GENERAL HAIL OCCURRENCE FREQUENCY IN CONVECTIVE STORMS USING MPING DATA

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ABSTRACT

While non-severe hail is perceived as having little direct societal impact, it can negatively impact the quantitative precipitation estimation (QPE), something that can have significant societal impact. Miscalculated QPE can lead to mismanagement of emergency services, poor hydrologic forecasts, and mismanagement of water resources. By determining the proportion of convective storms that are associated with any hail but, particularly small or non-severe, we can begin to understand the extent to which QPE is affected by small hail. The current hydrometeor classification algorithms have little skill at discriminating between small hail and large raindrops. Thus choosing a threshold at which to make adjustments to QPE due to hail is difficult. We can use meteorological Phenomena Identification near the Ground (mPING) crowd-sourced weather reports to make a rough estimate of how common small hail is at the surface within convective storms. By pairing mPING data with composite reflectivity within identified storms, no clear hail/no hail threshold emerges, and so adjusting QPE based on reflectivity values is unlikely to result in much improvement in QPE.

1. INTRODUCTION

The National Weather Service (NWS) has an operational responsibility to forecast and report severe hail, defined as hail that is greater than one inch in diameter. Not only is severe hail more likely to result in property damage, it also is one defining feature of a severe thunderstorm, making it an important threshold for verifying watches and warnings. While non-severe hail may cause roof or other property damage, it can destroy crops when paired with strong winds, and it also may negatively affect the quantitative precipitation estimation (QPE). QPE is used as guidance for flood watches and warnings, in hydrologic modeling, and in reservoir management. When QPE is overestimated, emergency management components may be unnecessarily deployed, leading to undue alarm and economic loss. When QPE is miscalculated, watershed and reservoir networks can be mismanaged, which may result in long-term problems for entire regions.

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HOW SMALL HAIL EFFECTS QPE

Algorithms that use dual polarization radar to determine precipitation type may categorize small hail as large raindrops. Because wet hail has a much higher reflectivity than pure water, this leads to an overestimation of rain rate. A primary predictor of hail is differential reflectivity (Z_{DR}), or the difference between the horizontal and vertical components of hydrometeor reflectivity. Thus, Z_{DR} is a function of the general shape of hydrometeors. Because large raindrops are larger horizontally than vertically, they yield a distinctive Z_{DR} return along with characteristically large reflectivity. Small raindrops are nearly spherical, and therefore create a very small Z_{DR} signature. The Z_{DR} return for hail is also usually near zero, even for non-spherical hail, because hail tends to be randomly oriented (Rhinehart ,2010), and often acts as non-Rayleigh scatterers, meaning that the overall reflectivity is no longer a monotonic function of hydrometeor size.

In contrast, as small hail falls, its radar properties become ambiguous. Rasmussen et al., (1984) shows that as small hail falls and either begins to melt or is in a wet growth phase, the liquid water creates a torus around the mid line of the hailstone. This effect causes the hailstone to return a Z_{DR} that is much like a large raindrop, that is one of an oblate hydrometeor. Without additional knowledge of the hydrometeor characteristics, whether the return is generated by a large raindrop, or small, wet hail, an incorrect rain rate is determined, thus, incorrect QPE will likely result.

2. METHODS

We use observations submitted through the Meteorological Phenomena Identification Near the Ground (mPING) app (Elmore et al., 2014) to identify convective storms that are associated with hail of any size and those for which no hail is reported. In order to determine the frequency for which convective storms are associated with small hail, we use a storm-tracking algorithm that identifies convective storm cells and tracks them through time until they dissipate or merge with another storm (Lakshmanan, 2009). While this automated storm-tracking algorithm is not without error, it is deemed adequate for the purposes of this study.

The study area is limited to a rectangular area bound in by four points at (46.424583, -105.733937), (30.471940, -105.733937), (30.471940, -81.48079), and (46.424583, -81.48079). Storm motion is examined subjectively at 400 km^2 saliency, within the warning decision support system – integrated information (WDSS-II) platform (Lakshmanan, et al., 2007). A total of 19 days are evaluated (Table 1), all of which had a high frequency of convective storms. A "day" is defined as spanning 1200 UTC through 0600 UTC, on the following UTC day. Storms are tracked and evaluated along with mPING reports at ten-minute intervals. mPING reports are matched with their associated storm cells, as identified by the storm-tracking algorithm. In order for an mPING report to be associated with a storm cell, a component of the cell needs to have passed over the point of the mPING report within 15 minutes of the report time. In cases that components of two separate cells are nearby, the radar product can be stepped backward in time in two minute intervals to determine which cell likely resulted in the mPING report at that particular point. The associated mPING reports are separated into four different categories: rain/drizzle, small hail, large hail, and other (winter weather, wind damage, etc.). Maximum composite reflectivity data for each storm cell at the time interval with which it is associated with a precipitation mPING report is also recorded.

Month	Day
April	26, 30
May	10, 11, 15, 16, 17, 18, 19, 24, 27, 31
June	01, 12, 13, 14, 15, 16, 17

Table 1. Days in 2017 selected for analysis. Days are chosen based on the overall level of convective storm activity.

3. RESULTS

During the evaluation of the 19 days used for this study, 19814 convective storm cells are identified. Of those storms, 3401 are associated with at least one mPING report. 2489 cells are associated with rain only (no hail report), 706 cells are associated with small hail, 134 cells are associated with large hail, and 627 are associate with other classes of mPING reports, such as winter weather or wind. The analysis of the composite reflectivity focuses on the distinction between cells that result in rain-only mPING reports, those that have small hail reports, and those that have large hail reports. In most cases, when a cell has a hail report, it also has a rain report. Composite reflectivity of all storms associated with "rain only" ranges from 34 dBZ to 72.5 dBZ with a mean of 53 dBZ. For storms that are associated with small hail, the composite reflectivity ranges from 37 dBZ to 73 dBZ with a mean of 60.1 dBZ. Large hail related cell composite reflectivity ranges from 36 dBZ to 72.5 dBZ with a mean of 56.6 dBZ. The interquartile range for the reflectivity of storms resulting in each precipitation type is largely overlapping, with the mean reflectivity for small hail being the highest. Large hail's lower mean composite reflectivity is likely due to the fact that large hail is no longer a Rayleigh scatterer and tends toward Mie scattering (Rinehart, 2010).

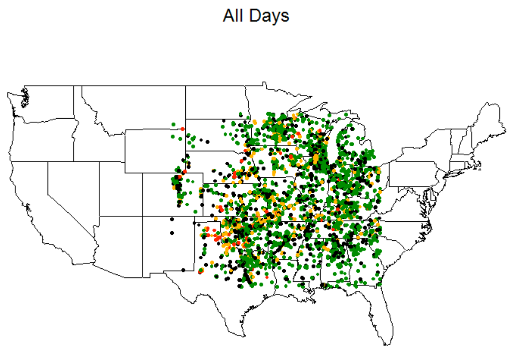

Figure 1. Distribution of all mPING reports submitted during our sample period. Green dots represent rain/drizzle, yellow is small hail, red is large hail, and black is any other mPING report type.

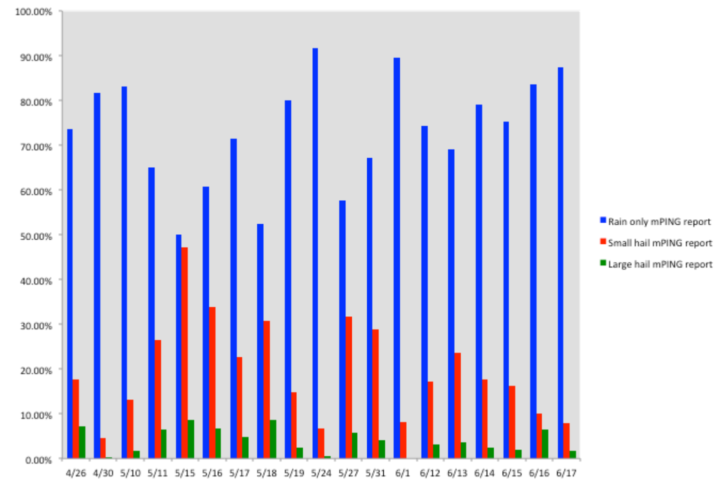

Figure 3. Percentage of mPING report by type for convective storms associated with at least one mPING report.

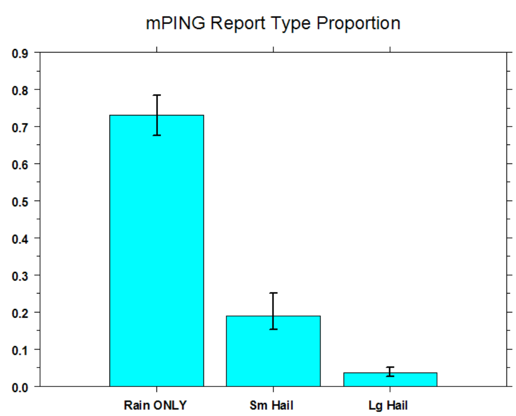

Figure 2. Percentage of storms associated with rain, small hail, and large hail mPING reports during our sample period. Error bars represent the 95th percentile confidence interval of the mean based on bootstrap resampling.

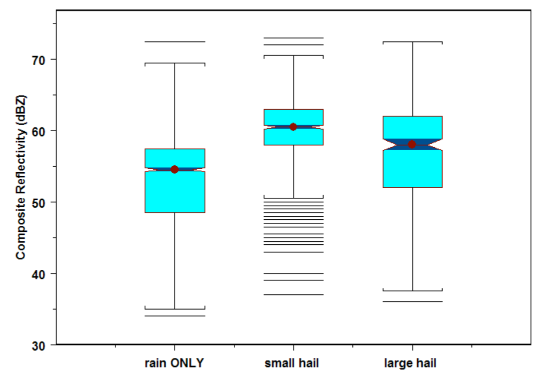

Figure 4. Distribution of composite reflectivity for storm cells reported to have each type of precipitation. Boxes represent the interquartile range. Box notches represent the 95th percentile confidence interval for the median.

Further analysis of convective storm cells on May 15, 2017 and June 12, 2017 show similar trends in composite reflectivity. The composite reflectivity range of storm cells results in significant overlap of the interquartile rang for each set of observations (Figs. 5 and 6). Figures 7 and 8 show the spatial distribution of all mPING reports for each day.

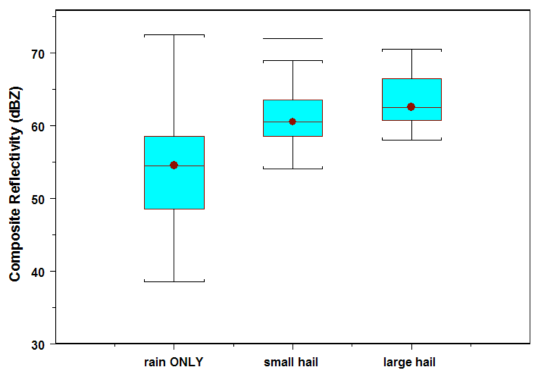

Figure 5: Composite reflectivity distribution for storms associated with mPING reports on May 5, 2017

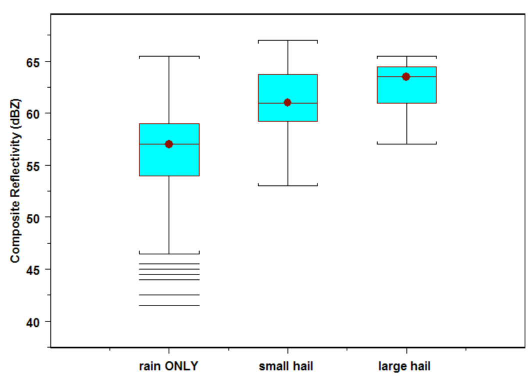

Figure 6: Composite reflectivity distribution for storms associated with mPING reports on June 12, 2017

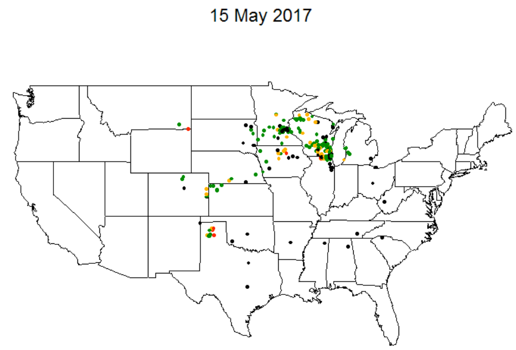

Figure 7. As in figure 1, but for May 15, 2017

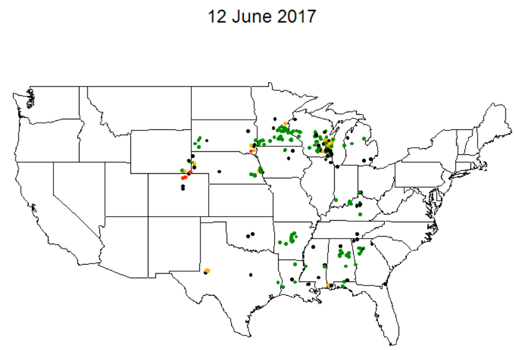

Figure 7. As in figure 1, but for June 12, 2017

4. CONCLUSION

Within the composite of all 19 days, 1 out of every 5 storms associated with an mPING report contains non-severe hail and so would not be noted in any logged report, such as Storm Data. Assuming this sample is representative, about 20 percent of convective storms will generate small hail at the surface. This proportion is significant and warrants further efforts to both record non-severe hail occurrence rate and to better mitigate its affects on QPE. One possible method to further study hail and its associated radar properties is to develop a way to automatically pair mPING reports with the related radar, satellite, and other relevant data sources. By pairing these data we can improve or adjust current hydrometeor classification algorithms to better account for the presence of hail.

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