Interim Report – Appendices (March 3, 2019)

Potential Implications of Sea-Level Rise and Changing Rainfall for Communities in Florida using Miami-Dade County as a Case Study

Florida Department of Business and Professional Regulation Florida Building Commission

And

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Appendix I. Future Land Use, Directly-Connected Impervious Areas, Groundwater Properties (Task I)

Future land use

The future scenarios previously simulated by the USGS using the Miami-Dade MODFLOW model used 2008 land use data to develop direct surface-water runoff, agricultural water demand, recreational irrigation, and monthly crop coefficient values (Hughes and White, 2016). However, for this project, we were able to obtain 2030 predicted land use from the Adopted 2020-2030 Comprehensive Development Master Plan (CDMP) for Miami-Dade County (Jerry H. Bell, Department of Regulatory and Economic Resources. Planning Division, pers. comm.). The map can be found at: https://www.miamidade.gov/planning/library/reports/planning-documents/cdmp/cdmp-land-use-map-2020-2030.pdf.

Jenifer Barnes at the South Florida Water Management District (SFWMD) assisted with cross-walking the land use categories in the 2030 CDMP into Florida Land Use, Cover, and Forms Classification System (FLUCCS) codes. In addition, since the 2030 CDMP does not provide detailed land use in natural and agricultural areas, Ms. Barnes added more details in these areas by intersecting the dataset with the SFWMD's 2018 permitted land use dataset. Subsequently, we added the 2018 permitted extent of quarry lakes from a shapefile provided by SFWMD which was used in the 2018 base case scenario for their RSMGL model. The FLUCCS codes were subsequently re-classified into the South Florida Water Management District's basic land use types (BLU) (Figure 1) as described in Table 1 of Hughes and White (2016). Finally, each MODFLOW grid cell was assigned its predominant BLU code (Figure 2).

Table 1 (Figure 4) below shows the percentage of cells on the onshore part of the model that had a predominant land use equal to a given BLU category in the year 2008 (Figure 3) and 2030 (Figure 2). Note that this table differs from Table 2 in Hughes and White (2016) in that their table shows overall polygon areas in each BLU category as opposed to percentage of cells with that BLU as predominant shown here.

Basic		Ye	ar
Land Use			
Code	Description	2008	2030
1	Low Dens. Urban (LDU)	3.58%	3.97%
3	Med. Dens. Urban (MDU)	23.45%	24.48%
11	High Dens. Urban (HDU)	12.25%	13.58%
2	Citrus (CIT)	5.31%	4.90%
7	Row Crops (ROW)	4.39%	3.92%
8	Sugar Cane (SUG)	0.00%	0.00%
9	Irrigated pasture (IRR)	0.19%	0.11%
6	Shrubland (SHR)	2.24%	1.83%
18	Marl Prairie	4.60%	4.50%
4	Sawgrass	25.55%	25.72%
15	Cattail	0.00%	0.00%

Table 1. Percentage of cells on the onshore part of the model with predominant land use in each basic land use category.

19	Mix Cattail/Sawgrass	0.00%	0.00%
5	Wet Prairie	2.19%	1.77%
12	Forested Wetland	3.18%	2.72%
16	Forested Upland	0.39%	0.26%
13	Mangroves	3.85%	3.72%
14	Melaleuca	2.73%	2.33%
20	Open Water	5.55%	3.83%
30	Offshore	0.31%	0.31%
31	Rock Quarries	0.24%	2.06%
Т	otal onshore area in squar	e miles = 1094	



Figure 1. Polygon-scale basic land use codes for 2030.



Figure 2. Predomiant basic land use codes for model grid cells in 2030.



Figure 3. Predomiant basic land use codes for model grid cells in 2008.



Figure 4. Number of onshore model cells with predominant basic land use category as given.

Future directly-connected impervious areas

Keith and Schnars (2004) provides a table of total impervious area (TIA) for each Level II/III land use code from the Miami-Dade County Department of Planning. After converting these land use codes into the equivalent FLUCCS codes, the TIA values were used to develop maps of directly-connected impervious area fractions (DCIA) based on a methodology similar to that of Hughes and White (2016). First, each land use polygon (Figure 1) was assigned a TIA based on its FLUCCS code (Table 2). Then DCIA was assumed to be 25% of TIA. Finally, an area-weighted average DCIA value was computed for each model grid cell based on the area of each grid cell occupied by each land use polygon on the grid cell. All open water, agricultural, and natural land uses were assigned TIA and DCIA values of 0.

Comparisons of DCIA fractions between the 2008 and 2030 land uses (Figure 5 and Figure 6) show that DCIA is expected to increase in the future as urban areas expand and densify. In the Miami-Dade MODFLOW model, DCIA * Rainfall is sent to the closest surface water feature in the SWR1 package (Figure 7), while (1 - DCIA) * Rainfall recharges the surficial aquifer.

TIA (%)					FLUCCS	CODES				
	1630	1660	1900	1920	2000	2110	2120	2140	2150	2160
	2210	2230	2240	2410	2420	2430	2500	2510	2540	2610
	3100	3200	3220	3300	4110	4200	4220	4240	4270	4340
0	4370	4410	5000	5110	5120	5200	5300	5410	5420	5430
	5710	6110	6111	6120	6170	6172	6180	6191	6210	6215
	6216	6250	6300	6410	6411	6420	6430	6440	6500	6510
	7200	7400	7430	7470	1650	1810				
3	1480	1820	1850	1860	1890	8115				
27	1460	8110	8113	8200	8300	8310	8320	8330	8340	8360
56.1	1700	1710	1730	1760						
64.62	1100	1110	1130	1180						
69.63	1330	1340								
70.5	1200	1210	1220	1230	1300	1310	1320	1350		
74.55	1500	1550	1560	1620						
74.71	1423	1840	8350							
78.42	1830	1870								
79.73	8120	8140	8150							
82.6	1400	1410	1411	8100						

Table 2. Total impervious area by FLUCCS code.



Figure 5. DCIA fractions for model grid cells in 2030.



Figure 6. DCIA fractions for model grid cells in 2008.



Figure 7. Cell-->SWR1 mapping. Cells with the same color have their DCIA * Rainfall routed to the same SWR1 reach.

Future groundwater properties

Due to the existence of additional quarry lakes in 2030 land use (based on 2018 permitted quarry lake coverage) compared to the 2008 land use (which assumed 1999 quarry lake coverage), the groundwater properties at quarry lake cells have to be modified for the future scenario model. Based on the Miami-Dade MODFLOW model documentation, it appears that the groundwater properties such as specific yield (Sy), specific storage (Ss), and hydraulic conductivity (Kh=Kv) for model layers 1-3 were first calibrated using PEST with pilot points and subsequently modified to reflect the presence of quarry lakes as of the year 1999. The following equation was likely used in estimating the effective Sy and Ss for model grid cells with some portion occupied by quarry lakes:

$$S_{y_{eff}} = \frac{(A_{cell} - A_{lake}) * S_{y_{cell}} + A_{lake} * 1}{A_{cell}}$$
(1)

Where $S_{y_{eff}}$ is the effective specific yield for the cell, $S_{y_{cell}}$ is the calibrated cell specific yield, 1 is the assumed quarry lake specific yield, A_{cell} is the total cell area, and A_{lake} is the surface area occupied by quarry lakes. By defining $Lakefrac = \frac{A_{lake}}{A_{cell}}$, the fraction of the cell occupied by quarry lakes, the above equation simplifies to the following:

$$S_{y_{eff}} = S_{y_{cell}} * (1 - Lakefrac) + Lakefrac$$
 (2)

The variable Lakefrac (based on 1999 quarry lake coverage) is given in file umd_frclake.ref and is shown in Figure 8. 1999 Lake fractionFigure 8 below.

Solving the above equation for $S_{y_{cell}}$, one can back-calculate the original calibrated specific yield for the cell for cells with Lakefrac smaller than 1:

$$S_{ycell} = \frac{S_{yeff} - Lakefrac}{(1 - Lakefrac)}$$
(3)

The resulting 1999 $S_{y_{cell}}$ map showed the bullseye pattern typical of pilot points. In areas with quarry lakes, the pattern seems consistent with nearby cells (Figure 10) and among the different model layers. Therefore, the above methodology seems reasonable in estimating S_{ycell} .

A total of 28 cells had Lakefrac equal to 1. Therefore, $S_{y_{cell}}$ was undefined for these 28 cells (white cells in Figure 10). However, 24 of these 28 cells also have a 2018 permitted Lakefrac of 1.0 (Figure 9); therefore, the 1999 $S_{y_{eff}}$ can still be used for these 24 cells. For cells with a 2018 permitted Lakefrac of 1, $S_{y_{cell}}$ is set to 1 for 2018. For cells with a 2018 permitted Lakefrac between 0 and 1 (exclusive), the 2018 $S_{y_{eff}}$ was computed based on Equation (2) using the 2018 Lakefrac.

For the 4 cells with a 1999 Lakefrac value of 1 (shown with '+' marks in Figure 10), and a 2018 Lakefrac value different from 1, $S_{y_{cell}}$ was averaged for surrounding cells and used in Equation 2 to obtain the 2018 $S_{y_{eff}}$. Inspection of recent aerial imagery shows no mining lakes present in two of these cells (R17C43, R17C44 on Figure 11). The two remaining cells (R34C40, R34C41) had 2018 Lakefrac of 0.92 and 0.96, respectively. These are different from 1 due to accounting for berms and rock washing facilities as separate from deep mining areas.

The above equations 1-3 were used for Sy and Ss for all layers. A similar methodology was used for the hydraulic conductivity with the following modifications (in units of ft/d), although it is unclear whether this type of equation was used by the original model developers. Alternatively, an equation based on assuming strata (cell/lake) being perpendicular or parallel to predominant groundwater flow direction may have been used by the original model developers. This approach would require detailed layer thickness/length information and due to its complexity was likely not used.

$$K_{eff} = \frac{(A_{cell} - A_{lake})K_{cell} + A_{lake} * \max(3.3 \times 10^5, K_{cell})}{A_{cell}}$$
(4)

Equations equivalent to equation 2 and 3 were derived and applied to estimate the 2030 hydraulic conductivity starting from equation 4. As discussed in the MODFLOW model documentation, the minimum hydraulic conductivity for lakes was set as 3.3E5 ft/d. Therefore, this minimum limit remained in the derivation. Missing values for the 4 cells identified above were filled in a similar manner but using equation 4. The resulting 1999 K_{cell} map shows consistency with nearby cells in areas with quarry lakes (Figure 12).

Please note that the Miami-Dade MODFLOW model uses metric units, but the documentation and the figures presented herein are in English units.



Figure 8. 1999 Lake fraction



Figure 9. 2030 Lake fraction



Figure 10. Back-calculated calibrated specific yield Sy_cell.



Figure 11. Model grid cells R17C43 and R17C44 (row from north, column from west) are occupied by an urban lake and an urban development. This was confirmed by inspection of mine boundary maps at the FLDEP Mining and Mitigation Program website (<u>https://ca.dep.state.fl.us/mapdirect/?focus=bmr</u>).



Figure 12. Back-calculated calibrated hydraulic conductivity for layer 1, K_cell.

References

Hughes, J.D., and White, J.T., 2016, Hydrologic conditions in urban Miami-Dade County, Florida, and the effect of groundwater pumpage and increased sea level on canal leakage and regional groundwater flow (ver. 1.2, July 2016): U.S. Geological Survey Scientific Investigations Report 2014–5162, 175 p., http://dx.doi.org/10.3133/sir20145162.

Keith and Schnars, 2004, South Miami-Dade watershed study and plan—Sub-task 1.5: Consultant report prepared for the South Florida Regional Planning Council, Miami-Dade County, and the South Florida Water Management District.

Appendix II. Future Rainfall (Tasks I & II)

Future rainfall

As part of a previous contract with the SFWMD, Continuity H2O, LLC evaluated the ability of various climate model outputs to capture the historical distribution of rainfall extremes for durations of 1-7 days in the state of Florida. In particular, the following statistically-downscaled data products, based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project (CMIP) phase 5 (CMIP5), were evaluated:

- US Bureau of Reclamation bias-corrected and statistically-downscaled climate projections (Maurer et al., 2007; Reclamation, 2013), which used daily Bias-Correction Constructed Analogues (BCCA) technique for statistical downscaling.
- University of California (San Diego)'s Localized Constructed Analogs (LOCA) product (Pierce et al., 2014).

SFWMD staff had previously evaluated these same statistically downscaled data products in terms of their ability to capture historical rainfall temporal and spatial patterns in south Florida. As part of this work, it was observed that LOCA generally did a better job than BCCA at capturing rainfall patterns in the state (Irizarry et al., 2016), particularly during extreme events. For this reason and also due to the fact that the LOCA product was used to guide the 4th US National Climate Assessment report (<u>https://scenarios.globalchange.gov/</u>), this dataset was chosen and further evaluated for this project. A description of the LOCA dataset is included below.

Localized Constructed Analogues technique (LOCA) is a statistical downscaling technique that uses past history to add improved fine-scale detail to global climate models (Pierce et al., 2014). First, a pool of candidate observed analog days is chosen by matching the model field to be downscaled to observed days over the region that is positively correlated with the point being downscaled, which leads to a natural independence of the downscaling results to the extent of the domain being downscaled. Then the one candidate analog day that best matches in the local area around the grid cell being downscaled is the single analog day used there.

Most grid cells are downscaled using only the single locally selected analog day, but locations whose neighboring cells identify a different analog day use a weighted combination of the center and adjacent analog days to reduce edge discontinuities. By contrast, existing constructed analog methods typically use a weighted average of the same 30 analog days for the entire domain. By greatly reducing this averaging, LOCA produces better estimates of extreme days, constructs a more realistic depiction of the spatial coherence of the downscaled field, and reduces the problem of producing too many light-precipitation days.

The University of California at San Diego has used LOCA to downscale 32 global climate models from the CMIP5 archive at a 1/16th degree (approx. 4.3 miles; 6.9 km) spatial resolution, covering North America

from central Mexico through Southern Canada. The historical period is 1950-2005, and there are two future scenarios available: RCP 4.5 and RCP 8.5 over the period 2006-2100 (although some models stop in 2099). RCP stands for representative concentration pathways (RCP). RCP 4.5 represents medium-low year 2100 radiative forcing (4.5 W/m²), while RCP 8.5 represents high radiative forcing (8.5 W/m²).

The variables currently available are daily minimum and maximum temperature, and daily precipitation. Over the next year they will be running the VIC hydrological model with the downscaled data, which will give many more variables, such as snow cover, soil moisture, runoff, and humidity, all at a 1/16th degree spatial resolution on a daily timescale. For more information see http://loca.ucsd.edu/.

Statistically downscaled daily rainfall timeseries from LOCA for 30 climate models were evaluated for grid cells in Miami Dade County in terms of their ability to match historical data. As described in the Miami-Dade MODFLOW model documentation, the model uses daily historical rainfall from NEXRAD at 2 km x 2 km for the calibration/verification period 1996-2010. In the model, a 1.05 multiplicative correction factor is applied to the NEXRAD rainfall due to previous evidence of bias compared to gage data. This data would have been ideal for evaluating and bias-correcting LOCA rainfall timeseries since the model was calibrated/verified to it. However, the LOCA historical period ends in 2005, which limits the comparison. For this reason, daily historical rainfall obtained from the South Florida Water Management Model v4.7 binary file on a 3.2 km x 3.2 km grid for the period 1991-2005 was used in evaluating LOCA historical performance for the same period.

Two analyses of LOCA performance were done to cull the LOCA models. One analysis looked at the annual total rainfall and the other one was based on wet season (May-October) precipitation. The R code is included in **Error! Reference source not found.**. Table 3 and Table 4 show the performance of each LOCA model run for the two periods of interest. It can be noticed that all models are negatively biased for annual total rainfall with biases ranging from -7.4 to -0.13 in/yr (average of -4.2 in/yr) over Miami-Dade County. In the wet season, 28/30 models are negatively biased with biases ranging from -6.4 in/season to +0.75 in/season (average of -3.1 in/season).

In order to account for these biases, the mean of future LOCA predictions for both the annual totals and wet season, were bias-corrected as follows:

$$R_{m-padj} = R_{m-p} * \frac{R_{o-c}}{R_{m-c}}$$
Equation 1

where R_{m-padj} is the adjusted future predicted annual total or wet season rainfall, R_{m-p} is the future predicted annual total or wet season rainfall, R_{o-c} is the observed current (historical) annual total or wet season rainfall, and R_{m-c} is the current (historical) predicted annual total or wet season rainfall. This equation is analogous to the Multiplicative Quantile Delta Mapping (MQDM) technique used for biascorrection of daily rainfall data, and which will be discussed later on. It assumes that the mean will also change in a multiplicative way, which is not necessarily the case. However, performing MQDM on daily rainfall data for all LOCA runs was found to be too computationally-intensive and the above simplified equation seems adequate as a first approximation for model culling.

Figure 13 and Figure 15 show the distribution of changes from SFWMM historical (1991-2005) to future (2055-2069) bias-corrected annual total and wet season rainfall, respectively. It can be noticed that about half of the models project a decrease in rainfall, while the other half project an increase in rainfall. The median projected change in annual total rainfall is slightly less than 0 (approximately -1.2 in/yr). During the wet season, 70% of models predict a decrease in rainfall, while 30% predict an increase. The median projected change in wet season rainfall is approximately -2.2 to -2.5 in/yr. Figure 14 and Figure 16 show scatterplots of the annual total and wet season rainfall pre and post bias-correction of the mean based on Equation 1.

In consultation with SLSC-FIU staff, it was decided that to be conservative in the estimation of average wet season water tables, a 90th-95th percentile of future bias-corrected rainfall should be selected for future modeling. Based on the analysis of annual total rainfall, the 95th percentile run was pr_MPI-ESM-MR_r1i1p1_rcp85 with 5.2 in/yr (9.0%) of additional rainfall in the future period compared to 1991-2005 SFWMM historical data. The run with the max change was pr_ACCESS1-0_r1i1p1_rcp45 with 8.7 in/yr (15.5%) extra rainfall. This run is shown with a red triangle marker on Figure 14 and Figure 16.

Based on the analysis of wet season rainfall, the 95th percentile run was pr_MPI-ESM-LR_r1i1p1_rcp45 with 3.6 in/season (8.2%) extra rainfall in the future period compared to 1991-2005 SFWMM historical data for wet season. The run with the max change was pr_MPI-ESM-MR_r1i1p1_rcp45 with 4.9 in/season (11.2%) extra rainfall.

As shown in Figure 14 and Figure 16, there are other runs showing similar future bias-corrected annual total and wet season rainfall, but which had much smaller biases in the historical period. In this figure, the closer a LOCA model run point is to the 1:1 line, the smaller its historical bias and the smaller the bias-correction of its future rainfall. LOCA run pr_MRI-CGCM3_r1i1p1_rcp85, shown as a yellow marker in these two figures, has similar bias-corrected annual total and wet season rainfall to the 95th percentile runs identified above. However, this run had a much smaller bias than the 95th percentile runs. Therefore, pr_MRI-CGCM3_r1i1p1_rcp85 was chosen for daily bias-correction for future scenario modeling. Figure 17 shows the spatial distribution of the observed and simulated means prior to and post bias-correction of the means using Equation 1. Despite the coarseness of the LOCA dataset, it is evident how the historical spatial pattern of precipitation is generally well-captured by this LOCA run. As a final check, Figure 18 shows that this LOCA model run does a decent job at capturing the historical seasonal cycle of rainfall in Miami-Dade County even prior to bias correction. It is evident that simulated variability is less in October, and the model overestimates variability in July and August.

Table 3. Comparison of LOCA run performance and predicted future annual total rainfall (in/yr). Note: SFWMM historical rainfall for 1991-2005 is 57.57 in/yr.

LOCA model run/RCP	Hist.	Hist. bias	Fut.	Fut.	Fut.	Percent	Percentile
	(1991-		(2055-	(2055-	(2055-	change	fraction
	2005)		2069)	2069)	2069) B.C.	hist. to	
	mean		mean	B.C. mean	mean	fut. B.C.	
					minus		
					hist. (1001		
					2005)		
					mean		
pr_ACCESS1-0_r1i1p1_rcp45	53.07	-4.5	61.06	66.23	8.66	15.04	1
pr_ACCESS1-0_r1i1p1_rcp85	53.07	-4.5	52.74	57.23	-0.34	-0.59	0.559
pr_ACCESS1-3_r1i1p1_rcp45	55.44	-2.13	52.86	54.99	-2.58	-4.48	0.457
pr_ACCESS1-3_r1i1p1_rcp85	55.44	-2.13	57.17	59.44	1.87	3.25	0.711
pr_CCSM4_r6i1p1_rcp45	52.54	-5.03	47.72	52.29	-5.28	-9.17	0.186
pr_CCSM4_r6i1p1_rcp85	52.54	-5.03	47.93	52.5	-5.07	-8.81	0.22
pr_CESM1-BGC_r1i1p1_rcp45	51.77	-5.8	50.71	56.4	-1.17	-2.03	0.491
pr_CESM1-BGC_r1i1p1_rcp85	51.77	-5.8	47.06	52.38	-5.19	-9.02	0.203
pr_CESM1-CAM5_r1i1p1_rcp45	52.33	-5.24	47.77	52.57	-5	-8.69	0.237
pr_CESM1-CAM5_r1i1p1_rcp85	52.33	-5.24	49.38	54.34	-3.23	-5.61	0.423
pr_CMCC-CMS_r1i1p1_rcp45	53.61	-3.96	54.6	58.7	1.13	1.96	0.661
pr_CMCC-CMS_r1i1p1_rcp85	53.61	-3.96	46.47	49.92	-7.65	-13.29	0.084
pr_CMCC-CM_r1i1p1_rcp45	53.22	-4.35	55.08	59.65	2.08	3.61	0.762
pr_CMCC-CM_r1i1p1_rcp85	53.22	-4.35	49.41	53.47	-4.1	-7.12	0.338
pr_CNRM-CM5_r1i1p1_rcp45	53.72	-3.85	56.24	60.28	2.71	4.71	0.83
pr_CNRM-CM5_r1i1p1_rcp85	53.72	-3.85	53.79	57.65	0.08	0.14	0.576
pr_CSIRO-Mk3-6-	51.7	-5.87	53.82	59.92	2.35	4.08	0.813
0_r1i1p1_rcp45							
pr_CSIRO-Mk3-6-	51.7	-5.87	54.65	60.85	3.28	5.70	0.898
pr CanESM2 r1i1p1 rcp45	54.45	-3 12	52.2	56.42	_1 15	-2.00	0 508
pr_canESM2_r1i1p1_rcp45	54.45	-3.12	/8 7	51 52	-6.04	-10.49	0.508
pr_contestint_ripr_repos	53.86	-3 71	52.88	56 58	-0.99	-1 72	0.132
pr_EC-EARTH_r8i1p1_rcp45	53.86	-3.71	49.72	53.2	-4.37	-7.59	0.288
pr FGOALS-g2 r1i1p1 rcp45	50.9	-6.67	52.56	59.48	1.91	3.32	0.728
pr FGOALS-g2 r1i1p1 rcp85	50.9	-6.67	47.46	53.69	-3.88	-6.74	0.355
pr GFDL-CM3 r1i1p1 rcp45	50.17	-7.4	53.32	61.23	3.66	6.36	0.915
pr_GFDL-CM3_r1i1p1_rcp85	50.17	-7.4	56.79	65.2	7.63	13.25	0.983
pr_GFDL-ESM2G_r1i1p1_rcp45	50.57	-7	46.25	52.64	-4.93	-8.56	0.254
pr_GFDL-ESM2G_r1i1p1_rcp85	50.57	-7	44.34	50.48	-7.09	-12.32	0.118
pr_GFDL-ESM2M_r1i1p1_rcp45	51.31	-6.26	47.51	53.38	-4.19	-7.28	0.322
pr_GFDL-ESM2M_r1i1p1_rcp85	51.31	-6.26	51.45	57.78	0.21	0.36	0.593
pr_GISS-E2-H_r2i1p1_rcp85	53.44	-4.13	50.58	54.55	-3.02	-5.25	0.44

pr_GISS-E2-H_r6i1p3_rcp45	53.44	-4.13	52.55	56.63	-0.94	-1.63	0.542
pr_GISS-E2-R_r2i1p1_rcp85	50.89	-6.68	52.6	59.5	1.93	3.35	0.745
pr_GISS-E2-R_r6i1p1_rcp45	50.89	-6.68	48.85	55.27	-2.3	-4.00	0.474
pr_HadGEM2-AO_r1i1p1_rcp45	56.95	-0.62	50.93	51.54	-6.03	-10.47	0.169
pr_HadGEM2-AO_r1i1p1_rcp85	56.95	-0.62	53.54	54.12	-3.45	-5.99	0.406
pr_HadGEM2-CC_r1i1p1_rcp45	52.47	-5.1	53.46	58.7	1.13	1.96	0.661
pr_HadGEM2-CC_r1i1p1_rcp85	52.47	-5.1	52.69	57.81	0.24	0.42	0.61
pr_HadGEM2-ES_r1i1p1_rcp45	53.42	-4.15	54.18	58.37	0.8	1.39	0.644
pr_HadGEM2-ES_r1i1p1_rcp85	53.42	-4.15	49.2	53.02	-4.55	-7.90	0.271
pr_IPSL-CM5A-LR_r1i1p1_rcp45	57.44	-0.13	53.88	54	-3.57	-6.20	0.389
pr_IPSL-CM5A-LR_r1i1p1_rcp85	57.44	-0.13	49.64	49.77	-7.8	-13.55	0.067
pr_IPSL-CM5A-	54.66	-2.91	50.51	53.2	-4.37	-7.59	0.288
MR_r1i1p1_rcp45							
pr_IPSL-CM5A-	54.66	-2.91	56.4	59.4	1.83	3.18	0.694
MR_r1i1p1_rcp85							
pr_MIROC-ESM-	54.71	-2.86	43.84	46.19	-11.38	-19.77	0.016
CHEM_r1i1p1_rcp45							
pr_MIROC-ESM-	54.71	-2.86	42.47	44.74	-12.83	-22.29	0
CHEM_r1i1p1_rcp85							
pr_MIROC-ESM_r1i1p1_rcp45	50.35	-7.22	50.9	58.2	0.63	1.09	0.627
pr_MIROC-ESM_r1i1p1_rcp85	50.35	-7.22	47.1	53.84	-3.73	-6.48	0.372
pr_MIROC5_r1i1p1_rcp45	51.99	-5.58	53.89	59.69	2.12	3.68	0.779
pr_MIROC5_r1i1p1_rcp85	51.99	-5.58	54.86	60.76	3.19	5.54	0.881
pr_MPI-ESM-LR_r1i1p1_rcp45	54.74	-2.83	57.63	60.6	3.03	5.26	0.864
pr_MPI-ESM-LR_r1i1p1_rcp85	54.74	-2.83	57.41	60.38	2.81	4.88	0.847
pr_MPI-ESM-MR_r1i1p1_rcp45	51.11	-6.46	57.03	64.25	6.68	11.60	0.966
pr_MPI-ESM-MR_r1i1p1_rcp85	51.11	-6.46	55.69	62.73	5.16	8.96	0.949
pr_MRI-CGCM3_r1i1p1_rcp45	56.68	-0.89	59	59.9	2.33	4.05	0.796
pr_MRI-CGCM3_r1i1p1_rcp85	<mark>56.68</mark>	<mark>-0.89</mark>	<mark>60.94</mark>	<mark>61.9</mark>	<mark>4.33</mark>	<mark>7.52</mark>	<mark>0.932</mark>
pr_NorESM1-M_r1i1p1_rcp45	56.48	-1.09	49.14	50.11	-7.46	-12.96	0.101
pr_NorESM1-M_r1i1p1_rcp85	56.48	-1.09	46.37	47.31	-10.26	-17.82	0.033
pr_bcc-csm1-1-m_r1i1p1_rcp45	56.41	-1.16	48.6	49.59	-7.98	-13.86	0.05
pr_bcc-csm1-1-m_r1i1p1_rcp85	56.41	-1.16	49.52	50.52	-7.05	-12.25	0.135

Table 4. Comparison of LOCA run performance and predicted future wet season rainfall (in/ wet season). Note: SFWMM historical rainfall for 1991-2005 is 43.61in/wet season.

LOCA model run/RCP	Hist.	Hist.	Fut.	Fut.	Fut.	Percent	Percentile
	(1991-	bias	(2055-	(2055-	(2055-	change	fraction
	2005)		2069)	2069)	2069)	hist. to	
	mean		mean	B.C.	B.C.	fut. B.C.	
				mean	mean		
					minus bist		
					(1991-		
					2005)		
					mean		
pr_ACCESS1-0_r1i1p1_rcp45	41.66	-1.95	43.2	45.22	1.61	3.69	0.813
pr_ACCESS1-0_r1i1p1_rcp85	41.66	-1.95	38.55	40.38	-3.23	-7.41	0.389
pr_ACCESS1-3_r1i1p1_rcp45	41.66	-1.95	36.4	38.22	-5.39	-12.36	0.203
pr_ACCESS1-3_r1i1p1_rcp85	41.66	-1.95	39.02	40.96	-2.65	-6.08	0.44
pr_CCSM4_r6i1p1_rcp45	39.18	-4.43	36.21	40.3	-3.31	-7.59	0.355
pr_CCSM4_r6i1p1_rcp85	39.18	-4.43	35.23	39.2	-4.41	-10.11	0.288
pr_CESM1-BGC_r1i1p1_rcp45	39.29	-4.32	36.9	40.98	-2.63	-6.03	0.457
pr_CESM1-BGC_r1i1p1_rcp85	39.29	-4.32	33.99	37.78	-5.83	-13.37	0.186
pr_CESM1-CAM5_r1i1p1_rcp45	39.53	-4.08	33.31	36.76	-6.85	-15.71	0.084
pr_CESM1-CAM5_r1i1p1_rcp85	39.53	-4.08	35.86	39.57	-4.04	-9.26	0.305
pr_CMCC-CMS_r1i1p1_rcp45	40.57	-3.04	43.08	46.39	2.78	6.37	0.898
pr_CMCC-CMS_r1i1p1_rcp85	40.57	-3.04	34.28	36.87	-6.74	-15.46	0.118
pr_CMCC-CM_r1i1p1_rcp45	40.46	-3.15	43.37	46.84	3.23	7.41	0.915
pr_CMCC-CM_r1i1p1_rcp85	40.46	-3.15	39.52	42.62	-0.99	-2.27	0.593
pr_CNRM-CM5_r1i1p1_rcp45	41.55	-2.06	43.13	45.28	1.67	3.83	0.83
pr_CNRM-CM5_r1i1p1_rcp85	41.55	-2.06	41.38	43.44	-0.17	-0.39	0.677
pr_CSIRO-Mk3-6-0_r1i1p1_rcp45	39.76	-3.85	39.45	43.26	-0.35	-0.80	0.661
pr_CSIRO-Mk3-6-0_r1i1p1_rcp85	39.76	-3.85	38.96	42.74	-0.87	-1.99	0.627
pr_CanESM2_r1i1p1_rcp45	41.89	-1.72	38.17	39.81	-3.8	-8.71	0.322
pr_CanESM2_r1i1p1_rcp85	41.89	-1.72	34.49	35.96	-7.65	-17.54	0.067
pr_EC-EARTH_r2i1p1_rcp85	41.65	-1.96	38.32	40.14	-3.47	-7.96	0.338
pr_EC-EARTH_r8i1p1_rcp45	41.65	-1.96	36.86	38.63	-4.98	-11.42	0.237
pr_FGOALS-g2_r1i1p1_rcp45	39.16	-4.45	39.58	44.11	0.5	1.15	0.745
pr_FGOALS-g2_r1i1p1_rcp85	39.16	-4.45	36.67	40.84	-2.77	-6.35	0.423
pr_GFDL-CM3_r1i1p1_rcp45	37.92	-5.69	38.3	44.08	0.47	1.08	0.728
pr_GFDL-CM3_r1i1p1_rcp85	37.92	-5.69	40.04	46.1	2.49	5.71	0.881
pr_GFDL-ESM2G_r1i1p1_rcp45	37.2	-6.41	35.31	41.38	-2.23	-5.11	0.508
pr_GFDL-ESM2G_r1i1p1_rcp85	37.2	-6.41	32.1	37.63	-5.98	-13.71	0.169
pr_GFDL-ESM2M_r1i1p1_rcp45	38.88	-4.73	36.23	40.7	-2.91	-6.67	0.406
pr_GFDL-ESM2M_r1i1p1_rcp85	38.88	-4.73	39.72	44.6	0.99	2.27	0.779

pr_GISS-E2-H_r2i1p1_rcp85	40.18	-3.43	37.83	41.11	-2.5	-5.73	0.491
pr_GISS-E2-H_r6i1p3_rcp45	40.18	-3.43	38.95	42.31	-1.3	-2.98	0.542
pr_GISS-E2-R_r2i1p1_rcp85	38.27	-5.34	38.2	43.53	-0.08	-0.18	0.694
pr_GISS-E2-R_r6i1p1_rcp45	38.27	-5.34	35.38	40.34	-3.27	-7.50	0.372
pr_HadGEM2-AO_r1i1p1_rcp45	43.74	0.13	36.85	36.8	-6.81	-15.62	0.101
pr_HadGEM2-AO_r1i1p1_rcp85	43.74	0.13	37.56	37.47	-6.14	-14.08	0.152
pr_HadGEM2-CC_r1i1p1_rcp45	39.56	-4.05	38.47	42.47	-1.14	-2.61	0.576
pr_HadGEM2-CC_r1i1p1_rcp85	39.56	-4.05	38.75	42.73	-0.88	-2.02	0.61
pr_HadGEM2-ES_r1i1p1_rcp45	41.08	-2.53	41.98	44.53	0.92	2.11	0.762
pr_HadGEM2-ES_r1i1p1_rcp85	41.08	-2.53	35.01	37.17	-6.44	-14.77	0.135
pr_IPSL-CM5A-LR_r1i1p1_rcp45	43.37	-0.24	42.61	42.83	-0.78	-1.79	0.644
pr_IPSL-CM5A-LR_r1i1p1_rcp85	43.37	-0.24	38.81	39.04	-4.57	-10.48	0.254
pr_IPSL-CM5A-MR_r1i1p1_rcp45	41.16	-2.45	40.08	42.46	-1.15	-2.64	0.559
pr_IPSL-CM5A-MR_r1i1p1_rcp85	41.16	-2.45	44.77	47.42	3.81	8.74	0.966
pr_MIROC-ESM-	41.24	-2.37	30.18	31.96	-11.65	-26.71	0
CHEM_r1i1p1_rcp45							
pr_MIROC-ESM-	41.24	-2.37	30.95	32.76	-10.85	-24.88	0.033
CHEM_r1i1p1_rcp85							
pr_MIROC-ESM_r1i1p1_rcp45	38.06	-5.55	36.27	41.55	-2.06	-4.72	0.525
pr_MIROC-ESM_r1i1p1_rcp85	38.06	-5.55	35.87	41.08	-2.53	-5.80	0.474
pr MIROC5 r1i1p1 rcp45	10.07						
	40.07	-3.54	40.15	43.71	0.1	0.23	0.711
pr_MIROC5_r1i1p1_rcp85	40.07	-3.54 -3.54	40.15 41.38	43.71 45.04	0.1 1.43	0.23 3.28	0.711 0.796
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45	40.07 40.07 41.04	-3.54 -3.54 -2.57	40.15 41.38 44.4	43.71 45.04 47.19	0.1 1.43 3.58	0.23 3.28 8.21	0.711 0.796 0.949
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45 pr_MPI-ESM-LR_r1i1p1_rcp85	40.07 40.07 41.04 41.04	-3.54 -3.54 -2.57 -2.57	40.15 41.38 44.4 42.85	43.71 45.04 47.19 45.55	0.1 1.43 3.58 1.94	0.23 3.28 8.21 4.45	0.711 0.796 0.949 0.847
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45 pr_MPI-ESM-LR_r1i1p1_rcp85 pr_MPI-ESM-MR_r1i1p1_rcp45	40.07 40.07 41.04 41.04 38.87	-3.54 -3.54 -2.57 -2.57 -4.74	40.15 41.38 44.4 42.85 43.24	43.71 45.04 47.19 45.55 48.52	0.1 1.43 3.58 1.94 4.91	0.23 3.28 8.21 4.45 11.26	0.711 0.796 0.949 0.847 1
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45 pr_MPI-ESM-LR_r1i1p1_rcp85 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp85	40.07 40.07 41.04 41.04 38.87 38.87	-3.54 -3.54 -2.57 -2.57 -4.74 -4.74	40.15 41.38 44.4 42.85 43.24 42.79	43.71 45.04 47.19 45.55 48.52 48	0.1 1.43 3.58 1.94 4.91 4.39	0.23 3.28 8.21 4.45 11.26 10.07	0.711 0.796 0.949 0.847 1 0.983
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45 pr_MPI-ESM-LR_r1i1p1_rcp85 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp85 pr_MRI-CGCM3_r1i1p1_rcp45	40.07 40.07 41.04 41.04 38.87 38.87 42.86	-3.54 -3.54 -2.57 -2.57 -4.74 -4.74 -0.75	40.15 41.38 44.4 42.85 43.24 42.79 44.83	43.71 45.04 47.19 45.55 48.52 48 48 45.6	0.1 1.43 3.58 1.94 4.91 4.39 1.99	0.23 3.28 8.21 4.45 11.26 10.07 4.56	0.711 0.796 0.949 0.847 1 0.983 0.864
pr_MIROC5_r1i1p1_rcp85pr_MPI-ESM-LR_r1i1p1_rcp45pr_MPI-ESM-LR_r1i1p1_rcp85pr_MPI-ESM-MR_r1i1p1_rcp45pr_MPI-ESM-MR_r1i1p1_rcp85pr_MRI-CGCM3_r1i1p1_rcp85	40.07 40.07 41.04 41.04 38.87 38.87 42.86 42.86	-3.54 -3.54 -2.57 -2.57 -4.74 -4.74 -0.75 -0.75	40.15 41.38 44.4 42.85 43.24 42.79 44.83 46.26	43.71 45.04 47.19 45.55 48.52 48 45.6 47.08	0.1 1.43 3.58 1.94 4.91 4.39 1.99 3.47	0.23 3.28 8.21 4.45 11.26 10.07 4.56 7.96	0.711 0.796 0.949 0.847 1 0.983 0.864 0.932
pr_MIROC5_r1i1p1_rcp85pr_MPI-ESM-LR_r1i1p1_rcp45pr_MPI-ESM-LR_r1i1p1_rcp85pr_MPI-ESM-MR_r1i1p1_rcp45pr_MPI-ESM-MR_r1i1p1_rcp85pr_MRI-CGCM3_r1i1p1_rcp85pr_NRI-CGCM3_r1i1p1_rcp85pr_NORESM1-M_r1i1p1_rcp45	40.07 40.07 41.04 41.04 38.87 38.87 42.86 42.86 44.36	-3.54 -3.54 -2.57 -2.57 -4.74 -4.74 -0.75 -0.75 0.75	40.15 41.38 44.4 42.85 43.24 42.79 44.83 46.26 35.4	43.71 45.04 47.19 45.55 48.52 48 45.6 47.08 34.82	0.1 1.43 3.58 1.94 4.91 4.39 1.99 3.47 -8.79	0.23 3.28 8.21 4.45 11.26 10.07 4.56 7.96 -20.16	0.711 0.796 0.949 0.847 1 0.983 0.864 0.932 0.05
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MRI-CGCM3_r1i1p1_rcp45 pr_NorESM1-M_r1i1p1_rcp45 pr_NorESM1-M_r1i1p1_rcp45	40.07 40.07 41.04 38.87 38.87 42.86 44.36	-3.54 -3.54 -2.57 -2.57 -4.74 -4.74 -0.75 -0.75 0.75 0.75	40.15 41.38 44.4 42.85 43.24 42.79 44.83 46.26 35.4 33.26	43.71 45.04 47.19 45.55 48.52 48 45.6 47.08 34.82 32.75	0.1 1.43 3.58 1.94 4.91 4.39 1.99 3.47 -8.79 -10.86	0.23 3.28 8.21 4.45 11.26 10.07 4.56 7.96 -20.16 -24.90	0.711 0.796 0.949 0.847 1 0.983 0.864 0.932 0.05 0.016
pr_MIROC5_r1i1p1_rcp85 pr_MPI-ESM-LR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MPI-ESM-MR_r1i1p1_rcp45 pr_MRI-CGCM3_r1i1p1_rcp45 pr_NorESM1-M_r1i1p1_rcp45 pr_NorESM1-M_r1i1p1_rcp45 pr_bcc-csm1-1-m_r1i1p1_rcp45	40.07 40.07 41.04 38.87 38.87 42.86 42.86 44.36 44.36 41.99	-3.54 -3.54 -2.57 -2.57 -4.74 -4.74 -0.75 -0.75 0.75 0.75 0.75 -1.62	40.15 41.38 44.4 42.85 43.24 42.79 44.83 46.26 35.4 33.26 37.66	43.71 45.04 47.19 45.55 48.52 48 45.6 47.08 34.82 32.75 39.08	0.1 1.43 3.58 1.94 4.91 4.39 1.99 3.47 -8.79 -10.86 -4.53	0.23 3.28 8.21 4.45 11.26 10.07 4.56 7.96 -20.16 -24.90 -10.39	0.711 0.796 0.949 0.847 1 0.983 0.864 0.932 0.05 0.016 0.271



Figure 13. Distribution of changes from SFWMM historical to future bias-corrected annual total rainfall.



Figure 14. Scatterplot of future annual total rainfall pre and post bias-correction.



Figure 15. Distribution of changes from SFWMM historical to future bias-corrected wet season rainfall.



Figure 16. Scatterplot of future wet season rainfall pre and post bias-correction.





Figure 17. Spatial distribution of (a) SFWMM historical rainfall (1991-2005), (b) Simulated historical rainfall (1991-2005), (c) Simulated future rainfall (2055-2069), (d) Bias-corrected simulated future rainfall, (e) = (d)/(a), (f) = (d) - (a). Note: Here, bias correction has been done on the annual total rainfall (mean) by applying Equation 1.

Seasonal cycle of Precip. for entire domain



Figure 18. Seasonal cycle of domain-averaged monthly total precipitation for the historical period (1991-2005) and the future period (2055-2069). The historical SFWMM data is shown in blue, the simulated historical data for LOCA model pr_MRI-CGCM3 r1i1p1 is in red, and the simulated future data for LOCA model pr_MRI-CGCM3 r1i1p1 rcp85 is in green.

Quantile mapping (QM), a CDF matching method (Panofsky and Brier, 1968), has been typically applied to bias-correct precipitation timeseries from climate model simulations. To avoid some common limitations of QM, other methods have been developed such as Quantile Delta Mapping (QDM). As shown in Cannon et al. (2015), QM tends to inflate trends in precipitation extreme indices projected by GCMs, whereas QDM is not as prone to this problem. QDM preserves model-projected changes in quantiles, while simultaneously correcting for systematic biases across quantiles (Cannon et al., 2015). QDM also attempts to bridge the gap between point estimates for the observations vs. grid cell estimates in the model. However, it is important to note that changes in the mean may not be preserved by QDM.

QDM can be applied in additive form or multiplicative form. Multiplicative QDM (MQDM) is better suited to correcting variables like precipitation where preserving relative changes is important in order to respect the Clausius-Clapeyron equation which relates the amount of atmospheric moisture to temperature changes simulated by the models. MQDM was used to bias-correct daily precipitation data for LOCA run pr_MRI-CGCM3_r1i1p1_rcp85 at every MODFLOW model grid cell independently.

The Multiplicative QDM (MQDM) method is described by

$$\hat{x}_{m-padj.} = x_{m-p} * \{F_{o-c}^{-1}[F_{m-p}(x_{m-p})]/F_{m-c}^{-1}[F_{m-p}(x_{m-p})]\}$$
Equation 2

which is equivalent to:

$$\hat{x}_{m-padj.} = F_{m-padj.}^{-1}(G) = F_{m-p}^{-1}(G) * \{F_{o-c}^{-1}(G)/F_{m-c}^{-1}(G)\}$$
Equation 3

where \hat{x}_{m-padj} is the adjusted quantile for the LOCA model (m) projections (p) for the future period (2055-2069), F_{o-c} is the CDF of the SFWMM observations (o) in the current (1991-2005) baseline period (c), F_{m-c} is the CDF of the LOCA model (m) in the current (1991-2005) baseline period (c), F_{m-p} is the CDF for the LOCA model (m) projections (p) for the future period (2055-2069), and x_{m-p} is the quantile for the LOCA model (m) projections (p) in the future (2055-2069) baseline period. F⁻¹ means the inverse of the CDF (i.e. the quantile function), *G* is the annual non-exceedance probability (CDF value) and is equal to 1-P, P is the annual exceedance probability (AEP) which is related to the return period *T* by 1/P = T (i.e. G=1-1/T). Figure 19 shows MQDM application for hypothetical data.

As part of this project, MQDM was applied to bias-correct future daily rainfall data for LOCA run pr_MRI-CGCM3_r1i1p1_rcp85 for each month of the year separately. In other words, twelve (12) CDFs were developed for each cumulative function shown in Equation 2 and Equation 3.

Figure 20 shows quantile-quantile plots of observed and simulated daily rainfall for the historical period (1991-2005) in the top panel, simulated historical (1991-2005) vs. future (2055-2069) projected daily rainfall in the middle panel, and the respective CDFs in the bottom panel, considering <u>all</u> daily values at a particular MODFLOW model grid cell together. As a reminder, MQDM was applied for different months of the year separately, but looking at all daily values lumped together is still helpful. It is evident that this LOCA run underestimates daily extremes at this location in the historical period, while it simulates an increase in future precipitation. Similar behavior is observed at most MODFLOW model grid cells in Miami-Dade County. Figure 21 shows how MQDM bias-correction fixes the extremes in the historical period (top panel), while still simulating increased precipitation in the future period (middle panel). The top panel in this figure shows the daily data points almost exactly on the 1:1 line; however, since MQDM is applied separately for different months of the year, there may be some small excursions from the 1:1 line at other model grid cells when plotting all daily values together.

Figure 22 shows the spatial distribution of the observed and simulated means prior to and post daily biascorrection using Equation 2. It is evident how daily bias correction corrects the mean historical spatial pattern to match that of the observed data (top 2 panels). The bias-corrected future precipitation (Figure 22d) has a similar spatial pattern to that of the historical period, as expected. The spatial pattern in Figure 22d is very similar to the case when the long-term mean was bias-corrected (Figure 17d). However, the magnitude of the rainfall is larger in the daily bias-correction case (63.9 in/yr or 11% higher than historical) than in the mean bias-correction case (61.9 in/yr or 7.5% higher than historical) due to non-linearities in the daily bias-correction process.



Multiplicative Quantile Delta Method

Figure 19. Diagram showing the Multiplicative Quantile Delta Method for hypothetical data.

F is the non-exceedance probability of interest. The quantiles corresponding to *F* are given by $CDF1^{-1}$: $F^{-1}_{0-c}(F)$ for the observed current baseline, $CDF3^{-1}$: $F^{-1}_{m-p}(F)$ for the model projected (future) period. The corresponding adjusted quantile for the model projected (future) period is $CDF4^{-1}$: $F^{-1}_{m-p}(F) = F^{-1}_{m-p}(F)^* \{F^{-1}_{0-c}(F)/F^{-1}_{m-c}(F)\}$. The distances *a* and *b* are different in MQDM due to the use of *a* ratio in the bias correction equation. However, *a* and *b* would be equal in Additive Quantile Delta Method.



Figure 20. Pre-bias correction: (a) Quantile-quantile plot of daily observed vs. simulated precipitation for the historical period (1991-2005), (b) Quantile-quantile plot of simulated historical (1991-2005) vs. simulated future (1991-2005) precipitation, (c) Cumulative distribution functions.


Figure 21. Pre-bias correction: (a) Quantile-quantile plot of daily observed vs. simulated precipitation for the historical period (1991-2005), (b) Quantile-quantile plot of simulated historical (1991-2005) vs. simulated future (1991-2005) precipitation, (c) Cumulative distribution functions.







Daily B.C.pr_MRI-CGCM3_r1i1p1_rcp85 (2055-2069) Daily B.C.pr_MRI-CGCM3_r1i1p1_rcp85 (2055-2069) to SFWMM rainfall (1996-2010) - SFWMM rainfall (1996-2010) (6.35 in/yr)

Figure 22. Spatial distribution of (a) SFWMM historical rainfall (1991-2005), (b) Bias-corrected simulated historical rainfall (1991-2005), (c) Simulated future rainfall (2055-2069), (d) Bias-corrected simulated future rainfall, (e) = (d)/(a), (f) = (d) - (a). Note: Here, bias correction has been done on the annual total rainfall (mean) by applying Equation 2.

Seasonal cycle of Precip. for entire domain



Figure 23. Seasonal cycle of domain-averaged monthly total precipitation for the historical period (1991-2005) and the future period (2055-2069). The historical SFWMM data is shown in blue, the simulated historical data for LOCA model pr_MRI-CGCM3_r1i1p1 after daily bias-correction is in red, and the simulated future data for LOCA model pr_MRI-CGCM3_r1i1p1_rcp85 after daily bias correction is in green.

Figure 23 shows the seasonal cycle of domain-average rainfall after daily bias-correction for the historical and future periods. It is evident how daily-bias correction makes the domain-average simulated monthly mean rainfall match that of the observations. However, the method is not always able to improve the monthly variability. For example, the variability of the bias-corrected historical simulated rainfall improves during the month of June, but is even larger than prior to bias-correction during August and October (Figure 18). This is due to the fact that the daily MQDM bias-correction method corrects only one grid cell at a time without considering the spatial and temporal variability of rainfall. This limitation is addressed by other bias-correction methods such as Bias-Corrected Stochastic Analogs (BCSA; Hwang and Graham, 2013). Comparison of Figure 23 with Figure 18 shows that the pattern of increased future precipitation at the end of the wet season (September-October) and slight decreases in January and August precipitation remain after daily bias-correction.

R code for rainfall bias correction

```
adjprecip <- function() {</pre>
```

```
******
#Note: Must re-do LOCA run 25 (i=25) manually by reading data using var.get.nc and
then creating the brick
#For some reason it does not work to create the brick directly from the netCDF file in
the loop.
#Therefore, one must run this script manually up to the foreach loop, and then
manually re-do
LOCA run 25 (i=25) as described above. Then run the rest of the script manually as
well.
LOCA CRS: crs="+proj=longlat +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0"
**********
library(reshape)
library(RNetCDF)
library(raster)
library(rgdal)
#library(fields)
#library(RColorBrewer)
library(pals)
library(foreach)
library(parallel)
library(doParallel)
#library(tcltk)
#library(doSNOW)
#library(gdalUtils)
library(rasterVis)
library(lattice)
library(magic)
#Main variables
vn="pr"
vnl="Precip"
#season=5:10 #wet season
season=1:12 #entire year
LOCA dir="Z:/miriza/Work/R/LOCA dataset/Data"
NEXRAD dir="Z:/miriza/Work/FIU/FL Building Code/Data/Rainfall/USGS MODFLOW NEXRAD"
SFWMM dir="Z:/miriza/Work/FIU/FL Building Code/Data/Rainfall/SFWMD"
setwd("Z:/miriza/Work/FIU/FL Building Code/Data/Rainfall/LOCA BC/LOCA vs SFWMM entirey
r")
#Future base period
startyr2=2055
endyr2=2069
nyrs2=endyr2-startyr2+1
allyrs2=startyr2:endyr2
ndays2=as.integer(difftime(strptime(paste("01.01.",endyr2+1,sep=""), format =
"%d.%m.%Y"),
               strptime(paste("01.01.", startyr2, sep=""), format =
"%d.%m.%Y"),units="days"))
dates2=seq(as.Date("2055/1/1"), as.Date("2069/12/31"),"days")
yrs2=as.numeric(format(dates2,'%Y'))
mos2=as.numeric(format(dates2,'%m'))
days2=as.numeric(format(dates2,'%d'))
#Historical date range in M-D MODFLOW NEXRAD rainfall dataset
startyrh=1996
endyrh=2010
```

```
nyrsh=endyrh-startyrh+1
allyrsh=startyrh:endyrh
ndaysh=as.integer(difftime(strptime(paste("01.01.",endyrh+1,sep=""), format =
"%d.%m.%Y"),
                strptime(paste("01.01.", startyrh, sep=""), format =
"%d.%m.%Y"),units="days"))
datesnh=seq(as.Date("1996/1/1"), as.Date("2010/12/31"),"days")
yrsnh=as.numeric(format(datesnh,'%Y'))
mosnh=as.numeric(format(datesnh,'%m'))
#Historical date range for Bias-correction (BC)
startyrh2=1991
endyrh2=2005
nyrsh2=endyrh2-startyrh2+1
allyrsh2=startyrh2:endyrh2
ndaysh2=as.integer(difftime(strptime(paste("01.01.",endyrh2+1,sep=""), format =
"%d.%m.%Y"),
                strptime(paste("01.01.", startyrh2, sep=""), format =
"%d.%m.%Y"),units="days"))
datesnh2=seq(as.Date("1991/1/1"), as.Date("2005/12/31"),"days")
yrsnh2=as.numeric(format(datesnh2,'%Y'))
mosnh2=as.numeric(format(datesnh2,'%m'))
daysnh2=as.numeric(format(datesnh2,'%d'))
#LOCA date range
#Historical period
startyrlh=1950
endvrlh=2005
nyrslh=endyrlh-startyrlh+1
allyrslh=startyrlh:endyrlh
ndayslh=as.integer(difftime(strptime(paste("01.01.",endyrlh+1,sep=""), format =
"%d.%m.%Y"),
                strptime(paste("01.01.", startyrlh, sep=""), format =
"%d.%m.%Y"),units="days"))
dateslh=seq(as.Date("1950/1/1"), as.Date("2005/12/31"),"days")
vrslh=as.numeric(format(dateslh,'%Y'))
moslh=as.numeric(format(dateslh,'%m'))
#Future period
startyrlf=2006
endyrlf=2099
nyrslf=endyrlf-startyrlf+1
allyrslf=startyrlf:endyrlf
ndayslf=as.integer(difftime(strptime(paste("01.01.",endyrlf+1,sep=""), format =
"%d.%m.%Y"),
                strptime(paste("01.01.", startyrlf, sep=""), format =
"%d.%m.%Y"),units="days"))
dateslf=seq(as.Date("2006/1/1"), as.Date("2099/12/31"),"days")
yrslf=as.numeric(format(dateslf,'%Y'))
moslf=as.numeric(format(dateslf,'%m'))
#Read in raster with 1996-2010 NEXRAD rainfall data on the M-D MODFLOW grid
#Proj4js.defs["EPSG:26917"] = "+proj=utm +zone=17 +ellps=GRS80 +datum=NAD83 +units=m
+no defs"
n=brick(paste(NEXRAD dir,"/nexrad rainfall.nc",sep=""),crs="+proj=utm +zone=17
+ellps=GRS80 +datum=NAD83 +units=m +no defs")
#Load offset mask
offsm=raster(paste(NEXRAD dir,"/UMD offshore.nc",sep=""),crs="+proj=utm +zone=17
+ellps=GRS80 +datum=NAD83 +units=m +no defs")
offsm[offsm==2]=0
#Adjust values
n=mask(n,offsm,maskvalue=0,updatevalue=NA)
```

```
print(paste("after mask-->n\n", sep=""))
#Subset data for months of interest
n=subset(n,which(mosnh%in%season))
print(paste("after subset-->n\n", sep=""))
#Get mean
nm=calc(n,mean)
print(paste("after temporal mean-->nm\n", sep=""))
minnm=minValue(nm)
maxnm=maxValue(nm)
#Get. extent.
extn=bbox(n)
#Go 1 SFWMM cell (2 mi = 3218.7 m) outside the NEXRAD extent
extn2=extn
extn2[,1]=extn2[,1]-3218.7
extn2[,2]=extn2[,2]+3218.7
#SFWMM date range
datessh=seq(as.Date("1914/1/1"), as.Date("2016/12/31"),"days")
yrssh=as.numeric(format(datessh,'%Y'))
mossh=as.numeric(format(datessh,'%m'))
#Read in SFWMM netCDF file
+k=0.9999411764705882 +x_0=200000 +y_0=0 +ellps=GRS80 +units=m +no_defs";
ncf=open.nc(paste(SFWMM dir,"/rain v4.7 1914 2016 sfwmd.nc",sep=""))
#SFWMM coordinates are in ft NAD1983 HARN StatePlane FL East FIPS0901 (but ESRI:102258
is in m)
cds=var.get.nc(ncf,"coords")
cds=cds
#Change SFWMM cell centroid coordinates to match projection of M-D MODFLOW grid
d <- data.frame(x=cds[1,], y=cds[2,])</pre>
coordinates(d) <- c("x", "y")</pre>
proj4string(d) <- CRS("+proj=tmerc +lat 0=24.333333333333333 +lon 0=-81
+k=0.9999411764705882 +x 0=200000 +y 0=0 +ellps=GRS80 +units=ft +no defs")
CRS.new <- CRS("+init=epsg:26917") #m
d.n <- spTransform(d, CRS.new) #m</pre>
d.ns=crop(d.n,extn2)
#plot(d.ns,pch=1)
cellsinmodel=which(d.n@coords[,1]>=extn2[1,1] & d.n@coords[,1]<=extn2[1,2] &</pre>
d.n@coords[,2]>=extn2[2,1] & d.n@coords[,2]<=extn2[2,2])
roco=var.get.nc(ncf, "roco")
rocosinmodel=roco[,cellsinmodel]
#range of rows 3-32
#range of cols 52-68
wmmrain=var.get.nc(ncf,"rainfall")[,,(which(yrssh%in%allyrsh2 & mossh%in%season))]
#This extract data for 1991-2005 and season of interest
#Start with an NA array to accomodate the subset of cells of interest
wmmraininmodel=array(dim=c(diff(range(rocosinmodel[1,]))+1, diff(range(rocosinmodel[2,]))
))+1,dim(wmmrain)[3]))
for (c in 1:dim(rocosinmodel)[2]) {
 wmmraininmodel[(rocosinmodel[1,c]-min(rocosinmodel[1,])+1),(rocosinmodel[2,c]-
min(rocosinmodel[2,])+1),]=
                 wmmrain[rocosinmodel[2,c],rocosinmodel[1,c],]
}
#Create a brick from the SFWMM rainfall data
#Range defined below are for outer boundaries of cells
wmmb=brick(arev(wmmraininmodel,1),xmn=min(cds[1,cellsinmodel])-
5280, xmx=max(cds[1,cellsinmodel])+5280,
          ymn=min(cds[2,cellsinmodel])-5280,ymx=max(cds[2,cellsinmodel])+5280,
          crs="+proj=tmerc +lat 0=24.33333333333333 +lon 0=-81 +k=0.9999411764705882
+x 0=200000 +y 0=0 +ellps=GRS80 +units=ft +no defs")
#Project SFWMM data to MODFLOW model grid
wmmb=projectRaster(wmmb, n, method='ngb')
```

```
print(paste("after projection-->wmmb\n", sep=""))
nds2=nlayers(wmmb)/nyrsh2 #number of days in the season
#Get mean
wmmbm=calc(wmmb,mean)
print(paste("after temporal mean-->wmmbm\n", sep=""))
#Adjust values
wmmbm=mask(wmmbm,offsm,maskvalue=0,updatevalue=NA)
print(paste("after mask-->wmmbm\n", sep=""))
minwmmm=minValue(wmmbm)
maxwmmm=maxValue(wmmbm)
#Read LOCA projections
projs=read.table(paste(LOCA dir,"/loca projections.txt", sep=""), stringsAsFactors=FALSE
nprojs=nrow(projs)
fns=paste(vn, " ", projs[, 1], sep="")
modelp=apply(projs,1,function(x) paste(c(strsplit(x,"")[[1]][1:2]),collapse=""))
modelpbase=apply(projs,1,function(x) strsplit(x," ")[[1]][1])
modelprip=apply(projs,1,function(x) strsplit(x," ")[[1]][2])
modelprcp=apply(projs,1,function(x) strsplit(x,"")[[1]][3])
modelpbases=unique(modelpbase)
minpm=vector(length=nprojs,mode="double")
maxpm=vector(length=nprojs,mode="double")
minpmbc=vector(length=nprojs,mode="double")
maxpmbc=vector(length=nprojs,mode="double")
meanpm=vector(length=nprojs,mode="double")
meanpmbc=vector(length=nprojs,mode="double")
hist=read.table(paste(LOCA dir,"/loca historical.txt",sep=""),stringsAsFactors=FALSE)
fnsh=paste(vn, " ", hist[, 1], sep="")
modelh=apply(hist,1,function(x) paste(c(strsplit(x,"")[[1]][1:2]),collapse=""))
modelhbase=apply(hist,1,function(x) strsplit(x," ")[[1]][1])
modelhrip=apply(hist,1,function(x) strsplit(x,"")[[1]][2])
minhm=vector(length=nprojs,mode="double")
maxhm=vector(length=nprojs,mode="double")
meanhm=vector(length=nprojs,mode="double")
#Define number of cores
ncore=3
#Create log file
st=Sys.time()
#logfil=paste("Log ",gsub("[ :]"," ",st),".txt",sep="")
#cat(paste("Log file:",st,"\n"),file=logfil)
#Register processors
outfil=paste("Out_",gsub("[ :]"," ",st),".txt",sep="")
cl <- makePSOCKcluster(ncore,outfile=outfil)</pre>
registerDoParallel(cl)
#registerDoSNOW(cl)
# Extract subset of data of interest for projections
foreach
(i=1:nrow(projs),.packages=c("raster","foreach","RNetCDF","rgdal","parallel","doParall
el")) %dopar% {
  logfil=paste("Log ",gsub("[ :]"," ",st)," ",i,".txt",sep="")
  cat(paste("Log file:", st, "\n"), file=logfil)
  cat(paste("i=",i,"\n",sep=""),file=logfil,append=TRUE)
  #Get LOCA data for projections
  #Get variable attributes from netCDF file
  ncfile<-open.nc(paste(LOCA dir,"/",fns[i]," 2006-2100.nc",sep=""))</pre>
```

```
units=att.get.nc(ncfile,fns[i],"units")
cat(paste(units, "\n", sep=""), file=logfil, append=TRUE)
if (units == "kg m-2 s-1") {
 conv=141.7323*24 #mm/s to in/day
} else if (units == "mm") {
 conv=1/25.4 #mm to in (per day of course)
} else {
 stop("Different type of units")
}
#scal=try(att.inq.nc(ncfile,fns[i],"scale factor"),silent=TRUE)
#if (class(scal) == "try-error") {
# scal=1
#} else {
# scal=att.get.nc(ncfile,fns[i],"scale factor")
#}
scal=1
cat(paste(scal, "\n", sep=""), file=logfil, append=TRUE)
close.nc(ncfile)
#get data as a brick
b=brick(paste(LOCA_dir,"/",fns[i],"_2006-2100.nc",sep=""))
cat(paste("after brick b\n", sep=""), file=logfil, append=TRUE)
#Fix longitudes to go from -180 to +180 so raster projection can proceed correctly
extent(b) = c(xmin(b) - 360, xmax(b) - 360, ymin(b), ymax(b))
#Extract subset of LOCA data for future years of interst
bproj=subset(b,which(yrslf%in%allyrs2 & moslf%in%season))
cat(paste("after subset-->bproj\n",sep=""),file=logfil,append=TRUE)
#Project LOCA data to MODFLOW model grid
#bproj=projectRaster(bproj,n,method='ngb')
#cat(paste("after projection-->bproj\n", sep=""), file=logfil, append=TRUE)
#Adjust values
#bproj=mask(bproj,offsm,maskvalue=0,updatevalue=NA)
#cat(paste("after mask-->bproj\n",sep=""),file=logfil,append=TRUE)
#bproj=calc(bproj,fun=function(x) x*conv*scal)
#cat(paste("after calculation-->bproj\n",sep=""),file=logfil,append=TRUE)
rm(b)
#Get mean
projm=calc(bproj,mean)
cat(paste("after temporal mean-->projm\n", sep=""), file=logfil, append=TRUE)
#Then project the mean
projm=projectRaster(projm,n,method='ngb')
cat(paste("after projection-->projm\n",sep=""),file=logfil,append=TRUE)
#Mask values
projm=mask(projm,offsm,maskvalue=0,updatevalue=NA)
cat(paste("after mask-->projm\n", sep=""), file=logfil, append=TRUE)
#Adjust values
projm=calc(projm,fun=function(x) x*conv*scal)
cat(paste("after calculation-->projm\n",sep=""),file=logfil,append=TRUE)
maxpm[i]=maxValue(projm)
minpm[i]=minValue(projm)
# Merge with historical data if available
idh=which(modelhbase %in% modelpbase[i])
if (length(idh) == 0) {
```

```
cat(paste("No historical data found for model:",modelp[i],"
(i=",i,") \n", sep=""), file=logfil, append=TRUE)
 } else if (length(idh) > 1) {
   stop(paste("Multiple historical data found for model:",modelp[i],"
(i=",i,")", sep=""))
 } else {
   cat(paste("Historical data found for model:",modelp[i],"
(i=",i,") \n", sep=""), file=logfil, append=TRUE)
   ncfile2<-open.nc(paste(LOCA dir,"/",fnsh[idh]," 1950-2005.nc",sep=""))</pre>
   units2=att.get.nc(ncfile2, fnsh[idh], "units")
   cat(paste(units2,"\n",sep=""),file=logfil,append=TRUE)
   if (units2 == "kg m-2 s-1") {
     conv2=141.7323*24 #mm/s to in/day
   } else if (units2 == "mm") {
     conv2=1/25.4 #mm to in (per day of course)
   } else {
     stop("Different type of units")
   }
   #scale2=try(att.inq.nc(ncfile2,fnsh[idh],"scale factor"),silent=TRUE)
   #if (class(scale2) == "try-error") {
   # scale2=1
   #} else {
   #
      scale2=att.get.nc(ncfile2, fnsh[idh], "scale factor")
   #}
   scale2=1
   cat(paste(scale2,"\n",sep=""),file=logfil,append=TRUE)
   close.nc(ncfile2)
   #get data as a brick
   b=brick(paste(LOCA dir,"/",fnsh[idh]," 1950-2005.nc",sep=""))
   cat(paste("after brick->b\n", sep=""), file=logfil, append=TRUE)
   #Fix longitudes to go from -180 to +180 so raster projection can proceed correctly
   extent(b) = c(xmin(b) - 360, xmax(b) - 360, ymin(b), ymax(b))
   #Extract subset of LOCA data for historical years of interest
   bhist=subset(b,which(yrslh%in%allyrsh2 & moslh%in%season))
   cat(paste("after subset-->bhist\n",sep=""),file=logfil,append=TRUE)
   #Project LOCA data to MODFLOW model grid
   #bhist=projectRaster(bhist,n,method='ngb')
   #cat(paste("after projection-->bhist\n",sep=""),file=logfil,append=TRUE)
   #Adjust values
   #bhist=mask(bhist,offsm,maskvalue=0,updatevalue=NA)
   #cat(paste("after mask-->bhist\n", sep=""), file=logfil, append=TRUE)
   #bhist=calc(bhist,fun=function(x) x*conv2*scale2)
   #cat(paste("after calculation-->bhist\n",sep=""),file=logfil,append=TRUE)
   rm(b)
   #Get mean
   histm=calc(bhist,mean)
   cat(paste("after temporal mean-->histm\n",sep=""),file=logfil,append=TRUE)
   #Then project the mean
   histm=projectRaster(histm,n,method='ngb')
   cat(paste("after projection-->histm\n",sep=""),file=logfil,append=TRUE)
   #Mask values
   histm=mask(histm,offsm,maskvalue=0,updatevalue=NA)
   cat(paste("after mask-->histm\n",sep=""),file=logfil,append=TRUE)
   #Adjust values
```

```
histm=calc(histm,fun=function(x) x*conv2*scale2)
    cat(paste("after calculation-->histm\n", sep=""), file=logfil, append=TRUE)
    maxhm[i]=maxValue(histm)
   minhm[i]=minValue(histm)
    #Get bias-corrected mean
    projmbc=(projm/histm) *wmmbm
    maxpmbc[i]=maxValue(projmbc)
    minpmbc[i]=minValue(projmbc)
    #Save data
save(bhist,histm,bproj,projm,n,nm,wmmbm,projmbc,file=paste(fns[i]," rasters.RData",sep
=""))
    rm(bhist, histm, bproj, projm, projmbc)
  }
}
#Clean up the cluster
stopImplicitCluster()
#Make levelplots of annual means
#Get overall ranges
minz=min(c(minpm,minhm,minpmbc,minwmmm))*nds2
maxz=max(c(maxpm,maxhm,maxpmbc,maxwmmm))*nds2
minz=floor(minz)
maxz=ceiling(maxz)
#Create levelplot of nm
#png("NEXRAD mean rainfall.png")
#col.regions=brewer.gnbu(100)
#print(levelplot(nm*nds2,margin=FALSE,at=seq(minz,maxz,1),
          main=paste("NEXRAD rainfall (",round(nds2*cellStats(nm,mean),2),"
in/yr) \n", startyrh, "-", endyrh, sep=""),
           xlab="X (m) UTM17N, NAD83", ylab="Y (m) UTM17N, NAD83"))
#
#dev.off()
#rm(n,nm)
#Create levelplot of wmmbm
png("SFWMM_mean_rainfall.png")
#col.regions=brewer.gnbu(100)
print(levelplot(wmmbm*nds2,margin=FALSE,at=seq(minz,maxz,1),
          main=paste("SFWMM rainfall (",round(nds2*cellStats(wmmbm,mean),2),"
in/yr) \n", startyrh2, "-", endyrh2, sep=""),
          xlab="X (m) UTM17N, NAD83",ylab="Y (m) UTM17N, NAD83"))
dev.off()
#Create levelplots for the projections
for (i in 1:nrow(projs)) {
  print(paste("i=",i))
  load(paste(fns[i]," rasters.RData", sep=""), verbose=TRUE)
  #Create levelplot of histm
  meanhm[i]=round(nds2*cellStats(histm,mean),2)
  png(paste("LOCA mean rainfall hist ",fns[i],".png",sep=""))
  print(levelplot(histm*nds2,margin=FALSE,at=seq(minz,maxz,1),
            main=paste("LOCA rainfall (",meanhm[i]," in/yr)\n",
            startyrh2,"-",endyrh2," (",fns[i],")",sep=""),
            xlab="X (m) UTM17N, NAD83",ylab="Y (m) UTM17N, NAD83"))
  dev.off()
  #Create levelplot of projm
```

```
meanpm[i]=round(nds2*cellStats(projm,mean),2)
  png(paste("LOCA mean rainfall proj ",fns[i],".png",sep=""))
  print(levelplot(projm*nds2,margin=FALSE,at=seq(minz,maxz,1),
            main=paste("LOCA rainfall (",meanpm[i]," in/yr)\n",
            startyr2,"-",endyr2," (",fns[i],")",sep=""),
            xlab="X (m) UTM17N, NAD83", ylab="Y (m) UTM17N, NAD83"))
  dev.off()
  #Create levelplot of projmbc
  meanpmbc[i]=round(nds2*cellStats(projmbc,mean),2)
  png(paste("LOCA_mean_rainfall_projbc_", fns[i],".png", sep=""))
  print(levelplot(projmbc*nds2,margin=FALSE,at=seq(minz,maxz,1),
            main=paste("B.C. LOCA rainfall (",meanpmbc[i]," in/yr)\n",
            startyr2, "-", endyr2," (", fns[i], ")", sep=""),
            xlab="X (m) UTM17N, NAD83",ylab="Y (m) UTM17N, NAD83",cex=0.5))
  dev.off()
  png(paste("LOCA projbc to SFWMM ratio ",fns[i],".png",sep=""))
  print (levelplot (projmbc/wmmbm, col.regions=brewer.rdbu (21), margin=FALSE,
            at = seq(0.70, 1.30, 0.025),
            main=paste("B.C.",fns[i]," (",startyr2,"-",endyr2,")\n",
            "to SFWMM rainfall (",startyrh,"-",endyrh,")",sep=""),
            xlab="X (m) UTM17N, NAD83",ylab="Y (m) UTM17N, NAD83",cex=0.5))
  dev.off()
  png(paste("LOCA projbc-SFWMM ", fns[i], ".png", sep=""))
  print (levelplot (nds2* (projmbc-wmmbm), col.regions=brewer.rdbu (29), margin=FALSE,
            at=seq(-16,16,1),
            main=paste("B.C.",fns[i]," (",startyr2,"-",endyr2,")\n",
            "- SFWMM rainfall (",startyrh,"-",endyrh,") (",
           round(nds2*cellStats((projmbc-wmmbm), mean), 2), " in/yr)", sep=""),
            xlab="X (m) UTM17N, NAD83", ylab="Y (m) UTM17N, NAD83", cex=0.5))
  dev.off()
}
statis=as.data.frame(cbind(meanhm,meanpm,meanpmbc))
rownames(statis)=fns
colnames(statis)=c('meanhm', 'meanpm', 'meanpmbc')
save(statis,file="mean rainfall stats.RData")
write.csv(statis,file="mean rainfall stats.csv")
png("Bias_correction_check.png")
plot(statis[,1]/(cellStats(wmmbm,mean)*nds2),statis[,2]/statis[,3],xlab="mean(hist)/me
an (WMM) ", ylab="mean (proj) /mean (projbc) ", main="Check of bias-correction")
grid()
dev.off()
#Chosing run i=56 (MRI-CGCM3 r1i1p1 rcp85) for daily bias-correction
i=56
load(file=paste(fns[i]," rasters.RData", sep=""), verbose=TRUE)
#Project LOCA future data to MODFLOW model grid
bproj=projectRaster(bproj,n,method='ngb')
print(paste("after projection-->bproj\n", sep=""))
#Adjust values
bproj=mask(bproj,offsm,maskvalue=0,updatevalue=NA)
print(paste("after mask-->bproj\n", sep=""))
conv=1/25.4
scal=1
bproj=calc(bproj,fun=function(x) x*conv*scal)
print(paste("after calculation-->bproj\n",sep=""))
```

```
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```

```
#Project LOCA historical data to MODFLOW model grid
bhist=projectRaster(bhist,n,method='ngb')
print(paste("after projection-->bhist\n", sep=""))
#Adjust values
bhist=mask(bhist,offsm,maskvalue=0,updatevalue=NA)
print(paste("after mask-->bhist\n", sep=""))
conv2=141.7323*24
scale2=1
bhist=calc(bhist,fun=function(x) x*conv2*scale2)
print(paste("after calculation-->bhist\n", sep=""))
#Adjust values of SFWMM rainfall data
wmmb=mask(wmmb,offsm,maskvalue=0,updatevalue=NA)
#Since it is missing values for cell #17705, assign it the values for cell #17704
wmmb[17705]=wmmb[17704]
#Get list of on-shore (active cells)
onsh=which(values(offsm!=0))
ngages=length(onsh)
#Only 1 run of interest
nruns=1
allprojs=projs[i,1]
#Initialize arrays
PU1=array(dim=c(ndaysh2, (ngages+3), nruns))
PU2=array(dim=c(ndays2, (ngages+3), nruns))
PUmoyr1=array(dim=c(nyrsh2,12,ngages,nruns))
PUyr1=array(dim=c(nyrsh2, ngages, nruns))
PUmol=array(dim=c(12, ngages, nruns))
PUmoyr2=array(dim=c(nyrs2,12,ngages,nruns))
PUyr2=array(dim=c(nyrs2, ngages, nruns))
PUmo2=array(dim=c(12,ngages,nruns))
PH1=array(dim=c(ndaysh2,(ngages+3)))
PHmoyr1=array(dim=c(nyrsh2,12,ngages))
PHyr1=array(dim=c(nyrsh2, ngages))
PHmol=array(dim=c(12, ngages))
#Populate the arrays
PU1[,(1:3),]=cbind(yrsnh2,mosnh2,daysnh2)
PU2[,(1:3),]=cbind(yrs2,mos2,days2)
PH1[, (1:3)]=cbind(yrsnh2,mosnh2,daysnh2)
PU1[, (4: (ngages+3)),]=aperm(getValues(bhist)[onsh,],c(2,1))
PU2[,(4:(ngages+3)),]=aperm(getValues(bproj)[onsh,],c(2,1))
PH1[, (4: (ngages+3))] = aperm (getValues (wmmb) [onsh,], c(2,1))
#Overall seasonal cycle boxplot
bproj gridave=cbind(yrs2,mos2,days2,cellStats(bproj,mean))
bhist gridave=cbind(yrsnh2,mosnh2,daysnh2,cellStats(bhist,mean))
wmmb gridave=cbind(yrsnh2,mosnh2,daysnh2,cellStats(wmmb,mean))
bproj_gridavemoyr=tapply(bproj_gridave[,4],
               list(bproj gridave[,1],bproj gridave[,2]),sum,na.rm=TRUE)
bhist gridavemoyr=tapply(bhist gridave[,4],
               list(bhist gridave[,1],bhist gridave[,2]),sum,na.rm=TRUE)
wmmb gridavemoyr=tapply(wmmb gridave[,4],
               list(wmmb_gridave[,1],wmmb_gridave[,2]),sum,na.rm=TRUE)
```

```
bproj gridavemo=tapply(bproj gridave[,4],
               list(bproj gridave[,2]),sum,na.rm=TRUE)/nyrs2
bhist gridavemo=tapply(bhist gridave[,4],
               list(bhist gridave[,2]),sum,na.rm=TRUE)/nyrsh2
wmmb_gridavemo=tapply(wmmb gridave[,4],
               list(wmmb gridave[,2]), sum, na.rm=TRUE) /nyrsh2
bproj gridavemod=by(data=bproj gridave[,4],INDICES=bproj gridave[,2],FUN=identity)
bhist gridavemod=by(data=bhist gridave[,4],INDICES=bhist gridave[,2],FUN=identity)
wmmb gridavemod=by(data=wmmb gridave[,4],INDICES=wmmb gridave[,2],FUN=identity)
png(paste("Allmodels moyrboxplot gridave curr.png", sep=""))
boxplot((bhist gridavemoyr),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1
,1,1,alpha=1),
        main=c(paste("Seasonal cycle of Precip. for entire domain", sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(min(bhist_gridavemoyr,bproj_gridavemoyr,wmmb_gridavemoyr),
                max(bhist_gridavemoyr,bproj_gridavemoyr,wmmb_gridavemoyr)))
boxplot((bhist gridavemoyr),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",box
wex=0.2, at=(1:12) - .3)
boxplot(wmmb gridavemoyr,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue", border="blue", boxwex=0.2, at=(1:12)+.3)
lines((1:12),bhist gridavemo,lwd=2,col="red")
lines((1:12),wmmb gridavemo,lwd=2,col="blue")
arid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Sim.:",startyrh2,"-",endyrh2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light blue"),
        lty=c(NA,NA),lwd=c(NA,NA),border=c("red","blue"),cex=0.6)
dev.off()
png(paste("Allmodels_modboxplot_gridave_curr.png", sep=""))
boxplot((bhist gridavemod),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1,
1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain", sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(0,
max(max(sapply(bhist_gridavemod,max,simplify="vector")),max(sapply(bproj gridavemod,ma
x,simplify="vector")),
                    max(sapply(wmmb gridavemod, max, simplify="vector")))))
boxplot((bhist gridavemod),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",boxw
ex=0.2, at=(1:12)-.3)
boxplot(wmmb gridavemod,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue", border="blue", boxwex=0.2, at=(1:12)+.3)
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Sim.:",startyrh2,"-",endyrh2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light blue"),
        lty=c(NA,NA),lwd=c(NA,NA),border=c("red","blue"),cex=0.6)
dev.off()
png(paste("Allmodels moyrboxplot gridave currfut.png", sep=""))
boxplot((bhist gridavemoyr),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1
,1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain", sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(min(bhist gridavemoyr,bproj gridavemoyr,wmmb gridavemoyr),
```

```
max(bhist gridavemoyr,bproj gridavemoyr,wmmb gridavemoyr)))
boxplot((bhist gridavemoyr),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",box
wex=0.2, at=(1:12) - .3)
boxplot((bproj gridavemoyr),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green", border="dark green", boxwex=0.2, at=(1:12))
boxplot(wmmb gridavemoyr,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue", border="blue", boxwex=0.2, at=(1:12)+.3)
lines((1:12),bhist_gridavemo,lwd=2,col="red")
lines((1:12),bproj_gridavemo,lwd=2,col="dark green")
lines((1:12),wmmb gridavemo,lwd=2,col="blue")
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft", legend=c(paste("Sim.:", startyrh2, "-
", endyrh2), paste("Sim.:", startyr2, "-", endyr2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light green","light
blue"),
        lty=c(NA,NA,NA),lwd=c(NA,NA,NA),border=c("red","dark green","blue"),cex=0.6)
dev.off()
png(paste("Allmodels_modboxplot_gridave_currfut.png", sep=""))
boxplot((bhist gridavemod),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1,
1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain", sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(0,
max(max(sapply(bhist gridavemod,max,simplify="vector")),max(sapply(bproj gridavemod,ma
x,simplify="vector")),
                    max(sapply(wmmb gridavemod,max,simplify="vector")))))
boxplot((bhist_gridavemod),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",boxw
ex=0.2, at=(1:1\overline{2})-.3)
boxplot((bproj gridavemod),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green", border="dark green", boxwex=0.2, at=(1:12))
boxplot(wmmb gridavemod,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue",border="blue",boxwex=0.2,at=(1:12)+.3)
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Sim.:",startyrh2,"-
", endyrh2), paste("Sim.:", startyr2, "-", endyr2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light green","light
blue"),
        lty=c(NA,NA,NA),lwd=c(NA,NA,NA),border=c("red","dark green","blue"),cex=0.6)
dev.off()
#For each active cell
for (i in 1:ngages) {
  print(paste("i = ",i,sep=""))
  PUi=as.matrix(PU1[,(i+3),])
  ffsU=apply(X=PUi,MARGIN=2,FUN=function(x) ecdf(x)(x))
  PUi2=as.matrix(PU2[,(i+3),])
  ffsU2=apply(X=PUi2,MARGIN=2,FUN=function(x) ecdf(x)(x))
  PHi=PH1[, (i+3)]
  ffsH=ecdf(PHi)(PHi)
  PHmoyr1[,,i]=tapply(PH1[,(i+3)],
               list(PH1[,1],PH1[,2]),sum,na.rm=TRUE)
  PHyr1[,i]=tapply(PH1[,(i+3)],list(PH1[,1]),sum,na.rm=TRUE)
  PHmo1[,i]=tapply(PH1[,(i+3)],list(PH1[,2]),sum,na.rm=TRUE)/nyrsh2
  #Only plot every 100 cells
  if (1%%100==0) {
```

```
print(paste("toplot"))
    png(paste("Allmodels CDFs gage",i," ",i," current.png",sep=""))
    matplot(PUi,ffsU,xlim=c(0,max(max(PUi,PHi))),cex=0.1,main=paste("CDFs for gage
",i," (",i,")",sep=""),
            xlab="Precip. (in)",ylab="Prob. exc.")
    points(PHi,ffsH,cex=0.1)
    legend("bottomright",legend=c(paste("Sim. (colors):",startyrh2,"-
",endyrh2),paste("Hist.:",startyrh2,"-",endyrh2)),
           pch=c(5,1),col=c("red","black"))
    grid()
    dev.off()
  }
  for (m in 1:nruns) {
    print(paste("m = ",m,sep=""))
    PUmoyr1[,,i,m]=tapply(PU1[,(i+3),m],
                   list(PU1[,1,m],
                   PU1[,2,m]),sum,na.rm=TRUE)
    PUyr1[,i,m]=tapply(PU1[,(i+3),m],
                list(PU1[,1,m]),sum,na.rm=TRUE)
    PUmo1[,i,m]=tapply(PU1[,(i+3),m],
                list(PU1[,2,m]),sum,na.rm=TRUE)/nyrsh2
    PUmoyr2[,,i,m]=tapply(PU2[,(i+3),m],
                   list(PU2[,1,m],
                   PU2[,2,m]),sum,na.rm=TRUE)
    PUyr2[,i,m]=tapply(PU2[,(i+3),m],
                list(PU2[,1,m]),sum,na.rm=TRUE)
    PUmo2[,i,m]=tapply(PU2[,(i+3),m],
                list(PU2[,2,m]),sum,na.rm=TRUE)/nyrs2
    #Only plot every 100 cells
    if (i%%100==0) {
      print(paste("toplot"))
png(paste("Model ",m," QQplot CDF gage",i," ",i," currfut.png",sep=""),height=960,poin
tsize=20)
      nf=layout((c(1,2,3)),heights=c(5,5,5))
qqplot(PHi,PUi[,m],xlim=c(0,max(max(PHi,PUi[,m]))),ylim=c(0,max(max(PHi,PUi[,m]))),
             main=c(paste("QQplot for gage ",i," (",i,")",sep=""),
             paste("m=",m," (",allprojs[m],"), ",startyrh2,"-",endyrh2,sep="")),
             xlab=paste("Hist. Precip. (in):",startyrh2,"-",endyrh2),ylab=paste("Sim.
Precip. (in):",startyrh2,"-",endyrh2))
      lines(c(0,max(max(PHi,PUi[,m]))),c(0,max(max(PHi,PUi[,m]))),col="red")
legend("topleft",legend=c("QQ","1:1"),pch=c(1,NA),col=c("black","red"),lty=c(NA,1))
      grid()
qqplot(PUi[,m],PUi2[,m],xlim=c(0,max(max(PUi[,m],PUi2[,m]))),ylim=c(0,max(max(PUi[,m],
PUi2[,m]))),
             main=c(paste("QQplot for gage ",i," (",i,")",sep=""),
paste("m=",m," (",allprojs[m],"), ",startyrh2,"-",endyrh2,sep="")),
             xlab=paste("Sim. Precip. (in):",startyrh2,"-",endyrh2),ylab=paste("Sim.
Precip. (in):",startyr2,"-",endyr2))
      lines(c(0,max(max(PUi[,m],PUi2[,m]))),c(0,max(max(PUi[,m],PUi2[,m]))),col="red")
legend("topleft",legend=c("QQ","1:1"),pch=c(1,NA),col=c("black","red"),lty=c(NA,1))
      grid()
```

```
plot(PUi[,m],ffsU[,m],xlim=c(0,max(PUi[,m],PUi2[,m],PHi)),cex=0.2,main="CDF",xlab="Pre
cip. (in)",
           ylab="Prob. exc.", col="red")
      points(PUi2[,m],ffsU2[,m],cex=0.2,col="green")
      points(PHi,ffsH,cex=0.2)
      legend("bottomright",legend=c(paste("Sim.:",startyrh2,"-
", endyrh2), paste("Sim.:", startyr2, "-", endyr2),
             paste("Hist.:",startyrh2,"-",endyrh2)),
             pch=1,col=c("red","green","black"))
      grid()
      dev.off()
    }
  }#end m
  #Only plot every 100 cells
  if (i%%100==0) {
    print(paste("toplot"))
    #Create boxplots for seasonal cycle and inter-annual variability
    png(paste("Allmodels_moboxplot_gage",i,"_",i," currfut.png",sep=""))
boxplot(t(PUmo1[,i,]),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1,1,1,a
lpha=1),
            main=c(paste("Seasonal cycle of Precip. for gage ",i," (",i,")", sep="")),
            xlab="Month",ylab="Precip. (in)",
ylim=c(min(PUmo1[,i,],PUmo2[,i,],PHmo1[,i]),max(PUmo1[,i,],PUmo2[,i,],PHmo1[,i])))
boxplot(t(PUmo1[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="red",border="red",boxwex=0.2
5, at = (1:12) - .15)
    boxplot(t(PUmo2[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green", border="light green", boxwex=0.25, at=(1:12)+.15)
    lines((1:12)-0.15, PHmo1[,i], lwd=2)
    grid()
    abline(v=1:12,lty=3,col="grey")
    legend("topleft",legend=c(paste("Sim.:",startyrh2,"-
", endyrh2), paste("Sim.:", startyr2, "-", endyr2),
           paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("red","light green",NA),
           lty=c(NA,NA,1),lwd=c(NA,NA,2),border=c("black","black",NA),cex=0.6)
    dev.off()
    png(paste("Allmodels moyrboxplot gage",i," ",i," currfut.png",sep=""))
boxplot((PUmoyr1[,,i,]),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1,1,1
,alpha=1),
            main=c(paste("Seasonal cycle of Precip. for gage ",i," (",i,")", sep="")),
            xlab="Month",ylab="Precip. (in)",
ylim=c(min(PUmoyr1[,,i,],PUmoyr2[,,i,],PHmoyr1[,,i]),max(PUmoyr1[,,i,],PUmoyr2[,,i,],P
Hmoyr1[,,i])))
boxplot((PUmoyr1[,,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="red",border="red",boxwex=0
.2, at = (1:12) - .3)
    boxplot((PUmoyr2[,,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green",border="light green",boxwex=0.2,at=(1:12))
boxplot(PHmoyr1[,,i],xaxt="n",yaxt="n",add=TRUE,boxfill="black",border="black",boxwex=
0.2, at = (1:12) + .3)
    arid()
    abline(v=1:12,ltv=3,col="grev")
    legend("topleft",legend=c(paste("Sim.:",startyrh2,"-
", endyrh2), paste("Sim.:", startyr2, "-", endyr2),
          paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("red","light green","black"),
```

```
lty=c(NA, NA, NA), lwd=c(NA, NA, NA), border=c("red", "light
green", "black"), cex=0.6)
    dev.off()
png(paste("Allmodels yrboxplot gage",i," ",i," currfut.png", sep=""), width=960, pointsiz
e=20)
boxplot(t(PUyr1[,i,]),names=allyrsh2,xlim=c(0.5,nyrsh2+0.5),boxfill=rgb(1,1,1,alpha=1)
, border=rgb(1,1,1,alpha=1),
            main=c(paste("Inter-annual var. of Precip. for gage ",i,"
(",i,")", sep="")),
            xlab="Year",ylab="Precip. (in)",
ylim=c(min(PUyr1[,i,],PUyr2[,i,],PHyr1[,i]),max(PUyr1[,i,],PUyr2[,i,],PHyr1[,i])))
boxplot(t(PUyr1[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="red",border="red",boxwex=0.2
5, at=(1:nyrsh2)-0.15)
    boxplot(t(PUyr2[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green",border="light green",boxwex=0.25,at=(1:nyrsh2)+0.15)
    lines((1:nyrsh2)-0.15,PHyr1[,i],lwd=2)
    grid()
    abline(v=allyrsh2,lty=3,col="grey")
    legend("topleft",legend=c(paste("Sim.:",startyrh2,"-
", endyrh2), paste("Sim.:", startyr2, "-", endyr2, "shifted"),
           paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("red","light green",NA),
           lty=c(NA,NA,1),lwd=c(NA,NA,2),border=c("black","black",NA),cex=0.6)
    dev.off()
  }
}#end i
#Save unadjusted data (pre-BC)
save (PU1, PUmoyr1, PUyr1, PUmo1, PU2, PUmoyr2, PUyr2, PUmo2, PH1, PHmoyr1, PHyr1, PHmo1, file="Pre
BC Precip.RData")
#Do AQDM or MQDM Bias Correction here
#Initialize BC matrices to uncorrected ones
PUBC1=PU1
PUBC2=PU2
PUBCmoyr1=PUmoyr1
PUBCyr1=PUyr1
PUBCmo1=PUmo1
PUBCmoyr2=PUmoyr2
PUBCvr2=PUvr2
PUBCmo2=PUmo2
if (file.exists("Inf cells.txt")) {
  file.remove("Inf cells.txt")
}
infc=0
l=list()
for (i in 1:ngages) {
  err1=0
  print(paste("i = ",i,sep=""))
  #This gives values for the month
  Ubymo=lapply(seq len(nruns), FUN=function(x) by(data=PU1[,(i+3),x],
                                               INDICES=PU1[,2,x],FUN=identity))
```

```
U2bymo=lapply(seq len(nruns), FUN=function(x) by(data=PU2[,(i+3),x],
                                               INDICES=PU2[,2,x],FUN=identity))
  H1bymo=by(data=PH1[,(i+3)],INDICES=PH1[,2],FUN=identity)
  #This gives sorted values for the month
  #sortedUbymo=lapply(seq len(nruns),FUN=function(x) by(data=PU1[,(i+3),x],
                                                INDICES=PU1[,2,x],FUN=sort))
  #This gives CDF value (non-exceedance prob.) for a particular value with a month's
CDF
  #ffsUbymo=lapply(seq len(nruns),FUN=function(x) by(data=PU1[,(i+3),x],
                                                INDICES=PU1[,2,x],FUN=function(x)
ecdf(x)(x))
  #This can be used to get quantile of interest
  #ecdfUbymo=lapply(seq len(nruns),FUN=function(x) by(data=PU1[,(i+3),x],
  #
                                                INDICES=PU1[,2,x],FUN=function(x)
ecdf(x))
  #ecdfU2bymo=lapply(seq len(nruns),FUN=function(x) by(data=PU2[,(i+3),x],
  #
                                                INDICES=PU2[,2,x],FUN=function(x)
ecdf(x)))
  #ecdfH1bymo=by(data=PH1[,(i+3)],INDICES=PH1[,2],FUN=function(x) ecdf(x))
  for (m in 1:nruns) {
   print(paste("m = ",m,sep=""))
    #MODM
    PUBC1[, (i+3),m]=mapply(function(mo,xmc) {
                                 if (xmc==0 ||
(quantile(H1bymo[mo][[1]],ecdf(Ubymo[[m]][mo][[1]])(xmc)))<=0.0001) {
                                   0
                                 } else {
xmc*(quantile(H1bymo[mo][[1]],ecdf(Ubymo[[m]][mo][[1]])(xmc)))/
(quantile(Ubymo[[m]][mo][[1]],ecdf(Ubymo[[m]][mo][[1]])(xmc)))
                                 } 
} 

                            mo=PU1[,2,m],xmc=PU1[,(i+3),m])
    if (length(which(PUBC1[,(i+3),m]==Inf))) {
      cat(paste("PUBC1: i",i,"\n"),file="Inf cells.txt",append=TRUE)
      arr=which(PUBC1[,(i+3),m]==Inf)
      PUBC1[arr, (i+3), m]=0
      err1=0 #used to be set to 1, but now set to 0 since Inf values changed to 0 (see
comment at bottom)
    }
    #AODM
    #PUBC1[, (i+3),m]=mapply(function(mo,xmc) {
xmc+(quantile(H1bymo[mo][[1]],ecdf(Ubymo[[m]][mo][[1]])(xmc)))-
(quantile(Ubymo[[m]][mo][[1]],ecdf(Ubymo[[m]][mo][[1]])(xmc)))
    #
                                  },
    #
                             mo=PU1[,2,m],xmc=PU1[,(i+3),m])
    #PUBC1[PUBC1[, (i+3),m]<0, (i+3),m]=0</pre>
    #MQDM
    PUBC2[,(i+3),m]=mapply(function(mo,xmp) {
```

```
if (xmp==0 ||
(quantile(H1bymo[mo][[1]],ecdf(U2bymo[[m]][mo][[1]])(xmp)))<=0.0001) {
                                   0
                                 } else {
xmp*(quantile(H1bymo[mo][[1]],ecdf(U2bymo[[m]][mo][[1]])(xmp)))/
(quantile(Ubymo[[m]][mo][[1]],ecdf(U2bymo[[m]][mo][[1]])(xmp)))
                                 }},
                            mo=PU2[,2,m],xmp=PU2[,(i+3),m])
    if (length(which(PUBC2[,(i+3),m]==Inf))) {
      infc = infc+1
      cat(paste("PUBC2: i",i,"\n"),file="Inf_cells.txt",append=TRUE)
      arr=which(PUBC2[,(i+3),m]==Inf)
      mos=PUBC2[arr,2,1]
      myl=list("cell"=i,"errarray"=arr,"xmp"=PU2[arr,(i+3),m],"mos"=mos,
"qq1"=(quantile(H1bymo[mos][[1]],ecdf(U2bymo[[m]][mos][[1]])(PU2[arr,(i+3),m]))),
"qq2"=(quantile(Ubymo[[m]][mos][[1]],ecdf(U2bymo[[m]][mos][[1]])(PU2[arr,(i+3),m]))))
      l[[infc]]=myl
      PUBC2[arr, (i+3), m]=0
      err1=0 #used to be set to 1, but now set to 0 since Inf values changed to 0 (see
comment at bottom)
    #AQDM
    #PUBC2[,(i+3),m]=mapply(function(mo,xmp) {
xmp+(quantile(H1bymo[mo][[1]],ecdf(U2bymo[[m]][mo][[1]])(xmp)))-
(quantile(Ubymo[[m]][mo][[1]],ecdf(U2bymo[[m]][mo][[1]])(xmp)))
    #
                                  },
    #
                             mo=PU2[,2,m],xmp=PU2[,(i+3),m])
    #PUBC2[PUBC2[, (i+3),m]<0, (i+3),m]=0</pre>
    ffsUBC1=ecdf(PUBC1[,(i+3),m])(PUBC1[,(i+3),m])
    ffsUBC2=ecdf(PUBC2[,(i+3),m])(PUBC2[,(i+3),m])
    ffsH=ecdf(PH1[,(i+3)])(PH1[,(i+3)])
    PUBCmoyr1[,,i,m]=tapply(PUBC1[,(i+3),m],
                   list(PUBC1[,1,m],
                   PUBC1[,2,m]),sum,na.rm=TRUE)
    PUBCyr1[,i,m]=tapply(PUBC1[,(i+3),m],
                list(PUBC1[,1,m]),sum,na.rm=TRUE)
    PUBCmo1[,i,m]=tapply(PUBC1[,(i+3),m],
                list(PUBC1[,2,m]),sum,na.rm=TRUE)/nyrsh2
    PUBCmoyr2[,,i,m]=tapply(PUBC2[,(i+3),m],
                   list(PUBC2[,1,m],
                   PUBC2[,2,m]),sum,na.rm=TRUE)
    PUBCyr2[,i,m]=tapply(PUBC2[,(i+3),m],
                list(PUBC2[,1,m]),sum,na.rm=TRUE)
    PUBCmo2[,i,m]=tapply(PUBC2[,(i+3),m],
                list(PUBC2[,2,m]),sum,na.rm=TRUE)/nyrs2
    #Now generate corrected plots
    #Only plot every 100 cells
    if (i%%100==0 & err1==0) {
      print(paste("toplot"))
```

```
png(paste("Model ",m," QQplot CDF gage",i," ",i," currfut BC.png",sep=""),height=960,p
ointsize=20)
      nf=layout((c(1,2,3)), heights=c(5,5,5))
qqplot(PH1[,(i+3)],PUBC1[,(i+3),m],xlim=c(0,max(max(PH1[,(i+3)],PUBC1[,(i+3),m]))),yli
m=c(0,max(max(PH1[,(i+3)],PUBC1[,(i+3),m]))),
             main=c(paste("Post-BC QQplot for gage ",i," (",i,")",sep=""),
             paste("m=",m," (",allprojs[m],"), ",startyrh2,"-",endyrh2,sep="")),
             xlab=paste("Hist. Precip. (in):",startyrh2,"-",endyrh2),ylab=paste("BC
Sim. Precip. (in):",startyrh2,"-",endyrh2))
lines(c(0,max(max(PH1[,(i+3)],PUBC1[,(i+3),m]))),c(0,max(max(PH1[,(i+3)],PUBC1[,(i+3),
m]))),col="red")
legend("topleft",legend=c("QQ","1:1"),pch=c(1,NA),col=c("black","red"),lty=c(NA,1))
      grid()
qqplot(PUBC1[,(i+3),m],PUBC2[,(i+3),m],xlim=c(0,max(max(PUBC1[,(i+3),m],PUBC2[,(i+3),m
]))),
             ylim=c(0,max(max(PUBC1[,(i+3),m],PUBC2[,(i+3),m]))),
             main=c(paste("Post B-C QQplot for gage ",i," (",i,")",sep=""),
             paste("m=",m," (",allprojs[m],"), ",startyrh2,"-",endyrh2,sep="")),
             xlab=paste("BC Sim. Precip. (in):",startyrh2,"-",endyrh2),ylab=paste("BC
Sim. Precip. (in):",startyr2,"-",endyr2))
lines(c(0,max(max(PUBC1[,(i+3),m],PUBC2[,(i+3),m]))),c(0,max(max(PUBC1[,(i+3),m],PUBC2
[,(i+3),m]))),col="red")
legend("topleft",legend=c("QQ","1:1"),pch=c(1,NA),col=c("black","red"),lty=c(NA,1))
      grid()
plot(PUBC1[,(i+3),m],ffsUBC1,xlim=c(0,max(PUBC1[,(i+3),m],PUBC2[,(i+3),m],PH1[,(i+3)])
),cex=0.2,
           main="Post-BC CDF",xlab="Precip. (in)",ylab="Prob. exc.",col="red")
      points(PUBC2[,(i+3),m],ffsUBC2,cex=0.2,col="green")
      points(PH1[,(i+3)],ffsH,cex=0.2)
      legend("bottomright",legend=c(paste("BC Sim.:",startyrh2,"-",endyrh2),paste("BC
Sim.:",startyr2,"-",endyr2),
             paste("Hist.:", startyrh2, "-", endyrh2)),
             pch=1,col=c("red","green","black"))
      grid()
      dev.off()
    }
 }#end m
  #Only plot every 100 cells
 if (i%%100==0 & err1==0) {
   print(paste("toplot"))
    #Create boxplots for seasonal cycle and inter-annual variability
    png(paste("Allmodels_moboxplot_gage",i,"_",i,"_currfut_BC.png",sep=""))
boxplot(t(PUBCmo1[,i,]),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1,1,1
,alpha=1),
            main=c(paste("Post-BC Seas. cycle of Precip.-gage ",i," (",i,")",sep="")),
            xlab="Month",ylab="Precip. (in)",
ylim=c(min(PUBCmo1[,i,],PUBCmo2[,i,],PHmo1[,i]),max(PUBCmo1[,i,],PUBCmo2[,i,],PHmo1[,i
1)))
```

```
boxplot(t(PUBCmol[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="red",border="red",boxwex=0
.25.at = (1:12) - .15)
    boxplot(t(PUBCmo2[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green", border="light green", boxwex=0.25, at=(1:12)+.15)
    lines((1:12)-0.15, PHmo1[,i], lwd=2)
    grid()
    abline(v=1:12,lty=3,col="grey")
    legend("topleft",legend=c(paste("BC Sim.:",startyrh2,"-",endyrh2),paste("BC
Sim.:",startyr2,"-",endyr2),
           paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("red","light green",NA),
           lty=c(NA,NA,1),lwd=c(NA,NA,2),border=c("black","black",NA),cex=0.6)
    dev.off()
   png(paste("Allmodels moyrboxplot gage",i," ",i," currfut BC.png",sep=""))
boxplot((PUBCmoyr1[,,i,]),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb(1,1
,1,alpha=1),
            main=c(paste("Seasonal cycle of Precip. for gage ",i," (",i,")",sep="")),
            xlab="Month",ylab="Precip. (in)",
ylim=c(min(PUBCmoyr1[,,i,],PUBCmoyr2[,,i,],PHmoyr1[,,i]),max(PUBCmoyr1[,,i,],PUBCmoyr2
[,,i,],PHmoyr1[,,i])))
boxplot((PUBCmoyr1[,,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="red",border="red",boxwex
=0.2, at=(1:12) - .3)
    boxplot((PUBCmoyr2[,,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green",border="light green",boxwex=0.2,at=(1:12))
boxplot(PHmoyr1[,,i],xaxt="n",yaxt="n",add=TRUE,boxfill="black",border="black",boxwex=
0.2, at = (1:12) + .3)
    grid()
    abline(v=1:12,lty=3,col="grey")
    legend("topleft",legend=c(paste("BC Sim.:",startyrh2,"-",endyrh2),paste("BC
Sim.:",startyr2,"-",endyr2),
          paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("red","light green","black"),
           lty=c(NA, NA, NA), lwd=c(NA, NA, NA), border=c("red", "light
green", "black"), cex=0.6)
    dev.off()
png(paste("Allmodels yrboxplot gage",i," ",i," currfut BC.png", sep=""), width=960, point
size=20)
boxplot(t(PUBCyr1[,i,]),names=allyrsh2,xlim=c(0.5,nyrsh2+0.5),boxfill=rgb(1,1,1,alpha=
1), border=rgb(1,1,1,alpha=1),
           main=c(paste("Post-BC Inter-annual var. of Precip.-gage ",i,"
(",i,")",sep="")),
            xlab="Year",ylab="Precip. (in)",
ylim=c(min(PUBCyr1[,i,],PUBCyr2[,i,],PHyr1[,i]),max(PUBCyr1[,i,],PUBCyr2[,i,],PHyr1[,i
1)))
boxplot(t(PUBCyr1[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="red",border="red",boxwex=0
.25, at=(1:nyrsh2)-0.15)
    boxplot(t(PUBCyr2[,i,]),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green",border="light green",boxwex=0.25,at=(1:nyrsh2)+0.15)
    lines((1:nyrsh2)-0.15, PHyr1[,i], lwd=2)
    arid()
   abline(v=allyrsh2,lty=3,col="grey")
    legend("topleft",legend=c(paste("BC Sim.:",startyrh2,"-",endyrh2),paste("BC
Sim.:",startyr2,"-",endyr2,"shifted"),
           paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("red","light green",NA),
```

```
lty=c(NA,NA,1),lwd=c(NA,NA,2),border=c("black","black",NA),cex=0.6)
    dev.off()
  }
}#end i
#Save list of cells with issues
save(l,file="List of list inf cells.RData")
#The list shows that the numerator (Xoc) is almost 0 (0.0001-0.007 in/d) when the
denominator (Xmc) is zero.
#Therefore, for all intents and purposes, one can make the Inf values equal to 0. Re-
run the code above setting Inf to 0.
#Save adjusted (post-BC) file
save (PUBC1, PUBCmoyr1, PUBCyr1, PUBCmo1, PUBC2, PUBCmoyr2, PUBCyr2, PUBCmo2, PH, PH1, PHmoyr1, PH
yr1, PHmo1,
     file="PostBC MQDM Precip.RData")
#Populate a new brick with the new post-BC data and save to ncfile to read in python
and create the binary files
onshrc=rowColFromCell(bhist,onsh)
bhbc=array(dim=c(nrow(bhist),ncol(bhist),nlayers(bhist)))
for (g in 1:ngages) {
  print(paste("g=",g))
  bhbc[onshrc[g,1],onshrc[g,2],]=PUBC1[,(g+3),1]
}
bhistbc=brick(bhbc,crs="+proj=utm +zone=17 +ellps=GRS80 +datum=NAD83 +units=m
+no defs")
extent(bhistbc) = extent(wmmbm)
writeRaster(bhistbc,paste(fns[56]," histBC Precip.nc",sep=""),format="CDF",varname="pr
", varunit="in/day",
            longname="Bias-corrected historical
precipitation",xname="x",yname="y",zname="t",zunit=paste("days since",startyrh2),
            NAflag=-999)
bpbc=array(dim=c(nrow(bproj),ncol(bproj),nlayers(bproj)))
bpbc=array(dim=c(nrow(bhist),ncol(bhist),nlayers(bproj)))
for (g in 1:ngages) {
  print(paste("g=",g))
  bpbc[onshrc[g,1],onshrc[g,2],]=PUBC2[,(g+3),1]
}
bprojbc=brick(bpbc,crs="+proj=utm +zone=17 +ellps=GRS80 +datum=NAD83 +units=m
+no defs")
extent(bprojbc) = extent(wmmbm)
writeRaster(bprojbc,paste(fns[56]," projBC Precip.nc",sep=""),format="CDF",varname="pr
", varunit="in/day",
            longname="Bias-corrected projected
precipitation",xname="x",yname="y",zname="t",zunit=paste("days since",startyr2),
            NAflag=-999)
save(bhistbc,bprojbc,file="PostBC MQDM Precip bricks.RData")
#Create levelplots for the bias-corrected model projection
print(paste("i=",i))
#Create levelplot of histmbc
histmbc=calc(bhistbc,mean)
meanhmbc=round(nds2*cellStats(histmbc,mean),2)
png(paste("LOCA mean rainfall hist ",fns[i]," dailyBC.png",sep=""))
print(levelplot(histmbc*nds2,margin=FALSE,at=seq(minz,maxz,1),
          main=paste("Daily B.C. LOCA rainfall (",meanhmbc," in/yr)\n",
          startyrh2,"-",endyrh2," (",fns[i],")",sep=""),
```

```
xlab="X (m) UTM17N, NAD83", ylab="Y (m) UTM17N, NAD83"))
dev.off()
#Create levelplot of projmdbc
projmdbc=calc(bprojbc,mean)
meanpmdbc=round(nds2*cellStats(projmdbc,mean),2)
png(paste("LOCA_mean_rainfall_proj_",fns[i],"_dailyBC.png",sep=""))
print(levelplot(projmdbc*nds2,margin=FALSE,at=seq(minz,maxz,1),
          main=paste("Daily B.C. LOCA rainfall (",meanpmdbc," in/yr)\n",
startyr2,"-",endyr2," (",fns[i],")",sep=""),
          xlab="X (m) UTM17N, NAD83", ylab="Y (m) UTM17N, NAD83"))
dev.off()
png(paste("LOCA projbc to SFWMM ratio ",fns[i]," dailyBC.png",sep=""))
print(levelplot(projmdbc/wmmbm, col.regions=brewer.rdbu(21), margin=FALSE,
         at = seq(0.70, 1.30, 0.025),
         main=paste("Daily B.C.",fns[i]," (",startyr2,"-",endyr2,")\n",
         "to SFWMM rainfall (", startyrh, "-", endyrh, ")", sep=""),
         xlab="X (m) UTM17N, NAD83", ylab="Y (m) UTM17N, NAD83", cex=0.5))
dev.off()
png(paste("LOCA_projbc-SFWMM_", fns[i], "_dailyBC.png", sep=""))
print (levelplot (nds2* (projmdbc-wmmbm), col.regions=brewer.rdbu (29), margin=FALSE,
          at = seq(-16, 16, 1),
          main=paste("Daily B.C.",fns[i]," (",startyr2,"-",endyr2,")\n",
          "- SFWMM rainfall (",startyrh,"-",endyrh,") (",
round(nds2*cellStats((projmdbc-wmmbm),mean),2)," in/yr)",sep=""),
          xlab="X (m) UTM17N, NAD83",ylab="Y (m) UTM17N, NAD83",cex=0.5))
dev.off()
#Overall seasonal cycle boxplot
bprojdbc gridave=cbind(yrs2,mos2,days2,cellStats(bprojbc,mean))
bhistdbc gridave=cbind(yrsnh2,mosnh2,daysnh2,cellStats(bhistbc,mean))
wmmb_gridave=cbind(yrsnh2,mosnh2,daysnh2,cellStats(wmmb,mean))
bprojdbc_gridavemoyr=tapply(bprojdbc_gridave[,4],
                list(bprojdbc_gridave[,1],bprojdbc_gridave[,2]),sum,na.rm=TRUE)
bhistdbc gridavemoyr=tapply(bhistdbc gridave[,4],
                list (bhistdbc gridave[,1], bhistdbc gridave[,2]), sum, na.rm=TRUE)
wmmb gridavemoyr=tapply(wmmb gridave[,4],
                list(wmmb_gridave[,1],wmmb_gridave[,2]),sum,na.rm=TRUE)
bprojdbc gridavemo=tapply(bprojdbc gridave[,4],
                list(bprojdbc gridave[,2]),sum,na.rm=TRUE)/nyrs2
bhistdbc_gridavemo=tapply(bhistdbc_gridave[,4],
                list(bhistdbc_gridave[,2]),sum,na.rm=TRUE)/nyrsh2
wmmb gridavemo=tapply(wmmb gridave[,4],
                list(wmmb gridave[,2]), sum, na.rm=TRUE)/nyrsh2
bprojdbc gridavemod=by(data=bprojdbc gridave[,4],INDICES=bprojdbc gridave[,2],FUN=iden
titv)
bhistdbc gridavemod=by(data=bhistdbc gridave[,4],INDICES=bhistdbc gridave[,2],FUN=iden
tity)
wmmb gridavemod=by(data=wmmb gridave[,4],INDICES=wmmb gridave[,2],FUN=identity)
png(paste("Allmodels moyrboxplot gridave curr dailyBC.png", sep=""))
```

```
boxplot((bhistdbc gridavemoyr),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rg
b(1,1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain", sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(min(bhistdbc gridavemoyr,bprojdbc gridavemoyr,wmmb gridavemoyr),
                max(bhistdbc gridavemoyr,bprojdbc gridavemoyr,wmmb gridavemoyr)))
boxplot((bhistdbc gridavemoyr),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",
boxwex=0.2, at=(1:12)-.3)
boxplot(wmmb gridavemoyr,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue",border="blue",boxwex=0.2,at=(1:12)+.3)
lines((1:12), bhistdbc gridavemo, lwd=2, col="red")
lines((1:12),wmmb gridavemo,lwd=2,col="blue")
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Daily B.C. Sim.:",startyrh2,"-",endyrh2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light blue"),
        lty=c(NA,NA),lwd=c(NA,NA),border=c("red","blue"),cex=0.6)
dev.off()
png(paste("Allmodels modboxplot gridave curr dailyBC.png", sep=""))
boxplot((bhistdbc gridavemod),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rgb
(1,1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain", sep="")),
         xlab="Month",ylab="Precip. (in)",
         vlim=c(0,
max(max(sapply(bhistdbc gridavemod,max,simplify="vector")),max(sapply(bprojdbc gridave
mod, max, simplify="vector")),
                    max(sapply(wmmb gridavemod, max, simplify="vector")))))
boxplot((bhistdbc gridavemod),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",b
oxwex=0.2, at=(1:12)-.3)
boxplot(wmmb gridavemod,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue", border="blue", boxwex=0.2, at=(1:12)+.3)
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Daily Sim.:",startyrh2,"-",endyrh2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light blue"),
        lty=c(NA,NA),lwd=c(NA,NA),border=c("red","blue"),cex=0.6)
dev.off()
png(paste("Allmodels moyrboxplot gridave currfut dailyBC.png", sep=""))
boxplot((bhistdbc gridavemoyr),xlim=c(0.5,12+0.5),boxfill=rgb(1,1,1,alpha=1),border=rg
b(1,1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain",sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(min(bhistdbc gridavemoyr,bprojdbc gridavemoyr,wmmb gridavemoyr),
                max(bhistdbc gridavemoyr,bprojdbc gridavemoyr,wmmb gridavemoyr)))
boxplot((bhistdbc gridavemoyr),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",
boxwex=0.2, at=(1:12)-.3)
boxplot((bprojdbc gridavemoyr),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green", border="dark green", boxwex=0.2, at=(1:12))
boxplot(wmmb_gridavemoyr,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue", border="blue", boxwex=0.2, at=(1:12)+.3)
lines((1:12),bhistdbc gridavemo,lwd=2,col="red")
lines((1:12),bprojdbc gridavemo,lwd=2,col="dark green")
lines((1:12),wmmb gridavemo,lwd=2,col="blue")
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Daily B.C. Sim.:",startyrh2,"-",endyrh2),paste("Daily
B.C. Sim.:", startyr2, "-", endyr2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light green","light
blue"),
        lty=c(NA,NA,NA),lwd=c(NA,NA,NA),border=c("red","dark green","blue"),cex=0.6)
dev.off()
```

```
png(paste("Allmodels modboxplot gridave currfut dailyBC.png", sep=""))
boxplot((bhistdbc gridavemod), xlim=c(0.5,12+0.5), boxfill=rgb(1,1,1,alpha=1), border=rgb
(1,1,1,alpha=1),
         main=c(paste("Seasonal cycle of Precip. for entire domain",sep="")),
         xlab="Month",ylab="Precip. (in)",
         ylim=c(0,
max(max(sapply(bhistdbc gridavemod,max,simplify="vector")),max(sapply(bprojdbc gridave
mod,max,simplify="vector")),
                    max(sapply(wmmb gridavemod, max, simplify="vector")))))
boxplot((bhistdbc gridavemod),xaxt="n",yaxt="n",add=TRUE,boxfill="pink",border="red",b
oxwex=0.2, at=(1:12)-.3)
boxplot((bprojdbc gridavemod),xaxt="n",yaxt="n",add=TRUE,boxfill="light
green",border="dark green",boxwex=0.2,at=(1:12))
boxplot(wmmb gridavemod,xaxt="n",yaxt="n",add=TRUE,boxfill="light
blue", border="blue", boxwex=0.2, at=(1:12)+.3)
grid()
abline(v=1:12,lty=3,col="grey")
legend("topleft",legend=c(paste("Daily B.C. Sim.:",startyrh2,"-",endyrh2),paste("Daily
B.C. Sim.:", startyr2, "-", endyr2),
      paste("Hist.:",startyrh2,"-",endyrh2)),fill=c("pink","light green","light
blue"),
        lty=c(NA,NA,NA),lwd=c(NA,NA,NA),border=c("red","dark green","blue"),cex=0.6)
dev.off()
```

```
}
```

References

Cannon A. J., Stephen R. S., Murdock T. Q. 2015. Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? Journal of Climate 28:6938-6959.

Codiga, D. L., 2011. Unified Tidal Analysis and Prediction Using the UTide Matlab Functions. Technical Report 2011-01. Graduate School of Oceanography, University of Rhode Island, Narragansett, RI. 59pp. <u>ftp://www.po.gso.uri.edu/</u> pub/downloads/codiga/pubs/2011Codiga-UTide-Report.pdf

Hwang, S. and Graham, W. D. 2013. Development and comparative evaluation of a stochastic analog method to downscale daily GCM precipitation, Hydrol. Earth Syst. Sci., 17, 4481–4502, doi:10.5194/hess-17-4481-2013.

Irizarry M., Obeysekera J., Dessalegne T. 2016. Determination of Future Intensity-Duration-Frequency Curves for Level of Service Planning Projects. Task 2 - Deliverable 2.1 to SFWMD - Conduct an extreme rainfall analysis in climate model outputs to determine temporal changes in IDF curves.

Maurer E. P., Brekke L., Pruitt T., Duffy P. B. 2007. Fine-resolution climate projections enhance regional climate change impact studies. Eos Trans. AGU, 88(47), 504.

Panofsky H. W., Brier G. W. 1968. Some Applications of Statistics to Meteorology. The Pennsylvania State University Press: Philadelphia.

Pierce D. W., Cayan D. R., Thrasher B. L. 2014. Statistical downscaling using Localized Constructed Analogs (LOCA). Journal of Hydrometeorology 15:2558–2585.

Reclamation. 2013. Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with preceding Information, and Summary of User Needs. U.S. Department of the Interior, Bureau of Reclamation, Technical Services Center, Denver, Colorado. 47pp.

Southeast Florida Regional Climate Change Compact Sea Level Rise Work Group (Compact). October 2015. Unified Sea Level Rise Projection for Southeast Florida. A document prepared for the Southeast Florida Regional Climate Change Compact Steering Committee. 35 p. At http://www.southeastfloridaclimatecompact.org/wp-content/uploads/2015/10/2015-Compact-Unified-Sea-Level-Rise-Projection.pdf

Appendix III. Future Ocean Boundary Condition (Task I)

Future ocean boundary condition

The Miami-Dade MODFLOW model uses daily historical water level data at Virginia Key (ft NAVD88) for the period 1996-2010 as the ocean boundary condition. The historical water level data includes both tidal forcing and sub-tidal forcing (i.e. meteorological effects, current effects, etc.), as well as land subsidence effects which are considered minimal in south Florida. Future (2055-2069) ocean boundary conditions reflecting sea level rise for modeling were obtained from the Unified Sea Level Rise (SLR) Projections developed by the Southeast Florida Regional Climate Change Compact (2015) for both the IPCC AR5 RCP8.5 Median curve and the USACE High curve as recommended by FIU. These future conditions reflect the effect of sea level rise on the predicted tides (based on harmonic analysis and fitting) for the two selected SLR scenarios. In other words, sub-tidal forcing is neglected due to the difficulty in predicting this component of the total ocean water levels.

The procedure to derive projected daily projected tides at NOAA primary harmonic station 8723214 (Virginia Key) for 2055-2069 was as follows:

- Hourly tide predictions for 1965-2016, based on harmonic analysis done by NOAA and a 1983-2001 National Tidal Datum Epoch (NTDE; with a mid-point in 1992) mean sea level (MSL = 0.67 ft NGVD29 = -0.90 ft NAVD88; Figure 27), were obtained from the NOAA website based on meters above the local MLLW datum and GMT timezone. In other words, the 1965-2016 data reflects mean sea level around the year 1992. This work was previously done by the sub-contractor at the South Florida Water Management District (SFWMD). This is reasonably close to the -0.808 ft NAVD88 average of calibration period (1996-2010; centered on ~2003) total water levels mentioned in the Miami-Dade MODFLOW documentation (p. 7). This gives a linear SLR rate of 0.00836 ft/yr (2.5 mm/yr), which is close to the SLR rate assumed in the model documentation on p. 94 (0.0073 ft/yr = 2.2 mm/yr).
- Scripts were used to convert the hourly tide predictions from 1965-2016 to ft NGVD29. According to VDatum tool, at Virginia Key (lat: 25° 43.9' N, lon: 80° 9.7' W), the offset from MLLW datum to NGVD29 datum is 0.430 ft, and the offset from MLLW datum to NAVD88 datum is 1.994 ft. Therefore, Water level in MLLW offset value (NGVD29 or NAVD88) = water level (in NGVD29 or NAVD88). This work was also previously done at the SFWMD.
- The 1965-2016 hourly tide predictions in ft NGVD29 and GMT timezone were input into MATLAB/Octave script proj_allstas.m, which calls projecttides_new.m, both are included in MATLAB/Octave code for future tidal prediction. These programs do the following:
 - a. First the tidal analysis and prediction code, UTIDE (Codiga, 2011), is run to fit harmonics to the hourly tide predictions at Virginia Key.
 - b. Then the harmonics are used by UTIDE to predict the hourly tide for the period 2055-2069 (Figure 24) based on the 1983-2001 NTDE (i.e. based on a 1992 MSL). Predicting the hourly tides for 1965-2016 result in almost the same timeseries as the input timeseries, confirming that the harmonic fit is adequate for future prediction. Note that UTIDE is run with lunar nodal corrections which affect daily tidal range and diurnal inequalities. This is

important for accurate future predictions. However, the effect of the lunar nodal cycle (LNC) on mean sea level (sinusoidal of 18.61-year period) is neglected.

- c. Finally, the hourly tide predictions for 2055-2069 based on 1992 MSL are shifted along a selected sea level rise curve. The SLR curve can be user-defined or based on one of the 4 curves defined in the Unified Sea Level Rise Projections by the Southeast Florida Regional Climate Compact (2015), which are based on sea level increase from a 1992 MSL and hardcoded in the program. For the Florida Building Commission Miami-Dade modeling effort, we selected two SLR curves: the IPCC AR5 RCP8.5 Median SLR curve (with linear coefficient (a) = 1.7 mm/yr, and quadratic acceleration coefficient (b) = 0.047 mm/yr²; Figure 25), and the USACE High SLR curve (a = 1.7 mm/yr, b = 0.113 mm/yr²; Figure 26). The final hourly tide predictions output by the code are in ft NGVD29, EST timezone and represent the sea level rise expected to occur from 2055-2069 under the two SLR scenarios.
- 4. The 2055-2069 hourly tide predictions in ft NGVD29 and EST timezone were imported into EXCEL and converted to daily averages using pivot tables. Finally, the datum was converted from ft NGVD29 to ft NAVD88 by subtracting 1.57 ft from elevations in ft NGVD29. The daily timeseries were saved as: Virg_Key_daily_tide_IPCC_AR5_Med_ftNAVD88.csv and Virg Key_daily_tide_USACE High ftNAVD88.csv and Emailed to FIU staff.
 - a. The timeseries based on IPCC AR5 RCP8.5 Median SLR curve reflects MSL of 1.63 ft NGVD29 (0.06 ft NAVD88; Figure 28), for a SLR of 0.96 ft from 1/1/1992 to 1/1/2055. The MSL on 12/31/2069 is 2.04 ft NGVD29 (0.47 ft NAVD88; Figure 29), for a SLR of 1.37 ft from 1/1/1992 to 12/31/2069.
 - b. The timeseries based on USACE High SLR curve reflects MSL of 2.49 ft NGVD29 (0.92 ft NAVD88; Figure 30), for a SLR of 1.82 ft from 1/1/1992 to 1/1/2055. The MSL on 12/31/2069 is 3.36 ft NGVD29 (1.79 ft NAVD88; Figure 31), for a SLR of 2.69 ft from 1/1/1992 to 12/31/2069.



Figure 24. Raw hourly tidal predictions at Virginia Key for 1965-2016, and predicted tides for 2055-2069. Both are in ft NGVD29 and based on 1983-2001 NTDE (without SLR).



Figure 25. Hourly predicted tides (ft NGVD29) at Virginia Key for 2055-2069 without SLR (blue trace) and with IPCC AR5 RCP8.5 Medium SLR curve (red trace). Note: The amplitude of the blue trace is similar to that of the red trace, the data is just hidden behind the red. The 1983-2001 NTDE MSL at Virginia Key is 0.67 ft NGVD29, while the MSL at the end of 2069 is 2.04 ft NGVD29 after considering SLR. Daily averages were computed and the datum converted to ft NAVD88 prior to input into the model.



Figure 26. Hourly predicted tides (ft NGVD29) at Virginia Key for 2055-2069 without SLR (blue trace) and with USACE High SLR curve (red trace). Note: The amplitude of the blue trace is similar to that of the red trace, the data is just hidden behind the red. The 1983-2001 NTDE MSL at Virginia Key is 0.67 ft NGVD29, while the MSL at the end of 2069 is 3.36 ft NGVD29 after considering SLR. Daily averages were computed and the datum converted to ft NAVD88 prior to input into the model.



Figure 27. Topography and extent of flooding (cells with '+' black markers) based on 1983-2001 NTDE mean sea level at Virginia Key (-0.90 ft NAVD88).



Figure 28. Topography and extent of flooding (cells with '+' black and white markers) for mean sea level on 1/1/2055 at Virginia Key for the IPCC AR5 RCP8.5 scenario (0.06 ft NAVD88). A total of 947 additional model grid cells would be flooded compared to the cells flooded based on 1983-2001 NTDE MSL.



Topography and extent of flooding for IPCC AR5 RCP8.5 MSL on 12/31/2069 (0.47 ft NAVD88)

Figure 29. Topography and extent of flooding (cells with '+' black and white markers) for mean sea level on 12/31/2069 at Virginia Key for the IPCC AR5 RCP8.5 scenario (0.47 ft NAVD88). A total of 1290 additional model grid cells would be flooded compared to the cells flooded based on 1983-2001 NTDE MSL.



Figure 30. Topography and extent of flooding (cells with '+' black and white markers) for mean sea level on 1/1/2055 at Virginia Key for the USACE High scenario (0.92 ft NAVD88). A total of 1773 additional model grid cells would be flooded compared to the cells flooded based on 1983-2001 NTDE MSL.


Figure 31. Topography and extent of flooding (cells with '+' black and white markers) for mean sea level on 12/31/2069 at Virginia Key for the USACE High scenario (1.79 ft NAVD88). A total of 2231 additional model grid cells would be flooded compared to the cells flooded based on 1983-2001 NTDE MSL.

MATLAB/Octave code for future tidal prediction

The code was developed under contract with the SFWMD. MATLAB/Octave code was developed to facilitate tide predictions at tide stations of interest for future periods based on UTIDE output adjusted by parameterized quadratic (or linear) sea level rise projection curves. The main script is proj_allstas.m and it calls projecttides_new.m. Both are included later in this appendix. To adjust all the data by a single SLR value (i.e. MSL constant in time) as described above, use adjtype=1 in call to proj_allstas.m. To adjust all the data along a SLR curve use adjtype=2. The header to the main function proj_allstas.m is:

function

proj allstas(outflag,csvname,fbase,nyrs,scen,RegRate,RegAccel,adjtype)

This function is used to project tides into the future for ALL stations of interest. It will typically be run using tidal predictions as input for NOAA stations and using raw water levels as input for ENP and SFWMD tailwater stations. It calls UTIDE codes ut_solv.m and ut_reconstr.m.

The input arguments to proj_allstas are:

outflag: 1 to output plots, 0 not to

csvname: name of CSV file with hourly tidal pred. and water level data for all stations (input times must be in GMT timezone but output from code will be in EST timezone). The code assumes data in ft NGVD29. If not, check conversion factors in code. Format: Year, Mo, Day, Hour, station 1 data, station 2, etc.

fbase: if(adjtype==1) future base MIDDLE year to project tides

(i.e. this is the year at which one single SLR value

will be computed to adjust MSL for ALL data)

Note: Must be >=1992

if(adjtype==2) future base STARTING year to project tides. Note: Must be >=1992

nyrs: if(adjtype==1) Number of years around fbase to project tides

(i.e. tides will be predicted for fbase+/-(nyrs/2))

if(adjtype==2) Number of years AFTER fbase to project tides

(i.e. tides will be predicted for fbase+nyrs)

scen: SLR scenario for future tide projections from SE FL Reg. Compact Climate Change (Oct. 2015): 0: User-defined SLR linear trend and acceleration

Pre-defined scenarios from SE FL Reg. Compact Climate Change (Oct. 2015):

1: USACE Low/NOAA Intermediate-Low

2: IPCC AR5 median

3: USACE High

4: NOAA High

RegRate (a): + regional SLR trend rate, linear part (mm/yr)

set to [] to use global rate instead (1.7 mm/yr)

RegAccel (b): + regional accel trend rate (mm/yr²)

set to [] to use the global acceleration given by scen

Note: If Regional SLR rate and acceleration are empty, then corresponding global values are used. This could mix and match regional and global rate and acceleration. Proceed with caution!!!

adjtype: 1: To shift entire timeseries by a certain SLR value (i.e. MSL constant in time)

2: To shift the timeseries ALONG a SLR curve (i.e. MSL varies with time)

The code proj_allstas.m reads a csv file with station metadata with the filename hardcoded as station_metadata.csv. This file is used for filtering data based on some criteria. It has one line per station and the columns are as follows:

1st column: station: station name

2nd column: minyr: minimum year, i.e. only data for years beyond the minyr will be considered 3rd column: minvald: minimum value--i.e. values less than that will be set to missing. Useful to eliminate low outliers from analysis.

4th column: byear: base year of data--i.e. 1992 for NOAA data which is the middle of 1983-2001 tidal epoch or -999 to allow code to determine it based on the mid-point of the raw water level data.

The general steps followed by this code are summarized in Figure 32. and briefly described below:

- Read station_metadata.csv.
- Read raw water level data and/or tidal prediction data for ALL stations of interest from csvname file.
- Based on fbase and nyrs it determines timestamps for future projection times of interest (on an hourly timestep).
- It then loops through each station in csvname file and does the following.
- It calls UTIDE function ut_solv.m with default settings but with no SLR trend, using OLS instead of the default IRLS and linearized confidence interval method with white noise floor assumption instead of Monte Carlo. For details see Codiga (2011).
- It calls UTIDE function ut_reconstr for projection times of interest to properly account for effects of lunar/nodal corrections (on daily tidal range and diurnal inequalities). However, the effect of lunar nodal cycle (LNC) on mean sea level (sinusoidal with 18.61-year frequency) is neglected.
- At stations with byear not equal to -999 (e.g. NOAA tidal stations), it calls project_tides_new.m to move the projected tide levels from ut_reconstr up on a SLR curve. The SLR curve is defined based on scen and the values of RegRate and RegAccel which are hardcoded in proj_allstas.m. See the description of project_tides_new.m below for more information.
- At non-NOAA stations, prior to project_tides_new.m being called, the mean fit by UTIDE based on all the available raw water level data at the station is adjusted to the mean for only the last 19 years of data (to average out effects of LNC). If less than 19 years of data are available, the adjustment=0. In general, this adjustment is minimal compared to subsequent SLR adjustment.
- Output is hourly projected tides with sea level rise adjustment. Time is local time (EST) and units are ft NGVD29. These are written to proj_tide_all.csv which can be imported into Excel and saved as DSS file using the DSS EXCEL Add-in and then averaged to daily within HEC-DSSVue.

The header to the function projecttides_new.m, which is called by proj_allstas.m, is:

```
function pred =
projecttides_new(outflag,station,csvf,fac,byear,fbase,scen,RegRate,Reg
Accel,adjtype)
```

The input arguments to projecttides_new are:

outflag: 1 to output plots, 0 not to

station: name of station to process

csvf: name of CSV file with current hourly or daily tidal data to be projected into the future

Format should be year, mo, day, [hr], tidal_value

fac: conversion factor from meters to match units in csv file (csvf)

byear: base year for historical raw water level data from which tidal predictions were made (e.g.

1992=middle of 1983-2001 tidal epoch for NOAA stations; must be >=1992)

fbase: future base year to project tides

scen: SLR scenario for future tide projections:

0: User-defined SLR linear trend and acceleration

Pre-defined scenarios from SE FL Reg. Compact Climate Change (Oct., 2015):

1: USACE Low/NOAA Intermediate-Low

- 2: IPCC AR5 RCP8.5 median
- 3: USACE High
- 4: NOAA High

See Table 5 below for more details.

RegRate (a): + regional SLR trend rate, linear part (mm/yr)

set to [] to use global rate instead (1.7 mm/yr)

RegAccel (b): + regional accel trend rate (mm/yr²)

set to [] to use the global acceleration given by scen

Note: If Regional SLR rate and acceleration are empty, then corresponding global values are used. This could mix and match regional and global rate and acceleration. Proceed with caution!!!

adjtype: 1: To shift entire timeseries by a certain SLR value (i.e. MSL constant in time)

2: To shift the timeseries ALONG a SLR curve (i.e. MSL varies with time)

projecttides_new.m uses the following quadratic equation to adjust predicted tides with sea level rise from a period centered at byear to a future period centered at fbase:

$$\Delta h_{SLR}(byear, fbase) = b[(fbase - 1992)^2 - (byear - 1992)^2] + (1)$$
$$a[(fbase - 1992) - (byear - 1992)]$$

Table 5. Coefficients for pre-defined quadratic SLR scenarios from SE FL Reg. Compact Climate Change (Oct., 2015). These equations give global sea level trends. For local trends could use a=0.0022 m/yr based on Key West data.

SLR Scenario	SLR Rate a (m/yr)	SLR acceleration b (m/yr^2)	$\Delta h_{SLR}(1992,2100)$ (m)
1:USACE Low/NOAA Intermediate-Low	0.0017	2.71262*10 ⁻⁵	0.5
2: IPCC AR5 RCP8.5 median	0.0017	4.684499*10 ⁻⁵	0.73
3: USACE High	0.0017	1.13*10 ⁻⁴	1.5
4: NOAA High	0.0017	1.56*10-4	2.0



Figure 32. Step-by-step procedure for projecting tides into the future based on quadratic sea level rise curves. Boxes and ovals in red and dashed lines are only performed for stations with byear initially defined as -999 in station_metadata.csv.

Scripts to develop tidal timeseries for future scenarios considering quadratic sea level rise curve:

proj_allstas.m:

```
function proj allstas(outflag,csvname,fbase,nyrs,scen,RegRate,RegAccel,adjtype)
  %function to project tides into the future for ALL stations
  %Will be run with tidal predictions as input for NOAA stations
  %and with raw water levels as input for ENP and SFWMD TW stations
 *Utide must be run for period centered around fbase to correctly
 %account for effects of lunar/nodal corrections (on daily tidal range
 %and diurnal inequalities). Effect of lunar nodal cycle (LNC) on
 %mean sea level (sinusoidal with 18.61 year frequency) is neglected.
 %However, at non-NOAA stations, the mean fit by Utide based on all the
 %available raw data at the station is adjusted to the mean for only the
 %last 19 years of data (to average out effects of LNC). If less than 19
 %years of data are available, adjustment=0. In general, this adjustment
 %is minimal compared to subsequent SLR adjustment.
 %There are two options to project tides into the future. In the first option,
  %the entire timeseries is raised by a certain SLR projection (a single value).
  %In the second option, the timeseries is adjusted in time by shifting it
  %ALONG a SLR curve.
  %outflag: 1 to output plots, 0 not to
  %csvname: name of CSV file with hourly tidal pred. and water level data
            for all stations (times must be in GMT timezone)
 %Assumes data in ft NGVD29. If not, check conversion factors in code
        Format: Year, Mo, Day, Hour, station 1 data, station 2, etc.
  %
 %fbase: if(adjtype==1) future base MIDDLE year to project tides
  %
                         (i.e. this is the year at which one single SLR value
 90
                         will be computed to adjust MSL for ALL data)
  %
                         Note: Must be >=1992
  2
          if(adjtype==2) future base STARTING year to project tides
                         Note: Must be >=1992
  2
  %nyrs: if(adjtype==1) Number of years around fbase to project tides
                        (i.e. tides will be predicted for fbase+/-(nyrs/2))
  2
  8
         if (adjtype==2) Number of years AFTER fbase to project tides
                        (i.e. tides will be predicted for fbase+nyrs)
  2
  %scen: SLR scenario for future tide projections:
         from SE FL Reg. Compact Climate Change (Oct 2015):
  8
         1: USACE Low/NOAA Intermediate-Low
  2
         2: IPCC AR5 median
  2
         3: USACE High
  2
         4: NOAA High
  %RegRate: + regional SLR trend rate (mm/yr)
           set to [] to use global rate instead (1.7 mm/yr)
  8
 %RegAccel: + regional accel trend rate (mm/yr^2)
           set to [] to use the global accel. given by scen
  8
 %If Regional SLR rate and accel. are empty, then corresponding global
 %values are used.
  %Note: This could mix and match regional and global rate and accel.
  %Proceed with caution!!!
  %adjtype: 1: To shift entire timeseries by a certain SLR value
               (i.e. MSL constant in time)
  8
 %
            2: To shift the timeseries ALONG a SLR curve
  %
               (i.e. MSL varies with time)
 %outflag=1; csvname='stations 35.csv'; fbase=1992; nyrs=109; scen=3;
 %adjtype=2;RegRate=[];RegAccel=[];
 %outflag=1; csvname='stations 35.csv'; fbase=2016; nyrs=52; scen=3;
  %adjtype=1;RegRate=4.2;RegAccel=0;
```

```
pkg load statistics
disp(adjtype)
%Read starting year and minimum value for filtering
%from a csv file (one line per station, 1st column is the
% station name; 2nd column is minimum year--
%i.e. only data for years beyond the minyr will be considered;
%3rd column is minimum value--i.e. values less than that will be set
%to missing; 4th column is base year of data--i.e. 1992 for NOAA data
%which is the middle of 1983-2001 tidal epoch or -999 to determine it
%based on the mid-point of the raw water level data)
[station,minyr,minvald,byear]=textread('station metadata.csv',...
    '%s %f %f%f', 'headerlines',1, 'delimiter', ', ');
%Read water level data
wl = csvread(csvname,1,0); %miriza-add c0=0 for octave
nstas = size(wl, 2) - 4;
%Prediction dates tt (GMT) and local dates tt2
if (adjtype==1)
  fb=round(fbase-(nyrs-1)/2);
  fe=round(fbase+(nyrs-1)/2);
  nyrs2=fe-fb+1;
  fmid=mean([fb,fe]);
else
  fb=fbase;
  fe=fbase+nyrs-1;
end
sd = datenum(['01-Jan-' num2str(fb) ' 05:00:00']); %add SS for octave
iv = 1/24; %hourly predictions
ed = datenum(['01-Jan-' num2str(fe+1) ' 04:00:00']); %add SS for octave
tt=(sd:iv:ed)'; %(simplified to make octave faster)
tt2=tt-5/24.;
stt2=datevec(tt2);
%Preallocate memory for final predictions
allstas = zeros(size(tt2,1), size(wl,2));
%Loop through all stations
for i = 1:nstas
  ista=i+4;
  a = wl:
  fprintf(1,'i=%s,ista=%s\n',num2str(i),num2str(ista))
  drawnow('expose');
  %drawnow('update');
  %j=find(a(:,ista) <= minvald(i));</pre>
  a(a(:,ista) <= minvald(i),ista)=NaN;</pre>
  a=a(:,[1:4,ista]);
  %j = find(a(:,1) >= minyr(i));
  a=a(a(:,1) >= minyr(i),1:5);
  %plot(a(:,5));
 Month=a(:,2);
  Year = a(:, 1);
  Day=a(:,3);
 Hour=a(:,4);
 t = datenum(Year, Month, Day, Hour, 0, 0);
 TW = a(:, 5);
  %plot(t,TW);
 more off;
  %Call ut solve
  fprintf(1,'starting ut solve for i=%s\n',num2str(i));
  %drawnow('update');
```

```
drawnow('expose');
coef = ut solv(t,TW,[],26.0,'auto','OLS','White','LinCI','NoDiagn',...
    'NoTrend');
%drawnow('update');
drawnow('expose');
%Call ut reconstr
fprintf(1,'starting ut reconstr for i=%s\n',num2str(i));
%drawnow('update');
drawnow('expose');
pp = ut reconstr(tt, coef);
%drawnow('update');
drawnow('expose');
pred = [stt2(:,1:4) pp];
figure;
%plot(tt2,pp);
plot(t-5/24., TW, '-g', tt2, pp, '-y');
datetick('x','YYYY');
legend('Raw data','Pred. tide w/o SLR','Location','northwest')
xlabel ('Time');
ylabel ('ft NGVD29');
limits=axis();
line([datenum(fbase,1,1) datenum(fbase,1,1)],[limits(3) limits(4) ],...
  'color','k');
text(datenum(fbase,1,1),limits(3),num2str(fbase),...
  'horizontalalignment','center','color','r');
line([datenum(fb,1,1) datenum(fb,1,1)],[limits(3) limits(4) ],...
  'color','k');
text(datenum(fb,1,1),limits(3),num2str(fb),...
  'horizontalalignment','center','color','r');
line([datenum(fe+1,1,1) datenum(fe+1,1,1)],[limits(3) limits(4) ],...
  'color','k');
text(datenum(fe+1,1,1),limits(3),num2str(fe+1),...
  'horizontalalignment','center','color','r');
if (byear(i) ~=999)
  line([datenum(byear(i),1,1) datenum(byear(i),1,1)],[limits(3) limits(4) ],...
    'color','k');
  text(datenum(byear(i),1,1),limits(3),num2str(byear(i)),...
    'horizontalalignment','center','color','b');
end
title (['Water level and tide at station ' char(station(i)) '(i=' ...
    num2str(i) ')']);
if(outflag==1)
 print(1,['pred tide ' char(station(i)) '.png'],'-dpng');
end
close;
csvf = ['pred tide ' char(station(i)) '.csv'];
csvwrite(csvf, pred);
%adjust data for SLR
fprintf(1, 'starting projecttides new for i=%s\n',num2str(i));
fac=39.3701/12;
%For stations with defined byear (e.g. NOAA),
%simply call projecttides_new to add in SLR
if (byear(i) ~= -999)
  predf=projecttides new(outflag,char(station(i)),csvf,...
      fac,byear(i),fbase,scen,RegRate,RegAccel,adjtype);
else %For other stations
  %Step 1: Subtract the mean from the Utide fit
  pp2 = pp - coef.mean;
  %Step 2: Get the mean of the raw data for the most recent 19 year
```

```
%period to define the MSL for a tidal epoch (so effects of lunar
%nodal cycle, LNC are averaged out). Assumption here is that if there
%are data gaps, they are uniformly distributed throughout the dataset,
%which may or may not be the case. Add that mean to result of Step 1.
%Note: Stations with less than 19 years of POR will still be
%processed but means may reflect influence of LNC!
%Convert raw times to EST first
t = t - 5/24.;
maxt = max(t);
tmp = datevec(maxt);
mint = datenum(tmp(1)-19, tmp(2), tmp(3), tmp(4), tmp(5), tmp(6));
midt = mean([mint maxt]);
midyr = midt/365.25;
jj=find(t >= mint & t <=maxt);
%If starting date of data is more than a year after mint,
%recompute mint, midt and midyr
%This will happen if station has less than 19 years of POR
% (may want to exclude these!)
if ((t(jj(1)) - mint) > 365)
    mint = t(jj(1));
    midt = mean([mint maxt]);
    midyr = midt/365.25;
end
%epoch mean=mean(TW(jj), 'omitnan');
epoch mean=nanmean(TW(jj));
pp3 = pp2 + epoch mean;
predadj = [stt2(:,1:4) pp3];
adj=epoch mean-coef.mean;
csvfadj = ['pred tide ' char(station(i)) ' adj.csv'];
csvwrite(csvfadj,predadj);
figure;
plot(tt2, pp, '-y', tt2, pp3, '-b');
datetick('x','YYYY');
legend('Pred. tide w/o SLR',...
    'Pred. tide w/o SLR (adj. mean)', 'Location', 'northwest')
xlabel ('Time');
ylabel ('ft NGVD29');
limits=axis();
line([datenum(fbase,1,1) datenum(fbase,1,1)],[limits(3) limits(4) ],...
  'color','k');
text(datenum(fbase,1,1),limits(3),num2str(fbase),...
  'horizontalalignment','center','color','r');
line([datenum(fb,1,1) datenum(fb,1,1)],[limits(3) limits(4) ],...
  'color','k');
text(datenum(fb,1,1),limits(3),num2str(fb),...
  'horizontalalignment','center','color','r');
line([datenum(fe+1,1,1) datenum(fe+1,1,1)],[limits(3) limits(4) ],...
  'color','k');
text(datenum(fe+1,1,1),limits(3),num2str(fe+1),...
  'horizontalalignment','center','color','r');
line([datenum(floor(midyr),1,1)+(((midyr)-floor(midyr))*365) ...
  datenum(floor(midyr),1,1)+(((midyr)-floor(midyr))*365)],...
  [limits(3) limits(4) ],'color','k');
text(datenum(floor(midyr),1,1)+(((midyr)-floor(midyr))*365),limits(3),...
  num2str(round(midyr*100)/100), 'horizontalalignment', 'center', 'color', 'b');
line([limits(1) limits(2)], [mean(pp) mean(pp) ],...
  'color','k');
line([limits(1) limits(2)], [mean(pp3) mean(pp3) ],...
  'color','k');
text(limits(1),mean(pp),num2str(round(mean(pp)*100)/100),... %round(mean(pp),2)
  'color','k');
```

```
text(limits(1),mean(pp3),num2str(round(mean(pp3)*100)/100),...
%round(mean(pp3),2)
        'color','k');
      title (['Pred. tide at ' char(station(i)) '(adj=' ...
        num2str(round(adj*100)/100) ' ft)']) %round(adj,2)
      if(outflag==1)
        print(1,['pred tide ' char(station(i)) ' adj.png'],'-dpng');
      end
      close;
      %Step 3: Call projecttides new to add SLR
      predf=projecttides new(outflag,char(station(i)),csvfadj,...
          fac,midyr,fbase,scen,RegRate,RegAccel,adjtype);
    end
    %Concatenate results to create a single csv file at the end
    if (i==1)
      allstas(:,1:5)=predf;
    else
      allstas(:,(i+4))=predf(:,end);
    end
  end
 %Finally write out all predictions to a single csv file
ofile=fopen('proj_tide_all.csv','w');
fmt=strcat(repmat('%f,',1,size(allstas,2)-1),'%f\n');
fprintf(ofile,fmt,allstas');
fclose(ofile);
end
function SetDefaultValue(position, argName, defaultValue)
% Initialise a missing or empty value in the caller function.
2
% SETDEFAULTVALUE(POSITION, ARGNAME, DEFAULTVALUE) checks to see if the
% argument named ARGNAME in position POSITION of the caller function is
% missing or empty, and if so, assigns it the value DEFAULTVALUE.
% Example:
% function x = TheCaller(x)
% SetDefaultValue(1, 'x', 10);
% end
% TheCaller()
                 8 10
% TheCaller([]) % 10
% TheCaller(99) % 99
00
% $Author: Richie Cotton $ $Date: 2010/03/23 $
if evalin('caller', 'nargin') < position || ...</pre>
      isempty(evalin('caller', argName))
   assignin('caller', argName, defaultValue);
end
end
```

Top 5 rows and 8 columns of stations_35.csv:

Year	Month	Day	Hour	BK	тс	8722371	8722381
1965	1	1	0	-902	-902	0.752	0.936

1965	1	1	1	-902	-902	0.832	1.039
1965	1	1	2	-902	-902	0.813	1.02
1965	1	1	3	-902	-902	0.702	0.884

Top 5 lines of station_metadata.csv:

station	minyr	minvald	byear
BK	1900	-900	-999
тс	1900	-900	-999
8722371	1900	-900	1992
8722381	1900	-900	1992

projecttides_new.m:

function pred = projecttides_new(outflag,station,csvf,fac,...
byear,fbase,scen,RegRate,RegAccel,adjtype)

Soutflag: 1 to output plots, 0 not to %station: name of station to process %csvf: name of CSV file with current hourly or daily tidal data to be projected into the future 2 2 Format should be year, mo, day, [hr], tidal value %fac: conversion factor from meters to match units in csv file (csvf) %byear: base year for historical raw water level data from which tidal predictions were made (e.g. 1992=middle of 1983-2001 8 tidal epoch for NOAA stations; must be >=1992) 8 (can have a fractional part) %fbase: future base year to project tides %scen: SLR scenario for future tide projections: % from SE FL Reg. Compact Climate Change (Oct 2015): 1: USACE Low/NOAA Intermediate-Low 2 2: IPCC AR5 RCP8.5 median 8 3: USACE High 8 4: NOAA High 8 %RegRate: + regional SLR trend rate (mm/yr) 8 set to [] to use global rate instead (1.7 mm/yr) %RegAccel: + regional accel trend rate (mm/yr^2) set to [] to use the global accel. given by scen 8 %If Regional SLR rate and accel. are empty, then corresponding global %values are used. %Note: This could mix and match regional and global rate and accel. %Proceed with caution!!! %adjtype: 1: To shift entire timeseries by a certain SLR value (single value) 2: To shift the timeseries ALONG a SLR curve % %outflag=0; station='Key West'; RegRate=1.7; fac=39.3701/12;adjtype=1; pkg load financial %Get tidal data (with MSL corresponding to byear) %[year,mo,day,hr,tdata]=textread(csvf,'%f,%f,%f,%f,%f',... 'headerlines',1); % M=csvread(csvf); year=M(:,1); mo=M(:,2); day=M(:,3); if (size(M,2)==4)

```
freq='daily';
 hr=0;
  tdata=M(:,4);
else
  freq='hourly';
 hr=M(:,4);
  tdata=M(:,5);
end
tcurr=datenum(year,mo,day,hr,0,0);
stcurr=datevec(tcurr);
nyears=(max(year)-min(year)+1);
%Prediction dates tt (GMT) and local dates tt2
if (adjtype==1)
 fb=round(fbase-(nyears-1)/2);
  fe=round(fbase+(nyears-1)/2);
 nyrs2=fe-fb+1;
  fmid=mean([fb,fe]);
else
  fb=fbase;
  fe=fbase+nyears-1;
end
%Determine future dates for predictions
sd=datenum(fb,1,1);
if (strcmp(freq, 'daily'))
    iv=1;
    ed=sd+(size(year,1)-1);
else
    iv=1/24;
    ed=sd+(size(year,1)-1)/24;
end
tfut=(sd:iv:ed)';
stfut=datevec(tfut);
*Derive acceleration rate b from year 2100 SLR projections from 1992 MSL
%in meters
gmsl=[0.5 0.73 1.5 2.0]; %Global MSL (m) for each scenario
scennames=char('USACE Low','IPCC AR5 RCP8.5 Med.','USACE High',...
    'NOAA High');
ag=1.7/1000; %global SLR rate (trend, 1.7/1000 m/year=1.7 mm/year)
%If Regional SLR rate and accel. not defined, then use global
%values. Note: This could mix and match regional and global rate
%and accel. Proceed with caution!
if (isempty(RegRate))
 a=ag;
else
 a=RegRate/1000;
end
if (isempty(RegAccel))
    b=(gmsl-ag*(2100-1992))/(2100-1992)^2; %global SLR acceleration
                                            %always derived based on ag
else
    b=RegAccel/1000;
end
if (adjtype==1)
  %Derive SLR from byear (must be >=1992) up to (fbase+1)
  %here t is integer year
  t=floor(byear):(fbase+1);
else
  %Derive SLR from sd to ed (here t is fractional year)
```

```
dv=stfut;
    dv(:, 2:3) = 1;
    dv(:,4:end)=0;
    doy=tfut-datenum(dv);
   yrs=stfut(:,1);
    yrsday=yeardays(yrs);
    t=(yrs + (doy ./ yrsday))';
  end
  %slr=(b.'*(((t-1992).^2)-((byear-1992).^2))+ a*((t-1992)-(byear-1992))).';
  %Use this version for compatibility with MATLAB R2016a
  %Note!!! Make sure this works for various scenarios and year fractions
  slr=(b.'*(((t-1992).^2)-((byear-1992).^2))+ ...
      repmat(a*((t-1992)-(byear-1992)),size(b,2),1)).';
  slrt=t;
  %Unit conversion
  slr=slr*fac;
  u=[transpose(t) slr];
  if (adjtype==1)
    %Determine the SLR adjustment for particular fbase year
    if (isempty(RegAccel))
      adj=slr(slrt==fbase,scen);
    else
      adj=slr(slrt==fbase);
    end
  else
    if (isempty(RegAccel))
      adj=slr(:,scen);
    else
      adj=slr;
    end
  end
  %Adjust data to future MSL
  tidefut=tdata+adj;
  figure;
  plot(tcurr,tdata,'b-',tfut,tidefut,'r-');
  if (isempty(RegRate) && isempty(RegAccel))
    legend('Pred. tide w/o SLR',['Proj. tide w/SLR: ' ...
        scennames(scen,:)],'Location','northwest');
  else
    legend('Pred. tide w/o SLR', 'Proj. tide w/SLR',...
    'Location', 'northwest');
  end
  datetick('x','YYYY');
  %axis([min([tcurr;tfut]) max([tcurr;tfut]) min([tdata;tidefut]) ...
  8
     max([tdata;tidefut]) ]);
  grid();
  xlabel('Time (Year)');
  ylabel('ft NGVD29');
  if (isempty(RegAccel))
    title ({['Pred. tide with and w/o SLR at ' station '(adj=' ...
      num2str(round(max(adj)*100)/100) ' ft)'],['a=' num2str(a*1000)... %round(adj,2)
      'mm/yr,b=' num2str(round(b(scen)*1000*1000)/1000) 'mm/yr^2']});
%round(b(scen)*1000,3)
  else
    title ({['Pred. tide with and w/o SLR at ' station '(adj=' ...
      num2str(round(max(adj)*100)/100) ' ft)'],['a=' num2str(a*1000)... %round(adj,2)
      'mm/yr,b=' num2str(b*1000) 'mm/yr^2']});
  end
  limits=axis();
```

```
line([datenum(fbase,1,1) datenum(fbase,1,1)],[limits(3) limits(4) ],...
    'color','k');
  text(datenum(fbase,1,1),limits(3),num2str(fbase),...
    'horizontalalignment','center','color','r');
  line([datenum(fb,1,1) datenum(fb,1,1)],[limits(3) limits(4) ],...
    'color','k');
  text(datenum(fb,1,1),limits(3),num2str(fb),...
    'horizontalalignment','center','color','r');
  line([datenum(fe+1,1,1) datenum(fe+1,1,1)],[limits(3) limits(4) ],...
    'color','k');
  text(datenum(fe+1,1,1),limits(3),num2str(fe+1),...
    'horizontalalignment', 'center', 'color', 'r');
 line([datenum(floor(byear),1,1)+(((byear)-floor(byear))*365) ...
    datenum(floor(byear),1,1)+(((byear)-floor(byear))*365)],...
    [limits(3) limits(4) ],'color','k');
  text(datenum(floor(byear),1,1)+(((byear)-floor(byear))*365),limits(3),...
    num2str(round(byear*100)/100), 'horizontalalignment', 'center', 'color', 'b');
 if (adjtype==1)
    line([limits(1) limits(2)],[mean(tdata) mean(tdata) ],...
        'color','k');
    line([limits(1) limits(2)], [mean(tidefut) mean(tidefut) ],...
        'color','k');
    text(limits(1),mean(tdata),num2str(round(mean(tdata)*100)/100),...
%round(mean(tdata),2)
        'color','k');
    text(limits(1),mean(tidefut),num2str(round(mean(tidefut)*100)/100),...
%round(mean(tidefut),2)
        'color','k');
 else
    line([limits(1) limits(2)], [mean(tdata) mean(tdata) ],...
        'color','k');
    line([limits(1) limits(2)], [mean(tdata)+max(adj) mean(tdata)+max(adj) ],...
        'color','k');
    text(limits(1),mean(tdata),num2str(round(mean(tdata)*100)/100),...
%round(mean(tdata),2)
        'color','k');
    text(limits(1), mean(tdata)+max(adj), num2str(round((mean(tdata)+max(adj))*100)/100)
,... %round(mean(tidefut),2)
        'color','k');
  end
 if(outflag==1)
   print(1,['Proj_tide_' station '.png'],'-dpng');
 end
 close;
 figure;
 plot(slrt,slr);
 grid();
 xlabel('Time (Year)');
 ylabel('ft');
 if (isempty(RegRate) && isempty(RegAccel))
    title({['Projected SLR at ' station ' since ' num2str(round(byear))], ...
        ['global rate a=' num2str(a*1000) 'mm/yr and global accel. b='...
        num2str(round(b(scen)*1000*1000)/1000) 'mm/yr^2']}); %round(b(scen)*1000,3)
    %legend(scennames,'location','northwest');
    legend(strcat(cellstr(scennames), ' b=',...
           arrayfun("num2str",round(1000*1000*b)/1000,"UniformOutput",false)',...
           'mm/yr^2'),'location','northwest');
 elseif (isempty(RegRate))
    title({['Projected SLR at ' station ' since ' num2str(round(byear))], ...
        ['global rate a=' num2str(a*1000)...
        'mm/yr and reg. accel. b=' num2str(b*1000) 'mm/yr^2']});
```

```
elseif (isempty(RegAccel))
    title({['Projected SLR at ' station ' since ' num2str(round(byear))], ...
        ['reg. rate a=' num2str(a*1000)...
        'mm/yr and global accel. b='...
        num2str(round(b(scen)*1000*1000)/1000) 'mm/yr^2']}); %round(b(scen)*1000,3)
    %legend(scennames,'location','northwest');
    legend(strcat(cellstr(scennames),' b=',...
           arrayfun("num2str",round(1000*1000*b)/1000,"UniformOutput",false)',...
            'mm/yr^2'), 'location', 'northwest');
  else
    title({['Projected SLR at ' station ' since ' num2str(round(byear))], ...
        ['reg. rate a=' num2str(a*1000)...
'mm/yr and reg. accel. b=' num2str(b*1000) 'mm/yr^2']});
  end
  if(outflag==1)
    print(1,['Proj_SLR_' station '.png'],'-dpng');
  end
  close;
  %Write out future predicted tide
  if (strcmp(freq,'daily'))
    pred = [year mo day tidefut];
  else
    pred = [year mo day hr tidefut];
  end
  csvwrite(['proj tide ' station '.csv'],pred);
end
function SetDefaultValue(position, arqName, defaultValue)
% Initialise a missing or empty value in the caller function.
%
% SETDEFAULTVALUE(POSITION, ARGNAME, DEFAULTVALUE) checks to see if the
% argument named ARGNAME in position POSITION of the caller function is
\% missing or empty, and if so, assigns it the value <code>DEFAULTVALUE</code> .
0
% Example:
\% function x = TheCaller(x)
% SetDefaultValue(1, 'x', 10);
% end
% TheCaller()
                 8 10
% TheCaller([]) % 10
% TheCaller(99) % 99
% $Author: Richie Cotton $ $Date: 2010/03/23 $
if evalin('caller', 'nargin') < position || ...</pre>
      isempty(evalin('caller', argName))
   assignin('caller', argName, defaultValue);
end
end
```

Appendix IV. Sensitivity Analysis of Ocean Boundary Condition (Task I)

Preliminary Work

Our initial efforts have focused on assessing the relative importance of wind-, current-, and rain-driven departures of ocean water levels from the predicted tides on model results. That is, we wanted to know if using the predicted Virginia Key tide as a key model input would be adequate to simulate the historical response of the groundwater system. If it is, then simpler predicted-tide-only projections of the future would be adequate for simulations of the future.

To asses this, we downloaded two sets of Virginia Key tide station data from the NOAA website: the observed water levels and the predicted water levels. The observed data were downloaded as hourly levels in feet (NAVD 88) and Local Standard Time (LST) zone from 1/1/1996 through 12/31/2018. We found that data were missing from 10/3/1997 through 11/8/1997 and from 2/13/2016 through 2/25/2016. We used predicted data to fill these data gaps. The data are plotted along with a fitted linear trend in Figure 33.



Figure 33. Daily observed data from Virginia Key tide station represented by blue line and linear trend represented by red line.

The linear trend is

Water level (feet NAVD) = $5.21785 * 10^5$ feet/d * x + 2.72485 feet, (1)

where x is the number of days since 1/1/1900. This corresponds to a rate of 5.8 mm/year between January 1996 and December 2017.

The predicted tide water levels were also downloaded as hourly water levels in feet (NAVD 88) and LST time zone from 12/31/1995 through 1/1/2026. These predictions do not have a significant sea level rise trend (Figure 34, dotted yellow line). To include the sea level rise in the prediction, we added the sea level rise trend from the observed data. Because the NOAA tidal epoch for the predicted tide data begins in 1992, we began adding the sea level rise on 6/15/1992. The predicted tend-only stage for the

6/15/1992 date was -0.9628 feet, and the stage for 12/31/1995 date, where our chart and simulations begin, was -0.8952 feet. The difference d = 0.06752 feet -- the amount of sea level increase between 6/15/1992 and 12/31/1995. This was added to the predicted tide on 12/31/1995 and to all subsequent dates along with the overall trend. Figure 34 shows the result. As expected, the trend of the predicted data with the added trend has the same trend (dotted red line in Figure 34) as the observed sea level rise trend (dashed red line in Figure 33).



Figure 34. Blue line represents predicted water level at Virginia Key tide station and dotted yellow line represents its small trend. Green line represents water level with added sea level rise trend and the dotted red line represents its trend.



Figure 35 compares the observed tide data and the predicted tides plus SLR trend.

Figure 35. Comparison between observed Virginia Key tide data and predicted tide plus trend.

Model Sensitivity Runs

For the model runs, we converted Virginia Key tide data to meters by multiplying them by 0.3048 and created .smp files starting with 1/1/1996 and ending 12/31/2025. We had three sets of data: observed tide, predicted tide, and predicted tide with added sea level rise trend. Before running the model, we ran the UMD_scenario_BND python script. In the code we adjusted the paths, so it reads and creates outputs in the correct folders. This script created binary data for GHB and DRN model input files. This

code also created umd_current.ghb and umd_current.drn files, which direct the model to read the binary files. We also created swr1 files for Virginia Key. In these files, the units are feet NAVD 88 because the model is set up to convert to meters NAVD 88. with the starting date 12/31/1995 and ending date 1/1/2026. With these changes, we ran the model for the current sea level scenario. The results of the model runs are shown below.

Figure 36 shows 2017 simulated wet season heads in feet NAVD. The heads are based on observed tide water level input (left), predicted tide without trend input (center), and predicted tide with added trend (right). Overall, the maps show that the heads simulated based on the predicted tides without the added trend (center) are slightly lower than those simulated with the observed tides (left) and with the predicted tides plus the SLR trend (right). Comparing the simulations with the observed tides and with the predicted tides plus the SLR trend (left and right panels of Figure 36), indicates that heads simulated with the predicted tides plus the SLR trend are almost indistinguishable. This is reasonable considering the generally small difference in the 2017 wet season observations and predictions in Figure 35; a key exception is when Hurricane Irma and a weaker Florida Current led to higher observed water levels for a short time. Similarly, Hurricane Joaquin is likely responsible for the observed water level peak in 2015, and Hurricane Nicole – together with a weak Florida Current – likely contributed to the observed water level peak in October of 2016. The impact of these differences between predicted and observed tide water levels is the key issue we seek to address here. On the basis of these preliminary simulations, it appears that the use of the predicted tides plus an SLR trend in the simulations captures the wet season heads adequately consistent with the original approach of the Urban Miami-Dade model of Hughes and White (2016), which used the observed tides.



Figure 36. 2017 simulated wet season heads in feet NAVD. Heads based on observed tide water level input (left), predicted tide without trend input (center), and predicted tide with added trend (right). Red dots are salinity control structures. White boxes with blue outlines are water supply/flood control structures.

Figure 37 shows the same results as Figure 36 displayed in terms of the depth to water. As expected, there are in general subtle increases in the simulated depth to water in case of the predicted tide without trend input (center), and the depths to water based on the observed tide water level input (left) and those based on the predicted tide with added trend (right) are nearly indistinguishable at this scale.



Figure 37. 2017 simulated wet season depths to water in feet. Depths to water based on observed tide water level input (left), predicted tide without trend input (center), and predicted tide with added trend (right). Red dots are salinity control structures. White boxes with blue outlines are water supply/flood control structures.

Figure 38 gives time series of observed and simulated heads for select wells (same wells as Figure 5-3 of Hughes and White (2016)) from 1996 through 2018 based on observed-tide water level input (green), predicted-tide-without-trend input (red), and predicted-tide-with-added-trend input (magenta). Wells G-3549 and G-3550 are closest to the tidal boundary and, as expected, show the greatest differences in the simulated heads as a function of the boundary type. The simulation based on the predicted tide-with-trend input tracks the simulation based on observations more closely. The deviation of the tide-without-trend input from the other simulations grows with time as the effect of the trend grows stronger. These results are consistent with the more generalized observations based on Figure 36.



Figure 38. Time series showing observed (gray) and simulated heads for select wells (same wells as Figure 5-3 of Hughes and White (2016)) from 1996 through 2018 based on observed tide water level input (green), predicted tide without trend input (red), and predicted tide with added trend input (magenta). Wells G-3549 and G-3550 are closest to the tidal boundary. Remainder of wells show observations through 2010 only.

Conclusion

The simulations conducted for this ocean boundary sensitivity analysis suggest that the use of predicted tides with an added sea level rise trend as key model input is adequate for the purpose of this project. The use of the predicted tides plus an SLR trend in the simulations reproduces the wet season heads in a way that is adequately consistent with the original approach of the Urban Miami-Dade model of Hughes and White (2016), which used the observed tides as input.

References

Hughes, J.D., and White, J.T., 2016, Hydrologic conditions in urban Miami-Dade County, Florida, and the effect of groundwater pumpage and increased sea level on canal leakage and regional groundwater flow (ver. 1.2, July 2016): U.S. Geological Survey Scientific Investigations Report 2014–5162, 175 p., http://dx.doi.org/10.3133/sir20145162.

Hughes, J.D., Langevin, C.D., Chartier, K.L., and White, J.T., 2012, Documentation of the Surface-Water Routing (SWR1) Process for modeling surface-water flow with the U.S. Geological Survey Modular Ground-Water Model (MODFLOW–2005): U.S. Geological Survey Techniques and Methods, book 6, chap. A40 (Version 1.0), 113 p. <u>https://doi.org/10.3133/tm6A40</u>.

Appendix V. Potential Implications for Florida Building Code (Task III)

Section B. FBC Code Recommendations

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Summary of Assessment To Date

To evaluate potential implications of sea-level rise and changing rainfall In the Florida Building Code for communities in Florida using Miami-Dade County as a Case Study, we are evaluating the current Florida Building Code requirements to recommend what additional steps will be necessary to incorporate results of the proposed study into the sections of the Codes mentioned above. Specifically, we are evaluating 1) how the changes to the rain loads and their implications for Rain Loads as applied to Figure 1611.1 and figure 1106.1 of the FBC, Plumbing are being evaluated, 2) how the groundwater table maps and the revised rainfall maps should be used to update the Flood loads as applied to (Chapter 16), Flood Resistant Construction (Chapter 3, Section R322) and the structures seaward of the coastal construction line (Chapter 31, Section 3109) of the FBC, and 3) specific recommendations for Code modifications to incorporate the updated information on groundwater elevation due to sea level rise and rainfall. Individual sections are being reviewed and a set of preliminary considerations are being put forth, that, when evaluated along with new flood and rain data, recommendations will be drawn. Preliminary considerations include defining a "coastal zone", similar to a "coastal A zone" for floodplain management, with implications for building, plumbing and residential sections of the code.

FBC Code Recommendations – DRAFT

FLOOD LOADS

FBC - Building

Chapter 16, Structural Design

Section 1605 - Load Combinations

Section 1610 - Soil Lateral Loads

Section 1612 - Flood Loads of Building

(Table 1612.1 also lists 1601 and 1603)

Chapter 18, Soil & Foundations

Section 1803 Geotechnical Investigations

section 1804 Excavation, Grading & Filling

Section 1805 Damp proofing & Waterproofing

Section 1806 Presumptive Load-Bearing Values of soils

Section 1807 Foundation Walls, Retaining Walls & embedded Posts & Poles

Section 1808 Foundations

Section 1809 Shallow Foundations

Section 1810 Deep Foundations

Chapter 31, Special Construction

Section 3109 Structures seaward of a coastal construction control line

(Table 1612.1 also lists sections of chapters 1,2,3,8,12,27)

FBC – Residential

Chapter 3,

Section R322 - Flood Resistant Construction

R322.1 General

Buildings and structures constructed in whole or in part in flood hazard areas, including A or V Zones and Coastal A Zones, as established in Table R301.2(1), and substantial improvement and restoration of substantial damage of buildings and structures in flood hazard areas, shall be designed and constructed in accordance with the provisions contained in this section. Flood hazards E.g. follow local floodplain management ordinance. An ordinance or regulation adopted pursuant to the authority granted to local

governments by Title 44 Code of Federal Regulations, Sections 59 and 60 for participation in the National Flood Insurance Program.

R322.1.1 Alternative provisions

As an alternative to the requirements in Section R322, ASCE 24 is permitted subject to the limitations of this code and the limitations therein.

NOTE: Does this mean ASCE24 can preempt the local floodplain ordinance?

Recommendation: Verify, then consider

R322.1.2 Structural systems

Structural systems of buildings and structures shall be designed, connected and anchored to resist flotation, collapse or permanent lateral movement due to structural loads and stresses from flooding equal to the design flood elevation.

NOTES: existing FIRM may not adequately estimate the risk from flotation, collapse or permanent lateral movement in areas that may otherwise be coastal A zone

<u>Recommendation</u>: Update from FEMA or Baker/AECOM? Or at least bring forward in review of new FIRM

(Table 1612.1 also lists R301 and R309)

(Table 1612.1 also lists sections of chapters 2,4,14,16,17,20,22,24,26,27,30,31,45)

FBC – Plumbing

Chapter 11, Storm Drainage

Section 1101 General

1101.1 Scope

The provisions of this chapter shall govern the materials, design, construction and installation of storm drainage.

1101.2 Disposal

Rainwater from roofs and storm water from paved areas, yards, courts and courtyards shall drain to an *approved* place of disposal. For one- and two-family dwellings, and where *approved*, storm water is permitted to discharge onto flat areas, such as streets or lawns, provided that the storm water flows away from the building.

NOTES: If landed is flooded, storm water will not flow away from building. What is "approved"?

<u>Recommendation</u>: Approved place for disposal of rainwater and storm water may need reconsideration. Currently permitted for one and 2 family dwellings and "where approved".

1101.3 Prohibited drainage.

Storm water shall not be drained into sewers intended for sewage only.

NOTES: Flooding above manholes can result in storm water entering sewers.

Recommendation: Reconsider height of man holes (also consistent with floodplain management regs).

1101.5 Change in size.

The size of a drainage pipe shall not be reduced in the direction of flow.

NOTES: Reversal of flow into drainage pipe results in flow in direction of reduced pipe size.

<u>Recommendation</u>: Include provisions to reduce incidence of flow reversal in drainage pipes (e.g., backflow preventer) for sites near the coast. Further consideration – redefine "coast" for FBC

1101.7 Roof design.

... The maximum possible depth of water on the roof shall include the height of the water required above the inlet of the secondary roof drainage means to achieve the required flow rate of the secondary drainage means to accommodate the design rainfall rate as required by Section 1106.

NOTES: This will be handled in Section 1106 and rain loads.

<u>Recommendation</u>: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

1101.8 Cleanouts required

Cleanouts shall be installed in the storm drainage system and shall comply with the provisions of this code for sanitary drainage pipe cleanouts.

NOTES: What is the typical height of a cleanout? Could there be flood conditions that prevent proper functioning of cleanout maintenance?

1101.9 Backwater valves

Storm drainage systems shall be provided with backwater valves as required for sanitary drainage systems in accordance with Section 715.

NOTES: Also pertains to reversal of flow (1105.1)

<u>Recommendation</u>: Consider whether backwater values need additional design features to accommodate greater backwater flow pressures

Section 1102 Materials

1102.4 Building storm sewer pipe

Building storm *sewer* pipe shall conform to one of the standards listed in Table 1102.4.

NOTES: some of the materials listed in Table are corrosive in sea water (e.g., cast iron, copper alloy, stainless steel).

Recommendation: Further consideration of corrosion resistant materials for "coastal" applications.

Again, define "coastal" for FBC e.g., limit of saltwater and tidal influence.

1102.5 Subsoil drain pipe

Subsoil drains shall be open-jointed, horizontally split or perforated pipe conforming to one of the standards listed in Table 1102.5.

NOTES: some of the materials listed in Table are corrosive in sea water (e.g., cast iron, stainless steel).

Recommendation: Further consideration of corrosion resistant materials for "coastal" applications. Again, define "coastal" for FBC e.g., limit of saltwater and tidal influence.

1102.6 Roof Drains

Roof drains shall conform to ASME A112.6.4 or ASME A112.3.1.

1102.7 Fittings

Pipe fittings shall be *approved* for installation with the piping material installed, and shall conform to the respective pipe standards or one of the standards listed in Table 1102.7.

NOTES: some of the materials listed in Table are corrosive in sea water (e.g., cast iron, stainless steel).

Recommendation: Further consideration of corrosion resistant materials for "coastal" applications. Again, define "coastal" for FBC e.g., limit of saltwater and tidal influence.

Section 1103 Traps

1103.1 Main trap

Leaders and *storm drains* connected to a combined sewer shall be trapped. Individual storm water traps shall be installed on the storm water drain *branch* serving each conductor, or a single trap shall be installed in the main *storm drain* just before its connection with the combined *building sewer* or the *public sewer*. Leaders and storm drains connected to a building storm sewer shall not be required to be trapped.

NOTES: Is there any reason a building storm drain might need a trap if it has regular backflow? Do the design features of the combined sewer trap need reconsideration?

Recommendations: Further consider notes

1103.2 Material

Storm water traps shall be of the same material as the piping system to which they are attached.

NOTES: some of the materials listed in Table are corrosive in sea water (e.g., cast iron, stainless steel).

Recommendation: Further consideration of corrosion resistant materials for "coastal" applications. Again, define "coastal" for FBC e.g., limit of saltwater and tidal influence.

1103.4 Cleanout

An accessible cleanout shall be installed on the building side of the trap.

NOTES: What are design features of cleanouts??

Recommendation: Further consideration of cleanout design.

Section 1105 Roof Drains

1105.2 Roof drain flow rate

The published roof drain flow rate, based on the head of water above the roof drain, shall be used to size the storm drainage system in accordance with Section 1106. The flow rate used for sizing the storm drainage piping shall be based on the maximum anticipated ponding at the roof drain.

NOTES: This will be handled in Section 1106 and rain loads.

Recommendation: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

Section 1106 Size of Conductors, Leaders and Storm Drains

1106.1 General

The size of the vertical conductors and leaders, building *storm drains*, building storm sewers and any horizontal branches of such drains or sewers shall be based on the 100-year hourly rainfall rate indicated in Figure 1106.1 or on other rainfall rates determined from *approved* local weather data.

NOTES: These tables are all about not exceeding flow rates specified. The dimensions of these pipes and gutters will likely need to change to not exceed these gpm for updated 100yr, 1in storms. Another issue is the frequency of 100yr, 1in storms. Consider trade-offs. This will be handled in Section 1106 and rain loads.

Recommendation: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

1106.2 Size of storm drain piping

Vertical and horizontal storm drain piping shall be sized based on the flow rate through the roof drain. The flow rate in storm drain piping shall not exceed that specified in Table 1106.2.

NOTES: This will be handled in Section 1106 and rain loads.

<u>Recommendation</u>: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

1106.3 Vertical leader sizing

Vertical leaders shall be sized based on the flow rate from horizontal gutters or the maximum flow rate through roof drains. The flow rate through vertical leaders shall not exceed that specified in Table 1106.3.

NOTES: This will be handled in Section 1106 and rain loads.

<u>Recommendation</u>: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

1106.4 Vertical walls

In sizing roof drains and storm drainage piping, one-half of the area of any vertical wall that diverts rainwater to the roof shall be added to the projected roof area for inclusion in calculating the required size of vertical conductors, leaders and horizontal storm drainage piping.

NOTES: This will be handled in Section 1106 and rain loads.

Recommendation: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

1106.6 Size of roof gutters

Horizontal gutters shall be sized based on the flow rate from the roof surface. The flow rate in horizontal gutters shall not exceed that specified in Table 1106.6.

NOTES: This will be handled in Section 1106 and rain loads.

<u>Recommendation</u>: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

Section 1107 Siphonic Roof Drainage Systems

1107.1 General

Siphonic roof drains and drainage systems shall be designed in accordance with ASME A112.6.9 and ASPE 45

Section 1108 Secondary (Emergency) Roof Drains

1108.2 Separate systems required

Secondary roof drain systems shall have the end point of discharge separate from the primary system. Discharge shall be above grade, in a location that would normally be observed by the building occupants or maintenance personnel.

<u>Recommendation</u>: Consider whether discharge should be a minimum height above grade.

1108.3 Sizing of secondary drains

Secondary (emergency) roof drain systems shall be sized in accordance with Section 1106 based on the rainfall rate for which the primary system is sized. Scuppers shall have an opening dimension of not less than 4 inches (102 mm).

NOTES: This will be handled in Section 1106 and rain loads.

Recommendation: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed.

Section 1109 Combined Sanitary and Storm Public Sewer

1109.1 General

Where the public sewer is a combined system for both sanitary and storm water, the storm sewer shall be connected independently to the public sewer.

NOTES: Are these still allowed in Florida?

Recommendation: Consider whether these should be removed as allowable under FBC.

Section 1110 Controlled Flow Roof Drain Systems

1110.1 General

The roof of a structure shall be designed for the storage of water where the storm drainage system is engineered for controlled flow. The controlled flow roof drain system shall be an engineered system in accordance with this section and the design, submittal, approval, inspection and testing requirements of Section 316.1. The controlled flow system shall be designed based on the required rainfall rate in accordance with Section 1106.1.

NOTES: This will be handled in Section 1106 and rain loads.

<u>Recommendation</u>: Consider whether roof design elements need to be modified pursuant to this section when updated rain loads are developed. Potential changes for control devices, and maybe also installation, and minimum number of roof drains.

Section 1111 Subsoil Drains

1111.1 Subsoil drains

Subsoil drains shall be open-jointed, horizontally split or perforated pipe conforming to one of the standards listed in Table 1102.5. Such drains shall not be less than 4 inches (102 mm) in diameter. Where the building is subject to backwater, the subsoil drain shall be protected by an accessibly located backwater valve. Subsoil drains shall discharge to a trapped area drain, sump, dry well or *approved* location above ground. The subsoil sump shall not be required to have either a gas-tight cover or a vent. The sump and pumping system shall comply with Section 1113.1.

Section 1112 Building Subdrains

1112.1 Building subdrains

Building subdrains located below the *public sewer* level shall discharge into a sump or receiving tank, the contents of which shall be automatically lifted and discharged into the drainage system as required for building sumps. The sump and pumping equipment shall comply with Section 1113.1.

Section 1113 Sumps and Pumping Systems

NOTES: Pending

Recommendation: Everything about these should be reconsidered; specific recommendations pending.

1113.1 Pumping system

The sump pump, pit and discharge piping shall conform to Sections 1113.1.1 through 1113.1.4.

1113.1.1 Pump capacity and head

The sump pump shall be of a capacity and head appropriate to anticipated use requirements.

1113.1.2 Sump pit

The sump pit shall be not less than 18 inches (457 mm) in diameter and not less than 24 inches (610 mm) in depth, unless otherwise *approved*. The pit shall be accessible and located such that all drainage flows into the pit by gravity. The sump pit shall be constructed of tile, steel, plastic, cast iron, concrete or other *approved* material, with a removable cover adequate to support anticipated loads in the area of use. The pit floor shall be solid and provide permanent support for the pump.

1113.1.3 Electrical

Electrical service outlets, when required, shall meet the requirements of NFPA 70.

1113.1.4 Piping

Discharge piping shall meet the requirements of Section 1102.2, 1102.3 or 1102.4 and shall include a gate valve and a full flow check valve. Pipe and fittings shall be the same size as, or larger than, the pump discharge tapping.

Exception: In one- and two-family dwellings, only a check valve shall be required, located on the discharge piping from the pump or ejector.

Other considerations – hydrostatic pressure on drainage and building sewer pipes??

Appendix B

References rainfall rates, in inches per hour, are based on a storm of 1-hour duration and a 100-year return period. Also references temperatures.

RAIN LOADS

FBC - Building

Chapter 16, Structural Design

Figure 1611.1

FBC – Plumbing

Chapter 11, Storm Drainage

Figure 1106.1

NOTES: I thought I saw these referred to somewhere else in the code. Maybe cross-referenced in building, structural design? However the maps are in Chapter 11, Plumbing. And the table with five cities listed, in Appendix B

Other topics e.g., Septic, sewage, storm drains not specifically identified in original scope\

FBC – Plumbing

Appendix B – design temperatures and humidity

Chapter 7, Sanitary Drainage

Broader scale considerations:

- Salinity is not considered (corrodibility of pipes) consider a "coastal zone" definition to provide additional provisions for salinity, subsurface water table FBC design features like the coastal A zone is for flood
- Many temperature related codes (design dry and wet-bulb temperatures) related to winter temps for plumbing, but may be some considerations for other parts of code