Improving situational awareness of heavy-snowfall using the geostationary lightning mapper

Sebastian S. Harkema

Follow this and additional works at: https://louis.uah.edu/uah-theses

Recommended Citation
Harkema, Sebastian S., "Improving situational awareness of heavy-snowfall using the geostationary lightning mapper" (2019). Theses. 276.
https://louis.uah.edu/uah-theses/276

This Thesis is brought to you for free and open access by the UAH Electronic Theses and Dissertations at LOUIS. It has been accepted for inclusion in Theses by an authorized administrator of LOUIS.
IMPROVING SITUATIONAL AWARENESS OF
HEAVY-SNOWFALL USING THE GEOSTATIONARY
LIGHTNING MAPPER

by

SEBASTIAN S. HARKEMA

A THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science
in
The Department of Atmospheric Science
to
The School of Graduate Studies
of
The University of Alabama in Huntsville

HUNTSVILLE, ALABAMA

2019
In presenting this thesis in partial fulfillment of the requirements for a master’s degree from The University of Alabama in Huntsville, I agree that the Library of this University shall make it freely available for inspection. I further agree that permission for extensive copying for scholarly purposes may be granted by my advisor or, in his/her absence, by the Chair of the Department or the Dean of the School of Graduate Studies. It is also understood that due recognition shall be given to me and to The University of Alabama in Huntsville in any scholarly use which may be made of any material in this thesis.

Sebastian S. Harkema

5/3/2019
(date)
THESIS APPROVAL FORM

Submitted by Sebastian S. Harkema in partial fulfillment of the requirements for the degree of Master of Science in Atmospheric Science and accepted on behalf of the Faculty of the School of Graduate Studies by the thesis committee.

We, the undersigned members of the Graduate Faculty of The University of Alabama in Huntsville, certify that we have advised and/or supervised the candidate of the work described in this thesis. We further certify that we have reviewed the thesis manuscript and approve it in partial fulfillment of the requirements for the degree of Master of Science in the Department of Atmospheric Science.

Committee Chair

Dr. John Meckikalski
4/25/2019
(Date)

Dr. Emily Berndt
4/25/2019
(Date)

Dr. Phillip Bitzer
2019/04/25
(Date)

Dr. Kevin Knupp
4/25/2019
(Date)

Dr. John Meckikalski
4/25/2019
(Date)

Department Chair

Dr. Sundar Christopher
5/3/2019
(Date)

College Dean

Dr. David Berkowitz
5/29/19
(Date)

Graduate Dean
ABSTRACT

School of Graduate Studies
The University of Alabama in Huntsville

Degree Master of Science College/Dept. Science/Atmospheric Science
in Atmospheric Science

Name of Candidate Sebastian S. Harkema

Title Improving Situational Awareness of Heavy-Snowfall Using
The Geostationary Lightning Mapper

While severe convective weather might be the focus of lightning data, studies regarding the use of these data for winter weather purposes are sparse. Next-generation satellite sensors, such as the Geostationary Lightning Mapper (GLM), provide new capabilities to gain a better understanding of the microphysical processes within heavy-snowfall. The advent of GLM provides a new opportunity to study how lightning is related to snowfall from a geostationary satellite perspective. Observed overlap between observations from GLM and National Environmental Satellite Data and Information Services (NESDIS) merged Snowfall Rate (mSFR) product indicate the existence of thundersnow (TSSN) and offers valuable insight to the rapidly changing environment in and around heavy-snowfall. A thundersnow detection algorithm was developed to objectively identify this phenomena and statistically significant (P<0.05) differences were observed for GLM flash area and flash energy; where GLM flashes that did not correspond to National Lightning Detection Network (NLDN) data were weaker in energy output and smaller in size compared to those that had at least one NLDN correspondence. Nearly 14% of TSSN flashes
observed by GLM corresponded with NLDN data near a tall human-made structure. Geographic locations that experience TSSN could expect to receive on average 9.81-in of accumulating snowfall. TSSN flashes occurred in snowfall rates less than 1.00-in hr\(^{-1}\) and were more likely to be associated with snow-to-liquid ratios between 8:1 and 9:1. With continuous high spatial and temporal resolution lightning observations, GLM improved the identification and characterization of TSSN events and situational awareness of significant snowfall events.

Abstract Approval: Committee Chair

Dr. John Mecikalski

Department Chair

Dr. John Mecikalski

Graduate Dean

Dr. David Berkowitz
ACKNOWLEDGMENTS

I would first like to thank my committee members for providing expertise and guidance navigating graduate school. I am also thankful for NASA SPoRT being the catalyst that made this project possible; specifically, I would like to thank Emily Berndt and Chris Schultz for always having an open door whenever I had a question about my writing or my research. Additionally, I would like to thank my fellow graduate students for providing support and ease the transition into graduate school. I would also like to acknowledge the support I have received from my sister and grandparents during my time at UAH. Finally, I would like to thank previous mentors; particularly, Steven Martinaitis, Heather Grams, and Daphne LaDue, for providing the first step towards graduate school and following a career in research.
# TABLE OF CONTENTS

## LIST OF FIGURES

x

## LIST OF TABLES

xiii

# Chapter

1 Introduction 1

2 Manuscript: Geostationary Lightning Mapper Flash Characteristics of Electrified Snowfall Events 5

## 2.0.1 Abstract 5

## 2.0.2 Introduction 6

## 2.0.3 Datasets 9

### 2.0.3.1 Geostationary Lightning Mapper 9

### 2.0.3.2 National Lightning Detection Network 10

### 2.0.3.3 merged Snowfall Rate product 11

### 2.0.3.4 Tall Human-made Structures 11

## 2.0.4 Methodology 12

### 2.0.4.1 Thundersnow Detection Algorithm Objective Identification 12

### 2.0.4.2 NLDN/GLM Matchup and Classification 16

## 2.0.5 Results 18
3 Manuscript: Characterization of Snowfall Rates, Totals, and Snow-to-Liquid Ratios in Electrified Snowfall Events from a Geostationary Lightning Mapper Perspective

3.0.1 Abstract ................................................................. 39
3.0.2 Introduction ............................................................ 40
3.0.3 Dataset ................................................................. 45
  3.0.3.1 Snow-to-Liquid Ratio ............................................. 45
  3.0.3.2 Snowfall Accumulation ........................................... 45
  3.0.3.3 merged Snowfall Rate (mSFR) product ....................... 46
  3.0.3.4 Multi-Radar Multi-Sensor (MRMS) .......................... 47
  3.0.3.5 Geostationary Lightning Mapper (GLM) .................... 48
3.0.4 Methodology ........................................................ 49
  3.0.4.1 The thundersnow detection algorithm ....................... 49
3.0.4.2 High Resolution snow-to-liquid ratio (SLR) Values . 50
3.0.4.3 Assignment of SLR, snowfall totals, and snowfall Rates at the location of GLM flashes . . . . . . . . . . . . 51
3.0.5 Results . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 53
  3.0.5.1 High Resolution SLR values . . . . . . . . . . . . . 53
  3.0.5.2 SLR and TSSN . . . . . . . . . . . . . . . . . . . . . . 54
  3.0.5.3 Snowfall Rates in TSSN . . . . . . . . . . . . . . . 56
  3.0.5.4 Snowfall Accumulation and TSSN . . . . . . . . . . 57
  3.0.5.5 13-17 April 2018 Blizzard Case Study . . . . . . . . 58
3.0.6 Discussion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 63
  3.0.6.1 Comparison to Previous Literature . . . . . . . . . 63
  3.0.6.2 TSSN Lightning Characteristics . . . . . . . . . . . 65
3.0.7 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 66
4 Conclusions 76
REFERENCES 79
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Depiction of TDA processes associated with determination of TSSN flashes observed by GLM and confidences with the red hues getting darker as the TDA process proceeds. The black arrows represent the progressive steps of the algorithm. The first step involves binning the GLM data in 10 minute increments to match the temporal resolution of the mSFR product. If the mSFR product has a time stamp of 1010 UTC the GLM data would be binned from 1000-1009 UTC. Second step involves the overlap of mSFR and GLM data. For example, the mSFR (blues and greens) and GLM (in white circle) data within for a Noreaster on 04 January 2018 at 1410 UTC over Long Island, New York displayed using the National Weather Services Advanced Weather Interactive Processing System. The third step involves identification of TSSN groups observed by GLM based on a 0.15-degree distance threshold (black circle). Lightning bolt represents a GLM group and the blue-filled boxes represent mSFR pixels. Pixel count equal to four results in a GLM group with low confidence of being TSSN. Step four is the GLM group classification based on number of mSFR pixels within distance threshold. If all GLM groups within that timeframe are process the TDA proceeds to step five and matches up the GLM groups by varies GLM flash characteristics and creates GLM quasi flashes. In the final step of the TDA, the GLM quasi flashes are matched up with the official GLM flashes. The light blue arrow represents a proposed alternative step to reduce computational calculations and create real-time operational product.</td>
</tr>
<tr>
<td>2.2</td>
<td>14 April 2018 1310 UTC NESDIS mSFR product overlaid with A) GLM group data and B) TSSN quasi flash data from 1300 - 1309 UTC. This represents before and after the TDA takes effect respectively.</td>
</tr>
<tr>
<td>2.3</td>
<td>Relationship between GLM flash energy and flash area. Blue represents all potential TSSN flashes observed by GLM and orange represents TSSN flashes observed by GLM with a mSFR count of 700 or greater.</td>
</tr>
</tbody>
</table>
2.4 Differentiation of GLM flashes with regards to flash: a) area, b) energy, and c) duration based on NLDN matchup characteristics. There is a total of 1,081 GLM flashes did not correspond with any NLDN data while the remaining 1,095 GLM flashes corresponded with NLDN data. The 1,095 GLM flashes subcategorized as IC-only (N=356), Tower (N=152) and Non-tower (N=587) initiated.

2.5 A) Depicts flashes observed by GLM that occurred during the times in Table 1. Blue dots represent potential TSSN flashes observed by GLM; while orange dots represent TSSN flashes observed by GLM with a mSFR count of 700 or greater. Finally, the black dots represent METAR reported TSSN that occurred in the same range of time. B) Flash density for potential TSSN flashes detected from the TDA from January-April 2018.

2.6 Demonstrates the GLM LCFA splitting a TSSN flash into three separate GLM flashes that occur sequentially near Peterborough, Ontario at 09:40:56 UTC on 23 January 2018. Dots and stars represent GLM events and flashes respectively. The solid lines represent the convex hull of the GLM flashes while the dashed line are the 50-km search radii in the NLDN/GLM matchup process. These three GLM flashes do not coincide spatially or temporally with any NLDN data.

3.1 SLR value distributions from A) Baxter et al. (2005) (Fig. 9) and B) derived SLR value estimates. The long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles. The orange line in B) represents the best-fit gamma function for the derived SLR value distribution.

3.2 A) Distribution of SLR values associated with TSSN. Orange line represents the best-fit gamma function and the long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles. B) Box and whisker plots of SLR values by TSSN category.

3.3 A, C) Distribution of Snowfall rates and estimated snowfall rates associated with TSSN. Orange line (A) represents the best-fit Gaussian function, (B) represents the best-fit gamma function and the long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles. C, D) Box and whisker plots of snowfall rates and estimated snowfall rates by TSSN category.
3.4 A) Distribution of snowfall accumulations associated with TSSN. Orange line represents the best-fit Gaussian function and the long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25th and 75th percentiles. B) Box and whisker plots of snowfall accumulation by TSSN category.

3.5 A) Total snowfall accumulation, B) Total mSFR liquid equivalent estimation, C) derived SLR estimate, and D) linearly interpolated COOP SLR values for the 13-17 April 2018 blizzard.

3.6 Box and whiskers for MRMS derived isotherm reflectivity, VII, and VIL values associated with TSSN flashes observed by GLM.

3.7 Box and whisker plots for the different TSSN categories (i.e., No NLDN, NLDN, IC-only, Tower, and Non-tower) for A) -10°C Isotherm reflectivity, B) -20°C Isotherm reflectivity, C) VII, and D) VIL.

3.8 Polar plots of frequency of snowfall rates greater than 1.75-in hr⁻¹ for A) all TSSN flashes observed by GLM and B) TSSN flashes observed by GLM for the 13-17 April 2018 blizzard.

3.9 HRRR-derived mean mid-level (850-600-hPa) frontogenesis at 1300 UTC on 14 April 2018 overlaid with TSSN flashes observed by GLM (black dots) that occurred between 1300 UTC and 1310 UTC. Wind barbs represent mid-level (850-600-hPa) bulk shear.
## LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1 Snowfall cases from January-April 2018.</td>
<td>31</td>
</tr>
<tr>
<td>2.2 GLM flash area (energy) statistics with regards to mSFR count. Units of flash area and energy are km$^2$ and fJ(1x10$^{15}$ J) respectively. Significance is relative to the GLM flashes within the highest mSFR confidence bin (i.e., GLM flashes with a mSFR pixel count $\geq$ 825).</td>
<td>32</td>
</tr>
<tr>
<td>2.3 TSSN Flash Characteristics Observed by GLM (i.e., GLM flashes with a mSFR pixel count $\geq$ 700)</td>
<td>33</td>
</tr>
<tr>
<td>2.4 NLDN Multiplicity (number of return strokes) and Polarity (kA) Characteristics.</td>
<td>33</td>
</tr>
<tr>
<td>3.1 Comparison of SLR values.</td>
<td>68</td>
</tr>
<tr>
<td>3.2 TSSN Flash Characteristics Observed by GLM.</td>
<td>68</td>
</tr>
<tr>
<td>3.3 TSSN Flash Characteristics Observed by GLM by TSSN Category.</td>
<td>69</td>
</tr>
</tbody>
</table>
CHAPTER 1

INTRODUCTION

The ability to characterize the environment for mid-latitude, wintertime, cyclones can be difficult because high-resolution diagnostics of processes associated with heavy-snowfall are limited value to forecasters beyond 12-hours (Uccellini et al. 1995; Moore and Graves 2005; Evans and Jurewicz 2009; Baxter and Schumacher 2017). Leveraging next-generation satellite sensors, such as the Geostationary Lightning Mapper (GLM), is paramount to improving short-term forecasting and reducing societal impacts for winter weather. The GLM provides unparalleled observations of lightning detection from geostationary orbit; providing near-uniform hemispheric coverage with a temporal and spatial resolution of 2-ms and 8-km respectively (Goodman et al. 2013). In contrast, National Environmental Satellite Data and Information Services (NESDIS) merged Snowfall Rate (mSFR; Meng et al. 2017a,b) product incorporates satellite passive microwave sensors and the Multi-Radar Multi-Sensor (MRMS; Zhang et al. 2016) to estimate snowfall rates prior to snowfall reaching the surface (Meng et al. 2017b; Ferraro et al. 2018). Schultz et al. (2018) were the first to demonstrate the ability of GLM to identify lightning in snowfall (i.e., thundersnow, TSSN) in a lake-effect snow event in New York and builds upon previous studies which have iden-
tified TSSN from ground-based lightning detection networks (e.g., Pettegrew 2008) or Meteorological Terminal Air Report (METAR) observations (e.g., Market et al. 2002). Based on the subjective identification of TSSN in previous studies, the reports of this phenomena may be drastically under-represented; for example, a TSSN tag would not be inserted into a METAR unless lightning/under was physically witnessed be a trained weather observer that also observes snowfall (Department of Commerce 2017).

Previous studies have subjectively characterized TSSN with regards to snowfall rates (Market and Becker 2009) and snowfall accumulations (Crowe et al. 2006). Market and Becker (2009) used radar reflectivity as a proxy for snowfall rates and determined that TSSN was more likely occurs downstream of the highest reflectivity values. Crowe et al. (2006) determined that TSSN does not occur in regions what will receive the highest total snowfall accumulations. However, no studies have examined the relationship between snow-to-liquid ratio (SLR) values and TSSN. As part of noninductive lightning initiation theory, TSSN indicates the simultaneous presence of supercooled liquid water, graupel, and ice crystals (Takahashi 1978; Saunders et al. 2006) and depending on the degree of riming occurring within heavy-snowfall all three precipitation particles exist; suggesting, a connection between TSSN and precipitation particle type and SLR values. These studies suggest that the existence of TSSN may be used as an objective predictor for SLR values, snowfall rates, and snowfall accumulation on a storm-scale time frame. Furthermore, no studies have provided in-depth examination of these variables with regards to intracloud (IC) and cloud-to-ground (CG) lightning. Additionally, tower structures have been acknowledged as an
initiation point for CG lightning and shorter towers in winter weather are more likely to be struck in the cold season because the charge centers in winter clouds are lower (Kingfield et al. 2017). Unlike the GLM, the National Lightning Detection Network (NLDN; Cummins and Murphy 2009) has the capacity to classify lightning flashes as IC or CG and can be used to classify whether a CG flash was associated with a tall human-made structure like an antenna or wind turbine.

Dye et al. (1986) illustrated that charge separation occurred between -10 and -20°C for noninductive charging. Numerous studies have built on this idea for increasing the predictability of lightning initiation by examining derived severe weather parameters including isotherm reflectivity and vertically integrated ice (VII; Carey and Rutledge 2000; Mosier et al. 2011; Seroka et al. 2012) and vertically integrated liquid (VIL; Greene and Clark 1972; Watson et al. 1995). Mosier et al. (2011) and Seroka et al. (2012) demonstrated that isotherm reflectivity and VII have some skill in predicting the occurrence of lightning in convective storms; whereas, Watson et al. (1995) showcased the potential relationship between VIL values and lightning. However, no studies have investigated VIL and VII with regards to lightning in snowfall. As for isotherm reflectivity, Adhikari and Liu (2019) found that most TSSN features have a maximum isotherm reflectivity value greater than 30-dBZ situated at isotherm levels colder than -10°C.

This study will use next-generation remote sensing instruments to answer the following questions for areas east of the Rocky Mountains: A) Can GLM and mSFR product efficiently differentiate TSSN and non-TSSN lightning? B) Are there favorable geographic regions for TSSN to develop? C) Are there common characteristics
of TSSN between different winter weather events? D) Can MRMS variables be useful for determining large TSSN outbreaks? Current hypotheses include: A) TSSN can be used as a proxy for SLR values, snowfall rates, and indicator for potential snowfall accumulation. B) TSSN can be utilized for evaluating hazardous surface conditions (i.e., low visibility, slick/icy surfaces). Specific objectives include:

1) Characterize and quantify the ability of the GLM instrument to objectively detect and observe TSSN through coincident observations from the mSFR product.

2) Statistically analyze GLM flash characteristics and place them in the context of lightning occurring in other regions of mid-latitude, wintertime, cyclones that do not produce snowfall.

3) Compare GLM to NLDN and METAR observations of TSSN to understand the ability of GLM compared to current sensors.

4) Investigate potential differences between different types of lightning classifications (IC vs. CG, and Tower CG vs. Non-tower CG).

5) Analyze a heavy-snowfall case study to investigate the predictability of TSSN by examining isotherm reflectivity, VII, and VIL and compare to previous literature.
CHAPTER 2

MANUSCRIPT: GEOSTATIONARY LIGHTNING MAPPER FLASH
CHARACTERISTICS OF ELECTRIFIED SNOWFALL EVENTS

2.0.1 Abstract

This study examines characteristics of lightning in snowfall events (i.e., thundersnow, TSSN) from the perspective of the Geostationary Lightning Mapper (GLM) and the National Environmental Satellite Data and Information Service (NESDIS) merged Snowfall Rate (mSFR) product. A thundersnow detection algorithm (TDA) was derived from the GLM and mSFR and compared directly to Meteorological Terminal Air Report (METAR) reports. The TDA had a probability of detection (POD) of 87.2% when compared to the METAR reports. However, using the TDA an additional 2,139 lightning flashes within snowfall were identified that were not observed by the METAR reports, indicating that TSSN has been under reported in the previous literature. These 2,176 GLM flashes had an average area (energy) of 779.13-km$^2$ (1.40933x10$^{-12}$-J) and an average flash duration of 820-ms. A comparison with data from the National Lightning Detection Network (NLDN) indicated that the NLDN had at least one cloud or ground flash detection in 1,095 of the 2,176 flashes observed by GLM in snowfall. An average of 6.59 NLDN flashes (7,218 total NLDN
flashes/1,095 GLM flashes with NLDN correspondence) were assigned to a single GLM flash when the NLDN flash data were constrained by the GLM flash duration and spatial footprint. Statistically significant (p<0.05) differences in flash area and flash energy were found between flashes that were observed by the NLDN and those that were not (p=0.003, p=0.021, respectively). Additionally, when GLM was combined with the NLDN, at least 13.9% of flashes involved a tall human-made object like an antenna or wind turbine.

2.0.2 Introduction

The Geostationary Lightning Mapper (GLM; Goodman et al. 2013; Rudlosky et al. 2019), onboard the Geostationary Operation Environmental Satellite - R (GOES-R; Schmit et al. 2005) Series satellites (now GOES-East and West), provides unprecedented observations for lightning detection with a near-uniform storm-scale coverage and a spatial and temporal resolution of 8-km and 2-ms respectively (Goodman et al. 2013). The GLM provides characteristics of lightning occurrence, flash size, and flash radiance that can be applied in the detection of severe storms, lightning ignited wildfires, and heavy snowfall rates in winter storms. Schultz et al. (2018) were the first to demonstrate the ability of GLM to identify lightning associated with snowfall (i.e., thundersnow, TSSN) for a lake-effect snow event in New York where lightning was detected in a winter environment in close proximity to tall man-made structures, thus providing evidence that GLM can detect lightning in winter environments on small scales and indicates promising results when utilized for TSSN and heavy-snowfall associated with mid-latitude cyclones.
TSSN is presently defined as concurrent surface observations of snowfall and lightning Schultz (1999). Previous literature studied TSSN with Meteorological Terminal Air Report (METAR) observations (e.g., Market et al. 2002), or ground-based lightning networks (Pettegrew 2008; Kumjian and Deierling 2015; Schultz et al. 2018). Market et al. (2002) developed a METAR-based climatology and found that the Intermountain West, Great Lakes, and Great Plains were areas where TSSN was most observed. The Market et al. (2002) climatology was limited due to subjective identification problems; for example, if lightning occurred nearby, according to a lightning detection network, and a trained weather observer observed snowfall at the station location, a TSSN tag would not be inserted into the METAR unless lightning/thunder was physically witnessed by the observer (Department of Commerce 2017). However, as Kumjian and Deierling (2015) discuss, this climatology may be under representing TSSN observations because they observed more TSSN events on the Colorado Front Range than the Market et al. (2002) study. Furthermore, Kumjian and Deierling (2015) state that one of these TSSN flashes along the Colorado Front Range was triggered by a tower.

Tall human-made structures have been known to be an initiation point for cloud-to-ground (CG) lightning. Kingfield et al. (2017) demonstrated a positive correlation with tower height and CG occurrence and found that towers taller than 400-m above ground level experience an increase of CG lightning density by a median of 150% compared to surrounding areas. Furthermore, they suggest that shorter towers were more likely to be struck in the cold season as a result of charge centers being lower in winter storms. Rather than examining stationary towers, Montanyá et al.
(2014) looked at lightning characteristics associated with wind turbines and found that the rotating blades of the wind turbines favored the occurrence of lightning. Safety wise, tower-initiated flashes were only present on 0.3% of days when lightning occurred in Huntsville, AL between 2003 and 2015 (Schultz et al. 2019, accepted, pending revision). But is more pronounced in winter because the tower can serve as a focusing mechanism that can directly interact with the main negative charge center Schultz et al. (2019).

The ability to characterize the environment for heavy-snowfall can be difficult to forecast owing to the mesoscale thermodynamic and microphysical processes within mid-latitude cyclones (Colle et al. 2014; Baxter and Schumacher 2017). High-resolution diagnostics of ingredients of heavy-snowfall beyond 12-hours are limited value to forecasters, as the details of these forecasts will likely contain timing and placement errors (Evans and Jurewicz 2009). Therefore, forecasting heavy-snowfall becomes a matter of nowcasting and increasing situational awareness rather than predictive in nature (Wiesmueller and Zubrick 1998). The ability to objectively identify lightning by GLM that occurs while snow is falling at the surface will lead to further understanding of thermodynamic and microphysical processes in mid-latitude cyclones because the GLM flash size are fundamentally controlled by these parameters (Saunders et al. 2006; Bruning and MacGorman 2013). Thus, the characterization of atmospheric profiles in which lightning develops provides the potential for development of innovative products tailored to increasing situational awareness of high impact events. The understanding of the ranges in flash sizes and total optical energies in
TSSN events have been very limited due to the lack of geostationary observations of lightning from GLM prior to 2017; therefore, the objectives of this work are to:

1) Characterize and quantify the ability of the GOES-East GLM instrument to detect and observe TSSN events compared to previous studies,

2) Statistically analyze the GLM flash characteristics of duration, area, and total optical energy, and place them in the context of lightning within other regions of mid-latitude cyclones not producing snowfall, and

3) Compare and contrast GLM to ground-based lightning network observations of TSSN to understand the capability of GLM compared to current sensors.

2.0.3 Datasets

2.0.3.1 Geostationary Lightning Mapper

GLM is an optically based instrument that has a hemispheric field-of-view between 52°N/S with a near-uniform spatial resolution of 8-km. GLM detects light in a narrow 1-nm band centered on the 777.4-nm wavelength (Christian and Goodman 1987; Goodman et al. 2013; Rudlosky et al. 2019). This particular wavelength allows GLM to observe lightning both during the day and at night. There are three basic components that GLM provides: events, groups, and flashes (Goodman et al. 2013). An event is when a single pixel in the GLM field-of-view becomes more illuminated than a background threshold. A GLM group is one or more events in a single frame that occur adjacent to each other. A GLM flash is presently defined as a set of groups within a weighted Euclidean distance bounded by 330-ms/16.5-km (Goodman
et al. 2013). Each GLM flash contains information on the area of the flash (km$^2$) and its total optical energy output (fJ). Additionally, GLM is designed to have a total lightning detection efficiency (i.e., probability of detection, POD) of at least 70% with 5% false alarms. For a full description of GLM specs and capabilities see Goodman et al. (2013). Level 2 GLM data utilized in this study was from the GOES-R Calibration/Validation (Cal/Val) Group.

### 2.0.3.2 National Lightning Detection Network

In contrast to GLM, the National Lightning Detection Network (NLDN; Cummins and Murphy 2009) does not detect lightning optically from space but rather is a system of ground-based sensors that can detect electromagnetic signals radiated by lightning. Unlike GLM, NLDN has the capacity to differentiate lightning flashes as CG or intracloud (IC) with detection efficiencies of 90-95% and 50-60% respectively (Cummins and Murphy 2009; Murphy and Nag 2015). Recent upgrades have improved the detection of IC flash information and provided IC flash multiplicity and connected IC flash information with CG flash locations (Murphy and Nag 2015). The point locations of the NLDN provides information about lightning characteristics during flash propagation that cannot be determined by examining GLM data alone (e.g., is the flash in the cloud or connecting to the ground). Currently, NLDN defines a flash as a grouping of CG strokes and/or cloud pulses that are bounded by 500-ms/10-km (Murphy and Nag 2015).
2.0.3.3 merged Snowfall Rate product

National Environmental Satellite Data and Information Service (NESDIS) merged Snowfall Rate (mSFR; Meng et al. 2017a; ?) product is a blended product utilizing passive microwave sensors and the Multi-Radar Multi-Sensor (MRMS; Zhang et al. 2016) to estimate snowfall rates. The passive microwave sensors used to develop the mSFR product are the: Advanced Microwave Sounding Unit (AMSU), Microwave Humidity Sounder (MHS), Advanced Technology Microwave Sounder (ATMS), Special Sensor Microwave Imager/Sounder (SSMIS), and Global Precipitation Measurement (GPM; Hou et al. 2014) Microwave Imager (GMI). The utilization of passive microwave sensors have been shown to estimate snowfall rates prior to snowfall reaching the surface (Meng et al. 2017b; Ferraro et al. 2018) and the MRMS portion fills in the gap between satellite overpasses with a spatio-temporal resolution of 1x1-km and 10-minutes and provides continuous coverage for the CONUS. The mSFR was utilized in conjunction with GLM to identify TSSN. In this study, TSSN was defined as lightning, observed from GLM, which simultaneously occurred in an area where the mSFR product depicted snowfall; the objective identification process will be described in more detail in section 3.

2.0.3.4 Tall Human-made Structures

Data from the Homeland Infrastructure Foundation-Level Data (HIFLD; Homeland Infrastructure Foundation-Level Data cited 2019) and the U.S. Wind Turbine Database (USWTDB; Hoen et al. 2018) were collected. Specifically, the cellular tow-
ers and antenna structure registration datasets in the HIFLD were collected. The cellular towers dataset consists of cellular tower locations that are recorded by the Federal Communications Commission (N=23,498) and the antenna structure registration contains antenna structure that are more than 60.96-m (200-feet) tall or antenna near airports (N=124,811). Furthermore, the USWTDB dataset contains the locations of 58,449 wind turbines within 43 states. Combined, these datasets provide locations where tall human-made object initiated TSSN may occur.

2.0.4 Methodology

2.0.4.1 Thundersnow Detection Algorithm Objective Identification

The domain of interest was from 23°N to 50°N latitude and from 110°W to 65°W longitude. Snowfall cases were collected based on snowfall accumulation potential rather than snowfall cases that were associated with TSSN. Potential cases were determined by examining National Weather Service (NWS) forecast discussions and numerical weather prediction output. Forecast discussions were automatically scanned for keywords (i.e., snowfall, frontogenesis, etc.) to identify geographic locations that would experience heavy-snowfall in the near-future. Cases were not collected prior to January 2018 given that GLM was still in the checkout phase and had not reached a provisional status (National Oceanic and Atmospheric Administration 2018).

Using the mSFR product, Level 2 GLM data, and nearest neighbor statistics (Bentley 1975), a thundersnow detection algorithm (TDA) was developed. Figure 2.1
demonstrates a flow chart of TSSN flash identification process within the TDA. The TDA utilized GLM groups rather than GLM events as it was computationally inexpensive compared to using events. Additionally, GLM groups provide more spatial information than a single GLM flash centroid coordinate and resulted in an increased likelihood of classifying TSSN. The first step of the TDA involved binning the GLM groups every 10-minutes to match the temporal resolution of the mSFR product. For example, if the mSFR product timestamp was 1030 UTC, the GLM groups were binned from 1020-1029 UTC. GLM data was binned 10-minutes prior to the mSFR timestamp to more closely resemble the environment in which lightning initiation took place. By using nearest neighbor statistics, step two involved the objective identification of the overlap between mSFR and GLM data. Nearest neighbor statistics were used to mitigate parallax issues within the GLM data and potential scattering effects in the mSFR product. The MRMS input of the mSFR product exploits higher resolutions compared to the passive microwave portion; thus, the examination between GLM and the mSFR product was based on the MRMS portion. In step three, a maximum distance threshold of 0.15-degrees was used to find mSFR pixels near a single GLM group. A distance of 0.15-degrees is approximately 16.6-km (roughly the same distance used to create an official GLM flash; Goodman et al. 2013). A confidence level for lightning flashes observed by GLM that occurred in snowfall was assigned based on the number of mSFR pixels that were identified as snow in the 16.6-km search area because the 1-km grid spacing of the mSFR product does not match the 16.6-km grid spacing of the TDA. The higher the mSFR pixel count within the maximum distance threshold, the higher the confidence the GLM group could be
classified as a GLM group associated with snowfall. A visualization on how the nearest neighbor statistics works can be found in Fig. 2.1 and showcases a single GLM group associated with snowfall with low confidence (mSFR pixel count of 4). Furthermore, if a GLM group had no mSFR pixels within the maximum distance threshold it would be classified as a GLM group not associated with snowfall. The classification process continued until all GLM groups were classified as TSSN or non-TSSN. Using GLM Flash IDs, the fourth major step of the TDA aggregated the identified TSSN groups to reduce the amount of data and to simplify further analysis. The aggregation process created a GLM quasi flash and the confidence level of these flashes became the average mSFR pixel count. The term quasi is used because the number of groups within one of these derived flashes may not be the same compared to the number of groups within corresponding GLM flashes. The main reason for the creation of these GLM quasi flashes was to take into account GLM groups that were on the edge of snow bands in regard to the mSFR product. The TDA then removed duplicate quasi flashes as some snowfall cases overlap with others. The creation of GLM quasi flashes provided a unique way to characterize TSSN. To facilitate analysis, the last step of the TDA matched the GLM quasi flashes up with their corresponding official GLM flash data based on several attributes (i.e., Flash ID, Date, Time, etc.). This matchup process was necessary as it allowed for analysis regarding official GLM flash variables (e.g., flash area) while still maintaining the characteristics of the lightning when associated with snowfall (i.e., average mSFR pixel count).

All GLM flashes that were identified by the TDA were classified as potential TSSN and were binned every 25 mSFR pixel count (i.e., 0, 25, 50, etc.); meaning
that the 25 mSFR confidence bin contained all potential TSSN flashes identified by
GLM that have a mSFR pixel count of 25 or greater. This allowed for statistical
analysis between the different confidence bins. Even though the mSFR pixel count
can exceed 860 (i.e., area of distance threshold ($\pi*16.6^2$)), the highest mSFR confi-
dence bin was set as 825 because of the need to have enough GLM flashes within the
bin for any statistical comparison. Based on the distribution characteristics of GLM
variables (i.e., flash energy and flash area) the different mSFR confidence bins were
compared to each other to determine which GLM flashes in various mSFR confidence
bins were statistically similar (i.e., p-value) to GLM flashes within the highest mSFR
confidence bin (i.e., GLM flashes with a mSFR pixel count $\geq$ 825). GLM flashes
within the confidence bin with the highest mSFR pixel count that do not exhibit
statistically significant differences (i.e., $p>0.01$) compared to the highest mSFR con-
fidence bin were objectively classified as TSSN. The 0.01 significance level was used
compared to the 0.05 to increase the number of objective classification of TSSN. As
a proof of concept of the TDA process, Fig. 2.2a illustrates a 10-minute bin of GLM
group (black dots) data overlapping with mSFR product data in southern Minnesota
and northern Iowa. The GLM groups in central Iowa were not overlapping any mSFR
data and therefore were classified as non-TSSN groups. In contrast, Fig. 2.2b depicts
GLM quasi flashes for the same timeframe and illustrates the effectiveness of the TDA
framework for disregarding GLM groups that were not overlapped with the mSFR
product. This demonstrates that the TDA can objectively identify the overlapping
of the mSFR product and GLM dataset and thus creates a reliable and robust way
of identifying TSSN.
2.0.4.2 NLDN/GLM Matchup and Classification

TSSN flashes observed by GLM were matched up with NLDN flashes to further quantify TSSN. Given that the GLM and NLDN flash locations are point locations, the datasets were matched up based on the timing and spatial footprint characteristics of a GLM flash. To be initially assigned to a GLM flash, a NLDN flash must occur within $\pm 1$-, $5$-, and $8$-second time buffers between the start and end time of a GLM flash. Various time buffers were utilized to examine the temporal correspondence between NLDN and GLM. Furthermore, the world’s longest duration lightning flash, measured by Lightning Mapper Array (LMA) data, lasted 7.74-seconds over southern France in 2012 (Lang et al. 2017); therefore, is within the largest time (i.e., 8-second) buffer of the matchup process. Two distance thresholds (i.e., 50-km and the square root of GLM flash area) were used in the spatial matchup process to account for diverse GLM flash area/spatial footprints. For a NLDN flash to spatially match a GLM flash, the great-circle distance between a GLM flash centroid coordinate and NLDN flash location must be less than the larger of the two distance thresholds (50-km or square root of GLM flash area). The use of the 50-km distance threshold accounted for small elliptical GLM flashes that were not well represented by the square root of the GLM flash area. The use of the spatial footprint, rather than the centroid coordinate, of a GLM flash allowed for a greater extent of the possibility to match GLM and NLDN. Additionally, the spatial footprint was also used given multiple NLDN flashes can coincide in space and time with a single GLM flash because the NLDN data do not contain information on the spatial extent of lightning (Schultz
et al. 2018).

Finally, the NLDN CG flash coordinates that matchup with the TSSN flashes observed by GLM were used to determine whether the GLM flash could be associated with a tall human-made object. Given the NLDN flash data has a median spatial error of 500-m (Cummins and Murphy 2009), a 500-m buffer was created around the tall human-made structures in the HIFLD and USWTDB datasets and determined which NLDN CG flashes occur in that buffer region and those that do not. The NLDN CG flashes that did occur in that buffer were classified as tower flashes and the remaining NLDN CG flashes within the CONUS were classified as non-tower flashes. The NLDN CG flashes that occurred in Canada were classified as tower and non-tower based on Google Earth imagery because the lack of tower related dataset. The TSSN flashes observed by GLM were then classified as: IC-only, tower, non-tower and no NLDN. IC-only TSSN flashes detected by GLM were those that only contain NLDN IC flashes. The tower and non-tower TSSN flashes observed by GLM were associated with at least one NLDN CG flash and the specific CG type classification was based on the timing of the first CG occurrence. For example, if a GLM flash had two NLDN CGs associated with it (one tower and one non-tower) and the first CG that occurred was classified as non-tower (i.e., occurring outside any 500-m buffer) the GLM flash would be classified as a non-tower TSSN flash. In contrast, GLM flashes that did not matchup with any NLDN data were classified as no NLDN as there was no way to classify the flashes as IC or CG with certainty.
2.0.5 Results

2.0.5.1 Objective Identification

A total of 21 heavy-snowfall cases that occurred from January-April 2018 were identified, with 18 of them producing at least one lightning flash during snowfall, cases numbered 1 to 21 are listed in Table 2.1. Eighteen of the 21 snowfall cases produced a total of 53,408 potential TSSN flashes observed by GLM (i.e., GLM flashes with a mSFR pixel count \(>0\)). The snowfall cases ranged from convective snowfall in Oklahoma and Texas, to heavy-snowfall in the Great Plains and Midwest regions to Noreasters along the East Coast. Of the 21 collected cases, 8-10 and 21 made up 89.4% of the TDA identified potential TSSN flashes with approximately 73.6% of them being from cases 8-10 (Table 2.1). It should be noted that cases 8-10, which occurred in Texas, Oklahoma, and Kansas were convective snowfall cases that produced little to no snowfall accumulation. The GLM flashes that occurred during these cases were not associated with a mid-latitude cyclone, but were rather associated with an influx of moisture from the Gulf of Mexico resulting from a strong cold front propagating from northwest to southeast. The case that produced the most potential TSSN flashes detected by GLM (N=8,449), with snowfall accumulation, was the 13-17 April 2018 blizzard (case 21; Table 2.1).

2.0.5.2 GLM Characteristics

Mann-Whitney-Wilcoxon two-sided test was used to compare GLM flash area and flash energy of the lower mSFR confidence bins (i.e., 0, 25, 50, etc.) to the highest
mSFR confidence bin of 825 to determine the appropriate bin for TSSN detection. In other words, how many mSFR pixels need to be associated with a GLM flash to confidently classify it as TSSN? Compared to the GLM flashes within the highest mSFR confidence bin, the GLM flashes within the 700 mSFR confidence bin were not statistically different at the 0.01 significance level with a p-value of 0.018 for both GLM flash area and flash energy which represents a z-score of 2.91 (Table 2.2); therefore, the GLM flashes within the 700 mSFR confidence bin could be objectively classified as TSSN at the 0.01 significance level. GLM flashes within the 700 mSFR confidence bin have over 80% of the mSFR pixels classified as snow and exhibit similar flash area and energy characteristics compared to GLM flashes within the 825 mSFR confidence bin which were characterized as containing all mSFR pixels classified as snow. Furthermore, when examining flash area and energy, GLM flashes within the 675 mSFR confidence bin and lower were statistically different (p<0.01) compared to the GLM flashes within the 825 mSFR confidence bin (Table 2.2) and have less than 80% of the mSFR pixels classified as snow; therefore, these GLM flashes could not be objectively classified as TSSN at the 0.01 significance level. This resulted in 2,176 of the 53,408 TDA identified GLM flashes as being objectively classified as TSSN. Table 2.2 contains GLM flash energy and flash area statistics for various mSFR confidence bins and demonstrates that as the mSFR count increases both flash energy and area increase. TSSN flashes observed by GLM (i.e., GLM flashes with a mSFR pixel count ≥ 700) had a mean flash area and flash energy of 779.130-km² and 1,409.326-fJ respectively (Table 2.3) and the mean duration of TSSN flashes identified by GLM was 820-ms with a maximum duration of 5,436-ms. Table 3 contains flash
area, energy, and duration statistics and demonstrates that TSSN flashes observed by GLM have some degree of variability. For example, a TSSN flash observed by GLM that occurred at 02:23:45 UTC on 14 April 2018 had the largest flash area (5,010.470-km²). Similarly, the largest TSSN flash detected by GLM also had the highest GLM flash energy value (28,889.663-fJ) and a shorter than average flash duration of 688-ms. The longest duration flash occurred at 18:23:28 UTC on 13 April 2018 and had a flash area and flash energy of 1,779.194-km² and 8,232.608-fJ respectively. Additionally, it was found that GLM flash energy was more correlated with flash area (e.g., Pearson correlation of 0.78) than flash duration (e.g., Pearson correlation of 0.45). Figure 2.3 illustrates that GLM flash size and flash energy of cases associated with snowfall (orange dots; TSSN flashes) are on the upper end of the flash energy per flash area spectrum, and exhibit less variability in size and energy than compared to potential TSSN events (blue dots; potential TSSN flashes) and more variability. The lack of variability for TSSN flashes compared to potential TSSN flashes observed by GLM suggest microphysical and thermodynamic differences exists between the two classifications; however, an in-depth analysis is beyond the scope of this study.

### 2.0.5.3 NLDN and GLM Intercomparison

For further characterization, the 2,176 TSSN flashes observed by GLM were matched with ground-based NLDN data. When using the 1- and 5-second time buffer and spatial matchup parameters, it was found that only 8.6% and 34.4% of TSSN flashes identified by GLM corresponded with at least one NLDN flash respectively. In contrast using the 8-second time buffer and spatial matchup parameters, it was found
that 1,095 TSSN flashes identified by GLM corresponded with at least one NLDN flash (i.e., 50.3%). Henceforth, given the lack of NLDN correspondence using the 1- and 5-second time buffer, all analysis regarding GLM and NLDN will be based on the 8-second time buffer matchup parameter. The median, mean, and maximum number of NLDN flashes to a GLM flash were 5.0, 6.6, and 44 respectively. Furthermore when adjusting for the GLM flash duration, the mean time difference between the onset of NLDN flashes and the start time of a GLM flash was 1.84-seconds. Overall, there were 7,218 NLDN flashes that corresponded, spatially and temporally, to 1,095 TSSN flashes identified by GLM. Of the 1,095 TSSN flashes observed by GLM, 739 of them were associated with at least one NLDN CG flash. Furthermore, a comparison of flash area, energy, and duration for GLM flashes that correspond to NLDN flashes (N=1,095) and those that did not correspond to a NLDN flash was performed (N=1,081; Fig. 2.4). The two samples resulted in statically significant differences for GLM flash area, energy, and duration with p-values of 0.003, 0.021, and 0.006 respectively; suggesting that GLM was more likely to identify flashes in snowfall that were on average spatially smaller with shorter flash durations (Fig. 2.4a,c). Additionally, GLM flashes that were associated with CGs (i.e., tower and non-tower; N=739) were on average spatially larger (911,657- vs. 610.331-km²; Fig. 2.4a), contain more total optical energy (1,805.096- vs. 857.072-fJ; Fig. 2.4b), and have a longer duration (918.424- vs. 764.045-ms; Fig. 2.4c) than IC-only TSSN flashes identified by GLM (N=356). Figure 2.4 showcases the flash area, energy, and duration distributions for TSSN flashes identified by GLM that were categorized as tower, non-tower, and IC-only flashes as well as the overall distributions of flashes associated with NLDN data.
and those that were not. Next, the polarity and multiplicity of the 1,391 NLDN CG flashes that matched up with GLM flashes were examined. Of the 1,391 CG NLDN flashes, 78.1% have a negative polarity with a mean value of -16.46-kA (Table 2.4). This result was comparable to the 80% in Market and Becker (2009) but was lower than the 96% in Rauber et al. (2014) and the 91% annual climatology in Orville and Huffines (2001). The cloud flash fraction of NLDN flashes that matched up with GLM (i.e., the ratio of the number of NLDN ICs (N=5,827) to the total number of NLDN flashes (N=7,218)) was found to be 0.81 and was comparable to the 0.79 for summer-time lightning in the Great Plains (Medici et al. 2017).

Using the USWTDB, HIFLD, and NLDN CG flash datasets, it was found that 152 tower and 587 non-tower TSSN flashes were detected by GLM. This resulted in 13.8% of the TSSN flashes observed by GLM that matchup with NLDN as being associated with tall human-made structures. Comparing tower (N=152) and non-tower (N=587) TSSN flashes observed by GLM revealed that the flash area and flash energy were not statistically different with p-values of 0.981 and 0.903 respectively (Fig. 2.4a,b). A random sample of the NLDN non-tower CGs (N=1,228) was used to compare those CGs with NLDN tower CGs (N=163). Using a random sample size of 163 resulted in NLDN non-tower CGs having fewer return strokes on average compared to NLDN tower CGs and were statistically significantly different (p=3.66x10^{-9}); however, from a polarity perspective NLDN non-tower and tower CGs were not statistically different (p=0.594). Table 2.4 contains the overall NLDN tower and non-tower CG multiplicity and polarity characteristics. NLDN may be geographically limited compared to GLMs field-of-view but can characterize lightning

22
in greater detail; however, given that this study comprises of a single winter season, further study is needed to investigate the comparisons of TSSN and non-TSSN flashes on a large scale.

**2.0.5.4 Spatial Distribution of TSSN from GLM**

The 21 cases from January-April 2018 can be compared directly with METAR reports to understand the distribution of TSSN flashes over the CONUS (Fig. 2.5a). Figure 2.5a also demonstrates the spatial distribution differences between TSSN flashes (mSFR pixel count $\geq 700$; orange dots) and potential TSSN flashes (mSFR pixel count $>0$; blue dots) identified by GLM. The TSSN flashes observed by GLM suggests that TSSN was common throughout the Great Plains region in this study. During the date/times of interest, there were only 39 METAR reports containing TSSN (Fig. 2.5a; black dots) compared to 2,176 TSSN flashes observed by GLM; suggesting that TSSN was more common than indicated by previous literature and confirming limited identification in surface reports. Furthermore, gridding all potential TSSN flashes observed by GLM and plotting flash density resulted in a large area stretching from Texas to Minnesota that could potentially be receiving elevated levels of TSSN flashes (Fig. 2.5b). The spatial distribution of the TSSN flashes (orange dots) match well with the gridded potential TSSN flashes observed by GLM and again reaffirms the idea that TSSN was more likely to occur in the Great Plains region and is aligned with findings from previous literature (Market et al. 2002). It should also be noted that the TDA identified 47 potential TSSN flashes in southwest New York along the Lake Erie shoreline and were associated with cases 12 and 20 and occurred
in March and April 2018 respectively. Of those 47 potential TSSN flashes observed by GLM along Lake Erie, only 17 of them were classified as TSSN flashes and were all associated with a Noreaster (i.e., case 12). Given the timeframe of this study (January-April), the TSSN flashes along the Great Lakes was more likely associated with lake-enhanced and not lake-effect snow (Harrington et al. 1987). This suggests further study is needed to demonstrate the ability of the TDA to identify TSSN in the early winter as lake-effect snow is more prominent (Steiger et al. 2009).

Contrasting the output of the TDA to METAR TSSN reports resulted in an extremely large false alarm rate (FAR); however, this was expected as the spatial and temporal coverage of GLM and mSFR are superior compared to METAR reports. Even though FAR was impractical in this study, the POD can still be calculated and was defined as:

\[
\text{POD} = \frac{N_{GLM}}{N_{METAR}}
\]

where \(N_{GLM}\) was the number of METAR TSSN reports that coincide with TSSN flashes observed by GLM and \(N_{METAR}\) was the total number of METAR TSSN reports. When comparing the METAR reports of TSSN to all GLM flashes that the TDA identified as being potential TSSN (\(N=53,408\)), the POD for this scenario was 87.2% and the TDA missed the four METAR TSSN reports in western Texas and northern Louisiana and the lone METAR TSSN report in Indiana. In contrast when examining all GLM flashes, not just those that were identified by the TDA, GLM detected lightning for 39 of those 39 METAR reports; thus the POD of TSSN, from a GLM perspective, was 100%. This suggests that the decrease of POD of
TSSN from the TDA was a result of the mSFR product portion of the algorithm and represents one of the largest potential errors of the TDA. When examining the cases, the mSFR product sometimes dropped snowfall rates in some timeframes and came back in the next timeframe and was likely a result of how MRMS assigned the precipitation flag (Zhang et al. 2016; Meng et al. 2017b). This phenomena is likely associated with a rain/snow transition region (i.e., mix precipitation) and the mSFR product drops some snowfall rates because the MRMS rain/snow transition is abrupt and MRMS is having trouble classifying the correct precipitation phase as it currently does not have a mixed precipitation flag (Steven Martinaitis, CIMMS/NSSL, personal communication). Regardless, with the advanced capabilities of GLM, identification of TSSN is robust and allows for expanded identification of the occurrence and spatial extent of TSSN compared to previous datasets.

2.0.6 Discussion

2.0.6.1 Comparison to Literature

The percentage of TSSN flashes involving towers in this study differs from Schultz et al. (2018) in which they found 11 of the 34 TSSN flashes were initiated from tall human-made objects. Even though this study contains more TSSN flashes, the discrepancy between these results were likely based on the locations in which the TSSN occur. The areas of interest in Schultz et al. (2018) were more heavily populated, compared to this study, resulting in a higher density of tall-human made structures and was a likely reason why tower TSSN was more preferential. Ad-
ditionally, the mean and maximum GLM flash area were spatially larger than the LMA-derived flash area in Schultz et al. (2018) (779- vs. 375-km$^2$ and 5,010- vs. 2,300-km$^2$ respectively). The large flash areas in this study were likely a result of: 1) how flash areas are determined based on very-high frequency (VHF) observations (i.e., LMA) compared to flash areas based on optical observations (i.e., GLM) and/or 2) LMAs limited range and lightning detection dropping off with distances exceeding 100-km from the network center (Fuchs et al. 2016; Koshak et al. 2004).

Furthermore, the comparison of TSSN flash characteristics observed by GLM to the overall GLM flash characteristics is paramount to understanding the microphysical differences in lightning initiation between different environments. Rudlosky et al. (2019) demonstrated that, on average, GLM flashes over the ocean contained more total optical energy (420- vs. 230-fJ), were spatially larger (570- vs. 431-km$^2$), and have a longer duration (345- vs. 293-ms) compared to GLM flashes over land. TSSN flashes detected by GLM on average contain more total optical energy (1,409-fJ), are spatially larger (779-km$^2$), and last longer (820-ms; Table 2.3). These three metrics fell between the 90$^{th}$ and 99$^{th}$ percentile of flash areas and total flash energies observed by GLM in Rudlosky et al. (2019) and were the reason behind the strong Pearson correlation of 0.78 between flash area and total flash energy. Thus, the flash properties in the present study can be placed into the context of the Bruning and MacGorman (2013) flash size spectra, and using knowledge from other studies that have examined the kinematic structure in mid-latitude cyclones (Rust and Trapp 2002; Rauber et al. 2014). It is speculated that the reason for the larger flash sizes and total optical energies observed in this study are due to the presence of broad, lam-
inar mesoscale updrafts given smaller flash sizes are typically associated with strong updrafts ($\geq 10$-m s$^{-1}$) in severe convection (e.g., Bruning and MacGorman 2013; Calhoun et al. 2013; Schultz et al. 2015, 2017).

2.0.6.2 Lack of Correspondence between GLM and the NLDN

Through the NLDN/GLM matchup process, 49.7% of GLM flashes did not correspond to any NLDN data. One possible explanation for the lack of NLDN/GLM correspondence was the GLM Lightning Cluster Filter Algorithm (LCFA) splitting spatially large and/or long duration TSSN flashes. If the GLM LCFA was splitting TSSN flashes, the end time of some GLM flashes would be the start time of other GLM flashes. If this phenomena happened and the GLM flash centroid coordinates were relatively close to each other provides evidence that the GLM LCFA was potentially splitting TSSN flashes. Using this methodology, it was found that 243 GLM flashes had start/end times the same as other flashes and 117 of those flashes were not associated with NLDN data; furthermore using concurrent GLM start/end times, it was found that these 243 GLM flashes could be condensed down to 111 flashes and 50 of these flashes were not associated with NLDN data. Figure 2.6 demonstrates the GLM events (dots) associated with three GLM flashes (stars) to showcase the spatial proximity between them. The dashed circles represent the 50-km search area in the NLDN/GLM matchup process for the individual GLM flashes; which resulted in no NLDN data in spatial or temporal proximity of the three GLM flashes. The solid lines represent the convex hull of the GLM flashes. These three GLM flashes sequentially occurred near Peterborough, Ontario at 09:40:56 UTC on 23 January 2018.
The maximum great-circle distance between the first GLM flash centroid coordinate and the other two GLM flashes was 15.82-km. This suggests that the GLM LCFA split a single TSSN flash into three GLM flashes. The TSSN flash splitting from the GLM LCFA reduces the amount of GLM flashes with no NLDN data; however, does not account for all GLM flashes with no NLDN data.

Given the fact that there were more NLDN IC flashes (N=5,827) compared to NLDN CG flashes (N=1,391), another possibility for the lack of GLM and NLDN correspondence was that NLDN was not detecting the TSSN because of the lower detection efficiency of IC flashes compared to CG flashes (Cummins and Murphy 2009; Murphy and Nag 2015). GLM flashes with no NLDN data (N=1,081) and GLM flashes that contain only ICs (N=356) were statistically different when examining GLM flash area (p<0.01) and energy (p<0.05) with p-values of 0.009 and 0.020 respectively. Furthermore, the flash duration distributions of GLM with no NLDN and those that contain only ICs were statistically similar (p=0.997). The p-values when comparing the GLM flashes with no NLDN and those that contain at least one CG (N=739) were 2.782x10^{-8} and 6.734x10^{-6} for flash area and flash energy respectively. Through these comparisons it is reasonable to assume that the GLM flashes with no NLDN data are statistically more likely to be IC-only flashes than flashes with at least one CG. Thus, suggesting that NLDN was not detecting TSSN ICs that GLM could detect. This again provides evidence that GLM and ground-based lightning data need to be used in tandem to characterize TSSN.
2.0.6.3 Future Improvements to the TDA

In this study, the MRMS portion of the mSFR product was exclusively used to detect TSSN. The opportunity to extend the TDA to incorporate passive microwave observations to discriminate TSSN from non-TSSN (e.g., Adhikari and Liu 2019) provides value to areas outside the CONUS. The main challenge will be that these products detect snowfall falling aloft and near the surface and the current passive microwave part of the mSFR product can only detect snow in regions that are warmer than \(-14^\circ C/7^\circ F\) (Meng et al. 2017a). Even with this limitation, this portion of the mSFR product provides valuable insight in data sparse regions and can be matched up with other lightning sensors to classify lightning as potential TSSN to understand the microphysical processes associated with the development of TSSN from a space-based remote sensing perspective. The implementation of a TDA-like algorithm towards these sensors and other lightning datasets would provide the first objective TSSN detection using passive microwave sensors and would provide global coverage; however, greater spatial and temporal sampling is needed for such an implementation.

2.0.7 Conclusion

Previous studies have subjectively identified TSSN; however, the TDA allowed for the objective identification of this phenomena by utilizing GLM, the mSFR product (i.e., MRMS data), and nearest neighbor statistics. Snowfall cases were collected from January-April 2018 and a TDA was developed to quantify the ability of GLM to identify TSSN events and resulted in the identification of 53,408 potential TSSN
flashes. The degree of confidence of a GLM flash being classified as TSSN was determined by the average mSFR pixel count and GLM flashes with a mSFR pixel count greater than or equal to 700 were objectively classified as TSSN (N=2,176). Utilizing METAR reports of TSSN as truth, the TDA identified TSSN with a POD of 87.2%. The TDA process also reiterates that TSSN was more likely to occur in the Great Plains, Intermountain West, and Great Lakes regions and was comparable to previous literature (i.e., Market et al. 2002; Schultz 1999). Compared to GLM flash characteristics in Rudlosky et al. (2019), TSSN flashes observed by GLM were found to be spatially larger, contain more total energy, and have a longer duration than non-TSSN flashes over land and ocean.

Of the 2,176 TSSN flashes observed by GLM, 1,095 of them correspond spatially and temporally to NLDN and were classified as IC-only (N=356), tower (N=152), and non-tower (N=587). This corresponds to 13.9% of TSSN flashes observed by GLM being associated with tall human-built objects like antenna or wind turbines. Furthermore, when comparing GLM flashes that matched up with NLDN to those that do not resulted in statistically significant differences for GLM flash area (p=0.003) and flash energy (p=0.021); suggesting that GLM was more likely to identify spatially smaller lightning flashes within snowfall. Nearly 50% of GLM flashes did not matchup with any NLDN flashes and was likely caused by: 1) TSSN flash splitting by the GLM LCFA and/or 2) the lower detection efficiency of ICs from NLDN. Several instances of GLM TSSN flash splitting were found (see Fig. 2.6 for an example) but does not completely account for the lack of NLDN/GLM correspondence. It was found that TSSN flashes detected by GLM without NLDN correspondence were sta-
### Table 2.1: Snowfall cases from January-April 2018.

<table>
<thead>
<tr>
<th>Case</th>
<th>Start date/time (UTC)</th>
<th>End date/time (UTC)</th>
<th>Classification</th>
<th>Number of potential TSSN flashes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2018-01-03 0000</td>
<td>2018-01-05 1500</td>
<td>Nor’easter</td>
<td>41</td>
</tr>
<tr>
<td>2</td>
<td>2018-01-10 0000</td>
<td>2018-01-13 1700</td>
<td>Frontal</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>2018-01-21 0000</td>
<td>2018-01-23 2350</td>
<td>Cyclone</td>
<td>224</td>
</tr>
<tr>
<td>4</td>
<td>2018-02-06 0000</td>
<td>2018-02-08 0950</td>
<td>Cyclone/Nor’easter</td>
<td>1638</td>
</tr>
<tr>
<td>5</td>
<td>2018-02-08 0000</td>
<td>2018-02-10 2350</td>
<td>Frontal</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>2018-02-17 0000</td>
<td>2018-02-18 1450</td>
<td>Nor’easter</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>2018-02-18 0000</td>
<td>2018-02-19 0550</td>
<td>Cyclone</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>2018-02-19 0000</td>
<td>2018-02-21 1400</td>
<td>Frontal</td>
<td>19438</td>
</tr>
<tr>
<td>9</td>
<td>2018-02-21 0000</td>
<td>2018-02-21 2350</td>
<td>Frontal</td>
<td>5870</td>
</tr>
<tr>
<td>10</td>
<td>2018-02-22 0000</td>
<td>2018-02-22 2030</td>
<td>Frontal</td>
<td>14015</td>
</tr>
<tr>
<td>11</td>
<td>2018-02-24 1000</td>
<td>2018-02-25 2350</td>
<td>Cyclone</td>
<td>21</td>
</tr>
<tr>
<td>12</td>
<td>2018-03-01 0000</td>
<td>2018-03-03 1440</td>
<td>Nor’easter</td>
<td>30</td>
</tr>
<tr>
<td>13</td>
<td>2018-03-04 1900</td>
<td>2018-03-09 0950</td>
<td>Cyclone/Nor’easter</td>
<td>1395</td>
</tr>
<tr>
<td>14</td>
<td>2018-03-12 0000</td>
<td>2018-03-15 1550</td>
<td>Nor’easter</td>
<td>25</td>
</tr>
<tr>
<td>15</td>
<td>2018-03-16 0600</td>
<td>2018-03-17 2210</td>
<td>Cyclone</td>
<td>1037</td>
</tr>
<tr>
<td>16</td>
<td>2018-03-20 0000</td>
<td>2018-03-23 0550</td>
<td>Nor’easter</td>
<td>40</td>
</tr>
<tr>
<td>17</td>
<td>2018-03-23 0600</td>
<td>2018-03-25 1150</td>
<td>Frontal/Cyclone</td>
<td>403</td>
</tr>
<tr>
<td>18</td>
<td>2018-03-30 0000</td>
<td>2018-03-31 2350</td>
<td>Cyclone</td>
<td>7</td>
</tr>
<tr>
<td>19</td>
<td>2018-03-31 1800</td>
<td>2018-04-02 1800</td>
<td>Frontal</td>
<td>515</td>
</tr>
<tr>
<td>20</td>
<td>2018-04-02 0600</td>
<td>2018-04-04 2359</td>
<td>Cyclone</td>
<td>229</td>
</tr>
<tr>
<td>21</td>
<td>2018-04-13 0000</td>
<td>2018-04-17 1620</td>
<td>Cyclone</td>
<td>8449</td>
</tr>
</tbody>
</table>

Statistically more likely to be classified as IC-only (p<0.05) compared to GLM flashes associated with at least one CG (p<0.01); suggesting, NLDN was not detecting ICs that GLM can detect. Overall, this study expands upon previous research by objectively identifying TSSN by utilizing next-generation satellite sensors and derived products; providing the first steps to characterize TSSN from a GLM perspective. Future work includes characterizing TSSN on a large scale from a thermodynamic and microphysical aspect.
Table 2.2: GLM flash area (energy) statistics with regards to mSFR count. Units of flash area and energy are km$^2$ and fJ(1x10$^{15}$ J) respectively. Significance is relative to the GLM flashes within the highest mSFR confidence bin (i.e., GLM flashes with a mSFR pixel count ≥ 825).

<table>
<thead>
<tr>
<th>mSFR Count</th>
<th>Minimum</th>
<th>25th Percentile</th>
<th>Mean</th>
<th>Median</th>
<th>75th Percentile</th>
<th>Maximum</th>
<th>Significance (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>66.735 (3.052)</td>
<td>223.530 (62.565)</td>
<td>591.575 (633.462)</td>
<td>426.574 (198.376)</td>
<td>740.770 (592.076)</td>
<td>426.574 (198.376)</td>
<td>1.194e-28 (2.139e-36)</td>
</tr>
<tr>
<td>100</td>
<td>66.735 (3.052)</td>
<td>223.985 (61.038)</td>
<td>593.288 (610.626)</td>
<td>427.333 (189.221)</td>
<td>741.984 (564.609)</td>
<td>427.333 (189.221)</td>
<td>4.506e-28 (7.440e-39)</td>
</tr>
<tr>
<td>200</td>
<td>66.735 (3.052)</td>
<td>226.032 (61.038)</td>
<td>596.552 (613.660)</td>
<td>428.546 (189.220)</td>
<td>744.865 (567.661)</td>
<td>428.546 (189.220)</td>
<td>4.359e-27 (1.497e-38)</td>
</tr>
<tr>
<td>300</td>
<td>66.735 (3.052)</td>
<td>229.899 (61.038)</td>
<td>602.561 (635.793)</td>
<td>431.730 (190.746)</td>
<td>764.881 (581.394)</td>
<td>431.730 (190.746)</td>
<td>6.003e-26 (3.771e-37)</td>
</tr>
<tr>
<td>400</td>
<td>66.735 (3.052)</td>
<td>246.597 (64.091)</td>
<td>616.784 (690.036)</td>
<td>438.706 (198.742)</td>
<td>790.963 (624.122)</td>
<td>438.706 (198.742)</td>
<td>2.371e-21 (1.324e-32)</td>
</tr>
<tr>
<td>500</td>
<td>66.735 (3.052)</td>
<td>286.460 (70.194)</td>
<td>653.063 (823.969)</td>
<td>454.173 (227.370)</td>
<td>846.197 (581.394)</td>
<td>454.173 (227.370)</td>
<td>3.118e-14 (2.898e-23)</td>
</tr>
<tr>
<td>675</td>
<td>66.735 (3.052)</td>
<td>295.862 (102.240)</td>
<td>770.508 (1344.212)</td>
<td>573.058 (418.116)</td>
<td>1047.991 (1471.035)</td>
<td>573.058 (418.116)</td>
<td>0.006 (0.002)</td>
</tr>
<tr>
<td>700</td>
<td>66.735 (3.052)</td>
<td>296.582 (105.292)</td>
<td>779.130 (1409.326)</td>
<td>577.304 (451.687)</td>
<td>1072.140 (1550.004)</td>
<td>577.304 (451.687)</td>
<td>0.018 (0.018)</td>
</tr>
<tr>
<td>725</td>
<td>66.735 (3.052)</td>
<td>348.935 (115.974)</td>
<td>799.360 (1512.342)</td>
<td>583.066 (483.732)</td>
<td>1092.725 (1744.947)</td>
<td>583.066 (483.732)</td>
<td>0.114 (0.148)</td>
</tr>
<tr>
<td>750</td>
<td>66.735 (3.052)</td>
<td>348.935 (117.450)</td>
<td>810.419 (1572.691)</td>
<td>588.980 (512.726)</td>
<td>1092.725 (1866.261)</td>
<td>588.980 (512.726)</td>
<td>0.311 (0.418)</td>
</tr>
<tr>
<td>775</td>
<td>66.735 (3.052)</td>
<td>355.873 (120.933)</td>
<td>825.034 (1613.292)</td>
<td>601.035 (520.356)</td>
<td>1093.407 (1871.221)</td>
<td>601.035 (520.356)</td>
<td>0.585 (0.598)</td>
</tr>
<tr>
<td>800</td>
<td>66.735 (3.052)</td>
<td>356.366 (119.789)</td>
<td>823.087 (1596.452)</td>
<td>602.023 (506.622)</td>
<td>1091.891 (2031.218)</td>
<td>602.023 (506.622)</td>
<td>0.557 (0.534)</td>
</tr>
<tr>
<td>825</td>
<td>66.735 (3.052)</td>
<td>361.635 (129.707)</td>
<td>829.319 (1656.523)</td>
<td>646.982 (509.674)</td>
<td>1153.191 (2063.493)</td>
<td>646.982 (509.674)</td>
<td>1.000 (1.000)</td>
</tr>
</tbody>
</table>
Table 2.3: TSSN Flash Characteristics Observed by GLM (i.e., GLM flashes with a mSFR pixel count $\geq 700$)

<table>
<thead>
<tr>
<th>Variable</th>
<th>25th Percentile</th>
<th>Mean</th>
<th>Median</th>
<th>75th Percentile</th>
<th>90th Percentile</th>
<th>99th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area (km$^2$)</td>
<td>296.58</td>
<td>779.13</td>
<td>577.30</td>
<td>1,072.14</td>
<td>1,741.89</td>
<td>2,970.85</td>
</tr>
<tr>
<td>Energy (fJ)</td>
<td>105.29</td>
<td>1,409.33</td>
<td>451.69</td>
<td>1,550.00</td>
<td>3,993.46</td>
<td>11,745.39</td>
</tr>
<tr>
<td>Duration (ms)</td>
<td>319</td>
<td>820</td>
<td>676</td>
<td>1,144</td>
<td>1,698</td>
<td>3,223</td>
</tr>
</tbody>
</table>

Table 2.4: NLDN Multiplicity (number of return strokes) and Polarity (kA) Characteristics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Minimum</th>
<th>25th Percentile</th>
<th>Mean</th>
<th>Median</th>
<th>75th Percentile</th>
<th>90th Percentile</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polarity</td>
<td>All CGs</td>
<td>-227.30</td>
<td>-31.70</td>
<td>-16.46</td>
<td>-14.00</td>
<td>-5.10</td>
<td>201.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tower CGs</td>
<td>-80.20</td>
<td>-20.10</td>
<td>-14.56</td>
<td>-14.50</td>
<td>-9.60</td>
<td>56.20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Non-tower CGs</td>
<td>-227.30</td>
<td>-35.75</td>
<td>-16.72</td>
<td>-13.90</td>
<td>-3.78</td>
<td>201.00</td>
<td></td>
</tr>
<tr>
<td>Multiplicity</td>
<td>All CGs</td>
<td>1.0</td>
<td>1.0</td>
<td>2.5</td>
<td>2.0</td>
<td>3.0</td>
<td>15.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tower CGs</td>
<td>1.0</td>
<td>1.5</td>
<td>4.2</td>
<td>3.0</td>
<td>6.0</td>
<td>15.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Non-tower CGs</td>
<td>1.0</td>
<td>1.0</td>
<td>2.2</td>
<td>1.0</td>
<td>3.0</td>
<td>15.0</td>
<td></td>
</tr>
</tbody>
</table>
Figure 2.1: Depiction of TDA processes associated with determination of TSSN flashes observed by GLM and confidences with the red hues getting darker as the TDA process proceeds. The black arrows represent the progressive steps of the algorithm. The first step involves binning the GLM data in 10 minute increments to match the temporal resolution of the mSFR product. If the mSFR product has a time stamp of 1010 UTC the GLM data would be binned from 1000-1009 UTC. Second step involves the overlap of mSFR and GLM data. For example, the mSFR (blues and greens) and GLM (in white circle) data within for a Noreaster on 04 January 2018 at 1410 UTC over Long Island, New York displayed using the National Weather Services Advanced Weather Interactive Processing System. The third step involves identification of TSSN groups observed by GLM based on a 0.15-degree distance threshold (black circle). Lightning bolt represents a GLM group and the blue-filled boxes represent mSFR pixels. Pixel count equal to four results in a GLM group with low confidence of being TSSN. Step four is the GLM group classification based on number of mSFR pixels within distance threshold. If all GLM groups within that timeframe are processed the TDA proceeds to step five and matches up the GLM groups by varies GLM flash characteristics and creates GLM quasi flashes. In the final step of the TDA, the GLM quasi flashes are matched up with the official GLM flashes. The light blue arrow represents a proposed alternative step to reduce computational calculations and create real-time operational product.
Figure 2.2: 14 April 2018 1310 UTC NESDIS mSFR product overlaid with A) GLM group data and B) TSSN quasi flash data from 1300 - 1309 UTC. This represents before and after the TDA takes effect respectively.

Figure 2.3: Relationship between GLM flash energy and flash area. Blue represents all potential TSSN flashes observed by GLM and orange represents TSSN flashes observed by GLM with a mSFR count of 700 or greater.
Figure 2.4: Differentiation of GLM flashes with regards to flash: a) area, b) energy, and c) duration based on NLDN matchup characteristics. There is a total of 1,081 GLM flashes did not correspond with any NLDN data while the remaining 1,095 GLM flashes corresponded with NLDN data. The 1,095 GLM flashes subcategorized as IC-only (N=356), Tower (N=152) and Non-tower (N=587) initiated.
Figure 2.5: A) Depicts flashes observed by GLM that occurred during the times in Table 1. Blue dots represent potential TSSN flashes observed by GLM; while orange dots represent TSSN flashes observed by GLM with a mSFR count of 700 or greater. Finally, the black dots represent METAR reported TSSN that occurred in the same range of time. B) Flash density for potential TSSN flashes detected from the TDA from January-April 2018.
Figure 2.6: Demonstrates the GLM LCFA splitting a TSSN flash into three separate GLM flashes that occur sequentially near Peterborough, Ontario at 09:40:56 UTC on 23 January 2018. Dots and stars represent GLM events and flashes respectively. The solid lines represent the convex hull of the GLM flashes while the dashed line are the 50-km search radii in the NLDN/GLM matchup process. These three GLM flashes do not coincide spatially or temporally with any NLDN data.
3.0.1 Abstract

It has long been accepted that thundersnow (TSSN) occurs in heavy snowfall rates and regions where heavy-banded and lake-effect snow occur more frequently. This study aims to objectively and quantitatively identify characteristics associated with TSSN to improve the situational awareness of heavy-snowfall and associated hazards. The Geostationary Lightning Mapper (GLM), National Environmental Satellite Data and Information Services (NESDIS) merged Snowfall Rate (mSFR) product, and surface observations were utilized to characterize snowfall accumulation, snow-to-liquid ratio (SLR) values, and radar characteristics of heavy-snowfall events from a GLM perspective. The thundersnow detection algorithm (TDA) demonstrated areas that experience TSSN will receive at least 3.36-in of snowfall accumulation with an average total of 9.81-in. TSSN was more likely to occur in snowfall rates less than 1-in hr$^{-1}$ and be associated with snow-to-liquid ratio (SLR) values between
8:1 and 9:1. It was determined that TSSN flashes observed by GLM occurred in
isotherm reflectivity values less than 30-dBZ and average spatial offsets of 124±65-
km between the lightning flash location and the heaviest snowfall rates were observed.
A heavy-snowfall event was analyzed with GLM, mSFR product, and Multi-Radar
Multi-Sensor (MRMS) to demonstrate where TSSN was more likely to occur and
provides the potential for predicting TSSN. Cloud-to-ground (CG) flashes that inter-
acted with tall structures were found to be statistically different (p<0.05) regarding
snowfall rates, SLR values, and various MRMS variables compared to flashes that
not come to ground; in contrast, CG flashes that did not interact with tall structures
were only statistically different for snowfall rates compared to intracloud (IC) flashes.

3.0.2 Introduction

It is commonly accepted that thundersnow (TSSN) is the coexistence of light-
ning and/or thunder and snowfall observations (Curran and Pearson 1971; Schultz
mentioned that the lack of scientific inquiry regarding TSSN, compared to lightning
in convective storms, was low because of the perceived rarity and perceived lack of
threat associated with the phenomena. As such TSSN draws a fascination with the
public and scientists alike; however, TSSN still poses safety hazards for the public
and has been shown to cause damage to life and property (Herschel 1888; Holle et al.
1997; Cherington et al. 1998). Kumjian and Deierling (2015) mention lightning-
related incidents at ski-resorts and the increased threat of aviation hazards (i.e.,
aircraft initiated lightning) in electrified winter clouds. Many studies have theorized
and examined lightning initiation and the charging mechanisms within clouds (e.g., Paluch and Sartor 1973; Takahashi 1978; Jayaratne et al. 1983). A leading theory for lightning initiation is associated with noninductive charging; which requires the coexistence of supercooled water, graupel, and ice particles (Takahashi 1978; Saunders et al. 2006). All three particle types exist within winter storms and thus make TSSN possible (e.g., Trapp et al. 2001; Rust and Trapp 2002; Rauber et al. 2014).

Market et al. (2002) identified 191 TSSN events from 1961-90 and mentioned that TSSN events were: limited in areal extent, short-lived, and typically have light to moderate snowfall rates. Rauber et al. (2014) found that TSSN tend to occur on the southern side of the snow band and comma head and suggests that mesoscale features were embedded within the larger synoptic snow band. TSSN occurring in this location was likely caused by the coexistence of supercooled water and heavily rimed particles (Reynolds et al. 1957; Takahashi 1978). This is in contrast to Market and Becker (2009) were they examined 1,088 flashes from 24 different cases and found that TSSN was more likely to occur on the leading edge of the snow band (i.e., equatorward edge of snow band if propagating from northwest to southeast). Additionally, using radar reflectivity as a proxy for snowfall rates, they found the relationship between TSSN flashes and maximum snowfall rates were not strongly correlated; however, more TSSN flashes occurred downstream of the highest radar reflectivity (i.e., inferred highest snowfall rates). Using high reflectivities as a proxy for higher snowfall rates is justifiable but gives little to no indication of quantifiable snowfall rates. Schultz et al. (2018) observed snowfall rates on the order of 5-8-cm hr$^{-1}$ in a TSSN event in Huntsville, Alabama on 10 January 2011. Furthermore,
Crowe et al. (2006) demonstrated that TSSN tended to be associated with storms that produce higher (>15-cm) storm-total snowfall accumulation but does not necessarily occur in regions with the highest accumulating snowfall. This suggests that TSSN can be used as an indicator for potential higher storm total snowfall accumulations if the phenomena occurs; however, the study does not discuss which regions of the storm to expect higher snowfall nor the snowfall accumulation where TSSN occurred.

Harkema et al. (2019), submitted, formulated a thundersnow detection algorithm (TDA) that objectively identified TSSN using Geostationary Operational Environmental Satellite East (GOES-East; Schmit et al. 2005) Level 2 Geostationary Lightning Mapper (GLM; Goodman et al. 2013) data, National Environmental Satellite Data and Information Service (NESDIS) merged Snowfall Rate (mSFR; Meng et al. 2017a,b) product, and nearest neighbor statistics (Bentley 1975). When comparing with Meteorological Terminal Air Report (METAR; Department of Commerce 2017) reports of TSSN as truth the TDA resulted in a probability of detection of 87.2%. Furthermore, Harkema et al. (2019) observed that 49.7% of TSSN flashes detected by GLM do not correspond with any National Lightning Detection Network (NLDN) data, meaning that TSSN is likely underreported globally.

Forecasting heavy-snowfall can be difficult owing to the spatial and temporal heterogeneity of mesoscale processes and microphysical characteristics within larger synoptic systems that generate bands of heavy-snowfall (Uccellini et al. 1995; Wiesmueller and Zubrick 1998; Nicosia and Grumm 1999; Moore and Graves 2005; Novak et al. 2006; Baxter and Schumacher 2017). Snow-to-liquid ratio (SLR) values are one
of many characteristics that can impact a forecast and Colle et al. (2014) demonstrated that large aggregates (i.e., dendrites) have high SLR values; while, compact ice particle habits and heavily rimed particles (i.e., needles, bullets, graupel) had lower SLR values. The variability of SLR values within heavy-snowfall vary drastically within the comma head of a cyclone. Near the cyclone center, heavily rimed particles were found; while plates and bullets commonly occurred in the outer comma head (Colle et al. 2014). The region of heavily rimed particles, near the center of the comma head, coincided with the environment that was preferential for TSSN (Rauber et al. 2014). This suggests that TSSN can potentially be used as a proxy for SLR values on a storm-scale timeframe.

To understand the physical processes that impact SLR values, Roebber et al. (2003) employed a neural network and found that four main factors can be utilized to forecast the potential for SLR values: surface winds, temperature, relative humidity, and time of year. Additionally, Baxter et al. (2005) created a SLR value climatology and found that mean SLR values are closer to 13.53-to-1 compared to the 10-to-1 rule of thumb. Unfortunately, this climatology only examines long-term themes of SLR and may not be representative for the processes on smaller time scales including those associated with heavy-snowfall. Currently, SLR values are determined by daily observations, from trained weather observers, from Cooperative Summary of the Day (COOP) stations or the Community Collaborative Rain, Hail, and Snow (CoCoRaHS) network. These data are a summary of what occurs in the previous 24-hours or a summation of four 6-hour observations. Examining COOP and CoCoRaHS derived SLR every 24-hours is certainly more representative than any individual climatology;
however, the use of these data still results in a coarse spatial resolution analysis.

Characterization of the environment in regard to the predictability of snowfall rates and the potential for snowfall accumulation could identify environments conducive for TSSN prior to initiation. Concurrently, this understanding could be utilized to quantify snowfall rates, liquid ratios, and totals in data sparse areas that are affected by heavy-snowfall (e.g., Dolif Neto et al. 2009; Adhikari and Liu 2019) through the use of the characteristics of lightning from the GLM (i.e., flash size and total optical energy). With the spatial and temporal availability of GLM and the development of the TDA, further objective characterization of the underlying microphysical characteristics of the parent environment in which the lightning develops is possible. Thus, the objectives of this study are:

1) Develop a high-spatial resolution SLR dataset and compare to Baxter et al. (2005).

2) Modify the TDA to characterize TSSN flashes observed by GLM based on derived high-resolution SLR values, snowfall rates, and snowfall accumulation.

3) Analyze the 13-17 April 2018 blizzard to investigate the predictability of TSSN by examining isotherm (i.e., -10, -15, -20°C) reflectivity, vertically integrated ice (VII), and vertically integrated liquid (VIL) to compare with previous work by Mosier et al. (2011), Seroka et al. (2012), and Adhikari and Liu (2019).
3.0.3 Dataset

3.0.3.1 Snow-to-Liquid Ratio

SLR values are directly correlated with observed total snowfall accumulations and have strict guidelines to properly measure snowfall compared to rainfall. Presently, there are over 10,000 trained volunteers that take daily observations as part of the National Weather Service (NWS) COOP program. COOP observers measure and report snowfall in tenths of an inch on a 24-hour basis and collect snow cores to be melted down to determine the liquid equivalent (NWS 2017). These measurements are invaluable for forecasters as they provide information in potentially data sparse regions and verification for numerical weather prediction models. SLR values are calculated by taking the ratio of measured snowfall accumulation and liquid equivalent. Currently, the National Oceanic and Atmospheric Administration (NOAA) Nation Centers for Environmental Information (NCEI) provides an archive of COOP data.

3.0.3.2 Snowfall Accumulation

To further validate and visualize snowfall accumulations the National Operation Hydrological Remote Sensing Center (NOHRSC) provides a national snowfall analysis. This analysis is generated by interpolating 24-hour observations of snowfall accumulations from COOP, CoCoRaHS observations and NWS spotter reports (NWS - NOHRSC cited 2019). This analysis provides high resolution snowfall accumulations on a 6-, 24-, 48-, and 72-hour durations as well as seasonal totals.
3.0.3.3 merged Snowfall Rate (mSFR) product

The mSFR product, from NESDIS, blends Multi-Radar Multi-Sensor (MRMS; Zhang et al. 2016) and Global Precipitation Measurement (GPM; Hou et al. 2014) passive microwave sensor data to estimate snowfall rates within the continental United States (CONUS) every 10-minutes with a spatial resolution of 1x1-km. The mSFR product currently utilizes the following passive microwave sensors: GPM Microwave Imager (GMI), Special Sensor Microwave Imager/Sounder (SSMIS), Advanced Technology Microwave Sounder (ATMS), Microwave Humidity Sounder (MHS), and Advanced Microwave Sounder Unit (AMSU). Snowfall rates derived from these sensors have been shown to approximate snowfall rates prior to snowfall reaching the surface (Meng et al. 2017b; Ferraro et al. 2018). This is particularly beneficial in data sparse regions that deal with radar beam blockages (e.g., Intermountain West). Given the lack of temporal coverage of the passive microwave sensors, MRMS is merged with the passive microwave observations to fill in the gap between satellite overpasses. Snowfall rates derived from MRMS are essentially precipitation rates associated with the snow precipitation flag (Huan Meng, NESDIS, personal communication). The ability to incorporate MRMS into this product allows for the ability to track local maxima within the snowfall as well as increasing the spatial resolution in order to depict mesoscale features. Assuming a 10:1 SLR, Meng et al. (2017b) highlighted that the mSFR product can only detect snowfall rates up to 2.00-in hr$^{-1}$ but cannot detect snowfall rates less than 0.08-in hr$^{-1}$.
3.0.3.4 Multi-Radar Multi-Sensor (MRMS)

MRMS provides a seamless national 3D radar mosaic with high spatial (1x1-km) and temporal (2-min) resolutions (Zhang et al. 2016). MRMS has seven surface precipitation classifications including snow which is defined as areas that are receiving precipitation and where the surface temperature is below 2°C and the wet-bulb temperature is below 0°C (Zhang et al. 2016). It should be noted that the MRMS rain/snow transition region is abrupt as there is no mixed precipitation flag and most likely classifies this region as cold stratiform rain (Steven Martinaitis, CIMMS/NSSL, personal communication). Furthermore, MRMS also produces severe weather products including VII, VIL, and isotherm reflectivity and allows for analysis of these variables on a larger scale compared to a single Doppler radar (Smith et al. 2016). For example, the derived VII from MRMS can be used to evaluate changes in updraft intensity which has been shown to have a positive relationship with total lightning activity (Deierling et al. 2005).

**Isothermal Reflectivity, Vertically Integrated Ice and Liquid**  Mosier et al. (2011) and Seroka et al. (2012) examined isotherm reflectivity (i.e., -10, -15, -20°C) and vertically integrated ice (VII; Carey and Rutledge 2000) to demonstrate the predictability of lightning. Specifically, Mosier et al. (2011) found that 25-dBZ reflectivity at -20°C and -15°C were the best predictors of cloud-to-ground (CG) and intracloud (IC) lightning respectively. In contrast, Gremillion and Orville (1999) and Vincent et al. (2003) demonstrated that the 40-dBZ echoes at the -10°C isotherm
level was the best predictor for the beginning of CG activity. It should be noted that VII is defined as:

\[
VII = 1000\pi \rho_i N_0^{3/7} \left(\frac{5.272 \times 10^{-18}}{720}\right)^{4/7} \int_{H_{-10}}^{H_{-40}} Z^{4/7} dH,
\]

where \( \rho_i \) is the density of ice (917 kg m\(^{-3}\)), \( N_0 \) is the intercept parameter (4x10\(^6\) m\(^{-4}\)), \( H_{-10} \) and \( H_{-40} \) are the height of the -10\(^\circ\)C and -40\(^\circ\)C levels (m), and \( Z \) is the reflectivity value. In contrast to VII, vertically integrated liquid (VIL; Greene and Clark 1972) represents the atmospheric water content that can be measured by radar and has been proven in the severe storm detection process (Boudevillain and Andrieu 2003).

### 3.0.3.5 Geostationary Lightning Mapper (GLM)

On 18 December 2017, the GLM onboard the GOES-East satellite, became operational and provides a hemispherical view of lightning from 54\(^\circ\)N/S with a temporal and spatial resolution of 2-ms and 8-km respectively (Goodman et al. 2013; Rudlosky et al. 2019). GLM is an optical sensor that utilizes a narrow 1-nm band centered on the 777.4-nm wavelength that allows for the observation of lightning during the day and night (Christian and Goodman 1987; Rudlosky et al. 2019). Beyond the detection of lightning in severe weather, GLM has been documented identifying TSSN in a variety of environments (Schultz et al. 2018; Harkema et al. 2019). GLM data consists of three main components: events, groups, and flashes Goodman et al. (2013). An event is when a single GLM pixel (64-km\(^2\)) is illuminated more than a background threshold. GLM events that are adjacent to each other and occur in a single frame
are classified as a GLM group. GLM flashes are currently defined as a conglomerate of GLM groups that occur within a Euclidean distance bounded by 330-ms/16.5-km of GLM groups that occur within a Euclidean distance bounded by 330-ms/16.5-km. For a complete description of GLM capabilities and specs see Goodman et al. (2013).

3.0.4 Methodology

3.0.4.1 The thundersnow detection algorithm

The TDA analyzes the potential overlap of GLM and mSFR and provides confidence of a GLM flash to be classified as TSSN and the process can be broken down into five steps:

1) First, GLM groups are binned to match the same 10 minute temporal resolution of the mSFR product. GLM groups were chosen because they provide spatial context to the flash's size given that GLM flash data reports the mean location of all GLM groups.

2) Next, nearest neighbor statistics are used to determine where overlap between GLM flash and group data and places where the mSFR product has identified snowfall.

3) The number of mSFR pixels a 0.15-degree distance around each GLM group location are then counted to characterize if the GLM flash entirely in snowfall (as identified by the mSFR algorithm) or if there are locations close to the flash that may be mixed precipitation or all rain. The maximum number of mSFR pixels for any 0.15 degree search radius is 866 \((\pi \times 16.6^2)\).
4) GLM groups are merged using common GLM Flash ID information contained in the level 2 data. The mSFR pixel count is then computed by averaging the number of snowfall pixels identified at each GLM group location for the entire GLM flash.

5) All GLM flashes with an average mSFR count of 700 or more are then identified as observed lightning within snowfall (i.e., TSSN) and snowfall rate, SLR, and snowfall total information are extracted.

For a full description and methodology of the TDA see Harkema et al. (2019).

3.0.4.2 High Resolution snow-to-liquid ratio (SLR) Values

For each of the 21 snowfall cases in Harkema et al. (2019) liquid equivalent was derived by aggregating the mSFR product using an assumed SLR value of 1:1 over time. Given the mSFR product has a temporal resolution of 10-minutes and a unit of \([\text{in hr}^{-1}]\), the snowfall rates were reduced by a factor of six to provide a liquid equivalent every 10-minutes. Aggregating each 1x1-km mSFR liquid equivalent value through the duration of each of the cases provides a spatially uniform estimated total liquid equivalent with a higher spatial resolution than interpolated liquid equivalent from COOP stations. Snowfall accumulations for the 21 cases were matched closely as possible using the available data from NOHRSC. For example, if a case lasted for 31-hours, a 24-hour and 6-hour snowfall accumulation file were aggregated rather than using a 48-hour accumulation to better represent the snowfall accumulation for the specific case. The snowfall accumulation data was then re-projected.
and interpolated to match the projection and resolution of the mSFR product. The ratio of the snowfall accumulation and the derived mSFR total liquid equivalent resulted in a high resolution derived SLR estimate. To combat unrealistic values, the minimum thresholds in Roebber et al. (2003) were incorporated to determine SLR values for locations that received at least 2.0- and 0.11-in of snowfall accumulation and derived total liquid equivalent respectively. The derived SLR values were than compared to the 30-year SLR climatology from Baxter et al. (2005) to validate the results. Furthermore, given the limited temporal extent of the data within this study (i.e., January-April 2018), the derived SLR values are not partitioned by month or geographic location compared to the SLR climatology from Baxter et al. (2005).

3.0.4.3 Assignment of SLR, snowfall totals, and snowfall Rates at the location of GLM flashes

A maximum distance threshold of 0.15 degrees, approximately 16.6-km, from the TDA (Harkema et al. 2019) was implemented to determine mSFR pixels (i.e., snowfall rate) near each GLM group. The assigned snowfall rate(s) for each of the GLM groups were then averaged during the GLM flash matchup process of the TDA; thus was more representative of the environment in which TSSN occurred. Additionally, a SLR value of 10:1 was used to find the snowfall rates as it can be easily converted for later analysis. The use of 10:1 is justifiable because the mSFR product assumes a uniform SLR when determining snowfall rates and 10:1 is a good first guess for simplicity. Snowfall accumulations and SLR values for TSSN flashes observed by GLM were determined using the same methodology as described above. A more real-
istic estimate of snowfall rates were also calculated using the product of the derived SLR value and the snowfall rate (assuming a 1:1 SLR) for each of the TSSN flashes detected by GLM. The 2,176 TSSN flashes with a mSFR pixel count greater than or equal to 700 from Harkema et al. (2019) were utilized for all TSSN flash analysis. Furthermore, TSSN categories of No NLDN, NLDN, IC-only, Tower, and Non-tower were examined with respect to snowfall rates, totals, and ratios to quantify possible differences between the categories. To matchup with a GLM flash, NLDN flashes must occur within ±8-seconds of the start and end times of a GLM flash and occur within the larger of two distances thresholds (i.e., 50-km or the square root of the GLM flash area; Harkema et al. 2019). The TSSN categories were defined as:

1) No NLDN  GLM flashes that did not spatially and temporally matchup with NLDN flashes.

2) NLDN  GLM flashes that did spatially and temporally matchup with NLDN flashes.

3) IC-only  GLM flashes that only matchup with NLDN intracloud (IC) flashes.

4) Tower  GLM flashes that are associated with at least one NLDN cloud-to-ground (CG) flash and the first CG flash occurring within 500-m of a tall human-made structure like an antenna or wind turbine.

5) Non-tower  GLM flashes where the first matchup NLDN CG flash occurred beyond 500-m of a tall human-made structure.
Differentiating these quantities provides in-depth understanding of the characteristics of IC and CG TSSN.

3.0.5 Results

3.0.5.1 High Resolution SLR values

Figure 3.1 demonstrates the comparison of the: Baxter et al. (2005) SLR climatology (Fig. 3.1a) and overall distribution of the derived SLR values. Visually, the two datasets are similar and both tail off toward larger SLR values. Given the values within the SLR climatology in Baxter et al. (2005) were unknown direct comparison between the two distributions was limited; however, using the same statistical metrics in Baxter et al. (2005) (i.e., mean, median, 25th, and 75th percentile), the two distributions could be compared in a limited extent. Compared to the mean SLR value in Baxter et al. (2005)(i.e., 13.53) the mean derived SLR value was 14.52 which corresponds to a percent different of -7.05. This means that the derived SLR estimate overestimated the mean observed SLR value by 7.05% and represented the largest percent difference of the four statistical metrics examined in the comparison (Table 3.1). Given that the percent differences were relatively small suggest that the derived SLR estimate dataset could be used to demonstrate the possible connection between SLR values and the existence of TSSN. To further characterize the derived SLR distribution, the bias corrected kurtosis (i.e., measure of peakness) and skewness (i.e., measure of symmetry) were found to be 2.67 and 1.50 respectively. The higher the kurtosis value the more peaked the distribution and for reference Gaussian dis-
tributions have a kurtosis of 3 (Wilks 2011). A positive skewness demonstrated that the right tail is longer and that the distribution was skewed to the left (Fig. 3.1b). A gamma function was fitted to the distribution (orange line; Fig. 3.1b); where the three parameters in the fitted normalized distribution were: $\alpha=3.32$, $\beta=4.08$, and location=0.96. Studies have shown and/or assumed that drop size distributions are associated with gamma functions (e.g., Ulbrich 1983; Ulbrich and Atlas 1998). Furthermore, Mosimann et al. (1994) found that dendrite and plate ice crystal diameter also follow a gamma distribution that were skewed toward larger diameter crystals. The ability to characterize and fit a gamma distribution allows for a direct comparison to SLR values associated with TSSN.

3.0.5.2 SLR and TSSN

Of the 2,176 TSSN flashes observed by GLM, 1,241 of them are associated with derived SLR values and the remaining were associated with snowfall and/or total liquid equivalent measurements below the minimum thresholds in Roebber et al. (2003). The mean and median SLR values associated with TSSN were 13.06 and 10.94 respectively (Table 3.2); however, the number of occurrences of TSSN in the 8:1-9:1 SLR value bin (N=85) was nearly twice as many compared to the bin with the next highest count (N=43; 9:1-10:1 SLR; Fig. 3.2a). This suggests that TSSN was more likely to occur in the lower range of the Medium Ratio (8:1-12:1; Colle et al. 2014) and were associated with medium to heavily rimed ice crystals or light rimed compact habits (e.g., dendrites, plates, needles, graupel, bullets). The discrepancy between the peak and the average SLR values resulted from relatively high derived
SLR values (>25) skewing the results. In fact, the skewness and kurtosis of the TSSN SLR distribution was 1.98 and 5.04 respectively; suggesting that the distribution (Fig. 3.2a) was skewed further to the left and more peaked compared to the overall derived SLR distribution (Fig. 3.1b). The fitted gamma function parameters for the TSSN SLR values (orange line, Fig. 3.2a) were: $\alpha=2.56$, $\beta=3.56$, and location=3.94. Taking a random sample of the overall derived SLR values (N=1,241) and comparing them to the TSSN SLR distribution resulted in a statistically significant (p<0.01) difference with a p-value of 5.93x10$^{-7}$. Comparing the SLR values associated with tower TSSN flashes (N=122) to non-tower TSSN flashes (N=285) and IC-only TSSN flashes (N=142) detected by GLM resulted in statistically significant (p<0.05) differences with p-values of 0.013 and 0.042 respectively (Fig. 3.2b). In fact, tower TSSN flashes observed by GLM have the highest median SLR value (12.40) and the IC-only TSSN flashes have the lowest median SLR value (9.86; Table 3.2). Therefore, tower TSSN flashes observed by GLM were more likely to occur in a snowfall regime that was associated with higher values in the Medium Ratio (8:1-12:1) and the lower portion of the High Ratio (13:1-17:1; Colle et al. 2014); suggesting that tower TSSN flashes observed by GLM, on median, transpire within dendritic and plate snowfall and correspond to ice crystals with little-to-light riming. Therefore, it can be inferred that the amount of supercooled water necessary for tower TSSN was less than the necessary amount for non-tower and IC-only TSSN detected by GLM.
3.0.5.3 Snowfall Rates in TSSN

SLR values play a major role in estimating snowfall rates and can vary drastically depending on where an observer is located in the heavy-snowfall. Assuming a constant SLR value, the snowfall rates associated with TSSN (N=2,176) were approximately Gaussian distributed (orange line; Fig. 3.3a). On average, TSSN flashes occurred when snowfall rates were 0.71-in hr$^{-1}$ (Table 3.2; SLR=10:1). TSSN did not occur in the heaviest snowfall rates given the mSFR product can estimate snowfall rates up to 2.00-in hr$^{-1}$ and the maximum snowfall rate that TSSN was associated with was 1.65-in hr$^{-1}$ and align with results from Market and Becker (2009). On average, CG TSSN flashes observed from GLM (i.e., tower and non-tower; N=739) occurred in higher snowfall rates and were statistically significant ($p=1.50\times10^{-6}$) compared to IC-only TSSN flashes observed by GLM (N=356; Fig. 3.3b). Furthermore, tower TSSN flashes observed by GLM (N=152) have the highest mean snowfall rate compared to the other TSSN categories (0.77-in hr$^{-1}$; Table 3.3).

However, SLR values are not constant in heavy-snowfall and can provide inaccurate snowfall rate estimates (Colle et al. 2014). Assuming the assigned derived SLR values for TSSN flashes was the actual SLR value in which the TSSN flashes occurred, the snowfall rates were adjusted, resulting in a mean and median snowfall rate of 0.88- and 0.75-in hr$^{-1}$ respectively (Table 3.2). This suggests that TSSN was occurring on average in snowfall rates less than 1.00-in hr$^{-1}$. The use of the derived SLR values to estimate more realistic snowfall rates resulted in a change of shape in the snowfall rate distribution (Fig. 3.3c). Instead of being a Gaussian distribution,
like the snowfall rate distribution, the estimated snowfall rate distribution was skewed
to the left (skewness=2.18) and more of a gamma distribution with a kurtosis of 6.22
that peaked at approximately 0.60-in hr$^{-1}$. Assuming that the estimated snowfall
rates greater than 4.00-in hr$^{-1}$ were anomalous resulted in a fitted gamma distribu-
tion with parameters of: $\alpha=2.69$, $\beta=0.27$ and location=0.14. The gamma distribution
of the estimated snowfall rates was the result of the utilization of the derived SLR
values which were also categorized as a gamma distribution. Physically, this makes
more conceptual sense given studies have shown that precipitation characteristics fol-
low gamma distributions (e.g., Ulbrich 1983). Breaking down the estimated snowfall
rates for each of the different TSSN categories, it was found that on average IC-only
TSSN flashes occurred in the lowest snowfall rates while the tower TSSN flashes iden-
tified by GLM occurred in the highest snowfall rates (Table 3.2). Estimated snowfall
rates for CG TSSN flashes (N=407) were statistically significant ($p<0.01$) compared
to IC-only TSSN flashes (N=356) observed by GLM with a p-value of $1.71\times10^{-4}$ (Fig.
3.3d).

### 3.0.5.4 Snowfall Accumulation and TSSN

Of the 2,176 TSSN flashes observed by GLM, 1,253 of them were associated
with snowfall accumulation. This suggests that TSSN can occur even when accumu-
lating snow was not expected; however, when snowfall accumulation was measured
and TSSN occurred an observer could expect at least 3.36-in of snowfall at that
location (Fig. 3.4a). Moreover, locations that experience TSSN with accumulating
snowfall can expect a mean and median snowfall total of 9.81- and 9.69-in respectively
Figure 3.4a also demonstrates that a Gaussian distribution can be fitted for locations that experience TSSN and snowfall accumulation (orange line). In some instances, nearly 20-in of total snowfall accumulation occurred when TSSN occurred but were still lower than the maximum total accumulation that occurred for individual cases. This reinforces the results in Crowe et al. (2006) in which they found TSSN does not occur in locations where the largest amount of snowfall accumulation was expected. Comparing the snowfall accumulations with regards to the different TSSN categories showcases slight differences between distributions (Fig. 3.4b); however, the differences were not statistically significant ($p > 0.10$). On average, IC-only TSSN flashes tended to have the lowest snowfall accumulation associated with them; while, TSSN flashes associated with CGs have the highest mean snowfall accumulations (Table 3.3). The differences between the highest and lowest mean snowfall accumulation was 0.42-in; therefore, it can be assumed that the lightning type classification (IC vs. CG) was not influenced by potential snowfall accumulation. In contrast, the maximum snowfall accumulation associated with IC-only TSSN flashes (i.e., 17.77-in) was less than that of the other TSSN categories; however, these differences were less than 2.00-in. The small differences between the TSSN categories was likely a result of the temporal resolution of lightning flashes being magnitudes ($10^{-1}$ to $10^0$-s; Rakov and Uman 2006) smaller compared to the synoptic scale ($10^5$-s; Martin 2006, .60 pp).

3.0.5.5 13-17 April 2018 Blizzard Case Study

**Synoptic Overview**  To further characterize and understand the potential predictability of TSSN, the 13-17 April 2018 blizzard (i.e., Case 21 from Harkema
et al. 2019) was examined in greater detail. At 00 UTC on 13 April 2018, several low pressures developed on the leeside of the Rocky Mountains including one in central Kansas with a frontal system stretching from the southern Great Lakes to eastern Colorado. A mature cyclone finally developed at 12 UTC along the eastern Kansas/Nebraska border with a surface pressure of 988-hPa. At this time, north-central South Dakota started to see widespread snowfall. The low-pressure system (992-hPa) started to occlude over the southern Nebraska/Iowa border at 00 UTC on 14 April 2018 with a single band of snowfall curving from central Nebraska into the Upper Peninsula of Michigan. At 12 UTC, the snow becomes more widespread shifting southeast with surface temperatures at or below freezing. During this time, GLM was observing widespread lightning over central Iowa where surface temperatures were a few degrees above freezing. Twelve hours later, the low pressure system (1004-hPa) was centered over Illinois with the majority of snowfall occurring in the upper-left quadrant of the cyclone with snowfall rates exceeding 2.00-in hr$^{-1}$ in Wisconsin. The system continued to track across the northern half of CONUS and eventually moved up the East Coast of the United States at which point lake-enhanced snow began to fall over the Great Lakes region. The slow progression of this system caused 9- to 30-inches of snowfall to accumulate in the Great Plains (Fig. 3.5a).

This case was chosen because of geographic coverage of the case, large number of GLM flashes, and the synoptic and mesoscale regime to the northwest of the cyclone center. Unfortunately, MRMS data was mostly limited to 13 April 2018 resulting in limited analysis of VII, VIL, and isotherm reflectivity. The duration of MRMS data may seem sparse compared to the overall case but provided superior coverage
compared to the other cases in Harkema et al. (2019). A smaller domain was defined from 43°N to 46°N latitude and from 100°W to 95°W longitude and encompasses the Iowa/Minnesota/South Dakota border region. This may be a relatively small domain when compared to the extent of the overall case but most of the TSSN occurred within this region and thus provided ample opportunity to characterize TSSN based on MRMS variables.

**Totals, Equivalents, and Ratios**  Figure 3.5a,b depict the total snowfall accumulation and the mSFR total liquid equivalent respectively for the 13-17 April 2018 blizzard. The highest snowfall accumulations (reds and oranges) and mSFR liquid equivalent (purples) occurred in Wisconsin and Michigan. Using the minimum thresholds in Roebber et al. (2003), the derived SLR values were found by the ratio of accumulation and liquid equivalent (Fig. 3.5c). In contrast, Fig. 3.5d depicts linearly interpolated SLR derived from COOP station data. Comparing the derived and COOP SLR values it becomes evident that the derived SLR depicts smaller scale features that are missed by the COOP SLR. For example, in southwestern Minnesota, the COOP SLR depicts two stations with relatively high SLR values (bright yellows) and the derived SLR depicts an arch of higher SLR (lime green to yellow) in the same locations. This suggests that the derived SLR values have the capacity to identify mesoscale phenomena that COOP stations cannot. In contrast, there were also major discrepancies in SLR values in western Nebraska where the derived SLR values demonstrated areas with SLR values exceeding 35:1; while observed SLR values were closer to 13:1-25:1. This was likely caused by the potential error in the MRMS
portion of the mSFR product by having the wrong precipitation flag. Even with the discrepancies, the new methodology qualitatively appears to match closely with the observed COOP SLR values but with greater spatial detail.

**Isotherm Reflectivity, Vertical Integrated Ice and Liquid**  The ability to predict when TSSN may occur enhances the situational awareness of heavy-snowfall beyond just knowing the characteristics of TSSN. During this case, 996 TSSN flashes occurred; however, 411 of them occurred when MRMS data was available. Therefore, TSSN analysis regarding isotherm reflectivity, VII, and VIL were limited to these 411 TSSN flashes observed by GLM. MRMS isotherm (i.e., -10, -15, -20°C) reflectivity, VII and VIL values were assigned to each TSSN flash using the same technique to assign other variables (e.g., snowfall rates) to remain homogeneous in the analysis process. The mean MRMS isotherm reflectivity values associated with TSSN flashes observed by GLM for the -10, -15, and -20°C isotherm levels were 21.86-, 21.17-, and 20.03-dBZ respectively (Table 3.2). Figure 3.6 demonstrates that isotherm reflectivity values associated with TSSN flashes never exceeded 30-dBZ for this case. These results contradict Adhikari and Liu (2019) where they found most TSSN have a maximum space-based radar reflectivity greater than 30-dBZ with temperatures colder than -10°C. The mean isotherm reflectivities associated with lightning in snowfall within this study were also lower than the best ground-based radar reflectivity threshold predictors for severe weather in Mosier et al. (2011) and Seroka et al. (2012). Unfortunately, these isotherm reflectivity values do little to demonstrate where TSSN was likely to occur given that there are large spatial areas of reflectivity between 10-
and 30-dBZ in snow storms (Thompson et al. 2014). However, this does suggest TSSN was not occurring in regions with the highest reflectivity values and is similar to results in Market and Becker (2009); suggesting, that TSSN does not occur in the highest snowfall rates. TSSN occurred on average in locations with higher amounts of VII compared to VIL with mean values of 1.44- and 0.53-kg m$^{-2}$ respectively (Table 3.2). This makes sense given that winter storms consist of more ice crystals compared to liquid water; however, given that MRMS does not detect VII less than 1.00-kg m$^{-2}$ these results were inconclusive. However, this does suggest that regions that experience snowfall and higher MRMS VII values were more likely to experience TSSN. The VIL values associated with TSSN flashes observed by GLM were less than the VIL values associated with lightning in summertime convective storms in Watson et al. (1995). Furthermore, given the lack of liquid water in wintertime storms, VIL indicated the total vertically integrated amount of supercooled liquid water. Contrasting the MRMS variables by the TSSN categories allowed for a greater understanding of the potential forcing necessary for different TSSN types (i.e., IC vs. CG). Figure 3.7 depicts isotherm reflectivity at the -10$^\circ$C and -20$^\circ$C isotherm levels, VII, and VIL. At both isotherm levels, IC-only TSSN flashes occurred in higher reflectivity compared to CG TSSN flashes (i.e., non-tower and tower; Fig. 3.7a,b). Comparing IC-only (N=85) and tower (N=31) TSSN flashes identified by GLM resulted in the two distributions being statistically significant at the 0.05 and 0.01 confidence levels for the -10$^\circ$C (p=0.022) and -20$^\circ$C (p=4.43x10$^{-3}$) isotherm levels respectively. IC-only TSSN flashes were also statistically significant for VII (p=0.027) and VIL (p=8.16x10$^{-5}$) when compared to tower TSSN flashes observed by GLM; in fact,
tower TSSN flashes have the lowest mean amounts of VII (1.21-kg m$^{-2}$) and VIL (0.39-kg m$^{-2}$). Furthermore, IC-only TSSN flashes observed by GLM have the highest median VII and VIL values compared to the other TSSN categories (Fig. 3.7c,d). Given the fact that IC-only flashes occur in the lowest SLR values suggests that the high median VII for IC-only was caused by relatively dense ice particles that have a large degree of riming caused by higher values of supercooled water.

3.0.6 Discussion

3.0.6.1 Comparison to Previous Literature

Examining the 21 snowfall cases, it appeared as though TSSN occurred more often on the equator-side of the major axis of the snow band regardless of orientation and enforces the results in Market and Becker (2009) and Rauber et al. (2014). Coincidentally, in this same region within the comma head, Colle et al. (2014) determined that the western quadrant and close to the cyclone center experience little-to-no and heavy riming respectively. Given how SLR values were determined and the fact a stereomicroscope was not used to identify ice crystal habit, the conceptual theory of preferential ice crystal habit and the presence of TSSN cannot be verified; however, the TSSN SLR results from this study adds evidence to the potential relationship between ice crystal habit and electrified snowfall. Furthermore, the high resolution derived SLR values are complimentary to future studies regarding potential ice crystal habit studies of mid-latitude wintertime cyclones; however, the derived SLR values were computationally expensive compared to interpolating COOP SLR values. As a
result, future studies should use the COOP SLR values as a first guess then explore the derived SLR values for detailed analysis.

Even though this study was temporally limiting compared to Crowe et al. (2006), the results were similar in suggesting that TSSN does not occur in the highest snowfall accumulations. Crowe et al. (2006) found that TSSN tend to be associated with events with accumulation totals greater than 5.90-in and approximately represents the 14th percentile in the TSSN snowfall accumulation distribution. The discrepancy between these two results was likely based on the TSSN identification process (i.e., sound audibility vs. optical light); thus suggesting that the TDA impacts the total accumulation distribution compared to using only METAR reports of TSSN. In comparison and similar to Market and Becker (2009), it was found that TSSN does not occur in the heaviest snowfall rates. Figure 3.8a demonstrates the locations of snowfall rates greater than 1.75-in hr$^{-1}$ with regards to all TSSN flashes observed by GLM which results in a mean distance between the heaviest snowfall rates and TSSN of 124±65-km. In contrast, Fig. 3.8b depicts the distribution snowfall rates with regards to TSSN flashes detected by GLM for the 13-17 April 2018 blizzard and suggests that TSSN is more likely to occur northeast of the heaviest snowfall rates and is similar to Market and Becker (2009) in which they found that two-thirds of lightning flashes in snow bands occur downstream from the very highest radar reflectivities. One plausible explanation for the separation of heaviest snowfall rates and the occurrence of TSSN is the heavy-banded snowfall formation concept model (Fig. 15 in Moore and Graves 2005). Heavy-banded snowfall partially occurs because of a slantwise circulation caused by mid-level frontogenesis (i.e., a region of
enhanced vertical velocity) and is on the northern extent of convective instability. Conceptually, TSSN occurring in this study (i.e., equator-side of the major axis of snow bands) and in Market and Becker (2009) (i.e., leading edge of snow band) are within this region. As a proof of concept, mean mid-level (i.e., 850-600-hPa) frontogenesis derived from the High-Resolution Rapid Refresh (HRRR; Alexander et al. 2010; Blaylock et al. 2017) model data was plotted alongside TSSN flashes observed by GLM and demonstrates that TSSN is occurring in regions of higher mean mid-level frontogenesis along the Minnesota/Iowa border (Fig. 3.9). Therefore, it can be suggested that TSSN occurs in regions where enhanced mid-level frontogenesis exists but is beyond the scope of this study and warrants future investigation.

3.0.6.2 TSSN Lightning Characteristics

Of all the results within this study, the tower TSSN flashes identified by GLM stand out with regards to: SLR values, snowfall rates, isotherm reflectivity, VII, and VIL. Tower TSSN flashes occurred in higher snowfall rates and SLR values; while also occurring in regions with lower isotherm reflectivity, VIL, and VII compared to non-tower and IC-only TSSN flashes observed by GLM. The enhancement of the electric field, caused by the higher snowfall rates and more ice crystal collision (i.e., charge transfer), and the fact that the negative charge center in winter storms are lower cause the dielectric breakdown and is a plausible reason why tower TSSN flashes is more preferential in winter storms compared to summer convection (Schultz et al. 2019, accepted, pending revisions). Together, the low values in VII and VIL resulted in further evidence that tower TSSN flashes observed by GLM were more likely to occur
in snowfall associated with higher SLR values because dendrites have a low density compared to other ice crystal and have a smaller degree of riming (Heysfield 1972; Colle et al. 2014). Given the relationship between reflectivity and updraft velocity (e.g., Kollias et al. 2001), it can be assumed that IC-only TSSN flashes were associated with slightly stronger updrafts than those associated with CGs. Stronger updrafts result in higher charging rates that produce greater amounts of smaller flashes and aligns with results in Harkema et al. (2019) where they found IC-only TSSN flashes observed with GLM were on average spatially smaller compared to TSSN flashes associated with CGs; however, further study is need to confirm this.

3.0.7 Conclusion

The development of the TDA allows for the objective characterization of TSSN from a GLM perspective and enhances the fundamental understanding of processes associated with heavy-snowfall. Societal impacts of heavy-snowfall vary by region but the objective characterization of TSSN beyond traditional ground-based observations is an opportunity to further explore fundamental understanding and processes that create lightning in snowfall events. It was found that TSSN SLR values were statistically significant (p<0.01) compared to the derived SLR values; on average, TSSN occurred in a SLR value of 13.06 but is more likely to occur between SLR values of 8:1-9:1. This suggests that TSSN was more likely to be associated with ice particles that have some degree of riming. Furthermore, it was found that tower TSSN flashes observed by GLM occurred in the highest median SLR value (12.40) and IC-only TSSN flashes were associated with the lowest median SLR value (9.86). This study
also adds further evidence that TSSN does not occur in the highest snowfall rates and occurred within a mean snowfall rate, assuming 10:1 SLR, of 0.71-in hr⁻¹; adjusting the snowfall rates to be more aligned with the derived SLR values resulted in a TSSN mean estimated snowfall rate of 0.88-in hr⁻¹. Tower TSSN flashes occurred in the highest mean snowfall rates (i.e., 0.77-in hr⁻¹). No statistically significant differences were found when examining the TSSN categories with regards to total snowfall accumulation; however, when snowfall accumulation is expected, TSSN occurred in areas that will receive on average 9.81-in of snowfall accumulation.

The 13-17 April 2018 blizzard was utilized to examine the potential capability to predict and further characterized TSSN. MRMS VII, VIL, and isotherm reflectivity values were examined in and around the Iowa/Minnesota/South Dakota border region. In this case study, the mean -10, -15, -20°C isotherm reflectivities associated with TSSN flashes observed by GLM were: 21.86-, 21.17-, and 20.03-dBZ respectively. TSSN flashes observed by GLM were also associated with mean values of 1.44- and 0.53-kg m⁻² for VII and VIL respectively. Comparing the MRMS variables for the different TSSN categories, it was found that tower TSSN flashes and IC-only TSSN flashes detected by GLM were statistically significant for isotherm reflectivity (p<0.05), VII (p<0.05), and VIL (p<0.01); furthermore, tower TSSN flashes occurred within the lowest mean isotherm reflectivity, VII, and VIL compared to the other TSSN categories.
Table 3.1: Comparison of SLR values.

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Mean</th>
<th>Median</th>
<th>25&lt;sup&gt;th&lt;/sup&gt; Percentile</th>
<th>75&lt;sup&gt;th&lt;/sup&gt; Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Derived SLR estimate</td>
<td>14.52</td>
<td>12.57</td>
<td>9.05</td>
<td>17.71</td>
</tr>
<tr>
<td>Difference</td>
<td>-0.99</td>
<td>-0.43</td>
<td>0.21</td>
<td>-1.04</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>-7.05</td>
<td>-3.48</td>
<td>2.29</td>
<td>-6.05</td>
</tr>
</tbody>
</table>

Table 3.2: TSSN Flash Characteristics Observed by GLM

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>25&lt;sup&gt;th&lt;/sup&gt; Percentile</th>
<th>75&lt;sup&gt;th&lt;/sup&gt; Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow-to-Liquid Ratio</td>
<td>13.06</td>
<td>10.94</td>
<td>8.50</td>
<td>15.97</td>
</tr>
<tr>
<td>Snowfall Rates (in hr&lt;sup&gt;-1&lt;/sup&gt;; 10:1)</td>
<td>0.71</td>
<td>0.69</td>
<td>0.57</td>
<td>0.82</td>
</tr>
<tr>
<td>Estimated Snowfall Rates (in hr&lt;sup&gt;-1&lt;/sup&gt;)</td>
<td>0.88</td>
<td>0.75</td>
<td>0.56</td>
<td>1.04</td>
</tr>
<tr>
<td>Snowfall Accumulation (in)</td>
<td>9.81</td>
<td>9.69</td>
<td>7.60</td>
<td>11.59</td>
</tr>
<tr>
<td>Vertically Integrated Ice (kg m&lt;sup&gt;-2&lt;/sup&gt;)</td>
<td>1.44</td>
<td>1.34</td>
<td>1.14</td>
<td>1.65</td>
</tr>
<tr>
<td>Vertically Integrated Liquid (kg m&lt;sup&gt;-2&lt;/sup&gt;)</td>
<td>0.53</td>
<td>0.47</td>
<td>0.36</td>
<td>0.65</td>
</tr>
<tr>
<td>Isotherm Reflectivity (-10°C; dBZ)</td>
<td>21.85</td>
<td>22.12</td>
<td>19.66</td>
<td>24.37</td>
</tr>
<tr>
<td>Isotherm Reflectivity (-15°C; dBZ)</td>
<td>21.17</td>
<td>21.49</td>
<td>19.19</td>
<td>23.65</td>
</tr>
<tr>
<td>Isotherm Reflectivity (-20°C; dBZ)</td>
<td>20.04</td>
<td>20.22</td>
<td>18.33</td>
<td>22.63</td>
</tr>
</tbody>
</table>
**Table 3.3: TSSN Flash Characteristics Observed by GLM by TSSN Category**

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>TSSN Category</th>
<th>Mean</th>
<th>Median</th>
<th>25&lt;sup&gt;th&lt;/sup&gt; Percentile</th>
<th>75&lt;sup&gt;th&lt;/sup&gt; Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow-to-Liquid Ratio</td>
<td>No NLDN</td>
<td>14.08</td>
<td>11.46</td>
<td>8.66</td>
<td>16.15</td>
</tr>
<tr>
<td></td>
<td>NLDN</td>
<td>12.79</td>
<td>10.36</td>
<td>8.34</td>
<td>15.89</td>
</tr>
<tr>
<td></td>
<td>IC-Only</td>
<td>12.09</td>
<td>9.86</td>
<td>8.29</td>
<td>14.24</td>
</tr>
<tr>
<td></td>
<td>Tower</td>
<td>13.74</td>
<td>12.40</td>
<td>8.81</td>
<td>16.74</td>
</tr>
<tr>
<td></td>
<td>Non-tower</td>
<td>12.73</td>
<td>9.97</td>
<td>8.21</td>
<td>15.98</td>
</tr>
<tr>
<td>Snowfall Rate (in hr&lt;sup&gt;-1&lt;/sup&gt;; 10:1)</td>
<td>No NLDN</td>
<td>0.70</td>
<td>0.67</td>
<td>0.55</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>NLDN</td>
<td>0.72</td>
<td>0.70</td>
<td>0.59</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>IC-Only</td>
<td>0.67</td>
<td>0.65</td>
<td>0.55</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Tower</td>
<td>0.77</td>
<td>0.75</td>
<td>0.63</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Non-tower</td>
<td>0.73</td>
<td>0.71</td>
<td>0.59</td>
<td>0.85</td>
</tr>
<tr>
<td>Estimated Snowfall Rate (in hr&lt;sup&gt;-1&lt;/sup&gt;)</td>
<td>No NLDN</td>
<td>0.89</td>
<td>0.77</td>
<td>0.56</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>NLDN</td>
<td>0.87</td>
<td>0.74</td>
<td>0.56</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>IC-Only</td>
<td>0.77</td>
<td>0.64</td>
<td>0.50</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>Tower</td>
<td>1.00</td>
<td>0.90</td>
<td>0.67</td>
<td>1.09</td>
</tr>
<tr>
<td></td>
<td>Non-tower</td>
<td>0.87</td>
<td>0.74</td>
<td>0.56</td>
<td>1.01</td>
</tr>
<tr>
<td>Snowfall Accumulation (in)</td>
<td>No NLDN</td>
<td>9.85</td>
<td>9.70</td>
<td>7.69</td>
<td>11.59</td>
</tr>
<tr>
<td></td>
<td>NLDN</td>
<td>9.75</td>
<td>9.66</td>
<td>7.37</td>
<td>11.59</td>
</tr>
<tr>
<td></td>
<td>IC-Only</td>
<td>9.47</td>
<td>9.50</td>
<td>7.58</td>
<td>10.42</td>
</tr>
<tr>
<td></td>
<td>Tower</td>
<td>9.89</td>
<td>9.74</td>
<td>6.57</td>
<td>12.99</td>
</tr>
<tr>
<td></td>
<td>Non-tower</td>
<td>9.84</td>
<td>9.79</td>
<td>7.51</td>
<td>11.67</td>
</tr>
</tbody>
</table>
Figure 3.1: SLR value distributions from A) Baxter et al. (2005) (Fig. 9) and B) derived SLR value estimates. The long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25th and 75th percentiles. The orange line in B) represents the best-fit gamma function for the derived SLR value distribution.
Figure 3.2: A) Distribution of SLR values associated with TSSN. Orange line represents the best-fit gamma function and the long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25th and 75th percentiles. B) Box and whisker plots of SLR values by TSSN category.
Figure 3.3: A, C) Distribution of snowfall rates and estimated snowfall rates associated with TSSN. Orange line (A) represents the best-fit Gaussian function, (B) represents the best-fit gamma function and the long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25th and 75th percentiles. C, D) Box and whisker plots of snowfall rates and estimated snowfall rates by TSSN category.
**Figure 3.4:** A) Distribution of snowfall accumulations associated with TSSN. Orange line represents the best-fit Gaussian function and the long dashed line represents the median, the short dashed line represents the mean and the solid lines represent the 25\textsuperscript{th} and 75\textsuperscript{th} percentiles. B) Box and whisker plots of snowfall accumulation by TSSN category.

**Figure 3.5:** A) Total snowfall accumulation, B) Total mSFR liquid equivalent estimation, C) derived SLR estimate, and D) linearly interpolated COOP SLR values for the 13-17 April 2018 blizzard.
**Figure 3.6**: Box and whiskers for MRMS derived isotherm reflectivity, VII, and VIL values associated with TSSN flashes observed by GLM.

**Figure 3.7**: Box and whisker plots for the different TSSN categories (i.e., No NLDN, NLDN, IC-only, Tower, and Non-tower) for A) -10°C Isotherm reflectivity, B) -20°C Isotherm reflectivity, C) VII, and D) VIL.
Figure 3.8: Polar plots of frequency of snowfall rates greater than 1.75-in hr$^{-1}$ for A) all TSSN flashes observed by GLM and B) TSSN flashes observed by GLM for the 13-17 April 2018 blizzard.

Figure 3.9: HRRR-derived mean mid-level (850-600-hPa) frontogenesis at 1300 UTC on 14 April 2018 overlaid with TSSN flashes observed by GLM (black dots) that occurred between 1300 UTC and 1310 UTC. Wind barbs represent mid-level (850-600-hPa) bulk shear.
While previous studies have subjectively identified TSSN using METAR reports and ground-based lightning detection, the onset of GLM and the TDA allows for the objective identification and characterization of TSSN. Twenty-one snowfall cases from January-April 2018 were collected and 18 of those cases involved 53,408 potential TSSN flashes observed by GLM. When these flashes were compared to METAR TSSN reports, the TDA resulted in a POD of 87.2% and adds evidence that TSSN is more likely to occur in the Intermountain West, Great Plains, and Great Lakes regions. Furthermore, GLM flashes with a mSFR pixel count of 700 or greater were objectively classified as TSSN (N=2,176). Comparing the objectively classified TSSN flashes observed by GLM to Rudlosky et al. (2019), resulted in TSSN flashes being optically brighter, spatially larger, and having long durations compared to non-TSSN flashes over ocean and land. Just over 50% of TSSN flashes detected by GLM correspond spatially and temporally with at least one NLDN flash and were classified as non-tower (N=587), tower (N=152), and IC-only (N=356). When examining GLM flash area and flash energy, it was found that GLM flashes that correspond with NLDN data were statistically significantly different (P<0.05) compared GLM flashes.
that did not correspond with NLDN data. The GLM flashes with no NLDN data correspondence were found to be statistically more likely to be classified as IC-only compared to be associated with at least one CG; suggesting, that GLM was more likely to detect IC TSSN flashes that NLDN could not detect. The lack of correspondence between GLM and NLDN was likely associated with the splitting of TSSN flashes by the GLM flash clustering algorithm and the lower detection efficiency of ICs from NLDN.

When examining the potential relationship between SLR values and TSSN it was found that TSSN occurred on average in a SLR value of 13.06 but was more likely to occur in SLR values between 8:1 and 9:1; suggesting that TSSN was more likely associated with ice particles that had some degree of riming. Additionally, it was found that tower TSSN flashes detected by GLM occurred in the highest median SLR value and IC-only TSSN flashes occurred in the lowest mean SLR value. Similar to previous research, it was found that TSSN did not occur in the heaviest snowfall rates and on average were associated with snowfall rates of 0.71-in hr$^{-1}$; however this value assumes a constant 10:1 SLR value. Adjusting the snowfall rates to account for the estimated derived SLR value resulted in a mean snowfall rates closer to 0.88-in hr$^{-1}$. IC-only TSSN flashes observed by GLM occurred in the lowest mean adjusted snowfall rate (0.77-in hr$^{-1}$); while tower TSSN flashes detected by GLM occurred in the highest mean adjusted snowfall rate (1.00-in hr$^{-1}$). No statistically significant differences (P>0.10) exist when examining the different TSSN categories to the total snowfall accumulation; however, when snowfall accumulation was expected, TSSN occurred on average in locations that would receive 9.81-in of snowfall accumul-
tion. Examining the 13-17 April 2018 blizzard, it was found that TSSN occurred in
isotherm reflectivities values less than 27-dBZ with mean VII and VIL values of 1.44-
and 0.53-kg m$^{-2}$ respectively. It was also determined that tower TSSN flashes ob-
served by GLM were statistically significant (P<0.05) for isotherm reflectivity, VIL,
and VII and occurred in the lowest mean values of these variables. Therefore, tower
TSSN flashes identified by the TDA standout with regards to SLR values, snowfall
rates, isotherm reflectivity, VII, and VIL compared to the other TSSN categories and
warrants further study. Overall, this study builds upon previous research by utilizing
geosynchronous lightning observations to objectively identify TSSN and provides the
initial steps to examine this phenomena on a large scale from a microphysical and
thermodynamic perspective.
REFERENCES


