Performance evaluation of ERA5 precipitation data for extreme events based on rain gauge data over Egypt.

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Abstract - *Precipitation is a vital part of the Earth's hydrological cycle, and precise measurement is necessary for several disciplines. Ground-based rain measurements have limitations as they only measure at one point and cannot cover inaccessible areas. Remote sensing rain is necessary to supplement these measurements and overcome limitations. Evaluating the accuracy of the remote sensing and reanalysis precipitation products are essential to know its reliability and potential. Reanalysis hourly precipitation (model-based) ERA5 along with gauge precipitation data, were collected for the sever flood events science 1979 to 2010 over Egypt in this study. The data has been first assessed visually prior to the statistical assessment. A set of metrics, including bias, RMSE, Pearson correlation coefficient, and coefficient of determination were used to measure the accuracy of reanalysis ERA5 precipitation relative to the gauge data in different locations. The investigation was conducted through an assessment of the coincidence between measurements taken on the ground gauges and data obtained from ERA 5 for a total of 12 occurrences. Although the two sets of data shared some similarities, it was necessary to make certain adjustments to bring the ERA 5 data close to the ground data. The ERA 5 data, on average, was found to be delayed and underestimated. The adjustment factor and ERA5 time shift averaged at 3.2 and -10.7 hours, respectively. The study draws attention to the importance of giving careful consideration and applying appropriate adjustment factors and time shifts to ensure that data comparison is accurate and reliable. The research also evaluated the statistical efficacy of the gathered gauge data, revealing that certain gauges displayed greater average MAE, PCC, and R-squared values compared to others. The 1983 occurrence demonstrated the strongest correlation between the datasets, while the 1993 event exhibited the largest discrepancy.*

Key Words: ERA5; reanalysis; quantitative precipitation; performance evaluation; extreme events; Egypt

1. INTRODUCTION

Precipitation is a crucial component of the Earth's hydrological cycle, and its accurate measurement is essential for various fields such as weather prediction, water resource management, agriculture, forestry, energy sectors, and climate research [1]–[3] . There are various sources of precipitation data, including gauge-based (in situ measurements), remotely sensed, and re-analyzed data (numerical simulation). Although the ground measurement is the most reliable data at point scale [4], [5], it is a great challenge to get continuous precipitation grids. Where the rain gauge networks density and distribution vary significantly over the world, with adequate dense networks of gauges in advanced nations, but rare or even not existing in the developing countries and inaccessible areas[6], [7].

Nonetheless, the current rain gauge networks on land are inadequate, and there are no existing ones at sea. Moreover, their quality differs across various regions worldwide. To supplement ground-based precipitation observations, weather radars can offer high-resolution precipitation data in both space and time. However, the weather radars spatial extent is insufficient when it comes to assessing weather and climate models on a global and continental scale.

By optimally combining observations and models, reanalysis indeed provide consistent “maps without gaps" of Earth Climate Variables (ECVs) and strive to ensure integrity and coherence in the representation of the main Earth system cycles[8]–[10] . Reanalysis have found a wide application in atmospheric sciences, not least in operational weather centers where, for example, reanalysis are used to assess the impact of observing system changes, to gauge progress in modelling and assimilation capabilities, and to obtain state-of-the-art climatologies to evaluate forecast-error anomalies[11], [12].

The European Centre for Medium-Range Weather Forecasts (ECMWF) has developed several reanalysis products, including ERA5 and ERA5-Land, which use a Numerical Weather Prediction Model and data assimilation system [12]–[14]. ERA5 uses a 2016 version of the ECMWF NWPM and data assimilation system (Integrated Forecasting System Cy41r2) to assimilate both in situ and satellite observations. ERA5-Land shares most of the parameterizations with ERA5, which guarantees the use of state-of-the-art land surface modeling applied to numerical weather prediction models[11], [16]–[20]. These reanalysis products have been used in various studies, including hydrological modeling, drought indices calculation, and surface and atmospheric field simulation [21]–[25].

Reanalysis precipitation data has several strengths and limitations. One of the strengths of reanalysis precipitation data is its high spatial and temporal resolution, which allows for global coverage and detailed analysis of precipitation patterns [26]. Another strength is that reanalysis precipitation data can be corrected for biases using frequency correction approaches [27], [28] or by using statistical methods to correct for time-series patterns [27], [29]. However, there are also limitations to reanalysis precipitation data. One limitation is that it may have severe biases, especially in extreme precipitation events [28], [30], [31]. Another limitation is that the performance of reanalysis precipitation data can vary depending on the number of precipitation observation stations involved and the type of variational analysis model used [29], [32]–[34]. Finally, the accuracy of precipitation estimation by means of reanalysis data can be affected by the spatial and temporal resolution of the meteorological data used [32], [33], [35].

various studies have evaluated the accuracy and reliability of reanalysis precipitation data. These studies have been conducted in different regions of the world, including India, China, Morocco, and Iran , [36]–[39]. Most studies have focused on assessing and simulating precipitation data[29], [40]–[44], and some have evaluated different reanalysis data for hydrological models[45], [46]. Additionally, some studies have evaluated gridded precipitation datasets from satellite and reanalysis for reliability[47]–[49].

It can be concluded that reanalysis precipitation products have both strengths and weaknesses when compared to other sources of precipitation data. Some studies have found that reanalysis products outperform other sources of precipitation data for certain variables, such as monsoon season precipitation, T_{max}, evapotranspiration, and soil moisture[50]–[52]. Other studies have shown that reanalysis precipitation products can be a reliable alternative to gauge-based data in poorly gauged areas [50], [53]. However, it is important to note that reanalysis precipitation products may exhibit high uncertainties over areas with complex climate and terrain [4], [54]–[58]. Additionally, some studies have found that gridded observation-based data sets generally provide better extreme value statistics of daily precipitation than reanalysis data sets [36], [44], [59]. Overall, the choice of precipitation data source should depend on the specific application and the strengths and weaknesses of each data source should be carefully considered.

This study aims to assess the reanalysis quantitative precipitation data (ERA5) and find a relation with ground measurements for extreme events to maximize the benefits of using such long time series data (1950-present) with spatial and temporal variation in the different fields in Egypt.

2. Study area and data interpretation

2.1. Description of the study area

Egypt is located in north Africa between latitudes 22° and 32 °N, and longitudes 25° and 35 °E, and is bordered by the Mediterranean Sea to the north, the Red Sea to the east, Sudan to the south, and Libya to the west with approximately area 1million km2 (
Figure **1**). The climate of Egypt is generally described as arid and semi-arid, with hot, dry summers and moderate wet winters [60], [61]. Rainfall in Egypt is scarce with an annual average of 12 mm and ranges from 0 mm/year in the desert to 200 mm/year in the north coastal region and the common characteristics are locality, convective, spatial variability, and short duration [62]–[64]. There is a lack of rainfall measurements in Egypt, and the available data is often incomplete or inaccurate[65]–[67]. However, some studies have attempted to assess rainfall in Egypt using satellite-based precipitation measurement products [65], [66] and regional climate model simulations [3], [60], [67]. The scarcity of rainfall data in Egypt makes it difficult to accurately map the rainfall spatial distribution over the country [65].

2.2. Ground gauges data

Historically, Flash floods have been a periodic geohazard in Egypt, affecting many parts of Upper Egypt, Sinai, and Red Sea areas. During the period from 1968 to 1998, 11 severe flood storms hourly data have been obtained from World Meteorological Organization (WMO) [68] in 12 stations over Egypt. Furthermore, the disaster storm in 2010 hourly records in 5 stations over Sinai has been obtained from the Water Resources Research Institute (WRRI) [69]. Table 1 provides a list of these stations along with is coordinates, while
Figure **1** presents their geographical locations. In addition, sample of the collected data is presented in
Figure **2**.

Table 1. gauges location coordinates.

STATION	LON	LAT	STATION	LON	LAT
CAIRO	31.40	30.13	HURGHADA	33.83	27.23
MINYA	30.73	28.08	KOSSIER	34.20	26.13
ASYUT	31.01	27.05	RAS-BINAS	35.30	23.58
SOHAG	31.78	26.56	EL-GUDAIRATE	34.41	30.64
LUXOR	32.70	25.66	EL-THEMED	34.31	29.68
ASWAN	32.78	23.96	EL-HAITHY2	34.71	29.47
EL-SUEZ	32.42	29.86	RAS-SHIRA	34.47	29.52
EL TOR	33.61	28.23	EL-RAWAFAA	34.15	30.83

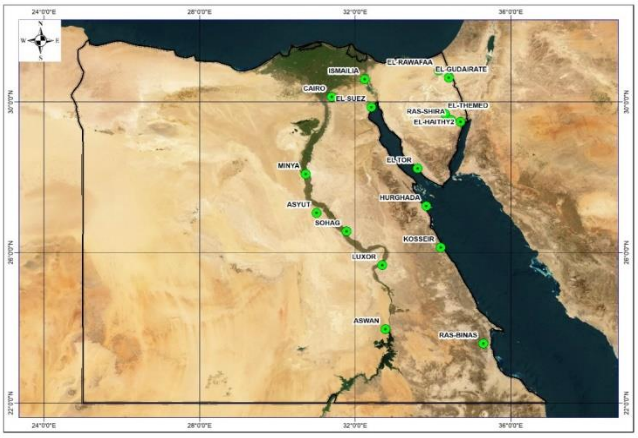


Figure 1. Study Area with gauges location

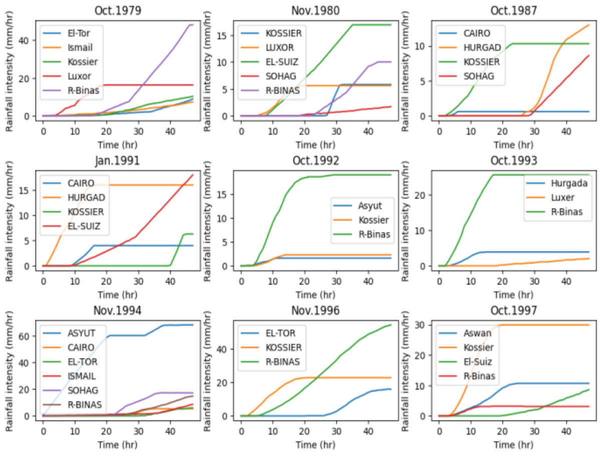
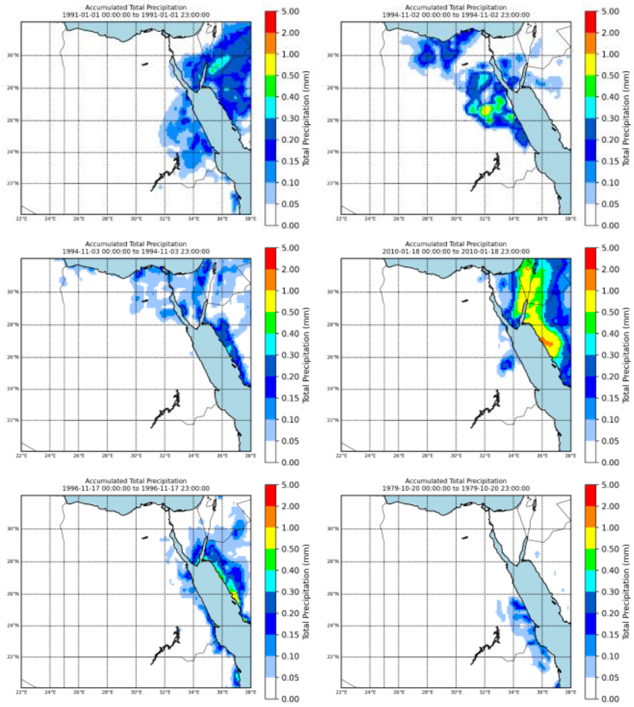


Figure 2. sample of ground gauges measurements for the collected events

2.3. Reanalysis precipitation data (ERA5).

ERA5 is a global atmospheric reanalysis dataset that covers the period from 1979 to present. The dataset has a horizontal resolution of approximately 31 km and 137 vertical levels, with the first level at 10 meters above the surface and the highest level at 0.1 hPa. ERA5 includes a wide range of atmospheric variables, such as temperature, humidity, wind, pressure, and precipitation, as well as derived variables like potential temperature, equivalent potential temperature, and geopotential height. ERA5 also includes several quality control measures, such as the use of bias correction and the removal of spurious data [12]–[14], [57]. The dataset is freely available for download from the ECMWF website in netCDF format. The data has been collected and manipulated using python programming language starting from downloading the data using AI codes and going through reading the data and extracting the required time series at certain locations. **Figure 7** showing a Sample of accumulated precipitation of the collected ERA 5 Data in different events; while
Figure **4** showing the total precipitation obtained at each gauge over the different event compared with ERA5.



Figur 3. Sample of accumulated precipitation of the collected ERA 5 Data in different events

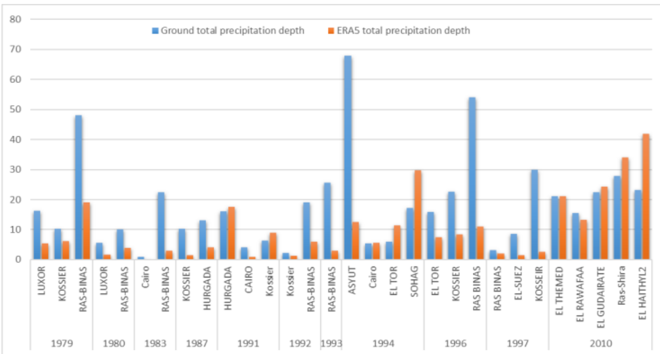


Figure 4. Total daily precipitation of gauges data and ERA5

3. Methodology

The statistical assessment of the ERA5 precipitation product is an important step in determining its suitability for a particular application. By using a variety of statistical metrics, it is possible to identify any potential problems with the ERA5 product and to make adjustments as needed. In addition, it is also important to visually inspect the ERA5 precipitation product to look for any systematic errors or biases. The following are the adopted statistical metrics for assessing the performance of reanalysis precipitation products:

1- Mean Bias (MB):

The bias is a measure of how much the ERA5 precipitation product tends to overestimate or underestimate the reference dataset. A positive bias indicates that the ERA5 precipitation product tends to overestimate the reference dataset, while a negative bias indicates that the ERA5 precipitation product tends to underestimate the reference dataset.

$$MB = \sum_{i=1}^{n} X_P - \frac{X_0}{n} \qquad (1)$$

Where X_p and X_0 are the ERA5 and observed data respectively, and n is the number of the observations.

2- Root Mean Square Error (RMSE):

Root Mean Square Error (RMSE) is frequently used to assess the precision of predictive data. The RMSE is a measure of the overall accuracy of the ERA5 precipitation product by measuring the square root of the average of the squared differences between the ERA5 and observed data. The RMSE has several advantages over other measures of error, such as the Mean Absolute Error (MAE). The RMSE gives more weight to large errors, as it squares the difference between the predicted and actual values which mean more sensitivity to outliers. A smaller RMSE indicates that the ERA5 precipitation product is more accurate.

$$RMSE = \left(\sum_{i=1}^{n} \frac{(X_p - X_0)^2}{n}\right)^{0.5} \qquad (2)$$

Where X_p and X_0 are the ERA5 and observed data respectively, and n is the number of the observations.

3- Pearson Correlation Coefficient (PCC):

Pearson Correlation Coefficient (PCC) is a statistical measure that quantifies the degree of linear association between two variables. It is commonly used to evaluate the strength and direction of the relationship between two variables in a dataset. The PCC measures the linear relationship between the gridded and gauge rainfall data. It ranges from -1 to 1, with values close to 1 indicating a strong positive correlation between the two datasets. The Pearson's correlation coefficient shall be calculated based on the study samples using the following equation.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})\,(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad (3)$$

Where r = correlation coefficient, x_i = values of the x-variable in a sample, $\bar{x}$ = mean of the values of the x-variable, y_i = values of the y-variable in a sample, and $\bar{y}$ = mean of the values of the y-variable.

4- Coefficient of Determination (R-squared):

The R-squared metric represents the extent to which the gridded data can account for the variability in the gauge data. Specifically, it is a statistical indicator utilized to assess the adequacy of a regression model's fit. It gauges the amount of variation in the dependent variable that the independent variable(s) can elucidate. Its range spans from 0 to 1, with results approaching 1 signifying a strong agreement between the two datasets.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \qquad (4)$$

Where,
$SS_{res} = \sum_i (y_i - P_i)^2$, SS_{res} is the sum of squared residuals, which is a measure of the error between the predicted values and the actual values.
$SS_{tot} = \sum_i (y_i - \bar{y})^2$, SS_{tot} is the total sum of squares, which is a measure of the overall variation in the data.
y_i is the observed data, P_i is the predicted data, and $\bar{y}$ is the average of the observed data.

4. Results and discussion

The profiles of storms that were observed in the ERA 5 data exhibited similarities with those that were identified in the ground data. However, the timing and overall values of these storms were found to be variable. Therefore, it has been deemed necessary to make certain adjustments to the timing and values of the ERA 5 data, in order to bring them in line with the ground data. A sample of the performed assessment between gauges and ERA 5 data is presented in Figure 7, which indicates that the data from ERA 5 is typically delayed and underestimated in the most cases. Furthermore, ERA5 data has been shifted and adjusted to match the gauges data timing and values.

The adjustment factor and ERA5 time shift values for events vary from 0.8 to 8.5 and -20 to 1.5 hours respectively, with an average of 3.2 with a standard deviation of 2.7, and average delay 10.7 hours. Events in 1997 and 1993 required significant corrections, while 2010 had the lowest average adjustment factor.
Figure 5 summarizes the average values, emphasizing the need for proper adjustment factors and time shifts for reliable data comparison.
Figure 6 depicts overall correlation between Gauge measurements and ERA5 data.

Statistically speaking, the calibration and verification of the adjustment factor has been conducted on a dataset comprising 32 records. In order to properly assess the performance of the adjustment factor, the dataset has been split into two groups, both of which cover the geographic expanse of Egypt. The first group of 22 records was used to estimate the unified adjustment factor, while the second group, consisting of 10 records, was employed to verify the efficacy of the aforementioned adjustment factor. This methodological approach has ensured the reliability and accuracy of the statistical inferences drawn from the collected data.

The evaluation of the ERA5 dataset, both prior to and post calibration against gauge measurements, has been subjected to examination utilizing four distinct metrics, namely RMSE, PCC, R-squared, and Bias. It is noteworthy to mention that the adjustment factor utilized spans a range of 0.5 to 11.4, with an average of 3. Table 2 presents a comprehensive overview of the minimum, maximum, and mean values pertaining to the statistics metrics (RMSE, PCC, R-squared, and Bias) for both the authentic ERA5 data as well as the calibrated ERA5 data.

The ERA5 dataset's root mean square error varies between 0.47 and 24.85, with an average of 7.64, indicating considerable disparities between the dataset and the gauge observations. Additionally, the Pearson correlation coefficient ranges from 0.28 to 0.99, with an average of 0.76, indicating a moderate to robust association between the dataset and the gauge observations. Furthermore, the R-squared values vary from 0.08 to 0.98, with an average of 0.63, with the dataset explaining 8% to 98% of the variability in the gauge observations. Finally, the Bias ranges from -13.2 to 22.94, with an average of 2.63, indicating that the dataset tends to either overestimate or underestimate the gauge observations. On the other hand, Regarding the Calibrated ERA5 dataset, it is noteworthy that the Root Mean Square Error (RMSE) fluctuates between 0.08 and 11.31, averaging at 2.67, thereby signifying that the errors between the dataset and the gauge observations are comparatively minimal after calibration. The Pearson Correlation Coefficient (PCC), on the other hand, ranges from 0.58 to 0.99, with the average being 0.90, indicating a robust correlation between the dataset and gauge observations after calibration. Moreover, the R-squared value spans from 0.34 to 0.99, with an average of 0.81, which implies that the dataset elucidates a significant portion of the variability in the gauge observations after calibration, ranging from 34% to 99%. Lastly, the bias ranges from -3.53 to 8.93, having an average of -0.04, which affirms that the dataset is moderately unbiased subsequent to calibration.

In conclusion, The RMSE and Bias values for the calibrated ERA5 data have been lowered on average by 65%, and 102% respectively lower than the corresponding values for the original ERA5 data. while the PCC and R-squared values for the calibrated ERA5 data have been increased on average by 18% and 29% higher than the subsequent values for the original ERA5 data.

For the purpose of verification, a comparative analysis of four distinct metrics is conducted to examine their performance before and after the application of a correction factor that was developed during the calibration stage. The four metrics under investigation are RMSE, PCC, Bias, and R-squared. The range of values for each metric, including minimum and maximum values, before and after the correction, as well as the average value are presented. Furthermore, the improvement rate is expressed as a percentage and tabulated for clarity (Table 3).

- The most significant improvement was in the Bias metric, which improved by 78%. This means that the model is now much less likely to over or underestimate the true value.
- The next most significant improvement was in the RMSE metric, which improved by 51%. This means that the model's predictions are now much closer to the actual values.
- The PCC and MAE metrics also showed significant improvement, with improvements of 12% and 53%, respectively.
- The minimum value for each metric decreased after the changes were made, which indicates that the model's performance improved across the board.

Overall, the findings of the study suggest that the implemented correction factor has led to considerable enhancements in the performance of ERA5. The average improvement rate across all the metrics was about 24%, which is a noteworthy improvement. Particularly, the Bias and RMSE metrics showed the most significant improvement, although the PCC and MAE metrics also displayed substantial enhancement. These results demonstrate the effectiveness of the adopted correction factor on the ERA5 performance.

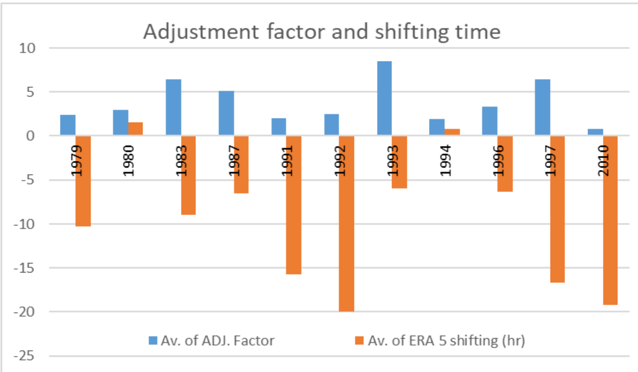


Figure 5 : ERA 5 adjustment factor and time shifting for the different events.

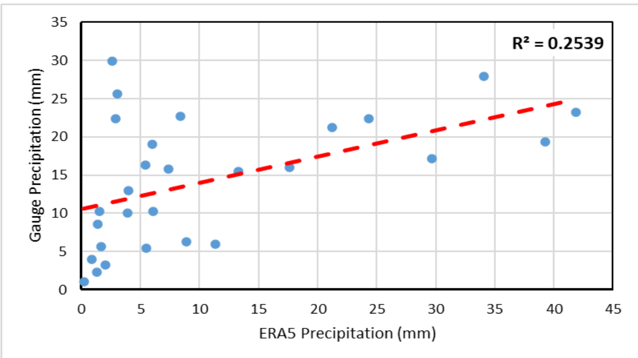


Figure 6 : overall correlation between Gauge measurements and ERA5 data.

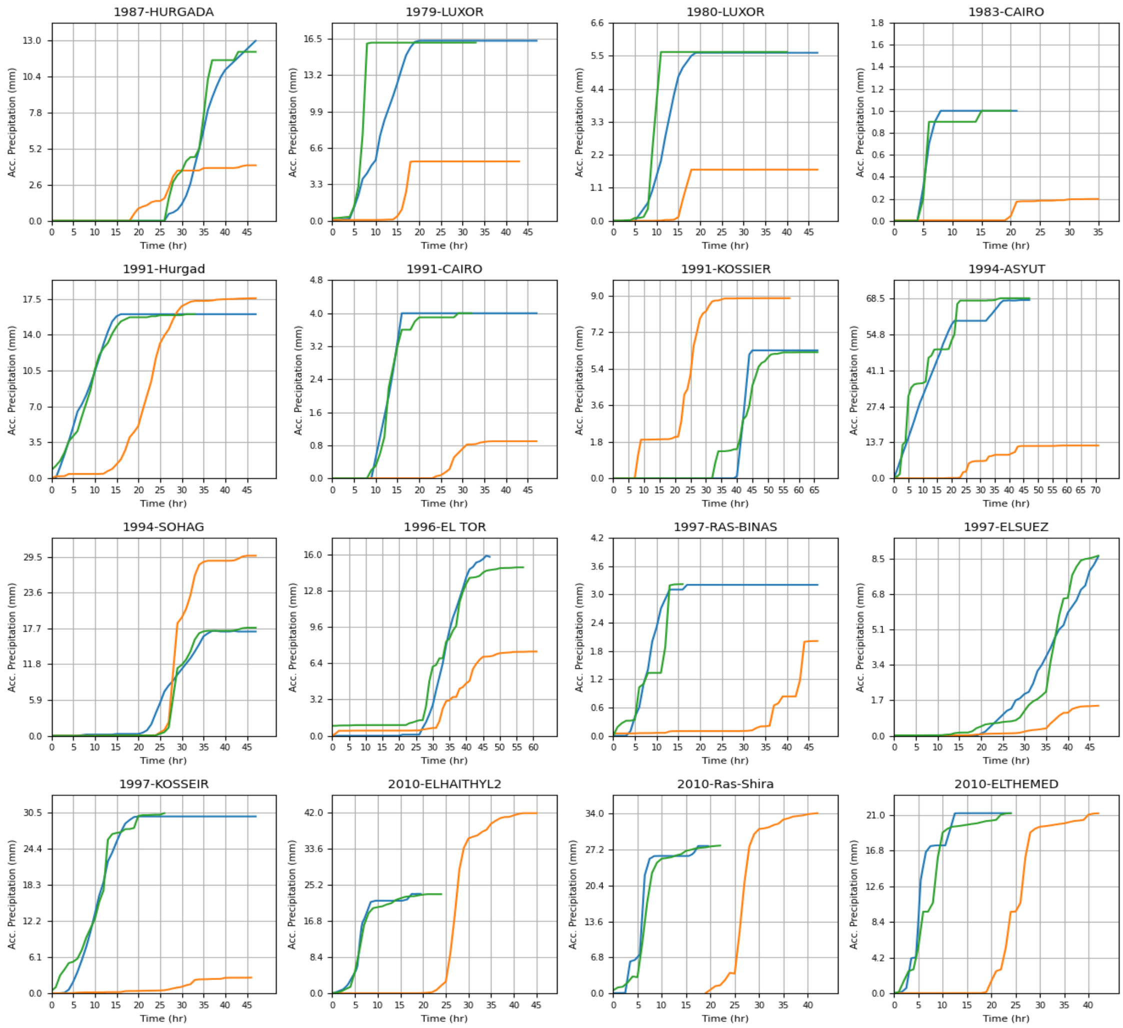


Figure 7. sample of the Comparison between gauges data (blue line), ERA5 data (Orange line), and adjusted (values & timing) ERA5 data (Green Line).

Table 2: Average of the Statistical measures for calibration data set before and after calibration.

Metric	ERA5 Vs. Gauges			Calibrated ERA5 Vs. Gauges			Min. change	Max. change	Average change
	Min.	Max.	Av.	Min.	Max.	Av.			
RMSE	0.47	24.85	7.64	0.08	11.31	2.67	-83%	-54%	-65%
PCC	0.28	0.99	0.76	0.58	0.99	0.90	107%	0%	18%
R-squared	0.08	0.98	0.63	0.34	0.99	0.81	325%	1%	29%
Bias	-13.2	22.94	2.63	-3.53	8.93	-0.04	-73%	-61%	-102%

Table 3: Summary of the different Statistical measures before and after correction.

Metric	minimum		maximum		Average		Improvement Rate
	before	after	before	after	before	after	
RMSE	3	0.8	44.6	22.9	13.90	6.8	-51%
PCC	0.57	0.81	0.97	1.00	0.84	0.94	12%
R-squared	0.32	0.65	0.95	0.99	0.72	0.89	24%
Bias	1.2	-8	42	20.7	11.70	2.6	-78%

5. Conclusion

The subsequent points serve to encapsulate and consolidate the inferences derived from the present investigation, whilst simultaneously engaging in a discourse pertaining to germane and prospective work that may ensue.

- The data obtained from the reanalysis (ERA5) usually provides an exact and precise depiction of the storm profile. However, it is important to note that the predictions derived from this data are often delayed.
- The timing of ERA5 data is always delayed beyond the gauge data by average 10.7 hrs.
- Furthermore, it is common for most of the collected events that the predictions to underestimate the true values of the storm's characteristics, highlighting the need for continued improvements and advancements in the field of meteorological science.
- The ERA5 values commonly need to be adjusted with average multiplier 3 (as per calibration and verification in this study) to be a reliable alternative/representative of the gauges data.
- Due to the technological revolution that occurred subsequent to 2010, coupled with a continued enhancement of the performance of NWPM, it is strongly advised that the conclusions of this research not be employed in tandem with data that is dated after 2010 unless they have undergone verification.
- The augmentation of the amount of data that is currently at our disposal in the recent years for the process of ensemble has resulted in the provision of a quantity of reanalysis that is of a proximity that is near to the values that have been measured. Nonetheless, it is imperative that further research be conducted in order to ensure that the accuracy of the values as well as the timing is verified. In addition, a data set that is of a reasonable gauge ought to be utilized over Egypt for the purpose of ascertaining the veracity of the values. Nevertheless, the accuracy of quantity of reanalysis precipitation is increasing by ensemble more data, the results still have time gape.
- Further extensive analysis could potentially be conducted utilizing a significantly augmented dataset of gauges to ascertain a more precise and constrained range with respect to temporal gaps as well as spatial inaccuracies.

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