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Enhancing Climate Forecast Precision in Specified Nigerian Regions Through Statistical Downscaling and Bias Correction Techniques

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Abstract

The focus of this research is to assess the effectiveness of statistical downscaling and bias correction methods in predicting future climate conditions under various climate change scenarios in Benin City, Enugu, Lokoja, and Port Harcourt. The study utilizes 14 years of daily precipitation data spanning from 1982 to 1995 obtained from four Food and Agricultural Organization (FAO) climate change meteorological stations. Simulated input data from Regional Circulation Models (RCMs) was acquired from The Earth System Grid Federation (ESGF) online platform. Daily precipitation data for the future period (2041–2050) from RCMs (AFR-44) was employed. The data underwent bias correction and statistical downscaling with a spatial resolution of 0.35 degrees. Analysis of the RCM-simulated historical data reveals intense precipitation activity, particularly in the Benin region and Port Harcourt city. However, a comparison with observed data from meteorological stations highlights significant discrepancies, underscoring the necessity of bias correction and downscaling techniques before utilizing such data for environmental analyses.

1.0.Introduction

Climate simulations are integral for assessing the impact of anthropogenic emissions of greenhouse gases, such as carbon dioxide, methane, and nitrous oxide, on Earth's climate dynamics [1, 2]. Moreover, they serve as indispensable tools for examining the consequences of climate change on the natural environment through various environmental modeling approaches [3, 4, 5]. Over the past decade, notable progress has been achieved in the field of climate modeling, including significant enhancements in the spatial resolution of global climate models (GCMs) spanning from the 1960s to the 2010s [6, 7, 8].

Statistical downscaling serves as a method utilized in climate modeling to acquire detailed forecasts of forthcoming climate conditions with heightened resolution. Its aim is to furnish more nuanced insights into future climate scenarios than what is achievable solely through global climate modeling [9, 10]. In instances where Regional Climate Model (RCM) data is either unavailable for a specific locale or remains excessively coarse, statistical downscaling can be deployed. Numerous statistical downscaling methodologies have been devised [11, 12]. While global climate models offer insights into overarching climate change patterns, they often fall short in capturing localized variations critical for numerous applications like agriculture, water resource management, and infrastructure planning. Statistical downscaling serves as a means to bridge this disparity by leveraging historical data to establish statistical correlations between large-scale and local-scale climate parameters. Consequently, statistical downscaling establishes a statistical linkage between historical observed climate data and the output of climate models for corresponding historical periods. This linkage is then harnessed to generate future climate projections [13, 14].

Statistical downscaling serves as a pivotal instrument for comprehending the potential ramifications of climate change at local scales. By furnishing intricate insights into forthcoming climate conditions, it facilitates strategic planning and adaptation efforts by decision-makers. However, statistical downscaling may introduce inaccuracies into projections if the statistical relationships employed in the process are flawed. To rectify this issue, bias correction comes into play. This method entails aligning statistical downscaling projections with observed data, thereby refining their accuracy [15]. Bias correction and statistical downscaling are frequently employed in conjunction to refine the precision of climate projections at local scales. While statistical downscaling yields high-resolution forecasts, bias correction ensures their fidelity. Both techniques synergize to enhance the accuracy of climate modeling projections [16, 17].

In preceding decades, available daily climate observations, typically at appropriate fine resolutions, have facilitated impact analyses. However, reliance on General Circulation Models (GCMs) predominates for generating simulated climate data for future periods. Nonetheless, the spatial resolutions of these models prove inadequate for direct application in detailed local impact assessments. Additionally, inherent biases permeate each model simulation, which, if unaddressed, could yield significant inaccuracies. Hence, prior to integrating GCM data into regional impact evaluations, the imperative need for bias adjustment and spatial downscaling persists [11].

2. Research Methodology

To adhere to the primary objective of this study, which aims to employ bias correction and statistical downscaling as modeling tools for climate change assessment, we integrated bias correction with statistical downscaling to precisely ascertain the projected climatic conditions. Consequently, bias correction and spatial downscaling were applied to outputs from a Global Circulation Model (GCM) simulation for both historical and scenario data simulations concerning a specific input variable, namely daily precipitation data. The procedural steps involved in bias correction and downscaling of climate data are depicted in the flowchart illustrated in Figure 1.

2.1 Data Acquisition

A prolonged period of model and corresponding observations is essential to ensure the statistical downscaling process produces dependable results. The data utilized for this investigation consists of 14 years of daily precipitation records spanning from 1982 to 1995. These records were sourced from four climate change meteorological stations affiliated with the Food and Agricultural Organization (FAO), strategically positioned across Nigeria. The primary emphasis was on stations situated in Edo, Enugu, Kogi, and Rivers states. Details regarding the geographical coordinates of these stations are provided in Table 1.

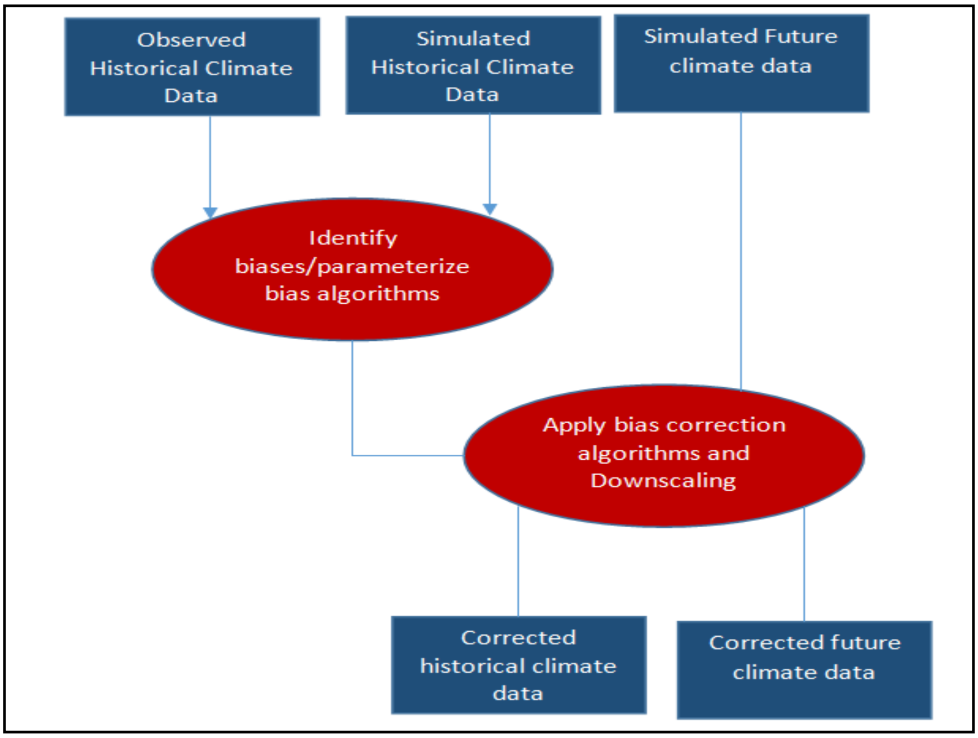


Figure 1: Methodological Flowchart [17]

Table 1: Spatial Location of Meteorological Observation Station in Nigeria

S/N	Station Location	Latitude	Longitude	Elevation
1	Benin City	6.3089	5.6054	93.92
2	Enugu	6.4509	7.4841	151.33
3	Lokoja	7.8135	6.726	167.21
4	PortHarcourt	4.8109	7.0477	27.2

The selection of Benin City, Enugu, Lokoja, and Port Harcourt as the study areas is grounded in several key considerations essential for addressing the research objectives effectively. Firstly, these cities represent diverse geographical and climatic conditions within Nigeria, allowing for a comprehensive assessment of climate change impacts across different regions. Moreover, they are centers of population, economic activity, and infrastructure development, making them particularly vulnerable to the effects of climate change. Additionally, the availability of long-term meteorological data from Food and Agricultural Organization (FAO) climate change meteorological stations in these cities facilitates robust analysis and comparison with simulated data from Regional Circulation Models (RCMs). By focusing on these specific locations, the study aims to provide insights that are relevant and applicable to local stakeholders, policymakers, and communities, thereby contributing to informed decision-making and climate resilience efforts in Nigeria.

Thus, General Circulation Models (GCMs) offer global-scale climate change data sourced from various channels. However, for this particular investigation, data from the Regional Circulation Model (RCMs) was acquired through The Earth System Grid Federation (ESGF) online platform. This platform serves as a repository of both historical and projected climate data, catering to researchers and end-users with customized datasets based on specific variables and criteria. Daily precipitation data for the future period (2041–2050) was extracted from RCMs

(AFR-44) and subsequently subjected to bias correction and statistical downscaling with a spatial resolution of 0.35 degrees. Further particulars regarding the specific RCM employed are delineated in Table 2.

Table 2: Corresponding details of the Regional Circulation model (RCM) used

RCMs	AFR-44
Project	CORDEX
Driving model	ICHEC-EC-EARTH
Variable	Precipitation (p)
Experiment	Historical and RCP4.5
Time frequency	Daily

A summary of the acquired data is presented in Tables 3, 4, 5, 6, 7 and 8 representing the daily average historical observed precipitation from 1982-1995, yearly average historical observed precipitation from 1982-1995, daily average historical simulated RCM precipitation from 1982-1995, yearly average historical simulated RCM precipitation from 1982-1995, daily average future simulated RCM precipitation (2041-2050) and yearly average future simulated RCM precipitation (2041-2050).

The analysis of the projected maps depicted in Figure 5 reveals significant insights into the historical precipitation patterns simulated by the Regional Climate Model (RCM). Specifically, our observations highlight a notable concentration of intensive precipitation activity, particularly evident in the vicinity of the Benin region and the city of Port Harcourt. However, upon comparison with data obtained from various meteorological stations, it becomes apparent that there exists a substantial disparity between the simulated RCM data and observed values. This incongruity underscores the necessity of implementing bias correction and downscaling techniques prior to utilizing such data for environmental studies. To address this issue, bias correction was performed on the historical precipitation data generated by the RCM, utilizing observation data as a reference input. The CMhyd software was instrumental in executing this corrective procedure. Furthermore, Figure 6 illustrates the contrast between the future simulated precipitation for the period 2041-2050 and the corrected future precipitation, presented in map format. Notably, the corrected future precipitation map indicates a reduced projection of precipitation compared to the uncorrected RCM simulation. Moreover, the analysis extends to incorporate additional crucial parameters such as standard deviations, variance, mean of wet days, and coefficient of variation. These metrics were meticulously examined for each of the four meteorological stations and are graphically represented in Figures 6 through 9, offering further insights for consideration.

Table 3: Daily average historical observed precipitation (1982-1995)

Years	Benin	Enugu	Lokoja	Portharcourt
1982	13.19085	11.1711	9.554356	16.70780822
1983	3.705753	3.518219	2.727534	7.196191781
1984	3.54082	3.258142	2.471721	6.150245902
1985	4.601808	4.042932	3.149479	7.576931507
1986	5.684767	4.171699	3.193151	7.171589041
1987	4.408795	3.957589	3.156986	6.668054795
1988	7.217842	6.879891	5.646557	10.75546448
1989	7.323014	5.898164	4.57274	9.506657534
1990	5.388493	5.340164	4.289726	9.418136986
1991	3.993315	3.537863	2.494822	6.235123288
1992	4.864098	3.876257	3.16653	7.274535519
1993	4.183644	3.95663	2.909781	8.74539726
1994	7.170356	5.529534	4.490904	8.185945205
1995	5.623068	5.460027	4.329178	9.207013699
Average	**5.77833**	**5.042729**	**4.010962**	**8.628506801**

Table 4: Yearly average historical observed precipitation (1982-1995)

Meteorological stations	14 Years Average
Benin	5.77833
Enugu	5.042729
Lokoja	4.010962
Portharcourt	8.628506801

Table 5: Daily average historical simulated RCM precipitation (1982-1995)

Years	Benin	Enugu	Lokoja	Portharcourt
1982	1.275726	1.469233	1.469233	1.655945205
1983	1.421288	1.286055	1.286055	1.33630137
1984	1.084795	0.984849	0.984849	1.098794521
1985	1.907315	1.724932	1.724932	1.913424658
1986	2.208082	1.745644	1.745644	1.710246575
1987	1.663571	1.345714	1.345714	1.396648352
1988	1.35418	1.367268	1.367268	1.494153005
1989	2.372329	2.068685	2.068685	2.11739726
1990	1.706411	1.680466	1.680466	1.810547945
1991	1.783753	1.826329	1.826329	1.930630137
1992	1.125929	1.148115	1.148115	1.330300546

1993	1.325699	1.429233	1.429233	1.693424658
1994	1.362301	1.07789	1.07789	1.097287671
1995	1.580384	1.482521	1.482521	1.528136986
Average	**1.583697**	**1.474067**	**1.474067**	**1.579517064**

Table 6: Yearly average historical observed precipitation (1982-1995)

Meteorological stations	**14 Years Average**
Benin	1.583697
Enugu	1.474067
Lokoja	1.474067
Portharcourt	1.579517064

Table 7: Daily average future simulated RCM precipitation (2041-2050)

Years	Benin	Enugu	Lokoja	Portharcourt
2041	0.953041	0.661425	0.661425	1.10739726
2042	1.278438	0.84074	0.84074	1.181342466
2043	0.935628	0.520027	0.520027	0.898715847
2044	1.189836	0.781562	0.781562	1.376657534
2045	1.591973	0.859205	0.859205	1.461616438
2046	0.87126	0.575589	0.575589	0.938684932
2047	0.936667	0.383661	0.383661	0.605874317
2048	0.850027	0.693918	0.693918	1.158986301
2049	1.588685	1.041863	1.041863	1.452054795
2050	1.334	1.054521	1.054521	1.415041096
Average	**1.152956**	**0.741251**	**0.741251**	**1.159637099**

Table 8: Year average future simulated RCM precipitation (2041-2050)

Meteorological stations	**10 Years Average**
Benin	1.152956
Enugu	0.741251
Lokoja	0.741251
Portharcourt	1.159637099

From the data presented in Tables 3 to 8, it was obvious that the observed and simulated data vary in significant amounts. This is because the Regional circulation model is meant to predict

(to a 3.5 degree) the amount of precipitation based on some computations which have proven to provide accuracy over a regional scale but if being used on a local scale, will accumulate biased readings. Thus, the Bias correction procedures are used to minimize the discrepancy between observed and simulated climate variables (precipitation) on a daily time frequency step so that hydrological simulations driven by corrected simulated climate data match simulations using observed climate data reasonably well. To extract and bias-correct data obtained from global and regional climate models, **CMhyd** tool was employed.
In bias correction techniques, a transformation algorithm is utilized to adjust the outputs of climate models. The underlying principle is to parameterize this algorithm to rectify simulated historical climate data by identifying disparities between observed and simulated historical climate variables. It is expected that the adjustment algorithm and its parameterization for bias correction methods remain consistent, ensuring the relevance of present climate conditions to future scenarios. Thus, forthcoming climate data undergo adjustment using the same algorithm

The steps involved in applying bias correction and statistical downscaling using CMhyd are as follows: (**a) Data preparation:** CMhyd organizes observed data in ASCII format, with each gauge's details recorded in separate files listed in the location file. Separate files are maintained for precipitation and temperature data. The latitude and longitude fields in the location files specify gauge locations, while the NAME fields indicate corresponding data files. The first line in data files denotes the time series start date, with subsequent lines representing each day. Missing values are indicated using a no-data value such as 99.9 or 0, with one record per day representing the daily sum of precipitation in millimeters. (b) **Extraction of climate model data**: Climate models typically provide time series data in the netCDF3 format, stored in multiple binary-decoded *.nc files. NetCDF facilitates the production, access, and exchange of array-oriented scientific data, endorsed as an open standard by the Open Geospatial Consortium. Each file contains various variables, dimensions, and attributes. CMhyd utilizes netCDF file metadata to identify model grid cells overlapping with gauge positions and convert precipitation data into millimeters. Time series data for relevant grid cells are then extracted from the netCDF files. (c) **Data processing:** CMhyd's Processing tab in the graphical user interface (GUI) guides users through data extraction and bias correction. This process typically involves five steps outlined in the CMhyd GUI depicted in Figure 2.

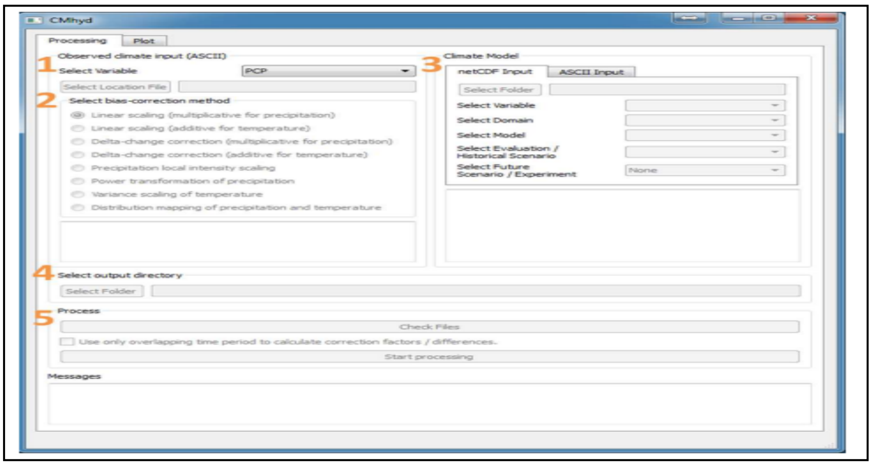


Figure 2: CMhyd graphical user interface. The orange numbering represents the processing steps

The step numbering (1) represent the process of importing the data into the software. Step (2) involves selecting the bias correction method using the Linear Scaling method, Step (3) involves selecting the Historical and future simulated climate data. Step (4) involves choosing a storage folder and step (5) involves processing the data.
The linear downscaling method, selected for this study, involves establishing statistical relationships between large-scale climate variables simulated by Regional Circulation Models (RCMs) and local-scale climate variables observed at specific locations. By quantifying these relationships through linear regression, the method enables the estimation of future local climate conditions based on RCM output. This approach is justified in the study for its simplicity, computational efficiency, and ability to capture linear relationships between large-scale and local-scale climate variables, making it suitable for downscaling daily precipitation data in the selected study areas. Additionally, linear downscaling is widely used in climate research and has been shown to produce reasonable results, especially when applied alongside bias correction techniques to account for discrepancies between simulated and observed data. Thus, by employing the linear downscaling method, the study aims to provide reliable projections of future climate conditions in Benin City, Enugu, Lokoja, and Port Harcourt, facilitating informed decision-making and adaptation planning in the face of climate change.

3. Results and Discussion

Following the bias correction of the input data, the daily average future corrected precipitation for the period 2041-2050 was derived and is displayed in Table 9. Additionally, the yearly average future corrected precipitation for the same period is showcased in Table 10.

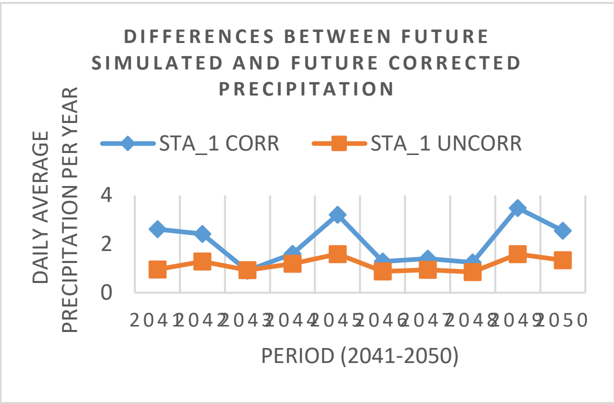
Table 9: Daily average future corrected precipitation (2041-2050)

Years	Benin	Enugu	Lokoja	Portharcourt
2041	2.61137	1.637863	1.196219	4.476246575
2042	2.408986	1.258493	0.822438	3.726849315
2043	0.906503	0.488415	0.363142	2.427459016
2044	1.600603	1.027288	0.660384	3.83490411
2045	3.208767	1.896603	1.290986	5.308191781
2046	1.286603	0.863699	0.573041	2.422219178
2047	1.396667	0.651011	0.518142	2.806666667
2048	1.245589	1.209562	0.847233	3.938027397
2050	2.546466	1.724658	1.080849	4.378410959
Average	**2.069706**	**1.287277**	**0.881068**	**3.922785171**

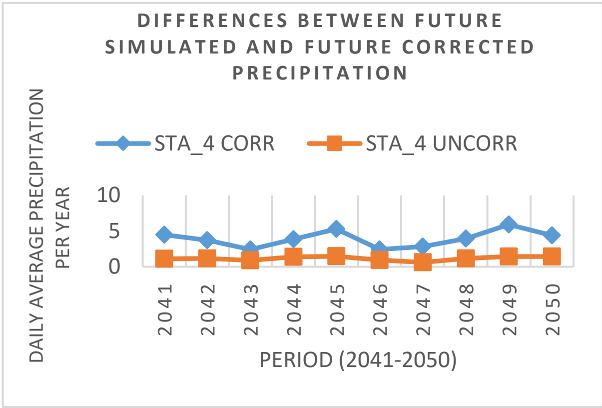
Table 10: Year average future corrected precipitation (2041-2050)

Meteorological stations	10 Years Average
Benin	2.069706
Enugu	1.287277
Lokoja	0.881068
Portharcourt	3.922785171

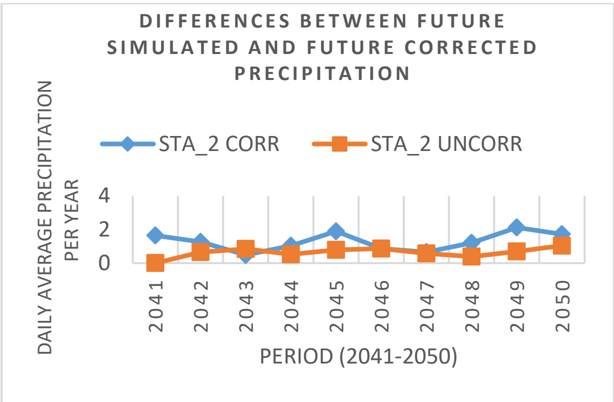
To illustrate the distinct contrast between the bias-corrected and downscaled future climate data and the RCM-simulated future data, graphical visualization plots and spatial maps were generated and are presented in Figures 3, 4, and 5, respectively.

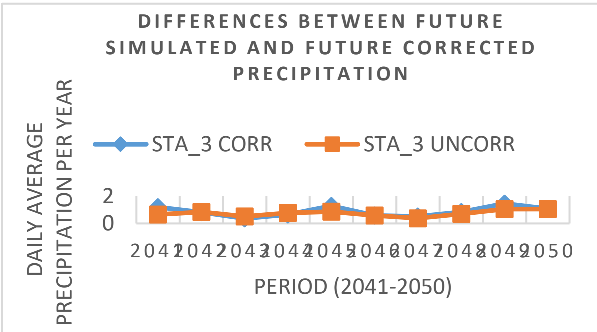


(A)



(B)





(c) (D)

Figure 3: Line graphs showing the difference between corrected and uncorrected future precipitation data for each of the station; (A) represents station at Benin, (B) represents station at Enugu, (C) represents station at Lokoja and (D) represents station at Portharcourt

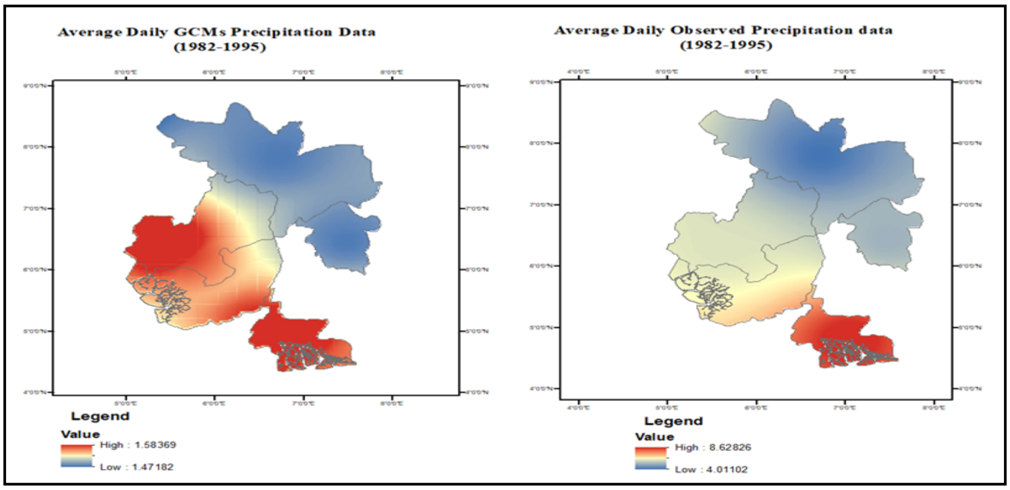


Figure 4: Map showing the average daily precipitation as produced by the GCM (Left side) and Average daily precipitation as produced by observation stations (Right side) for historical Climate change

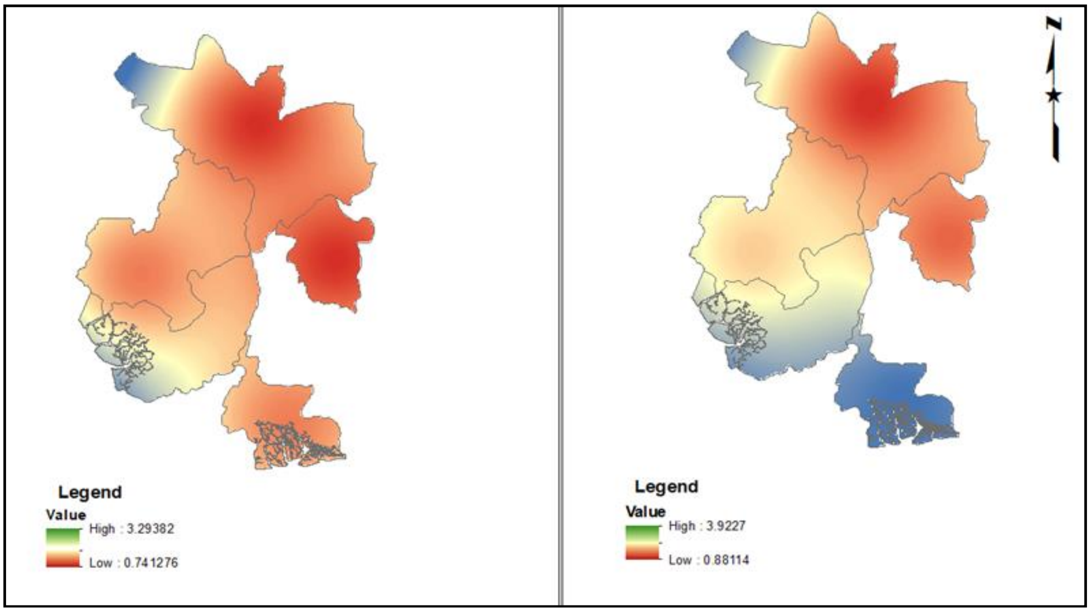


Figure 5: Map showing the average daily precipitation as produced by the GCM (Left side) and Average daily precipitation as produced by observation stations (Right side) For Future climate change (2041-2050)

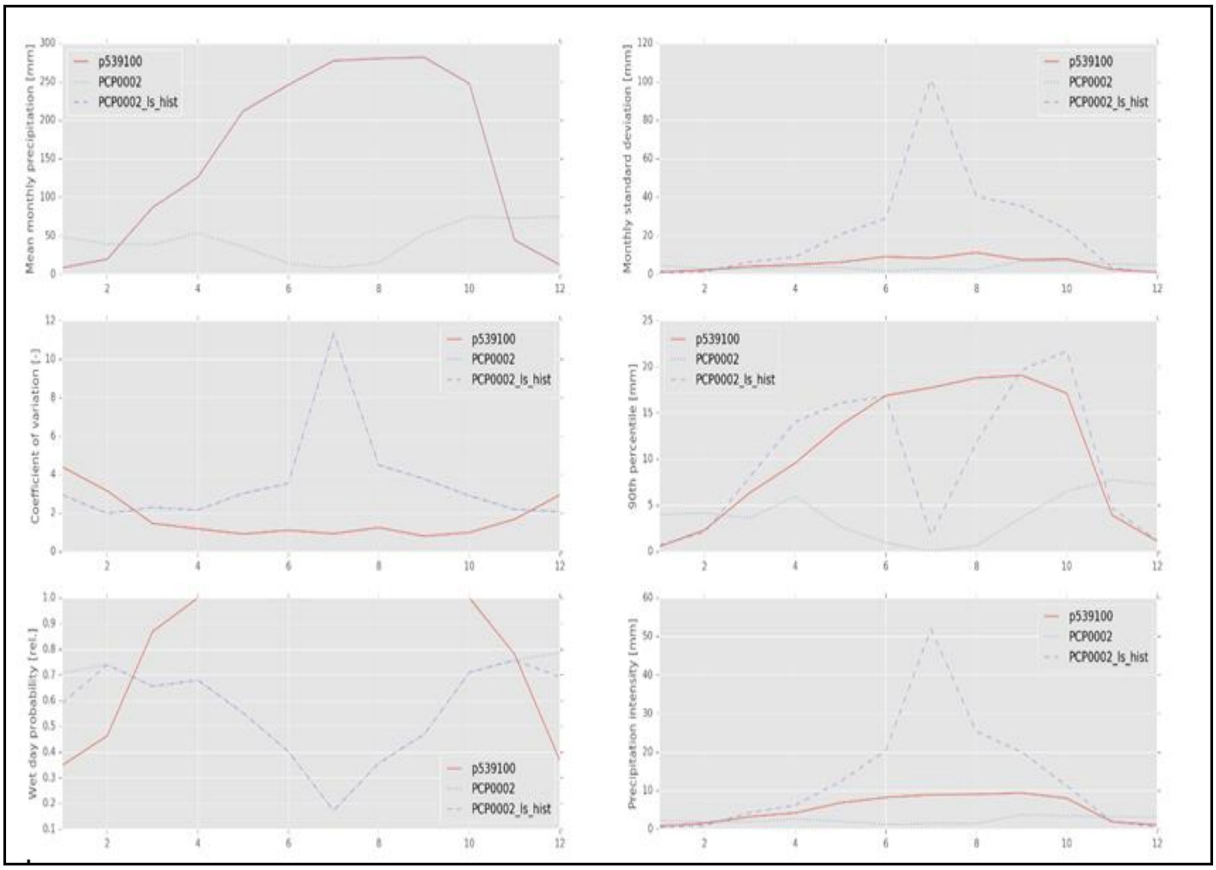


Figure 6: Additional plots for Benin station

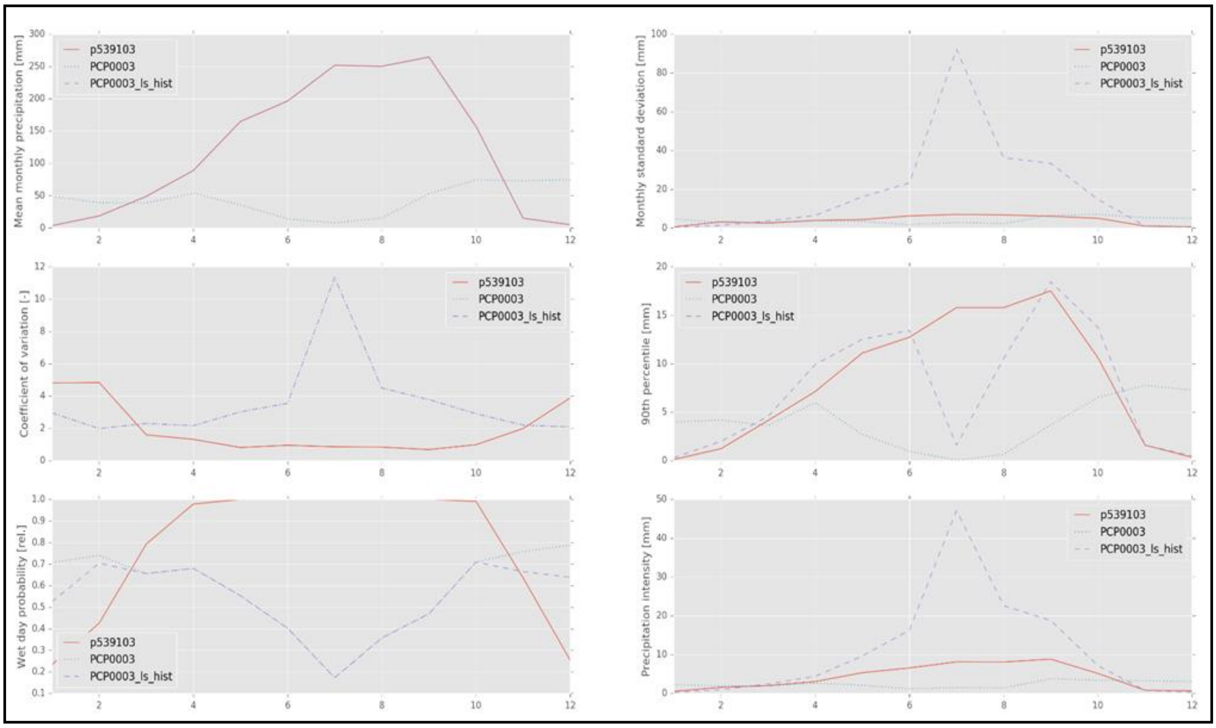


Figure 7: Additional plots for Enugu station

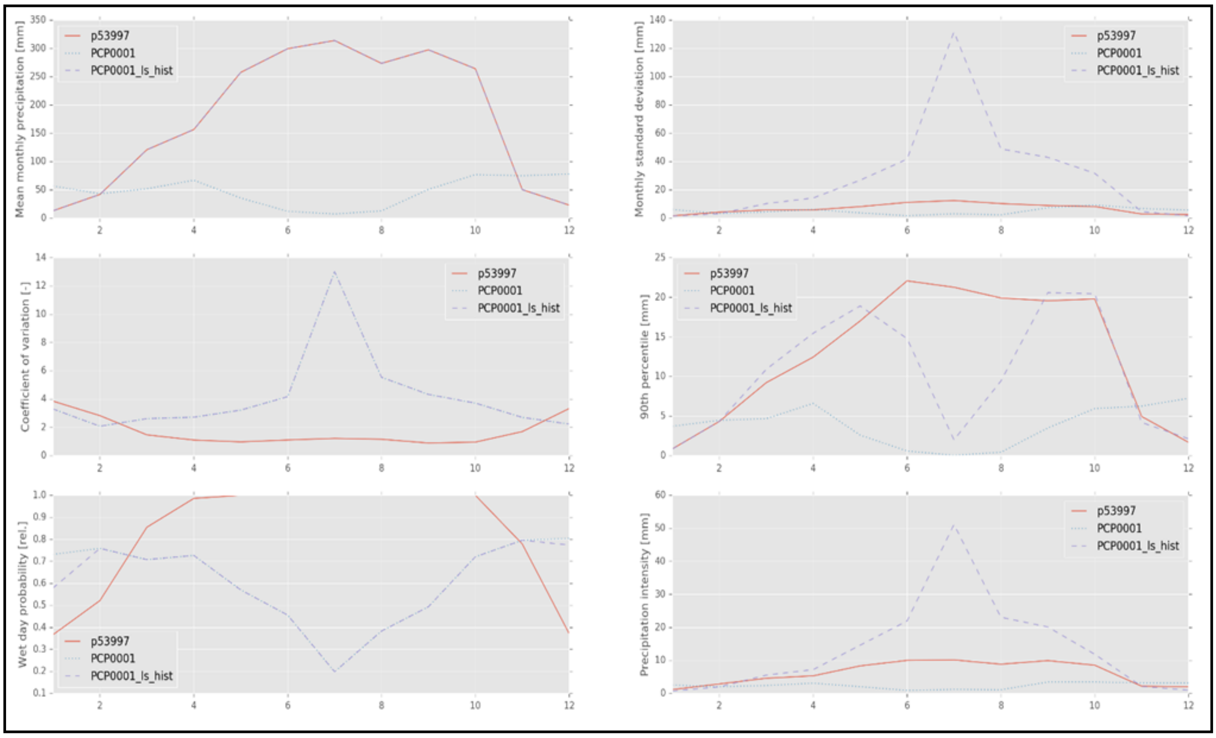


Figure 8: Additional plots for Lokoja station

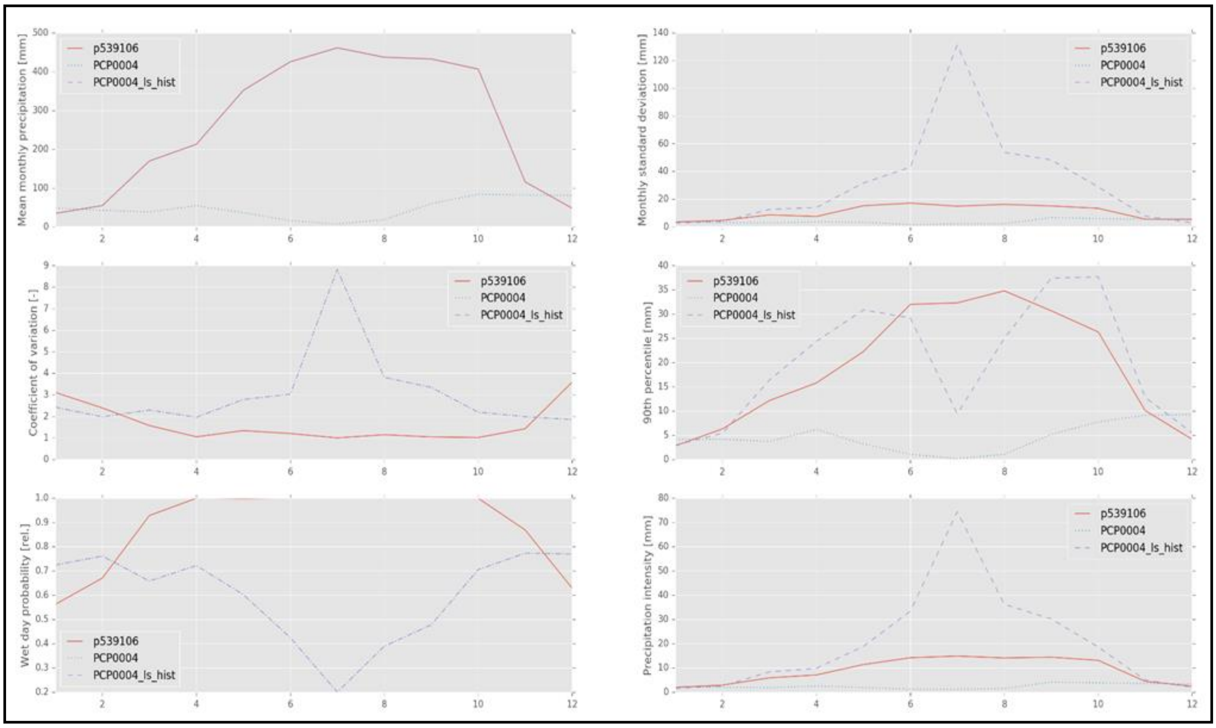


Figure 9: Additional plots for Portharcourt station

4. Conclusion

In order to generate the requisite future climate data crucial for assessing the impacts of climate change, we employed bias correction and statistical downscaling techniques. Although originally designed for handling monthly data, we adapted this approach to accommodate daily precipitation information. Operating at a spatial resolution of 3.5°x3.5°, this method successfully yielded bias-corrected daily precipitation data derived from the AFR-44 Regional Climate Model (RCM) spanning the years 2041 to 2050. The availability of bias-corrected future climate projections from the RCM facilitates impactful analyses of climate change effects. As such, our study underscores the critical significance of bias correction and downscaling methodologies in climate change research. These techniques are indispensable for effectively scaling general circulation models to local contexts, thereby informing climate change studies and facilitating informed environmental planning decisions.

The implications of our findings highlight the importance of employing bias correction and statistical downscaling techniques in climate change research, particularly in regions like Benin City, Enugu, Lokoja, and Port Harcourt. By successfully adapting these methods to accommodate daily precipitation data, we have demonstrated their utility in generating future climate projections at a local scale. This has significant implications for understanding and preparing for the impacts of climate change in these regions, where accurate climate data is crucial for informed decision-making in environmental planning, infrastructure development, and resource management. Furthermore, our study underscores the need for continued research and improvement in bias correction and downscaling methodologies. Future research efforts should focus on refining these techniques to enhance their accuracy and reliability, especially in regions characterized by complex climate dynamics. Additionally, there is a need to explore alternative downscaling approaches and evaluate their performance against existing methods to identify the most suitable techniques for specific climate modeling applications. Moreover, incorporating uncertainty quantification techniques into bias correction and downscaling frameworks can provide valuable insights into the reliability and robustness of future climate projections, further improving their usefulness for decision-makers and stakeholders. In conclusion, our study emphasizes the critical role of bias correction and statistical downscaling in generating reliable future climate projections for climate change impact assessments. Moving forward, continued research and innovation in these methodologies are essential for advancing our understanding of regional climate dynamics and supporting effective climate change adaptation and mitigation strategies in vulnerable regions like Benin City, Enugu, Lokoja, and Port Harcourt.

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