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DISMANTLING UNCERTAINTIES ASSOCIATED WITH RAINFALL PROJECTION USING STATISTICAL DOWNSCALING TECHNIQUES UNDER CLIMATE CHANGE SCENARIOS

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Abstract: Downscaling is a quantitative way of relating the large-scale climatic predictor variables to the local scale meteorological variables to overcome the ineffectiveness of the GCM model output. However, despite the high relevance and sophistication of this new method in climatological studies, the results are not completely free of uncertainties. The aim of the study was to assess the level of uncertainties associated with rainfall projection using statistical downscaling techniques under climate change scenarios over the south-south region, Nigeria. The expost-facto research design was adopted for the study while the quadrat sampling technique was used to determine the sample size by stratifying the area into 2° x 2° latitude and longitude intersections and each weather station that fall within the grids (Asaba, Warri, Uyo and Port Harcourt) was calibrated and selected for the study. Data used for this study were mainly secondary data and it includes 30 years rainfall data (1985-2015) which was acquired from the archives of Nigerian Meteorological Agency (NiMet) and large-scale predictors assessed from the archives of the National Centre for Environmental Prediction (NCEP). The Multiple Regression Analysis was used in the selection of large-scale predictors with strong relationship with the predictand. Consequently, shum, rhum, r850, r500, p5_u, p_u, & p5th were selected as the principal large-scale predictors of rainfall in the area. On the other hand, Wilcoxon signed rank test was employed to perform the uncertainty analysis and the results shows uncertainty associated with rainfall projections in the area at $P<0.05$ in some of the months. The validation process reveals R and RMSE ranging between, R (0.64-0.91) and RMSE (0.11-0.43) indicating a better performance of the model on seasonal timescale particularly in Asaba at DJF, Warri in JJA while Port Harcourt and Uyo in SON. Based on the findings of the study, development of a local climate management system in preparedness for climate change, climate change planning and policy formuations and committed efforts to maintain B2 scenario with reduced GHG's emission were recommended.

Keywords: Uncertainties, Projection, Rainfall, Scenarios, Climate Change.

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Introduction

Rain is liquid water in form of droplets that have condensed from atmospheric water vapour, it then becomes heavy enough to fall under gravity. Rain is not only the most popular form of precipitation, but also the most variable component of the climate system and has a vital role in equal balancing of surface and sub-surface water resources through the hydrologic cycle process in nature. Rainfall is a vital weather element which can give information on the state of an environment (Afangideh *et al.*, 2010). In a related development, rainfall is an important weather and climate parameter that affects socio-economic livelihood of people within the global community. It is one of the most important climatic variables because of its two-sided effects - as a deficient resource, such as droughts and as a catastrophic agent, such as floods. It is believed that the climate system will continue to change under the prevailing human activity and that humanity will be faced with more of these extreme events (Yang *et al.*, 2011). This situation therefore prompts the increasing concern and studies on changes in frequency, intensity, and/or magnitude of such events in the past and for estimating climate that will occur in the future. Thus, Global Climate Models (GCMs) are essential to study global patterns of temperature, precipitation, and upper-ocean heat content in response to changes in the concentration of greenhouse gases and variations in the composition of the atmosphere, Intergovernmental Panel on Climate Change (IPCC), (2021). General Circulation Models (GCMs) are the main state-of-the- science source for information about future climate change. However, the outputs from GCMs tend to be spatially coarse and biased for application at local scales (Benestad, 2010; Di Luca *et al.*, 2012; Li *et al.*, 2010; Mehrotra & Sharma 2010; Piani *et al.*, 2010; Shiru *et al.*, 2019). Although, there is essential advancements in GCMs application with satisfactory results, it exhibits uncertainties when it comes to simulating climate variables, particularly with respect to annual and seasonal variations (IPCC, 2013; Kundzewicz *et al.*, 2018). Due to their coarse spatial resolutions, GCMs are inadequate to simulate regional-scale temperature, precipitation, cloud and aerosol processes, and climate of mountainous and coastal regions (IPCC, 2013; Flato *et al*., 2013). Additionally, GCMs also have limitations when it comes to reproducing cloud cover and are characterized by overestimation of heavy precipitation events, wet days, and underestimation of dry days frequencies (IPCC, 2013; Woldemeskel *et al*., 2015). As a result, it is recommended to downscale GCM simulations to regional, basin, and watershed scales in order to obtain good quality climate information from GCMs for use in climate change and impact studies. Downscaling techniques are used to improve the spatial resolution and correct systematic biases in climate projection data (Ali *et al*. 2019; Gudmundsson *et al*., 2012). This method is considered to be more useful than General Circulation Models for assessing impacts of climate change scenarios at a higher resolution, by forging a mathematical relationship between large scale predictors and predictand(s). However, despite the high relevance and sophistication of this new method in climatological studies, rainfall is a random hydrologic event whose occurrence cannot be predicted with certainty especially in the developing world making uncertainties an important aspect of consideration in climate change studies as effort are made to achieve more reliable results through climate modeling (Semenov & Stratonovitch 2010). It is on this note that this study aims at dismantling uncertainties associated with rainfall projection particularly when the downscaling procedures is involved over the study area.

Materials and Methods

Description of the Study Area

This study was carried in the South-South region located in the Niger Delta region of Nigeria and lying between latitudes 3°25'30"N – 8°28'30"N and longitudes 5°10'0"E – 9°22'30"E. It is one of the six geopolitical zones in Nigeria, signifying both the geographic and political districts of east coast of Nigeria. The ecosystem of the area is highly diverse and supportive of numerous species of terrestrial and aquatic flora and fauna and human life. According to Food and Agriculture Organization, (2001), the region is divided into four ecological zones namely freshwater zone, coastal inland zone, lowland rain forest zone and mangrove swamp zone. Lambin, (2002), pointed out that the South-South has the largest mangrove swamps in Africa, with its stagnant swamp covering about 8600 squares, and about 2,370 square kilometers of the area consist of estuaries, creeks and rivers. It covers over 70,000km^2 and constitutes about 7.5% of Nigeria's land mass. With a total annual rainfall varying from 2400mm to 4000mm within West Africa. The monsoon wet (rainy) season over the area begins in May, as result of the seasonal northward movement of the Intertropical Convergence Zone (ITCZ), with termination in October (Myers *et al*., 2010). The region is dominated by mining activity (petroleum) and has about 70% of its population living in rural areas. Rain-fed agriculture is the major means of sustenance of the people. The region is swayed by the localized convection of the West African monsoon with less contribution from the mesoscale and synoptic system of the Sahel (Thomas & Baltzer, 2002). Although, the study area is situated in the southern part of Nigeria comprising six states; Akwa Ibom, Delta, and Rivers were the sampled states as shown in Figure 1.

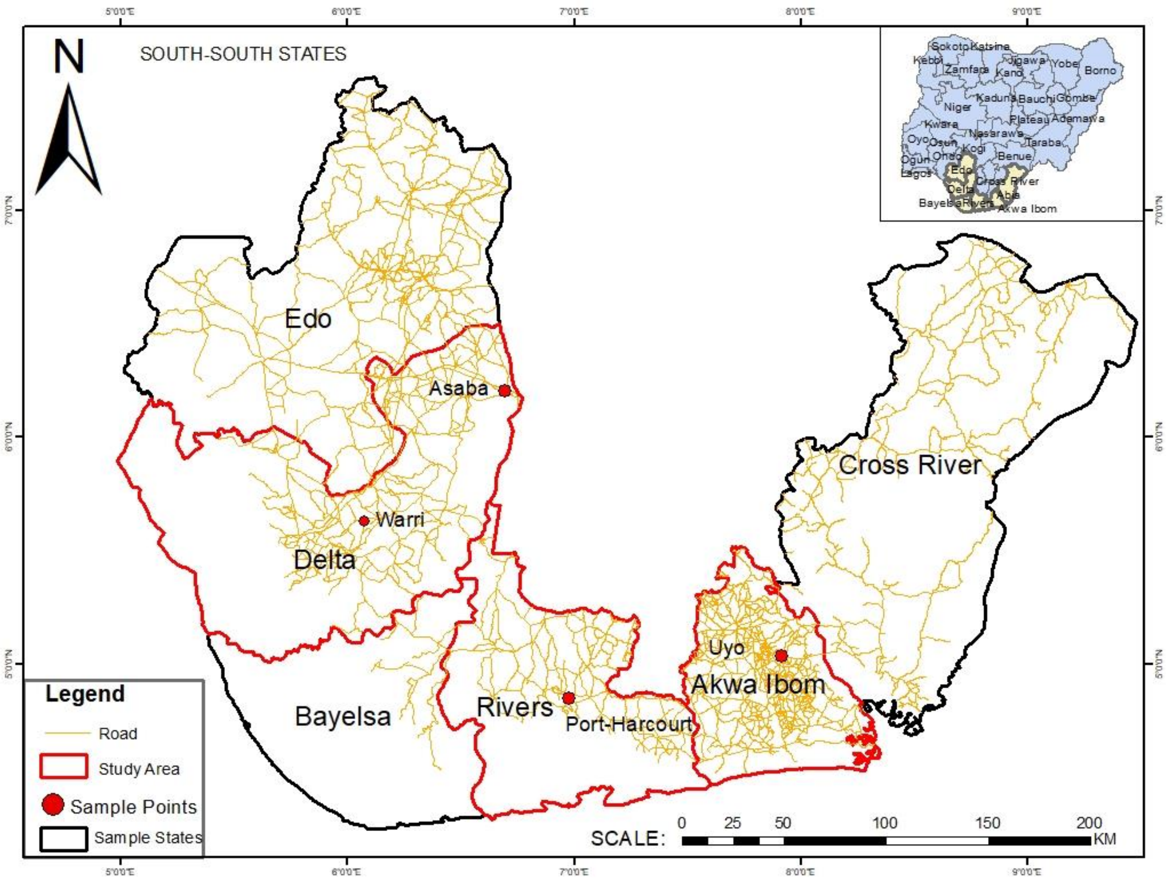

Figure 1: Study area - South-South States

Downscaling Procedure

The main tool for providing insights into possible future climate change is climate modelling. Climate models are mathematical models that stimulate the behaviour of Earth climate system (atmosphere, hydrosphere, lithosphere, cryosphere and biosphere) based on the fundamental laws of physics. Climate models are important tools for improving our understanding and predictability of climate behaviour on seasonal, annual, decadal and centennial time scales. Of all the known climate models, the General Circulation Models (GCMs) are the most important and are the main tools used for projection of global climate into the future and as well as important tools to assess potential impacts of global climate warming (Gagnon, Singh, Rousselle & Roy, 2005). General Circulation Models are computer models that mathematically represent various physical processes of the global climate system. As a result, GCM based projections may not be robust for local impact studies. To overcome this problem downscaling techniques have been developed which take the large-scale predictions provided by a GCM and apply methods to extract implied climate change information at more regional/local scales. Furthermore, downscaling is used to converting the coarse spatial resolution of the GCMs output into a fine resolution which can involve generating point/station data of a specific area by using the GCM climatic output variables (Wilby & Wigley 1997; Dawson & Wilson 2007; Fowler *et al*., 2007). According to Mekonnen & Schumitter, downscaling requires at least 30 years of observed data for the base term is essentially carried out according to the following procedural steps; Quality control and data transformation, screening of predictor variables, model calibration, weather generation, statistical analyses, graphing model output and scenario generation as shown in Figure 2.

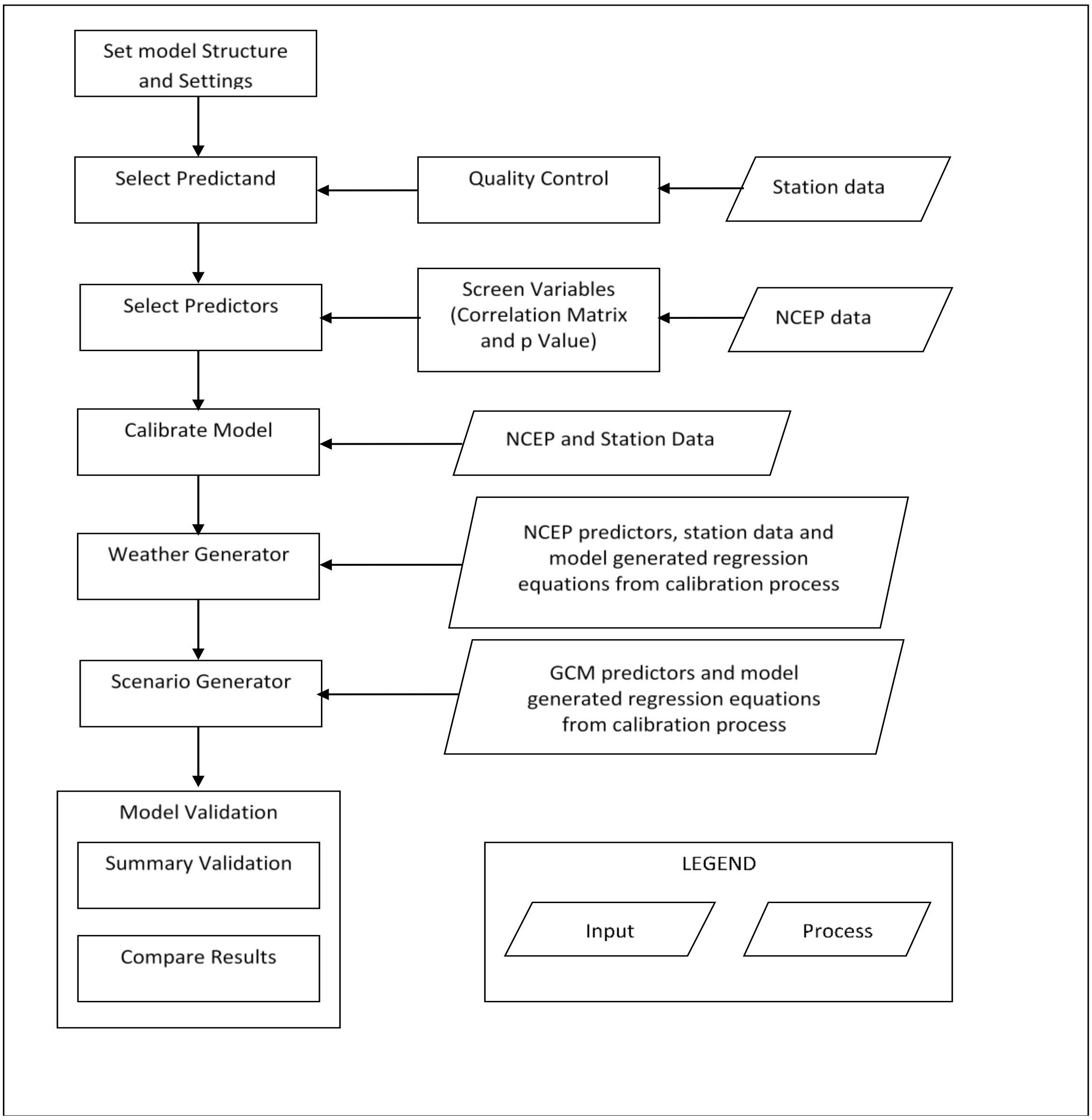

Figure 2: Flow chart showing steps involved in downscaling and scenario generation (modified from Wilby & Dawson, 2007).

Selection of Large-Scale Predictors used in the Study

Predictor selection is an important aspect of downscaling. It usually involves identifying relationships between climate variables and daily rainfall from each meteorological station to gather an appropriate set of predictors (Huang *et al*., 2011). The SP method was established by Mahmood & Babel (2012) and uses the results from the SDSM function to consider the correlation coefficient, partial correlation coefficient, and p-value and it has been adopted in several studies for variable selection (Singh *et al*., 2015; Pathan & Waikar 2020; Ahsan *et al*., 2021). According to (Khadka & Pathak 2016), multicollinearity between more than two independent variables can be reduced by selecting variables using this method. The Correlation coefficients (R) were calculated between the 26 NCEP variables and rainfall and empirical relationships between selected large-scale indices of the NCEP dataset and local variables were generated using multiple linear regression and their regression parameters produced during the process of calibration. Finally, future climates were then predicted using the scenario generator operator in the SDSM. In this study, the SDSM model was set up following the instructions of Wilby & Dawson (2007) presented in Figure 2; this application was also employed in the works of Mekonnen & Disse (2018), Molina & Bernhofer (2019), and Hassan & Hashim (2020). The investigation revealed (shum, rhum) as super predictors showing significant correlation with the measured rainfall for all stations, whereas (shum, rhum, r850 and r500) demonstrated correlations with three stations. In a related development, P5_u showed a strong relationship with rainfall data obtained from two stations while P_u and P5th were observed to show significant relationship with the predictand at one station as displayed in Table 1.

Table 1: Selected Large-Scale predictors in the study area

Stations	Predictors	Coefficients
Asaba	Shum	0.70
	Rhum	0.71
	r850	0.78
	r500	0.70
	P5th	0.74
Warri	shum	0.66
	r850	0.74
	P5_u	0.73
	P_u	0.59
Uyo	Shum	0.67
	Rhum	0.66
	r850	0.72
	r500	0.64
	P5_u	0.71
Port Harcourt	Shum	0.69
	Rhum	0.70
	r850	0.77
	r500	0.68

Calibration and Validation of the Statistical Downscaling Model

After successfully screening the variables using the methods itemized and presented in Figure 2, the process of calibration was continued using the selected variables of NCEP and daily rainfall observations within the period 1985–2000 and regression parameters were generated. The parameters together with the NCEP variables and the other part of the measured daily rainfall covering 2001–2015 were then employed in the weather generator function for the validation step. The scenario generator operation was then applied using the selected predictors supplied by HadCM3 for either historical or future climate to generate daily simulated rainfall. The Root Mean Square Error (RMSE), the coefficient of determination (R^2), and Ratio of Standard Deviation (RSD) was calculated and used to test the model's performance in consonance with other studies which studies such as (Hassan & Harun (2012), Dibike & Coulibaly, (2005), Yadav *et.al*., (2010), Wilby & Dawson, (2013), Goyal *et al.* (2012), Hassan *et al.* (2014). It is important to mention that the model was segmented into four seasons December, January, February (DJF); March, April, May (MAM); June, July, August (JJA) and September,

October, November and its performance between the observed and simulated predictand based on NCEP predictors for both calibration and validation periods was measured on a seasonal time scale.

The calibrated data were then used to generate

$$R = \frac{\sum_{i=1}^{n}(\mathrm{Obs_i}-\overline{\mathrm{Obs}}).(\mathrm{Pred_i}-\overline{\mathrm{Pred}})}{\sqrt{\sum_{i=1}^{n}(\mathrm{Obs_i}-\overline{\mathrm{Obs}})^2.\sum_{i=1}^{n}(\mathrm{Pred_i}-\overline{\mathrm{Pred}})^2}} \ldots\ldots\ldots 2$$

$$\mathrm{RSME} = \frac{\sum_{i=1}^{n}(X_{\mathrm{Obs,i}}-X_{\mathrm{Model,i}})^2}{n} \ldots\ldots\ldots\ldots\ldots\ldots 3$$

Where: Obs = observed data value

Pred = predicted data value

$\overline{\mathrm{Obs}}$ = mean observed data value

$\overline{\mathrm{Pred}}$ = predicted mean data.

The summary of the results of the validation indices of the sub-model for seasonal rainfall predictions presented in Table 2 shows the values of R and RMSE and it ranges between 0.63-0.96 and 0.11- 0.42 respectively at p> 0.05 which indicate that there is a significant relationship between the simulated and observed data for the period of validation (2001-2015) at the sub- seasonal timescale.

Table 2: Validation of SDSM for Seasonal Rainfall Projection

Station	Scale of SDSM	Rainfall seasons	R	r^2	RMSE	RSD	P value at 0.05
Asaba	Seasonal	DJF	0.91	0.83	0.20	0.72	0.00
		MAM	0.72	0.52	0.37	0.89	0.00
		JJA	0.83	0.69	0.21	1.20	0.00
		SON	0.74	0.55	0.31	0.22	0.00
Portharcourt	Seasonal	DJF	0.64	0.41	0.42	0.88	0.00
		MAM	0.75	0.56	0.41	1.00	0.00
		JJA	0.86	0.74	0.23	1.02	0.00
		SON	0.91	0.83	0.11	1.11	0.00
Uyo	Seasonal	DJF	0.72	0.52	0.41	0.12	0.00
		MAM	0.69	0.48	0.43	0.23	0.00
		JJA	0.68	0.46	0.42	1.03	0.00
		SON	0.91	0.83	0.25	0.11	0.00
Warri	Seasonal	DJF	0.75	0.56	0.32	1.79	0.00
		MAM	0.69	0.48	0.37	0.23	0.00
		JJA	0.91	0.83	0.21	0.73	0.00
		SON	0.87	0.76	0.36	0.76	0.00

***R**- stand for correlation coefficient between simulated and observed data; **r^2**- coefficient of determination; **RMSE**- root mean square error**, RSD**- ratio of standard deviation 0.05 P value – alpha for significance between simulated and observed data set.*

The high values of R and low values of RMSE sufficiently explains the model's predictive ability. However, the model is concluded to provide a better performance in Asaba in DJF, Warri (MAM) in JJA while Port Harcourt and Uyo perform better in SON. The results on the basis of the R and RMSE values shows the performance of SDSM for accurately developing long-term mean rainfalls and has the capacity to predict rainfall in the region on a seasonal timescale and agrees with the recommendation of Mekonnen & Disse (2018) to be selected as the best model for achieving rainfall downscaling.

Observed and Modelled Seasonal Rainfall for the area.

The record of the observed and modeled rainfall data for the seasons DJF, MAM, JJA and SON is presented in Table 3 and it is clear that the validation record shown in Table 2 is valid indicating that the model sufficiently captures the local data characteristics for rainfall in the areas and that the observed and simulated data within the period of validation sufficiently matches. From Table 3, it is clear that the observed and simulated data within the period of validation sufficiently matches with the following results: Warri observed data in SON is 292.2mm while the simulated is 290.5mm. in the same vein, it is noted that in JJA, modelled data for Asaba records only 1.9 mm higher than the observed whereas the simulated in Uyo stands at 6.7mm higher than the observed in SON and the observed is merely 0.6mm higher than the modelled in Port Harcourt in the same season. On the other hand, MAM shows that observed data for Asaba is 2.4mm higher than simulated whereas for the same sub-seasonal timescale Port Harcourt records for observed is 0.9mm above the modelled. In JJA, Warri observed data is 4.2mm higher than the simulated and the observed is lower than the modelled data by 1.4mm in Port Harcourt within the same season. The records for all the stations within the season timescale investigated reveals no significant difference between the observed and simulated data suggesting that the data sufficiently matches affirming the validation earlier done.

Table 3: Summary of Observed and Modelled Seasonal Rainfall Data for the area

Station	Source	Warri	Asaba	Uyo	Port Harcourt
DJF	Observed	37.1	34	25.6	33.3
	Modeled	36.7	33.5	24.9	33
MAM	Observed	205.9	190.3	204.9	178.6
	Modeled	204.6	187.9	204.2	177.7
JJA	Observed	403.7	349.2	356.6	320.6
	Modeled	399.5	349.5	358.5	322.5
SON	Observed	292.2	261.1	253.4	234.8
	Modeled	290.5	263.2	260.1	234.2

Method of Data Collection and Analysis

The data for this study were acquire from two major secondary sources and for this reason the expost-facto research design was adopted in this study. The data used includes 30 years rainfall data from 1985 - 2015 acquired from the records of the Nigerian Meteorological Agency as well as large scale predictors and this was assessed from the archive of working groups such as Hadley Centre for Global Climate model version 3 (HadCM3) and National Centre for Environmental Prediction (NCEP) reanalysis project. Rainfall data used for this study was for one climatic normal (1985-2015) and this is so because apart from being the maximum data field limit for operationalizing the SDSM as proposed by the builder of the model, 30 years period has also been recommended as the minimum requirement for climate studies (IPCC, 2007). The quadrat sampling technique was used in this study by stratifying the area stratified into 2° x 2° latitude and longitude intersections and on the basis of the stratification (Asaba, Warri, Uyo and Port Harcourt) local meteorological stations that fall within the grids calibrated were selected for the study. The Wilconsin signed rank test which is suitable for comparing two related samples or paired observations was employed in this study for purposes of addressing the issues of uncertainty which is a fundamental challenge associated with climate prediction.

Results and Discussions

Uncertainty Analysis

GCM outputs based on the Special Report on Emission Scenarios (SRES) have been used extensively to project future meteorological variables for use as inputs into hydrological models at a regional scale (Kour *et al*., 2016). Large-scale averages with little spatial reliability from GCMs characterize the direct representations of hydrological quantities for specific regions. In assessing climate change, there are also many sources of uncertainty which is categorized into two broad groups such as uncertainties related to dynamic structure of GCMs and that related to amount of greenhouse gas emissions (Covey *et al*., 2003). Therefore, in order to achieve more reliable results uncertainties are considered very important in climate change studies (Semenov & Stratonovitch, 2010). Uncertainty issues in downscaling models have received much attention in recent times in view of its great effects on climate prediction and further on decision making.

Following the fact that the confidence on the reliability of the climate change anomalies computed from the scenarios is dependent on the downscaled outputs' ability to represent the baseline climate (Dibike *et al*., 2008). The uncertainty analysis was performed to establish confidence in the downscaled data from GCM scenario outputs. Therefore, the evaluation of the performance of the downscaling method in reproducing the mean and variability of the observed rainfall by comparing downscaled rainfall provided with climate predictors with station-observed rainfall from 1986-2015 was done and the relative uncertainties in downscaled HadCM3 rainfall was assessed on the basis of its ability to simulate seasonal cycles in comparison to the mean seasonal cycle of the observed rainfall. The test results (p-values) of the Wilcoxon Signed Rank sum test for the difference of the means of observed and simulated rainfall data together with the observed HadCM3 rainfall data at the 95% confidence level at a monthly scale are shown on the respective tables for all the stations in the study area.

In Table 3, the uncertainty information of the projections made by the model based on the observation period at Warri station is displayed. In the Table the observed and simulated data is paired and the hypothesis which states that, 'there is no significant difference between the simulated data and observed data is tested to verify if there are uncertainties.

Table 3: Rainfall Uncertainty Analysis for Warri

Months	HadCM3	A2 Scenario	B2 Scenario
January	0.241	0.221	0.317
February	0.311	0.031	0.067
March	0.112	0.334	0.050
April	0.112	0.412	0.070
May	0.103	0.115	0.121
June	0.312	0.224	0.223
July	0.110	0.113	0.112
August	0.023	0.061	0.219
September	0.221	0.551	0.112
October	0.115	0.110	0.105
November	0.210	0.212	0.089
December	0.121	0.114	0.541

On the other hand, if any significant difference exists between the simulated and observed data, it implies that there are some uncertainties that may be peculiar to that particular station. Consequently, uncertainty only exist in the month of August at $p<0.05$ (0.023) and for A2 scenario uncertainty exist in the month of February at $p<0.05$(0.031) while for B2 scenario there are no uncertainties. This suggests that the said prediction is valid for Warri at 95% confidence level for all other months except the month of August. This also indicates that the use of the A2 scenario for projected period for August should be used with caution as it may not capture the exact situation. Again, the month of February under the A2 scenario reveals that the projection for that month may not represent the reality because of the existing uncertainties.

The uncertainty result of the projections made by the model for Port Harcourt is presented in Table 4 and the analysis reveals that uncertainties exists in the months of October at $p<0.05$ (0.006) and April under the A2 scenario at $p<0.05$ (0.023) and in the month of December under the B2 scenario at $p<0.05$ (0.039).

Table 4: Rainfall Uncertainty Analysis for Port-Harcourt

Months	HadCM3	A2 Scenario	B2 Scenario
January	1.121	0.102	0.231
February	0.362	0.231	1.231
March	2.210	1.207	0.991
April	0.171	0.023	1.231
May	0.341	0.241	0.451
June	0.211	0.112	0.921
July	0.231	0.521	0.234
August	0.351	2.411	0.251
September	0.122	0.123	0.052
October	0.006	0.501	0.921
November	0.231	2.871	0.712
December	1.102	0.769	0.039

The p-values are above 0.05 for all months except for these months, October, April and December under scenarios A2 and B2 respectively. This finding reveals that the null hypothesis was not rejected; suggesting that observed and SDSM simulated estimates were statistically significant for every month except October, April and December. For these months, the null hypothesis was rejected because the p-values were below the critical value of 0.05. This implies that the prediction is true for Port Harcourt station and at 95% confidence level for all other months except for October, April and December. This also reveals that the accuracy of the model's prediction for the months of October, April and December under scenarios A2 and B2 respectively is not guaranteed as it may not capture the true situation. Hence projections result for those months within the projected period need to be used with absolute caution.

The uncertainty results of the projections for Uyo as revealed by the model is clearly displayed in Table 5 and the simulated data and observed data is tested to verify if there are uncertainties. It is obvious as reported in the Table that there are some uncertainties and that is captured in the months of October at $p<0.05$ (0.002) and also in the month of March under the A2 scenario at $p<0.05$ (0.017) while under the B2 scenario uncertainties exist in the month of May at $p<0.05$ (0.021).

Table 5: Rainfall Uncertainty Analysis for Uyo

Months	HadCM3	A2 Scenario	B2 Scenario
January	0.111	0.707	0.231
February	0.842	0.831	1.231
March	2.711	0.017	0.991
April	0.971	0.823	1.231
May	0.341	0.241	0.021
June	0.211	0.512	0.921
July	0.231	0.721	0.234
August	0.379	1.411	0.059
September	1.822	0.123	0.062
October	0.002	1.541	0.121
November	3.231	1.671	0.412
December	0.912	1.023	0.159

The p-values are above 0.05 for all months except for the months October, March and May. This finding reveals that the null hypothesis was not rejected; suggesting that observed and SDSM simulated estimates were statistically similar for every month except October, March and May. For these months, the null hypothesis was rejected because the p-values were below the critical value of 0.05. This implies that the prediction is accurate for Uyo station and at 95% confidence level for all other months except for October, March and May. This also reveals that the accuracy of the model's prediction for the month of October, March and May did not capture the true situation in Uyo in those stations. Hence the projection results for these months within the projected period need to be used with absolute caution under the corresponding emission scenarios as shown in table 5 above.

Table 6 shows the uncertainty results of the projections made by the model at Asaba evidently, uncertainties are observed in the months of May and June at $p<0.05$ (0.031 and 0.001) respectively whereas uncertainties are observed in the month of September under the B2 scenario at $p<0.05$ (0.001) and none under the A2 scenario.

Table 6: Rainfall Uncertainty Analysis for Asaba

Months	HadCM3	A2 Scenario	B2 Scenario
January	0.331	0.117	0.364
February	0.312	0.153	0.117
March	0.611	0.317	0.891
April	0.151	0.723	0.431
May	0.031	0.241	0.951
June	0.001	0.212	0.621
July	2.286	0.321	0.634
August	1.451	0.221	0.891
September	0.322	0.203	0.001
October	0.892	2.371	1.751
November	0.233	0.671	0.318
December	0.214	0.191	0.129

The p-values are above 0.05 for every other month except for May, June and September. This finding reveals that the null hypothesis was not rejected; suggesting that observed and SDSM simulated estimates were statistically similar for every month except May and June. For these months within the projected period, the null hypothesis was rejected because the p-value was below the critical value of 0.05. This implies that the prediction is accurate for Asaba station and at 95% confidence level for all other months except for May and June. This also reveals that the accuracy of the model's prediction for the month of September under the B2 scenario may not capture the true situation in Asaba. It is also implied that using the B2 scenario to predict for May and June at Asaba station may not produce accurate result hence the results for these months within the projected period need to be used with extreme caution. Accuracy in downscaling, using multiple linear regression techniques as in SDSM, is based largely on the assumption of predictor-predictand relationships (Wilby & Dawson, 2007). However, the physical processes of the atmosphere make the prediction of weather variables by GCMs very uncertain owing to complexity. Downscaled scenarios in this study were generated using the HadCM3 model. Therefore, to establish confidence in the projected rainfall data downscaled from GCM scenario outputs and depend on the projection results to give explanation to changes in climate variables, it was important that the downscaled outputs reasonably represent the current state of the rainfall conditions in the area. In fact, the confidence on the reliability of the climate change anomalies computed from the scenarios run depend on the downscaled outputs' ability to represent the baseline climate (Dibike *et al*., 2008). In order to have a dependable projection outputs that can be used for planning and other decision on climate change considerations, the uncertainty test was performed using the Wilcoxon Signed Rank test (Wilcoxon, 1945) which is one of the best nonparametric methods for conducting hypothesis tests (Conover, 1980) and widely used in uncertainty analysis of downscaled climate parameters provided with predictor scenarios of the GCMs (Dibike *et al*., 2008; Khan *et al*., 2006 a,b).The model provided that the output was dependable based on the quality of results revealed. However, uncertainties were revealed in some months at some stations for the period under review and under the two scenarios using the HadCM3 were $p< 0.05$ which implies that the result for those months should be used with caution as they might not capture the exact situation in the area. Therefore, in Warri uncertainty is revealed in February under the A2 at $p< 0.031$. Similarly, Port Harcourt shows uncertainties in the month of October at $p< 0.006$ for Hadcm3, April and December at $p< 0.023$, 0.039 under A2 and B2 scenarios respectively whereas Uyo also recorded uncertainty in the month of October at $p<0.002$ for Hadcm3 and March at $p <0.017$ and May at $p<0.021$ for A2 and B2 scenarios. On the other hand, May, June and September were noted as months of uncertainties for Asaba at $p<0.031$, $p<0.001$ for Hadcm3 and $p<0.001$ for September under B2 scenario. The results were all significant at $p > 0.05$ for all the months at the different stations which implies that the predictions were accurate for the different stations except for the months were uncertainties were observed implying that the result for those months should be used with caution as it may not capture the existing realities on ground or local climate characteristics of the area.

Conclusion and Recommendations

Regardless of the fact that the predictor's relationship with the predictand vary from station to station in the region as revealed by their respective correlation coefficients, shum, rhum, r850 and r500 showed significant relationship with the predictand, hence the super predictors in the area. It is concluded that rainfall in the region depends on these global climate variables because they significantly predict rainfall in the area particularly at $p<0.05$. Therefore, strict adherence to adequate validation and calibration procedures of the model, unbiased selection of predictor variables and development of local GCM that will capture all drivers of local climate are strongly recommended.

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