An investigation of seasonal precipitation patterns for rainfed agriculture in the Southeastern region of the United States

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ABSTRACT
Over the last two decades, signs of precipitation irregularity were frequently reported across the Southeastern United States (US). Even though the region receives a relatively high annual precipitation, the precipitation events are not equally distributed in the time and space. Hence, rainfed agriculture, a common practice in the region is threatened by changes in precipitation frequencies during the crop growing seasons. With this situation, a better understanding of the actual patterns of precipitation irregularity is needed to support the local agriculture. This study uses a spatial regionalization approach to delineate precipitation regions for an area spanning the states of South Carolina, North Carolina, and Georgia. The data used include time-series of seasonal precipitation totals and seasonal numbers of precipitation events > 5 mm over the period 1960–2017. A regionalization method which combines principal components and cluster analyses was applied to 208 precipitation stations selected across the study region. Finally, three precipitation regions were delineated based on statistics and similarity criteria. A comparative analysis of these three regions shows significant differences in the seasonal precipitation totals and the seasonal number of precipitation events. In addition, the differences were examined using a probabilistic approach. As a result, tables of probabilities and seasonal precipitation characteristics (precipitation totals and number of events > 5 mm) were generated for each region. These tables could provide information about the chances of precipitation deficits or excesses relatively to a crop and henceforth be useful for agricultural water use planning.

1. Introduction
Worldwide, rainfed agriculture is a very common practice which plays an important role in food and livestock production (Rockström et al., 2010). Rainfed agriculture generally depends on crops, soils, environment, and most importantly, seasonal precipitation totals and their distribution over the crop-growing season. However, rainfed agriculture is vulnerable to climate hazards and its practice does not ensure crop yield stability (Rockström et al., 2010). For instance, when precipitation events are irregular, crops are often subjected to short-term water deficits which cause crop yield losses (Kistner et al., 2018). Indeed, several studies reported the negative impact of short-term water deficit on annual crops yields (Bauer et al., 2009). Particularly, under rainfed conditions, substantial yield gap values (i.e. difference between average and yield potential) are often reported as the consequence of water stress (Lobell et al., 2009). In humid regions such as the Southeastern United States (US), the cumulative annual precipitation totals are relatively high and virtually sufficient to grow a wide range of crops under rainfed conditions. Yet, the sole consideration of annual precipitation amounts may shade critical patterns of precipitation irregularity during the crop growing seasons. This is particularly true in the Southeastern US where short-term precipitation deficits are usual during the crop season (Mo and Schemm, 2008). These short-term precipitation deficits are not necessarily a consequence of a decrease of the total annual or seasonal precipitation as they also seem to be a result of changes in the timely distribution of precipitation events (Kistner et al., 2018). Studies evidenced that changes of precipitation frequency and the subsequent short-term water deficits reduce biomass production, shorten grain filling periods, and lower crop yields (Högy et al., 2013; Katerji et al., 2004). Therefore, an understanding of precipitation patterns (total amount and frequency) is useful for the decision making toward crops management and yields stability.

The frequency of precipitation is critical in rainfed agriculture because it indicates how often the soil water is replenished by natural precipitation events during a given time slice (e.g. month, season, year). In general, the number of precipitation events is assimilated to the number of wet days which can be defined based on a precipitation threshold. Unfortunately, not all precipitation amounts are effective for

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crops (Rockström et al., 2003; Dastane, 1974). Hence, it is important to define the frequency of precipitation events by referring to daily total thresholds. For instance, the threshold of 5 mm/day (0.2 inch/day) was used in different irrigation scheduling manuals as a minimal daily water need even though the actual need depends on the crop growth stage, the atmospheric water demand, and the antecedent soil moisture condition (Curwen and Massie, 1994). Nevertheless, the 5 mm threshold has been consistently used to study the trend and effects of precipitation events (Goswami et al., 2006; Sala and Lauenroth, 1982). As an example, Mulhouse et al. (2017) considered daily precipitation events of > 5 mm to address vegetation response to precipitation timing. Our study also uses the 5 mm threshold to define and address the seasonal number of precipitation events in the Southeastern US.

The climate of the Southeastern US is humid, and the region receives an annual precipitation above 1200 mm. Historically, farmers in the Southeastern US relied on natural precipitations to grow annual crops such as corn, cotton, soybean, peanut, etc. However, the absolute reliance on natural precipitations is nowadays threatened by cases of short-term precipitation deficits occurring during crop growing seasons. Although these precipitation deficits often cause a decrease in crop yield (Rockström et al., 2010), their occurrence is still very unpredictable and therefore needs research attention. To improve the understanding of the occurrence and severity of short-term precipitation deficits, our study had the following three objectives: (i) propose a coherent precipitation regionalization for the Southeastern US, (ii) examine the long-term patterns of precipitation, and (iii) establish a probabilistic framework to support agricultural water management.

2. Data and method

2.1. Data

The study addresses the part of the Southeastern US encompassing the States of Georgia (GA), North Carolina (NC), and South Carolina (SC). The study aims to regionalize the Southeastern US based on the long-term patterns of precipitations. Hence, data were collected from a total of 422 land-based weather stations distributed across the Southeastern US (Fig. 1). For the 422 stations, all the available daily precipitation records over the period 1960 to 2017 were obtained from the National Oceanic and Atmospheric Administration’s Global Historical Climatology Network (NOAA-GHCN) database (Menne et al., 2012). It is important to note that the period 1960 to 2017 satisfies the minimum of 30 years recommended for climate studies (Sohoulande and Singh, 2016). However, not all of the 422 stations have a continuous long-term precipitation record. Out of these stations, 208 stations have less than 10% data gap over the study period. As shown by Fig. 1, the 208 stations are well distributed across the study region (average 0.13 decimal degree between neighboring stations) and will therefore be used in the spatial regionalization. For each of the 208 stations, data gaps (i.e. missing values) in daily precipitation were filled using the inverse distance weight (IDW) average of daily precipitation data from the neighboring stations. Preferentially, the neighboring stations used to fill data gaps for the 208 stations are stations with gaps > 10% (i.e. 214 stations in total). This allowed data consistency since many of the 214 stations with gaps > 10% are located at the vicinity of the stations with gaps < 10% (Fig. 1). Hence, 208 gap-free time-series of daily precipitation over the entire period 1960 to 2017 were obtained. Each time-series was later processed to generate time-series of seasonal precipitation totals and number of precipitation events > 5 mm. The four seasons of the year were targeted including the winter season December to February (DJF), the spring season March to May (MAM), the summer season June to August (JJA), and the fall season September to November (SON). For each station, the gap-free precipitation time-series was used to generate separate time-series of seasonal precipitation totals and seasonal numbers of precipitation events > 5 mm. As mentioned earlier in the introduction, the 5 mm threshold was used to define the seasonal number of precipitation events (Mulhouse et al., 2017; Goswami et al., 2006; Curwen and Massie, 1994). Fig. 2 presents the following two correlations: the average annual precipitation total versus the annual frequency of precipitation events > 0 mm ($R^2 = 0.29$); and the average annual precipitation total versus the annual frequency of precipitation events > 5 mm ($R^2 = 0.74$) for the 208 stations. The analysis of Fig. 2 confirms the importance of the 5 mm threshold as the frequency of the events > 5 mm explains 74% of the variance of precipitation total across the Southeastern US.

2.2. Method

2.2.1. Spatial regionalization

The objective of the spatial regionalization is to subdivide the Southeastern US into homogeneous regions based on the long-term precipitation patterns. To achieve that objective, the study used a regionalization method which combines principal component analysis (PCA) with a k-means cluster analysis (Raziei, 2018; Sohoulande, 2018). Worldwide, variants of PCA and cluster analysis have been developed as spatial regionalization techniques. For instance, Comrie and Glenn (1998) successfully used a PCA based spatial regionalization to determine precipitation regions for the Southwest United States. Baeriswyl and Rebetez (1997) used the PCA technic with a varimax rotation to delineate homogenous climate regions for Switzerland. Raziei (2018) used PCA along with a cluster analysis to regionalize precipitation across Iran. The present study used a similar method by combining a varimax rotated PCA and a k-means clustering. The approach is developed to identify regions based on the variability of seasonal precipitation total and the seasonal frequency of precipitation events > 5 mm. As the number of regions to identify is initially unknown, k-mean clustering was appropriate because it offers the flexibility to group elements into different numbers k of clusters. However, for the k-mean clustering to capture well the spatial variability PCA is used to reduce the precipitation time-series size. Note, in this paper the term seasonal frequency of precipitation events > 5 mm refers to the absolute frequency which is also the seasonal number of precipitation events > 5 mm.

Fig. 3 illustrates the spatial regionalization procedure which was applied separately to the time-series of seasonal total precipitation and seasonal frequency of precipitations events (> 5 mm). The procedure consists of two stages including the PCA analysis followed with the k-means clustering. As mentioned in section 2.1, each of the 208 selected precipitation stations is associated with 58 years (i.e. 232 seasons) time-series of seasonal precipitation total and seasonal frequency of precipitation events > 5 mm. Hence, the precipitation data are represented as an m by n matrix where m is the number of stations (m = 208) and n is the size of the time-series of seasonal precipitation total or frequency (n = 232 seasons). The finality of the spatial regionalization procedure (Fig. 3) is to group the m stations into k subsets (i.e. cluster) such that each subset corresponds to a spatial domain of high similarity of precipitation patterns (i.e. seasonal total precipitation and number of events distinctly). Note, the m by n matrix is two dimensional (i.e. space and time). The varimax rotated PCA (Baeriswyl and Rebetez, 1997) is applied to reduce the time dimension by capturing the essential variability contained in the n seasonal observations into a fewer n’ number of principal components (PCs). The n’ PCs are those having their eigenvalues greater than one (Jolliffe, 2011; Kaiser, 1966). Each of the stations is henceforth associated with n’ PCs loading values and a new two-dimensional m by n’ matrix is generated (Fig. 3). The cluster analysis is thereafter conducted to group the m stations into k distinct subsets based on the stations’ PC loading values. Indeed, cluster algorithms generally perform better when the variance contained in a large time-series is captured into fewer components. Especially, the k-means clustering method is used in the study for its consistency to capture meaningful spatial patterns (Sohoulande, 2018). However, one
The challenge that comes out with the cluster analysis is to determine the adequate number \( k \) of subsets that express the variability of both seasonal precipitation total and frequency. To overcome this challenge, the cluster analysis was conducted with different values of \( k \) (i.e. 2, 3, … 12). For each value of \( k \), subsets of precipitation stations were identified separately based on seasonal precipitation total and frequency variability. A Jaccard similarity index (Real and Vargas, 1996) was estimated between the subsets resulting from the seasonal precipitation
total variability and the subsets resulting from the seasonal frequency of precipitation events (>5 mm). The formulation of the Jaccard index employed is presented by Eq. (1). The k corresponding to the highest similarity is retained and the related subsets of precipitation stations were considered to delineate k precipitation regions within the South-eastern US.

\[
\text{Jaccard index} = \frac{A_1 \cap B_1 \cup A_2 \cap B_2 \ldots \cup A_k \cap B_k}{A_1 \cup B_1 \cup A_2 \cup B_2 \ldots \cup A_k \cup B_k}
\]  

(1)

Where \((A_1, A_2, \ldots, A_k)\) stands for the k subsets of precipitation stations identified based on seasonal precipitation totals, \((B_1, B_2, \ldots, B_k)\) represents the k subsets of precipitation stations identified based on seasonal frequencies of precipitation events (>5 mm).

2.2.2. Statistics and probability analyses

Statistics and probability analyses were used to examine the physical meaning of the outcomes of the spatial regionalization. For each of the k delineated regions, the encompassed precipitation stations were considered and the time-series of their seasonal precipitation characteristics (i.e. total precipitation and frequency of precipitation events >5 mm) were analyzed. A pair-wise Student’s t-test was conducted to compare the average values of precipitation characteristics among the delineated regions. Especially, for the average values comparison, the raw precipitation data were first normalized and for each seasonal precipitation value \(x_{ki}\), a z-score (Jain et al., 2005) was calculated using the Eq. (2) where \(\mu\) and \(\sigma\) are respectively the pooled mean and standard deviation of the study region. In lieu of the raw precipitation data, the z-scores were used to conduct the pair-wise Student’s t-test.

\[
z = \frac{x_{ki} - \mu}{\sigma}
\]  

(2)

A Mann-Kendall trend analysis (Yue et al., 2002), was also conducted on the seasonal precipitation time-series and the Kendall’s \(\tau\) statistics were evaluated. Given the seasonal or annual precipitation values \(x_i\) and \(x_j\) at times \(t_i\) and \(t_j\) such that \(i > j\), the Kendall’s \(\tau\) statistics were calculated using Eqs. (3),(4), and (5).

\[
Kendall's \tau = \frac{S}{D}
\]  

(3)

\[
S = \sum_{i<j} \text{sign}(x_i - x_j) \cdot \text{sign}(t_i - t_j)
\]  

(4)

\[
D = \left[ \frac{\eta(\eta - 1)}{2} - \frac{1}{2} \sum_{k=1}^{\eta} x_k(x_k - 1) - \frac{1}{2} \sum_{p=1}^{\eta} y_p(y_p - 1) \right]^{0.5}
\]  

(5)

Where \(\eta\) is the time-series size, and \(\eta = 58\) years or annual seasons (i.e. DJF, MAM, JJA, SON); \(n_x\) and \(n_y\) represents the number of ties in the variables precipitation and time respectively. Ties are any set of identical values in the time-series; \(u_k\) and \(v_p\) are respectively the numbers of elements in the \(\lambda\) tie of precipitation variable and \(\theta\) tie in the time variable.

A probabilistic assessment was conducted to determine the probability of occurrence of different ranges of precipitation totals and frequencies of precipitation events >5 mm. The probability analyses focused on each of the delineated precipitation regions. The weather stations encompassed by each region were pooled in the same group, then the seasonal precipitation data (i.e. precipitation totals and number of precipitation events >5 mm) were addressed separately. The analyses were also conducted on the annual time scale (ANN). For each delineated precipitation region and each season, the corresponding precipitation data were fitted to a probability distribution model. The probability density function (pdf) of seasonal precipitation total data were found to follow the gamma distribution [see Eq. (6)], while the pdf of annual precipitation total followed the lognormal distribution [see Eq. (7)]. However, the pdf of seasonal and annual number of precipitation events (>5 mm) fitted the normal distribution [see Eq. (8)].

\[
f(x|\alpha, \beta) = \frac{1}{\beta x^\alpha \Gamma(\alpha)} \exp\left(-\frac{\beta x}{\alpha}\right)
\]  

(6)

\[
f(y) = \frac{1}{y_\beta \sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{y - \mu}{\sigma_y}\right)^2\right)
\]  

(7)

\[
f(x) = \frac{1}{\alpha x_\alpha \sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{x - \mu}{\sigma}\right)^2\right)
\]  

(8)

Where \(x\) is a random precipitation value (i.e. seasonal total or seasonal frequency), \(y\) is the logarithmic transformation of \(x\); \(f(x)\) and \(f(y)\) are the pdf; \(\alpha\) and \(\beta\) are respectively the shape and scale parameters of the gamma pdf. The parameters of the normal pdf are \(\mu_x\) and \(\sigma\) which equal respectively the mean and the standard deviation of the precipitation data. The lognormal pdf parameters \(\mu_y\) and \(\sigma_y\) which equal respectively the mean and the standard deviation of the logarithmic transformation of precipitation data.

3. Results

3.1. Principal components and cluster analysis

The PCA conducted on the seasonal precipitation total and the seasonal frequency of precipitation events >5 mm yielded respectively 19 PCs and 15 PCs with an eigen value greater than one. After the varimax rotation, the 19 PCs obtained from the seasonal precipitation total captured 84% of the total variability in the time-series, while the 15 PCs obtained from the seasonal number of precipitation events >5 mm captured 80% of the variability. The original \(m\) by \(n\) (i.e. 208×232) matrix of precipitation data yielded respectively a 208×19 and a 208×15 matrix of PCs loading values. The k-means
clustering was carried out on each of these matrices using successively $k = 2$, $k = 3$, …, $k = 12$. The clusters obtained with the different $k$ values were considered to compute the Jaccard index. The results of the cluster analysis and the Jaccard similarity evaluation is reported by Table 1. With $k = 3$ the Jaccard index indicates a 90% similarity between the clusters (i.e. groups of precipitation stations) obtained based on seasonal precipitation total and the clusters obtained based on seasonal precipitation events $> 5$ mm. The high similarity value suggests the consistency of the clusters to represent both the seasonal precipitation total and the frequency of precipitation events within the studied region in the Southeastern US.

### 3.2. Delineated precipitation regions and land resources areas

Fig. 4a presents the distribution of the precipitation stations associated with each of the 3 clusters. For individual clusters, the corresponding stations virtually span a continuous spatial domain. Hence, three major precipitation regions were delineated including Region 1 (based on cluster 1), Region 2 (based on cluster 2), and Region 3 (based on cluster 3). The three precipitation regions cover distinctly the southern area (Region 1), the Northwest area (Region 2), and the Northeast area of the Southeastern US. Fig. 4b presents an overlay of the delineated precipitation regions on the land resources area of the Southeastern US as developed by the Natural Resources Conservation Service of the U.S. Department of Agriculture (USDA-NRCS, 2006). The land resource areas of the Southeastern US vary from the coast to the inland. Hence, Region 1 and Region 3 share similar land resource areas including the tidewater area, the Atlantic coast flatwoods, the southern coastal plain, the sand hills, and a part of the southern piedmont. However, Region 2 spans a different configuration of land resources as it encompasses the southern piedmont, the southern blue ridge, the Appalachian ridges and valleys, and accessorially the sand mountain. In the Southeastern US, precipitations are influenced by factors such as the North Atlantic Subtropical High, the El Niño Southern oscillation, topography, wind circulations, etc. (Li et al., 2012; Dixon and Mote, 2003). The presence of the Blue Ridge Mountains in the northwest area is likely to affect precipitation in Region 2 (see Southern Blue Ridge’s land resource area in Fig. 4b). Virtually, the results of the spatial regionalization have somewhat captured the complexity of the factors affecting precipitation variability in the Southeastern US (Engström and Waylen, 2018; Li et al., 2012). Thus, next section will provide further insights into the delineated precipitation regions.

### 3.3. Interregional analysis of precipitation patterns

Fig. 5 presents the variability of the annual precipitation total and the annual frequency of precipitation events $> 5$ mm across the Southeastern US. A comparison of both Fig. 5a and 5b shows a clear differentiation between Region 2 on one side, Region 1 and 3 on the other side. Compared to Region 1 and Region 3, Region 2 is relatively moist. The high precipitation observed in Region 2 may be attributed in part to the presence of the Blue Ridge Mountains in the northwest area (see Fig. 4b). Analyses were performed on the time-series of the seasonal precipitation totals and the frequency of events $> 5$ mm. For each delineated region, the seasonal precipitation data of the corresponding stations were equally averaged for individual years over the period 1960–2017. The 58 years’ time-series of DJF, MAM, JJA, SON, and annual precipitation total and frequency of precipitation events $> 5$ mm were obtained for each region. Table 2 reports the pair-wise Student’s $t$-test of the mean of the $z$-scores of precipitation characteristics. The results of the $t$-statistics indicate that the annual values of precipitation in Region 2 is significantly higher than the values in Region 1 and 3. This confirms the patterns described in Fig. 5. However, an analysis of the seasonal precipitation data shows that Region 1 and 3 are moister than Region 2 during JJA. Yet, the tendency is different during MAM as Region 2 receives a higher amount of precipitation compared to Region 1 and 2. This contrast within seasons may find an explanation in the mechanisms controlling moisture circulation in the Southeastern US. Table 3 reports the Mann-Kendall trend analysis of seasonal precipitation total and frequency of events $> 5$ mm. Even though few of the computed Kendall’s $\tau$ statistics were significant at p-value $= 0.05$, it is difficult to establish a coherent connection between the trend of seasonal precipitation total and the trend of the seasonal number of precipitation events $> 5$ mm. However, the weakness of these trend does not rule out the consistency of the Student’s $t$-statistics reported in Table 2. Yet, the physical meaning of these statistics may be relevant to include the delineated precipitation regions in decision making for a better agricultural water management.

### 3.4. Precipitation regions and rain-fed agriculture

Despite the high variability of precipitations in the Southeastern US (Li et al., 2012) and the related risks of yields instability, the transition from rainfed to a water-controlled agriculture is still slow across the region. Indeed, the USDA’s National Agricultural Statistics Services’ reported that the total irrigated lands in North Carolina, South Carolina, and Georgia during 2012, represented respectively 2.9%, 6.8%, and 28.6% of the total croplands across each of the listed State (USDA-NASS, 2014). Even though the percentage of irrigated lands differs state-wise, North Carolina, South Carolina, and Georgia have in common a certain number of crops with similar agricultural calendars. Table 4 illustrates the extended growing season for different crops including corn, cotton, peanuts, and soybean as reported by USDA-NASS (2010). For each of these crops, the regularity of precipitations during spring (MAM), summer (JJA), and fall (SON) is desirable to ensure a stable yield. Fig. 6 illustrates the contrasts of seasonal precipitation patterns among Region 1, 2, and 3. Note, Fig. 6 presents the average values of the seasonal precipitation totals and the frequency of precipitation events $> 5$ mm.
precipitation events > 5 mm as reported in Table 3. In practice, the use of average tendencies in decision making is often considered as a default. Especially in agricultural water management, making decisions on a crop calendar based on average precipitation values may sound superficial due to the lack of information on the risk level. Instead, the use of probabilistic information on seasonal precipitation patterns seems more comprehensive as it informs decision makers on the different risk levels.

3.5. Probability of seasonal precipitation

Probability analyses of the seasonal precipitation totals and the seasonal frequency of precipitation events > 5 mm were conducted separately for the seasons DJF, MAM, JJA, and SON. The analyses were based on the procedure described in section 2.2.2. For individual precipitation region, the 58 years of precipitation data from the corresponding stations were pooled and fitted to a probability density function. Table 5 and 6 report the pdf of the seasonal precipitation totals and frequencies in each of the delineated precipitation regions (i.e. Region 1, 2, and 3). Fig. 7 and 8 portray the pdf of seasonal and annual precipitation totals and number of events > 5 mm. Note, the graphs in Fig. 7 and 8 are created using estimates of discrete probabilities for increments of 10 mm within the range of total precipitation and 1 event within the range of the number of precipitation events >
Fig. 5. Overlay of the delineated precipitation regions on the annual precipitation total and the annual number of precipitation events (> 5 mm) in the Southeastern US (Georgia, North and South Carolina). Fig. 5a presents the spatial distribution of precipitation total and Fig. 5b presents the distribution of precipitation events > 5 mm.

### Table 2
Interregional comparison based on the z-scores of total precipitation and number of precipitation events > 5 mm using a pair-wise Student’s t-test.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Total Precipitation</th>
<th>Number of precipitation events &gt; 5 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DJF</td>
<td>MAM</td>
</tr>
<tr>
<td>Region 1</td>
<td>0.00b</td>
<td>−0.23b</td>
</tr>
<tr>
<td>Region 2</td>
<td>0.38a</td>
<td>0.47a</td>
</tr>
<tr>
<td>Region 3</td>
<td>−0.38c</td>
<td>−0.24a</td>
</tr>
</tbody>
</table>

Following the t-test with p-value = 0.05; letters a, b, and c are employed to indicate the significantly higher values of each column such that a > b > c. Values with the same letter are not significantly different.
5 mm. The disparity of shape of the graphs in Fig. 7 suggests significant inequalities of the probabilities of seasonal precipitation patterns within the precipitation regions. From Fig. 8a, one may notice that pdf of the annual precipitation total in Region 1 and 3 are similar. However, this similitude does not mean that the seasonal precipitation patterns are alike for these two precipitation regions. Indeed, the pdf of seasonal precipitation (Fig. 7) shows critical discrepancies between Region 1 and Region 3 (Fig. 7). This example of contrast reinforces the importance of the consideration of the seasonal patterns in this study. Using the inverse cumulative probability density functions, seasonal precipitation values were estimated for different values of probability of exceedance. Table 7 and 8 summarize the probabilities of receiving annually a certain minimum of seasonal precipitation at any given location of each precipitation region. An example for reading the values in Table 7 and 8 is provided as a footnote. For each region, Table 7 and 8 report precipitation values along with their probability of exceedance. Compare to the simple average value, the inclusion of the values reports in Table 7 and 8 could help improve decision making for agricultural water management in each precipitation region.

### 4. Synthesis, discussion and application

The study analyzed precipitation patterns across the Southeastern US of the United States and outlined implications for agricultural water management. The analyses used 58 years (i.e. period 1960 to 2017) daily precipitation data obtained from 208 synoptic stations distributed across the Southeastern US. The yearly seasons winter (DJF), spring (MAM), summer (JJA), and fall (SON) were considered to generate time-series of seasonal precipitation totals and seasonal numbers of precipitation events > 5 mm. A spatial regionalization method was developed to identify precipitation regions with high similarity. The regionalization method uses PCA with a varimax rotation in combination with a k-means cluster analysis. The spatial regionalization was distinctly conducted on the precipitation totals data and the seasonal frequency of precipitation events > 5 mm data. An analysis of Jaccard similarity index was considered to identify the configuration of clusters which reflects at the same time the variability of the seasonal precipitation totals and the seasonal frequency of precipitation events > 5 mm. In total three precipitation regions were delineated across the Southeastern US. Region 1 spans the south part of the Southeastern US while Region 2 and Region 3 span respectively the northwest and the northeast parts. A statistical analysis of the seasonal precipitation totals and the seasonal frequency of precipitation events > 5 mm shows significant differences between the three regions. Especially, based on the annual precipitation analysis, Region 2 is found more humid compared to Region 1 and 3. However, this difference does not reflect likewise during the different seasons of the year as Region 1 and 3 appeared more humid than Region 2 during the summer season (JJA) whereas Region 2 receives more precipitation during the spring season (MAM). This contrast of precipitation patterns may be partially explained by the diverse mechanisms controlling precipitation in the Southeastern US (Li et al., 2012; Dixon and Mote, 2003). For instance, the fact that Region 2 receives more precipitation (total and number of events > 5 mm), can be somewhat linked to the orographic influence of the Blue Ridge Mountains (Konrad, 1996). Beside this orographic effect, precipitation in the Southeastern US is highly influenced by complex mechanisms which take place seasonally (Katz et al., 2003). This is true with the North Atlantic Subtropical High which is the main driver of summer (JJA) precipitation in the Southeastern US (Li et al., 2012). The North Atlantic Subtropical High is a system of fronts (cold polar air colliding with warm subtropical air) which moves northward during JJA. At its landfall, the North Atlantic Subtropical High landfalls brings precipitations which decrease as it extends from the coast toward the continent. This explains the disparity observed during JJA as the Region 1 and 3 which are coastal, receives higher amounts of precipitation compared to Region 2. However, the orographic influence on precipitation in Region 2 is relatively more perceptible during the spring season MAM. Regardless of these differences among the precipitation regions, the Southeastern US encompasses various land resources which annually receives enough precipitation to grow different types of crops.

Under a rainfed condition, crop yields are often affected by the seasonal variability of precipitation (Rockström et al., 2010). In the Southeastern US, the practice of rainfed agriculture is very common, but recent signals of precipitation irregularity have raised the debate on

### Table 3
Mann-Kendall trend analysis for both precipitation total and the number of precipitation events (> 5 mm). Kendall’s τ statistics are reported and “*” indicates significant trends at p-value = 0.05.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Total Precipitation</th>
<th>Number of precipitation events &gt; 5 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DJF</td>
<td>MAM</td>
</tr>
<tr>
<td>Region 1</td>
<td>−0.06</td>
<td>−0.13</td>
</tr>
<tr>
<td>Region 2</td>
<td>−0.06</td>
<td>−0.11</td>
</tr>
<tr>
<td>Region 3</td>
<td>−0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

### Table 4
Crop calendar of selected common crops in the States of Georgia (GA), North Carolina (NC), and South Carolina (SC). Crop seasons span between the most active planting and harvest months (USDA-NASS, 2010).

<table>
<thead>
<tr>
<th>Crops</th>
<th>State</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
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<th>Dec</th>
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<td></td>
<td></td>
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<td>NC</td>
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</table>
transiting toward a water-controlled agriculture system. Indeed, it is difficult to maintain stable crop yields in a situation of precipitation irregularity (Kistner et al., 2018; Lobell et al., 2009). Instead, the inclusion of irrigation system is likely to suppress potential yield decreases caused by water stress. However, irrigation systems represent an important financial investment and many farmers are doubtful on the related opportunity cost. This context probably justifies the low rates of irrigated crop lands particularly in North and South Carolina (2.9% and 6.8% based on USDA-NASS, 2013’ statistics). However, it is evident that changes in precipitation patterns exposes the rainfed agriculture to significant yield losses.

The probability assessment conducted in this study is a timely contribution as it provides insights into the exceedance probabilities for different values of seasonal total precipitation and seasonal frequencies of precipitation events > 5 mm in each of the precipitation regions of the Southeastern US. Indeed, decision making based on probabilistic

Table 5
Fitting the probability distribution of seasonal and annual total precipitation in the three precipitation regions of the Southeastern US.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Probability Distribution</th>
<th>Parameters</th>
<th>Total precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>DJF</td>
<td>MAM</td>
</tr>
<tr>
<td>Region 1</td>
<td>Gamma</td>
<td>α 7.094</td>
<td>β 42.875</td>
</tr>
<tr>
<td></td>
<td>Log-normal</td>
<td>μ 19.752</td>
<td>σ 49.587</td>
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<tr>
<td>Region 2</td>
<td>Gamma</td>
<td>α 7.476</td>
<td>β 45.113</td>
</tr>
<tr>
<td></td>
<td>Log-normal</td>
<td>μ 19.752</td>
<td>σ 49.587</td>
</tr>
<tr>
<td>Region 3</td>
<td>Gamma</td>
<td>α 10.013</td>
<td>β 27.077</td>
</tr>
<tr>
<td></td>
<td>Log-normal</td>
<td>μ 19.752</td>
<td>σ 49.587</td>
</tr>
</tbody>
</table>

Table 6
Fitting the probability distribution of seasonal and annual number of precipitation events > 5 mm in the three precipitation regions of the Southeastern US.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Probability Distribution</th>
<th>Parameters</th>
<th>Number of precipitation events &gt; 5 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>DJF</td>
<td>MAM</td>
</tr>
<tr>
<td>Region 1</td>
<td>Normal</td>
<td>μ 14.571</td>
<td>σ 4.143</td>
</tr>
<tr>
<td>Region 3</td>
<td>Normal</td>
<td>μ 14.957</td>
<td>σ 3.778</td>
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</table>
values are more effective than a simple consideration of average tendencies. This tables of probabilities generated in this study may help water resources managers and farmers to better understand precipitation patterns in their regions and probably consider the information to enhance their water management practices. In this paragraph, we provide an example to illustrate the applicability of the probability tables. The example uses data from a water use efficiency study conducted by Stone et al. (2016) as they grew corn (Zea mays) under a conservation tillage in Florence, South Carolina. Corn was grown for three consecutive years (i.e. 2012 to 2014). However, this example emphasizes data for year 2014 which showed an average water use efficiency of 24 kg grain/ha/mm for corn (Dekalb DKC66-97) grown in a condition where a supplement irrigation was applied based on measurements of soil water potential indicated (Stone et al., 2016). The experimental conditions and the management practices associated with the example are explicitly reported by Stone et al. (2016). An average grain yield of 13.5 tons/ha was obtained while the crop received during JJA a total water of 394.6 mm (rainfall = 242.2 mm, irrigation = 152.4 mm). Assuming in this case, the total JJA water supply being the limiting factor for the corn yield, the probability to maintain

Fig. 7. Comparing the probability distribution of seasonal precipitation total and number of events > 5 mm in the three precipitation regions of the Southeastern US. The estimates are discrete probabilities for increments of 10 mm within the range of total precipitation and 1 event within the range of the number of precipitation events > 5 mm.
that level of corn yield while relying on rainfall only would be 0.45 in Region 1, 0.32 in Region 2, and 0.43 in Region 3. However, these probabilities would increase to 0.89 in Region 1, 0.77 in Region 2, and 0.88 in Region 3 when one considers applying a supplement irrigation of 152.4mm to compensate the moisture deficit. This type of interpretation may be used by crops advisors, and extension services to apprehend the exposure of rainfed crops to water stress and the relevance of opting for a supplement irrigation. Yet, an extensive crop database is needed to envision a broad use of such probabilistic tool. Hence, future studies are encouraged to build on the present results by developing a convenient GIS-based crop advisory tool which would integrate precipitation probabilities and crops databases for the Southeastern region of the US.

5. Conclusion

Under rainfed systems, Lobell et al. (2009) indicated that crop yields are in average 50% or less below yield potentials due to water stress. Although this tendency is global, it presumes room for improving yields in regions dominated by rainfed agriculture practices such as the Southeastern US. Indeed, several studies supported the possibility of ceiling yield potential with supplement irrigation (Van Ittersum et al., 2013; Grassini et al., 2011). However, yield gaps vary consistently from one region to another same as the precipitation patterns, suggesting potential time-space scale effects (Sohoulande et al., 2019; Lobell, 2013). Therefore, an understanding of the regional precipitation patterns is needed to envision better rainfed agricultural practices. This study used 58 years precipitation data from 208 stations across the Southeastern US and providing the following three major key findings:

i Three precipitation regions are delineated for the Southeastern US. Each precipitation region encompasses locations with high similarity of seasonal precipitation totals and seasonal frequency of precipitation events > 5 mm over the period 1960–2017.

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i Three precipitation regions are delineated for the Southeastern US. Each precipitation region encompasses locations with high similarity of seasonal precipitation totals and seasonal frequency of precipitation events > 5 mm over the period 1960–2017.

Table 7

Probability table for seasonal and annual precipitation totals in the three precipitation regions of the Southeastern US.

<table>
<thead>
<tr>
<th>Prob.</th>
<th>Region1</th>
<th>Region2</th>
<th>Region3</th>
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<td>125</td>
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<td>0.90</td>
<td>170</td>
<td>151</td>
<td>231</td>
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<tr>
<td>0.85</td>
<td>190</td>
<td>170</td>
<td>256</td>
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<tr>
<td>0.80</td>
<td>206</td>
<td>186</td>
<td>277</td>
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<tr>
<td>0.75</td>
<td>221</td>
<td>201</td>
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<tr>
<td>0.70</td>
<td>236</td>
<td>215</td>
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<tr>
<td>0.65</td>
<td>249</td>
<td>228</td>
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<tr>
<td>0.60</td>
<td>263</td>
<td>241</td>
<td>348</td>
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<tr>
<td>0.55</td>
<td>276</td>
<td>255</td>
<td>364</td>
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<tr>
<td>0.50</td>
<td>290</td>
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<tr>
<td>0.45</td>
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<td>0.40</td>
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<td>352</td>
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</table>

Fig. 8. Comparing the probability distribution of annual precipitation total (Fig. 8a) and number of events > 5 mm (Fig. 8b) in the three precipitation regions of the Southeastern US. The estimates are discrete probabilities for increments of 10 mm within the range of total precipitation and 1 event within the range of the number of precipitation events > 5 mm.
ii Statistics on precipitation characteristics confirmed the spatial variability of precipitation across the Southeastern US for the three regions delineated in the study.

iii Probability tables were developed for seasonal precipitation totals and seasonal frequencies of precipitation events > 5 mm.

Potential uses of these outcomes in the decision making for agricultural water management were discussed. For instance, the probability analysis reported different values of seasonal precipitation values and their probabilities of exceedance in each of the three precipitation regions. However, the spatial area covered by each precipitation region is relatively large to miss local climate variability. Hence, this research may be extended by developing a comprehensive and site-specific assessment of seasonal precipitation in the Southeastern US. Further research is needed to create a GIS interface which provides point-based values of season precipitation totals, seasonal number of precipitation events, and the related probabilities of occurrence. Having these values at a given location, can help to make the decision on whether to grow a specific crop under a rainfed condition or consider a water-controlled option such as a supplemental irrigation (Stone et al., 2015).

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References


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