Climate change impact and uncertainty analysis of extreme rainfall events in the Apalachicola River basin, Florida

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SUMMARY

Climate change impact on rainfall intensity–duration–frequency (IDF) curves at the Apalachicola River basin (Florida Panhandle coast) is assessed using an ensemble of regional climate models (RCMs) obtained from the North American Regional Climate Change Assessment Program. The suitability of seven RCMs on simulating temporal variation of rainfall at the fine-scale is assessed for the case study region. Two RCMs, HRM3–HADCM3 and RCM3–GFDL, are found to have good skill scores in generating high intensity events at the mid-afternoon (2:00–4:00 PM). These two RCMs are selected for assessing potential climate change impact on IDF curves. Two methods are used to conduct bias correction on future rainfall IDF curves, i.e., maximum intensity percentile-based method, and sequential bias correction and maximum intensity percentile-based method. Based on the projection by HRM3–HADCM3, there is no significant change in rainfall intensity at the upstream and middle stream stations but higher intensity at the downstream station. RCM3–GFDL projected increased rainfall intensity from upstream to downstream, particularly at the downstream. The potential temporal shift of extreme rainfall events coupled with overall increased intensities may exacerbate flood magnitudes and lead to increased sediment and nutrient loadings to the estuary, especially in light of sea level change.

1. Introduction

Changing climate has been altering the hydrologic cycle and exerting global scale impacts on our environment with significant implications for water resources (Barnett et al., 2008; Milly et al., 2008). Climate change impact related to water resources can be characterized by changes in temperature and precipitation. During the last century, significant decreasing trends in precipitation in October and May and increasing temperature particularly in the period of 1970–2009 have been found in Florida (Christopher et al., 2012). The re-distribution of precipitation produces a mixed response, which is highly region-specific, i.e., precipitation increases in some regions and decreases in other regions, and further affects streamflow discharge (Vörösmarty et al., 2000). For example, Mulholland et al. (1997) assessed the climate change impact on hydroclimatology in the south-eastern United States using regional climate models, and they found that annual air temperatures may increase by 3–4 °C in due to a doubling of the pre-industrial levels of atmospheric CO2. They also found that the most probable scenario shows increased precipitation in summer primarily due to higher storm intensity but runoff is likely to decline over much of the region owing to increases in evapotranspiration (Mulholland et al., 1997). Increases in storm intensity and clustering during summer are likely to result in more extreme floods.

Besides the amount of precipitation, global climate models show substantial increases in potential storm intensities due to global warming (Emanuel, 1987) and increases in the destructiveness of tropical cyclones due to longer storm lifetimes and greater storm intensities (Emanuel, 2005). Based on the Clausius–Clapeyron relation, daily precipitation extremes increase by ~7% with one degree of warming, and this relationship was found in global climate models and observations (Lenderink and Van Meijgaard, 2008; Hardwick-Jones et al., 2010). Based on historical rainfall records, increased frequency of heavy rainfall events has been reported in the continental US in the past century (Karl et al., 1995; Karl and Knight, 1998). In the Florida coastal region, although the overall frequency of Atlantic tropical cyclones could decrease in response to global warming, the frequency of category 4 and 5 storms is projected to double by the end of the 21st century (Bender et al., 2010). The potential future increases in rainfall intensity of short duration will affect the coastal ecosystems, soil erosion, and the design of urban infrastructures (Denault et al., 2006; Greaver and Sternberg, 2010).

Due to the non-stationarity of rainfall under changing climate conditions, the change of intensity for design storm under given duration and frequency has been observed in many regions (Adamowski et al., 2010; Willems and Vrac, 2011; Olsson et al., 2012). Nadarajah (2005) applied the generalized extreme value (GEV) distribution to fit the annual maximum of daily rainfall data during 1901–2003 in West Central Florida, and found evidence of
non-stationarity in the location parameter of the GEV distribution. As a result, the intensity–duration–frequency (IDF) curves for rainfall with short durations need to be updated (Madsen et al., 2009; Soro et al., 2010). The design criteria of urban drainage infrastructures need to be revised because the flood frequency may be enhanced due to increased intensity and frequency of extreme rainfall events (Mailhot and Duchesne, 2010).

The goal to assess the future change in extreme rainfall due to climate change can be achieved through two approaches. The first approach is to base the projection of extreme hydro-meteorological events on the projection of large scale atmospheric circulation indices, such as El Niño-Southern Oscillation (ENSO), which have been found to be related to extreme events (such as drought and flood) for various climatic regions (e.g., Jain and Lall, 2000, 2001; Sankarasubramanian and Lall, 2003). Similarly, sea level extremes have been found to be related with Atlantic Multi-decadal Oscillations (AMO) in the observation of tidal gages in Florida coast (Park et al., 2010). Hurricanes in the North Atlantic have been found to be significantly related to La Nina and El Nino events (Pielke and Landsea, 1999) and AMO (Goldenberg et al., 2001). In Florida, seasonal rainfall and streamflow have been found to be related to the ENSO (Schmidt et al., 2001). Kwon et al. (2009) utilized these indicators for low frequency variation to project long-term regional climate change.

The second approach is to project the future rainfall characteristics by using general circulation models (GCMs) or regional climate models (RCMs) (e.g., Zwiers and Khairin, 1998; Jones and Reid, 2001; Ekström et al., 2005; Frei et al., 2006; Weiland et al., 2010). RCMs have been used predominantly at higher latitudes to predict extreme rainfall events at the daily or multi-day scales (e.g., Mailhot et al., 2010; Fowler et al., 2005), but there are fewer instances of their use in the subtropics. Compared with observed rainfall data, RCMs would have skills in predicting how rainfall extremes might change under enhanced greenhouse conditions (Fowler et al., 2005). Johnson and Sharma (2009) found that the convergence skill for GCM precipitation simulations was around 7%, in comparison to equivalent skill of 80% for temperature. RCMs have also been utilized to assess the extreme rainfall change at sub-daily temporal and regional scales (Grum et al., 2006; Mailhot et al., 2007). Based on a delta change method where mean monthly changes of precipitation captured by RCM simulations are applied to scale up or down the observed historical rainfall time series by a multiplicative factor, Semadeni-Davies et al. (2008) studied the impact of projected increases in heavy rainfall from a RCM as well as potential urbanization for a watershed in Sweden, and found that the peak flow volumes and flood risk would be increased. As an extension of the delta change method, Mailhot et al. (2007) and Olsson et al. (2009) estimated the multiplicative factors as percentile ratios between future intensity distribution and historical distribution, i.e., the multiplicative factor varies with rainfall intensity. The percentile-based multiplicative factor has been used for bias correction of long-term monthly precipitation of GCMs (Wood et al., 2002).

In this study, outputs from an ensemble of RCMs are used to assess changes in rainfall patterns, which include the spatial and temporal variability of both monthly rainfall values and extreme rainfall intensity and frequency. The analysis is applied to the Apalachicola River basin located on the Florida Panhandle coast (Fig. 1). Future rainfall IDF curves at the local scale are assessed based on two methods which downscale the extreme rainfall distribution from the regional scale to the local scale.

2. Study area

The Apalachicola River, an alluvial river in the north Florida panhandle (Fig. 1), is the largest river by discharge in Florida (Iseni and Langbein, 1974). The river is the home to a diverse range of aquatic species and greatly influences the nutrient inflow and productivity of Apalachicola Bay. Apalachicola River is formed by the confluence of the Chattahoochee and Flint Rivers and is a wide meandering coastal plain-type estuary (drowned river valley) with extensive floodplains. The Apalachicola–Chattahoochee–Flint (ACF) River basin is an important ecological and economic component of a tri-state region (Florida, Alabama and Georgia) in the southeastern US (Stallins et al., 2010). The critical water need in the Apalachicola River and Bay is the provision of sufficient instream water quantity and quality to support the rich ecosystem and thriving seafood industry. Florida desires to sustain a flow regime that will maintain the biological diversity and productivity of the Apalachicola River and Bay, e.g., year-round operations to support flow needs for sturgeon spawning, young sturgeon, mussels, and host fish for mussels. The upper Chattahoochee is heavily relied upon to provide drinking water for Atlanta, one of the fastest growing metropolitan areas in the US; the primary water use in the Flint River basin is to supply water for nearly 900,000 acres of irrigated cropland. In conjunction with a drier climate (Groisman and Knight, 2008), these human demands have lowered flows into the Apalachicola and fomented debate among Florida, Alabama and Georgia over water allocation in the ACF river basin (Feldman, 2008).

In the Florida Panhandle region, thunderstorms occur about 70 days per year (Fueberg and Biggar, 1994). The observed climatological rainfall peaks at 16:00 EST over the panhandle (Misra et al., 2011). The locations for storm development are mainly controlled by the prevailing low-level wind direction and the shape of the coastline (Smith, 1970). Low-level convergence, which provides lift to destabilize the atmosphere, is a major influence on convective development over the Florida Panhandle (Ulanski and Garstang, 1978; Cooper et al., 1982; Watson et al., 1991). The midtropospheric humidity and low-level instability have been found important for thunderstorm development over the Florida Panhandle (Fueberg and Biggar, 1994). Wind direction over the Florida Panhandle was also found to be related to convective activity, and winds in the lower and midtroposphere tend to be from the southwest during days with strong convection. Therefore, the moisture transported from the Gulf of Mexico by prevailing southerly flow has a strong influence on convective development (Fueberg and Biggar, 1994). Local convergence, augmented by the convex coastal line, enhances differential heat induced convergence (Pielke, 1974). Thunderstorm initiation takes place upon maturation of sea-breeze flows and during a time of maximum heating and thermodynamic instability (Medlin and Croft, 1998).

Along the Apalachicola River in northwest Florida, the duration of floodplain inundation has decreased as a result of declining river levels (Stallins et al., 2010). Spring and summer flows have diminished in volume because of water use, storage and evaporation in reservoirs, and other anthropogenic and climatic changes in the basin upstream. The floodplain forest of the Apalachicola is Florida’s largest, and has long been recognized for its tree species richness (Stallins et al., 2010). The river and its floodplain are also coupled to estuarine trophic webs that support a commercial seafood industry and nursery grounds for Gulf of Mexico fisheries (Livingston et al., 1997).

The assessments of climate change impact on the streamflow of Apalachicola River have been reported in several studies. Lettenmaier et al. (1999) assessed the climate change impact on ACF basin by transferring GCM scenarios to the local level using a simple downscaling approach that scales local weather variables by fixed monthly ratios (for precipitation) and fixed monthly shifts (for temperature). Gibson et al. (2005) assessed the impacts of future climate scenarios on flow regimes and river ecosystems by statistical downscaling of one GCM simulation. They found that
runoff decreased significantly due to a minor decrease in precipitation and a large increase in potential evaporation, and minimum flows would be lower under future climate scenarios, and these changes could decrease the connectivity of the channel and the floodplain, decrease habitat availability, and potentially lower the ability of the river to assimilate wastewater treatment plant effluent. Sobolowski and Pavelsky (2012) assessed the potential climate change impact on temperature and precipitation over the southeast United States using the regional climate model outputs from North American Regional Climate Change Assessment Program (NARCCAP) with a focus on the seasonal climate. They found that temperature changes are universally positive and outside the bounds of natural variability over the entire region and in all seasons and future precipitation changes are modest, are of mixed sign, and vary by season and location. Water stress is most likely to come from increased temperatures and not changes in mean seasonal precipitation which is consistent with the findings by Lettenmaier et al. (1999) and Gibson et al. (2005). Due to the impact of the flood condition on the river ecosystems and fishery in the Apalachicola Bay, it is important to assess extreme rainfall events under climate change at the river basin scale. In addition, results and implications from GCMs can be communicated to a wider audience via an IDF curve that is recognized and understood by a wide range of stakeholders.

3. Historical rainfall data

Three weather stations with hourly rainfall observations obtained from National Climatic Data Center (NCDC) are located within the Apalachicola River basin as shown in Fig. 1. The mean annual rainfall from the downstream to upstream stations decreases from 1370 mm to 1287 mm, then to 1155 mm. The spatial and temporal variability of rainfall in the Apalachicola River basin can be analyzed by studying the historical records from the three weather stations. Fig. 2 shows the regime curve, i.e., mean monthly rainfall distribution. From upstream to downstream, the coefficient of variation (CV), defined as the ratio of standard deviation to mean monthly rainfall, increases from 0.20 to 0.29 to 0.41. The rainfall depth during July, August, and September in the downstream station occurs in March and is comparable with those during summer months. To compare the interannual variability of rainfall depth among the three weather stations, the CV of annual rainfall depth is computed during 1970–1999 for the purpose of consistency, and the value of CV decreases from upstream to downstream, i.e., from 0.27 to 0.25 and to 0.23.

For cross comparison among the weather stations, the extreme rainfall intensity analysis is based on the period of 1970–1999. The

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**Fig. 1.** Apalachicola–Chattahoochee–Flint River basin, weather stations, and grid boxes of the regional climate model.

**Fig. 2.** Mean monthly rainfall observed at three weather stations.
exceedance probability distributions of annual maximum rainfall intensity for duration 3-h, 6-h, and 24-h are plotted in Fig. 3. For 24-h storms, the extreme rainfall intensity is comparable at the three stations. However, the intensity of extreme rainfall with short duration (e.g., 3-h) decrease significantly from downstream (i.e., near the coast) to upstream (i.e., inland). For example, the maximum intensity for a 3-h storm decreases from 47 mm/h (downstream) to 40 mm/h (middle stream) to 30 mm/h (upstream).

4. Rainfall projections

In this study, we use RCM simulations from the NARCCAP to evaluate potential rainfall IDF changes in the Apalachicola River basin. NARCCAP is an international program that serves the climate change projection needs over a domain covering the contiguous US, northern Mexico, and most of Canada (Mearns et al., 2009). The future climate at the regional scale is projected for the mid-21st century by nesting an ensemble of RCMs within GCMs forced with the A2 scenario of the Special Report on Emissions Scenarios (Nakicenovic and Swart, 2000). The outputs from the RCMs under NARCCAP have been used to assess climate change impacts on regional extreme monthly precipitation (Gutowski et al., 2010), intense precipitation over Canada (Mailhot et al., 2011), streamflow of the Colorado River (Gao et al., 2011), and wind energy resources over the US (Pryor and Barthelmie, 2011). Di Luca et al. (2011) evaluated the potential added value in precipitation from these RCMs and found that the added value is much higher for short temporal scales than for long temporal scales due to the filtering resulted from the time-averaging process.

The RCM simulations obtained from NARCCAP are at a grid resolution of approximately 50 km x 50 km, and the rainfall outputs from the models were archived at a 3 hourly interval. Five selected RCMs in this study are Weather Research and Forecasting model (WRF) (Leung et al., 2005), Canadian Regional Climate Model (CRCM) (Laprise et al., 1998), Experimental Climate Prediction Center Regional Spectral Model (ECPC) (Juang et al., 1997), Regional Climate Model version 3 (RCM3) (Giorgi et al., 1993), and Hadley Regional Model 3 (HRM3) (Jones et al., 2004). The hosting GCMs include CGCM3, CCSM, GFDL, and HADCM3 (Mearns et al., 2009). Seven nested RCM–GCM are selected in this study, i.e., WRF–CGCM3, CRCM–CCSM, CRCM–CGCM3, ECPC–GFDL, HRM3–HADCM3, RCM3–CCSM, and RCM3–GFDL. 3-hourly rainfall simulations are obtained from the seven nested RCM–GCMs for baseline years (1970–1999) and the future time period (2040–2069).

5. IDF curves in baseline and future years

This section assesses IDF curves as influenced by potential climate change. IDF curves are site-specific and usually developed based on historical observations of rainfall at the point scale. The rainfall projections by RCMs are at the spatial scale of ~50 km grid box as shown in Fig. 1. Therefore, IDF curves based on direct rainfall projections from RCMs may be not comparable with the IDF curves assessed at the weather stations (point scale). To that end, bias correction is usually applied to the projected time series of precipitation, such as delta change method and percentile-based method. The delta change method has been used in many climate change assessment studies (e.g., Semadeni-Davies et al., 2008; Cai et al., 2009). The mean monthly changes (such as temperature and precipitation) are computed based on the simulations of GCM or RCM during the baseline and future years. An additive factor is usually used for temperature, while a multiplicative factor is usually used for precipitation:

\[ \Delta R_m = \frac{R_{r,m} - R_{b,m}}{R_{b,m}} \]

where \( R_{r,m} \) and \( R_{b,m} \) are the RCM simulated (superscript r) precipitation at month \( m \) during baseline (subscript b) and future (subscript f) years, respectively. Then, the computed multiplicative factor \( \Delta R_m \) is applied to time series of observed precipitation, e.g., from a daily precipitation record. IDF curves for future years can then be developed based on the perturbed precipitation time series.

However, the delta-change method is not suitable for extreme rainfall events (Johnson and Sharma, 2011). The future IDF curves will be computed by the percentile-based method (i.e., quantile mapping) and the sequential bias correction method in the case study watershed.

5.1. RCM suitability assessment for temporal variability of rainfall at the fine-scale

Since this research focuses on the extreme rainfall events, it is necessary to assess the suitability of the 7 RCMs for simulating the temporal variability of rainfall at the fine-scale. In order to evaluate whether RCMs generate occasional high intensity events or nominal amount of rainfall in consecutive days, the total number of events with rainfall depth higher than 30 mm is computed for both observations and the seven RCMs during the 30-year baseline periods. As shown in Table 1, the number of rainfall events from observations ranges from 173 to 210. The number of high intensity rainfall events generated by WRF–CGCM3 is comparable to that of observations. The other three RCMs (i.e., HRM3–HADCM3 RCM3–CGCM3 RCM3–GFDL) generated considerable number of such events, even though the number is smaller than that from observation. However, CRCM–CCSM and CRCM–CGCM3 failed to generate convective events since there is no occasional high intensity event. The number of events by ECPC–GFDL is small ranging from 10 to 20. Therefore, CRCM–CCSM, CRCM–CGCM3, and
ECPC–GFDL may not capture the processes of high rainfall intensity in the study region. The occurrence time of the high rainfall intensity events defined above is further assessed. Table 1 shows the 3-h periods with maximum number of the high intensity events. Based on the observations, more high intensity events occurred in the mid-afternoon from 2:00 PM to 4:00 PM at the upstream and middle stream. At the downstream, the number of high intensity events is 45 from 5:00 AM to 7:00 AM and 24 from 2:00 PM to 4:00 PM. The downstream weather station is located at the coast shoreline (Fig. 1), and the rainfall process may be different with the other two weather stations. As shown in Table 1, the maximum number of high intensity events generated by WRFG–CGCM3 occurred in the late-afternoon from 5:00 PM to 7:00 PM; while HRM3–HADCM3 and RCM3–GFDL have the maximum number of high intensity event at the mid-afternoon.

Considering the temporal variation of rainfall at the fine-scale as discussed above, HRM3–HADCM3 and RCM3–GFDL are selected for future rainfall projections since these two RCMs have better performance on capturing the rainfall processes in the case study region.

### 5.2. Maximum intensity percentile-based method

To preserve the extreme rainfall distribution predicted by RCM, the multiplicative factors in equation (1) are assumed to be dependent on the exceedance probability of maximum time series (Mailhot et al., 2007; Olsson et al., 2009). For baseline years, the hourly rainfall data during 1970–1999 from the three weather stations are aggregated to 3-hourly rainfall. For the future years, bias corrections are conducted for the RCM simulations during baseline years and future years for the three grid boxes containing the three weather stations. The multiplicative factors, which are computed as the ratio between percentiles in the simulated and observed maximum intensity distribution at the baseline years, are assumed for future rainfall projections since these two RCMs have better performance on capturing the rainfall processes in the case study region.

### Table 1

3-h Rainfall events with depth higher than 30 mm.

<table>
<thead>
<tr>
<th>RCM</th>
<th>Number of events</th>
<th>Maximum number of events and occurrence time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Upstream</td>
<td>Middle stream</td>
</tr>
<tr>
<td>Observation</td>
<td>187</td>
<td>173</td>
</tr>
<tr>
<td>WRFG–CGCM3</td>
<td>181</td>
<td>177</td>
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<tr>
<td>CRCM–CCSM</td>
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<td>0</td>
</tr>
<tr>
<td>CRCM–CGCM3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>ECPC–GFDL</td>
<td>10</td>
<td>18</td>
</tr>
<tr>
<td>HRM3–HADCM3</td>
<td>70</td>
<td>48</td>
</tr>
<tr>
<td>RCM3–CGCM3</td>
<td>59</td>
<td>64</td>
</tr>
<tr>
<td>RCM3–GFDL</td>
<td>49</td>
<td>67</td>
</tr>
</tbody>
</table>

Fig. 4. IDF curves at the baseline years (red line) and 2046–2069 from HRM3–HADCM3 (.), and RCM3–GFDL (.), and the average of them (blue line). A-1, A-2, and A-3 are for rainfall duration of 3-h. B-1, B-2, and B-3 are for rainfall duration of 24-h. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
to be the same in the future years. The procedures for the maximum intensity distribution based method are:

1. Given duration $D$, compute the maximum time series of observed rainfall intensity from weather station ($I_{obs}$) and simulated rainfall from RCM ($I_{sim}$) during the baseline years.

2. Generalized extreme value (GEV) distributions are fitted for the two maximum time series, and the corresponding exceedance probability for the weather station and RCM are denoted as $P_{s,i}(i.D)$ and $P_{r,i}(i.D)$ respectively. The intensity for a given exceedance probability is denoted as $P^{-1}_{s,i}(1/T,D)$ and $P^{-1}_{r,i}(1/T,D)$ where $T$ is return period.

3. The multiplicative factor, which is dependent on the exceedance probability, is computed as:

$$f\left(\frac{1}{T},D\right) = \frac{P^{-1}_{s,i}(1/T,D)}{P^{-1}_{r,i}(1/T,D)}$$

(2)

4. A GEV distribution is fitted to the maximum rainfall intensity from the RCM projections, and the exceedance probability is denoted as $P_{r,i}(i.D)$. The intensity for a given exceedance probability is denoted as $P^{-1}_{r,i}(1/T,D)$.

5. The projected rainfall intensity for duration $D$ and return period $T$ at the local scale is computed as:

$$i(D,T) = P^{-1}_{r,i}(\frac{1}{T},D) \cdot f\left(\frac{1}{T},D\right).$$

(3)

The IDF curves from percentile-based method during 2040–2069 are plotted in Fig. 4-Panel A for 3-h duration and Fig. 4-Panel B for 24-h duration, and they are compared with the IDF curves from baseline years (bold red lines). The spatial pattern of maximum rainfall intensity in the future years will be the same as the baseline years, i.e., extreme rainfall intensity decreases from the inland to coast. For 3-h duration, the rainfall intensity is projected to increase by RCM3–GFDL for all return periods; HRM3–HADCM3 projects increased rainfall intensity for downstream but a little bit lower rainfall intensity for 25-year and 30-year events at the upstream and downstream stations. For 24-h events, RCM3–GFDL projects higher rainfall intensity, particularly at the downstream. As shown in Fig. 4, the projected rainfall intensity varies significantly among the two RCMs given a certain return period and duration, and the range of variability is of the order of the rainfall intensity. The projections by the two RCMs provide different scenarios on future IDF curves. The average of projected intensities by the 2 RCMs is computed and represented by bold blue lines. As we can see, the rainfall intensities are projected to increase for all the durations and return periods, particularly for inland.

5.3. Sequential monthly bias correction and maximum intensity percentile-based method

The generated IDF curves based on the maximum intensity percentile-based method conserve the characteristics of individual extreme rainfall events, but the total amount of rainfall may be not conserved. Therefore, the method is adapted as follows: first, bias correction is conducted on the monthly precipitation; then the correction on the maximum rainfall intensity is applied. The corrections are based on the distributions of mean monthly rainfall and maximum rainfall, respectively. The procedures are as follows:

1. For time series of monthly rainfall $R_{m}$, where $i = 1,2,...,N$ is the year index, a Gamma distribution is fitted for each month $m$. The cumulative probability of the fitted Gamma distribution is denoted as $F_{sim}(R)$ for observed rainfall from weather stations; the cumulative probability of fitted
Gamma distribution for simulated rainfall from RCM functions are denoted as $F_{b_m}(R)$ and $F_{f_m}(R)$ for the baseline years and future years, respectively.

(2) For a given month with monthly rainfall $R_m$ in the future years from RCM, the cumulative probability can be computed by $f = F_{f_m}(R_m)$. The bias correction factor is computed as the ratio of the monthly rainfall depths, which correspond to cumulative probability $f$, between observations and RCM during baseline years:

$$b_m(f) = \frac{F_{s_m}^{-1}(f)}{F_{b_m}^{-1}(f)}$$

where $F_{s_m}^{-1}$ and $F_{b_m}^{-1}$ are inverse functions of the corresponding cumulative functions.

(3) The 3-h rainfall time series in the given month are scaled by the bias correction factor $b_m(f)$. Therefore, the bias correction factor in each month is dependent on the percentile of the monthly rainfall.

(4) Once monthly bias corrections have been conducted for RCM simulations of both baseline and future years, the maximum intensity percentile-based method is applied to the time series of extreme rainfall intensity.

Bias correction is conducted for monthly rainfall at each station. Fig. 5a presents the difference of mean monthly rainfall between observation and the two RCMs’ simulation at the middle stream during baseline years. During summer months of July, August and September, the rainfall depths from HRM3–HADCM3 match the observations very well and RCM3–GFDL overestimated 45–60 mm/month. After bias correction is applied, the difference of mean monthly rainfall depth is negligible, as shown in Fig. 5b. The mean monthly rainfall change is assessed based on the RCM outputs from the baseline years and future years after bias correction. Fig. 6 shows the projected mean monthly rainfall change from 1970–1999 to 2040–2069, respectively. The monthly rainfall change varies with RCM. However, it is observed that HRM3–HADCM3 tended to project higher monthly rainfall depth. RCM3–GFDL projected higher rainfall depth in May and September for all the stations, and projected lower rainfall depth in June and August. The increase of monthly rainfall at the downstream is significant and up to 270 mm/month in July according to HRM3–HADCM3 which has small bias correction as shown in Fig. 5.

After bias correction on monthly rainfall, percentile-based bias correction is conducted on the annual maximum time series. Fig. 7 shows the IDF curves developed after the two sequential bias corrections. For 3-h duration, RCM3–GFDL projected increased
rainfall intensity. For example, for 24-h duration with 25-year return period, the rainfall intensity at the upstream is 9 mm/h during baseline years and the projected intensity is in the range of 7 mm/h by HRM3–HADCM3, at the downstream, the rainfall intensity is 8 mm/h during baseline years, and RCM3–GFDL projects the largest increase with 24 mm/h. However, based on the projection by HRM3–HADCM3, there is no significant change of rainfall intensity (a little bit lower) at the upstream and middle stream stations and higher intensity at the downstream station. Considering the average intensities projected by the 2 RCMs (bold blue lines), the rainfall intensities will increase for all the durations and return periods, particularly for downstream.

As shown in Tables 2 and 3, compared with the method correcting the maximum intensity only, there is no significant difference between the percentile-based and the sequential bias correction methods except the downstream station. At the upstream and middle stream stations, the projected rainfall intensity usually increases 20% compared with the baseline condition; while the rainfall intensity at the downstream station is projected to increase about 2–3-fold compared with the baseline value. For example, for 3-h rainfall with return period of 25-year at the downstream, the rainfall intensity is 47 mm/h at baseline years and is projected to be 119 mm/h based on the sequential method.

### Table 2

<table>
<thead>
<tr>
<th>Station</th>
<th>Rainfall intensity (mm/h)</th>
<th>Baseline</th>
<th>Future projections (average from 2 RCMs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Future</td>
<td>Future (HRM3-HADCM3)</td>
<td>Future (RCM3-GFDL)</td>
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<tr>
<td>Upstream</td>
<td>34</td>
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<tr>
<td>Middle</td>
<td>38</td>
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<tr>
<td>Downstream</td>
<td>47</td>
<td>42</td>
<td>119</td>
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### Table 3

<table>
<thead>
<tr>
<th>Station</th>
<th>Rainfall intensity (mm/h)</th>
<th>Baseline</th>
<th>Future projections (average from 2 RCMs)</th>
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<td></td>
<td>Future</td>
<td>Future (HRM3-HADCM3)</td>
<td>Future (RCM3-GFDL)</td>
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</tr>
<tr>
<td>Middle</td>
<td>8</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Downstream</td>
<td>8</td>
<td>71</td>
<td>20</td>
</tr>
</tbody>
</table>

5.4. Time of occurrence of extreme rainfall

Fig. 8 compares the number of extreme rainfall intensity events (i.e., the maximum rainfall intensity in each year) given durations of 3- and 24-h occurred in each month. In the baseline year, more extreme rainfall with 3-h duration occurs in August and November at the inland, in January at the middle stream, and in July and September at the coast. HRM3–HADCM3 projected more extreme events in the winter season at the upstream and middle stream and more extreme events in September at the downstream. RCM3–GFDL projected more extreme events in August and September.

5.5. Uncertainty of RCMs’ projection

It should be noted that significant uncertainty exists in the rainfall simulations from some RCMs. Gutowski et al. (2010) compared
the ability of NARCCAP RCMs to reproduce extreme monthly rainfall and circulation patterns during the cold half of the year from October to March in the coastal California and upper Mississippi River basin. They found that the models reproduce well the seasonal variation and interannual variability of the timing of extremes. However, the simulated rainfall in the base line period by RCM3–GFDL is significantly overestimated during summer season as shown in Fig. 5. This could be induced by the following possible reasons. Regional climate models fail to improve long-term climate projection accuracy beyond what could be achieved by interpolating global model predictions onto a finer-scale landscape (Pielke et al., 2012). Therefore, the projections from RCMs are only a subset of possible future climate risks (Pielke and Wilby, 2012). The rainfall observation is obtained from weather stations which are point-based rainfall depth, but the rainfall depth from RCMs is the average value at the spatial scale of 50 km. Furthermore, the driving AOGCMs generally do not allow for clear representation of the Florida peninsula which is left out of the analysis in the work by Sobolowski and Pavelsky (2012). The moist convection, sea breeze, and the convex coastal line need to be parameterized correctly so that the meteorological processes in the Apalachicola River region can be presented correctly in the RCMs. For example, for the choice of cumulus parameterization schemes, the Grell (1993) scheme underestimates the summer rainfall amounts from moist convection governed by near-surface forcing in the southeast (Liang et al., 2006).

6. Summary and conclusion

Based on hourly rainfall data at three weather stations during 1970–1999 and the 3-hourly rainfall simulated by an ensemble of regional climate models in the Apalachiocla River basin, two methods are used to assess the climate change impact on the rainfall intensity–duration–frequency curves, i.e., maximum intensity percentile-based method, and sequential bias correction and maximum intensity percentile-based method. The first method has been used in other studies, and the second method is proposed in this study. The extreme rainfall intensity increases considerably based on the two methods with the increase of rainfall intensity being more in the coastal region than inland.

The suitability of seven RCMs on simulating temporal variation of rainfall at the fine-scale is assessed for the case study region. Two RCMs, HRM3–HADCM3 and RCM3–GFDL, are found to have...
good skill scores in generating high intensity events at the mid-afternoon (2:00–4:00 PM). Then two RCMs are selected for assessing potential climate change impact on IDF curves in the Apalachicola River basin. Based on the projection by HRM3-HADCM3, there is no significant change in rainfall intensity at the upstream and middle stream stations but higher intensity at the downstream station. RCM3–GFDL projected increased rainfall intensity from upstream to downstream.

The potential temporal shift of extreme rainfall events coupled with overall increased intensities may exacerbate flood magnitudes and lead to increased sediment and nutrient loadings to the estuary. Recognizing that the monthly precipitation will likely increase and the increased rainfall intensities, the rich ecosystem and thriving seafood industry, especially in light of sea level change will be affected. The implication of the time shift of extreme rainfall occurrence for water resources management includes, but is not limited to, the adaptation of reservoir operations for both flood management and water supply.

In closing, based on the ensemble regional climate models under emission scenario A2, even though some models project decreased rainfall intensity, the extreme rainfall intensity and frequency are projected to increase by most models at the Apalachicola River basin. Further, by use of the methodology presented herein results and implications from GCMs can be communicated to a wider audience via an IDF curve that is recognized and understood by a wide range of stakeholders. Future work will apply the ensemble of rainfall projections to assess the hydrologic responses to potential climate changes.

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References
