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The Minimum and Maximum Temperature Forecast Using Statistical Downscaling Techniques for Port-Harcourt Metropolis, Nigeria

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Abstract

This study centers on applying the statistical downscaling technique to the daily minimum and maximum temperatures of Port Harcourt from the period 1985-2014. To select the period of calibration, the wilby and wigley assumption of 2014 was adopted. However, the Bruckner circle assumption was adopted in selecting the normal under review. Secondary data of minimum and maximum temperatures for Port Harcourt were collected from the archive of Nigerian meteorological agency (NIMET). The grid cell of the HadCM3 corresponding to the Port Harcourt meteorological station was selected from the HadCM3 website to generate the largescale predictors. Data for temperature was there after normalized for the period of calibration. To analyze data, ANOVA and Paired t tests were used. Result showed that, the model was significant at $p < 0.05$ implying that the largescale predictors of the HadCM3 have performed significantly and that temperature pattern in the area is significantly dependent on them. The Duncan statistics showed that in the A2 scenario Maximum temperature will rise with a mean difference of 3.1˚C from 1960-2080, while for B2 the increase will be 0.18˚C for same period. For minimum temperature, the ANOVA also showed a difference of 0.21˚C and 0.11˚C for A2 and B2 respectively. The paired t test statistics showed that these variations in temperatures for both maximum and minimum at A2 and B2 scenarios are significant at $p < 0.05$. Reforestation, afforestation, carbon sequestration are strongly advocated.

Keywords

HadCM3, Temperature, Downscaling, Port–Harcourt, Normal

1. Introduction

Temperature has been described to be the degree of hotness or coldness of a body. The degree to which the temperature of a body reaches, that is how hot or cold a body can reach can be caused by a factor or a number of factors. These factors may range from terrestrial to atmospheric or in another classification, natural and anthropogenic factors. The natural factors of temperature change include continentality, elevation, flow of surface winds and vorticity, changes in waves and ocean currents etc. while the manmade causes range from deforestation, use of power generating sets, and other combustive engines and activities that emits greenhouse gases into the atmosphere.

The rate of change in the global temperature since the industrial revolution era is alarming and if nothing is done there will be grave consequences, which will range from climate change, species selection or extinction droughts and dehydration to large scale migration or even deaths of humans. To be able to understand the enormity of the problem, that changing patterns of temperature is going to cause and what implication(s) it is going to have for social and natural systems, adequate investigation of climate elements is needed [1] [2] [3] [4]. This has led several authors in the literature to investigate climate elements in terms of variability, patterns amount and degree.

The intergovernmental panel on climate change has been working on several General Circulation Model projects (GCMS), some of which are CORDEX, CMIP2, CGCM, NCEP, RegCM2, HadCM2, HadCM3 etc. The reason behind the provision of these GCMs is to provide climate based information to scientists and non-scientists globally. However, the resolutions at which these GCMs are coupled are too coarse or large to provide information that will be relevant at local scale for sectors that are climate dependent, hence the need to downscale [4]-[9].

Downscaling has emerged as a method in climatological research, because of its ability to provided climate information at resolutions that make the outcome useable for impact studies at regional, sub-regional, local and point scales. Generally, there are two types of downscaling, dynamic and statistical downscaling [10] [11] [12]. However, the paper is concerned with statistical downscaling. Statistical downscaling method lies in the ability to use the properties of the free atmosphere as predictors of the local climate elements (which are called the predictand). Information on the large-scale predictors may be generated from direct weather observation or from some climate model output, yet downscaling as a technique is yet termed very important [13] [14], because of the usability of findings for climate impact and risks assessments.

Generally, there have been several to apply the downscaling technique to the investigation of climate parameters with a view to projecting future impacts based on some scenarios attempts [10] [14] [15] [16] [17] [18]. However, the only attempt in literature for West Africa is the one done by [19] which used HadCM2 in their study. There is paucity of information on statistical downscaling techniques especially using HadCM3 which was coupled at a higher resolution for projecting temperature at different scenarios in West Africa and indeed in Nigeria. This is the gap in the literature which this study intends to fill. Therefore, the thrust of the work is to downscale temperature for the two scenarios present in the HadCM3 data set with a view to projecting future impacts on minimum and maximum temperature based on the adoption of either pathways.

2. Materials and Methods

This study was carried out in Port Harcourt, which is located within longitude 6˚56'E and 7˚03'E and latitude 4˚43'N and 4˚54'N of the equator. The area is bordered to the North by Obio/Akpor Local Government area, to the South by Okrika, to the East by Eleme and to the West by Degema Tour Local Government Areas [20] and [21]. In terms of drainage, the area is drained by Bonny River with an average elevation of about 18 m above sea level [22] [23]. Port Harcourt lies in the sub-equatorial region, with the tropical monsoon climate which has high temperatures, low pressure and high relative humidity throughout the year. Rain is also experienced all year round. This particularly makes waste management in the area so difficult due in part to the waste management practice which is still very crude. The weather of the area among other local forcing is influenced by mT and cT airmasses [24]. The population of the area has witnessed such tremendous growth over the years without corresponding improvement in social infrastructures. This partly accounts for the poor sanitation conditions in the area. For example, estimates showed that the population of the area was around 500 people as at 1915 which rose to 30,200 in 1944. The population was 179,563 as at 1963 and in 1973 rose to become 231, 532 people. The 1991 census put population figure of Port Harcourt at 440,399 people which rose to 1,255,387 persons in 2006 census [25], by using the growth rate of 5.8%, the population is projected to be 2,085,204 in 2015 [20].

In terms of method, the study adopted the expost-facto research design, and Secondary data of temperature for Port-Harcourt was collected from the archive of Nigerian meteorological agency (NIMET) at Oshodi Lagos. On the other hand, large scale predictors data were collected from the HadCM3 website. To be able to identify the grid cell of the HadCM3 corresponding to the station at Port Harcourt, the grid cells of the HadCM3 was first super imposed on the Niger delta region and the grid cell corresponding to Port Harcourt was selected. However, the Bruckner circle assumption was adopted in selecting the normal under review. To select the period of calibration the [26] which stipulates that the calibration period be taken within half of the observation period but not more than the NCEP predictor period of 2001 (for HadCM 3). Since there were about 26 large scale predictors they needed to be first screened using Pearson's product moment correlation (PPMC) in the SDSM environment, so that the predictors that performed significantly with the predictor were selected for calibration (see Table 1). After selection of the predictors calibration of the model was carried out. However, there were various predictors predicting minimum and maximum temperature or even mean temperature, see Table 2. After calibration, the modeled data was synthesized and 20 assembles were created. After which a future temperature of the area was generated using the two scenarios in the HadCM3 predictor file in the SDSM version 4.2.9 environment. The analysis of variance was used to identify the variation in minimum and maximum temperature amounts over the years while, the paired t test was used to identify the difference between the B2 and A2 scenarios to see if there was a significant difference and what to expect from which ever pathways in Port-Harcourt using SPSS.

3. Results and Discussions

Table 1 refers to the yardsticks for selection of the predictors, for the study. In the table MSLP (r-0.384, Pr-0.326, $P < 0.05$) and Zaf (r-0.340, Pr-0.317, $P < 0.05$) were selected for the calibration of Maximum temperature. Predictors for minimum temperature MSLP (r-0.54, Pr-0.426, $P < 0.05$) and Temp.af (r-0.62, Pr-0.43, $P < 0.05$); and finally mean temperature had the following predictors, MSLP (00.511, Pr-0.395, $P < 0.05$), Temp-af (r-0.485, Pr-0.397, $P < 0.05$) and r500 (r-0.559, Pr-0.369, $P < 0.05$). These large-scale predictors have also been used for analysis by [27]. Furthermore, they also show some scientific and rational relationship with the predictands (Mean, maximum & minimum temperature). Again, the predictors were all significant at $P < 0.05$.

Table 1. Selected predictors for Tmax and Tmin en-route to calibration of the model for Port Harcourt city.

Temperature	Predictor and r values	Partial correlation	*P*. Value 0.05
Maximum temperature	Mslp-0.384	0.326	0.0000
	Zaf-0.340	0.317	0.0004
Minimum temperature	Mslp-0.54	0.426	0.0000
	Temp.af-0.62	0.431	0.0000
Mean temperature	Mslp-0.511	0.395	0.0000
	r500-0.559	0.369	0.0000
	Temp.af-0.485	0.397	0.0000

Table 2. Performance assessment of SDSM output and observed data during validation (1986-2001) for maximum and minimum temperature, in Port-Harcourt.

Temperature characteristics	r values	*P* value 0.05
Mean temp	0.76	0.0000
Max	0.87	0.0000
Min	0.84	0.0000

This therefore reveals a statistical significance hence they were selected for calibration. They also signify the determinants of temperature in Port Harcourt under the various GHGs forcing of the NCEP 1960-2099 experiment.

Table 2 shows the performance of the SDSM when comparing the modeled data with that of the observed data. The performance of the model shows that there is a significant relationship between the modeled and observed Tmax (r-0.87, $P < 0.05$); Tmin (r-0.84, $P < 0.05$) and mean temperature (r-0.76, $P < 0.05$). This method of validation has been used by [28], but it however varies from the one adopted by [29].

However, the statistical significance in the modeled and observed data (at $P < 0.05$) justified the use of this method to validate the modeled data.

Table 3 explains the characteristics of maximum temperature in Port Harcourt between 1960-2080. The Anova model is significant at $P < 0.05$ revealing that, there has been a change in the maximum temperature characteristics in the area and that there will continue to be some changes in the future. This is reveled in Table 4 where the Duncan statistics is computed.

In the Table 4, the first normal (1960-1990) and the second normal (1990-2020) had only the temperature difference of 1.112˚C and r value of 0.56, thereby revealing that the changes were yet minimal at those normals. However, between 2020 and 2050 maximum temperature of the area will yet rise at 1˚C per normal. By 2050 the maximum temperature of the area will yet increase to 34.9851˚C which is a 1.0132˚C rise from 2050 and a 3.13˚C rise from mean

Table 3. ANOVA analysis of Maximum temperature 1960-2080 A scenario.

Temperature	Sum of squares	df	Mean square	F	Sig.
Between groups	329.003	3	109.678	43.700	0.000
Within groups	108413.754	43196	2.510		
Total	108742.787	43199			

Table 4. Duncan statistics showing variation in maximum temperature patterns 1960-2080 for A scenario.

Duncan[a]				
Identifiers	N	Subset for alpha = 0.05		
		1	2	3
1.00	10800	31.855		
2.00	10800	32.967		
3.00	10800		33.9719	
4.00	10800			34.9851
Sig.		.56	1.000	1.000

Means for groups in homogeneous subsets are displayed. a. Uses Harmonic Mean Sample Size = 10800.000.

maximum temperature from the 1960-1990 normal. This is particularly dangerous for dwellers in the city of Port Harcourt.

Table 5 shows the maximum temperature characteristics in Port Harcourt for B2 scenario. From the table it is lucid that maximum temperature has significantly changed from 1960-2050 at $p < 0.05$.

However, to check where the difference lies we refer to Table 6.

In the Table 6 the normal 1960-2050 mean maximum temperature was 31.74˚C while the normal 1990-2020 and that of 2050-2050 have a relationship of 0.77 and hence in the same category with temperature of 31.8˚C and 31.84˚C. However, the normal with the highest temperature is that of 2050-2080 which has a temperature of 31.93˚C. There by representing a temperature increase of 0.1844˚C or 0.18˚C from 1960-2080.

In Table 7 the paired statistics shows a mean difference of 3.1˚C for the A2 and B2 scenarios. This assertion is also significant at $P < 0.05$ (see Table 8) showing that there is a significant difference between mean temperature at different normal from 1960-2080.

4. Minimum Temperature Analysis

There is a significant difference in minimum temperature between 1960 and 2080 at $p < 0.05$ (see Table 9). Although to show where the difference lies, we see Table 10. In that table the minimum temperature is projected to charge and

Table 5. ANOVA analysis of Minimum temperature 1960-2080 B scenario.

Temperature	Sum of squares	df	Mean square	F	Sig.
Between groups	192.849	3	64.283	25.508	0.000
Within groups	108858.227	43196	2.520		
Total	109051.076	43199			

Table 6. Duncan statistics showing variation in maximum temperature patterns 1960-2080 for B scenario.

Temperature_parameters				
		Duncan[a]		
		Subset for alpha = 0.05		
Identifiers	N	1	2	3
1.00	10800	31.7468		
2.00	10800		31.8085	
3.00	10800		31.8467	
4.00	10800			31.9312
Sig.		1.000	0.77	1.000

Means for groups in homogeneous subsets are displayed. a. Uses Harmonic Mean Sample Size = 10800.000.

Table 7. Paired statistics for maximum temperature A and B scenarios.

Paired Samples Statistics					
		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	B Scenario	31.9333	43200	1.58883	0.00764
	A Scenario	34.9823	43200	1.58659	0.00763

Table 8. Paired statistics for maximum temperature A and B scenario.

Paired Samples Test									
		Paired Differences							
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	Df	Sig. (2-tailed)
					Lower	Upper			
Pair 1	B Scenario-A Scenario	3.1342	0.97034	0.00467	−0.02820	−0.00990	−4.080	43199	0.000

Table 9. ANOVA analysis of Minimum temperature 1960-2080 A scenario.

ANOVA					
Min_tempt.					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	278.826	3	92.942	224.266	0.000
Within Groups	17901.596	43196	0.414		
Total	18180.422	43199			

Table 10. Duncan statistics showing variation in minimum temperature patterns 1960-2080 for A scenario.

A scenario Min_tempt					
Duncan[a]					
Identifiers	N	Subset for alpha = 0.05			
		1	2	3	4
1960-1990	10800	23.3900			
1990-2020	10800		23.4253		
2020-2050	10800			23.5029	
2050-2080	10800				23.6092
Sig.		1.000	1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed. a. Uses Harmonic Mean Sample Size = 10800.000.

mean minimum temperature charged from 23.39˚C in 1960-1990 to 23.6˚C in 2050 revealing a temperature charge of 0.21˚C in minimum temperature. This however partially explains the changes in night-time temperature pattern in the Port-Harcourt city.

In Table 11, the B2 scenario shows that minimum temperature has also changed significantly from the 1960 period till 2080 at $P < 0.05$. This rate of changes can be identified in Table 12.

The rate of change from 1960-2080 showed that every normal is statistically significantly different from each other and the temperature (minimum) change is 0.11˚C.

In Table 13, the comparison between A2 and B2 minimum temperature is shown, from the table. It is clear that if Port Harcourt city has a temperature difference of 0.45˚C, in terms of minimum temperature in the A2 and B2 scenario. This temperature difference is also significant at $P < 0.05$ (see Table 14), which means that there is a significant difference in the minimum temperature over the years between A2 and B2 scenarios.

Table 11. ANOVA analysis of Minimum temperature 1960-2080 A scenario.

ANOVA					
Min_temp					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	169.003	3	56.334	143.297	0.000
Within Groups	17414.019	44296	0.393		
Total	17583.022	44299			

Table 12. Duncan statistics showing variation in minimum temperature patterns 1960-2080 for B scenario.

Min_temp					
Duncan[a,b]					
Identifiers	N	Subset for alpha = 0.05			
		1	2	3	4
1960-1990	10800	23.3908			
1990-2020	10800		23.4509		
2020-2050	10800			23.4824	
2050-2080	11900				23.5099
Sig.		1.000	1.000	1.000	1.000

Means for groups in homogeneous subsets are displayed. a. Uses Harmonic Mean Sample Size = 11055.484. b. The group sizes are unequal. The harmonic mean of the group sizes is used.

Table 13. Paired statistics for minimum temperature A and B scenarios.

Paired Samples Statistics					
		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Scenario A	23.4794	43200	0.64873	0.00312
	Scenario B	23.0209	43200	0.62464	0.00301

Table 14. Paired statistics for minimum temperature A2 and B2 scenarios.

Paired Samples Test									
		Paired Differences					T	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Scenario A–Scenario B	0.4544	0.55318	0.00266	0.00222	0.01265	2.794	43199	0.005

5. Conclusions

Table 1 shows the predictors that were selected for the study. This selection was based on the correlation and partial correlation analysis values as displayed from the correlation runs and the level of significance realised in the SDSM environment (see **Table 1**). These variables also show consistency with the physical and climatological controls in the study area, the analysis of which has also been analysed and consistent with the findings of [10] [30]. However, during calibration, the correlation method was utilized. More so, the validation of the model was based on correlation values between observed and that of modelled data (see **Table 2**). The model is therefore valid and thus shows that the selected predictors explain the pattern of temperature in the area.

The variation in daily maximum and minimum temperature reveals that there are higher temperature characteristics in the A2 scenario than in the B2 scenario. It therefore follows that the following urgent steps must be taken to restore effective temperature characteristics in the area.

1. Reforestation and afforestation of the area are recommended. This is because the trees still serve as one of the surest source of carbon sink in the environment. This is different with the current practice in the region where it is a show of affluence to cut down trees and replace them with concreted surfaces. This act will lower the concentration of GHGs in the environment.
2. Sequestration of carbon and other oxides by introducing an effective and efficient transport system in the area. This may include introduction of mass transport schemes such as midi buses, luxury buses, and efficient rail system. By so doing the number of combustive engine will reduce since residents of the area will be advised to use the transport system.

3. Generally, there is need to create a GCM with a higher resolution than that of the HadCM3 which will synchronize all the local features that determine local climate.
4. Activities that increase the amount of GHGs in the atmosphere, such as deforestation, use of wood as such of energy, use of power generating sets need to be stopped immediately in the city.

When these and more are done, there will be a reduction in temperature in the city of Port Harcourt as expressed in B2 scenario and hence a safer and more comfortable environment in the city.

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