UNDERSTANDING SPATIAL VARIABILITY OF RAINFALL IN THE SOUTHEAST U.S.A. AT DIFFERENT TIMESCALES

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ABSTRACT

Farmers producing crops under rainfed conditions face rainfall variability as a major risk factor. Numerical climate models and crop simulation models are tools that can support decision making to manage such climate risks. However, temporal and spatial variability in rainfall and differences in the scales at which these tools represent processes make it difficult to combine them for use in climate risk analysis. The objective of this study was to understand the rainfall spatial variability in the Southeast US at daily and monthly time scales as a basis for developing bridges between these tools. We first determined the historical record length that is stationary followed by an analysis of the monthly spatial characteristics of rainfall variables. Rainfall data from 523 weather stations (National Climate Data Center – NOAA) were obtained for the period 1915 to 2004 and divided into 15-year subsets for comparisons. Differences in rainfall were found between the most recent 15-year period and all others occurring during 90 years period of record. Thus only data from 1990 to 2004 (208 weather stations) were used to avoid the detected changes in rainfall in the region. Correlation, covariance, and variance matrices of daily and monthly rainfall amounts were calculated at monthly steps. The same statistics were also computed for frequency of rainfall events and monthly number of rainy days. Results show different spatial patterns at different temporal scales. Two spatial patterns were well established: 1) a widely spread correlation in a northeast – southwest direction was found around weather stations during the frontal rainy season; and 2) concentric short distance-decay in correlations existed around weather stations during the convective season. Spatial correlations among daily rainfall amounts are needed for spatial weather generators in a storm-by-storm basis whereas monthly spatial statistics are needed to ensure the validity of downscaled data from numerical seasonal rainfall forecasts.

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INTRODUCTION

Rainfall varies considerably over space and time. Agricultural systems have evolved in response to this variability, but in most regions of the world, rainfall variability continues to be a major source of risks for agricultural production. For example, a widespread persistent drought, can threaten the economies and food security of entire communities and regions. Research is being conducted to better understand climate variability, its impacts on agricultural systems, and how to reduce those risks through decisions and policies that take climate variability into account.

Crop simulation models (Jones et al., 2003) are now widely used to analyze climate variability impacts on agricultural systems. Limited availability of daily weather variables over long time periods continues to be a problem for researches in most regions of the world. Yet variability is high so that only a few years of data are not adequate for representing a location. In order to have sufficient lengths of record, statistical methods are used to generate daily realizations of rainfall and other variables for use in crop models for many applications (Hansen and Indeje, 2004; Podestá et al., 2002). These daily stochastic weather generators are also being used to downscale climate forecasts for use in environmental models (Briggs and Wilks, 1996; Grondona et al., 2000; Wilks, 2002). One goal of our research is to use daily weather generators to downscale 6-month climate forecasts from the Florida State University climate model (Cocke and LaRow, 2000) coupled to the Community Land Model (Bonan et al., 2002; Zeng et al., 2002) - FSUCLM (Shin et al., 2005) to any point in the Southeast (SE) USA.

The problem with most currently available weather generators, such as those of Parlange and Katz (2000), Racsko et al. (1991), Richardson and Wright (1984), and Schoof et al. (2005), is that they create daily realizations for points in space without considering spatial correlation or persistence of rainfall events and amounts over space. This is not a problem if one's interest is in statistical properties of rainfall, other weather variables, and crop production in a single location or field. But if spatially independent generated weather data are used to aggregate rainfall or crop model outputs over space for subsequent analyses of these aggregated variables, spatial correlations of the variables must be taken into account for the same time scale at which the data are used as inputs to models. Because crop models respond to daily rainfall, if two months have the same rainfall amounts but different temporal distributions, simulated crop responses may differ widely.

A number of questions arose as we considered how to incorporate spatial correlations in generating rainfall over large areas. For example, what are the inherent correlations of rainfall across the SE USA, and how do those correlations vary with time? Are correlations of rainfall over space the same for monthly and daily rainfall amounts? This study was conducted to help answer these questions and to guide us in designing a daily weather generator that will produce realizations of daily weather that preserves spatial patterns of the original data. Objectives were: 1) to quantify spatial correlations of daily rainfall events and daily amounts over this region; 2) to determine how these correlations vary during the year; and 3) to compare spatial correlations at daily and monthly time scales.

STUDY AREA

The study area consists of the states of Alabama, Florida, and Georgia, between 35°23’ N, 88°59’ W and 24°57’ N, 79°26’ W. Elevations range from 0 to 1435 meters above sea level and covers a total area of 421,072 km^2. This region has some of the warmest conditions in the US. However, it is the only region in the USA to show widespread but discontinuous cooling of 1 to 2° C over almost the entire area between 1910 and 1997 (Karl et al., 1993). Annual rainfall averages from 1100 to 1400 mm, with the highest annual precipitation along the Gulf of Mexico coast and in south Florida (USGS, 2006). Rainfall occurs throughout the year caused by two different processes. During most of fall and winter, rainfall occurs by fronts coming from the northwestern US crossing the area (Frontal rainy season; FR). During most of spring and summer, rainfall occurs mainly by convective processes and tropical storms (Convective rainy season; CR). The temporal trend in annual precipitation shows rainfall increases by 20 to 30 % or more from 1910 to 1997 across Mississippi, Arkansas, South Carolina, Tennessee, Alabama, and parts of Louisiana, with mixed changes across most of the remaining area. Trends in wet and dry spells during the 20th century, as indicated by the Palmer Drought Severity Index (PDSI), are spatially consistent with the region’s annual precipitation trends, showing a strong tendency to more wet spells in the Gulf Coast states and a moderate drought tendency in most other areas. (SRAT, 2002).

DATA AND METHODOLOGY

Weather station network

The historical daily weather data record for 1048 weather stations was obtained from the National Climate Data Center (http://nndc.noaa.gov/?home.shtml). The period from 1915 to 2004 was selected from this record due to the quality and quantity of rainfall data. This information was organized and checked for errors and missing values. Range errors and zeros substituted for replacing missing values were identified and deleted. For monthly analyses, months with less than 20 days for which data were recorded were not considered. Weather stations beyond their state and county limits for which coordinates could not be corrected were deleted. After this screening process, 523 weather stations remained for further analyses.

Selecting the historical record length for spatial analyses

Before analyzing the spatial correlations of daily and monthly rainfall data, we analyzed the data to determine whether significant shifts in rainfall had occurred over the 90 years of record. Few weather stations had a complete 90-year historical record, making it difficult to identify these shifts. Therefore all available monthly weather station data across the 90-year period were spatially interpolated using ordinary Kriging (Clark and Harper, 2001; Isaaks and Srivastava, 1989). Interpolation was performed on the residuals after removing the spatial trends. Observed data at weather stations were preserved during these interpolations. Each pixel from the resulting monthly rainfall maps were divided into 6 periods of 15 years each and statistically compared using Analysis of Variance F statistic followed by a Duncan’s multiple range test for each grid cell.

De-trending spatial data

Most geo-statistical techniques assume that sample data come from a fixed distribution. Because there were spatial trends in the rainfall values, the trends were modeled by a polynomial equation using latitude and longitude as predictors (Clark and Harper, 2001). Polynomial equations from first to third degree were fitted by the least squares method. The degree of the polynomial equation for each month and year was selected by comparing the sum of squared residuals as a percentage of the original variation. This process yielded 1080 polynomial equations of first and third degrees. Afterwards, trend values were calculated and subtracted from the monthly observed rainfall values to compute residuals. These residuals were not significantly different from a normal distribution for any of the cases. Then, for each month and year, semivariograms were calculated using the following algorithm (Isaaks and Srivastava, 1989; Table 1):

$$g(h) = \frac{1}{2N(h)} \sum_{(i,j)|h_{ij} \approx h} (x_i - x_j)^2 \qquad \text{Eq. [1]}$$

After obtaining the *g(h)* values, models were fit to describe the changes in variance of rainfall amounts versus distance from each station, using a weighted non-linear least-squares method (Jian et al., 1996; Whelan et al., 2001). The Stable model of Whelan et al. (2001) was used to fit the semivariograms, defined as (Table 1):

$$\hat{g}(h) = d_0 + d_1\left[1 - e^{-\left(h/A\right)^b}\right] \qquad \text{Eq. [2]}$$

Table 1: Variable description.

Symbol	Definition	Units
i, j	Weather stations	unitless
x_i, x_j	Rainfall amount at weather stations *i* and *j*	mm
m_i, m_j	Mean rainfall amount at weather stations *i* and *j*	mm
s_i, s_j	Standard deviation rainfall amount	mm
$g(h)$	Semi-variance at distance *h*	mm^2
$\hat{g}(h)$	Estimated semi-variance at distance *h*	mm^2
n	Number of observations	unitless
$N(h)$	Number of pairs of weather stations whose location are separated by *h*	unitless
h	Distance	km
d_0	Nugget (vertical jump from the value of 0 at the origin to the value of the semivariogram at small distances)	mm^2
d_1	Sill (the semi-variance at which semivariogram reaches a plateau after adding d_0)	mm^2
A	Range (the distance at which the semivariogram reaches a plateau)	km
b	A parameter ranging from 0 to 2	unitless
r_{ij}	Correlation between weather stations *i* and *j*	unitless
C_{ij}	Covariance between weather stations *i* and *j*	mm^2
V_{ij}	Variance between weather stations *i* and *j*	mm^2

The Range (A), Nugget (d_0), and Sill (d_1) were then analyzed. To preserve the observed data where weather stations were located, the Nugget was always forced to 0. The sum of squared error, the root mean square error and Akaike information criterion (AIC; Webster and McBratnew, 1989) were evaluated to determine the best fit model. The AIC evaluates the goodness of fit as well as the parsimony of the model. Smaller values of AIC determine the best model.

After the semivariogram models were fit, monthly rainfall residuals were interpolated by using ordinary Kriging to obtain monthly maps of the residuals in a 5 km × 5 km grid resolution. Spatial trends were added to these interpolated residuals, yielding the monthly rainfall maps for all 90 years of the historical record.

Statistical analysis of climate

These analyses were performed to find areas where rainfalls mean (variance) were statistically different in time, i.e. areas affected by changes in climate. The 90-year historical record was divided into six periods of 15 years each (1915-1929, 1930-1944, 1945-1959, 1960-1974, 1975-1989, and 1990-2004). All analyses were performed on a monthly basis.

The six 15-year periods were statistically compared through an Analysis of Variance F statistic for each 5 km × 5 km grid cell. The probability value (P-value) that the F test statistic is at least as large as the observed F value was assessed by using the F distribution table ($a = 0.05$) with 5 and 84 degrees of freedom. After P-values were calculated for each grid cell, they were spatially aggregated to obtain probability maps of statistical differences. Each map showed areas where statistically significant shifts of monthly rainfall amounts were found in at least one of the six 15-year periods.

Because some areas showed statistically significant differences, the next step was to know when these differences occurred. This was done in order to select the number of years to use to analyze spatial variability of current climate conditions for use in this study. Duncan's multiple range tests were performed for each grid cell across the domain. Results were spatially aggregated producing maps; however in this case, 5 maps for each month were generated. Each map compared the latest period of record (1990 through 2004) versus one of the five remaining 15-year periods.

Correlation, Covariance and Variance of rainfall over space

To avoid the effects of the rainfall shift detected in the study area, only the period from 1990 to 2004 was used for further analysis. For this period, only 208 weather stations were available. In this section we determined how correlation (r_{ij}), covariance (C_{ij}), and variance (V_{ij}) vary monthly during the year by using daily and monthly rainfall amounts and frequencies.

Analyses using daily data

Rainfall amount: Daily rainfall amount data from this 15-year period were split into 12 monthly subsets of data. Each subset, containing 15 years of daily rainfall data, was used to calculate r_{ij}, C_{ij}, and V_{ij} among all the weather stations, thus forming matrices of rank 208. To avoid overestimation of r_{ij} and C_{ij} as well as the underestimation of V_{ij}, days without rainfall at both weather stations were not used. Calculations were performed using the following equations (Table 1):

$$r_{ij} = \frac{C_{ij}}{s_i s_j} \qquad \text{Eq. [3]}$$

$$C_{ij} = \frac{1}{n}\sum (x_i - m_i)(x_j - m_j) \qquad \text{Eq. [4]}$$

$$V_{ij} = \frac{1}{n}\sum \left(x_i - x_j\right)^2 \qquad \text{Eq. [5]}$$

The distance between each pair of weather stations was calculated by using its geographical coordinates and applying the Pythagorean Theorem. Results from the three statistics at different distances were analyzed as monthly scatter plots. Because of the scatter in the data, results were classified into five distance classes: 0-50, 51-150, 151-350, 351-700, and 701-1400 km. For each class, means and standard deviations of the three statistics were calculated.

To visualize the spatial variability of r_{ij} of one weather station (i) against the remaining (j), one weather station from each state was used as examples. Thus, values of r_{ij} were assigned at the geographical coordinates of the remaining 207 weather stations. At the selected weather stations (i), r_{ii} was assigned a value of 1.0. Finally, all values were interpolated using ordinary Kriging. The analysis was performed taking only one of the three selected weather stations at a time. The selected weather stations were: Sylacauga, AL (33°12' N latitude, 86°16' W longitude, and 149 m altitude), Mountain Lake, FL (28°56' N latitude, 81°36' W longitude, and 38 m altitude), and Hawkinsville, GA (32°17' N latitude, 83°28' S longitude, and 83 m altitude). Results are presented for the months of January and July.

Occurrence of rainfall events: To calculate the r_{ij}, C_{ij}, and V_{ij} matrices of occurrence of rainfall events, values of 1 and 0 replaced the values of rainfall amount for days with and without rainfall, respectively, over the 15-year period used in the study. As in the previous step, the data were divided into monthly subsets. Afterwards, Eq. [3], [4], and [5] were applied to each sub-dataset containing the 208 weather stations, thus producing the respective matrices. The data were further divided into the same five distance-based classes of the previous step for further analysis. To visualize the spatial correlation (r_{ij}) of one weather station versus the remaining stations, the same three weather stations selected in the previous step were used. Ordinary Kriging was used to interpolate r_{ij} values.

Analyses using monthly data

Rainfall amount: Rainfall data aggregated at different temporal scales explain different spatial processes and relationships among weather stations. To understand the effects of this temporal aggregation, for each year and weather station, the total monthly rainfall amount was computed by summing all daily values in the month. Next, the 15-year period was divided into subsets for each of the 12 months of the year. Eq. [3] to [5] were then modified for analyzing monthly rainfall values. These modified equations were applied to the monthly sub-datasets for obtaining the r_{ij}, C_{ij}, and V_{ij} matrices. As before, results were classified according to their distances between stations. Finally mean and standard deviation of each distance-based class were calculated. To visualize the spatial variability of r_{ij}, the same three weather stations selected in the previous step were used. Ordinary Kriging was used to interpolate r_{ij} values.

Monthly number of rainy days: To perform this analysis, the number of rainy days was computed for each month of each year of the 15-year period. As in the previous step, the dataset was divided into subsets for the 12 months of the year. For each subset, Eq. [3] to [5] were modified to compute r_{ij}, C_{ij}, and V_{ij} for number of rainy days per month. The same methodologies used in the steps before for estimating mean and standard deviation of r_{ij} in the distance-based classes as well as the correlation's spatial variability visualization were used for this variable.

RESULTS AND DISCUSSION

Changes in rainfall over the 90-year time period

The spatial trends of monthly rainfall amounts over 90 years from December to April followed first-degree polynomial equations. For the remaining months, trends corresponded to cubic equations. These monthly spatial trends were used for interpolation, and will also be used later to evaluate the spatial structure of seasonal rainfall forecasts and spatial weather generator performance. These polynomial equations explained from 40 to 81% of the rainfall spatial variability when aggregated over the 90-year period. Analyzing individual trends by month and by year (Table 2), these percentages explained on average from 31 to 55% of the spatial variability. However, for individual months and years, these trends explained up to 91% of the spatial variability.

Table 2: Statistics of the monthly coefficients of determination (R^2) obtained from year-by-year polynomial equation fitting.

Month	Mean	Standard deviation
Jan	0.408	0.228
Feb	0.380	0.231
Mar	0.378	0.236
Apr	0.313	0.199
May	0.396	0.173
Jun	0.434	0.182
Jul	0.387	0.159
Aug	0.431	0.149
Sep	0.506	0.166
Oct	0.532	0.189
Nov	0.545	0.180
Dec	0.403	0.219

Maps of probabilities (not shown) demonstrated that were significantly different monthly rainfall amounts for the different 15-year periods of time for January and July. Areas with *p*-values less than 0.05 indicated areas where at least one of the 15-year periods was significantly different from the others. Areas where statistical differences were found varied monthly. This suggests that the processes leading to the changes were not a result of local conditions but were related to broader climate processes.

After finding these significant differences, Duncan's Multiple Range Test was used to determine whether each 15-year period of time differed from the most recent period of record (1990 through 2004). Figure 1 shows for January and July the areas where significant differences occurred. January maps indicated that the Panhandle of Florida, southeastern Alabama and part of southwestern Georgia showed significantly different rainfall regimen in the last 15 years. July maps indicated that central western Georgia showed a significantly different rainfall regimen in the last 30 years when compared to earlier periods. For January monthly rainfall in the changed areas increased over time while during July monthly rainfall decreased. These results are consistent with those reported by Maul and Hanson (1990) and Stahle and Cleaveland (1992) and possibly related to the less common summer blocking pattern of the Atlantic Subtropical Anticyclone reported by Davis et al. (1997).

These results demonstrated statistically significant spatial and temporal changes in the rainfall regimens during the last 90 years. Our goal was to provide information on spatial characteristics of current rainfall regimes for downscaling numerical climate forecasts and for generating spatially coherent rainfall events and amounts. Thus, further spatial analyses used only the 1990 through 2004 rainfall data.

Correlation, Covariance and Variance

Analyses using daily data

Rainfall amount: Each point in Figure 2 represented the covariance of rainfall between each station and one other specific station, computed using the daily data for the 15 years for each month. Thus, there was a maximum of about 450 days of data to estimate each point, but this was reduced since only days when rainfall occurred in at least in one station were used. The shape of the cloud of points and the absolute values were similar during both Spring-Summer and Fall-Winter seasons, and similar between those seasons. However at short distances, March and September showed greater covariance values than the other months. These are the transitional months that include the vernal and autumnal equinoxes. These months also include the transitions from frontal rainy (FR) season, which occurs from October to March, to the convective rainy (CR) season, from April to September.

As expected, the correlation of rainfall amounts over space decayed versus distance, and the variance increased with distance (Sumner, 1983). Correlation indices at all distances were greater during the FR season than during the CR season. Correlations during the CR season were statistically non-significant at closer distances than during the FR season. On the other hand, monthly standard deviations increased versus distance but did not show any apparent relationship to the FR and CR seasons. During the CR season, correlations did not exceed values of 0.8, whereas a few values near 1.0 were observed during the FR season. Large variance values were found at short distances during the CR season in comparison with the FR season.

At short distances there were also some small correlation and covariance values as well as large values of variance. Different rainfall regimens can be expected when daily data are analyzed (Romero and Baigorria, in press). In the Peninsula of Florida, for example, weather stations located near the Atlantic coastline had different rainfall regimes than those near the Gulf of Mexico coastline. Similarly, weather stations near the coastline may differ from those further from the coastline. Thus, rainfall is not stationary over space, which would violate assumptions used in computing semivariograms with only one realization of spatial data unless the data are de-trended.

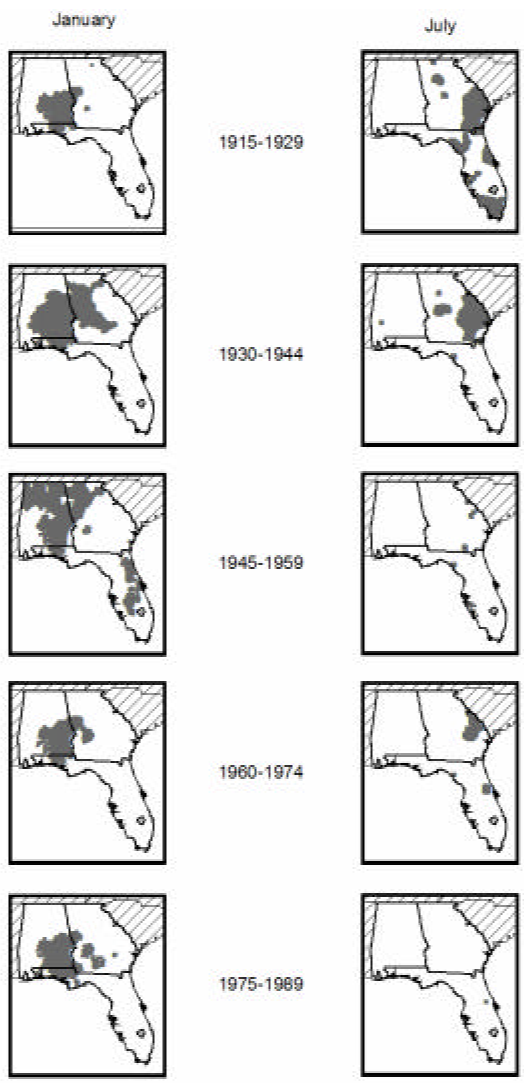

Fig. 1 Maps of Duncan's multiple range tests (a = 0.05) for January and July. Shadow areas show areas where shifts in rainfall have been detected between the last 15-year period and each remaining period.

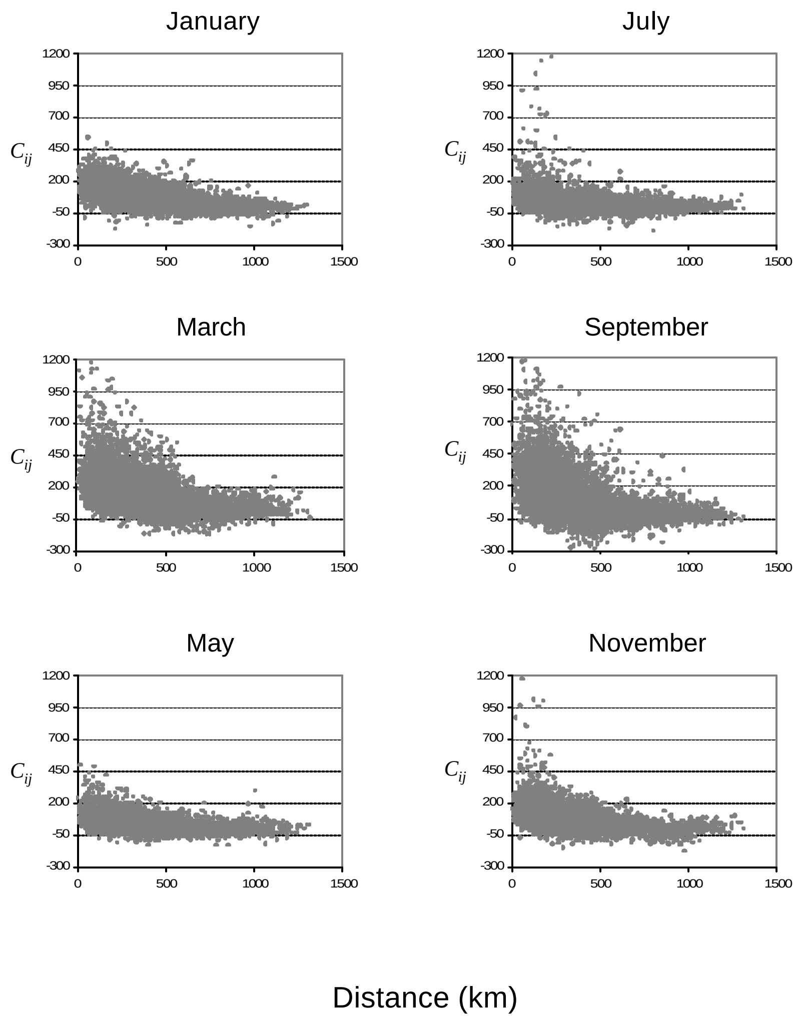

Fig. 2: Monthly variation of the covariance matrices for daily rainfall amounts versus distance for six months of the year (1990 – 2004).

Figures 3 and 4 show spatial patterns in r_{ij} in all directions. Variations in absolute values of r_{ij} showed larger correlations (smaller variances) around the selected weather stations during the FR season (Figure 3) than during the CR season (Figure 4). This is explained by the size of the weather fronts or cells involved in the precipitation process. Geographic areas with strong correlations and small variances were larger during the FR season than during the CR season. Correlations were less concentric in January than in July. Both correlations and variances showed a more diagonal pattern during the FR season than during the CR season. There was more directionality (anisotropy) (northeast – southwest) in the spatial variation of r_{ij} during FR season than during the CR season. This directionality was parallel to the usual weather front patterns in this region. In concordance with Sharon (1974), daily spatial variation of r_{ij} and rainfall occurring from convective systems (CR season) typically showed correlations that decreased rapidly in all directions over short distances.

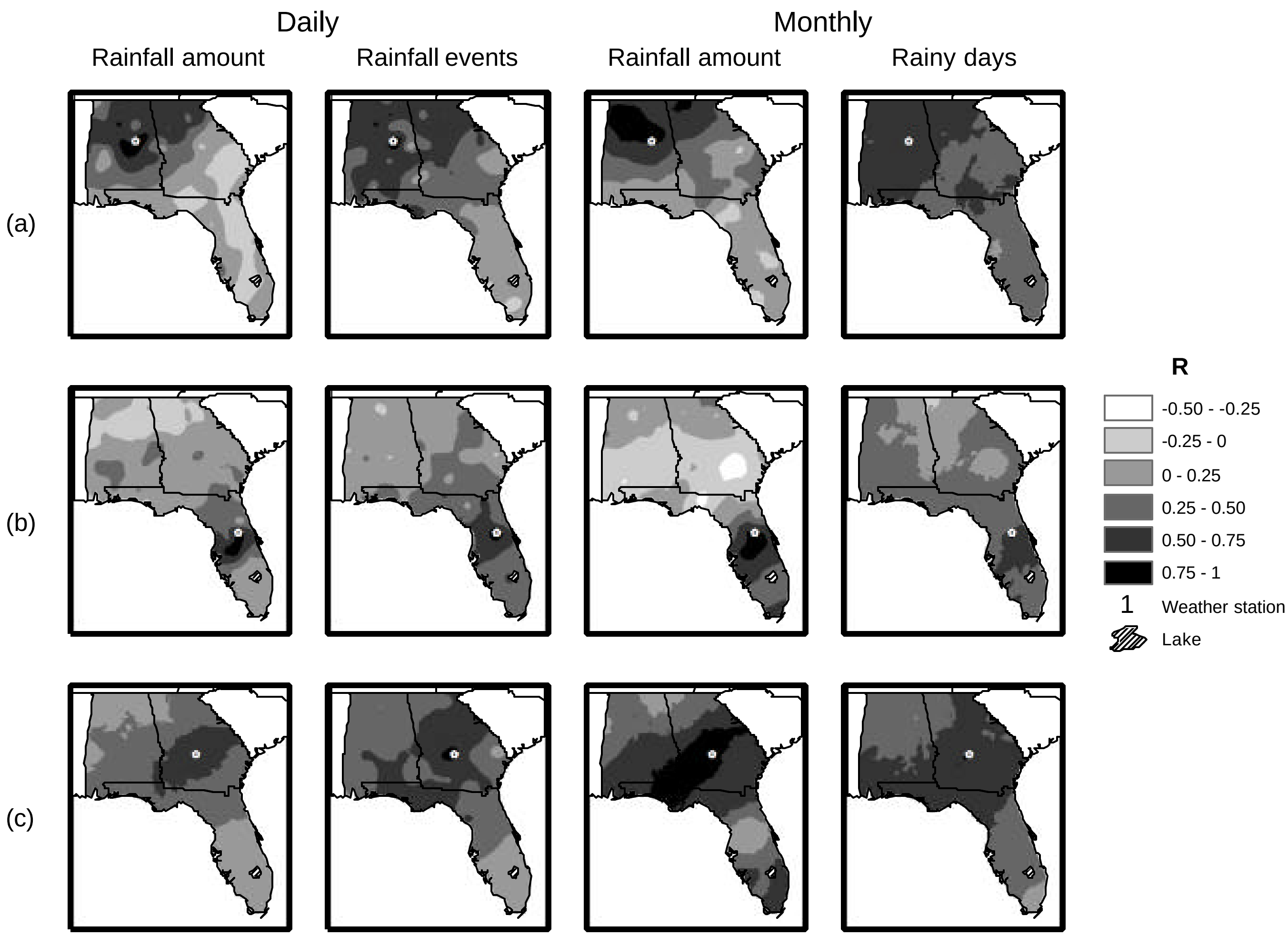

Fig. 3: Spatial variability of correlations for daily rainfall amount, frequency of rainfall events, monthly rainfall amount, and rainy days in January (1990 – 2004). (a) Sylacauga, AL, (b) Mountain Lake, FL, and (c) Hawkinsville, GA.

Occurrence of rainfall events: These results showed how each rainfall event was correlated with rainfall events at other weather stations on a daily basis. This variable responded similarly to that for r_{ij} values relative to the FR season versus the CR season. However, monthly variations in the maximum and minimum correlations for rainfall occurrences were less than those for daily rainfall amounts. Individual correlation values for July showed a maximum of 0.65 compared with the maximum in January of 0.9; however, both of these values were lower than those obtained for rainfall amount. The V_{ij} cloud shape in July (not shown) increased faster over short distances than in January, where low variance values were found at about 400 km or less. Despite variances during January and July reaching values greater than 0.4, in general terms, variance in January reached a plateau of around 0.23, while in July it reached a plateau around 0.30, both around 250 km from the station.

Spatial variations of daily rainfall event correlations showed characteristics similar to those for daily rainfall amount in terms of seasonal differences (Figures 3 and 4). Concentric and short distance decay functions occurred around selected weather stations for the CR season (Figure 4), whereas they were widely spread in a northeast – southwest direction for the FR season (Figure 3). For all weather stations, FR season showed stronger correlations than CR season.

Analyses of monthly data

Rainfall amount: Strong correlations in monthly rainfall amounts were found as far away as 600 km from the selected stations during January (Figures 3 and 4). In July however, these same values occurred around 200 km or less. Many negative correlations as well as larger variances were reached at shorter distances during July than during January, which corresponds to the different atmospheric physics producing the rainfall. Variances during the CR season had maximum values around 24,000 mm^2, while for the FR season values reached a maximum of only 16,000 mm^2.

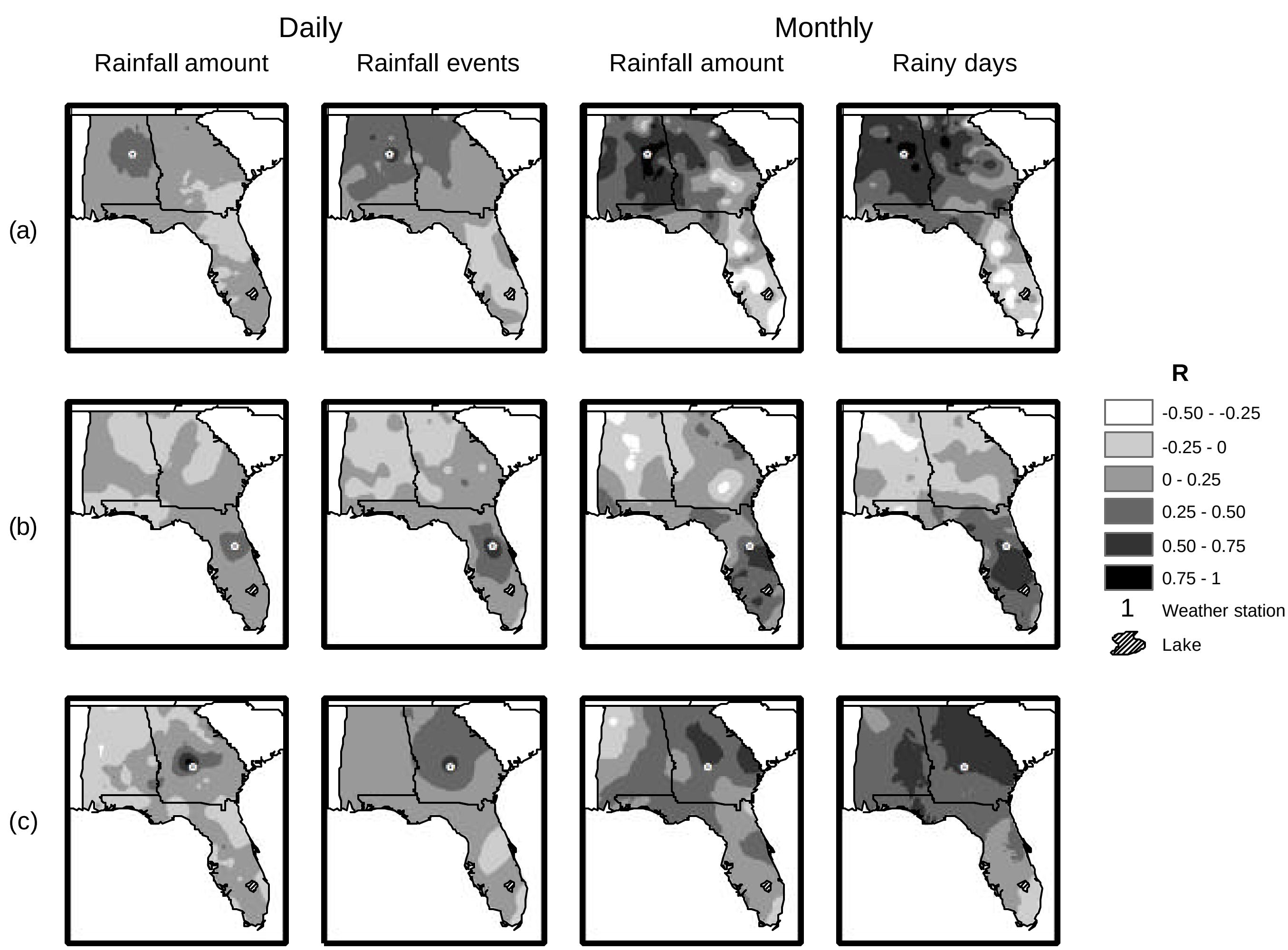

Fig. 4: Spatial variability of correlation for daily rainfall amount, frequency of rainfall events, monthly rainfall amount, and rainy days in July (1990 – 2004). (a) Sylacauga, AL, (b) Mountain Lake, FL, and (c) Hawkinsville, GA.

There were differences in spatial patterns of rainfall amount correlation values relative to those found for daily rainfall data vs. monthly rainfall data. Positive correlation values higher than 0.8 were found using monthly rainfall amounts, whereas for daily data all correlations were less than 0.7. Higher standard deviations of correlation values were found using monthly data compared to daily data. Correlation values and homogeneous correlation areas using monthly data were respectively higher and larger than the ones using daily data, independently of the analyzed month (Figures 3 and 4). This correlation pattern was because using daily data, rainfall amounts were correlated on a storm by storm basis. This, together with the rainfall event data, showed the size of the rainfall cell producing rainfall in a specific event. For using in a daily spatial weather generator, the highly correlated areas showed the size of the areas that would be involved in a storm event and how much rainfall would fall in every rain-gage. Spatial relationships among different monthly rainfall variables are governed by different climatic, oceanic, topographic and geographic drivers at different times. Thus, monthly spatial statistics would be useful to ensure the validity of downscaling data from numerical seasonal rainfall forecasts, which are produced based on atmospheric circulation patterns.

Monthly number of rainy days: Number of rainy days with measured rainfall larger > 0.1 mm divided by the total number of days is an estimate of the probability of rainfall in a specific month and weather station. Thus the correlation among weather stations showed how rainfall occurrence was likely to persist over space. Even though the absolute number of rainy days varied from season to season, there was no seasonal pattern in the correlation values. Figures 3 and 4 showed that homogeneous areas of correlation were larger compared with the daily occurrences of rainfall events. Correlation values were less concentric around the weather station using monthly data than daily data.

CONCLUSIONS

In the SE-USA, changes in rainfall amounts during the last ninety years were observed. These changes varied over space and time of year. To avoid influences of climate change in our study, only the last 15-year period was used to characterize spatial variability of rainfall. For this time period, rainfall amounts in Alabama, Florida, and Georgia were found to have a linear geographical trend during December to April and cubic during the remaining months.

Using both daily and monthly rainfall data, two well defined rainfall spatial correlation patterns were found corresponding to the weather frontal and the convective rainy seasons. Spatial correlations during the frontal rainy season were characterized by a widely spread pattern in a northeast – southwest direction around weather stations, which is perpendicular to the usual weather front paths. During the convective rainy season, correlations were characterized by small concentric patterns in which correlations decreased rapidly over short distances from each weather station. However, larger areas of higher correlations were found using monthly rainfall amounts than when using daily rainfall amounts. Spatial correlations among daily rainfall amounts and occurrence of events are needed for spatial weather generators on a storm-by-storm basis. Spatial correlations among monthly rainfall amounts and rainfall persistence are needed to ensure the validity of downscaled data from numerical seasonal rainfall forecasts.

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