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NBI Technical Reports: Water Resources Management Series

Climate change projections data set for impact studies in Nile Basin

WRM-2019-10

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Document Sheet

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The purpose of the technical report series is to support informed stakeholder dialogue and decision making in order to achieve sustainable socio-economic development through equitable utilization of, and benefit from, the shared Nile Basin water resources.

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Contents

INTRODUCTION

Background to the assignment

One of the important aspects of sustainable water resources management is addressing the challenges of equitable water allocation for transboundary water bodies such as rivers, lakes and groundwater sources. The Nile River, which is considered the longest river in the world crosses multiple countries before it drains to the Mediterranean Sea. The management challenges that come with the transboundary nature of the river required the establishment of a River Basin Initiative (NBI), which is a partnership of 10 riparian states with the objective "to achieve sustainable socio-economic development through the equitable utilization of, and benefit from, the common Nile Basin water resources" (www.nilebasin.org).

According to UN (2017), population in the basin countries is projected to reach 0.9 to 1.1 billion inhabitants. Currently, about 40% of the population in Africa lives in urban areas, and it is expected to grow to about 60% by 2050 (UN-HABITAT and UNEP, 2010). It is conceivable to see competing demand for water for different sector in the future. Climate change may result in additional stress to the region beyond the population growth. Recognizing the importance of potential impact of climate change, NBI has explicitly addresses this challenge in their 10-year strategic plan with Goal 5 identifying two primary areas: "a) Provision of well vetted climate change projection data at appropriate spatial and temporal resolution for key target end users; and b) provision of scenarios of hydrology of the Nile Basin for various climate change projections." (This current work).

Careful assessment and production of actionable relevant climate projection data that is spatially and temporally consistent with the impact assessment objective is the first step in understanding climate change impact for a region. These assessments are cornerstone for charting potential adaptation pathways.

Statement of the problem and objectives

Water scarcity is expected to be one of the great challenges facing many regions, including Africa. According to the 2030 Water Resources Group (2030wrg.org) current global water withdrawal for different uses exceeds the existing accessible, reliable, and sustainable supply of water. Assuming an average economic growth scenario and no efficiency gains (through conservation measures or those realized by passive or active efficiency measures), by 2030, the water withdrawal is expected to grow significantly with approximately a 40% deficit in water availability. Based on such predictions, nearly half of the world's population is projected to live under severe water stress, especially areas in North and South Africa and South and Central Asia.

While these projections indicate serious challenges to sustainable water supply, some progressive approaches have been developed to address them, such as the Integrated Water Resources management (IWRM). A successful IWRM would have an adaptation strategy to alleviate impact of climate change on water resource. This will depend on developing decision support tools that incorporate water resource management tools that in turn would depend on credible-consistent future climate projection data in order to have a realistic scenario that is actionable.

The objective of this project is to prepare bias corrected and downscaled climate change projections data appropriate for select targeted end-users in the Nile basin

The specific objectives include:

I. Selection of GCMs that are informative and representative for impact study in the Nile Basin Countries
II. Development of bias corrected downscaled data that is actionable for specific type of end use such as water resources planning, flood mitigation, and drought analysis,
III. Development of data guide for method and tools used, and
IV. Training NBI staff in downscaling and bias correcting to build internal capacity

The science and art of downscaling climate projections

General Circulation Models (GCMs) represent physical processes in the atmosphere, ocean, and land surface. They are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. Due to uncertainties of future greenhouse gas emission level (dependent on future human activity), Representative Concentration Pathways (RCPs) scenarios are used to bracket future climate projections. Each RCP would result in corresponding future scenario that has an associated climatic outcome. It is not possible to predict what would actually end up being in the future as that depends on what humans will do and continue to do. Instead, one employs a what-if scenario to guide an adaptation measure that must be in place to counter climate change impact on a regions such as the Nile Basin Initiative countries. Typically GCMs are run at 200 Km to 600 Km horizontal and as many as 50 vertical layers (Figure 1)

Coarse scale nature of GCM outputs, by necessity, introduce spatial uncertainty. In addition, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modelled. This forces one to average over a larger scale through parameterization resulting in additional source of uncertainty. Parametrization issues as well as the way certain processes are handled (e.g., feedback mechanisms in models concerning, for example, water vapor and warming, clouds and radiation, and ocean-land interaction) would result in different future projections across different models even for given emission scenarios. In order to extract relevant information from this low-resolution data regarding future climate states, one usually bias correct and downscale large-scale climate model outputs into relevant spatiotemporal local scale. Doing so is a combination of art and science as there is no one size fit all solution.

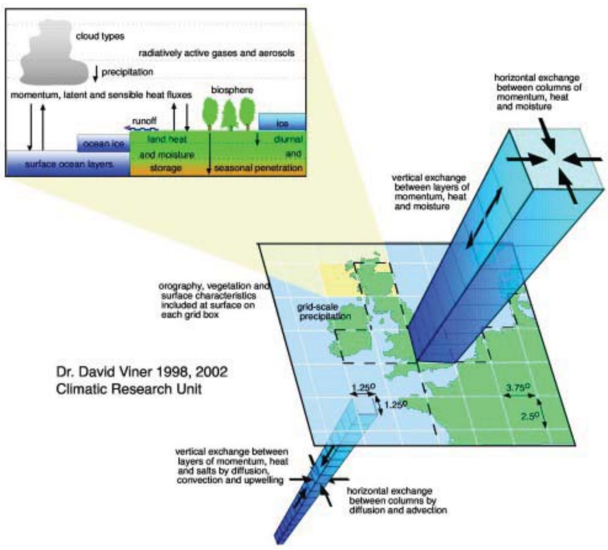


Figure 1. Schematic representation of a General Circulation Model (*Source*: http://www.ipcc-data.org/guidelines/pages/gcm_guide.html)

DATA SOURCES

IPCC CMIP 5 for Nile Basin

Monthly data were downloaded from http://climexp.knmi.nl/start.cgi. These data include both precipitation and average temperature for both Representative Concentration Pathways (RCP) 4.5 and RCP 8.5. Data include 2.5^{o} latitude and longitude which was further processed to isolate grid cells that cover the Nile Basin Initiative (NBI) watersheds (Figure 2). In total 105 – RCP45 Rainfall, 108 RCP45 Temperature, 78-RCP85 Rainfall, and 81 RCP85 Temperature scenarios.

GCM realizations are the result of initial state, initialization methods, or physics in the form of, for example, r1i1p1, which represents realization #1, initialization I #2, and physics p #1. Figure 1 shows an example of two realization with 2 different initial states that came from Control runs (with pre-industrial greenhouse gas concentration)

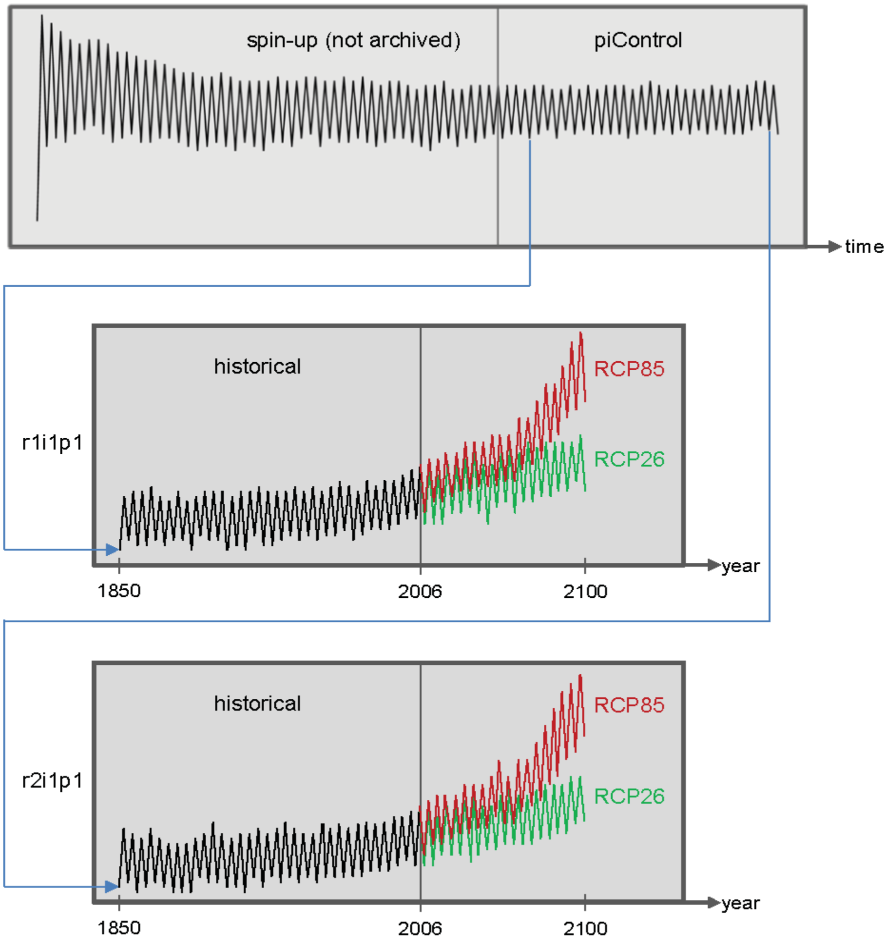


Figure 2: GCM ensemble representation (Source: https://portal.enes.org/data/enes-model-data/cmip5/datastructure)

An area covering 15E to 45E and 10S to 35N was used to extract GCM data. Once these data were downloaded, further processing was conducted to isolate grid cells that cover NBI watersheds as shown in Figure 2.

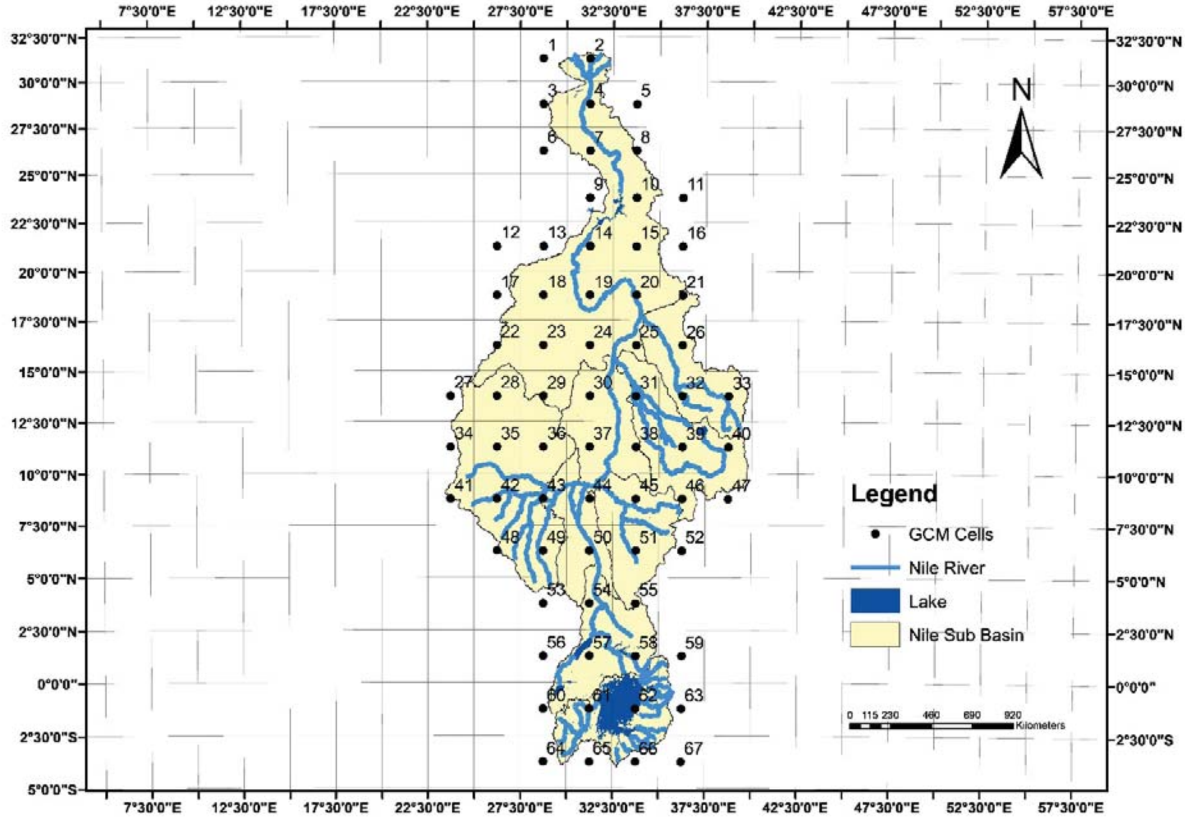


Figure 2. GCM grid cells overlain with 2.5 degree cell centers defining the extent

In total 67 GCM cells were processed covering nine subbasins as shown in Figure 2. Two matlab data files (*rawRainfallCMIP5*.mat and r*awTemperatureCMIP5*.mat) were created to store the raw files with all the metadata that came along with the projections. Another set of data (*processedRainfallCMIP5*.mat and *processedTemperatureCMIP5*.mat) containing preprocessed info for those 67 Grid Cells were created. Initial Exploratory Data Analysis was made using a subset of these cells as shown in Table 1 (see Supplemental Data report, Appendix A and Appendix B).

Table 1: NBI basins and CMIP5 grid cells

Sub-Basin	Grid Cell IDs
Lake Victoria	61, 62, 66

Victoria Nile	54, 57, 58
Lake Albert	54, 57, 70
Baro Akobo Sobat	45, 46, 57
Sudd	43, 44, 50
Bahr El Ghazal	27, 28, 29, 34, 35, 36, 41, 42, 43
Lower White Nile	30, 37, 38
Blue Nile	31, 39, 40
Tekeze Atbara	26, 32, 33
Main Nile	2, 4, 7, 10, 14, 15, 18, 19, 20, 23, 24, 25

The GCM dataset include monthly times series for each of the 67 cells 1861 through 2100. Data from 1861 through 2005 are retrospective (historical) runs while 2006 through 2100 are future runs for both RCP45 and RCP85 greenhouse gas emission scenarios.

Global Forcing Data

Global Forcing data are used to conduct an assessment of how good are retrospective GCM runs. One of the most used widely used dataset is one constructed by combining a suite of global observation-based datasets with the NCEP/NCAR reanalysis (Sheffield et al., 2006, https://rda.ucar.edu/datasets/ds314.0/). The data set consists of six metrological variables (air temperature, humidity, longwave radiation, precipitation, shortwave radiation, surface pressure, ad surface winds) at 3h interval and 0.25 degrees. These dataset was aggregated at daily and monthly time steps. Monthly data will be used along with CRU data (see below discussion) to asses GCM retrospective runs while daily variables will be use to assess whether a bias correction would be needed to the CORDEX data. While rainfall and temperatures are the main target climate forcing for this project, other dataset were also downloaded and processed that may be relevant and to NBI modeling group. Fourteen matlab data files (e.g., *rawRainfallGFdata*.mat) have all the data for 67 NBI cells as wells as all metadata is stores in its native 3-hr time step for further use by NBI, as needed. A second processed date set (e.g., *processedRainfalGF*.mat and *processedTemperatureGF*.mat) stores the daily and monthly dataset for use with this project. Since the Global Forcing data comes at 0.25 degrees, upscaling of 10 by 10 cells were made to aggregate values for comparison with CMIP5 GCM data. These data set is inclusive of 1948 to 2010. The summary of this data set if given in Table 3.

High Resolution Gridded Data set from Climate Research Unit (CRU)

Another data source is a high-resolution CRU data set (https://crudata.uea.ac.uk/cru/data/hrg/) version 4.02 released in 18 November 2018. These data set goes through 1901 to 2017 at 0.5

degrees resolution (Harris et al., 2014). Both temperature and precipitation were downloaded for NBI and 5 by 5 grid cells were averaged to provide data at GCM grid levels. Two matlab data files (*rawRainfallCRUdata*.mat and *rawTemperatureCRUdata*.mat) have all the data for 67 NBI cells as wells as all metadata that came with the files. A second processed set (*processedRainfalCRU*.mat and *processedTemperatureCRU*.mat) stores the monthly dataset for use with this project including select metadata. Table 3 summarizes these data set along with datafile identification, time covered, etc.

Table 3: Summary of conditioning data

File Name (*.mat)	Description	Period	Source
processedTemperatureGF	Daily average, daily min, daily max, and monthly average data for 67 NBI Cells at 2.5-degree resolution.	1948 – 2007	NCEP/NCAR
processedSurfaceWindGF	Daily and monthly average data for 67 NBI Cells at 2.5-degree resolution	1948 - 2009	NCEP/NCAR
processedSurfacePressureGF	Daily and monthly average data for 67 NBI Cells at 2.5-degree resolution	1948 - 2009	NCEP/NCAR
processedShortWaveRad	Daily and monthly average data for 67 NBI Cells at 2.5-degree resolution	1948 - 2009	NCEP/NCAR
processedRainfallGF	Daily and monthly average data for 67 NBI Cells at 2.5-degree resolution	1948 - 2009	NCEP/NCAR
processedLongWaveRadGF	Daily and monthly average data for 67 NBI Cells at 2.5-degree resolution	1948 - 2009	NCEP/NCAR

processedHumidityGF	Daily and monthly average data for 67 NBI Cells at 2.5-degree resolution	1948 - 2009	NCEP/NCAR
rawTemperatureGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2008	NCEP/NCAR
rawSurfaceWindGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR
rawSurfacePressureGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR
rawShortWaveRad	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR
rawRainfallGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR
rawLongWaveRadGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR
rawHumidityGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR
rawTemperatureGF	3-h bias corrected air temperature for the world at 0.25-degree resolution	1948-2009	NCEP/NCAR

CORDEX Data

The Coordinated Regional Downscaling Experiment (CORDEX) was wet up by the World Climate Research Program (https://www.wcrp-climate.org/) in order to coordinate Regional Climate Downscaling providing high-resolution regional climate for impact and adaptation community. All CORDEX data of processed files were downloaded and NBI's boundary was generated in netCDF format. Table 4 shows the list of Regional Climate Models (RCMs) and their driving General Circulation Models (GCMs). Quality Assurance/Quality Control (QA/QC) of the data indicated there were significant mismatch between the metadata and the actual data in terms of data time description. The mismatches were corrected, and updated information is highlighted in "pink" color. Other colors indicate differences from the main data. The following Table summary of the different colors.

Color	Description
	Different time period different from original metadata in CORDEX
	Missing RCP85 tasmin
	Missing RCP 85 tasmin and tasmax
	Missing rcp45
	Significantly less historical data

RCM	GCM	Calendar	Version	Experiment			Ensemble
				historical	rcp45	rcp85	
BCCR-WRF331	NCC-NorESM1-M	Standard	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
CLMcom-CCLM4-8-17							
	CNRM-CERFACS-CNRM-CM5	proleptic_gregorian	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
	ICHEC-EC-EARTH	proleptic_gregorian	v1	19500101-20051231	20060101-20981231	20060101-20981231	r12i1p1
	MOHC-HadGEM2-ES	360_day	v1	19510101-20051230	20060101-20981231	20060101-20981231	r1i1p1
	MPI-M-MPI-ESM-LR	proleptic_gregorian	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
CNRM-ALADIN52							
	CNRM-CERFACS-CNRM-CM5	Standard	v1	19500101-20051231	20060101-21001231	20060101-21001231	r1i1p1
DMI-HIRHAM5							
	ICHEC-EC-EARTH	proleptic_gregorian	v1	19510101-20051231	20060101-20981231	20060101-20981231	r3i1p1
ICTP-RegCM4-3							
	MOHC-HadGEM2-ES	360_day	v4	19760101-20051130		20051201-20991230	r1i1p1
	MPI-M-MPI-ESM-MR	Gregorian	v4	19760101-20051130		20051201-20991231	r1i1p1
KNMI-RACMO22T							
	ICHEC-EC-EARTH	Standard	v1	19500101-20051231	20060101-21001231	20060101-21001231	r1i1p1
MPI-CSC-REMO2009							
	MPI-M-MPI-ESM-LR	proleptic_gregorian	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
SMHI-RCA4							
	CCCma-CanESM2	365_day	v1	19510101-20051231	20060101-20981231	20060101-20881231	r1i1p1
	CNRM-CERFACS-CNRM-CM5	Standard	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
	ICHEC-EC-EARTH	Standard	v1	19510101-20051231	20060101-20981231	20060101-20981231	r12i1p1
	IPSL-IPSL-CM5A-MR	365_day	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
	MIROC-MIROC5	365_day	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
	MOHC-HadGEM2-ES	360_day	v1	19510101-20051230	20060101-20981231	20060101-20981231	r1i1p1
	MPI-M-MPI-ESM-LR	proleptic_gregorian	v1	19510101-20051231	20060101-20981230	20060101-20981230	r1i1p1
	NCC-NorESM1-M	365_day	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1
	NOAA-GFDL-GFDL-ESM2M	365_day	v1	19510101-20051231	20060101-20981231	20060101-20981231	r1i1p1

Data info that were different from the original metadata

Exploratory Data Analysis (EDA)

For all NBI cells (Table 1) both Global Forcing Data and CRU data were compared seasonally (monthly time steps) as well as their exceedance probability. Appendix A and B of Supplemental Data report have the rainfall and temperature comparison. In addition, all other steps including GCM selection, bias correction, and statistical downscaling use EDA to make sure data and theory are consistent.

GCM SELCTION CRITERIA

One of the first steps of climate change impact assessment is selecting GCM projections that would drive an impact assessment study for a region. Available GCM projections for impact assessment are quite a bit (> 100, currently about 30 models by different climate research centers around the world, some with 5 to 10 ensembles corresponding to different parametrization and initial condition, and 4 RCP emission scenario, from most optimistic (RCP 2.6) to business as usual (RCP 8.5)). If one includes different types of bias correction and downscaling as another option, the sample size one ultimately would look at could easily balloon. In addition, typically one looks at retrospective runs (historical runs) as well as two future scenarios (usually mid-century and end of century). These future scenarios are usually referred as near future (2031 to 2060) and far future (2071 to 2100) by applied community. Sometimes where three scenarios are desired as in this reports 2006 to 2035, 2036 to 2065, and 2066 to 2095.

Typically, practitioners use some criteria to narrow down the number of scenario/size of data that must go through the impact assessment model. Some of the factors impacting GCM selections are:

1) Complexity of the impact assessment model (typically hydrologic model for water resources management). The more complex the model is the more time it would need to complete scenarios. Unless there is access to a distributed computing capability (Asefa et al, 2014) using cluster of computers, it may be impractical to run all the scenarios.

2) Specific criteria that one wants to explore such as El Nino Southern Oscillation (ENSO), seasonal changes in climatic variables such as rainfall, start and of rainy season, length of rainy season, etc. In this case, one tries to identify GCMs that reproduces important parameters of interest. For example, our recent study provided a critical assessment of whether GCMs were able to reproduce important parameters such as persistent in wet or dry state, and transition probabilities. These are important for water resources management (Panaou et al., 2018). Such criterion can be used for GCM selection.

3) One can also look at the overall agreement of retrospective runs to historical data without isolating any event in particular (see criteria based on skill and agreement to consensus weighting below).

The amount effort that one needs to accomplish the selection process depends on the type of problem that one is trying to solve.

In this research, several criteria were used to guide "best" performing GCMS and assign weight based on their performance for that measure. These includes: a) Independence measure; b) Historical overall skill performance assessment; c) whether a GCM is able to reproduce historical variability (both seasonal and annual); d) whether a GCM's future projection consistent with other; and e) whether the GCM is able to reproduces extreme statistics (such as dry, wet, cold, warm) in historical dataset. The first realization, initialization, and physics (r1i1pi) of each the GCM families were selected for this purpose giving a total of 34 GCMs for the analysis. These criteria are discussed below.

Independence Weight Approach

The hypothesis behind the independence weight approach is that GCMs that come from the same "family" are considered "siblings" and may provide similar results in the historical retrospective run, and similar results potentially in the future. These GCMs may not be so much different from each either to be much more informative for future projection such that important future condition that decision makers interested in may not be captured by these GCMs. When one tries to assign weight to each of the GCM projections, an approach that doesn't include this fact may unfairly weight higher a set of GCMs whose "relatives" are (Sanders et al., 2015). The independence weight approach is done by first calculating the Inter Model Distance (IMD) between each of the GCMs as well as observation.

IMD is calculated as (Sanderson et al., 2017) (calculateIMD.m)

$$\delta = \sum_{v} \delta_v$$

Figure 3 shows the IMD for the selected GCMs using seasonal root squared mean error distance metrics as distance measure amongst and between the GCMs and observation. This is done using "selectGCM.m" matlab script and

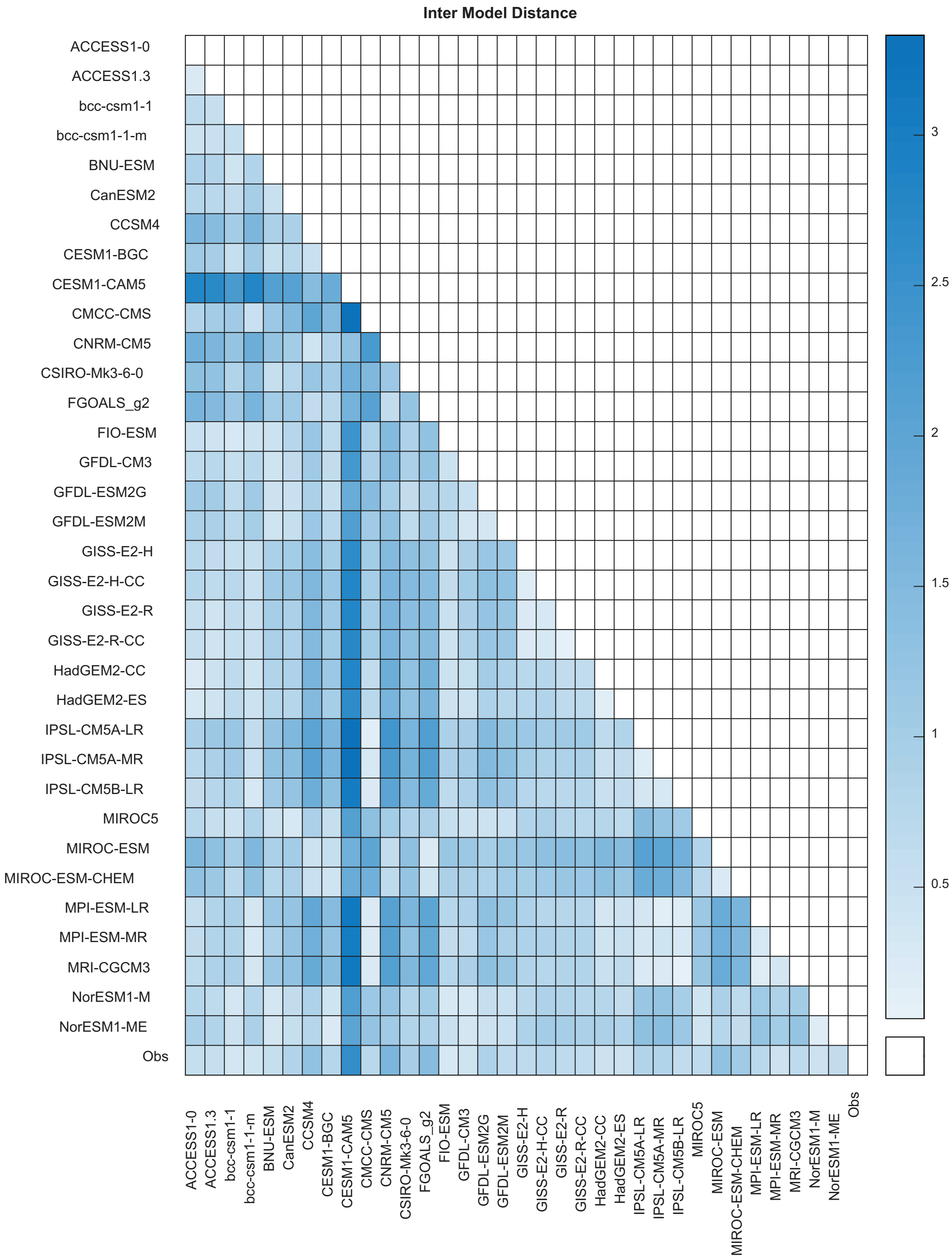


Figure 3: Inter Model Distance (IMD) for n plus observation. IMD is calculated as root mean squared error of seasonal (monthly) climatological (1970 to 2000) data. IMD with observation is the indicator of a GCM's skill in reproducing the historical mean seasonal precipitation.

A similarity score is then calculated as (selectGCM.m)

$$S(\delta_{ij}) = e^{-\left(\frac{\delta_{ij}}{D_u}\right)^2}$$

Where D_u is a parameter called radius of similarity or distance scale that indicates whether models should be considered co-dependent. It determines how a given model should be weighted down depending on how many similar models are in the set of GCMs that are D_u apart. By definition, D_u would correspond to K-models that are within D_u distance away from each other[1]. D_u is estimated through a sensitivity analysis as the one show in Figure 4. The implied number of models for a given Du is shown in Figure 5. A value of 0.5 for Du was selected based in the sensitivity analysis in Figure 4

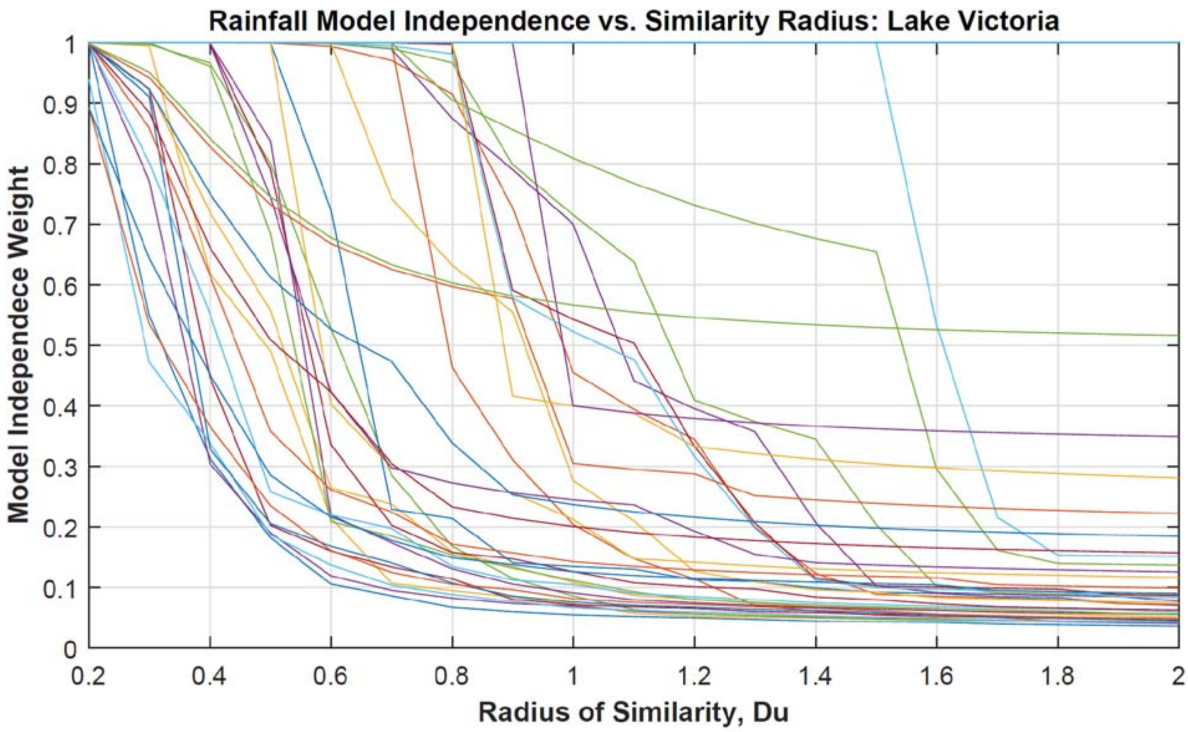


Figure 4: Sensitivity of Radius of Similarity, Du, with independence weight for Lake Victoria sub basin.

A given models effective repetition is then calculated as

$$R_u = 1 + \sum_{j \neq i}^{n} S(\delta_{ij})$$

[1] K-nearest neighbor approach has been widely used in hydrology (Lall and Sharma, 1996, WRR) among others for streamflow disaggregation (Asefa et al., 2014, J. Hydrology)

The independent weight, W_u is then calculated as the inverse of a model's effective repetition.

$$w_u(i) = {R_u}^{-1}$$

A large value of D_u will assign equal weight for all models whereas small number tends to restrict the number of models that should be considered codependent. Supplemental Data report Appendix C shows the sensitivity of this parameter. The Appendix also shows the number of implied models (K-models) corresponding to a given radius of similarity. Figure 6 shows the weight assigned for each of the Nile Basin Initiative basin based on independence weight criteria.

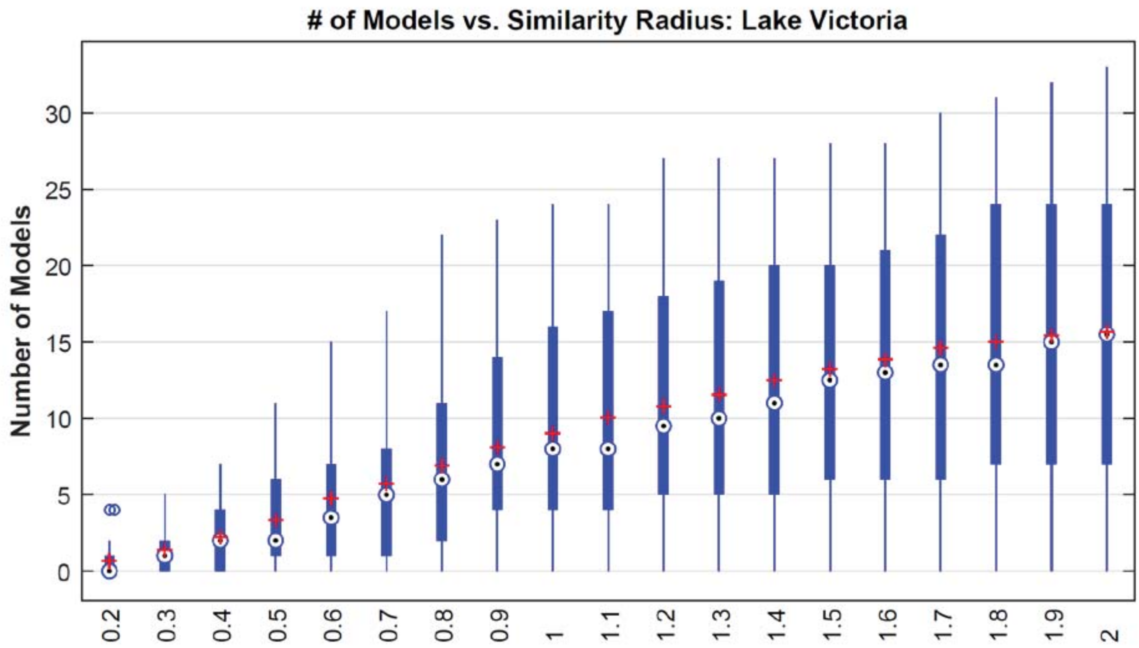


Figure 5: The number of models as a function of Radius of Similarity, Du.

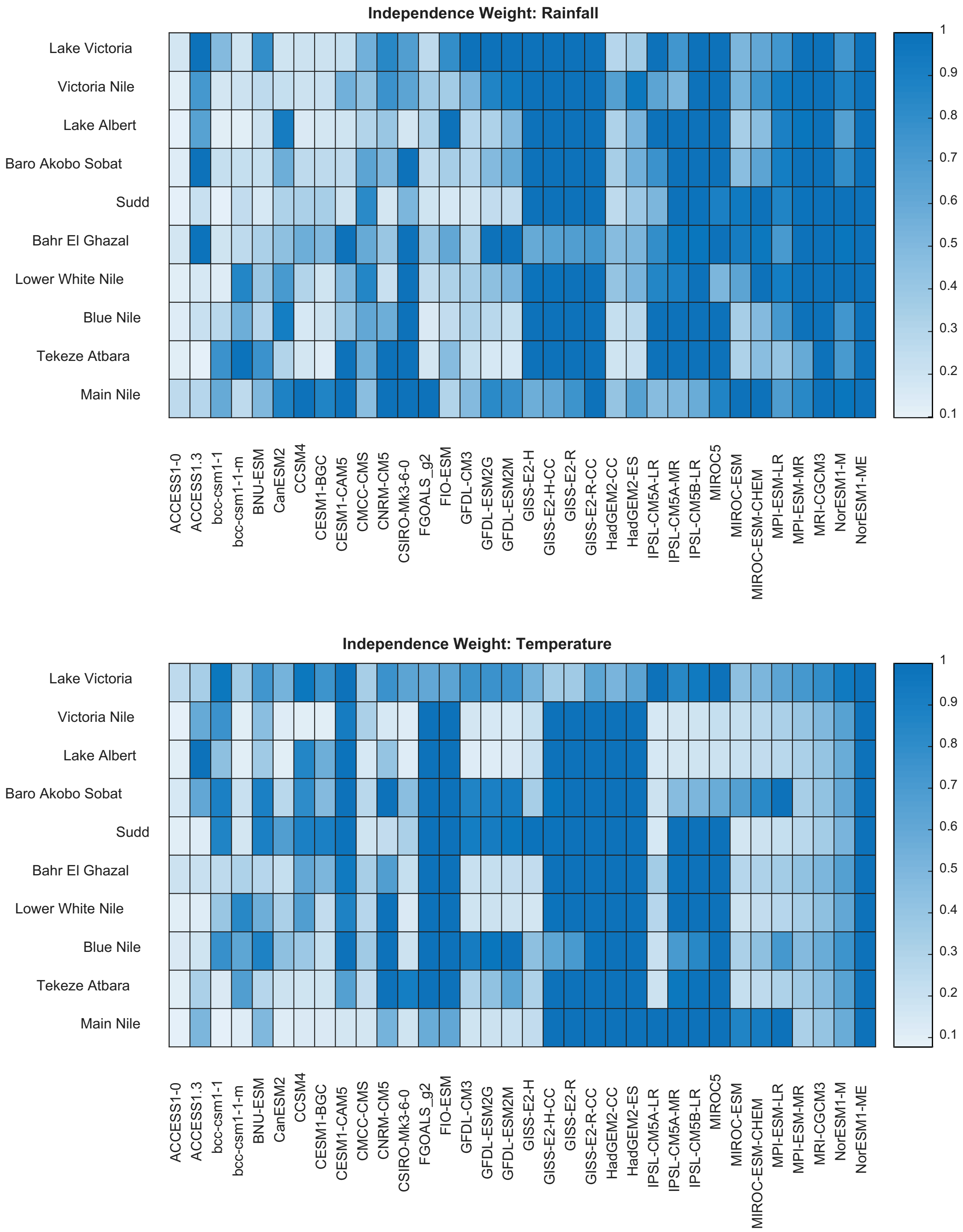


Figure 6: Independence weights assigned to each GCM based on their Inter Model Distance (selectGCM.m)

A combined weight of rainfall and temperature is given in Figure 7. The combined weight is scaled such that it ranges between 0 and 1.

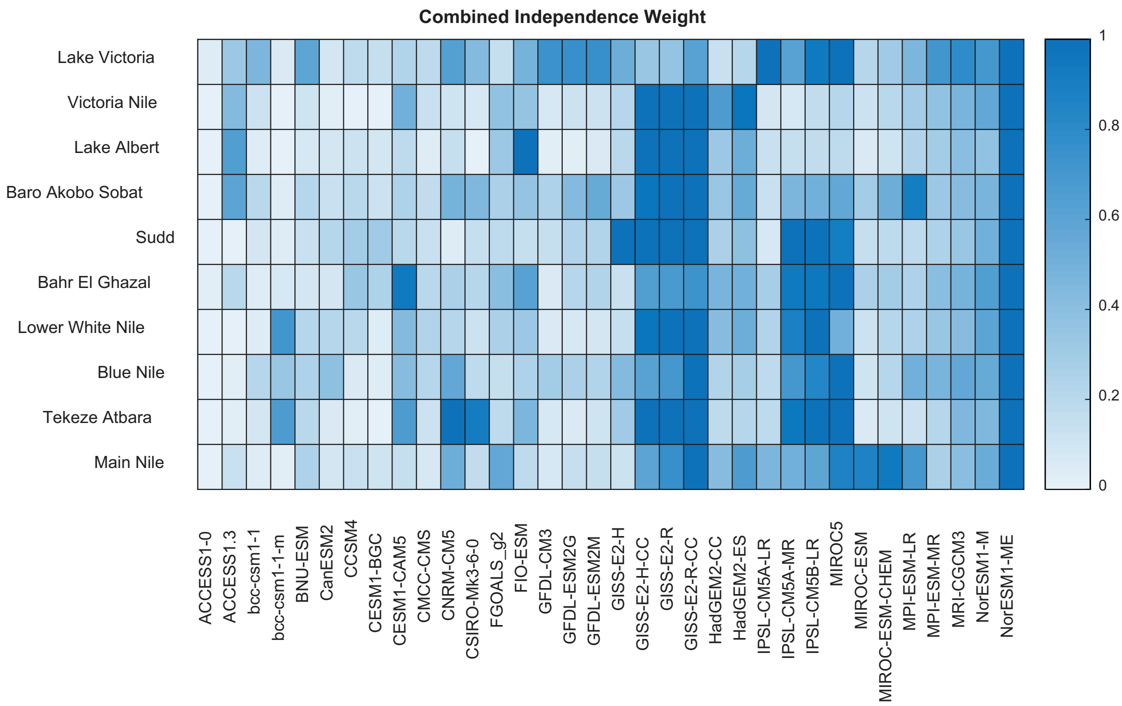


Figure 7: Combined rainfall and temperature independence weights assigned to each GCM based on their Inter Model Distance (selectGCM.m)

Overall Skill Based weight

Skill weights are calculated based on each model's ability to reproduce historical observation in the form of seasonal climatological data. The skill weight is calculated as

$$w_q(i) = e^{-\left(\frac{\delta_{obj}}{D_q}\right)^2}$$

Where W_q is the skill weight D_q is the radius of model quality which determines the degree to which model with poor seasonal climatology reduction should be downgraded. A small D_q will place a large weight to a single "best" performing model. This parameter is estimated using a sensitivity analysis such that the parameter value covers the whole range of weight (0 to 1) as much as possible. This helps to discriminate models based on their skills doesn't place the selection to few highly performing GCMs only. Figure 8 shows the range of model skill weights as a function of the Radius of Model Quality, Dq for Sudd sub-basin. δ_{obj} is distance from GCM projection to historical observation. Appendix D (Supplemental Data report) shows sensitivity of the radius of model quality vs. weight.

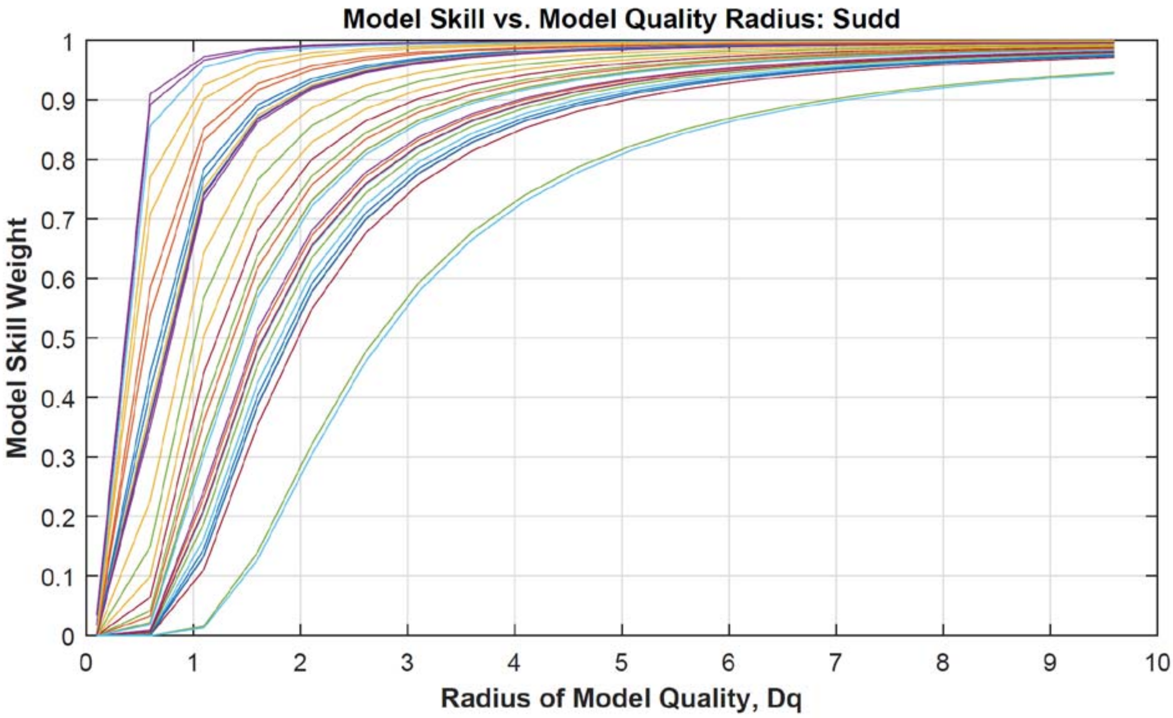


Figure 8: Variation of model skill weight as a function of Radius of Model Quality, Dq.

Figure 9 shows the resulting skill-based weight for rainfall and temperature. Figure 10 shows the combined skill weight for both temperature and rainfall.

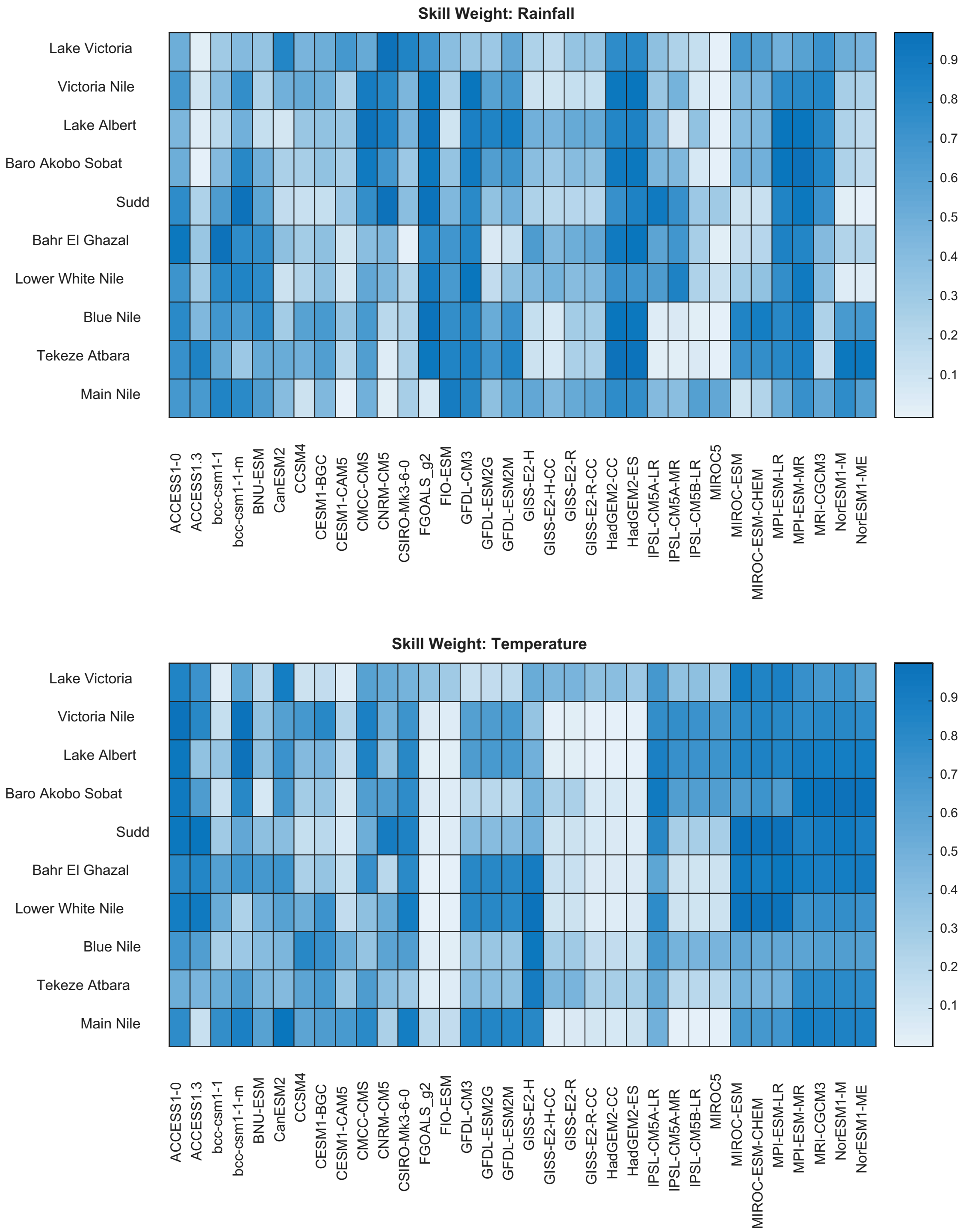


Figure 9: Skill weight calculated as the distance between each GCM's projection during retrospective run. ("heatmap" function in selectGCM.m)

A combined weight of rainfall and temperature skill is given in Figure 7. The combined weight is scaled such that it ranges between 0 and 1.

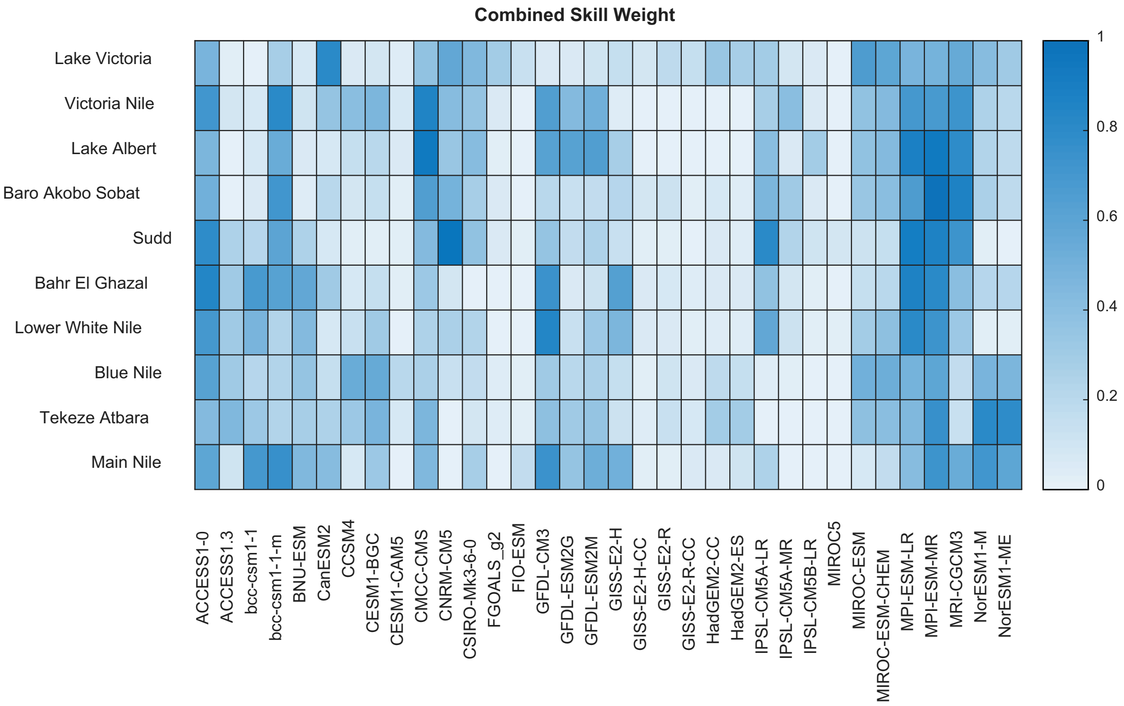


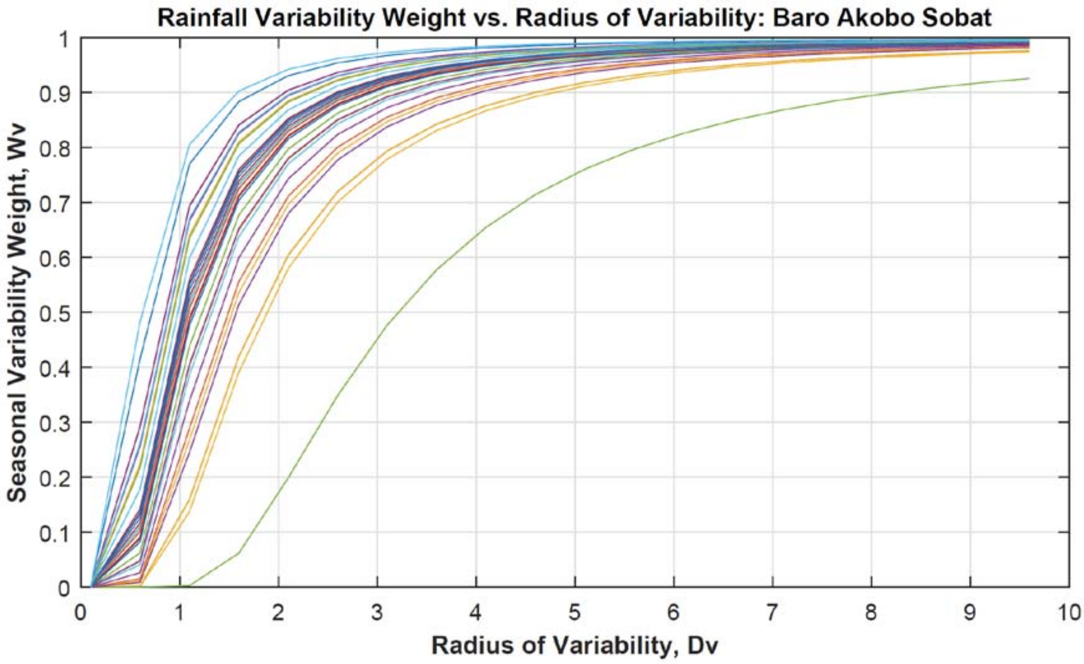
Figure 10: Combined skill weight calculated as the distance between each GCM's projection during retrospective run. (selectGCM.m and heatmap functions are used to produce this figure)

Reproducing Seasonal (monthly) and Annual Variability

The third GCM section criterion is based on reproducing variability that was recorded in the historical data. Variability is defined as the coefficient of variation (both seasonal and annual). Similar to independence and skill-based weights, variability skill also used exponential based weighting scheme to identify how far a GCMs should be downgraded if it did not produce the historical coefficient of variation compared to historical data. This weight is determined as follows:

$$w_v(i) = e^{-\left(\frac{\delta_{cv}}{D_v}\right)^2}$$

Where w_v is the weight assigned for a GCM, based on reproducing historical coefficient of variation. δ_{cv} distance between GCM projections vs. historical observation for both seasonal and annual coefficient of variation. D_v is a parameter that would determine how high or low GCM projection that are different from historical observation should be down weighted. Figure 11 shows range of seasonal (monthly) and annual variability weight as a function of Radius of Variability, Dv.



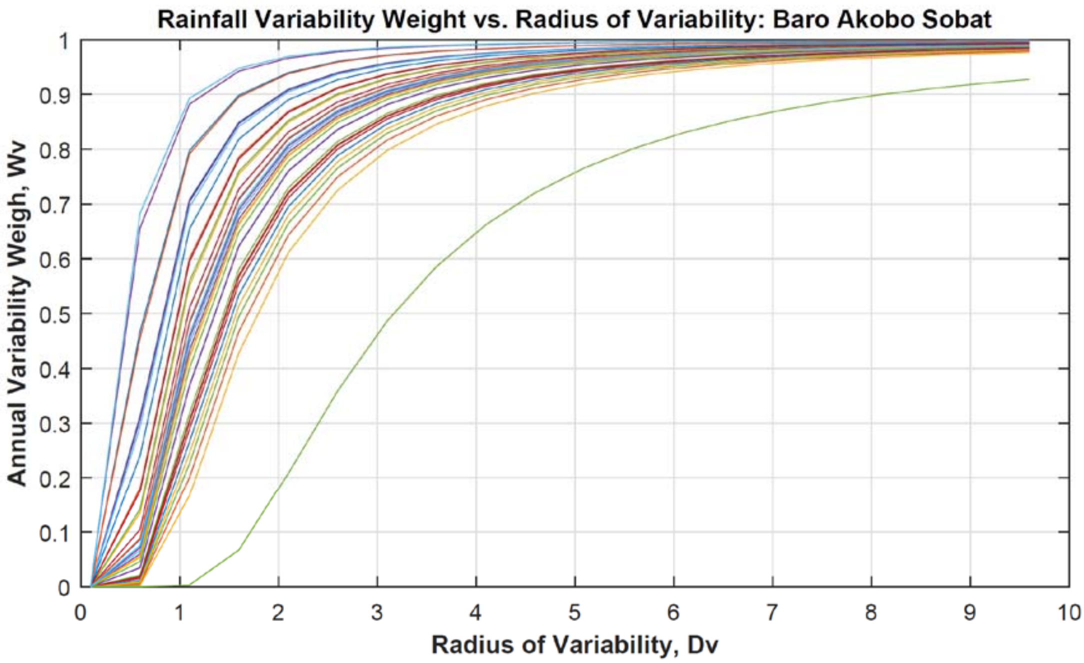


Figure 11: Seasonal (monthly) and annual variability weight as a function of radius of variability, Dv (selectGCM.m matlab cell Criteria 2 and 3 are used for this)

Appendix E (Supplemental Data report) shows the sensitivity of this parameter. Figure 12 through 14 show GCM skill based on variability scores and combined scores.

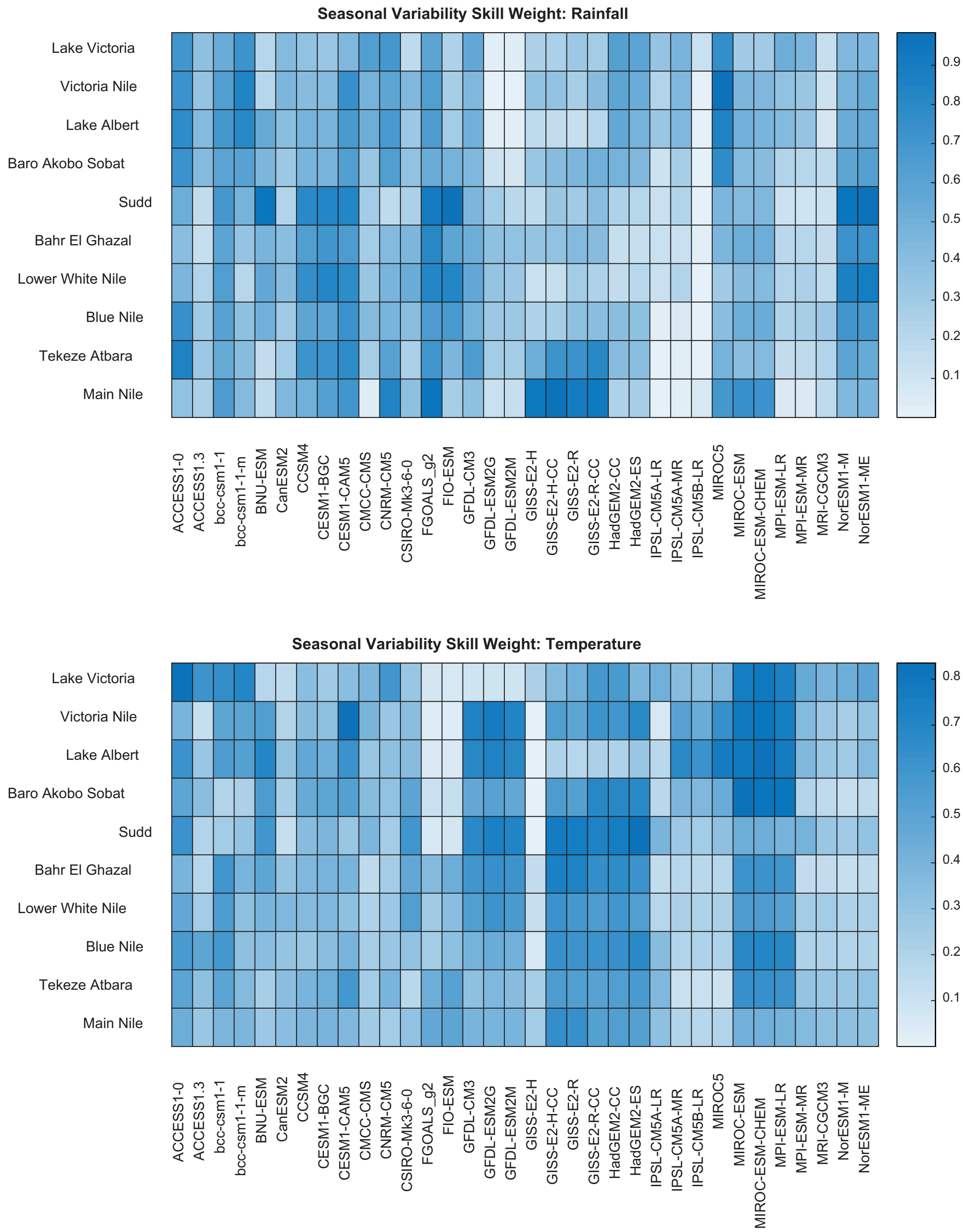
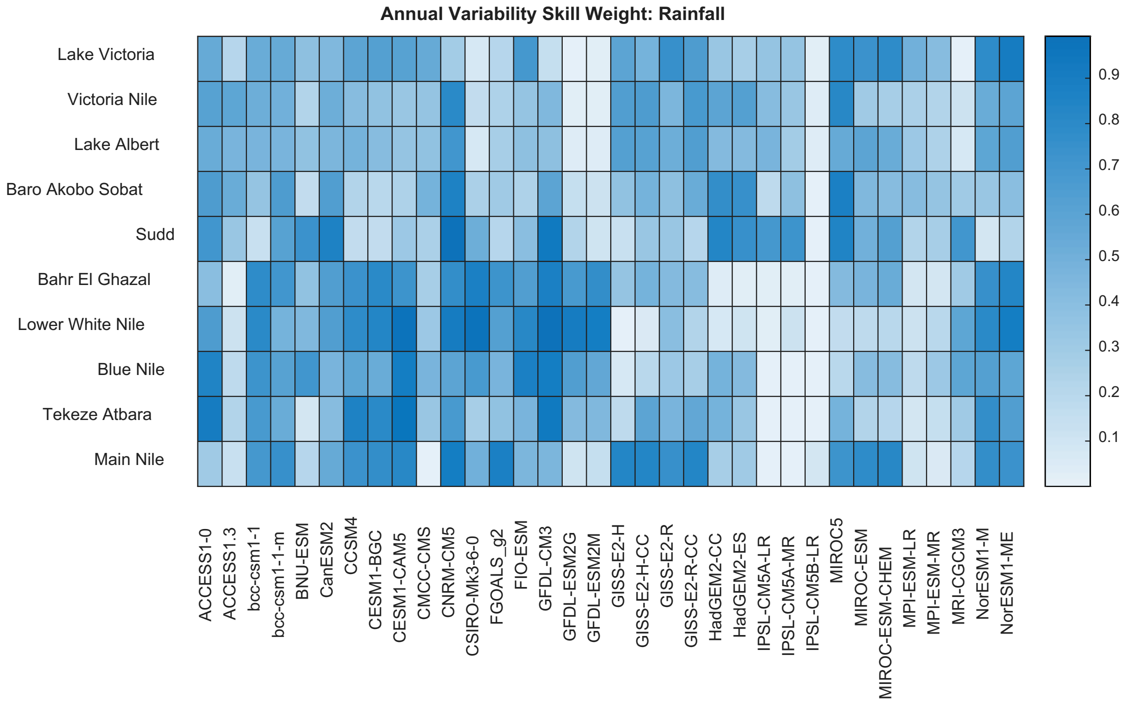


Figure 12: Seasonal variability based GCM weight. Seasonal variability is defined by monthly coefficient of variation. (selectGCM.m)



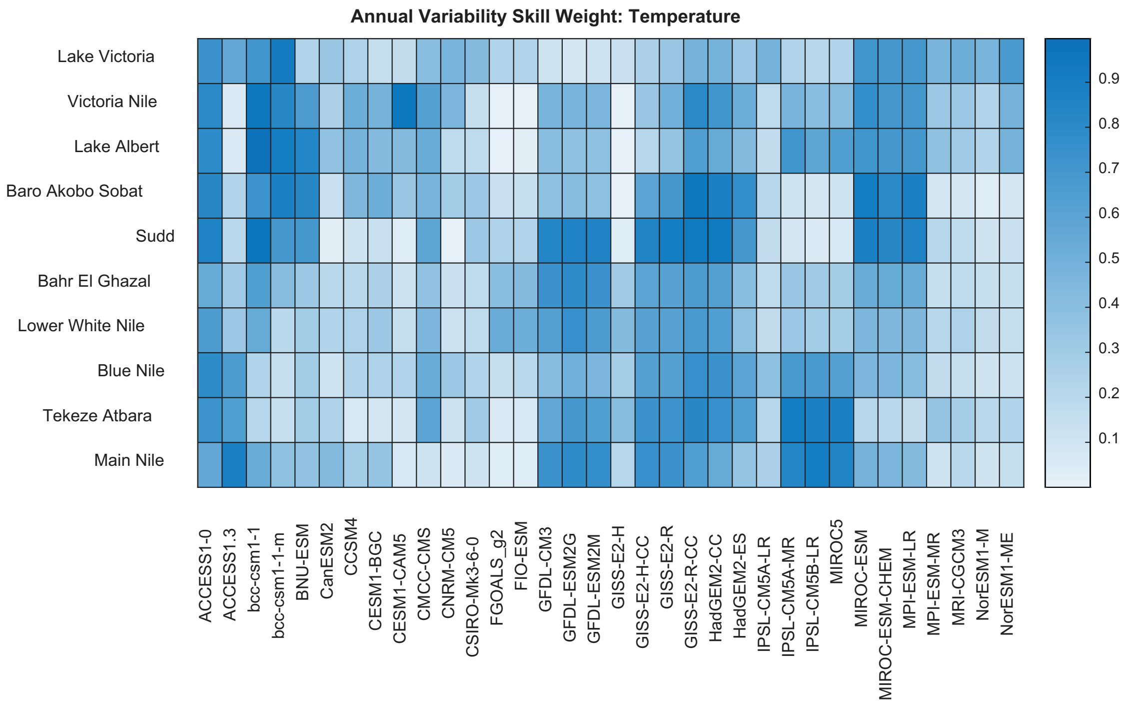


Figure 13: Annual variability based GCM weight. Annual variability is defined as annual coefficient of variation. (selectGCM.m)

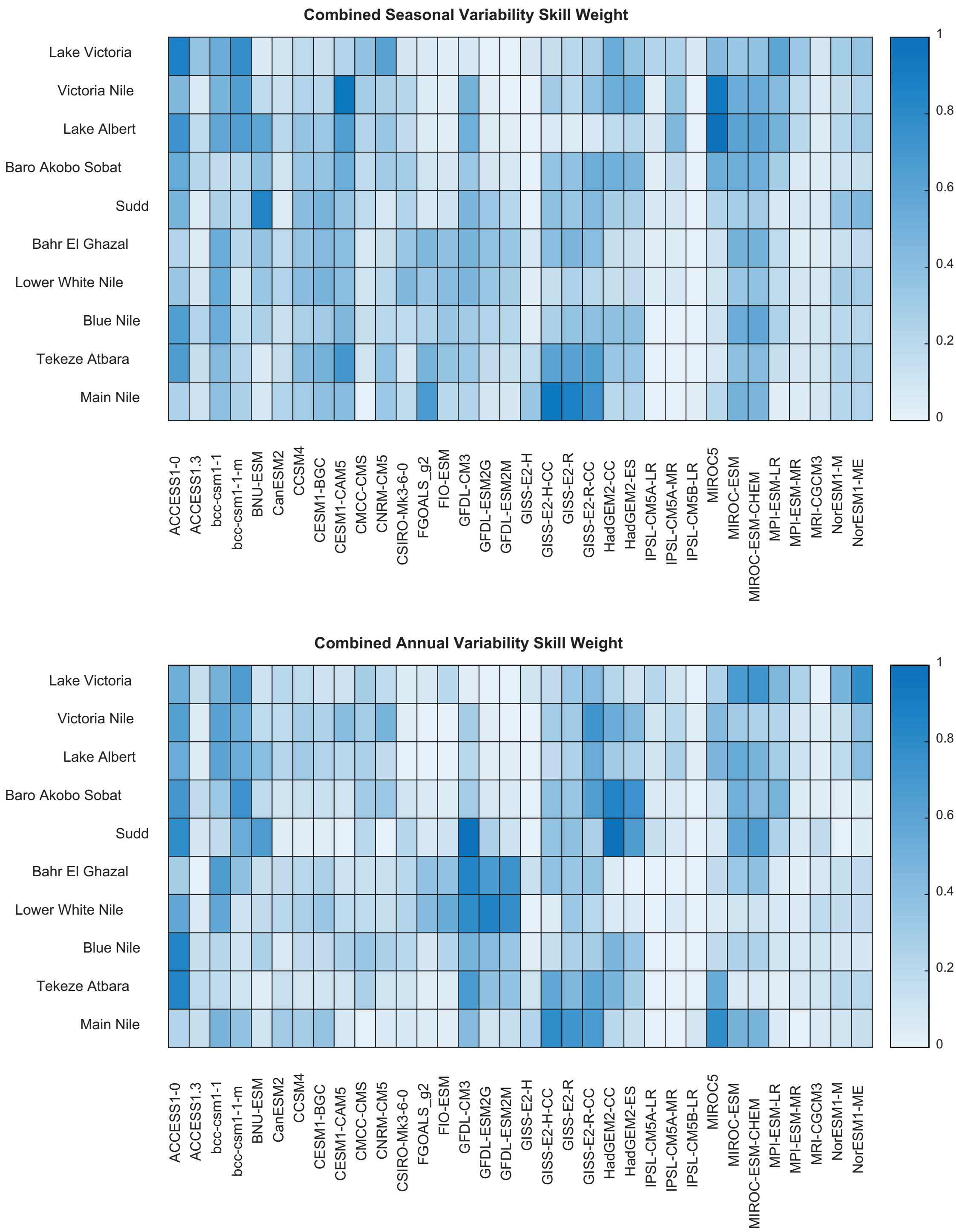


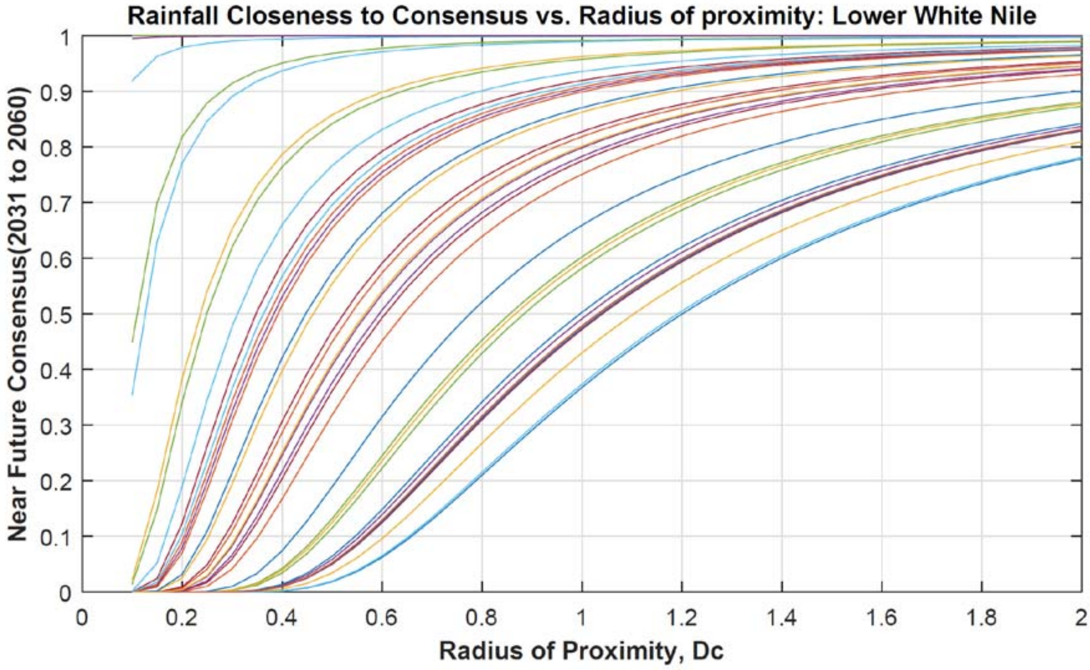
Figure 14: Combined seasonal and annual variability based GCM weight. (selectGCM,m)

Agreement to Consensus Weight

While the above criteria depend on historical data to assess a GCM skill, there is no guarantee that past performance may translate into future projection accuracy (Knutti et al., 2010 Asefa and Adams, 2013). On the other hand, future projection cannot be validated how accurate they repsent the future since that data is not available. One of the prevailing school of thoughts that is used in practice to address this is the “truth centered” approach that says historical retrospective runs of GCMs are assumed to be sampled from a distribution that is centered on observation plus some error (skill weight is used for this measure) and future GCM projections are centered in the ensemble mean. This approach makes the ensemble mean to be a better predictor of the future than what a single GCM will be able to say. Under this assumption for the future, weights are then derived based on their distance from ensemble mean. Like prior weight derivations above, an exponential weight with a parameter that determine the distance of a GCM from the ensemble mean was used. Parameter value was estimated through a sensitivity analysis shown in Figure 15 and Appendix F (Supplemental Data report). Figure 17 through 19 show these weights derived on closeness to consensus criterion for near (2031 to 2060) and far (2071 to 2100) futures for temperature, rainfall and combined skill.

$$w_{con}(i) = e^{-\left(\frac{\delta_{con}}{D_{con}}\right)^2}$$

Where w_{con} is weight assigned to a GCM projection based on how far its projection is from ensemble mean for both near and far futures. D_{con} is a parameter that determine how GCMs that are far from ensemble should be down weighted.



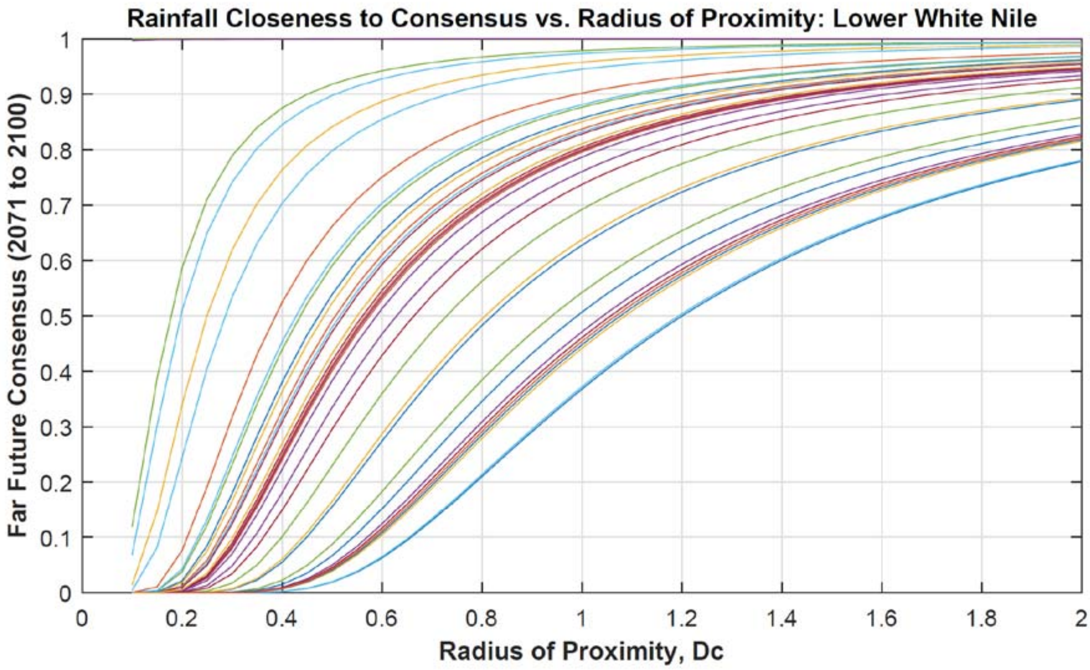
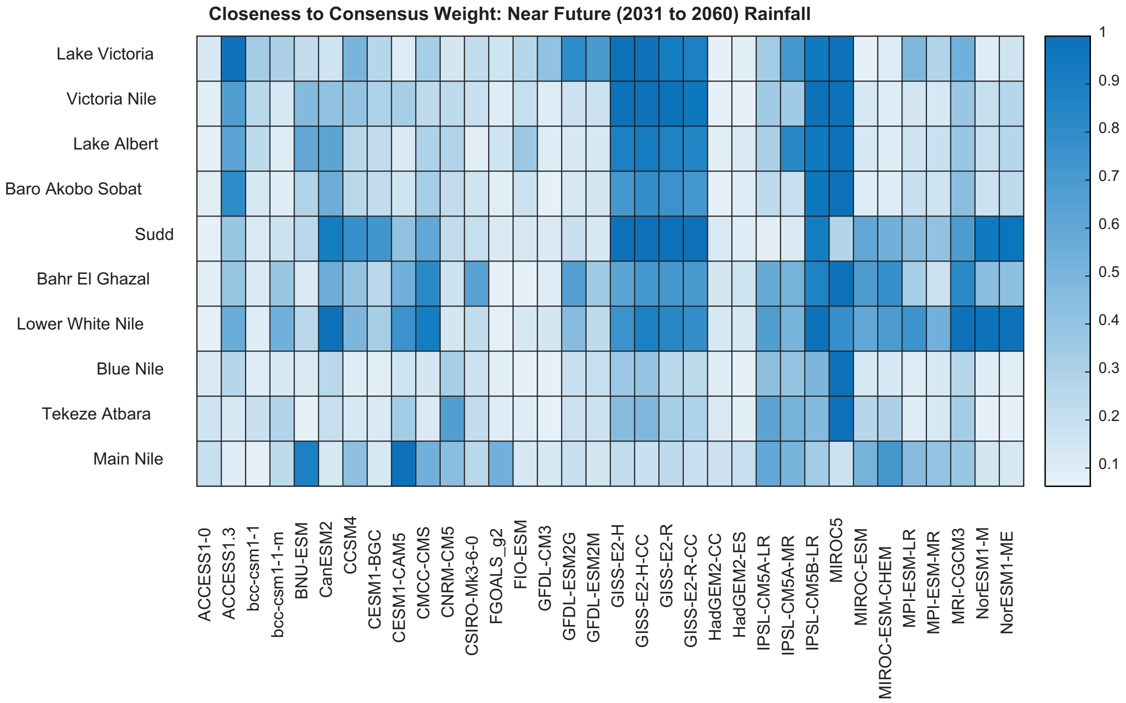


Figure 16: Weight assigned to GCMs based on closeness to consensus for near future (above) and far future (below) (selectGCM.m)



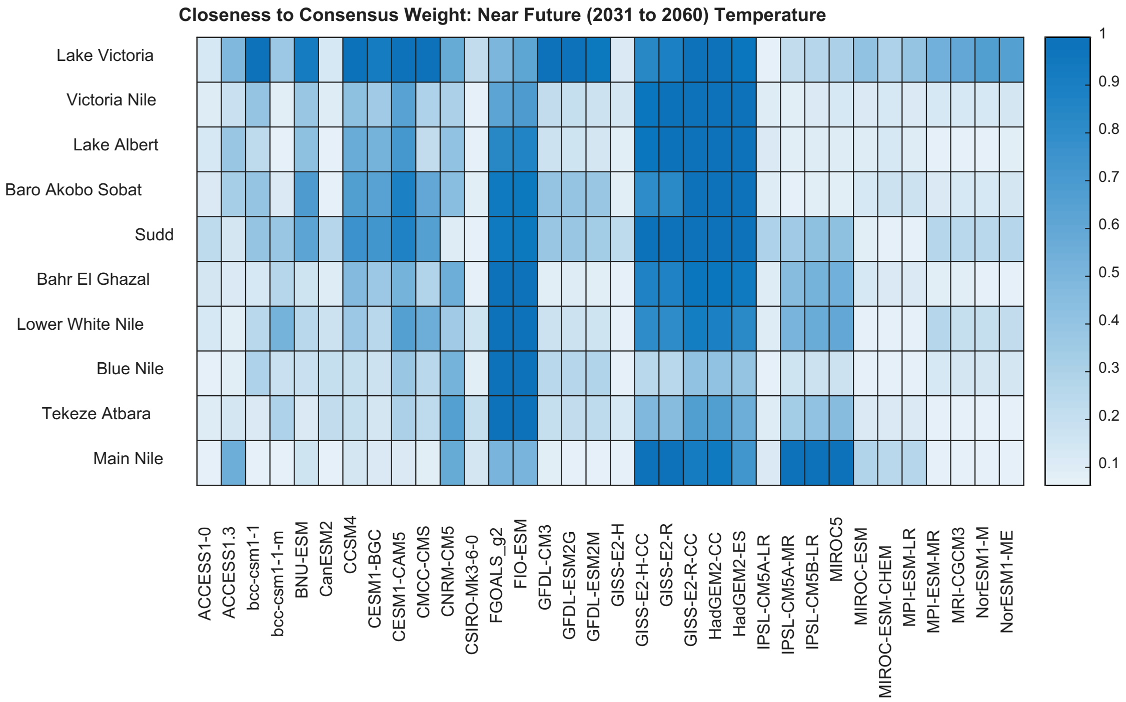


Figure 17: GCM weight based on closeness to the ensemble mean for near future (2030 to 2060).

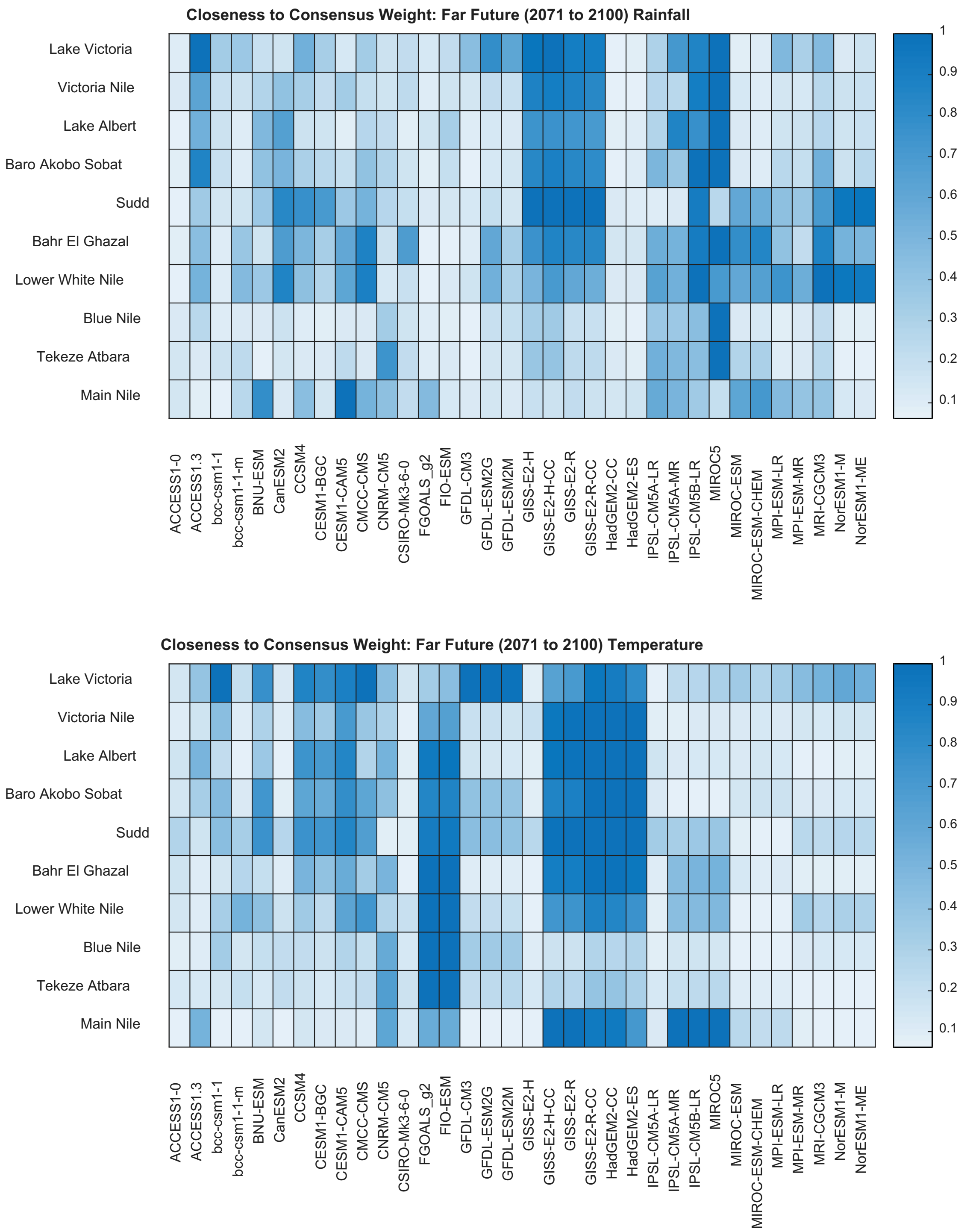


Figure 18: GCM weight based on closeness to the ensemble mean for far future (2071 to 2100).

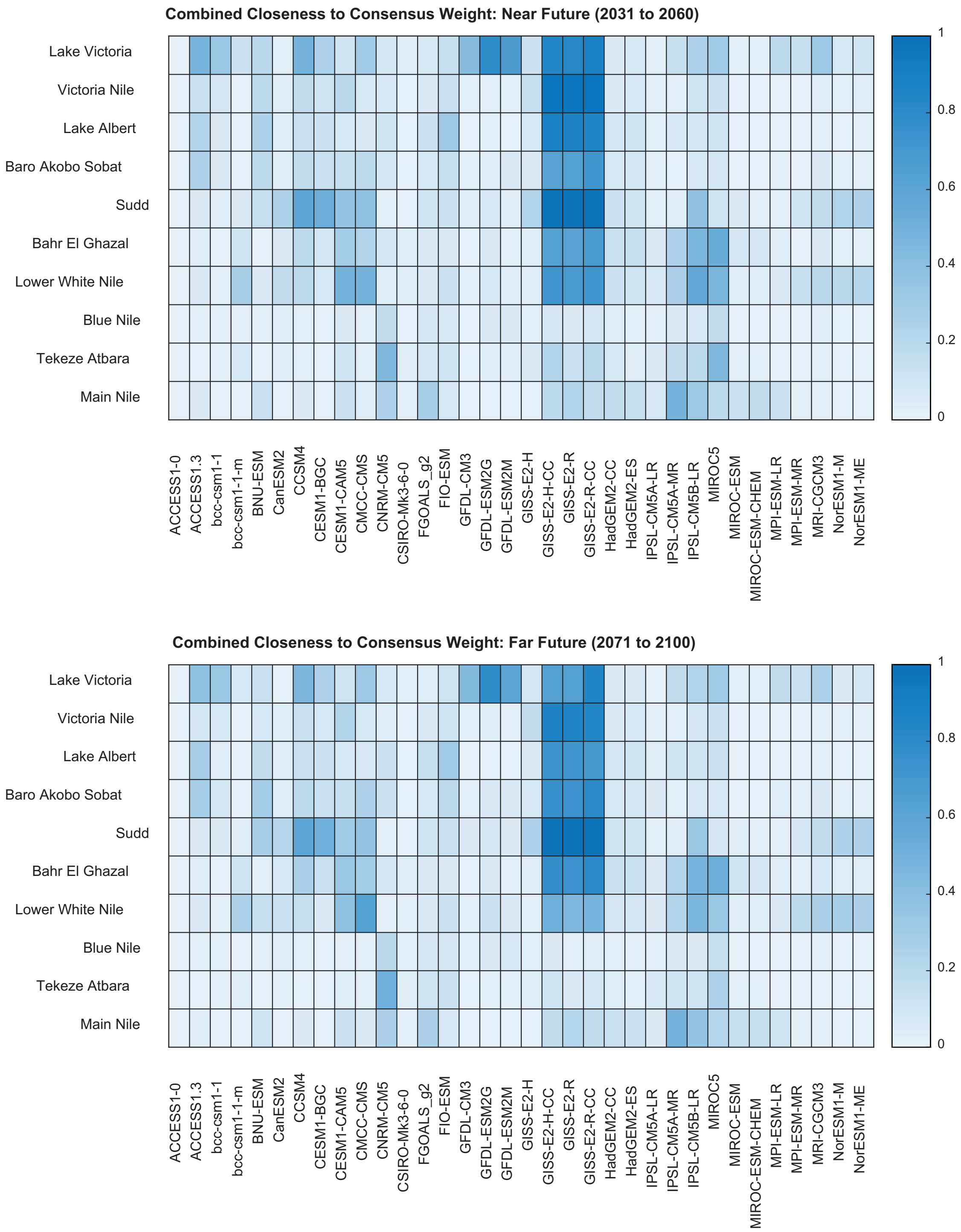


Figure 19: GCM weight based on combined closeness to the ensemble mean for near future (2030 to 2060) above and far future (2071 to 2100).

Reproducing Extreme Statistics

Depending on the application of impact study, often time practitioners would like to see if a GCM is able to reproduce extreme statistics that is useful for a given task. Extreme statistics include dry/wet condition and/or cold/warm for temperature. "Extreme" is typically defined as percentile of seasonal data, e.g., 10th percentile of rainfall data would constitute a dry condition that has a once in ten-year return period. Whereas the 90th percentile would correspond to a once in ten-year wet condition.

$$w_{ex}(i) = e^{-\left(\frac{\delta_{ex}}{D_x}\right)^2}$$

Where w_{ex} is weight assigned to a GCM projection based on how far its projection is from historical seasonal extreme values. D_x is a parameter that determine how GCMs that are far from percentile values should be down weighted. Parameter value was estimated through a sensitivity analysis shown in Figure 20 and Appendix G (Supplemental Data report). As shown in the figure the models have better separation in predicting wet condition than dry (shown by the cluster of the weight for different distance value). Figures 21 through 23 show the resulting weights for all the Nile Basin Initiative sub-basins.

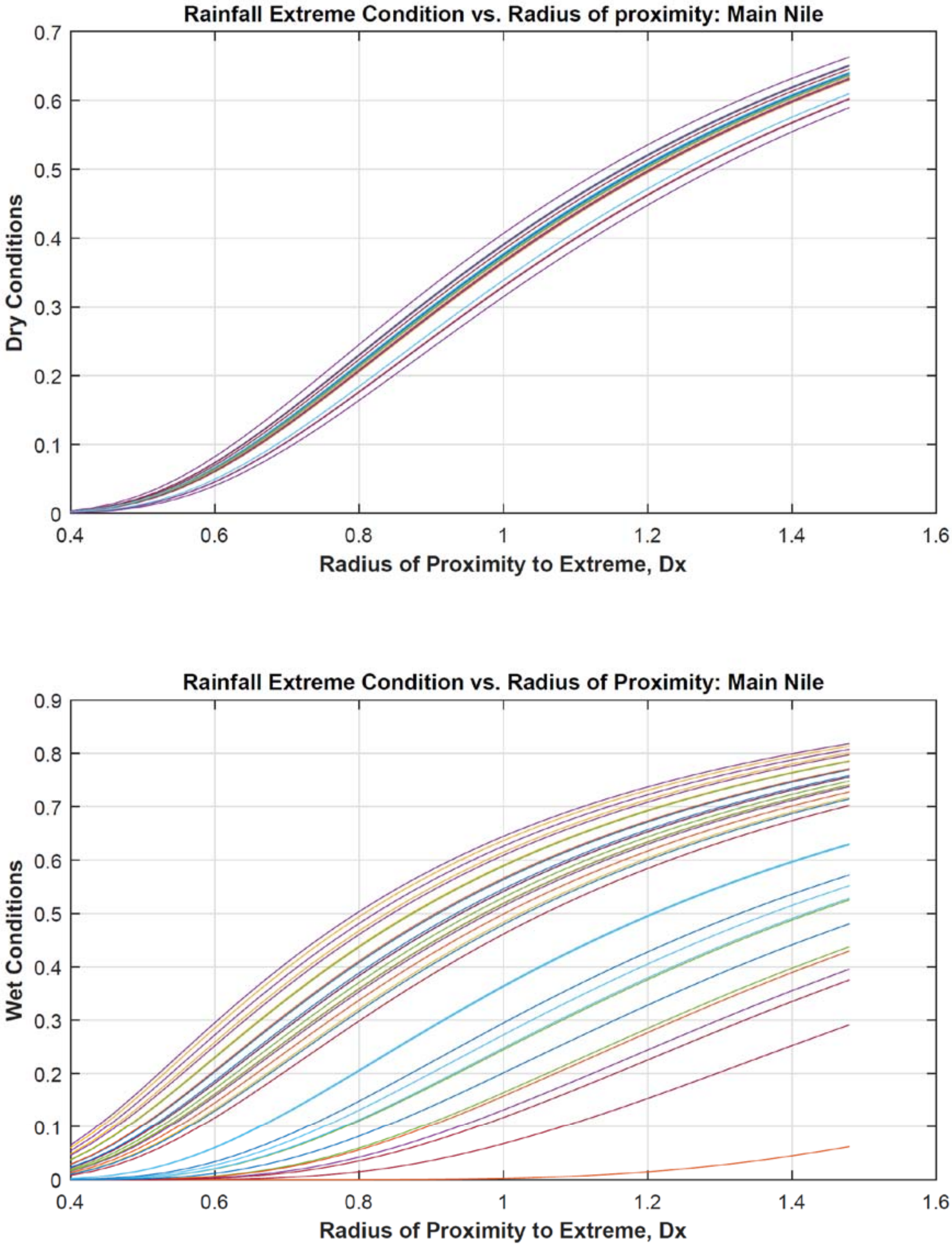


Figure 20: Weight derived from rainfall extremes as a functions of the radius of proximity to extreme for dry (above) and wet (below) condition.

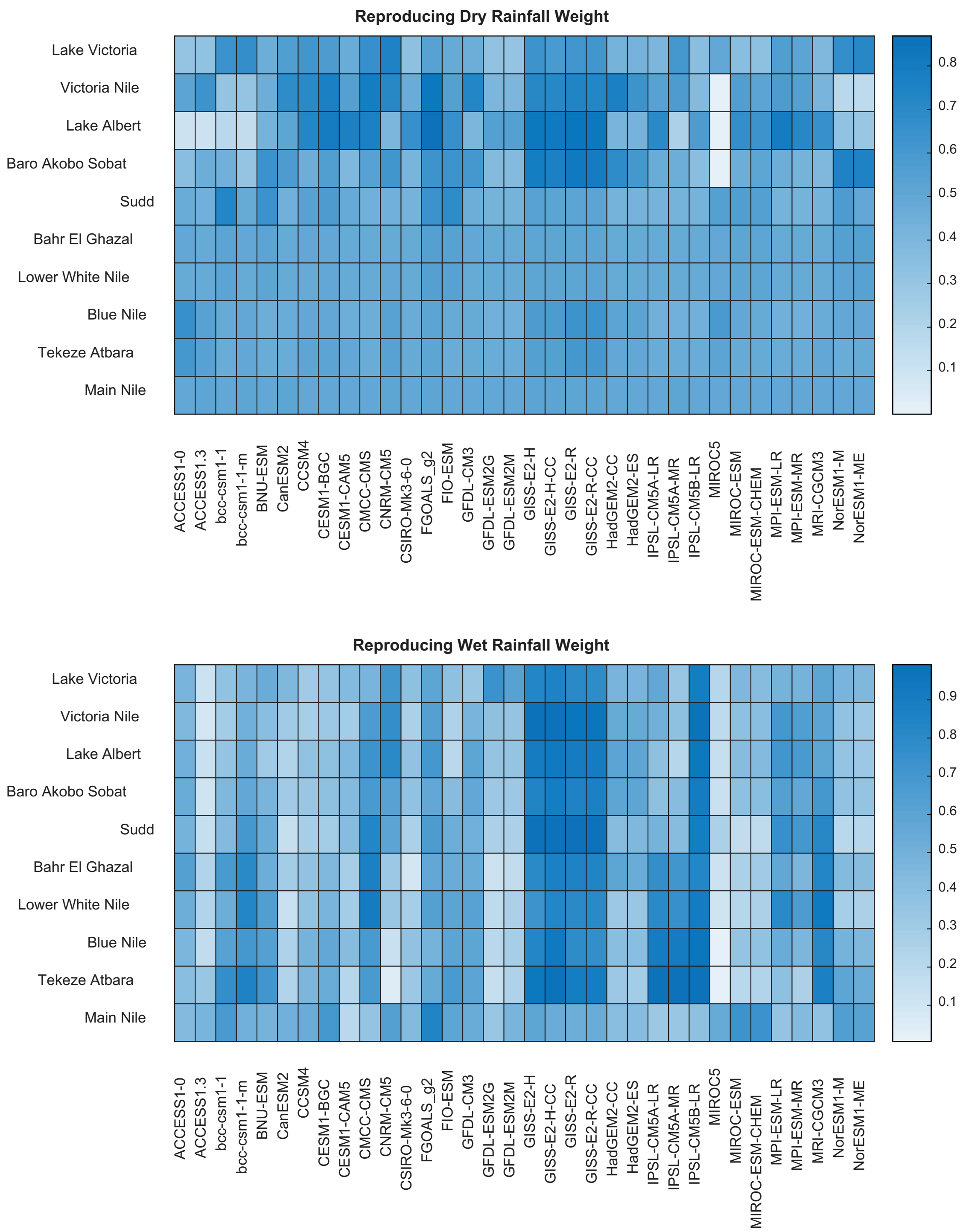
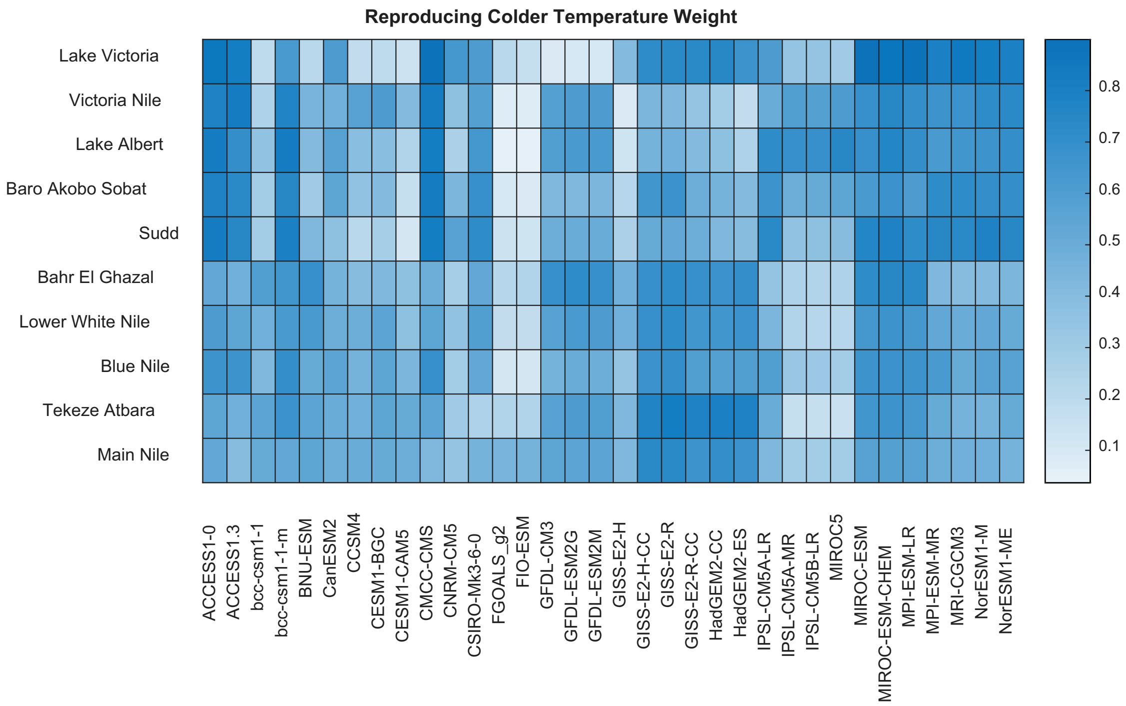


Figure 21: GCM weight based on reproducing rainfall extreme. Dry and wet conditions are defined as 10th and 90th percentile values for a season. (selectGCM.m)



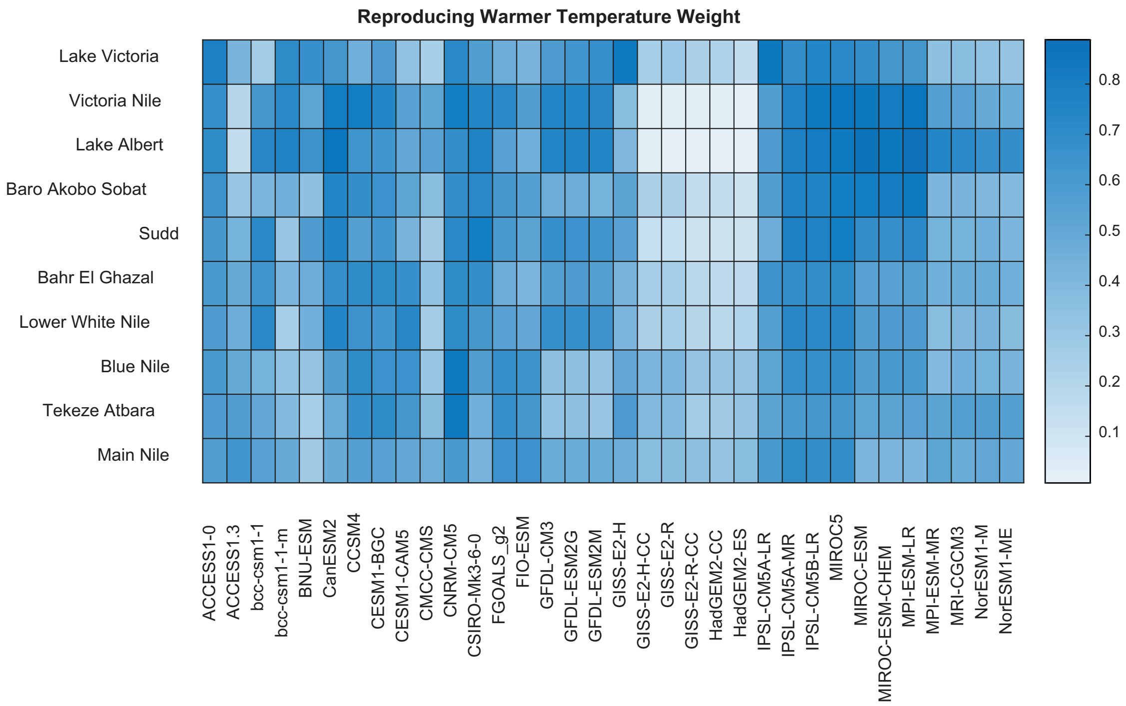
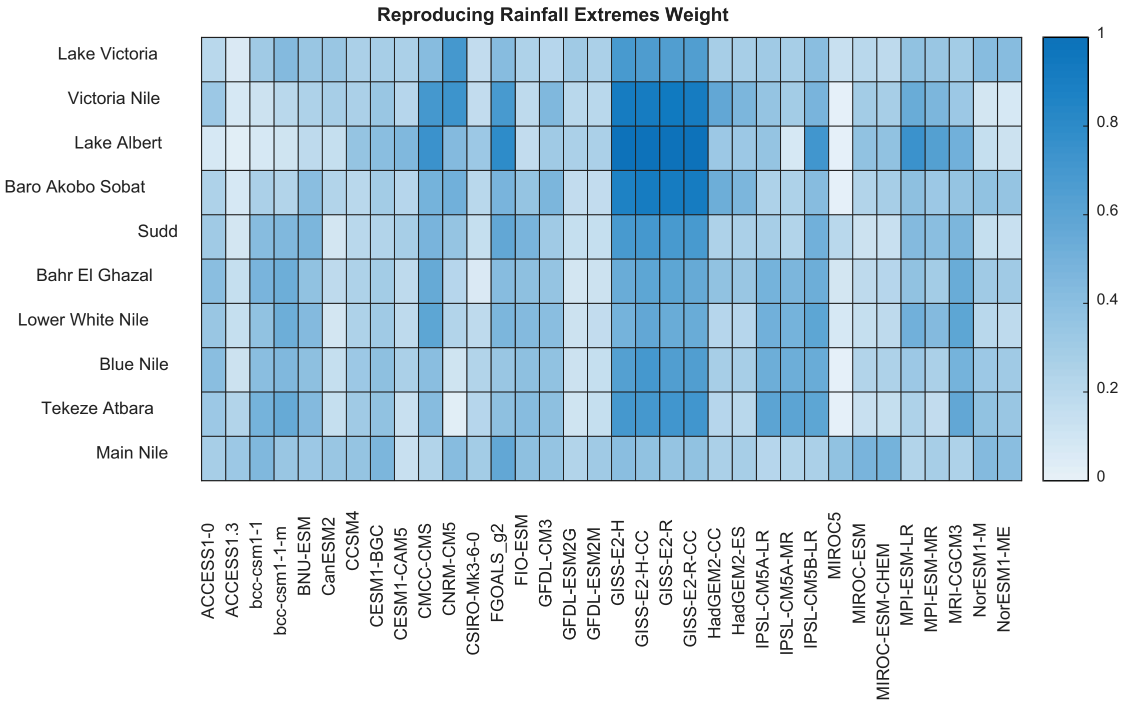


Figure 22: GCM weight based on reproducing temperature extreme. Colder and warmer conditions are defined as 10th and 90th percentile values for a season. (selectGCM.m)



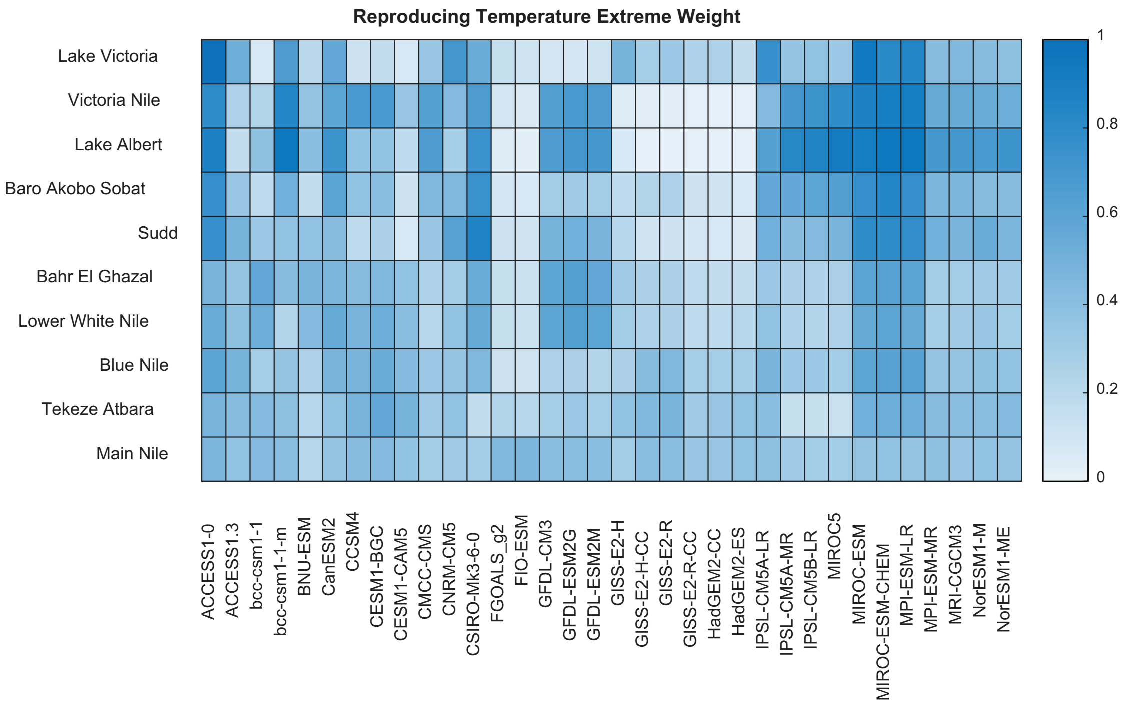


Figure 23: Combined GCM weight based on reproducing rainfall and temperature extremes.

Table 3 through Table 12 summarizes the performance of the GCM for 7 selected performance criteria for each of the Nile Basins. As shown in the table, the performance of GCMs widely vary across criteria and basins.

Summary

Three criteria were further used to select the top performing GCM according to NBI' needs assessment for use of climate projection data. 1) water resources planning that relies on long term statistics of hydrologic variables was represented by skill, seasonal, and variation performance 2) "Extreme" dry condition was represented with a metrics that ranked GCM based on reproducing drier rainfall condition wit once-in-ten years return period. 3) "Extreme" wetter conditions were represented with a performance measure that measures GCMs whether they can reproduce a rainfall with only 10 percent chance of being exceeded in any given year. A threshold of 70% was used to screen the list. A lesser threshold level would result in more GCMs being selected and a higher threshold would result in fewer GCMs being selected. Table 13 summarizes these results for each of the ten Nile Basin. Note that for some criterion and some basins the 70% threshold may not be met. In this case the single highest performed GCM was selected and this is highlight with light brown color in the table.

Basin Names: Lake Victoria

Table 3

Rank Criteria

Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'IPSL-CM5A-LR'	1.00	'CanESM2'	0.80	'ACCESS1-0'	0.88	'NorESM1-ME'	0.80	'GISS-E2-R-CC'	0.87	'CNRM-CM5'	0.70	'ACCESS1-0'	1.00
'MIROC5'	1.00	'MIROC-ESM'	0.66	'bcc-csm1-1-m'	0.77	'MIROC-ESM-CHEM'	0.71	'GFDL-ESM2G'	0.79	'GISS-E2-H'	0.69	'MIROC-ESM'	0.94
'NorESM1-ME'	1.00	'MIROC-ESM-CHEM'	0.59	'CNRM-CM5'	0.62	'MIROC-ESM'	0.68	'GISS-E2-H-CC'	0.73	'GISS-E2-H-CC'	0.66	'MPI-ESM-LR'	0.83
'IPSL-CM5B-LR'	0.93	'CNRM-CM5'	0.57	'MPI-ESM-LR'	0.58	'bcc-csm1-1-m'	0.66	'GISS-E2-R'	0.73	'GISS-E2-R'	0.65	'MIROC-ESM-CHEM'	0.81
'MRI-CGCM3'	0.80	'MRI-CGCM3'	0.55	'HadGEM2-CC'	0.54	'ACCESS1-0'	0.53	'GFDL-ESM2M'	0.63	'GISS-E2-R-CC'	0.64	'IPSL-CM5A-LR'	0.76
'GFDL-ESM2M'	0.76	'MPI-ESM-MR'	0.50	'bcc-csm1-1'	0.53	'bcc-csm1-1'	0.48	'CCSM4'	0.48	'bcc-csm1-1-m'	0.42	'CNRM-CM5'	0.69
'GFDL-ESM2G'	0.75	'ACCESS1-0'	0.48	'MIROC5'	0.43	'NorESM1-M'	0.47	'ACCESS1.3'	0.43	'NorESM1-M'	0.42	'bcc-csm1-1-m'	0.66
'GFDL-CM3'	0.75	'MPI-ESM-LR'	0.47	'CMCC-CMS'	0.37	'MPI-ESM-LR'	0.45	'GFDL-CM3'	0.42	'NorESM1-ME'	0.42	'CanESM2'	0.56
'MPI-ESM-MR'	0.71	'CSIRO-Mk3-6-0'	0.45	'MIROC-ESM-CHEM'	0.37	'GISS-E2-R-CC'	0.41	'bcc-csm1-1'	0.34	'FGOALS_g2'	0.42	'CSIRO-Mk3-6-0'	0.53
'NorESM1-M'	0.69	'NorESM1-M'	0.41	'ACCESS1.3'	0.36	'GISS-E2-R'	0.32	'CMCC-CMS'	0.32	'CMCC-CMS'	0.41	'ACCESS1.3'	0.52
'CNRM-CM5'	0.64	'CMCC-CMS'	0.36	'NorESM1-ME'	0.35	'CMCC-CMS'	0.28	'MIROC5'	0.30	'IPSL-CM5B-LR'	0.40	'GISS-E2-H'	0.50
'IPSL-CM5A-MR'	0.62	'HadGEM2-CC'	0.33	'HadGEM2-ES'	0.35	'MPI-ESM-MR'	0.25	'MRI-CGCM3'	0.27	'MPI-ESM-LR'	0.36	'MRI-CGCM3'	0.45
'GISS-E2-R-CC'	0.62	'NorESM1-ME'	0.30	'MIROC-ESM'	0.34	'MIROC5'	0.24	'CESM1-BGC'	0.24	'MPI-ESM-MR'	0.34	'NorESM1-M'	0.41
'BNU-ESM'	0.58	'FGOALS_g2'	0.29	'MPI-ESM-MR'	0.32	'IPSL-CM5A-LR'	0.21	'IPSL-CM5B-LR'	0.23	'CanESM2'	0.34	'MPI-ESM-MR'	0.41
'GISS-E2-H'	0.53	'IPSL-CM5A-LR'	0.28	'NorESM1-M'	0.29	'HadGEM2-CC'	0.21	'MPI-ESM-LR'	0.17	'BNU-ESM'	0.33	'NorESM1-ME'	0.39
'FIO-ESM'	0.50	'HadGEM2-ES'	0.28	'GISS-E2-R-CC'	0.25	'FIO-ESM'	0.20	'BNU-ESM'	0.17	'bcc-csm1-1'	0.31	'IPSL-CM5B-LR'	0.37
'bcc-csm1-1'	0.46	'bcc-csm1-1-m'	0.27	'IPSL-CM5A-MR'	0.25	'CanESM2'	0.19	'IPSL-CM5A-MR'	0.15	'GFDL-ESM2G'	0.30	'IPSL-CM5A-MR'	0.34
'MPI-ESM-LR'	0.46	'GISS-E2-R'	0.18	'IPSL-CM5A-LR'	0.23	'CCSM4'	0.19	'MPI-ESM-MR'	0.14	'IPSL-CM5A-LR'	0.30	'CMCC-CMS'	0.34
'CSIRO-Mk3-6-0'	0.43	'GISS-E2-R-CC'	0.15	'CESM1-CAM5'	0.22	'CNRM-CM5'	0.17	'FIO-ESM'	0.12	'MRI-CGCM3'	0.29	'MIROC5'	0.32
'GISS-E2-R'	0.35	'GISS-E2-H'	0.14	'GISS-E2-R'	0.20	'GISS-E2-H-CC'	0.17	'CESM1-CAM5'	0.11	'HadGEM2-ES'	0.27	'GISS-E2-R'	0.32
'GISS-E2-H-CC'	0.34	'FIO-ESM'	0.13	'CCSM4'	0.18	'ACCESS1.3'	0.15	'NorESM1-ME'	0.10	'IPSL-CM5A-MR'	0.27	'GISS-E2-H-CC'	0.27
'ACCESS1.3'	0.32	'GFDL-ESM2M'	0.11	'GISS-E2-H-CC'	0.14	'CESM1-BGC'	0.12	'GISS-E2-H'	0.10	'CESM1-BGC'	0.27	'GISS-E2-R-CC'	0.25
'MIROC-ESM-CHEM'	0.30	'CESM1-BGC'	0.09	'CESM1-BGC'	0.13	'CESM1-CAM5'	0.12	'bcc-csm1-1-m'	0.09	'HadGEM2-CC'	0.27	'HadGEM2-CC'	0.24
'CESM1-CAM5'	0.23	'IPSL-CM5A-MR'	0.09	'CanESM2'	0.10	'HadGEM2-ES'	0.11	'CNRM-CM5'	0.08	'CESM1-CAM5'	0.26	'BNU-ESM'	0.20

'HadGEM2-ES'	0.22	'GISS-E2-H-CC'	0.09	'MRI-CGCM3'	0.09	'BNU-ESM'	0.11	'HadGEM2-ES'	0.07	'GFDL-ESM2M'	0.26	'CESM1-BGC'	0.16
'MIROC-ESM'	0.21	'BNU-ESM'	0.07	'GISS-E2-H'	0.09	'GISS-E2-H'	0.10	'NorESM1-M'	0.06	'CCSM4'	0.25	'HadGEM2-ES'	0.16
'CCSM4'	0.19	'CCSM4'	0.06	'CSIRO-Mk3-6-0'	0.08	'IPSL-CM5A-MR'	0.10	'FGOALS_g2'	0.06	'FIO-ESM'	0.24	'FGOALS_g2'	0.14
'CMCC-CMS'	0.18	'IPSL-CM5B-LR'	0.06	'GFDL-CM3'	0.08	'FGOALS_g2'	0.06	'HadGEM2-CC'	0.06	'GFDL-CM3'	0.21	'CCSM4'	0.11
'FGOALS_g2'	0.15	'GFDL-ESM2G'	0.05	'IPSL-CM5B-LR'	0.07	'CSIRO-Mk3-6-0'	0.03	'CSIRO-Mk3-6-0'	0.03	'MIROC-ESM'	0.20	'FIO-ESM'	0.10
'CESM1-BGC'	0.15	'GFDL-CM3'	0.05	'FGOALS_g2'	0.06	'GFDL-CM3'	0.02	'MIROC-ESM'	0.03	'ACCESS1-0'	0.19	'GFDL-ESM2M'	0.10
'HadGEM2-CC'	0.14	'CESM1-CAM5'	0.04	'BNU-ESM'	0.06	'IPSL-CM5B-LR'	0.01	'MIROC-ESM-CHEM'	0.02	'MIROC-ESM-CHEM'	0.18	'GFDL-ESM2G'	0.09
'CanESM2'	0.09	'ACCESS1.3'	0.02	'FIO-ESM'	0.02	'GFDL-ESM2M'	0.00	'IPSL-CM5A-LR'	0.02	'CSIRO-Mk3-6-0'	0.17	'GFDL-CM3'	0.08
'bcc-csm1-1-m'	0.06	'bcc-csm1-1'	0.01	'GFDL-ESM2M'	0.00	'MRI-CGCM3'	0.00	'CanESM2'	0.02	'MIROC5'	0.14	'bcc-csm1-1'	0.07
'ACCESS1-0'	0.03	'MIROC5'	0.00	'GFDL-ESM2G'	0.00	'GFDL-ESM2G'	0.00	'ACCESS1-0'	0.01	'ACCESS1.3'	0.05	'CESM1-CAM5'	0.06

Basin Names: Victoria Nile

Table 4

Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'NorESM1-ME'	1.00	'CMCC-CMS'	0.86	'CESM1-CAM5'	0.95	'GISS-E2-R-CC'	0.70	'GISS-E2-H-CC'	0.92	'GISS-E2-R'	0.93	'MIROC-ESM-CHEM'	0.90
'GISS-E2-R-CC'	1.00	'bcc-csm1-1-m'	0.80	'MIROC5'	0.93	'ACCESS1-0'	0.63	'GISS-E2-R'	0.91	'GISS-E2-R-CC'	0.92	'MPI-ESM-LR'	0.90
'GISS-E2-R'	1.00	'MRI-CGCM3'	0.72	'bcc-csm1-1-m'	0.65	'bcc-csm1-1'	0.62	'GISS-E2-R-CC'	0.90	'GISS-E2-H'	0.92	'MIROC-ESM'	0.88
'GISS-E2-H-CC'	1.00	'ACCESS1-0'	0.72	'HadGEM2-ES'	0.55	'HadGEM2-CC'	0.54	'CESM1-CAM5'	0.21	'GISS-E2-H-CC'	0.91	'bcc-csm1-1-m'	0.84
'HadGEM2-ES'	0.95	'MPI-ESM-LR'	0.69	'MIROC-ESM-CHEM'	0.54	'bcc-csm1-1-m'	0.54	'GISS-E2-H'	0.15	'CNRM-CM5'	0.73	'MIROC5'	0.79
'HadGEM2-CC'	0.67	'MPI-ESM-MR'	0.69	'MIROC-ESM'	0.54	'CNRM-CM5'	0.47	'CCSM4'	0.15	'CMCC-CMS'	0.69	'ACCESS1-0'	0.79
'NorESM1-M'	0.57	'GFDL-CM3'	0.64	'HadGEM2-CC'	0.53	'MIROC5'	0.43	'BNU-ESM'	0.12	'FGOALS_g2'	0.68	'IPSL-CM5B-LR'	0.72
'CESM1-CAM5'	0.51	'GFDL-ESM2M'	0.50	'GFDL-CM3'	0.49	'HadGEM2-ES'	0.43	'FIO-ESM'	0.12	'HadGEM2-CC'	0.57	'IPSL-CM5A-MR'	0.70
'MRI-CGCM3'	0.48	'CESM1-BGC'	0.46	'bcc-csm1-1'	0.48	'CESM1-CAM5'	0.41	'MIROC5'	0.11	'MPI-ESM-LR'	0.53	'CESM1-BGC'	0.68
'ACCESS1.3'	0.42	'GFDL-ESM2G'	0.43	'ACCESS1-0'	0.45	'NorESM1-ME'	0.38	'ACCESS1.3'	0.11	'IPSL-CM5B-LR'	0.47	'GFDL-ESM2G'	0.68
'MPI-ESM-MR'	0.37	'MIROC-ESM-CHEM'	0.43	'MPI-ESM-LR'	0.43	'GISS-E2-R'	0.30	'IPSL-CM5B-LR'	0.10	'MPI-ESM-MR'	0.47	'CCSM4'	0.68
'FGOALS_g2'	0.36	'CNRM-CM5'	0.42	'GISS-E2-R-CC'	0.37	'MIROC-ESM'	0.30	'CESM1-BGC'	0.08	'HadGEM2-ES'	0.47	'GFDL-ESM2M'	0.67
'FIO-ESM'	0.35	'CCSM4'	0.41	'IPSL-CM5A-MR'	0.35	'GISS-E2-H-CC'	0.29	'bcc-csm1-1'	0.08	'GFDL-CM3'	0.45	'CSIRO-Mk3-6-0'	0.66

'MPI-ESM-LR'	0.29	'IPSL-CM5A-MR'	0.40	'GISS-E2-H-CC'	0.30	'CMCC-CMS'	0.29	'HadGEM2-ES'	0.07	'IPSL-CM5A-LR'	0.36	'GFDL-CM3'	0.65
'GISS-E2-H'	0.21	'MIROC-ESM'	0.36	'CMCC-CMS'	0.29	'CCSM4'	0.27	'CMCC-CMS'	0.07	'CESM1-BGC'	0.33	'CMCC-CMS'	0.64
'MIROC5'	0.21	'CSIRO-Mk3-6-0'	0.36	'CNRM-CM5'	0.25	'GFDL-CM3'	0.27	'FGOALS_g2'	0.06	'MRI-CGCM3'	0.33	'CanESM2'	0.58
'MIROC-ESM-CHEM'	0.19	'CanESM2'	0.34	'NorESM1-ME'	0.24	'MIROC-ESM-CHEM'	0.24	'HadGEM2-CC'	0.06	'ACCESS1-0'	0.31	'MRI-CGCM3'	0.56
'IPSL-CM5B-LR'	0.17	'IPSL-CM5A-LR'	0.27	'CCSM4'	0.22	'CESM1-BGC'	0.23	'CNRM-CM5'	0.05	'IPSL-CM5A-MR'	0.29	'MPI-ESM-MR'	0.56
'CMCC-CMS'	0.13	'NorESM1-M'	0.24	'CSIRO-Mk3-6-0'	0.22	'MPI-ESM-LR'	0.23	'MRI-CGCM3'	0.04	'MIROC-ESM'	0.28	'NorESM1-M'	0.54
'GFDL-ESM2M'	0.12	'NorESM1-ME'	0.20	'CESM1-BGC'	0.21	'IPSL-CM5A-MR'	0.20	'CanESM2'	0.04	'CanESM2'	0.28	'NorESM1-ME'	0.52
'bcc-csm1-1'	0.12	'BNU-ESM'	0.10	'GISS-E2-R'	0.20	'BNU-ESM'	0.19	'GFDL-ESM2G'	0.03	'MIROC-ESM-CHEM'	0.27	'IPSL-CM5A-LR'	0.44
'GFDL-ESM2G'	0.12	'ACCESS1.3'	0.09	'MPI-ESM-MR'	0.18	'CanESM2'	0.18	'NorESM1-ME'	0.03	'CCSM4'	0.25	'CNRM-CM5'	0.44
'MIROC-ESM'	0.11	'CESM1-CAM5'	0.06	'BNU-ESM'	0.17	'NorESM1-M'	0.15	'GFDL-ESM2M'	0.03	'BNU-ESM'	0.24	'BNU-ESM'	0.35
'BNU-ESM'	0.10	'bcc-csm1-1'	0.06	'NorESM1-M'	0.17	'IPSL-CM5A-LR'	0.10	'NorESM1-M'	0.02	'CESM1-CAM5'	0.21	'CESM1-CAM5'	0.33
'CNRM-CM5'	0.10	'IPSL-CM5B-LR'	0.06	'CanESM2'	0.13	'MPI-ESM-MR'	0.09	'IPSL-CM5A-LR'	0.02	'GFDL-ESM2G'	0.20	'ACCESS1.3'	0.24
'IPSL-CM5A-LR'	0.09	'FGOALS_g2'	0.05	'ACCESS1.3'	0.06	'MRI-CGCM3'	0.05	'IPSL-CM5A-MR'	0.02	'bcc-csm1-1-m'	0.20	'bcc-csm1-1'	0.23
'GFDL-CM3'	0.07	'GISS-E2-H'	0.04	'MRI-CGCM3'	0.05	'ACCESS1.3'	0.04	'GFDL-CM3'	0.02	'GFDL-ESM2M'	0.19	'FGOALS_g2'	0.08
'IPSL-CM5A-MR'	0.07	'FIO-ESM'	0.01	'FGOALS_g2'	0.03	'CSIRO-Mk3-6-0'	0.03	'MPI-ESM-MR'	0.01	'FIO-ESM'	0.18	'FIO-ESM'	0.05
'CSIRO-Mk3-6-0'	0.06	'HadGEM2-CC'	0.01	'IPSL-CM5A-LR'	0.02	'IPSL-CM5B-LR'	0.02	'MPI-ESM-LR'	0.01	'CSIRO-Mk3-6-0'	0.17	'GISS-E2-H'	0.04
'CanESM2'	0.02	'MIROC5'	0.00	'GFDL-ESM2G'	0.02	'GFDL-ESM2G'	0.02	'bcc-csm1-1-m'	0.01	'bcc-csm1-1'	0.12	'GISS-E2-H-CC'	0.02
'CESM1-BGC'	0.01	'GISS-E2-R'	0.00	'FIO-ESM'	0.02	'GFDL-ESM2M'	0.01	'MIROC-ESM'	0.01	'NorESM1-M'	0.08	'GISS-E2-R'	0.02
'bcc-csm1-1-m'	0.01	'GISS-E2-H-CC'	0.00	'GFDL-ESM2M'	0.01	'FIO-ESM'	0.00	'MIROC-ESM-CHEM'	0.01	'ACCESS1.3'	0.08	'GISS-E2-R-CC'	0.01
'CCSM4'	0.01	'HadGEM2-ES'	0.00	'IPSL-CM5B-LR'	0.00	'FGOALS_g2'	0.00	'CSIRO-Mk3-6-0'	0.01	'NorESM1-ME'	0.07	'HadGEM2-CC'	0.01
'ACCESS1-0'	0.00	'GISS-E2-R-CC'	0.00	'GISS-E2-H'	0.00	'GISS-E2-H'	0.00	'ACCESS1-0'	0.01	'MIROC5'	0.00	'HadGEM2-ES'	0.00

Basin Names: Lake Albert

Table 5

Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'FIO-ESM'	1.00	'MPI-ESM-MR'	0.93	'MIROC5'	1.00	'bcc-csm1-1'	0.60	'GISS-E2-H-CC'	0.81	'GISS-E2-R'	1.00	'MIROC-ESM-CHEM'	0.94
'NorESM1-ME'	1.00	'CMCC-CMS'	0.92	'ACCESS1-0'	0.74	'MIROC-ESM'	0.55	'GISS-E2-R'	0.79	'GISS-E2-H'	1.00	'bcc-csm1-1-m'	0.94

'GISS-E2-R-CC'	1.00	'MPI-ESM-LR'	0.88	'bcc-csm1-1-m'	0.65	'ACCESS1-0'	0.55	'GISS-E2-R-CC'	0.77	'GISS-E2-R-CC'	1.00	'MPI-ESM-LR'	0.94
'GISS-E2-R'	1.00	'MRI-CGCM3'	0.78	'CESM1-CAM5'	0.65	'bcc-csm1-1-m'	0.54	'FIO-ESM'	0.31	'GISS-E2-H-CC'	0.99	'MIROC5'	0.92
'GISS-E2-H-CC'	1.00	'GFDL-ESM2M'	0.66	'MIROC-ESM-CHEM'	0.60	'GISS-E2-R-CC'	0.53	'ACCESS1.3'	0.25	'FGOALS_g2'	0.79	'MIROC-ESM'	0.90
'ACCESS1.3'	0.65	'GFDL-CM3'	0.62	'MIROC-ESM'	0.60	'MIROC-ESM-CHEM'	0.48	'BNU-ESM'	0.21	'MPI-ESM-LR'	0.75	'ACCESS1-0'	0.88
'HadGEM2-ES'	0.52	'GFDL-ESM2G'	0.61	'BNU-ESM'	0.59	'MIROC5'	0.46	'FGOALS_g2'	0.13	'CMCC-CMS'	0.74	'IPSL-CM5B-LR'	0.84
'MRI-CGCM3'	0.40	'bcc-csm1-1-m'	0.54	'bcc-csm1-1'	0.57	'NorESM1-ME'	0.41	'CCSM4'	0.13	'IPSL-CM5B-LR'	0.71	'IPSL-CM5A-MR'	0.81
'NorESM1-M'	0.37	'ACCESS1-0'	0.47	'GFDL-CM3'	0.52	'BNU-ESM'	0.39	'MIROC5'	0.11	'MPI-ESM-MR'	0.64	'CSIRO-Mk3-6-0'	0.74
'FGOALS_g2'	0.32	'MIROC-ESM-CHEM'	0.42	'MPI-ESM-LR'	0.49	'CCSM4'	0.30	'CESM1-BGC'	0.11	'MRI-CGCM3'	0.51	'CanESM2'	0.73
'HadGEM2-CC'	0.31	'CSIRO-Mk3-6-0'	0.42	'IPSL-CM5A-MR'	0.45	'HadGEM2-CC'	0.30	'CNRM-CM5'	0.11	'CESM1-CAM5'	0.45	'NorESM1-ME'	0.72
'MPI-ESM-MR'	0.30	'IPSL-CM5A-LR'	0.41	'CCSM4'	0.35	'MPI-ESM-LR'	0.29	'HadGEM2-ES'	0.11	'CNRM-CM5'	0.42	'GFDL-ESM2G'	0.70
'MPI-ESM-LR'	0.22	'MIROC-ESM'	0.36	'CNRM-CM5'	0.33	'IPSL-CM5A-MR'	0.26	'IPSL-CM5B-LR'	0.09	'CESM1-BGC'	0.40	'GFDL-ESM2M'	0.69
'GISS-E2-H'	0.19	'CNRM-CM5'	0.33	'CESM1-BGC'	0.31	'CMCC-CMS'	0.26	'HadGEM2-CC'	0.08	'MIROC-ESM'	0.37	'MPI-ESM-MR'	0.69
'MIROC5'	0.18	'IPSL-CM5B-LR'	0.29	'NorESM1-ME'	0.31	'HadGEM2-ES'	0.24	'IPSL-CM5A-MR'	0.08	'MIROC-ESM-CHEM'	0.36	'MRI-CGCM3'	0.69
'CESM1-CAM5'	0.17	'GISS-E2-H'	0.27	'CMCC-CMS'	0.23	'GISS-E2-R'	0.23	'CESM1-CAM5'	0.07	'CCSM4'	0.36	'NorESM1-M'	0.67
'IPSL-CM5B-LR'	0.16	'NorESM1-M'	0.23	'HadGEM2-ES'	0.21	'CESM1-BGC'	0.23	'GISS-E2-H'	0.07	'IPSL-CM5A-LR'	0.35	'CMCC-CMS'	0.67
'CNRM-CM5'	0.15	'CESM1-BGC'	0.19	'NorESM1-M'	0.20	'CanESM2'	0.21	'CMCC-CMS'	0.06	'HadGEM2-CC'	0.33	'GFDL-CM3'	0.67
'IPSL-CM5A-MR'	0.14	'NorESM1-ME'	0.18	'MPI-ESM-MR'	0.19	'CESM1-CAM5'	0.20	'bcc-csm1-1'	0.04	'CSIRO-Mk3-6-0'	0.33	'IPSL-CM5A-LR'	0.64
'IPSL-CM5A-LR'	0.13	'CCSM4'	0.15	'CanESM2'	0.19	'GFDL-CM3'	0.19	'CanESM2'	0.04	'HadGEM2-ES'	0.32	'BNU-ESM'	0.39
'CCSM4'	0.12	'bcc-csm1-1'	0.07	'ACCESS1.3'	0.18	'NorESM1-M'	0.17	'IPSL-CM5A-LR'	0.03	'GFDL-CM3'	0.31	'bcc-csm1-1'	0.39
'MIROC-ESM-CHEM'	0.10	'CanESM2'	0.07	'HadGEM2-CC'	0.17	'CNRM-CM5'	0.17	'MRI-CGCM3'	0.02	'GFDL-ESM2G'	0.26	'CCSM4'	0.37
'CESM1-BGC'	0.09	'CESM1-CAM5'	0.06	'CSIRO-Mk3-6-0'	0.17	'GISS-E2-H-CC'	0.16	'GFDL-ESM2G'	0.02	'GFDL-ESM2M'	0.25	'CESM1-BGC'	0.36
'CanESM2'	0.09	'BNU-ESM'	0.06	'IPSL-CM5A-LR'	0.09	'MPI-ESM-MR'	0.12	'MPI-ESM-LR'	0.01	'BNU-ESM'	0.18	'CNRM-CM5'	0.27
'BNU-ESM'	0.07	'IPSL-CM5A-MR'	0.05	'GISS-E2-R-CC'	0.07	'IPSL-CM5A-LR'	0.10	'NorESM1-ME'	0.01	'FIO-ESM'	0.17	'CESM1-CAM5'	0.18
'MIROC-ESM'	0.06	'FGOALS_g2'	0.03	'GISS-E2-H-CC'	0.05	'ACCESS1.3'	0.04	'GFDL-ESM2M'	0.01	'CanESM2'	0.15	'ACCESS1.3'	0.16
'GFDL-ESM2M'	0.05	'ACCESS1.3'	0.01	'FGOALS_g2'	0.04	'IPSL-CM5B-LR'	0.03	'GFDL-CM3'	0.01	'NorESM1-M'	0.15	'GISS-E2-H'	0.07
'bcc-csm1-1'	0.04	'GISS-E2-R'	0.01	'GISS-E2-R'	0.04	'MRI-CGCM3'	0.03	'NorESM1-M'	0.01	'NorESM1-ME'	0.12	'FGOALS_g2'	0.03
'CMCC-CMS'	0.04	'GISS-E2-H-CC'	0.01	'MRI-CGCM3'	0.04	'GFDL-ESM2G'	0.02	'MIROC-ESM-CHEM'	0.01	'bcc-csm1-1-m'	0.10	'FIO-ESM'	0.02
'GFDL-ESM2G'	0.03	'HadGEM2-CC'	0.01	'GFDL-ESM2G'	0.03	'GFDL-ESM2M'	0.02	'MIROC-ESM'	0.01	'bcc-csm1-1'	0.08	'GISS-E2-H-CC'	0.01

'GFDL-CM3'	0.02	'GISS-E2-R-CC'	0.00	'FIO-ESM'	0.02	'CSIRO-Mk3-6-0'	0.02	'MPI-ESM-MR'	0.01	'ACCESS1-0'	0.07	'GISS-E2-R'	0.01
'CSIRO-Mk3-6-0'	0.01	'FIO-ESM'	0.00	'GFDL-ESM2M'	0.02	'FIO-ESM'	0.01	'ACCESS1-0'	0.00	'IPSL-CM5A-MR'	0.07	'GISS-E2-R-CC'	0.01
'bcc-csm1-1-m'	0.00	'HadGEM2-ES'	0.00	'IPSL-CM5B-LR'	0.00	'FGOALS_g2'	0.01	'CSIRO-Mk3-6-0'	0.00	'ACCESS1.3'	0.02	'HadGEM2-CC'	0.00
'ACCESS1-0'	0.00	'MIROC5'	0.00	'GISS-E2-H'	0.00	'GISS-E2-H'	0.00	'bcc-csm1-1-m'	0.00	'MIROC5'	0.00	'HadGEM2-ES'	0.00

Basin Names: Baro Akobo Sobat												Table 6	
Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'NorESM1-ME'	1.00	'MPI-ESM-MR'	1.00	'ACCESS1-0'	0.55	'HadGEM2-CC'	0.86	'GISS-E2-R-CC'	0.76	'GISS-E2-R-CC'	0.92	'MIROC-ESM-CHEM'	0.83
'GISS-E2-R-CC'	1.00	'MRI-CGCM3'	0.87	'MIROC5'	0.53	'HadGEM2-ES'	0.74	'GISS-E2-H-CC'	0.69	'GISS-E2-R'	0.92	'ACCESS1-0'	0.76
'GISS-E2-R'	1.00	'bcc-csm1-1-m'	0.72	'CESM1-CAM5'	0.52	'bcc-csm1-1-m'	0.74	'GISS-E2-R'	0.69	'GISS-E2-H-CC'	0.91	'MPI-ESM-LR'	0.75
'GISS-E2-H-CC'	0.96	'MPI-ESM-LR'	0.67	'MIROC-ESM'	0.52	'ACCESS1-0'	0.69	'ACCESS1.3'	0.26	'GISS-E2-H'	0.87	'MIROC-ESM'	0.75
'MPI-ESM-LR'	0.90	'CMCC-CMS'	0.64	'GISS-E2-R-CC'	0.52	'GISS-E2-R-CC'	0.65	'BNU-ESM'	0.24	'HadGEM2-CC'	0.53	'CSIRO-Mk3-6-0'	0.74
'ACCESS1.3'	0.60	'ACCESS1-0'	0.51	'HadGEM2-CC'	0.51	'MIROC-ESM'	0.51	'CMCC-CMS'	0.21	'CNRM-CM5'	0.51	'MIROC5'	0.65
'MIROC5'	0.57	'CNRM-CM5'	0.50	'MIROC-ESM-CHEM'	0.50	'MPI-ESM-LR'	0.47	'CCSM4'	0.18	'CMCC-CMS'	0.49	'CanESM2'	0.61
'HadGEM2-ES'	0.55	'IPSL-CM5A-LR'	0.46	'HadGEM2-ES'	0.45	'MIROC-ESM-CHEM'	0.43	'FIO-ESM'	0.16	'FGOALS_g2'	0.47	'IPSL-CM5B-LR'	0.59
'GFDL-ESM2M'	0.55	'MIROC-ESM-CHEM'	0.39	'BNU-ESM'	0.38	'GISS-E2-H-CC'	0.38	'CESM1-CAM5'	0.15	'HadGEM2-ES'	0.47	'IPSL-CM5A-LR'	0.57
'MIROC-ESM-CHEM'	0.52	'MIROC-ESM'	0.34	'GISS-E2-R'	0.36	'GISS-E2-R'	0.34	'CESM1-BGC'	0.14	'GFDL-CM3'	0.46	'IPSL-CM5A-MR'	0.57
'IPSL-CM5B-LR'	0.51	'IPSL-CM5A-MR'	0.31	'CESM1-BGC'	0.36	'CNRM-CM5'	0.32	'CNRM-CM5'	0.10	'IPSL-CM5B-LR'	0.42	'bcc-csm1-1-m'	0.50
'CNRM-CM5'	0.49	'CSIRO-Mk3-6-0'	0.27	'GISS-E2-H-CC'	0.35	'bcc-csm1-1'	0.32	'HadGEM2-ES'	0.09	'BNU-ESM'	0.40	'MRI-CGCM3'	0.46
'NorESM1-M'	0.47	'NorESM1-M'	0.26	'CCSM4'	0.33	'CMCC-CMS'	0.30	'MIROC5'	0.08	'MPI-ESM-LR'	0.38	'MPI-ESM-MR'	0.46
'IPSL-CM5A-MR'	0.45	'GISS-E2-H'	0.21	'GFDL-CM3'	0.32	'GFDL-CM3'	0.29	'IPSL-CM5B-LR'	0.07	'NorESM1-M'	0.37	'CMCC-CMS'	0.45
'CSIRO-Mk3-6-0'	0.44	'GFDL-CM3'	0.19	'CNRM-CM5'	0.30	'BNU-ESM'	0.17	'FGOALS_g2'	0.07	'MRI-CGCM3'	0.35	'CNRM-CM5'	0.44
'GFDL-ESM2G'	0.43	'CanESM2'	0.19	'CSIRO-Mk3-6-0'	0.29	'ACCESS1.3'	0.16	'HadGEM2-CC'	0.07	'NorESM1-ME'	0.35	'NorESM1-M'	0.42
'MRI-CGCM3'	0.41	'NorESM1-ME'	0.18	'MPI-ESM-LR'	0.28	'CESM1-BGC'	0.13	'GISS-E2-H'	0.07	'FIO-ESM'	0.34	'NorESM1-ME'	0.41
'FIO-ESM'	0.34	'GFDL-ESM2M'	0.16	'ACCESS1.3'	0.21	'CCSM4'	0.13	'bcc-csm1-1'	0.06	'MPI-ESM-MR'	0.32	'CESM1-BGC'	0.40

'HadGEM2-CC'	0.34	'CESM1-BGC'	0.14	'bcc-csm1-1-m'	0.20	'MIROC5'	0.11	'MRI-CGCM3'	0.06	'CESM1-BGC'	0.28	'CCSM4'	0.36
'GISS-E2-H'	0.32	'GFDL-ESM2G'	0.14	'CMCC-CMS'	0.18	'CanESM2'	0.10	'GFDL-ESM2M'	0.05	'MIROC-ESM-CHEM'	0.28	'ACCESS1.3'	0.33
'MPI-ESM-MR'	0.31	'GISS-E2-R'	0.11	'bcc-csm1-1'	0.17	'CSIRO-Mk3-6-0'	0.10	'GFDL-ESM2G'	0.05	'bcc-csm1-1'	0.25	'GFDL-ESM2G'	0.30
'MIROC-ESM'	0.29	'CCSM4'	0.08	'IPSL-CM5A-MR'	0.16	'CESM1-CAM5'	0.10	'CanESM2'	0.04	'IPSL-CM5A-MR'	0.25	'GFDL-CM3'	0.29
'FGOALS_g2'	0.26	'GISS-E2-H-CC'	0.08	'NorESM1-ME'	0.15	'GFDL-ESM2G'	0.08	'IPSL-CM5A-LR'	0.04	'ACCESS1-0'	0.25	'GFDL-ESM2M'	0.29
'CESM1-CAM5'	0.25	'HadGEM2-CC'	0.07	'NorESM1-M'	0.11	'GFDL-ESM2M'	0.06	'MPI-ESM-LR'	0.03	'IPSL-CM5A-LR'	0.24	'GISS-E2-R'	0.24
'GFDL-CM3'	0.24	'bcc-csm1-1'	0.06	'CanESM2'	0.11	'FGOALS_g2'	0.05	'NorESM1-ME'	0.03	'MIROC-ESM'	0.23	'GISS-E2-H-CC'	0.22
'BNU-ESM'	0.21	'IPSL-CM5B-LR'	0.05	'FGOALS_g2'	0.10	'IPSL-CM5A-MR'	0.05	'GFDL-CM3'	0.02	'CanESM2'	0.23	'GISS-E2-H'	0.18
'bcc-csm1-1'	0.20	'FGOALS_g2'	0.05	'FIO-ESM'	0.09	'IPSL-CM5A-LR'	0.05	'NorESM1-M'	0.02	'bcc-csm1-1-m'	0.23	'bcc-csm1-1'	0.18
'CCSM4'	0.20	'BNU-ESM'	0.04	'GFDL-ESM2G'	0.09	'FIO-ESM'	0.05	'MPI-ESM-MR'	0.02	'CESM1-CAM5'	0.22	'BNU-ESM'	0.16
'CMCC-CMS'	0.16	'HadGEM2-ES'	0.03	'GFDL-ESM2M'	0.07	'NorESM1-ME'	0.05	'IPSL-CM5A-MR'	0.01	'CCSM4'	0.20	'CESM1-CAM5'	0.12
'IPSL-CM5A-LR'	0.14	'GISS-E2-R-CC'	0.03	'MPI-ESM-MR'	0.06	'MPI-ESM-MR'	0.04	'MIROC-ESM-CHEM'	0.01	'CSIRO-Mk3-6-0'	0.20	'GISS-E2-R-CC'	0.11
'CanESM2'	0.13	'CESM1-CAM5'	0.03	'MRI-CGCM3'	0.04	'MRI-CGCM3'	0.03	'CSIRO-Mk3-6-0'	0.01	'GFDL-ESM2M'	0.16	'HadGEM2-CC'	0.11
'CESM1-BGC'	0.12	'FIO-ESM'	0.01	'IPSL-CM5A-LR'	0.03	'NorESM1-M'	0.02	'MIROC-ESM'	0.01	'GFDL-ESM2G'	0.16	'FGOALS_g2'	0.09
'bcc-csm1-1-m'	0.04	'ACCESS1.3'	0.00	'GISS-E2-H'	0.00	'GISS-E2-H'	0.01	'bcc-csm1-1-m'	0.01	'ACCESS1.3'	0.07	'FIO-ESM'	0.07
'ACCESS1-0'	0.01	'MIROC5'	0.00	'IPSL-CM5B-LR'	0.00	'IPSL-CM5B-LR'	0.00	'ACCESS1-0'	0.01	'MIROC5'	0.00	'HadGEM2-ES'	0.06

Basin Names: Sudd

Table 7

Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'NorESM1-ME'	1.00	'CNRM-CM5'	0.96	'BNU-ESM'	0.85	'HadGEM2-CC'	1.00	'GISS-E2-R-CC'	1.00	'GISS-E2-H-CC'	0.69	'CSIRO-Mk3-6-0'	0.86
'GISS-E2-R-CC'	0.99	'MPI-ESM-LR'	0.89	'CESM1-BGC'	0.48	'GFDL-CM3'	1.00	'GISS-E2-R'	0.99	'GISS-E2-H'	0.69	'MIROC-ESM-CHEM'	0.79
'IPSL-CM5A-MR'	0.99	'MPI-ESM-MR'	0.87	'ACCESS1-0'	0.48	'ACCESS1-0'	0.79	'GISS-E2-H-CC'	0.98	'GISS-E2-R'	0.69	'MIROC-ESM'	0.78
'GISS-E2-R'	0.99	'IPSL-CM5A-LR'	0.80	'GFDL-CM3'	0.47	'HadGEM2-ES'	0.66	'CCSM4'	0.59	'GISS-E2-R-CC'	0.68	'MPI-ESM-LR'	0.77
'GISS-E2-H'	0.98	'ACCESS1-0'	0.79	'NorESM1-ME'	0.45	'BNU-ESM'	0.66	'CESM1-BGC'	0.52	'FGOALS_g2'	0.57	'ACCESS1-0'	0.76
'GISS-E2-H-CC'	0.97	'MRI-CGCM3'	0.72	'GISS-E2-R-CC'	0.43	'MIROC-ESM-CHEM'	0.66	'CMCC-CMS'	0.37	'IPSL-CM5B-LR'	0.50	'CNRM-CM5'	0.61
'IPSL-CM5B-LR'	0.97	'bcc-csm1-1-m'	0.61	'CCSM4'	0.42	'MIROC-ESM'	0.57	'IPSL-CM5B-LR'	0.35	'CMCC-CMS'	0.48	'NorESM1-M'	0.53

'MIROC5'	0.89	'CMCC-CMS'	0.43	'GISS-E2-H-CC'	0.38	'bcc-csm1-1-m'	0.53	'CESM1-CAM5'	0.33	'FIO-ESM'	0.47	'IPSL-CM5A-LR'	0.51
'NorESM1-M'	0.51	'CSIRO-Mk3-6-0'	0.37	'NorESM1-M'	0.37	'GISS-E2-R'	0.39	'NorESM1-M'	0.24	'BNU-ESM'	0.46	'GFDL-ESM2G'	0.50
'HadGEM2-ES'	0.38	'GFDL-CM3'	0.35	'CESM1-CAM5'	0.35	'GISS-E2-H-CC'	0.36	'NorESM1-ME'	0.24	'MRI-CGCM3'	0.46	'MPI-ESM-MR'	0.50
'MRI-CGCM3'	0.34	'ACCESS1.3'	0.24	'GISS-E2-R'	0.34	'GFDL-ESM2G'	0.26	'GISS-E2-H'	0.23	'bcc-csm1-1-m'	0.44	'ACCESS1.3'	0.50
'CESM1-BGC'	0.30	'BNU-ESM'	0.24	'GFDL-ESM2G'	0.32	'GISS-E2-R-CC'	0.26	'CanESM2'	0.22	'MPI-ESM-LR'	0.43	'GFDL-CM3'	0.49
'CCSM4'	0.29	'GFDL-ESM2M'	0.24	'MIROC-ESM-CHEM'	0.29	'MPI-ESM-LR'	0.25	'BNU-ESM'	0.21	'bcc-csm1-1'	0.41	'MRI-CGCM3'	0.48
'HadGEM2-CC'	0.26	'IPSL-CM5A-MR'	0.22	'MIROC-ESM'	0.28	'CSIRO-Mk3-6-0'	0.22	'MRI-CGCM3'	0.17	'MPI-ESM-MR'	0.39	'GFDL-ESM2M'	0.47
'MPI-ESM-MR'	0.24	'bcc-csm1-1'	0.21	'HadGEM2-CC'	0.28	'CMCC-CMS'	0.19	'FIO-ESM'	0.12	'CNRM-CM5'	0.35	'MIROC5'	0.47
'GFDL-ESM2M'	0.23	'GFDL-ESM2G'	0.17	'bcc-csm1-1'	0.26	'MRI-CGCM3'	0.16	'HadGEM2-CC'	0.11	'GFDL-CM3'	0.30	'NorESM1-ME'	0.46
'GFDL-ESM2G'	0.23	'MIROC-ESM-CHEM'	0.14	'HadGEM2-ES'	0.26	'bcc-csm1-1'	0.16	'FGOALS_g2'	0.10	'ACCESS1-0'	0.30	'IPSL-CM5B-LR'	0.43
'CanESM2'	0.21	'GISS-E2-H'	0.13	'CSIRO-Mk3-6-0'	0.22	'IPSL-CM5A-LR'	0.15	'MIROC5'	0.10	'IPSL-CM5A-LR'	0.28	'CanESM2'	0.41
'CESM1-CAM5'	0.19	'MIROC-ESM'	0.12	'MIROC5'	0.22	'FIO-ESM'	0.11	'HadGEM2-ES'	0.10	'CESM1-CAM5'	0.27	'IPSL-CM5A-MR'	0.41
'MIROC-ESM-CHEM'	0.18	'IPSL-CM5B-LR'	0.09	'bcc-csm1-1-m'	0.22	'GFDL-ESM2M'	0.11	'MPI-ESM-MR'	0.10	'HadGEM2-ES'	0.25	'BNU-ESM'	0.37
'FGOALS_g2'	0.18	'MIROC5'	0.09	'GFDL-ESM2M'	0.21	'ACCESS1.3'	0.08	'GFDL-ESM2G'	0.08	'HadGEM2-CC'	0.24	'bcc-csm1-1-m'	0.36
'MPI-ESM-LR'	0.17	'CanESM2'	0.07	'CMCC-CMS'	0.17	'MIROC5'	0.08	'bcc-csm1-1-m'	0.05	'IPSL-CM5A-MR'	0.23	'CMCC-CMS'	0.34
'GFDL-CM3'	0.16	'HadGEM2-CC'	0.05	'FIO-ESM'	0.12	'IPSL-CM5A-MR'	0.08	'bcc-csm1-1'	0.05	'CESM1-BGC'	0.23	'bcc-csm1-1'	0.31
'FIO-ESM'	0.15	'FGOALS_g2'	0.05	'IPSL-CM5A-MR'	0.09	'MPI-ESM-MR'	0.07	'ACCESS1.3'	0.05	'CCSM4'	0.20	'CESM1-BGC'	0.25
'CSIRO-Mk3-6-0'	0.15	'HadGEM2-ES'	0.04	'IPSL-CM5A-LR'	0.08	'FGOALS_g2'	0.07	'MIROC-ESM'	0.05	'MIROC5'	0.19	'GISS-E2-H'	0.22
'MIROC-ESM'	0.14	'CESM1-BGC'	0.03	'FGOALS_g2'	0.08	'NorESM1-ME'	0.04	'GFDL-ESM2M'	0.05	'NorESM1-M'	0.15	'CCSM4'	0.18
'CMCC-CMS'	0.14	'GISS-E2-R'	0.03	'MPI-ESM-LR'	0.07	'CanESM2'	0.03	'GFDL-CM3'	0.05	'GFDL-ESM2G'	0.15	'FGOALS_g2'	0.12
'BNU-ESM'	0.14	'CESM1-CAM5'	0.02	'MPI-ESM-MR'	0.07	'CESM1-BGC'	0.03	'IPSL-CM5A-MR'	0.04	'GFDL-ESM2M'	0.15	'GISS-E2-R'	0.11
'bcc-csm1-1'	0.09	'CCSM4'	0.02	'CNRM-CM5'	0.07	'CCSM4'	0.02	'MIROC-ESM-CHEM'	0.03	'CSIRO-Mk3-6-0'	0.15	'GISS-E2-H-CC'	0.11
'IPSL-CM5A-LR'	0.07	'GISS-E2-H-CC'	0.02	'MRI-CGCM3'	0.05	'CESM1-CAM5'	0.01	'MPI-ESM-LR'	0.03	'NorESM1-ME'	0.14	'FIO-ESM'	0.10
'CNRM-CM5'	0.03	'FIO-ESM'	0.02	'ACCESS1.3'	0.05	'NorESM1-M'	0.01	'IPSL-CM5A-LR'	0.02	'MIROC-ESM-CHEM'	0.13	'GISS-E2-R-CC'	0.08
'bcc-csm1-1-m'	0.03	'NorESM1-M'	0.02	'CanESM2'	0.04	'CNRM-CM5'	0.01	'CNRM-CM5'	0.02	'MIROC-ESM'	0.12	'CESM1-CAM5'	0.07
'ACCESS1.3'	0.01	'GISS-E2-R-CC'	0.01	'GISS-E2-H'	0.00	'GISS-E2-H'	0.01	'ACCESS1-0'	0.01	'CanESM2'	0.09	'HadGEM2-CC'	0.07
'ACCESS1-0'	0.00	'NorESM1-ME'	0.01	'IPSL-CM5B-LR'	0.00	'IPSL-CM5B-LR'	0.00	'CSIRO-Mk3-6-0'	0.01	'ACCESS1.3'	0.09	'HadGEM2-ES'	0.06

Basin Names: Bahr El Ghazal

Table 8

Rank Criteria

Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'MIROC5'	1.00	'MPI-ESM-LR'	0.86	'bcc-csm1-1'	0.53	'GFDL-CM3'	0.84	'GISS-E2-R-CC'	0.74	'GISS-E2-H-CC'	0.59	'GFDL-ESM2G'	0.64
'NorESM1-ME'	1.00	'ACCESS1-0'	0.83	'MIROC-ESM-CHEM'	0.49	'GFDL-ESM2M'	0.72	'GISS-E2-H-CC'	0.70	'GISS-E2-R'	0.58	'MIROC-ESM-CHEM'	0.62
'IPSL-CM5B-LR'	0.95	'MPI-ESM-MR'	0.80	'MIROC-ESM'	0.48	'GFDL-ESM2G'	0.69	'GISS-E2-R'	0.68	'CMCC-CMS'	0.56	'MPI-ESM-LR'	0.61
'IPSL-CM5A-MR'	0.93	'GFDL-CM3'	0.74	'GFDL-CM3'	0.47	'bcc-csm1-1'	0.66	'MIROC5'	0.53	'GISS-E2-R-CC'	0.56	'MIROC-ESM'	0.60
'CESM1-CAM5'	0.93	'bcc-csm1-1'	0.68	'GISS-E2-R'	0.46	'MIROC-ESM-CHEM'	0.39	'IPSL-CM5B-LR'	0.46	'GISS-E2-H'	0.54	'GFDL-CM3'	0.59
'GISS-E2-R-CC'	0.73	'GISS-E2-H'	0.64	'FGOALS_g2'	0.45	'bcc-csm1-1-m'	0.38	'CESM1-CAM5'	0.31	'MRI-CGCM3'	0.53	'GFDL-ESM2M'	0.58
'GISS-E2-R'	0.68	'bcc-csm1-1-m'	0.62	'CESM1-BGC'	0.43	'GISS-E2-H-CC'	0.37	'CMCC-CMS'	0.26	'IPSL-CM5B-LR'	0.53	'bcc-csm1-1'	0.57
'GISS-E2-H-CC'	0.65	'BNU-ESM'	0.57	'GISS-E2-R-CC'	0.40	'FGOALS_g2'	0.37	'IPSL-CM5A-MR'	0.23	'bcc-csm1-1-m'	0.52	'CSIRO-Mk3-6-0'	0.55
'NorESM1-M'	0.65	'MRI-CGCM3'	0.40	'GISS-E2-H-CC'	0.40	'FIO-ESM'	0.36	'CCSM4'	0.22	'IPSL-CM5A-LR'	0.49	'ACCESS1-0'	0.48
'FIO-ESM'	0.61	'IPSL-CM5A-LR'	0.37	'CESM1-CAM5'	0.40	'GISS-E2-R-CC'	0.36	'HadGEM2-ES'	0.14	'bcc-csm1-1'	0.47	'BNU-ESM'	0.48
'HadGEM2-ES'	0.50	'CMCC-CMS'	0.32	'FIO-ESM'	0.38	'GISS-E2-R'	0.34	'HadGEM2-CC'	0.14	'IPSL-CM5A-MR'	0.46	'CanESM2'	0.47
'MRI-CGCM3'	0.50	'ACCESS1.3'	0.30	'GFDL-ESM2G'	0.37	'MIROC-ESM'	0.33	'CESM1-BGC'	0.11	'FGOALS_g2'	0.42	'CESM1-BGC'	0.45
'HadGEM2-CC'	0.47	'CanESM2'	0.30	'CCSM4'	0.36	'ACCESS1-0'	0.28	'bcc-csm1-1-m'	0.10	'ACCESS1-0'	0.41	'CCSM4'	0.41
'MPI-ESM-MR'	0.41	'NorESM1-ME'	0.22	'BNU-ESM'	0.35	'CESM1-BGC'	0.26	'MIROC-ESM'	0.09	'FIO-ESM'	0.39	'bcc-csm1-1-m'	0.41
'FGOALS_g2'	0.40	'NorESM1-M'	0.21	'GFDL-ESM2M'	0.34	'CSIRO-Mk3-6-0'	0.20	'CNRM-CM5'	0.09	'HadGEM2-CC'	0.37	'CESM1-CAM5'	0.37
'CCSM4'	0.33	'MIROC-ESM-CHEM'	0.20	'CSIRO-Mk3-6-0'	0.33	'CCSM4'	0.19	'MIROC-ESM-CHEM'	0.08	'BNU-ESM'	0.37	'ACCESS1.3'	0.35
'MIROC-ESM-CHEM'	0.28	'MIROC-ESM'	0.16	'ACCESS1-0'	0.23	'NorESM1-ME'	0.16	'MRI-CGCM3'	0.06	'MPI-ESM-LR'	0.37	'IPSL-CM5A-LR'	0.32
'IPSL-CM5A-LR'	0.27	'CESM1-BGC'	0.14	'bcc-csm1-1-m'	0.21	'MIROC5'	0.16	'FGOALS_g2'	0.06	'GFDL-CM3'	0.35	'NorESM1-ME'	0.30
'CNRM-CM5'	0.26	'GFDL-ESM2M'	0.12	'MPI-ESM-LR'	0.18	'CanESM2'	0.16	'FIO-ESM'	0.06	'HadGEM2-ES'	0.34	'GISS-E2-H'	0.30
'MIROC-ESM'	0.25	'IPSL-CM5A-MR'	0.09	'CanESM2'	0.17	'BNU-ESM'	0.15	'CanESM2'	0.06	'NorESM1-M'	0.31	'NorESM1-M'	0.30
'CESM1-BGC'	0.25	'CNRM-CM5'	0.09	'NorESM1-ME'	0.17	'NorESM1-M'	0.15	'GFDL-ESM2G'	0.06	'NorESM1-ME'	0.31	'CNRM-CM5'	0.29
'MPI-ESM-LR'	0.24	'GISS-E2-R'	0.08	'CNRM-CM5'	0.16	'CNRM-CM5'	0.14	'IPSL-CM5A-LR'	0.05	'CESM1-BGC'	0.29	'MRI-CGCM3'	0.28
'GFDL-ESM2M'	0.23	'CCSM4'	0.08	'HadGEM2-CC'	0.14	'GISS-E2-H'	0.14	'GISS-E2-H'	0.04	'MPI-ESM-MR'	0.29	'MPI-ESM-MR'	0.28
'CSIRO-Mk3-6-0'	0.21	'GISS-E2-H-CC'	0.06	'NorESM1-M'	0.14	'CMCC-CMS'	0.13	'ACCESS1.3'	0.04	'CCSM4'	0.24	'MIROC5'	0.26

'GFDL-ESM2G'	0.21	'HadGEM2-CC'	0.06	'HadGEM2-ES'	0.13	'CESM1-CAM5'	0.12	'CSIRO-Mk3-6-0'	0.04	'CNRM-CM5'	0.21	'GISS-E2-R'	0.26
'CMCC-CMS'	0.19	'HadGEM2-ES'	0.05	'MIROC5'	0.12	'MRI-CGCM3'	0.07	'MPI-ESM-LR'	0.04	'MIROC-ESM-CHEM'	0.21	'IPSL-CM5A-MR'	0.26
'ACCESS1.3'	0.19	'GFDL-ESM2G'	0.05	'GISS-E2-H'	0.08	'MPI-ESM-LR'	0.06	'NorESM1-M'	0.04	'CanESM2'	0.18	'GISS-E2-H-CC'	0.25
'GISS-E2-H'	0.13	'GISS-E2-R-CC'	0.04	'CMCC-CMS'	0.06	'HadGEM2-CC'	0.03	'NorESM1-ME'	0.03	'MIROC-ESM'	0.18	'IPSL-CM5B-LR'	0.24
'CanESM2'	0.08	'IPSL-CM5B-LR'	0.03	'MPI-ESM-MR'	0.04	'MPI-ESM-MR'	0.02	'GFDL-ESM2M'	0.03	'CESM1-CAM5'	0.17	'CMCC-CMS'	0.24
'BNU-ESM'	0.08	'CESM1-CAM5'	0.02	'ACCESS1.3'	0.04	'HadGEM2-ES'	0.02	'BNU-ESM'	0.02	'ACCESS1.3'	0.15	'GISS-E2-R-CC'	0.18
'bcc-csm1-1-m'	0.07	'CSIRO-Mk3-6-0'	0.01	'IPSL-CM5A-MR'	0.03	'ACCESS1.3'	0.01	'MPI-ESM-MR'	0.01	'GFDL-ESM2M'	0.11	'HadGEM2-CC'	0.17
'GFDL-CM3'	0.06	'FGOALS_g2'	0.00	'MRI-CGCM3'	0.03	'IPSL-CM5A-MR'	0.01	'bcc-csm1-1'	0.01	'GFDL-ESM2G'	0.08	'HadGEM2-ES'	0.17
'bcc-csm1-1'	0.04	'MIROC5'	0.00	'IPSL-CM5A-LR'	0.03	'IPSL-CM5A-LR'	0.00	'ACCESS1-0'	0.01	'MIROC5'	0.08	'FGOALS_g2'	0.15
'ACCESS1-0'	0.03	'FIO-ESM'	0.00	'IPSL-CM5B-LR'	0.00	'IPSL-CM5B-LR'	0.00	'GFDL-CM3'	0.01	'CSIRO-Mk3-6-0'	0.06	'FIO-ESM'	0.14

Basin Names: Lower White Nile

Table 9

Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'NorESM1-ME'	1.00	'GFDL-CM3'	0.84	'bcc-csm1-1'	0.55	'GFDL-ESM2G'	0.87	'GISS-E2-H-CC'	0.61	'MRI-CGCM3'	0.59	'GFDL-ESM2G'	0.63
'IPSL-CM5B-LR'	1.00	'MPI-ESM-LR'	0.80	'CESM1-BGC'	0.47	'GFDL-CM3'	0.79	'GISS-E2-R-CC'	0.59	'IPSL-CM5B-LR'	0.59	'MIROC-ESM-CHEM'	0.59
'GISS-E2-R-CC'	1.00	'MPI-ESM-MR'	0.72	'GFDL-CM3'	0.46	'GFDL-ESM2M'	0.77	'CMCC-CMS'	0.57	'CMCC-CMS'	0.58	'GFDL-ESM2M'	0.58
'GISS-E2-R'	0.98	'ACCESS1-0'	0.70	'CSIRO-Mk3-6-0'	0.44	'bcc-csm1-1'	0.57	'GISS-E2-R'	0.56	'GISS-E2-H-CC'	0.56	'GFDL-CM3'	0.58
'GISS-E2-H-CC'	0.96	'IPSL-CM5A-LR'	0.56	'CCSM4'	0.42	'ACCESS1-0'	0.57	'IPSL-CM5B-LR'	0.52	'GISS-E2-R'	0.54	'MPI-ESM-LR'	0.56
'IPSL-CM5A-MR'	0.88	'bcc-csm1-1'	0.47	'FIO-ESM'	0.42	'FIO-ESM'	0.55	'CESM1-CAM5'	0.44	'GISS-E2-R-CC'	0.54	'CSIRO-Mk3-6-0'	0.55
'bcc-csm1-1-m'	0.70	'GISS-E2-H'	0.46	'CESM1-CAM5'	0.39	'FGOALS_g2'	0.44	'MIROC5'	0.40	'bcc-csm1-1-m'	0.53	'CanESM2'	0.55
'NorESM1-M'	0.60	'BNU-ESM'	0.43	'MIROC-ESM-CHEM'	0.36	'CESM1-BGC'	0.34	'bcc-csm1-1-m'	0.26	'IPSL-CM5A-LR'	0.51	'MIROC-ESM'	0.55
'HadGEM2-ES'	0.52	'MIROC-ESM-CHEM'	0.39	'MIROC-ESM'	0.34	'GISS-E2-R'	0.32	'IPSL-CM5A-MR'	0.24	'MPI-ESM-LR'	0.51	'ACCESS1-0'	0.54
'MIROC5'	0.51	'GFDL-ESM2M'	0.32	'ACCESS1-0'	0.34	'CCSM4'	0.25	'NorESM1-M'	0.24	'GISS-E2-H'	0.49	'CESM1-BGC'	0.53
'CESM1-CAM5'	0.43	'MRI-CGCM3'	0.32	'BNU-ESM'	0.34	'CSIRO-Mk3-6-0'	0.23	'NorESM1-ME'	0.24	'IPSL-CM5A-MR'	0.48	'bcc-csm1-1'	0.52
'MRI-CGCM3'	0.42	'CESM1-BGC'	0.30	'FGOALS_g2'	0.33	'CanESM2'	0.19	'MRI-CGCM3'	0.23	'FGOALS_g2'	0.46	'CCSM4'	0.48
'HadGEM2-CC'	0.41	'ACCESS1.3'	0.30	'GFDL-ESM2G'	0.33	'GISS-E2-R-CC'	0.19	'MPI-ESM-MR'	0.16	'BNU-ESM'	0.44	'BNU-ESM'	0.43

'MPI-ESM-MR'	0.33	'MIROC-ESM'	0.29	'NorESM1-ME'	0.30	'CMCC-CMS'	0.19	'CCSM4'	0.16	'FIO-ESM'	0.43	'CESM1-CAM5'	0.39
'FIO-ESM'	0.32	'CNRM-CM5'	0.26	'GFDL-ESM2M'	0.28	'MRI-CGCM3'	0.18	'CanESM2'	0.15	'MPI-ESM-MR'	0.43	'ACCESS1.3'	0.38
'FGOALS_g2'	0.25	'CMCC-CMS'	0.24	'NorESM1-M'	0.27	'CESM1-CAM5'	0.18	'FIO-ESM'	0.12	'GFDL-CM3'	0.40	'IPSL-CM5A-LR'	0.37
'MPI-ESM-LR'	0.24	'bcc-csm1-1-m'	0.22	'GISS-E2-R'	0.25	'NorESM1-M'	0.16	'BNU-ESM'	0.10	'bcc-csm1-1'	0.37	'CNRM-CM5'	0.37
'CMCC-CMS'	0.23	'CSIRO-Mk3-6-0'	0.22	'CanESM2'	0.23	'NorESM1-ME'	0.16	'HadGEM2-CC'	0.10	'ACCESS1-0'	0.34	'NorESM1-M'	0.34
'IPSL-CM5A-LR'	0.23	'GFDL-ESM2G'	0.14	'GISS-E2-R-CC'	0.20	'BNU-ESM'	0.16	'GFDL-ESM2G'	0.09	'CESM1-BGC'	0.31	'MRI-CGCM3'	0.30
'BNU-ESM'	0.22	'CCSM4'	0.13	'CNRM-CM5'	0.19	'CNRM-CM5'	0.15	'HadGEM2-ES'	0.09	'CCSM4'	0.23	'GISS-E2-H'	0.29
'MIROC-ESM-CHEM'	0.22	'IPSL-CM5A-MR'	0.11	'MPI-ESM-LR'	0.17	'bcc-csm1-1-m'	0.12	'CESM1-BGC'	0.07	'CNRM-CM5'	0.22	'NorESM1-ME'	0.29
'CanESM2'	0.21	'CanESM2'	0.08	'HadGEM2-ES'	0.16	'MIROC-ESM-CHEM'	0.11	'FGOALS_g2'	0.06	'HadGEM2-ES'	0.22	'MPI-ESM-MR'	0.28
'CNRM-CM5'	0.21	'GISS-E2-H-CC'	0.05	'HadGEM2-CC'	0.15	'MIROC-ESM'	0.11	'IPSL-CM5A-LR'	0.06	'HadGEM2-CC'	0.21	'GISS-E2-R'	0.26
'CCSM4'	0.19	'GISS-E2-R'	0.05	'GISS-E2-H-CC'	0.15	'MPI-ESM-LR'	0.07	'MPI-ESM-LR'	0.05	'NorESM1-M'	0.19	'GISS-E2-H-CC'	0.25
'GISS-E2-H'	0.14	'HadGEM2-ES'	0.04	'CMCC-CMS'	0.10	'MIROC5'	0.06	'ACCESS1.3'	0.05	'CESM1-CAM5'	0.18	'IPSL-CM5A-MR'	0.25
'CSIRO-Mk3-6-0'	0.12	'HadGEM2-CC'	0.04	'bcc-csm1-1-m'	0.10	'HadGEM2-CC'	0.06	'GFDL-ESM2M'	0.04	'NorESM1-ME'	0.18	'MIROC5'	0.24
'MIROC-ESM'	0.11	'NorESM1-M'	0.03	'MIROC5'	0.10	'HadGEM2-ES'	0.05	'MIROC-ESM-CHEM'	0.04	'MIROC-ESM-CHEM'	0.18	'IPSL-CM5B-LR'	0.23
'GFDL-ESM2M'	0.09	'NorESM1-ME'	0.03	'MPI-ESM-MR'	0.09	'IPSL-CM5A-MR'	0.05	'MIROC-ESM'	0.04	'CSIRO-Mk3-6-0'	0.18	'bcc-csm1-1-m'	0.23
'GFDL-ESM2G'	0.07	'IPSL-CM5B-LR'	0.03	'ACCESS1.3'	0.08	'MPI-ESM-MR'	0.05	'CNRM-CM5'	0.04	'GFDL-ESM2M'	0.17	'CMCC-CMS'	0.21
'GFDL-CM3'	0.05	'GISS-E2-R-CC'	0.02	'IPSL-CM5A-MR'	0.07	'ACCESS1.3'	0.05	'GISS-E2-H'	0.04	'ACCESS1.3'	0.15	'HadGEM2-ES'	0.20
'bcc-csm1-1'	0.04	'MIROC5'	0.02	'MRI-CGCM3'	0.07	'GISS-E2-H-CC'	0.04	'CSIRO-Mk3-6-0'	0.03	'MIROC-ESM'	0.15	'GISS-E2-R-CC'	0.18
'CESM1-BGC'	0.03	'CESM1-CAM5'	0.02	'IPSL-CM5A-LR'	0.04	'GISS-E2-H'	0.01	'GFDL-CM3'	0.02	'GFDL-ESM2G'	0.12	'HadGEM2-CC'	0.17
'ACCESS1.3'	0.01	'FGOALS_g2'	0.00	'GISS-E2-H'	0.02	'IPSL-CM5A-LR'	0.00	'bcc-csm1-1'	0.02	'CanESM2'	0.09	'FGOALS_g2'	0.15
'ACCESS1-0'	0.00	'FIO-ESM'	0.00	'IPSL-CM5B-LR'	0.00	'IPSL-CM5B-LR'	0.00	'ACCESS1-0'	0.00	'MIROC5'	0.06	'FIO-ESM'	0.13

Basin Names: Blue Nile

Table 10

Rank Criteria

Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'MIROC5'	1.00	'ACCESS1-0'	0.61	'ACCESS1-0'	0.65	'ACCESS1-0'	0.85	'CNRM-CM5'	0.17	'GISS-E2-H-CC'	0.70	'MIROC-ESM-CHEM'	0.62

'NorESM1-ME'	1.00	'MPI-ESM-MR'	0.59	'MIROC-ESM-CHEM'	0.57	'GFDL-CM3'	0.47	'MIROC5'	0.16	'GISS-E2-R'	0.65	'MPI-ESM-LR'	0.61
'GISS-E2-R-CC'	0.98	'CESM1-BGC'	0.55	'bcc-csm1-1'	0.54	'HadGEM2-CC'	0.47	'FGOALS_g2'	0.09	'GISS-E2-R-CC'	0.65	'ACCESS1-0'	0.60
'IPSL-CM5B-LR'	0.84	'CCSM4'	0.53	'MIROC-ESM'	0.54	'GFDL-ESM2G'	0.42	'GISS-E2-H-CC'	0.08	'GISS-E2-H'	0.64	'MIROC-ESM'	0.59
'GISS-E2-R'	0.70	'MIROC-ESM-CHEM'	0.52	'CESM1-CAM5'	0.45	'GFDL-ESM2M'	0.33	'FIO-ESM'	0.08	'IPSL-CM5B-LR'	0.55	'CESM1-BGC'	0.53
'IPSL-CM5A-MR'	0.70	'MIROC-ESM'	0.51	'HadGEM2-ES'	0.39	'CMCC-CMS'	0.33	'GISS-E2-R-CC'	0.07	'IPSL-CM5A-MR'	0.53	'ACCESS1.3'	0.49
'GISS-E2-H-CC'	0.61	'MPI-ESM-LR'	0.50	'HadGEM2-CC'	0.38	'HadGEM2-ES'	0.33	'IPSL-CM5B-LR'	0.07	'IPSL-CM5A-LR'	0.52	'CCSM4'	0.48
'MRI-CGCM3'	0.57	'NorESM1-M'	0.47	'GISS-E2-R-CC'	0.38	'GISS-E2-R-CC'	0.27	'GFDL-ESM2M'	0.06	'MRI-CGCM3'	0.50	'CanESM2'	0.48
'CNRM-CM5'	0.56	'NorESM1-ME'	0.47	'GISS-E2-R'	0.36	'GISS-E2-R'	0.26	'IPSL-CM5A-MR'	0.05	'bcc-csm1-1-m'	0.45	'IPSL-CM5A-LR'	0.47
'NorESM1-M'	0.55	'BNU-ESM'	0.35	'FIO-ESM'	0.34	'CESM1-CAM5'	0.26	'GFDL-ESM2G'	0.05	'CMCC-CMS'	0.40	'CSIRO-Mk3-6-0'	0.45
'MPI-ESM-LR'	0.51	'ACCESS1.3'	0.31	'CESM1-BGC'	0.30	'BNU-ESM'	0.26	'GISS-E2-R'	0.04	'ACCESS1-0'	0.40	'GISS-E2-R'	0.44
'MPI-ESM-MR'	0.47	'GFDL-CM3'	0.30	'GFDL-CM3'	0.30	'CNRM-CM5'	0.25	'CESM1-CAM5'	0.04	'bcc-csm1-1'	0.40	'CESM1-CAM5'	0.43
'GISS-E2-H'	0.43	'GFDL-ESM2M'	0.26	'GISS-E2-H-CC'	0.26	'MIROC-ESM-CHEM'	0.24	'CanESM2'	0.04	'BNU-ESM'	0.38	'GISS-E2-H-CC'	0.42
'CESM1-CAM5'	0.41	'CMCC-CMS'	0.26	'BNU-ESM'	0.25	'MIROC-ESM'	0.24	'bcc-csm1-1'	0.03	'FIO-ESM'	0.38	'NorESM1-M'	0.38
'CanESM2'	0.39	'bcc-csm1-1-m'	0.23	'CCSM4'	0.25	'FIO-ESM'	0.23	'MRI-CGCM3'	0.03	'CESM1-BGC'	0.38	'NorESM1-ME'	0.37
'bcc-csm1-1-m'	0.34	'bcc-csm1-1'	0.21	'MPI-ESM-LR'	0.25	'bcc-csm1-1'	0.21	'HadGEM2-CC'	0.03	'GFDL-CM3'	0.37	'MPI-ESM-MR'	0.35
'GFDL-CM3'	0.28	'GFDL-ESM2G'	0.20	'FGOALS_g2'	0.25	'CSIRO-Mk3-6-0'	0.20	'GISS-E2-H'	0.03	'FGOALS_g2'	0.33	'MRI-CGCM3'	0.35
'HadGEM2-ES'	0.27	'CESM1-CAM5'	0.20	'ACCESS1.3'	0.23	'CESM1-BGC'	0.17	'IPSL-CM5A-LR'	0.02	'CCSM4'	0.32	'CNRM-CM5'	0.35
'GFDL-ESM2G'	0.26	'HadGEM2-CC'	0.17	'GFDL-ESM2G'	0.22	'CCSM4'	0.17	'CMCC-CMS'	0.02	'NorESM1-M'	0.32	'bcc-csm1-1-m'	0.34
'BNU-ESM'	0.24	'CSIRO-Mk3-6-0'	0.17	'GFDL-ESM2M'	0.21	'MIROC5'	0.16	'HadGEM2-ES'	0.02	'MPI-ESM-LR'	0.31	'IPSL-CM5A-MR'	0.32
'FIO-ESM'	0.24	'MRI-CGCM3'	0.16	'NorESM1-ME'	0.21	'GISS-E2-H-CC'	0.15	'ACCESS1.3'	0.02	'NorESM1-ME'	0.30	'IPSL-CM5B-LR'	0.32
'HadGEM2-CC'	0.22	'GISS-E2-H'	0.15	'NorESM1-M'	0.20	'ACCESS1.3'	0.15	'BNU-ESM'	0.02	'HadGEM2-CC'	0.28	'CMCC-CMS'	0.32
'GFDL-ESM2M'	0.22	'HadGEM2-ES'	0.15	'CNRM-CM5'	0.20	'bcc-csm1-1-m'	0.12	'bcc-csm1-1-m'	0.02	'HadGEM2-ES'	0.27	'MIROC5'	0.29
'CMCC-CMS'	0.21	'CanESM2'	0.14	'CSIRO-Mk3-6-0'	0.18	'MRI-CGCM3'	0.11	'CCSM4'	0.02	'MPI-ESM-MR'	0.26	'HadGEM2-ES'	0.29
'MIROC-ESM-CHEM'	0.21	'CNRM-CM5'	0.13	'bcc-csm1-1-m'	0.18	'MPI-ESM-LR'	0.10	'CSIRO-Mk3-6-0'	0.01	'CESM1-CAM5'	0.25	'GISS-E2-R-CC'	0.28
'bcc-csm1-1'	0.20	'GISS-E2-R'	0.09	'CMCC-CMS'	0.15	'FGOALS_g2'	0.09	'GFDL-CM3'	0.01	'MIROC-ESM-CHEM'	0.24	'bcc-csm1-1'	0.27
'IPSL-CM5A-LR'	0.19	'GISS-E2-R-CC'	0.05	'CanESM2'	0.13	'NorESM1-ME'	0.09	'CESM1-BGC'	0.01	'MIROC-ESM'	0.23	'HadGEM2-CC'	0.27
'CSIRO-Mk3-6-0'	0.18	'FGOALS_g2'	0.04	'MIROC5'	0.12	'NorESM1-M'	0.08	'MPI-ESM-MR'	0.01	'CSIRO-Mk3-6-0'	0.22	'GFDL-ESM2G'	0.26
'FGOALS_g2'	0.15	'IPSL-CM5A-LR'	0.03	'MRI-CGCM3'	0.10	'MPI-ESM-MR'	0.07	'NorESM1-M'	0.01	'GFDL-ESM2M'	0.16	'GISS-E2-H'	0.26

'MIROC-ESM'	0.10	'IPSL-CM5A-MR'	0.03	'MPI-ESM-MR'	0.08	'CanESM2'	0.06	'NorESM1-ME'	0.01	'CanESM2'	0.16	'BNU-ESM'	0.25
'CCSM4'	0.05	'FIO-ESM'	0.02	'GISS-E2-H'	0.02	'GISS-E2-H'	0.02	'MIROC-ESM'	0.00	'ACCESS1.3'	0.12	'GFDL-CM3'	0.23
'CESM1-BGC'	0.04	'GISS-E2-H-CC'	0.02	'IPSL-CM5A-MR'	0.01	'IPSL-CM5A-MR'	0.00	'MIROC-ESM-CHEM'	0.00	'GFDL-ESM2G'	0.12	'GFDL-ESM2M'	0.23
'ACCESS1.3'	0.03	'IPSL-CM5B-LR'	0.01	'IPSL-CM5A-LR'	0.01	'IPSL-CM5A-LR'	0.00	'ACCESS1-0'	0.00	'CNRM-CM5'	0.10	'FGOALS_g2'	0.11
'ACCESS1-0'	0.01	'MIROC5'	0.00	'IPSL-CM5B-LR'	0.00	'IPSL-CM5B-LR'	0.00	'MPI-ESM-LR'	0.00	'MIROC5'	0.00	'FIO-ESM'	0.10

Basin Names: Tekeze Atbara												**Table 11**	
Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'CNRM-CM5'	1.00	'NorESM1-M'	0.81	'CESM1-CAM5'	0.69	'ACCESS1-0'	0.86	'CNRM-CM5'	0.47	'GISS-E2-R'	0.71	'CESM1-BGC'	0.57
'MIROC5'	1.00	'NorESM1-ME'	0.79	'ACCESS1-0'	0.66	'GFDL-CM3'	0.68	'MIROC5'	0.35	'GISS-E2-R-CC'	0.71	'MPI-ESM-LR'	0.53
'NorESM1-ME'	1.00	'MPI-ESM-MR'	0.75	'GISS-E2-R-CC'	0.64	'GISS-E2-R-CC'	0.59	'GISS-E2-H-CC'	0.17	'GISS-E2-H-CC'	0.70	'MIROC-ESM-CHEM'	0.53
'GISS-E2-R-CC'	1.00	'CESM1-BGC'	0.47	'GISS-E2-R'	0.61	'GISS-E2-H-CC'	0.57	'GISS-E2-R-CC'	0.14	'GISS-E2-H'	0.69	'MIROC-ESM'	0.51
'GISS-E2-R'	1.00	'CMCC-CMS'	0.46	'GISS-E2-H-CC'	0.61	'MIROC5'	0.55	'IPSL-CM5B-LR'	0.14	'IPSL-CM5A-MR'	0.60	'CESM1-CAM5'	0.49
'GISS-E2-H-CC'	0.99	'MPI-ESM-LR'	0.44	'CESM1-BGC'	0.49	'HadGEM2-CC'	0.47	'IPSL-CM5A-MR'	0.13	'IPSL-CM5A-LR'	0.60	'ACCESS1-0'	0.48
'IPSL-CM5B-LR'	0.97	'ACCESS1.3'	0.44	'FGOALS_g2'	0.47	'GISS-E2-R'	0.44	'FIO-ESM'	0.11	'IPSL-CM5B-LR'	0.59	'CCSM4'	0.47
'IPSL-CM5A-MR'	0.94	'ACCESS1-0'	0.43	'CCSM4'	0.43	'GFDL-ESM2G'	0.38	'GISS-E2-R'	0.10	'MRI-CGCM3'	0.57	'GISS-E2-R'	0.47
'CSIRO-Mk3-6-0'	0.91	'MIROC-ESM-CHEM'	0.40	'bcc-csm1-1'	0.42	'GFDL-ESM2M'	0.37	'FGOALS_g2'	0.09	'bcc-csm1-1-m'	0.56	'GISS-E2-H-CC'	0.45
'bcc-csm1-1-m'	0.66	'MIROC-ESM'	0.39	'MIROC-ESM-CHEM'	0.41	'HadGEM2-ES'	0.28	'CESM1-CAM5'	0.07	'bcc-csm1-1'	0.49	'bcc-csm1-1'	0.43
'CESM1-CAM5'	0.66	'GFDL-CM3'	0.38	'MIROC-ESM'	0.38	'CMCC-CMS'	0.25	'IPSL-CM5A-LR'	0.06	'BNU-ESM'	0.43	'NorESM1-ME'	0.43
'FIO-ESM'	0.47	'GFDL-ESM2M'	0.35	'CNRM-CM5'	0.37	'NorESM1-M'	0.20	'bcc-csm1-1-m'	0.06	'FIO-ESM'	0.42	'ACCESS1.3'	0.41
'MRI-CGCM3'	0.45	'CCSM4'	0.32	'FIO-ESM'	0.35	'NorESM1-ME'	0.19	'HadGEM2-CC'	0.06	'CMCC-CMS'	0.42	'MPI-ESM-MR'	0.41
'NorESM1-M'	0.45	'bcc-csm1-1'	0.32	'HadGEM2-ES'	0.34	'ACCESS1.3'	0.18	'GISS-E2-H'	0.05	'GFDL-CM3'	0.39	'IPSL-CM5A-LR'	0.40
'GISS-E2-H'	0.30	'GFDL-ESM2G'	0.30	'HadGEM2-CC'	0.33	'bcc-csm1-1'	0.18	'CSIRO-Mk3-6-0'	0.04	'FGOALS_g2'	0.38	'NorESM1-M'	0.40
'HadGEM2-ES'	0.21	'HadGEM2-ES'	0.29	'GFDL-CM3'	0.32	'CanESM2'	0.13	'GFDL-ESM2M'	0.03	'NorESM1-M'	0.37	'MRI-CGCM3'	0.40
'MPI-ESM-MR'	0.21	'HadGEM2-CC'	0.28	'NorESM1-ME'	0.26	'CSIRO-Mk3-6-0'	0.11	'CanESM2'	0.03	'CESM1-BGC'	0.36	'bcc-csm1-1-m'	0.39
'BNU-ESM'	0.20	'BNU-ESM'	0.27	'NorESM1-M'	0.25	'CESM1-CAM5'	0.11	'HadGEM2-ES'	0.03	'NorESM1-ME'	0.33	'GISS-E2-H'	0.37

'HadGEM2-CC'	0.18	'CanESM2'	0.25	'bcc-csm1-1-m'	0.22	'bcc-csm1-1-m'	0.10	'GFDL-ESM2G'	0.03	'ACCESS1-0'	0.32	'HadGEM2-ES'	0.37
'IPSL-CM5A-LR'	0.18	'bcc-csm1-1-m'	0.23	'GISS-E2-H'	0.17	'MRI-CGCM3'	0.10	'MIROC-ESM-CHEM'	0.03	'CCSM4'	0.31	'CNRM-CM5'	0.36
'FGOALS_g2'	0.17	'MRI-CGCM3'	0.14	'GFDL-ESM2G'	0.17	'GISS-E2-H'	0.10	'MIROC-ESM'	0.03	'MPI-ESM-LR'	0.24	'CanESM2'	0.36
'CMCC-CMS'	0.12	'GISS-E2-R'	0.13	'MPI-ESM-LR'	0.16	'CNRM-CM5'	0.10	'CMCC-CMS'	0.02	'ACCESS1.3'	0.23	'HadGEM2-CC'	0.33
'MPI-ESM-LR'	0.12	'GISS-E2-H'	0.11	'ACCESS1.3'	0.15	'CESM1-BGC'	0.09	'bcc-csm1-1'	0.02	'HadGEM2-CC'	0.22	'GFDL-ESM2G'	0.32
'MIROC-ESM-CHEM'	0.11	'CSIRO-Mk3-6-0'	0.09	'GFDL-ESM2M'	0.15	'CCSM4'	0.08	'CCSM4'	0.02	'CSIRO-Mk3-6-0'	0.20	'GISS-E2-R-CC'	0.31
'GFDL-ESM2M'	0.09	'GISS-E2-R-CC'	0.08	'CanESM2'	0.15	'MPI-ESM-MR'	0.07	'MRI-CGCM3'	0.01	'HadGEM2-ES'	0.19	'CMCC-CMS'	0.31
'bcc-csm1-1'	0.09	'CESM1-CAM5'	0.07	'CMCC-CMS'	0.10	'MIROC-ESM'	0.06	'ACCESS1-0'	0.01	'MPI-ESM-MR'	0.16	'GFDL-CM3'	0.28
'GFDL-CM3'	0.06	'FGOALS_g2'	0.04	'MRI-CGCM3'	0.10	'MIROC-ESM-CHEM'	0.05	'ACCESS1.3'	0.01	'GFDL-ESM2M'	0.15	'GFDL-ESM2M'	0.28
'MIROC-ESM'	0.06	'GISS-E2-H-CC'	0.03	'MPI-ESM-MR'	0.08	'FIO-ESM'	0.04	'GFDL-CM3'	0.01	'MIROC-ESM-CHEM'	0.15	'FGOALS_g2'	0.23
'GFDL-ESM2G'	0.06	'FIO-ESM'	0.03	'MIROC5'	0.08	'BNU-ESM'	0.03	'CESM1-BGC'	0.01	'CanESM2'	0.14	'FIO-ESM'	0.21
'CanESM2'	0.05	'CNRM-CM5'	0.02	'CSIRO-Mk3-6-0'	0.06	'FGOALS_g2'	0.02	'MPI-ESM-LR'	0.01	'CESM1-CAM5'	0.13	'BNU-ESM'	0.21
'ACCESS1.3'	0.03	'IPSL-CM5A-LR'	0.01	'BNU-ESM'	0.06	'MPI-ESM-LR'	0.02	'BNU-ESM'	0.00	'MIROC-ESM'	0.13	'CSIRO-Mk3-6-0'	0.17
'CCSM4'	0.02	'IPSL-CM5B-LR'	0.01	'IPSL-CM5A-MR'	0.00	'IPSL-CM5A-MR'	0.01	'MPI-ESM-MR'	0.00	'GFDL-ESM2G'	0.10	'IPSL-CM5B-LR'	0.16
'CESM1-BGC'	0.01	'IPSL-CM5A-MR'	0.01	'IPSL-CM5B-LR'	0.00	'IPSL-CM5B-LR'	0.01	'NorESM1-M'	0.00	'CNRM-CM5'	0.03	'IPSL-CM5A-MR'	0.15
'ACCESS1-0'	0.00	'MIROC5'	0.00	'IPSL-CM5A-LR'	0.00	'IPSL-CM5A-LR'	0.00	'NorESM1-ME'	0.00	'MIROC5'	0.00	'MIROC5'	0.14

Basin Names: Main Nile

Table 12

Rank Criteria													
Independence		Skill		Seasonal variation		Annual variation		Close to consensus		Rainfall Extreme		Temperature Extreme	
GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCMs	Weight	GCM	Weight
'NorESM1-ME'	1.00	'bcc-csm1-1-m'	0.75	'GISS-E2-H-CC'	0.94	'GISS-E2-H-CC'	0.79	'IPSL-CM5A-MR'	0.50	'FGOALS_g2'	0.57	'ACCESS1-0'	0.46
'GISS-E2-R-CC'	1.00	'GFDL-CM3'	0.73	'GISS-E2-R'	0.88	'MIROC5'	0.78	'IPSL-CM5B-LR'	0.34	'MIROC-ESM-CHEM'	0.49	'FIO-ESM'	0.46
'MIROC-ESM-CHEM'	0.92	'MPI-ESM-MR'	0.72	'GISS-E2-R-CC'	0.74	'GISS-E2-R'	0.71	'FGOALS_g2'	0.26	'MIROC-ESM'	0.47	'FGOALS_g2'	0.44
'MIROC5'	0.87	'NorESM1-M'	0.72	'FGOALS_g2'	0.69	'GISS-E2-R-CC'	0.69	'CNRM-CM5'	0.25	'CESM1-BGC'	0.45	'CESM1-BGC'	0.43
'MIROC-ESM'	0.86	'bcc-csm1-1'	0.70	'MIROC-ESM'	0.49	'MIROC-ESM'	0.50	'GISS-E2-R'	0.22	'bcc-csm1-1'	0.44	'bcc-csm1-1'	0.43
'GISS-E2-R'	0.75	'ACCESS1-0'	0.58	'MIROC-ESM-CHEM'	0.47	'MIROC-ESM-CHEM'	0.48	'MIROC5'	0.19	'NorESM1-M'	0.42	'CCSM4'	0.42

'MPI-ESM-LR'	0.69	'NorESM1-ME'	0.58	'CESM1-CAM5'	0.41	'bcc-csm1-1'	0.47	'GISS-E2-H-CC'	0.17	'CNRM-CM5'	0.42	'GISS-E2-R'	0.40
'HadGEM2-ES'	0.66	'MRI-CGCM3'	0.53	'bcc-csm1-1'	0.38	'GFDL-CM3'	0.43	'GISS-E2-R-CC'	0.16	'NorESM1-ME'	0.40	'GFDL-ESM2G'	0.40
'GISS-E2-H-CC'	0.60	'GFDL-ESM2M'	0.52	'CESM1-BGC'	0.38	'bcc-csm1-1-m'	0.37	'MIROC-ESM-CHEM'	0.16	'GISS-E2-H'	0.40	'GFDL-ESM2M'	0.40
'IPSL-CM5B-LR'	0.58	'GISS-E2-H'	0.50	'GISS-E2-H'	0.34	'CESM1-BGC'	0.35	'HadGEM2-CC'	0.15	'FIO-ESM'	0.38	'GISS-E2-H-CC'	0.40
'FGOALS_g2'	0.57	'CMCC-CMS'	0.44	'CNRM-CM5'	0.31	'CanESM2'	0.30	'MIROC-ESM'	0.14	'GISS-E2-H-CC'	0.37	'bcc-csm1-1-m'	0.40
'NorESM1-M'	0.55	'BNU-ESM'	0.44	'CCSM4'	0.29	'CCSM4'	0.27	'HadGEM2-ES'	0.13	'GISS-E2-R-CC'	0.37	'GFDL-CM3'	0.39
'CNRM-CM5'	0.53	'CanESM2'	0.42	'bcc-csm1-1-m'	0.25	'ACCESS1-0'	0.23	'BNU-ESM'	0.12	'MIROC5'	0.36	'IPSL-CM5A-LR'	0.38
'IPSL-CM5A-MR'	0.50	'MPI-ESM-LR'	0.41	'ACCESS1-0'	0.24	'GISS-E2-H'	0.22	'CESM1-CAM5'	0.12	'GISS-E2-R'	0.36	'MPI-ESM-MR'	0.38
'IPSL-CM5A-LR'	0.47	'GFDL-ESM2G'	0.34	'GFDL-CM3'	0.23	'HadGEM2-CC'	0.19	'MPI-ESM-LR'	0.11	'CCSM4'	0.35	'ACCESS1.3'	0.37
'HadGEM2-CC'	0.41	'CESM1-BGC'	0.32	'CanESM2'	0.23	'ACCESS1.3'	0.15	'FIO-ESM'	0.07	'GFDL-CM3'	0.35	'CESM1-CAM5'	0.37
'MRI-CGCM3'	0.40	'CSIRO-Mk3-6-0'	0.27	'NorESM1-ME'	0.23	'GFDL-ESM2M'	0.14	'IPSL-CM5A-LR'	0.06	'bcc-csm1-1-m'	0.34	'HadGEM2-ES'	0.36
'MPI-ESM-MR'	0.26	'IPSL-CM5A-LR'	0.24	'HadGEM2-ES'	0.22	'NorESM1-ME'	0.14	'CCSM4'	0.06	'CanESM2'	0.34	'NorESM1-M'	0.36
'BNU-ESM'	0.24	'MIROC-ESM-CHEM'	0.17	'NorESM1-M'	0.22	'HadGEM2-ES'	0.14	'ACCESS1.3'	0.05	'BNU-ESM'	0.32	'MIROC-ESM-CHEM'	0.36
'FIO-ESM'	0.17	'FIO-ESM'	0.16	'FIO-ESM'	0.20	'NorESM1-M'	0.11	'CMCC-CMS'	0.05	'ACCESS1.3'	0.32	'CanESM2'	0.36
'CSIRO-Mk3-6-0'	0.17	'ACCESS1.3'	0.10	'MIROC5'	0.20	'GFDL-ESM2G'	0.10	'CSIRO-Mk3-6-0'	0.03	'GFDL-ESM2M'	0.31	'MIROC-ESM'	0.35
'GFDL-ESM2M'	0.15	'HadGEM2-ES'	0.10	'HadGEM2-CC'	0.19	'BNU-ESM'	0.10	'MPI-ESM-MR'	0.03	'CSIRO-Mk3-6-0'	0.28	'NorESM1-ME'	0.35
'GFDL-ESM2G'	0.15	'MIROC-ESM'	0.08	'CSIRO-Mk3-6-0'	0.18	'IPSL-CM5B-LR'	0.09	'MRI-CGCM3'	0.02	'MPI-ESM-MR'	0.28	'MPI-ESM-LR'	0.35
'CESM1-CAM5'	0.15	'CCSM4'	0.07	'ACCESS1.3'	0.11	'CSIRO-Mk3-6-0'	0.07	'bcc-csm1-1-m'	0.01	'ACCESS1-0'	0.28	'MRI-CGCM3'	0.34
'ACCESS1.3'	0.14	'GISS-E2-R-CC'	0.06	'GFDL-ESM2M'	0.09	'CESM1-CAM5'	0.07	'CESM1-BGC'	0.01	'HadGEM2-ES'	0.27	'GISS-E2-R-CC'	0.34
'CCSM4'	0.13	'HadGEM2-CC'	0.06	'GFDL-ESM2G'	0.08	'MPI-ESM-LR'	0.05	'GISS-E2-H'	0.01	'HadGEM2-CC'	0.27	'HadGEM2-CC'	0.34
'GISS-E2-H'	0.12	'GISS-E2-R'	0.03	'MRI-CGCM3'	0.08	'CNRM-CM5'	0.05	'ACCESS1-0'	0.01	'IPSL-CM5B-LR'	0.25	'CNRM-CM5'	0.31
'CESM1-BGC'	0.10	'GISS-E2-H-CC'	0.02	'BNU-ESM'	0.07	'MRI-CGCM3'	0.05	'GFDL-ESM2G'	0.01	'MRI-CGCM3'	0.24	'IPSL-CM5A-MR'	0.30
'CanESM2'	0.09	'FGOALS_g2'	0.01	'MPI-ESM-MR'	0.03	'FGOALS_g2'	0.04	'GFDL-CM3'	0.01	'MPI-ESM-LR'	0.23	'CSIRO-Mk3-6-0'	0.30
'GFDL-CM3'	0.08	'CNRM-CM5'	0.01	'MPI-ESM-LR'	0.03	'FIO-ESM'	0.02	'GFDL-ESM2M'	0.01	'CMCC-CMS'	0.23	'CMCC-CMS'	0.29
'CMCC-CMS'	0.06	'MIROC5'	0.00	'IPSL-CM5B-LR'	0.02	'MPI-ESM-MR'	0.01	'NorESM1-M'	0.00	'IPSL-CM5A-MR'	0.23	'GISS-E2-H'	0.29
'bcc-csm1-1'	0.04	'IPSL-CM5B-LR'	0.00	'CMCC-CMS'	0.01	'IPSL-CM5A-MR'	0.00	'CanESM2'	0.00	'GFDL-ESM2G'	0.22	'MIROC5'	0.29
'bcc-csm1-1-m'	0.02	'IPSL-CM5A-MR'	0.00	'IPSL-CM5A-MR'	0.01	'CMCC-CMS'	0.00	'NorESM1-ME'	0.00	'IPSL-CM5A-LR'	0.21	'IPSL-CM5B-LR'	0.29
'ACCESS1-0'	0.01	'CESM1-CAM5'	0.00	'IPSL-CM5A-LR'	0.00	'IPSL-CM5A-LR'	0.00	'bcc-csm1-1'	0.00	'CESM1-CAM5'	0.13	'BNU-ESM'	0.22

Table 13: Selected GCMs according to NBI using a 70% performance criterion. Shaded did not met the 70% threshold.

NBI Criterion	Water resources Planning			Flood/Wet Condition	Drought
Selection Criteria	Skill	Seasonal Variability	Annual Variability	Rainfall Extreme (wet 10th percentile)	Rainfall Extreme (dry 10th percentile)
Lake Victoria	CanESM2	ACCESS1-0 bcc-csm1-1-m	NorESM1-ME MIROC-ESM-CHEM	IPSL-CM5B-LR GISS-E2-H-CC GISS-E2-H GISS-E2-R GISS-E2-R-CC GFDL-ESM2G CNRM-CM5	CNRM-CM5 NorESM1-Me NorESM1-M bcc-csm1-1-m CMCC-CMS bcc-csm1-1 GISS-E2-H GISS-E2-R-CC GISS-E2-R CCSM4
Victoria Nile	CMCC-CMS bcc-csm1-1-m MRI-CGCM3 ACCESS1-0	CESM1-CAM5 MIROC5	GISS-E2-R-CC	GISS-E2-H-CC IPSL-CM5B-LR GISS-E2-H GISS-E2-R-CC GISS-E2-R CNRM-CM5	FGOALs_g2 CMCC-CMS HadGEM2-CC CESM1-BGC GISS-E2-R GFDL-CM3 GISS-E2-R-CC CNRM-CM5 GISS-E2-H GISS-E2-H-CC CCSM4 CanESM2 ACCESS1.3 HadGEM2-ES
Lake Albert	MPI-ESM-MR CMCC-CMS MPI-ESM-LR MRI-CGCM3	MIROC5 ACCESS1-0		IPSL-CM5B-LR GISS-E2-H-CC GISS-E2-H GISS-E2-R-CC GISS-E2-R CNRM-CM5 CMCC-CMS MPI-ESM-LR	FGOALs_g2 GISS-E2-R GISS-E2-H GISS-E2-R-CC GISS-E2-H-Cc MPI-ESM-LR CESM1-BGC CESM1-CAM5 CMCC-CMS CCSM4 MPI-ESM-MR IPSL-CM5A-LR MIROC-Esm FIO-ESM CSIRO-Mk3-6-0 MRI-CGCM3 MIROC-ESM-CHEM
Baro Akobo Sobat	MPI-ESM-MR MRI-CGCM3 bcc-csm1-1-m	ACCESS1-0	HadGEM2-CC HadGEM2-ES bcc-csm1-1-m	IPSL-CM5B-LR GISS-E2-H-CC GISS-E2-R-CC GISS-E2-R GISS-E2-H	GISS-E2-R GISS-E2-R-CC GISS-E2-H GISS-E2-H-CC NorESM1-ME NorEsm1-M HadGEM2-CC BNU-ESM FIO-ESM FGOALS_g2 CNRM-CM5

Sudd	CNRM-CM5 MPI-ESM-LR MPI-ESM-MR IPSL-CM5A-LR ACCESS1-0 MRI-CGCM3	'BNU-ESM'	HadGEM2-CC GFDL-CM3 ACCESS1-0	GISS-E2-R GISS-E2-H-CC GISS-E2-R-CC GISS-E2-H IPSL-CM5B-LR CMCC-CMS MRI-CGCM3 MPI-ESM-LR	bcc-csm1-1 FIO-ESM FGOALS_g2 BNU-ESM
Bahr El Ghazal	MPI-ESM-LR ACCESS1-0 MPI-ESM-MR GFDL-CM3	bcc-csm1-1	GFDL-CM3 GFDL-ESM2M	CMCC-CMS GISS-E2-H-CC GISS-E2-R GISS-E2-R-CC MRI-CGCM3 IPSL-CM5B-LR GISS-E2-H bcc-csm1-1-m IPSL-CM5A-LR IPSL-CM5A-MR	NorESM1-M
Lower White Nile	GFDL-CM3 MPI-ESM-LR MPI-ESM-MR	bcc-csm1-1	GFDL-ESM2G GFDL-CM3 GFDL-ESM2M	MRI-CGCm3 IPSL-CM5B-LR CMCC-CMS GISS-E2-H-CC bcc-csm-1-1m GISS-E2-R IPSL-CM5A-LR GISS-E2-R-CC MPI-ESM-ESM-LR IPSL-CM5A-MR GISS-E2-H	FGOALS_g2
Blue Nile	'ACCESS1-0'	ACCESS1-0	ACCESS1-0	IPSL-CM5B-LR GISS-E2-H-CC IPSL-CM5A-MR IPSL-CM5A-LR GISS-E2-H MRI-CGCM3 GISS-E2-R GISS-E2-R-CC	ACCESS1-0 GISS-E2-R-CC GISS-E2-R
Tekeze Atbara	NorESM1-M NorESM1-ME MPI-ESM-MR	CESM1-CAM5	ACCESS1-0	IPSl-CM5A-MR IPSL-CM5A-LR GISS-E2-H-CC IPSL-CM5B-LR GISS-E2-H GISS-E2-R GISS-E2-R-CC MRI-CGCM3 bcc-csm1-1-m bcc-csm-1-1 BNU-ESM	ACCESS1-0
Main Nile	bcc-CSM1-1-m GFDL-CM3 MPI-ESM-MR NorESM1-M	GISS0E2-H-CC GISS-E2-R GISS-E2-R-CC	GISS-E2-R-CC MIROC5 GISS-E2-R	FGOALS_g2 MIROC-ESM-CHEM MIROC-ESM	GISS-E2-H

BIAS CORRECTION AND DOWNSCALING APPROACHES

It is well known that GCMs have significant bias in their simulation of important climatic variables that are used to drive hydrologic models based on which important water resources management decision has to be made. Bias in GCMs are primarily a result of structural uncertainty that is tied to their inability to describe a known process accurately given the resolution of the model being simulated (usually >200Km). Our experience shows raw data output from some GCMs may not even reproduce well defined seasonal cycle adequately, would also under or over predict certain parameters at certain times. This is typically adjusted through bias correction methods. In doing so, bias correction tries to inject local variability into an otherwise much smoother outputs of the parent GCMs. Bias corrections are done for two specific times of a GCM run: retrospective (historical) run and future scenario run. In doing so, the implicit assumption is that a GCM will carry the same bias that it showed in the past into the future. Note that by definition, after bias correction, retrospective GCM outputs will have the same statistical characteristics as the observed historical data albeit different values in their time sequences. These two approaches are briefly explained below. Refer to appendix on Data Guide for description of the codes.

Bias correcting retrospective runs

Historical run by GCMs do not necessarily reproduce what is actually observed in a region. This bias is usually corrected and used to also bias correct future projections (see below). One of most commonly used bias correction technique attempts to match probability density function of retrospective run to what was observed in the field. In mathematical form it is represented by:

$$x_{m-p.adjst} = F^{-1}_{o-c}\left(F_{m-c}(x_{m-r})\right) \qquad \text{(Equation 1)}$$

Where $x_{m-p.adjst}$ is the adjusted retrospective run of a GCM output of x_{m-r}, F_{m-c} is GCM probability distribution for current (a.k.a. retrospective runs) time, and F^{-1}_{o-c} is inverse CDF of the observation data. Simply put, the procedure calculates the cumulative probability value for a given retrospective run and swap that value with the one observed at that percentile (noting this differences for use in adjusting future projections, see below).

It is important to note that historical bias correction does not try to just modify the values of retrospective run individually but tries to match their Cumulative Distribution Functions (CDFs). Hence, it is usually termed as CDF matching or quantile mapping technique (Wood et al., 2002). As a result, the time sequence of adjusted values for retrospective runs may be different from the actually historical time sequence while matching its statistical characteristics. Our experience shows that there are important practical implications to note depending on the type of hydrologic application and time interval of the hydrologic model that will be using this information.

Bias correcting future RCM and GCM runs

The basic premise of bias correction of future projection is that a GCM or an RCM will have the same bias in the future as it did in retrospective runs, hence, the idea of bias correcting historical runs and noting those differences to guide future projection adjustments. One of the most commonly used is the so-called equidistant approach (Li et al., 2010, Asefa and Adams, 2013). Mathematically, this is represented as:

$$X_{m-p.adjst} = X_{m-p} + F^{-1}_{o-c}\left(F_{m-p}(X_{m-p})\right) - F^{-1}_{m-c}\left(F_{m-p}(X_{m-p})\right) \qquad \text{(Equation 2)}$$

Graphically, this is represented by Figure 16

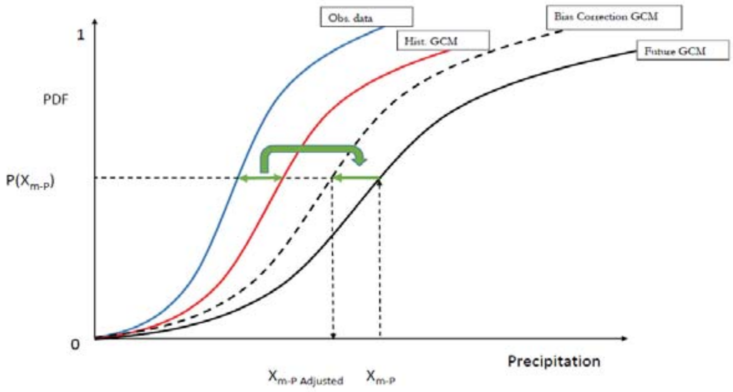


Figure 17. Schematic presentation of equidistant approach for bias correction. The method first calculates a GCM's or an RCM's over or under estimation for retrospective run at a given percentile and apply that "bias" at the same percentile in the future projected values.

The equidistant approach relies on the assumption that GCM modeling errors are similar at given percentile (probability level) than the actual value. While this may be a good assumption in certain cases, at other times, it may be a better idea to assume that GCM modeling errors are rather tied to the actual amount (having difficulty in simulating small or larger quantities of say precipitation) than the probability describing the distribution in and itself (Obeysekera et al., 2017). The method notes GCMs skill (difficulty or ease of simulation a parameter) at certain level of the parameter in question and carries this "error" forward to adjust future projections.

Mathematically, this is represented as

$$X_{m-p.adjst} = X_{m-p} + F_{o-c}^{-1}(X_{m-p} - F_{m-c}^{-1}\left(X_{m-p}\right)) \qquad \text{(Equation 5)}$$

Figure 18 depicts this approach in a schematic representation. The main difference between this technique and the equidistant approach is that GCMs are assumed to have the same bias at a given amount of the climatic variable value explicitly than at a given percentile of the distribution. Whether this approach provide additional value to NBI could be investigated in the future.

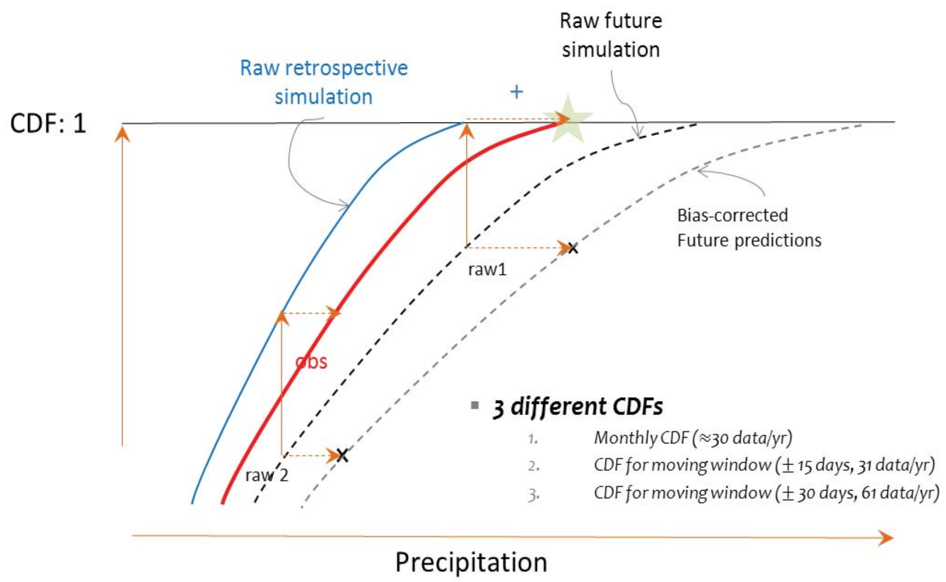


Figure 18. Bias correction approach that applies adjustment at a given simulated parameter level than percentile basis as is the case in equidistant method (method developed by the consultant's group).

In both approaches the corrections can be done at both daily and monthly time scales whether the analysis is done in daily time scale or monthly scale depending on the objective of the research. When one is interested in capturing the monthly time scales variabilities and would like to keep the historical daily frequency, monthly time scale bias corrections are performed and subsequent disaggregation to daily time scale is obtained using historical "observed" or reanalysis data. In this project both daily and monthly bias corrections were performed, respectively, for RCMs and GCMs.

Bias correcting CORDEX data

Regional Climate Models (RCMs) that typically simulate the land-ocean-atmosphere processes at much smaller scale than GCMs. Even though this spatial resolution (0.44 degrees or ~48km at the equator) is close to what water resources decision makers are interested in, results are still biased compared to historical data. This bias is primarily because of the influence of their boundary conditions data, which is derived from parent GCMs as well as still unresolved processed at those scales. In this project CORDEX data was bias corrected using the quantile mapping technique. The process followed the following steps:

1) Global forcing data was selected with Nile Basin footprint (see Data Sources section of the report)
2) Global forcing data was aggregated up to match the CORDEX 0.44-degree grid cell size
3) An experimental Probability Distribution Function (PDF) was fit to global forcing data for each month maintaining seasonality and capturing the difference in PDF in each month. This was done for 3526 covering NBI.
4) Once bias corrections were performed for retrospective data, error in PDF mismatch were calculated and stored to bias correct future projections.

5) Historical period of 1971 to 2000 was used as base line that was used to bias correct three future scenarios: near term (2006 to 2035), mid century (2036 to 2065), and late century (2066 to 2095).
6) These was done for both precipitation and temperature correction

Figure 17 shows an example of bias corrected cell (#2294 with lat 8.36 degrees North and lon 39.16 degrees in basin cell #47) for mid-century (2036 to 2065) climate projections for SMHI_RCA4CCCma_CanESM2. At very small rainfall the quantile mapping may become less accurate because the probability distribution (experimental PDF) include both rainy and none rainy days. Some researchers have looked the idea of segregating the data and fitting a parametric model to the data to only the rain amount and conduct the correction to also rain amount in future simulation. But this approach fails to recognize retrospective RCM or GCM daily rain bias of rainy/none rainy days. This is especially important because of the "drizzle effect" of GCMs where they tend to simulate small amount of rain in an otherwise dry season. Another approach that avoids this approach is conducting the bias correction at monthly times scale where typically data is well behaved and devoid of this issue and disaggregating the data into daily time series. This later approach, while avoiding this specific issue, it also runs into another issue in that the daily sequence of rainfall that come from the GCMs end up hidden and historical daily sequences are used. Depending on the type of end use of the data, one or more of these techniques may be used. Investigating different approaches in handing this challenge could be pursued by NBI in the future.

Figure 20 and 21 show the same bias correction made but for minimum and maximum temperature for SMHI_RCA4CCCma_CanESM2. Similar technique was applied for all the CORDEX data (see COREDEXcells data for each cell and location)

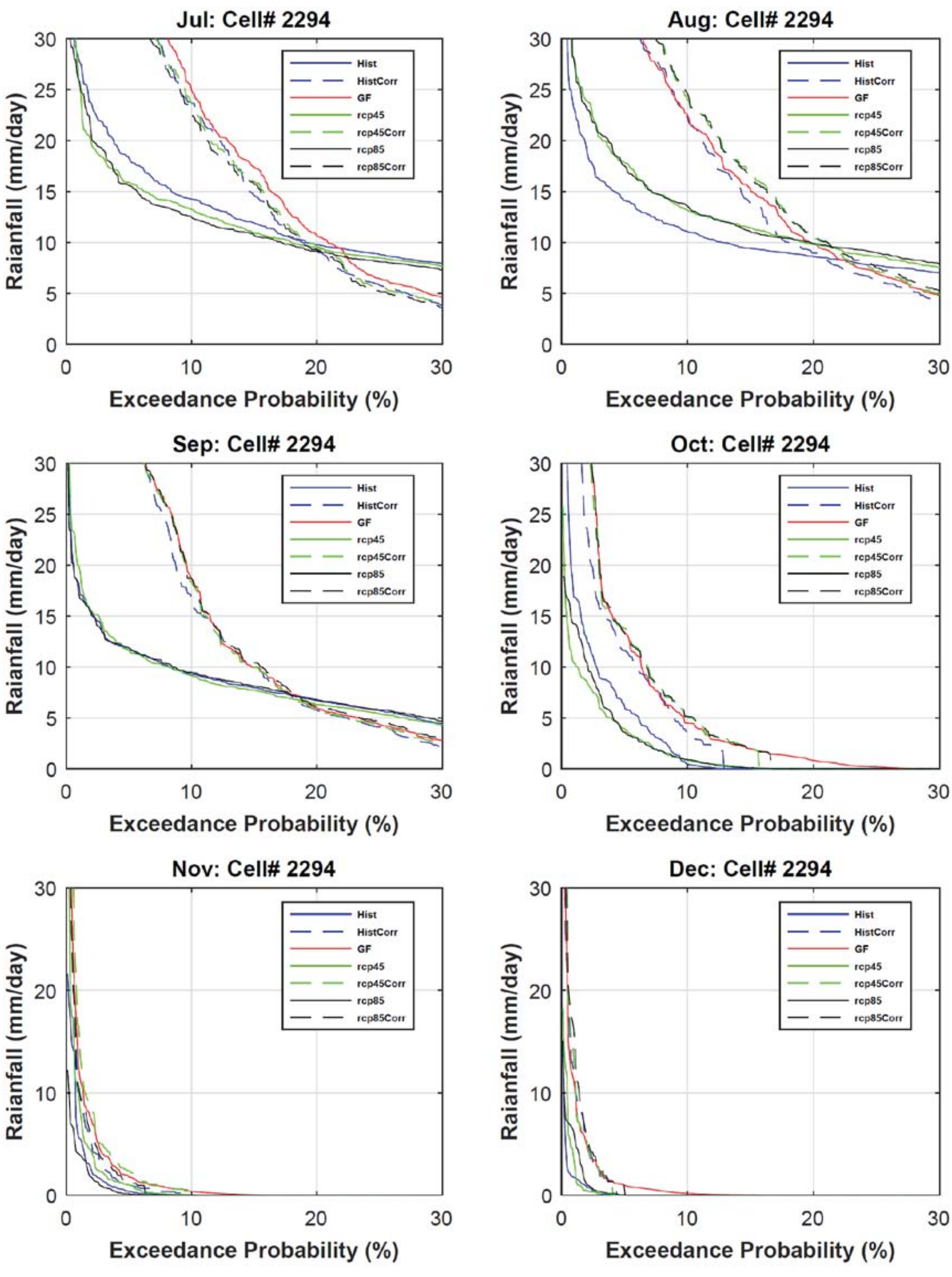


Figure 19. Bias corrected rainfall CORDEX data for cell 2294 (lat 8.36, long 39.16, in #47 cell Basin). Solid lines indicate "observation" (GF) or raw RCM projections while broken line indicate bias corrected data. Blue line represents RCP45 RCM output and green represent RCP85. (plotSMHI.m)

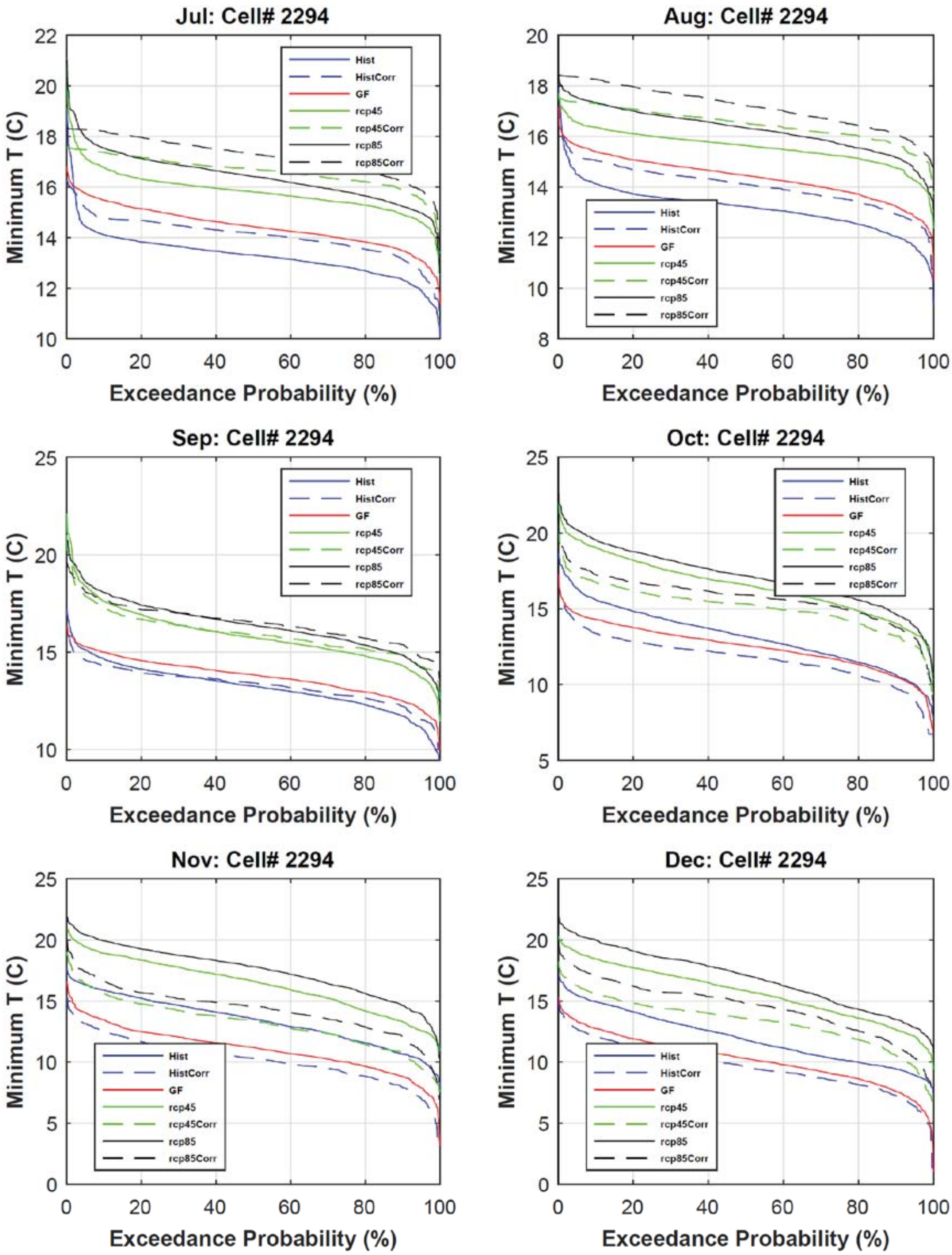


Figure 20. Bias corrected minimum temperature CORDEX data for cell 2294 (at 8.36, long 39.16, in #47 cell Basin). Solid lines indicate "observation" (GF) or raw RCM projections while broken line indicate bias corrected data. Blue line represents RCP45 RCM output and green represent RCP85. (plotSMHI.m)

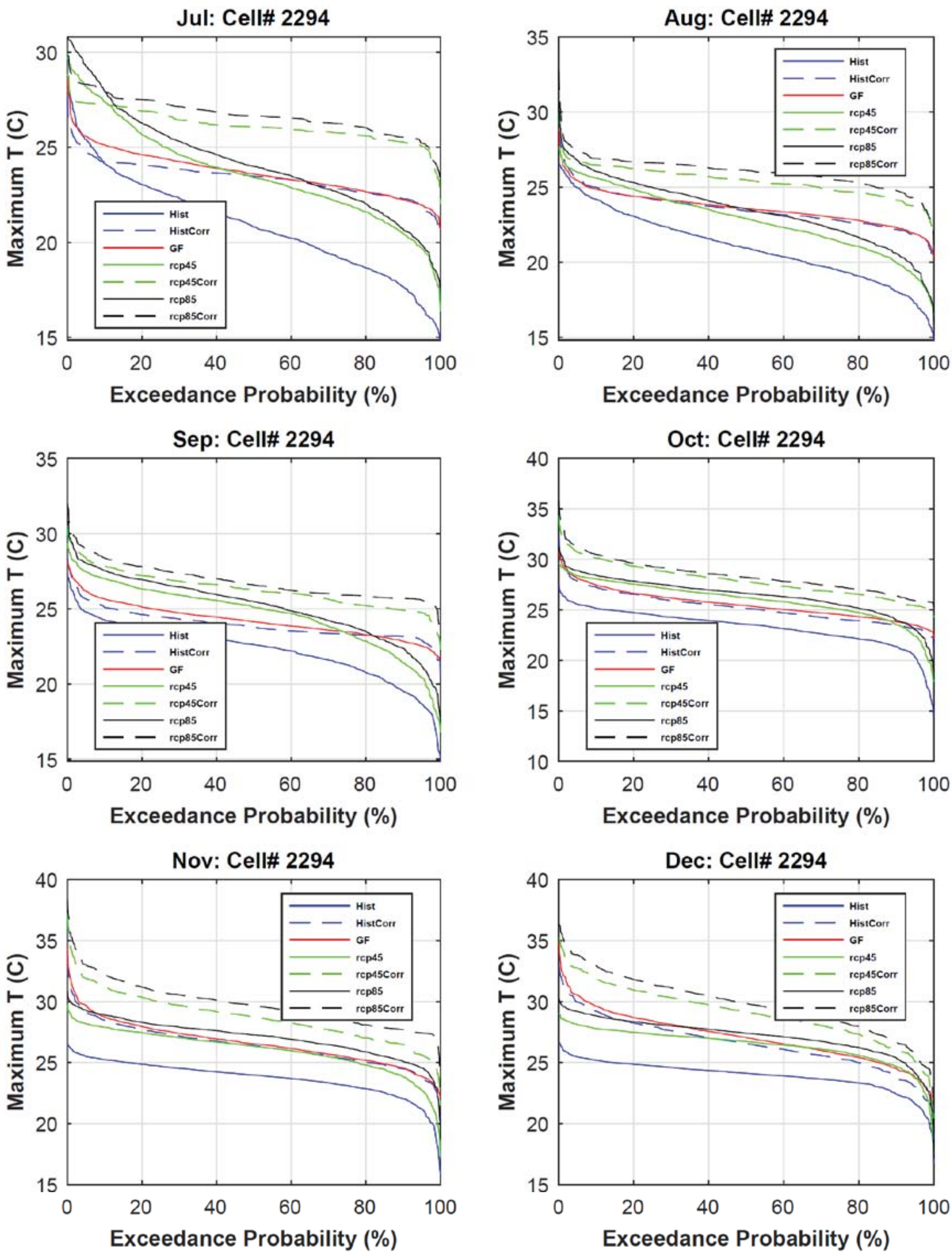


Figure 21. Bias corrected maximum temperature CORDEX data for cell 2294 (at 8.36, long 39.16, in #47 cell Basin). Solid lines indicate "observation" (GF) or raw RCM projections while broken line indicate bias corrected data. Blue line represents RCP45 RCM output and green represent RCP85. (plotSNHI)

Bias correcting General Circulation Models (GCMs) output

Similar to CORDEX data, GCMs data were also bias corrected using quartile mapping for each of the 67 NBI 2-degree cells covering the entire watershed (see Figure 2). The High Resolution Gridded data set from Climate Research Unit (CRU) (Harris et al., 2014) was used for this purpose. The bias correction was made at monthly scale in order to capture the seasonality of data and differences in the probability density functions. Figure 22 through Figure 24 shows precipitation data for near term (2006 to 2035), mid century (2036 to 2065) and end of the century (2066 to 2095). Figures 25 through Figures 27 shows similar data but for temperature. These bias corrections were done for all the GCMs and all grid cells that are shown in Table 3 through Table 12. See supplemental data and plots.

Downscaling General Circulation Models (GCMs) output

Raw GCM data came at 2-degree spatial resolution that need to be disaggregated at small grid size. Statistical downscaling methods rely on developing a transfer function between GCM outputs and hydrological model inputs observed at local scale. The transfer function could be as simple as an interpolation from a center of GCM cell to the local scale data to sophisticated regression that relate one or more GCM output to local scale input parameters. In the case of transfer function that are based on predictand/predictor relationship one tries to follow the physics-based relationship that is known. This is common in weather generator type of downscaling.

A typical functional (regression or otherwise) relation based statistical downscaling model first establishes model-observation relationship based on re-analysis GCM data and local observation, then predict future parameter of interest based on projected values that came from future GCM scenarios. The implicit assumption in such an approach is that model output-historical data relationship (regression or otherwise) will be the same in a changing climate. There are several approaches of downscaling that are used in practice: Statistically Downscaled and Bias Correction (SDBC) and Bias Corrected Statistically Downscaled (BCSD) techniques both of which use an Inverse Distance Weighting interpolation (IDW) scheme to map variables spatially after or before the bias correction steps. These two methods tend to give "drizzling" effect even in cells that have otherwise zero rains because of the inverse distance weighting interpolation approach and have not been used in this project. The Bias Corrected Stochastic Analog (BCSA) method is an improvement over BCSD and BCSD in that it maintains a stochastically generated spatial field and then scale total precipitation amounts at larger grid cells (Hwang and Graham, 2013, and Chang et al., 2018). BCSA tries to keep observed spatial correlation in the data to be downscaled using a kriging type algorithm. While BCSA is one of the most sophisticated downscaling technique, the computational requirement to execute this approach at the Nile Basin level was a limiting factor for use in this project.

Other popular downscaling approaches relay on using historical analogs with different flavors on how the "selection" of spatial relations are being made[2], all of whom are a variation of the K-

[2] For example, LOCA-Localized constructed analog, http://loca.ucsd.edu/. MACA- Multi-variate Adaptive Constructed Analog, https://climate.databasin.org/articles/d8260be3eb4246b1a76bc5a8f54727d0

Nearest Neighbor selection approach that was originally developed by Lall and Colleague (Lall and Sharma 1996, Asefa et al., 2014) for a variation of this approach developed for streamflow application of the method).

In this project a localized analog selection method was used to disaggregate the 2-degree GCM cells into 0.44-degree CORDEX grid size such that results of the downscaled GCMs will be consistent with CORDEX data. To do so, the Global forcing data was used to determined historical analog that was used for the disaggregation. The procedure followed a two steps process shown below.

1) For each monthly GCM future projections, find Global Forcing (GF) data that are within the GCM grid cell for that month and calculate the areal average value for those cells.
2) Repeat step one for all the months in the reference period (1971 to 2000)
3) Select the closes (Euclidean distance) monthly aggregate GF data to the projected monthly GCM data
4) Scale all 0.44-degree cell data proportional to their historical observation but matching the projected GCM data at 2-degree cell.

This approach maintains historical observed spatial correlation for a given month while rescaling back to the bias corrected GCM monthly output such that month to month correlations are maintained. MasterBiasCorrectCMIP5.m plots Figures 22 through Figures 27.

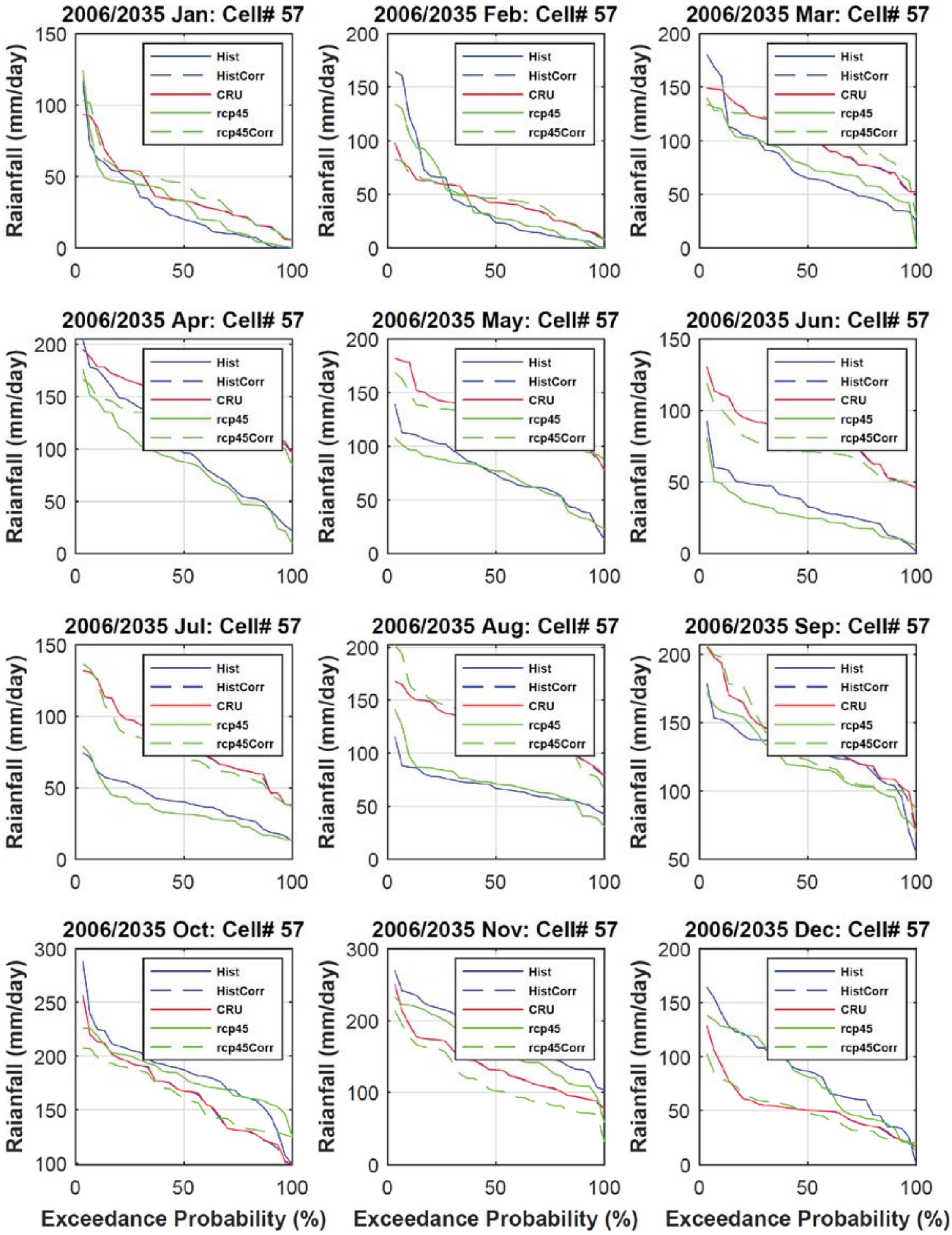


Figure 22. Bias corrected precipitation for CMCC-CMS GCM data Cell 57, Victoria Nile sub basin (see Figure 2). Solid lines indicate "observation" (CRU) or raw GCM projections while broken line indicate bias corrected data. Green represent RCP45 future projections for 2006 to 2035.

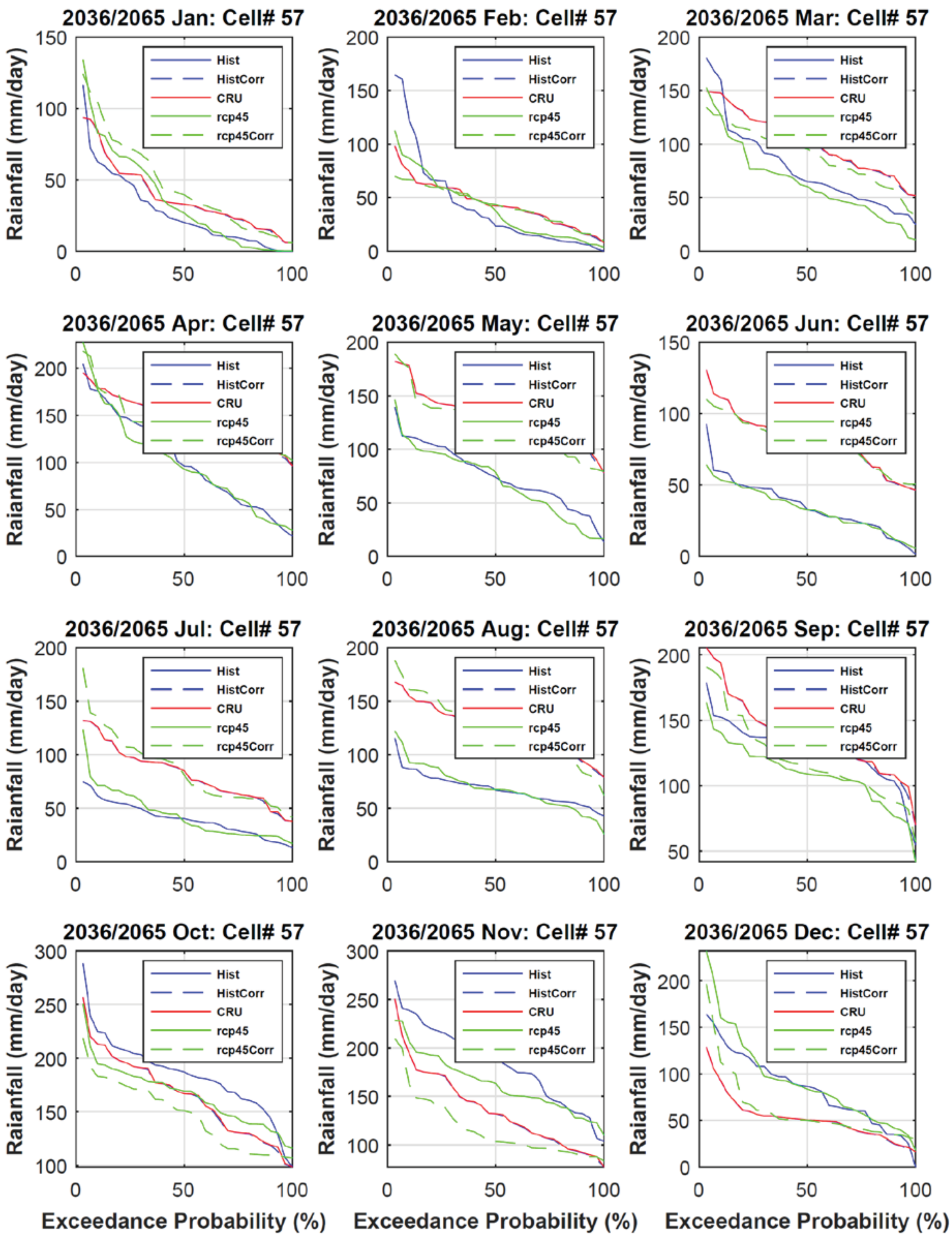


Figure 23. Bias corrected precipitation for CMCC-CMS GCM data Cell 57, Victoria Nile sub basin (see Figure 2). Solid lines indicate "observation" (CRU) or raw GCM projections while broken line indicate bias corrected data. Green represent RCP45 future projections for 2036 to 2065.

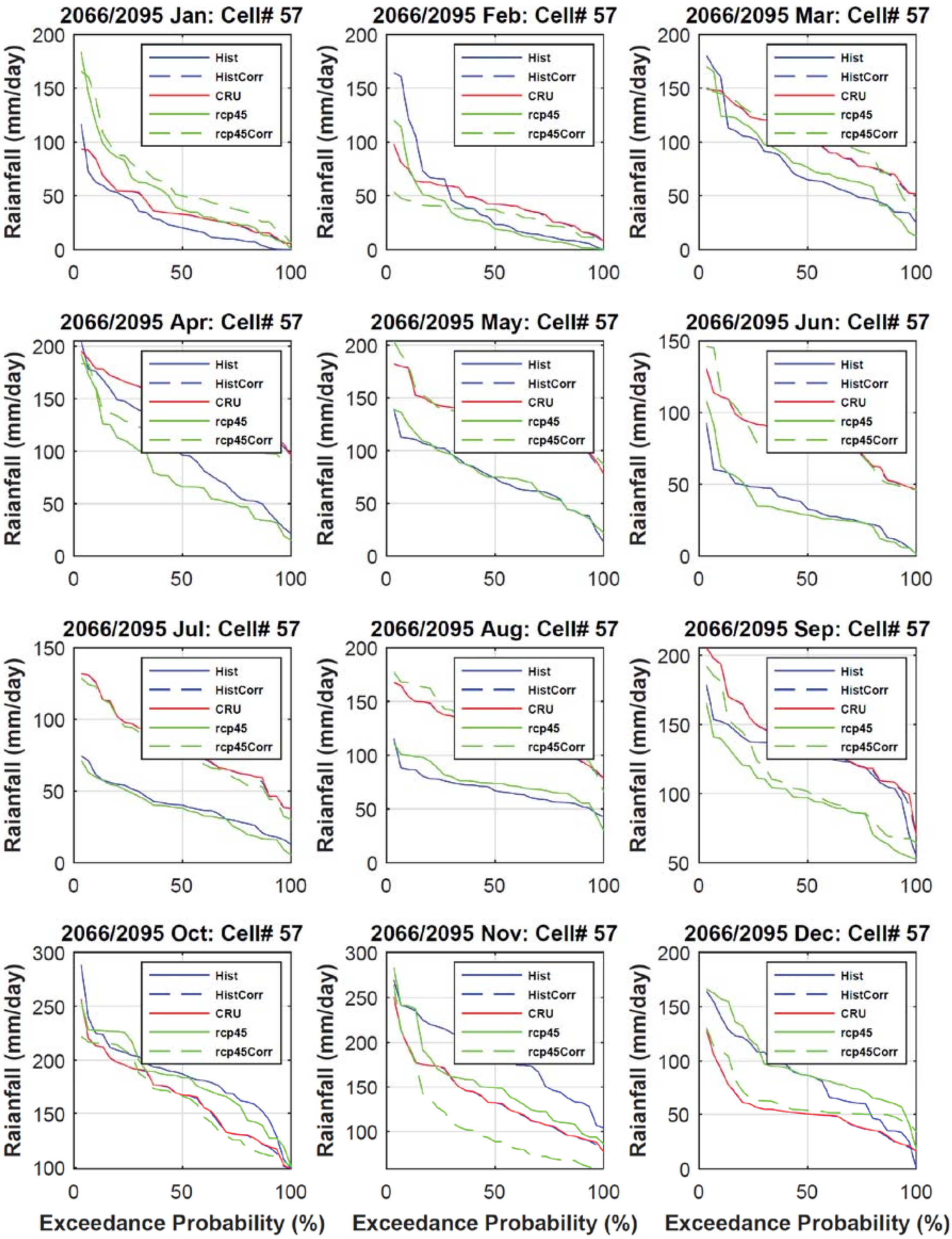


Figure 24. Bias corrected precipitation for CMCC-CMS GCM data Cell 57, Victoria Nile sub basin (see Figure 2). Solid lines indicate "observation" (CRU) or raw GCM projections while broken line indicate bias corrected data. Green represent RCP45 future projections for 2066 to 2095.

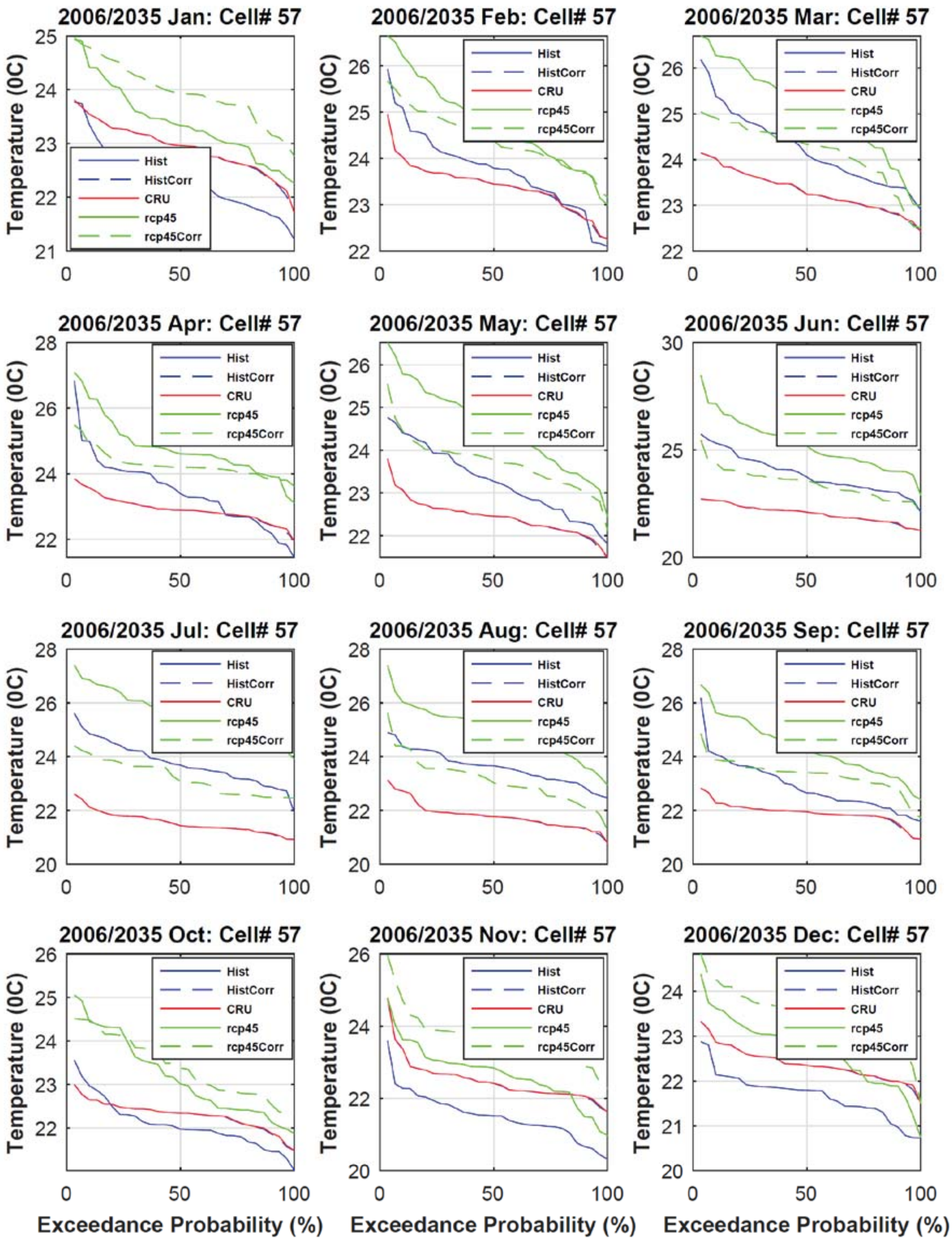


Figure 25. Bias corrected temperature for CMCC-CMS GCM data Cell 57, Victoria Nile sub basin (see Figure 2). Solid lines indicate "observation" (CRU) or raw GCM projections while broken line indicate bias corrected data. Green represent RCP45 future projections for 2006 to 2035.

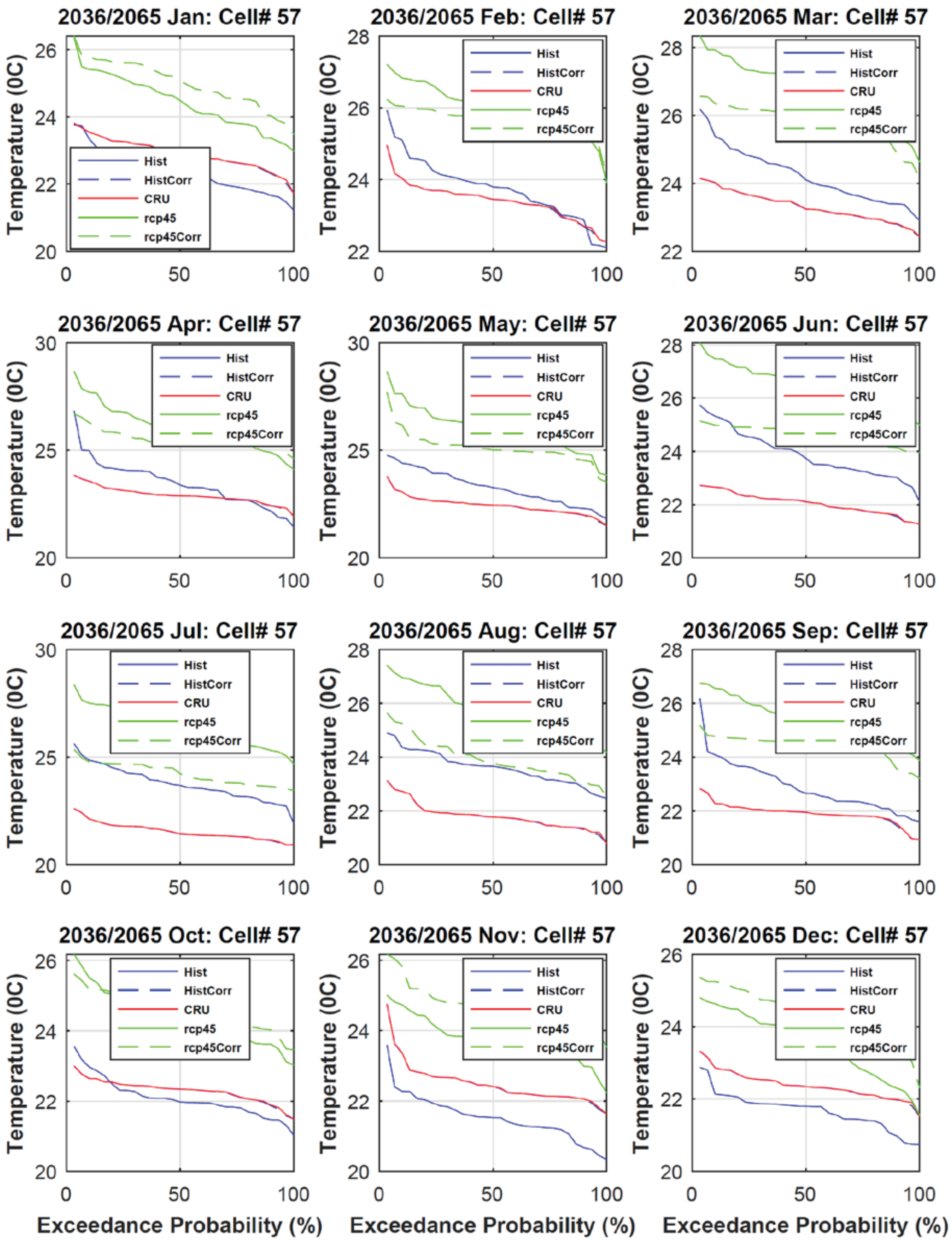


Figure 26. Bias corrected temperature for CMCC-CMS GCM data Cell 57, Victoria Nile sub basin (see Figure 2). Solid lines indicate "observation" (CRU) or raw GCM projections while broken line indicate bias corrected data. Green represent RCP45 future projections for 2036 to 2065.

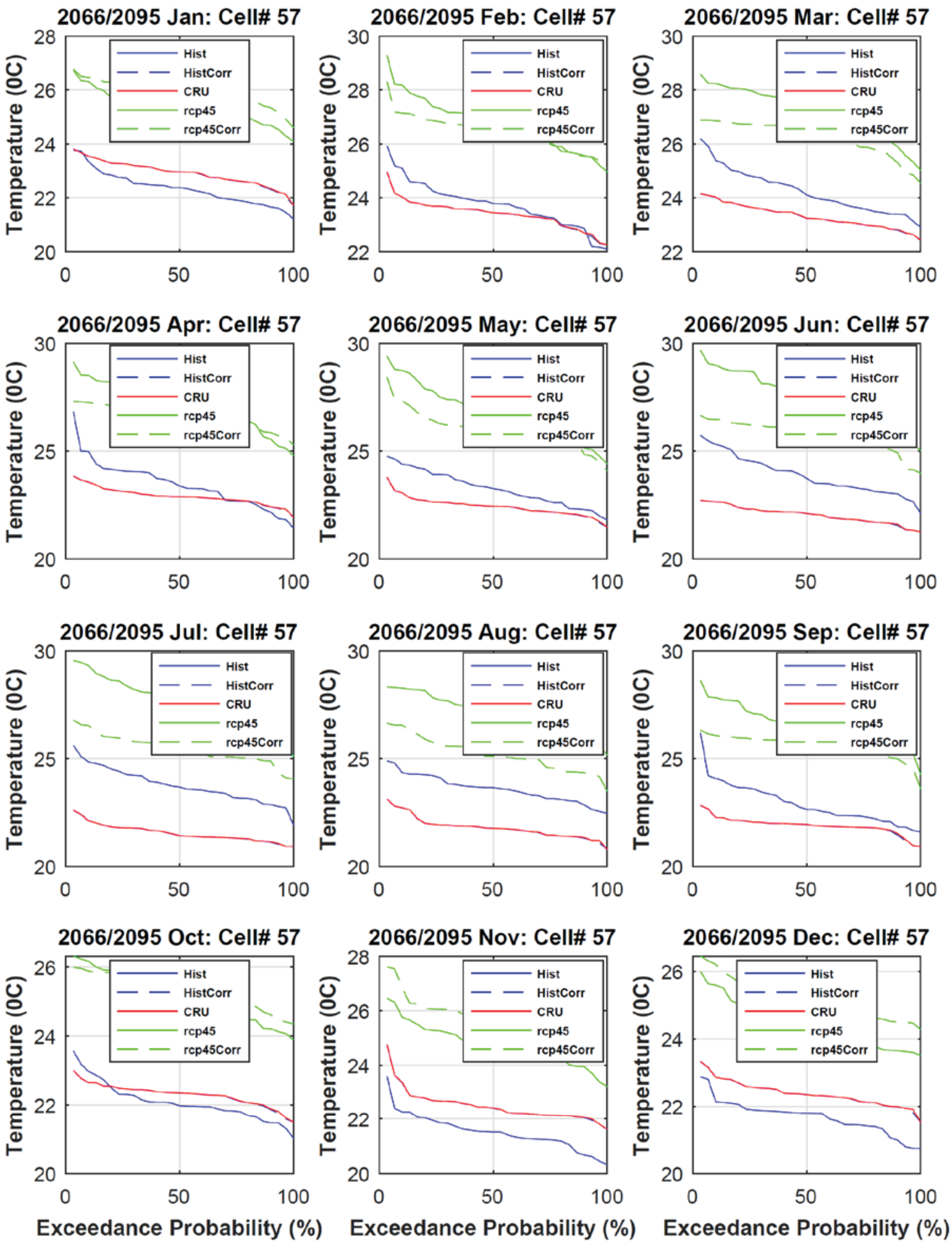


Figure 27. Bias corrected temperature for CMCC-CMS GCM data Cell 57, Victoria Nile sub basin (see Figure 2). Solid lines indicate "observation" (CRU) or raw GCM projections while broken line indicate bias corrected data. Green represent RCP45 future projections for 2066 to 2095.

CONCLUSION AND RECOMENDATION

Conclusion

This project has conducted bias correction and downscaling of Regional Climate Model (CORDEX) and General Circulation Models (CMIP5 GCM). Given the extensive size of the dataset that had to be processed, a cluster based distributed computing platform was used to complete the task in a reasonable time. An extensive data Quality Control and Quality Assurance (QA/QC) was performed to make sure the final product is consistent and thoroughly vetted. Several graphical plots (in the orders of thousands of pages) were produced to help the process and catch any inconsistency in the data. These includes from the raw conditioning data (Global Forcing and Climate Research Unit gridded datasets) to outputs of bias correction procedures. These QA/QC efforts identified several issues with CORDEX data such as inconsistencies of data time periods compared to the metadata provided regarding the start and end dates, missing projection scenarios, or missing data within a given projection. For example, rcp85BCCR_WRF331NCC_NorESM1_M_pr had missing data for 54 dates between 3/25/2011 through 12/28/2015. A separate spreadsheet was prepared to highlight these missing dates.

Extensive data analytics through Expropriate Data Analysis (EDA) framework were conducted to help GCM selection process using a variety of metrics to see if these metrics were reproduced by GCM retrospective runs. These metrics were 1) independence of GCMs from each other's forecast, 2) skill of reproducing historical mean climate, 3) their ability to reproduce seasonal variation, 4) reproduce annual variations, 5) closeness to consensus that measures whether projection from a GCM conforms with mean consensus in future times, and 6) whether they can reproduce extremes through the 10^{th} or 90^{th} (return interval of once in ten years) of wet/dry and cold/warm conditions. As an aggregate these metrics provided insight as to which of the GCMs have better performance and where within the Nile Basin sub basins. A summary table provides the results.

Bias correction for both RCM and GCMs were done using the quantile mapping technique that is one of the most complete approach and widely used in practice. The method accounts for potential RCM/GCM bias by looking at a given parameter's entire probability distribution rather than just the mean as is the case in some climate change impact studies (e.g., "delta" methods).

Historical period of 1970 to 2000 was used to correct retrospective climate projection data and derive the potential bias that present in climate models. Calculated biases based on historical performance were then used to correct future RCM/GCM projections by applying those "correction" for each probability level of a parameter. In consultation with NBI staff, three future time periods, each 30-years long were selected to generate future scenarios that will be used for water resources management and impact assessment. These were near term projections (2006 to 2035) mid- century (2036 to 2065) and end of century (2066 to 2095) outlooks. The 30-years correction corresponds to the 30-year historical bias that was calculated for the base year using retrospective runs for each GCM. It is important to note that if one is interested in looking at another 30-year future time period, say, 2031 to 2060, it is not appropriate to use the concatenated data series that came from the three-time spans projections. This is because it would imply the first and second half of 2031 to 2060 would have the same probability distribution which may not be the case. Typically, a 30-year long period is assumed where stationary can be assumed in a climatological data. A separate bias corrected time series for 2031 to 2060 should be prepared and used if the 2031 to 2060 data is needed.

Recommendation

1) GCM selections

The scope of work in this project identified GCM selections process to address three categories: a) water resources planning; b) flood mitigation on extreme wet situations; and c) drought mitigation on extreme dry situation. GCMs selections were made as such. In addition, GCMs performance in temperature extremes were also investigated. These weights for extreme temperature were note used in the final selections reported. Exploratory analysis on those indicates GCM performance in reproducing temperature extremes vary widely and by Nile Basin (see Figure 15, Figure 16 and Tables 3 through Table 12). Understanding extreme temperature and its correlation with precipitations are as valuable as looking at only precipitation. It is recommended that NBI should investigate this correlation and perhaps look at which of the GCMs co-reproduces these two parameters. This is especially important for basin scale water balance study as increased temperature would impact water demand (ET or municipal and industrial) while precipitation impacts supply side but policy decisions are made through assessment of demand and supply side modeling. This study also looked at model consensus criteria as a measure of how GCMs agree with an ensemble projection of all. Since future observation are not yet available and past projections accuracy may not guarantee accuracy of future projections, researcher use a statistical assumption that is based on ensemble (group consensus) is the best one measure one could use (note that this approach is often used with success in other fields such as computer science where Bayesian committee model ("machines"), among others, often time are demonstrated to outperform any single model performance). This criterion, however, was not used in the final ranking of the GCMs reported. NBI may want to investigate the value of using such criteria in the future.

In addition, in this project, no attempt was made to come up with a single criterion that would aggregate the different metrics that were used for GCM selection. Coming up with a single criterion would require understanding the sensitivity of each as well as exploring different aggregation technique that may be useful to NBI. Having an aggregate metrics at NBI basin or across a larger spatial domain, it may provide policy relevant information that may require such consistency across the Nile Basin and its utility should be investigated. But this it is not a substitute and is not recommended to be a replacement for performance identification of individual basins and three objective criteria (mentioned above) that was the task of this project. They should be complementary based on future needs of the NBI.

2) Downscaling CMIP5 data

This project used one of the most widely used downscaling approach in practice: localized analog section method based on literature review, prior experience, and the scope and time of the project at hand. There are several variants of this technique that could be explored by NBI should capturing historical spatial correlation within NBI basin and across basin is something NBI is interested in. One such approach is the Stochastic Analog (Hwang and Graham, 2013 and Chang et al., 2018) that uses variogram (kriging) to capture spatial correlation in producing an analog that can be scaled according to future climate projection. This technique was not pursued because of the scope and time limitation of the current project. NBI may want to investigate the value of such an approach that may have implication for hydrological modeling that may benefit in generating spatially correlated hydrological parameters within or across sub-basins.

3) Daily time step bias correction

This project used quantile mapping technique, which is widely used in practice, for bias correcting daily RCMs using experimental Probability Distribution Function (PDF). As are the topics discussed above, there are different flavors of this approach in practice including those that fit parametric PDF functions than using the experimental PDF that could be explored in the future. Other approaches that could also be explored are primarily on the difference on the handling of the no-rain event. Some approaches bias correct only the rain amount distribution after segregating the rain/no rain events. This may require an assumption that need to be investigated regarding how the proportion of no-rain events should propagate into the future as there is no clear way to apply errors from no-rain/rain event. To circumvent this issue, some researchers conduct bias correction at monthly scale and disaggregate into daily using historical analogs. Then again, this approach also has its weakness as it ignores the daily sequence of GCM projection that may be important for practitioners as it rely solely in historical daily pattern. The later approach cannot produce a climate daily pattern that is outside of the historical period. The pro and cons of all these approaches could be investigated in the future.

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APPENDIX: DATA GUIDE

CORDEX Data import and process

CODEX data for Africa was downloaded and boundary of coordinates that covers NBI basin was used to extract. This provided a boundary of 22.44 to 40.04-degree longitude to -4.84 to 32.56 degrees longitude. ImportCORDEX.m file imports all the RCMs with structured field that can be expandable if additional CORDEX data are available in the future. ImportCORDEX.m script saves processed data in *.mat files. An exportNetCDFfile.m converts these processed matlab files into netCDF, if needed.

CORDEX Data bias correction

The Global forcing data is first prepared for CORDEX data bias correction by GFforCORDEX.m script by spatially aggregating Global Forcing data to match the CORDEX cells. This file also has a quick check plot script to verify data consistency. masterBiasCorrectionCORDEX.m script performs bias correction for historical and future time spans and call several scripts to accomplish this. As much as possible when there is similarity in data a single script is used with generalized function inside. When this is not possible a separate script is written for two sets of data. This include.

- First set of data is SMHI historical precipitation data performed by histBiassCorrectSMHI.m
- Second set of data of precipitation is done through histBiasCorrectRestOfData.m
- First set of precipitation data for future bias correction biasCorrFuturePrSMHI.m
- Second set of data future bias correction, biasCorrFuturePrRestOfData.m
- First set of temperature historical bias correction, histBiasCorrectSMHItemperature.m
- Bias correct future temperature for both first and second set of data biasCorrFutureTemp.m
- Plot bias corrected data either precipitation or temperature plotSMHI.m
- Plot second set of data errHistoTemp.mat

Once this is done exportNetCDFfileBiassCorrectedData.m exports results of CORDEX bias correction. It calls writeNetCDF.m for the actual execution of files. The parent file is constructed in such away to take advantage of distributed computing set up.

Bias corrected data (both *.mat and corecponding netCDF files) have three primary files inside: original data as obtained that can be used to reproduce the work done in this project; 1) near term (2006 to 2035), mid century (2036 to 2065) and late century (2066 to 2095). In each of the last three data is bias corrected for historical reference period (1971 to 2000) and the respective time spans that the bias correction is made. The rest of the data are left as original. For example, the 2006 to 2035 data has the 1971 to 2000 and 2006 to 2035 bias corrected, and so on.

CMIP5 GCM processing and selection

CMIP5 data are first imported using import_CMIP_netcdf_file.m and extract data for NIB's 67 cells that cover the 10 basins (see Table 2) and saves in *.mat file for further analysis. Several matlab scripts are used to conduct GCM selection criteria and sensitivity analysis.

- Reproducing seasonal behavior is done through the calculation of skill and inter modal distance that is used to assess model independence, calculatIDM.m
- Reproducing variability, this is done through calculateIAV.m
- Closeness to consensus for future projection is done through calculateC2C/m
- Reproducing extremes is done through calculateDorW.m

CMIP5 GCM bias correction

The file masterBiasCorrectionCMIP5.m is used for bias correcting CMIP5 monthly data. The file calls different script: biasCorrectCMIP5precip file bias corrects precipitation and returns bias corrected data as well as error found during bias correction. BiasCprrectCMIP5temperature.m corrects temperature data for both RCP45 and RCP85.

CMIP5 GCM downscaling

The file statisticalDownScale.m statistically downscales CMIP5 data using the localized analog technique. The version of localized analog technique that is used here uses the procedure of spatial downscaling by searching an analog of historical data for the same month and scaling that up to the projected future climate information for that month and saves into *.mat file. The analog is found from the Global Forcing data that is upscaled at CORDEX size. Once this is done a utility scrip exportSTDtoNetCDF.m converts matlab files into netCDF. This file calls writeCMIP5intoNetCDF.m calls to do the actual writing.

The following Table summarizes major matlab script and their specific utilization. Additional utility scripts such as those used for plotting and exporting figures are not included.

	Major Matlab Code Name	Description
1	Import_CMIP5_netcdf_file.m	This code reads raw CMIP5 rainfall and temperature data, process to 67 NBI cell and save the result in matlab rawRainfallCMIP5.mat, processedRainfallCMIP5.mat, rawTemperatureCMIP5.mat, and processedTemperatureCMIP5.mat. Raw is original data comparable to the netCDF original file
2	ImportGlobalForecingData.m	Imports all GF data (temperature, precipitation, daily surface wind, longwave radiation, short wave radiation, humidity, surface pressure) and save into *mat files. There is a code that exports this into netCDF files
3	ImportCRUData.m	Imports Climate Research Center high-resolution monthly temperature and rainfall data for CMIP5 monthly bias correction and saves into matlab *.mat files
4	importCORDEX.m	Imports CORDEX data that covers Africa and process to the NBI boundary and saves a *.mat file for each CORDEX file. For each family of RCM, it import and export data to *.mat file for use later on.
5	exportNetCDFfile	Converts the matlab files into netCDF files generated in 4. This code was written to right intial RCM data (CORDEX) not the bias corrected results
6	GFforCORDEX.m	Prepares GF data matching the grid cell of CORDEX data. This script also has quick check plot to verify data is QA/QC
7	masterBiasCorrectionCORDEX.m	Conducts bias correction of the CORDEX data for historical and future projection and calls several other scripts to accomplish this.
8	histBiasCorrectSMHI	Bias correction code for precipitation using Quantile Mapping. Done at daily time steps with seasonality included. Returns bias corrected data as well as errors to be used for future projection data correction using the equi-distant approach (Li et al. 2010, WRR, Asefa and Adams, 2013 Reg. Env. Change
9	histBiasCorrectRestOfData	Bias correction code using Quantile Mapping for 8 additional RCM runs. Done at daily time steps with seasonality included. Returns bias corrected data as well as errors to be used for future projection data correction using the equi-distant approach (Li et al. 2010, WRR, Asefa and Adams, 2013 Reg. Env. Change
10	biasCorrFuturePrSMHI	Using pdf error during quantile mapping, it corrects future precipitation projection (see code #8). Equidistant bias correction approach is used

11	biasCorrFuturePrRestOfData	Using pdf error during quantile mapping, it corrects future precipitation projection (see code #9) for additional RCMs. Equidistant bias correction approach is used
12	histBiasCorrectSMHItemperature	Bias correction code for minimum and maximum temperature using Quantile Mapping. Done at daily time steps with seasonality included. Returns bias corrected data as well as errors to be used for future projection data correction using the equi-distant approach (Li et al. 2010, WRR, Asefa and Adams, 2013 Reg. Env. Change
13	biasCorrFutureTempSMHI	Using pdf error during quantile mapping, it corrects future precipitation projection (see code #12). Equidistant bias correction approach is used
14	plotSMHI	Plot bias corrected historical, RCP45 RCP85 for temperature or precipitation. The bias correction for historical and future time must be completed before this script is used.
15	errHistoTemp	Plots bias corrected second set of data. Because of the difference in the dataset this script is similar to plotSMHI but with slight difference.
16	exportNetCDFfileBiassCorrectedData	Exports bias corrected *.mat files into netCDF file. This file calls writeNetCDF.m to make the actual file writing.s
17	selectGCM	Pulls preprocessed GCM files and CRU monthly data to conduct analysis on GCM selection
18	masterBiasCorrectionCMIP5	Bias corrects CMIP5 data
19	biasCorrectCMIP5preicp	Correct bias in precipitation for both RCP45 and RCP85
20	biasCorrectCMIP5temperature	Correct bias in temperature for both RCP45 and RCP85
21	statisticalDownScale	Statistically downscale CMIP5 data into CORDEX sells using the global forcing data as an analog

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