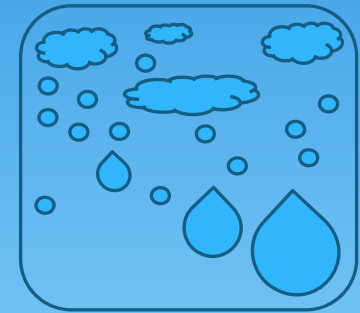
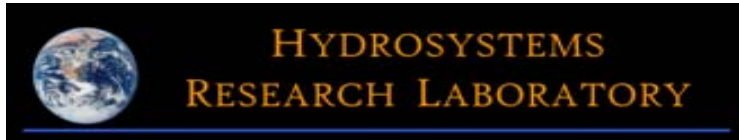


Experiments with Statistical Downscaling of Precipitation for South Florida Region: Issues & Observations



Ramesh S. V. Teegavarapu
Aneesh Goly

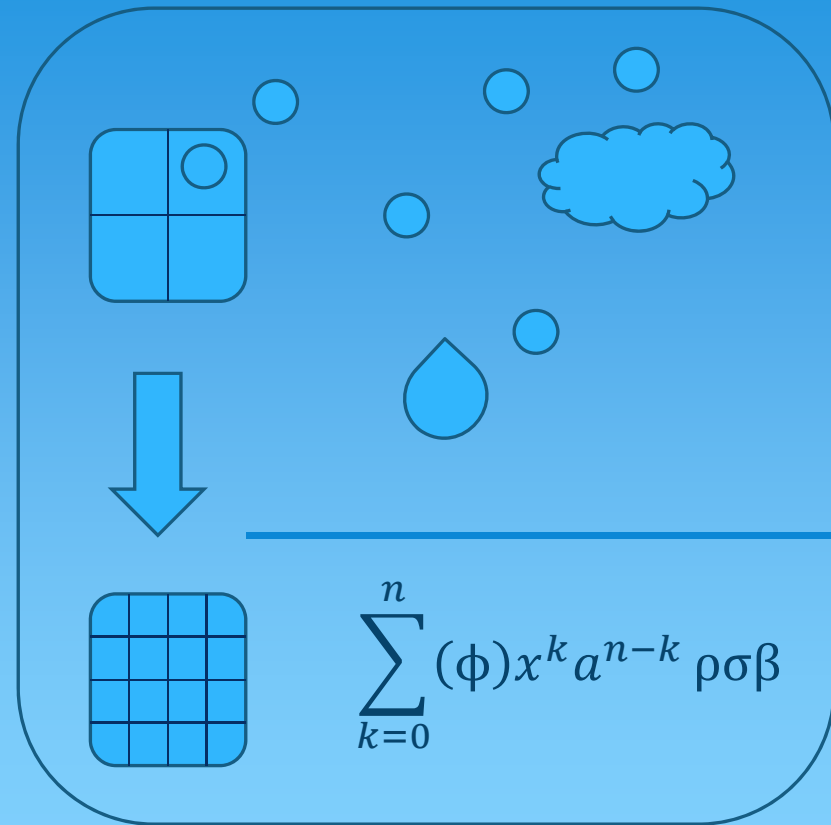
Hydrosystems Research Laboratory (HRL)
Department of Civil, Environmental
and Geomatics Engineering,
Florida Atlantic University, Boca Raton, FL, 33431



Everglades Workshop, March 29, 2012

Statistical Downscaling

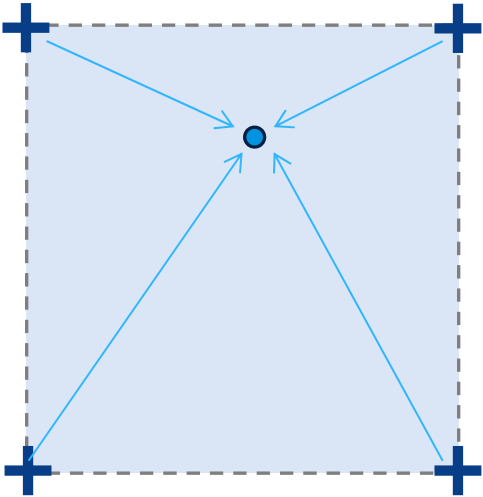
From a drop of water a
logician could predict
an Atlantic or a Niagara
- Sir Arthur C. Doyle.



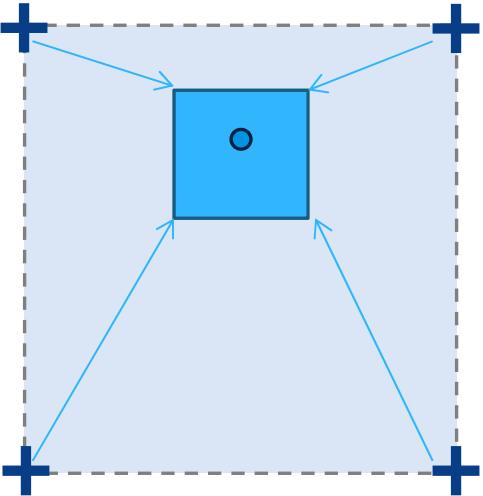
Downscaling methods

- Main Focus
 - Statistical downscaling of Precipitation
 - Florida and South Florida.
- Spatial Resolution
 - Point and Different Grid Scales
- Temporal Resolution
 - Monthly and Daily (work in progress)
- Analyses
 - Evaluation of different Methodologies
 - Comparative evaluation of other methodologies (e.g., BCSD-based data)
 - Optimal Predictor sets
 - Use of available traditional and machine learning techniques to develop transfer functions
 - Downscaling skill – use of performance measures
 - Extreme Events
 - Methodologies to handle stationarity issues

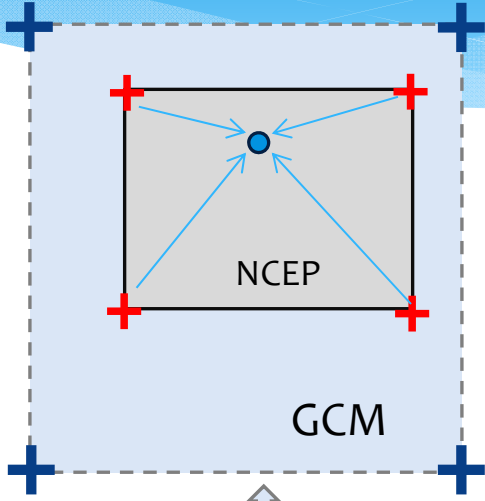
Point and Grid Scale Downscaling (GCM and NCEP)



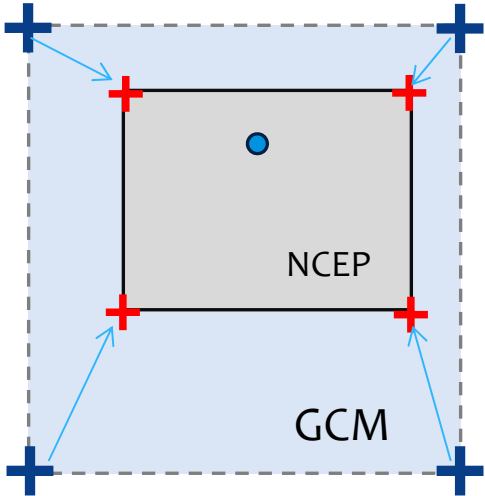
Point scale
downscaling
directly from
GCM



Grid scale
downscaling
directly from
GCM



NCEP Grid to
Point Scale



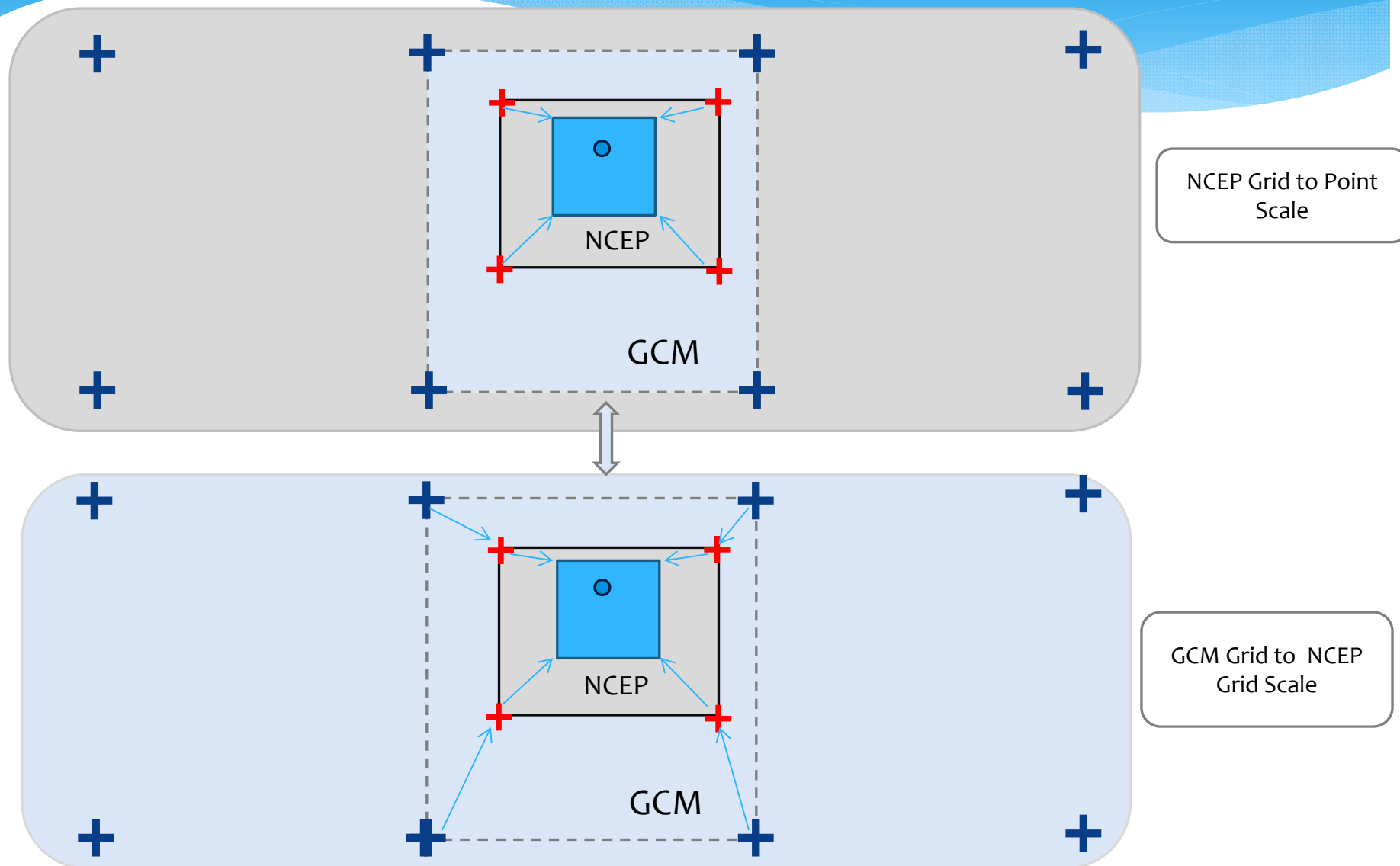
GCM Grid to
NCEP Grid Scale

● Rain gage /Observation Site

+ GCM Grid Centers

+ NCEP Grid Centers

Grid Scale Downscaling (NCEP)

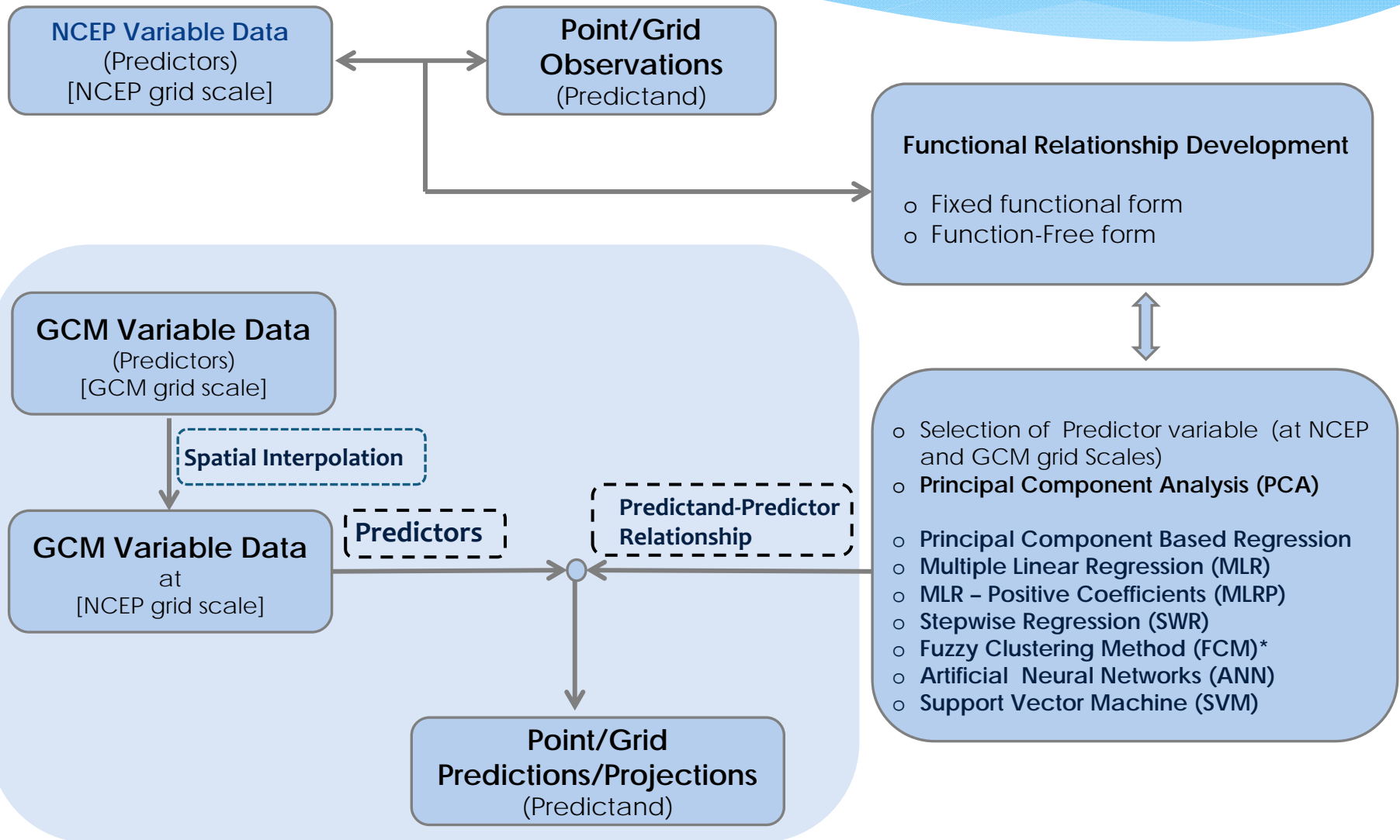


● Rain gage /Observation Site

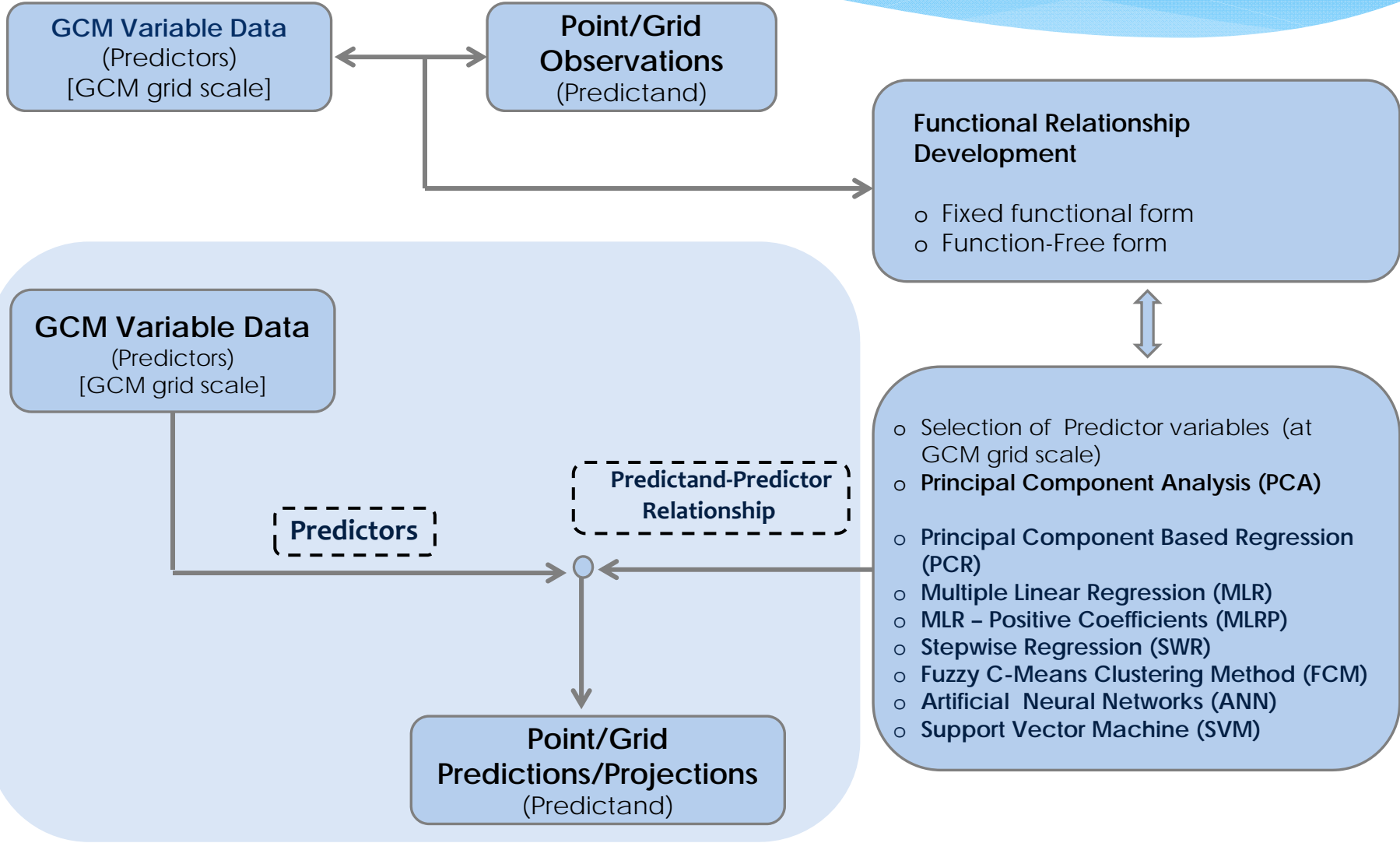
+ GCM Grid Centers

+ NCEP Grid Centers

NCEP – GCM Modeling Approach



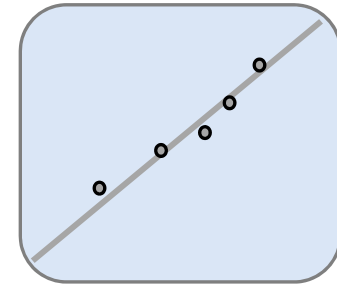
Direct GCM-based Approach



Functional Forms for Transfer Functions.

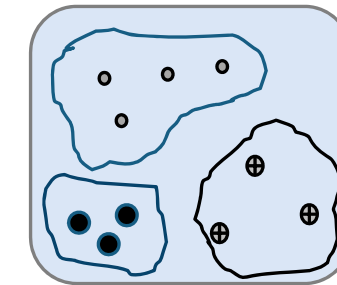
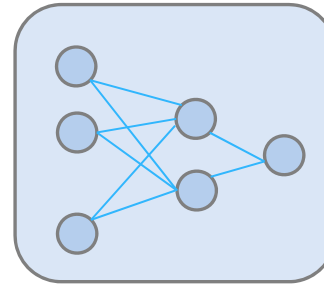
- **Pre-Fixed Functional Forms**

- Regression
 - Variants – Stepwise.
 - Negative values.
- Nonlinear Optimization with Positive Coefficients.
 - Dummy Variables (Binary Variables).



- **Function Free Forms**

- Artificial Neural Networks
- Negative Values
- Over Fitting Issues

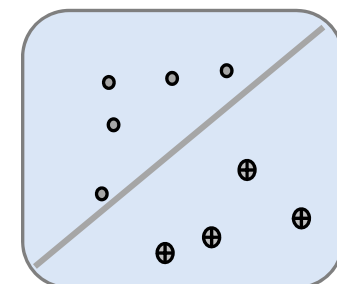


- **Fuzzy C-Means Clustering (FCM)**

- Clusters of data, evaluation of membership functions, regression

- **Support Vector Machines (SVM)**

- Classification of data and regression using a machine learning technique
- Negative Values



- **Evaluation is required for different time-slices.**

Nonlinear Optimization with Positive Coefficients.

Nonnegative constraints requirements to obtain positive weights can be enforced using the nonlinear least square constraint formulation defined by equation.

$$\text{Minimize } \|G \cdot x - H\|_2^2$$

Subject to:

$$v_{\alpha,j} \geq 0$$

The formulation minimizes the norm given by the above equation with constraint on the weights

G is the $n_o \times j$ matrix of *predictor* values, x is the matrix $j \times 1$ of $v_{\alpha,j}$ weight values and H is the matrix of $n_o \times 1$ values of observed precipitation data at a point or in a grid

Fuzzy C-Means Clustering (FCM)

FCM clustering is used with an assumption that there exists **classes or clusters** in predictors, which may lead to different relationships between predictors and rainfall for different clusters. To improve the performance of the statistical downscaling model, an approach with clustering is coupled with the model.

In the **fuzzy clustering technique**, the crisp classification is extended to fuzzy classification using the concept of membership values. Membership values are assigned to the various data points for each fuzzy set/cluster/class.

FCM has improved the model performance compared to PCA-based regression alone.

$$J(U, V) = \sum_{i=1}^n \sum_{j=1}^c (\mu_{ij})^m \|x_i - v_j\|^2$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}}$$

$$v_j = \frac{\sum_{i=1}^n (\mu_{ij})^m x_i}{\sum_{i=1}^n (\mu_{ij})^m} \quad \forall j = 1, 2, \dots, c$$

- Stationarity
- Statistical relationship between the predictor and the predictand **does not change over time**
 - Florida experienced land use changes over the last few decades –that may render stationarity assumption invalid.
- The plan to **capture future patterns** from scenarios via exploring **temporal analogues** from the past and develop corresponding statistical relationships.
- This is being explored and experimented in the current research integrating classification approaches.
- Evaluation of how well the large scale gridded data of a specific variable predicts the local variable (of same parameter)
- Predictor Variable Selection
 - Physics-inspired
 - Correlation Selection
 - All available variables with PCA

GCM Data Details

GCM Details:

Modeling Agency : Canadian Centre for
Climate Modelling and Analysis

Model and Version: CGCM3.1/T63 Model

Scenario: IPCC SRES A1B Experiment

IPCC SRES A1B 720 ppm stabilization
experiment with CGCM3.1/T63 for years
2001-2100 is selected for this analysis.

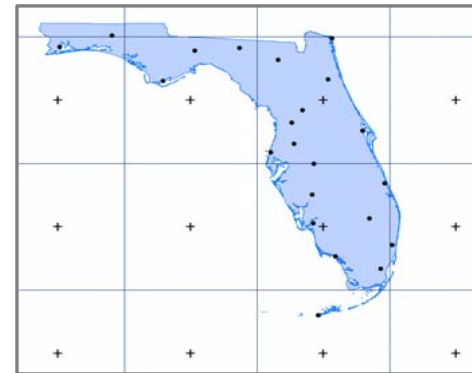
Monthly values from Jan 2001 to Dec 2100 is
available.

IPCC 20-th Century experiment monthly values
with CGCM3.1/T63 for years 1850-2000 is
available.

Spatial Resolution: $2.81^{\circ} \times 2.81^{\circ}$

Temporal resolution : day, Month

Time period : 1948 – 2000.
: 2001-2100



NCEP Reanalysis Data Details

NCEP Details:

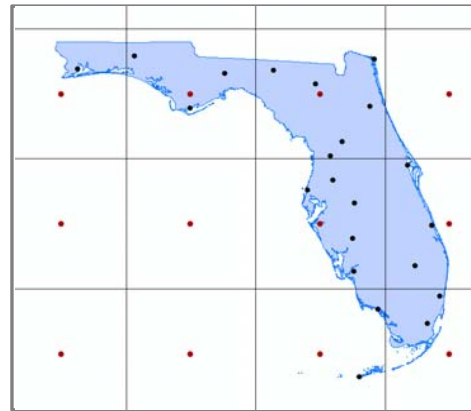
Agency : National Center for
Environmental Protection

Available through: Physical Sciences
Division: Data Management
NOAA/ESRL/PSD
Model and Version: Reanalysis 1

Spatial Resolution: $2.5^{\circ} \times 2.5^{\circ}$

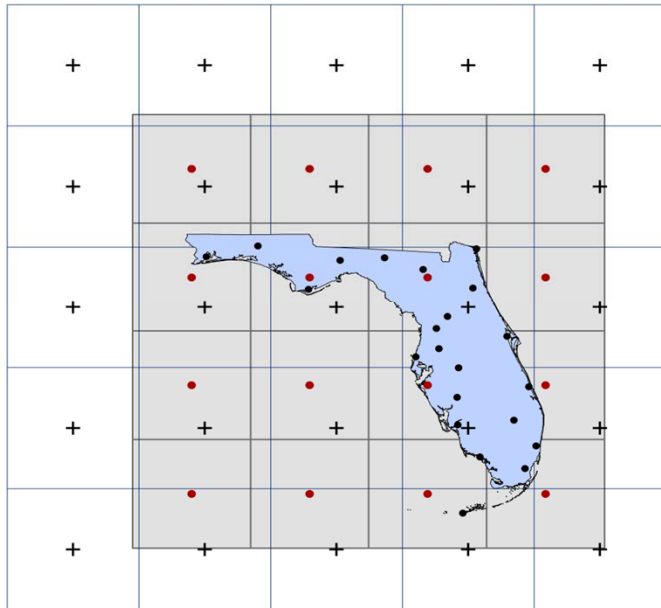
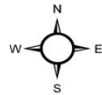
Temporal resolution : day, Month

Time period : 1948 – 2012.

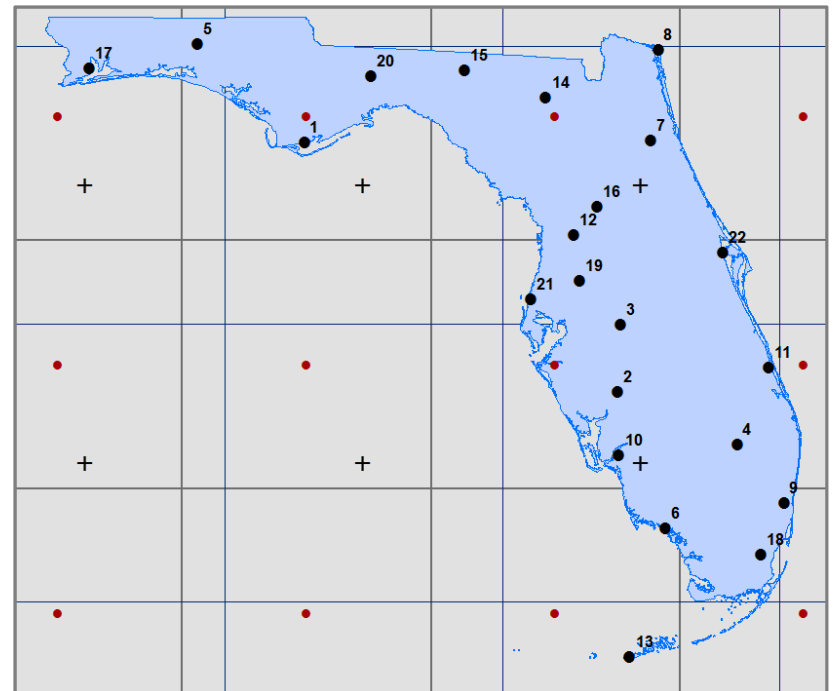


NCEP – GCM Results Point Scale Downscaling

Grids & Grid Centres



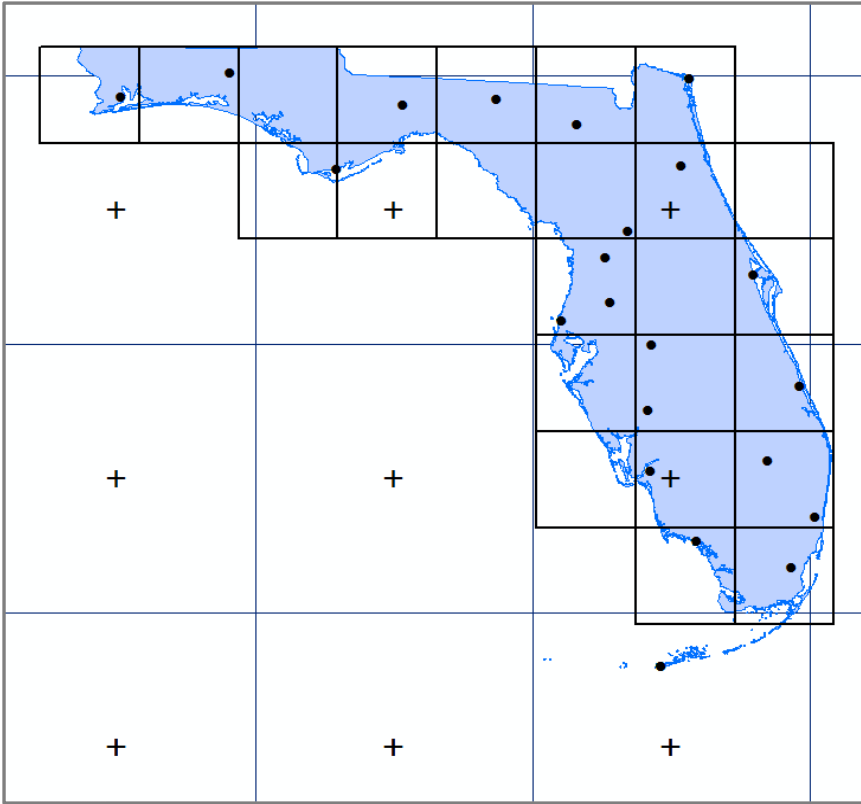
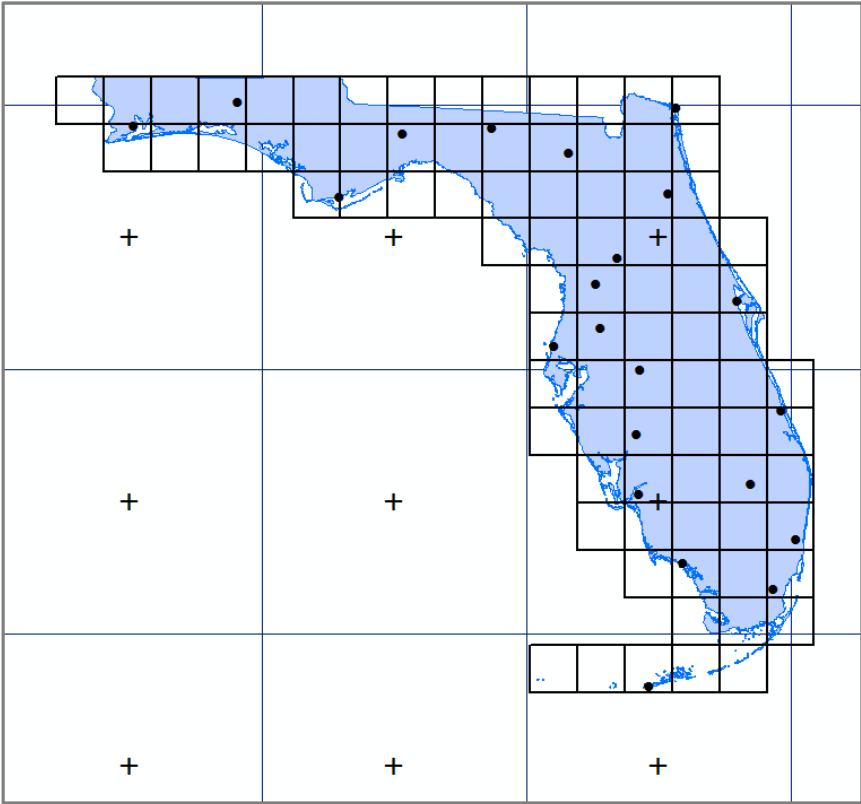
- + GCM Grid Centroid
- NCEP Grid Centroid
- USHCN Station
- Florida
- GCM Grid
- NCEP Grid



USHCN Stations

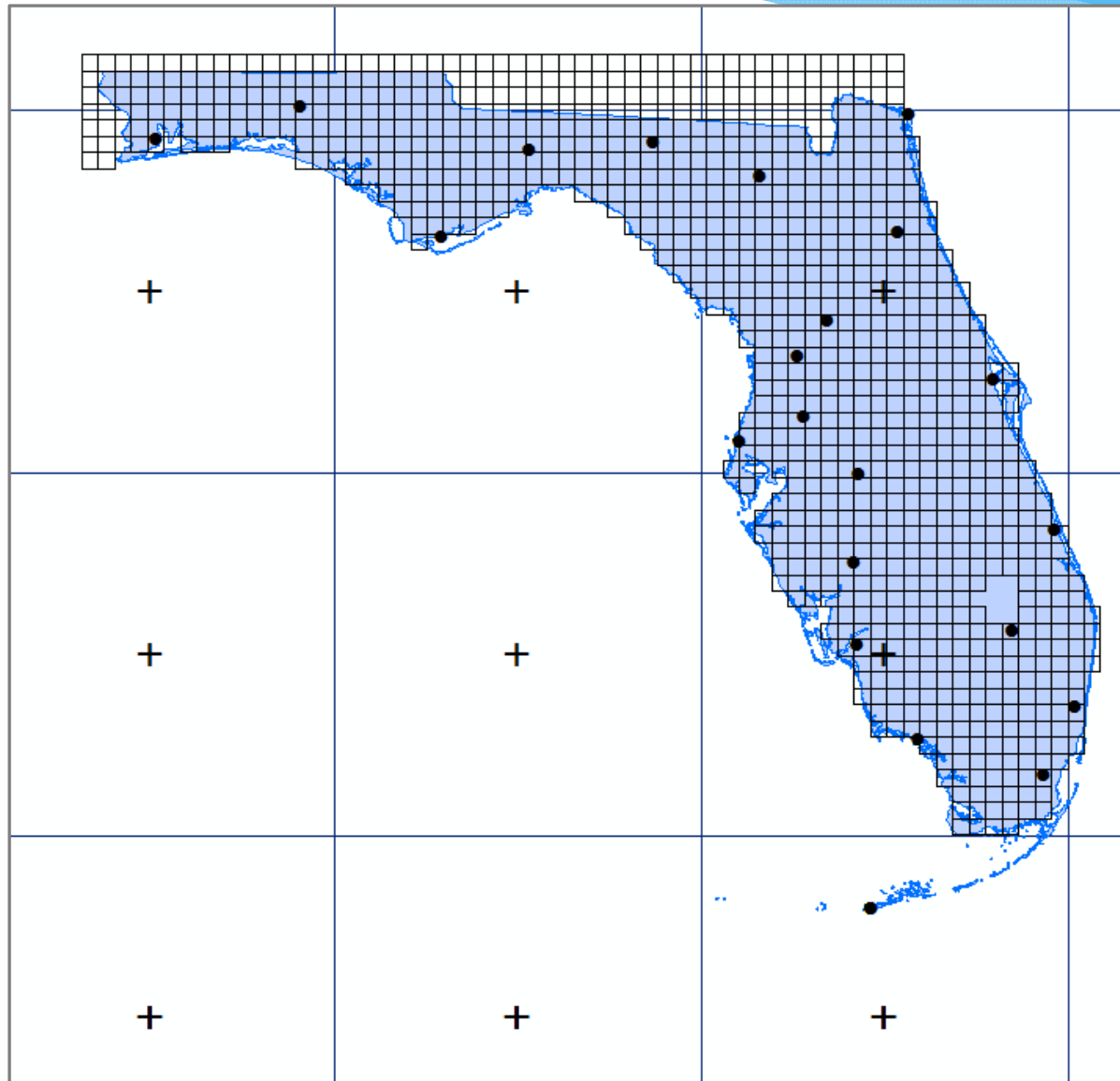
GPCC Grid Specifications

GPCC 0.5 Degree



GPCC 1 Degree

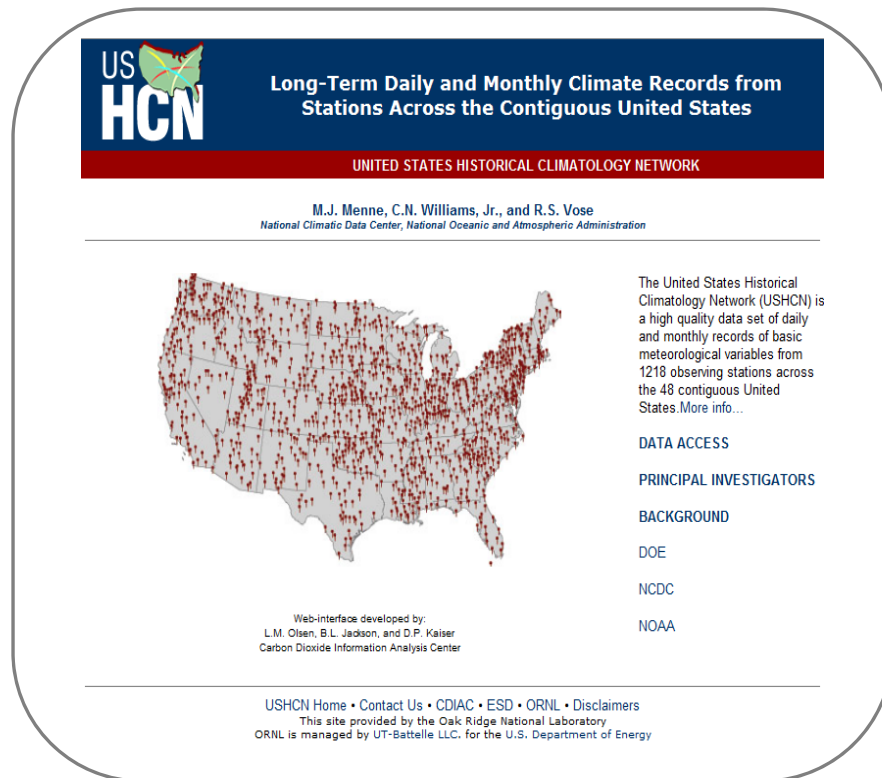
BCSD Grid Specifications



- Bias Corrected Statistical Downscaling (BCSD)
- Observed Data Sets
- Resolution : $1/8^\circ$
- Data Availability: 1949 – 2011.

Observed Precipitation Products Point and Grid-based

- **United States Historical Climatology Network (USHCN)**
 - 22 Stations spread through out Florida
 - Daily and Monthly data for both precipitation and temperature.
 - Data Availability: 1895-2010.
- **Global Precipitation Climatology Center (GPCC)**
 - GPCC station database (67 200 stations with at least 10 years of data) available at the time of analysis. Gauge-based gridded monthly precipitation available in $2.5^\circ \times 2.5^\circ$, $1.0^\circ \times 1.0^\circ$, $0.5^\circ \times 0.5^\circ$, and $0.25^\circ \times 0.25^\circ$ resolution)



US HCN
Long-Term Daily and Monthly Climate Records from Stations Across the Contiguous United States
UNITED STATES HISTORICAL CLIMATOLOGY NETWORK

M.J. Menne, C.N. Williams, Jr., and R.S. Vose
National Climatic Data Center, National Oceanic and Atmospheric Administration

The United States Historical Climatology Network (USHCN) is a high quality data set of daily and monthly records of basic meteorological variables from 1218 observing stations across the 48 contiguous United States. [More info...](#)

DATA ACCESS

PRINCIPAL INVESTIGATORS

BACKGROUND

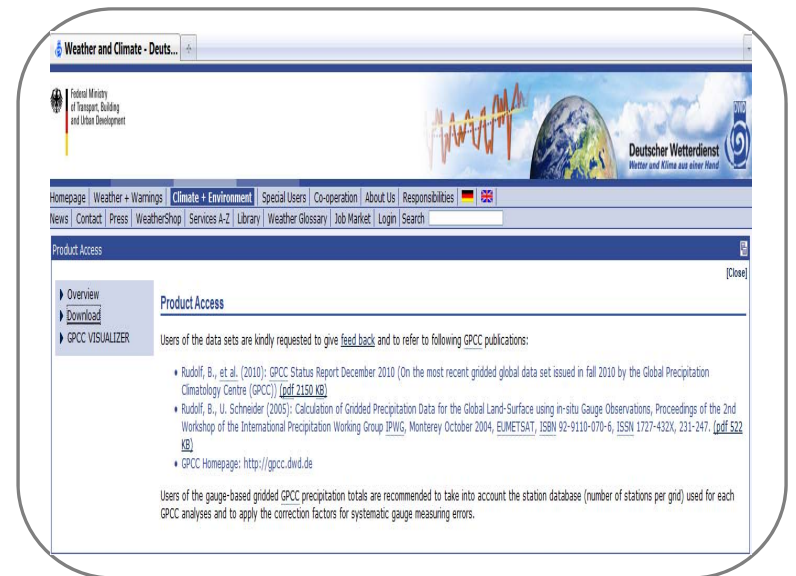
DOE

NCDC

NOAA

Web-interface developed by:
L.M. Olsen, B.L. Jackson, and D.P. Kaiser
Carbon Dioxide Information Analysis Center

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Federal Ministry of Transport, Building and Urban Development
Deutscher Wetterdienst
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Product Access (Close)

Overview
Download
GPCC VISUALIZER

Product Access

Users of the data sets are kindly requested to give [feedback](#) and to refer to following GPCC publications:

- Rudolf, B., et al. (2010): GPCC Status Report December 2010 (On the most recent gridded global data set issued in fall 2010 by the Global Precipitation Climatology Centre (GPCC)) [\[pdf 2150 KB\]](#)
- Rudolf, B., U. Schneider (2005): Calculation of Gridded Precipitation Data for the Global Land-Surface using in-situ Gauge Observations, Proceedings of the 2nd Workshop of the International Precipitation Working Group (IPWG), Monterey October 2004, EUMETSAT, ISBN 92-9110-070-6, ISBN 1727-432X, 231-247, [\[pdf 522 KB\]](#)
- GPCC Homepage: <http://gpcc.dwd.de>

Users of the gauge-based gridded GPCC precipitation totals are recommended to take into account the station database (number of stations per grid) used for each GPCC analyses and to apply the correction factors for systematic gauge measuring errors.

Rudolf, B., C. Beck, J. Grieser, U. Schneider (2005): Global Precipitation Analysis Products. Global Precipitation Climatology Centre (GPCC), DWD,

Gridded Observed Meteorological Data BCSD Grid Resolution

- **Gridded Observed Meteorological Data**
- 1/8° Spatial Resolution
- Period: 1949-2011

- Maurer, E.P., A.W. Wood, J.C. Adam, D.P. Lettenmaier, and B. Nijssen, 2002, A Long-Term Hydrologically-Based Data Set of Land Surface Fluxes and States for the Conterminous United States, *J. Climate* 15(22), 3237-3251

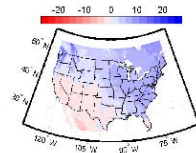


DATA AND FILES:

This page provides links to data files. These are provided for convenience of downloading related to specific projects or particular data requests, and are not fully explained here.

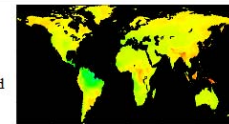
Library of Downscaled Climate Projections

A data set of 112 downscaled climate projections, based on output from 16 GCMs and 3 different SRES emissions scenarios (A2, A1B, B1) has been made available for public downloading. The spatial domain is shown in the figure, covering the conterminous US plus portions of Canada and Mexico. The resolution is 1/8 degree (~140 km² per grid cell). Raw monthly data for any region as well as summary statistics may be specified. The data set is formally introduced in *AGU's Eos* 88(47), 11/2007. [Click here](#) to be redirected to the web site, hosted by the [Green Data Oasis](#).



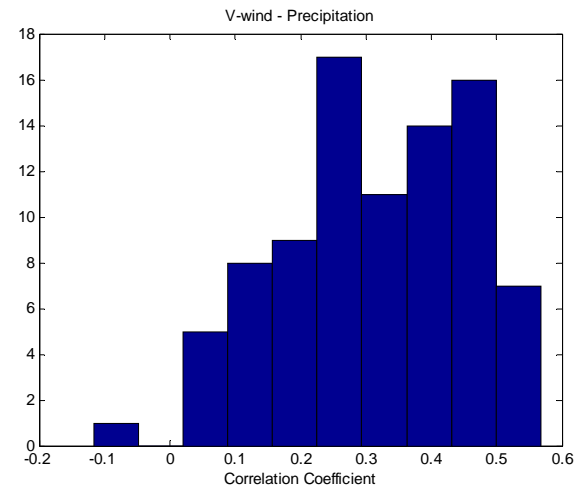
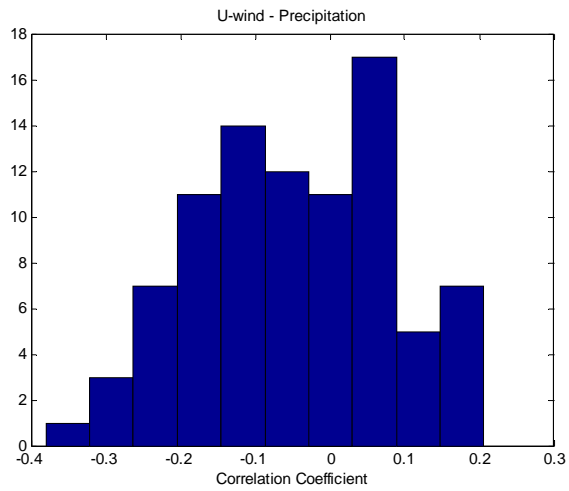
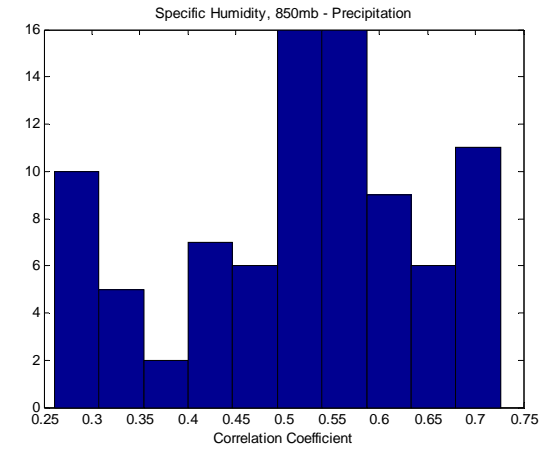
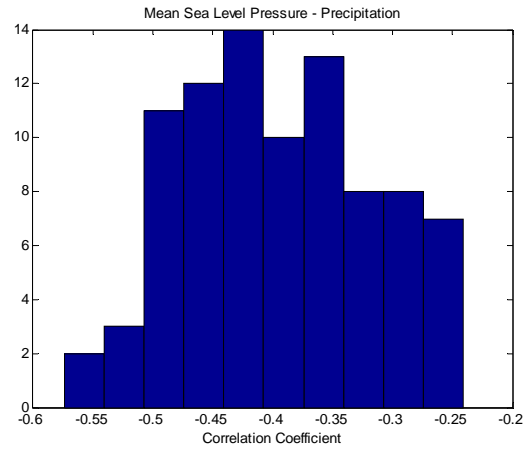
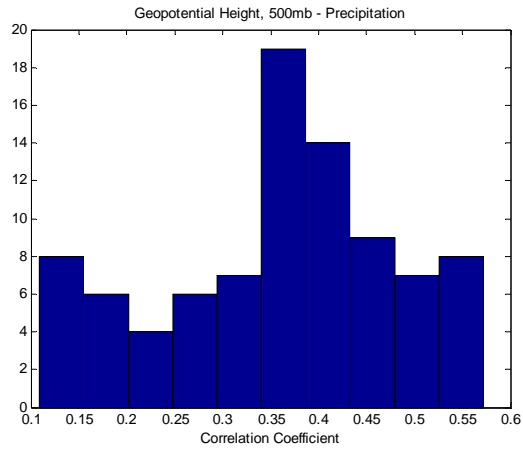
Global Downscaled Data

Preliminary data are served [here](#). These will be moved to a new location eventually, with a fancy new interface to allow subsetting and some analysis. The collection of downscaled simulations will be expanded as well.

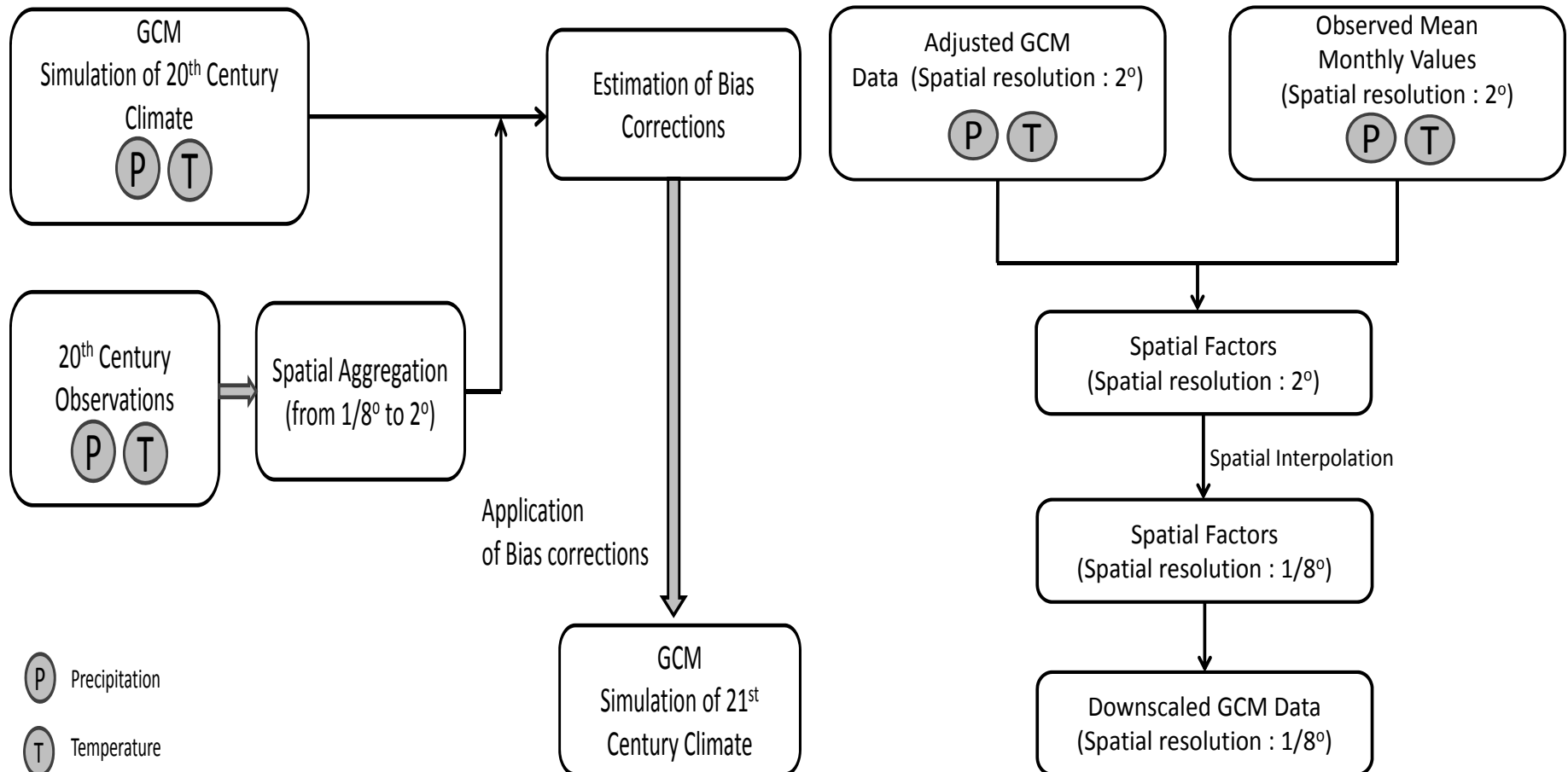


Both the global and US-wide datasets are (or are in the process of being) included in the Climate Wizard: <http://www.climatewizard.org>.

Predictor- Predictand Correlations



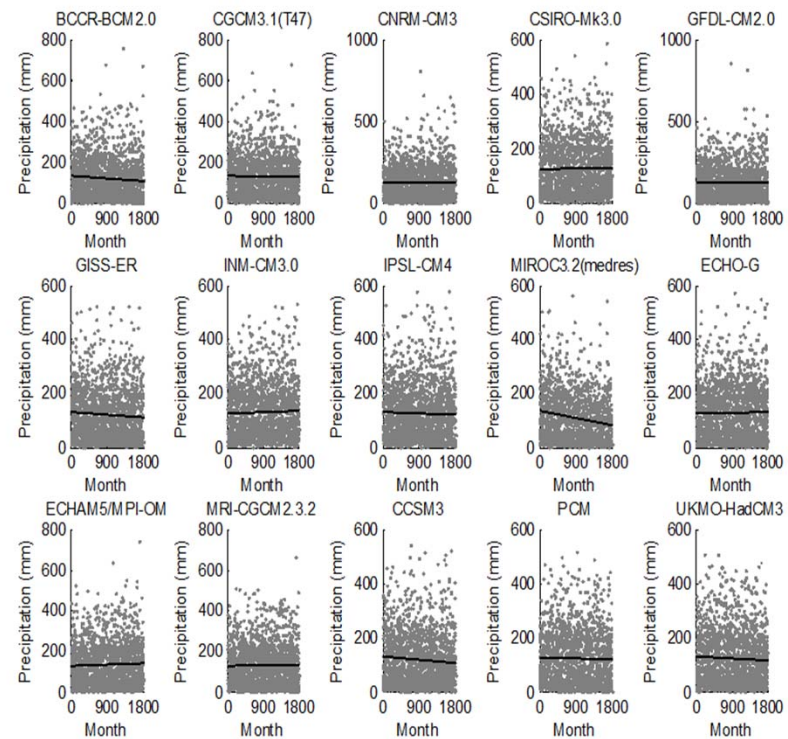
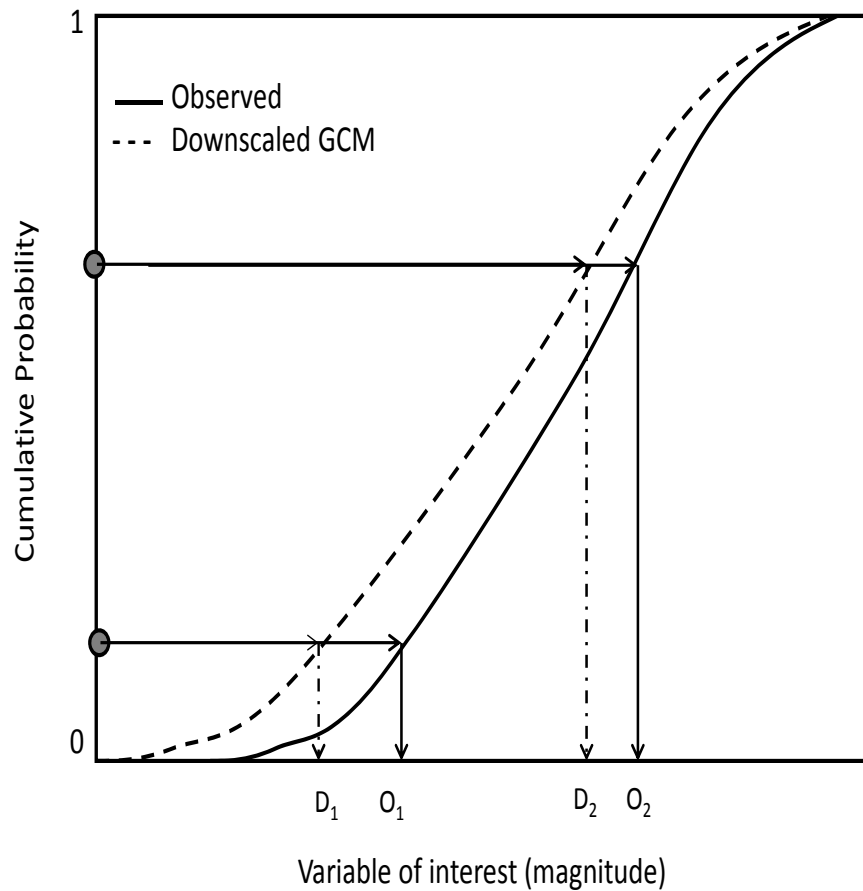
Bias Correction- Spatial Disaggregation (BCSD)



Models

Model Number	Modeling Group and Country of Origin	WCRP CMIP3 I.D.
1	Bjerknes Centre for Climate Research	BCCR-BCM2.0
2	Canadian Centre for Climate Modeling & Analysis	CGCM3.1 (T47)
3	Meteo-France / Centre National de Recherches Meteorologiques, France	CNRM-CM3
4	CSIRO Atmospheric Research, Australia	CSIRO-Mk3.0
5	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory, USA	GFDL-CM1.0
6	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory, USA	GFDL-CM2.0
7	NASA / Goddard Institute for Space Studies, USA	GISS-ER
8	Institute for Numerical Mathematics, Russia	INM-CM3.0
9	Institut Pierre Simon Laplace, France	IPSL-CM4
10	Center for Climate System Research (The University of Tokyo)	MIROC3.2 (medres)
	National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan	
11	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA	ECHO-G
12	Max Planck Institute for Meteorology, Germany	ECHAM5/ MPI-OM
13	Meteorological Research Institute, Japan	MRI-CGCM2.3.2
14	National Center for Atmospheric Research, USA	CCSM3
15	National Center for Atmospheric Research, USA	PCM
16	Hadley Centre for Climate Prediction and Research / Met Office, UK	UKMO-HadCM3

Performance Measures, Selection of Models Skill of Models - Precipitation



Goly and Teegavarapu (2012)

Performance Measures for Skill Assessment

- Mean absolute error (MAE): absolute difference in precipitation totals based on GCM-based and historical data.
- Correlation coefficient (ρ): correlation between historical and GCM-based precipitation data.
- Absolute Probabilistic Error (APE): absolute difference in values based on Cumulative density plots based on historical and GCM-based data.
- Probabilistic Correlation: correlation based on magnitudes from historical and GCM-based data obtained from pre-specified non-exceedence probabilities.
- Absolute Deviations in Annual Values: absolute deviation in annual values as opposed to monthly deviations (GCM-based temporal resolutions).
- Absolute Deviation in Month/Year Ratios: absolute deviation in ratios.

Correlations based on USHCN and BCSD downscaling results for different models (Temperature)

Station \ Climate Model	BCCR-BCM2.0	CGCM	CNRM-CM	CSIRO-Mk	GFDL-CM	GISS-ER	INM-CM	IPSL-CM	MIROC	ECHO-G	ECHAM5	MRI-CGCM	CCSM3	PCM	UKMO-HadCM
1	0.92	0.91	0.92	0.91	0.92	0.92	0.92	0.92	0.92	0.91	0.91	0.92	0.92	0.92	0.91
2	0.92	0.91	0.92	0.92	0.93	0.93	0.93	0.92	0.92	0.91	0.92	0.92	0.92	0.92	0.92
3	0.91	0.90	0.91	0.90	0.91	0.91	0.91	0.91	0.90	0.90	0.90	0.91	0.90	0.91	0.91
4	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
5	0.93	0.92	0.92	0.92	0.93	0.93	0.94	0.93	0.93	0.92	0.93	0.93	0.93	0.93	0.93
6	0.90	0.89	0.89	0.89	0.89	0.90	0.90	0.90	0.89	0.89	0.89	0.90	0.89	0.89	0.89
7	0.92	0.91	0.92	0.91	0.92	0.92	0.92	0.92	0.91	0.91	0.91	0.92	0.91	0.91	0.91
8	0.91	0.90	0.91	0.90	0.91	0.91	0.91	0.91	0.91	0.90	0.90	0.91	0.90	0.91	0.90
9	0.93	0.92	0.92	0.92	0.93	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.93	0.92
10	0.94	0.93	0.93	0.93	0.94	0.94	0.94	0.94	0.93	0.93	0.94	0.93	0.94	0.94	0.93
11	0.94	0.94	0.93	0.93	0.94	0.94	0.94	0.94	0.94	0.93	0.94	0.93	0.94	0.94	0.94
12	0.93	0.92	0.92	0.92	0.93	0.93	0.93	0.93	0.93	0.92	0.92	0.92	0.93	0.93	0.92
13	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
14	0.90	0.90	0.90	0.89	0.90	0.90	0.90	0.90	0.90	0.89	0.90	0.90	0.89	0.89	0.90
15	0.92	0.91	0.92	0.92	0.93	0.93	0.93	0.92	0.92	0.91	0.92	0.92	0.92	0.93	0.92
16	0.94	0.94	0.94	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
17	0.93	0.92	0.92	0.92	0.93	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
18	0.92	0.91	0.92	0.91	0.92	0.92	0.92	0.92	0.92	0.91	0.91	0.92	0.92	0.92	0.91

Model Rankings based on Different Performance Measures (Temperature)

Model	RMSE	MAE	Monthly Corr	Probabilistic Error	Diff in Yearly Means	Probabilistic Corr	Diff in Ratios (Month/Year)	Total Weights	Rank
bccr_bcm2_0.1.	365.45	371.17	1665.00	1247.90	1329.55	1748.53	466.25	7193.85	1
cccma_cgcm3_1.1.	297.39	329.96	1652.26	1195.38	1266.44	1748.54	404.78	6894.74	12
cnrm_cm3.1.	319.79	352.82	1657.66	1206.93	1293.53	1747.74	449.47	7027.94	8
csiro_mk3_0.1.	287.43	329.20	1650.10	1190.31	1274.18	1745.77	413.42	6890.42	13
gfdl_cm2_0.1.	354.35	367.44	1663.22	1196.30	1316.69	1737.87	447.99	7083.87	6
giss_model_e_r.2.	376.17	366.90	1667.24	1201.16	1292.38	1746.01	435.22	7085.08	5
inmcm3_0.1.	382.54	403.43	1668.80	1164.05	1272.10	1744.35	511.22	7146.49	3
ipsl_cm4.1.	348.02	397.50	1662.90	1204.26	1295.93	1746.80	458.32	7113.74	4
miroc3_2_medres.1.	325.15	351.87	1658.63	1192.23	1272.21	1747.30	438.62	6986.02	10
miub_echo_g.1.	289.74	318.63	1651.54	1183.80	1255.00	1746.93	398.77	6844.42	15
mpi_echam5.1.	322.87	355.71	1655.98	1231.45	1307.16	1751.46	449.04	7073.68	7
mri_cgcm2_3_2a.1.	321.23	361.94	1658.18	1181.93	1253.22	1751.74	439.54	6967.78	11
ncar_ccsm3_0.1.	327.47	349.19	1657.20	1180.70	1284.96	1741.97	445.78	6987.26	9
ncar_pcm1.1.	346.92	372.62	1661.30	1232.98	1353.39	1739.99	445.17	7152.35	2
ukmo_hadcm3.1.	311.57	330.02	1654.96	1162.23	1244.70	1746.05	426.90	6876.43	14

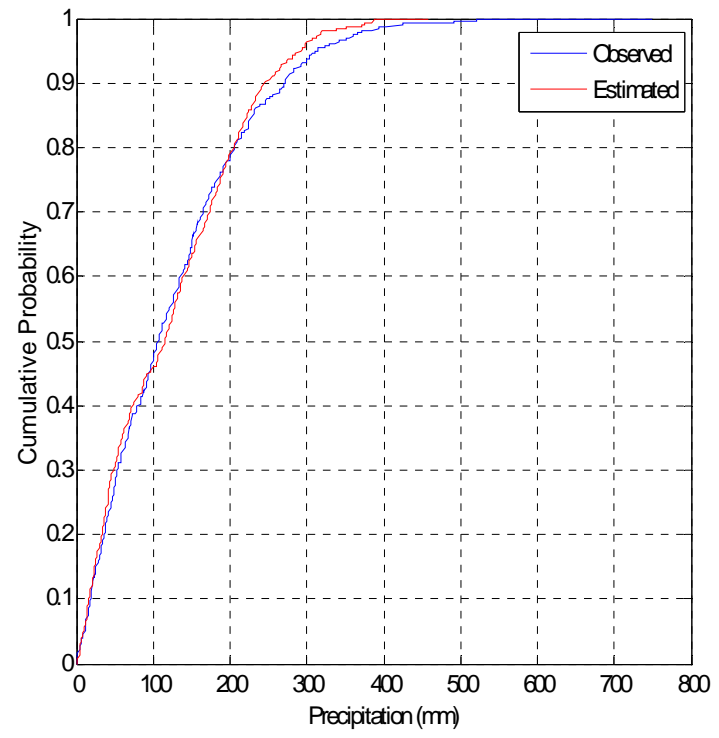
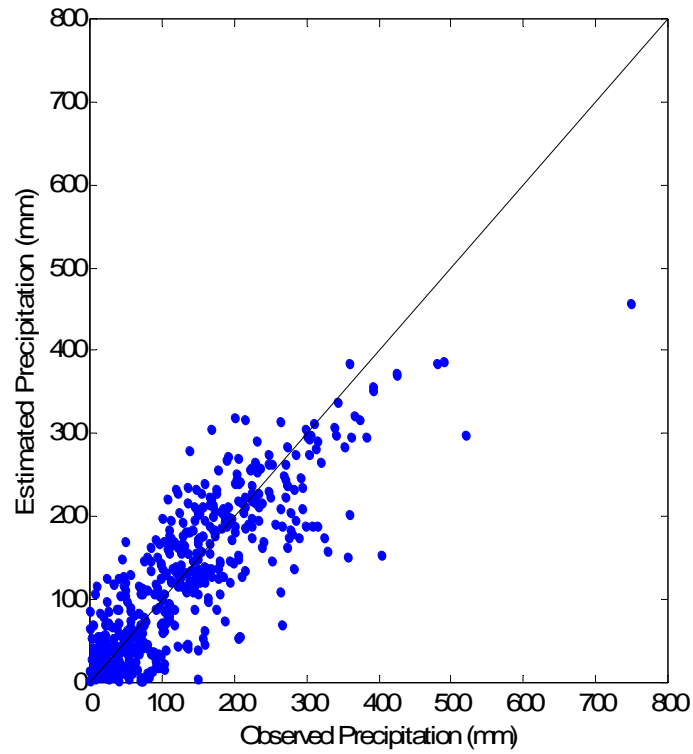
Correlations based on USHCN and BCSD downscaling results for different models (Precipitation)

Station \ Climate Model	BCCR-BCM2.0	CGCM	CNRM-CM	CSIRO-Mk	GFDL-CM	GISS-ER	INM-CM	IPSL-CM	MIROC	ECHO-G	ECHAM5	MRI-CGCM	CCSM3	PCM	UKMO-HadCM
1	0.58	0.49	0.55	0.55	0.51	0.57	0.52	0.49	0.51	0.51	0.56	0.52	0.58	0.57	0.56
2	0.54	0.49	0.49	0.51	0.49	0.55	0.51	0.46	0.49	0.48	0.52	0.51	0.50	0.54	0.51
3	0.53	0.49	0.52	0.52	0.51	0.54	0.53	0.51	0.51	0.51	0.52	0.49	0.57	0.55	0.54
4	0.19	0.16	0.12	0.13	0.17	0.14	0.20	0.20	0.23	0.16	0.19	0.12	0.23	0.21	0.16
5	0.41	0.37	0.37	0.34	0.36	0.37	0.44	0.33	0.40	0.37	0.39	0.39	0.39	0.44	0.39
6	0.45	0.40	0.43	0.45	0.44	0.38	0.44	0.38	0.42	0.45	0.41	0.44	0.46	0.43	0.44
7	0.66	0.63	0.66	0.63	0.63	0.59	0.63	0.60	0.65	0.62	0.63	0.60	0.65	0.64	0.66
8	0.38	0.34	0.38	0.37	0.37	0.39	0.38	0.39	0.39	0.35	0.35	0.36	0.42	0.38	0.36
9	0.47	0.45	0.46	0.48	0.48	0.52	0.48	0.44	0.48	0.45	0.48	0.51	0.46	0.52	0.51
10	0.29	0.34	0.30	0.32	0.35	0.37	0.36	0.32	0.35	0.34	0.34	0.34	0.39	0.39	0.33
11	0.20	0.22	0.15	0.16	0.20	0.26	0.20	0.24	0.24	0.22	0.22	0.19	0.30	0.28	0.21
12	0.38	0.39	0.34	0.40	0.42	0.43	0.43	0.37	0.42	0.43	0.40	0.42	0.41	0.46	0.44
13	0.14	0.15	0.10	0.10	0.10	0.08	0.18	0.15	0.14	0.10	0.10	0.08	0.17	0.15	0.11
14	0.55	0.53	0.55	0.55	0.58	0.52	0.55	0.51	0.56	0.56	0.55	0.53	0.60	0.56	0.59
15	0.43	0.40	0.42	0.46	0.45	0.49	0.46	0.39	0.45	0.43	0.48	0.48	0.45	0.48	0.46
16	0.23	0.25	0.16	0.18	0.22	0.21	0.27	0.27	0.26	0.22	0.25	0.19	0.32	0.29	0.24
17	0.47	0.45	0.45	0.47	0.50	0.46	0.47	0.43	0.46	0.45	0.46	0.50	0.48	0.51	0.49
18	0.44	0.42	0.38	0.41	0.42	0.45	0.44	0.39	0.43	0.38	0.42	0.43	0.43	0.45	0.44

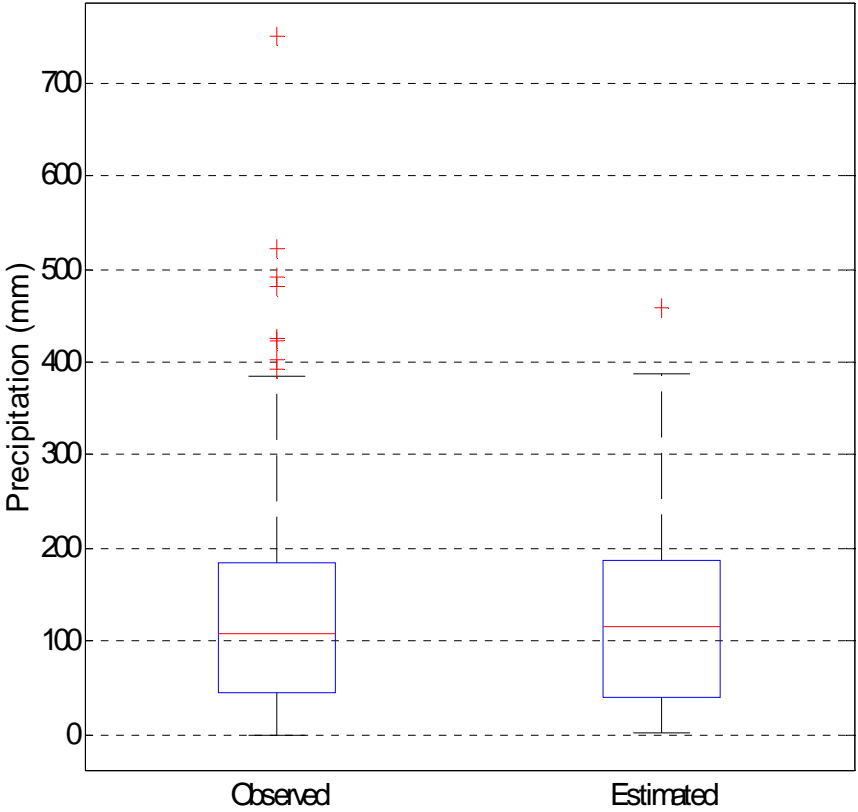
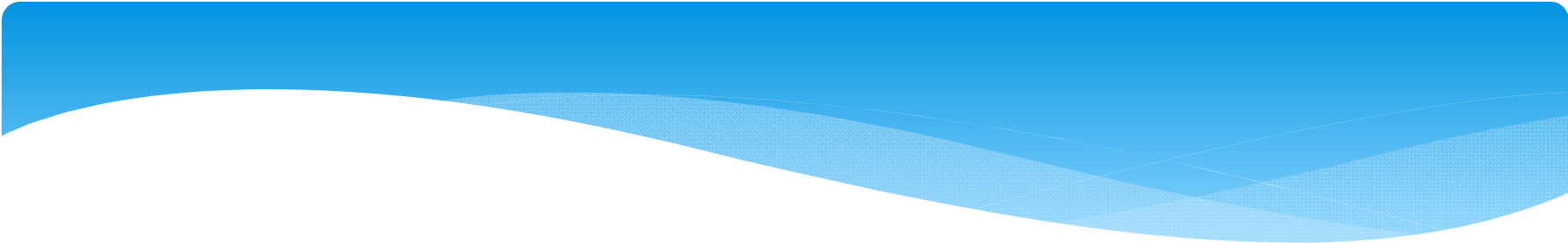
Model Rankings based on Different Performance Measures (Precipitation)

Model	RMSE	MAE	Monthly Corr	Probabilistic Error	Diff in Yearly Means	Probabilistic Corr	Diff in Ratios (Month/Year)	Total Weights	Rank
bccr_bcm2_0.1.	379.95	360.38	733.55	612.96	1305.80	1748.64	168.68	5309.97	5
cccma_cgcm3_1.1.	359.83	361.80	697.36	613.39	1322.01	1748.37	167.95	5270.70	6
cnrm_cm3.1.	359.24	346.12	681.37	542.13	1336.05	1744.42	169.93	5179.25	15
csiro_mk3_0.1.	378.13	363.70	702.87	575.81	1314.20	1743.08	161.37	5239.17	12
gfdl_cm2_0.1.	371.04	356.89	720.72	622.17	1286.69	1747.83	158.60	5263.94	7
giss_model_e_r.2.	374.84	370.27	733.86	628.67	1300.08	1750.68	155.63	5314.03	4
inmcm3_0.1.	394.75	373.38	749.85	539.72	1263.09	1743.59	186.71	5251.09	9
ipsl_cm4.1.	348.08	331.59	685.10	658.04	1322.34	1751.29	150.76	5247.21	10
miroc3_2_medres.1.	388.59	387.63	738.66	636.74	1258.64	1751.56	194.41	5356.23	3
miub_echo_g.1.	361.91	343.81	701.97	656.09	1329.57	1748.62	118.94	5260.91	8
mpi_echam5.1.	375.67	364.09	727.53	586.65	1269.48	1746.83	176.07	5246.31	11
mri_cgcm2_3_2a.1.	370.48	368.81	708.08	540.57	1314.99	1744.63	165.78	5213.34	14
ncar_ccsm3_0.1.	400.18	389.62	779.32	569.79	1135.69	1749.62	213.65	5237.88	13
ncar_pcm1.1.	414.34	396.86	785.22	629.55	1319.47	1747.39	206.98	5499.81	1
ukmo_hadcm3.1.	387.62	374.84	745.06	676.87	1320.32	1752.37	182.79	5439.86	2

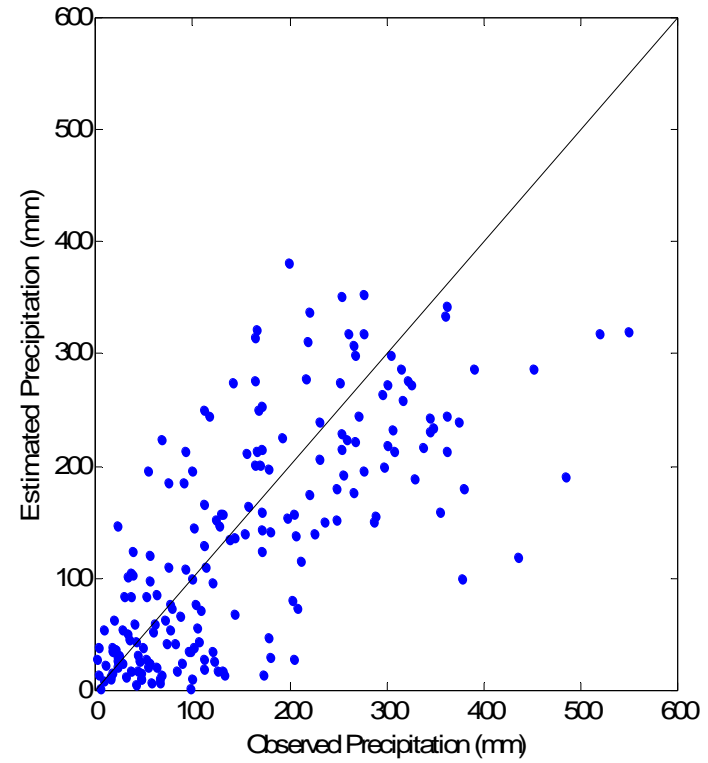
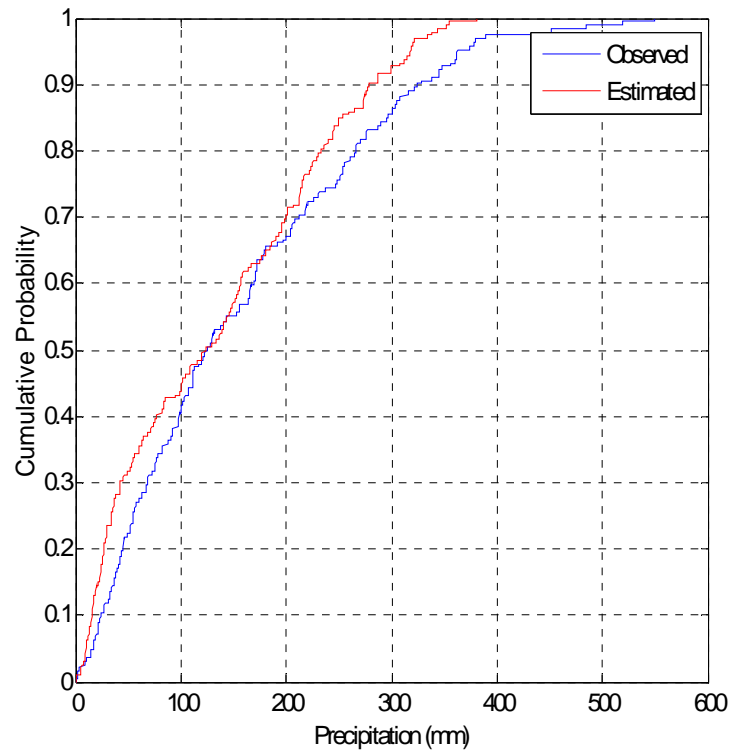
NCEP –based Model Calibration Data



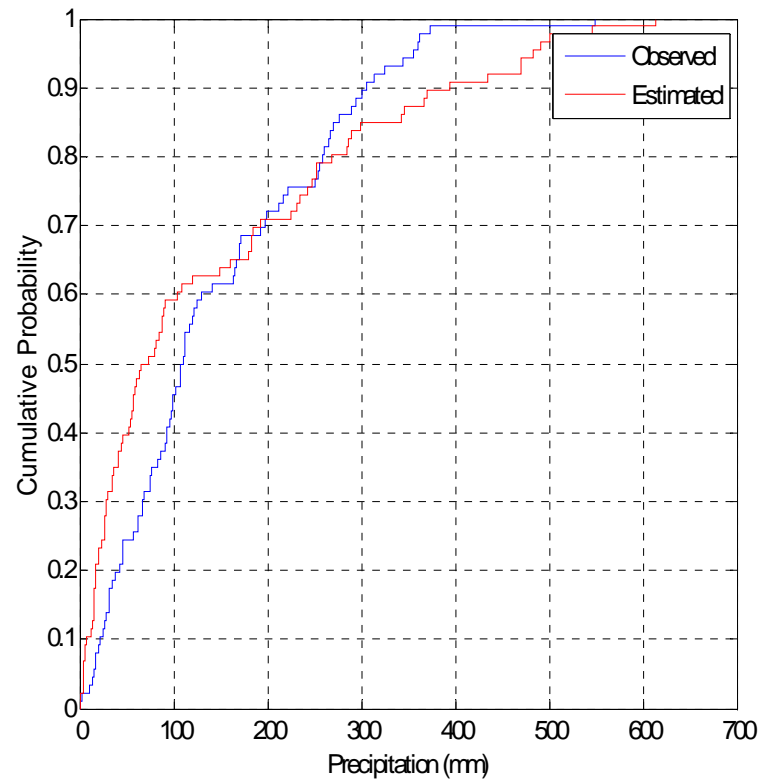
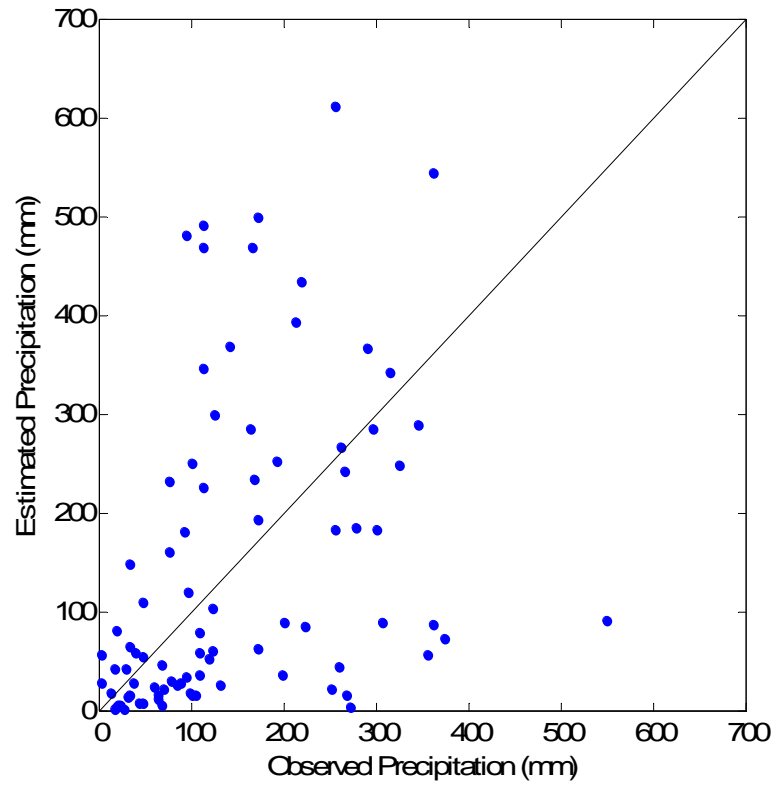
Station # 18

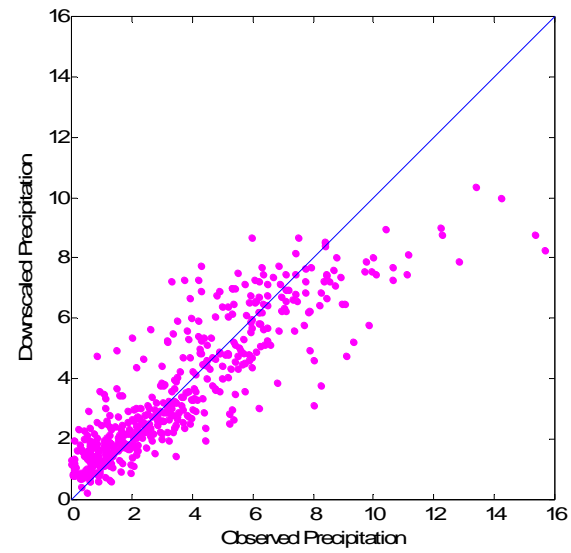
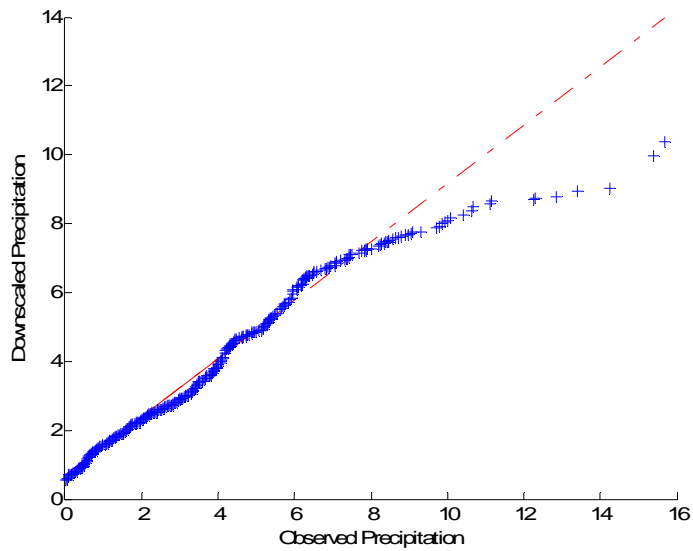
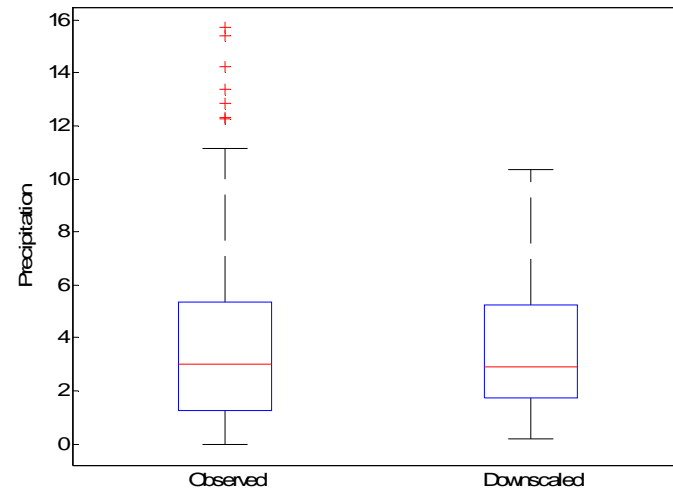
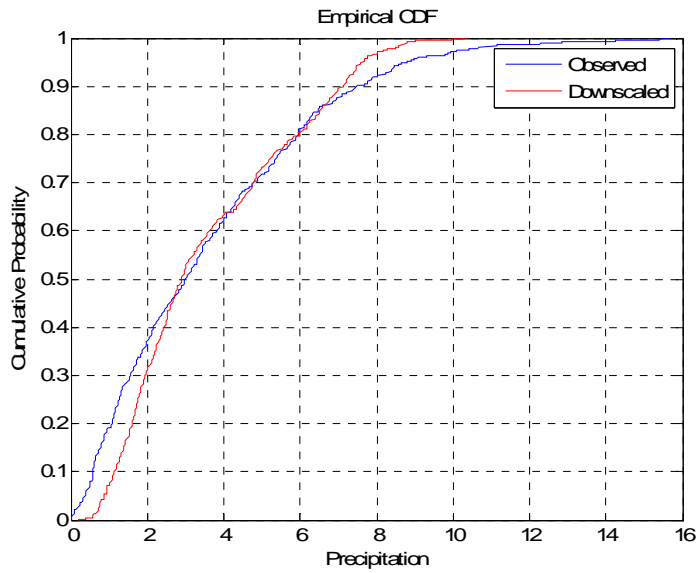


Test Data based on NCEP Model

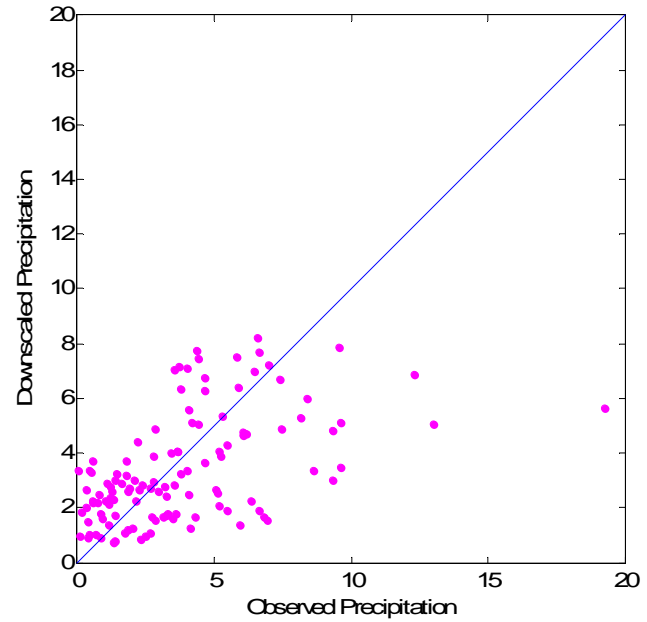
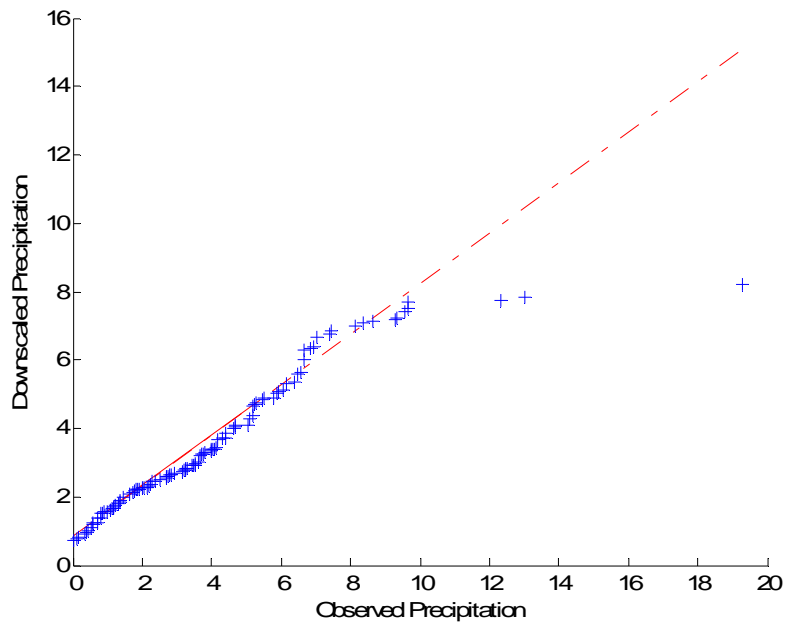
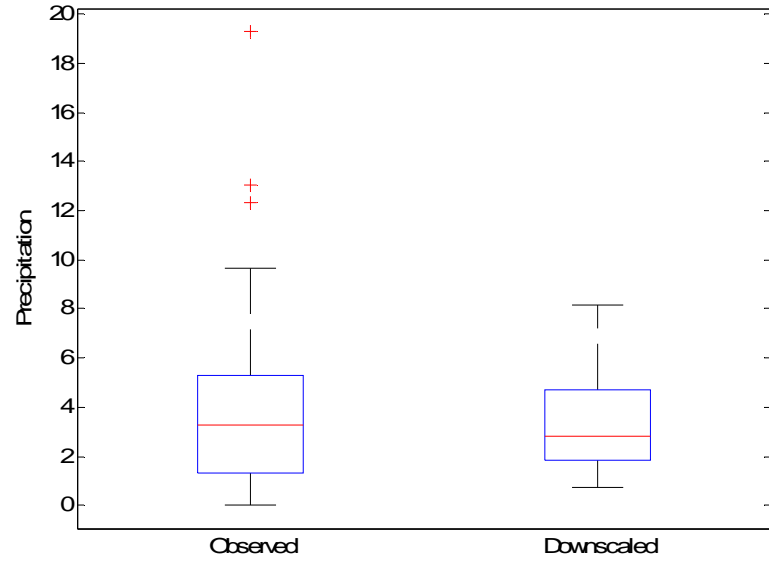
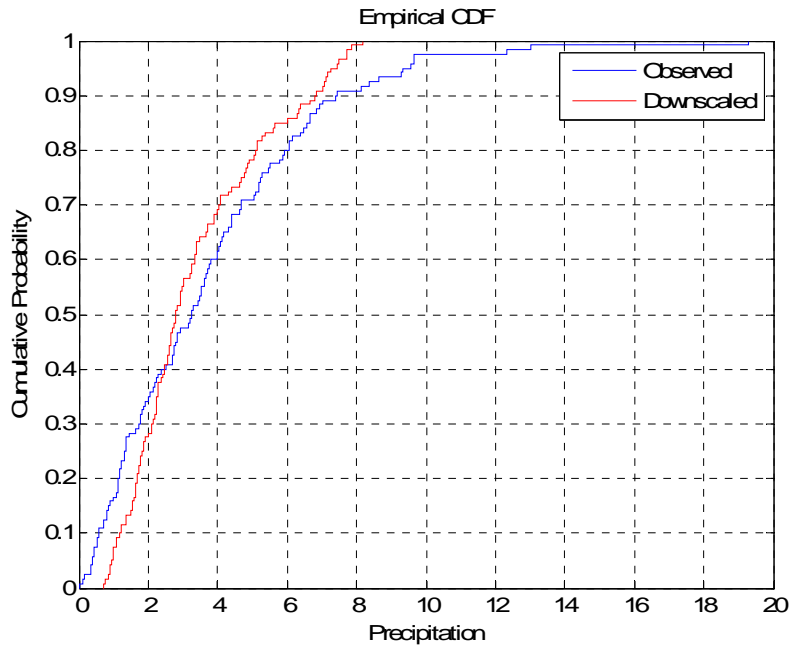


GCM-based Testing



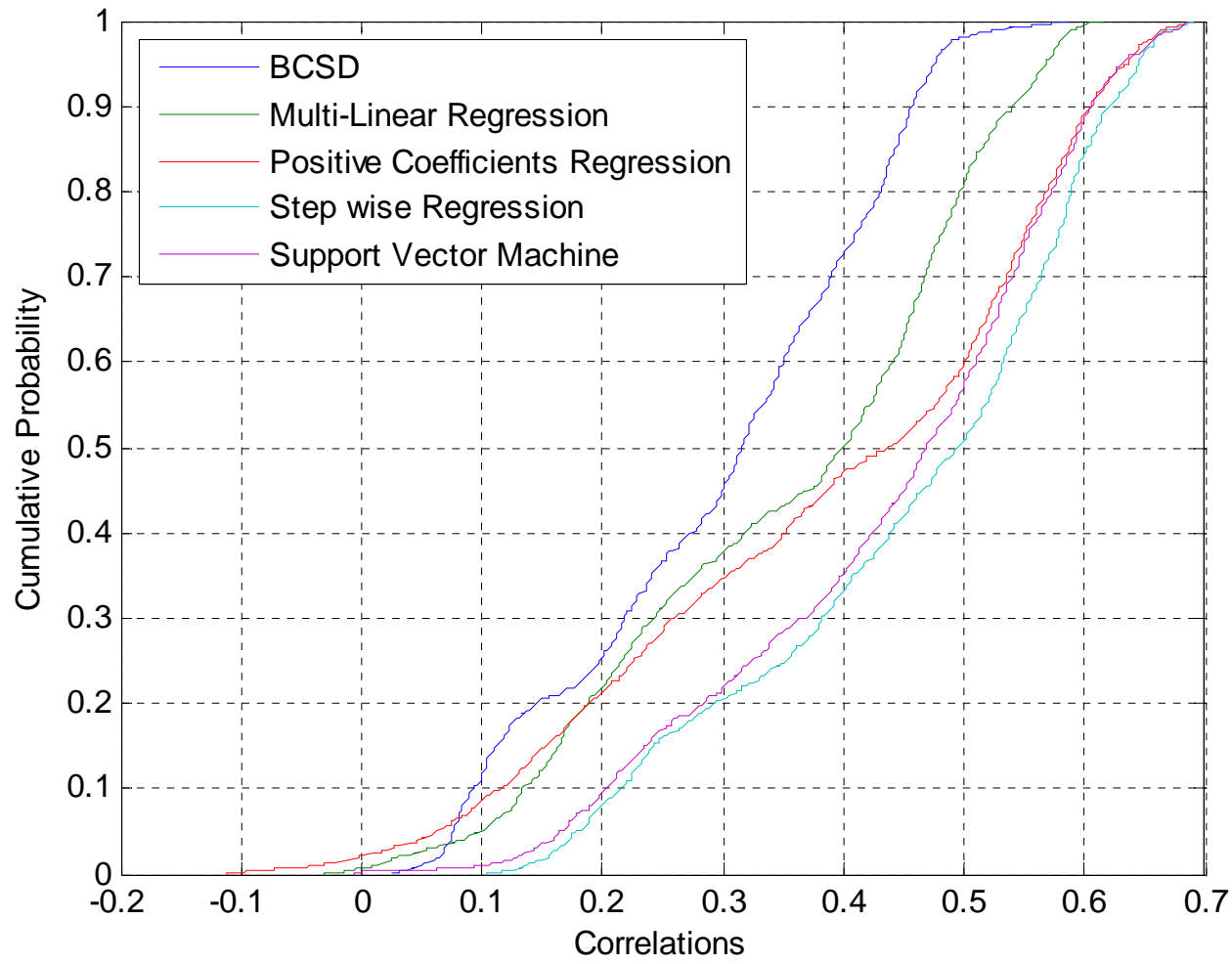


GCM-based Model (calibration) –using BCSD grid resolution

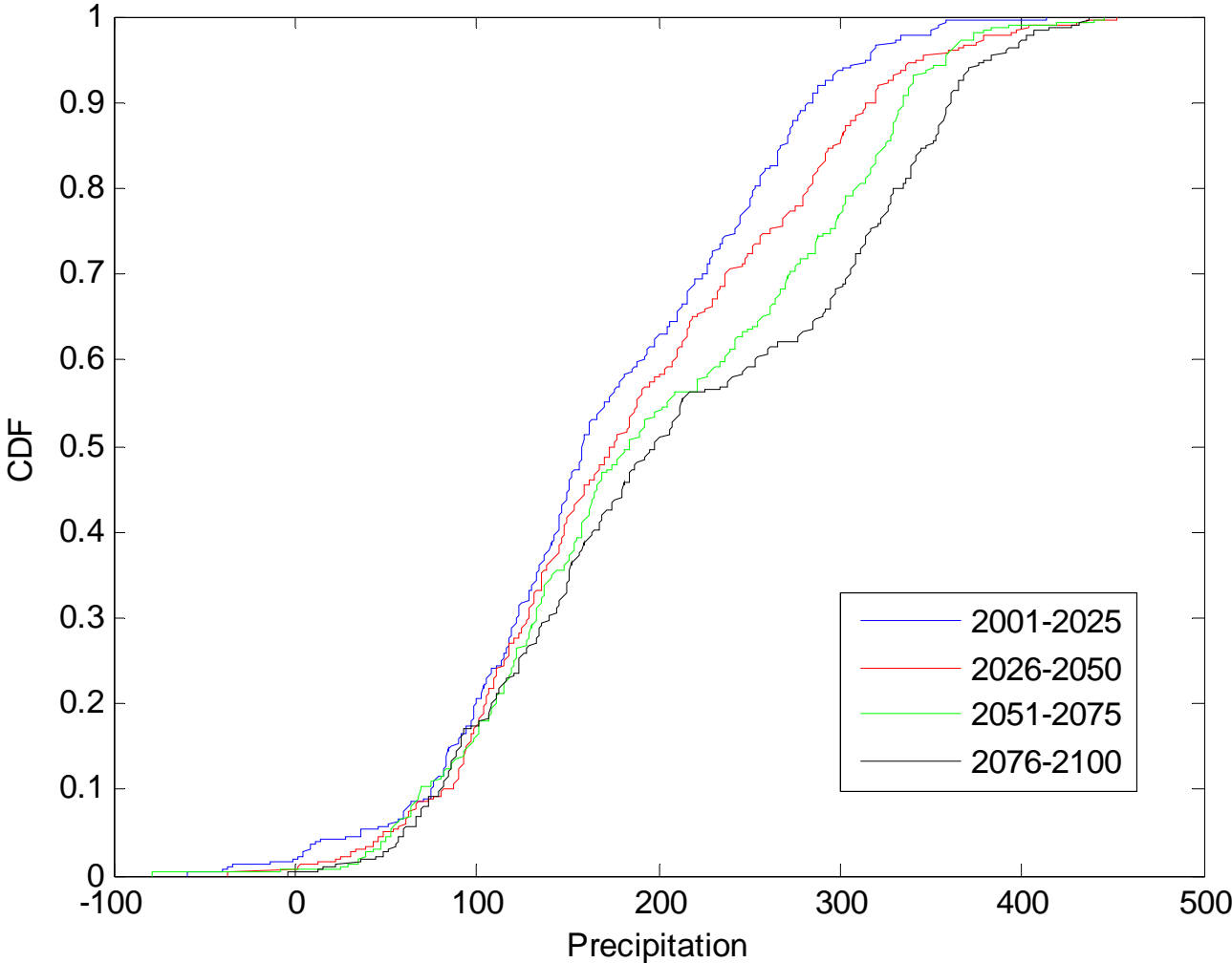


GCM-based Model (Testing)

Comparison of Downscaling Methods (correlations)



Future Projections For Precipitation NCEP-GCM-based Model



Conclusions

- Different methods are experimented for downscaling precipitation data in Florida.
- NCEP-GCM and GCM-based downscaling methods are evaluated at point and different grid scale resolutions for Precipitation.
- The grid-scale resolutions include : $1/8$, $1/2$ and 1 Degree resolutions.
- Transfer functions linking GCM scale and grid-scale predictors in NCEP-GCM approach is critical in obtaining improved downscaling values at different resolutions.
- The downscaling models provided improved precipitation estimates (based on Canadian Centre for Climate Modeling and Analysis model – CGCM- CGCM3.1/T63 Model) compared to those from BCSD approach at different stations in Florida. It is important to note that no bias corrections have been applied to the outputs of downscaling methods.
- A search for optimal selection of variables (as predictors) is on and methodologies are planned for selection of optimal number and type.