LIGHTNING JUMP ALGORITHM FOR GOES-R GEOSTATIONARY LIGHTNING MAPPER (GLM) PROXY DATA

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1. INTRODUCTION

Previous work by Williams (1999), Schultz et al. (2009), and Gatlin and Goodman (2010) demonstrate the correlation between rapid increases in total flash rate (i.e., "lightning jumps") and severe weather occurrence. Recent studies (Schultz et al. 2009, Gatlin and Goodman 2010, Schultz et al. 2011) have quantified the lightning jump based on statistical measures. Schultz et al. (2009, 2011) presented strong results for the use of total lightning from lightning mapping arrays (LMAs) to aid in the prediction of severe and hazardous weather using an objective lightning jump algorithm (LJA) with semi-automated tracking on a large number of storms. Schultz et al. (2009) developed and tested 4 different lightning jump algorithm configurations and found that the 2σ algorithm had the best skill in nowcasting severe weather potential.

However, Schultz et al. (2009, 2011) lack full automation and objective tracking techniques that utilizes both radar and satellite based products. Also, these studies did not account for what the Geostationary Lightning Mapper (GLM) will observe once on orbit in the GOES-R satellite (Goodman et al. 2013). Therefore, the goal of this study is to develop a fully automated framework, encompassing objective tracking, GLM proxy lightning data and the LJA. This aspect is an important element in the transition of the total LJA concept from a research based algorithm to an operational algorithm. This framework will also serve as a vessel to refine the LJA itself to enhance its operational applicability.

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2. DATA AND METHODOLOGY

The system in which the lightning jump is implemented consists of three components: lightning data, thunderstorm tracking, and the LJA. Each component plays a vital role in the automation of the LJA for operational uses. A GLM proxy dataset has been developed for use within the system because an optical instrument does not currently exist at geostationary orbit. Also, GLM observes a different component of lightning than the LMA (optical radiances at cloud top vs. VHF observations). It is necessary to utilize an automated, objective tracking scheme to assign lightning flashes to individual storms in order to compute lightning time histories necessary for jump identification. Finally, the algorithm itself is needed to calculate lightning jumps.

2.1 *Domain*

This research study includes > 90 event days consisting of ~500-1000 storm clusters between 2002 and 2011 within 125 km range of the network center of the North Alabama Lightning Mapping Array (Fig. 1; Table 1). This dataset is a significant subset of the events included in Schultz et al. (2011).

Table 1. Comparison of the tunable parameters in the LJA, verification, and database used in Schultz et al. (2011) and this study.

Tunable Parameter	Schultz et al. 2011	This study
Sigma threshold statistical jump threshold	2.0	0.75, 1.0, 1.25, 1.5, 1.75, 2.0, 2.25, 2.5
Flash rate threshold Minimum flash rate (flashes/min^{1}) required to activate the algorithm	10	1, 5, 10, 15, 20
Algorithm Spin-up Minimum time required to determine a jump	14 minutes	14 minutes
Storm report distance Additional distance from cell boundary	0 (Only area within cell)	5 km
Forecast period Time following a jump	45 minutes	45 minutes
Domain range From NALMA center	200 km (most within 150 km)	125 km
Spatial Scale Based on WDSSII tracking parameters	-----	5 (storm area of ~160 km^2)

Storm clusters are included in the database if they have a minimum lifetime of at least 30 minutes within the domain. Only the portion of the cluster track that is within the domain is included in the dataset.

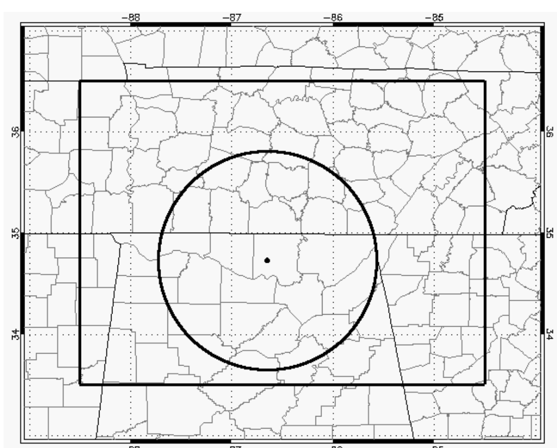

Fig 1. The large rectangle indicates storm tracking domain with 125km range ring centered at the LMA center.

2.2 *GLM Proxy Data*

Previous implementations of the LJA algorithm involved ground-based datasets using three-dimensional LMAs. For this study, the GLM Proxy Data set (Bateman 2013) is used. The GLM Proxy Data was developed from an empirical model between the space-borne lightning imager sensor (LIS) and the North Alabama LMA (Bateman et al. 2008). The LIS, like the GLM, records optical events which are grouped and combined into flashes (Mach et al. 2007) whereas the LMA detects VHF electromagnetic radiation which are combined into flashes using a clustering algorithm. An example flash visual comparison between the LIS and LMA is shown in Fig. 2. The comparative analysis of these two lightning data sets created a Monte Carlo look-up table to select realistic optically-based flashes at GLM resolution based on the input of LMA flashes for a selected case. Each GLM Proxy flash location is determined by the amplitude weighted centroid of the groups/events. GLM Proxy flashes are gridded to a 0.08° x 0.08° grid at 1 and 5 minute running averages every minute.

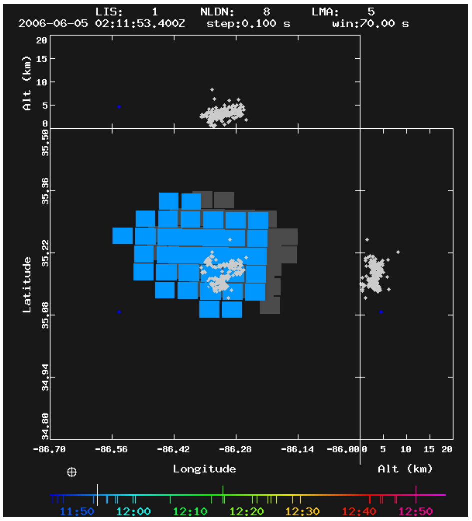

Fig. 2. An example visual comparison of the spatial differences of a single flash between an optical observation from the TRMM-LIS and the VHF radiation from the North Alabama LMA on 5 June 2006. Each LIS flash location is determined by the amplitude weighted centroid of the groups/events. The LMA flash consist of clustered radiation sources recorded at 80 µs intervals along the path of the flash.

2.3 *Thunderstorm Tracking*

Previous studies have used reflectivity based thresholds for thunderstorm tracking (35 dBZ at -15°C, Schultz et al. 2009). This study combines the 5-minute GLM Proxy flash rate density (FLCT5; Fig. 3a) with Vertically Integrated Liquid (VIL) from merged and gridded NEXRAD radar data for the closest five radars (KHTX, KGWX, KOHX, KFFC, KBMX) into a new product called VILFRD (Equation 1; Fig. 3c) which is tracked using K-means clustering in w2segmotionll in the Warning Decision Support System – integrated information (WDSSII) (Lakshmanan et al., 2007).

$$VILFRD = 100 \times \left[\left(\frac{VIL}{45} \leq 1 \right) + \sqrt{\frac{FLCT5}{45}} \leq 1 \right] \quad (1)$$

WDSSII w2segmotionll is used to track features where VILFRD values are ≥ 20, at increments of 20. Any pixel with a value greater than 100 is assigned the value of 100. Clusters are built until a minimum size or spatial scale threshold is met (Table 2) with a maximum overlap approach for associating cells from one time step to the next. Individual cells at a select time are shown as an example in Fig. 3d. Outside of WDSSII, "broken tracks" are objectively merged if a WDSSII cell begins at t+1 within 15 km of where a previous track ended at time t. Time histories are tied together for merged cells.

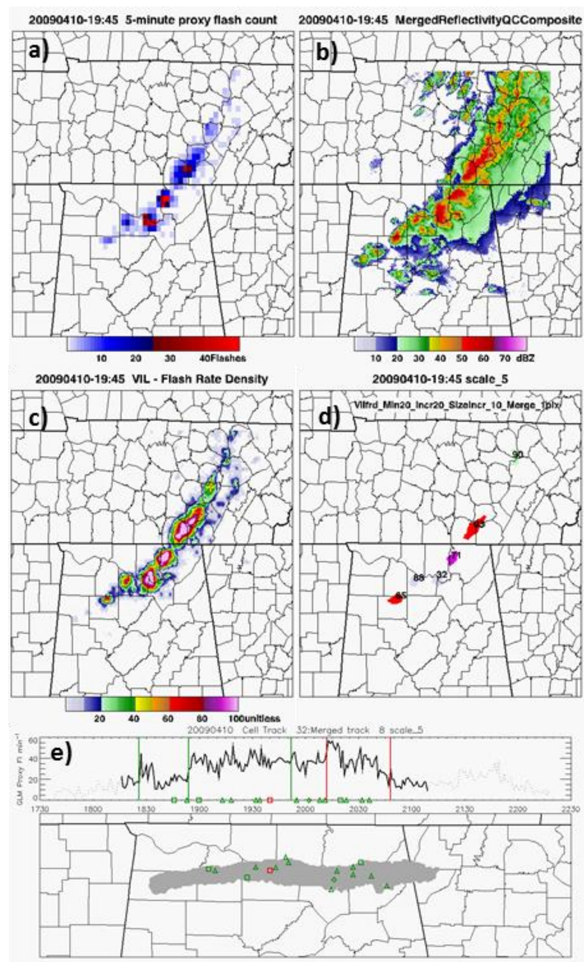

Fig. 3. a) 5 minute GLM Proxy gridded flash count, b) Merged composite reflectivity, c) VILFRD, d) tracked clusters, e) The top panel depicts the lightning trend, lightning jumps and severe storm reports. Color coded lines/symbols indicate hits (green) and false alarms/misses (red), using the algorithm defaults outlined in Table 2. on x-axis (green=hit, red=miss) and lightning jump hits as vertical lines at time of jump (green=hit, red=false alarm), bottom: cluster lifetime swath with storm reports (green=hit, red=miss)

Table 2. Spatial scale labels with minimum area needed to be met to track using WDSSII

Spatial Scale	~Area (km^2)
1	32
2	65
3	97
4	130
5	162
6	243

2.4 Lightning Jump Algorithm

Lightning jumps were objectively identified using the 2σ algorithm from Schultz et al. (2009, 2011). A flow chart for the lightning jump algorithm process is shown in Fig. 4. As defined in Schultz et al. (2009, 2011), the algorithm is a 5 step process.

1) The total flash rate from the time period, t, is binned into 2 minute time periods, and the total flash rate is averaged.
2) The time rate of change of the total flash rate (DFRDT) is calculated by subtracting consecutive bins from each other (i.e., bin_2-bin_1, bin_3-bin_2,… bin_t-bin_{t-1}). This results in DFRDT values with the units of flashes min^{-2}.
3) Next the 5 previous DFRDT values are used to calculate a standard deviation of the population. Twice this standard deviation value determines the jump threshold.
4) If the newest DFRDT time exceeds the jump threshold, the minimum spin-up time of 14 minutes is reached, and the current flash rate exceeds the flash rate threshold of 10 flashes min^{-1}, a jump has occurred. The classification of an individual jump ends once DFRDT drops below 0 flashes min^{-2}.
5) This process is repeated every two minutes as new total lightning flash rates are collected until the storm dissipates.

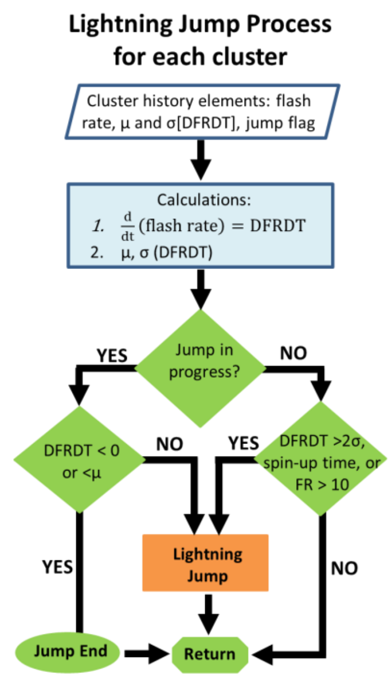

Fig. 4. Flowchart for the process to classify a lightning jump

In the event multiple jumps occur within 6 minutes of each other, only the first jump remains for verification (Table 3). A discussion of the LJA's tunable parameters is included in the next section.

2.5 Parameter Sensitivity Testing

Seven parameters (Table 1) have been identified for sensitivity testing of the lightning jump system. Schultz et al. (2009) tested a 2σ and 3σ configuration of the LJA and determined that the 2σ version produced more optimal skill scores when a 10 flash per minute flash rate threshold was implemented Based on the Schultz et al. (2009) findings, the 2σ configuration was tested further in Schultz et al. (2011). Herein, this study expands upon the results of Schultz et al. (2009, 2011) through further sensitivity testing of the sigma threshold by varying sigma from 0.75 to 2.5 in 0.25σ increments (Table 1). Furthermore, a range of flash rate thresholds are tested in order to determine the algorithm sensitivity (Table 1). The minimum time required for the spin-up of the algorithm is 14 minutes (12 minutes to calculate the jump threshold, 2 additional minutes to determine if a lightning jump has occurred; Section 2.4).

Tunable parameters that are investigated within the verification framework are storm report distance and forecast period. Severe storm reports were obtained from NOAA National Climatic Data Center's (NCDC) Storm Data and used as ground truth for validation. Storm Data has known issues such as time/location displacement and data sparse regions (e.g., Williams et al. 1999), so effort is taken to mitigate small timing and spatial errors that may exist in the database. This mitigation includes an additional "buffer" space around the footprint of a tracked storm cluster at each time step to assign reports to specific clusters. Storm report distance is defined as the maximum distance from the storm cluster's footprint edge that a storm report can be associated with that storm. This distance is initially set to 5 km. The forecast period is the time period starting at the occurrence of a jump and lasting for 45 minutes (default) or set length of time. Reports that occur within this forecast period or validation window are used to verify the jump.

Finally, two parameters are used to define the available database itself. The domain range is limited to the areal coverage of the LMA network. The closer the lightning activity is to the network, the higher the detection efficiency. Therefore, extending the domain can decrease the detectable flashes and decrease flash rates which can have an effect on the classification of jumps. The spatial scale introduced in this study, not present in Schultz et al. (2009, 2011), is a result of the options available in WDSSII to track features at different areal extents. Six different scales (Table 2) were chosen ranging in sizes from that of small thunderstorms to that of larger storm clusters. These values serve as the initial or baseline comparisons for sensitivity tests performed in this study.

2.6 Verification

This study's initial verification methodology closely follows the methodology outlined in Schultz et al. (2009). In order to evaluate the lightning jump system, severe storm reports are used as ground truth validation. As mentioned above, there are caveats with using Storm Data. In attempt to mitigate these effects, a temporal clustering of reports in 6 minutes bins was implemented. This binning begins at the initial point that the storm cluster enters or develops within the domain. These grouped reports count as single event.

The forecast period or validation window for jump verification is the 45 minute window starting at the time of the jump. However, in the method outlined by Schultz et al. (2009), only one jump can be evaluated at a given time. As mentioned in Section 2.4, jumps are grouped if they occur within 6 minutes of each other. This leaves open the potential for additional jumps to occur within the validation window (after the 6 minute potential grouping) of a previous jump. In these cases, we will differentiate the jumps as "first" jump and "second" or subsequent jumps. The first jump is verified and a hit (defined as the number of storm report groups) if a storm report occurs during the validation window. A second jump's validation window, however, is limited to the time period following the expiration of the first jump's validation window. For example, if the second jump started 30 minutes after the first, its validation window would expire 15 minutes later (considering a 45 minute forecast period) leaving a 30 minute validation window for the second jump. Despite what reports exist within the 15 minute overlap of the two jumps, the second jump is classified as a false alarm if no reports are present for the remaining 30 minutes.

In order to evaluate the algorithm, the skill scores of Probability of Detection (POD) and False Alarm Ratio (FAR) (Wilks 2011, 310-311) were calculated. In the process, a hit is defined as the grouped severe storm reports that occur during a validation window of a jump with the set bounds or buffer around a storm cluster. A miss is defined as the grouped severe storm reports that occur outside of a validation window. A false alarm is defined as a jump that is not followed by any storm reports within the associated

Table 3. A comparison of verification methodologies between the method used in Schultz et al. (2009, 2011) and a method aligning with the National Weather Service.

Verification Methodologies	Verification Schultz et al. 2009, 2011	Alternative Verification (Based on NWS, NWS-HUN personal communication)
Storm report grouping	Yes (6 minutes)	no
1 storm report verifies 2 overlapping forecasts	No (only first forecast, 1 hit)	Yes (1 hit)
Jump grouping	Yes (6 minutes)	Yes (6 minutes)
False alarm	No report during forecast OR For overlapping forecasts, no report in time period following first forecast expiration	No report during forecast

validation window as well as the qualification of subsequent jumps described in the previous paragraph.

The Schultz et al. (2009, 2011) verification methodology is not equivalent to that of the methodology employed by the National Weather Service (NWS) storm warning verification (NWS 2011). The main differences that exists between these two is severe storm grouping and the false alarm determination for subsequent jumps. Unlike Schultz et al. (2009), the NWS validates each warning separately even if they overlap. However, reports that are in the overlapping region only count once in the statistics. In an effort to closer compare our results to the techniques used by the NWS, we included what we will call an alternative (to Schultz et al. 2009) verification method. The discussion of our results will use both of these verification methods to evaluate the LJA algorithm and analyze sensitivity within the tunable parameters listed in Table 1.

3 RESULTS

Several trials of the lightning jump system using the tunable parameters listed in Table 1 were evaluated using the skill score metrics of POD and FAR. The sensitivity analysis revealed the level of influence that some of the tunable parameters have on the skill scores. In addition, while not surprising, the verification methodology notably affected the evaluation of the system performance. The main results shown are the influence of spatial scale used in storm cluster tracking, the effect of sigma and the flash rate threshold on the LJA and the impact verification methodology has on these results.

A comparison between the 6 spatial scales (Table 2) that were used by WDSSII to track storm clusters is shown in Fig. 5 where color indicates the difference scales. Larger spatial scales lead to increased POD, due to the larger areal extent of the storm cluster's footprint and thus limiting exclusion of storm reports located on the periphery of the storm, with values increasing from a range (due to a variance of other parameters) of 0.19 to 0.88 at scale 1 to 0.44 to 0.97 at scale 6. FAR value ranges tighten with increasing spatial scales, from 0.5 to 0.91 at scale 1 to 0.63 to 0.86 at scale 6. During early investigation of spatial scale and tracking, it was found that smaller scales were more ideal for isolated, small-scale thunderstorms as they were easier for the tracker to separate. Larger scales worked better for more complex and larger storms such as supercells. The larger scales were less likely to split a cluster apart that would naturally be considered as one entity. Based on these early results, and the distribution in Fig. 5, scale 5 was used as the default scale for further analysis in this study.

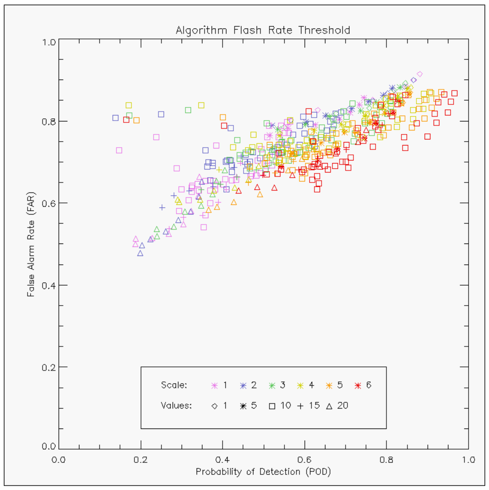

Fig. 5. Comparison of the 6 spatial scales (areal extent). Color represent the spatial scale at which storms are tracked and symbols represent flash rate thresholds for the Schultz et al. 2009, 2011 verification method.

Ongoing sensitivity analysis on the LJA and verification parameters listed in Table 1 showed that sigma and flash rate threshold had the largest impact on the overall performance of the algorithm. The combined effect of the sigma and flash rate thresholds for the Schultz et al. (2009) and alternative verification methods are shown in Figs. 6 and 7, respectively. The Schultz verification methodology (Fig. 6) shows that decreasing sigma values (cooler colors) and lowering the flash rate threshold (symbols) results in the POD increasing slightly more than the FAR. The POD and FAR were strongly coupled with a correlation coefficient of 0.95. Separating the effects of sigma and flash rate as sigma decreases, the effect of flash rate become more pronounced as linear regression slopes (0.57 at 0.75σ to 0.88 at 2.5σ) show a greater increase in POD values than in FAR values. Analyzing the effect of sigma and flash rate threshold on the algorithm using the alternative verification (Fig. 7) shows a de-coupled POD-FAR relationship (R^2=0.20) with decreasing sigma values resulting in an increase POD with little change in FAR. In addition, decreasing flash rate threshold leads to an increased POD but only slightly more than the FAR. Linear regression analysis while holding sigma constant revealed slopes of 0.99 (at 0.75σ) to 0.59 (at 2.5σ) quantifying the coupled effect flash rate threshold has on the POD-FAR relationship at low sigma values and the decoupling of this relationship with increasing sigma.

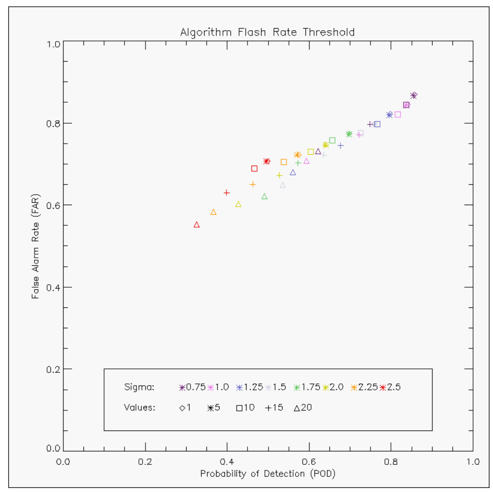

Fig. 6. The Schultz verification methodology showing the relationship of sigma (color) and flash rate threshold (symbols) on the algorithm's performance at spatial scale 5. A linear regression analysis (y=0.52x+0.40) for these data resulted in a strong correlation between POD and FAR (R^2=0.95). A linear regression analysis while holding each sigma level constant resulted in R^2=0.99 and slopes ranging from 0.57 (at 0.75σ) to 0.88 (at 2.5σ).

Finally, Figure 8 shows the spread of the method established in Schultz et al. (2009; black) and the alternative verification method (red) for all spatial scales. As mentioned, the Schultz et al. (2009) verification shows how closely coupled the relationship is between POD and FAR. The alternative method of verification shows improved performance of the LJA system on the order of reducing the FAR by 20% while maintaining a high POD. This is most likely due to the reduced amount of subsequent jumps classified as false alarms in Schultz et al.'s methodology.

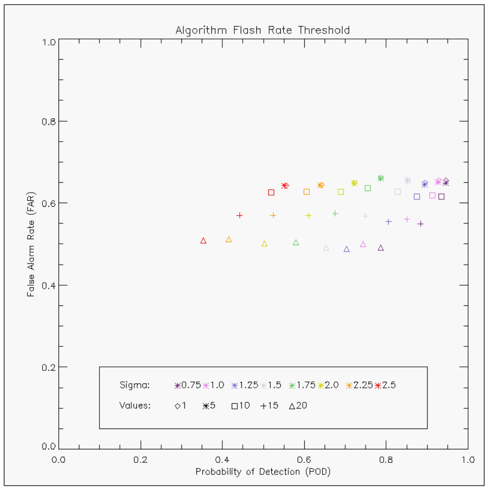

Fig. 7. The alternative verification method showing the relationship of sigma (color) and flash rate threshold (symbols) on the algorithm's performance at spatial scale 5. A linear regression analysis (y=0.16x+0.48) for these data resulted in almost no correlation between POD and FAR (R^2=0.20). A linear regression analysis while holding each sigma level constant resulted in correlation values above 0.9 (R^2=0.93 to 0.99) and slopes ranging from 0.99 (at 0.75σ) to 0.59 (at 2.5σ).

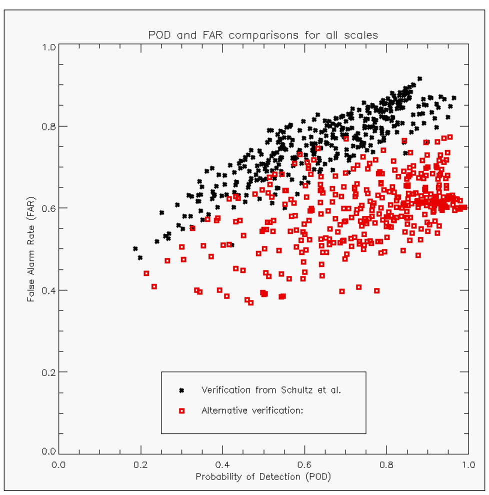

Fig. 8. A complete dataset distribution showing the differences between the verification Schultz et al. (2009; black) and alternative (red) verification methodologies.

4 SUMMARY

Analysis shows that key components of the algorithm (flash rate and sigma thresholds) have the greatest influence on the performance of the algorithm when validating using Storm Data. The analysis of the lightning jump system using GLM proxy data has shown probability of detection (POD) values around 60% with false alarm rates (FAR) around 73% using similar methodology to Schultz et al. (2011). However, when applying verification methods similar to those employed by the National Weather Service, POD values increase slightly (69%, range of 35%-95%) and FAR values decrease (63%, range of 0.48%-0.66%). These results show the POD and FAR are highly correlated (R^2=0.95) in the Schultz verification but not in the alternative verification (R^2=0.20). This evaluation also highlights the sensitivity of the algorithm's evaluation based on verification methodologies involving storm reports.

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