Correction of Climate Model using Remote Sensing Rainfall Data for Egyptian North Western Coast Zone (NWCZ)

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ABSTRACT

Before using Regional Climate Models (RCMs) for hydrological study, bias correction is required since RCM outputs diverge from the climatological data that have been recorded. Linear scaling (LS) and Power transformation (PT) are two bias correction techniques that were used to estimate the rainfall correction. The two techniques are tested on Egyptian North Western Coast Zone (NWCZ) to estimate the adjusted rainfall. Up to 2100, the adjustment was applied to the Radiative Concentration Pathways (RCP 4.5 and RCP 8.5) scenarios. To select historical data needed for rectification, Climate Hazards Group Infrared Precipitation with Station data (CHIRPS-V2) and climate Research Unit (CRU) data were put to the test. The findings showed that the CHIRPS-V2 is much more trustworthy than CRU data in research area. A variety of statistical measurements were used to assess the effectiveness of the corrective procedures. (PT) demonstrated better agreement than (LS). To make the correction procedure easier, (PT) parameters (a) and (b) were added as a maps covering the rainy months.

Keywords *: Power transformation technique, bias correction, RCMs, and linear scaling approach.*

1. INTRODUCTION

Global Climate Models (GCMs) are essential tool for estimating future climate precipitation. (GCMs) do not represent small scale features that have impact on precipitation. Therefore, they cannot be utilized directly for regional hydrological modelling. [1,2,3,4]. From the outputs of global climate models, regional information on climatic variables may be extracted using downscaling techniques [5]. These methods consider geographical features like lakes and land surface that have an effect on the local climate [6]. Both statistical and dynamical downscaling may be used to reduce the resolution of global climate model simulations. By incorporating actual correlations between global climate patterns and local climatic variables into GCM outputs, the statistical downscaling (SD) method may obtain regional information [7]. Regional climate models (RCMs) with high resolution are nestled inside global climate model (GCM) outputs in the dynamical downscaling (DD) technique in order to acquire regional weather and climatic parameters with enough data that are physically compatible. Due to significant errors in (GCMs) variables, as well as the RCM's own biases due to model construction, make RCMs susceptible to bias [8]. Biases are corrected using several methods to provide accurate climate models [9]. There is a multiplicity of bias correction techniques available for use in adjusting RCM simulations. Methods range from just adjusting the mean to more complex ones that includes adjusting the variance and, eventually, the quantile values [10]. Both linear scaling and power transformation are mean-based techniques used to change the monthly averages of precipitation data, with the latter also adjusting the variance [11]. The purpose of this research is to evaluate and contrast the two approaches of bias correction methods. Historical precipitation data from Climate Hazards Group Infrared Precipitation with Station data (CHIRPS-V2) is consulted. In order to verify these data, we compare them to rainfall observations from five locations covering the research region.

2. STUDY AREA

The research region (Figure1) is situated in the northwestern of Egypt extends for about 500 km from Alexandria to Salloum on the Egyptian-Libyan border. The study area comprised within 25º 0´ 0" and 31º 0´ 0" E and 30º 0´ 0" and 31º 30´ 0" N. It is bounded by the Mediterranean Sea to the north, Alexandria to the east, and the Libyan border (Salloum crossing) to the west with a north-south depth varying from 30 to 50 km. It covers an area of about 2.4 million hectares. Mild, rainy winters and hot, dry summers describe the subtropical Mediterranean climate belongs to (NWCZ). In most years, precipitation occurs between September and May. Approximately 75% of the annual precipitation occurs between November and February, whereas just 10% occurs throughout.

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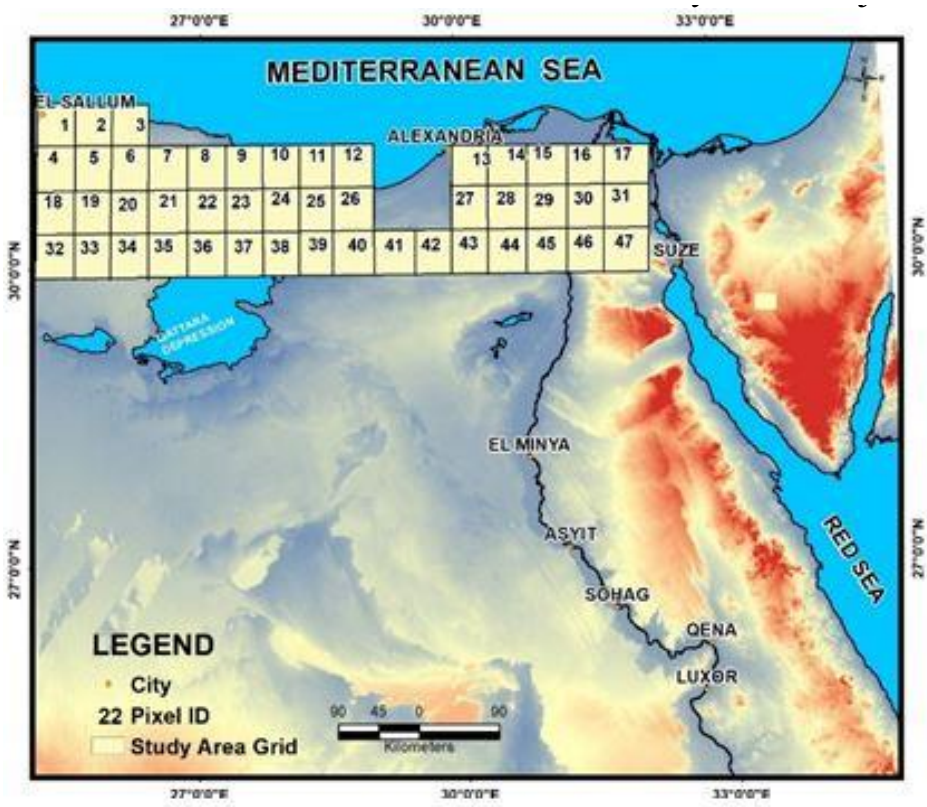

Fig. 1 : Location map of the study area

3. MATERIALS AND METHODS

The used methodology intends to use two correction approaches to rectify monthly rainfall bias in RCM simulations.

3.1 Materials

- **Rainfall Data**

In this research, different types of rainfall data are used (observed data, climate Research Unit (CRU), Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) and Regional Climate model data. Table 1 illustrates the description of each type.

3.2 Methods of Bias Correction

There have been investigations with two different methods for rainfall bias correction, both of which rely on monthly correction factors. This study requires adjusting the historical control data. Two examples are given: (1) linear scaling, and (2) power transformation. The next sections go into explaining these procedures.

- **Rainfall linear Scaling (LS) Methods**

Research has shown that (LS) is the simplest bias correction method [13,14,15]. It adjusts the RCM mean value so that it's in agreement with the data we actually have. Then, using equations (1) and (2), we modify the control and scenario (future period) precipitation based on ratio of monthly mean observed to control/scenario rainfall data. However, the monthly mean values are necessary for this method to accurately modify the climate parameters.

$$P^*_{control} = P_{control} \cdot \left(\frac{\mu_m(P_{observed})}{\mu_m(P_{control})} \right) \quad ...(1)$$

$$P^*_{scenario} = P_{scenario} \cdot \left(\frac{\mu_m(P_{observed})}{\mu_m(P_{control})} \right) \quad ...(2)$$

Where:

P: uncorrected rainfall;

P*: corrected rainfall.

μ: mean

control: RCM-simulated 1981-2021

scenario: RCM-simulated 2022-2100

- **Power Transformation (PT) Method**

Although mean-bias correction through linear scaling is feasible, it cannot do the same for variations in the variance. A precipitation time series' variance statistics may be adjusted using the (PT) method's [11,16]. based exponential form.

Table 1 : Data Description

Name	Source	Period	Description
Observed data	Egyptian Meteorological Authority (EMA)	1975–2005	Monthly rainfall data covers the study area at five ground stations (Alexandria-Dabaa-Marsa Matrouh- Barrani -Salloum).
CRU	Created by the interpolation of monthly climate anomalies based on data collected by networks of weather stations	1901–2018	Monthly climatological data at a latitude and longitude resolution of 0.5 degrees
CHIRPS-2.0	Derived from satellite data	1981-2021	Monthly gridded 0.05° ×0.05° (5km).
Regional Climate model data	CORDEX (Middle East North Africa) (MENA) domain	1951-2100	(MENA) domain |0.44° (50km). (RCA4) the RCM available for analysis driven by GCM (Ec-earth13). Radiative Concentration Pathways[12] (RCP) 4.5 and 8.5 data monthly will be used as intermedia and extremes socioeconomic scenarios respectively

Parameter (b) is estimated using 3-months window centered on the interval. without resorting to any distributions. To begin, corrected RCM rainfall (P^b) coefficient of variation (CV) is compared to coefficient of variation (CV) of observed rainfall (P_{obs}) with every month m:

Obtain b_m such that $f(b)_m = 0 = CV_m(P_{observed}) - CV_m(P^{b_m}_{control})$

$$= \frac{\sigma_{m P_{observed}}}{\mu_m P_{observed}} - \frac{\sigma_m (P^{b_m}_{control})}{\mu_m (P^{b_m}_{control})} \quad ...(3)$$

$$P^*_{control} = P^{b_m}_{control} \quad ...(4)$$

$$P^*_{scenario} = P^{b_m}_{scenario} \quad ...(5)$$

$$P_{corrected\ (control)} = P^*_{control} \cdot [\frac{\mu_m (P_{observed})}{\mu_m (P^*_{control})}] \quad ...(6)$$

$$P_{corrected\ (scenario)} = P^*_{scenario} \cdot [\frac{\mu_m (P_{observed})}{\mu_m (P^*_{control})}] \quad ...(7)$$

- **Methods of Evaluation the Bias Correction Methods**

Nash Sutcliffe efficiency Coefficient (NSE), percent bias (PB), and ratio of the root mean square error to the standard deviation of measured data (RSR) are used to assess the effectiveness of the two approaches to bias reduction.

- **Nash-Sutcliffe Efficiency (NSE)**

As mentioned in [17], (NSE) is a standardized statistic that compares the residual variance to the variance in the observed data. The NSE measures how close the observed data are to the 1:1 line in a plot with the simulated data. The equation for determining NSE is as follows (8).

$$NSE = 1 - \frac{\sum_{i=1}^{n} (y_i^{obs} - y_i^{sim})^2}{\sum_{i=1}^{n} (y_i^{obs} - y_i^{mean})^2} \quad ...(8)$$

Where:

(Yi^{obs}): observed values, (Yi^{sim}): simulated value, (Yi^{mean}): mean of observed data, and (n): the total number of observations. The optimal value of NSE is 1, though values between 0 and 1.0 are all acceptable. whereas performance below 0 suggests that the mean observed value is a better predictor than the simulated value.

- **RMSE - Observations Standard Deviation Ratio (RSR)**

The root-mean-squared error (RMSE) is a popular error index statistic [18, 19], 20]. The root-mean-squared error-observation standard deviation ratio (RSR) was devised by [19] as a new metric for evaluating models. It includes both an error index (RMSE) and a standard deviation (the standard deviation of the data). The ratio of root-mean-squared error (RMSE) to standard deviation (SD) is the RSR, and it is computed using the formula (9). The advantages of error index statistics are incorporated into RSR, along with a scaling/normalization factor, which allows the resulting statistic and reported values to be used across a wide range of components. The residual standard error of a model (RSEM) may range from zero to a significant positive number, with zero being ideal model simulation. As RSR decreases, RMSE decreases, and model simulation performance improves.

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n} (y_i^{obs} - y_i^{sim})^2}}{\sqrt{\sum_{i=1}^{n} (y_i^{obs} - y_i^{mean})^2}} \quad ...(9)$$

- **Percent of Bias (PB)**

The percent bias (PB) quantifies the typical deviations among the simulated data compared to the observed data [21]. Values of PB close to zero indicate that the model is being simulated correctly. Bias in the model may be either under- or overestimated, with positive values indicating the former and negative values the latter, [21]. PBIAS is calculated with the equation (10). Table 2 displays evaluations of performance for (NSE, RSR &PBIAS).

$$PBIAS = \frac{\sum_{i=1}^{n} (y_i^{obs} - y_i^{sim}) \cdot 100}{\sum_{i=1}^{n} (y_i^{obs})} \quad ...(10)$$

4. SELECTION OF HISTORICAL RAINFALL DATA

Several type of data are available, table 1, and it can be used as a base for climate model data correction. Observed ground data is available only at 5 stations covering the shoreline. While, CRU&CHIRPS-2.0 data are available in a grid format covering all the study area grids.

CHIRPS-2.0 resolution is 5 km, CRU data is 50 km and RCM data is 50 km. However, all the rainfall data is prepared in resolution of 50 km. To compare the data of CRU& CHIRPS-2.0 with the observed data, rainfall values are computed at station locations. Then, the performance of these rainfall data are evaluated using the observed ground stations to compare the statistical measured (NSE, RSR&PB) as presented in Table 3.

Table 2 : Assessments of Statistical Data Analysis Efficiency

Performance Rating	RSR	NSE	PBIAS	Data Classification
Very good	0.00 < RSR < 0.50	0.75 < NSE < 1.00	PBIAS < ± 10	very good good Satisfactory Unsatisfactory
Good	0.50 < RSR < 0.60	0.65 < NSE < 0.75	± 10 ≤PBIAS <±15	
Satisfactory	0.60 < RSR < 0.70	0.50 < NSE < 0.65	± 15 ≤PBIAS < ±25	
Unsatisfactory	RSR > 0.70	NSE < 0.50	PBIAS ≥ ±25	

Source: [22]

Table 3 : Values of the Statistical Measures

stations	CRU			CHIRPS-2.0		
	NSE	RSR	PB	NSE	RSR	PB
Alex	0.25	0.87	-28.9	0.50	0.70	9.4
Dabaa	-0.14	-5.90	1.1	0.61	0.60	2.5
Matrouh	-0.02	1.00	18.0	0.51	0.69	-16.1
Barrani	-3.97	2.23	-138.0	0.53	0.60	13.8
Salloum	-5.30	2.50	-278.0	0.66	0.59	-23.2

As shown in Table 3 the results yielded that CHIRPS-2.0 data give a good and satisfactory performance in (NSE, RSR) at all stations except for (Alex & Dabaa) have very good in (PB) measures. On the other hand, CRU data give unsatisfactory performance at all stations except for (Dabaa& Matrouh) give very good & good performance in (PB) according to the performance ratings presented in Table 2. Therefore, CHIRPS-2.0 data is used as base data to correct the RCM results.

5. SELECTION OF BIAS CORRECTION METHODS

Corrections are made to precipitation readings from 47 pixels throughout the study region using two different bias correction techniques (linear scaling (LS) and power transformation methods (PT)). Several statistical measures (NSE, PB, RSR) are used to evaluate and compare the performance of each method. Then, the suitable method for the correction will be selected according to the good agreement with the observed data.

- **Linear Scaling Method (LS)**

(LS) method is applied to adjust arithmetic mean at all pixels of control data (RCM-simulated 1981-2021) with respect to historical CHIRPS data. The results of the statistical measures give NSE < 0.50, RSR > 0.70, r > 0.5 and PBIAS > ± 25 at all pixels. These values indicate unsatisfactory performance according to Table 2. This means that (LS) method is not suitable for RCM rainfall data correction in the study area.

- **Power transformation Method (PT)**

(PT) method is applied to adjust both mean and variance at all pixels of control data (RCM-simulated 1981- 2021) with respect to historical CHIRPS data. The results of the statistical measures give several performance ranges from very good to satisfactory at all pixels except for pixels (46&37). These two pixels have unsatisfactory performance which give NSE < 0.50, RSR > 0.70 according to table (2). Accordingly, PT approach is adapted to adjust the future projections by estimating the values of the two parameters (a&b) for the study area.

6. ESTIMATIONS OF PARAMETERS (A&B) FOR (PT) METHOD

The rainy months of the study area start from September to May. So, only these months were included in the analysis. The length of historical rainfall data series is 40 years (1981-2021). After several iterations, parameter (a&b) were estimated, Monthly values of (a&b) were estimated at each pixel. Table (4) presents the Max, Min and average values of parameters (a&b) over the study area for each month.

It can be noticed from table (4) that the values of parameter (b) varied from 0.03 (Dec, Jan & May) to 0.67 (March). The average values of parameter (b) over the study area ranged from 0.17 for May to 0.47 for March. On the other hand, the values of parameter (a) varied from 0.34 for Sept. to 38.45 for Jan. The average values of parameters (a) over the study area are ranged from 1.27 for Sept to 17.7 for January. However, detailed maps with the actual values of (a&b) at each pixel are illustrated in Figures 2 & 3.

It can be noticed from Figure 2 that the value of parameter (b) is increased toward the shoreline and decrease as going deeper in the study area far from the shoreline. Months;

Feb., Mar., April and Oct. give higher values of parameters (b) than Jan. May, Sep., Nov. and Dec. months.

On the contrary, the parameter (a), as shown in Fig. 3, is decreased towards the shoreline and increase as going deeper in the study area far from the shoreline.

The highest values of parameter (a) is produced during Jan& Dec and the lowest values is produced during Sept.

The produced values of parameter (a) during Feb. & Nov. are relatively higher than that produced during Mar., April, May, Sep.& Oct.

- **Sensitivity of (a&b) Parameters to Data Length**

The effect of base historical data length on estimation of parameters (a&b) is examined using periods of 40,30,20 and 10 years, Table 5.

Table 5 presents the results of this analysis at pixel (1) as an example. It can be noticed from the table that data length of 30& 20 years gives closer values to 40 years. On the other hand, 10 years' data series give far values from 40 years. So, it is recommended to use historical data with length not less than 20 years to estimate the parameters (a&b) and get satisfactory corrected rainfall.

Table 4 : (PT) method parameter values (a&b)

Month	Min.		Max.		Average	
	b	a	b	a	b	a
September	0.09	0.34	0.55	4.22	0.33	1.27
October	0.17	1.86	0.63	7.29	0.40	4.11
November	0.07	2.41	0.61	16.92	0.37	8.16
December	0.03	2.67	0.55	33.86	0.29	16.09
January	0.03	4.68	0.42	38.45	0.22	17.7
February	0.21	3.47	0.62	26.89	0.39	8.87
March	0.30	1.39	0.67	11.66	0.47	3.66
April	0.20	1.52	0.61	7.78	0.40	2.67
May	0.03	1.37	0.46	3.60	0.17	2.2

7. PERFORMANCE EVALUATION OF (PT) METHOD ON THE HISTORICAL DATA (1981-2021)

The mean of observed data and corrected data were computed after bias correction. Calculations illustrate that the mean of the corrected data close to the mean of observed data and almost has the same value of observed data. As a very important index to evaluate the corrected data, (NSE), (RSR) and (PB) were calculated and the results are illustrated in Table 6.

Fig. 2 : Parameter (b) values at different months

Table 5 : Comparison of data length for (a&b) estimation

	b				a			
month	**40 year**	**30 year**	**20 year**	**10 year**	**40 year**	**30 year**	**20 year**	**10 year**
September	0.55	0.48	0.47	0.10	0.98	1.08	1.56	3.08
October	0.52	0.50	0.46	0.31	4.27	5.72	5.05	9.14
November	0.47	0.46	0.50	0.40	9.70	8.74	7.83	8.37
December	0.37	0.36	0.43	0.41	15.18	13.33	16.75	13.92
January	0.37	0.35	0.34	0.36	11.58	9.95	13.24	14.93
February	0.50	0.54	0.55	0.74	6.29	5.96	5.35	3.56
March	0.55	0.52	0.57	0.67	3.99	3.70	3.40	1.97
April	0.59	0.53	0.49	0.33	2.77	2.70	3.05	3.45
May	0.28	0.23	0.22	0.00	2.25	2.38	2.02	3.39

Fig. 3 : Parameter (a) values at different months

Table 6 : Summary of statistical measure range

Statistical Index	Range		Rate	Remarks
	from	to		
NSE	0.52	0.77	Good- very good	Pixels (37&46) have unsatisfactory performance
RSR	0.47	0.69	Satisfactory-very good	
PB	-5.7	9.5	Very good	

Table 6 shows that the corrected data has different performance according to NSE index which ranging from very good & good at all pixels except pixels (37 & 46) have unsatisfactory performance which have NSE< 0.5. according to RSR index the data performance ranging from satisfactory &very good at all pixels except pixels (37 & 46) have unsatisfactory performance which have error about 0.76 and 0.74 respectively. Regarding Percent bias (PB), calculations indicate that all stations have very good performance. Positive values indicate the data under estimation bias, and negative values indicate the data overestimation bias.

8. PROJECTIONS USING (PT) METHOD IN RCP SCENARIO

Data from the RCP 4.5 and 8.5 scenarios have had their biases removed using the (PT) approach. There are two different time intervals within the simulated period (2022–2100): the mid-century (2022–2060) and the far-century (2061–2100).

- **Comparison Between Observed and Corrected Control Data (1981 – 2021)**

The result reveals that the model under-estimates 16 times and over-estimates 18 times compared with the correct control data. 17% average positive deviation and 16% average negative deviation are noticed between observed and corrected historical data.

- **The Mid-century (2022 to 2060) of RCP 4.5 and RCP 8.5**

It is notice that in years 2022, 2024, and 2037, RCP 4.5 has high rainfall than RCP 8.5, whereas in years 2022 and 2055, RCP 8.5 has more precipitation than RCP 4.5, Figure 4. By comparing the corrected data to the observed data, results show that under RCP 4.5, precipitation was increased by (9%) with repeatedly rate (17%). and decreased rainfall values (16%) with repeatedly rate of 19. On the other hand, RCP 8.5 has 15% high precipitation at a frequency rate of 12, and 15% decreased precipitation at a frequency rate of 21.

Annual mean precipitation distributions for RCP4.5 and RCP8.5 in the mid-century are shown in Figure 5.

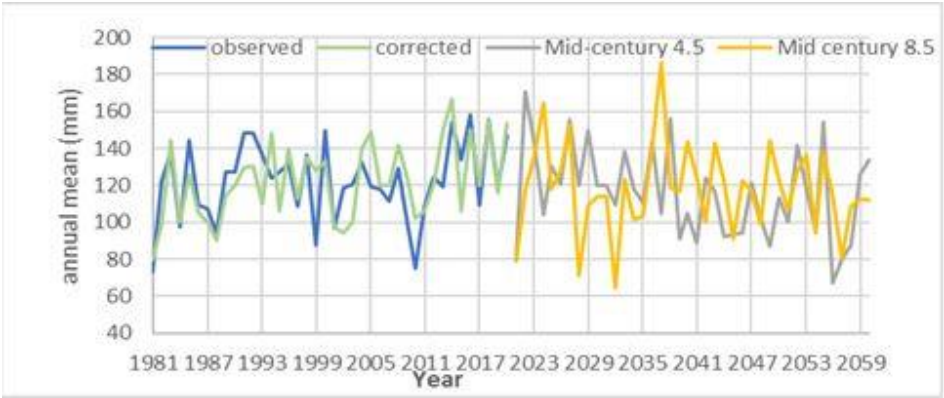

Fig. 4 : Average precipitation (mm) at RCP4.5 and RCP8.5 for observed, corrected data at Mid-century

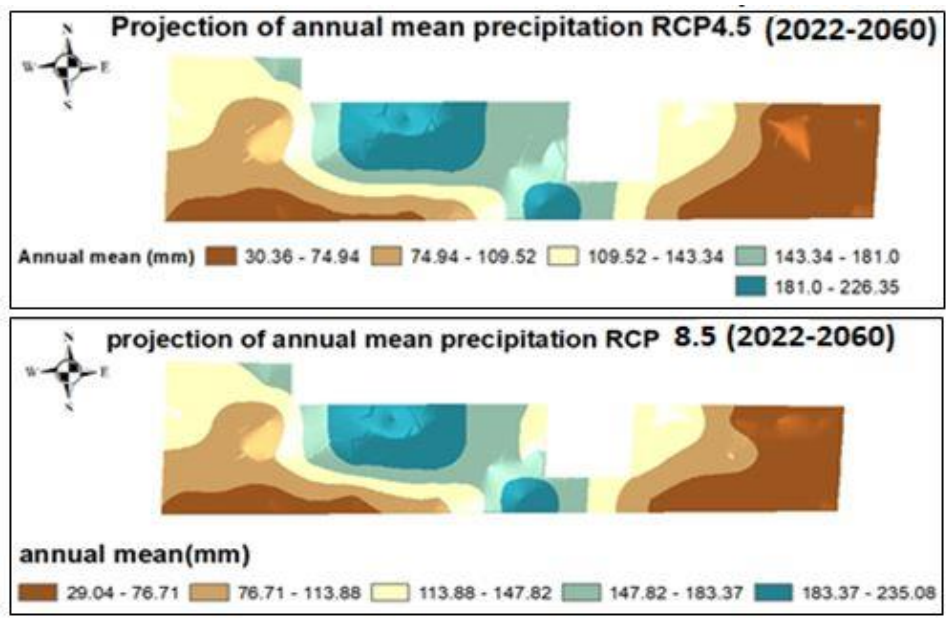

Fig. 5 : Annual mean precipitation distributions for RCP4.5 and RCP8.5 at the Mid- century

In RCP 4.5, the east and west part of study area receive precipitation range from (30.3 to 143.3mm), whereas the center of study area receives high precipitation (143.3 to 226.3 mm). While in RCP 8.5, the east and west part of study area receive precipitation range from (29 to 147.8 mm), whereas the center of study area receives high precipitation (147.8 to 235 mm).

- **The Far Century (2061 – 2100) of RCP 4.5 and RCP 8.5**

It is determined that in the year 2066, Precipitation is higher in RCP 4.5 than RCP 8.5, while in the year 2084, RCP 8.5 has more precipitation than RCP 4.5 (Figure 6). In compared to the observed data, RCP 4.5 predicts higher rainfall (11% with a repeatedly rate of 14) and lower rainfall (14% with a repeatedly rate of 20). On the other hand, RCP 8.5 gives 10% increased precipitation at a frequency rate of 7, and a 23% reduction in precipitation quantity at a frequency rate of 29 compared with observed data. Annual mean precipitation distributions for both scenarios in the far-century is represented in Figure 7. In RCP 4.5, the east and west part of study area receive precipitation range from (32.5 to 144.5 mm), whereas the center of study area receives high precipitation (144.5 to 225.5 mm). While in RCP 8.5, the east and west part of study area receive precipitation range from (27 to 121.2 mm), whereas the center of study area receives high precipitation (121.2 to 201.8 mm).

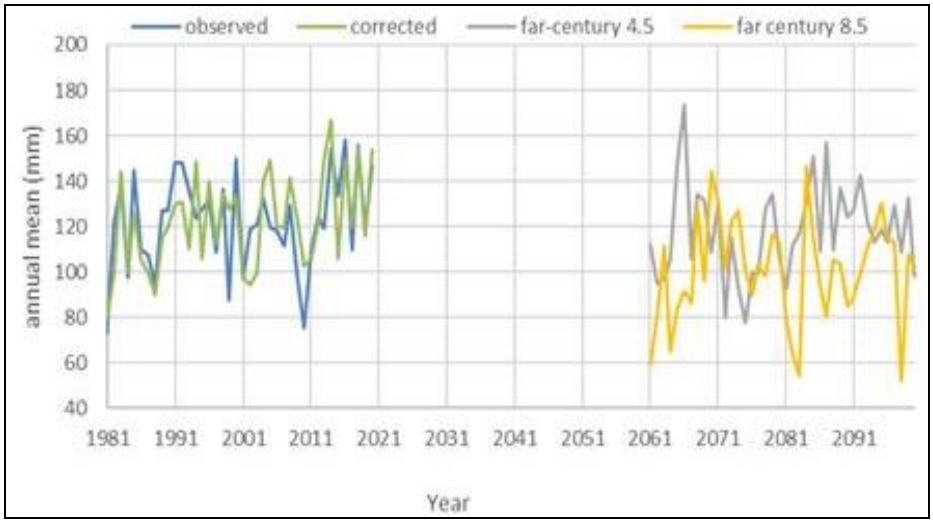

Fig. 6 : Average precipitation (mm) at RCP 4.5 and RCP8.5 for observed, corrected data at Far-century

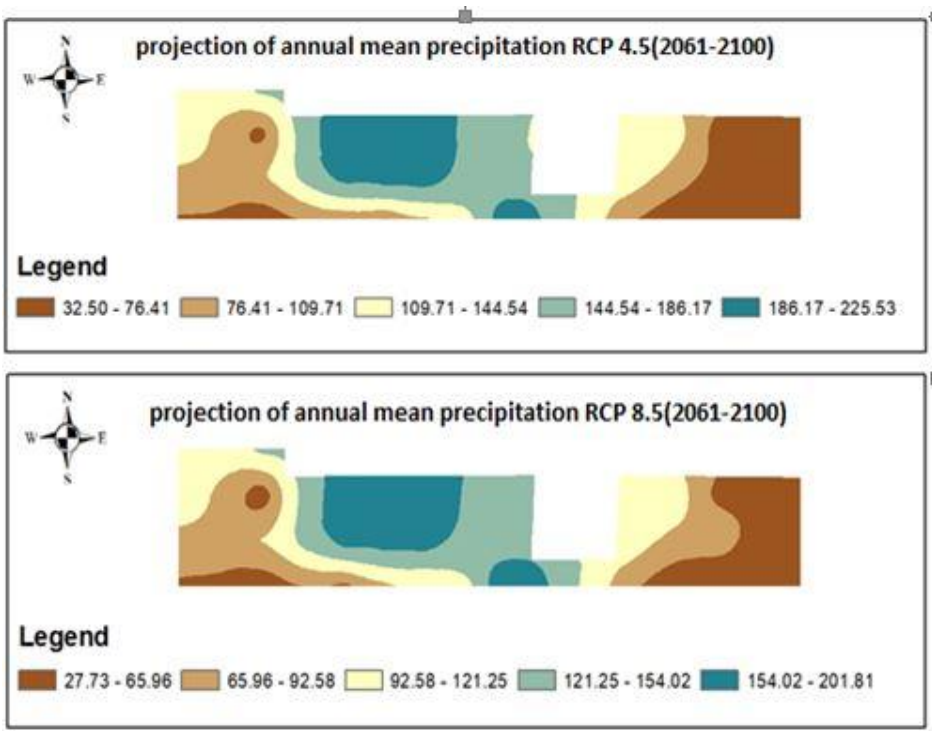

Fig. 7 : Annual mean precipitation distributions for RCP 4.5 and RCP8.5 at Far-century

. SUMMARY AND CONCLUSION

The performance of two type of precipitation data (CHIRPS-V2, CRU) was assessed by using statistical measures (NSE, RSR&PB) at (5) ground stations locations from Alex to Salloum. In order to identify the most efficiency product that could accurately be used as a base data to correct the RCM in the study area. The results yielded that CHIRPS-V2 is better than CRU. Two commonly bias correction methods (Linear scaling (LS) and Power transformation (PT)) were assessed to identify which one give better performance compared with the observed monthly data (1981-2021). Then (PT) method is used to adjust the future rainfall data covers the study area until 2100. (PT) method parameters (a&b) are estimated for the study area based on 40 years' rainfall data series. The produced values are presented in maps to facilitate the correction process. The values of the two parameters (a&b) are estimated for the rainy months (Sep. to May). These values are illustrated in grid format and it used to correct the RCP 4.5&RCP8.5 for EC-earth -13 model (2022-2100). The rainfall behavior in the future is investigated in Mid-century (2022-2060) and far century (2061-2100).

It can be concluded that this research represents an added value to the environmentalist and urban planners as it gives clear information on future precipitation as a main key factor to future development related to agriculture and disaster management in NWCZ. The research concluded that the CHIRPS-V2 is much more reliable when compared to observed data of the study area. However, more earth observation data of rainfall must be tested. In addition, the two methods used for bias correction proved that that power transformation method is much more reliable for the study area. The study introduced maps covering the rainfall months for the (a and b) parameters which will make it much easier for the researcher to correct the RCM information. The validity of these parameters is restricted to the research study area and it can be tested for new areas have similar characteristics.

Acknowledgement

This research was supported by the Science and Technology Development Fund (STDF) through the research project "Strategies for increasing the WATER use efficiency of semi-arid Mediterranean Watersheds and agrosilvopastoral systems under climate CHange (SWATCH)" which was awarded through a PRIMA call. The PRIMA programme is an Art.185 initiative supported and funded under Horizon 2020, the European Union's Framework Programme for European Commission.

REFERENCES

[1] J. W. Hansen, A. Challinor, A. Ines, T. Wheeler, and V. Moron, "Translating climate forecasts into agricultural terms: Advances and challenges," Clim. Res., vol. 33, no. 1, 2006, pp. 27–41.

[2] D. Sharma, A. Das Gupta, and M. S. Babel, "Spatial disaggregation of bias-corrected GCM precipitation for improved hydrologic simulation: Ping River Basin, Thailand," Hydrol. Earth Syst. Sci., vol. 11, no. 4, 2007, pp. 1373–1390.

[3] J. Chen, F. P. Brissette, A. Poulin, and R. Leconte, "Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed," Water Resour. Res., vol. 47, no. 12, 2011, pp. 1–16.

[4] K. Salvi, K. S., and S. Ghosh, "High-resolution multisite daily rainfall projections in India with statistical downscaling for climate change impacts assessment," J. Geophys. Res. Atmos., vol. 118, no. 9, 2013, pp. 3557–3578.

[5] M. Jakob Themeßl, A. Gobiet, and A. Leuprecht, "Empirical-statistical downscaling and error correction of daily precipitation from regional climate models," Int. J. Climatol., vol. 31, no. 10, 2011, pp. 1530–1544.

[6] J. Murphy, "An evaluation of statistical and dynamical techniques for downscaling local climate," J. Clim., vol. 12, no. 8 PART 1, 1999, pp. 2256–2284.

[7] H. J. Fowler, S. Blenkinsop, and C. Tebaldi, "Linking climate change modelling to impacts studies: Recent advances in downscaling techniques for hydrological modelling," Int. J. Climatol., vol. 27, no. 12, 2007, pp. 1547–1578.

[8] D. PaiMazumder and J.M. Done, "The roles of bias correction and resolution in regional climate simulations of summer extremes", vol. 45,2015, pp.1565–1581.

[9] J. H. Christensen, F. Boberg, O. B. Christensen, and P. Lucas-Picher, "On the need for bias correction of regional climate change projections of temperature and precipitation," Geophys. Res. Lett., vol. 35, no. 20, 2008.

[10] M. a. Sunyer et al., "Inter-comparison of statistical downscaling methods for projection of extreme precipitation in Europe," Hydrol. Earth Syst. Sci., vol. 19, no. 4,2015, pp. 1827–1847.

[11] R. Leander, T. A. Buishand, B. J. J. M. van den Hurk, and M. J. M. de Wit, "Estimated changes in flood quantiles of the river Meuse from resampling of regional climate model output," J. Hydrol., vol. 351, no. 3–4, 2008, pp. 331–343.

[12] D. P. van Vuuren et al., "The representative concentration pathways: An overview," Clim. Change, vol. 109, no. 1, 2011, pp. 5–31.

[13] A.V.M. Ines, JW. Hansen, "Bias correction of daily GCM rainfall for crop simulation studies ". Agric. 439 For. Meteorol, 2006, pp. 44-53.

[14] C. Teutschbein and J. Seibert, "Bias correction of regional climate model simulations for hydrological climate-change impact studies": review and evaluation of different methods. J Hydrol 456:12-29, 2012.

[15] Shrestha, Druga Lal, E. Robertson David, C. Bennett James, and Q. J. Wang. "Improving Precipitation Forecasts by Generating Ensembles through Post processing". Monthly Weather Review, vol. 9, 2015, PP. 3642–63.

[16] R. Leander and T.A Buishand, "Resampling of regional climate model output for the simulation of extreme river flows". J. Hydrol. 332 (3–4), 2007, PP. 487–496.

[17] J. E. Nash and J. V. Sutcliffe, "River flow forecasting through conceptual models part I—A discussion of principles", 1970.

[18] T. Chu, A. Shirmohammadi, "Evaluation of the SWAT model's hydrology component in the piedmont physiographic region of Maryland ",2004.

[19] J. Singh, H. V. Knapp, and M. Demissie. "Hydrologic modeling of the Iroquois River watershed using HSPF and SWAT,2004.

[20] G. Vazquez-Amábile, B. A. Engel. "Use of SWAT to compute groundwater table depth and streamflow in the Muscat tuck River watershed", vol. 48, no. 3, 2005, pp. 991–1003.

[21] H. Gupta, S. Sorooshian, and P. O. Yapo. "Status of automatic calibration for hydrologic models", Comparison with multilevel expert calibration. J. Hydrologic Eng. 4(2),1999, PP.135-143.

[22] D. Moriasi, J. Arnold, R. Bingner, R. Harmel, R. Veith, "Model evaluation guidelines for systematic quantification of accuracy in watershed simulations", Trans. ASABE, 50, 2007, PP.885–900.

Nothing is softer or more flexible than water, yet nothing can resist it