Can Climate Projection Uncertainty be Constrained over Africa Using Metrics of Contemporary Performance?

Dave Rowell, Cath Senior, Michael Vellinga & Richard Graham

Climatic Change, 134, 621-633

1. Motivation

Climate change projections over Africa are highly uncertain. There is wide disparity amongst models in the magnitude of local rainfall and temperature change, and in some regions even disparity in the sign of rainfall change. This has significant implications for decision-makers, particularly in the context of a vulnerable population with few resources for adaptation.

A common approach has been to rank models according to their historical climate performance and disregard those with least skill. We evaluate this approach for two vulnerable regions of Africa, the Sahel and the Greater Horn of Africa.

2. Scope, Data, Metrics

Model Data:
- 39 CMIP5 models
- Historical & AMIP simulations to assess model performance
- RCP8.5 projections

Observed Data:
- GPCC-Reanalysis v4 precip
- GPCP v2.1 pentad precip
- Berkley surface air temperature
- HadISST1.1

Focus is on 4 'Region-Season Combinations' (RSCs) (Fig.1) :
- West Sahel (W.Sahel) and Central to East Sahel (Cen+E.Sahel) (both JAS wet season averages)
- The Greater Horn of Africa Long Rains (GHA-LR, MAM) and Short Rains (GHA-SR, OND)

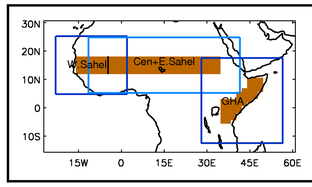

Fig.1: Definition of regions used to compute model performance metrics and projected change. Shaded regions are RCSs used for averaging, and boxes are the Large RSCs used for spatial RMSEs.

Primary Metric	Variable	Model	Sub-Metrics (Regions/Seasons)
RMSE	Precipitation	AOGCM	4 x Africa LRSCs
RMSE	Precipitation	AGCM	4 x Africa LRSCs
RMSE	Surf Air Temp	AOGCM	4 x Africa LRSCs
RMSE	Surf Air Temp	AGCM	4 x Africa LRSCs
(Abs) Bias	Precipitation	AOGCM	4 x Africa RSCs
(Abs) Bias	Precipitation	AGCM	4 x Africa RSCs
(Abs) Bias	Surf Air Temp	AOGCM	4 x Africa RSCs
(Abs) Bias	Surf Air Temp	AGCM	4 x Africa RSCs
Mean AnnCyc	Precipitation	AOGCM	4 x Africa RSCs
Mean AnnCyc	Precipitation	AGCM	4 x Africa RSCs
Mean AnnCyc	Surf Air Temp	AOGCM	4 x Africa RSCs
Mean AnnCyc	Surf Air Temp	AGCM	4 x Africa RSCs
(Abs) CV	Precipitation	AOGCM	4 x Africa RSCs
(Abs) CV	Precipitation	AGCM	4 x Africa RSCs
(Abs) SD	Surf Air Temp	AOGCM	4 x Africa RSCs
(Abs) SD	Surf Air Temp	AGCM	4 x Africa RSCs
(Abs) Mean Onset	Onset Index	AOGCM	West Africa
(Abs) SD Onset	Onset Index	AOGCM	West Africa
RMSE	SST	AOGCM	Tropics
(Abs) Bias	SST	AOGCM	13 x SST-SCs
Mean AnnCyc	SST	AOGCM	11 x SST-SCs
(Abs) SD	SST	AOGCM	11 x SST-SCs
Teleconnections	SST-to-Precip	AOGCM	Africa

Table 1: Metrics of Model Performance

- RMSE = Root mean squared error of 30yr average
- (Abs) Bias = (Absolute) Bias of 30yr area average
- Mean AnnCyc = RMSE of seasonal cycle (seas ± 1mon) of 30yr area average
- (Abs) SD = Model/Obs ratio of interannual SD over 30yrs
- (Abs) CV = Model/Obs ratio of interannual coefficient of variation
- (Abs) Mean Onset = (Absolute) Bias of WAM onset date
- (Abs) SD Onset = Model/Obs ratio of interannual SD of WAM onset date
- Teleconnections = % SST-to-Precip teleconn with signif diff model-obs strength
- RSC = Region-Season Combinations shown in Fig.1
- LRSC = Large boxes shown in Fig.1 (only used for 'RMSE')
- SST-SC = SST-Index-Season Combinations: Tropical Atlantic Dipole (JAS), Equatorial East Atlantic (JAS), Central Indian Ocean (JAS, MAM, OND), Indian Ocean Dipole (MAM, OND), Nino-3.4 (JAS, MAM, OND), Mediterranean (JAS), Tropical Mean (Ann), Tropics-wide Mean Intensity of Equatorial Peak (Ann)

3. Discrimination of Models

Method: Rank models for each 'Primary Metric', using average rank from appropriate sub-metrics (see paper for details).

Figure 2 shows histograms of each model's ranks for these 23 primary metric s, for the Cen+E.Sahel.

If there were no discrimination between models, the histograms would be flat (+ noise).

If there were clear discrimination, the histograms would show narrow peaks, eg. close to 1 (39) for the best (worst) models.

Figure 2 shows some (statistically significant) discrimination. But the ranking of each model varies considerably amongst metrics. So inferences about a model's relative contemporary skill depends on the choice of metrics, especially if only a small subset is used. Conclusions are the same for other RSCs, but the overall ranking of each model is diverse, so relative model capability cannot be extrapolated between regions or seasons.

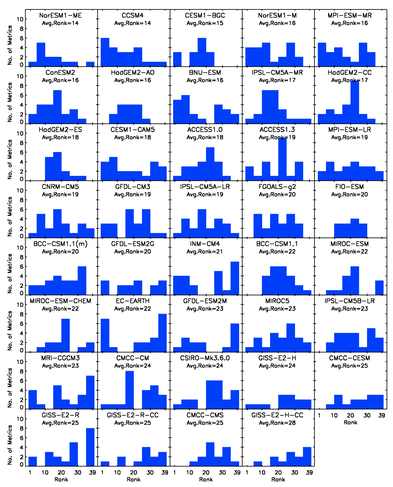

Fig.2. Histograms of a model's ranking for each of the 23 primary metrics for the Cen+E.Sahel. Low values indicate highest skill. Models are ordered by their overall (average) rank.

4. Impact on Projection Uncertainty

Figure 3 shows CMIP5 projections for rainfall and surface air temperature for each RSC for 20yr averages centred on 2050.

Modelling uncertainty is substantial, and much greater than natural variability (vertical bar).

W.Sahel Rainfall: Excluding the worst 25 or 50% of models (X's and optionally ?'s) – judged by standard metrics of contemporary climate – does not lead to any statistically significant reduction in uncertainty or any consensus on the sign of change. This is because these models are distributed throughout the uncertainty range. Note that the apparent reduction arising from the 50% cull is dependent on the reliability of the ranks of two outlying models.

Cen+E.Sahel Rainfall: Excluding the poorest 25% of models has little impact on uncertainty. Further culling the next poorest 25% of models leads to a large and statistically significant reduction in uncertainty and a robustness in the sign of response. These models (?'s) cluster towards the ends of the ensemble. However, the size of this uncertainty reduction depends on the reliability of the ranking of the two outliers.

Greater Horn of Africa Rainfall: Excluding the models least able to represent current climate has no statistically significant impact on uncertainty. Again, these models are scattered throughout the CMIP5 ensemble.

Surface Air Temperature: Projections are wide-ranging, implying considerable uncertainty in impacts. For all four RSCs, the apparently poorest models are scattered throughout the ordered anomalies. So excluding these models has no statistically significant impact on the uncertainty range.

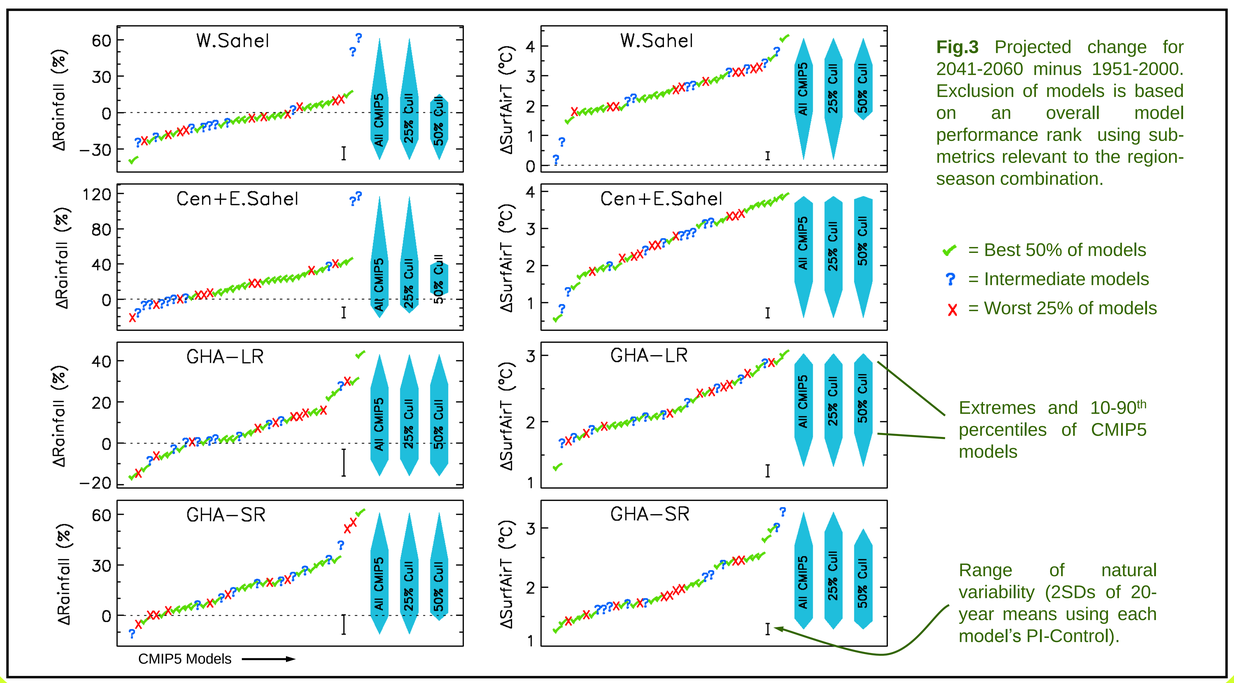

Fig.3 Projected change for 2041-2060 minus 1951-2000. Exclusion of models is based on an overall model performance rank using sub-metrics relevant to the region-season combination.

✔ = Best 50% of models
? = Intermediate models
X = Worst 25% of models

Extremes and 10-90th percentiles of CMIP5 models

Range of natural variability (2SDs of 20-year means using each model's PI-Control).

5. Conclusions

- Some discrimination in the performance of 39 CMIP5 models is achieved.
- Different metrics differ in their ranking of climate models, *i.e.* there is some uncertainty in their judgement of models' relative performance.
- When the more capable models are selected by an overall performance measure, projection uncertainty is not reduced. This is because models are typically spread across the full range of projections (except perhaps for Cen+E.Sahel rainfall).
- This suggests that the method's underlying assumption is false, this assumption being that the modelled processes that most strongly drive errors and uncertainty in projected change are a subset of the processes whose errors are observed by standard metrics of historical climate.
- Further research must now develop an 'expert judgement' approach that will discriminate models using an in-depth understanding of the mechanisms that drive the errors and uncertainty in projected changes over Africa.

Met Office Hadley Centre, Exeter, UK
Tel: +44 7887 630920
Email: dave.rowell@metoffice.gov.uk

Climate Science Research Partnership
Dept. International Development – Met Office Hadley Centre