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ORIGINAL ARTICLE

The impact of climate change on rainfall Intensity–Duration–Frequency (IDF) curves in Alabama

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Abstract Changes in the hydrologic cycle due to increase in greenhouse gases are projected to cause variations in intensity, duration, and frequency of precipitation events. Quantifying the potential effects of climate change and adapting to them is one way to reduce vulnerability. Since rainfall characteristics are often used to design water management infrastructures, reviewing and updating rainfall characteristics (i.e., Intensity–Duration–Frequency (IDF) curves) for future climate scenarios is necessary. This study was undertaken to assess expected changes in IDF curves from the current climate to the projected future climate. To provide future IDF curves, 3-hourly precipitation data simulated by six combinations of global and regional climate models were temporally downscaled using a stochastic method. Performance of the downscaling method was evaluated, and IDF curves were developed for the state of Alabama. The results of all six climate models suggest that the future precipitation patterns for Alabama are expected to veer toward less intense rainfalls for short duration events. However, for long duration events (i.e., >4 h), the results are not consistent across the models. Given a large uncertainty existed on projected rainfall intensity of these six climate models, developing an ensemble model as a result of incorporating all six climate models, performing an uncertainty analysis, and creating a probability based IDF curves could be proper solutions to diminish this uncertainty.

Keywords Climate change · Intensity–Duration–Frequency (IDF) curve · Temporal downscaling · General Circulation Models (GCMs)

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Introduction

Degradation of water quality, property damage, and potential loss of life due to flooding is caused by extreme rainfall events. Damage from erosion can impact areas from farm fields to stream banks adjacent to important infrastructure (Wright et al. 2010). Historic rainfall event statistics (in terms of intensity, duration, and return period) are used to design stormwater management facilities, erosion and sediment control structures, flood protection structures, and many other civil engineering structures involving hydrologic flows (McCuen 1998; Prodanovic and Simonovic 2007). An IDF curve presents the probability of a given rainfall intensity and duration expected to occur at a particular location. Standards have been developed for designing infrastructures based on IDF curves (Wolcott et al. 2009).

During the last century, the concentration of carbon dioxide (CO_2) and other greenhouse gases (GHGs) in the earth's atmosphere has risen due to increased industrial activities (Prodanovic and Simonovic 2007). This increase

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in GHG concentrations is causing large-scale variations in atmospheric processes, which can then lead to changes in precipitation and temperature characteristics. The changes in rainfall characteristics can change IDF curves. Anticipating the potential effects of climate change (as manifested by IDF curves) and adapting to them is one way to reduce vulnerability to adverse impacts (Prodanovic and Simonovic 2007).

Changes in extreme rainfall events can lead to a revision of standards for designing civil engineering infrastructures. It can also lead to reconstruction and/or upgrade of existing civil engineering infrastructures. Current design standards are based on historic climate information. For example, a dam that is designed to control a 100-year flood event will provide a significantly lower level of protection if the intensity and duration of the 100-year flood event increases. To prepare for future climate changes, it is imperative that we review and update the current standards for water management infrastructure design. This would prevent water management infrastructures from performing below the designated guidelines in the future (Prodanovic and Simonovic 2007). This study was funded by the National Oceanic and Atmospheric Agency (NOAA) Regional Integrated Sciences and Assessments (RISA) program. Its main objective was to create IDF curves for Alabama using high-resolution projections (for 2038–2070) derived from dynamical downscaling of General Circulation Models (GCMs) by Regional Climate Models (RCMs) and to evaluate the impact of climate change on IDF curves.

Methodology

Stations and data

The stations providing long-term historical precipitation data for Alabama are shown in the supplementary material (Online Resource 1). Observed (historical) precipitation data at 15-min intervals were obtained from NOAA National Climatic Data Center (NCDC Online Climate Data Directory). Historical simulations of precipitation for the period 1968–2000 and future projections for the period 2038–2070 were obtained from the North American Regional Climate Change Assessment Program (NARCCAP) at 3-h intervals with a spatial resolution of 50 km (Sebastien et al. 2007; Richard et al. 2007). NARCCAP was designed to investigate the uncertainties in future climates at regional scales (Mearns et al. 2007). To this end, it uses several GCM historical simulations and projections from the Intergovernmental Panel on Climate Change (IPCC) Coupled Model Intercomparison Project and dynamically downscales them using a set of RCMs. The regional downscaling process uses the relatively coarse resolution output from the GCMs as a continuously updated boundary condition for the high-resolution RCMs. The regional downscaling domain of NARCCAP covers the United States and most of Canada (Mearns et al. 2007, 2009; Sebastien et al. 2007; Richard et al. 2007).

Models used

As mentioned above, future projections of precipitation data for this study were obtained from the NARCCAP website. Six different dynamically downscaled datasets were used (in the entries below, the datasets are named with the RCM identifier, followed by the identifier of the GCM providing boundary conditions):

1. HRM3-HadCM3: HRM3 is the Hadley Centre Regional Model. HadCM3 is the Hadley Centre Coupled Model. Both developed at the Hadley Centre in the United Kingdom.
2. CRCM-CGCM3: CRCM 4.2 is a Canadian Regional Climate Model developed at the Université du Québec à Montréal, and CGCM3 is the Coupled Global Climate Model, developed at the Canadian Centre for Climate Modelling and Analysis (CCCma).
3. HRM3-GFDL: GFDL CM 2.1 is a coupled atmosphere–ocean general circulation model (AOGCM) developed by Geophysical Fluid Dynamics Laboratory (GFDL), Princeton University.
4. CRCM-CCSM: The Community Climate System Model (CCSM) is a coupled climate model developed at the National Center for Atmospheric Research (NCAR) in Boulder, Colorado.
5. RCM3-GFDL: RCM3 or RegCM is a regional climate model originally developed at the National Center for Atmospheric Research (NCAR).
6. ECP2-GFDL: The updated data from the Regional Spectral Model developed at the Experimental Climate Prediction Center at Scripps Institute of Oceanography.

Bias correction

Models are not perfect; a twentieth century–simulated climate, projected from a model, is not the same as the climate of the twentieth century coming from observations. Hence, GCMs precipitation outputs cannot be used in hydrological models or in decision making without performing some form of bias correction (Sharma et al. 2007; Hansen et al. 2006; Feddersen and Andersen 2005). A realistic presentation of future precipitation from global climate models is extremely important for vulnerability and impact assessment (Wood et al. 2004; Schneider et al. 2007). Therefore, modelers use bias correction techniques to represent more realistic GCM outputs by establishing a relationship between climate model outputs and observations, then using that relationship to transform the simulated twenty-first-century climate to a "best guess" twenty-first-century climate. These techniques are given a variety of names in the literatures, such as statistical downscaling, histogram equalizing, and quantile-based mapping (Piani et al. 2010).

For this study, a quantile-based mapping method proposed by Li et al. (2010) was used. In this method, monthly rainfall values were used to define the CDF error of historical model runs relative to observations. This error was used to correct the model CDF for the future period by calculating a scaling factor from the monthly totals. The scaling factor is defined as bias-corrected rainfall total for a given month, divided by the non-bias-corrected total. Prior to disaggregation of 3-hourly rainfall events, the 3-hourly totals were multiplied by this scaling factor (Li et al. 2010).

Temporal downscaling

High-temporal-resolution (e.g., 15, 30 min, and 1-h) data are needed to create the IDF curves. Since NARCCAP provides future climate data at 3-h intervals, it is necessary to temporally downscale the precipitation data. Different types of downscaling techniques have been developed over the years; they can be categorized as weather generators, transfer functions (e.g., linear regression, stochastic method, and artificial neural networks), and weather-typing schemes (Von Storch 1999).

The temporal downscaling method employed in this study is a modified version of a stochastic method introduced by Socolofsky et al. (2001). They used the method to downscale daily precipitation data to hourly data. The method developed for this project breaks 3-hourly precipitation into possible storm intensity patterns by selecting samples of measured event statistics from a 15-min observed precipitation data (Socolofsky et al. 2001). Most stochastic methods are based on two popular models, Neyman–Scott and Bartlett and Lewis (Rodriguez-Iturbe et al. 1987; Islam et al. 1990). One of the main reasons of selecting Socolofsky method was the reduction of computational effort needed to perform the method compared the above-mentioned approaches.

Stochastic method

For the purposes of the stochastic disaggregation, a month-specific database of 15-min observed precipitation data was created. An "event" was defined as a continuous sequence of precipitation, separated by 30 min of dry weather. In case, an event was longer than 3 h; it was further divided into 3-h subintervals starting from the beginning of the rainfall. As such, the database was composed of several observed events, no longer than 3 h each. Following the stochastic method, each 3-hourly predicted precipitation (X) was disaggregated into a randomly selected collection of N rainfall events of xi magnitude ($i = 1,\ldots, N$), such that $\Sigma x_i = X$ ($i = 1,\ldots, N$). These rainfall events are selected from the formed database. Finally, to form 15-min distribution of X, each selected event was randomly placed throughout the 3-h interval. More explanation on stochastic method is presented in supplementary material document (page 3–4).

Performance

This method's performance was tested to ensure its ability to disaggregate the 3-hourly precipitation data to 15-min data. Three-hourly precipitation time series at each 15-min gauge were created by adding the measured 15-min precipitation, and the disaggregation method was tested in its ability to disaggregate the 3-hourly data into a 15-min synthetic time series. To evaluate the performance of the disaggregation method, the statistics of measured and synthetic time series were compared as suggested by Socolofsky et al. (2001) and Choi et al. (2008). The statistical parameters of the maximum rainfall values were also calculated to ensure the model captured the peaks. Since the disaggregation method is stochastic, 30 model runs were performed at each station, and the mean value of statistics over all 30 runs was used in the error quantification.

Creating IDF curves

Generalized Extreme Value (GEV) distribution was selected as the best probability distribution for Alabama based on different tests (e.g., probability plots, goodness of fit, and L-moment ratio) in a study by Durrans and Brown (2001). The GEV distribution is a continuous probability distribution that combines Gumbel, Frechet, and Weibull distributions, and it is based on extreme value theory (Coles 2001). This distribution was used in this study for creating IDF curves. GEV parameters have been estimated using the method of moments (MOM) (Hosking et al. 1985; Bhunya et al. 2007). Kolmogorov–Smirnov (K–S) test was used to evaluate the performance of the fit.

The steps below describe the process of creating IDF curves:

1. Obtain annual maximum series of precipitation depth for a given duration (15, 30, and 45 min, 1, 2, 3, 6, 12, 24, and 48 h)
2. Use GEV distribution to find precipitation depths for different return periods (2, 5, 10, 25, 50, and 100 years)
3. Repeat the first two steps for different durations
4. Plot depth versus duration for different frequencies.

Results and discussion

Bias correction

As mentioned earlier, the quantile-based mapping method proposed by Li et al. (2010) was used in this study. Bias correction was done on a monthly basis for each of the six climate models. CDFs of observed data from all stations and CDFs of climate model data for the same period were compared with each other. The twenty-first-century projections were then corrected based on the differences between theses CDFs. The resulting bias-corrected model projections were used for the remainder of this study.

Performance

The statistical measures used in the error quantification for typical months in winter (February) and summer (August) are presented in the supplementary material (Online Resource 2). In addition, statistical parameters of maximum rainfall values were calculated to make sure that the disaggregation model was capturing the peaks (Online Resource 3). These results show that the method was performing well in disaggregating the 3-h interval precipitation to 15-min data. Performance of GEV parameter estimation was also evaluated using Kolmogorov–Smirnov (K–S) test (Massey 1951). The critical value between sample and theoretical cumulative distributions at 95 % level of confidence ($\alpha = 0.05$) was 0.234. The maximum distance between the sample and theoretical cumulative distributions needs to be less than the critical value. Table presented in the supplementary material (Online Resource 4) shows statistical measures used for this evaluation. Based on the K–S test results, on all attempts, GEV distribution fitted to the sample CDFs with minimal error. The test results were always smaller than the critical value at 95 % confidence and had a small standard error.

IDF curves

Intensity–Duration–Frequency curves for Alabama were created as a series of 60 maps for each of the 6 NARCCAP

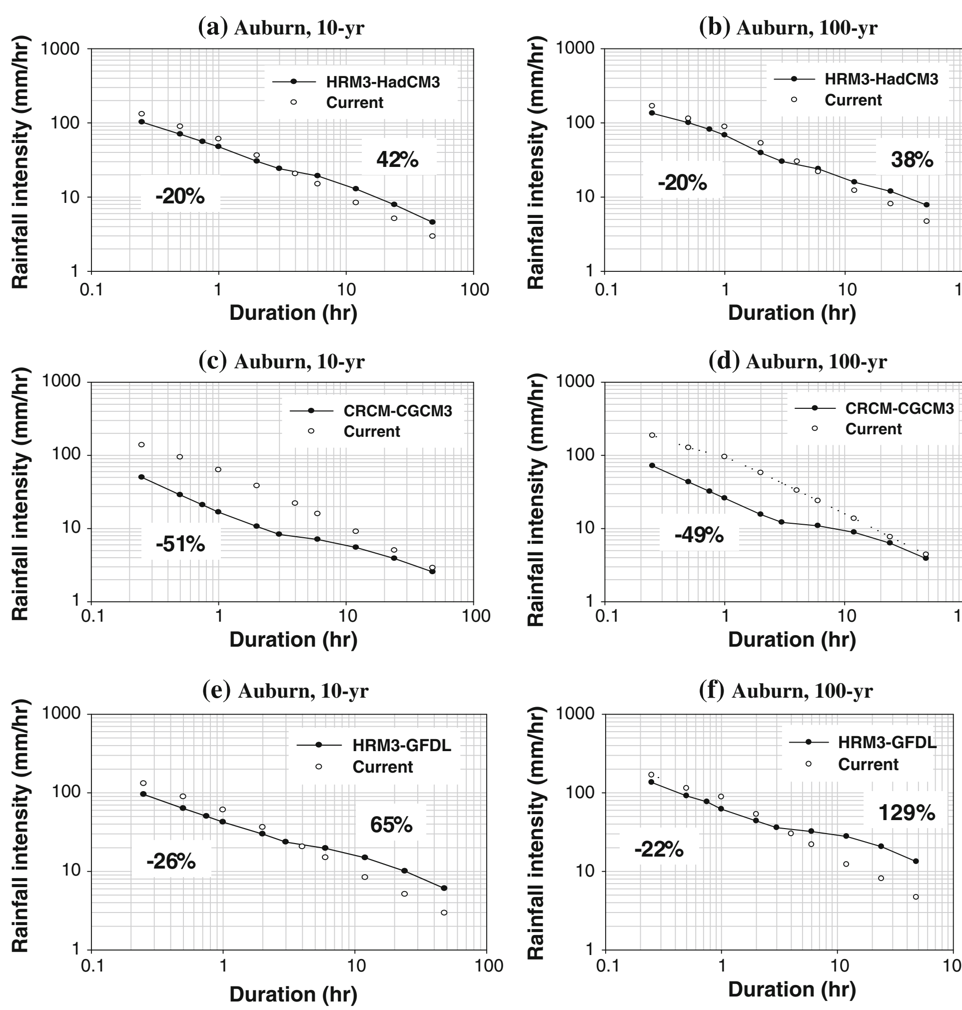

Fig. 1 IDF curves under current and future climate using HRM3-HadCM3, CRCM-CGCM3, and HRM3-GFDL models for Auburn, AL

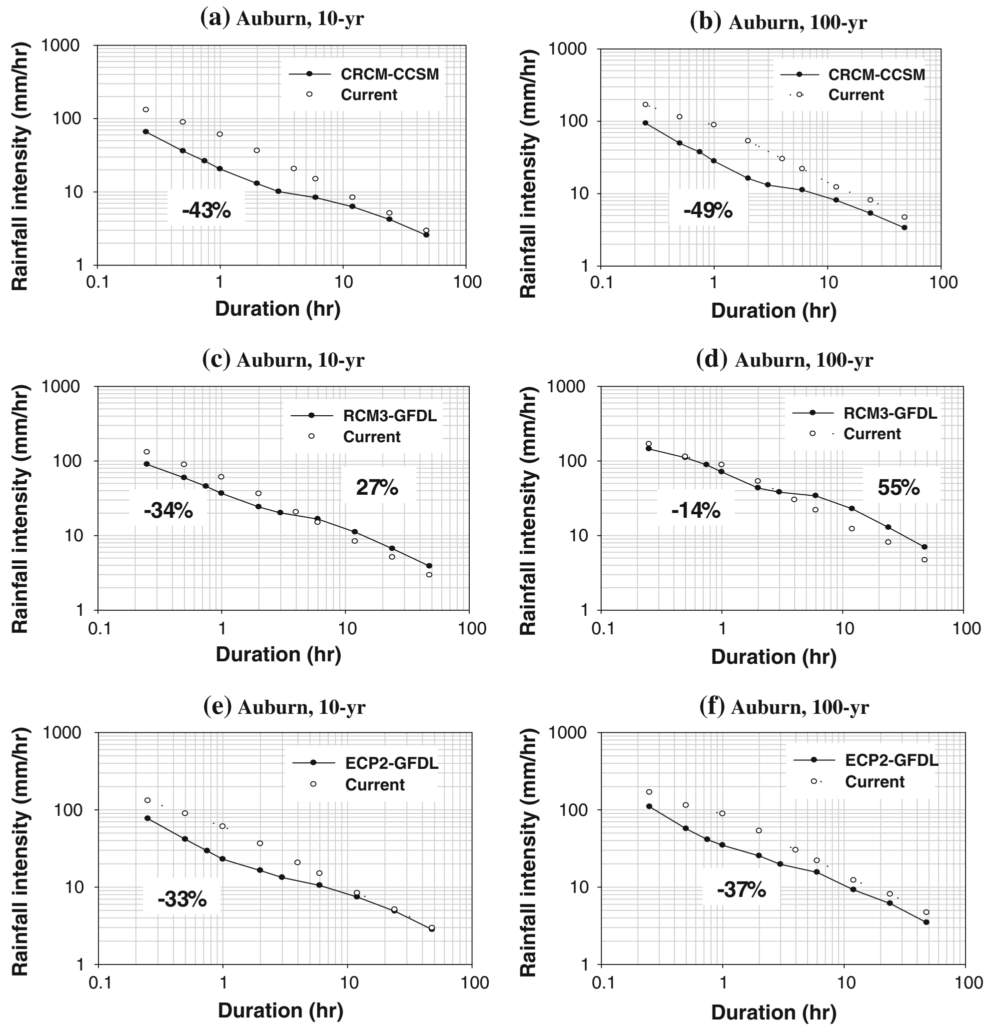

Fig. 2 IDF curves under current and future climate using CRCM-CCSM, RCM3-GFDL, and ECP2-GFDL models for Auburn, AL

regional climate projections (360 maps total) for 10 different rainfall durations and 6 different return periods.

An example of the type of maps that can be generated is illustrated in the supplementary material (Online Resource 5) using HRM3-HadCM3 projections. Comparing these maps with NOAA, Technical Paper 40 (TP-40) (Hershfield 1961) shows that changes in future IDF curves are expected with the future climate (TP-40 is not shown in the figure). For example, for a 50-year return period with 6-h duration, about 7.5 inches of precipitation is expected to fall in the southwestern part of the state. Based on TP-40, this amount is currently 6 inches—about 25 % less than what is predicted for the future. The largest projected 12-h rainfall value (about 11.5 inches) is expected to happen in southwest Alabama. For the same region and duration, TP-40 (Hershfield 1961) demonstrates about 8 inches of rainfall, 44 % less than what is predicted by IDF curves under the future climate scenario. Changes in future rainfall intensity are expected to continue for other rainfall durations and return periods, but it is not possible to discuss the results of all 360 maps here. Therefore, City of Auburn in Alabama was selected as an example from which to discuss the results in more detail. Figures 1 and 2 show the future and current IDF curves using all six NARCCAP regional climate projections for Auburn, AL for the two different return periods of 10 and 100 years.

Figure 1a, b shows IDF curves under both the future and current climates for Auburn when HRM3-HadCM3 projections were used to develop future IDF curves. Figure 1a demonstrates that the projected rainfall intensity for a 10-year return period tends to decrease by 20 % when the rainfall duration is less than 4 h and is expected to increase by 42 % for rainfall durations of more than 4 h. Also, rainfall intensity tends to increase by 38 % if the rainfall duration exceeds 6 h and is expected to decrease by 20 % for durations less than 6 h when the return period is 100 years (Fig. 1b).

Figure 1c, d depicts the changes in IDF curves when CRCM-CGCM data were used. For a 10-year return period, rainfall intensity tends to be reduced by 51 %. Results also show a 49 % decrease for a 100-year return period. Using HRM3-GFDL projections present a 26 % decline in rainfall intensity for durations less than 4 h and a 65 % increase for durations more than 4 h (Fig. 1e). Likewise, a 22 % decrease and a 129 % increase are expected to be observed for durations of less than and more than 4 h, respectively (Fig. 1f).

Figure 2a, b displays future and current IDF curves developed using the CRCM-CCSM model. Forty-three percent and 49 % declines are expected to be noticed for all durations when the return period is 10- and 100-year, respectively. The result of utilizing the RCM3-GFDL model for developing IDF curves is presented in Fig. 2c, d. It can be seen that a 34 % rainfall intensity reduction was observed for durations of less than 5 h, while there was a 27 % increase for periods longer than that (Fig. 2c). A 14 % decline for durations of less than 3 h and a 55 % increase in rainfall intensities for longer durations was also observed (Fig. 2d). Figure 2e, f demonstrates changes in rainfall intensity employing the ECP2-GFDL model. Both the 10- and 100-year return periods saw 33 and 37 % reductions, respectively, for all rainfall durations. Table 1 summarizes the discussed results for different return periods using six climate models for Auburn, AL.

As the results above clearly demonstrate, the six different NARCCAP-based projections are not identical. Analyzing all the developed maps for the state of Alabama also shows the same disparity as Auburn. Two of the models (CRCM-CGCM3 and CRCM-CCSM) show a decrease in future rainfall intensity for all return periods and all rainfall durations for Alabama. The other four suggest that, depending on the return period, future rainfall intensities could decrease below and increase above a specific rainfall duration. The disparity in results could be due to many factors. Dai (2006) performed a study in which precipitation characteristics in eighteen climate models were analyzed and compared with historical data. The study pointed out that some of the climate models' (like CGCMs) deficiencies in measuring tropical rainfall were correlated with biases in the sea surface temperature (SST) areas (Dai 2006). The SST biases in the CGCM3 model are in accordance with dry biases in the Caribbean Sea and the Gulf of Mexico, so it may underestimate variables such as precipitation (Dai 2006). It was also noted that the HadCM3 model simulates a realistic precipitation pattern, but that the results of climate models vary for different regions in the world (Dai 2006). Therefore, it should be noted that these models are different in nature, and many different variables could be involved in creating discrepancies. Differing results could be attributed to different types of GCMs and RCMs or to initial conditions and boundary conditions for each climate projection—but they all agree that for short durations of rainfall (usually less than 4 h), rainfall intensity is expected to decrease or remain close to the current one. It suggests that the current standard and guidelines, which use short rainfall durations for designing water management infrastructures (e.g., a roadside channel, a detention pond for a small drainage area), can serve their purpose in the future well.

Table 1 Comparisons of IDF curves under the current and future climate scenario for Auburn, AL

Model	Return period	Average percentage difference in rainfall intensity
HRM3-HadCM3	2 and 5 years	Duration(t) >3 h: 49 % increase
		$t < 3$ h: 22 % decrease
	10 years	$t > 4$ h: 42 % increase
		$t < 4$ h: 20 % decrease
	50 years	$t > 5$ h: 33 % increase
		$t < 5$ h: 20 % decrease
	100 years	$t > 6$ h: 38 % increase
		$t < 6$ h: 20 % decrease
CRCM-CGCM3	All return periods	50 % decrease for all durations
HRM3-GFDL	2–5 and 10 years	$t > 4$ h: 50 % increase
		$t < 4$ h: 29 % decrease
	50 years	162 % increase for all rainfall durations
	100 years	$t > 4$ h: 129 % increase
		$t < 4$ h: 22 % decrease
CRCM-CCSM	All return periods	44 % decrease for all durations
RCM3-GFDL	2 years	$t > 12$ h: 13 % increase
		$t < 12$ h: 38 % decrease
	5 years	$t > 6$ h: 23 % increase
		$t < 6$ h: 34 % decrease
	10 years	$t > 5$ h: 27 % increase
		$t < 5$ h: 34 % decrease
	50 years	$t > 4$ h: 44 % increase
		$t < 4$ h: 20 % decrease
	100 years	$t > 3$ h: 55 % increase
		$t < 3$ h: 14 % decrease
ECP2-GFDL	2-year	$t > 12$ h: 15 % increase
		$t < 12$ h: 46 % decrease
	5-year	$t > 17$ h: 3 % increase
		$t < 17$ h:41 % decrease
	10, 50 and 100 years	36 % decrease for all durations

As mentioned earlier, the results of six different NARCCAP-based projections are not consistent with respect to larger events. To further explore the results of

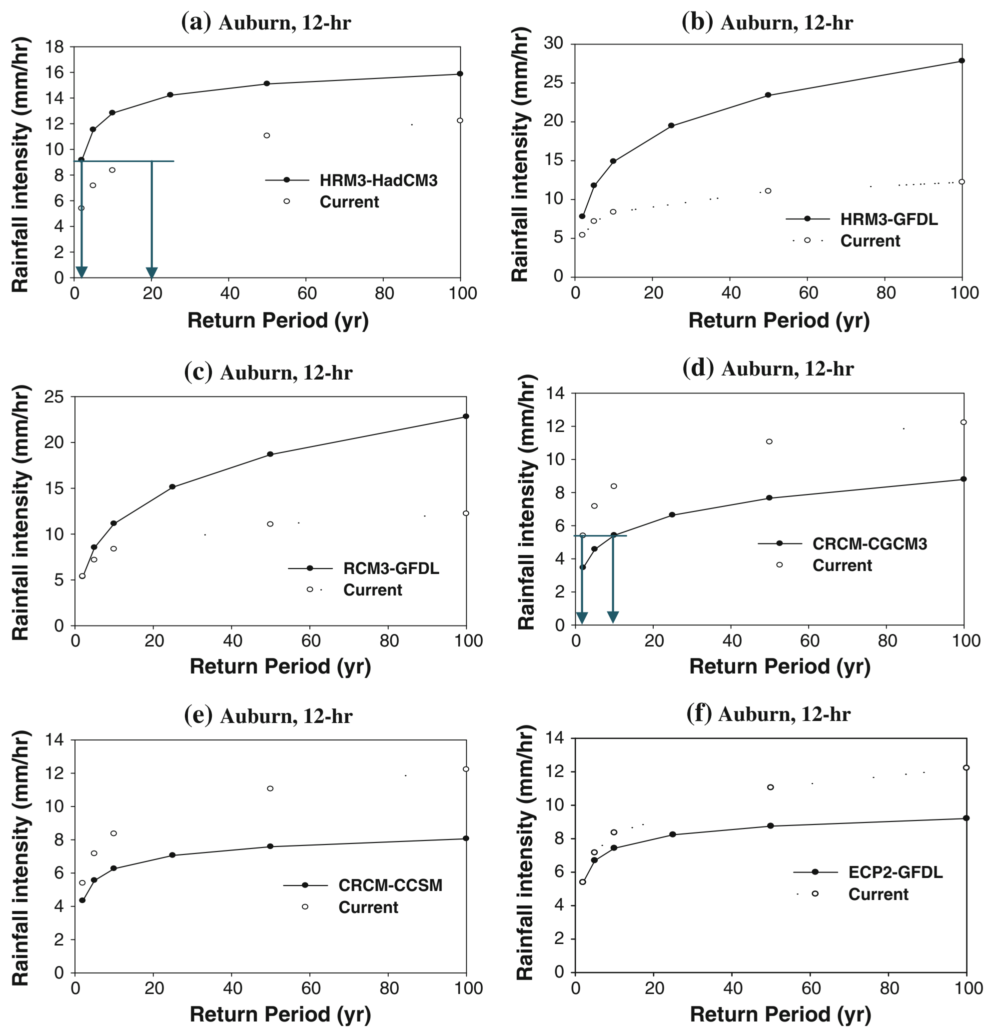

Fig. 3 Rainfall intensity versus return period under current and future climate for a 12-h rainfall using **a** HRM3-HadCM3, **b** HRM3-GFDL, **c** RCM3-GFDL, **d** CRCM-CGCM3, **e** CRCM-CCSM, and **f** ECP2-GFDL model

larger events, graphs presented in Fig. 3 were prepared. In this figure, rainfall intensity for a 12-h rainfall under future and current climate was plotted for different return periods. Figure 3a presents the results when HRM3-HadCM3 projections were used to develop future IDF curves. It shows that if a given rainfall intensity under current climate occurs once every 20 years (the probability of that given rainfall happening in any year; $p = 5$ %), the same rainfall intensity is expected to happen once every 2 years ($p = 50$ %), under future climate. Figure 3b, c also shows increase in rainfall intensity under future climate using HRM3-GFDL and RCM3-GFDL projections. On the other hand, Fig. 3d that presents the results of using CRCM-CGCM3 projections suggests that if a given rainfall intensity under current climate occurs once every 2 years ($p = 50$ %), the same rainfall intensity is expected to happen once every 10 years ($p = 10$ %) under future climate. Likewise, Fig. 3e, f shows reduction in future rainfall intensity. How these results will affect designing different structures will be discussed below.

The first step toward designing different water management structures (dams, channels, detention ponds, etc.) is to identify the characteristics of design storm in terms of duration, return period, and intensity. Time of concentration of the watershed draining to the hydraulic structure usually dictates the design storm duration. Storm return period is assigned based on economic assessments and risk analysis (probability of damage, loss of life, etc., in case of failure). For example, a 5–10-year return period is used for designing roadside channels (Brown et al. 1996) where the cost of failure is negligible whereas a much larger return period is used for designing small dams (100-year and over) where there is a great risk of life in case of failure. Knowing the storm return period, the design rainfall intensity is then acquired from developed IDF curves of the region. Rainfall intensity and duration of design storm dictate the cost of the hydraulic structure, and any uncertainty bound to estimation of these parameters can greatly impose design uncertainties. For example, Fig. 3a–c suggests design rainfall intensities of 16, 28, and 23 mm/h, respectively, for a 100-year return period and 12-h duration while Fig. 3d, f recommend 9 mm/h, and Fig. 3e proposes 8 mm/h as a design rainfall intensity (design rainfall intensity based on current IDF curves for this specific example is 12 mm/h). As can be clearly seen, there is a large uncertainty existed on projected rainfall intensity of these six climate models for long durations. Developing an ensemble model as a result of incorporating all six climate models could be a proper solution to diminish this uncertainty.

Summary and conclusions

This study developed IDF curves under the future climate scenarios for Alabama, which were then compared with the IDF curves under the current climate. Six dynamically downscaled projections were used in this study. Results of the four climate model projections suggest that future rainfall intensity could be subject to decreases or increases depending on the return period. Analysis of the results of the remaining two model projections indicates a reduction in future rainfall intensity for all return periods and all rainfall durations for Alabama. A large uncertainty on projected rainfall intensity of these six climate models for long durations (i.e., larger than 4 h) makes it difficult to obtain any strong conclusions about the expected changes on future rainfall intensity in Alabama. A variety of factors cause the differing results; a likely reason is the difference in physical parameterizations, especially of radiative and precipitation-forming processes, among different GCMs and RCMs, as well as the difference in initial and boundary conditions for each climate projection—but the result they all have in common is that the precipitation pattern for Alabama veers toward less intense rainfalls for short rainfall durations (i.e., less than 4 h). From this, we can conclude that the current standards and guidelines for designing municipal management infrastructures based on short rainfall durations can continue to serve well in the future. This conclusion is solely based on the results of the six climate model projections used in this study and not all existing climate models and scenarios. Using additional climate model projections in the future will help to make a stronger conclusion in this regard. Also, given the large uncertainty in the output from GCMs, performing an uncertainty analysis and creating a probability based IDF curves has been considered top priority for future work.

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