Automated Identification of Anomalous SSMIS Brightness Temperatures Using a Neural Network

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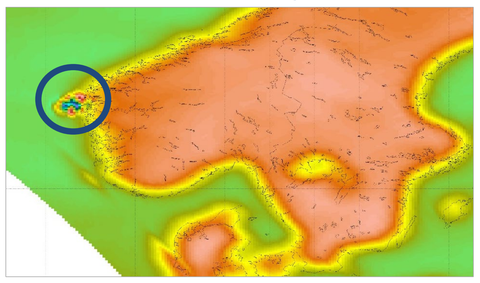
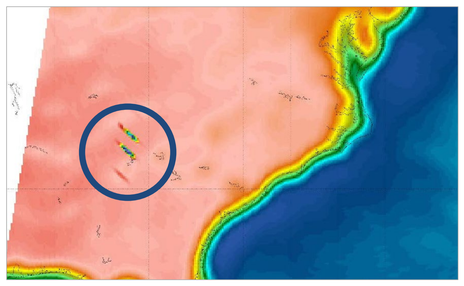
Background

Anomalies reported by Northrop Grumman in channels 12-14 (19.35 GHz H/V, 22.24 GHz V), for example:

Norway



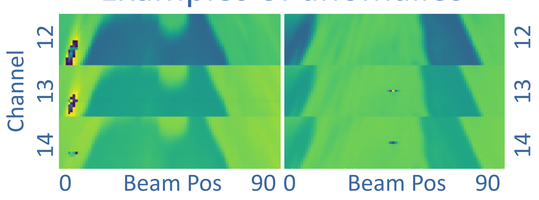
Southeast USA



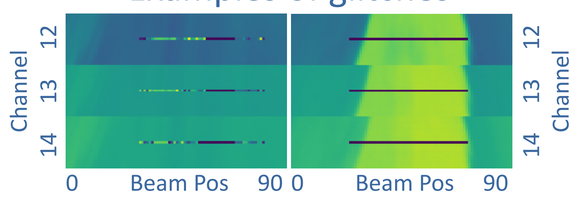
First Pass Anomaly Search

- Enormous amount of SSMIS data back to 2004: need to efficiently search for anomalies (but don't need every single anomaly)
- Filter for extreme T_B (> 310K or < 80K) and capture surrounding scans
- Ignore files containing many extreme T_B values (these are instrument tests, malfunctions, etc)
- Found over 16,000 possible anomaly incidents, but some of these are calibration/instrument glitches that are not relevant:

Examples of anomalies



Examples of glitches

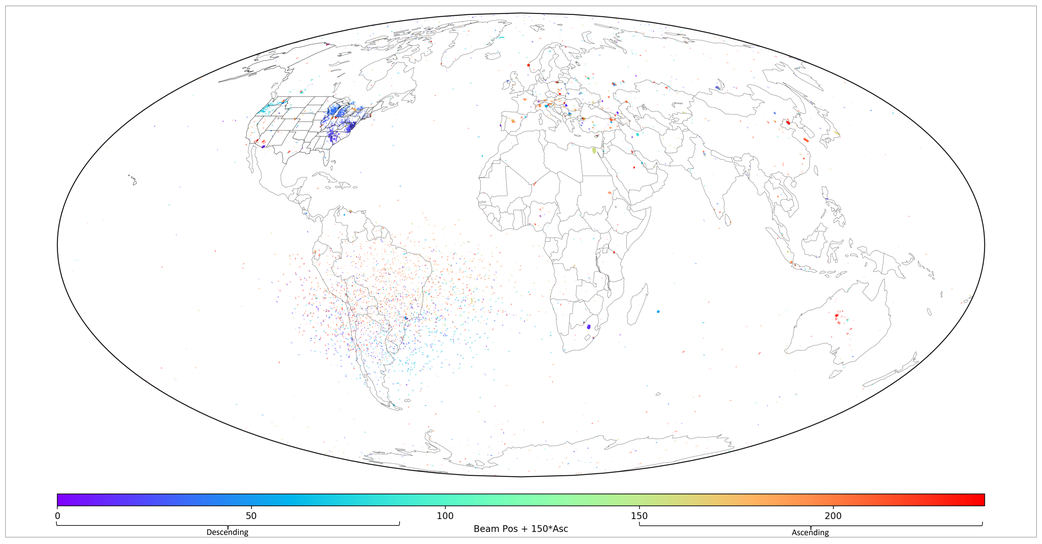


Dataset Thinning: Neural Net & Active Learning

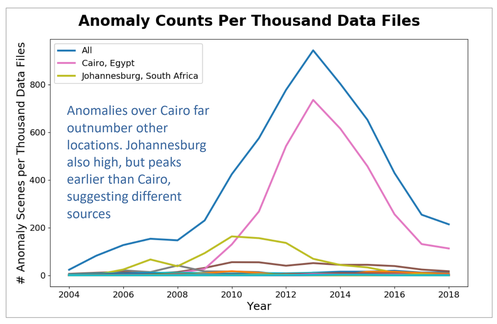
- Significant variation was found in the patterns of the glitches and anomalies, so it was very difficult to obtain just the anomalies of interest using conventional software methods
- Applied a Convolutional Neural Network (CNN) using an iterative process of active learning:
  1. Manually label a few hundred images as anomalies or glitches
  2. Train/test the CNN and apply it to the remaining images
  3. Manually label the remaining images that the CNN is least certain about and add these to the training/test set
  4. Repeat steps 2-3, training the CNN on the most difficult patterns (a form of active learning)
- Repeated this until ~2,800 images were manually labeled
  - >90% accurate on the test set (most difficult patterns)
  - ~12,000 anomalies confidently identified (>95%) by CNN
  - >99% accurate on these high-confidence anomalies. A few were actually glitches but could easily be removed

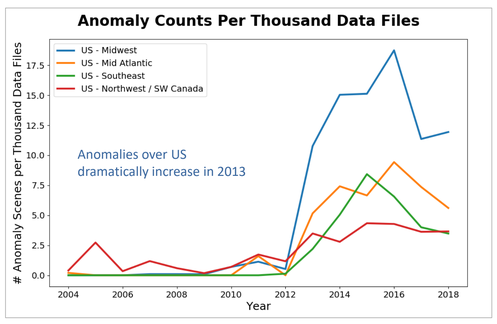
Anomaly Trends Analysis

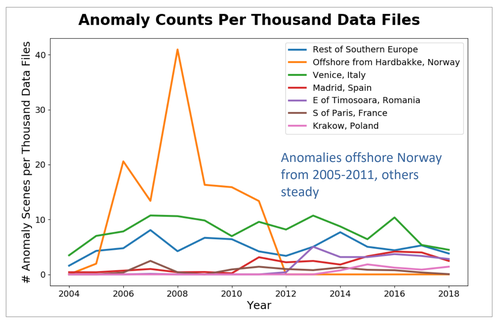
- No significant trends based on time of day, season of the year, or satellite number
- Most geographic locations experience anomalies at specific look angles, suggesting consistent sources of interference transmitted from or reflected off of these locations

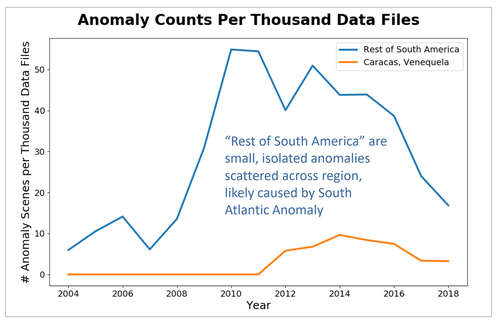


Anomaly Counts Over Time









Possible Geostationary Sources Over USA

For anomalies over the US, the location at geostationary altitude from which a signal would reflect directly into the sensor was calculated. The following broadband internet satellites transmit on 18.8-19.3GHz and appear to match the clusters of locations and time frames:

- Viasat 1: 115W, launched 2011
- Echostar 17: 107W, launched 2012
- Echostar 19: 97W, launched 2016 (operational 2017)

This is concerning as thousands of broadband satellites (SpaceX Starlink) were recently authorized to transmit on these frequencies from low earth orbit. Due to the quantity and lack of fixed locations, it will be difficult to account for these using typical glint-angle calculations