12A.4 CLIMATOLOGY OF WARM SEASON PRECIPITATING STORMS IN THE SOUTHERN GREAT PLAINS

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1. INTRODUCTION

The climatology of thunderstorms in the United States has interested meteorologists for over 100 years. Earlier studies have been summarized by Court and Griffiths (1986). Studies of mesoscale weather systems have typically focused on their structure and dynamics (see summary by Doswell 2003). There have been studies done for seasonal or annual convective precipitation (e.g. Chagnon 2001, Market et al. 2002) but fewer on the storm level. Except for storms of notable intensity, the precipitation amounts from individual storms or small groups of storms have been of secondary importance. This situation has occurred because of the difficulty in determining precipitation amounts. Studies examining precipitation (e.g. Kane et al. 1987, Chagnon 2001, Ashley et al. 2003) have generally relied primarily on rain gage data. Although precipitation is the most densely and routinely measured meteorological quantity in the United States, rain gage networks still do not resolve many details of the precipitation field. Estimates of precipitation amounts from radar alone are not consistently accurate.

Kane et al. (1987) examined the precipitation from individual Mesoscale Convective Complexes (MCCs) and other large Mesoscale Convective Systems (MCSs) in the central United States. They examined two years worth of these storms and attempted to relate the precipitation patterns to the satellite imagery. They found that the right rear and right front quadrants of these storms were most likely to have heavier precipitation. In a related study Fritsch et al. (1986) used the same data set to show that the MCCs and large MCSs account for 30-70% of the precipitation during the warm season (April-September) over the central United States. Ashley et al. (2003) examined precipitation from MCCs over a longer period of time relying primarily on gage data. They found large interannual variability in the percentage of warm season (May - August) precipitation accounted for by the MCCs.

A number of questions remain unanswered by these studies. We know little about the precipitation produced by storms smaller than MCS. How many smaller storms are there? Does the ratio of small to large storms change from year to year? Ashley's study does not completely address the last problem because it was limited to storms meeting the criteria for MCCs. What is the average size and distribution of sizes of convective storms in the south central U.S.? What is the average duration of a convective storm in the south central U.S.? How does the amount of precipitation produced vary with the size of the storms? Answers to these questions

*Corresponding author address: Donna F. Tucker, 1475 Jayhawk Blvd, rm 213, University of Kansas, Lawrence, KS 66045-7613; email:dtucker@ku.edu are important for agricultural and hydrological applications in assessing the likelihood that a storm of a certain size or duration will form. Other applications such as planning for the protection of outdoor workers from lightning and for the efficiency of wireless communications (Tucker et al. 2008).

Around year 2000 the National Weather Service in the United States started producing a product that combines radar, rain gage and satellite precipitation estimates. Although this product still has errors, it provides greater spatial resolution than the rain gage network alone and greater accuracy than the radar estimates alone. Since its resolution is about 5 km, it still misses very small scale precipitation features. Nevertheless, we believe this data set can reveal a great deal about the nature of convective precipitation in the central U.S.

One of the challenges of this data set is its vast size and the need to process it in a timely fashion. Hocker and Basara (2007, 2008) recently studied squall lines and supercell storms using Geographic Information Systems (GIS). They were concerned with the numbers and spatial distribution of the storms rather than storm precipitation and relied almost exclusively on raw radar reflectivity data. Baldwin et al. (2005) developed an automated procedure to analyze the gridded radar and rain gage merged product. They were more concerned with identifying structural and dynamic features of the storms in the data set than the amount of precipitation itself. We would like to explore the application of similar techniques to the problem of precipitation produced by convective storms and to address questions of size and duration of these storms.

2.0 DATA AND METHODOLOGY

The National Weather Service's Next Generation Weather Data WSR-88D (NEXRAD) is a network of Doppler weather radars deployed throughout the United States to detect and indirectly measure meteorological and hydrological phenomena. Based on the amount of processing, calibration and quality control performed, several rainfall products are derived from the radar measurements. Precipitation is estimated with a Z-R relationship, integrated over time to produce hourly values, and quality controlled and gridded at the individual river forecast offices. The resulting product is known as the hourly digital precipitation (HDP) array with a cell size of 4762.5 m which has been used for subsequent products. The NWS River Forecast Centers (RFCs) then use the rain gage data to correct biases in the radar data to produce a product known as Stage II (Fulton et al. 1998). The Stage II data from the individual radars are combined to form a gridded product over the entire RFC region. This process is performed with input from the human forecasters and the final product is known as Stage III (Smith and Krajewski, 1991; Anagnostou et al., 1999).

Instead of using the standard bias correction method, the Arkansas-Red River Basin River Forecast Center (ABRFC) developed its own local approach. A ratio between the gage data and the HDP products is computed and the ratio is interpolated at each cell. The radar data are multiplied by the ratio and further examined and adjusted by the human forecasters. The approach is known as P1 algorithm. The P1 product is generally better at detecting light precipitation than the Stage III estimates and has fewer effects from the partial blocking of the radar beam (Young et al., 2000).



Figure 1. Study area. Actual Arkansas-Red River Drainage is outlined in solid black, the study domain is outlined in dotted black and U.S. states are outlined in solid gray.

The rainfall data used in this study are the hourly Stage III and P1 products provided by the ABRFC for the second phase of the Distributed Model Intercomparison Project (DMIP2), which was organized by the Hydrology Laboratory of the NWS. The study domain is limited to the forecast area of the ABRFC (Fig. 1). The actual Arkansas-Red River Basin is shown as a solid black line and the study domain is the dotted black rectangle circumscribing the basin. The Rocky Mountains comprise the extreme western part of the domain and the Ouachita Mountains make up the southeastern portion of the domain but the majority of the domain is relatively flat. The rainfall data we used span a period of 11 years from 4/01/1996 to 09/30/2006. Since we are examining precipitation during the warm season, we have only included the months of April-September. We expect the vast majority of the precipitation in this area to be from convective storms although the contribution from stratiform rain may be a larger component during April and May than in other months. Chagnon (2001) estimated that over 80% of the June - August rainfall in this region was from thunderstorms. The ABRFC relied on a standard algorithm for Stage III production prior to late 1996 after which it adapted the locally developed process (P1) to produce the precipitation data. We have not noticed that this change of methodology gave any dramatic differences in the nature of the precipitation patterns for 1996. It should be noted that this data set contains no missing data. All cells at all times contain the best precipitation estimate that can be made with the Stage III or P1 method with the data available.

A storm consists of a set of connected precipitation cells delineated from stacked hourly NEXRAD precipitation grids. The method used to identify contiguous regions in space and time is based on the component labeling algorithm in digital image processing (Haralick and Shapiro 1992). Three parameters, the minimum hourly precipitation (MHP) in a cell, the minimum time span (MTS) of a storm, and the definition of spatial and temporal connectivity, were used to control storm delineation. Only the cells with hourly precipitation greater than or equal to the MHP are considered as precipitation cells. The MTS parameter specifies the minimum time span for a storm. The spatial and temporal connectivity of the precipitation cells is defined by a 3 x 3 x 3 binary matrix where 1-valued elements are connected to the center element. In our analysis of the DMIP2 NE-XRAD precipitation data, MHP and MTS were set to 1 mm and 1 hour, respectively. The one hour threshold for MHP allows us to include single-ordinary-cell thunderstorms which often have small precipitation amounts as well as to completely represent the stratiform region of MCS. The connectivity was defined as the following matrix:

	Time = t-1	Time = t	Time = t+1	
	010	111	010	
у	111	111	111	
	010	111	010	
		×		

where the 1 indicates a cell which could potentially be in the storm if it has precipitation. The above matrix allows side and point connectivity between precipitation cells in space but limits their connectivity to side and face only in time. Note that a storm's lifetime ends if it ceases producing precipitation or leaves the study domain. This method has some differences from that of Baldwin et al. (2005). Storms in their study are delineated as contiguous regions in space but not in time. Their storms, therefore, are defined without regard to temporal continuity. We did not attempt to connect precipitation areas separated by small gaps but considered all areas not connected as being separate storms. Likewise, a storm at one hour had to be connected to a storm at the next hour in order to be considered part of the same storm. These differences occur because we think that storm lifespan should have temporal continuity and contiguity in space and time is a natural way of delineating storms.

3. NUMBER, SIZE, AND DURATION

Based on the above method, a total of 519,562 storms have been delineated for the 11 year time period. The number of storms varies by year (Fig. 2) and month (Fig. 3). The average number of storms per year is 47,232. The number of storms in the year with the most storms (1999) is 46% higher than the number in the year with the fewest (2005). The numbers have more dramatic variations seasonally with the numbers rising from April until August before decreasing in September. Note that 1997 had the highest precipitation of any year in the data set with a high (but not the highest) number of storms and 1998 had the lowest precipitation with close to an average number of storms.



Figure 2. Number of storms (grey) and amount of precipitation (black) by year.

We use two ways to measure storm size: maximum size and footprint. The maximum size is the maximum number of cells receiving precipitation at any specific hour during the storm's lifespan. The footprint consists of all the cells that receive precipitation from the storm during its lifetime. Thus, the maximum size and the footprint will be the same for storms lasting less than two hours . The footprint, however, is dependent on duration as well as maximum size. The mean maximum size for all storms in the 11 year period is 21.1 cells (478.6 km²). The maximum size and footprint vary from year to year (Fig. 4). The linear correlation coefficient between the maximum size and the number of storms on a yearly basis is -0.77. Thus, years with more storms also tend to have smaller storms. The maximum size and footprint also have a strong monthly variation (Fig. 5) with August having the smallest storms. The seasonal decrease in vertical wind shear during the mid to late summer months, which favors more widely scattered and unorganized storms, is one likely contributor to the decrease in storm size during the month of August.



Figure 3. Number of storms (grey) and amount of precipitation (black) by month.



Figure 4. The mean maximum size (grey) and the mean footprint (black) for storms each year of the study. Size is measured in cells.

The average duration of storms in the data set is 1.4 hours. This time is consistent with the finding above that most storms are relatively small in size. This finding is also consistent with the study by Robertson and Easterling (1988) who found an average duration of thunderstorms in the central U.S. to be 77 minutes during the summer. Robertson and Easterling's stations were all north of our domain and since they used station data, they had an Eulerian approach to measuring duration as opposed to the Lagrangian approach used here. Since a storm's lifetime ceases when it leaves the domain, our estimates of storm duration may be somewhat reduced. Nevertheless, there is an average of over 14 storms per six months that lasted over 24 hours – about

one every other week. These very long lived storms were more common in the June-August period than for other months. There is some variation between months (Fig. 6) and surprisingly, the months with smaller storms (mean maximum size, Fig. 5) are also the months with longer average duration of storms. Robertson and Easterling also found that thunderstorms in the central U.S. lasted longer in summer than in spring.

The linear correlation between maximum size and duration is 0.75 in April but averages 0.68 for other months with little variability. The smallest and most numerous storm duration is less than 2 hours and within this group there is some storm size variability. With finer time increments the correlation might be higher although April with the largest percentage of short duration storms had the highest correlation between size and duration. Correlation between storm size and duration might be nonlinear but no other functional relationship was apparent. Several storms of fairly large sizelasted less than two hours . Some such storms possibly left the study domain quickly. Some other storms were stratiform precipitation regions and were more common during April and May.



Figure 5. The mean maximum size (grey) and the mean footprint (black) for storms by month. Size is measured in cells.

4. STORM TYPES

Assuming all precipitation to be convective, we can do roughly divide the storms into three different types. Thunderstorms have customarily been divided into single ordinary cells, supercells, multiple cells, and MCSs which include squall lines and MCCs (Lin 2007). A single ordinary cell thunderstorm will not last more than one hour. Within this one hour, we would not expect this storm to affect more than 20 cells (453.6 km²). Mesoscale convective systems (MCSs) are defined to last at least 6 hours and have a dimension of at least 100 km in at least one direction (Glickman 2000). Thus, storms lasting 6 hours or more with a maximum size of 21 cells or more are defined MCSs. Since we measure size as the size of precipitating area, this method could underestimate the number of MCSs. But storms lasting more than 6 hours with a maximum size of larger than 21 cells are quite uncommon in our 11 years of data. Supercell thunderstorms are comparable in size to multiple cell thunderstorms (Lin 2007) but the two types cannot be distinguished with the information in our data set. Storms not meeting the criteria for either a single ordinary cell thunderstorm or an MCS are therefore defined as multiple in this paper. Based on these definitions, single ordinary cell thunderstorms, multiple, and MCSs make up 78%, 21% and 1% of the storms in the database respectively. From year to year these percentages vary surprisingly little (Table 1). The year with the highest percentage of single ordinary cell thunderstorms, 2003, had 81% and the year with the lowest percentage of these storms, 2005, had 74%.



Figure 6. The average duration of storms in hours by month.

4. PRECIPITATION

As would be expected considering the small size and short duration of most storms, their precipitation is fairly light. Overall MCS account for 86% of the precipitation in the database even though they are only about 1% of all storms. Fritsch et al (1986) estimated that MCSs account for 30-70% of the warm season precipitation in the central United States. Most of our study domain is in areas that would be on the higher side of their estimate. Fritsch et al. (1986) included only the larger MCS in their study and considered their estimates to be conservative. Ashley et al. (2003) estimated that the central United States receives between 8 and 18% of its warm season precipitation from MCCs alone. For most of our study areas they found these percentages were in the 12-25% range. We point out that we have included more than just MCCs in the MCS category and our definition of MCSs was broader than that of Fritsch et al. Multiple thunderstorms account for about 13% of the

precipitation and single ordinary cell thunderstorms, in spite of their great numbers, account for only about 1% of the total precipitation.

Some examination of storm characteristics can be helpful to explain what features produce a drought year or a year with abundant precipitation. With MCS controlling so much of the precipitation, one might think that their numbers would be indicative of the amount of precipitation in a given year. We found the case for this to be weak. The overall linear correlation between number of MCS per year and total amount of precipitation was 0.42. . The two years with the lowest numbers of storms, 2004 and 2005, had moderate amounts of precipitation (Fig. 2). Notably, these were also the years with the highest average storm maximum size and footprints. Thus, storms were fewer but they were larger and lasted longer. In particular 2005 had the highest percentage of multiple thunderstorms and one of the higher percentages of MCS storms but the actual numbers of these storms were the lowest of all years studied. The year with the lowest precipitation, 1998, had a moderately large number of storms. But 1998 had the smallest average storm size and the smallest average storm footprint. The year with the highest precipitation, 1997, was also the year with the greatest number of storms. Its maximum storm size and footprint are below average. Interestingly, both 1997 and 1998 were years with below average numbers of supercells across the state of Oklahoma (Hocker and Basara 2008). The year 1999 had the most storms of any in the database but the average storm size and footprint were relatively low. It had the second highest amount of precipitation of the years in our database and the most supercells in Hocker and Basara's (2008) database. The year 2000 is also an interesting one for precipitation amounts. It had the shortest average duration of storms and the second lowest number of storms. Its storm average footprint and maximum size are only the 3rd lowest of all years. Its precipitation per cell was 2.0 mm. It still managed a little more precipitation than 1998. Thus, the mean maximum size and footprint of storms appear to be the primary factors determining precipitation amounts but the number of storms in a year is also important.

The interplay among these factors can be seen in the variation of precipitation between months. Jun e is the month with the highest precipitation (Fig. 4). It is not the month with the largest size of storms, the longest duration of storm, the largest footprint of the storms or the most storms. April and May have larger storms but there are many fewer of them. July and August have many storms but they are small and have smaller footprints.

5. CONCLUSIONS

Our work shows that the vast majority of storms in the Arkansas-Red River Basin during the warm season are small and short lived. Nevertheless, the database contains a number of very long lived storms. The intraseasonal variations in numbers of storms exceed the year to year ones. Midsummer storms had smaller average size but longer average duration. We could roughly divide the storms into single ordinary cell thunderstorms, multiple thunderstorms and MCSs. The MCSs account for a small percentage of the numbers of storms but they do account for the vast majority of the precipitation during the warm season. Although the MCSs have larger values of precipitation per cell than the other types of storms, precipitation per cell is generally only weakly correlates with the storm's maximum size - it is better correlated with the storm's duration.

This study generated many questions concerning the factors that determine the lifetime and amount of precipitation produced by convective storms. Such questions were especially applicable for the multiple thunderstorms. Although supercell thunderstorms have been extensively studied, small multiple cell thunderstorms have not received much attention from the research community. We do not know much about how the duration or the amount of precipitation produced by these storms is affected by the microphysics.

Since this study was observational, it did not generally address issues as to why particular relationships existed. It does, however, point out several areas where our knowledge of these storms is lacking and where more research is required. It is not clear what determines the number of storms per year or the distribution of storm types. It is puzzling why the smaller storms of midsummer should last longer than the larger storms of late spring and early summer. We did not find any particular characteristic associated with drought years or years with heavy precipitation. Although the mean size of the storms was important, other features also contributed heavily

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	Number Single	Percent Single	Number	Percent	Number	Percent
	Ordinary	Ordinary	Multiple	Multiple	MCS	MCS
1996	34370	75.9	10313	22.8	599	1.3
1997	41205	78.3	10860	20.6	561	1.1
1998	38862	78.9	9896	20.1	475	1.0
1999	43443	78.7	11168	20.2	581	1.0
2000	34364	79.0	8718	20.1	403	0.9
2001	41104	77.8	11176	21.1	580	1.1
2002	37407	76.9	10681	21.9	587	1.2
2003	38480	78.9	9896	20.1	475	1.0
2004	29404	76.9	8950	23.0	548	1.4
2005	27794	73.5	9476	25.1	536	1.4
2006	36180	74.6	11624	24.0	669	1.4

Table 1. Total number and percentage of thunderstorm types by year