

An Automated Pipeline for Detecting Gigantic Jets: Preliminary Results

12/13/2023

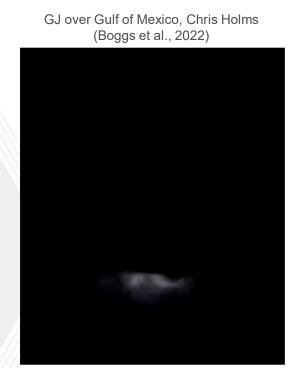
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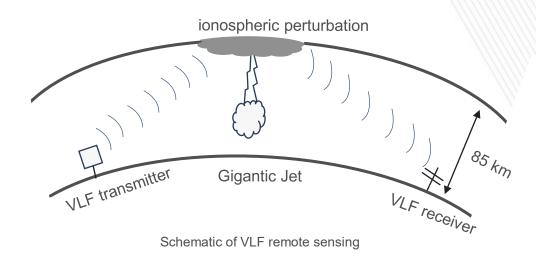
- 1: Georgia Tech Research Institute
- 2: Georgia Tech
- 3: SETI Institute
- 4: USRA
- 5: Duke



Introduction and Background



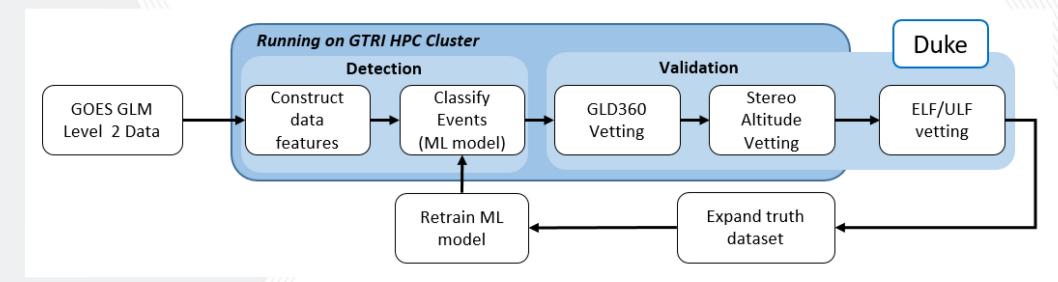




- Questions: What are the upper atmospheric effects caused by GJs? What is the climatology (location, frequency) of GJs?
- Goal: Significantly increase detections via GLM, machine learning, and ground-based networks
- Perform VLF remote sensing to understand how they perturb the ionosphere and Global Electric Circuit (Cohen et al. 2009)



Detection Pipeline

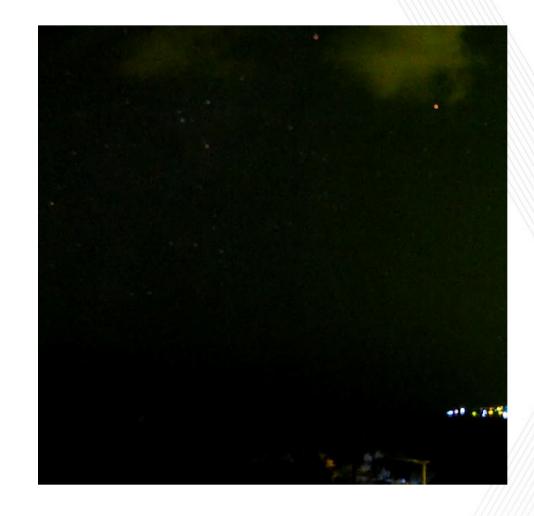


- Detection: supervised machine learning classifier that operates on GLM group data
- Validation: vet GJ candidates with GLD360 model, ABI model, stereo altitude model, and finally with ELF/ULF model.
- We are developing in conjunction with the NASA Bolide Pipeline (Smith et al. 2021)



Truth Database

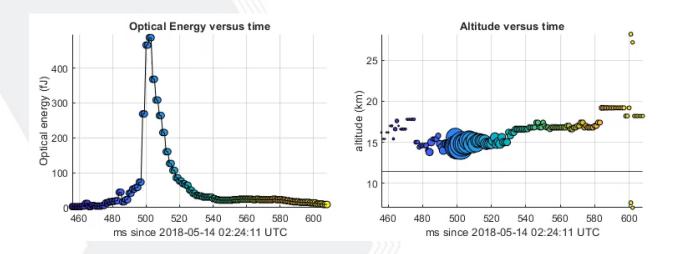
- We have collected ground-based video from several sources, mostly citizen scientists
- Captures come from cameras located in Puerto Rico, Colombia, Hawaii, Oklahoma, and Brazil
- Currently have 65 ground-truth GJ events
- Find matching GLM flashes
 - Note: we only find clear, unambiguous GJ signatures for 50% of ground-based video captures → most likely only detecting Type I GJs (Chou et al. 2010)



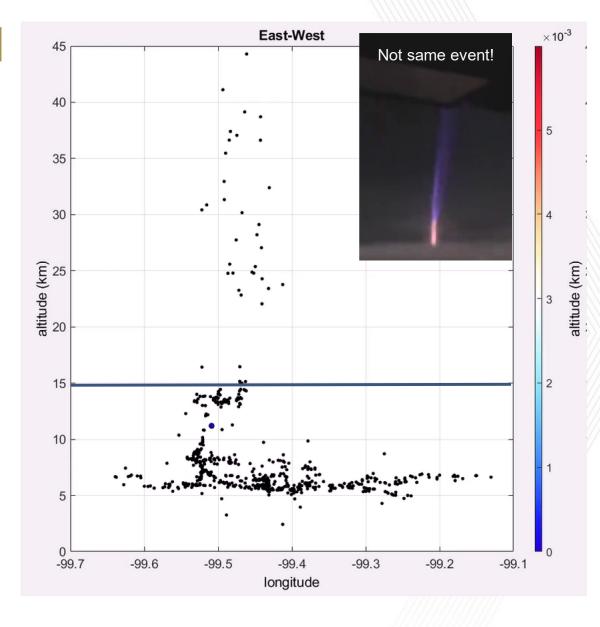
Photographer credit: Chaim Scowcroft



Gigantic Jet Signatures - GLM

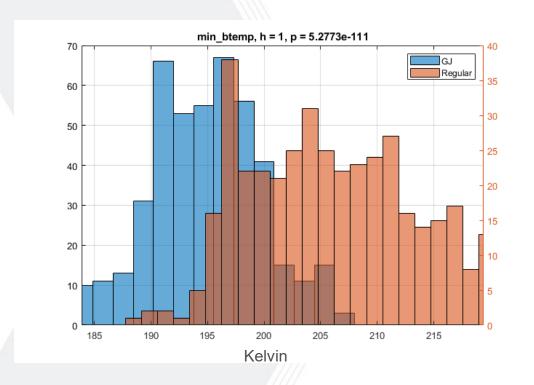


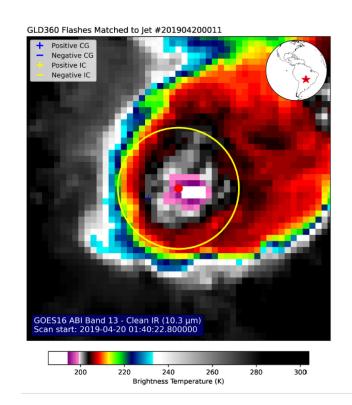
- Long continuing current and impulsive lightcurve (Boggs et al. 2019, 2022)
- Stereo altitudes increase over time
- GLM primarily detects the leader above the cloud top

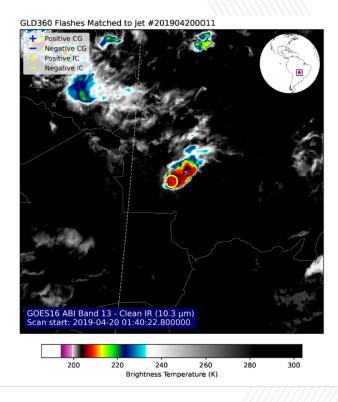




Gigantic Jet Signatures – ABI brightness temperature



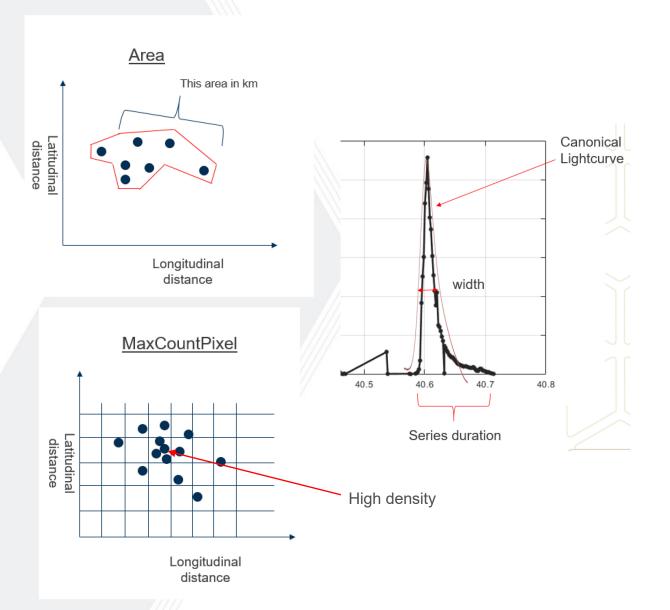




- True GJs → Colder cloud tops when compared with traditional flashes
- ABI IR → GJ typically located near tallest cloud top, with large gradient in brightness temperatures



GLM Machine Learning Model



 Many different features capturing spatial and temporal differences between GJ and nonGJ flashes

Spatial:

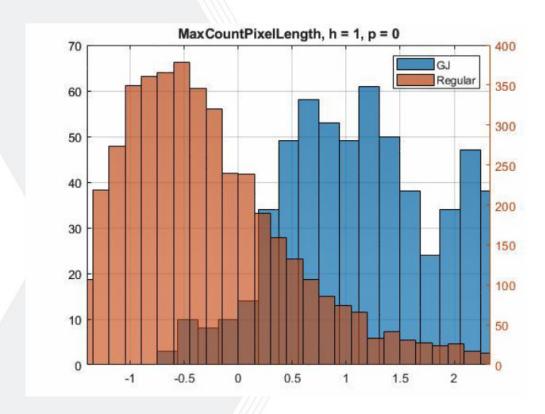
 features that calculate things like flash size, distance traveled, and energy flux

Temporal:

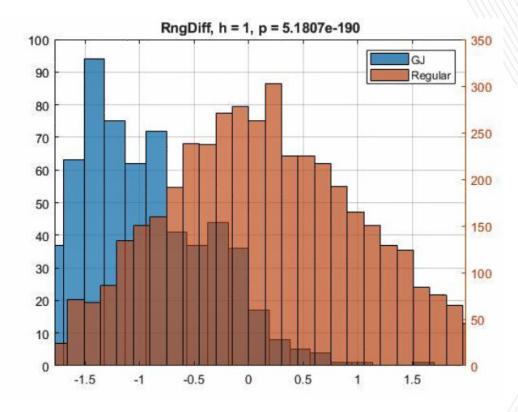
 features that calculate properties from the lightcurve, such as FWHM, continuous duration, correlation with canonical jet lightcurve



GLM Machine Learning Model



Example of a spatial feature



Example of a temporal feature



Current Status and Next Steps

- We have deployed a preliminary ML model (random forest) to ~6 months of data
- Currently vetting the data: stereo altitudes, ABI and GLD model, and finally ELF/ULF model
- Continually expanding our 'truth' dataset with new vetted events
- Precision is low as expected (~1%), but goal at this stage is to get more truth data
- Next two years: begin correlating our GJ detections to VLF remote sensing data, in addition to other lightning physics data (LMAs, ASIM, RF SENSER).



References

- Cohen, Morris B., Umran S. Inan, and Evans W. Paschal. "Sensitive broadband ELF/VLF radio reception with the AWESOME instrument." *IEEE Transactions on Geoscience and Remote Sensing* 48.1 (2009): 3-17.
- Smith, Jeffrey C., et al. "An automated bolide detection pipeline for GOES GLM." *Icarus* 368 (2021): 114576.
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