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A TECHNIQUE FOR SELECTION OF MULTIPLE Z-R RELATIONSHIPS WITHIN A SINGLE DOMAIN

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1. INTRODUCTION

We propose to develop a climatology of mesoscale convective systems (MCSs), with an emphasis on MCS morphology and its relationships with the storm environment and the production of heavy rainfall. Our goal is to evaluate the environmental conditions that are associated with MCS development and dissipation, as well as the transition from one MCS configuration to another, and how these relate to heavy rainfall. Because of the spatial scale of an MCS, it is likely to be sampled by many rain gages. However, it is much less certain that the heaviest rainfall will be well-resolved by typical rain gage networks. To better assess heavy rainfall produced by MCSs, we are developing an algorithm to estimate rainfall using radar reflectivity and model analysis. This algorithm allows the use of multiple Z-R relationships within a single domain, determined based on the structure of the precipitation system and the storm environment. The algorithm will also attempt to correct for some radar errors, such as bright banding.

In addition to the problem of the limited spatial resolution of typical rain gage networks, the de facto standard instrumentation of tipping bucket gages is prone to underestimating heavy rainfall. While there are many potential errors that can contaminate radar-based rainfall estimates, they are not prone to this underestimation bias. Although the algorithm is still under development, the techniques will be described in this paper, along with a brief discussion of the overall goals of the project.

2. OPERATIONAL RAINFALL ESTIMATION

Rainfall estimation is accomplished by estimating the amount of liquid water in a volume scanned by radar. The relationship between radar reflectivity and the volume of liquid water depends primarily on three hydrometeor characteristics: size, number, and refractive index. Because there are three variables and one observed parameter, two additional assumptions are necessary. The refractive index is assumed to be that of liquid water, regardless of the actual composition of the hydrometeors. Additionally, the distribution of raindrop size is parameterized, using a power-law equation known as a Z-R relationship.

$$Z=aR^b \quad (1)$$

Many such relationships exist, of the form of (1), depending on pseudo-constants *a* and *b*, which are modified to allow for various distributions of drop size. Indeed, a plethora of Z-R relationships have been empirically derived (Battan 1973).

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The current WSR-88D rainfall algorithm (Fulton et al. 1998) applies a single forecaster-selected Z-R relationship after correcting for a few radar errors such as anomalous propagation, ground clutter, and beam blockage. There are five Z-R relationships used operationally (Nelson et al. 2010): the Marshall-Palmer Z-R relationship (Marshall and Palmer 1948), the WSR-88D convective Z-R relationship, the Rosenfeld tropical Z-R relationship (Rosenfeld et al. 1993), and two Z-R relationships for cool season stratiform rain.

Other rainfall products postprocess output from the WSR-88D rainfall algorithm, usually creating mosaics using data from multiple radars and incorporating other observations, including calibration of radar-based estimates using rain gage totals (Lin and Mitchell 2006; Nelson et al. 2010). One such product, the Multisensor Precipitation Estimator (MPE), incorporates radar data, gage data, satellite data, and climatological inputs to produce a mosaic. The first step in the MPE is to mosaic precipitation estimates from individual radars, which are computed using the WSR-88D rainfall algorithm. Manual adjustments are applied, based on rain gage observations, to account for local variations in rainfall rate not otherwise represented in the analysis.

Klazura et al. (1999) noted that, when using the WSR-88D rainfall algorithm, convective rain was underestimated at distant ranges and overestimated at mid-ranges, whereas stratiform rain was consistently underestimated. Additionally, Rosenfeld et al. (1992) found that partial beam filling led to underestimation of rainfall at distant ranges. Bright banding (Austin and Bemis 1950), caused by melting hydrometeors, also can cause substantial overestimation of rainfall (Fabry and Zawadzki 1995; Smith 1986). Also, drop size distribution is highly variable, even within a single storm (Uijlenhoet et al. 2003), suggesting that multiple Z-R relationships may provide the best rainfall estimation, even from one region to another within a storm. Although the MPE does correct for some of these issues, heavy rainfall is frequently underestimated, likely due to the climatological inputs and the rarity of such events. Additionally, areas that are covered sparsely by rain gages receive poorer calibrations, and therefore are subject to greater error (Limpert 2008).

3. PROPOSED ALGORITHM

There are many sources of error in radar observations that can adversely affect rainfall estimates. For this algorithm, we have chosen to address the issues of refractive index, including bright banding, errors due to an incorrect Z-R relationship, beam blockage, and partial beam filling. Each of the potential errors, and the methods for correcting them will be discussed in this section. Fig 2. shows the flow of data and the processing within the proposed rainfall algorithm.

3.1. ***Beam Blockage and Beam Filling***

Beam filling is an issue at distant ranges from a radar, in which the radar beam, even at its lowest tilt, may be partially or entirely above any hydrometeors that are present. As a result, the measured reflectivity is weaker than what would be sampled at lower altitudes, resulting in underestimation of rainfall. In the proposed algorithm, this is accounted for by incorporating data from multiple radars to generate mosaics. Algorithms within the Warning Decision Support System – Integrated Information (WDSS-II) (Lakshmanan et al. 2007) are used to manipulate the radar data. Level II WSR-88D data are ingested and the w2merger algorithm (Lakshmanan et at. 2006) is used to mosaic data from multiple radars, transforming the data from a polar grid to a lat-lon-height grid. To the extent that there is a nearer radar, providing coverage at a lower altitude, beam blockage and beam filling can be corrected by incorporating multiple radars.

3.2. ***Bright Banding***

This correction, while largely intended to address bright banding, accounts for variability in hydrometeor refractive index, both in the melting layer and above it, in which the hydrometeors will be predominantly ice crystals. Bright banding occurs as a result of melting hydrometeors, in which the scattering cross section is wider than a more spherical raindrop, but still has the refractive index of liquid water, thus resulting in anomalously strong reflectivity.

Melting layer height is determined using temperature profiles from RUC model output. At each lat-lon point within the domain, the lowest altitude is chosen that is at least 1 km above the surface and is not within the melting layer. If the selected altitude is above the freezing level, hydrometeors are likely to be mostly ice crystals, and a correction of 7 dBZ will be added to account for the much lower refractive index of ice compared with liquid water (Rinehart 2004). The output of this step is a lat-lon reflectivity grid.

3.3. ***Z-R Relationship Variability***

The five Z-R relationships that are used operationally in the WSR-88D rainfall algorithm are points along a continuum of possible Z-R relationships. While it certainly is possible to improve upon the operational WSR-88D rainfall algorithm by selecting between, say, the Marshall-Palmer Z-R relationship and the WSR-88D convective Z-R relationship, it does not fully represent the spectrum of drop size distributions. Rather, the goal is to compute a reasonable Z-R relationship from the available data, including radar-measured parameters and objective analysis of the atmospheric conditions. This can be achieved through multiple regression, in which the output is two parameters, *a* and *b*, that are used in the Z-R relationship.

The first consideration is representing the structure of the storms. Klazura et al. (1999) associated convection with strong horizontal reflectivity gradients and stratiform precipitation with weak gradients. Similar techniques, such as the Fourier transform and the wavelet transform can be used in an automated routine to distinguish between convective and stratiform precipitation (Limpert et al. 2008). We propose to use the wavelet transform to identify storms within radar imagery. By scaling the wavelet function, it is possible to identify storms at multiple scales. Small wavelengths with strong reflectivity peaks can be associated with convection whereas larger wavelengths and weaker reflectivity maxima can be associated with stratiform precipitation. Updrafts in convection are much stronger than in stratiform precipitation systems, which results in a significantly different drop size distribution, and therefore a different Z-R relationship is needed.

Hail, which is rarely associated with tropical convection, produces anomalously strong reflectivity. In the central United States, reflectivity input to Z-R relationships is generally capped at 53 dBZ to prevent contamination of rainfall estimates with hail. The hail cap varies seasonally and geographically. While a hail cap is necessary, the presence of particularly strong reflectivity also provides information as to the characteristics of storms. The presence of hail suggests that the storm environment is unlikely to be similar to tropical environments. A hail detection algorithm will be used to provide information on the presence of hail and the size of any hail that is present.

Additionally, atmospheric conditions will be used from an objective analysis to provide additional meteorological data that may be useful in identifying an appropriate Z-R relationship. We expect these parameters will influence the drop size distribution and may be significant enough to include. The parameters are as follows:

- Mid-level thickness, to account for warm temperatures aloft, affecting the processes by which raindrops grow in size
- Low- and mid-level moisture, expecting that abundant moisture will reduce evaporation of smaller drops as well as providing abundant moisture for drop growth
- Deep layer bulk shear and upper level storm relative winds, because strong winds aloft can advect hydrometeors away from the storm, affecting the drop size distribution

Using the available inputs, a Z-R relationship will be selected at each point in the domain where reflectivity is strong enough to suggest that precipitation is cocurring. The output of this step of the algorithm is a lat-lon grid containing estimated rainfall rates.

Dual-polarization radar data will be obtained for selected cases, which can be used to compute the drop size distribution and identify the type of hydrometeors within a storm. Given this information, it will be possible to compute a “truth” *a* and *b* in a Z-R relationship. The hydrometeor identification from the dual-polarization data will be used in place of the hail detection algorithm for these cases. Scale inputs, hail detection, and storm environment parameters will be recorded for the cases, and a multiple regression will be performed to determine weights for each of the parameters. The equations that are computed will be used to calculate an appropriate Z-R relationship, given the parameters, but without knowing *a* and *b* a priori.

4. VERIFICATION

Most operationally deployed rain gages are tipping bucket gages, and therefore are prone to underestimating heavy rainfall events, which are the most interesting for the MCS study. Verification of the algorithm will be conducted by comparing rainfall estimates against rain gages in the United States Climate Reference Network (US-CRN). CRN gages are weighing-type rain gages, which are less prone to some of the errors that can reduce the quality of observations taken using tipping bucket gages. It is also possible to test the algorithm by considering another set of events observed using dual-polarization radar, and using the “truth” drop size distribution to calculate an *a* and *b* that can be compared against the algorithm *a* and *b*.

5. MCS TRACKING

MCSs will be tracked using radar imagery and will be classified based on the structure of the thunderstorm complex and whether the MCS is intensifying, maintaining its strength, or diminishing. MCS configuration, examples of which are shown in Fig. 1, will be determined by examining the radar imagery. Infrared satellite imagery will be used to identify trends in MCS intensity. The MCS tracks will be combined with the rainfall data and atmospheric parameters derived from objective analysis. Rainfall estimates from the algorithm described in this paper will be used in this study. Multivariate analysis of variance and other multivariate statistical methods will be used to identify relationships between the data. Our goal is an understanding of the atmospheric conditions that govern the MCS lifecycle and the transition from one configuration to another, such as an MCS with parallel stratiform precipitation transitioning to an MCS with trailing stratiform precipitation. An additional goal is to understand the factors, including MCS type and environmental conditions, that are favorable for heavy rainfall.

6. CONCLUSION

Our goal is to understand how atmospheric conditions affect MCS morphology, and how these relate to heavy rainfall events. We plan to accomplish this by tracking MCSs, classifying the MCSs periodically, and recording various atmospheric parameters and measures of rainfall produced. Multivariate statistical methods will be used to relate these together, with an emphasis on understanding MCS lifecycles and heavy rainfall production. Rain gage networks are likely insufficient to accomplish these goals, so we are developing the algorithm presented in this paper to provide a high resolution rainfall data set comparable to the other data that will be used in this study. Many radar-based products only employ a single Z-R relationship within a given radius of a radar site. A large portion of the MCSs that will be tracked are likely to have regions of convection and stratiform rain in close proximity, making such a scheme unsuitable. We believe that this algorithm will provide more suitable estimates of rainfall for our purposes, and quite possibly for many other uses.

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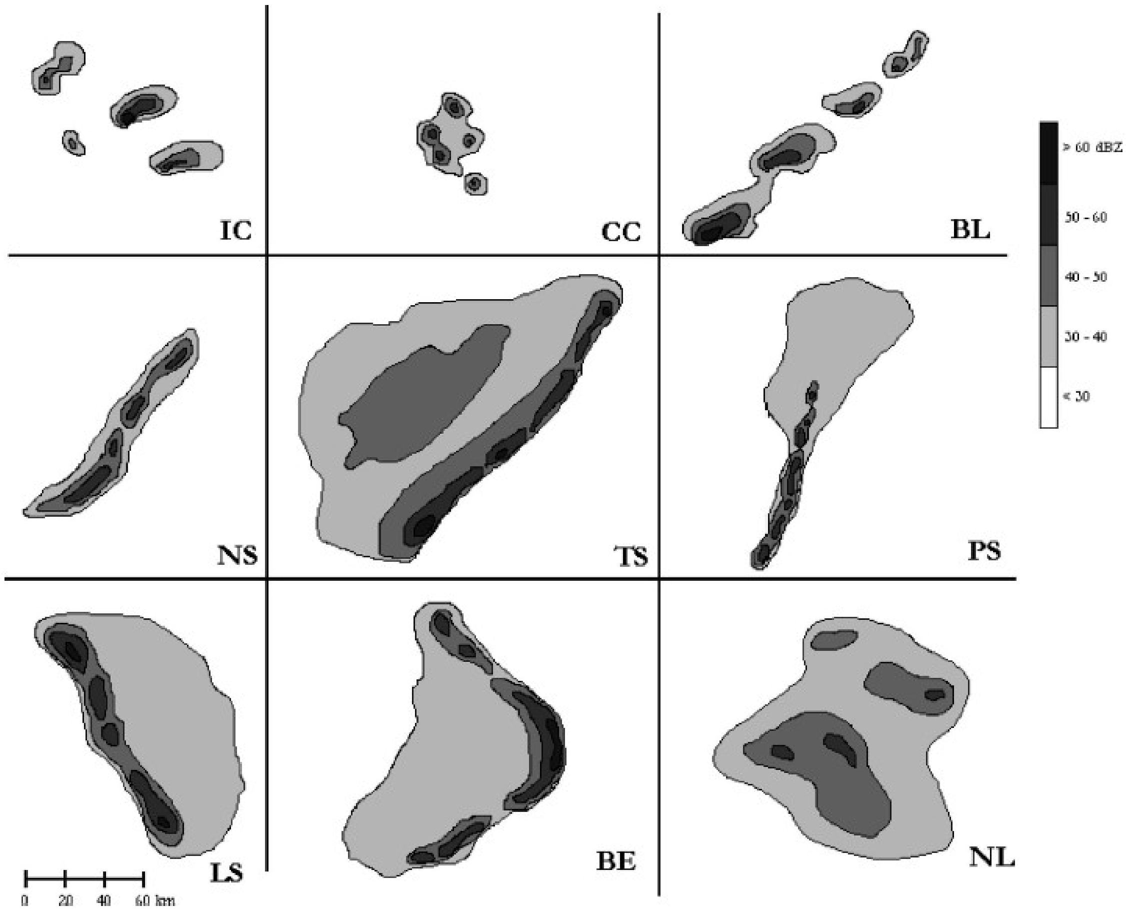

Fig. 1. From Gallus et al. (2008), showing nine different classifications for storms. These include isolated cells, clustered cells, broken lines, lines with no stratiform precipitation, lines with trailing statiform, lines with parallel stratiform, lines with leading stratiform, bow echoes, and non-linear MCSs.

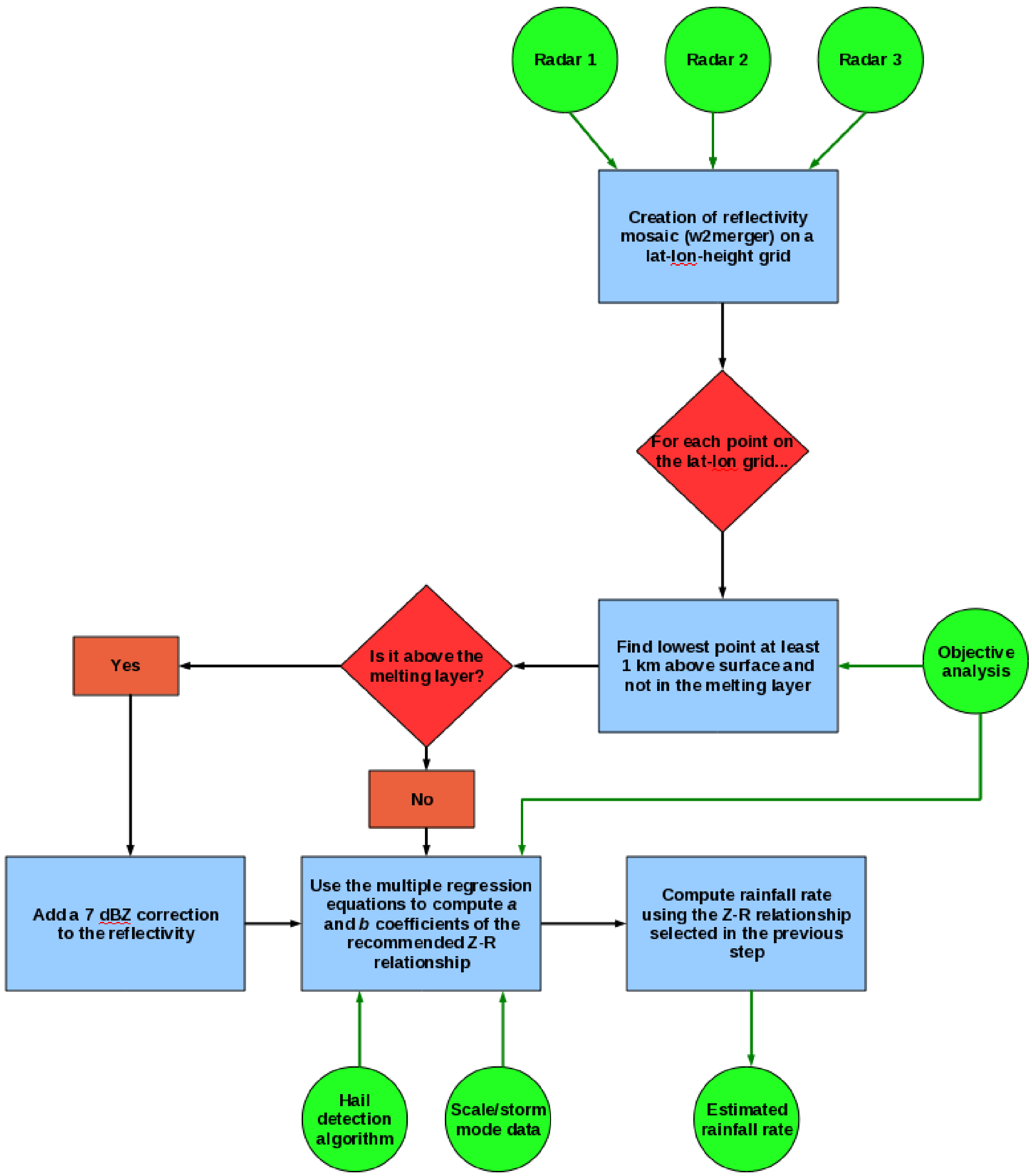

Fig. 2. This shows the flow of data and processing within the proposed rainfall algorithm.