

CHAPTER 3: WATERSHED HYDROLOGY
APPENDIX 3.F: CLIMATE CHANGE EVALUATION

The St. Johns River Water Management District (SJRWMD) develops a Water Supply Plan every five years to estimate the future water needs given the expected economic and population growth. The Water Supply Plan is an estimation necessary for planning and permitting with a time horizon of 2030. Even though there is no expectation of significant climate changes that would modify current rainfall patterns in the SJRWMD before 2030, as part of the continuing review of the Water Supply Impact Study (WSIS), the National Academy of Sciences (NAS) panel asked that the SJRWMD look at the influence of climate change on surface waters out to 2100. In addition to answering this question from the NAS review panel, an understanding of climate change impacts to hydrology is important for the long term planning needs of the SJRWMD.

Recent work identified four sources of uncertainty in the application of GCMs downscaled to regional hydrology (Lin et al. 2011). These are:

1. Choice of greenhouse gas emission scenario
2. Choice of global circulation model
3. Downscaling process from coarse global models to individual rain stations
4. Structure and parameter choices in the hydrologic model

The largest uncertainty was from the choice of greenhouse gas emission scenario and choice of global circulation model, with the smallest amount of uncertainty attributable to the structure and parameters in the hydrologic model. Hydrological models driven by the GCM-projected climate conditions may be used to evaluate the long-term water availability, but such GCM climate conditions have limited uses in impact analysis when the seasonal characteristics of a region's future water availability is the main interest.

The SJRWMD contracted with Dr. David Yates from University Corporation of Atmospheric Research (UCAR) to evaluate available Global Climate Models (GCMs) and develop reasonable future estimates of precipitation and temperature. Dr. Yates has been an author on several papers on effective methods to regionalize GCM output and develop coherent and consistent meteorologic time series informed by GCM results (Yates et al. 2003, Yates et al. 2005a, Yates et al. 2005b, Yates et al. 2009). The developed meteorologic time-series were used as input into the SJRWMD's Hydrologic Simulation Program Fortran (HSPF) models used throughout the WSIS project that cover the entire St. Johns River watershed to evaluate the impact of possible future precipitation and temperature changes to regional hydrology. Dr. Yates developed thirty ensemble time-series of daily precipitation and daily temperature minimum and maximums from 2020 to 2100 using a weighted K Nearest Neighbor (K-NN) sampling process. The standard, unbiased K-NN sampling process can be used to develop a statistically similar data set to a source data set. In addition, the K-NN sample selection process was weighted, or biased, using results from the GCMs. This bias was also documented with existing precipitation and temperature data. The source data were from 48 rain stations and 19 daily min/max temperature stations from 1950 to 2008. An overview of the process is illustrated in Figure 3 F.1. See Yates and Towler (2010) for the detailed analysis and report.

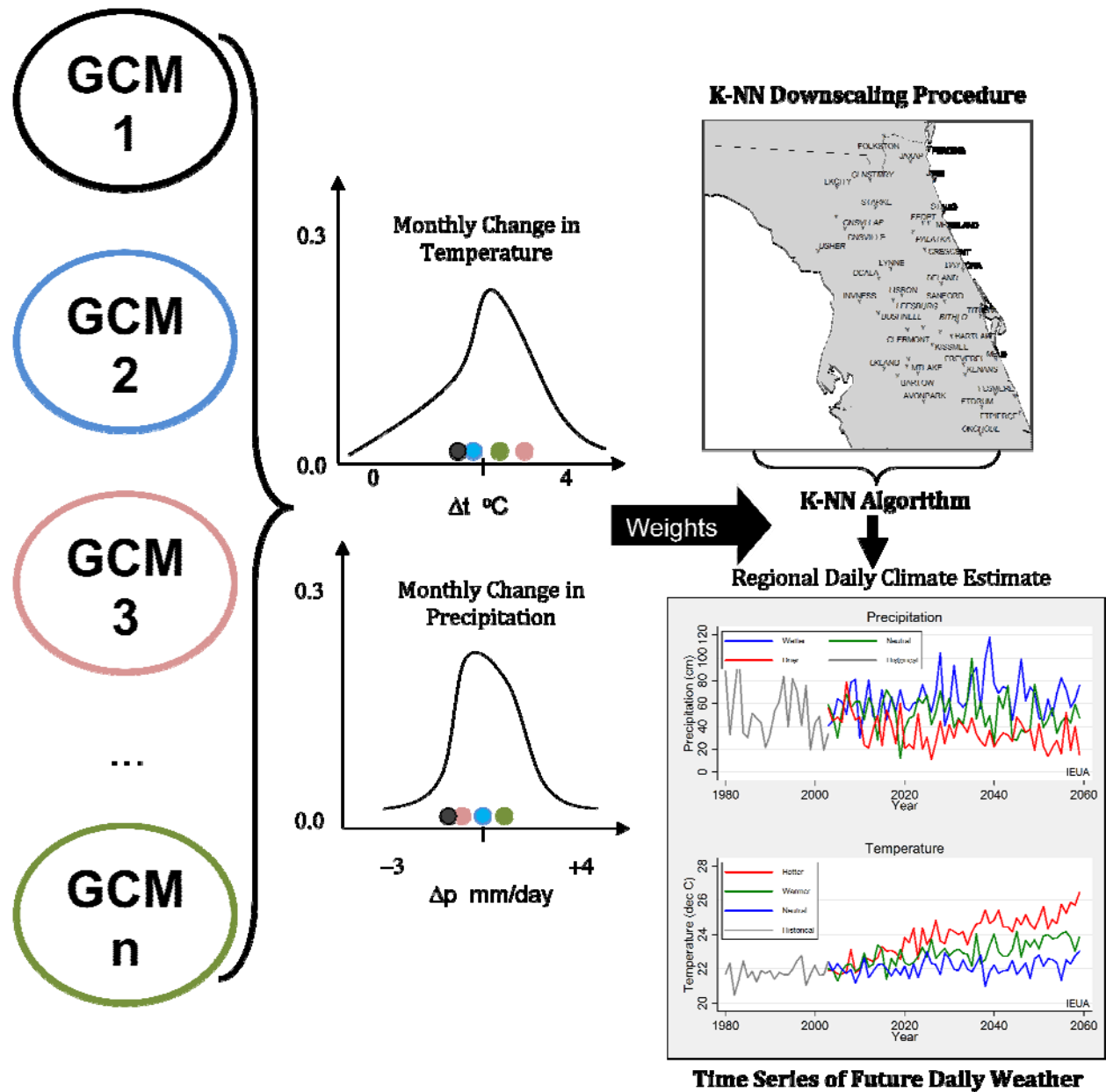


Figure 3 F.1: Diagram illustrating process incorporating Bayesian uncertainty estimation and K-NN sampling. Adapted from Yates and Towler (2010).

The A1B greenhouse gas emissions scenario was chosen for this study as being the most likely. The major scenarios are described in Table 3.F.1.

Table 3.F.1: Description of IPCC global climate scenarios. For this analysis we used the highlighted A1B scenario.

	A1	A2	B1	B2
Population growth	Low ~7 billion	High ~15 billion	Low ~7 billion	Medium ~10 billion
GDP growth	Very high	Medium	High	Medium
Energy use	Very high/high	High	Low	Medium
Land use changes (1990 to 2100)	Low-medium	Medium-high	High	Medium
Favored energy	A1FI: Fossil fuels Intensive A1B: Balanced sources A1T: non-fossil	Regional diversity	Efficiency and dematerialisation	“Dynamics as usual”

The first part of the project was to evaluate the performance and characterize results from the GCMs to represent Florida. The results from 21 models were Bayesian averaged with each model having an assigned weight depending on performance on simulating climate from 1900 to 2000. The Bayesian averaging process requires at least four data points. The four cells selected from the GCM data sets are illustrated in Figure 3.F.2.

Figure 3.F.3 shows an example of the Bayesian uncertainty analysis of 21 GCMs temperature estimates for the year 2040. This Bayesian analysis was performed for each decade in the prediction period and the results used to weight the K-NN sampling process.

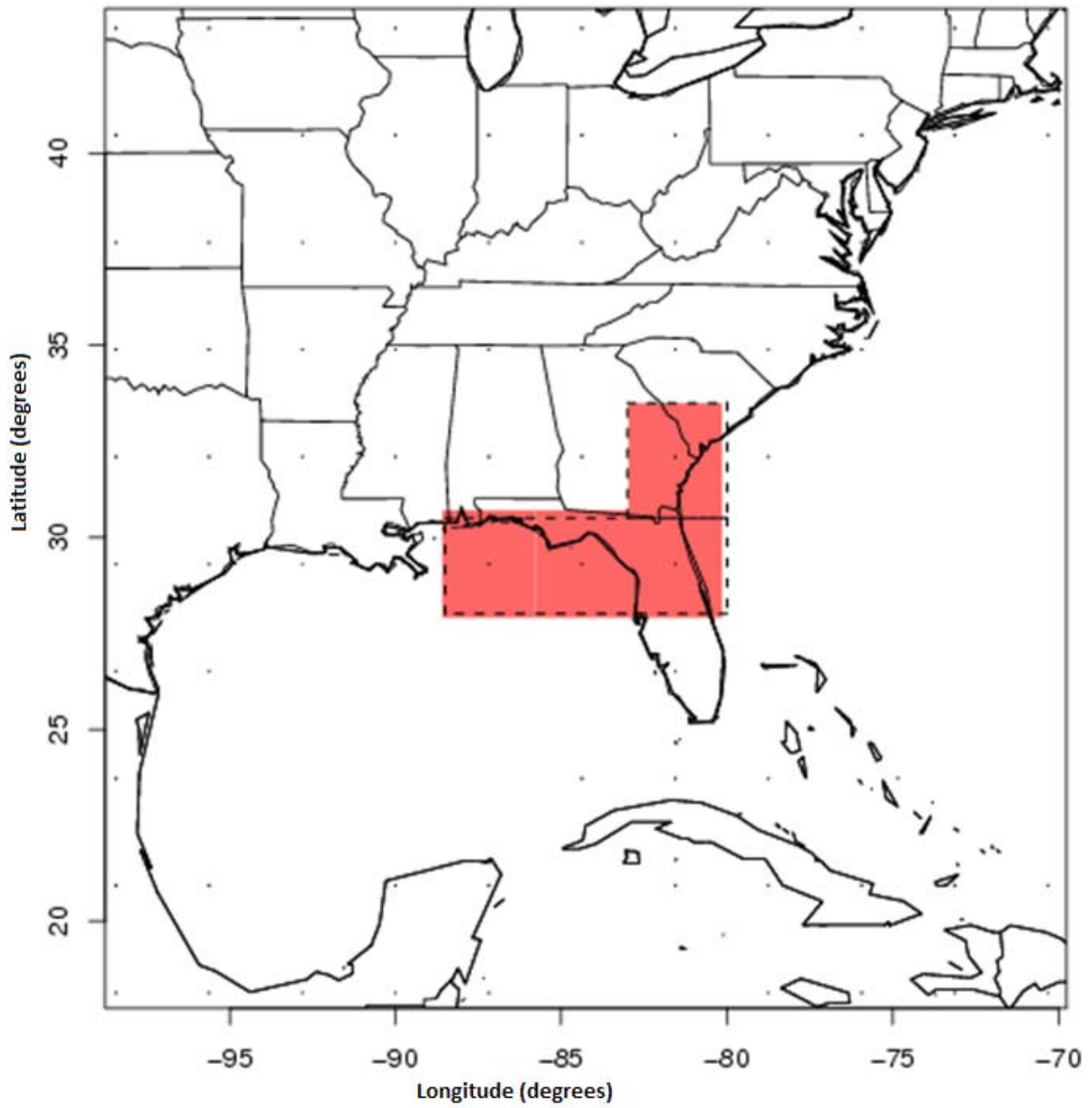


Figure 3.F.2: Map showing cells chosen for Bayesian analysis to represent Florida. Adapted from Yates and Towler (2010).

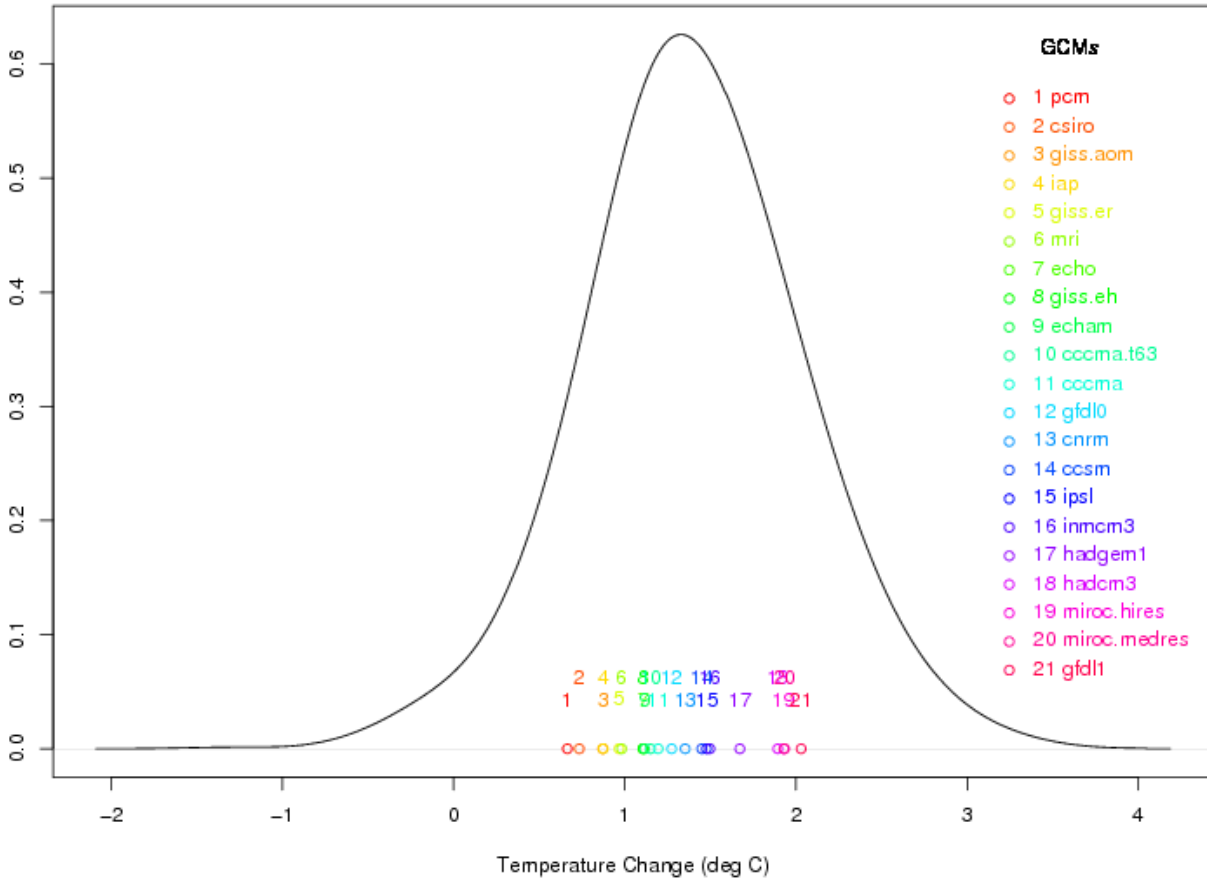


Figure 3.F.3: Bayesian uncertainty of temperature results from 21 A1B GCM models for year 2040. Zero on x axis represents no change from recent conditions. Adapted from Yates and Towler (2010).

In dealing with the overall uncertainty as described in Lin et. al (2011) we minimized the uncertainty by choosing one combined GCM representation and down-scaling the GCM results with the Bayesian averaging and K-NN processes. Instead of taking only the maximum expectation (50 percentile, near the peak of the Bayesian curve), we also have developed meteorologic time-series at 30 percentile (cooler) and 70 percentile (warmer) to have a simplified representation of other greenhouse gas scenarios.

The results from the GCMs are illustrated in Figure 3.F.4. For the A1B scenario, there is an expectation of slightly increased precipitation throughout the 2010-2099 interval.

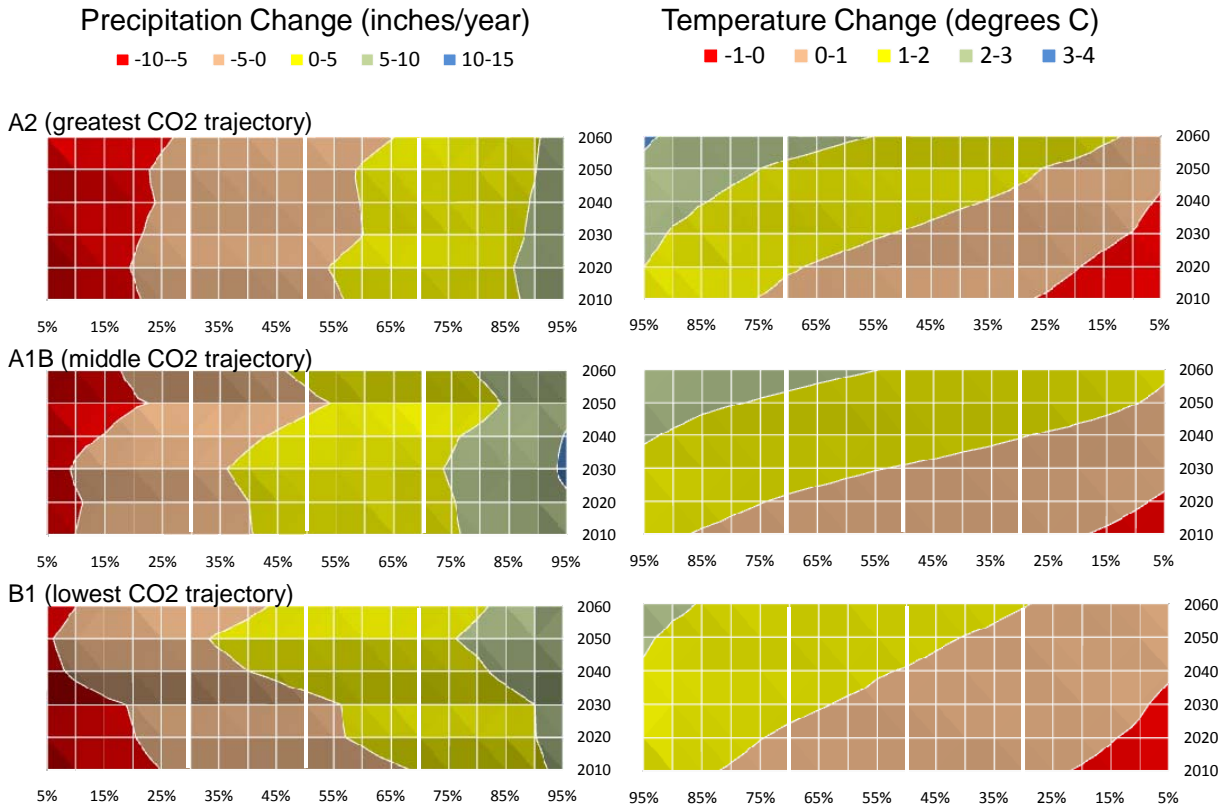


Figure 3.F.4: Results from Bayesian averaging process illustrating precipitation and temperature changes for north Florida. The vertical white bars represent the 30, 50, and 70 percentile of the resulting Bayesian distribution. Adapted from Yates and Towler (2010).

Precipitation data sets were developed from the 1950-2008 base set were developed for each precipitation station illustrated in Figure 3.F.5. Daily minimum and maximum temperature stations were developed in addition to the precipitation stations. The daily minimum and maximum temperatures were used to calculate evaporation estimates by the Hargreaves equation used for the watershed modeling. This allowed for a direct comparison of evaporation results.



Figure 3.F.5: Map of rain and temperature min/max stations that supplied source data.

Initial comparisons between the source and K-NN meteorologic data sets show only small differences (Figure 3.F.6 and Figure 3.F.7). Figure 3.F.6 shows an expectation of precipitation decreasing. There was a mix of increasing and decreasing precipitation among the stations. Further work is required to analysis the between station differences, but a cursory look indicates that inland stations are decreasing and near shore stations are increasing. It is a well know phenomena in Florida that rainfall increases as you move toward the ocean and the K-NN downscaling may be indicating an even greater difference between inland and shore stations is likely. The evaporation comparison in Figure 3.F.7 shows a slight increase, especially at the high and low ends of the frequency exceedance curve. This increased evaporation was consistent among all of the evaporation stations.

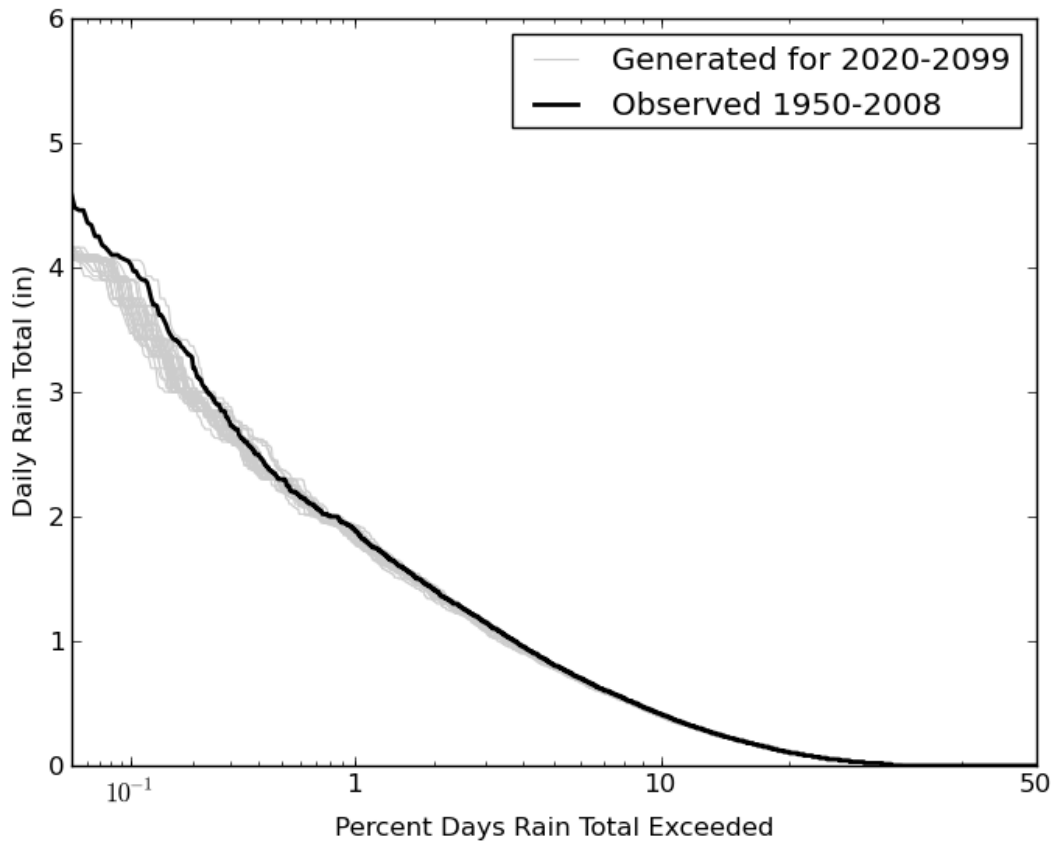


Figure 3.F.6: Comparison of frequency exceedence of daily precipitation between source data set (1950-2008) and 30 K-NN created data sets (2020-2099) weighted with the GCM maximum expectation from the Bayesian averaging for Lisbon rain gauge. The weighting is adjusted every decade, informed by the GCM models.

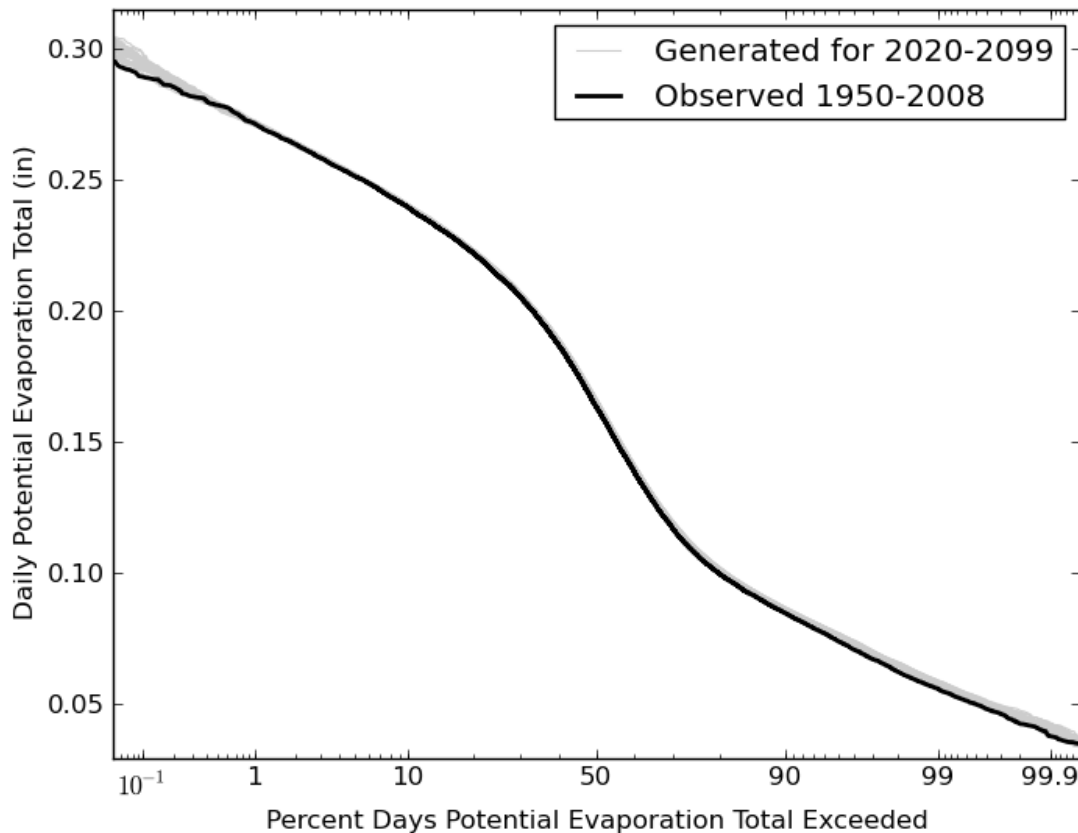


Figure 3.F.7: Comparison of frequency exceedence of daily potential evaporation between source data set (1950-2008) and 30 K-NN created data sets (2020-2099) weighted with the GCM maximum expectation from the Bayesian averaging for Lisbon rain gauge. Potential evaporation calculated Hargreaves equation. The weighting is adjusted every decade, informed by the GCM models.

As expected, the reduced rainfall amounts and increased evaporation led to decreased surface water flows (Figure 3.F.8). This is just an one example out of 94 watersheds. Since some precipitation stations indicate an increased precipitation amount, there are watersheds that also show an increase. Some watershed models even indicate significant increases in flood amounts and relatively small changes in middle and lower flows.

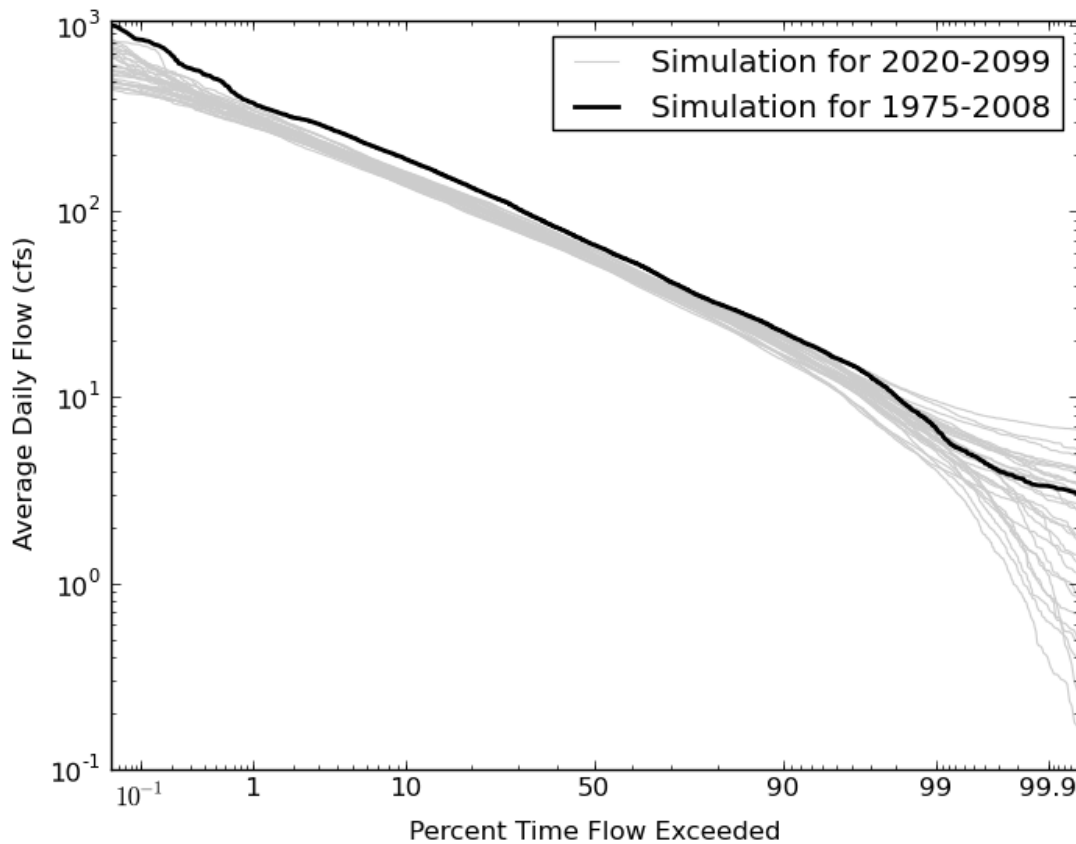


Figure 3.F.8: Plot of simulated flows from MSJ13 watershed comparing 1975-2008 model driven by observed precipitation and evaporation to 30 ensemble model runs driven by K-NN created time-series representing 2020-2099.

In conclusion, the changes associated with the climate change scenario downscaling from GCM's to individual data stations and the impact of these changes on runoff hydrology for 2030 was determined to be *de minimis*. Further, NCAR provided a Change Table (Table 3.F.2), that describes precipitation changes for the near term impacts, up to 2030, as dominated by natural variability, with no change in annual precipitation and drought frequency, and an actual improvement relative to drought severity due to an anticipated increase in winter precipitation.

Table 3.F.2: Evaluation of climate change impact on north Florida. Adapted from Yates and Towler (2010).

	Near-Term Impact (<2030)	Future climate attributes, guided by Global Climate Model results and analysis (2030 to 2100)
Precipitation Changes (Dry vs. Wet Season)	Natural Variability Dominates	Longer drought periods. More uncertainty in winter precipitation.
Annual Precipitation (in northeast Florida)	None	GCM consensus suggests both lower (A2) and higher (B1) likelihood of increases in annual precipitation.
Drought Severity	Greater Winter Precipitation	Greater uncertainty in winter precipitation.
Drought Frequency	None	Longer drought periods, which occur more often
Precipitation Intensity/Frequency		When it rains, it rains harder while the period between rainfall increases
Changes in Other Meteorological Variables (Tmax,min, Wind, etc.)		Higher winter temperatures, particularly night time minimums.

REFERENCE

Lin, Z., A. Kirikenko, and M. Rahman, 2011. Coping with uncertainty in assessing climate change impacts on streamflows. Presented at AWRA 2011 Spring Specialty Conference, Baltimore, MD. In press.

Yates, D. E. Towler, 2011. Global climate change screening analysis for the St. Johns River Water Supply Impact Study. Report delivered to the St. Johns River Water Management District. National Center for Atmospheric Research.

Yates, D., D. Purkey, J. Sieber, A. Huber-Lee, H. Galbraith, J. West, S. Herrod-Julius, C. Young, B. Joyce and M. Rayej, 2009: A climate driven water resources model of the Sacramento Basin, California. *Journal of Water Resources Planning and Management*, 135(5), 303-313.

Yates, D., J. Sieber, D. Purkey and A. Huber-Lee, 2005: Weap21 - a demand-, priority-, and preference-driven water planning model part 1: Model characteristics. *Water International*, 30(4), 487-500.

Yates, D., D. Purkey, J. Sieber, A. Huber-Lee and H. Galbraith, 2005: Weap21 - a demand-, priority-, and preference-driven water planning model part 2: Aiding freshwater ecosystem service evaluation. *Water International*, 30(4), 501-512.

Yates, D., S. Gangopadhyay, B. Rajagopalan and K. Strzepek, 2003: A technique for generating regional climate scenarios using a nearest-neighbor algorithm. *Water Resources Research*, 39(7)