



Article

Rainfall Consistency, Variability, and Concentration over the UAE: Satellite Precipitation Products vs. Rain Gauge Observations

Faisal Baig ^{1,2} , Muhammad Abrar ², Haonan Chen ³ and Mohsen Sherif ^{1,2,*} ¹ Department of Civil and Environmental Engineering, College of Engineering, United Arab Emirates University, Al Ain, Abu Dhabi 15551, United Arab Emirates² National Water and Energy Center, United Arab Emirates University, Al Ain, Abu Dhabi 15551, United Arab Emirates³ Department of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO 80523, USA

* Correspondence: msherif@uaeu.ac.ae

Abstract: Recent advancements in remote sensing have led to the development of several useful technologies that would significantly improve our understanding of atmospheric sciences. The ability to identify atmospheric conditions and determine the possibility and intensity of rainfall over a specific location represents one of the most important advantages. However, the use of remote sensing to measure precipitation in arid regions has revealed significant disparities due to a mixture of climatic and terrestrial factors. The objective of this study is to assess the precipitation consistency, variability, and concentration over the UAE using four multi-satellite remote sensing products, namely CHIRPS, CMORPH, GPM-IMERG, and the PERSIANN-CDR, considering daily rainfall data from 50 rain gauges for the period from 2004 through 2020. The study area is divided into various geomorphological regions to assess the accuracy of the products in different regions. Results reveal that the products with a finer spatial resolution such as CHIRPS and CMORPH are better in terms of annual and daily average values. CHIRPS and GPM-IMERG demonstrated better POD values of 0.80 and 0.78, respectively, while CMORPH and the PERSIANN-CDR showed POD values of 0.72 and 0.44, respectively. The correlation and error estimate analysis showed that the performance of different products varies in each region. The PERSIANN-CDR registered the highest correlation of 0.8 for the East Coast, while for other regions it could not correlate well. IMERG and CHIRPS were able to exhibit a good correlation value (up to 0.8) with the gauge observations. Precipitation concentration and variability analysis revealed that GPM-IMERG represents a better alternative to gauge data. It is concluded that multiple hydro-climatological measures should be utilized to assess the effectiveness of satellite products and select the best product for specific studies.

Keywords: precipitation consistency; precipitation concentration; satellite precipitation products; rainfall variability; UAE



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1. Introduction

Accurate assessment of precipitation is vital to manage water resources and understand hydrological processes. Precipitation is one of the fundamental elements of the planetary energy cycle [1,2] and a key input for all climatological models that are used to forecast natural calamities including floods, landslides, and droughts [3,4]. Moreover, hydrological cycles and energy distributions are significantly influenced by spatial distribution, duration, and precipitation concentration [5,6]. Therefore, almost all hydrological investigations primarily require precipitation information with high spatio-temporal resolution. The most imperative task for carrying out any hydrological analysis is the collection of precipitation data and the quality check of rainfall products [7–9]. Rain gauges (in situ measurements) and remote sensing techniques, including commercial microwave links, satellite sensors, and ground-based weather radars, are the most frequently used approaches to estimate precipitation [10–13]. Comparing their accuracy with other sensors and rain gauges

offer direct rainfall readings and can be considered ground truths for most hydrological and climatological studies. The under-estimation of heavy precipitation, owing to splashing, is one of the many measurement issues that affect all types of gauges. Other issues include instrument errors and external influences such as wind, precipitation, evaporation, and observer mistakes. Additionally, gauge readings are point values rather than aerial readings, so they are incapable of characterizing the spatial variations in precipitation. Ground-based weather radars monitor a broad area in real time while estimating precipitation at high spatio-temporal resolutions as compared to rain gauges [14–17]. Radars are essentially available over land, in areas where rain gauges are typically widely distributed. Additionally, it might be challenging to translate the radar reflectance at a particular height and distance from the radar into a precise precipitation estimation. Drop size distribution, melting precipitation, low-level precipitation, attenuation, surface impacts, beam blockage, or beam-filling issues are only a few of the concerns [18]. Furthermore, due to cost and lack of technological expertise, radar networks are not available in many areas. Contrary to weather radars, satellite precipitation products offer an alternative to quickly estimate near-global precipitation. Recent satellite-based precipitation products have high geographical and temporal resolutions for measuring precipitation [19–21]. They blend IR pictures with passive microwave data to create precipitation estimates at high resolutions. Many researchers have carried out extensive investigations to evaluate and validate satellite-based precipitation products because of their enormous potential [1–3,7,8,22–25]. However, limited research was conducted to confirm their effectiveness in semi-arid and arid regions and in areas with challenging topography [26–28]. With advancements in spatial and temporal resolution, the performance of space-born precipitation products has enhanced substantially. High-quality rainfall estimates have been obtained over the past two decades by NASA's Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA) [19]. TRMM data were used to build many cutting-edge products, including several iterations of TRMM and Artificial Neural Networks-based (PERSIANN) products [24]. Ashouri et al. (2015) developed and distributed the PERSIANN-Climate Data Record (PERSIANN-CDR) for long-term hydro-climatic change studies, with approximately 40 years (1983 to current) of daily precipitation data coverage. The 60°N–60°S latitude range is covered by the 0.25° spatial resolution of the PERSIANN-CDR. The gauge-adjusted Global Satellite Mapping of Precipitation (GSMaP), developed by the Japan Exploration Agency's Earth Observation Research Center (EORC), is another global product [29–31]. The Integrated Multi-Satellite Retrievals (IMERG) for the Global Precipitation Mission (GPM) and the Climate Prediction Center (CPC) MORPHing (CMORPH) approach are two of the most widely used multi-satellite sensor precipitation products [2,23,25]. With information from geostationary satellite IR data combined with estimates of precipitation generated from microwave observations, the CMORPH employs morphing algorithms to retrieve the areal precipitation. The CMORPH, which has an 8 × 8-km grid resolution and spans the years 1998 to present, includes the whole combined periods of the TRMM and GPM. Global precipitation estimates are provided by the GPM in almost real time; however, periodically, the data stream is interrupted. Operating in low Earth orbit (LEO), the GPM Core Observatory satellite carries two instruments for measuring worldwide precipitation and serves as a reference for other GPM satellites in the constellation. The primary goal of the mission is to improve available precipitation products by extending the visit period and improving the algorithms to retrieve the precipitation. From raw data to precipitation rates, the GPM offers a range of outputs at different levels. It was put into operation in 2014 and it offers IMERG rainfall products with a temporal resolution of 30 min and a spatial precision of 0.1° × 0.1°.

According to validation and verification assessments, the correctness of recent satellite rainfall products differs spatially and is influenced by the hydro-climatic parameters of the area. For instance, Shen et al. [32] found that CMORPH performed better than both TRMM 3B42 and PERSIANN in capturing the spatial and temporal precipitation patterns in China. CMORPH was demonstrated to depict the spatial distribution of rainfall across

Indonesia with the least accuracy when compared to other satellite-based products [33]. The results of a study by Ghajarnia [34] across the Urmia Basin in Iran were in agreement with those of Wehbe et al. [21]. They asserted that a previous edition of CMORPH (v0.1) was not very successful in creating a meaningful connection with rain gauges in the United Arab Emirates (UAE). It was further discovered that near the Yangtze River in China, CMORPH showed the highest correlation with the rain gauge network among all the precipitation products [35]. Additionally, CMORPH provided the highest accuracy among other products over Italy's Adige Basin [36].

To achieve advancements in satellite precipitation products' algorithms, a preliminary validation of these products for a particular region is necessary. To advance the standards in operational analysis and validation methods for satellite precipitation products, the International Precipitation Working Group (IPWG) was founded in 2006 [37]. Since then, efforts have been made to validate satellite precipitation products in several regions of the world, including Africa [38], Asia [39,40], Australia [41], Europe [42], North America [43], South America [44], and the Middle East [21,22,45,46]. These investigations demonstrated that there are regional variations in the performance of these products. The understanding of the performance of satellite-based precipitation products in a given region is, therefore, crucial. Moreover, since water resources are directly influenced by changes in rainfall regimes, spatio-temporal analysis of rainfall becomes vital, as argued by many researchers [47–53].

The UAE is situated in an arid region with rare precipitation events. Water management and surface water harvesting plans in the UAE need to be based on accurate measurements and assessment of precipitation. Due to the country's substantial temporal and spatial variability, as well as the randomness and scarcity of precipitation events, the assessment of rainfall across the UAE is challenging [54]. It is vital to have a better understanding of rainfall variability and pattern to improve rainwater harvesting and develop plans for flash flood risk mitigation. Remotely sensed precipitation data in arid regions have not been extensively studied. Adeyewa and Nakamura [55] attempted to correlate rainfall data from the TRMM with rain gauge observations in five climate zones in Africa: savanna, tropical wet, semiarid, arid, and the South Atlantic Ocean. They found that during dry seasons when rainfall is low, satellite bias was higher across drier regions. Four remote sensing satellite products were studied by [38] in African dry regions. It was concluded that sub-cloud evaporation was the main reason for the over-estimation of satellite data. Sultana and Nasrollahi [56] used information from 29 rain gauges to evaluate high-resolution global rainfall products, including PERSIANN, TRMM, and CMORPH, for the eastern and western regions of Saudi Arabia. They performed daily and monthly assessments of the satellite data using a spatial resolution of 0.25° and found that the projected rainfalls were not accurate during dry seasons. However, better results were achieved during wet seasons. Similarly, the PERSIANN-CDR and CHIRPS were analyzed in a semi-arid subtropical climatic region by Anjum et al. [57]. They deduced that on all seasonal scales, CHIRPS was better than the PERSIANN-CDR.

More recently, several researchers have utilized satellite-based precipitation products to assess rainfall regimes over the UAE. For instance, Wehbe et al. [21] calibrated four products (GPCC, TRMM, WM, CMORPH) over the UAE using rainfall data from 2000 to 2010. They performed spatial analysis of the products' consistency in comparison with land use and topography of the country. Mahmoud et al. [45] compared early, late, and final run products of GPM-IMERG over the UAE for a period of 3 years (2015–2017) and reported that the final run product outperformed its counterparts in statistical and qualitative analysis. CMORPH and GPM-IMERG products were further analyzed by [22], who found that both products are equally good at filling spatial gaps in rainfall observation over the UAE. They utilized the gauge rainfall observations from 2010–2018 to perform analysis at various temporal scales. A similar study was conducted by [58] while exploiting three satellite precipitation products over 18 gauge stations across the UAE. The study included a variety of statistical analyses and concluded that these products can significantly complement station-based data to develop intensity duration frequency curves in dry regions.

All the available studies either used limited data for the rainfall analysis or considered few gauge stations for spatial comparison. Moreover, the main focus of previous studies was devoted to the statistical comparison between gauge records and satellite products and to check the consistency of the products. However, the UAE encompasses different geomorphological regions. These regions have not been adequately investigated for precipitation extreme indices, concentration, and variability.

Unlike others, this study considers four distinct regions in the UAE based on geomorphological characteristics. The precipitation concentration and diversity analysis for the satellite precipitation products are performed for the different regions. The UAE usually receives intense rainfall with a shorter duration. Therefore, the knowledge of precipitation extremes becomes substantial to adequately understand precipitation regimes in the country. To recognize precipitation extremes, multiple extreme precipitation indices were calculated for the gauge data and the results were compared with satellite data. In addition, precipitation concentration and variability analysis for the selected satellite products were conducted. Long-term daily rainfall data (2004–2020) from 50 rain gauges covering the UAE were used to perform a comparison with the daily measurements of four satellite precipitation products, namely, GPM-IMERG, CMORPH, CHIRPS, and the PERSIANN-CDR. Apart from the statistical analysis, and to judge the accuracy and consistency of remote sensing products, various qualitative and quantitative analyses were conducted including precipitation extreme indices, concentration, and variability using well-known indices.

2. Materials and Methods

2.1. Study Area

The United Arab Emirates (UAE) is considered to conduct the comparison of satellite precipitation products and rain gauge observations (Figure 1). The country occupies the southeastern part of the Arabian Peninsula (51° – 57° E, 22° – 26° N) and is classified as a semi-arid to arid country. It has a 740 km long coastal stretch along the Arabian Gulf and Gulf of Oman [21]. The country consists of seven emirates and has boundaries with other Gulf Cooperation Council (GCC) Countries that include Saudi Arabia and Oman to the southwest and northeast of the UAE, respectively, in addition to Bahrain, Kuwait, and Qatar. The country experiences moderate winters and extreme summers with a maximum average monthly temperature of 40.3° C. Humid southeasterly winds prevail during summer which results in humidity levels as high as 95%. The western parts of the country are mostly flat, while the northeast area has a mountainous terrain with a maximum height of 1800 m above mean sea level (alms). According to the geomorphology of the area, the UAE is broadly classified into East Coast (EC) which lies along the Gulf of Oman, Mountains (M), Gravel Plains (GP), and Desert Foreland (DF) (Figure 1). The water year spans from October to September, while the rainy season is from late November to early April. Several researchers [54,59,60] reported that the country faced a plunging shift in annual rainfall in 1999. The average annual rainfall ranges from 80 mm in the Desert Foreland areas to 140 mm on the East Coast and Mountains.

2.2. In Situ Data

Daily precipitation data from 50 rain gauges covering the study area were collected for the period 2004–2020 (Figure 1). The data were provided by the National Center of Meteorology (NCM), UAE. The gauges electronically report rainfall observations which are automatically logged into a central database. The NCM verifies the accuracy of the datasets and daily and monthly gauge accumulations are the typical distribution formats for rain gauges. All the stations used in this study are inland and none of the marine stations were utilized. Station-based statistical metrics based on monthly and annual rainfall data are presented in Tables A1 and A2 respectively.

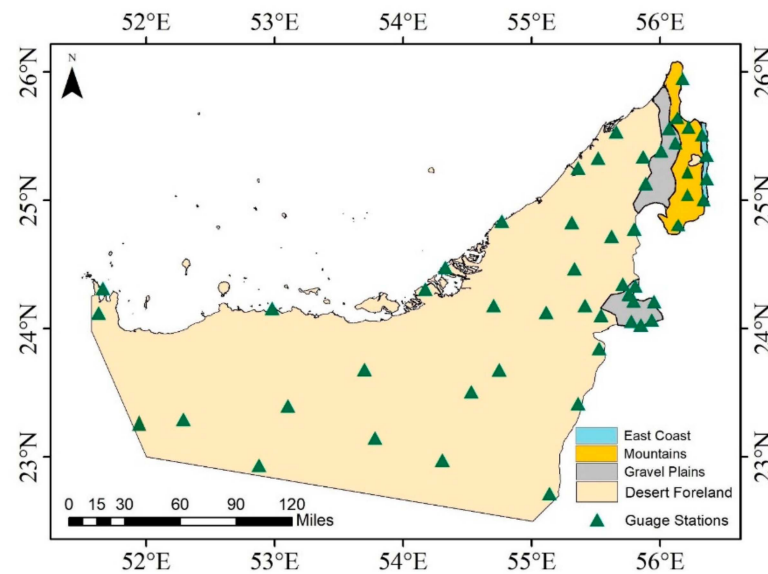


Figure 1. The study area including the geomorphological regions and locations of rain gauges.

2.3. GPM-IMERG

The Global Precipitation Measurement (GPM) is a multinational satellite mission. It offers 3-hourly global measurements of snow and precipitation. The Integrated Multi-satellite Retrievals for GPM (IMERG) algorithm, which combines information from all passive-microwave devices in the GPM constellation, provides rainfall estimates in multiple runs. The Late run product has a 14-h delay, while the Early run product offers data that are practically real-time with a 4-h latency. Since the Final run product utilizes gauge information and has a latency period of two months post-observation, it is considered the most accurate version. The spatio-temporal resolutions of the IMERG Final run product are $0.1^\circ \times 0.1^\circ$ and 30 min. To produce rainfall data, IMERG calibrates, combines, and appends satellite-based microwave estimates with infrared (IR) satellite estimations [23]. In this study, IMERG Final run is used. Additional details of the IMERG and other GPM products can be found in [5,23,25].

2.4. CMORPH

The two products offered by CMORPH are CMORPH (V0.x) and CMORPH (V1.0). CMORPH (V1.0) reduces the significant inhomogeneity generated by the changing algorithm in CMORPH-V0.x. The most recent edition of the product contains data from 1998 to present, while the earlier version covers the years 2002 to 2018. Bias-corrected precipitation products are also included in CMORPH-V1.0 along with the raw, satellite-only precipitation estimates. The CMORPH precipitation data used in this study was acquired from the National Oceanic and Atmospheric Administration (NASA) Climate Prediction Center (CPC) [61]. The downloaded data have a spatial resolution of 8×8 km and a temporal resolution of 30 min.

2.5. PERSIANN-CDR

The PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record) product, was developed by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine (UCI). It computes rainfall estimates at every $0.25^\circ \times 0.25^\circ$ pixel using neural network function classifier techniques. When independent rainfall estimates are available, the updating of the network parameters is made by an adaptive training function. Based on geostationary infrared imagery, the PERSIANN system was eventually expanded to make use of both infrared and daytime visible information. To provide worldwide rainfall, the PERSIANN algorithm is based on geostationary longwave infrared images. The

global range of the rainfall product is 60°S to 60°N. The PERSIANN-CDR belongs to the PERSIANN family. Detailed information about the product can be found in [24]. In this study, the PERSIANN-CDR product is used to analyze the changes and trends in daily precipitation, particularly extreme precipitation events.

2.6. CHIRPS

An extensive 35+ year quasi-global precipitation record is available from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). For trend analysis and seasonal drought monitoring, CHIRPS creates a gridded rainfall time series utilizing in-house climatology, CHPclim, 0.05° resolution satellite imagery, and in situ station data. The data span 50°S–50°N (and all longitudes) and are available from 1981 to present. CHIRPS has shown promising results in terms of low bias and operational monitoring in various studies [62,63]. In this study, 5 × 5 km daily data were obtained from the Climate Hazard Center of UC Santa Barbara. Table 1 briefly lists the satellite precipitation data sets utilized in this study.

Table 1. Details of the utilized remotely sensed satellite precipitation products with their spatial and temporal resolutions and source.

	GPM-IMERG	CMORPH	CHIRPS	PERSIANN-CDR
Source	NASA	NOAA	CHC, UCB	CHRS, UCI
Spatial Distribution	10 × 10 km	8 × 8 km	5 × 5 km	25 × 25 km
Temporal Distribution	Daily	Half-Hourly	Daily	Daily
Data Availability	2000–Present	1998–Present	1981–Present	2000–Present
Span	60°S–60°N	60°S–60°N	50°S–50°N	60°S–60°N

2.7. Methodology

The current study involves several steps to accurately estimate the consistency of the selected satellite precipitation products and analyze rainfall characteristics in the UAE. The process starts with the acquisition of daily ground observations from the National Center of Meteorology (NCM) of the UAE. The matching time series of the satellite precipitation products were then downloaded through various sources (Table 1) and extracted at the gauge locations. The methodological framework is represented in Figure 2.

2.8. Data Acquisition

Rainfall data were acquired from NCM from 2004–2020 on daily basis. For coordinates-based analysis, the exact coordinates of the gauge stations were acquired from NCM [64]. A total of 50 stations covering the four geomorphological regions of the UAE were considered. The EC region has the least number of gauge stations (4), while DF region has the maximum number of stations (28) due to its larger area (Figure 1). The GP and M regions have 12 and 6 gauge stations, respectively. The data from the satellite products are usually available in NetCDF (Network Common Data Form), HDF (Hierarchical Data Format), OpeNDAP (Open-source Project for a Network Data Access Protocol), or GeoTIFF (Georeferenced Tagged Image File Format). The data were downloaded in NetCDF format for all the selected precipitation products based on the respective grids. The data were downloaded using the MATLAB program.

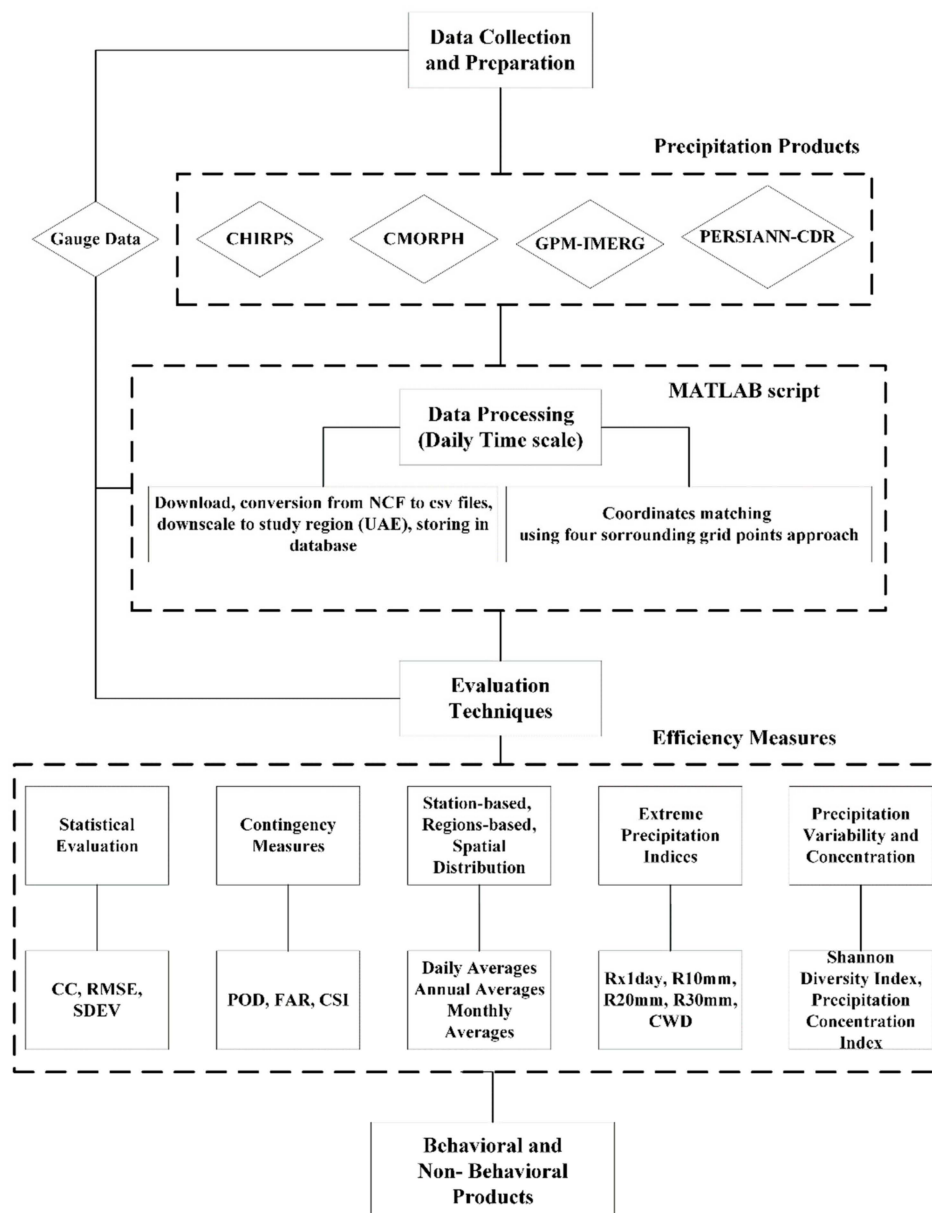


Figure 2. Flow chart of the implemented methodology.

2.9. Selection of the Grid Coordinates

The selection of grid coordinates, based on locations of gauges, is considered the most vital step to ensure reliable results. The process was programmed in MATLAB to precisely select the neighboring grid coordinates containing the gauge location. The code performs the following operations: (1) selecting the grid containing the gauge and recording the rainfall measurements for the four surrounding grid points; (2) taking the weighted average of the four nearest neighboring grid points and comparing it with the gauge rainfall data; (3) alternatively, selecting the single grid point if the gauge location is within a predefined threshold distance from the nearest grid. Since the weighted average approach was applied while selecting four neighboring grid points, the grid point closest to the gauge location receives the highest weightage for the average calculations. However, if the distance of any grid point is small enough that it surpasses the pre-defined threshold, that grid point would receive the full weightage of 1 and the contribution from the rest of the three grid points becomes practically null. However, the overall percentage of these single-gridded matched points was not more than 10–20% for all the products. In other related studies, the

grid points were selected based on the minimum distance from the gauge location only [45]. This would equally under-estimate or over-estimate the actual rainfall. In this study, the weighted average of four neighboring points was better calculated to acquire more reliable matching rainfall data.

2.10. Interpolation Technique

To compare point-based rain gauge data with grid-based satellite remote sensing data, spatial interpolation or simple averaging approaches were used. However, due to interpolation algorithms, rain gauge densities, systematic errors, and other factors, the interpolated data may have some uncertainties. Therefore, a rigorous and precise method was required to compare gauge-based vs. satellite precipitation products. Inverse Distance Weighting (IDW) is a widely used method in the literature and is recognized as one of the standard spatial interpolation procedures [65–67]. IDW uses the average of all sample data points in the neighboring cells to predict the value in a particular cell. More weight is assigned to the points that are closer to the center of the cell being predicted during the averaging process. Therefore, the IDW interpolation technique was utilized due to its robustness and ease of use.

2.11. Performance Measures

The performance of the satellite products to accurately detect rainfall is assessed through various statistical performance measures. Prior studies categorized these measures based on contingency estimates, error estimates, and correlation consistency between the observed and estimated rainfall values [24,27,68–71].

Contingency measures are vital to reveal the correctness of the products in identifying rainfall events. Prominent contingency measures include, among others, Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI). Table 2 provides the basis for the formulation of the three mentioned measures.

Table 2. Criteria for defining the contingency measures.

		Satellite Estimates	
		Yes	No
Ground Observations	Yes	A = Hits (Accurate forecasts)	B = Miss (Missed/unwarned events)
	No	C = False Alarm (Wolf Cry)	D = Correct No (Usually, we ignore this as rare event)

Based on Table 2, the three contingency measures can be formulated as:

$$POD = \frac{A}{A + B}; \quad (1)$$

$$FAR = \frac{C}{A + C}; \quad (2)$$

$$CSI = \frac{A}{A + B + C}; \quad (3)$$

where *POD* stands for correctly detected events out of total events; *FAR* stands for falsely reported events out of all warnings; and *CSI* stands for correctly detected events out of all warned and unwarned events. All the above measures have a value ranging from 0–1. *POD* is perfect at value 1 and *FAR* is perfect at zero value. A value of 1 for *CSI* also portrays the best value. Similarly, Root Mean Square Error (*RMSE*), Pearson Correlation Coefficient (*CC*) [72], and Standard Deviation (*SD*) are used to quantify the accuracy and agreement of the products with the observed values. These measures are described in Equations (4)–(6).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (prediction - observed)^2}{n}} \quad (4)$$

$$CC = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (5)$$

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{n}} \quad (6)$$

where x_i and y_i denote the gauge rainfall and satellite rainfall estimates, respectively, while $\bar{x}$ and $\bar{y}$ are their mean values. Similarly, σ represents the population standard deviation and x_i denotes each value from the population, and n is the size of the whole population. The Pearson Correlation, which can vary from -1 to 1 , illustrates the statistical relationship between variables. Whereas 0 indicates no linear correlation, -1 implies a full negative linear correlation, and 1 indicates a total positive linear correlation. *RMSE* tends to reveal the average error of the products in assessing the observed precipitation.

2.12. Precipitation Extreme Indices

A determined value that can be used to characterize the status and changes in the climate system is known as a climate index. It helps understand the precipitation and temperature extreme patterns over time. Climate indices are also referred to as annual or monthly statistics of weather and are very helpful for a comprehensive understanding of regional climatic trends. Moreover, spatial trends in precipitation extreme indices are imperative to study the changes in rainfall characteristics [47]. The *R* software package was utilized to summarize the selected indices over the UAE and to analyze how the satellite products behave in comparison to gauge data. To check the extremes in precipitation values, various precipitation indices were calculated to show the maximum one-day and yearly values along with the number of days when a specific threshold rainfall amount was surpassed [73,74]. The indices are explained in Table 3 with formulas based on monthly or yearly statistics of predicted and observed climatic data.

Table 3. Climate indices and their definition (additional details: www.climdex.org (accessed on 3 July 2022)).

Indices	Symbology	Units
Rx1 day	Maximum 1-day precipitation over a given period	mm
R10 mm	Yearly days count when Rainfall ≥ 10 mm	days
R20 mm	Yearly days count when Rainfall ≥ 20 mm	days
R30 mm	Yearly days count when Rainfall ≥ 30 mm	days
CWD	The maximum length of the wet spell. Max number of continuous days when Rainfall ≥ 1 mm	days

2.13. Precipitation Concentration Index (PCI)

The uneven spatial and temporal distribution of precipitation, aggravated by climate change, has recently received significant attention. More extreme weather events, such as floods and droughts, are likely to occur due to precipitation frequency, concentration, and variability. Especially, the variation in precipitation concentration has an impact on ecosystems, human health, and the environment. For instance, floods are likely to occur when wet days account for a higher percentage of annual precipitation. Similarly, intense rainstorms may trigger flash floods, landslides, and water accumulation in urban areas. Statistical indices, including Concentration Index (CI) and Precipitation Concentration

Index (*PCI*) based on daily and monthly precipitation data, were developed to investigate the concentration of precipitation and demonstrate the changing weight of seasonal precipitation variations. The Precipitation Concentration Index (*PCI*) was conceived and established by [75,76] and was utilized at the annual and seasonal scales by various researchers [49,70]. The precipitation can be considered as regularly distributed ($PCI < 10$), moderately concentrated ($PCI = 10\text{--}15$), having irregular distribution ($PCI = 16\text{--}20$), and exhibiting severe irregular distribution when the *PCI* value is above 20 [76]. Moreover, the temporal analysis of the *PCI* values also demonstrates the decrease or increase in the temporal trend in precipitation concentration. The *PCI* was derived for rain gauge and satellite observations to determine the concentration at the yearly scales. The following formula was used to compute the seasonal and yearly precipitation concentrations.

$$PCI_{annual} = \frac{\sum_{i=1}^{12} p_i^2}{\left(\sum_{i=1}^{12} p_i\right)^2} \times 100 \quad (7)$$

where p_i denotes the rainfall amount in i th month.

2.14. Precipitation Variability

To study the variability in precipitation within a year and assess the evenness of total annual precipitation, various diversity indices are used [77]. The precipitation pattern and the seasonality in precipitation can be detected through these indices in a decadal period. The Shannon Diversity Index [78] is one of the most used diversity indices and has been effectively utilized for rainfall variability analysis [77,79–81]. The Shannon Diversity Index of any gauge station can be calculated by considering the monthly proportion of precipitation and multiplying it with the natural log of itself.

$$D = \frac{-\sum_{i=1}^n x_i (\ln x_i)}{\ln(12)} \quad (8)$$

where x_i denotes the monthly proportion of precipitation and D is the Shannon Diversity Index. Generally, the value of Shannon Diversity Index ranges from 1.5 to 3.5. However, for the rainfall variability analysis, it can be standardized to be within the range of 0–1 by dividing by the natural log of 12. Moreover, the zero monthly values were replaced by a small number of 0.01 to refrain from systematic errors as the negative logarithm of zero is undefined.

3. Results

3.1. Spatial and Temporal Precipitation Distribution

Based on satellite products, the annual average rainfall distribution over the UAE showed a consistent geographical pattern with the gauge data. (Figure 3). However, the plots also show over- and under-estimation in the average rainfall. The observed rainfall or gauge data subplot indicates that the highest average rainfall value lies in the range of 93–110 based on the data of 17 years and 50 gauge stations covering the country (Figure 3a). Higher values of average annual rainfall occur mostly in the East Coast (EC), Mountains (M), and some parts of the Al-Ain region. The western part, which largely lies in the Desert Foreland (DF), receives the least rainfall throughout the year.

Although the spatial distribution of all satellite products follows an analogous pattern with the gauge data, the number of lower and higher average annual values differs significantly. Almost all the products over-estimated the gauge data except the PERSIANN-CDR, which displayed a substantial under-estimation. The highest value of the average annual rainfall was shown by the CMORPH product, where it reached up to 146 mm, whereas IMERG and CHIRPS provided 133 and 123 mm, respectively. The under-estimation of the PERSIANN-CDR product can be ascribed to its relatively coarse spatial resolution as compared to other products. This behavior of the PERSIANN-CDR was also reported by [21].

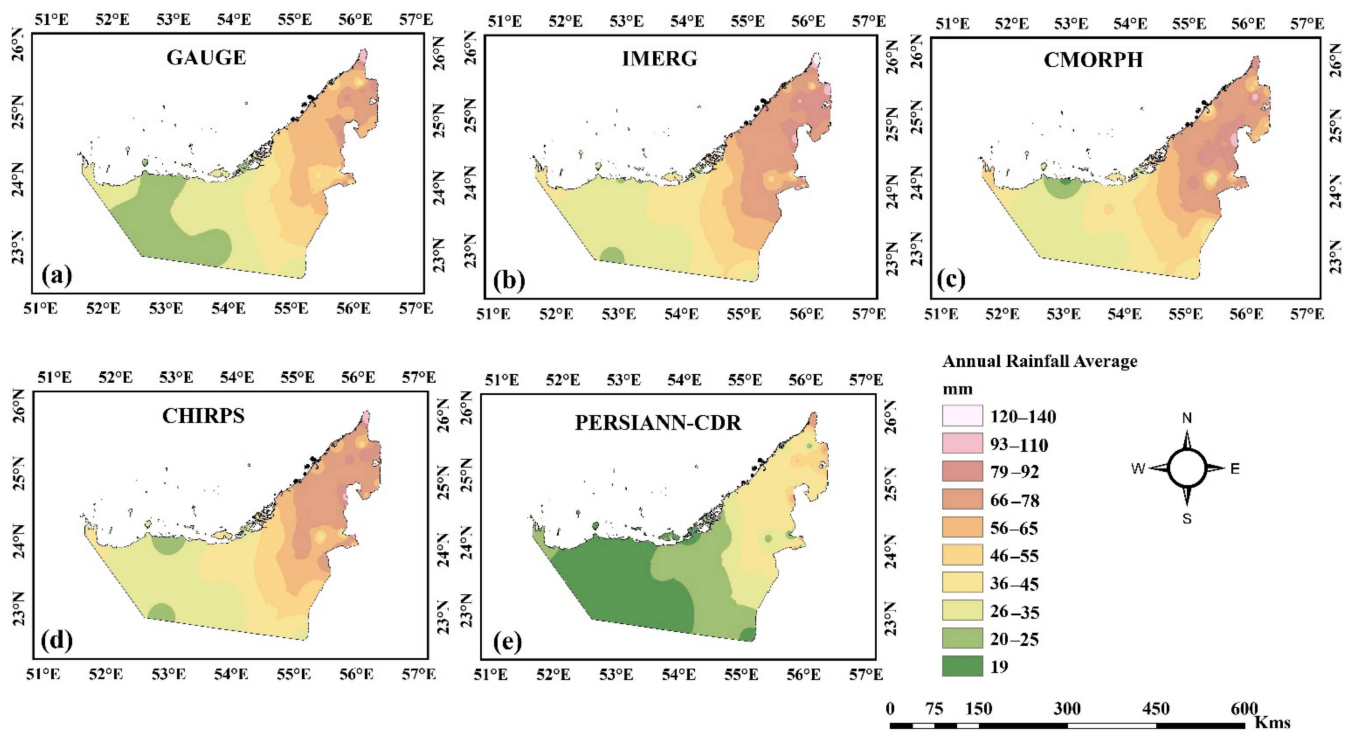


Figure 3. Annual average rainfall distribution for gauge (a) and satellite products (b–e).

Figure 4 represents the daily average rainfall comparison between the products and gauge values. The spatial plots are delineated to further elaborate the over- and under-estimation of the products. Very low daily averages reflect the maximum number of dry days in the country. The gauge data (Figure 4a) displays the daily average rainfall in the range of 0.1–0.48. The western part of the Abu Dhabi emirate shows very low values for daily average rainfall with an increase in the northern emirates and mountainous regions. Almost all the products over-estimated the daily average rainfall in the western region of Abu Dhabi. IMERG and CMORPH (Figure 4b,c) have even shown relatively higher daily averages in some western coastal regions which could not be captured by the other two products. CHIRPS showed an average value of less than 0.2 in most of the country's stations, except in the northeastern mountains, where it exhibited values ranging between 0.2 and 0.3. The relatively higher values of daily averages in the East Coast and Mountains areas, depicted by gauge data, were successfully captured by almost all the products.

All the products, including rain gauges, showed a steady pattern in the areal average monthly rainfall as shown in Figure 5. According to rain gauge data, Jan–March were the wettest months in the analysis of the previous 17 water years. Summer months are usually dry and all the products were consistent with the gauge data during the summer months. CMORPH and GPM-IMERG showed increased monthly averages which were expected as represented in the annual average rainfall plots. Figure 5 shows the comparison between rainfall values among rain gauge and four satellite products at mean monthly scales.

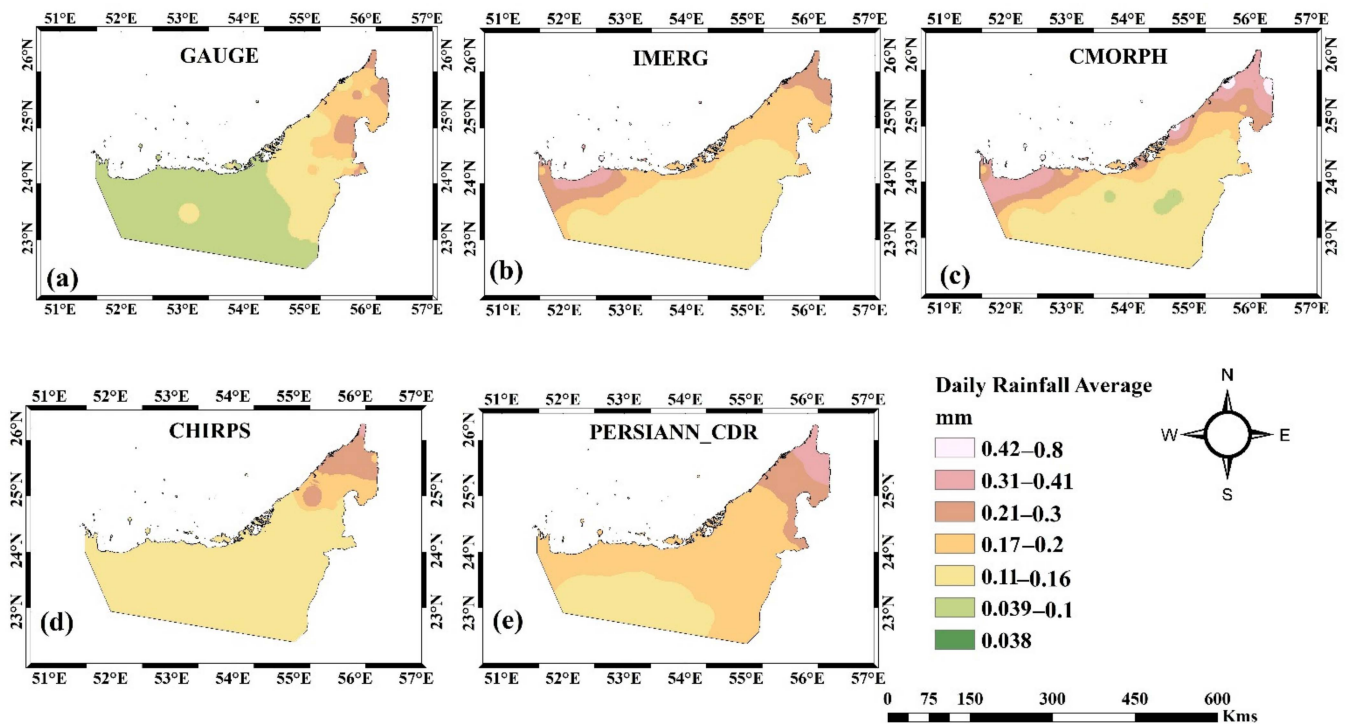


Figure 4. Average daily rainfall distribution for the gauge observation (a), IMERG (b), CMORPH (c), CHIRPS (d), PERSIANN-CDR (e).

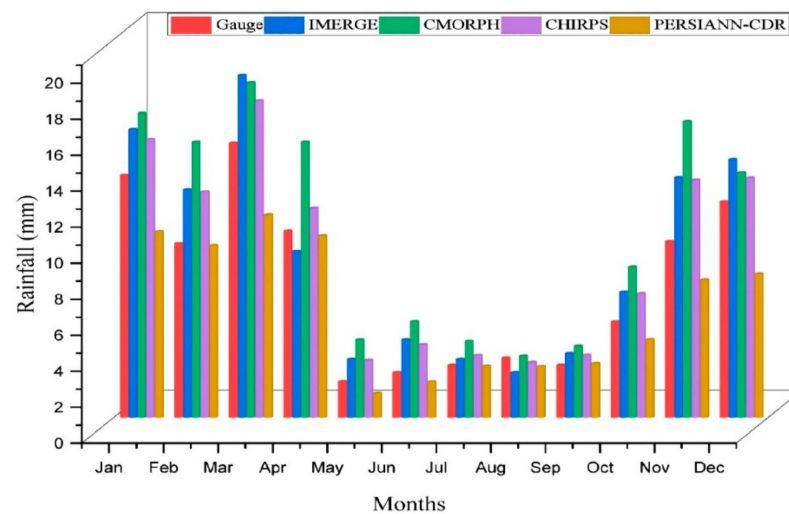


Figure 5. Mean monthly rainfall for gauge and remote sensing products.

3.2. Comparative Analysis of the Products

3.2.1. Statistical Performance

A Taylor diagram [82] provides an effective method for summarizing multiple statistical tools in a single figure to showcase the statistical performance of prediction models. Figure 6 is developed by calculating CC, RMSE, and Standard Deviation (SD) to assess the performance of satellite products over different regions of the UAE.

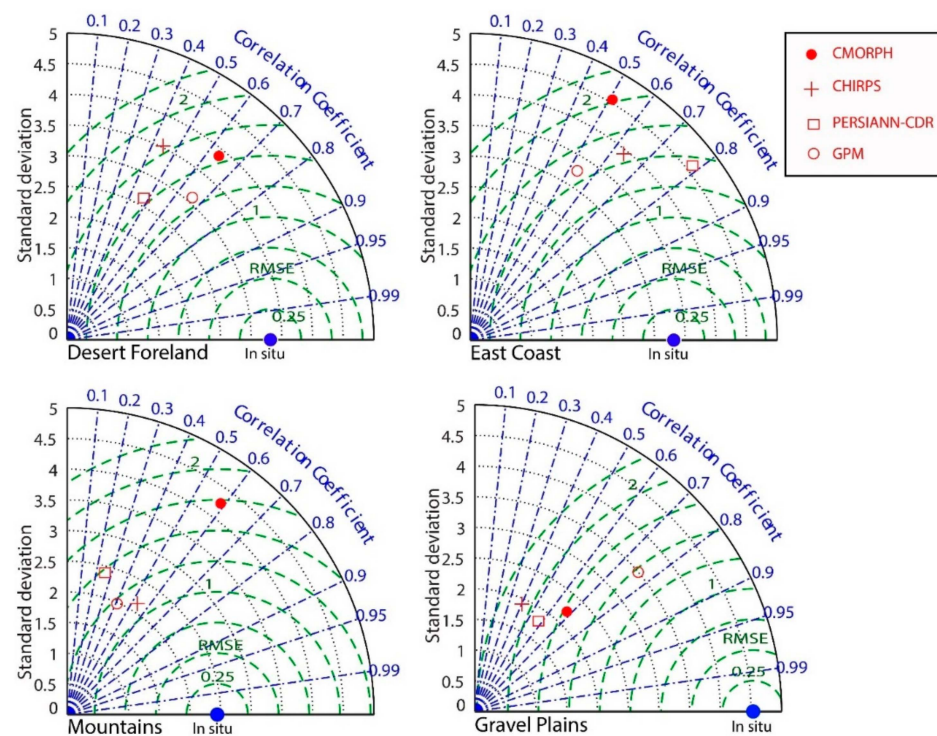


Figure 6. Taylor diagram depicting the performance of satellite products based on selected statistical measures over four climatological regions. The hollow circles represent the GPM-IMERG product while the solid circles represent the CMORPH product. Similarly, plus sign and hollow squares represent CHIRPS and PERSIANN-CDR, respectively.

Four different plots were developed for the four climatological regions. GPM-IMERG showed the highest CC in the Gravel Plains, while in the Mountain area, it showed the lowest value of 0.4. CMORPH showed the best agreement with the gauge data in the Gravel Plains in line with GPM-IMERG and the least agreement on the East Coast. Similar behavior was shown by CMORPH in the Desert Foreland and Mountains where the CC values were above 0.6. However, on the East Coast, the CMORPH product exhibited the lowest CC value of 0.5. Contrarily, the PERSIANN-CDR was the best among all the products on the East Coast, although it underperformed in terms of quantitative analysis for those regions. This might be attributed to the strong post-processing methodological framework in the development of CDR products.

CHIRPS performed equally well in all regions except the East Coast, where it was slightly better than CMORPH and GPM. RMSE values were between 1 and 2 mm for all products in the Desert Foreland and East Coast. For the other two regions, the values were slightly higher than 2 mm. Overall, GPM-IMERG showed the least error among all products. The statistical performance measures indicated that GPM-IMERG and CMORPH are comparatively better in terms of correlation and prediction errors with the gauge observations.

3.2.2. Detection Accuracy

The most common contingency measures were utilized to examine the efficacy of the products in capturing rainfall events. POD, FAR, and CSI were calculated based on Equations (1)–(3) and Table 2. POD describes the ability of the model to capture the real event as recorded by the gauge (Hit), whereas FAR is the probability of detecting a false event that has not been recorded by the rain gauges. Figure 7 shows the spatial distribution of the POD, FAR, and CSI across the UAE. The GPM-IMERG product successfully captured the actual rainfall events; however, the numbers were relatively low as compared to previous studies, where IMERG exhibited comparatively high values of POD [69,71]. This might be associated with the averaging effect as the time series data in the current study

are longer than those of previous studies. The FAR value for GPM-IMERG was generally similar for most of the stations with an overall good CSI value ranging from 0.5 to 0.7.

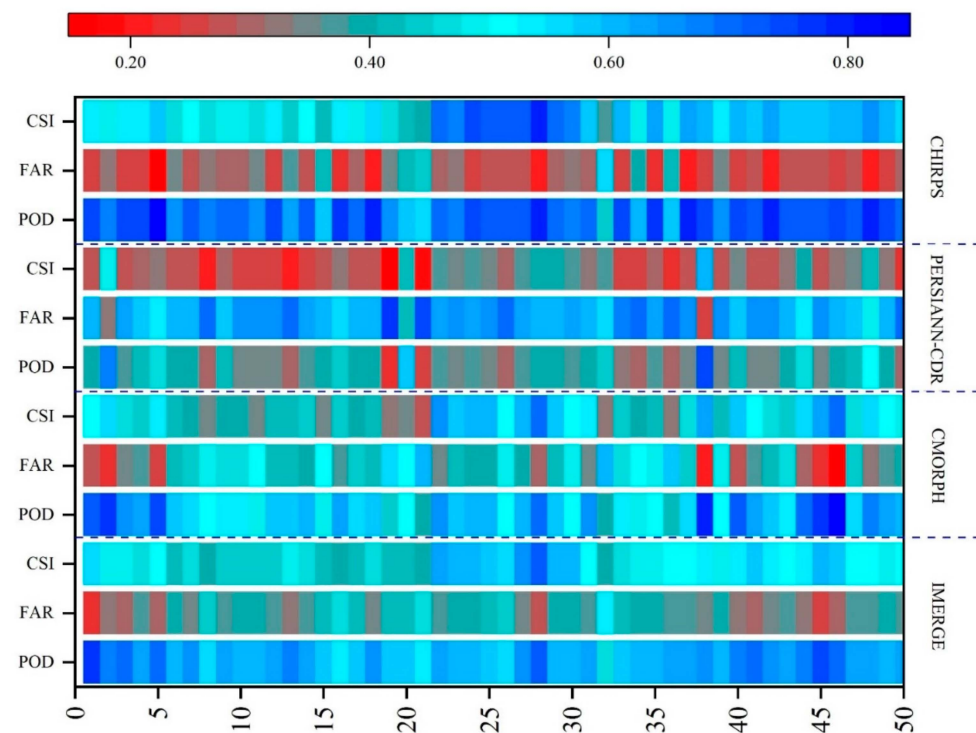


Figure 7. Heat map showing the contingency measures for each product. The X-axis shows the number of stations. POD stands for Probability of Detection, FAR denotes False Alarm Ratio, and CSI represents Critical Success Index.

CMORPH presented a wider range of POD values, with the best correlation for northeastern stations. The range of FAR for CMORPH was also wider as compared to IMERG. Again, CHIRPS provided the best POD values in almost all stations, reaching a maximum value of 0.9, while FAR values were substantially lower with most stations having values in the range of 0 to 0.2. Moreover, the PERSIANN-CDR displayed lower values of POD indicating that the product failed to capture true events as compared to other products. As a result, FAR values were also high for the PERSIANN-CDR. CSI values of all products were between 0.4 and 0.6, except the PERSIANN-CDR, which showed a value of less than 0.3 for most stations.

3.3. Rainfall Analysis Based on Climate Indices

The analysis was carried out based on the four climatological regions. Figure 8 maps the results of the five precipitation indices for rain gauges and satellite products. The figure reveals that CMORPH surpasses its counterparts in all five indices, especially on the East Coast and Mountains. However, IMERG is comparatively consistent with the gauge results. The results for the gauge rainfall data reveal that all regions have very few days with rainfall amounts of more than 20–30 mm. The products agreed with the gauges except for CHIRPS which under-estimated all indices. It should be noted that the spatial and temporal averaging of rainfall data might reflect relatively lower values for all the indices. The daily maximum average value in a year was observed in Gravel Plains for the gauge data, followed by East Coast. IMERG provided comparatively close measurements to the gauge values for Rx1 day analysis. The mountainous region experienced the maximum consecutive wet days (7), followed by the East Coast. For this index, the PERSIANN-CDR over-estimated and recorded CWD as high as 11 on the East Coast and Mountains. CHIRPS provided almost similar values as of the gauge data for CWD.

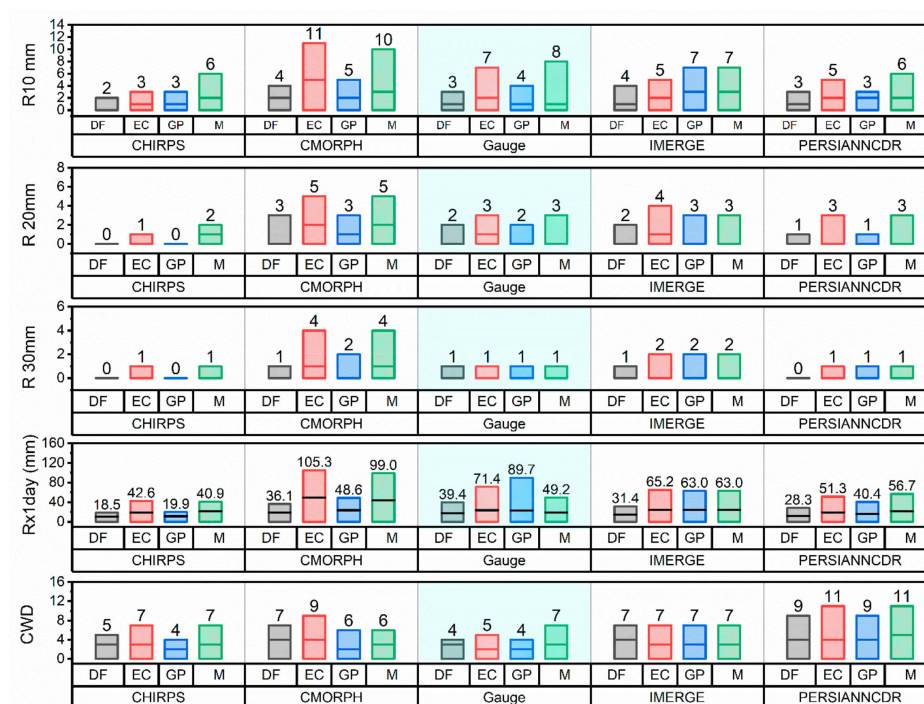


Figure 8. Results of climate indices analysis based on the products and the climatological regions (DF = Desert Foreland, EC = East Coast, GP = Gravel Plains, M = Mountains). CWD is consecutive wet days, Rx1day is the maximum one-day precipitation in millimeters in the given period, and R10, R20, and R30 are the annual count of days when rainfall was greater than 10, 20, and 30 mm, respectively.

3.4. Precipitation Variability

The Shannon Diversity Index was utilized to identify the evenness or precipitation variability over the UAE for the period 2004–2020. For the months having zero precipitation, the value was replaced with a small value (0.01) to avoid mathematical errors as the formula takes the logarithmic of the monthly rainfall values. The range of the Shannon index usually lies between 1.5 and 3.5. However, after standardization, it ranges between 0 and 1. A high index value shows a high precipitation variability and vice versa.

Figure 9 shows the spatial distribution of the precipitation variability over the UAE for gauge rainfall and satellite products. First, the ranges for all the plots reveal that the UAE experiences high variability of rainfall across the country. The lowest index value was higher than 0.6 for all products and gauge data. Interestingly, all products were consistent for the upper value of the index as compared to gauge data. IMERG, CMORPH, and CHIRPS exhibited spatial evenness in rainfall variability, whereas the PERSIANN-CDR showed higher variability, approaching a value of 0.9. However, the value of the index decreases rapidly in the northern mountainous region. CHIRPS showed the highest variability in the Al-Ain region and for some gauges located in the western area. All products displayed maximum rainfall variability in the Al-Ain region, most of the western area, and in some cases, the East Coast as well. IMERG, CMORPH, and the PERSIANN-CDR over-estimated the concentration values and the index was mostly higher than 0.75. It can be inferred that most of the products performed well in the variability analysis with some exceptions. For example, the lower index values were only captured well by CHIRPS.

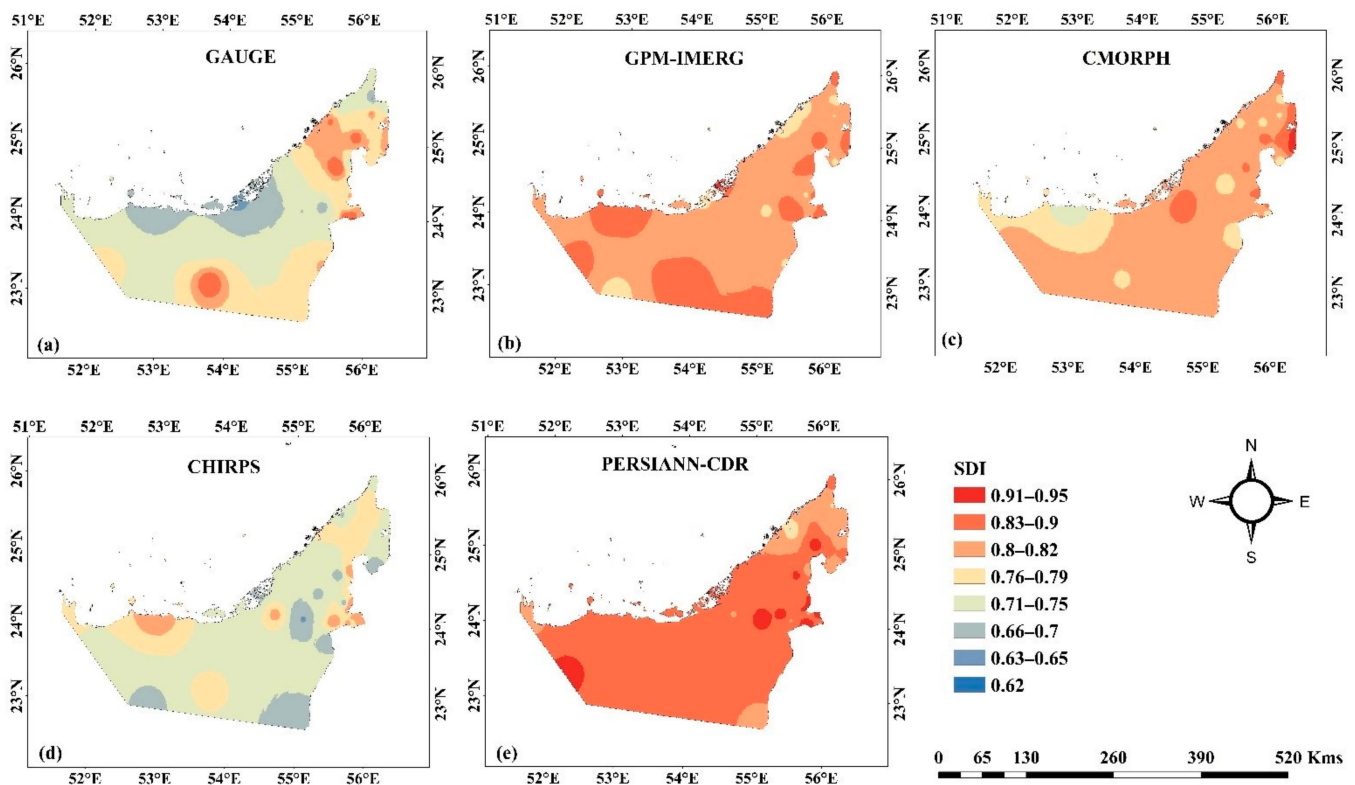


Figure 9. Precipitation variability distribution over UAE for the period of 2004–2020. Plots (b–e) represent the four satellite products while plot (a) shows the precipitation variability of rain gauge observations.

3.5. Precipitation Concentration Index (PCI)

The Precipitation Concentration Index provides a useful tool to analyze temporal rainfall distribution [83–85]. The results for the *PCI* are represented in Figure 10. The figure shows a visual comparison between rain gauge data and satellite products. It can be observed that the rainfall concentration in the UAE is extremely irregular, according to the ranges defined by [76]. Overall, the satellite products are consistent with in situ observations, with some exemptions in a few years (2010 and 2015). Except for CMORPH, the confidence bands of all the products displayed a decreasing trend during the study duration, which is in agreement with the gauge observation. The gauge observations depict that the year 2008 showed an extremely irregular precipitation distribution with the highest *PCI* value. Interestingly, this behavior was captured by all products; however, the *PCI* values were relatively lower than the gauge *PCI*. In terms of temporal trend and *PCI* values, the IMERG product closely followed the gauge *PCI* values. The other three products exhibited lower *PCI* values as compared to gauge data. The wide yellowish bands in Figure 10 represent the maximum/minimum value of the *PCI* which could ever occur based on rainfall data used in calculating the *PCI*. IMERG and gauge showed similar *PCI* values throughout the study period, while CHIRPS displayed relatively low *PCI* values as compared to its counterparts. Overall, the studied products could provide promising results while analyzing the precipitation concentration in the UAE.

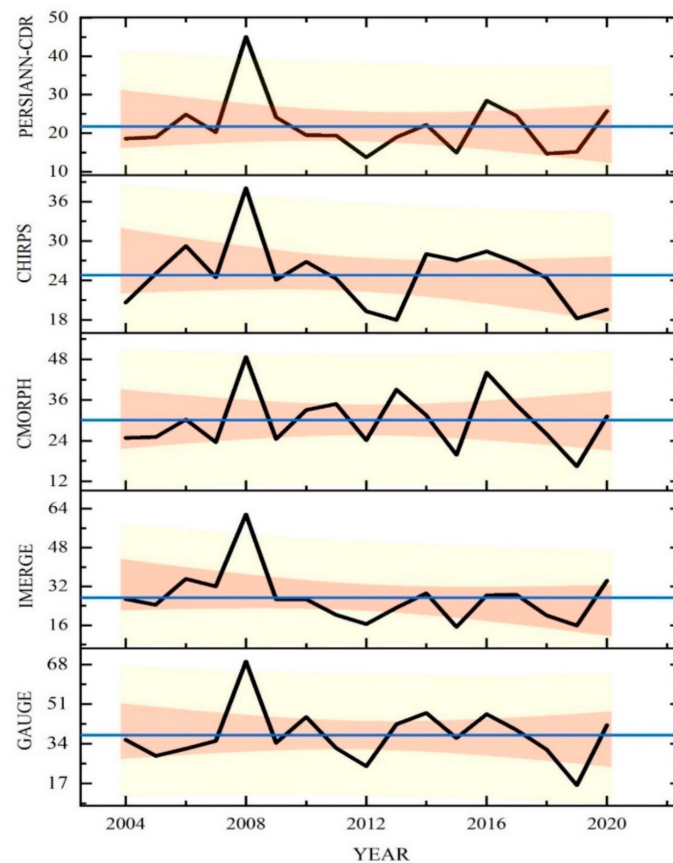


Figure 10. Precipitation Concentration Index (*PCI*) distribution over the study period for different satellite products and rain gauge observations over UAE. Thick continuous black line = *PCI*, straight blue line = mean value, light brown band = confidence band, yellowish wider band = prediction band.

4. Discussions

The discrepancies between measured rainfall data at gauge stations and satellite products may come from different scales [86,87]. While satellite precipitation products represent an average estimate of the specific pixel's or grid's precipitation, the rainfall gauge station provides a point estimate [88]. Due to the large regional variability of rainfall, this disparity in the spatial scale of the data constitutes a significant contributor to discrepancies between the estimations of satellite products and ground observations [1]. This hypothesis may provide an argument for the better performance of products with comparatively higher spatial resolution. For instance, in the present study, the highest-resolution product was CHIRPS, having a 5×5 km spatial resolution, followed by CMORPH and GPM-IMERG, having an 8×8 km and 10×10 km spatial resolution, respectively, while the PERSIANN-CDR has a 25×25 km spatial resolution. This prognosis becomes true when the total annual average rainfall maps (Figure 3) are analyzed for all products. CHIRPS provided a much closer spatial distribution to the gauge data, while the PERSIANN-CDR performed the least. The daily averaged maps showed discrepancies, as seen in Figure 4, where both CMORPH and IMERG over-estimated the gauge data in most parts of the country. CHIRPS showed over-estimation only in the eastern part of the Abu Dhabi emirate, while it under-estimated the rainfall in the western part of the country. Figures 3 and 4 demonstrate that CHIRPS, CMORPH, and IMERG performed better on annual scales rather than daily scales. This can be ascribed to the fact that as the data accumulate on the temporal scale, the extent of error becomes marginalized [28] and, therefore, the performance of the products becomes reasonable at higher temporal scales.

Similarly, monthly average rainfall revealed a good match of all products with gauge data (Figure 5). However, in February, the PERSIANN-CDR was equally on par with the

gauge data, while all the other products over-estimated the monthly average. The summer months were almost consistent in terms of rainfall quantity, which signifies that all the four products are efficient in capturing low rain (especially during July–September). Overall, the products yielded higher values than the gauge data for wet months, except for the PERSIANN-CDR. Some researchers also characterized the best precipitation products for each month [68]; however, this can only be viable to marginalize the products based on months for particular gauge stations. The generalization of this hypothesis is not feasible, as the purpose of identifying the best suitable alternative products to gauge data is usually to develop long-term databases.

The comparison of statistical measures including correlation coefficient and *RMSE* (Figure 6) over the four different climatological regions of the UAE revealed the performance of all the products. In the Desert Foreland part, which comprises the largest portion of the country's area and the maximum number of gauge stations, IMERG was better in terms of error measurement, while CMORPH and IMERG showed the best correlation coefficient. For Gravel Plains and Mountains, IMERG and CMORPH performed well, while CHIRPS and the PERSIANN-CDR did not provide good rainfall estimates. The PERSIANN-CDR displayed the best agreement with the gauge data on the East Coast, showing a correlation coefficient close to 0.8. CMORPH was the least performing, with a value of 0.5.

The product's efficiency in capturing events is usually measured with various contingency measures [19,42,71], which include the Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI). Average values, as well as station-based values of these measures, are important in understanding the event-capturing ability of these products. Figure 7 indicates that CHIRPS, CMORPH, and IMERG were best at capturing the events. Although it is not necessarily true that higher POD values should yield lower FAR values and vice versa, the FAR values for almost all the stations were relatively low for CHIRPS followed by CMORPH and IMERG. This can again be associated with the finer resolution of these three products that enabled them to capture the true events. The PERSIANN-CDR missed many localized events owing to its coarser resolution as compared to the other products. Therefore, the contingency measures confirm the correlation between the products' resolutions and their accuracy.

Previous investigations focused on the consistency analysis of satellite products by exploiting various statistical measures and only discussed the trend analysis of the products [21,58,69,71]. In this study, climate indices, Precipitation Concentration Index, and Shannon Diversity Index were incorporated to thoroughly examine the performance of the selected products. The findings of all five precipitation indicators were plotted over various geographic areas and for gauge and satellite products, as seen in Figure 8. CMORPH outperformed its counterparts, particularly in the East Coast and Mountains. IMERG, however, was more consistent with the gauge results. The gauge data revealed very few days with a rainfall intensity higher than 20 to 30 mm. All products displayed a similar trend except for CHIRPS, which under-estimated all indices. It should be noted that all the indicators may have provided significantly lower values because of the spatial and temporal averaging of rainfall data. Gravel Plains had the highest daily average value over a year for the gauge data, trailed by the East Coast. The gauge values for the Rx1 day analysis and the IMERG products were relatively close. The East Coast followed the Mountains region had the highest consecutive wet days (seven). The PERSIANN-CDR over-stated this index and recorded CWD in the East Coast and Mountains as high as 11. The values from CHIRPS were almost identical to those from the CWD gauge. In terms of five selected climate indices, IMERG performed better than the other products.

The results of the Shannon Diversity Index and the Precipitation Concentration Index further classify the products as behavioral or non-behavioral. Figure 9 shows that the ranges of all the plots in the UAE varies greatly across the region. The lowest index value for all the products and gauge data was higher than 0.6. Contrary to gauge observations, all the products exhibited consistency for the upper index value. The geographic evenness of

rainfall variability was shown by IMERG, CMORPH, and CHIRPS, but the PERSIANN-CDR exhibited more variability, with a value close to 0.9. The Desert Foreland and Mountain regions, however, had a sharp interface, and the value of the index was lower in the northern Mountain region. In a few gauges located in the western region and Al-Ain region, CHIRPS revealed the largest variability. Overall, the products showed precipitation evenness in agreement with the gauge data, except for the north-western part of Abu Dhabi, where the satellite products showed relatively higher variability as compared to the gauge data. Temporal distribution of precipitation provides useful information to assess the long-term trends and seasonal precipitation [85]. The results of *PCI* present the temporal variation in rainfall concentrations. The *PCI* analysis revealed that IMERG displayed the temporal distribution of the precipitation concentration with a minimum error as compared to gauge values. The highest *PCI* values were observed in the year 2008, which was captured accordingly by all the products. CMORPH, CHIRPS, and the PERSIANN CDR under-estimated the highest value. Figure 10 showed a declining trend in *PCI* values which was closely imitated by the products as well. Hence, the results indicated that while the selected precipitation products can be utilized for precipitation concentration analysis, IMERG provides better results for the case of the UAE.

5. Conclusions

Unlike other investigations, this study considered a four-grid-point neighboring weighted average approach to extract the satellite precipitation corresponding to the gauge station and accounted for the spatial heterogeneity of the study area. The extreme precipitation indices were calculated and analyzed for the UAE to study the ability of the satellite products in simulating precipitation extremes. In addition, the precipitation diversity and concentration were analyzed explicitly to better understand the precipitation regimes.

Four satellite precipitation products, namely GPM-IMERG, CMORPH, CHIRPS, and the PERSIANN-CDR, were considered to evaluate their effectiveness in capturing rainfall consistency, variability, and concentration over the UAE. The records of 17 years of daily data (2004–2020) were utilized for the analysis over the whole country by using rainfall data from 50 gauge stations as ground truth references. Various statistical, contingency, and precipitation indices were calculated to determine the satellite precipitation product performance over various domains. In addition to the daily analysis, the products were investigated on monthly and annual scales to further validate their performance.

The CC and RMSE results revealed that CHIRPS performed equally well in all regions, except for the East Coast, where it performed slightly better than CMORPH and IMERG. Following GPM-IMERG, CMORPH demonstrated the best consistency in the Gravel Plains and the least agreement in the East Coast. A similar agreement was seen in the Mountains and Desert Foreland, where the correlation was between 0.5 and 0.7. The RMSE values of all products for Desert Foreland and East Coast products ranged from 1 mm to 2 mm, while the RMSE values for the other two regions were slightly greater than 2 mm. Overall, GPM-IMERG had the lowest error rate of all the products in most of the regions. As a result, GPM-IMERG and CMORPH are deemed to be superior in terms of correlation and prediction errors. CHIRPS showed the highest POD values, followed by IMERG and CMORPH, while PERSIANN-CDR demonstrated the least POD values. Similarly, *CSI* values for all the stations was between 0.4 and 0.6, except the PERSIANN-CDR, which showed much smaller *CSI* values (less than 0.2 for most stations). The False Alarm Ratio was the least for CHIRPS and similar for the other three products.

The analysis of extreme precipitation indices revealed that GPM-IMERG was better in capturing the Rx1 day, R10 mm, and R20 mm, while it over-estimated the extreme index of R30 mm. In terms of consecutive wet days (CWD), CHIRPS provided similar results with the gauge data, while the PERSIANN-CDR over-estimated the CWD. For almost all the five indices, CMORPH was over-estimating rainfall as compared to the gauge data. The results for the precipitation variability and concentration revealed that both IMERG and

CHIRPS performed better than the other products in displaying the spatial evenness of the rainfall and the temporal variation.

Previous studies did not discuss at length the post-processing of a satellite-based data set. The focus remained on their accuracy based on spatial and temporal resolution. However, each product is unique in terms of the techniques and processes used for post-processing. Although the CHIRPS product has the finest spatial resolution and CMORPH produces half-hourly estimates, IMERG demonstrated promising ability, especially in analyzing the rainfall evenness and precipitation concentration variation. Therefore, it is suggested that the studies focusing on satellite precipitation products should thoroughly investigate their applicability to various hydro-climatological measures in addition to finding their correlation, error measures, and overall trend.

The finer temporal and spatial resolution of the remote sensing satellite products can augment the ground observations for various hydro-climatological studies. One of the major limitations of satellite products is the availability of a limited temporal domain. Detailed statistical analysis should be carried out when longer records are available for these products. The overall applicability of these products is promising for arid regions, apart from the apparent over-estimation, especially for low rainfalls. The results of the study can be utilized to perform hydro-climatological forecasts and develop sustainable policies which were otherwise limited due to the unavailability of dense rain gauge stations in dry and regions. The future aspects of this study are to minimize the bias from satellite products by incorporating information from various climatic parameters, such as temperature and humidity, and to develop a consistent, grid-based, and long-term rainfall database for the study area.

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Data Availability Statement: The satellite data used in the research were obtained from the respective websites of the satellite products, which is publicly available. The rain gauge observations were obtained from the National Center of Meteorology (NCM) of the UAE and cannot be provided publicly.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Station-based rainfall statistics based on total monthly rainfall values for the study area for the selected time period (2011–2020).

Stations	Mean	SE Mean	StDev	Var	CoefVar	Min	Q1	Median	Q3	Max	Range	IQR	Skewness	Kurtosis
Abu Al Abyad	48.2	18.4	63.7	4061.7	132.13	0.0	0.0	20.6	89.6	194.6	194.6	89.6	1.33	1.09
Abu Al Bukhoosh	52.9	20.1	69.6	4838.6	131.37	0.0	0.0	12.8	127.7	187.0	187.0	127.7	1.00	−0.59
Abu Dhabi	56.9	22.5	77.9	6064.5	136.79	0.0	0.0	19.5	121.9	216.8	216.8	121.9	1.23	0.13
Al Ain	62.5	24.2	83.7	7012.0	133.89	1.8	16.1	22.4	91.5	255.4	253.6	75.4	1.75	1.88
Al Aryam	27.8	12.1	42.0	1761.6	150.84	0.0	0.0	7.9	48.4	126.8	126.8	48.4	1.63	1.83
Al Faqa	140.4	33.7	116.8	13,631.3	83.14	25.0	41.0	101.9	237.0	354.0	329.0	196.1	0.92	−0.47
Al Jazeera B.G	30.7	11.1	38.4	1473.1	125.15	0.0	7.5	18.8	31.6	133.8	133.8	24.1	2.14	4.69
Al Malaiha	86.0	24.7	85.5	7304.7	99.33	8.8	25.4	52.9	140.4	283.3	274.5	115.1	1.37	1.22
Al Qattara	36.0	12.4	43.0	1846.3	119.25	1.8	8.8	23.8	34.4	143.5	141.7	25.5	1.95	3.22
Al Shiweb	125.3	49.4	171.0	29,254.2	136.55	5.1	17.8	42.0	179.6	569.2	564.1	161.8	1.94	3.62
Alarad	89.6	30.0	104.0	10,808.2	115.99	8.6	17.6	57.0	97.4	305.0	296.4	79.8	1.66	1.65
Alfoah	115.6	45.1	156.1	24,355.3	135.01	0.0	12.2	57.2	163.8	491.3	491.3	151.6	1.78	2.37
Al Ghweifat	57.7	16.4	56.9	3232.8	98.53	0.0	62.0	62.0	105.9	161.7	161.7	105.9	0.35	−1.14
Al Khazna	80.1	35.5	122.8	15,091.9	153.31	0.0	1.1	29.9	137.2	410.8	410.8	136.1	2.06	4.53
Alqlaa	51.1	16.1	55.9	3126.6	109.37	3.8	12.5	16.1	110.3	165.1	161.3	97.8	1.05	−0.33
Alquaa	71.0	21.6	75.0	5619.8	105.56	5.4	13.5	25.8	133.0	210.8	205.4	119.5	0.86	−0.83
Al Wathbah	60.5	23.4	81.2	6588.9	134.15	0.0	0.0	30.9	93.8	253.4	253.4	93.8	1.60	1.94
Al Tawiyen	39.2	15.7	54.4	2958.7	138.79	0.0	3.5	18.9	45.5	162.6	162.6	42.1	1.77	2.05
Bu Hamrah	56.9	21.8	75.4	5682.7	132.58	0.0	0.0	23.5	121.5	226.4	226.4	121.5	1.27	0.78
Das Island	53.7	26.3	91.2	8321.7	169.82	0.0	2.6	20.0	34.3	253.0	253.0	31.7	1.97	2.44
Damsa	38.4	16.8	58.3	3399.5	151.67	0.0	0.0	14.2	50.8	166.9	166.9	50.8	1.66	1.66
Dhudna	135.3	48.5	168.0	28,233.6	124.18	0.0	0.4	59.7	294.7	495.1	495.1	294.3	1.24	0.35
Falaj Al Moalla	117.6	39.0	135.3	18,293.0	114.98	0.0	1.7	93.4	180.1	394.8	394.8	178.4	1.20	0.51
Hamim	52.2	16.9	58.5	3426.1	112.17	0.0	1.0	27.1	96.5	173.0	173.0	95.6	0.98	−0.11
Hatta	92.0	27.8	96.2	9263.5	104.58	1.1	8.2	49.3	175.3	293.2	292.1	167.0	0.88	−0.25
Jabal Hafeet	85.5	21.1	73.2	5354.6	85.62	2.1	27.4	63.2	137.2	248.1	246.0	109.9	1.03	0.62
Jabal Jais	153.7	52.5	182.0	33,105.9	118.40	0.0	0.9	112.8	228.3	526.4	526.4	227.4	0.98	0.02
Jabal Mebreh	84.9	35.0	121.2	14,683.4	142.67	0.0	1.2	24.2	165.2	376.5	376.5	164.0	1.52	1.80
Khatam Al Shaklah	149.3	47.9	166.0	27,564.8	111.18	0.0	24.1	94.9	225.1	551.0	551.0	201.0	1.52	2.08
Madinat Zayed	46.3	17.0	58.9	3467.6	127.19	0.0	1.6	27.0	76.8	191.2	191.2	75.1	1.58	2.34
Manama	44.0	14.5	50.1	2512.2	113.87	0.0	0.0	26.1	90.0	123.1	123.1	90.0	0.55	−1.42
Makassib	72.7	21.5	74.3	5525.2	102.30	8.5	21.6	41.8	130.5	248.9	240.4	108.9	1.49	1.61
Masafi	97.4	31.1	107.7	11,603.8	110.57	1.5	15.6	39.8	206.9	295.0	293.5	191.3	1.00	−0.67
Mezaira	54.5	13.1	45.4	2061.9	83.36	0.6	15.8	49.2	70.6	157.1	156.5	54.8	1.01	1.20
Mezyed	107.3	23.3	80.6	6494.7	75.10	13.6	47.2	95.9	135.1	301.2	287.6	87.9	1.28	1.98
Mukhariz	75.3	20.3	70.5	4965.9	93.56	19.8	26.1	43.4	91.7	262.5	242.7	65.6	1.98	4.21
Mwtaid	62.2	18.7	64.7	4181.5	103.93	0.1	10.4	54.4	88.6	237.1	237.0	78.2	1.89	4.80
Qarnen	41.5	15.7	54.3	2948.6	130.82	0.0	0.0	16.8	80.0	153.6	153.6	80.0	1.16	0.16
Raknah	91.4	32.5	112.6	12,673.4	123.22	1.5	9.4	46.3	200.6	315.5	314.0	191.3	1.24	−0.06
Ras Ghanadah	58.3	21.7	75.1	5635.9	128.75	0.0	19.3	10.2	102.2	213.2	213.2	102.2	1.11	0.12
Ras Musherib	25.19	8.95	31.02	962.07	123.13	0.00	0.00	8.85	47.90	96.30	96.30	47.90	1.22	0.92
Rowdah	72.6	29.8	103.3	10,663.2	142.17	6.4	17.6	30.0	74.2	327.2	320.8	56.7	2.02	3.11
Saih Al Salem	66.1	24.8	85.9	7379.2	130.04	0.0	2.3	42.7	93.9	286.4	286.4	91.6	1.80	3.33
Sir Bani Yas	46.4	14.9	51.7	2674.6	111.36	0.0	0.1	22.3	108.3	116.8	116.8	108.2	0.42	−1.93

Table A1. Cont.

Stations	Mean	SE Mean	StDev	Var	CoefVar	Min	Q1	Median	Q3	Max	Range	IQR	Skewness	Kurtosis
Sir Bu Nair	45.3	16.7	58.0	3366.4	128.01	0.0	0.0	7.0	104.4	143.5	143.5	104.4	0.79	−1.21
Swiehan	92.1	32.7	113.2	12,823.3	123.01	1.0	13.0	29.4	131.5	345.4	344.4	118.6	1.51	1.35
Um Azimul	38.4	11.1	38.5	1483.8	100.40	0.0	0.5	33.7	69.5	112.2	112.2	69.0	0.69	−0.63
Um Ghafa	57.3	17.6	60.9	3711.3	106.38	1.7	8.4	33.3	104.8	168.1	166.4	96.4	1.01	−0.37
Umm Al Quwain	65.9	23.3	80.8	6522.8	122.49	0.0	2.3	22.7	140.6	231.4	231.4	138.3	0.99	−0.32
Yasat	37.8	13.8	47.7	2271.7	126.23	0.0	0.0	19.1	73.7	134.9	134.9	73.7	1.04	−0.07

Appendix B

Table A2. Station-based rainfall statistics based on total annual rainfall values for the study area for the selected time period (2011–020).

Stations	Mean	StDev	Var	CoefVar	Min	Q1	Med	Q3	Max	Range	IQR	Skewness	Kurtosis
Abu Al Abyad	34.04	37.28	1389.91	109.54	0.00	2.80	19.40	64.75	126.40	126.40	61.95	1.08	0.56
Abu Al Bukhoosh	37.3	42.4	1794.2	113.44	0.0	3.2	13.6	71.4	146.2	146.2	68.2	1.24	1.10
Abu Dhabi	39.9	44.6	1985.0	111.70	0.0	6.0	21.0	69.9	157.6	157.6	63.9	1.46	1.68
Al Ain	44.1	54.4	2960.9	123.31	0.0	1.7	30.2	62.5	194.6	194.6	60.8	1.84	3.25
Al Aryam	19.58	24.77	613.47	126.52	0.00	0.30	7.80	42.60	65.80	65.80	42.30	1.01	−0.63
Al Faqa	98.5	69.7	4863.6	70.81	0.4	41.3	96.7	169.0	222.6	222.2	127.7	0.51	−1.04
Al Jazeera B.G	21.64	23.73	563.18	109.66	0.00	0.00	12.60	41.05	77.80	77.80	41.05	0.94	0.13
Al Malaiha	60.2	56.0	3137.9	93.09	0.0	16.5	42.8	103.9	203.8	203.8	87.4	1.27	1.20
Al Qattara	24.84	37.78	1426.96	152.07	0.00	0.30	6.60	38.40	136.40	136.40	38.10	2.02	4.13
Al Shiweb	88.0	85.1	7236.0	96.61	0.2	25.9	60.8	134.3	327.2	327.0	108.4	1.47	2.63
Alarad	62.6	61.7	3807.6	98.54	0.0	15.9	44.6	86.1	208.9	208.9	70.2	1.55	2.00
Alfoah	81.2	76.8	5891.0	94.52	0.2	18.0	75.8	106.8	286.8	286.6	88.8	1.39	2.09
Al Gheweifat	40.7	41.4	1715.3	101.67	0.0	5.0	25.4	78.3	128.9	128.9	73.3	0.87	−0.47
Al Khazna	56.12	38.92	1514.91	69.35	0.00	22.50	50.60	88.90	134.60	134.60	66.40	0.38	−0.67
Alqlaa	35.9	52.6	2766.9	146.59	0.2	2.2	13.4	50.1	166.2	166.0	47.9	1.88	2.73
Alquaa	49.9	68.0	4628.7	136.28	0.0	2.8	22.4	67.5	223.2	223.2	64.7	1.65	1.72
Al Wathbah	42.7	42.2	1781.7	98.84	0.0	3.2	24.6	79.6	121.9	121.9	76.4	0.75	−0.85
Al Tawiyen	26.55	35.65	1270.70	134.25	0.00	1.90	17.80	39.20	139.80	139.80	37.30	2.25	5.99
Bu Hamrah	40.1	54.6	2977.0	135.95	0.4	6.8	16.2	64.2	219.8	219.4	57.4	2.47	7.26
Das Island	37.8	63.6	4041.3	168.02	0.0	0.0	9.6	54.9	238.2	238.2	54.9	2.35	5.85
Damsa	27.11	36.45	1328.84	134.48	0.00	0.00	5.40	63.30	101.00	101.00	63.30	1.08	−0.42
Dhudna	91.9	94.6	8941.6	102.93	2.0	16.1	59.8	157.5	285.3	283.3	141.4	1.06	−0.03
Falaj Al Moalla	82.5	86.1	7419.9	104.43	0.6	25.5	58.0	112.0	303.0	302.4	86.5	1.77	2.68
Hamim	35.5	43.3	1876.4	121.88	0.0	6.2	14.6	55.5	158.0	158.0	49.3	1.75	2.92
Hatta	61.2	62.2	3874.1	101.66	0.0	10.1	43.2	105.0	208.9	208.9	94.9	1.08	0.40
Jabal Hafeet	59.0	61.4	3764.5	104.00	0.0	14.3	50.4	85.1	246.0	246.0	70.8	1.95	4.70
Jabal Jais	108.4	128.5	1614.7	118.51	0.0	17.0	58.0	174.8	461.6	461.6	157.8	1.67	2.39
Jabal Mebreh	58.8	86.5	7490.6	147.29	0.0	0.2	15.2	83.1	252.2	252.2	82.9	1.53	1.06
Khatam Al Shaklah	103.7	91.5	8380.6	88.25	0.0	18.3	81.8	168.8	305.7	305.7	150.5	0.71	−0.28
Madinat Zayed	31.58	29.05	843.80	91.98	0.00	8.30	24.00	50.90	109.40	109.40	42.60	1.28	1.82
Manama	30.89	39.22	1538.44	126.96	0.00	3.45	13.00	56.45	143.80	143.80	53.00	1.77	3.16

Table A2. Cont.

Stations	Mean	StDev	Var	CoefVar	Min	Q1	Med	Q3	Max	Range	IQR	Skewness	Kurtosis
Makassib	48.8	57.1	3264.9	117.19	0.4	10.8	21.0	89.9	206.9	206.5	79.1	1.56	2.31
Masafi	68.71	38.95	1516.83	56.69	0.00	40.20	61.60	104.90	124.80	124.80	64.70	−0.45	−0.92
Mezaira	35.1	59.4	3530.8	169.12	0.0	5.4	15.4	26.6	200.8	200.8	21.2	2.42	4.88
Mezyed	74.14	36.91	1362.05	49.78	28.00	39.96	61.80	113.26	127.58	99.59	73.30	0.27	−1.62
Mukhariz	51.0	95.6	9140.6	187.62	0.0	5.6	18.6	36.4	347.0	347.0	30.8	2.63	6.33
Owtaid	42.22	38.15	1455.34	90.35	0.00	13.35	28.60	54.10	131.00	131.00	40.75	1.35	1.37
Qarnen	29.28	27.37	748.95	93.48	0.00	5.50	17.00	55.15	79.10	79.10	49.65	0.69	−0.98
Raknah	64.1	59.2	3509.7	92.47	0.0	20.8	56.4	81.3	232.2	232.2	60.5	1.51	3.08
Ras Ghanadah	41.0	53.9	2905.1	131.44	0.0	3.7	19.0	63.3	185.5	185.5	59.6	1.75	2.42
Ras Musherib	17.30	20.25	409.95	117.04	0.00	1.95	4.60	34.45	63.10	63.10	32.50	1.04	−0.15
Rowdah	51.2	61.7	3809.1	120.51	0.0	2.2	29.2	68.6	230.0	230.0	66.4	1.79	3.48
Saih Al Salem	46.4	61.9	3831.0	133.51	2.2	8.8	20.8	68.4	242.9	240.7	59.6	2.33	6.02
Sir Bani Yas	32.32	41.08	1687.58	127.09	0.00	2.35	16.60	51.50	132.80	132.80	49.15	1.47	1.24
Sir Bu Nair	31.88	32.83	1078.00	102.98	0.00	5.60	17.80	67.95	92.20	92.20	62.35	0.79	−0.95
Swiehan	64.7	55.7	3105.0	86.06	0.0	10.9	55.8	101.2	192.1	192.1	90.3	0.76	0.01
Um Azimul	26.38	28.92	836.36	109.62	0.00	4.50	14.60	57.70	84.70	84.70	53.20	1.00	−0.61
Um Ghafa	37.9	50.5	2551.6	133.18	0.0	0.7	21.0	58.3	165.5	165.5	57.6	1.64	1.94
Umm Al Quwain	46.5	49.2	2424.0	105.97	0.0	10.0	32.6	58.8	177.4	177.4	48.8	1.63	2.47
Yasat	26.64	34.97	1223.16	131.31	0.00	3.90	6.40	44.15	108.00	108.00	40.25	1.48	1.16

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