Using GLM to Improve the Safety and Effectiveness of Wildfire Response

National Environmental Satellite, Data, and Information Service

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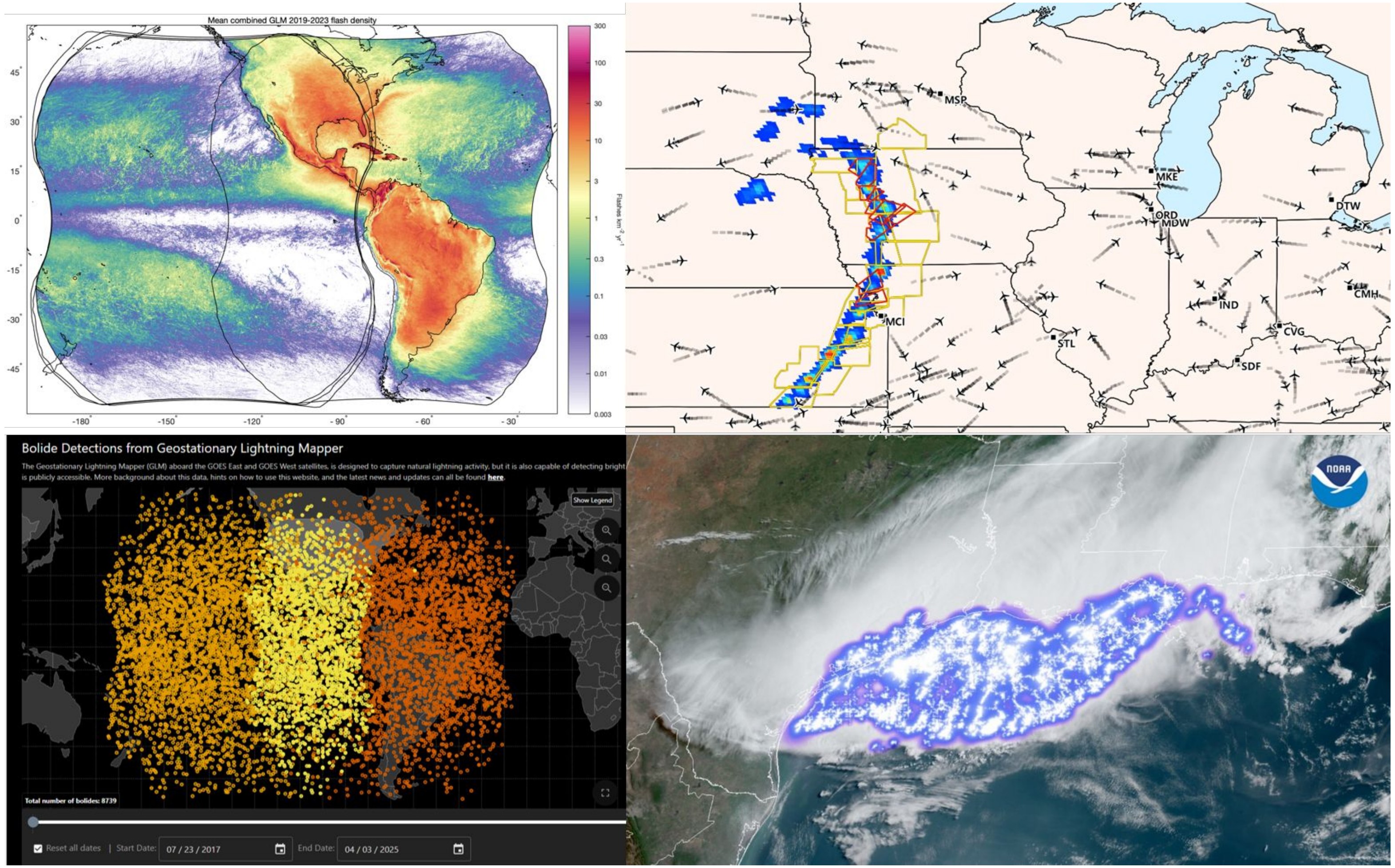
GLM Overview

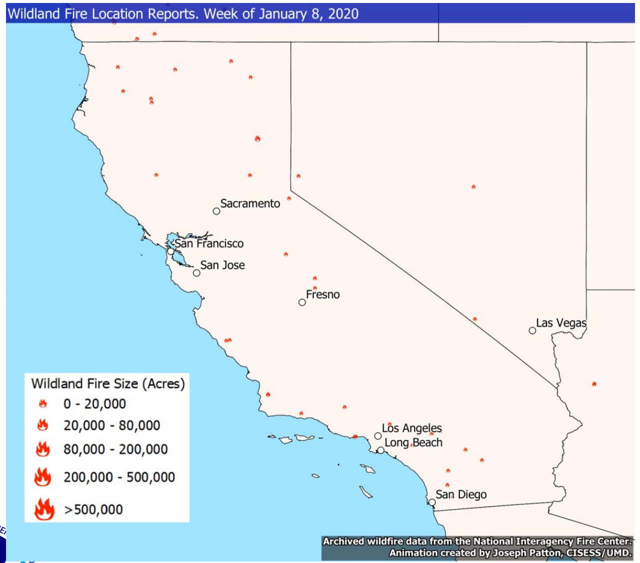
- **Two Geostationary Lightning Mappers (GLMs) continuously observe total lightning (both intra-cloud and cloud-to ground) over a vast region**
- **Operational users have embraced this new source of lightning information and incorporated it into their workflow**

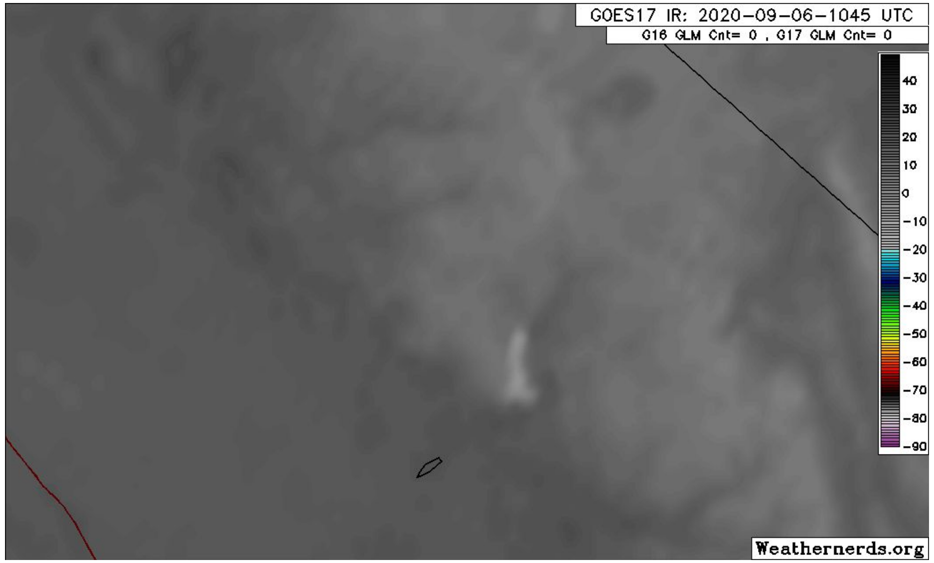


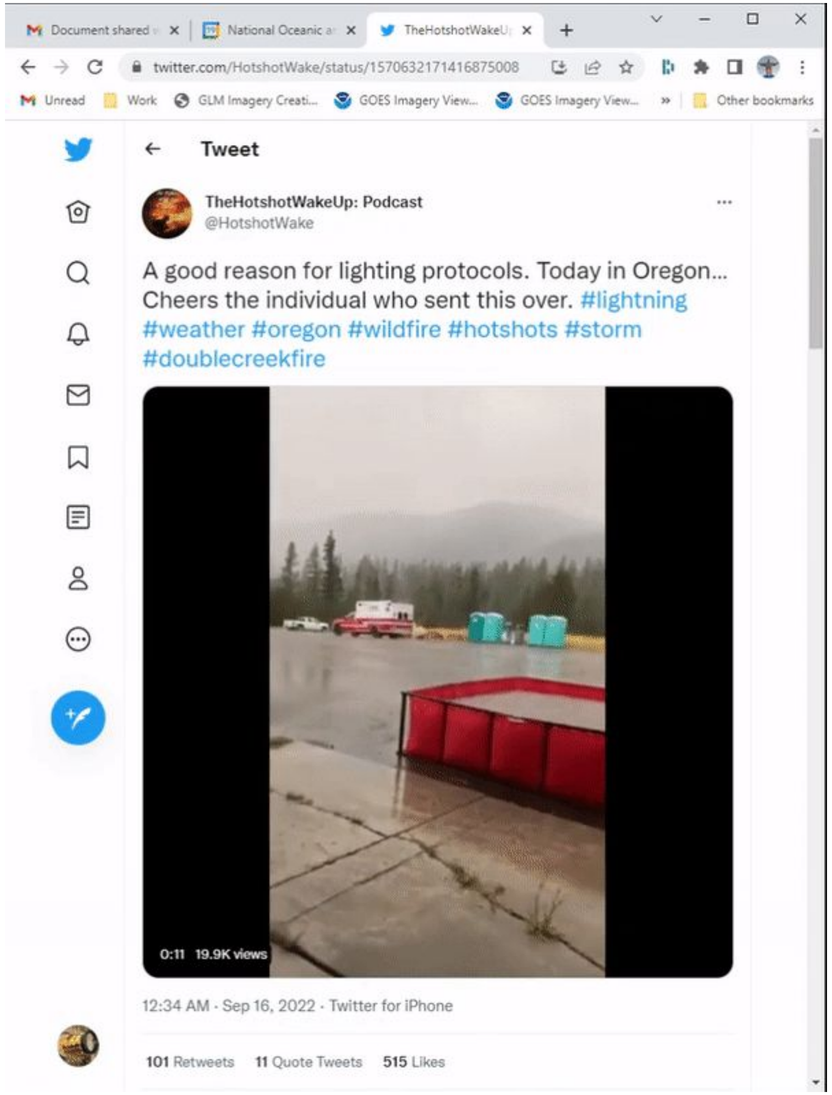
Clockwise from top left, Geostationary Lightning Mapper (GLM) lightning climatology (2019-2023); GLM flash extent density, severe thunderstorm and tornado warning polygons, and airplane positions and paths; Advanced Baseline Imager (ABI) and GLM depiction of a line of storms that produced the longest flash ever recorded (horizontal distance stretched 477 miles, from the central coast of Texas to southern Mississippi on April 29, 2020); and the locations of nearly 9,000 bolides observed by the GLMs since 2017.

Improving Safety and Effectiveness of Wildfire Response

- **The GLM benefits the firefighting community through unique identification of continuing current lightning strikes most likely to ignite fires, better pyrocumulonimbus characterization, and thunderstorm tracking in areas lacking robust radar coverage.**







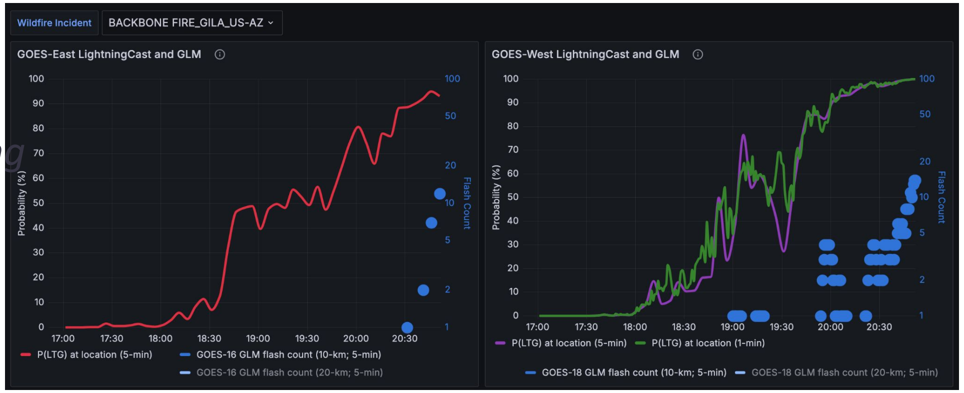
GLM Application

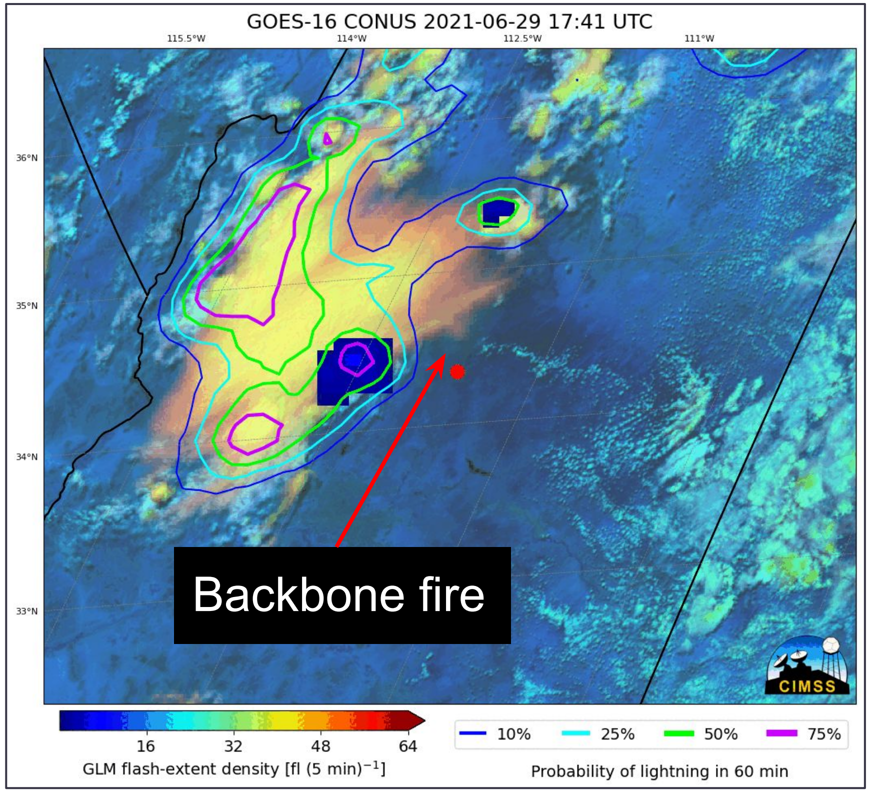
- **National Weather Service (NWS) forecasters use the GLM to monitor the spatial extent of lightning flashes to provide awareness to airports, outdoor venues, and firefighting operations as part of the NWS mission to provide impact-based decision support services (IDSS/DSS).**
- **The GLM observes the full spatial extent of total lightning flashes which helps anticipate cloud-to-ground lightning strikes that pose a direct safety threat to firefighters and a secondary threat via new fire starts.**
- **The GLM also aids storm tracking which is vital to determining storm motion and anticipating sudden shifts in thunderstorm intensity that can quickly shift fire lines and threaten firefighters and the public.**

Combining Observations

- **NWS forecasters use a satellite-based one-hour lightning forecast system that uses artificial intelligence to predict the probability of lightning from GOES-R ABI imagery.**
- **LightningCast aids decision-support services for: Firefighters, FAA (aviation), concerts, stadiums, fairs, and other large events.**
- **In this case, fire incident coordinators monitor the potential for lightning to directly impact firefighting efforts, and the intensity of nearby storms for their potential impact on wind direction and fire conditions.**

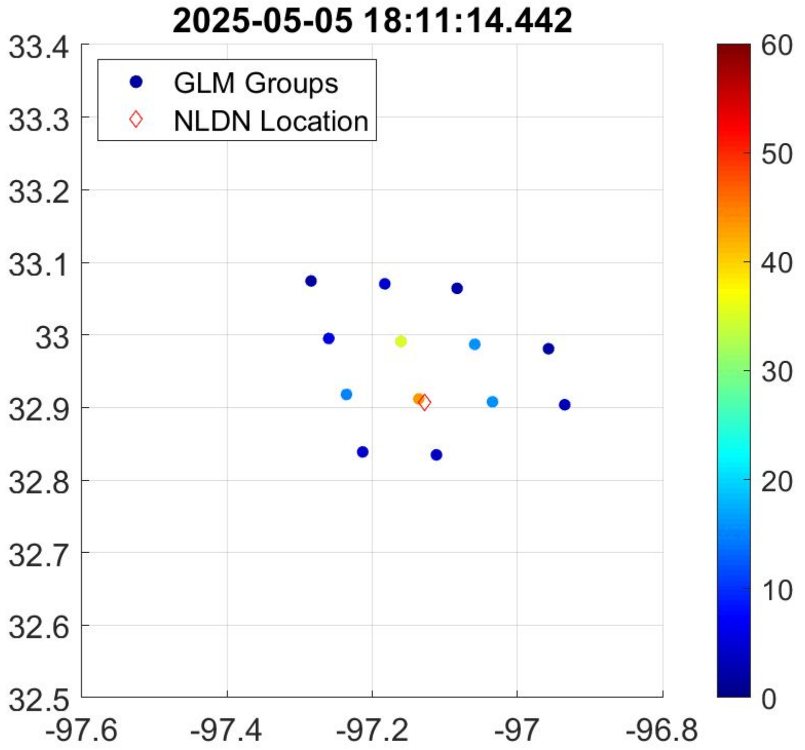
Probabilities of lightning (lines) and observed lightning strikes (dots) near the Backbone fire, from GOES-East and GOES-West





Long Continuing Current (LCC)

- **Lightning ignited a house fire in Colleyville, Texas on 5 May 2025**
- **National Lightning Detection Network (NLDN) reported a single stroke +64 kA CG flash**
- **GLM reported a roughly 53 ms LCC**



https://www.foxweather.com/extreme-weather/video-lightning-strikes-texas-home-displacing-family

Identifying Lightning Ignited Wildfires Earlier

- **Compiled a fire-centric lightning climatology that provides great insights into the types of lightning that ignites fires.**
- **Findings indicate clear differences between both the ignition and null environments, and the fires detected the day of the lightning versus those that dwell.**
- **Analysis reveals that distributions of lightning, land surface, and meteorological conditions can be used to help identify locations most vulnerable to lightning ignitions.**
- **Developing two models to alert to the potential for lightning-ignited wildfires**

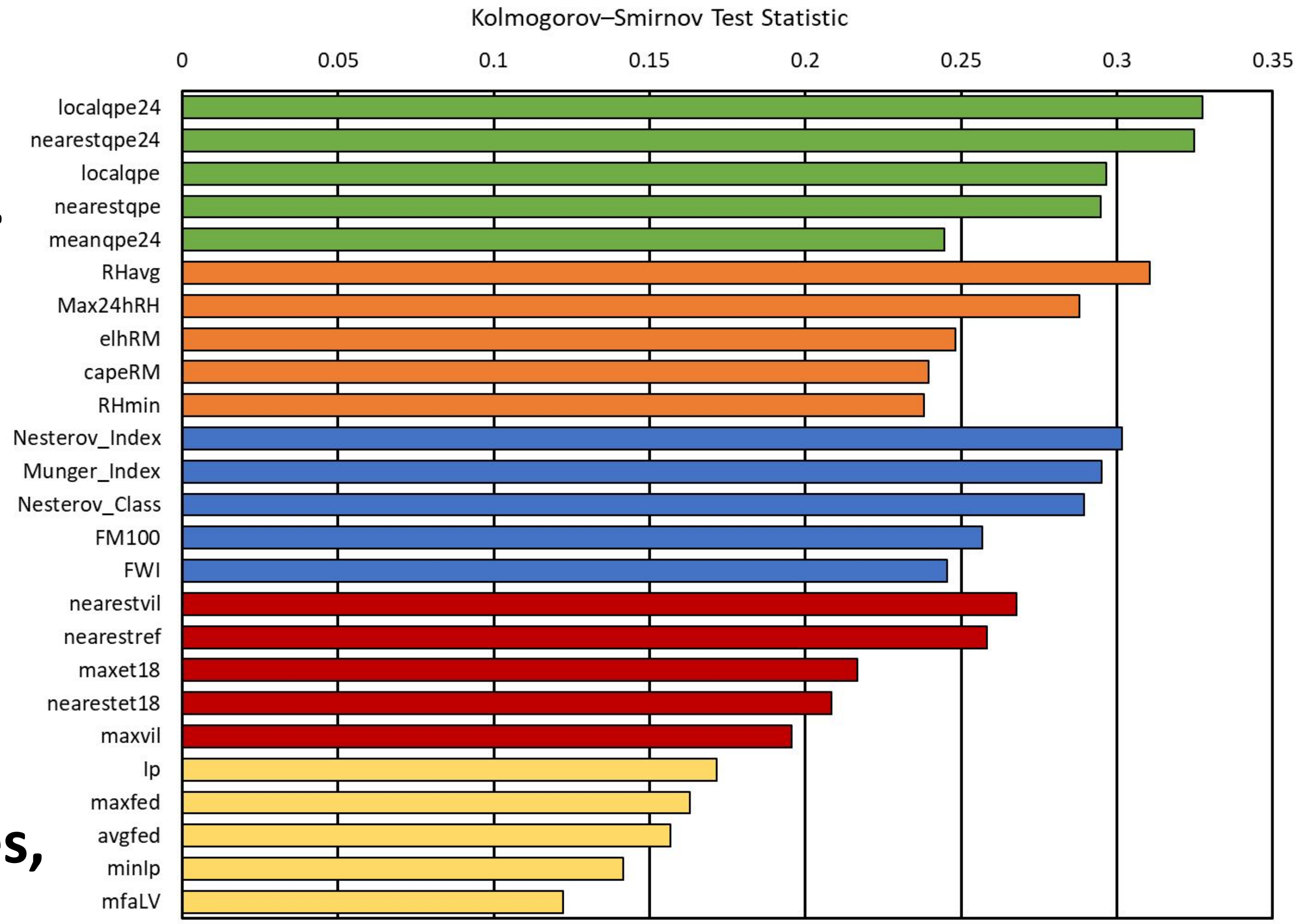
  1) **Lightning Ignition Likelihood Index (LILI) will be produced every 15 min and will indicate the likelihood that lightning has ignited a fire during the previous 15 min**
  2) **Lightning Ignition Region of Interest (LIROI) will be produced once daily and will indicate the potential that lightning ignited a wildfire the previous day**

Characterizing the Weather, Surface, and Lightning

- **Characterizing the Areal Precipitation – Gathered the blended MRMS radar/gauge product (both locally and in the surrounding 1°×1° grid box)**
- **Characterizing the Near-Storm Environment – Used High-Resolution Rapid Refresh (HRRR) data**
- **Characterizing the Storm Environment – Gathered additional MRMS data on storm environment (i.e., composite reflectivity, echo top height, and VIL)**
- **Characterizing the Land Surface – Used the LANDFIRE dataset and computed many fire weather parameters**
- **Characterizing the Lightning – Included both NLDN stroke and flash level information, and used the GLM gridded products to describe the lightning nearest and surrounding the fire ignitions**

Comparing Ignition and Null Distributions

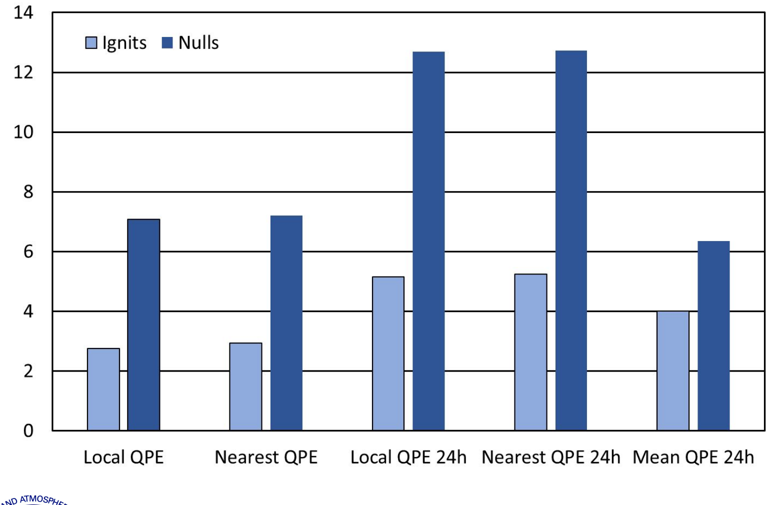
- **Kolmogorov-Smirnov (KS) tests help determine which variables differ most between the ignition and null datasets.**
- **Each variable group shows differences between the ignition and null samples.**
- **The 1 h and 24 h local/nearest quantitative precipitation estimate (QPE) differed most between samples (i.e., largest KS statistics).**
- **Several relative humidity (RH) measures, fire weather indices, and lightning variables also differ between samples.**

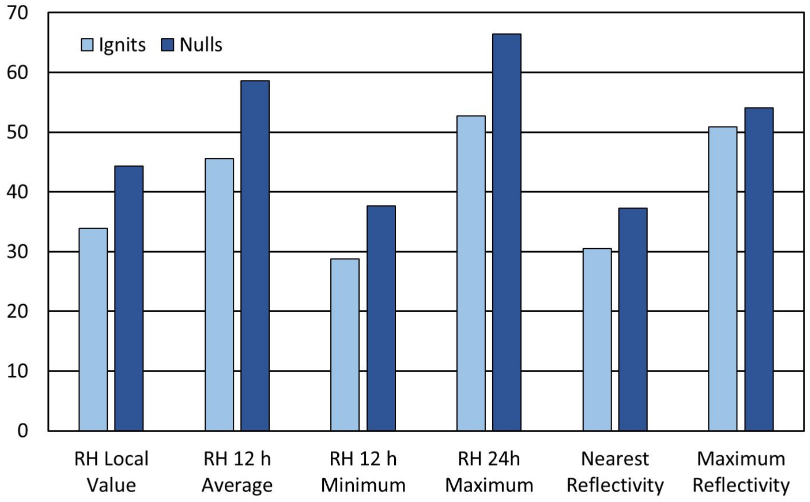


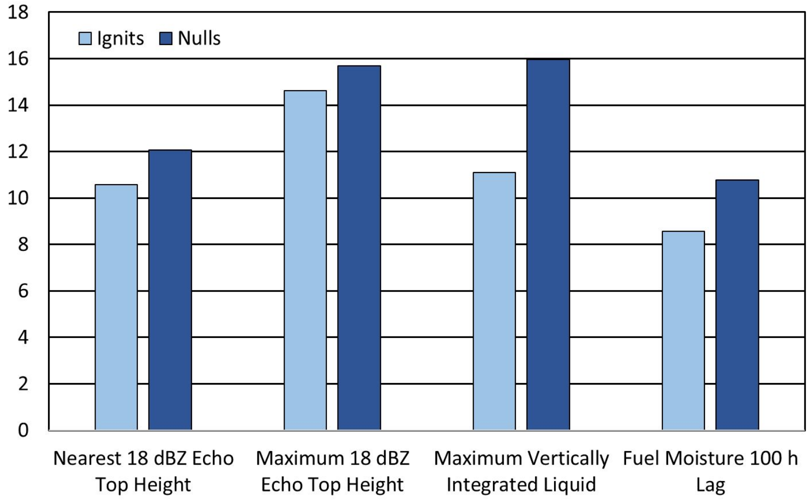
KS test statistics for select variables from each variable group

Comparing Ignition and Null Distributions

- **Many variables reveal a clear distinction between the ignition and null environments.**
- **Ignitions have less than half the precipitation, with average daily (hourly) QPE of 12.69 (7.08) mm for the null flashes and only 5.16 (2.76) mm for the ignitions.**
- **The multi-radar multi-sensor (MRMS) variables indicate weaker storms surrounding the ignitions and several different RH values indicate ≈10% drier environments.**



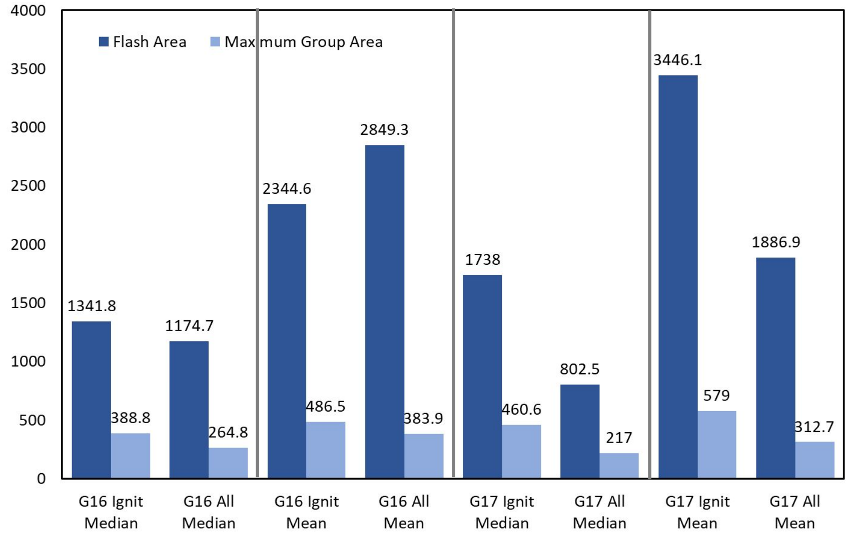


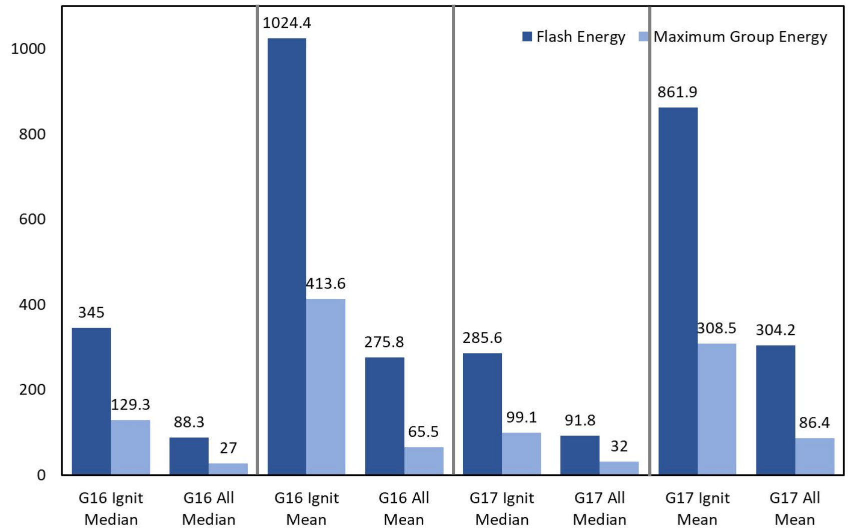


Comparing Ignition and Null Distributions

- **Both the NLDN and GLM observations can help identify lightning more likely to ignite wildfires.**
- **On average, positive and negative ignition flashes are 3.8 kA and 4.8 kA stronger than null flashes.**
- **Both GLMs indicate that ignition flashes are larger and 3-4 times brighter than the domain-wide sample.**

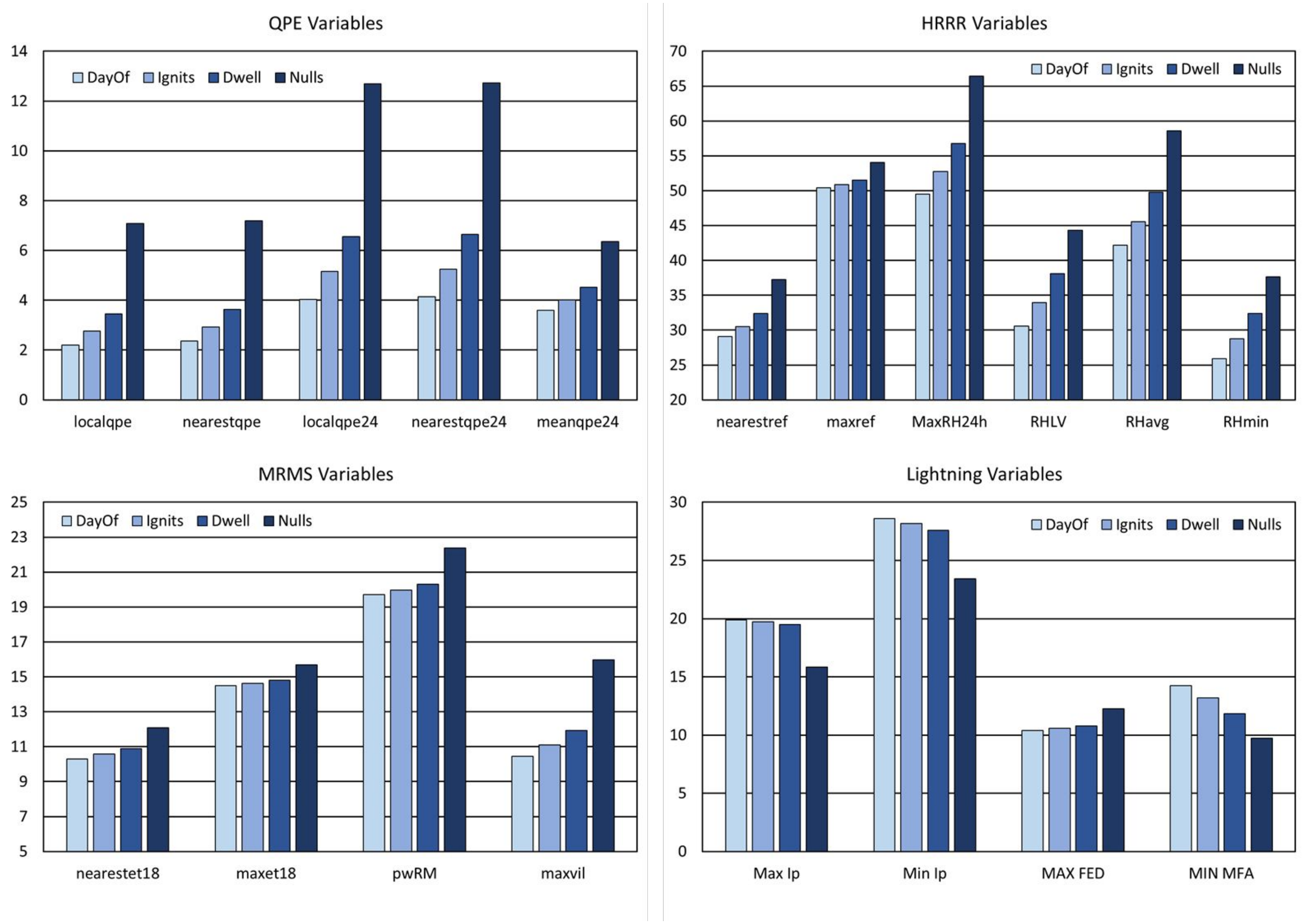
	CG	IC	maxIp	minIp	duration
Ignits	88.5%	11.5%	19.7	-28.2	0.172
Nulls	87.8%	12.2%	15.9	-23.4	0.165





Characterizing Fires that Dwell

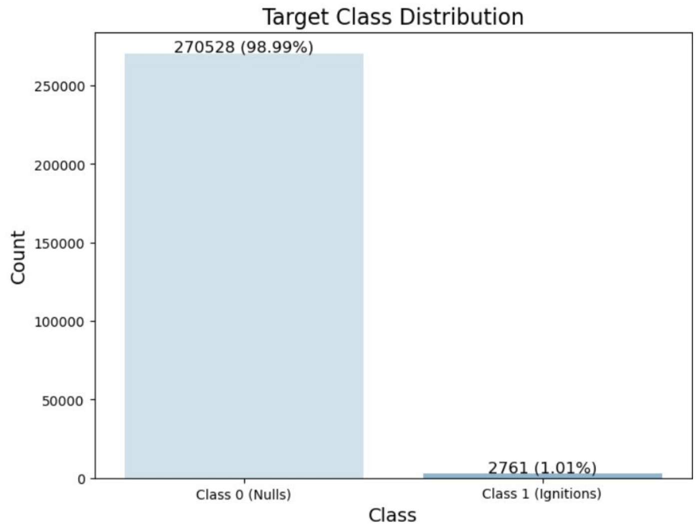
- **Day of detections have ≈33% of the 1 h and 24 h precipitation and ≈15% less RH than the null cases.**
- **The average 1 h (24 h) QPE is 1.26 (2.51) mm greater and the RH is ≈7% greater for the dwell cases than day of detections.**
- **Most variables indicate that day of fires occur in the most fire-prone environments, null environments are least conducive, and fires that dwell are somewhere in between.**

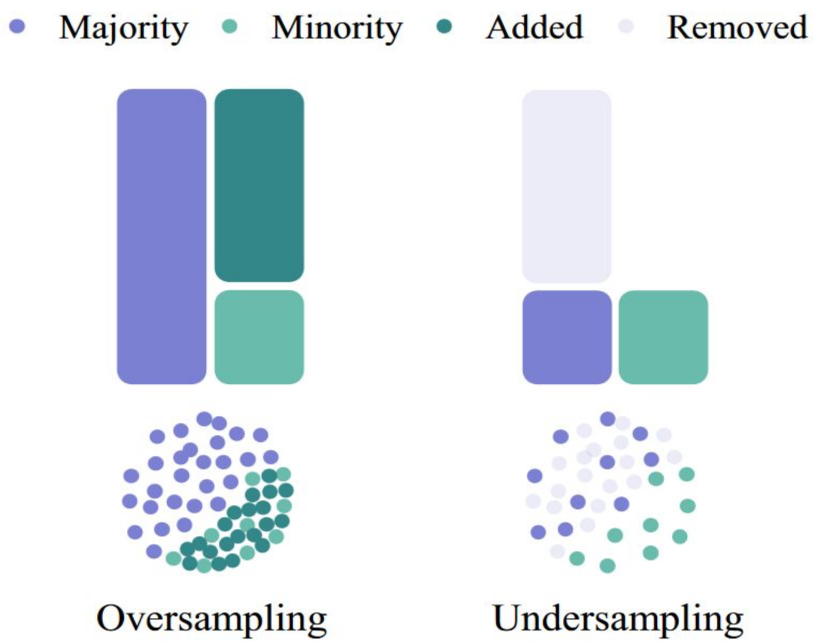


Mean values of various QPE, High-Resolution Rapid Refresh (HRRR), Multi-radar multi-sensor (MRMS), and lightning variables by fire ignition category

Machine Learning Approach

- Dataset spans from 2020 to 2022, containing 273,289 cases
- Outcome consists of 2 target classes: Nulls and Ignitions
- Evaluate the performance of AdaBoost and XGBoost, the effect of feature selection, and the effectiveness of Undersampling versus SMOTE approaches.
- Handling Imbalance:
  - Addressed the significant class imbalance (20:1 ratio of Nulls to Ignitions) by applying undersampling to reduce the size of majority class (Nulls)
  - Implemented SMOTE (Synthetic Minority Over-sampling Technique) to generate synthetic samples for the minority class (Ignitions), improving model performance on imbalanced data





Selected Features

Variables Common to Both Feature Selection Techniques

- %Vegetation
- Angstrom_Index
- capeRM
- Elev
- elhLV
- elhRM
- FWI
- GACC
- localqpe24
- Max_24h_Dpt
- Max_24h_RH
- maxet18
- maxqpe24
- medianref
- medianvil
- minIp
- Munger_Index
- nearestet18
- nearestqpe24
- nearestref
- Nesterov_Ignition_Index
- Nesterov_Index_Class
- pwRM
- Refl
- RHavg
- types
- umotRM
- VPD
- Year

Variables Exclusive to Manual Feature Selection

- %GrassDominated
- %TimberLitter
- 24h_Precip
- 2m_RH
- avgfed
- BI
- capeLV
- coverage
- coverage24
- dewptLV
- dewptRM
- ERC
- Flash_extent_density_window
- FM100
- FM1000
- h0LV
- h0RM
- Ip
- localqpe
- maxfed
- maxqpe
- maxref
- maxvil
- meanet18
- meanref
- meanvalue
- meanvalue24
- meanvil
- medfed
- median
- median24
- Min_24h_RH
- Minimum_flash_area_window
- nearestdist
- nearestqpe
- nearestvil
- pwLV
- RHLV
- RHmin
- Soilw_0.0m
- tavg
- tmax
- umotLV

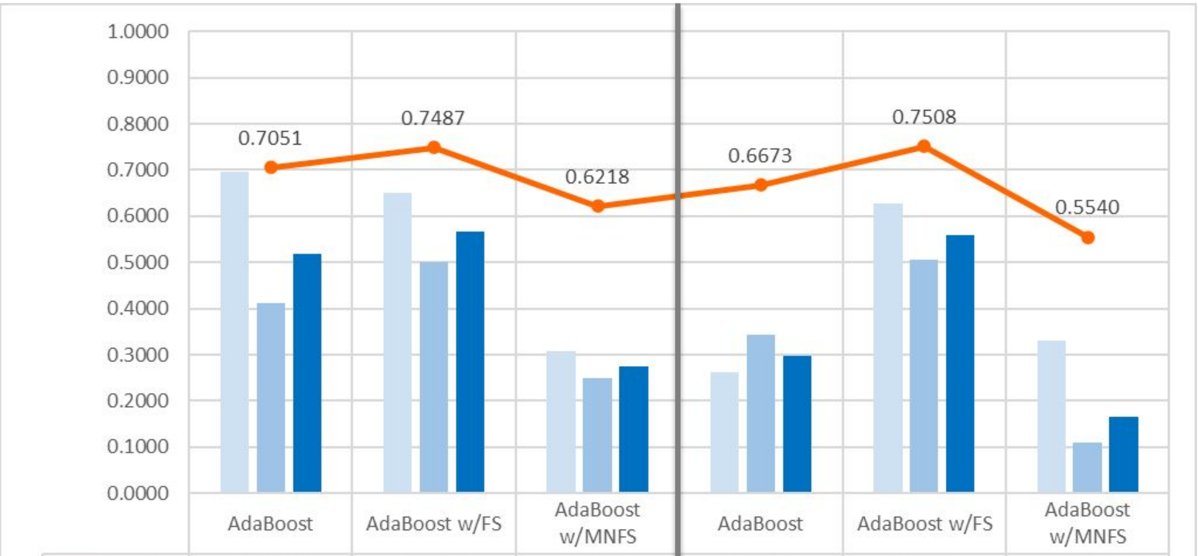
Variables Exclusive to Mutual Information-based Feature Selection

- 2m_Temp
- Baumgartner_Index
- ccLV
- ccRM
- CGcount
- daynight
- ESI_56Days
- ESI_7Days
- ESI_84Days
- FFWI
- ICcount
- Max_24h_Temp
- maxet18dist
- maxIp
- maxrefdist
- maxvildist
- Min_24h_Temp
- minmfa
- month
- nearestet18dist
- nearestrefdist
- nearestvildist
- pblRM
- percentile25
- polarity
- ref25
- RHRM
- sensor
- SPI_30Days
- SPI_60Days
- strokecount
- summ24
- ushearRM
- vil25
- vil75
- vmotRM
- vshearRM
- wgRM
- wsRM

Model Performance

- Evaluate the performance of *AdaBoost* and *XGBoost*
- Evaluate the effect of feature selection: compare models without feature selection, with feature selection, and with manually selected features.
- Compare the effectiveness of Undersampling versus SMOTE approaches.

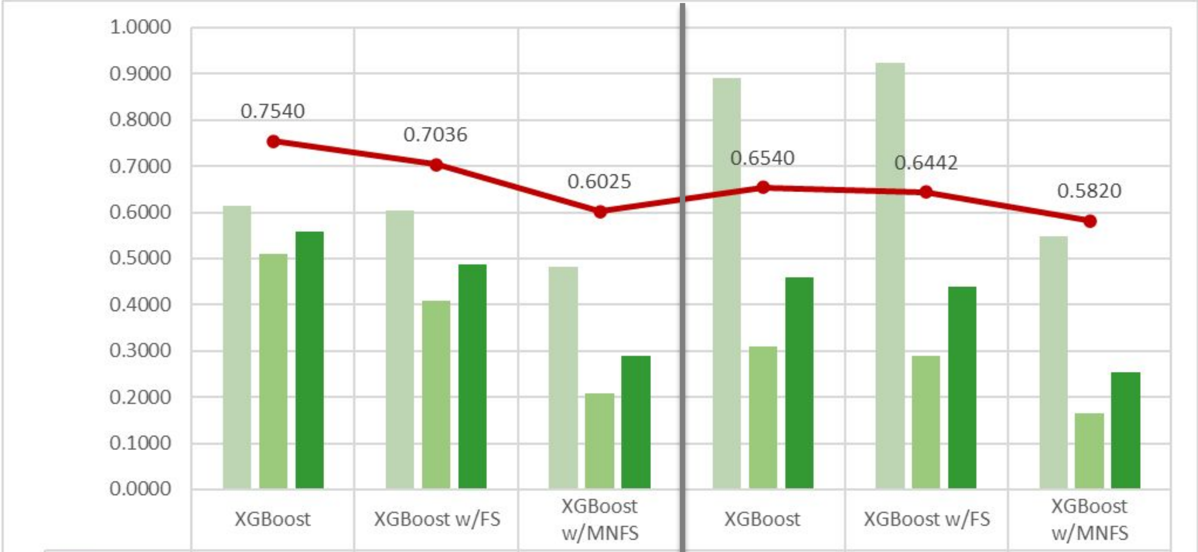
AdaBoost Model with *Undersampling* (20:1) | AdaBoost Model with *SMOTE*



	AdaBoost	AdaBoost w/FS	AdaBoost w/MNFS	AdaBoost	AdaBoost w/FS	AdaBoost w/MNFS
Precision	0.6952	0.6504	0.3079	0.2631	0.6274	0.3311
Recall	0.4119	0.5000	0.2489	0.3436	0.5044	0.1101
F1-Score	0.5173	0.5654	0.2753	0.2980	0.5592	0.1653
Bl-Acc	0.7051	0.7487	0.6218	0.6673	0.7508	0.5540

Fig1. AdaBoost Model Performance

XGBoost Model with *Undersampling* (20:1) | XGBoost Model with *SMOTE*



	XGBoost	XGBoost w/FS	XGBoost w/MNFS	XGBoost	XGBoost w/FS	XGBoost w/MNFS
Precision	0.6138	0.6039	0.4821	0.8917	0.9225	0.5474
Recall	0.5110	0.4097	0.2070	0.3084	0.2885	0.1652
F1-Score	0.5577	0.4882	0.2897	0.4583	0.4396	0.2538
Bl-Acc	0.7540	0.7036	0.6025	0.6540	0.6442	0.5820

Fig2. XGBoost Model Performance

Model Performance (Cont.)

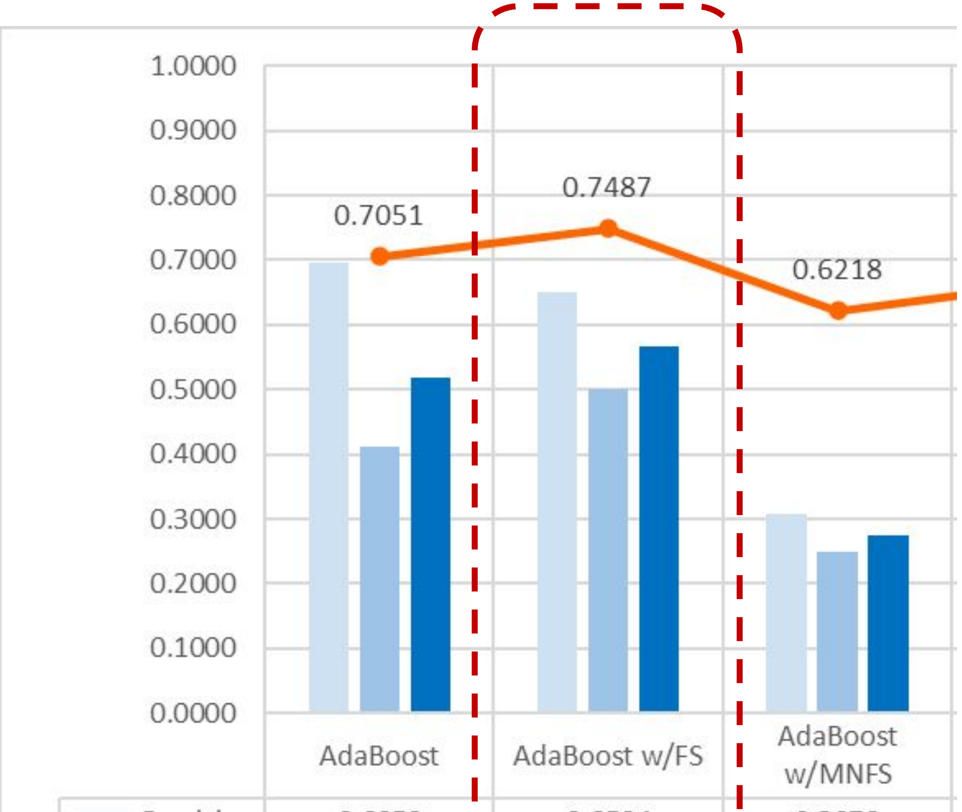


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Table1. Confusion matrix for AdaBoost Model with Undersampling 20:1

True label	Nulls	48616	122
	Ignitions	227	227
		Nulls	Ignitions
		Predicted label	

Summary

- The GLM benefits the firefighting community through unique identification of continuing current lightning strikes most likely to ignite fires, better pyrocumulonimbus characterization, and thunderstorm tracking in areas lacking robust radar coverage.
- Many weather, land surface, and lightning variables reveal a clear distinction between the ignition and null environments.
- Developing two models to alert to the potential occurrence of lightning-ignited wildfires

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