ISSN 2250-3153

An evaluation of the performances of Global Climate Models (GCMs) for predicting temperature and rainfall in Zimbabwe

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Abstract: A global climate model (GCM) should be able to reproduce features of the distribution of the regional to local-scale climate in which it is applied. Such features include: the climatological mean, correlation, monthly or daily variance, thresholds, extremes etc, of the distribution of climate variables of interest. Most researchers need to know how GCM simulations vary depending on climatic variables, the choice of GCM and place. These variations can be understood by studying the descriptive statistics above, and inference can be made based on these sample statistics. However, there is no standard approach to test the features above in order to determine the skill of GCMs. In this paper, we focus on correlation and regression to evaluate the performances of five coupled global climate models for simulating monthly rainfall, minimum and maximum temperatures at five stations in northeastern Zimbabwe. We use observed historic climatic data (rainfall and air temperature) as well as downscaled model predictions of the same parameters. The global climate models used were the same as those used by the Intergovernmental Panel on Climate Change (IPCC) in formulating the IPCC Special Report on Emissions Scenarios (SRES). The GCMs were evaluated by comparing observed historic climatic data with hindcast downscaled model predictions. We use the error measures for correlation to assess model performance: coefficient of determination (R^2), root mean square error (RMSE) and model efficiency (ME). For each model, a t-test was performed at 5 % level of significance to assess the usefulness of the correlation between observed and simulated data. Comparison of the error measures reveals that the GCMs simulate temperature better than rainfall and therefore there is more confidence in predictions of temperature than rainfall. The performance of individual GCMs informs the research community of the need to select better GCMs for multi-model climate predictions. Global climate model performance varied from place to place i.e. the GCMs were site specific and therefore a GCM may need to be calibrated each time it is transferred to a different region.

Index Terms: *global climate model, correlation, error measures, inference*

1.0 Introduction

Despite limitations that lead to uncertainties, global climate models (GCMs) have consistently provided a robust and unambiguous picture of the climate system [1]. Currently, there is considerable confidence in global climate model simulations mainly because GCM principles are based on well established fundamental laws of physics such as conservation of mass, energy and momentum [2]. In addition, another source of confidence lies in the models' ability to simulate important aspects of the current and past climates as well as their changes [3]. Multi-model climate predictions have in recent years demonstrated that combining models generally increases the skill, reliability and consistency of model predictions [4]; [5]; [6]; [7]; [8]; [9]. A wide range of measures of climate model skill have been developed over the past decade for example, [10]; [11]; [12]; [13]; [14]. All provided measures of model skill using monthly to annual time-scale data, sometimes over ensemble means of several climate models. However there is no standard approach to determine the skill of GCMs. In this paper, we use a simple statistical approach, the correlation to study the skill of global climate models. Many researchers have recently been able to quantify GCM performance in simulating various climate variables [15]; [16]; [17]; [18]; [19]; [20], but such work has not yet received well documentation in Zimbabwe. We evaluate five GCMs for simulating monthly rainfall, minimum and maximum temperatures at some selected sites in Zimbabwe. The global climate models used were the same as those used by the Intergovernmental Panel on Climate Change (IPCC) in formulating the IPCC Special Report on Emissions Scenarios (SRES). Although more than five GCMs were available in the ensemble, our selection of the five was based on the following criteria: (i) only well established models were considered, those that are extensively described in peer-reviewed scientific literature [21]; [22]; [15] and (ii) only models that perform adequately in inter-comparison studies [23]. The paper is organized as follows: Section 2 describes the materials and methods used in this study. Main results and discussion are presented in section 3. Finally, conclusions are summarized in section 4.

2.0 Materials and Methods

2.1 The study area

The study was carried out in an agro ecological zone known as Natural Region 2 which is located in the middle of the north of Zimbabwe, covering parts of Harare, Mashonaland East, Mashonaland West, Mashonaland Central and Manicaland provinces. The region has a total area of 58600 km^2 which is about 15 % of the total area of Zimbabwe [24]. Data from five climatic stations: Karoi, Mutoko, Mt Darwin, Rusape and Wedza were used in this research. Table 1 shows the characteristics of the stations used in the study, while Figure 1 is a map of Zimbabwe showing all the natural regions with locations of the climatological stations overlaid.

Table 1 Characteristics of the stations used in the study

Station	Region	Location		Altitude (m)	Period for the observed data	
					Minimum/Maximum Temperature	Rainfall
Karoi	2a	16° 50´S	29° 37´E	1343	1971-2000	1970-2000
Wedza	2b	18° 37´S	31° 34´E	1384	1971-2000	1970-2007
Rusape	2b	18° 32´S	32° 08´E	1430	1971-2000	1970-2007
Mt Darwin	2b	16° 47´S	31° 35´E	965	1971-2000	1970-1999
Mutoko	2b	17° 25´S	32° 13´E	1244	1971-2000	1970-2003

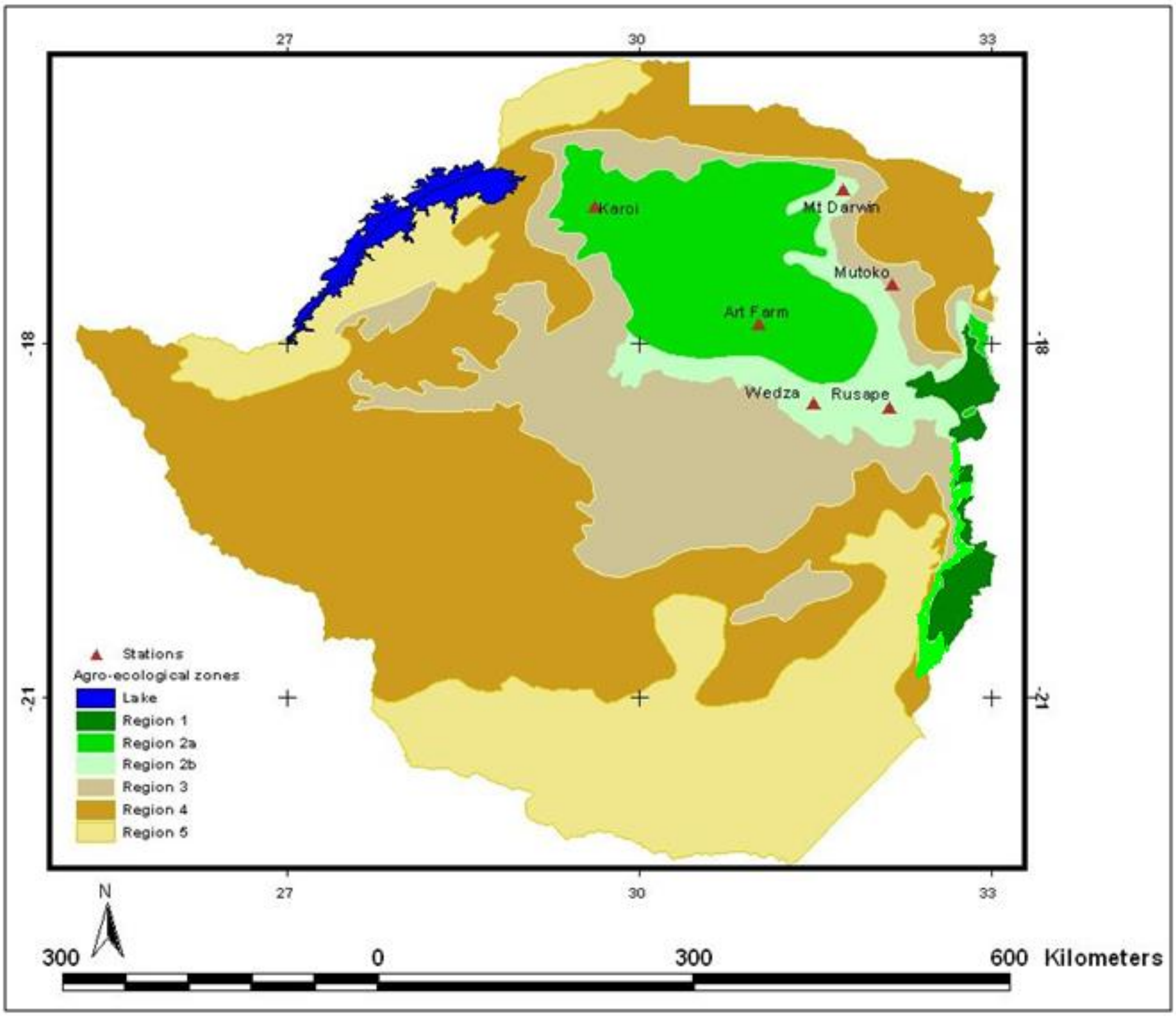

Figure 1: The study area, showing the locations of the climatological stations used in this study.

2.2 Sources and types of data

In this paper, we used observed as well as downscaled model data. Observed data was obtained from the Zimbabwe Meteorological Services Department (ZMSD). Downscaled data from five different global climate models from the Intergovernmental Panel on Climate Change Assessment Report (IPCC-AR4) was directly downloaded from the Earth System Grid (ESG) data portal (http://data.csag.uct.ac.za/) for the A2 socio-economic scenario.

Observed rainfall data were daily totals for the periods shown in Table 1. RAINBOW [25] was used to test the homogeneity of rainfall data for each station. RAINBOW is a software package for hydro meteorological frequency analysis and testing the homogeneity of historical data sets. All the stations confirmed homogeneity of rainfall data. The changes in rainfall for all stations were therefore assumed to have been caused by variations in climate only and not by factors such as changes in instruments, observation procedures, monitoring station relocations, changes of the surroundings, changes in calculation procedures, etc. Downscaled model data consisted of daily and monthly totals for the period 1961-2000. Observed temperature data were mean monthly minimum and maximum temperatures for the period shown in Table 1. Downscaled model data were average daily and monthly minimum and maximum temperatures over the same period.

2.3 Comparison of global climate model performances

The five GCMs used are listed in Table 2.

Table 2 Global climate models used in the study

Acronym	Name and Institute	Atmospheric resolution (latitude x longitude)
CCCMA_CGCM3_1	The third generation coupled global climate model (CGCM3.1 Model, T47). Canadian Centre for Climate Modelling and Analysis, Canada.	3.75 ° x 3.75 °
CSIRO_MK3_5	Mark 3.5 Model. Commonwealth Scientific and Industrial Research Organization, Australia.	1.88 ° x 1.88 °
GFDL_CM2_0	CM2.0 coupled climate model. Geophysical Fluid Dynamics Laboratory, United States.	2.0 ° x 2.5 °
GISS_MODEL_E_R	ModelE20/Russell. Goddard Institute for Space Studies, United States.	4.0 ° x 5.0 °
MPI_ECHAM5	European Centre Hamburg Model. Max Planck Institute for Meteorology, Germany.	1.88 ° x 1.88 °

All the models listed in Table 2 are based on the A2 climate change scenario. According to [26], the A2 scenario is characterized by heterogeneity, self reliance, an emphasis on local identities and global population increases continuously, reaching over 10 billion by 2050. Economic development is regionally oriented and economic and technological development is relatively slow for the A2 scenario as compared to the other scenarios.

The performances of the models were evaluated by comparing hindcast model simulations with observed climatic data separately for rainfall, minimum and maximum temperature. It was then possible to determine the variation in prediction skill across models as well as variation in skill due to change of climatic variable. Each model data set was compared with observational data and the results statistically analyzed. We applied the error measures of correlation:

2.3.1 Coefficient of determination (R^2)

A scatter plot of observed against model data in EXCEL clearly demonstrated the relationship between the two variables. The closeness of the relationship was assessed by the coefficient of determination (R^2).

2.3.2 Model efficiency (ME)

The efficiency of each model to simulate the variables was calculated for each of the five models. The ME approach [27] is computed as:

$$\mathrm{ME} = 1 - \frac{\sum_{i=1}^{n} (O_i - M_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O}_i)^2} \quad (1)$$

where ME is model efficiency, O_i is an elementary observation in the observed data set (n observations), $\bar{O}_i$ is the mean of i observations and M_i represents an elementary observation in the modelled dataset (n predictions).

2.3.3 Root mean square error (RMSE)

The RMSE for each model for simulating the variables was calculated. The RMSE approach is computed as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (O_i - M_i)^2}{n}} \quad (2)$$

A t-test was carried out at 5 % level of significance to assess the reliability of the null hypothesis (H_o) which was formulated as follows: observed and simulated data are not significantly different. A two tailed test was performed for each pair of data set. The null hypothesis was rejected when the t-value obtained (t_{stat}) was greater than t-critical (t_α). That is, H_o was rejected when $|t_{stat}| > t_\alpha$ otherwise it was not rejected. The value of t_α was 2.25. Model performance was judged by the magnitude of the coefficient of determination (R^2), root mean square error (RMSE), model efficiency (ME) and the t-value.

3.0 Results and discussion

3.1 Minimum air temperature

The statistics used to assess global climate model performance in simulating minimum temperature are shown in Table 3.

Table 3: Quantitative measures of the performance of the five global climate models for simulating minimum temperature at the 5 stations

Statistic	Station	CCCMA_CGCM3_1	CSIRO_MK3_5	MPI_ECHAM5	GFDL_CM2_0	GISS_MODEL_E_R
R^2	Karoi	0.92	0.89	0.88	0.82	0.69
	Wedza	0.89	0.85	0.79	0.76	0.73
	Rusape	0.87	0.84	0.84	0.81	0.69
	Mt Darwin	*	*	*	*	*
	Mutoko	0.86	0.81	0.77	0.69	0.67
ME (%)	Karoi	91.72	87.17	85.9	78.23	66.05

	Wedza	88.89	82.86	74.98	74.33	71.36
	Rusape	86.73	83.44	81.56	77.13	67.2
	Mt Darwin	*	*	*	*	*
	Mutoko	85.33	80.2	77.13	78.56	83.44
RMSE	Karoi	3.21	3.08	2.88	2.58	2.32
	Wedza	2.88	2.66	2.46	2.48	2.36
	Rusape	3.81	3.47	3.3	3.19	2.89
	Mt Darwin	*	*	*	*	*
	Mutoko	3.81	3.49	3.19	3.66	3.47
t_{stat}	Karoi	-0.07	7.23	-5.5	-5.6	-2.34
	Wedza	-2.1	-6.04	-6.06	-1.69	-0.64
	Rusape	-1.76	4.61	-6.44	-6.44	-2.09
	Mt Darwin	*	*	*	*	*
	Mutoko	-1.16	-1.79	-6.44	-6.44	4.61

* Missing data

At Karoi, the CCCMA_CGCM3_1 model showed the greatest values of R^2, ME and RMSE as shown in Table 3. We failed to reject the null hypothesis at 5 % level of significance as $|t_{stat}| < t_{\alpha}$. The GISS_MODEL_E_R model showed the smallest values of R^2, ME, RMSE and H_o was rejected. For the remaining models, H_o was rejected ($|t_{stat}| > t_{\alpha}$) at Karoi indicating that they did not perform well in simulating minimum temperature at the station. The CCCMA_CGCM3_1 model therefore obtained the highest performance for simulating minimum temperatures at this station.

Values of R^2, ME and RMSE were greatest for the CCCMA_CGCM3_1 model at Wedza and we also failed to reject H_o for this model. Although we failed to reject H_o for the CSIRO_MK3_5 and the GISS_MODEL_E_R models; the coefficient of determination, model efficiency and root mean square error values were however smaller that those obtained for the

CCCMA_CGCM3_1 model. The CCCMA_CGCM3_1 model showed the greatest skill for simulating minimum temperatures at Wedza.

Rusape minimum temperatures were best simulated by the CCCMA_CGCM3_1 model. Although H_o was not rejected for the GISS_MODEL_E_R model at Rusape, the R^2, ME and RMSE values for this model are weaker than those of the former, thus making the CCCMA_CGCM3_1 model the best.

The statistical measures were greatest for the CCCMA_CGCM3_1 model at Mutoko and we failed to reject H_o for this model. Although H_o was also not rejected for the GISS_MODEL_E_R model; its statistical measures were smaller than those obtained for the CCCMA_CGCM3_1 model.

3.1.2 Maximum air temperature

The statistics used to assess global climate model performance in simulating maximum temperature are shown in Table 4.

Table 4: Quantitative measures of the performance of the five global climate models for simulating maximum temperature at the 5 stations

Statistic	Station	CCCMA_CGCM3_1	CSIRO_MK3_5	MPI_ECHAM5	GFDL_CM2_0	GISS_MODEL_E_R
R^2	Karoi	0.67	0.61	0.61	0.56	0.4
	Wedza	0.69	0.63	0.58	0.56	0.33
	Rusape	0.67	0.6	0.6	0.59	0.38
	Mt Darwin	0.68	0.62	0.6	0.54	0.42
	Mutoko	0.78	0.71	0.68	0.66	0.62
ME (%)	Karoi	64.6	60.24	49.15	54.68	37.33
	Wedza	60.78	60.45	57.82	54.57	28.48
	Rusape	62.36	59.9	55.28	58.24	36.66
	Mt Darwin	63.95	61.79	44.55	52.37	41.27
	Mutoko	68.2	65.11	57.83	64.35	50.24
RMSE	Karoi	2.31	1.91	1.58	1.49	1.77
	Wedza	2.74	2.19	2.09	2.18	1.98
	Rusape	2.74	1.97	1.92	2.16	1.93
	Mt Darwin	2.55	2.05	1.61	1.81	1.89
	Mutoko	2.41	1.99	1.71	1.83	1.75

t_{stat}	Karoi	-1.48	-3.23	9.73	0.81	-3.24
	Wedza	-2.22	-4.54	-0.86	-3.53	-3.58
	Rusape	-0.91	0.17	6.38	-2.66	-3.08
	Mt Darwin	2.21	-0.05	10.9	3.6	-0.63
	Mutoko	2.11	3.62	-4.95	-0.31	3.91

At Karoi, the CCCMA_CGCM3_1 model best resembled observations. H_o was not rejected for the GISS_MODEL_E_R model; however the weaker statistics showed a lesser skill as compared to the CCCMA_CGCM3_1 model.

The greatest values of R^2, ME and RMSE for the CCCMA_CGCM3_1 model that are shown in Table 4 indicate the highest skill in simulating maximum temperatures at Wedza.

At Rusape, all other models did not perform well in simulating maximum temperatures at the station and the CCCMA_CGCM3_1 model showed the highest skill. Although the null hypothesis was not rejected for the GISS_MODEL_E_R model, its statistical measures were weaker than those of the CCCMA_CGCM3_1 model.

Maximum temperatures at Mt Darwin were best simulated by the CCCMA_CGCM3_1 model as shown by the statistics in Table 4. All other models performed poorly in simulating temperatures at Mt Darwin. The CCCMA_CGCM3_1 model however showed weaker values of R^2, ME and RMSE in simulating maximum temperature as compared to the same statistical quantities for simulating minimum temperature. This indicates that its skill in simulating minimum temperatures in higher than the skill for simulating maximum temperatures

The CCCMA_CGCM3_1 model showed the greatest skill for simulating maximum temperatures at Mutoko as shown by the statistical measures in Table 4.

We failed to reject the null hypothesis at all stations for the CCCMA_CGCM3_1 model. This is confirmed by the t-values obtained in the significance tests. The CCCMA_CGCM3_1 model therefore obtained the highest performance for simulating both minimum and maximum temperature at all stations. The GISS_MODEL_E_R model showed weaker values of R^2, ME and RMSE; however for this model, H_o was not rejected at Wedza, Rusape and Mutoko for simulating minimum temperature and was also not rejected at Wedza, Rusape, Mutoko and Karoi for simulating maximum temperature. This model was second in simulating both minimum and maximum temperature. For the MPI_ECHAM5 model, H_o was not rejected only at Mt Darwin for simulating maximum temperature. For the CSIRO_MK3_5 model, H_o was not rejected only at Wedza. The GFDL_CM2_0 model performed well in simulating maximum temperature at Mt Darwin only and it performed poorly for all other stations.

3.1.3 Rainfall

Summary statistics used to assess global climate models' performances in simulating rainfall are shown in Table 5.

Table 5: Quantitative measures of the performance of the five global climate models for simulating rainfall at the 5 stations

Model	CCCMA_CGC	CSIRO_MK3	MPI_ECHA	GFDL_CM2	GISS_MODEL_

Statistic	Station	M3_1	_5	M5	_0	E_R
R^2	Karoi	*	*	*	*	*
	Wedza	0.33	0.22	0.39	0.18	0.32
	Rusape	0.33	0.37	0.42	0.21	0.31
	Mt Darwin	0.33	0.41	0.42	0.41	0.35
	Mutoko	0.36	0.43	0.35	0.3	0.39
ME (%)	Karoi	*	*	*	*	*
	Wedza	33.97	10.93	18.33	39.92	49.21
	Rusape	15.73	29.11	51.45	24.3	17.22
	Mt Darwin	26.63	23.01	32.13	46.51	20.08
	Mutoko	30.06	22.25	10.38	38.62	13.14
RMSE	Karoi	*	*	*	*	*
	Wedza	72.9	66.4	89.4	65.3	73.2
	Rusape	52.7	64.5	64.6	40	51.9
	Mt Darwin	55.8	76.8	73.2	66.6	55.3
	Mutoko	53	71.4	72.6	46	53.2
t_{stat}	Karoi	*	*	*	*	*
	Wedza	3.69	2.67	-0.59	1.51	0.04
	Rusape	6.54	3.28	3.16	6.04	3.94
	Mt Darwin	-7.25	-11.01	-10.54	-2.19	-10.98
	Mutoko	-7.28	3.66	4.82	-10.12	4.61

* Missing data

The statistical measures are very low for all the models at Wedza; however the null hypothesis was not rejected for the GFDL_CM2_0, GISS_MODEL_E_R and the MPI_ECHAM5 models. The statistical indicators show that the null hypothesis was rejected for all the models at Rusape thus the models performed poorly in simulating rainfall at this station.

All models performed poorly in simulating rainfall at Mt Darwin. This is shown by the weak values of R^2 and low values of ME and RMSE for each model in Table 5. The null hypothesis was not rejected only for the GISS_MODEL_E_R model thus making it a better GCM amongst the five models. It is interesting to note that the CCCMA_CGCM3_1 model which best simulated temperature at Mt Darwin was found to be the worst for simulating rainfall at the same station. Table 5 shows inaccuracy of all climate models in simulating rainfall at Mutoko. Results of the analysis showed that all the models are poor in predicting rainfall for all the stations. Inaccuracy of global climate models to predict precipitation was reported by many researchers. [28] point out that that the space-time correlation between models and observations is small, only about 50 to 60 %, particularly in the tropics where the spatial variation of precipitation is great. According to [29], strong horizontal gradients in the field lead to a significant drop in correlations between model output and observations. Another discrepancy between models and observations is that when precipitation is categorised into light, moderate and heavy, models reproduce the observed extent of moderate precipitation (10 to 20 mmday^{-1}) but underestimate that of heavy precipitation and overestimate the extent of light precipitation [30]. [31] report that for precipitation, the Geophysical Fluid Dynamics Laboratory (GFDL) model reveals significant widespread errors in the tropics, mostly in the Intertropical Convergence Zone (ITCZ) where precipitation is underestimated by several millimetres per day. However, despite these shortcomings, the GISS_MODEL_E_R showed relatively better skill for predicting rainfall at Mt Darwin, Karoi and Mutoko, while the MPI_ECHAM5 and the GFDL_CM2_0 models were skilful at Wedza and Rusape, respectively.

4.0 Conclusions

We evaluated the performances of five global climate models for simulating rainfall, minimum and maximum temperature. The three main questions were centred on the variation of GCM skill with climatic variable, choice of GCM and place. The results indicate that most GCMs can reproduce the observed temperature better than rainfall and that the difference between the rainfall predictions from the different GCMs can be significant. The CCCMA_CGCM3_1 model was shown to be a better performing GCM amongst the five. Global climate models are place sensitive; a GCM that performs well in one region may not do the same when transferred to a different region.

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