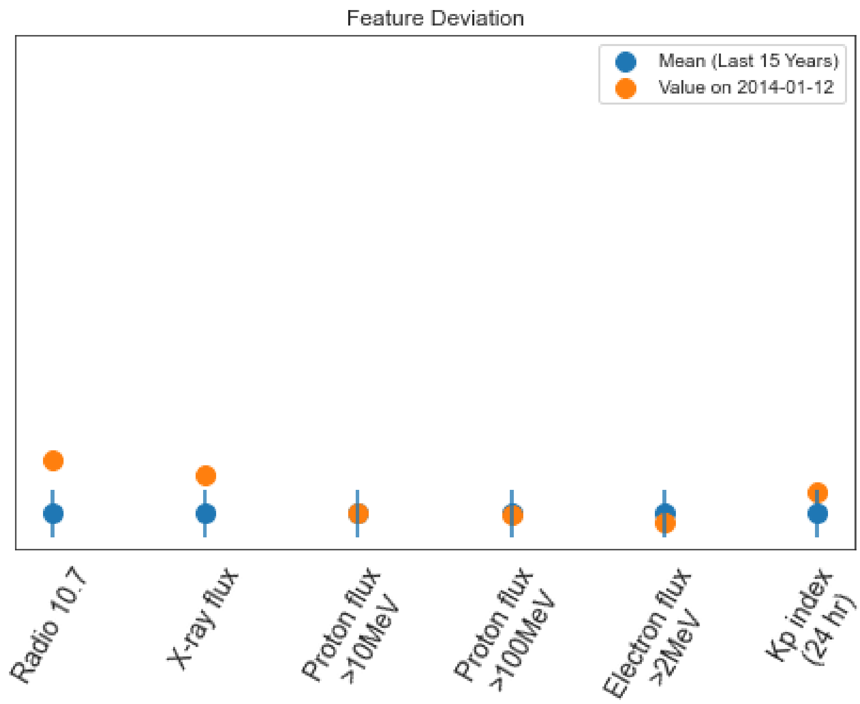

Figure 3. Plot of Space Weather Outliers on 2014-01-12

Although more information would be needed to further analyze this particular case and determine if space weather factors were causal or coincidental, this serves as an example of the potential for analytics to uncover patterns of correlations in historical data that were previously not identified. A model constructed to include such patterns could be helpful for both forensics and forecasting in future cases.

3. CONCLUSION AND FUTURE DIRECTIONS

One of the results from performing an experiment with level two fusion of space weather and spacecraft health data was the identification of avenues for further investigation that would help advance the goals toward a deployable capability. These are summarized below.

- What space weather measures have the most value as indicators for impacts on satellites? The initial analysis for this experiment used 6 space weather measures that are commonly referenced, but there are others that could have value, and this is worth exploring.

- What kinds of temporal intervals are valid for a correlation between a space weather event and spacecraft effects, potentially with different intervals relating to different indicators? The initial analysis for this experiment used time intervals of same day, 3 days, and 7 days, but the choice of intervals may be refined based on further input from subject matter experts and also based on patterns observed in data analysis.

- How do spatial relationships factor into the correlations between space weather measures taken at certain locations, vs. possible effects on satellites in different locations? Such positional calculations were not factored into this initial analysis, but this is an example where the hybrid approach combining physics-based methods with data-driven methods can have merit.

- What historical data are available, at what degree of fidelity, for both space weather and satellite anomalies (e.g., are telemetry data available for higher fidelity historical satellite health)? NOAA provides a great deal of space weather data, but spacecraft health data are more likely to be nonstandard and also come from diverse sources. While it is ideal to base analytics on data at the highest possible fidelity, it will be unlikely to have a consistent level of fidelity for satellite health data from different space vehicle owners, platforms, etc.

- What spacecraft features are most predictive for relating a historical anomaly case to a possible future case? For example, a higher risk may be posed for satellites with the same bus type as that in a past anomaly that occurred under similar space weather conditions. So additional features of historical anomaly case data like the bus type can be important predictors to factor into analytics.

The initial experiment illustrates, with real-world examples using readily available data, how an unsupervised analysis can identify new correlations between space weather and spacecraft health data. Out of 151 candidate anomalies listed in the sample data, 18 had current or recent outlier space weather conditions. Among those 18 anomalies, 5 were previously attributed to space weather, and 13 were not. Although closer examination would be needed to draw conclusions about the 13 anomaly cases that were not previously attributed to space weather factors despite a temporal correlation, this preliminary analysis illustrates the possible results from synthesizing these data sources in a model to support SDA decision-making. Specifically, for both forensics and forecasting purposes, a derived model for correlations between space weather events and satellite anomalies can be extremely valuable.

Finally, one more consideration to be factored into future analysis is an awareness of how and when space weather analytics factor into space operators' decisions. Ultimately the purpose performing level two fusion for this application is to help operators with sensemaking, to generate estimates for the likely attributions for the behavior they encounter. The forecasting use case relates to the potential anticipation of space weather impacts on satellite operations, for example to proactively put a space vehicle into "safe mode" during a geomagnetic storm. The forensic use case involves the analysis of abnormal or anomalous behavior by a satellite, not only for the purposes of insurance claims, but also potentially to rule out other explanations of concern. The use case ideally guides the analytical methods, so that input data mirror the likely data that will be available to operators in the operational setting, and output results especially with the characterization of certainties are in a form that can be meaningful for operators.

4. ACKNOWLEDGMENTS

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5. REFERENCES

[1] Camporeale, E., Wing, S., & Johnson, J. *Machine learning techniques for space weather*. Amsterdam: Elsevier, 2018.