Technical Memorandum

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Date: *November 24, 2021*

Subject: Determining Future Rainfall Frequency Estimates for MNGWPD Service Area

1 Introduction and Summary of Findings

Historically, rainfall frequency and intensity are derived using stationary (historical) data using NOAA Atlas 14 as the basis for these calculations. However, in the last two decades we are seeing measurable increases in both frequency and intensity of rainfall events when compared to historical referenced data. Understanding changes in future frequency and intensity of rainfall events is important for planning and design of stormwater and flood control systems.

The purpose of this technical memorandum is to provide the scientific context, information and approach used to develop localized future precipitation frequency estimates reflecting potential climate change for the Metro North Georgia Water Planning District (MNGWPD) service area. It provides a detailed description of the information on the data sources used and types of analyses performed to develop future 24-hour duration design storm precipitation frequency estimates and the 85th percentile design storm for the project area. The 24-hour design storm is the main metric for the stormwater forecasting and hydraulic/ hydrologic stormwater modeling and planning of this project. The 85th percentile storm event contains a significant percentage of the total pollutant load inherent in stormwater runoff. In Georgia, this equals 1.2 inches and is used to appropriately size post-construction stormwater control measures for water quality volume.

The major findings of this analysis are summarized in the table below showing frequency and intensity of rainfall events for the MNGWPD service area under current or stationary NOAA Atlas 14 and a future condition that reflects climate change.

Design Storm	AVERAGE RECURRENCE INTERVAL OF RAINFALL EVENTS (Inches in 24-Hours)				
	1-y	2-y	5-y	10-y	25-y
NOAA Atlas 14 (Current)	3.32	3.75	4.5	5.16	6.13
NOAA Atlas 14 (Future)	3.80	4.39	5.33	6.16	7.40
	50-yrs	100-yrs	200-yrs	500-yrs	1000-yrs
NOAA Atlas 14 (Current)	6.92	7.75	8.64	9.88	10.90
NOAA Atlas 14 (Future)	8.44	9.57	10.84	12.74	14.45

* https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_map_cont.html?bkmrk=ga (accessed on 9/30/2021)

The analysis shows that the 50-year frequency rainfall event under the current NOAA Atlas 14 of 6.9 inches/24-hour could occur as frequently as 15 years under future climate change. Based on this analysis, it is further recommended to increase the 85th percentile storm by 19% from 1.2 inches to 1.43 inches for the second half of this century (2050-2100). It should be noted, however, that the scientific study and understanding of climate science is continuously advancing, so climate change adaptation is an iterative process. As new information emerges, it is recommended to revisit projections on a regular basis.

2 Development of Future Precipitation Frequency Estimates

2.1 Approach Overview

It is expected that climate change will result in an increase in rainfall amounts, intensities, and frequencies since a warmer, more humid atmosphere with warmer oceans creates a more active hydrologic cycle. These changes in rainfall will have a significant impact on the urban environment and infrastructure across the MNGWPD service area. In particular, high-intensity rainfall may cause more frequent flooding as the capacities of urban drainage systems are exceeded. Thus, it is critical to develop precipitation projections that are actionable and can be used to assess the impacts of changing design storm size, and intensity on the stormwater and wastewater collection systems and associated infrastructure.

This section provides the description of the development of future precipitation frequency estimates for a 24-hour storm and the local 85th percentile design storm used by the project. It describes information on the data sources used and types of analyses performed to develop future precipitation information for different greenhouse gas (GHG) emission scenarios. The result is a set of future change factors for the standard return periods 1 through 1000 years which can be applied to NOAA Atlas 14 precipitation frequency estimates for the locations of interest.

This information can be directly used to assess stormwater flooding and determine critical water levels and it provides a common planning and design tool reflecting future conditions that can directly be used for stormwater modeling purposes.

2.2 Data Sources

Global Climate Models (GCMs) simulate major climatological processes on a global scale, including atmospheric and ocean circulation, aerosol impacts and the carbon cycle. GCM output is used to simulate the climate under current and future emission scenarios for the project area. The resolution of raw GCM output is too coarse to be used on the local level (e.g., for hydrologic and hydraulic modeling applications). Consequently, GCM output requires downscaling[1] to smaller temporal and spatial scales using one or a combination of different dynamical or statistical downscaling methods.

CDM Smith proposed using statistically downscaled GCM output which is made available online through a collaboration of multiple agencies including the U.S. Bureau of Reclamation (BoR), the United States Geological Survey (USGS) and the National Center for Atmospheric Research (NCAR),

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[1] Downscaling is the translation of low spatial resolution climate model output to higher spatial resolution output using additional physical information about the specific region of interest.

Climate Analytics Group, Climate Central, Lawrence Livermore National Laboratory, Santa Clara University, Scripps Institution of Oceanography, U.S. Army Corps of Engineers, , National Center for Atmospheric Research, and Cooperative Institute for Research in Environmental Sciences. The data portal, which is known as the *U.S. Bureau of Reclamation's Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections website*, contains translations of climate projections from the latest set of Global Climate Models (CMIP5) for the United States[2]. The widely used archive is meant to provide access to climate and hydrologic projections at spatial and temporal scales relevant to watershed and water management applications and for water and natural resource managers and planners dealing with climate change.

This archive contains fine spatial resolution translations of climate projections over the contiguous United States (U.S.) developed using three downscaling techniques:

- Bias Corrected Spatial Disaggregation (BCSD) providing GCM output at a monthly timestep and spatial resolution of 1/8 degree (approx. 13.75 km grid cells)
- Bias Corrected Constructed Analogue (BCCA) providing GCM output at a daily timestep and spatial resolution of 1/8 degree (approx. 13.75 km grid cells)
- Localized Constructed Analogs (LOCA) providing GCM output at a daily timestep and spatial resolution of 1/16 degree (approx. 6.9 km grid cells)

We suggest using the LOCA output because it has proven to be more accurate for extreme rainfall events than BCCA output and provides a higher spatial resolution which can represent local rainfall patterns better[3]. The LOCA method is a statistical downscaling technique that uses past history to add improved fine-scale detail to GCMs projections and is available for multiple emission scenarios.

It should be noted a subset of a new generation of climate models (CMIP6) was used in the most recent 2021 IPCC sixth assessment report (IPCC WGI, 2021). In this next generation of climate modeling experiment, CMIP6 is being conducted at a larger scale with additional participating modeling groups. In comparison to CMIP5, CMIP6 includes new and updated emission pathways that address a larger set of possible future scenarios (see next section for more details). However, at this point access to CMIP6 model output is still limited and is mostly used by researchers for inter-comparison (CMIP5 & CMIP6) and validity studies and thus premature for practical applications.

2.3 Emission Scenario and Global Climate Model Selection

Climate model simulations from a variety of GCMs have generated output that varies depending on the emissions scenario and time period being considered. The models are forced by anthropogenic emissions of greenhouse gases. In the latest set of Intergovernmental Panel on Climate Change

[2] https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

[3] http://loca.ucsd.edu/

(IPCC) emissions scenarios, different future trajectories of global emissions are represented by Representative Concentration Pathways (RCPs) as shown in **Figure 1.**

2.3.1 Emission Scenario Selection

Four RCPs are available which include one mitigation scenario (RCP2.6), one low-medium scenario (RCP4.5), one high-medium scenario (RCP6.0) and one high scenario (RCP8.5). RCP2.6 is representative of the low end of scenarios in the literature. As conservative but realistic scenarios need to be applied for this study, consideration of the RCP2.6 mitigation scenario is not recommended. Most mitigation scenarios reaching warming levels equivalent to RCP2.6 (1.5^{o}C warming by 2100) rely on the concept of "negative emissions." This concept refers to CO_2 removal from the atmosphere, CO_2 capture and geologic storage methods. These technologies are still unproven and/ or non-existent on a large scale and have substantial technological and economic barriers to overcome if they are to be employed on a large scale (Hayhoe et al. 2017; Jackson et al 2015 & 2016; Anderson and Peters 2016; Jabbour and Flachsland 2017). Thus, using the low-medium scenario RCP4.5 and the high scenario RCP8.5 is recommended to consider a plausible range of possible future emission scenarios for the study area.

Future precipitation patterns are influenced by GHG emissions and associated increases in air and ocean temperatures. However, for many areas in the U.S., precipitation is highly dependent on natural variability which can exacerbate the impacts of climate change. Natural climate variability is also often the main source of uncertainty in rainfall in the short-term and even beyond mid-century as local and regional studies have shown (Deser et al. 2012, Deser et al. 2014, Hingray and Saïd 2014).

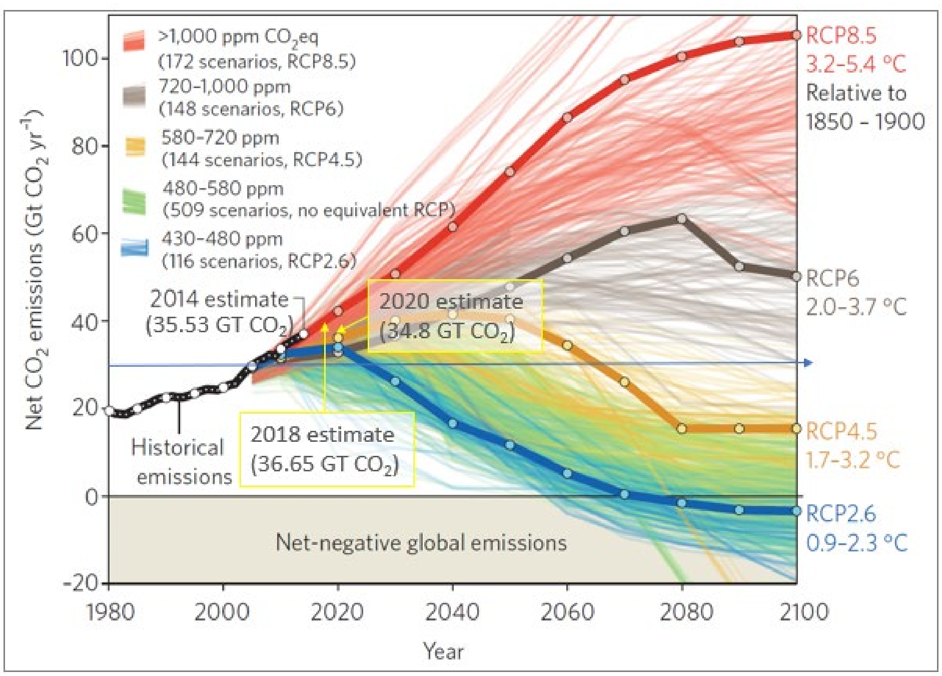

Figure 1: Pathways of global GHG emissions (from fossil fuels and cement in GtCO2eq/yr.) for baseline and mitigation scenarios under various RCPs used to project climate change (Fuss et. al 2014). Modified to include 2018 and 2020 estimates based on https://ourworldindata.org/emissions-by-fuel (accessed on 11/18/2021)

As mentioned earlier, the new CMIP6 generation of models are driven by new emission known as Shared Socioeconomic Pathways (SSPs). SSPs will replace CMIP5's Representative Concentration Pathways (RCPs) which rely on different levels of greenhouse gases and other radiative forcing that might occur in the future but are not associated with a consistent set of socioeconomic assumptions. Unlike RCPs, SSPs are explicitly related to and incorporate socioeconomic factors such as population, economic growth, education, urbanization, and the rate of technological development into their future emissions and warming outcomes (O'Neill 2014). While CMIP6 projections are not recommended yet for practical applications, it is recommended to continue to monitor CMIP6's progress and determine at what point it is appropriate to begin evaluating and potentially adopting CMIP6 projections for MNGWPD applications.

2.3.2 Global Climate Projection Selection

LOCA projections are available for the period 1950 – 2099 for a total of 32 GCMs and several emission scenarios from different modeling centers around the world (see Appendix 3-1) and on a 1/16 degree x 1/16 degree grid. To capture some of the uncertainty GCMs inherently contain, the climate adaptation community suggests the use of multiple models as it provides additional and more reliable information than one single model (Knutti et al. 2010). Additionally, model diversity is considered a healthy aspect in the climate modeling community and the "multi-model" approach is a standard technique used by climate scientists to assess projections of a specific climate variable (IPCC, 2014).

However, the selection of climate models is not straightforward and can be done using different methods (Lutz et al. 2016, Herger et al. 2018). This is particularly challenging when it comes to applications which are based on extreme rainfall statistics, because current GCMs do not simulate extreme precipitation events well which can lead to potential underestimation of the future extreme precipitation values. Few methods exist to address this challenge, including regional climate modeling or stochastic methods which are more resource extensive (Cheng et al. 2014, Maimone et al. 2019). A more practical approach proposed here is to identify a subset of projections which exhibit a statistically significant trend in modeled 24-hour precipitation frequency estimates. It is assumed that trend exhibiting projections can be considered more representative of extreme rainfall conditions in the future. The trend analysis was carried out using a Mann–Kendall non-parametric test (statistically significant levels were defined as $p < 0.1$), trend bearing projections in the annual maximum 24-hour events were selected for further analysis. For those projections without trends, it is assumed that any differences in calculated design storms can be attributed to random variability within the sampling periods, rather than relevant and significant changes in the projected rainfall.

Using the data sources mentioned above, precipitation projections were downloaded for all 32 GCMs and the two emission scenarios RCP4.5 and RCP8.5 as shown in **Appendix 1**. Files from the *BoR data portal* are provided in NetCDF format[4] which contain modeled historic and future

[4] Highly compressed file format which is a standard format for storing large amounts of climate data produced by climate modeling centers.

precipitation projections covering a total period from 1950 to 2099 on a gridded scale for the Continental United States (CONUS). Multiple GCM grid locations within the project areas were downloaded to explore any spatial variable rainfall patterns in projected output. The downloaded rain gage locations are shown in **Figure 2** and explained in further detail below.

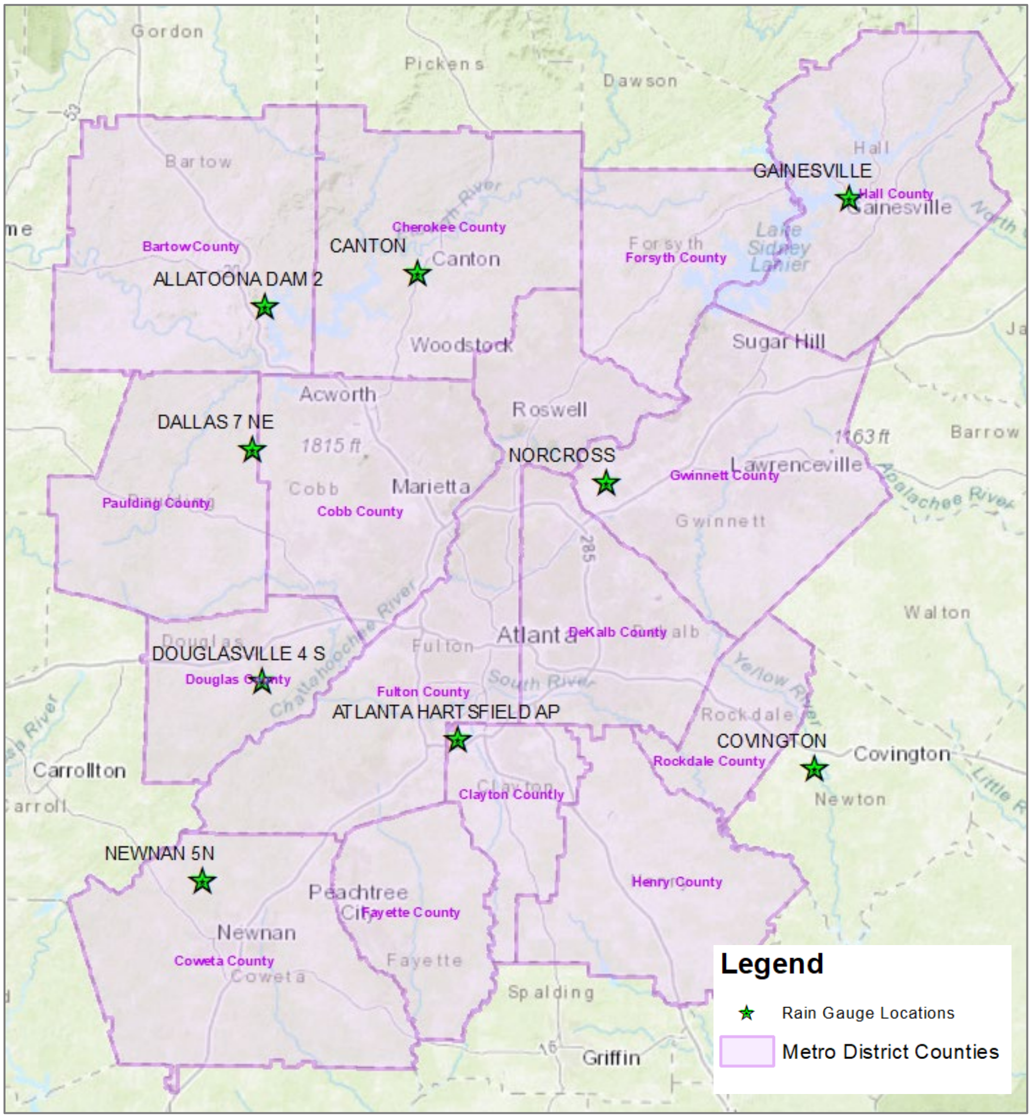

Figure 2: Rain gauge locations considered in the analysis

To reduce data processing time, five (5) out of the nine (9) rain gauges were selected based on visually identifying spatial variability patterns of 24-hour precipitation frequency estimates using NOAA Atlas 14 grids[5] for the project region. Spatial variability in the 24-hour precipitation is different for each return period. **Figure 3** shows precipitation depths for the 10-year, 25-year, 50-

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[5] https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_gis.html

year and 100-year return periods. As shown, spatial variability increases slightly with return period. It appears that for the 50-year and 100-year precipitation values the center (Norcross) of the region shows slightly lower precipitation depths than areas in the south (Newnan) or north (Gainesville). The five (5) locations selected for further analysis are Allatoona Dam-2, Gainesville, Norcross, Atlanta Hartsfield AP, and Newnan-5N. These locations can be considered representative of the spatial variability in the project area for the 24-hour precipitation frequency estimates.

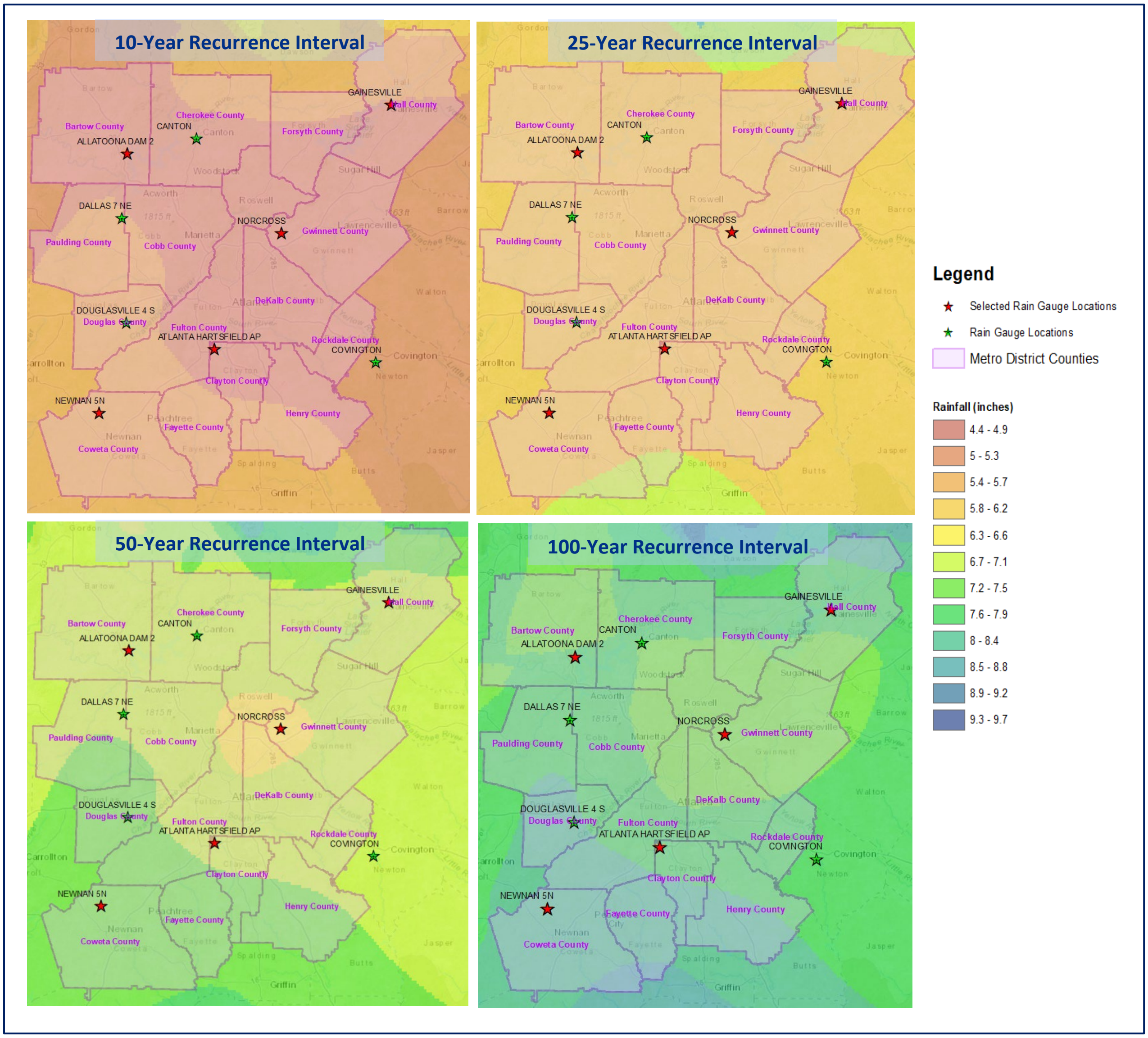

Figure 3: NOAA Atlas 14 precipitation frequency grids for the 10-year, 25-year, 50-year and 100-year return periods 24-hour precipitation depths.

2.4 Global Climate Model Output Analysis

2.4.1 Methodology

A total of 64 daily projections (RCP4.5 and RCP8.5 scenarios combined) for the selected grid cells were used in the subsequent analysis. Even though the GCM output provided by the *BoR web platform* is already downscaled to a daily time step, limitations in its applicability remain. GCM output typically does not represent local rainfall patterns correctly due to a wet bias resulting in overestimating the number of wet days compared to observed rainfall. It is not possible to generate future design storms directly (Maimone et al. 2018, Cox et al., 2019). Thus, an approach to project future precipitation is needed that does not rely on directly using GCM output and has the ability to represent extreme precipitation properly.

The proposed approach calculates change factors based on the change in modeled future and hindcast 24-hour frequency estimates which can then be applied to existing precipitation frequency estimates. Change factors are determined by comparing modeled past and future extreme precipitation values which were calculated using the water resources software Netstorm (Heineman, 2004). Netstorm determines return periods using ranked precipitation depths fitted to a generalized extreme value (GEV) distribution following the method of L moments, as described by Hosking (1990).

This approach is recommended to adjust local precipitation frequency estimates for climate change seeking the optimal balance between ensuring that the results accurately represent projected changes for extreme climate conditions while preserving local rainfall characteristics.

The analysis consists of the following main steps:

1. Data collection and processing: Downloading GCM Output for all 32 GCMs for the RCP4.5 and RCP8.5 emission scenarios covering nine (9) rain gauges across the project region and identifying a subset of representative locations as explained above to reduce data processing needs. Further, NOAA Atlas 14 24-hour precipitation frequency estimates were collected using the NWS website[6];
2. Identifying trend bearing projections for the selecting of projections used for the delta change factor development;
3. Developing delta change factors for the 1-year through 1000-year return period 24h-hour precipitation frequency estimate by using the baseline (1950-1999) and future (2050-2100) modeled climate projections as input for the GEV analysis performed through Netstorm;
4. Developing an 85th percentile change factor using a percentile-based delta change factor approach. This involves ranking model projections by wet day size for baseline (1950-1999) and future (2050-2100) modeled climate projections. The derived change factor at

[6] http://www.dynsystem.com/netstorm/index.html

the 85th percentile can then be used to calculate the future 85th percentile storm value (currently 1.2 inches).

5. Develop future precipitation frequency estimates by applying a spatially averaged delta change factor distribution to the existing NOAA Atlas 14 24-hour frequency estimates. An example is provided for the Atlanta Hartsfield-Jackson International Airport (Atlanta Hartsfield AP) location.

2.4.2 Development of 24-Hour Precipitation Change Factors

The detailed steps and results of the climate projection development are outlined below.

Step 1: Data Collection and Pre-processing

Five (5) locations were selected based on the spatial distribution of extreme rainfall as provided by NOAA Atlas 14 frequency estimate maps for the area. Identifying a subset of locations was necessary to limit data processing in later steps of the analysis. While actual rain gauge data is not used in this report, having projections readily available for each of the rain gauges may be useful for additional in-depth statistical analyses if desired in the future.

Step 2: Selection of Trend Bearing Climate Projections

As noted above, a non-parametric Mann-Kendall test was performed using R programming software (package *Trends*) on the annual maximum 24-hour events of all 64 climate projections for each of the five (5) locations used in this analysis. A total of 320 projections were analyzed, of which 79 (25%) exhibited statistically significant levels at $p < 0.1$ level (see p-values in **Appendix 2**). 67% of the projections with trend are associated with the RCP8.5 emission scenario. This is expected as it represents the highest emissions corresponding with the largest radiative forcing and associated climate response. As mentioned above, it is assumed that trend bearing climate projections better represent extreme rainfall conditions in the future. Projections without trends were excluded from subsequent planning analysis, thereby streamlining the process, and reducing the level of effort otherwise needed to process all 320 projections in Netstorm. Given the majority of trend exhibiting projections are based on RCP8.5 (higher end emission scenario) the results of the analysis can be considered as conservative estimates of 24-hour precipitation frequency values for the project region.

Each projection includes a model hindcasting 'overlap' period of 1950 to 1999 and a forecasting period of 2000 to 2100. For the trend analysis the full forecasting period of 2000-2100 was used to be able to be able to detect a long-term trend in the simulated output.

Step 3: Delta Change Factor Development

This step describes the development of return period-based delta change factor distributions which can be used to determine future 24-hour precipitation frequency estimates. As mentioned earlier, 1950-1999 was defined as the baseline period and 2050-2100 as the future reference period. A baseline period of at least 20 years is recommended to produce useful statistical measures of climate conditions when working with GCM output as climate models perform best at multi-decadal scales. The 50-year baseline and future period used in this analysis meets that criterion.

As described above, it is not possible to use the projection values directly due to their inability to represent local precipitation patterns properly. A common practice to overcome this issue is to derive change factors based on the percentage change of modeled future and hindcast (baseline) periods. Following this approach, 24-hour precipitation frequency estimates were determined for each location by fitting the simulated daily precipitation values from the baseline period and future period, respectively, to an extreme value distribution. Netstorm, water resources software, was used which determines return periods using ranked precipitation depths fitted to a GEV distribution following the method of L moments, as described by Hosking (1990). Table 1 shows the percent change between baseline and future period for the trend bearing projection ensemble for each location (including the projection 90th confidence interval). A table with individual projection results is provided in the **Appendix 3**.

Table 1: Percent increase in 24-hour precipitation frequency estimates for the project region by 2050-2100 compared to the 1950-1999 baseline period (climate projection ensemble average 90% confidence interval)

Location Name	Ensemble Statistic	AVERAGE RECURRENCE INTERVAL									
		1-y		2-y		5-y		10-y		25-y	
Allatoona	Mean (%)	16%		21%		23%		24%		24%	
	90th CI	12%	20%	16%	26%	17.5%	29%	18%	29.5%	18%	30%
Atlanta Hartsfield AP	Mean (%)	13%		14%		17%		20%		25%	
	90th CI	10%	16%	11%	17%	13%	20.5%	14%	25%	16%	34%
Gainesville	Mean (%)	18%		19%		20%		20%		20%	
	90th CI	14%	22%	15%	24%	15.5%	24%	16%	24%	15%	24%
Newnan	Mean (%)	12%		15%		16%		16%		15%	
	90th CI	9%	15%	11%	20%	12%	20%	12%	20%	11%	20%
Norcross	Mean (%)	13%		15%		17%		18%		20%	
	90th CI	11%	16%	12.5%	18%	13.5%	20%	14%	22%	14%	26%
Area Average		**14.6%**		**17.0%**		**18.5%**		**19.4%**		**20.8%**	
Location Name	Ensemble Statistic	AVERAGE RECURRENCE INTERVAL									
		50-yrs		100-yrs		200-yrs		500-yrs		1000-yrs	
Allatoona	Mean (%)	24%		24%		24%		23%		24%	
	90th CI	18%	30%	14.5%	33%	15%	33%	11%	36%	8%	39%
Atlanta Hartsfield AP	Mean (%)	30%		36%		43%		56%		69%	
	90th CI	17%	42%	19%	53%	21%	66%	25%	88%	28%	110%
Gainesville	Mean (%)	20%		19%		19%		19%		20%	
	90th CI	14%	25%	13%	26%	11%	28%	7.5%	31.5%	5%	35%
Newnan	Mean (%)	15%		15%		15%		15%		16%	
	90th CI	9%	21%	6%	23%	3%	26%	-1.5%	32%	-5%	37%
Norcross	Mean (%)	22%		24%		26%		30%		35%	
	90th CI	14%	30%	13%	34%	13%	40%	12%	49%	12%	57%
Area Average		**22.0%**		**23.5%**		**25.4%**		**29.0%**		**32.5%**	

*values are rounded to 0.5%

As shown in Table 1, the area around the Atlanta Hartsfield AP rain gauge and Norcross has a steady increase in precipitation with increasing recurrence interval, between 13% (1-year) to 69% (1000-year) and 13% (1-year) to 35% (1000-year), respectively. The other locations show rather steady increase with small variations across recurrence intervals. The lowest increase for the remaining locations was calculated for Newnan-5N (12% to 16%) and the highest increase was calculated for Allatoona Dam-2 (16% to 24%). There appears to be no clear spatial pattern in the projections as all locations show varying degrees of increases in rainfall throughout the project region. The varying degrees of percent increase can mostly be attributed to climate model uncertainty (see **Section 2.8 Uncertainty Considerations** for more details).

The large increases at the Atlanta Hartsfield AP location, however, could be attributed to how climate is modeled over the highly urbanized area of the location. Dense urban environment can have significant impacts on climate as shown in the literature. For example, the heat island effect and increased surface roughness over urban areas can affect wind patterns and can be a source of lifting warm air masses leading to cloud development and precipitation. Other factors at play are higher emissions including aerosol release compared to less urbanized areas which also influences cloud formation (Bader et al. 2018, Burian and Shepherd, 2005; Han et al., 2014).

Given the spatial variability in modeled precipitation it is recommended to average the results of all five (5) locations for each return period to determine one set of delta change factors which can then be applied across the region. Using the average of several locations will make the results more robust, potentially smoothing out anomalies that may be associated with one location in the project area. Grid cell averaging is also considered best practice when working with multiple grid cells covering an area of interest[7]. Further, it will increase practicality when applying the information as one set of change factors can be applied throughout the region. The recommended final subset of change factors is shown in Table 2 below for RCP4.5 and RCP8.5.

Table 2: Recommended percent increase of 24-hour precipitation frequency estimates for the project region

AVERAGE RECURRENCE INTERVAL				
1-y	2-y	5-y	10-y	25-y
15%	**17%**	**18.5%**	**19%**	**21%**
50-yrs	100-yrs	200-yrs	500-yrs	1000-yrs
22%	**23.5%**	**25%**	**29%**	**32.5%**

Step 4: Applying precipitation change factors

During this last step the developed percent increases can be applied to the existing 24-hour precipitation frequency estimates to develop a set of localized future projections. Several options exist such as applying the factor set to frequency estimates developed from individual rain gauges

[7] CMIP Climate Data Processing Tool User's Guide (DOT, 2015), https://www.fhwa.dot.gov/environment/sustainability/resilience/tools/user_guide/index.cfm

or applying to NOAA Atlas 14 24-hour precipitation frequency estimates as shown in the next section.

Step 5: Change Factor for the 85th Percentile Storm

The 85th percentile storm used in the project region is currently 1.2 inches. Change factors for the 85th percentile storm are determined using a percentile based delta change factor at the 85th percentile. The daily annual maximum baseline and future precipitation projections are ranked by wet day size as shown in **Figure 4** for the five (5) locations. Similar to the approach above, delta change factors for each region are averaged to obtain one single 85th percentile design storm which can be used for the project region.

Table 3: Delta Change Factors for the 85th Percentile Storm

Location Name	85th percentile change
Allatoona Dam-2	25%
Atlanta Hartsfield AP	19%
Gainesville	19%
Newnan-5N	14%
Norcross	17%
Area Average	**19%**

Based on this analysis, it is recommended to increase the 85th percentile storm by 19% from 1.2 inches to 1.43 inches.

2.5 Future 24-hr Precipitation Frequency Design Storm Estimates

The following section provides future IDF estimates for the Atlanta Hartsfield AP location as an example. The change factors as provided in Table 3 can be applied to any 24-Hour precipitation depth available in the project region. The example below shows the updated design storms for the Atlanta Hartsfield AP in tabular and graphical form.

Table 4: Annual Maximum 24-hr Precipitation Estimates and Changes under future climate (2050-2100) compared to the Baseline Period 1950-1999 (90% confidence interval)

Design Storm	AVERAGE RECURRENCE INTERVAL				
	1-y	2-y	5-y	10-y	25-y
NOAA Atlas 14 (Current)	3.32	3.75	4.5	5.16	6.13
NOAA Atlas 14 (Future)	**3.82**	**4.39**	**5.33**	**6.16**	**7.40**
	50-yrs	100-yrs	200-yrs	500-yrs	1000-yrs
NOAA Atlas 14 (Current)	**6.92**	**7.75**	**8.64**	**9.88**	**10.90**
NOAA Atlas 14 (Future)	**8.44**	**9.57**	**10.84**	**12.74**	**14.45**

* **https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_map_cont.html?bkmrk=ga** (accessed on 9/30/2021)

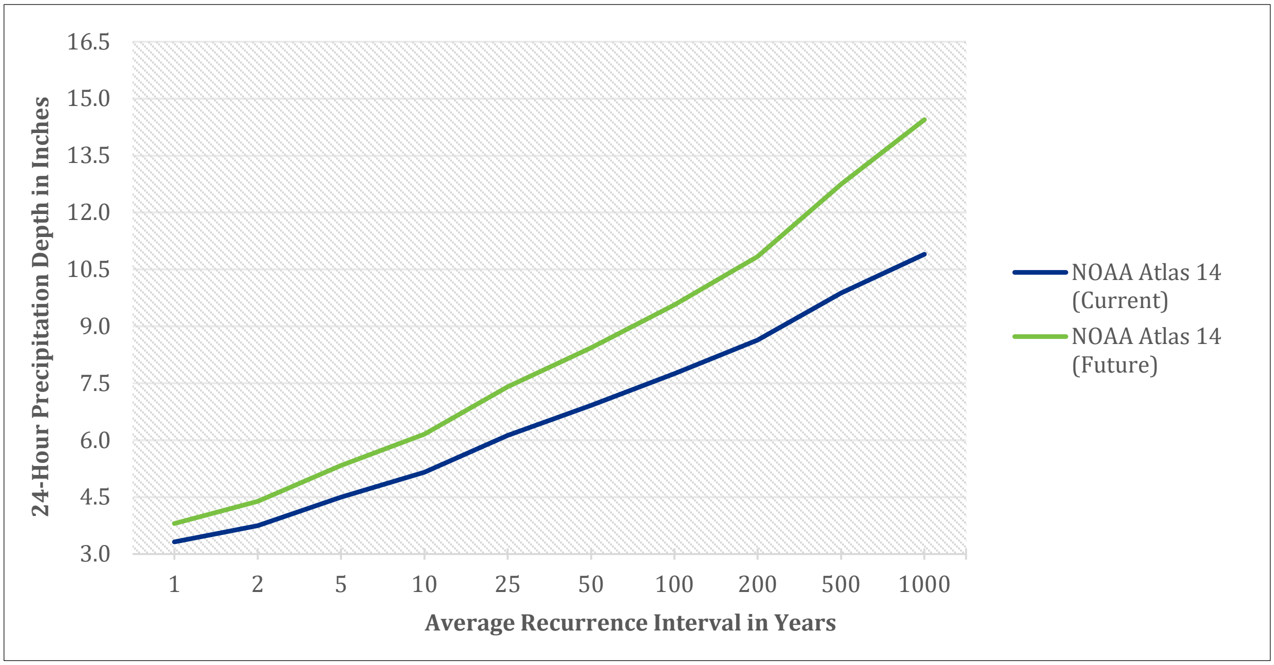

Figure 4: 24-Hour Precipitation Frequency Estimates for current and future conditions at the Atlanta Hartsfield AP location.

2.6 Future 24-hr Precipitation Frequency Design Storm Estimates for Different Planning Horizons

Sections 2.4 & 2.5 describe a practical approach to develop future precipitation projections using a time period of 2050-2100 (second half of the 21st century). The same approach and steps described above can also be used to develop future precipitation frequency estimates for near-term projections (first half of the 21st century).

Another possibility to determine near-term projections without the need to rerun the analysis described above is to interpolate the NOAA Atlas 24-hr precipitation frequency estimates with the 2050-2100 future estimates developed in this document. This can be done by using a simple linear interpolation between the NOAA Atlas 14 precipitation frequency estimates (with 2010 as the starting year) and the future estimates for 2050 which are shown Table 4 above. Table 5 provides the interpolated design storms for the years 2020, 2030 and 2040.

It should be noted that a simple interpolation is a practical method to determine near-term change in rainfall. However, it does not allow for evaluating the potential uncertainty range of future projections which can be significant depending on emission scenario, time period, location of interest and average recurrence interval as shown in Table 1 and further explained in Section 2.8: Uncertainty Considerations.

Table 5: Annual Max 24-hr Precipitation Estimates and Changes for different time periods (2010 - 2050) based on a simple interpolation between NOAA Atlas 14 values and future projected values (2050-2100)

24-hr Precipitation Frequency Estimates (inches)					
ARI	2010	2020	2030	2040	2050
1-y	3.32	3.44	3.56	3.68	3.82
2-y	3.75	3.91	4.07	4.23	4.39
5-y	4.50	4.71	4.92	5.12	5.33
10-y	5.16	5.41	5.66	5.91	6.16
25-y	6.13	6.45	6.77	7.09	7.40
50-yrs	6.92	7.30	7.68	8.06	8.44
100-yrs	7.75	8.21	8.66	9.12	9.57
200-yrs	8.64	9.19	9.74	10.29	10.84
500-yrs	9.88	10.60	11.31	12.03	12.74
1000-yrs	10.90	11.79	12.67	13.56	14.45
85th %	1.20	1.26	1.32	1.37	1.43

2.7 Assumptions and Limitations

The primary purpose of the approach presented herein is to make GCM output actionable for stormwater management and flood modeling applications. While the approach can be applied to existing 24-hr precipitation frequency estimates, there are important assumptions and limitations to acknowledge:

- The frequency and duration of storms in Georgia, as well as absolute daily precipitation totals, are not accurately simulated by the GCMs. A key underlying and frequently applied assumption is that that the percentage change derived from current and future simulated wet days (i.e., delta change factors) can be applied to observed storm events to create a future time series.
- The approach relies on the ability of GCMs to simulate precipitation intensities in current and future climates. Currently, GCMs do not simulate extreme precipitation events originating from small to meso-scale weather systems (i.e., convective summer storms), which can lead to potential underestimation of the future extreme precipitation values. This is partly addressed in the approach selected for this study which is based on identifying a subset of projections which are assumed to simulate days with more extreme rainfall.
- The approach is based on a modified delta change method which is standard practice in climate adaptation applications. Applying the delta change method acknowledges that GCMs more reliably simulate relative changes between a future period and baseline period rather than absolute values. The delta change method also assumes that the modeled change in rainfall is associated with increased precipitation intensity, but that storm duration and number of storms will be similar in the future.
- The results of the analysis can only be applied to existing 24-hr frequency estimates available in the region (such as NOAA Atlas 14). Applications which require continuous time series require a modified approach. If desired additional analyses can be performed to calculate high resolution future precipitation time series.

2.8 Uncertainty Considerations

Sources of Uncertainty in Climate Impact Studies

GCMs are currently the most credible source available for providing information about the response of global climate systems to increasing GHG concentrations (Hailegeorgis and Burn 2009). These models are simplified representations of the complex physical processes occurring on Earth and the GHG emissions scenarios used to drive GCMs are based on uncertain future socio-economic conditions. Confidence in climate models comes from the fact that they are based on physical principles and can reproduce many aspects of the current climate, including observed trends that are driven by human-induced changes, or anthropogenic forcing (Barnett et al. 2005, Knutti 2008, Hayhoe et al 2017).

Climate change impact assessments which use GCM output to inform planning and decision-making processes are subject to uncertainties which originate from multiple sources, including unknowable amounts of future GHG emissions as well as complex natural and physical processes and how they are parameterized by the GCMs. Results of this analysis confirm the uncertainties inherent in climate modeling as shown in the change factors derived from each projection but also location.

It should be further noted that precipitation is highly variable by nature and the assessment of natural variability is generally recommended as it may contribute substantially to the uncertainty associated with climate change projections. As mentioned in the previous sections, local and regional studies have shown natural variability to be the dominant source of uncertainty in projections of mean and extreme rainfall, especially for short lead times (a few decades) and in some cases even for end-of-century projections.

Despite these uncertainties, it is imperative to consider potential climate change effects in water resource planning and management.

3 Recommendations for Additional Analyses

The information developed in this report can be used to incorporate future changes in climate into stormwater modeling, planning and design applications which are based on 24-hour precipitation frequency estimates and the 85th percentile design storm.

However, other water resources planning, and engineering applications may require different statistical input parameters for which additional climate change analyses will be needed. These include:

- Development of Precipitation Frequency Estimates for different durations (e.g., sub-daily, sub-hourly) which requires observed records from individual rain gauges;
- Stochastic Rainfall Generator to further explore possible low-probability but high-consequence extreme rainfall scenarios. The application of a stochastic rainfall generator is recommended if more detailed analyses are desired in the future as stochastic methods have the ability to factor in year-to-year variability on top of the climate change signal and as a result has the ability to simulate very low probability but realistic future extreme rainfall events without having to use additional climate models;

- Temperature Projections Analysis for assessments of source water quality impacted by changing source water temperatures including the impact of changing climate and nutrient loads on biological processes such as harmful algal blooms;

- Precipitation and temperature projection analyses targeted for drought risk screening. Areas with increasing rainfall are less susceptible but not immune to increased drought. As temperatures increase and growing season lengthens there will be a greater demand for water (agriculture, residential).

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Appendix 1 CMIP5 Suite of Global Climate Models

Global Climate Models Considered for the Development of Rainfall Projection

Projection ID*	GCM Name	Climate Modeling Organization
Projection 1 (RCP4.5) Projection 2 (RCP8.5)	access1-0.1	CSIRO Climate Science Centre in Aspendale, Melbourne, Australia
Projection 3 (RCP4.5) Projection 4 (RCP8.5)	access1-3.1	
Projection 5 (RCP4.5) Projection 6 (RCP8.5)	bcc-csm1-1.1	Beijing Climate Center, China Meteorological Administration, China
Projection 7 (RCP4.5) Projection 8 (RCP8.5)	bcc-csm1-1-m.1	
Projection 9 (RCP4.5) Projection 10 (RCP8.5)	canesm2.1	Canadian Centre for Climate Modeling and Analysis
Projection 11 (RCP4.5) Projection 12 (RCP8.5)	ccsm4.6	Community Earth System Model, National Center for Atmospheric Research (NCAR), USA
Projection 13 (RCP4.5) Projection 14 (RCP8.5)	cesm1-bgc.1	
Projection 15 (RCP4.5) Projection 16 (RCP8.5)	cesm1-cam5.1	
Projection 17 (RCP4.5) Projection 18 (RCP8.5)	cmcc-cm.1	European Network of Earth System Modeling
Projection 19 (RCP4.5) Projection 20 (RCP8.5)	cnrm-cm5.1	
Projection 21 (RCP4.5) Projection 22 (RCP8.5)	csiro-mk3-6-0.1	CSIRO Climate Science Centre in Aspendale, Melbourne, Australia
Projection 23 (RCP4.5) Projection 24 (RCP8.5)	ec-earth.8	European Network of Earth System Modeling
Projection 25 (RCP4.5) Projection 26 (RCP8.5)	fgoals-g2.1	Climate Change Research Center, Chinese Academy of Sciences, Beijing, China
Projection 27 (RCP4.5) Projection 28 (RCP8.5)	gfdl-cm3.1	National Oceanic and Atmospheric Administration (NOAA) Geophysical Fluid Dynamics Laboratory (USA)
Projection 29 (RCP4.5) Projection 30 (RCP8.5)	gfdl-esm2g.1	
Projection 31 (RCP4.5) Projection 32 (RCP8.5)	gfdl-esm2m.1	
Projection 33 (RCP4.5) Projection 34 (RCP8.5)	giss-e2-r.6	National Aeronautics and Space Administration, NASA, USA
Projection 35 (RCP4.5) Projection 36 (RCP8.5)	hadgem2-ao.1	National Meteorological Service, UK

Projection ID*	GCM Name	Climate Modeling Organization
Projection 37 (RCP4.5) Projection 38 (RCP8.5)	hadgem2-cc.1	National Meteorological Service, UK
Projection 39 (RCP4.5) Projection 40 (RCP8.5)	hadgem2-es.1	
Projection 41 (RCP4.5) Projection 42 (RCP8.5)	inmcm4.1	National Centre for Meteorological Research (CNRM), France
Projection 43 (RCP4.5) Projection 44 (RCP8.5)	ipsl-cm5a-lr.1	Institut Pierre-Simon Laplace (France)
Projection 45 (RCP4.5) Projection 46 (RCP8.5)	ipsl-cm5a-mr.1	
Projection 47 (RCP4.5) Projection 48 (RCP8.5)	miroc-esm.1	Meteorological Research Institute, University of Tokyo
Projection 49 (RCP4.5) Projection 50 (RCP8.5)	miroc-esm-chem.1	
Projection 51 (RCP4.5) Projection 52 (RCP8.5)	miroc5.1	
Projection 53 (RCP4.5) Projection 54 (RCP8.5)	mpi-esm-lr.1	Max Planck Institute for Meteorology (Germany)
Projection 55 (RCP4.5) Projection 56 (RCP8.5)	mpi-esm-mr.1	
Projection 57 (RCP4.5) Projection 58 (RCP8.5)	mri-cgcm3.1	Meteorological Research Institute of the Korea
Projection 59 (RCP4.5) Projection 60 (RCP8.5)	noresm1-m.1	Norwegian Meteorological Institute (Norway)
Projection 61 (RCP4.5) Projection 62 (RCP8.5)	cmcc-cms.1	European Network of Earth System Modeling
Projection 63 (RCP4.5) Projection 64 (RCP8.5)	giss-e2-h.6	National Aeronautics and Space Administration, NASA, USA

*Projection IDs are assigned for data processing needs.

Appendix 2 Global Climate Model Selection

List of projections for the five locations used in this analysis (p-values at <0.1 level are highlighted in bold)

Projection ID	Allatoona Dam-2	Atlanta Hartsfield AP	Gainesville	Newnan-5N	Norcross
01	0.759	**0.081**	**0.032**	0.264	0.239
02	0.280	0.430	**0.063**	0.870	0.108
03	0.357	0.112	0.111	**0.066**	0.117
04	0.290	0.214	0.197	0.111	**0.023**
05	0.526	0.931	0.199	0.809	0.441
06	0.623	**0.017**	0.111	0.157	**0.085**
07	0.926	0.473	0.427	0.499	0.102
08	0.649	0.542	0.296	0.561	**0.083**
09	0.451	0.796	0.128	0.926	0.357
10	0.376	0.538	0.594	0.688	0.941
11	0.154	0.993	0.657	0.745	0.644
12	0.181	0.420	**0.079**	0.219	0.462
13	0.586	0.701	0.931	0.636	0.274
14	0.586	**0.059**	0.247	**0.023**	**0.050**
15	0.988	0.714	0.893	0.399	0.538
16	0.623	0.526	0.121	0.598	0.764
17	0.142	**0.031**	**0.017**	**0.016**	**0.074**
18	**0.019**	0.139	**0.023**	0.313	**0.012**
19	**0.072**	0.208	0.179	0.420	0.837
20	0.828	0.856	0.688	0.837	0.819
21	0.491	0.389	0.313	0.736	0.922
22	0.247	0.301	0.152	0.530	0.574
23	0.128	0.448	0.125	0.134	0.150
24	**0.017**	**0.002**	**0.005**	**0.002**	0.112
25	0.908	0.386	0.409	0.847	0.653
26	0.330	**0.040**	0.847	0.945	0.814
27	0.155	**0.016**	0.545	0.159	0.522
28	**0.040**	0.499	0.714	0.102	0.252
29	0.741	0.602	0.480	0.819	**0.046**
30	0.437	**0.086**	**0.059**	0.293	**0.035**
31	0.917	0.917	0.254	0.221	0.823
32	0.917	0.396	0.330	0.705	0.879

Projection ID	Allatoona Dam-2	Atlanta Hartsfield AP	Gainesville	Newnan-5N	Norcross
33	**0.012**	**0.006**	0.122	0.175	**0.015**
34	**0.055**	**0.001**	**0.001**	**0.091**	**0.005**
35	0.636	0.383	0.189	0.561	0.364
36	**0.034**	**0.026**	0.119	**0.000**	0.121
37	0.606	0.242	0.657	0.139	0.244
38	**0.000**	**0.005**	**0.000**	**0.002**	**0.000**
39	**0.003**	**0.086**	**0.022**	**0.045**	**0.001**
40	**0.058**	**0.008**	**0.054**	**0.015**	**0.001**
41	0.542	0.912	0.819	0.484	0.884
42	0.466	0.675	0.147	0.941	0.773
43	0.903	0.842	0.150	0.998	**0.085**
44	**0.021**	0.705	0.139	**0.050**	0.175
45	0.437	0.115	**0.096**	**0.034**	0.342
46	0.950	0.649	0.488	0.293	0.244
47	0.950	0.373	0.782	0.354	0.569
48	0.870	0.736	0.657	0.856	0.170
49	0.931	0.526	0.696	0.545	0.782
50	0.125	0.922	0.201	0.219	0.357
51	0.318	0.903	0.282	0.304	0.336
52	**0.071**	0.136	0.102	0.277	**0.027**
53	0.441	0.267	0.118	0.108	0.409
54	0.189	0.437	0.249	**0.023**	0.304
55	0.823	0.389	0.134	0.128	0.185
56	0.354	0.223	**0.014**	**0.006**	**0.004**
57	**0.065**	0.898	**0.091**	**0.011**	**0.002**
58	**0.035**	**0.011**	**0.003**	**0.001**	**0.005**
59	0.602	0.786	0.206	0.530	0.301
60	0.274	0.809	0.310	0.354	0.267
61	0.553	0.396	0.518	0.282	0.282
62	0.206	0.518	0.175	0.549	**0.056**
63	**0.073**	0.488	0.574	0.941	0.865
64	0.133	0.666	0.288	0.125	0.339

Appendix 3 Delta Change Factor Distribution

Delta change factor distribution for each location and projection used in this analysis (1950-1999 vs. 2050-2100)

Location: Allatoona Dam-2

Projection	AVERAGE RECURRENCE INTERVAL									
	1-y	2-y	5-y	10-y	25-y	50-y	100-y	200-y	500-y	1000-y
Projection 18	29%	33%	35%	37%	39%	40%	41%	42%	43%	43%
Projection 19	3%	2%	1%	1%	1%	2%	2%	2%	3%	4%
Projection 24	25%	30%	25%	19%	11%	4%	-3%	-11%	-20%	-27%
Projection 28	19%	19%	23%	25%	31%	36%	42%	49%	60%	69%
Projection 33	15%	21%	25%	27%	30%	31%	33%	34%	35%	36%
Projection 34	22%	15%	15%	18%	25%	33%	45%	60%	86%	111%
Projection 36	22%	38%	45%	48%	49%	49%	49%	47%	45%	42%
Projection 38	23%	32%	34%	33%	30%	27%	22%	17%	10%	4%
Projection 39	15%	26%	30%	30%	27%	21%	15%	7%	-4%	-12%
Projection 40	23%	32%	37%	38%	38%	34%	30%	25%	16%	9%
Projection 44	-5%	3%	8%	10%	13%	14%	15%	15%	16%	15%
Projection 52	17%	23%	26%	28%	29%	30%	30%	31%	31%	31%
Projection 57	8%	8%	9%	11%	13%	15%	17%	20%	24%	27%
Projection 58	12%	15%	15%	15%	14%	13%	12%	11%	9%	7%
Projection 63	17%	19%	18%	16%	14%	11%	8%	4%	0%	-4%
Mean	**16.3%**	**21.0%**	**23.1%**	**23.8%**	**24.2%**	**24.1%**	**23.9%**	**23.6%**	**23.4%**	**23.6%**

Location: Atlanta Hartsfield AP

Projection	AVERAGE RECURRENCE INTERVAL									
	1-y	2-y	5-y	10-y	25-y	50-y	100-y	200-y	500-y	1000-y
Projection 1	14%	18%	24%	30%	38%	46%	55%	66%	82%	96%
Projection 6	14%	12%	14%	17%	24%	31%	41%	52%	71%	88%
Projection 14	11%	9%	3%	-2%	-10%	-16%	-23%	-29%	-37%	-43%
Projection 17	14%	13%	12%	11%	10%	9%	8%	7%	5%	4%
Projection 24	12%	15%	18%	21%	26%	30%	36%	41%	50%	56%
Projection 26	2%	3%	4%	5%	6%	6%	7%	8%	9%	10%
Projection 27	12%	11%	8%	5%	1%	-2%	-6%	-9%	-15%	-19%
Projection 30	4%	10%	21%	31%	51%	68%	91%	115%	159%	197%
Projection 33	20%	16%	14%	14%	15%	17%	19%	22%	27%	32%
Projection 34	21%	25%	26%	27%	27%	27%	26%	25%	24%	23%
Projection 36	10%	19%	24%	27%	31%	33%	34%	36%	37%	36%
Projection 38	25%	12%	12%	18%	31%	47%	69%	99%	153%	208%
Projection 39	9%	18%	32%	46%	70%	93%	123%	157%	215%	268%
Projection 40	16%	20%	24%	27%	30%	33%	36%	39%	43%	45%
Projection 58	6%	11%	14%	16%	19%	20%	22%	23%	24%	26%
Mean	**12.8%**	**14.0%**	**16.6%**	**19.6%**	**24.6%**	**29.5%**	**35.9%**	**43.4%**	**56.4%**	**68.6%**

Location: Gainesville

Projection	AVERAGE RECURRENCE INTERVAL									
	1-y	2-y	5-y	10-y	25-y	50-y	100-y	200-y	500-y	1000-y
Projection 1	21%	22%	21%	20%	17%	14%	11%	8%	3%	-1%
Projection 2	22%	27%	25%	22%	17%	13%	8%	2%	-5%	-11%
Projection 12	6%	7%	14%	21%	32%	42%	54%	68%	90%	109%
Projection 17	19%	18%	18%	17%	15%	14%	13%	11%	9%	7%
Projection 18	22%	19%	16%	13%	10%	8%	6%	3%	0%	-3%
Projection 24	22%	19%	18%	17%	17%	16%	16%	16%	16%	16%
Projection 30	11%	13%	16%	19%	23%	26%	30%	34%	40%	46%
Projection 34	20%	16%	18%	21%	27%	33%	40%	49%	64%	77%
Projection 38	32%	34%	33%	31%	27%	23%	19%	15%	9%	4%
Projection 39	20%	26%	27%	26%	24%	21%	17%	13%	7%	2%
Projection 40	26%	24%	22%	21%	19%	17%	16%	14%	12%	10%
Projection 45	1%	3%	3%	4%	4%	5%	5%	6%	6%	6%
Projection 56	27%	38%	42%	43%	42%	40%	37%	32%	26%	20%
Projection 57	6%	10%	10%	10%	8%	7%	5%	3%	0%	-2%
Projection 58	16%	15%	15%	15%	15%	15%	15%	16%	16%	17%
Mean	**18.1%**	**19.4%**	**19.8%**	**19.9%**	**19.7%**	**19.5%**	**19.4%**	**19.3%**	**19.5%**	**19.8%**

Location: Norcross

Projection	AVERAGE RECURRENCE INTERVAL									
	1-y	2-y	5-y	10-y	25-y	50-y	100-y	200-y	500-y	1000-y
Projection 3	17%	19%	19%	19%	17%	15%	12%	10%	6%	2%
Projection 14	9%	10%	12%	13%	15%	16%	18%	21%	24%	27%
Projection 17	13%	18%	18%	16%	13%	10%	6%	2%	-4%	-9%
Projection 24	14%	17%	17%	16%	13%	11%	7%	3%	-3%	-8%
Projection 34	11%	15%	22%	28%	41%	53%	67%	84%	111%	136%
Projection 36	13%	13%	12%	10%	8%	6%	4%	2%	-1%	-4%
Projection 38	25%	30%	30%	28%	24%	20%	15%	10%	2%	-4%
Projection 39	16%	20%	21%	21%	20%	19%	17%	14%	10%	7%
Projection 40	20%	27%	26%	24%	19%	14%	9%	2%	-7%	-13%
Projection 44	-4%	-5%	-2%	2%	9%	17%	27%	40%	60%	80%
Projection 45	0%	-5%	-5%	-5%	-2%	1%	5%	9%	17%	23%
Projection 54	11%	15%	16%	15%	13%	10%	7%	3%	-3%	-7%
Projection 56	16%	15%	17%	21%	27%	32%	39%	48%	61%	72%
Projection 57	12%	19%	17%	13%	6%	-1%	-8%	-15%	-24%	-31%
Projection 58	13%	21%	19%	15%	8%	1%	-6%	-13%	-23%	-30%
Mean	**12.2%**	**15.3%**	**15.9%**	**15.9%**	**15.4%**	**15.0%**	**14.7%**	**14.5%**	**15.0%**	**16.0%**

Location: Newnan-5N

Projection	AVERAGE RECURRENCE INTERVAL									
	1-y	2-y	5-y	10-y	25-y	50-y	100-y	200-y	500-y	1000-y
Projection 4	21%	24%	24%	24%	23%	21%	19%	17%	14%	12%
Projection 6	9%	10%	13%	17%	24%	30%	37%	46%	61%	73%
Projection 8	11%	17%	17%	14%	9%	4%	-2%	-9%	-18%	-25%
Projection 14	19%	16%	15%	13%	11%	10%	9%	7%	6%	4%
Projection 17	13%	13%	13%	13%	13%	14%	14%	15%	16%	16%
Projection 18	9%	14%	20%	24%	30%	34%	39%	45%	52%	59%
Projection 29	11%	12%	11%	11%	11%	11%	11%	10%	10%	10%
Projection 30	5%	11%	16%	20%	24%	28%	32%	35%	40%	45%
Projection 33	14%	7%	4%	4%	5%	7%	9%	13%	19%	25%
Projection 34	13%	11%	15%	20%	31%	43%	57%	76%	106%	135%
Projection 38	28%	26%	25%	24%	24%	23%	24%	24%	24%	24%
Projection 39	18%	22%	27%	32%	39%	45%	53%	61%	73%	83%
Projection 40	20%	19%	20%	21%	23%	25%	27%	30%	35%	39%
Projection 43	15%	12%	9%	6%	2%	-1%	-4%	-7%	-12%	-15%
Projection 52	10%	21%	26%	29%	31%	32%	32%	31%	30%	28%
Projection 56	18%	24%	33%	39%	49%	57%	65%	75%	89%	101%
Projection 57	9%	11%	8%	4%	-2%	-9%	-16%	-24%	-34%	-41%
Projection 58	8%	16%	17%	15%	9%	3%	-4%	-12%	-24%	-32%
Projection 62	6%	5%	9%	14%	25%	35%	49%	65%	92%	118%
Mean	**13.5%**	**15.3%**	**17.0%**	**18.1%**	**20.0%**	**21.7%**	**23.6%**	**26.2%**	**30.5%**	**34.6%**