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COMPARING MRMS DATA TO SINGLE RADAR DATA TO IMPROVE SEVERE THUNDERSTORM WARNINGS

JENNIFER ANNA D'IORIO
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Reviewed and approved* by the following:

Matthew R. Kumjian
Associate Professor of Meteorology and Atmospheric Science
Thesis Supervisor

Johannes Verlinde
Professor of Meteorology and Atmospheric Science
Honors Adviser

* Signatures are on file in the Schreyer Honors College.

ABSTRACT

Improvements to the forecasting of hail, especially severe hail (≥1inch in maximum dimension), can lead to advancements in the issuance of severe thunderstorm warnings. This improvement will not only aid National Weather Service (NWS) forecasters in severe storm verification and credibility, but will support their continued mission to protect life and property. The Multi-Radar/Multi-Sensor System (MRMS) developed at the National Severe Storms Laboratory (NSSL) has been used operationally by NWS forecasters since 2016. By rapidly integrating data from multiple platforms including radar, satellite, observational data, and numerical weather prediction models, MRMS can provide valuable and robust severe weather products to NWS forecasters. An independent sample of hail-producing thunderstorms that occurred across central North Carolina and central South Carolina from 2017, 2018, and 2019 was examined. A statistical analysis of MRMS products (NSSL Archive), including the Maximum Expected Size of Hail (MESH), was performed on the data. A statistical analysis was also completed on the GR2Analyst Hail Algorithm (Gibson Ridge Software) using Level-II single radar data retrieved from the National Centers for Environmental Information archive. A Contingency Table of Absolute Frequencies was made using the forecasted hail size from each product and the observed hail size for each event. The Probability of Detection (POD), Critical Success Index (CSI), False Alarm Rate (FAR), Hit Rate, and bias were calculated, and a comparison of these calculations from both products was performed. As hypothesized, it was determined that MESH from MRMS is more successful in accurately forecasting severe hail. The purpose of the analyses was to quantify the potential statistical correlations between the products and the occurrence of severe hail, determine product severe hail forecast skill, and any biases.

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Chapter 1
Introduction

Hail is a common type of severe convective weather throughout the world, especially in the U.S. However, little attention has been given to forecasting hail when compared to forecasting damaging winds and tornadoes (Brimelow and Jewell 2009). Death and severe damage to property, although not as imminent when compared to the effects of strong tornadoes, can result from severe hail (Brimelow and Jewell 2009). The annual damage due to hail in 1999 in the U.S. was an estimated $1.2 billion, accounting for both property and crop loss, and has likely increased since then (Cintineo et al. 2012). Improvements to the forecasting of hail, especially severe hail (≥1inch in maximum dimension), can lead to advancements in the issuance of severe thunderstorm warnings. This improvement will not only aid National Weather Service (NWS) forecasters in severe storm verification and credibility with their forecasts due to increased accuracy, but will support their continued mission to protect life and property. The study of two different types of radar data, the Multi-Radar/Multi-Sensor System (MRMS) products and Level-II single radar data as displayed in Gibson Ridge Software (GR2Analyst), and their respective hail algorithm outputs, was investigated. This allowed for the determination of which product is more accurate in forecasting severe hail, improving operational abilities and therefore the issuance (or non-issuance) of severe thunderstorm warnings.

Previous attempts to forecast hail have proven to be challenging due to hail growth being extremely complex and dependent on parameters and processes not well observed (Brimelow and Jewell 2009). Radar-based methods for detection of hail exist, but are only useful once storms have formed, and therefore are unable to predict hail formation (Brimelow and Jewell 2009). Forecasting hail size has been attempted through the use of various environmental parameters, including convective available potential energy (CAPE), height of the environmental 0°C level, and updraft velocity. However, the use of these methods allowed for forecasting of unrealistically large hail sizes and lack of differentiation between small and large hail (Brimelow and Jewell 2009). This study presents the discovered benefits in using radar systems and their respective hail detection algorithms in forecasting severe hail, as well as the determination of which radar system is more skillful in detecting this hail formation.

The Multi-Radar/Multi-Sensor System (MRMS; Smith et al. 2016) developed at the National Severe Storms Laboratory (NSSL) has been used operationally by NWS forecasters since 2016. It rapidly integrates data from multiple platforms, including radar (143 WSR-88D radars across the U.S.), satellite (GOES series), observational data (terrain elevation, National Lightning Detection Network, etc.) and numerical weather prediction models (surface and upper-air analysis from the rapid refresh model; Smith et al. 2016). These various data sets are produced at high resolution on the CONUS scale, but can be sized to a certain area of interest for greater specificity. MRMS can provide valuable and robust severe weather products to NWS forecasters. Products that can aid forecasters in determining storm strength and the likelihood of severe hail formation include the Maximum Expected Size of Hail (MESH; Witt et al. 1998), Vertically Integrated Ice (VII; Carey and Rutledge 2000), Echo Top Heights (Richter and Deslandes 2007)**,** reflectivity values at various isotherms (Tilly et al. 2006), and many more (Smith et al. 2016). MESH, specifically, shows the spatial extent and radar-inferred distribution of hail sizes within a thunderstorm at a given time within a particular storm.

The GR2Analyst is a NexRad Level-II application (data retrieved from single WSR-88D radars) with high-resolution derived products, including the GR2Analyst Hail Algorithm (Gibson 2018). GR2Analyst has features including dual-polarization data, cross sections, volumetric display, and high-resolution derived products, including Echo Tops and MEHS (Gibson 2018). The GR2Analyst Hail Algorithm, or Maximum Expected Hail Size (MEHS), is adapted from the NWS WSR-88D radar Hail Detection Algorithm (HDA). The HDA determines a storm's hail potential based on the creation of a vertical reflectivity profile (height and maximum reflectivity of each storm component) for the storm cell (Witt et al. 1998). MEHS was formulated such that 75% of the hail observations would be less than the value predicted by the product since it is to forecast maximum expected hail size (Witt et al. 1998). Although MEHS can increase a forecaster's situational awareness of severe hail, limitations to the algorithm have been identified. Specifically, the algorithm was not designed to predict the exact deterministic size of hail. Rather, it over-predicts the true severe hail size by design, as stated above (Ortega et al. 2009, Ortega 2018, Murillo and Homeyer 2019). As a result, although it can be a useful forecasting tool for increasing confidence on the existence of large hail size, MEHS can allow for high false alarm rates when used on its own, and is best utilized when combined with other forecasting methods and techniques (Frugis and Wasula 2011).

Research has proven that utilizing data from multiple radars, which is done in the MRMS system, can be extremely beneficial for analyzing storm structures and characteristics. Using reflectivity from multiple radars overcomes deficiencies in coverage due to radar beam geometry (storms at far ranges from the radar may not be adequately sampled), cone of silence issues, volume coverage pattern selection, and/or beam blockages from terrain or other obstructions (Ortega 2018). Regarding hail detection algorithm performance, it has been shown that multi-radar MESH techniques substantially outperform single radar hail detection algorithm techniques (Cintineo et al. 2012). Further research is therefore needed to analyze the performance of these radar systems and their capabilities in accurately detecting hail, especially severe hail.

An independent sample of hail-producing thunderstorms that occurred across central North Carolina and central South Carolina from 2017, 2018, and 2019 was examined. An analysis was completed on both MRMS and GR2Analyst products to quantify the potential statistical correlations between the products and the occurrence of severe hail, determine product severe hail forecast skill, and any biases. The determination of the discriminating product values between non-severe and severe hail would be ascertained, hopefully leading to improved severe thunderstorm warnings. As a result of prior knowledge, background information, and observations, it was predicted that the MESH product from MRMS is more successful in accurately forecasting severe hail when compared to MEHS from GR2Analyst.

Chapter 2
Data and Methodology

Data were requested from the National Centers for Environmental Information (NCEI) NEXRAD Radar Data (Level-II) Archive site. These data included 82 individual cases where hail was observed/reported within range of the KCAE WSR-88D (Columbia, S.C.) radar site and 72 individual cases where hail was observed/reported within range of the KRAX WSR-88D (Raleigh, N.C.) radar site (154 cases in total). The DOS command prompt was used to download the radar data from these 154 cases onto a desktop computer. Data were then imported into GR2Analyst for further analysis. The Iowa Environmental Mesonet (IEM) Cow, or NWS Storm Based Warning Verification site, was referenced in order to record specific information regarding the 154 observed hail cases, including the time of the storm/hail report, the latitude and longitude at which the hail was found, the county in which the hail was found, etc. It also assisted in recognition of the exact location of the hail report on a well-defined geographical map for easier detection in GR2Analyst. After the radar data for a specific case from NCEI was loaded into GR2Analyst (Figure 1), the MEHS output data between 20 minutes before the hail report time, through 5 minutes after the hail report time, in the exact location of the recorded hail report, was investigated. The reason for applying this 25-minute window, in similarity with Frugis and Wasula (2011), was to account for any errors in both space and time that may have occurred during the hail reporting procedure. Some of these errors in hail reporting have been identified in Allen and Tippett (2015). This process ensured that the most accurate values for the hail detection algorithm output were selected. The highest value of MEHS during this time period, the date and time (UTC) of this maximum MEHS output, and the lead time (how many minutes between the highest MEHS value and the observed hail report), were recorded.

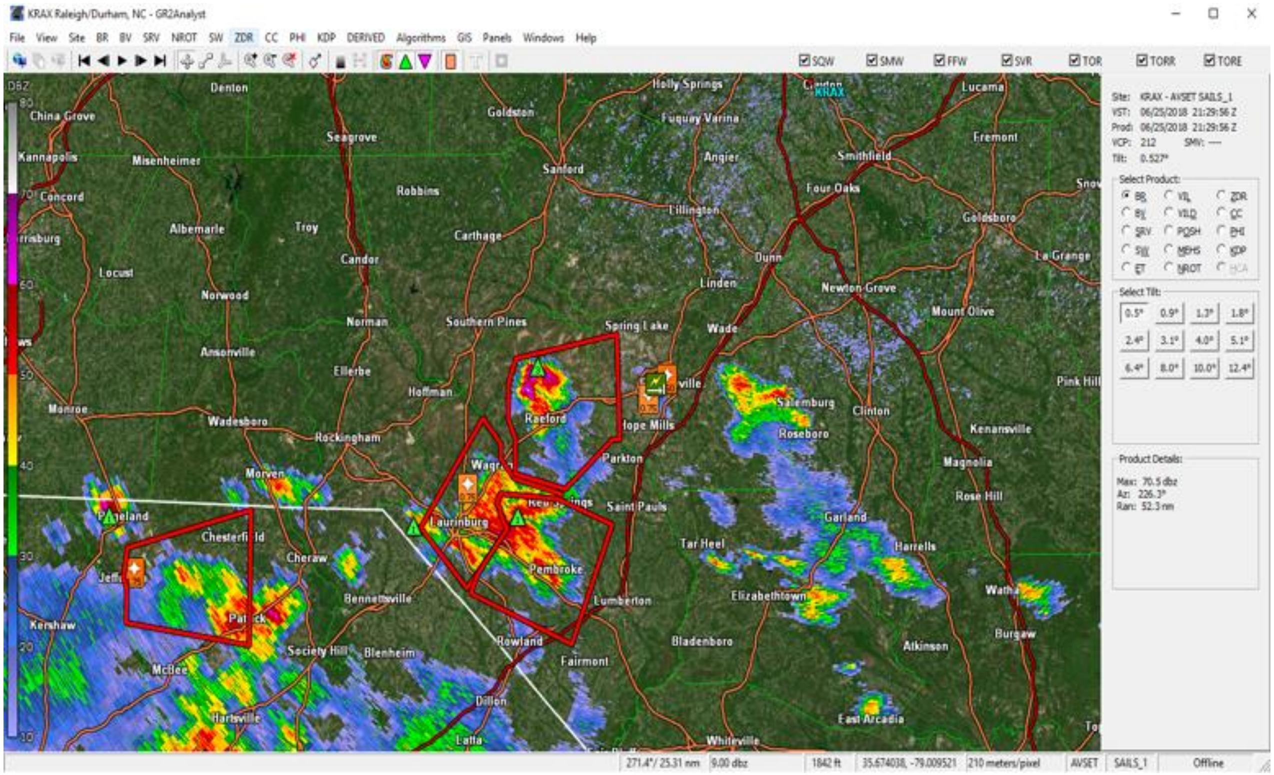

Figure 1: GR2Analyst Product Display

Example of GR2Analyst Hail Algorithm (MEHS) output (for specific RAH case (6/25/18 21:30, Ashley Heights in Hoke County, N.C.) Reflectivity is displayed, red polygons indicate severe thunderstorm warnings issued by the local NWS office, and the green triangles indicate the MEHS output for a given storm at the specific time.

The developmental version of the vMRMS Product Viewer from NSSL (Figure 2) was used to collect and analyze MRMS data and products for 163 specific cases where hail was observed/reported in both the Columbia S.C. (CAE) and Raleigh, N.C. (RAH) County Warning Areas. MRMS products that were recorded include Vertically Integrated Liquid (VIL), Vertically Integrated Liquid Density, Vertically Integrated Ice (VII), Maximum Expected Size of Hail (MESH), Reflectivity at 0°C and -20°C, Height of 50 dBZ above 0°C and -20°C, Height of 60 dBZ above 0°C and -20°C, and the height of the 0°C level. After selecting the specific MRMS parameter in the product viewer and the time/date of the hail report (after referencing IEM Cow), the location of the observed hail report in the County Warning Area was found using Google

Maps. The maximum value of the MRMS product between 20 minutes before the hail report time through 5 minutes after the hail report time (again following a procedure similar to Frugis and Wasula 2011), at the exact latitude and longitude of the observed hail report, was recorded. The date and time (UTC) of when this maximum value occurred was also recorded. For both the GR2Analyst cases as well as the MRMS cases, any observed hail report that did not seem to logically match up with the radar data and its derived hail algorithm products was thrown out to preserve consistency from case to case, as well as to maintain the integrity of the study. This was completed following the guidance presented by Frugis and Wasula (2011).

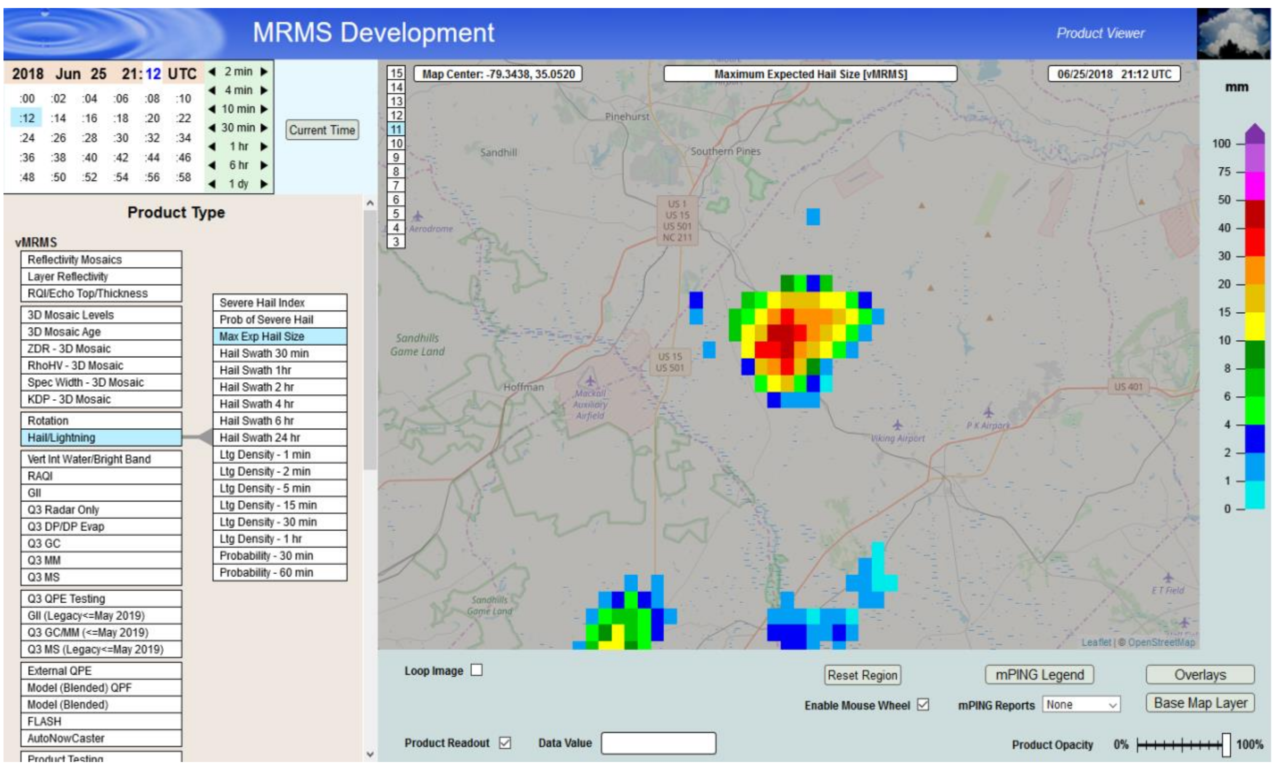

Figure 2: MRMS Product Display

Example of vMRMS product viewer MESH output for specific RAH case (6/25/18 21:30, Ashley Heights in Hoke County, N.C.)

Chapter 3
Results

Box-and-whisker plots were produced for the 163 MESH cases (Figure 3) and 154 MEHS cases (Figure 4) to show the data distributions of each product in detecting both non-severe and severe hail events. The box is the middle 50% of the distribution, the top whisker extends to the 90th percentile, and the bottom whisker extends to the 10th percentile. The plots were produced in a manner corresponding to the methods in Brimelow and Jewell (2009). To test their model's ability in discriminating between SIG (≥2inches in maximum dimension) and NON-SIG (<2inches in maximum dimension), they divided their dataset into two subsets based on hail maximum dimension. In this study, we also divided our dataset into two subsets: hail maximum dimension ≥1inch, and hail maximum dimension <1inch. This was done to determine the abilities of both MESH and MEHS in discriminating between severe and non-severe hail cases, respectively.

The interquartile range (IQR) for the MESH severe cases is mainly above 1inch, with positive skewness (Figure 3). The IQR for the MESH non-severe cases includes some near 1inch. The medians are statistically significantly different because the 95% confidence intervals are separated. When significant interquartile separation exists between the two groups, as seen with the MESH groups in Figure 3, it is indicative that the hail detection algorithm possesses skill in discriminating between severe and non-severe cases. MEHS shows the IQR of severe cases largely above 1inch, with its median value close to 2inches. Non-severe cases have an IQR above 1inch in as well with a median value near 1.5inch, indicating an overestimation of hail size. The medians differ slightly since the 95% confidence intervals are separated, but not as separated as the MESH.

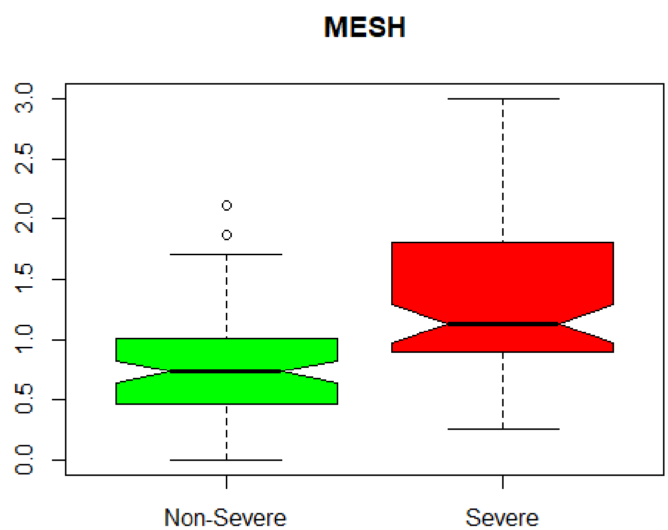

Figure 3: MESH Box and Whisker Plot

Box and whisker plots for both severe (red) and non-severe (green) hail events for MESH. The y-axis indicates maximum hail dimension. Notch indicates 95% confidence interval for median and circles are outliers

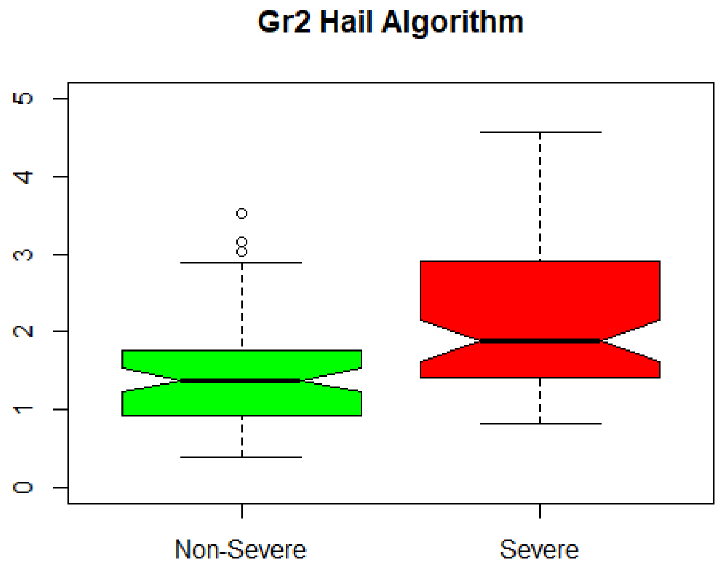

Figure 4: GR2Analyst Box and Whisker Plot

Box and whisker plots for both severe (red) and non-severe (green) hail events for MEHS (GR2Analyst Hail Algorithm). The y-axis indicates maximum hail dimension. Notch indicates 95% confidence interval for median and circles are outliers.

A Contingency Table of Absolute Frequencies, which displays the possible combinations of forecasts and event pairs, was produced for both the MESH and MEHS cases (Table 1). Our statistical methods followed the approach of Wilks (1995). For MESH, out of the 163 cases from CAE and RAH, there were 49 HIT events (severe hail was predicted by the hail detection algorithm and was observed), 24 False Alarm Events (severe hail was predicted by the hail detection algorithm but not observed), 32 MISS events (severe hail was not predicted by the hail detection algorithm but was observed and reported), and 58 non-severe cases (severe hail was not predicted by the hail detection algorithm nor observed). Meanwhile, out of the 154 MEHS cases, there were 67 HIT events, 56 False Alarm Events, 6 MISS Events, and 25 non-severe events.

Table 1: Continency Tables of Absolute Frequencies

Contingency Tables of Absolute Frequencies for 163 MRMS MESH cases and 154 MEHS (GR2Analyst Hail Algorithm) cases.

		Severe Hail Observed	
Severe Hail		Y	N
Forecasted	Y	49	24
by MESH	N	32	58

		Severe Hail Observed	
Severe Hail		Y	N
Forecasted	Y	67	56
by GR2	N	6	25

From here, the POD, or Probability of Detection (fraction of occasions when severe hail event occurred when it was also forecasted, best being equal to 1), CSI, or Critical Success Index (number of correct forecasts divided by number of occasions in which a severe hail event was forecasted and/or observed, best being equal to 1), the FAR, or False Alarm Rate (proportion of events that forecasted severe hail when it was not actually observed, best being equal to 0), and Hit Rate (fraction of events when the product forecast accurately anticipated the severe/non-severe hail event, best being equal to 1) were calculated for both MESH and MEHS (Wilks 1995). These values, as well as values from the contingency tables, are displayed in the form of scatter plots for MESH (Figure 5) and MEHS (Figure 6) similarly to the methods used by Brimelow and Jewell (2009). MISS events are plotted in the upper left-hand corner of the graph, HIT events in the upper right-hand corner of the graph, False Alarm events in the bottom right hand corner of the graph, and non-severe events in the bottom left hand corner of the graph. In both cases, MESH and MEHS exhibit a positive correlation with the observed hail size, and events falling on the line can be considered a perfect forecast (Brimelow and Jewell 2009). Events to the left of the line indicate hail occurrences where maximum dimension was under forecasted by the hail detection algorithm, while events to the right of the line indicate hail occurrences where maximum dimension was over forecasted by the respective algorithm. Figure 6 demonstrates the extremely large over-forecasting bias by MEHS, with most events falling to the right of the perfect forecast line.

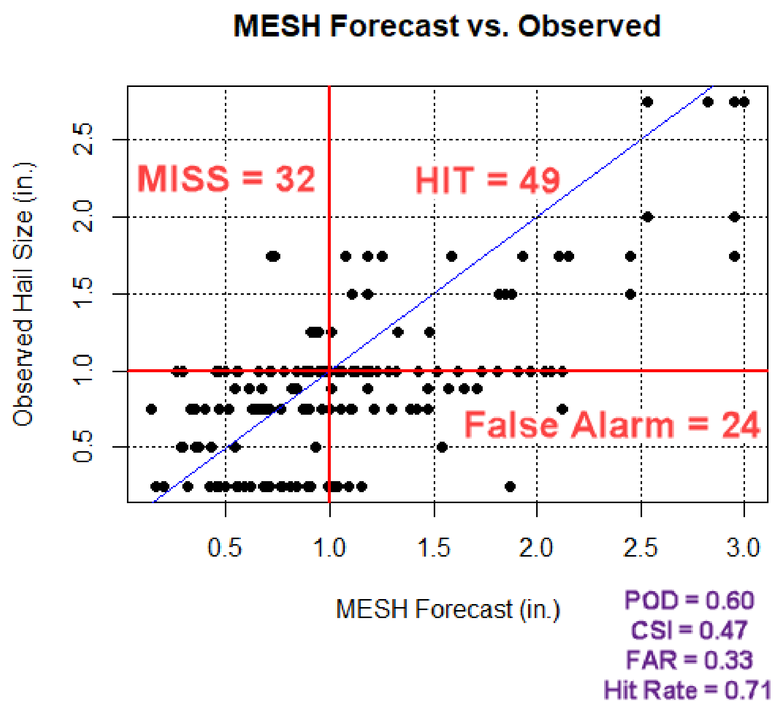

Figure 5: MESH Scatter Plot

MESH forecasted hail size vs observed hail size.

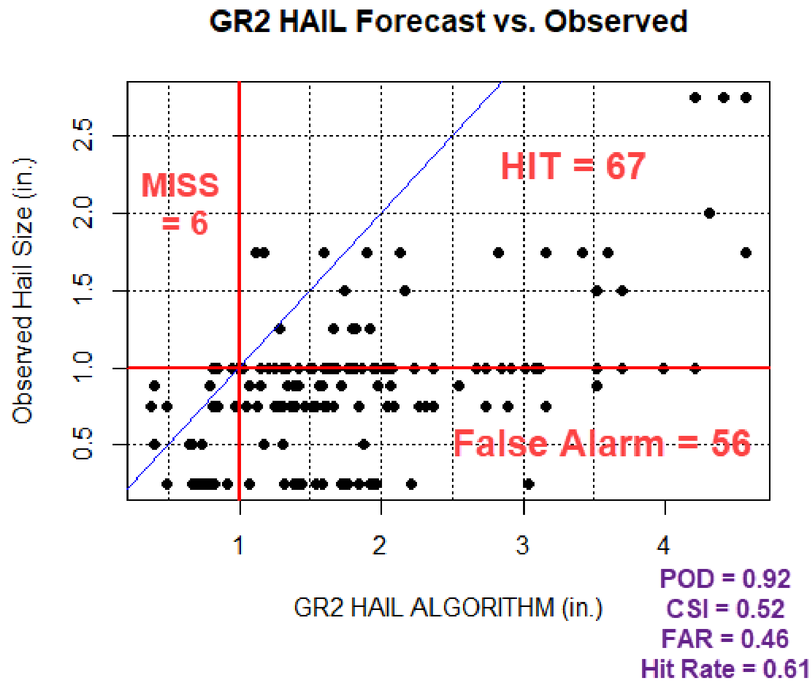

Figure 6: GR2Analyst Scatter Plot

MEHS (GR2Analyst Hail Algorithm) forecasted hail size vs observed hail size.

In an attempt to improve these statistics, a bias (a comparison of the average forecast with the average observation, where B=1 indicates a perfect forecast, B>1 indicates over forecasting, and B<1 indicates under forecasting) was calculated for both MESH (B=.90) and MEHS (B=1.68). Bias calculations hint at a drastic overestimation by MEHS. A contingency table was then produced for both the bias-corrected MESH and bias-corrected MEHS (Table 2).

Table 2: Contingency Table of Absolutely Frequency (Bias-Corrected)

Contingency Tables of Absolute Frequencies for 163 MRMS MESH cases and 154 MEHS (GR2Analyst Hail Algorithm) cases (bias-corrected).

		Severe Hail Observed	
Severe Hail		Y	N
Forecasted	Y	58	31
by MESH (bias)	N	21	53

		Severe Hail Observed	
Severe Hail		Y	N
Forecasted	Y	45	25
by GR2 (bias)	N	27	57

These numbers can be interpreted in the same way as the prior contingency tables stated above. The POD, CSI, FAR, and Hit Rate was also calculated for both bias-corrected products, and again displayed in graphical form for MESH (Figure 7) and MEHS (Figure 8). It has been suggested that applying a bias correction to the hail detection algorithms will result in improved reliability and accuracy in each product's individual forecasting of maximum hail size (Brimelow and Jewell 2009).

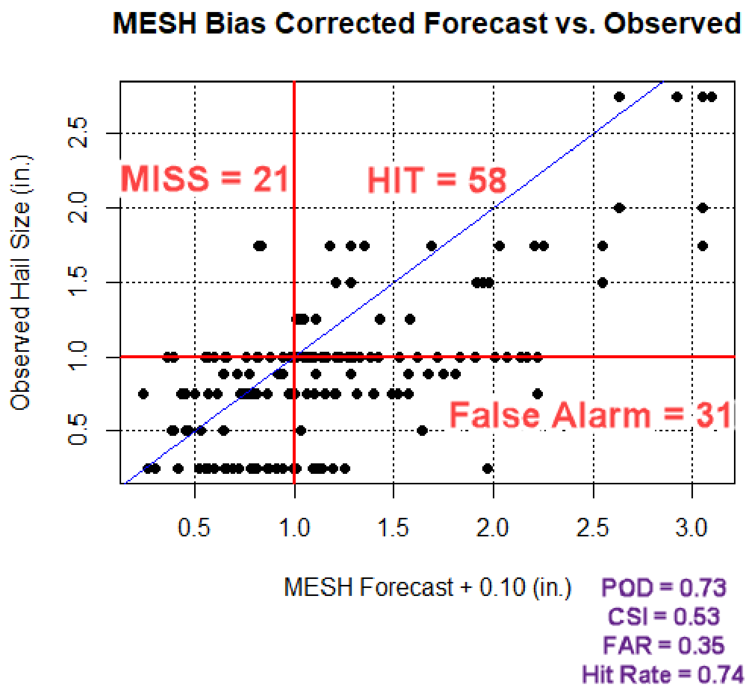

Figure 7: MESH Scatter Plot (Bias-Corrected)

MESH forecasted hail size (bias corrected) vs observed hail size.

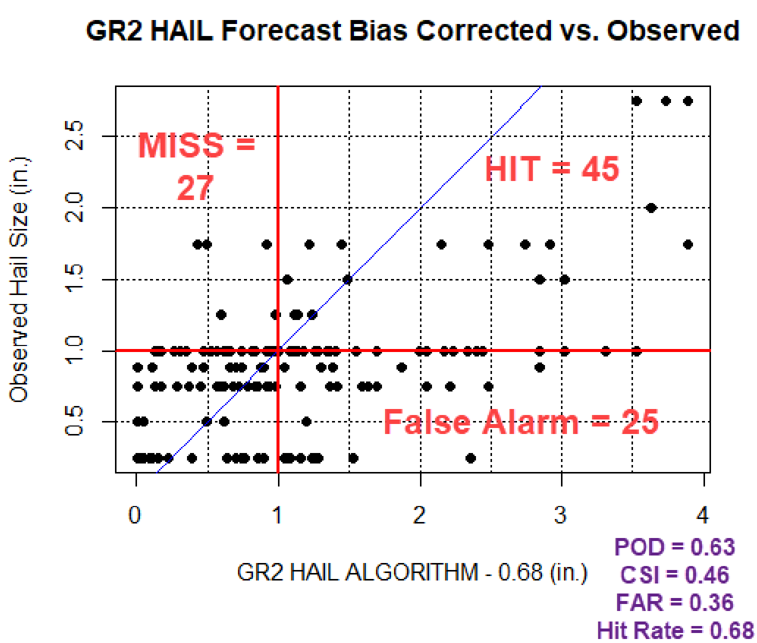

Figure 8: GR2Analyst Scatter Plot (Bias-Corrected)

MEHS (GR2Analyst Hail Algorithm) forecasted hail size (bias corrected) vs observed hail size.

Other discriminating factors for hail prediction collected from the vMRMS product viewer, including VII, VIL, etc. (Table 3) can be used in an operational meteorological setting. Frugis and Wasula (2011) state that there is a relationship between hail size and the height of various dBZ levels, reflectivity values at different temperature levels, as well as other derived products such as VIL. In this study, VII has the highest correlation coefficient to hail formation (.72), and its median value of 40.7 is consistent with observations of severe hail occurrence. At and above this value of 40.7 can therefore be considered a baseline for hail formation. Reflectivity at the -20°C isotherm level has a high correlation coefficient to hail formation (.59), and its median value of 59 dBZ is associated with severe hail formation.

Table 3: Hail Prediction Statistics

Determining factors for hail prediction. VII, MESH, and Reflectivity at -20°C have the largest/strongest correlation coefficients to look at hail prediction and size.

Summary Statistics Hail Prediction

Parameter r hail	NON-Severe (mean)	Severe (mean)
VIL 0.49	35.1 kg m^{-2}	45.2 kg m^{-2}
VILD 0.54	2.3 g m^{-3}	2.9 g m^{-3}
VII 0.72	25.9 kg m^{-2}	55 kg m^{-2}
MESH 0.68	0.78 in.	1.34 in.
Gr2 Hail Algorithm 0.53	1.42 in.	2.19 in.
REF 0C 0.58	59 dBZ	63 dBZ
REF -20C 0.59	53 dBZ	59 dBZ
REF 50 Above 0C 0.48	14800 ft.	19953 ft.
REF 50 Above -20 0.40	7649 ft.	10552 ft.
REF 60 Above 0C 0.56	7759 ft.	11007 ft.
	NON-Severe (median)	Severe (median)
VIL	36.2 kg m^{-2}	46.3 kg m^{-2}
VILD	2.4 g m^{-3}	2.8 g m^{-3}
VII	22.1 kg m^{-2}	40.7 kg m^{-2}
MESH	0.74 in.	1.13 in.
Gr2 Hail Algorithm	1.38 in.	1.88 in.
REF 0C	59 dBZ	62 dBZ
REF -20C	53 dBZ	59 dBZ
REF 50 Above 0C	13968 ft.	18538 ft.
REF 50 Above -20	5940 ft.	8809 ft.
REF 60 Above 0C	6713 ft.	10591 ft.

Chapter 4
Discussion

The MESH product from MRMS is more accurate in forecasting the occurrence of severe hail when compared to the MEHS from GR2Analyst. Automated algorithms that operate on data from multiple radars can provide information with greater temporal resolution and spatial coverage than their single-radar counterparts (Smith et al. 2016). The results presented in Figures 1-6 provide statistics supporting these conclusions. The existence of the IQR above 1inch with positive skewness for the MESH severe cases (Figure 3) suggests the accuracy of MESH in forecasting severe hail, especially very large hail (consistent with results from Murillo and Homeyer 2019). However, the IQR for the MESH non-severe cases includes some values near 1inch, suggesting possible under-forecasting of lower-end severe hail. This conclusion is similar to findings from Murillo and Homeyer (2019). Due to the IQR of both MEHS severe and non-severe cases existing above 1inch (Figure 4), the box and whisker plots suggest overestimation of hail size by MEHS from GR2Analyst in both severe and non-severe cases.

Our conclusions are supported by our statistical analysis that followed Wilkes' method. Although the MEHS POD=.92 and MESH POD=.60, the False Alarm rates are much higher for MEHS. The alarmingly higher number of False Alarms produced by MEHS, which was developed from the HDA, was also found in the results of Witt et al. (1998). The Hit Rate for MESH is higher, at a value of .71, as compared to the MEHS value of .61, meaning that the MESH more accurately anticipated the occurrence of severe or non-severe hail. We can also see based on the scatterplots (Figures 5 and 6) that MEHS tends to overestimate the size of hail to a greater extent than the MESH. This overestimation is also seen by the box and whisker plots and the MEHS distribution of IQR greater than 1inch for both severe and non-severe cases (Figure 4). Bias calculations show this drastic overestimation, since B=1.68 for MEHS and B=.90 for MESH. MESH does slightly underestimate the size of smaller and low-end severe hail, as displayed by both the bias and box and whisker plots for non-severe cases. It can even be interpreted to slightly overestimate the size of larger severe hail based on the positive skewness of the IQR (similar to findings Murillo and Homeyer 2019), although this is minor when compared to the overestimation from MEHS.

Our conclusions are only solidified after the bias-corrected values for MESH and MEHS are calculated (Figures 7 and 8). Although the bias correction drastically improved the number of MEHS cases that were False Alarm, the number of MISS cases increased, and the POD went down significantly. The bias improved the number of HIT cases and MISS cases for the MESH, and dramatically increased its POD from .60 to .73. Therefore, our original prediction that MESH is more accurate in forecasting severe hail than MEHS is now born out of observations and further supported by our analysis. These findings that MEHS from GR2Analyst tends to overestimate the size of severe hail is consistent with prior research (Witt et al. 1998, Ortega et al. 2009, Frugis and Wasula 2011, Cintineo et al. 2012, Ortega 2018, Murillo and Homeyer 2019) and consistent with the design of MEHS, which was created such that 75% of the reports would be less than the predicted size (Witt et al. 1998).

We do, however, have to identify the limitations and assumptions made within our research. Local storm reports may have an impact on the validity of our data. We are assuming that they are correct in time and space, meaning the observed hail size is factual, it fell at the correct time recorded on the report, and the location of the report is true to the actual location of the fallen hail. We are also assuming that the hail size reported was the maximum size associated with the storm, and that the maximum hail stone did not fall before or after the time of the report. Without a high-density hail-observing network, there is no way to truly know the size of the largest hail being produced by a storm at any time (Witt et al. 1998). These limitations have been identified in each of the studies presented in the references section of this paper. Allen and Tippett (2015) explicitly state that the existence and distributions of hail reports are influenced by population, road networks, storm chasers, and the time of day. Additionally, it cannot be confirmed that all hail reports are measured accurately with a ruler (Frugis and Wasula 2011), and those who do report hail often draw comparisons to reference objects such as coins and balls to determine hail size or just simply estimate, resulting in a hail size distribution that is not representative of the true hail size (Allen and Tippett 2015). Unfortunately, we cannot determine whether local storm reports are 100% accurate, and inadequacies in the ground-truth database of observed hail reports can likely have an impact on the performance of both hail detection algorithms and therefore our analysis on the accuracy of each (Witt et al. 1998).

As a result of this research, NWS operational forecasters can make inferences regarding hail sizes from MESH and MEHS in order to better determine when hail will be severe or non-severe, calling for warnings. This can be done simply by using the calculated biases to accurately determine the true hail size expected with a storm.

Chapter 5
Conclusion

The MESH product from MRMS is more accurate in forecasting the occurrence of severe hail when compared to the MEHS from GR2Analyst. MEHS from GR2Analyst tends to overestimate the size of hail to a greater magnitude than the MRMS MESH. A bias correction improved forecasting statistics for both MRMS and GR2Analyst. MRMS MESH is especially useful for detecting very large hail, and is one of the best discriminators for hail occurrence overall (Ortega 2018, Murillo and Homeyer 2019).

The results of this study will allow NWS forecasters to more accurately forecast severe and non-severe hail, leading to improvements in the issuing of severe thunderstorm warnings. It will not only aid in storm warning verification due to the more accurate forecasting of hail size, but also in a forecaster's decision in whether or not to issue a severe storm warning. This in turn will protect life and property, a continued goal of NWS. Although it has been determined that MRMS MESH output is useful and more accurate than single radar data, MESH values alone should not be used as a direct proxy for the actual size of hail developing in a storm. Rather, other factors, such as a bias correction, should be incorporated for hail identification and size discrimination procedures (Ortega 2018). Forecasters can simply use the calculated biases for each of the products when using the given MESH and MEHS output by adding .1 to the smaller/low-end severe MESH value and subtracting .68 from the MEHS value to give them a more accurate value of the true hail size occurring with a storm, at least in this region of the U.S. This will aid in improving the issuance of severe thunderstorms. However, it is important to note that although bias-corrected statistics are beneficial in determining true hail size, operational forecasters must maintain situational awareness when there is an ongoing and developing convective episode, and must not merely rely on biases and other statistics when issuing warnings (Frugis and Wasula 2011). Additionally, when warning for severe hail, median values of discriminating factors highly correlated to hail prediction, such as VII (Table 3), can be used by a forecaster as a starting point when looking to issue a warning. This is due to median values giving a more accurate measure of the central tendency of the hail dataset (Frugis and Wasula 2011). These factors require further investigation, setting the groundwork for future research.

Storm structures, including updraft intensity and bounded weak echo regions, as well as dual-pol signatures, will also be investigated in the future to determine if any of these patterns have an effect on severe hail formation. Using a product such as GR2Analyst can allow forecasters to view vertical cross section of storms, allowing them to identify specific storm structures that correlate to severe hail formation. This future work would expand the completed research to a number of other geographical locations across the U.S., not just the region of the central Carolinas.

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ACADEMIC VITA
JENNIFER ANNA D'IORIO

EDUCATION:
The Pennsylvania State University, Schreyer Honors College Graduation: Spring 2020
Bachelor of Science in Meteorology and Atmospheric Science
Minor in Earth Systems

EXPERIENCE/RESEARCH:
2018 NOAA Hollings Scholarship Recipient May 2018-May 2020
Scholarship Recipient/2019 Summer Intern at NWS WFO Columbia, S.C.

- **Project Title: Comparing MRMS Data to Single Radar Data to Improve Severe Thunderstorm Warnings (Preliminary)**
- Poster Presentation at 2019 Hollings Scholarship Symposium at NOAA HQ
- Poster Presentation at 2020 American Meteorological Society Student Conference

Department of Energy Student Undergraduate Laboratory Internship
Intern/Student Researcher at Brookhaven National Laboratory June 2018-August 2018

- **Project Title: Analyzing Buoyancy and Deep Convective Outflow during GoAmazon (2014-15)**
- Poster and selected oral presentation at 2019 SULI symposium at BNL
- Project further developed by mentor and abstract (Title: An Observational Study of Bulk Entrainment by Proxy in Tropical Deep Convective Clouds and their Environments) submitted to the Journal of Geophysical Research for Publication; currently a preprint in Earth and Space Science Open Archive

National Weather Service State College WFO Student Volunteer Program
Student Volunteer Fall 2018, Spring 2020

- **Project Title: Updates to the Crisis Communication Handbook for Operational Use by local NWS Weather Forecast Offices**

CAUSE 2018 Undergraduate Research Experience (Plate Tectonics and Processes)
Penn State College of Earth and Mineral Science Fall 2017-Fall 2018

- **Project Title: Physical and Anthropogenic Causes of Microclimates in the Pacific Northwest**
- Poster Presentation at Fall 2018 PSU EMS Poster Exhibition

AWARDS:
Penn State's College of Earth and Mineral Science Academy for Global Experience (EMSAGE) Laureate Award December 2019

SCHOLARSHIP/HONORS:
Dean's List	Fall 2016, Fall 2017-Fall 2019
Schreyer Academic Excellence Scholarship	Fall 2016-Spring 2020
Hosler Scholarship in Meteorology	Fall 2016- Spring 2018, Spring 2020
Matthew J. Wilson Honors Scholarship	Fall 2016-Spring 2017, Fall 2018
Strickler Honors Scholarship EMS	Fall 2017-Spring 2018, Fall 2019-Spring 2020
Cole Scholarship in Meteorology	Fall 2018, Fall 2019-Spring 2020
Panofsky Hans A Scholarship	Fall 2019

INVOLVEMENT:

Penn State Campus Weather Service August 2016-May 2020
Forecaster/Forecasting Shift Leader, Communications Shift Member/Social Media Team

Volé: Penn State Dance Company, Dancer/Choreographer August 2016-May 2020

Storm Chase Team at Penn State, Vice President (18-19)/Member Aug 2017-May 2020

Chi Epsilon Pi-Meteorology Honor Society, Member March 2018-May 2020

Penn State Branch of the American Meteorological Society Member Sept 2018- May 2020

Penn State Music Ensembles, Flautist August 2016-May 2018

F.O.R.M. Consulting, Member/Consultant May 2017- May 2018

ADDITIONAL WORK:

Hurricane Sandy's Synoptic Scale Features and Impact on the Northeast: What is Being Done to Prepare for the Next Major Storm to Hit the Northeastern Coast? Research Paper, Schreyer Honors College Honors Option, METEO 411-Synoptic Meteorology (Fall 2018)

Atmosphere-Ocean-Ice Interactions: A Positive Feedback Loop that Influences the Decline of Arctic Sea Ice, Research Paper, METEO 470-Climate Dynamics (Fall 2018)

The Use of WSR-88D Radial Velocity Data to Demonstrate Asymmetric and Cold Core Characteristics of Hurricane Sandy, Research Project/Paper and Oral Presentation, METEO 434-Radar Meteorology (Fall 2019)

Investigating the Design and Accuracy of a 3D Printed Pufferfish Rain Gauge through Measurement by Mass, Research Project/Paper and Oral Presentation, METEO 440W-Principles of Atmospheric Measurement (Fall 2019)

Meteotsunamis: A Climatology of Formation, Detection, and Warning Practices Around the World, Research Paper (in final stages), Schreyer Honors College Honors Option, METEO 414-Mesoscale Meteorology (Spring 2020)