Evaluation and downscaling of CMIP5 climate simulations for the Southeast US

FINAL PROJECT MEMORANDUM

August 21, 2015

1. ADMINISTRATIVE

Project title: Evaluation and downscaling of CMIP5 climate simulations for the Southeast US

Agreement #: G13AC00407
Award recipients:
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Time period covered by report: 6/15/2014 through 2/28/2015
Actual total cost: $30,000

2. PUBLIC SUMMARY

This project has generated a series of freely available datasets that provide projections of climate change at appropriate spatial scales that can directly address specific management questions. These climate change projections are the result of "downscaling" output from global climate models (GCMs) that formed the basis of many conclusions in the Intergovernmental Panel on Climate Change (IPCC) Assessment Report 5 (AR5). The datasets include projections of climate variables in addition to daily temperature and precipitation such as surface winds, humidity and solar radiation that are needed in hydrologic and ecological modeling. Two products, one at a 4-km resolution, the other at a 6-km resolution, cover the continental United States have been completed and are available through dataservers including **https://www.northwestknowledge.net/**

Moreover, an evaluation was done of how well the GCMs reproduce the historical climate of Southeast US and surrounding region. This evaluation can be used as one source of information when a user is faced with selecting a small number of climate projections from the larger set of available projections for an impacts assessment.

Collectively, the guidance on the credibility of GCMs over the southeastern US and the downscaled datasets provide necessary information and data to develop strategies for coping with climate change.

3. TECHNICAL SUMMARY

Downscaling methods are used to bridge the spatial mismatch and biases between output from global climate models (GCMs – typical spatial resolution is several degrees latitude by longitude) and input required by secondary modeling applications. We advanced several details of statistical downscaling to facilitate that downscaled data represent the signal of changes as simulated by the GCM while retaining many of the properties of the training datasets to ensure compatibility for impacts modeling.

In addition to downscaling GCMs, we evaluated the GCMs with respect to their ability to reproduce the observed 20th century climate for the Southeast United States (US) and surroundings. A suite of statistics that characterize various aspects of the regional climate was calculated from both model simulations and observation-based datasets. Lastly, GCMs models were ranked by their fidelity to the observations.

4. PURPOSE AND OBJECTIVES:

GCM Downscaling

The first objective of this project was to generate a more physically consistent and detailed set of projected meteorological variables than found in existing downscaled climate projections. While previous downscaling efforts such as Bias-Correction Statistical Disaggregation (BCSD) and Bias-Correction Constructed Analogs (BCCA) are undoubtedly valuable, they have limitations or drawbacks that may make them less desirable for particular uses. These limitations include a restricted set of variables (typically only temperature and precipitation), inability to utilize daily GCM output and preserve co-variability across variables, and issues involving the treatment of model biases. The Multivariate Adaptive Constructed Analogues (MACA, Abatzoglou and Brown 2012), and augmentations therefore (Hegewisch and Abatzoglou, forthcoming) largely overcome some of these limitations and allow for a more comprehensive set of downscaled climate products. However, MACA is not a panacea for downscaling, as it cannot 'correct' for a global climate model's deficiency in simulating spatial patterns of convective precipitation, or resolve changes in climate that arise from atmosphere-surface feedbacks. Likewise, resolving the spatial details of convectively driven precipitation is challenging for all downscaling methods.

GCM Evaluation

Climate simulations from global climate models (GCMs) are often relied upon to provide plausible future climate scenarios in climate change impacts assessments at regional and local scales. Frequently, users are constrained to select a subset of the many climate projections available from a large suite of GCMs. Model fidelity is one criterion that may be used to wean the large pool of available projections. Our second objective of the project was to aid users in selecting GCM simulations by evaluating how individual GCMs performed with respect to reproducing the historical 20th-century climate of the southeast USA.

5. ORGANIZATION AND APPROACH

GCM Downscaling

Climate scenarios from 20 CMIP5 GCMs with the requisite daily data were statistically downscaled using the Multivariate Adaptive Constructed Analogues (MACA, Abatzoglou and Brown 2012), 1950-2005 for historical runs and 2006-2099 for RCP 4.5 and 8.5 (Table 1). Outputs from two GCMs that had 360-day years were rescaled to conform to a 365-day year calendar.

Two downscaling products were produced: macav2livneh and macav2metdata. First, building off the downscaling performed for the Northwest Climate Science Center (which used "training" data from the surface gridded meteorological dataset of Livneh et al. (2013) at 1/16th-degree resolution), we expanded the downscaling domain from the Northwest US to the contiguous United States to create the macav2livneh downscaled product. Second, utilizing the 'training' data from the gridded meteorological dataset of Abatzoglou (2013), that includes additional variables such as downward shortwave radiation and the surface, humidity, and 10-m wind velocity at a common 1/24th-degree spatial resolution, we created the macav2metdata product. The list of variables that are available from these products is provided in Table 2.

For this work, we augmented the original MACA downscaling approach to better address some of the biases inherent in GCMs. The updates included (i) continuous trend preservation of the original GCM signal using a 31-year, 21-day smoothing window, 2) use of a reduced set of analog patterns but inclusion of a residual term from the constructed analogs, and 3) joint bias correction of temperature and precipitation to remove intermodel biases in temperature coincident with precipitation (Hegewisch and

Abatzoglou, forthcoming). These modifications resulted in significant improvements in downscaling, as seen in a cross-validation study.

In summary, MACA was chosen for this downscaling over other methods for the following reasons:

• MACA uses daily output from GCMs and is more readily able to capture changes in higher-order climate statistics (e.g., extremes) than methods that temporally disaggregate from monthly projections.

• The spatial downscaling from MACA uses observed spatial patterns rather than using interpolation approaches.

• MACA can be extended to multiple variables. We downscaled daily temperature, precipitation, wind speed, downward shortwave radiation and humidity.

• MACA downscales some of the variables in sets in order to preserve the dependencies between the variables. For example, the downscaling of temperature jointly with precipitation has been seen to produce better results in capturing historical statistics of snowfall and correct for model biases specific to precipitating days and thus precipitation phase.

GCM Evaluation

Retrospective (i.e., 20^{th} century) climate scenarios from 41 CMIP5 GCMs were examined. We compared relevant 20th-century observations with the suite of CMIP5 global model results according to a suite of metrics designed to determine their suitability for Southeast climate studies following the procedures outlined by Rupp et al. (2013).

The metrics listed in Table 1 were calculated from up to 5 observational datasets and all the GCM-simulated datasets of temperature and precipitation. The GCMs were then ranked according to their overall fidelity with respect to observations.

6. PROJECT RESULTS

GCM Downscaling

Between the two downscaling products of macav2livneh and macav2metdata, a total of 26 terabytes of downscaled data were produced. Although there are numerous ways to analyze the data, we provide a couple examples here that can be explored in further detail through our webpage (see Sec. 9). Figure 1 shows the 20-model mean projected change in Mar-May downward shortwave radiation and precipitation for years 2070-2099 of experiment RCP 8.5 with respect to late 20^{th} century climatology. Figure 2 shows differential rates of warming between the coldest day of the winter and mean winter temperature. This elucidates the additional type of information that can be gleaned from MACA downscaling that incorporates daily GCM projections.

GCM Evaluation

The project generated a large number of climate metrics per GCM and observational dataset. These have been presented in figures that may be used to compare among GCMs or to assess the ability of the CMIP5 models as a whole to faithfully simulate the climate of the southeastern US. As an example, Figure 3 gives a means of comparing all GCMs and all metrics at once, and thus can be used as an initial means of identifying GCMs that do poorly in a particular metric, of set of metrics, that may be of interest for a particular use. A detailed assessment of the GCMs with respect to each metric is provided in the technical report “An Evaluation of CMIP5 20th Century Climate Simulations for the Southeast USA”.

7. ANALYSIS AND FINDINGS

GCM Downscaling

Downscaled climate projections have all been converted to NetCDF format using CF metadata standards to ensure compatibility across platforms. We provide both daily and aggregated monthly NetCDF files, acknowledging the different needs of end users. All datasets have been transferred to the Northwest Knowledge Network (NKN) including the Regional Approaches to Climate Change (REACCH) subserver. NKN provides several services to aid users in acquiring the hosted data.

First, NKN provides a data catalog to aid users in finding information about the data, as well as to manually download single data files (or subsets) from the internet in different formats (i.e. ascii, NetCDF). The data catalogs for the 2 downscaled products are:

- http://thredds.northwestknowledge.net:8080/thredds/catalog/NWCSC_INTEGRATED_SCENARIOS_ALL_CLIMATE/macav2livneh/catalog.html
- http://reacchpna.org/thredds/reacch_climate_CMIP5_macav2_catalog.html

Second, NKN provides THREDDS services to the hosted datafiles. THREDDS enables users to more easily download spatial/temporal subsets of the data, including the use of OPeNDAP to extract subsets of the data from within the user's favorite software program (R, MATLAB, Python, IDL, etc.).

Lastly, though each of the raw NetCDF files represent only 5 or 10-year time spans of data, NKN has aggregated all the yearly files for each of the scenarios (historical, rcp45, rcp85) into a single pointer file, which can be used to aid users for accessing all years of the data.

Through NKN's services, users are able to download spatial subsets of the data, as well as each daily variable aggregated to monthly averages. Data storage and access for the Southeast datasets would be decided upon consultation with SECSC.

GCM Evaluation

The ranking of GMCs is not a straightforward endeavor. Any ranking will vary with the particular metric, or set of metrics, chosen. Also, in some cases, metrics will be physically related to the extent they provide redundant information. Finally, we may have low large uncertainties about the accuracy of our estimation of the metric itself. Giving consideration to the latter two issues, we ranked the models using a methodology that accounted for information redundancy and favored the metrics we believed were more reliable. Using the approach, we found that models from the CCSM/CESM1, CNRM, CMCC, HadGEM2, GISS-E2, and MPI-ESM families ranked higher than the others (Figure 4). This overall ranking, however, is provided as a suggestion. Individuals can examine the results presented in the technical report and use these a guide to a model selection suited to their particular needs and objectives.

9. MANAGEMENT APPLICATIONS AND PRODUCTS

In addition to downscaling the datasets, we have created a web interface for potential data users to learn more about the downscaling methodology and visualize certain aspects of the datasets at **http://climate.northwestknowledge.net/MACA/**
This website provides several visualization tools, including the ability for users to examine spatial patterns of change for the variables that have been downscaled across seasons, variable and scenarios. These decision support tools are of utility both for direct users of the climate datasets, as well as for general depiction of projections across the region. Moreover, the technical report "An Evaluation of CMIP5 20th

Century Climate Simulations for the Southeast USA" will be available on website once report has obtained OFR citation.

We are currently working on a data portal to aid users in downloading spatial subsets of the downscaled daily data, as well as aggregations of each variable to monthly values, in formats such as csv.

10. OUTREACH

We have continued to update our webpage to provide visualizations, guidance and data.

Presentations

Katherine Hegewisch, John Abatzoglou, David Rupp, Phil Mote. " Statistically downscaled climate data using the Multivariate Adaptive Constructed Analogs approach " 5th annual Pacific Northwest Climate Science Conference **(PNW CSC), Sept, 2014** Seattle

Publications

Hegewisch, K.C., Abatzoglou, J.T., 'An improved Multivariate Adaptive Constructed Analogs (MACA) Statistical Downscaling Method', in preparation.

Rupp, D.E., 2015, An Evaluation of CMIP5 20th Century Climate Simulations for the Southeast USA, USGS Open File Report XXXXX

References

Rupp, D. E., J. T. Abatzoglou, K. C. Hegewisch, and P. W. Mote (2013), Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest USA, J. Geophys. Res. Atmos., 118, 10,884–10,906, doi: 10.1002/jgrd.50843.

Table 1. Available downscaled CMIP5 global climate simulations using MACA, 1950-2099, RCP4.5 and RCP8.5

BCC-CSM1-1
BCC-CSM1-1-M
BNU-ESM
CanESM2
CCSM4
CNRM-CM5
CSIRO-Mk3-6-0
GFDL-ESM2G
GFDL-ESM2M
HadGEM2-CC
HadGEM2-ES
INMCM4
IPSL-CM5A-LR
IPSL-CM5A-MR
IPSL-CM5B-LR
MIROC5
MIROC-ESM
MIROC-ESM-CHEM
MRI-CGCM3
NorESM1-M

Table 2. Downscaled variables

Variable	Abbreviation	Height
Temperature, maximum	tasmax	2 m
Temperature, minimum	tasmin	2 m
Precipitation rate	pr	Surface
Relative humidity, maximum	rhsmax	2 m
Relative humidity, minimum	rhsmin	2 m
Specific humidity	huss	2 m
Wind, speed	was	10 m
Wind, eastward	vas	10 m
Wind, eastward	vas	10 m
Downwelling solar radiation	rsds	Surface

Table 3. Definitions of global climate performance metrics, the confidence in the metrics for model ranking, and observational datasets used by metric.

Metric[a]	Confidence category	Description	Observation datasets
Mean-T Mean-P	Highest Highest	Mean annual temperature (T) and precipitation (P), 1960-1999	CRU, PRISM, UDelaware, ERA40[d], NCEP[d]
DTR-*MMM*[c]	Highest	Mean diurnal temperature range, 1950-1999	CRU[e], PRISM[e], NCEP
SeasonAmp-T SeasonAmp-P	Highest Higher	Mean amplitude of seasonal cycle as the difference between warmest and coldest month (T), or wettest and driest month (P). Monthly precipitation calculated as percentage of mean annual total, 1960-1999.	CRU, PRISM, UDelaware, ERA40[d], NCEP[d]
SpaceCor-*MMM*-T[b,c] SpaceCor-*MMM*-P[b,c]	Highest Higher	Correlation of simulated with observed the mean spatial pattern, 1960-1999.	ERA40, NCEP[e]
SpaceSD-*MMM*- T[b,c] SpaceSD-*MMM*-P[b,c]	Highest Higher	Standard deviation of the mean spatial pattern, 1960-1999. All standard deviations are normalized by the standard deviation of the observed pattern.	ERA40, NCEP[e]
TimeVar.1-T TimeVar.8-T	Lower Lowest	Variance of temperature calculated at frequencies (time periods of aggregation) ranging for N = 1 and 8 years, 1901-1999.	CRU, PRISM, UDelaware
TimeCV.1-P TimeCV.8-P	Lower Lowest	Coefficient of variation (CV) of precipitation calculated at frequencies (time periods of aggregation) ranging for N = 1 and 8 water years, 1902-1999.	CRU, PRISM, UDelaware
TimeVar-*MMM*-T[c]	Lower	Variance of seasonal mean temperature, 1901-1999.	CRU, PRISM, UDelaware
TimeCV-*MMM*-P[c]	Lower	Coefficient of variation of seasonal mean precipitation, 1901-1999.	CRU, PRISM, UDelaware
Trend-T Trend-P	Lower Lowest	Linear trend of annual temperature and precipitation, 1901-1999.	CRU, PRISM, UDelaware
ENSO-T ENSO-P	Lower Lowest	Correlation of winter temperature and precipitation with Niño3.4 index, 1901-1999.	CRU, PRISM, UDelaware
Hurst-T Hurst-P	Lowest Lowest	Hurst exponent using monthly difference anomalies (T) or fractional anomalies (P), 1901-1999.	CRU, PRISM, UDelaware

[a]Unless otherwise noted, metrics are average over Southeast US. [b]Expanded domain: 115°W – 50°W, 15°N – 55°N.

[c]*MMM* is the season designation: DJF, MAM, JJA, and SON.

[d]Temperature only used in ranking, not precipitation. [e]Not used in ranking.

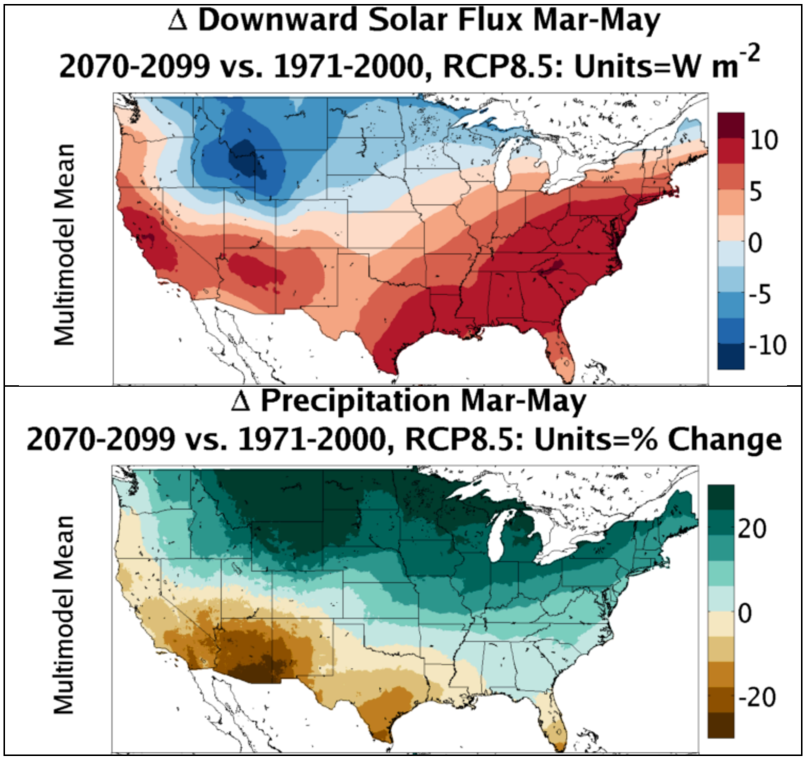

Figure 1: Projected 20 model mean change in (top) Mar-May downward radiation and in (top) Dec-Feb precipitation for years 2070-2099 of experiment RCP8.5 versus the historical climate experiment for 1950-2005 from downscaled CMIP5 climate model outputs.

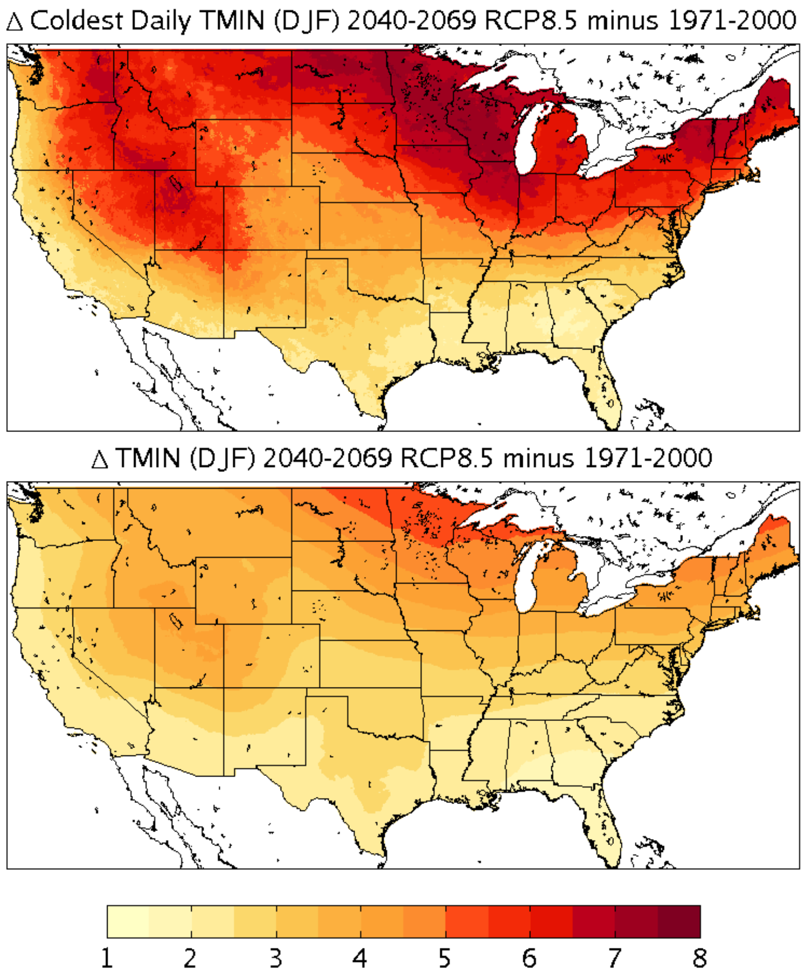

Figure 2: Projected 20 model mean change (in degrees C) in (top) coldest minimum temperature (TMIN) and (bottom) average minimum temperature (TMIN) each winter (Dec-Feb) for years 2040-2069 of experiment RCP8.5 versus the historical climate experiment for model years 1971-2000 .

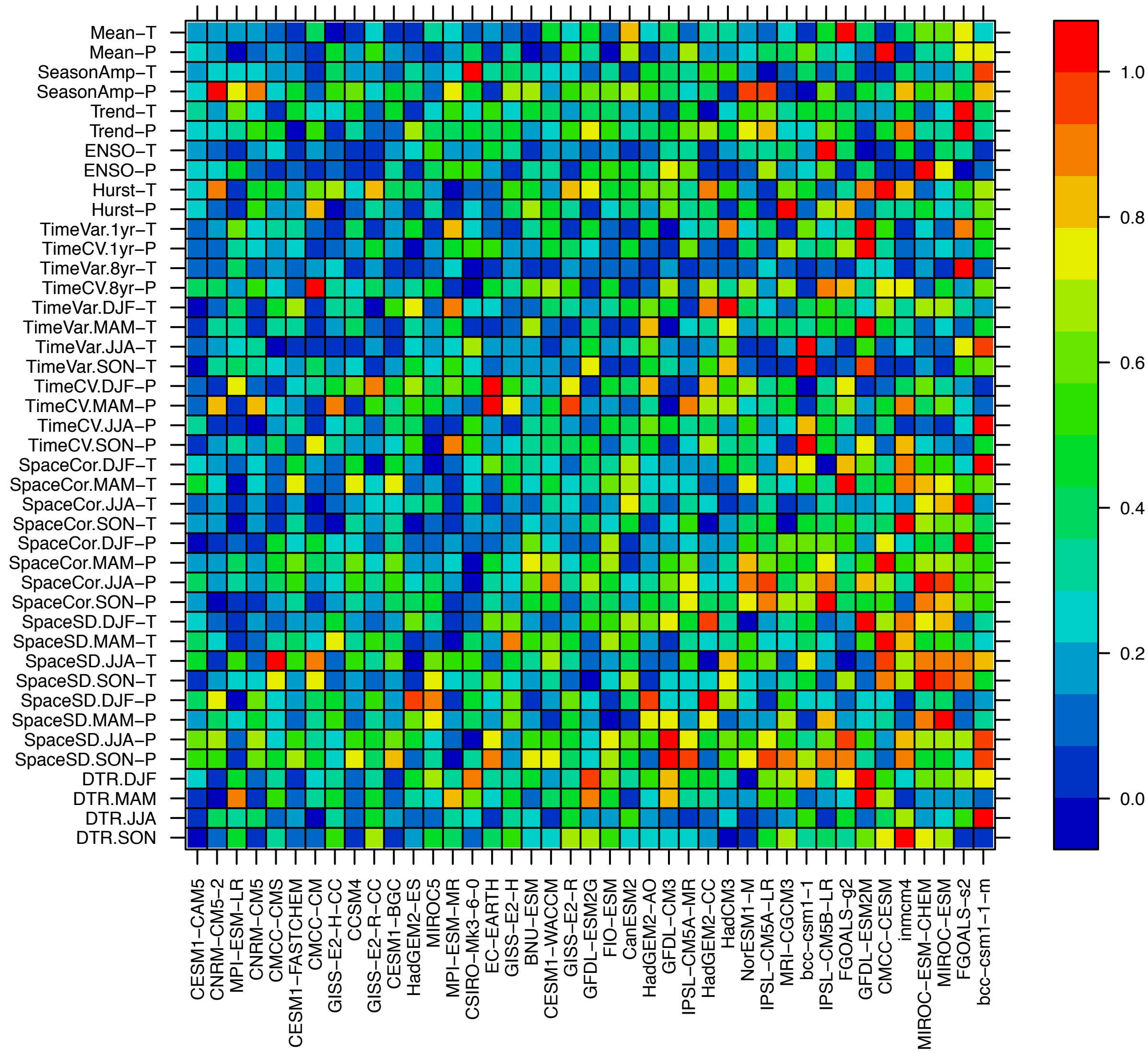

Figure 3: Relative error of the ensemble mean of each metric for each CMIP5 GCM. Models are ordered from least (left) to most (right) total relative error, where total relative error is the sum of relative errors from all metrics.

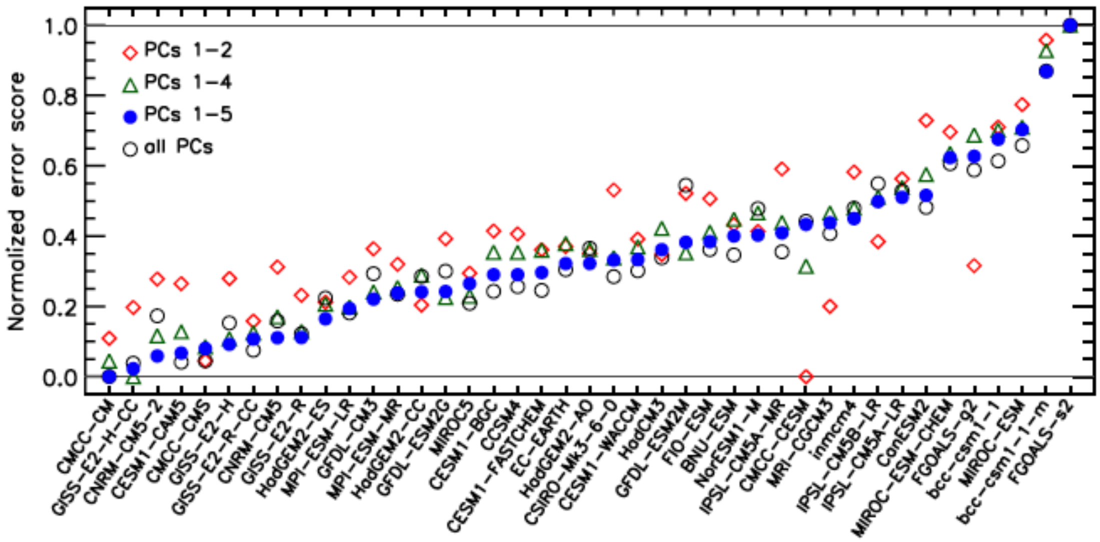

Figure 4: 41 CMIP5 GCMs ranked according to normalized error score from EOF analysis of performance metrics. Ranking is based on the first 5 principal components (filled blue circles). The open symbols show the models' error scores using the first 2, 4, and all 22 principal components (PCs). Relative error of the ensemble mean of each metric for each CMIP5 GCM. Models are ordered from least (left) to most (right) total relative error, where total relative error is the sum of relative errors from all metrics.