Using spacecraft anomalies to evaluate space environment models

T.P. O'Brien

Space Sciences Department, The Aerospace Corporation, El Segundo, California, USA
Outline

• Space weather-related satellite anomaly types
• Modeling space weather anomaly risk
• The “green anomalies” metric
• Estimating the impact of model errors on green anomaly rate
• Results for some sample anomalies
Space weather-related satellite anomaly types

- **Event Total Dose (ETD)** occurs primarily in orbits that rarely see trapped protons in the 1-20 MeV range (e.g., GEO, GPS) because these are the orbits for which solar particle events and transient belts make up a majority of the proton dose (including displacement damage).

- **Single Event Effects (SEE)** tend to occur in the inner (proton) belt and at higher L shells when a solar particle event is in progress.

- **Internal charging (IC)** and resulting electrostatic discharges (ESD) occur over a broad range of L values corresponding to the outer belt, where penetrating electron fluxes are high.

- **Surface charging (SC)** and resulting ESD occur when the spacecraft or surface potential is elevated: at 2000-0800 local time in the plasma sheet and in regions of intense field-aligned currents. It has also been observed, but not explained, at very low L.
Modeling space weather anomaly risk - I

- Multiple anomaly investigations have established that the anomaly rate can be described with a power-law:
  - \( r(x) \sim x^{\gamma} \)
  - \( x = \) particle flux, dose rate, current, etc., suitably time averaged.
  - \( \gamma = \) empirically determined parameter
- A fitting procedure allows us to select an appropriate \( x \) and estimate \( \gamma \) when we have reasonably long-term measurements and a statistical sample (>~5) of similar anomalies
- See, e.g., O’Brien 2009, Space Weather
## Modeling space weather anomaly risk - II

<table>
<thead>
<tr>
<th>Hazard</th>
<th>Example Hazard Indicator</th>
<th>Typical Time Averaging (hours)</th>
<th>Typical exponent ($\gamma$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface Charging</td>
<td>&gt;10 keV electron flux&lt;br&gt;Electron temperature&lt;br&gt;Field-aligned current intensity</td>
<td>NONE</td>
<td>1-4</td>
</tr>
<tr>
<td>Internal Charging</td>
<td>&gt;1 MeV electron flux&lt;br&gt;Current beneath 100 mils Al shielding&lt;br&gt;Dose rate (outer zone) below 100 mils Al</td>
<td>1-72</td>
<td>0.7-2</td>
</tr>
<tr>
<td>Event Total Dose</td>
<td>&gt;5 MeV proton flux&lt;br&gt;Dose rate below 5 mils Al</td>
<td>12-72</td>
<td>1</td>
</tr>
<tr>
<td>Single Event Effects</td>
<td>&gt;30 MeV proton flux&lt;br&gt;&gt;30 MeV cm$^2$/mg flux</td>
<td>NONE</td>
<td>0.5-2</td>
</tr>
</tbody>
</table>

$x =$ trailing time average of the hazard indicator
**Green anomalies**

- Operators typically interact with stoplight charts that use a red-yellow-green color scheme.
- “Green anomalies” refers to anomalies that occur when the environment is “green”.
- We define “green” conditions as having $x$ below the 75th percentile.
- Given $p(x)$, the statistical distribution of $x$, and the exponent $\gamma$, we can estimate what fraction of anomalies occur when $x$ is in the lower 75th percentile, i.e., when the environment is “green”.
Computing the green anomaly rate

• The fraction of anomalies under green conditions is given by:

\[ G = \frac{\int_{0}^{x_{75}} x^\gamma p(x)\,dx}{\int_{0}^{\infty} x^\gamma p(x)\,dx} \]

• Where \( x_{75} \) is the 75\(^{th} \) percentile of \( x \) for surface and internal charging

• For single event effects and event total dose, \( x_{75} \) is the 75\(^{th} \) percentile of \( x \) during solar particle event times only

• Larger \( \gamma \) leads to smaller \( G \)

• A fatter tail in \( p(x) \) leads to smaller \( G \)
Estimating the impact of model errors on green anomaly rate

• Now we add multiplicative random noise to \( x \)
  \[
y = x \exp[\sigma \eta] = xF^\eta, \quad \eta \sim N(0,1)
\]
• The random noise \( \eta \) is drawn from a Gaussian with zero mean and unit variance
• \( F \) is the error factor, and can be thought of as the half-width at half-max of the error distribution
• Interpretation of \( F \): \( \sim 95\% \) of the time, truth will fall within \( F^2 \) of the observation/model
• Example: if \( F=4 \) (i.e., \( 4x \) error), then \( 95\% \) of the time, the truth falls within a factor of \( 16 \) of the observation/model
• The green anomaly fraction for noisy data is given by:
  \[
  G = \frac{\int_0^{y_{75}} x^\gamma p(y)dy}{\int_0^{\infty} x^\gamma p(y)dy} = \frac{\int_0^{y_{75}} \int_{-\infty}^{+\infty} y^\gamma F^{-\gamma\eta} p(y)N(\eta)d\eta dy}{\int_0^{\infty} \int_{-\infty}^{+\infty} y^\gamma F^{-\gamma\eta} p(y)N(\eta)d\eta dy} \approx \frac{\sum_{y<y_{75}} x_i^\gamma}{\sum x_i^\gamma}
  \]
• Important: compute \( 75^{th} \) percentile \( y_{75} \) from noise-added data
1. For infinite error, we expect the IC and SC curves to saturate at 75%, while the SEE and DOSE curves should saturate well above that.

2. We see that even large errors, $10^4$, do not erase all utility.

3. The HEO case shows that there is no truly universal rule-of-thumb for how much error is tolerable. It depends.

*Flux variation half-width (log-normal sense) = “1-sigma” value of multiplicative flux variation. E.g., for a value of 10, ~2/3 of the flux values fall within a factor of 10 of the median flux.
Results - II

4. The greatest return on improvement appears to be obtained when cutting the error down from ~30x to ~4x.

5. There is often no improvement reducing error less than 2x.

*Flux variation half-width (log-normal sense) = “1-sigma” value of multiplicative flux variation. E.g., for a value of 10, ~2/3 of the flux values fall within a factor of 10 of the median flux.
Conclusions

• Even very large multiplicative errors do not erase all of a model’s value for anomaly attribution, at least for the “green anomalies” metrics
• The greatest value for improvement occurs when decreasing the error from ~30x to ~4x

Caveats
  – There are going to be exceptions (e.g., HEO surface charging)
  – Confounding parameters (e.g., temperature, materials, attitude) also affect how model error impacts anomaly analysis