

## Characteristics of warm season precipitating storms in the Arkansas–Red River basin

Donna F. Tucker<sup>1</sup> and Xingong Li<sup>1</sup>

Received 3 September 2008; revised 31 March 2009; accepted 14 April 2009; published 14 July 2009.

[1] Analysis of a multisensor precipitation product enables us to extract the precipitation from individual storms in the Arkansas–Red River drainage basin over a period of 11 years. We examine the year-to-year and intraseasonal variations of storm numbers, duration, sizes, and precipitation in the data set. Intraseasonal variations in numbers of storms exceed their year-to-year variations. More mountainous regions had greater numbers of storms than flatter regions. Most storms are small, last less than 2 h, and produce modest amounts of precipitation. The maximum size of storms and the number of storms are negatively correlated on a yearly basis. Midsummer months had a greater percentage of smaller storms but the storms were of longer average duration. We can roughly divide the storms into three different types, single ordinary cell storms, multiple storms (includes supercells), and mesoscale convective systems, and look at their year to year and intraseasonal variability in the data set. The most storms occur around 1700 local time but the most precipitation falls around 0100 local time. Storm duration was the most important factor determining how much precipitation storms generate per cell. We do not find that drought years or years with abundant precipitation had any particular characteristics but occur as a result of simultaneous occurrence of several features.

**Citation:** Tucker, D. F., and X. Li (2009), Characteristics of warm season precipitating storms in the Arkansas–Red River basin, *J. Geophys. Res.*, 114, D13108, doi:10.1029/2008JD011093.

### 1. Introduction

[2] 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* [2001]). There have been studies done for seasonal or annual convective precipitation [e.g., *Changnon*, 2001; *Market et al.*, 2002] but fewer at 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; *Changnon*, 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.

[3] *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 2 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.

[4] 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 et al.*'s [2003] 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 United States? What is the average duration of a convective storm in the south central United States? How does the amount of precipitation produced vary with the size of the storms? Answers to these questions 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

<sup>1</sup>Department of Geography, University of Kansas, Lawrence, Kansas, USA.

of outdoor workers from lightning and for the efficiency of wireless communications [Tucker *et al.*, 2008].

[5] In the early 1990s 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 United States.

[6] 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.

[7] In the next section, we will describe the data set and algorithm we used for extracting individual storms. In section 3 we will focus on fundamental questions of numbers, size, and duration of these storms as well as their variations by season and year. Precipitation amounts and how they are affected by the size and duration of the storms will be examined in section 4. We will summarize and describe future work in section 5.

## 2. Data and Methodology

### 2.1. Precipitation Data

[8] Precipitation has traditionally been measured with rain gages. There are several difficulties with these measurements but the most serious is that they are point measurements and precipitation varies greatly even within small areas. Precipitation has also been estimated from radar returns using a Z-R relationship. Radar provides measurements which have greater spatial resolution than almost all rain gage networks. One problem with this method is that the Z-R relationship is not constant and varies with time and location. Other problems can include variations in accuracy and resolution depending on distance from the radar, partial blocking of radar beam, storm sampling limitations at near (cone of silence) and far ranges (overshooting) from the radar, and contamination from bright band echoes. It is not surprising, therefore, that precipitation products have been developed that combine both types of data.

[9] 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. On the basis of the amount of processing, calibration and quality control performed, several rainfall products are derived from the radar measurements.

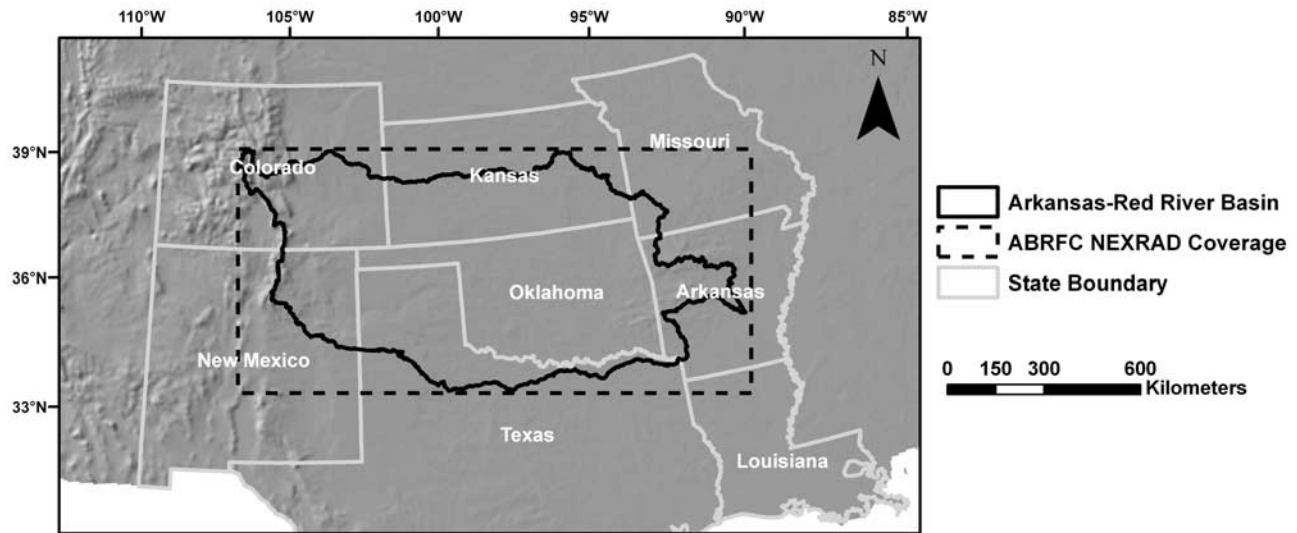
Precipitation is estimated with a Z-R relationship, integrated over time to produce hourly values, and quality controlled and gridded at the individual river forecast offices. The resulting product is known as the hourly digital precipitation (HDP) array with a cell size of 4762.5 m which has been used 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]. These data have been used for a variety of applications: hydrometeorology and climatology [Seo *et al.*, 1999; Krajewski and Smith, 2002], weather forecasting [Greco and Krajewski, 2000], and flood modeling and forecasting [Johnson *et al.*, 1999; Young *et al.*, 2000; Knebl *et al.*, 2005].

[10] 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].

[11] 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 (Figure 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 and the majority of the domain is relatively flat. The rainfall data we used span a period of 11 years from 1 April 1996 to 30 September 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. Changnon [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.

### 2.2. Storm Delineation

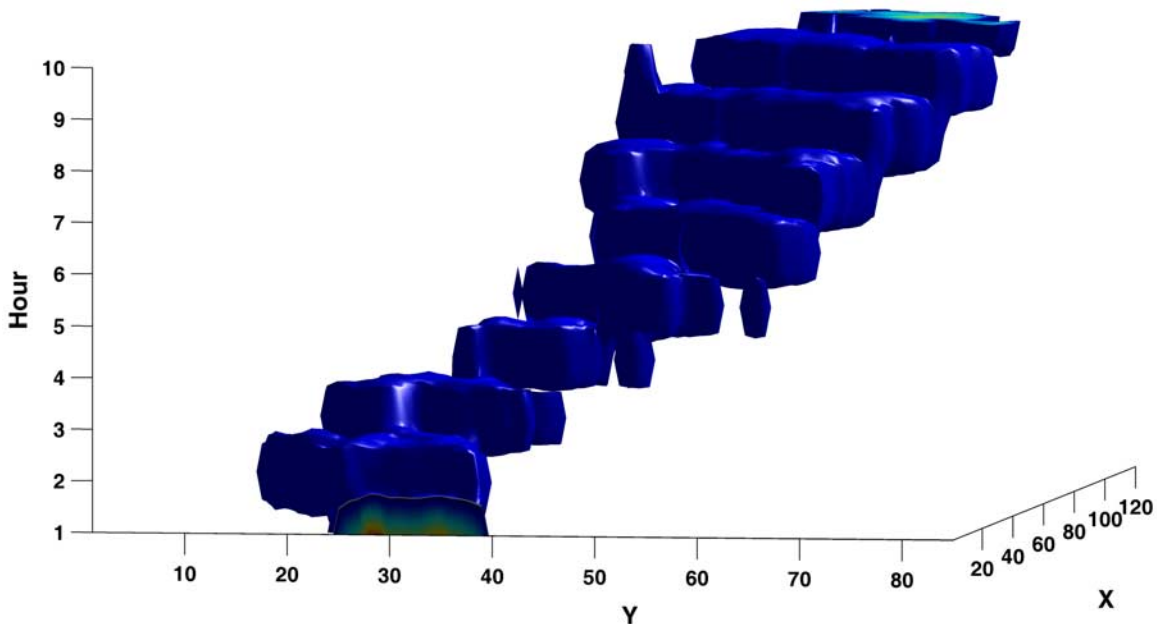
[12] A storm in this study is defined as a contiguous precipitation object in space and time (Figures 2a and 2b). It



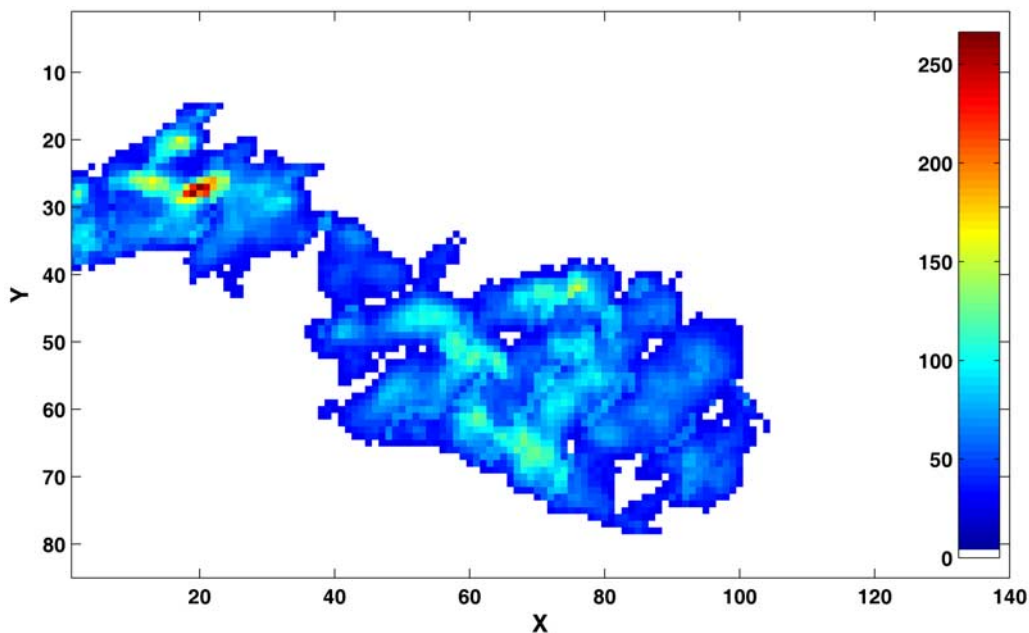
**Figure 1.** Study area. Actual Arkansas–Red River Drainage is outlined in solid black, the study domain is outlined in dotted black, and U.S. states are outlined in solid gray.

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 pre-

cipitation 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  $3 \times 3 \times 3$  binary matrix where 1-valued elements are connected to the center element. In our analysis of the DMIP2 NEXRAD precipitation data, MHP and MTS were set to 1 mm and 1 h, respectively. The 1-h threshold for MHP allows us to include single-ordinary-cell thunderstorms which often have small precipitation amounts as well as to completely repre-



**Figure 2a.** A 10-h-long storm, which occurred on 12 June 2002, is delineated as a contiguous precipitation object in space and time. The areas receiving precipitation in each hour are shown as blue 3-D patches. X and Y are in the unit of cells which have a size of 4762.5 m.



**Figure 2b.** The same storm projected onto the  $x - y$  plane. The  $x$  and  $y$  axes are in the unit of cells which have a size of 4762.5 m. Precipitation is in millimeters.

sent the stratiform region of MCS. The connectivity was defined as the following matrix:

|     | Time = $t - 1$ | Time = $t$ | Time = $t + 1$ |
|-----|----------------|------------|----------------|
|     | 0 1 0          | 1 1 1      | 0 1 0          |
| $y$ | 1 1 1          | 1 1 1      | 1 1 1          |
|     | 0 1 0          | 1 1 1      | 0 1 0          |
|     |                | $x$        |                |

where the 1 indicates a cell is connected to the center cell (at row 2 and column 2 at time  $t$ ) and is potentially in the storm if it has precipitation and the 0 indicates a cell is not connected to the center cell and is not in the storm even 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 may last more than 1 h and contiguous precipitation regions in space and time is a natural way of delineating storms.

[13] A software tool was developed to process NEXRAD precipitation data using MATLAB<sup>®</sup>. The tool creates a precipitation database by converting raw data into MATLAB file format to take the advantage of data compression capability in MATLAB. Because of the size of the data set (more than 96,360 hourly precipitation grids during the

11-year period), the component labeling algorithm cannot be directly applied to the entire database. The precipitation database was therefore first scanned to identify cubes of continuous precipitation hours which were separated by no rain hour(s) across the grid. Those precipitation cubes were then used to delineate contiguous precipitation regions (i.e., storms). Several properties were calculated for the storms, including the number of precipitation cells, the total amount of precipitation, duration, maximum size, and footprint size. In addition, the precipitation-weighted centroids of the storms were also calculated and used to represent the storms as points in space and time.

### 3. Number, Size, and Duration

[14] On the basis of 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 (Figure 3) and month (Figure 4). 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. We can also look at the numbers in terms of the spatial distribution of the storms. The storm frequency grid (Figure 5) was calculated by counting the number of storms occurred in each cell during the 11-year period. In May, and to a lesser extent, April, there is an increase in the number of storms per cell from west to east. By July, this pattern has reversed and there are more storms in the western part of the domain until September where numbers increase in the eastern part of the domain. Over the entire 11 years of warm seasons, there is a high storm frequency

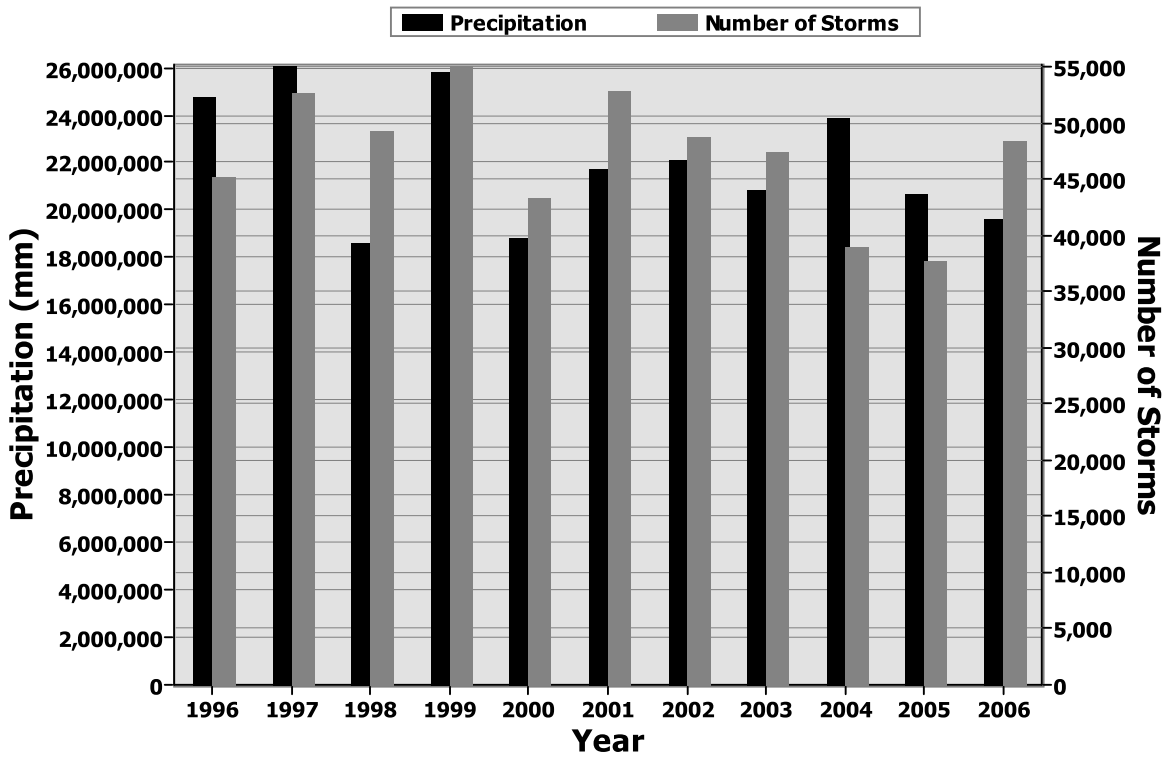


Figure 3. Total number of storms (gray) and total amount of precipitation (black) by year during the 11-year period.

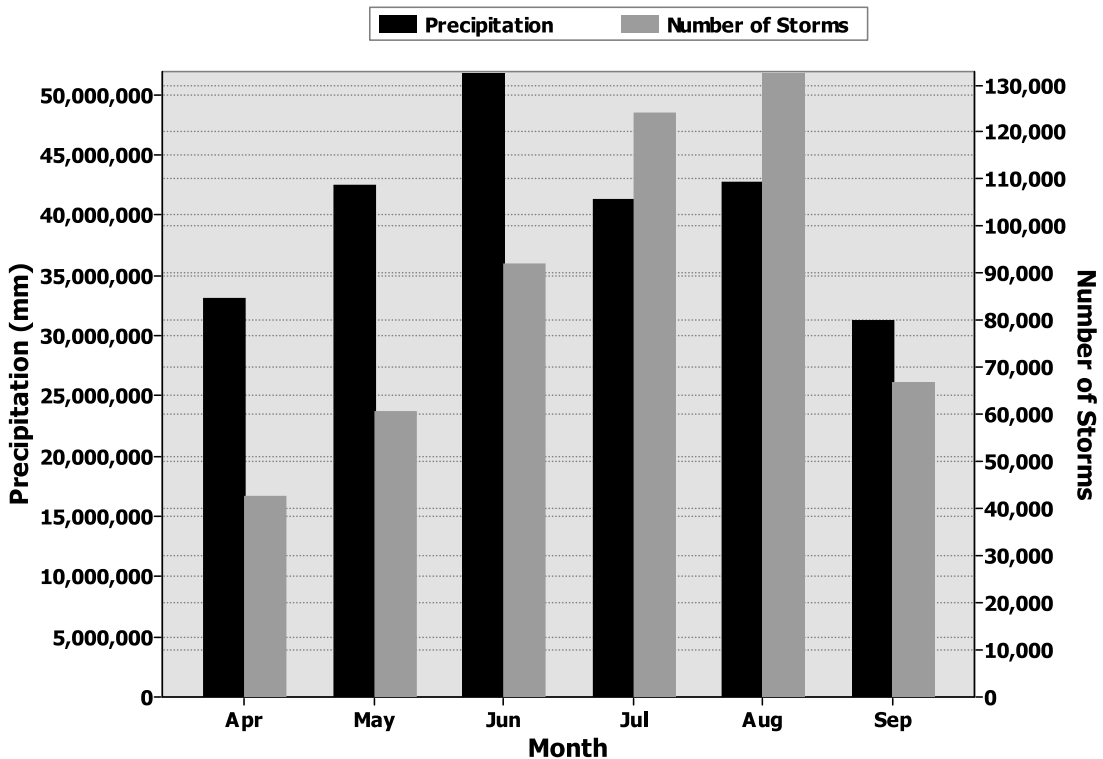
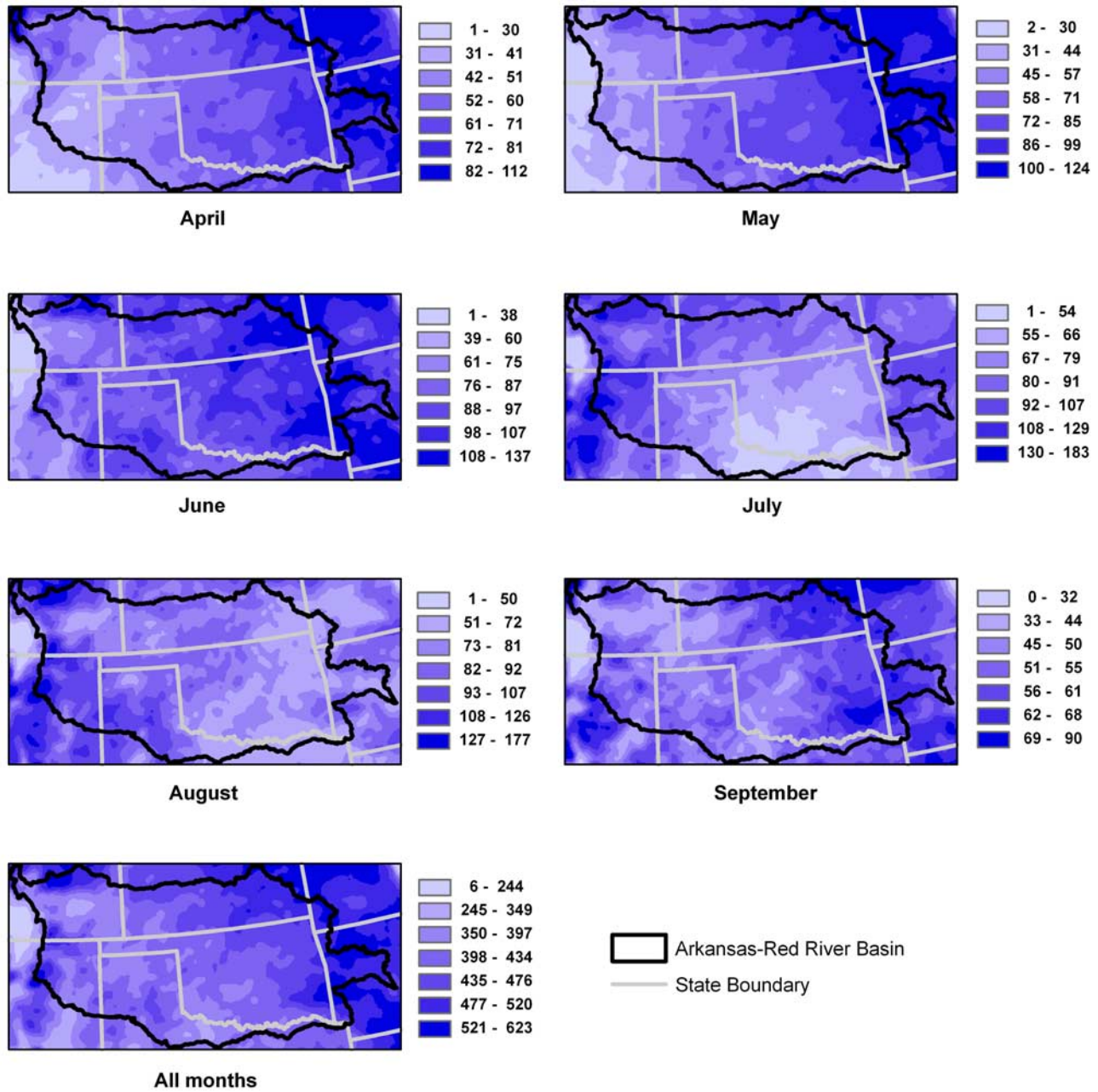


Figure 4. Total number of storms (gray) and total amount of precipitation (black) by month during the 11-year period.

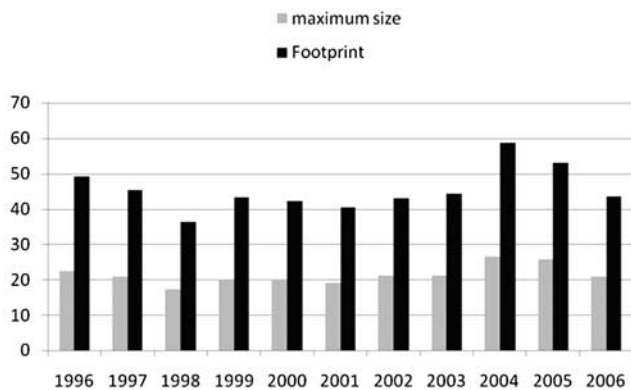


**Figure 5.** Total number of storms that occurred at each location in April, May, June, July, August, September, and all months during the 11-year period.

near the Rocky Mountains in the western extreme of the domain. This area is known for its large number of thunderstorms per year [Court and Griffiths, 1986] but we see here that these high frequencies are almost all from July and August. The highest spatial frequencies of storms correspond to complex topography, particularly the eastern slopes of the Rocky Mountains in the western portion of the study area as well as the Ozarks and Ouachitas across the eastern part of the study domain.

[15] 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

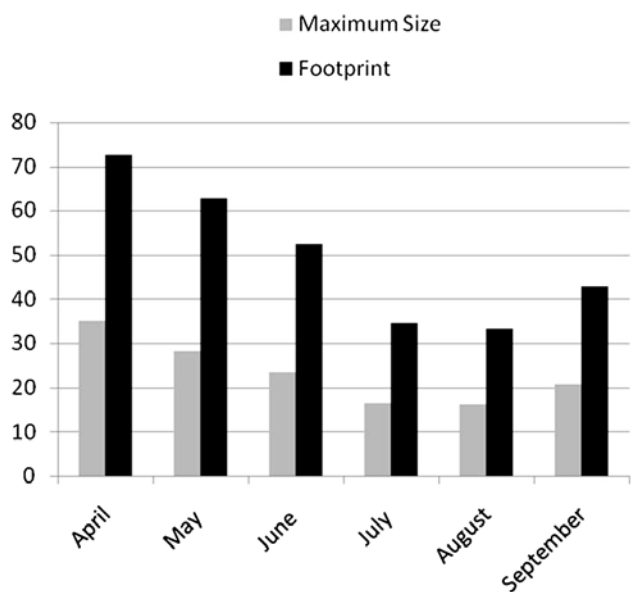
lifetime. Thus, the maximum size and the footprint will be the same for storms lasting less than 2 h. The footprint, however, is dependent on duration as well as maximum size. The mean maximum size for all storms in the 11-year period is 21.1 cells (478.6 km<sup>2</sup>). The maximum size and footprint vary from year to year (Figure 6). 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 (Figure 7) 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



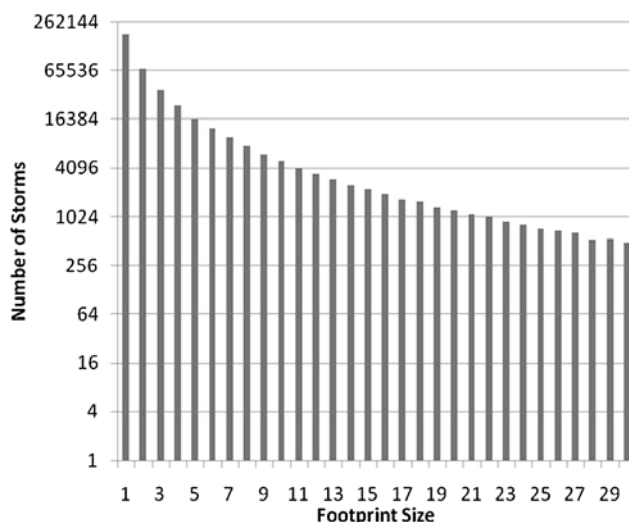
**Figure 6.** Mean maximum size (gray) and the mean footprint (black) for storms each year of the study. Size is measured in cells, and cell size is 4762.5 m.

and unorganized storms, is one likely contributor to the decrease in storm size during the month of August.

[16] 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 1 h. Within this 1 h, we would not expect this storm to affect more than 20 cells (453.6 km<sup>2</sup>). If we look at all storms with a footprint of 30 cells or less (Figure 8), we see that the number of storms levels out at 21 cells before decreasing again. To minimize the contamination between different types of storms we will consider all storms lasting less than 2 h with a size of 20 cells or less to be single ordinary cell thunderstorms [Byers and Braham, 1949]. We recognize that without a method to distinguish the storms physically we cannot be sure that all the storms in our single ordinary



**Figure 7.** Mean maximum size (gray) and the mean footprint (black) for storms by month. Size is measured in cells, and cell size is 4762.5 m.



**Figure 8.** Histogram showing numbers of storms with footprint sizes of 30 cells or less. Cell size is 4762.5 m.

cell thunderstorm category are in fact this type of storm. We consider the contamination to be small enough that the classification is still useful. Mesoscale convective systems (MCSs) are defined to last at least 6 h and have a dimension of at least 100 km in at least one direction [Glickman, 2000]. Thus, storms lasting 6 h 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 h 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. On the basis of these definitions, single ordinary cell thunderstorms, multiple, and MCSs make up 78%, 21% and 1% of the storms in the database respectively. Variation from month to month is small (Table 1). April, interestingly, has the high of 82% and August the low of 75% of storms being single ordinary cell thunderstorms. Percentages of storms that are MCS varied, at most 0.5%, between months. July and August have the highest percentage of multiple cell thunderstorms, therefore, conditions in July and August slightly favor the multiple type thunderstorm more than the other months. From year to year these percentages vary surprisingly little (Table 2). 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%.

[17] The time of day that storms occurred is presented in Figure 9. The time is at the precipitation weighted center of the storm’s lifetime. It can be seen that there is a strong tendency for storms to occur near 2300 and 0000 UTC. This would be in the early evening local time. This time would be preferred for single cell and small multicellular thunderstorms. Maximum precipitation, however, is at 0100 local time (0700 UTC). MCSs are more likely to occur in the late evening and maximize during the nighttime and are likely

**Table 1.** Total Number and Percentage of Thunderstorm Types by Month

| Month     | Number<br>Single<br>Ordinary | Percent<br>Single<br>Ordinary | Number<br>Multiple | Percent<br>Multiple | Number<br>MCS | Percent<br>MCS |
|-----------|------------------------------|-------------------------------|--------------------|---------------------|---------------|----------------|
| April     | 35,253                       | 82.2                          | 7218               | 16.8                | 412           | 1.0            |
| May       | 48,488                       | 79.7                          | 11,664             | 19.2                | 701           | 1.1            |
| June      | 71,363                       | 77.4                          | 19,621             | 21.3                | 1178          | 1.3            |
| July      | 93,817                       | 75.5                          | 28,945             | 23.3                | 1486          | 1.2            |
| August    | 99,458                       | 74.9                          | 31,755             | 23.9                | 1625          | 1.2            |
| September | 52,132                       | 78.0                          | 14,003             | 20.9                | 707           | 1.1            |

responsible for most of this precipitation [Fritsch and Forbes, 2001].

[18] The average duration of storms in the data set is 1.4 h. 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 Robinson and Easterling [1988] who found an average duration of thunderstorms in the central United States to be 77 min during the summer. Robinson 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 6 months that lasted over 24 h, about one every other week. These very long lived storms were more common in the June–August period than in other months. There is some variation between months (Figure 10) and surprisingly, the months with smaller storms (mean maximum size, Figure 7) are also the months with longer average duration of storms. Robinson and Easterling also found that thunderstorms in the central United States lasted longer in summer than in spring. The summer months, however, do favor the very long lived storms but these storms are only a small percentage of the total storms. Emanuel [1994] has argued from theoretical considerations that lifetime of a convective cell is inversely proportional to its vertical velocity. Percentage wise summer favors the multiple thunderstorms and these storms will last longer than the single ordinary celled storms. The multiple thunderstorms in our data set are much smaller in August than in April (33.3 cells in August versus 92.5 cells in April) but last longer (2.30 h in August versus 1.97 h in April). More investigations are needed as to what factors influence the size and lifetimes of the small multiple cell thunderstorms.

[19] 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 h 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 size lasted less than 2 h. Some such storms possibly left the study domain quickly. Some other storms

were stratiform precipitation and were more common during April and May.

#### 4. Precipitation

[20] As would be expected considering the small size and short duration of most storms, their precipitation is fairly light. The spatial distribution of precipitation is shown in Figure 11. Precipitation generally increases from west to east. This type of increase is not surprising as the atmosphere generally has more moisture available in the eastern part where it is closer to the Gulf of Mexico. July, however, has more precipitation in the northern part of the domain than the southern part. August has a more uniform distribution of precipitation throughout the study area. At the height of summer the southern portion of the domain is influenced by the stabilizing effect of the subtropical high. Overall MCSs account for 86% of the precipitation in the database even though they are only about 1% of all storms. Figure 12 displays the spatial distribution of the percentage of precipitation produced by MCSs by month. Overall around 90% of the precipitation in the eastern part of the drainage basin came from MCSs. But the percentage is slightly reduced during July and August. The western part of the domain has a much lower percentage of precipitation produced by MCSs. 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 MCSs 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.

[21] The precipitation per cell indicates how efficient the storm is in producing precipitation. Note that here efficiency is defined in terms of how much precipitation the storm

**Table 2.** Total Number and Percentage of Thunderstorm Types by Year

| Year | Number<br>Single<br>Ordinary | Percent<br>Single<br>Ordinary | Number<br>Multiple | Percent<br>Multiple | Number<br>MCS | Percent<br>MCS |
|------|------------------------------|-------------------------------|--------------------|---------------------|---------------|----------------|
| 1996 | 34,370                       | 75.9                          | 10,313             | 22.8                | 599           | 1.3            |
| 1997 | 41,205                       | 78.3                          | 10,860             | 20.6                | 561           | 1.1            |
| 1998 | 38,862                       | 78.9                          | 9896               | 20.1                | 475           | 1.0            |
| 1999 | 43,443                       | 78.7                          | 11,168             | 20.2                | 581           | 1.0            |
| 2000 | 34,364                       | 79.0                          | 8718               | 20.1                | 403           | 0.9            |
| 2001 | 41,104                       | 77.8                          | 11,176             | 21.1                | 580           | 1.1            |
| 2002 | 37,407                       | 76.9                          | 10,681             | 21.9                | 587           | 1.2            |
| 2003 | 38,480                       | 78.9                          | 9896               | 20.1                | 475           | 1.0            |
| 2004 | 29,404                       | 76.9                          | 8950               | 23.0                | 548           | 1.4            |
| 2005 | 27,794                       | 73.5                          | 9476               | 25.1                | 536           | 1.4            |
| 2006 | 36,180                       | 74.6                          | 11,624             | 24.0                | 669           | 1.4            |



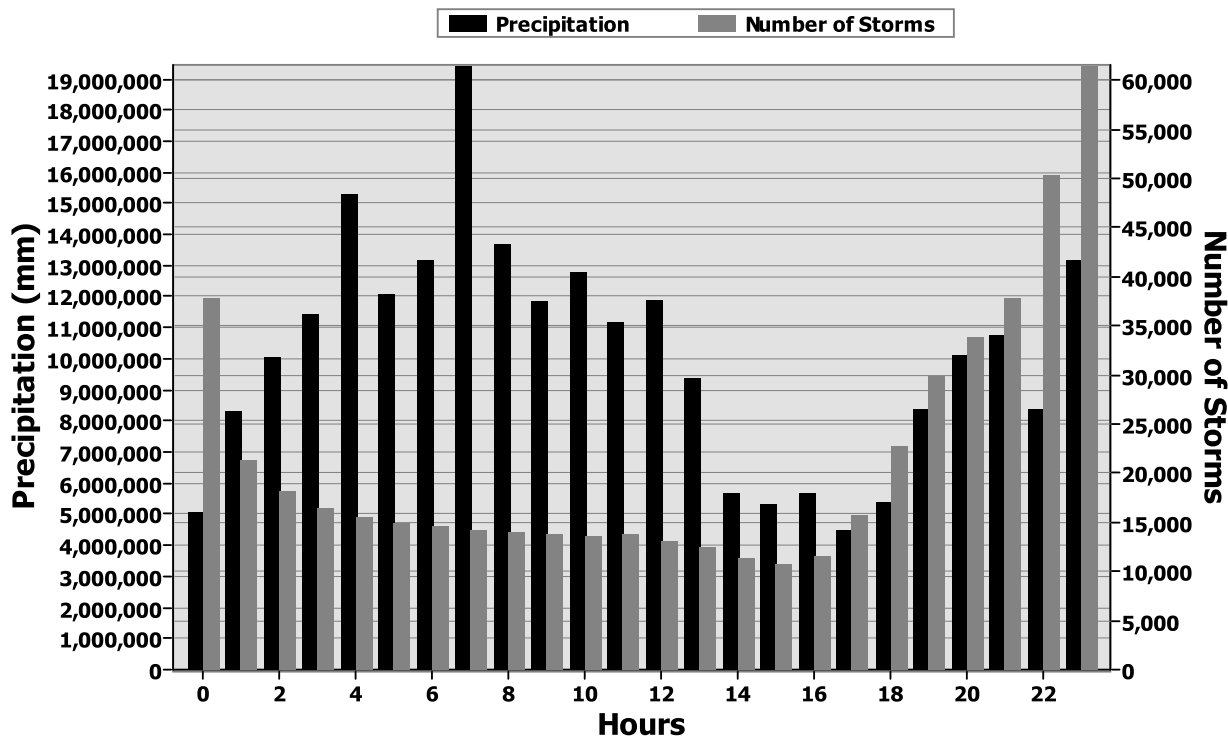


Figure 9. Total number of storms (gray) and total amount of precipitation (black) by the time of day during the 11-year period.

delivers without regard to the amount of water vapor available. The overall average precipitation per cell per storm is 2.1 mm. Figure 13 shows that small amounts of precipitation are most common which would be expected with most storms of small size and short duration. A small percentage but still a noticeable number of storms produced over 23.5 mm per cell. Precipitation per cell appears to be determined mostly by storm duration (linear correlation 0.67 in April and 0.54 in August). But maximum size and total precipitation amounts are of moderate importance in April (correlations 0.51 and 0.57, respectively) and less important in August (correlations 0.23 and 0.37, respectively). Yet during August the MCSs have a mean precipitation per cell of 8.0 mm compared to 3.8 for the multiple thunderstorms and 1.7 for the single ordinary cell thunderstorms. Overall, July and August have the most precipitation per cell. These are the warmest months and the air can potentially contain greater amounts of water vapor. It might be expected that size would be more important as single ordinary cell thunderstorms have precipitation efficiencies of only about 10% [Braham, 1952] but a squall line can have precipitation efficiencies of up to 50% [Newton, 1966]. Market et al. [2003] showed that precipitation efficiencies increase with a reduced vertical wind shear, high subcloud-based moisture and low convective inhibition, all conditions which would be more likely to occur during July and August than the other months.

[22] Some examinations of storm characteristics can be helpful to explain what features produce a drought year or a year with abundant precipitation. With MCSs 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 MCSs 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 (Figure 3). 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

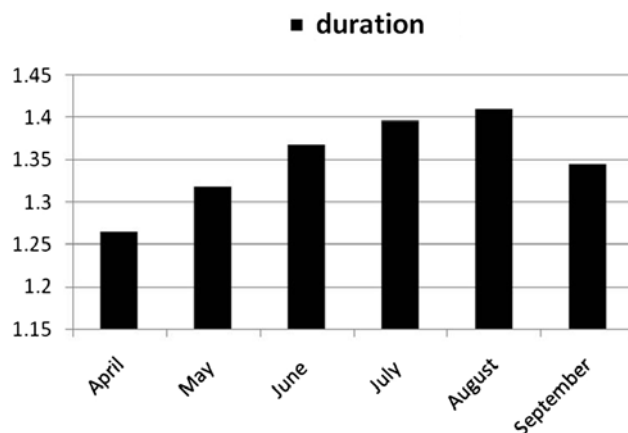
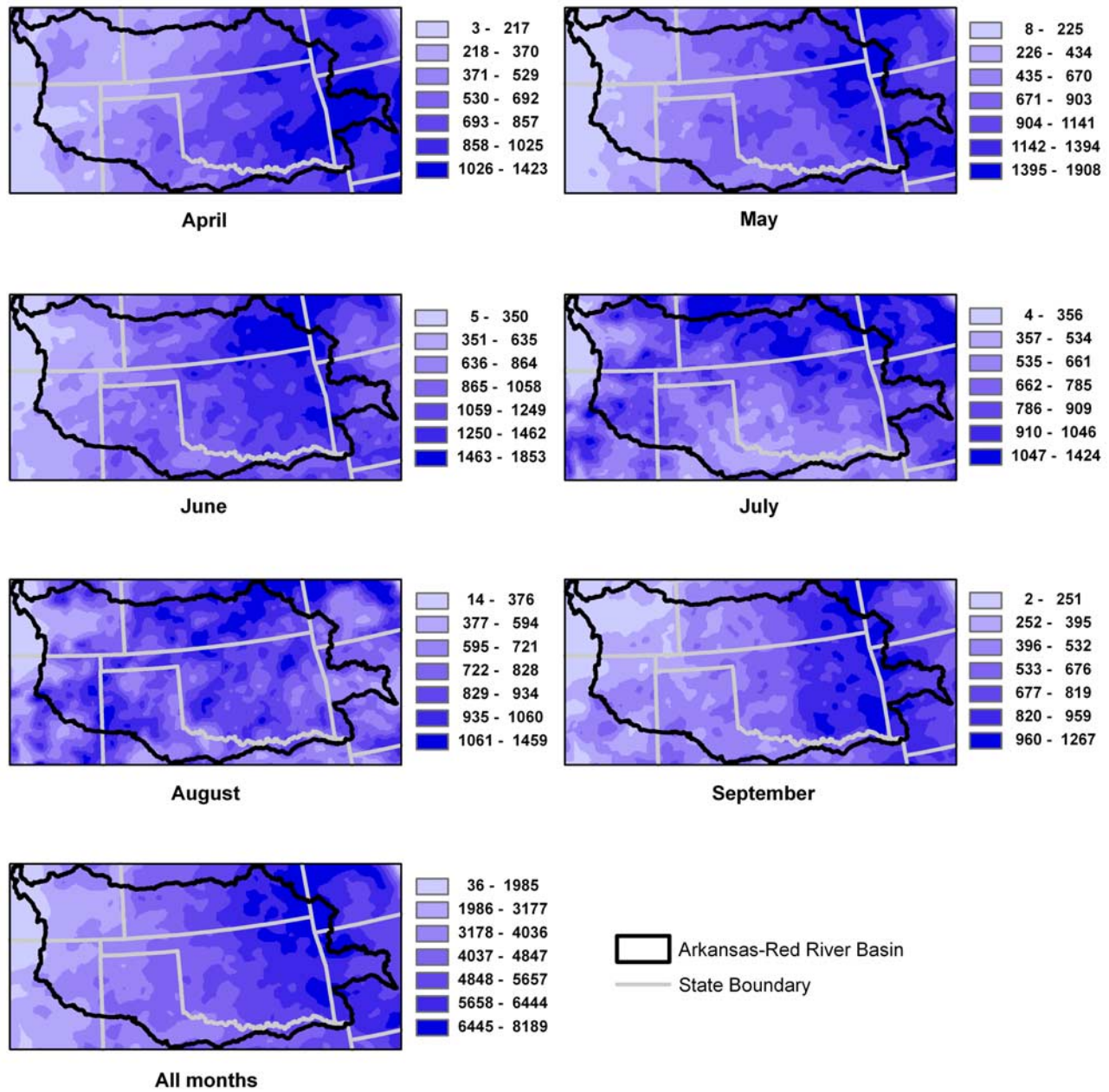


Figure 10. Average duration, in hours, of storms by month.

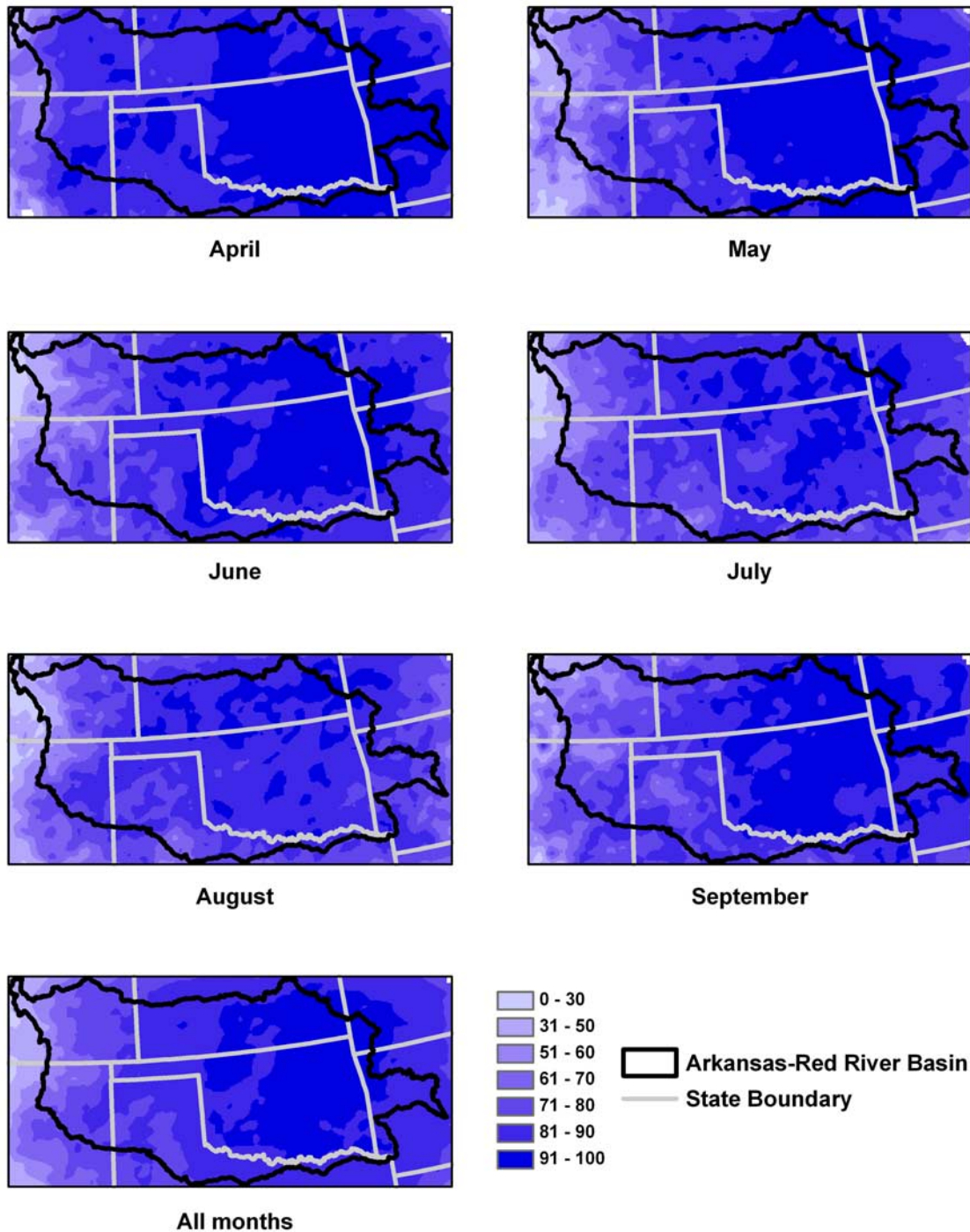


**Figure 11.** Total amount of storm precipitation in millimeters in April, May, June, July, August, September, and all months during the 11-year period.

large number of storms. But 1998 had the smallest average storm size and the smallest average storm footprint. The precipitation per cell in 1998 was 2.2 mm, higher than average. We are not able to show any relationship between storm size and precipitation per cell. 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 but its precipitation per cell was 2.2 mm. 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 third 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 and the average precipitation per cell are also important factors.

[23] The interplay among these factors can be seen in the variation of precipitation between months. June is the month with the highest precipitation (Figure 4). It is not the month with the largest size of storms, the longest duration of storm, the largest footprint of the storms, the



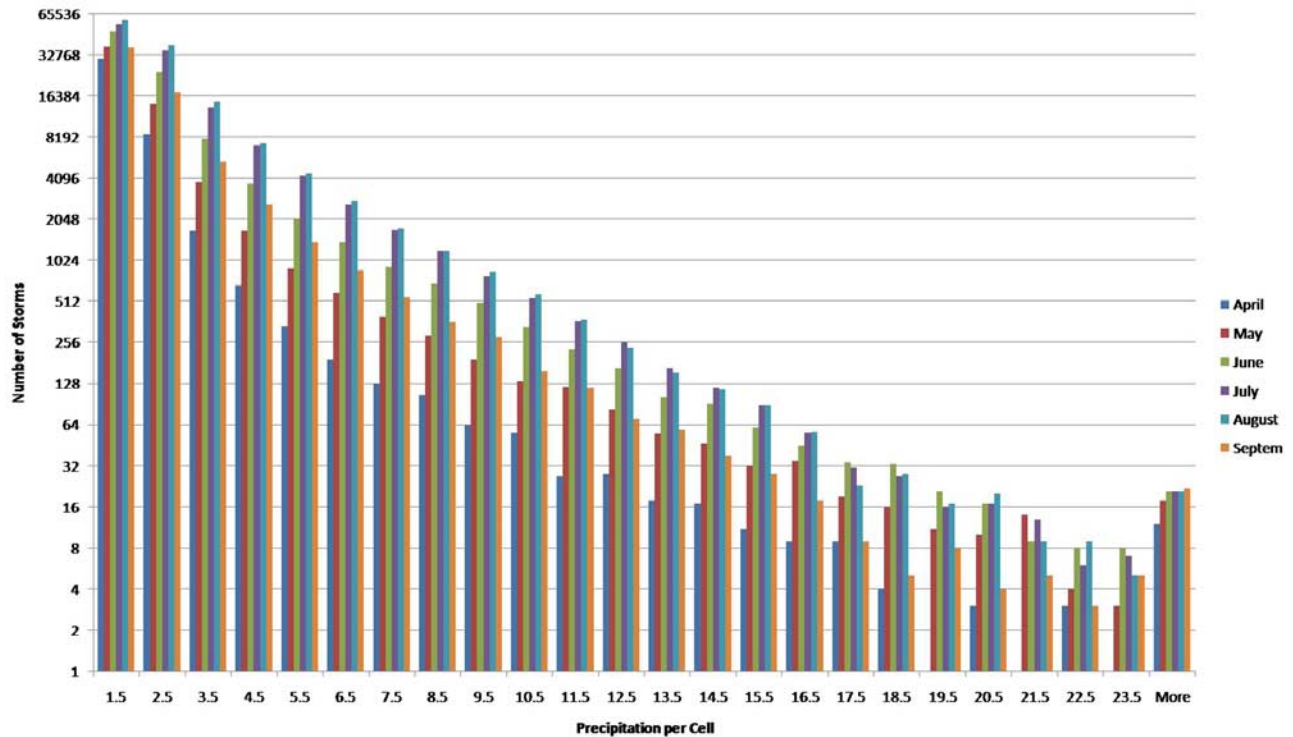
**Figure 12.** Percentages of precipitation from MCS in April, May, June, July, August, September, and all months during the 11-year period.

most storms or the largest amount of precipitation per cell. April and May have larger storms but there are fewer of them. July and August have many storms but they are small and have smaller footprints.

### 5. Conclusions

[24] Our work shows that the vast majority of storms in the Arkansas–Red River Basin during the warm season of the 11 years are small and short-lived. Nevertheless, the

rainfall database of the 11 years contains a number of very long lived storms. The intraseasonal variations in numbers of storms exceed their year-to-year variations. The more mountainous regions had greater numbers of storms but less precipitation per cell than the flatter areas. 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. Intra-seasonal and year-to-year variations in the percentage of storms of each type were relatively small. The MCSs



**Figure 13.** Total number of storms by the amount of precipitation per cell for each month during the 11-year period.

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. It follows that the most storms occur around 1800 local time but the most precipitation around 0100 local time. Although the MCSs have larger values of precipitation per cell than the other types of storms, precipitation per cell is generally only weakly correlated with the storm's maximum size; it is better correlated with the storm's duration.

[25] 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.

[26] 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. Likewise, we cannot determine whether there is a general relationship between storm size and precipitation amount per cell. Finally, 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.

[27] This data set has the potential to yield many more insights on these storms. The frequency with which storms of different sizes and durations affect particular areas is of interest. We also wish to examine the initiation and termination times of the various types of thunderstorms. We can also examine the speed and direction in which storms move. In addition, we believe the data set can provide information about the frequency and nature of storm mergers and splits.

[28] Our investigation of warm season storms emphasizes the amount and intensity of the precipitation they produce. This approach has a number of applications. The expected duration of storms can be important in planning activities that are weather sensitive. The expected amount of precipitation from storms can be useful for water resources planning. Continued studies along these lines can provide more specific information tailored for particular applications.

[29] **Acknowledgments.** This research was partially supported by the United States Department of Agriculture under grant FED38300.

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X. Li and D. F. Tucker, Department of Geography, University of Kansas, 1475 Jayhawk Boulevard, Room 213, Lawrence, KS 66045-7613, USA. (dtucker@ku.edu)