

CMIP5 GCM Selection for future climate simulations over Zvishavane, Zimbabwe

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Abstract

This study applies an objective method to select a sub-set of General Circulation Models (GCMs) that capture the diverse projections from a large multi-model ensemble. Results shows that the Fifth Coupled Model Inter-comparison Project (CMIP5) GCM projections in southern Africa are broader than the Intergovernmental Panel on Climate Change (IPCC) global averages - or inter-GCM differences are wider than single models' inter-Representative Concentration Pathways (RCPs) projections. The projections have a cool/wet versus hot/dry skewness, and a hot and dryer tendency during the period 2040-2069 under RCP8.5.

Key words: *CMIP5, CSI, AgMIP GCM Sub-setting approach, Southern Africa, Zimbabwe*

Introduction

Although *ex ante* model-based climate projections are essential in solving several societal issues, past efforts have been hampered by model selection biases which sometimes lead to policy inconsistencies and mal-adaptation (Cubasch et al., 2013; Ruane and McDermid, 2017). Past studies have also often used few General Circulation Models (GCMs), selected based mostly on availability of model outputs or reproduction of past climate. This was due to the absence of methods to evaluate GCM performance in a future climate to justify selection of one model in place of the other, given the non-linearity between past and future climate due to climate change. Despite an increase in GCMs under Fifth Coupled Model Inter-comparison Project (CMIP5) and new emission scenarios, uncertainties still exist (Lutz et al., 2016). Furthermore,

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using all GCMs for climate projections, vulnerability assessment and adaptation is difficult as this requires substantial resources. An objective way to select a sub-set of GCMs that represent the diverse climate projections, model uncertainty and ensure that critical model properties and projections are not lost is therefore critical.

Methodology

This study uses the GCM sub-Setting approach, developed by the Agriculture Model Inter-comparison Project (AgMIP) to objectively select a practical sub-set of representative GCMs for future climate and impacts assessment without losing the model spread (Hudson & Ruane, 2013, Ruane and McDerimid, 2017). The method is similar to Semenov and Stratonovitch (2015)'s Climate Sensitivity Indices (CSIs), where each CSI is calculated as differences between GCM absolute future and baseline mean air temperature, or percentage change in precipitation against baseline values for a specific RCP and site. Temperature and precipitation change projections are selected because of their indicative large-scale energy and water budget changes which consequently affects other climate variables and thus the importance in assessing sectoral climate impacts (Semenov and Stratonovitch, 2015).

This paper analyses 29 CMIP5 GCMs' mid-century (2040-2069) projections relative to 1980-2009 baseline for Zvishavane, Zimbabwe (Lat -20.32 °, Lon 30.07°), representing southern Africa during October to March period which captures the southern hemisphere/austral unimodal summer season which is determined by rainfall, under RCP8.5. The chosen site represents a large portion of southern Africa which is semi-arid.

It is a confluence of the regional climate systems as it is affected by both tropical and mid-latitudes systems, such as the Inter-Tropical Convergence Zone (ITCZ), transient westerly cloud bands and the Temperate—Tropical Cloud bands. The methodology used and parameters investigated are the most critical for southern Africa, and is applicable to southern Africa. The site is part of a DPhil Thesis which investigated three sites for many future periods under RCP4.5 and RCP8.5.

Each GCM's projected percentage precipitation change is plotted against projected temperature changes and assigned to a quadrant by classifying it as either cool or hot and wet or dry relative to the 29 CMIP5 GCM multi-model ensemble's median precipitation and median temperature absolute change, respectively. This creates four quadrants (see **Figure 1a**): "cool/wet", "cool/dry", "hot/wet", "hot/dry". An additional fifth "Middle"/"Central" quadrant is created by grouping models whose projections are within the ensemble standard deviation

and multiplied by a factor ($\sigma=0.50$), meant to ensure an estimated 1/5th of GCM projections is selected.

One model (ideally closest to the quadrant centre of mass shown by a coloured dot in each quadrant in **Figure 1b**) is selected to represent GCMs in each quadrant. Some degree of subjectivity is allowed in the choice of representative after considering issues such as model consistency across time scales and RCPs, availability of comparative studies, models' ability to represent atmospheric circulations, or better representation of the class of model. For example, choosing a dryer and hotter model (than centre of mass) is preferred for dry/hot quadrant than choosing the wettest and coolest model in that quadrant. Diagonal and extreme skewness of each site's projections is assessed by checking if more than 60% ($\#GCMs > 17.4$) of the GCMs are in one diagonal orientation and if any quadrant has less than 20% of GCMs ($GCMs < 5.8$), respectively. Skewness and spread of projections which reflect model uncertainty is quantified by calculating each quadrant's weighting factor ($W_{quadrant}$) i.e. dividing the number of GCMs in each quadrant by the total number of GCMs in the ensemble ($W_{quadrant} = N_{quadrant}/N_{Total}$).

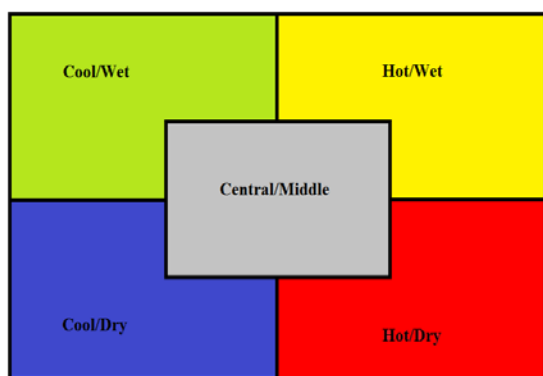


Figure 1a. Characterisation of GCMs using T & P Sub-setting Approach (Source: after Ruane and McDermaid, 2017)

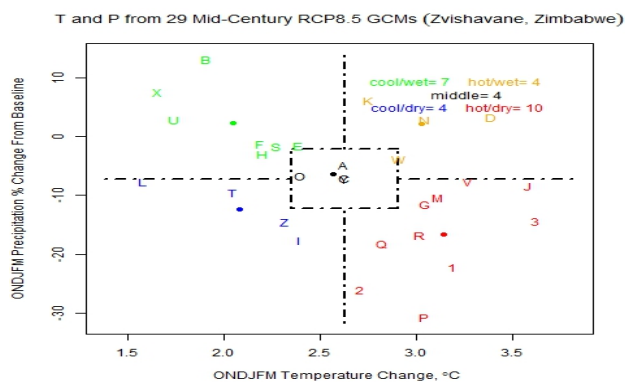


Figure 1b. Zvishavane RCP8.5 CMIP5 projected temperature and precipitation change (represented by AgMIP GCM IDs⁴) for the 2040-2069 period against

4 Legend

AgMIP CMIP5 GCM IDs

- | | |
|---------------------|--------------------|
| # A = ACCESS1-0 | # Q = MPI-ESM-LR |
| # B = bcc-esm1-1 | # R = MPI-ESM-MR |
| # C = BNU-ESM | # S = MRI-CGCM3 |
| # D = CanESM2 | # T = NorESM1-M |
| # E = CCSM4 | # U = FGOALS-g2 |
| # F = CESM1-BGC | # V = CMCC-CM |
| # G = CSIRO-Mk3-6-0 | # W = CMCC-CMS |
| # H = GFDL-ESM2G | # X = CNRM-CM5 |
| # I = GFDL-ESM2M | # Y = HadGEM2-AO |
| # J = HadGEM2-CC | # Z = IPSL-CM5B-LR |
| # K = HadGEM2-ES | # 1 = GFDL-CM3 |
| # L = Inmcm4 | # 2 = GISS-E2-R |
| # M = IPSL-CM5A-LR | # 3 = GISS-E2-H |
| # N = IPSL-CM5A-MR | |
| # O = MIROC5 | |
| # P = MIROC-ESM | |

1980-2009 baseline (Source: Authors own, after Ruane and McDermid, 2017)

Findings

Based on the model selection criteria described above, selected GCMs are: HadGEM2-ES (Hot/Wet), GISS-E2-H (Hot/Dry), GFDL-ESM2G (Cool/Wet), NorESM1-M (Cool/Dry) and ACCESS-1-0 (central), **Figure 1b**. Projections are exhibiting *hot/dry vs. cool/wet diagonal skewness* with the quadrant weights (W_q) suggesting the highest probable projections being hot/dry conditions (34%) (see **Table 1**).

Furthermore, the projected ensemble precipitation median is -8% and ‘dry’ models’ precipitation reductions are much larger projections than the wet models’ projected precipitation increase as the entire ensemble range is +12% to -34%. Precipitation projections are also more variable than temperature. All GCMs project varying degrees of temperature rise ranging from 1.6°C to 3.7°C with a median of 2.7°C. It is therefore critical to note that even GCMs regarded as cool according to the Approach are still projecting absolute temperature rise and GCMs regarded as wet may still be projecting precipitation reduction given the precipitation and temperature ensemble medians are -8% and 2.7°C respectively. The projected rates of warming and precipitation changes are above the Inter-governmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) global projected average precipitation rates (1 to 3% °C⁻¹) (Cubasch et al., 2013).

Table 1: Zvishavane CMIP5 representative GCMs and quadrant weights for 2040-2069 under RCP8.5 (Source: Authors own)

| Quadrant | Representative GCM | RCP8.5 Mid Century $W_{quadrant}$ |
|-----------|--------------------|-----------------------------------|
| Central | ACCESS 1-01 | 0.14 |
| Hot-Wet | HadGEM2-ES | 0.14 |
| Cool-Dry | NorESM1-M | 0.14 |
| Hot-Dry | GISS-E2-H | 0.34 |
| Cool- wet | GFDL -ESM2G | 0.24 |

HadGEM2-ES and GISS-E2-H models’ distinct and consistent hot/wet and hot/dry respective projections concur with Ruane and McDermid (2017)’s findings for southern Africa. Results, however, bring out the masking effect of averaging large regions; comparisons with Lutz et al.

(2016)'s precipitation CSIs for 18 CMIP5 GCMs for southern Africa show projected precipitation decrease (-27%), even for models such as HadGEM2-ES which are projecting rise (+7%) for these parts of the same region. This further stresses the need to understand models' projections for specific sites, seasons and periods, each model classification (relative to other GCMs within the ensemble), and possible sources of uncertainties before use of results in adaptation planning.

Conclusion

The approach allows objective selection of manageable representative GCMs which preserves the projection spread and enables passing on the confidence levels to impact assessments and adaptation planning. It enables determination of climate risk and possible adaptation solutions by showing probabilities of specific type of projections, including any skewness for specific geographic sites, Representation Concentration pathways (RCPs) and seasons. It also overcomes the masking effect of multi-model ensembles or averaging large spatial areas since the result shows that the projected precipitation changes for the specific sites vary greatly with GCMs and location in southern Africa. Furthermore, it also helps to design further analyses to understand the model physics, probability of certain projections and determination of current and future climate risks (climate prediction). CMIP5 projections show higher chances of a hot and dryer future climate for southern Africa which increases future climate predictability for better adaptation planning and policy-making. Whereas adaptation efforts consider the projections diversity and probabilities in adaptation planning, further research is needed to understand the physical basis of the differences in projections.

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References

- Cubasch, U., D. Wuebbles, D. Chen, M.C. Facchini, D. Frame, N. Mahowald, and J.-G. Winther, (2013). *Introduction*. Climate Change 2013: The Physical Science Basis. Contribution of WG1 to the Fifth Assessment Report of the IPCC. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- Hudson N. and Ruane A. C. (2013) *Guide for Running AgMIP Climate Scenario Generation Tools with R. AgMIP*, CCSR | Columbia University, New York.
- Lutz AF, ter Maat HW, Biemans H, Shresth AB, Wester P, Immerzeel WW (2016) Selecting representative climate models for climate change impact studies: an advanced envelope-based selection approach. *Int J Climatol* 36:3988– 4005. doi:10.1002/joc.4608.
- Semenov M.A., Stratonovich P. (2015). Adapting wheat ideotypes for climate change: accounting for uncertainties in CMIP5 climate projections. *Clim Res Vol* 65:123–139. doi:10.3354/cr01297.
- Ruane A. C, McDermid S. P. (2017) Selection of a representative subset of global climate models that captures the profile of regional changes for integrated climate impacts assessment. *Earth Perspectives* 4:1. SpringerOpen in Germany