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A STATISTICAL EXPRESSION FOR THE ESTIMATION OF MCS PRECIPITATION EFFICIENCY

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1. INTRODUCTION

The precipitation efficiency (PE) of various rain and snow systems has been a topic of serious scientific inquiry since Braham (1952) completed the water budget for a convective system observed during The Thunderstorm Project. In the intervening years, the PE has been evaluated for both warm season (e.g., Marwitz 1972; Fankhauser 1988) and cold season (e.g., Szeto et al. 1997) systems, although the historical emphasis has tended toward a more thorough understanding of deep moist convection. Recent activity in this arena has focused on the numerical modeling of tropical and mid-latitude convection (e.g., Ferrier et al. 1996; Li et al. 2002).

However, in all this time, the efficiency with which precipitation systems process moisture has remained a largely academic pursuit. The precipitation efficiency of a rain or snow system can best be determined as a time average over its lifetime (Doswell et al. 1996), so its value as a *prediction* tool would seem non-existent. One method for approximating the precipitation efficiency has been derived by and shown to perform well as a component for estimating convective precipitation (Scofield et al. 2000). Known as the “moisture correction factor,” it is the product of the precipitable water (PW) and the surface-to-500 mb mean relative humidity (RH), factors important in the generation of convective rainfall. This method focuses on using a PE proxy to estimate convective rainfall.

The goal of the current work is on improving PE estimation in order to highlight regions of flash flood potential up to 6 *h* in advance using variables derived largely from GOES soundings. Consider two columns of large but equal precipitable water. If convection occurs in both columns, the one with the higher PE would likely be the one that generates the greater rainfall totals. As such, the PE was calculated for a number of Midwestern MCSs, and GOES sounding profiles from the precursor environment of Midwestern MCSs were analyzed to determine if a predictive equation for the PE might be determined.

2. METHOD

A first step in this work was to calculate the PE of individual MCSs. Choosing a method of calculating PE that would be easily reproducible given data currently available within the meteorological community became a primary goal. Consequently, the Sellers (1965) method (hereafter called the Sellers method) of calculating precipitation efficiency stood out. The Sellers method defines PE climatologically as the ratio of mean daily precipitation to the average precipitable water of a given location.

For this study of mesoscale features, it was necessary to scale down the time interval to capture the life cycle of MCSs. The six-hour total precipitation amounts available from Stage III radar mosaic estimates (e.g., Seo et al. 1998) lent themselves well to this study. The accumulated six-hour periods often capture the formation, maturity, and dissipation of an entire MCS lifecycle. Although a climatological approach originally, the statistical basis of the Sellers method also lent itself to the datasets available for this study. Because time averaging of both precipitation and PW became necessary (discussed later), the Sellers approach was all the more attractive. Again, a time-average PE is often more revealing than an instantaneous value.

2.1 Data

The two terms in the Sellers definition of PE require precipitation data and precipitable water. Grids of precipitation depth (Sellers numerator), in millimeters, accumulated over six-hour periods ending at 00Z, 06Z, 12Z, and 18Z were archived for summertime MCS cases. The rainfall totals from the Stage III radar mosaic are created on a four-kilometer square grid from combined radar ranges. Rain gauge networks are used to quality check the precipitation values reported via radar measurement, and then the data is put into gridded GEMPAK format files.

The denominator of the Sellers PE definition requires computation of average precipitable water (PW). In order to determine average precipitable water during the corresponding six-hour time period as precipitation depth, it became necessary to track PW with the motion of the MCS. To do this, Rapid Update Cycle model initialization output was used to calculate PW for the area of our grid.

The last major data source is GOES soundings. In order to create a predictive equation for PE based on GOES sounding parameters, hourly GOES soundings were collected. Winds were obtained from the corresponding hour’s Rapid Update Cycle initialization for levels of GOES temperature and moisture. Menzel et al. (1998) outlines the role of these new sounders to fill

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in the gaps of the traditional rawinsonde network, be they over data-sparse oceans, areas within the network that need additional coverage, or at times between traditional balloon launches. For this study, vertical sounding profile images were archived from the many locations available within our area of interest for as many hours prior to convection as possible.

2.2 *PE Calculation*

To prepare the precipitation grids for calculation, the fine scale detail of the four-kilometer resolution must be made more representative of the scale of PW supplied by the Rapid Update Cycle. Averaging 100 adjoining four-kilometer grid boxes (10 x 10 grid) enlarges the six-hour precipitation depth to a 40-kilometer grid. Because precipitable water is found at each hour and precipitation depth should be temporally the same (but is a six-hour accumulation), we assume that the precipitation is evenly distributed across the six-hour period and so divide each grid point value by six. The output is an hourly area-average precipitation depth in millimeters.

Precipitable water, as derived from Rapid Update Cycle hourly initializations, is on a slightly larger grid with different reference points than our precipitation grid. Grid bilinear interpolation is used to match up the two different grids point-to-point, and maps of hourly PW for our area of interest are produced.

From radar mosaics over the central United States, areas over which the MCS precipitates at the top of the hour are outlined on a numbered grid template for each hour within the six-hour period. From these outlined grids, the total hourly average precipitation of the MCS can be determined. The corresponding grid points are added to find the total PW of the MCS environment for that hour. This summation is done for all hours within the period to obtain a total of hourly average precipitation depths (in millimeters) and total precipitable water (in millimeters) processed by the MCS. According to the Sellers PE definition, precipitable water should be an average value over the same time period as the total precipitation. To obtain a six-hour average PW value, the total PW is divided by six before the final PE calculation is completed. To find the final hourly average PE, the ratio of total of hourly average precipitation to hourly average precipitable water is then computed.

2.3 *Sounding Choice*

For each calculation of precipitation efficiency, a GOES sounding must be chosen so that environmental variables can be correlated to the PE value found. Chosen soundings are representative of the environment into which an MCS will move or develop, and provide information about low-level moisture content, mid-level lapse rates, and environmental wind shear. For each period that has a calculated PE, a sounding near the MCS formation location or in the path of a mobile MCS is chosen for an hour early in the period, or one or two hours before the beginning of the period. The earlier a sounding is chosen, the more likely a proximity sounding will be available because a less developed MCS will have a smaller shield of cirrus clouds to obscure the GOES soundings. Another reason for choosing soundings early in the period is to avoid MCSs that alter their environments via cold low-level outflow. After considering these factors, sounding choices were made to enable calculation of precursor environmental variables that influence PE.

3. RESULTS

3.1 *Sellers Method*

Before beginning steps to create a predictive equation for PE, the validity of this newly applied PE calculation method had to be established. Because other PE calculation methods have provided consistency throughout the years, calculating via a method originally proven only in climate studies required comparison to ensure that the method is valid. Values from 2000 and 2001 cases range from a minimum of 4% to a maximum of 48% PE, which is consistent with the preponderance of the literature. Still, averages near 25% show that the Sellers method provides values lower than those of other methods, highlighting a systematic error.

By assuming that the six-hour accumulated precipitation fell equally among all six hours, we neglect the fact that some points received all of their precipitation in one or two hours, not six. This assumption tends to decrease the total precipitation accounted for in the Sellers PE numerator, causing the PE percentage to decrease. This is especially true for cases of fast-moving MCSs since they drop significant rainfall in a short time. For example, one grid point may receive 6 inches of rain in one hour (an extreme rainfall), and no rain in the other 5 hours because the MCS has moved out of the area. Our average method would divide that total by six, giving an average rainfall of one inch per hour. So, when adding up the hourly rainfall from our outlined MCS areas, only one inch of the total six that fell will be accounted for because for only one hour did the MCS precipitate on that grid point.

In this way, fast-moving MCSs will systematically have diminished PEs, and slow moving MCSs will be more accurately represented. Still, no correction was made for this systematic error because problems of the like described before were not that common, due in part to the large region of “stratiform” rainfall commonly found in the midst of the convective cells of an MCS (e.g., Houze 1997). Moreover, the Sellers PE calculation method does discriminate between high and low (48 to 4% PE), which can be useful to forecasters looking for the most critical precipitation systems.

3.2 *Statistical Analyses*

The GOES soundings chosen to be representative of the MCS environment for the 2000 summer season were used in performing both single correlations and creating a predictive equation. The dataset included the PE for 20 six-hour periods and their corresponding soundings, which were analyzed with a version of the software developed by Moore and Pino (1990). The output variables include a host of stability indices, measures of moisture, shears over various depths, and results from parcel manipulations (lifting).

The most significant of these variables, along with outputs of the same or similar quantities from the GOES sounder, were input to a statistical program for correlation to PE. Of the correlation coefficients obtained, the quantities having coefficients with confidence intervals in excess of 90% were isolated for further scrutiny and are outlined in Table 1. An inverse correlation was found between the PE of an MCS and the wind shear in the pre-MCS environment, concurring with the findings of Marwitz (1972). Thus, the notion of lower shear allowing for more erect cumulonimbi, less entrainment, and enhanced collision-coalescence in the warm cloud are supported. The positive correlation between PE and the mean relative humidity in the surface-LCL layer is not surprising given that the primary moisture source for most convection is from beneath cloud base. A relatively strong negative correlation exists between PE and the convective inhibition (CIN) of parcels from the lowest 100 mb. The significance of this finding is discussed further below.

One such parameter is CAPE, or convective available potential energy. Fankhauser (1988) also believed that CAPE should correlate to PE, but found no such relationship. It would seem that the potential for strong updrafts could enhance PE, but our correlations suggest that it is the amount of energy to be overcome to create and maintain updrafts that affects PE more. An assumption why this relationship exists lies in the fact that when CIN is minimized, even modest amounts of CAPE will produce updrafts strong enough to effectively collect precipitation particles, but even for large CAPE, CIN can be large and updrafts may never get to form, making CIN the dominant force.

Other variables that did not correlate well include the precipitable water, while intuitively it would seem that adding more moisture to the atmosphere would increase precipitation. Increasing PW does not necessarily increase PE, it only increases the denominator of the PE expression, which could cause PE to decrease overall if the amount of actual precipitation remained constant. Next is the warm cloud depth, measured from cloud base up to where core cloud temperatures reach freezing. The warm cloud depth is important because it defines the depth of the cloud wherein collision-coalescence is the dominant process for rain droplet growth; it would probably correlate better to PE if our dataset contained more variety of depths. Considering that the range on calculated warm cloud depths is small in the summertime, PE studies incorporating year-round calculations would have better opportunity to capture a systematic relationship. Lastly, environmental relative humidity surrounding the cloud would seem to also influence PE, since very dry surroundings would tend to evaporate cloud material from the sides and decrease the moisture available to create precipitation. However, the range of extra-cloud humidity is small in the summer, making a relationship difficult to determine. This is especially significant because Newton (1966) postulated that drier environmental air surrounding a cloud being entrained in was the cause of the decrease of PE with increasing shear. While this may well be true for the individual cumulonimbus, such does not appear to be the case for large collections of cumulonimbi manifested by an MCS.

Table 1: Significant variables from year 2000 cases with correlation coefficients and confidence intervals provided.

Variable	Corr. Coef.	Conf. Interval
Surface to LCL RH	0.392	90%
CIN of lowest 100mb parcel	-0.481	95%
Shear over warm cloud depth	-0.384	90%

After finding few of the more significant individual variables that vary systematically with PE, a predictive equation was created using the 2000 dataset. The forward stepwise statistical method employed by Klein (1983) was chosen because it eliminates the interdependency between predictors. Since meteorological variables such as low-level relative humidity and LCL height are related, the two should not be used as independent variables in creating a predictive equation. Stepwise regression chooses the first predictor that explains the most variance in the predictand, and then chooses the second predictor that explains the most of the remaining variance after the effect of the first predictor is held constant. The method is repeated until a sufficient number of variables and a suitable significance level are reached.

Using statistical software, both variables derived from GOES soundings and those calculated via the stability program of Moore and Pino (1990) were input with PE to create a predictive equation. After many trials, the two equations significant at the 95% level with the fewest number of variables were found and are presented in Table 2. Both equations have as their first predictor the CIN calculated from a parcel of air with the mean properties of the lowest 100mb of the atmosphere. Both also have CIN calculated from the low-level parcel with the highest θ_e. The two methods of calculating CIN prove useful for different convective environments, with the first encompassing surface-based convection, and the second capturing elevated convection. The last term or terms in the stepwise regression equations are the same as were found during the individual correlations, those being cloud shear and low-level relative humidity.

Prediction of 2001 PE from the equations was accomplished for fourteen MCS cases, and results of the prediction equation paired with the calculated PE are presented in Table 3. Each calculated PE is for the first six-hour period the MCS existed on our grid. The root-mean-square error (RMSE) for each equation shows that the predictive equation with four variables provides a slightly more accurate predictor of PE. If an equation is to be used to predict PE in advance, the three variable equation is recommended because their RMSEs are almost identical and fewer variables require calculation.

4. CONCLUSIONS

A predictive relationship between warm-season Midwestern MCS PE and GOES sounding profiles has been established. To achieve this goal, a PE calculation method was presented based on a climatological PE definition. By decreasing the time step to six-hour precipitation for the Sellers PE numerator and corresponding precipitable water for the denominator, the definition can capture mesoscale features like MCSs.

Using these PE values in conjunction with environmental parameters derived from GOES soundings representative of the environmental air available to the MCS, statistical analyses were performed on the data. The single correlations affirm that PE is controlled by certain environmental factors, namely vertical wind shear, the sub-cloud base moisture, and the convective inhibition. The implications of these statistically significant relationships reach into the realm of forecasting, providing a basis for advance prediction capability. Predictive equations created using the stepwise regression method are significant at the 95% level and have RMSEs near 5%, yielding acceptable predictions. Therefore, PE can be predicted in advance due to its dependence on environmental factors measured by the GOES sounder.

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Table 2: Stepwise regression equations based on 2000 PE values. *CIN1* is the CIN as calculated from a parcel with the mean conditions of the lowest 100mb. *CIN2* is the CIN as calculated from a parcel with the maximum θ_e in the lowest levels. *CS* is the cloud shear from base to top of the warm cloud. *RH* is the relative humidity from the surface to LCL.

	Equation
Three Variables	PE = 0.306 – 0.00173(CIN1) + 0.000855(CIN2) – 10.5(CS)
Four Variables	PE = 0.308 – 0.00174(CIN1) + 0.000856(CIN2) – 10.5(CS) – 0.002(RH)

Table 3: Prediction of 2001 PE values using both the three and four variable equations. The RMSE of each equation is shown along with the percent variance accounted for by each equation.

Date	Predicted PE (3-Var)	Predicted PE (4-Var)	Calculated PE
4 June	31%	31%	48%
21 June	31%	31%	26%
3 July	30%	30%	34%
16 July	30%	30%	22%
18 July	24%	24%	19%
25 July	25%	25%	28%
26 July	22%	22%	23%
24 Aug	27%	27%	29%
29 Aug	27%	30%	33%
30 Aug	30%	22%	27%
8 Sept	22%	22%	33%
9 Sept	27%	27%	41%
19 Sept	28%	28%	27%
21 Sept	33%	33%	28%
RMSE	4.38%	4.36%	-------
% Variance	51.5%	51.5%	-------